Spatial Decision Support

for

Urban Water Management

A thesis submitted to the University of London

for the degree of Doctor of Philosophy

by

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Abstract

The research presented here describes the development of a Spatial Decision Support System for Urban Water Management and its application in the particular domain of Water Demand Management. The primary hypothesis stated and discussed is that the development of decision support systems with a distinct spatial character (i.e. spatial decision support systems (SDSS)) based on soft computing can assist the decision maker within the urban environment and result in more informed decisions. The thesis investigates the use, within an integrated decisional platform, of different tools (including mathematical modelling, geographic information systems, decision support techniques, spatial analysis, fuzzy inference systems and evolutionary programming). It develops new soft computing techniques, adapts techniques that are available in other domains and combines them in an innovative way to facilitate urban water planning and management. The prototype Spatial Decision Support System developed is tested under a variety of different user inputs and assumptions and is used to discuss alternative water demand management strategies. It is concluded that the prototype developed is a flexible tool that can be adapted to the characteristics of the problem at hand while its transparent nature greatly enhances the inclusion and handling of uncertainty and risk throughout the decision making process. Although the work presented here is open to further development, improvement and testing, it is felt that it is a promising research direction and could be of great potential benefit to the decision making process within the water industry.

Keywords: *Soft Computing, Spatial Decision Support, Urban Water, Water Demand Management*

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PhD acknowledgements are notoriously political statements. Yet I would prefer this to be read with a more personal ring to it. So here goes:

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Abbreviations

AHP	Analytical Hierarchy Process
CR	Consistency Ratio
DBMS	Database Management System
DSS	Decision Support Systems
FIS	Fuzzy inference system
FMF	Fuzzy membership function
FOU	Footprint of Uncertainty
GA	Genetic Algorithms
GIS	Geographic Information Systems
GUI	Graphical User Interface
MCA	Multi-Criteria Analysis
MOGA	Multi-Objective Genetic Algorithm
OWA	Ordered Weighted Averaging
RC	Recycling
REP	Regional Environmental Planning
RMS	Root Mean Square
SDSS	Spatial Decision Support Systems
SEA	Strategic Environmental Assessment
SOGA	Single Objective Genetic Algorithm
SOWA	Spatial Ordered Weighted Averaging
SQP	Sequential Quadratic Programming
SUDS	Sustainable Urban Drainage Systems
WDM	Water Demand Management
WFD	Water Framework Directive
WLC	Weighted Liner Combination

1 Introduction

"To the red country and part of the grey country of Oklahoma, the last rains came gently and they did not cut the scarred earth...The sun flared down on the growing corn day after day until a line of brown spread along the edge of each green bayonet. The clouds appeared and went away, and in a while they did not try anymore."

John Steinberg: "The Grapes of Wrath"

1.1 Setting the scene

The uprooting of Oklahoma's poorest inhabitants due to the drought discussed in Steinberg's novel and the exploitation that awaited them in California serves only as small reminder that the bond of water availability and human society's well-being is as old as mankind itself. The construction of settlements that were later to become cities was always connected to water sources, for consumption, agriculture, transportation, commerce and, lately, industry. Water availability is a function of the climatic zone and so is, by result, water "value". In the semi-arid areas in the Middle East, empires such as the Egyptian and the Babylonian, owed their strength in the control they had over a river system. Western Europe, although not in the same position, situated its capitals on riverbanks. The Thames, the Danube, the Seine have been central to the social, financial and structural fabric of the cities they support. The situation has not changed significantly in the past 3000 years. The dependence is still there although now there are at least three factors complicating water use patterns:

- **Dependence** has become significantly higher following the Industrial Revolution shifting water demand from agriculture to industry.
- **Water quality** has emerged as a particularly intense problem due to growing environmental awareness, following the rapid post-industrial environmental degradation, particularly in Western Europe.
- **Water scarcity**, ever present in North Africa and the Middle East, has begun to make its appearance in the Western World, due to two interrelated reasons: Rapid growth of industrial and urban areas with an additional change in consumption patterns[1], and global warming (Vlachos and Braga, 2001).

[1] Consumption patterns shifts are an indicator of economic development and living standard. As the living standard rises, water consumption rises with it, in an antagonistic relationship with technological development, the latter striving for less water demanding procedures and appliances.

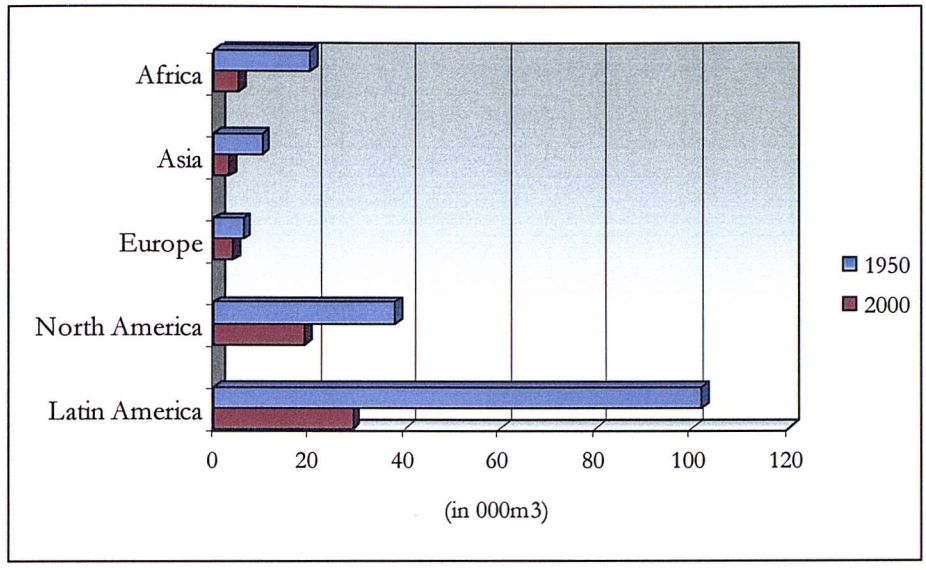


Figure 1.1 Water availability per capita (000m³)

(Source: FAO, 1996)

Figure 1.1, illustrates the trends in water availability for the past 50 years in both the developed and the developing world. Although the water cycle guarantees in principle the renewable nature of water, this is not true in all cases. Demands upon the worlds finite supply of water pose threats to both the quality and the quantity of one of the most crucial elements of social and economic activity as well as to human life itself (European Union, 2000b). Water abstraction from groundwater sources is the classic example of the classification of water as a *not-always-renewable* resource. The rate of abstraction is generally far greater than the natural recharge rate. The city of Tucson in Arizona for example, following the current abstraction rate, will exhaust its underlying aquifers in less than 100 years (Tietenberg, 1997). It is estimated (European Union, 2000b), that 230 million people live in 26 countries now classified as water-deficient (mostly in the Middle East, Mediterranean and the sub-Saharan Africa).

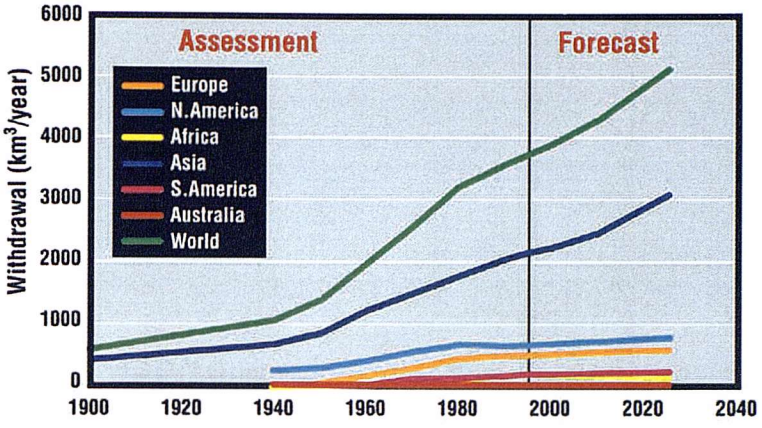


Figure 1.2 Current and estimated world water withdrawal

(UNESCO, 2000)

The figure above shows the dynamics of water use by continent for the current century and for the future up to 2025. Total global water withdrawal in 1995 was comprised of some 3750 km3/year, with actual consumption at some 2270 km3/year (= 61% of withdrawal). In the future, total water withdrawal is expected to grow by about 10-12% every ten years, and by 2025 it will reach approximately 5100 km3/year, a 1.38-fold increase (UNESCO, 2000b). At the present time, about 57% of total water withdrawal occurs in Asia where the major irrigated lands of the world are located. During the next few decades, the most intensive growth in water withdrawal is expected to occur in Africa and South America (by 1.5-1.6 times) and the smallest in Europe and North America (1.2 times).

The European Union has begun to pay significant attention to the water quality issue in the past two decades, and has recently introduced the Water Framework Directive (European Union, 2000a). The Directive which came into force as of the 22nd December 2000, emphasises the following key aims:

- Incorporating all requirements for management of water status into **one single system**
- Co-ordinating all the different **objectives** for which water is protected (ecology, drinking water, bathing water, particular habitats) and filling any gaps

- Co-ordinating all the **measures** taken on individual problems and sectors to achieve the objectives so defined, and defining the relationship between emission limit value measures and quality standards
- Increasing **public participation** in water policy to provide for greater transparency, with the advantages in enforceability that will result.

Discussion on water resources management involves most of the productive sectors from social welfare to agriculture, industry and urban development. In essence this is a textbook example of the "commons dilemma" paradigm.

The *commons dilemma*[1] describes situations where the individual and collective rationalities in determining an optimal resource use collide. A commons dilemma starts from the perspective of the resource, addressing environmental problems in terms of their behavioural causes. In a commons dilemma a collective opportunity exists for all individuals to consume. If this collective opportunity has a certain growth capacity, we may conceive it as a renewable resource. If such a resource, e.g., fresh water or natural forest, is being consumed at a rate that overshoots its natural growth, the availability of the resource will decrease. If consumption remains at a high level, the resource may even cease to exist. The risk of exhaustion is determined both by the consumption of the resource and the growth capacity of the resource. A certain limitation to the consumption of the resource is required to preserve it for a longer time, allowing its consumption to be sustainable. Many environmental issues where no property rights exist on a certain exhaustible resource can be understood as a commons dilemma. Examples are ocean fishing, waste dumping, fresh water consumption and forest management. The commons dilemma paradigm has proven to be fruitful in describing a variety of situations where individual and collective interests collide. Such conflicts between individual and collective interests have intrigued scientists since Machiavelli (1525), who addressed this issue in the context of the political consequences of social (in)equality. The dilemma is presented in the form of a story of the decline of the common pastures for herding cattle (Jager, 2000). The story is told in the following way:

[1] The discussion on the *commons dilemma* is based on (Jager, 2000)

The tragedy of the commons develops in this way. Picture a pasture open to all. It is to be expected that each herdsman will try to keep as many cattle as possible on the commons. Such an arrangement may work reasonably satisfactory for centuries because tribal wars, poaching, and disease keep the numbers of both man and beast well below the carrying capacity of the land. Finally, however, comes the day of reckoning, that is, the day when the long-desired goal of social stability becomes a reality. At this point, the inherent logic of the commons remorselessly generates tragedy. As a rational being, each herdsman seeks to maximize his gain. Explicitly or implicitly, more or less consciously, he asks "What is the utility to me of adding one more animal to my herd?" This utility has one negative and one positive component. 1) The positive component is a function of the increment of one animal. Since the herdsman receives all the proceeds from the sale of an additional animal, the positive utility is nearly +1. 2) The negative component is a function of the additional overgrazing created by one more animal. Since, however, the effects of overgrazing are shared by all the herdsmen, the negative utility for any particular for any particular decision-making herdsman is only a fraction of –1. Adding together the component particular utilities, the rational herdsman concludes that the only sensible course for him to pursue is to add another animal to his herd. And another; and another. . .. But this is the conclusion reached by each and every rational herdsman sharing a commons. Therein is the tragedy. Each man is locked into a system that compels him to increase his herd without limit – in a world that is limited. Ruin is the destination toward which all men rush, each pursuing his own best interest in a society that believes in the freedom of the commons. Freedom in a commons brings ruin to all.

The commons dilemma paradigm has been useful for understanding how people manage common resources. It has been used as a conceptual framework for understanding the processes leading towards many environmental problems, such as deforestation, over-fishing, air-pollution and freshwater abstraction. Such environmental commons dilemmas are usually quite complex because of the various personal and collective outcomes involved, the specific dynamics of the resource and uncertainty about the outcomes. A resource dilemma can be considered as a specific type of commons dilemma. Basically, the resource dilemma offers each individual the choice between harvesting now a lot at the risk of exhausting the resource, versus harvesting less so as to sustain the resource. The more people harvest a lot, the quicker the resource may get exhausted. It has to be noted however that a significant restraint in personal harvesting, which can be considered to be cooperative, may or may not yield the highest collective outcomes (Jager, 2000).

Within this framework, the aim of water management schemes, for both quantity (in view of resource depletion) and quality (in view of environmental awareness associated with target "living standards"), should be to regulate resource consumption to maximise collective outcomes. On an *urban level*, water management schemes function within a complicated social, economical and engineering environment, and should attempt to take into account, simultaneously, multiple constraints and significantly varying objectives. The same applies on a *regional level*, where water management at a river basin scale is considered to be the favourable option as it provides adequate control of the total water system balance and can – in principle – cope with the conflicting priorities and water demands through an integrated, even holistic approach (i.e. co-ordination of both objectives and measures) (e.g. Maksimovic and Makropoulos, 2002).

1.2 Urban Planning

1.2.1 Preamble

Urban planning, moving away from its classic origins of utilitarianism[1] (function over form), as well as from Murray Bookchin's anarchist views on social ecology (Bookchin, 1986) turns into diverse routes. Routes, which are effectively outside its physical realm, the effort that is of central government and local authorities, to enforce their policies of social justice and equity by redistributing the surplus value, produced by construction within the city. The degree of interventionism, through urban planning, allowed under each political system reflects the systems concepts on welfare policy, the degree of laissez-faire allowed in the economy, communication, encouragement or discouragement practices, the very essence of democratic perceptions.

Post modernity is, however, changing this. The new spatial planning concept is not so much planning as design (Leontidou, 1993). Design is the new tool for governmental intervention on cities. Modernity debated that use dictates the form. The new concept is exactly the opposite. The major constructions in Western cities (mainly capitals) are front-end constructions, show-offs. The aim is to gain what is now known as urban visibility through "urban boosterism" or simply place marketing. High capital mobility in

[1] As an isomorphism to Utilitarianism as a moral theory that claims "good" is what avoids pain and maximizes pleasure. As David Hume said: "an action or sentiment, or character is virtuous or vicious...because its view causes a pleasure or uneasiness of a particular kind". In urban planning the form is equivalent to an abstract quality (e.g. "virtue") and as such is dictated by the function (e.g. "easiness").

the post industrialist age, where economy is rapidly shifting from industry to increasingly abstract forms of production (services, tourism, travelling, web-pages[1]!), is forcing western urban centres (such as London) to engage into a race for differentiation. Standards of living, social equity, infrastructure and communication, are secondary to the effort of cities to attract attention. The Dome, the Wheel, the Millennium Footbridge, even the Docklands are striking example of the new post-modern concept of form over function. The attraction of tourists, rather than the welfare of citizens is central to the post-modern urban planning, or should we say design. Cities have to look better. They have to reinvent their uniqueness, attracting investment and tourists, which mean money (without production). The new investments – it has to be noted – are not generally beneficial for all. At least not for the ones who actually pay for the "monumental" urban "lifting": the citizens. The wealth attracted through this expensive make-up, is not distributed, but is rather concentrated into the hands of a small economic elite. The constructions themselves are of little use to the citizens as such, and can in some cases be considered against them, as they tend to move the previous owners away from their properties, to build something that is eventually not accessible to them. Olympic games constructions (Barcelona, Athens etc.) as well as the Docklands development scheme are good examples of such a practice. Fountains and old lamps in main roads are typical of this new, decorative aspect of urban planning, only to be expected under the current situation of antagonistic relationships, viewing the city as a product – or rather a commodity.

On the other side of the mirror lie the fundamental priorities for city planning that were partly described at the 1996 UN Habitat II conference, termed the City Summit. Transport and the water cycle were defined as the most critical factors determining the future of the city in the 21st century. This might very well be, but this rather technical approach fails to conceptualise the real core issues lying behind these two systems.

The aim of transport is communication. Media, social interaction, the Internet, public transport and newspapers all contribute towards communication and interaction. Urban planning rather than design can be a tool supporting local communities in their effort of bringing people closer together. Parks, public places, community used multi-purpose

[1] The recent take over of Time-Warner (an entertainment company) by AOL (an information company) is characteristic of the more and more abstract form of the economy and thus of employment.

spaces (for theatre, discussions, or exhibitions) are all elements of a communication-oriented high-quality urban environment. The use of these spaces is then up to local communities, as this communication and interaction should be based on the root-upwards evolution, rather than being introduced from top. Grotowski's para-theatre innovations and Boal's Forum are basically forms of this public participation-communication ideal. They both, implicitly, show the same thing: that planning can facilitate, but never dictate, human interaction. In contrast, the novel urban advertisement focus of planning has frequently the opposite effect. Original inhabitants, particularly in centre-city areas (which was by the end of the 80's populated by low-income groups in the Northern Capitals) are pushed away to make room for re-development plans, to act as a magnet for high-income population groups and corporate offices. Thus a paradox comes into being, where homelessness and high rental rates in cities coexist with the emptiness of a significant part of (new) buildings. The issue of communication and social interaction is in fact a measure of democracy and their promotion or demotion through central planning is a measure of the central government's commitment towards democratic practices (and the extent these practices are actually desirable by the governing elites).

1.2.2 City and Environment interactions

At a second level, a level on which this discussion focuses, are the interactions, not between citizens but rather between the city and its surrounding environment. Within this context, urban planning should focus its attention on existing urban settlements in order to minimise their questionable but unquestioned dual role in a catchment's fragile equilibrium: the role of sink for resources and source for pollution. This is by no means a trivial task, further complicated by the fact that public perception of the relevant problems does not adequately grasp the interdependencies between the urban and regional scale. The fact that when an economic activity causes damage to some environmental value, we call it "negative externality" reveals the place of the environment on the periphery of modern consciousness (Wackernagel and Rees, 1996). One must bear in mind that urban systems, apart from being social, economic and cultural "producers" are at the same time resource consuming and waste generating mechanisms. The apparent social and political implications are in fact primarily ethical, in the sense that the self-preservation mechanisms of cities make sure that their impact is not (at least directly) imported into the city, but rather exported to its surroundings,

(directly) affecting population outside the city. The scale of the "surroundings" can range from simple downstream or downwind catchments to nearby countries, as is the case, for example, with acid rain. At this point an additional problem is being imposed: population affected by the City is often not in the position of affecting its politics. This is because of an obvious distance in space (in the case of most waste generation issues) but also in time (in the case of resources utilisation) when future generations are affected – and where the "without" clause of the Brutland Committee's definition comes into place (WCED, 1987). The notion of the "ecological footprint" of a city (Wackernagel and Rees, 1996), although lacking precise physical meaning and strict scientific validation, can be invaluable as a tool for changing public perception on this subject. It reveals something that is known but never thought of in clear terms: The fact that the sheer area needed by a city to fulfil its basic needs in resources and dilute its waste is hundreds of times larger than the city itself, a phenomenon increasing from south to north and from east to west in a geopolitical sense.

The issue of city impact is fundamentally different from the communication problem at yet another level. The initiation of the process for minimising this impact cannot possibly come from the public, although altering human behaviour is a very important target, but should be conceptualised, planned, applied, monitored and promoted by central government and expert planners in order to achieve maximum impact. This is because the interconnections between the various aspects of the issues involved are so complex that they require vast amounts of information and a sound knowledge of the systems' operation to be taken into account. There is subsequently a dual minimisation problem to be solved: Minimising resources consumption and minimising waste generation.

1.2.3 Water and the City

Water should be thought of as a primary target for this minimisation process for a number of reasons: (a) Although it is in principle a renewable resource, this ability of renewal depends on the timescale of the water cycle's observation, making a number of water reserves (such a groundwater) almost non-renewable for all practical purposes. (b) The practice of using water as a pollution carrier is conceptually subject to the second law of thermodynamics, entropy being indirectly but quite explicitly indicated by the degree of disorder caused in an ordered system (clean water) when suspended and diluted pollutants are introduced to it (Thomas *et al.*, 2000). The energy (and cost) needed to

restore the system to its former ordered state (by means of wastewater treatment) is all but conceptual. (c) Climate change is expected to result in disturbances in the water cycle, which clearly suggest a change in paradigm in our current water consuming and polluting practices (IPCC 2001).

The two main inputs of water into the urban environment are water supply and rainfall. Strategies of minimising fresh water demand for public as well as private use within the city in the form of Water Demand Management (WDM) will result in minimising water resource consumption, thus attaining the first goal. The same strategies coupled with minimising rainfall-runoff entering the drainage system (Sustainable Urban Drainage Systems (SUDS)) should result in less wastewater generation, improving treatment costs and attaining the second goal. Waste minimisation by itself, however useful, should be also coupled with the effect of these minimisation strategies on waste water quality: either directly (through the purification capabilities of methods used for minimisation e.g. grass swales in rainfall runoff source control, gully pots viewed as reactors (Memon, 2000)) or indirectly (through the effect the minimised and more concentrated waste water volumes will have in treatment plants from an engineering and a cost effectiveness point of view). An extended discussion on WDM is included later in this chapter.

The identification, application and quantification of the effect of urban water management strategies is of a highly spatial nature (Larsen and Gujer, 1997; Seder *et al.*, 2000). Each location within the city boundaries has its own properties and its own set of constraints (social, economic and engineering). The decision maker in urban areas asks for higher quality of information including intelligent decision support for time and investment-critical planning.

Taking into account these site-specific characteristics rather than drawing a black box around the cities is more realistic and therefore has more chances of actually being applied. The environmental administration in the urban environment is thus in need of tools that would be able to address the following issues (Seder *et al.*, 2000):

- Integrate and coordinate information on a domain-oriented scale
- Support analysis, observation, valuation and forecast of environmental objects and their conditions

- Support decisions as a balance between economic and ecological objectives based on expert knowledge
- Use an information system which is natural to the user and which offers transparency without requiring knowledge of some computer language.

The stated requirements imply that the tools (or decision support systems) should in principle integrate knowledge and reasoning as an essential part of the system's functionality while dealing with the inherent ambiguities and uncertainties of any reasoning/decision making process.

In this research we will be dealing with a specific type of urban water management problem: the *object location problem*, which is defined in this work as the determination of optimum locations for facilities in a given geographical area with respect to environmental and economic objectives. The importance of this type of problems within the Urban Water Management environment will be discussed through specific applications in Water Demand Management. Solving an object location problem within the urban environment is a complex problem, usually semi-structured, which requires taking into account multiple objectives as well as value judgement by experts (Seder *et al.*, 2000). This is a demanding decision-making environment, where optimal planning presupposes a synthesis of heterogeneous information of high spatial resolution to ensure site-specific implementation (Makropoulos *et al.*, 2003).

The primary hypothesis of this research is therefore that the development of decision support systems with a distinct spatial character (i.e. spatial decision support systems (SDSS)) based on soft computing will assist the decision maker in this task by meeting all the above stated requirements.

1.3 Aims and objectives

In view of the fore-stated hypothesis, the aim of the research undertaken here is to: (a) investigate the use, within an integrated decisional platform, of different tools (including mathematical modelling, geographic information systems, decision support techniques, spatial analysis, fuzzy inference systems and evolutionary programming) to facilitate

environmental planning on an urban scale[1], (b) develop a framework for coordinating these tools (i.e. a prototype Spatial Decision Support System), (c) investigate the use of soft computing in general and fuzzy logic in particular within this framework as a means to include and process heterogeneous information (from engineering data to public perception data) and quantify the corresponding decisional uncertainty, (d) identify the extent to which a SDSS can be applied to complex urban water planning and management problems and assist in reaching informed decisions (e) identify future research objectives for use of SDSS within integrated, sustainable urban water management.

It is the author's intention to present this discussion in a comprehensive, self-contained manner with sufficient conceptual, theoretical, mathematical and technical depth; to the extent this is possible due the obvious limitations of a PhD thesis in time, size and scope.

1.4 Introducing the main concepts: a literature review

1.4.1 Decision support systems: the framework

The core concept of decision support systems (DSS) was introduced in 1960 by Herbert Simon (Simon, 1960), with his work on *structured* versus *unstructured* systems. According to Simon (who received the Nobel Prize for Economics in 1978 for his work on decision support), every problem falls within the continuum ranging from completely structured to unstructured decision problems. In the case of structured problems, the decision maker knows all relevant information on the system and its rules in advance. The solution to the problem is then scaled-down to a series of programmed tasks, which can be essentially solved by a computer program (Malczewski, 1999). In contrast, ill-defined problems, with no programmable/repetitive solution are termed unstructured. The experience of the decision maker is the key factor determining the solution process of the problem. Computers can be of no significant help to this type of problem. In real life situations, however, problems are seldom within the domain of these two extremes. The intermediate type of problem is defined as *semi-structured* (Harris and Batty, 1992; Hopkins, 1984; Malczewski, 1999). This is the domain of application of *decision support systems*. Densham (1991) quotes Geoffrion's (1983) definition of Decision Support Systems suggesting that DSS has six characteristics: 1) explicit design to solve ill-structured or semi-structured problems; 2) powerful and easy-to-use user interface;

[1] Within the concept of *hydroinformatics* as advocated, for example, in Savic and Walters (1999).

3) ability to flexibly combine analytical models with data; 4) ability to explore the solution space by building alternatives; 5) capability of supporting a variety of decision-making styles; and 6) allowing interactive and recursive problem-solving. These characteristics are accepted in the framework of this research, bearing in mind that the problems addressed here are semi-structured rather than ill-structured in that both actual data processing and decision maker's expertise are needed to solve them. Modelling for decision support, or model based decision support systems for environmental and resource management problems have been discussed and advocated for some time (Fedra, 1996; Jamieson and Fedra, 1996; Krysanova *et al.*, 1998). Success stories of actual use in the public debate and policy-making process are somewhat rarer, in particular at the societal rather than commercial end of the spectrum of possible applications.

When the character of the problem is highly spatial, DSS give rise to the **spatial DSS**. These systems can thus be considered a subset of the broader set of decision support systems. Densham (1991), states the additional capabilities and functions of spatial decision support systems, which need to:

- Provide mechanisms for the input of spatial data
- Allow representation of the spatial relations and structures
- Include the analytical techniques of spatial and geographical analysis
- Provide output in a variety of spatial forms, including maps.

Spatial decision support systems have been covered in the literature in the last decade (Craig and Moyer, 1991, Densham, 1991, Moon, 1992, NCGIA, 1992). The need for using such systems comes from situations in which complex spatial problems are semi-structured and decision makers cannot define their problem or fully articulate their objectives (Leung, 1997). The decision making process adopted to solve semi-structured spatial problems is often perceived as unsatisfactory by decision makers. What they really need is a flexible, problem-solving environment in which the problem can be explored (through modelling techniques and development scenarios), understood and redefined, trade-offs between conflicting objectives investigated and priority actions set.

The structure of a typical SDSS includes three generic components: (a) a database management system (DBMS) together with a spatial database, (b) a model-based management system (MBMS) together with a model base and (c) a user interface and

dialogue/scenario generation system. This third part should be able to provide intelligent control over the utilisation of spatial information, declarative[1] and procedural[2] knowledge (Leung, 1997).

Applications range from water resources planning and management to habitat restoration to site-selection and regional risk management. To name a few indicative examples, Negahban *et al.*, 1995 describe a regional planning SDSS for managing agricultural practices to solve an eutrophication problem in a number of lakes. Mailhot *et al.*, (1997) as well as Krysanova *et al.*, (1997), developed models, which although not explicitly stated as SDSS, include all the aspects of an SDSS to deal with surface water quality management. Bender and Simonovic (1995; 1996) developed a system for sustainable collaborative water resource planning at the University of Manitoba in Canada. Carver and Openshaw (1992) developed an Internet based system for site-selection of radioactive waste disposal in the UK, Gheorghe *et al.*, (2000) developed an SDSS framework and application for regional risk assessment and safety management including various models and decisions support techniques (i.e. multi-criteria ranking), while Seder *et al* (2000), developed the IDEA SDSS to support decision-making in the urban environment including a knowledge-base with IF-THEN rules. Within the same general concept of integrating GIS, soft computing, heuristics and modelling lie also, for example, the GANET work of Atkinson *et al.* (1998), in the Water System's Group at the University of Exeter for water network analysis, as well as the work by Tarantilis and Kiranoudis (2002) on vehicle routing.

The use of the term SDSS in the context of the above-mentioned examples is quite diverse and although the main concepts and elements of the system (as identified previously) are there, the details of the system's structure, process and uses are completely different. In view of the recent emergence of both the terms used and the associated field this cannot be considered an inconsistency, but rather an indication of the ongoing efforts to evolve these systems and the notions of integrated planning that go with them. For an overview of systems and techniques for SDSS development the reader is referred to Leung (1997).

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[1] Human experience, valuation, intuition and expertise cannot often be captured by rigid procedures. They are *declarative* in nature and can only be represented by logic (e.g. IF-THEN type of inference procedures).

[2] Precise problem structures and clear cause-and-effect relationships enable deterministic procedures to human reasoning. This is termed *procedural* knowledge (Leung, 1997).

The very development of the area and scope of application of SDSS has brought about considerable discussion. Cooke (in Goodchild and Densham, 1990) questions the desirability or the near-term possibility of creating a general SDSS while Anselin (in Goodchild and Densham, 1990) advances, as a research priority, the development of "spatial" models of decision making for a range of different decision situations, e.g. single decision maker, multiple decision makers with common goals, conflicting interest groups, etc. He even questions the need for such spatial models rather than just applying known techniques like Analytical Hierarchy Process (AHP) to spatial decision situations. Other experts are more optimistic about the possibilities for developing SDSS by loose or tight coupling of GIS tools with tools for modelling, simulation, statistical analysis, image processing, temporal and volumetric visualization and expert reasoning (Davidson, 1992). Davidson outlines strategies for implementing "open-systems" frameworks in which application-specific tools may be configured into a scalable, extensible and inter-operable application environment.

Further to the subject of applications and possibilities of development, the discussion on SDSS has also included the actual efficiency of these systems as decision support tools. Crossland *et al.* (1995), has conducted series of laboratory experiments to investigate the effects on decision maker performance of using geographic information system technology, such as SDSS. In that study, which was based on image theory[1], the (volunteer) subjects' performance was operationalised as elapsed time and accuracy. The study found unequivocal evidence that addition of GIS technology to the decision environment for a spatially referenced decision task reduced the decision time and increased the accuracy of individual decision makers (Crossland *et al.*, 1995), due to, mainly, providing a better understanding of the task to be solved. The reverse design process has been adopted by Pettit and Pullar (1999), proposing a decision support system for urban planning applications, based on customising the interface for particular user groups. This is achieved by surveys among the users to identify the way the expert user reaches decisions without a decision support system and then customise the system to support this process.

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1 Image theory discusses, for example, problem solving with and without visualization (e.g. Abarbanel, 1993) or the use and function of the semiology of graphics to the decision maker (e.g. Bertin, 1983).

A discussion of issues arising from and associated with the development and operation of SDSS is also included in the Chapter 2, as this concept is central to the work presented is this thesis.

1.4.2 Fuzzy Logic: the computational tool

This research argues that the concept of taking into account political, economic and social interactions, within the engineering framework, allows for a better (more pragmatic) formulation of water management and conservation scenarios. The reason behind the choice of fuzzy logic for this analysis is that it provides a rigorous mathematical framework for including diverse input elements and information (from water distribution system characteristics and soil properties to economic and census data) throughout the modelling and decision analysis process. This ability greatly improves the integrated nature of the decision support system and its combination with GIS creates a powerful, spatially sensitive, tool for urban and regional environmental planning. Fuzzy inference is currently well established as a tool for representing procedural knowledge (Leung, 1997) as well as for handling uncertainty and ambiguity inherent in human reasoning. This is the reason why it is thought of as a primary tool in developing "intelligence" modules in an SDSS as discussed above.

A brief discussion of recent research on the subject is now presented to provide the background for this choice.

Complexity, naturally occurring in real life, is transformed into uncertainty when building an abstraction of the real world: a model. If a system is fairly simple, and therefore little uncertainty is inherent in the associated model, closed form mathematical expressions can be used to provide insight to the way the system functions. For more complex systems for which significant data exist, model-free methods (such as neural networks) provide a methodology for dealing with uncertainty through learning based on patterns in available data (Ross, 1995). Finally, for more complex systems where scarce data exist and where only ambiguous or imprecise information is available (which is generally the case in environmental planning), fuzzy logic provides a framework for handling and formally expressing this uncertainty, assisting the understanding of the system's functions. The imprecision therefore in fuzzy systems is generally high. It is thus evident that the successful application of fuzzy logic, apart from the knowledge of the theory

involved, is dependent on the correct identification of the type of uncertainty involved in the system's structure. Despic and Simonovic (1997), identify two basic forms of uncertainty in environmental modelling. Uncertainty caused by inherent stochastic variability and uncertainty due to fundamental lack of knowledge (including, but not restricted, to model structure, model parameters and data reliability). Intuitively, the second form can be more readily modelled by fuzzy sets, particularly if there is need for quantification of qualitative criteria and synthesis of non-homogeneous information (technical, economical, political etc), where lack of knowledge of the model structure and properties is coupled with scarce available data. This is in agreement with Despic and Simonovic (1997), who argue that it is primarily the data sufficiency that determines the appropriate way of modelling.

Environmental modelling and management theory includes a growing number of applications accepting fuzzy logic as a formal method of incorporating uncertainty into the decision making process. Sorbal *et al.*, (1981) illustrate a fuzzy methodology in the comparison of alternative solutions to solid waste disposal, Wenger and Rong (1987) illustrate two fuzzy methods to identify priority watersheds in Wisconsin, US, while Smith (1994), discusses the use of fuzzy sets in assessing four alternative routes for a proposed transport corridor in Australia. Ahamed *et al* (2000a) present a GIS application of fuzzy logic for land suitability analysis and the same authors (Ahamed *et al.*, 2000b), apply fuzzy logic to soil erosion modelling. Davis and Keller (1997), model uncertainty in natural resources using fuzzy sets and predict slope stability and Bender and Simonovic (1996) develop a fuzzy compromise programming technique and apply it in water resources planning and management in Canada.

Mathematical paradigms have been very slow in realizing that one of the most important ways of conveying information and therefore knowledge is natural language (Ross, 1995). Despite its inherent ambiguities, people speaking in the same language have very few problems in conveying their thoughts and inferring consequents from antecedents. This is actually the only way to teach and therefore communicate experiences, rules and accumulated knowledge. It is also the only way people arrive at decisions in everyday life, from the simpler to the more complex ones and therefore the uncertainty involved in these decisions due to the imprecise nature of linguistic variables or linguistic rules is something *de facto* acceptable in everyday human practice (Makropoulos and Butler (*in*

press- a)). Fuzzy logic provides a formal mathematical framework for expressing linguistic variables and rules and in that context it should be clear that it would also inherit the same ambiguity and impression, which follows human reasoning and therefore decision making in everyday life. This fact should not be considered a drawback but rather an intuitively familiar and thus acceptable fact.

Systems that use IF-THEN rules to represent human knowledge within a fuzzy logic framework are called Fuzzy Inference Systems (FIS) (Mendel, 2001) and they will be extensively used in our decision support system structure. Two fundamental characteristics of environmental planning, account for this fact: *Data scarcity* and the need to make decisions taking into account, simultaneously, *complex quantitative and qualitative criteria.* The situation is, not surprisingly, very similar to everyday, informal, decision making, which thus lends itself to soft-computing modeling framework simulating human reasoning.

As Lotfi Zadeh (the founder of Fuzzy Logic) puts it (MathWorks, 2000):

Fuzzy logic, neurocomputing, and genetic algorithms may be viewed as the principal constituents of what might be called soft computing. Unlike the traditional, hard computing, soft computing is aimed at an accommodation with the pervasive imprecision of the real world. The guiding principle of soft computing is: Exploit the tolerance for imprecision, uncertainty, and partial truth to achieve tractability, robustness, and low solution cost. In coming years, soft computing is likely to play an increasingly important role in the conception and design of systems whose MIQ (Machine IQ) is much higher than that of systems designed by conventional methods.

The need to provide a structured representation of knowledge so that processing elements can correspond to meaningful concepts and inference can be traced and explained, together with the data scarce nature of the problems addressed led to the exclusion of neural networks as a viable alternative to fuzzy logic as an inference procedure in this particular work (in accordance to Leung, (1997)). A more extensive discussion on the principles of fuzzy logic, neural networks and evolutionary programming is included in following chapters to the extent that these concepts were used in the development of the thesis.

1.5 Proposed decision support system framework

This research focuses on urban water management and in particular *water demand management* (WDM) as a means to achieve more sustainable terms for the symbiosis between the city and it's surrounding region.

1.5.1 Water Demand Management

1.5.1.1 The concept

Contrary to the predominant approach to water resources development - focusing on developing new supplies and structures to manipulate available supplies - demand management (WDM) focuses at the other end of the pipe aiming to meet water needs perceived as *requirements* to be met rather than *demands* that are changeable. While not dismissing traditional approaches it relies on water conservation techniques, reduction of unaccounted for water and reuse (Makropoulos and Butler (*in press-b*)).

Recent discussions on water scarcity issues under the prism of mega-cities' development (Baumann and Boland, 1998; Water Policy, 2001) identified WDM as a key intervention method. It was estimated that WDM has the potential to make available the same volume of water as a new supply side intervention for less than 30% of the direct cost. Water demand management measures have the added dimension of cost reduction by avoiding costs from not having to build extended water and wastewater treatment capacity.

1.5.1.2 Tools for WDM

The different types of tools available for WDM can be subdivided into four main categories: technical measures, financial implementation incentives, legal instruments and institutional arrangements (Mohamed and Savenije, 2000). The research presented here aims to provide support for the first category by discussing a prototype spatial decision support system (SDSS) developed to assist the optimal planning of technical measures from a water saving and an economic perspective.

It is noted, however, that in the broader sense of water demand management, additional tools (such as financial implementation incentives, legal instruments and institutional arrangements) can – interchangeably- play a significant role in the overall formation of a water demand management strategy. From the point of view of planning water demand management, these four categories can be grouped differently to allow for a qualitative

evaluation of available options. Mohamed and Savenije (2000), propose the categorisation of these options into three:

- Positive incentives
- Negative incentives
- Water-quota regulations

They propose the evaluation of these options through a number of criteria including economic efficiency, effectiveness (i.e. technical and political "implementability") and cost recovery. In general, the four main categories of measures (technical measures, financial implementation incentives, legal instruments and institutional arrangements) can be implemented through positive or negative incentives and quota regulations. For example, a technical measure such as a grey water recycling scheme can be implemented by the government through: (a) positive incentives e.g. subsidizing the market price of a grey water recycling scheme, (b) negative incentives e.g. introducing volumetric water pricing therefore forcing the users to buy water reducing devices or (c) through quota regulations e.g. when government decreases the water-quota through command-and-control type of measures. The difference in the net benefit to society (i.e. the economic efficiency) can be negligible, but for effectiveness, positive incentives might be more advantageous, while for cost recovery, negative incentives would probably be needed (Mohamed and Savenije, 2000).

As mentioned above, economic efficiency is a key term for the evaluation of water demand management projects. It is important at this point to distinguish economic efficiency from a term that is widely used for project evaluation in general: financial feasibility. Financial feasibility does not internalise non-financial costs (e.g. pollution costs, public health or recreational amenity). It implies cost recovery as well as profit making and is generally used for assessing projects rather than policies. Economic efficiency on the other hand, used primarily for evaluating policies, implies a Pareto optimality thus internalising non-financial costs and benefits. It is assessed for the production, distribution and use of natural resources rather than capital and does not necessarily imply cost recovery[1]. The following diagram (Figure 1.3) illustrates this point.

[1] Cost recovery is implied only if the only method used is negative incentives (i.e. pricing measures) and not positive incentives or quota regulations.

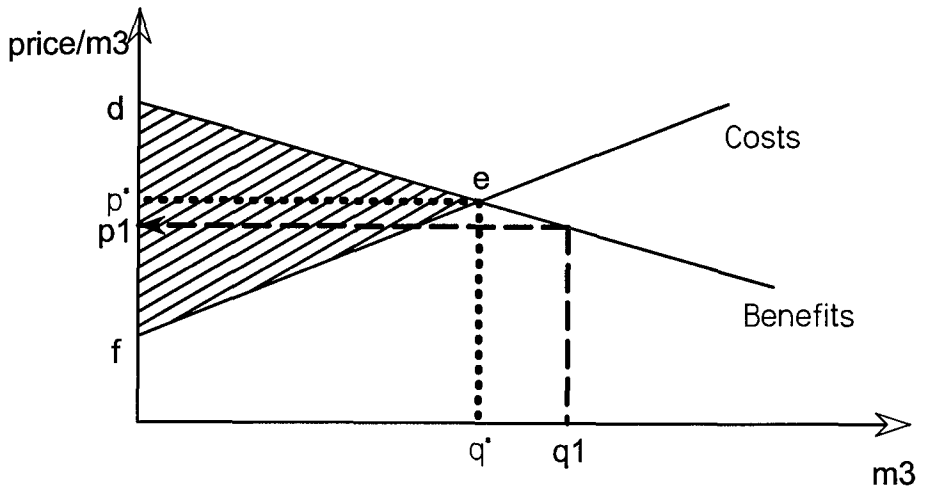


Figure 1.3. Economic Efficiency

The consumer and producer surplus equals the shaded area (d-e-f), which is an indicator of net socio-economic benefit. It can be maximised using, for example, quota regulations fixing consumption at q^*. Cost recovery can be attained only if the price per m^3 for consumption q^* is p^*.

In short, positive incentives, negative incentives and quota regulations are alternatives to each other and can be used interchangeably according to the situation at hand. For instance, if the users' exhibit a rigid elasticity towards water consumption even after the introduction of positive or negative incentives (i.e. when their income allows them to ignore financial measures) command and control might be the only viable alternative. This does not mean that negative incentives in this particular situation are not applicable: their introduction on low-elasticity users may enable the income in subsidising water-saving technologies to be used for low-income users thus achieving higher efficiency. It must be stressed however that efficiency should not result in depriving even one user of his/her basic water needs as the aim is to maximise the net benefit to society. This implies that basic needs and public health requirements should be given an infinite benefit value in the demand curves of water.

1.5.1.3 WDM in this SDSS

Three water demand management strategies (typical of western European countries) were considered by way of an example (Foxon *et al.*, 2000; BSRIA, 2001): *Leakage reduction*, *water consumption metering* and *water recycling*, including grey water recycling,

rainwater recycling and combined grey water and rain water recycling systems. All three strategies examined here have the advantage of presenting low entropy solutions to water demand management, in the sense that they minimise the use of high quality water, thus water with low incorporated disorder (in this case, disorder is represented by pollution in the form of solutes or particles in suspension). A discussion on the possibilities of the entropy-water utility paradigm in water management can be found in Thomas *et al.* (2000). Furthermore, systems for rain water collection and use can be considered as a type of "sustainable urban drainage systems" (SUDS) (CIRIA, 1999) or more generally "source control" (Urbonas and Stahre, 1993) or urban drainage "best management practices" (BMPs) (Jefferies *et al.*, 1999) and have a role to play in reducing urban flood risk (Makropoulos et al., 2001a ; 2001b).

These strategies can be thought of as examples of all three options available while planning WDM (i.e. positive incentives, negative incentives and quota regulations):

Leakage reduction is a strategy internal to the water provider and can be employed at no additional burden to the consumer allowing industry to reach water saving targets without interacting with their consumers. Consumer water consumption rates remain unaltered, but the water needed to cover this consumption is reduced. An added effect of reducing leakage (and main bursts) is the fact that this practice significantly reduces the risk of urban flooding caused by main bursts (Cooper *et al.*, 2000). The way this strategy is supported by our SDSS is by providing a master plan for *pipe replacement prioritisation* based on the characteristics of the pipes and their location as well as the risk associated with urban flooding due to pipe bursts.

Compulsory metering introduction is a negative incentive type of strategy, which enables the volumetric pricing of water. As such, it can either serve as a drive for reductions in water use or increase the income of the water provider (in cases of low-elasticity users) enabling the subsidisation of alternative measures (such as water reducing technologies). A number of criteria (or decisional attributes) are included in producing a prioritisation scheme for metering introduction, including income and education level information as well as water consumption, indirectly assessed through occupancy.

Water Recycling as an example of water saving technologies, could be either subsidised by the water provider (a positive incentive providing a solution to the negative incentive of volumetric pricing) or be compulsory (a kind of quota regulation as the water consumption is governed by a command-and-control type of strategy). Water-saving technologies do not reduce water consumption as such (from the point of view of the consumer), but rather reduce water demand (from the point of view of the provider). This research supports (interchangeably) grey water recycling, rainwater collection and use and combined grey water and rainwater recycling systems' planning installation. The criteria used include income, population density and education level information as well as water consumption, indirectly assessed through occupancy. Acknowledging that such a system requires extensive reconstruction activities for a household, the prioritisation scheme favours houses under renovation. Due to the link between rainfall runoff and urban flooding, the option of taking into account the spatially variable effect of urban flooding into the decision making process when deciding on the siting of rainwater collection or combined rainwater and grey water systems was specifically built in the SDSS.

The analysis undertaken here is a tool for urban planners and water companies to:

(a) Compare different water demand reducing scenarios,
(b) Plan the site-specific implementation of these scenarios and
(c) Assess the investment needed to achieve a desired reduction or
(d) Identify the best composite scenario dependent on a desired investment scheme

1.5.1.4 Assessing the impact of WDM

The result of the above assessment can be taken into account in a regional planning context. Although regional planning is beyond the scope of this study, the impact of WDM on the regional scale is briefly discussed here for reasons of completeness. The expected environmental impact from the application of a combination of these strategies is dual: The effect on water abstraction sources from meeting the same demand with less water (leakage reduction) or even reducing demand (metering and water saving technologies) is not trivial. In the case of economic development under water scarcity (as is the case in most Middle East Countries as well as in certain areas of European

Mediterranean Countries) the effect of WDM can be described in terms of the Malthus[1]-Ricardo theory of resource scarcity, stating that resource scarcity is the ultimate limit to economic growth. Water might be a special case of resource, as it cannot be completely depleted due to the (effectively) infinite supply of water from the oceans. The use of seawater through desalination, however, imposes energy, political and logistical constraints that are a limiting factor to water availability in these regions. Figure 1.3 reflects this situation for the case of agriculture in Egypt. WDM strategies are therefore tools that can help keep water prices in these regions affordable for both agricultural and urban use.

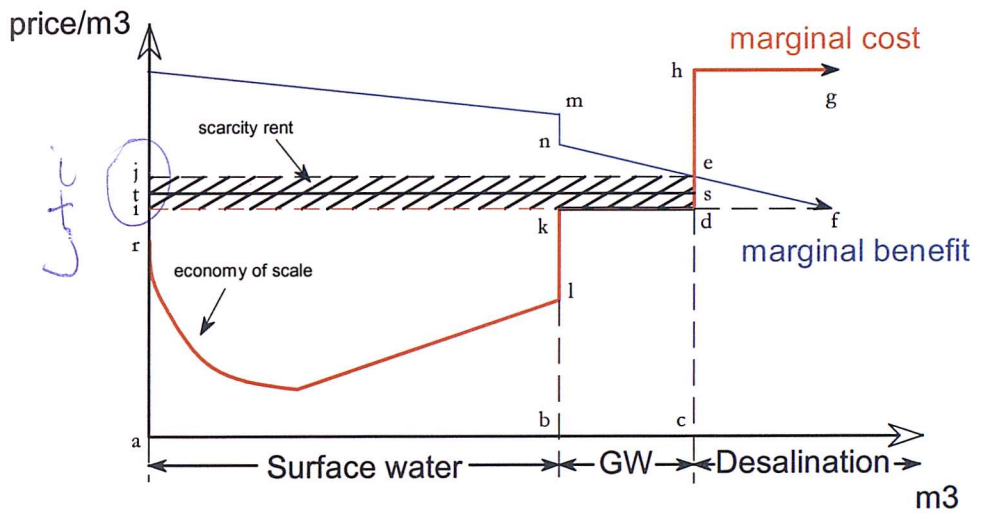


Figure 1.4 Economy Efficiency of Irrigation for Different Water Sources

(after Mohamed and Savenije, 2000)

If, in Fig. 1.4, we include under "costs" the combined social-economic-environmental costs of both water scarcity and using alternative water sources (depletion of semi-renewable[2] water sources like groundwater, sea water intrusion to fresh water aquifers due to over-abstraction as well as energy sources depletion for increased energy production requirements associated with desalination) the role of WDM becomes more important.

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1 Malthus was Professor of Political Economy (the first) at the East India College, Hailbury from 1805. His three main publications were: Essay on the Principle of Population, (1803); An Inquiry into the Nature and Progress of Rent (1815) and Principles of Political Economy (1820). Ricardo and Malthus were the two leading theorists of Political Economy as introduced in Adam Smith's work.

2 In the sense of the low rate with which a groundwater aquifer can be renewed.

The question arising from the discussion so far is whether there is scope to apply WDM in western counties as well; countries that exhibit, up to now, no serious water scarcity problems. This question will have to be answered within the framework of the current environmental legislation whose primary instrument is at this stage for the EU the Water Framework Directive (WFD).

The WFD reminds Member States (MS) that there is a clear need to conserve adequate supplies of water, a resource with a continuously increasing demand. For this purpose one of the most important innovations of the EU legislation is the introduction of negative incentives (pricing) following the principle that charges will reflect the true costs (social, economic and environmental) for the use of water as a resource. The new stringent ecological and hydro-morphological objectives (what is referred to as "good ecological status") and control strategies set by the Directive for a variety of water body types (including lakes, rivers and more importantly groundwater) imply significant minimum flow requirements and low abstraction rates to ensure balanced ecosystem development (Welcomme, 2001). The broader picture is completed by taking into account the increase in measures taken within the river basin in order to control the emissions of individual pollution sources - initially based on existing national and regional legislation, as well as on existing EU Directives (specifically the Integrated Pollution and Prevention Control (IPPC) Directive and the Urban Waste Water Directive) and thus the increased difficulty in discharge of effluents into water bodies (European Union, 2000a).

WDM presents one of the few viable alternatives in addressing, cost-effectively, both aspects of this problem. The reduction in abstraction needed to meet water demand will allow for protection of ground and surface water resources and facilitate the pursuit of ecological targets. Reducing consumption results in reduced wastewater generation, thus reducing the wastewater volume to be treated (although not the pollutant load). Apart from the obvious economic incentive, this could possibly result in the introduction of tertiary treatment methods, which would be difficult from an economic perspective under larger volumes of wastewater.

There is also an open ethical discussion relevant to WDM (at least as far as commercial uses are concerned) which will presented in brief here based purely on economic terms.

We refer again to Fig.1.3: If the water provider charges the users a volumetric price j, it will recover the financial costs, which are denoted by the area r-l-k-d-f. The consumers, however, have no incentive to reduce consumption, but rather will try to maximise their profits by moving along the benefits curve towards f. This could be achieved for instance via overexploitation of groundwater sources or by extensive water reuse, two options which would significantly affect water quality in the long run. If the water provider charges j but regulates water consumption using quota regulations keeping consumption to point c, the provider still recovers its costs, while the consumer makes a profit. There is, however, a part of the profit that does not (in economic terms) belong to the consumers. This is the profit made under water shortage conditions, and is referred to by Mohamed and Savenije (2000) as "scarcity rent" (represented in Fig. 3.1. by the shaded area d-e-j-i). At point e the user can still make a profit even if the scarcity rent is not included in it. This, however, could be unacceptable from a social welfare perspective. In that case a compromise charge (s) may be a viable alternative.

This is essentially a compromise between social welfare policy and sustainability, as the scarcity rent could be used by the water provider to ensure that water quantity c is available for future consumers (e.g. by investing in new water resources schemes or in water loss minimisation techniques etc). Otherwise, future generations are actually subsidising present users by d-e-j-i, which is probably the definition of unsustainable practices. In short, in terms of environmental ethics, negative incentives (taxation, volumetric pricing etc) implicitly favour the sustainability criterion over present welfare policy, while positive incentives and quota regulations imply the opposite. The reason for the latter is that they cannot recover the scarcity rent and thus they do not redistribute the cost of resources uses between present and future generations. The same applies to the other end of the pipe, wastewater generation, which was discussed earlier: Emission standards (like quota regulations) cannot recover the unavoidable costs to society by pollution (or the "pollution rent"), while effluent charges can. Raising effluent charges over the static efficiency threshold would mean that current polluters pay the pollution rent on behalf of future generations favouring the sustainability criterion. Maximising the present value of the socio-economic net benefits could be a way of sharing both these rents (water scarcity and pollution) between present and future users. It is argued therefore, that volumetric pricing and quota regulations are not necessarily socially undesirable practices and that social welfare can still be maintained by the State through

other financial measures rather than endangering scarce resources. There remains, of course, an issue of how to distribute this cost among present users (whether this can be done on the basis of income, or water use or even benefits from water use) but this issue, which is a fundamental one for social equity and welfare policy is outside the scope of this research.

1.6 Originality of work and contribution to knowledge

The notion of Spatial Decision Support Systems is relatively new and their applications in the environmental planning field are still in their infancy. Furthermore the use of fuzzy logic and evolutionary programming in this domain and more particularly in Urban Water Management is even scarcer although there seems to be considerable potential benefit from such an application.

This research contributes to all of the above-mentioned fields by developing, presenting and discussing a unique synthesis of tools forming a state-of-the-art Water Demand Management SDSS. Most of the techniques used as building blocks for the overall tool were already available in the environmental research field, or used for various purposes in different fields (i.e. type-1 fuzzy inference systems in control engineering and type-2 in signal processing) but have never been used in this combination and more importantly for this application, while some (e.g. the Spatial Ordered Weighted Averaging technique) were developed for the purposes of this particular research. The code used within the SDSS was developed exclusively for this application and made little or no use of existing libraries (for example the evolutionary programming optimisation algorithm was developed as an entirely new code) whenever it was felt that developing new code was a better choice to address the specific needs of the problem at hand. It should therefore be considered as a novel contribution to research into SDSS development.

The investigation of the extent to which this synthesis can increase the decision maker's ability to solve complex urban water management problems, such as WDM, is considered to be valuable both for pure research purposes (in decision making and environmental planning) and for operational practices in the water and environment industry. It has to be noted that the relevant (public domain) literature on WDM is scarce, which indicates that there is a lack of research focus in this particular area. This thesis addresses the need for research focus on certain aspects of WDM application. The

use of widely known and accepted general-purpose software for the development of specialised domain-oriented spatial decision support systems (such as ArcGIS, Matlab mathematical environment, EPAnet water distribution system model), which is also investigated, provides added value to the work, promoting the applicability of the concepts developed in a wide range of problems and environments.

1.7 Thesis Outline

The conceptual development of this thesis as well as the decision support system structure that is presented herein uses a mathematical and analytical framework, which cannot be considered mainstream in research in the urban water management domain. The thesis, therefore, includes specific background material essential for the understanding of the concepts, methodologies and mathematical tools used. In every case, when a new concept is presented, its relevance to research development is explicitly stated.

Chapter 1 provides an overview of the area of interest, namely the urban water management domain in general and water demand management in particular, and introduces the concepts of spatial decision support systems (SDSS) and fuzzy logic. It also discusses the aims, objectives, and innovative aspects of the work and sets the framework for the development of our specific SDSS.

Chapter 2 discusses the main concepts and mathematical domains that will be used throughout this research, setting the scene for the adoption of specific tools within the structure of the SDSS in the following chapter.

Chapter 3 is a detailed presentation of specific mathematical tools adopted from the general domains introduced in Chapter 2 and adapted to fit the particular needs of our urban water management SDSS.

Chapter 4 is a presentation of the SDSS developed for the Water Demand Management (WDM) application including descriptions of the two case studies used.

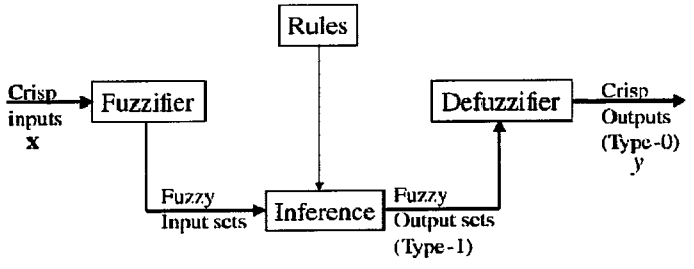
Chapter 5 is a presentation of the results of the system's analysis of the case study data presented in Chapter 4 under various alternative scenarios and user controls.

Comparative analysis of the results and sensitivity to parameter and user control variations are also included in this chapter.

Chapter 6 discusses the need, basic concepts, development issues, results and usefulness of a spatial decision support system for urban water management.

Chapter 7 summarises the main conclusions of the work performed, discusses the level of attainment of the aims set and proposes future research objectives.

2 Conceptual and Mathematical Background



$$y = f(\mathbf{x})$$

2.1 Decision Support Systems: a general framework

According to Malczewski, (1999), following the generic definition of DSS by Keen and Scott-Morton (1978), spatial decision support systems can be defined as:

> *an interactive, computer based system, designed to support the user or group of users in achieving a higher effectiveness of decision making while solving a semi-structured spatial decision problem.*

Densham (1991), identified the main characteristics of such a system:

1. Designed to solve semi-structured problems
2. Possessing a powerful and easy to use user-interface
3. Able to support a variety of decision making styles
4. Able to explore alternatives
5. Allowing interactive problem solving

To improve decision making, the system should take into account knowledge, intuition, experience and combine all available forms of information (both "hard" and "soft") in a common plateau to arrive at informed, inclusive and therefore "better" decisions. This implies the use of a particular domain of decision theory, termed multi-criteria analysis and more specifically spatial multi-criteria analysis. The main components of the SDSS, as mentioned earlier and as will be evolved during the present study, can be considered to be: a geographic database, a model base, an analysis base and a user interface. No reasoning capability is incorporated in the system, thus distinctly separating SDSS from expert systems. The objective is to support the decision maker, who will ultimately make the decision, and not to recommend a solution or substitute him altogether.

As explained previously, this research explores the application of well-established concepts that have seldom been applied in environmental planning (i.e. fuzzy logic and spatial multicriteria decision theory) and introduces some state-of-the-art concepts (i.e. type-2 fuzzy sets which have just recently been explored for the domain of signal processing only and spatial optimisation). This chapter introduces some key elements of theory of various knowledge domains (decision theory, multicriteria analysis, spatial

analysis, fuzzy logic, neural networks and evolutionary programming) before reaching the core of the on-going research on the SDSS field and its applications to environmental planning in the urban and regional scale. Therefore the chapter is organised as follows:

1. Elements of soft computing with emphasis on fuzzy inference systems (type-1 and type-2), neural networks as a means to train a fuzzy inference system and evolutionary programming as an optimisation method are discussed, providing the underlying mathematical basis of the research.
2. Elements of decision support theory with emphasis on multi-criteria analysis is followed by a discussion on the specific issue of spatial multi-criteria analysis providing the over-arching research umbrella.
3. Discussion of fundamental concepts and ideas behind an SDSS and relevant software interaction principles are introduced to provide the reader with a good understanding of the particular research framework, bringing together elements of the two first theoretical paragraphs.

2.2 Elements of Soft Computing: Fuzzy Logic, Neurofuzzy Systems and Genetic Algorithms

2.2.1 Why Fuzzy sets?

Complexity, naturally occurring in real life, is transformed into uncertainty when building an abstraction of the real world: a model. If a system is fairly simple, and therefore little uncertainty is inherent in the associated model, closed form mathematical expressions can be used to provide insight to the way the system functions. For more complex systems for which significant data exist, model-free methods (such as neural networks) provide a methodology for dealing with uncertainty through learning based on patterns in available data (Ross, 1995). Finally, for more complex systems where scarce data exist and where only ambiguous or imprecise information is available (which is generally the case in environmental planning), fuzzy logic provides a framework for handling and formally expressing this uncertainty, assisting the understanding of the system's functions. The imprecision therefore in fuzzy systems is generally high. It is thus evident that the successful application of fuzzy logic, apart from the knowledge of the theory involved, is dependent on the correct identification of the type of uncertainty involved in the system's structure. Despic and Simonovic (1997), identify two basic forms of uncertainty in environmental modelling; uncertainty caused by inherent stochastic variability and uncertainty due to fundamental lack of knowledge. Intuitively, the second

form can be more readily modelled by fuzzy sets, particularly if there is need for quantification of qualitative criteria and synthesis of non-homogeneous information (technical, economical, political etc), where lack of knowledge is coupled with scarce available data. This is in agreement with Despic and Simonovic (1997) who argue that it is primarily the data sufficiency, which determines the appropriate way of modelling. Environmental modelling and management theory includes a growing number of applications accepting fuzzy logic as a formal method of incorporating uncertainty into the decision making process. Sorbal *et al.*, (1981) illustrate a fuzzy methodology in the comparison of alternative solutions to solid waste disposal, Wenger and Rong (1987) illustrate two fuzzy methods to identify priority watersheds in Wisconsin, US, while Smith (1994), discusses the use of fuzzy sets in assessing four alternative routes for a proposed corridor in Australia. Ahamed *et al* (2000a) present a GIS application of fuzzy logic for land suitability analysis and the same authors (Ahamed *et al.*, 2000b), apply fuzzy logic to soil erosion modelling. Davis and Keller (1997), model uncertainty in natural resources using fuzzy sets and predict slope stability and Bender and Simonovic (1996) develop a fuzzy compromise programming technique and apply it in water resources planning and management in Canada.

2.2.2 Possibility vs. Probability

Historically, probability theory was the primary tool to represent uncertainty. Probability theory implies however, that uncertainty is random. It implies therefore that the outcome of an action or process is, although accurately defined, dependent on chance. A prediction of events in that – random- sense is not possible. What is possible is to describe the long-term statistics of the events. Probability theory therefore handles the need to "predict" a well-defined outcome that either occurs or not. There is no ambiguity about the set boundaries but rather about the belonging or not of an element or event in a set (Pal, 1999). In the real world, however, and especially in the context of complex environmental systems, uncertainty randomness is seldom a valid assumption. It can be argued (Ross, 1995) that, in fact, most real-world complex systems are characterised by non-random uncertainty. Especially when dealing with models where understanding is judgemental or when human reasoning, perception or decision-making is inextricably involved, there is a very strong case for the use of fuzzy set theory. Possibility theory (or fuzzy set theory) is therefore a tool to model systems where the outcome of an event or

process is uncertain not because of randomness but because the outcome itself is imprecise or ambiguous.

The underlying power of fuzzy set theory is that it can use linguistic variables in a formal mathematical way, therefore providing a linguistic calculus (Despic and Simonovic, 1997). Linguistic variables (vulnerable, suitable, tall, short etc), although generally ignored in modelling, are in reality the main way human reasoning works, incorporating the fundamental concepts of judgement and intuition (Ross, 1995). Fuzzy logic is used in the context of this research as a tool to model non-random uncertainty (imprecision, or vagueness) in both system rules (modelling of linguistic reasoning processes) and outcomes.

It is understood that fuzzy logic and probability theory are complementary rather than competitive and that in specific cases, the concepts of *plausibility measure* in Dempster-Shafer Belief Theory and *possibility measure* in Fuzzy Logic can coincide (Zadeh, 1986). For an extended discussion of the reasons why classical probability theory cannot deal comprehensively with imprecision and ambiguity, the reader is referred to Zadeh (1995).

2.2.3 Fuzzy Logic

Lofti Zadeh introduced the main concepts of fuzzy set theory in his seminal 1965 paper (Zadeh, 1965). Zadeh extended the notion of binary set membership to accommodate various degrees of membership on the real continuous interval [0, 1], where the endpoints of 0 and 1 are associated with no membership and full membership respectively. Contrary to binary logic an element x within the universe of discourse can belong in more than one (fuzzy) set within the universe with varying degrees of membership. The function that associates the value of the element x and the membership of the element in a given fuzzy set is termed a membership function ($\mu_{(x)}$) Figure 2.1 is an example of a membership function in crisp (binary) and fuzzy sets. In this figure it can be observed that in crisp sets, all elements either belong to the set or not (i.e. their membership function is either 1 or 0). In fuzzy sets, however, elements belong to a (fuzzy) set to "a certain degree" (given by the continuum of membership values between 0 and 1).

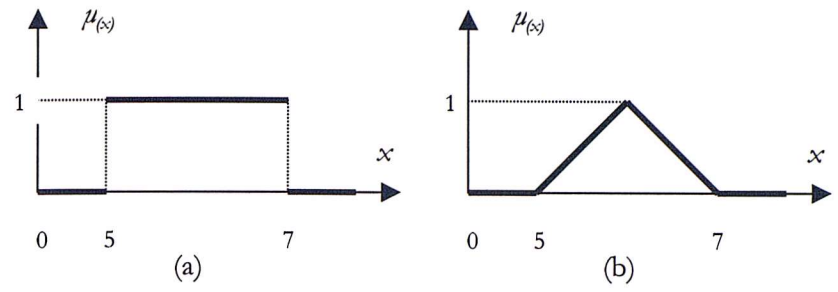


Figure 2.1 Membership functions in (a) crisp and (b) fuzzy sets

It has to be noted, however, that there is no unique membership function describing the membership values of element x in a number of sets, within the universe of discourse. For example, the identification of the membership of a particular height in the set of "tall" people, although related conceptually to the set and its rules, is more or less a responsibility of the analyst and is decided based on his or her perceptions. Therefore the actual shape of the membership function is not deterministically defined. More than one shape is actually possible to describe the varying degrees of membership of a given situation, a fact that is a direct result of the imprecise properties of real life situations and therefore the corresponding sets. Several techniques for building fuzzy membership functions (fmf) have been proposed in the literature and will be summarised within this section.

The relationship between the classic notion of crisp sets (binary logic) and fuzzy sets has been explored in a number of textbooks (Dubois and Prade, 1980; Klir and Folger, 1988; Zimmerman, 1987; Ross, 1995). Within this formation framework of fuzzy logic, crisp sets are considered a special form of fuzzy sets (i.e. fuzzy sets with membership functions of the shape seen in Figure 2.1. (a)). All of the axioms, definitions and principles of classic sets (with one exception) are applicable in fuzzy logic. It is well outside the scope of this research to state the properties of classic sets in order to establish their relevance and continuity with fuzzy logic, as this has been extensively accomplished in relevant literature in the past, forming the principles of what is now considered a rigorous mathematical theory. A summary of the basic properties of fuzzy sets will, however, be included as there will be mention of these properties while using fuzzy sets throughout this thesis.

2.2.4 Fuzzy set operations

A fuzzy set is defined as a set containing elements that have varying degrees of membership in the set (Graham and Jones, 1988). This definition contrasts these sets with classic (binary) sets in the sense that in classic sets an element cannot be part of a set unless its membership is full (i.e. membership equal to 1). A specific function (termed *membership function* maps these elements to the real number interval 0 to 1. Therefore by definition: $\mu_{A(x)} \in [0,1]$, where x is an element of a fuzzy set A. For three fuzzy sets A, B and C, in the universe X, union, intersection and compliment operations are defined as follows:

Union: $\mu_{A\cup B(x)} = \mu_{A(x)} \vee \mu_{B(x)}$ **Eq. 2.1**

Intersection: $\mu_{A\cap B(x)} = \mu_{A(x)} \wedge \mu_{B(x)}$ **Eq. 2.2**

Compliment: $\mu_{\bar{A}(x)} = 1 - \mu_{A(x)}$ **Eq. 2.3**

Where $\wedge$ denotes the logical OR and $\vee$ the logical AND. The membership value of any element x in the null set ($\varnothing$) is 0 and any element in the whole set X is 1. The null and the whole set cannot, therefore, be considered in that sense fuzzy sets. De Morgan's laws apply as in crisp sets:

$$\overline{A \cap B} = \bar{A} \cup \bar{B} \qquad \textbf{Eq. 2.4}$$

$$\overline{A \cup B} = \bar{A} \cap \bar{B} \qquad \textbf{Eq. 2.5}$$

The only exception is the inapplicability of the excluded middle laws in the case of fuzzy sets. The expression of the excluded middle laws for fuzzy sets can be defined as:

$$A \cup \bar{A} \neq X \qquad \textbf{Eq. 2.4}$$

$$A \cap \bar{A} \neq \varnothing \qquad \textbf{Eq. 2.5}$$

The properties of commutativity, associativity, distributivity, involution and idempotency hold for fuzzy sets exactly as they do for crisp sets.

2.2.5 The extension principle

Any function y=f(x) is a *mapping* where the transfer function f relates the independent variable x to a dependant variable y. To extend this mapping to fuzzy sets one must be able to determine the degree of fuzziness in the output y, given the fact that input x is

fuzzy and/or the function f is fuzzy. Zadeh (1975) and later Yager (1986) developed an "extension principle" which enables such a mapping to be introduced in the fuzzy sets realm. The extension principle is a basis for most of the calculations involving fuzzy sets within this research and will therefore be discussed in some detail.

Let X and Y be two universes of discourse and y=f(x) a (non-fuzzy) functional transform from one to the other (a mapping). A fuzzy set A in X will be mapped in Y as a new fuzzy set B, where B=f(A). The membership functions defining A and B will be:

$$\mu_B(y) = \vee_{f(x)=y} \mu_A(x) \qquad \textbf{Eq. 2.5}$$

The logical OR in equation 2.5, can be substituted with a composition operator, such as the max-min operator. In the general case, where image fuzzy set B=f(A1,A2,...,An), equation 2.5 becomes:

$$\mu_B(y) = \max_{y=f(x1,x2,\ldots xn)}\left(\min[\mu_{A1}(x1), \mu_{A2}(x2),\ldots, \mu_{An}(xn)]\right) \qquad \textbf{Eq. 2.6}$$

Equation 2.6 is called Zadeh's extension principle (Ross, 1995). In the form that is written here it applies for discrete value functions. If the function (f) is continuous then the maximum (max) operator is substituted with the supremum[1] (sup).

2.2.6 Membership functions

2.2.6.1 Terminology

Since the membership function incorporates all the information contained within a fuzzy set, it is important to describe its basic elements and introduce a terminology that will be used throughout the text:

1. *Normal* fuzzy sets are sets with include at least one element with membership value of one. The opposite constitutes a sub-normal set.
2. *Convex* fuzzy sets are sets where, for $x<y<z \rightarrow \mu(y)>\min[\mu(x), \mu(z)]$. The most common type of sets are normal and convex.
3. *Fuzzification* is the process of making a crisp value fuzzy; conceptually this is achieved by incorporating the uncertainty associated with it.

2.2.6.2 Membership value assignment

Dubois and Prade (1980) discuss a number of processes to assign membership values to fuzzy variables and an update of this discussion can be found in Ross (1995). Despic and

[1] Supremum is the least upper bound

Simonovic (1997) provide a detailed analysis of several methods for constructing membership functions for the particular case of quantifying qualitative criteria in environmental modelling. Deformable prototypes (Bremermann, 1976), implicit analytical definitions (Kochen and Badre, 1976), relative preferences (Saaty, 1974) and genetic algorithms (Lee and Takagi, 1993) are only a few examples of methods for constructing membership functions found in the literature. The list provided includes most of these methods as found in Ross (1995):

- Intuition
- Inference
- Rank ordering
- Angular fuzzy sets
- Neural networks
- Genetic algorithms
- Inductive reasoning
- Soft partitioning
- Meta rules
- Fuzzy statistics

As a detailed description of these methods is well outside the scope of this research and adequate discussion is included in fuzzy logic text books (including Kaufmann and Gupta, 1988; Zimmermann, 1986; Klir and Folger, 1988; Graham and Jones, 1988; Ross, 1995), Appendix 2 includes a brief summary of the main concepts of some of these methods (the last two are not discussed at all here as they involve an extended analysis which is not relevant to this research).

The actual construction process of a membership function generally involves some kind of subjective assessment. In most cases, membership functions are designed by the experts whose knowledge of the system under consideration is crucial (Homaifar and McCormick, 1995). Depending on what kind of initial assessments are made, we categorize the existing methods into direct and indirect methods for the membership function estimation. Direct methods refer to those methods where the assessments are made directly on the relations between the elements of X and the values from the interval [0,1]. Indirect methods, on the other hand, make the initial assessments on certain relations among the elements within the universal set X. These results are then

used for the construction of the membership function. A brief description of both direct and indirect methods for membership evaluation are included in Appendix 2.

2.2.7 Fuzzy Numbers

A special case of fuzzy sets are *fuzzy numbers* which are defined on the set of real numbers, that are both normal and convex (Figure 2.2). In our discussion we will be using fuzzy numbers to model input data uncertainty in our system. In the case seen in Figure 2.2, a fuzzy number with a Gaussian membership function has a mean (and therefore most probable value) set at the value of an original data measurement and the standard deviation quantifies our belief in the measurement accuracy. This practically means that there is a "most probable" value for the data input (equal to the measurement) but there is also a (lower) possibility of the value being slightly lower or higher. We will be discussing the exact applications of this concept in our SDSS in following chapters.

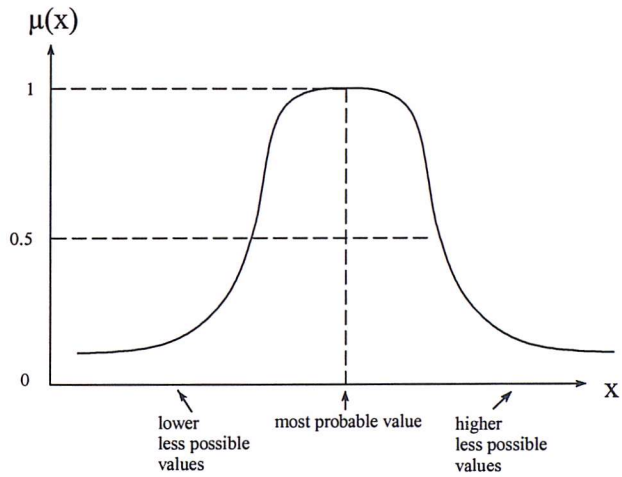


Figure 2.2 A Fuzzy Number quantifying data uncertainty

2.2.8 Defuzzification

There are cases where the output of a fuzzy process needs to be a crisp number. The mathematical operation converting fuzzy numbers or sets to crisp (which can be considered the opposite of membership function definition, i.e. fuzzification) is termed defuzzification. At least seven methods can be found in the literature for defuzzification, out of which the three more common ones are summarized below:

- Max-membership principle: This method, applicable to peaked output functions and the crisp output value z^*, is given by the following equation:

$$\mu(z^*) \geq \mu(z), \text{ for all } z \qquad \textbf{Eq. 2.19}$$

The idea is illustrated in Figure 2.3.

- Centroid method: This is the most widely used method and assigns the fuzzy output to a single crisp number, which is the membership of the centre of gravity of the output (Figure 2.4). The value z^* is given by the equation:

$$z^* = \frac{\int \mu(z) \cdot z dz}{\int \mu(z) dz} \qquad \textbf{Eq. 2.20}$$

- Mean-max membership: The crisp output is located in the middle of the distance between the maximum values. It is closely related to the first method, but can take into account cases where the maximum value is not unique (peaked output). Figure 2.5 illustrates the point. The expression giving the value of z^* (Lee, 1990) is:

$$z^* = (a+b)/2 \qquad \textbf{Eq. 2.21}$$

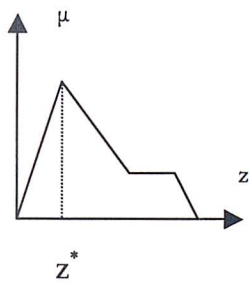


Figure 2.3 Max-membership

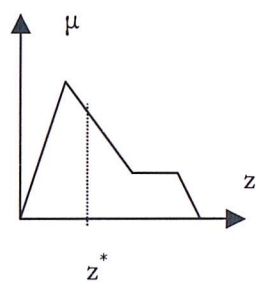


Figure 2.4 Centroid

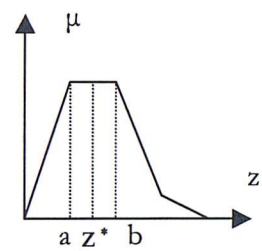


Figure 2.5 Mean-max

Other defuzzification procedures include the centre of sums, the centre of the largest area and the first maxima. There is no specific rule assisting the choice of one of these procedures and can be considered to depend on the nature of the particular problem at hand.

2.2.9 Quantifying uncertainty – entropy

The formal distinction between the three major types of uncertainty (randomness, non-specificity and fuzziness) can be better understood by means of an example. The example given here is taken from a review paper by Nikhil Pal (Pal, 1999) and touches on all three types of uncertainty which, as discussed in the introduction to this section, are of central

importance to the decision making process. Consider the classic die throwing experiment. If the top face is covered and you are asked to guess it, you are faced with uncertainty. The best way to express the answer (or ignorance), is by stating the probability of occurrence of different outcomes: this is uncertainty arising from **randomness** and is known as probabilistic uncertainty. Note that there is no ambiguity as to the result of the experiment when the experiment is actually over. Now suppose that an artificial vision system examines the top face of the die and, based on the evidence, suggests the value of the unknown result. The information provided by the vision system is termed **body of evidence**. Let us further assume that the system assigns a confidence level of 0.67 to the top face being 1, 2 or 3 and a confidence level of 0.33 of the top face being 4, 5 or 6. Clearly there is uncertainty in the body of evidence. In fact there are two types of uncertainty: randomness involved in which hypothesis of the two ({1,2,3} OR {4,5,6}) is true and **non-specificity** as to the exact value within the true hypothesis. The two hypothesis sets are called **focal sets** and non-specificity can arise when and only when there is at least one focal set with more than one elements. On the other hand, random uncertainty can arise when and only when there is more than one focal element. Systems like these are generally modelled with Dempster–Shafer theory of evidence. Finally, let us suppose that the evidence provided by the vision system cannot be exact but is limited to linguistic descriptions, such as the top face value being "high" or "low". Here a third type of uncertainty arises due to linguistic imprecision or vagueness: this is called fuzzy uncertainty. In this case the outcome (or our perception of the outcome) is not clearly defined after the end of the experiment, it remains ambiguous.

The best-known measure of uncertainty for probabilistic systems is Shannon's entropy (Shannon, 1948). It can also be thought of as the amount of information carried within the system (Gershenfeld, 1999). The notion of information is closely related with the classical notion of entropy in statistical mechanics. Just as the information in a system is an indication of its degree of organisation, entropy is an indication of it's degree of disorganisation (Graham and Jones, 1988). The notion of entropy is closely related with the idea that states within a system can occur with varying degrees of probability (which sum up to 1). The entropy of a system is given by:

$$H = -\sum p_i \log(p_i) \qquad \textbf{Eq. 2.22}$$

where p_i is the probability of occurrence of the i^{th} state. This is the negative information carrying capacity of the system (Graham and Jones, 1988).

For the particular case of information carried within a fuzzy set, Graham and Jones (1988), based on De Luca and Termini's (1972) conditions applicable to any fuzzy information measuring function, suggested that the entropy of a fuzzy set can be defined as:

$$d(\mu)=k\sum S(\mu(x)) \qquad \textbf{Eq. 2.23}$$

where **S** is the Shannon function defined as $S(x)=-x\log(x)-(1-x)\log(1-x)$, k is a positive constant, μ is a fuzzy subset of **X** and **x** is an element of **X**. Several authors have proposed alternative measures of quantification of fuzziness: Kaufmann (1975), introduced linear and quadratic indices of fuzziness, Yager (1980), associated fuzziness with the lack of distinction between a proposition and its negation and proposed a family of measures of fuzziness, Kosko (1986), defined fuzziness as the ratio of the distances between the fuzzy set A and its nearest and furthest non-fuzzy sets. In general, a measure of fuzziness estimates the average ambiguity of a fuzzy set. Intuitively there are a number of properties that such a measure must include: (a) The fuzziness of a crisp set is zero, (b) if a set is maximally ambiguous (i.e. $\mu_A(x)=0.5, \forall x$) then the fuzziness must be maximum, (c) when a membership value for any element approaches either 0 or 1 then the fuzziness decreases and finally (d) the fuzziness measure of a set and its complement must be the same (i.e. the ambiguity between a set "tall" and "not tall" cannot be different). The measures of fuzziness proposed in the literature (such as Equation 2.23), satisfy these properties. In the specific case of ordered weighted averaging (OWA) (Yager, 1988), which will be discussed in following paragraphs and which is used in the development of the SDSS, entropy is considered as the degree of information carried by the attributes taken into account in the final aggregation (Filev and Yager, 1998). This aspect of entropy has been used within the SDSS to define the final aggregation procedure of the criterion maps[1]. The quantification of total uncertainty (Probabilistic + Non-specificity + Fuzziness) is not a trivial subject[2], and is a target of on going research (Pal, 1999).

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[1] A discussion on the use of entropy measures in identifying a desirable aggregation system out of the family of OWA aggregation operators is included in Chapter 3 on model development.

[2] For a detailed discussion on attempts at quantifying total uncertainty, see Pal (1999).

2.2.10 Fuzzy rule-based systems

Mathematical paradigms have been very slow at realizing that one of the most important ways of conveying information, and therefore knowledge, is natural language (Ross, 1995). Despite its inherent ambiguities, people speaking in the same language have very few problems in conveying their thoughts and inferring consequent from antecedent. This is actually the only way to teach and therefore communicate experiences, rules and accumulated knowledge. It is also the only way people arrive at decisions in everyday life, from the simpler to the more complex ones, and therefore the uncertainty involved in these decisions due to the imprecise nature of linguistic variables or linguistic rules is something *de facto* acceptable in everyday human practice. Fuzzy logic provides a formal mathematical framework for expressing linguistic variables and rules and, in that context, it should be clear that it will also inherit the same ambiguity and impression which follows human reasoning and therefore decision making in everyday life. This fact should not be considered a draw back but rather an intuitively familiar and thus acceptable fact.

Systems that use IF-THEN rules to represent human knowledge within a fuzzy logic framework are called Fuzzy Inference Systems[1] (FIS) and they have been extensively used in the literature[2] and will form the basis of our decision support system structure. Two fundamental characteristics of environmental planning account for this fact: Data scarcity and the need to make decisions taking into account, simultaneously, complex quantitative and qualitative criteria. The situation is, not surprisingly, very similar to everyday, informal, decision making, which thus lends itself to modelling by fuzzy inference systems simulating human reasoning. Two types of FIS have been used in this research: type-1 and type-2. They both use IF-THEN rules to derive consequent from antecedent (both of which can be linguistic variables and therefore fuzzy sets), an aggregation procedure and a defuzzification rule. These systems will be described separately in the following paragraphs.

2.2.10.1 Type –1 fuzzy inference systems

Type-1 FIS (Figure 2.6) are widely used in fuzzy control engineering and signal processing applications. Such a system maps crisp inputs to crisp outputs and is

[1] The abbreviation FIS will be used henceforth for both the singular and the plural form (i.e. system and systems) for reasons of simplicity.
[2] For a comparison between different forms of inference, see Mizumoto and Zimmermann, 1982

comprised of four parts: a fuzzifier, a defuzzifier, a set of rules (IF- THEN) and an inference procedure. Once the rules are established, the system can be viewed as a mapping from inputs to outputs and this mapping can be generally expressed as y=f(x) (Mendel, 2000). A fuzzy set can be represented by its membership function (as seen earlier in this section), which assigns a value of the interval [0,1] to each element x of the universe of discourse. This is the procedure undertaken by the fuzzifier. In the case of a **singleton fuzzifier** the crisp point x is mapped into a fuzzy set X with support x_i where $\mu(x_i)=1$ for $x=x_i$ and $\mu(x_i)=0$ for $x\neq x_i$ (i.e. only one point x_i has a non-zero membership function). In the case of a **non-singleton fuzzifier** (which is useful when there is uncertainty in the input variables), the point x is treated as a fuzzy number achieving a maximum at x_i, but values close to x_i also have high membership values. The shape of the membership function is determined by the designer according to the kind of uncertainty present in the problem. Gaussian or triangular membership functions are generally used for modelling data uncertainty (Mendel, 2001), under an assumption of symmetric uncertainty around a "most probable" value (for example the mean of the Gaussian function). Both type-1 and type-2 FIS can be divided into singleton and non-singleton, dependent on the input values being either crisp or fuzzy numbers.

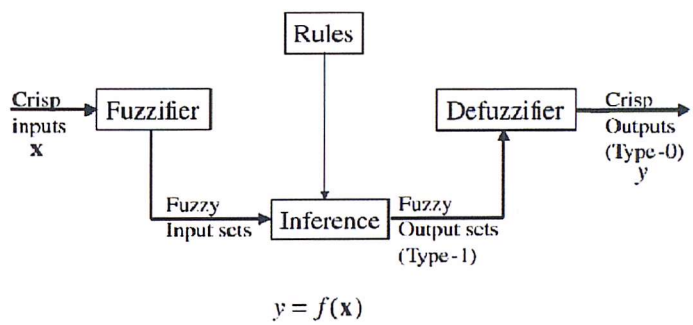


Figure 2.6 Type-1 Fuzzy inference system

Type-1 FIS contain parameters that can either be pre-defined or can be tuned during a training process. For the more general case of non-singleton type-1 FIS that uses for example a Gaussian membership function, with p antecedents and M rules, there can a maximum of M(2p+2)+p parameters.

2.2.10.2 *Type-2 fuzzy inference systems*

Both the rules used to construct a FIS and the membership functions involved in the fuzzification and defuzzification process are usually, to a great extent, uncertain. According to Mendel (2000), the uncertainty stems from the following reasons:

- Words included in the rule based system can mean different things to different people
- Consequences of the same rule, obtained by polling a group of experts, can be different as the experts will not necessarily agree
- There is uncertainty in the antecedent data (field data)

Antecedent and consequent uncertainties result in uncertain fuzzy membership functions. Type-1 FIS whose membership functions are type-1 fuzzy sets (ordinary fuzzy sets as described in this section), cannot capture uncertainty resulting from uncertain rules (caused by uncertain knowledge used to construct these rules). This kind of uncertainty can be better handled by fuzzy sets whose membership function is also a fuzzy set. These fuzzy sets are called **type-2 or ultra-fuzzy sets** (Graham and Jones, 1988). The concept was introduced by Zadeh (1975) as an extension to the concept of ordinary fuzzy sets (type-1). They are characterized by a fuzzy membership function, which practically means that each membership value of each element in a set is a fuzzy number in [0,1], in contrast to type-1 fuzzy sets whose membership value is a crisp number in [0,1]. The notion of type-2 fuzzy sets is analogous to our classic representation of random variables using at least two moments (mean and variance). Type-1 fuzzy membership functions are the analogue of the mean of a probability density function (pdf), while type-2 include the variance (the dispersion around the mean). In principle, just as in random uncertainty one can work with higher order moments ($n \geq 2$), one can work with higher order fuzzy sets. The complexity, however, will increase rapidly and therefore higher than second order systems are not used for practical purposes (Mendel, 2000).

The basic analogy between type-1 and type-2 systems can be described by the following design requirement (Karnik *et al.*, 1999): *When all uncertainties disappear, a type-2 FIS reduces to a comparable type-1 FIS.*

Type-2 fuzzy sets have been studied by a small number of researchers including Dubois and Prade (1978; 1979), Yager (1980), Turksen (1986), Park and Kim (1996), Mabuchi (1997) and Mendel (2000). Figure 2.7 shows a type-2 fuzzy set whose membership value for each point is a crisp set within the interval [0,1]. Such type-2 sets are called interval type-2 sets and the interval in the secondary membership function can be represented by its left and right end points [l, r].

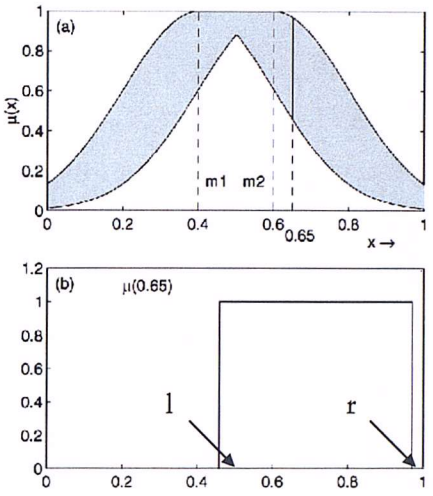


Figure 2.7 An interval type-2 fuzzy set (a) primary and (b) secondary membership (with its left and right end points)

(source: Mendel, 2000)

The shaded area in Figure 2.7 is a footprint of uncertainty for the membership function (in this case Gaussian) whose mean value is uncertain but is known to lie in the interval [m1, m2]. The footprint of the uncertainty represents the domain of the secondary membership function. In principle, the secondary membership function can be any type-1 fuzzy set. However, if the secondary membership function is of, for example, triangular or Gaussian shape this presupposes an *a priori* judgement that the greatest emphasis will be placed on the midpoint of the primary membership function. This judgement is not needed when using interval shape secondary membership functions. For this reason, as well as for computational efficiency, only type-2 sets *with interval secondary membership functions* were used in the development of the SDSS. Figure 2.8 shows the structure of a type-2 FIS.

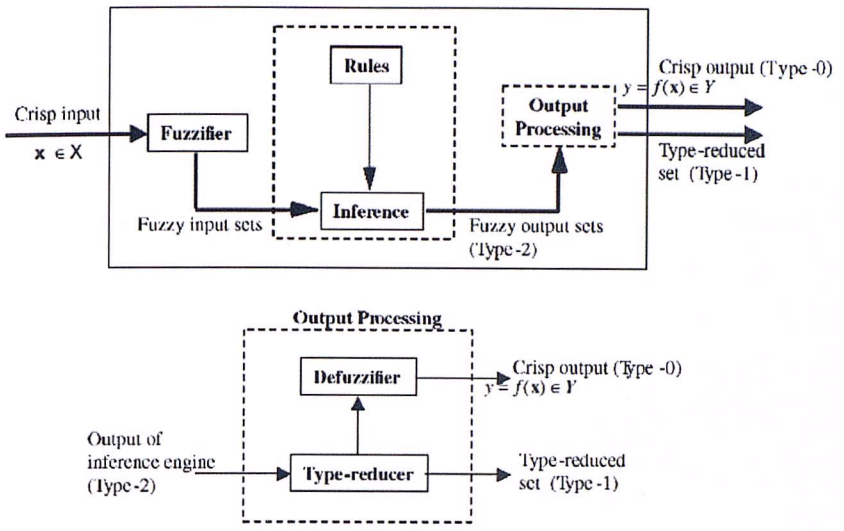


Figure 2.8 A type-2 fuzzy inference system including a type reducer (t-2 to t-1)

(source: Mendel, 2000)

The structure is quite similar to the type-1 FIS, the only difference being that antecedent and consequent sets are type-2 sets. A mathematical operation termed "type reduction" is applied to transform type-2 to type-1 sets (a procedure analogous to defuzzification in type-1-to-crisp transformation). The operation is based on the centroid concept (Equation 2.20). Using the Extension Principle (Equation 2.6), a similar centroid can be identified (Mendel, 2000) for a type-2 set $\boldsymbol{A}$ as:

$$C=(\int_{\theta 1}\ldots\int_{\theta N} \mu_{D1}(\theta_1) \bullet \ldots \bullet \mu_{DN}(\theta_N))/(\sum x_i\theta_i/\sum\theta_i) \qquad \textbf{Eq. 2.24}$$

where $D_i=\mu_{\boldsymbol{A}}(x_i)$, $\theta_i \in D_i$ are type-1 fuzzy sets, all integrals denote logical union and $\bullet$ denotes a chosen t-norm (i.e. a product or a minimum operator). Equation 2.24 is central to the operation of a type-2 FIS and therefore will be discussed in more detail.

Every combination $\{\theta_1\ldots\theta_N\}$ considered when computing C of a fuzzy type-2 set $\boldsymbol{A}$, can be thought to form the membership function of some type-1 set $\boldsymbol{A}^*$, which has the same domain as $\boldsymbol{A}$. These type-1 sets are called embedded sets (Mendel, 2000). Every embedded type-1 also has a weight associated with it which is calculated as the t-norm of the secondary memberships corresponding to $\{\theta_1\ldots\theta_N\}$, that make up the set. Type-2 can therefore be thought of as *a large collection of embedded type-1 sets, each having a weight associated with it.* The centroid, in analogy, can be thought of as a type-1 element whose elements

are the centroids (computed by Equation 2.20), of all embedded type-1 sets in $\boldsymbol{A}$ and their memberships are the weights associated with the corresponding embedded sets.

Just as a type-2 set can be thought of as a collection of embedded type-1 sets, a type-2 FIS can be thought of as a collection of a large number of embedded type-1 FIS, each with a certain weight associated with it. In principle, the number of type-1 sets embedded in a type-2 is infinite. However for practical purposes (i.e. for being able to calculate Equation 2.24), the type-1 sets are discretised and a finite number is assumed to be embedded in any one type-2 set.

In both type-1 and type-2 FIS, fuzzy logic principles combine IF-THEN rules into a mapping from fuzzy input sets to fuzzy output sets. This mapping process is termed a "fuzzy inference engine". Due to the extent of the fuzzy calculus necessary to completely describe all relevant operations associated with the fuzzy inference engines of the four types of FIS used in the development of the SDSS, (namely singleton and non-singleton[1] type-1, singleton and non-singleton type-2) and the length limitations and objectives of this thesis, the complete mathematical operations, and necessary theorems will not be included here. Instead illustrative schematics of the basic antecedent and consequent processes are included in Figures 2.9 – 2.15. The general expressions of the functions involved and their specific mathematical interpretation under the assumptions made in the development of the SDSS will also be included in the chapter on mathematical development.

[1] The most general case of non-singleton FIS is the case where the input is type-2 fuzzy number. This case, however, has not been included in the development of the SDSS (the user has no option of analysing information with such a general system), due to the mathematical complexity of the associated processes, resulting in disproportionate computation times. The author feels that even if such a system were computationally inexpensive, it would have been of limited importance to the outcome, due to the large number of variables to be tuned and the resulting counter-intuitiveness of the process.

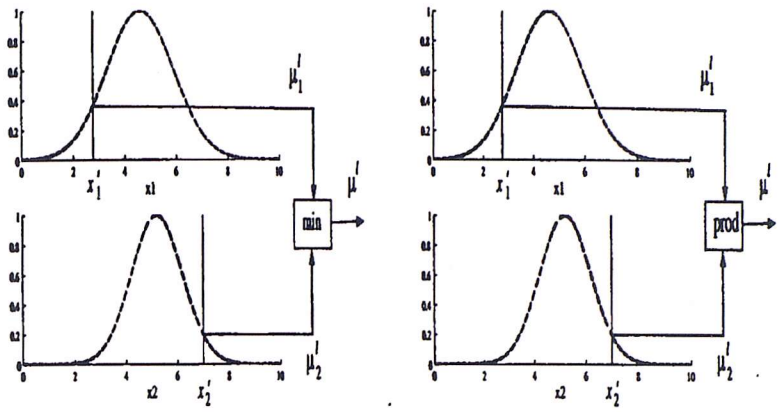


Figure 2.9 Input and antecedent operations for a type-1 singleton FIS (min and product t-norms)

(source: Mendel 2001)

In Figure 2.9, the first part of the inference procedure is schematically presented for a minimum (left) and product (right) combination rule (t-norm). In the first case, the resulting *firing level*, which is the value that propagates from antecedent to consequent operations when two values enter the inference system (in this case x'_1 and x'_2), is calculated as the **minimum** between the two resulting membership values of x'_1 and x'_2 respectively. In the second case the firing level is the **product** of the two membership values. If the upper fuzzy set was set A and the lower fuzzy set was set B, then Figure 2.9 is the representation of the rule *IF* x'_1 *IS A and* x'_2 *IS B THEN* for two alternative combination rules. This is of course because Figure 2.9 describes only the antecedent operations. The second part of the inference can be seen in the following Figure.

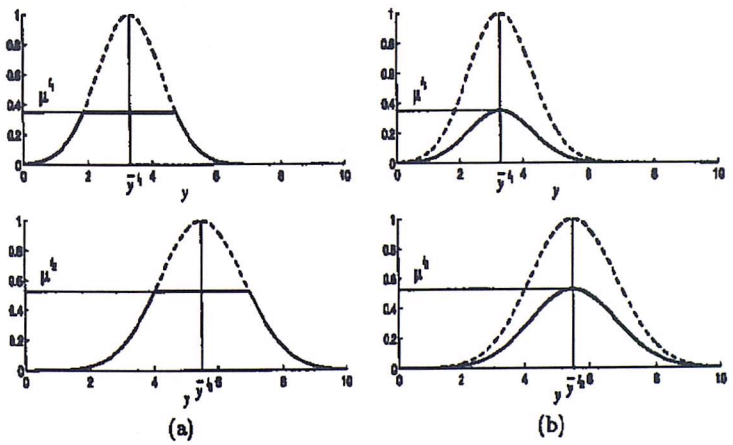


Figure 2.10 Consequent operations for a type-1 singleton FIS (min and product t-norms)

(source: Mendel 2001)

Figure 2.10 is schematically describing the consequent operations that result from the propagation of the firing level of, for example, Figure 2.9. The figure on the left describes how the resulting value is calculated for a minimum combination rule and the right for a product combination rule. In minimum t-norms the resulting fuzzy set is the one *clipped* below the firing level, while in product t-norms the fuzzy set is a "re-sized" set whose highest point is that of the firing level. If the upper fuzzy set (in both cases) is termed C and the lower D then the interpretation of the (two) rules described in Figure 2.10 is (a) *THEN result IS C* and (b) *THEN result IS D.*

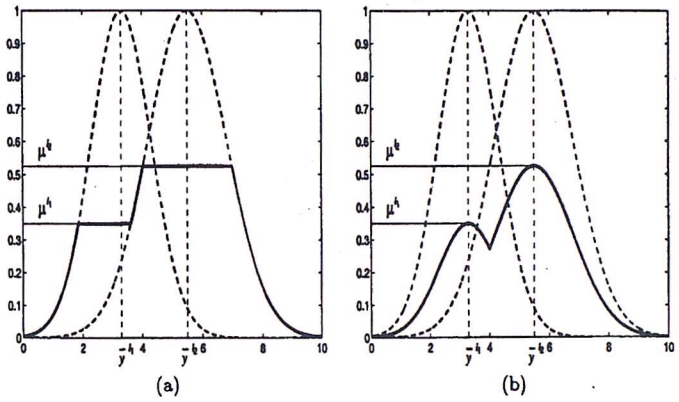


Figure 2.11 Combined output sets for the fired output sets of Figure 2.11

(source: Mendel 2001)

Figure 2.11 is describing the resulting fuzzy set when combining all the rules (in this case two) of Figure 2.10 using a maximum of union operation. All these figures refer to type-1 singleton FIS. The following ones refer to type-1 non-singleton and type-2 singleton and non-singleton but follow the same principles of rule combinations.

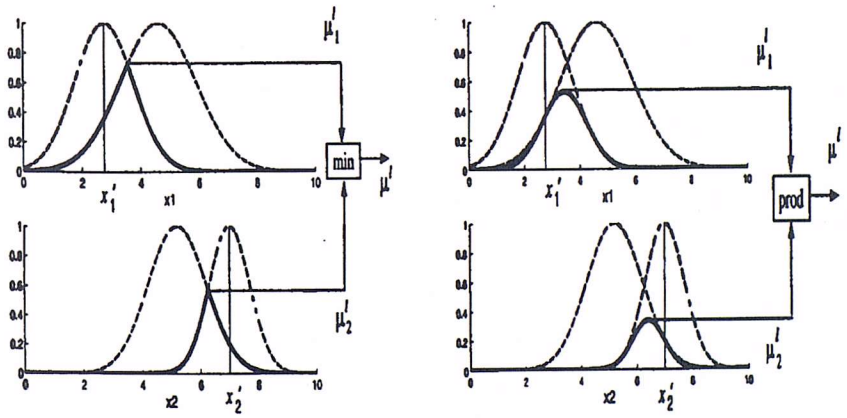


Figure 2.12 Input and antecedent operations for a type-1 non-singleton FIS

(source: Mendel 2001)

In Figure 2.12, the input value is a fuzzy set and not a crisp number. In the upper figures it is the fuzzy set to the left of the membership function that is centered around x'_1 and in the lower figures it is the right one centered around x'_2. In type-1 non-singleton FIS the firing level is a number as was in type-1 singleton. As this is the case the consequent operations of type-1 non-singleton FIS are exactly the same as in Figure 2.10.

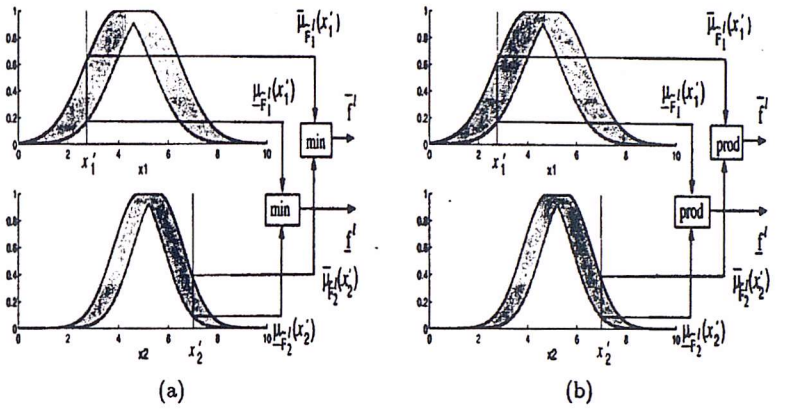


Figure 2.13 Input and antecedent operations for a type-2 singleton FIS

(source: Mendel 2001)

In Figure 2.13 antecedent operations for singleton type-2 FIS are described. Note that this time the firing level is not a number but an interval type-1 set. The consequent operations are therefore different from type-1 FIS and can be seen in Figure 2.14.

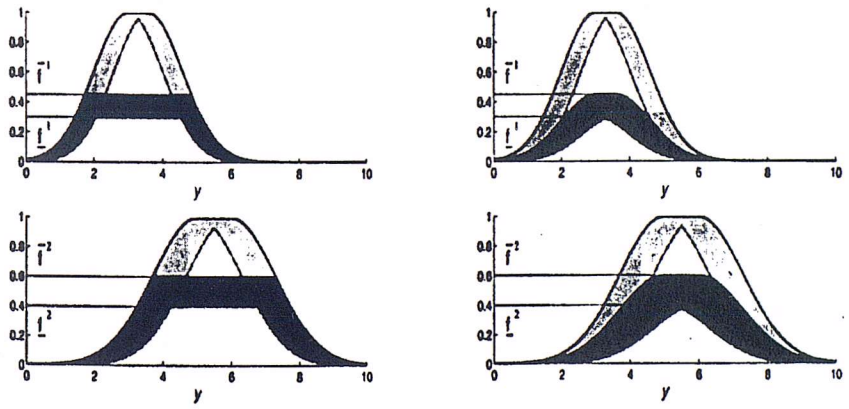


Figure 2.14 Consequent operations for a type-2 singleton FIS

(source: Mendel 2001)

The consequent operations for type-2 FIS can be seen in Figure 2.14. The principle mechanisms remain the same but an interval rather than a number specifies this time the clipping level.

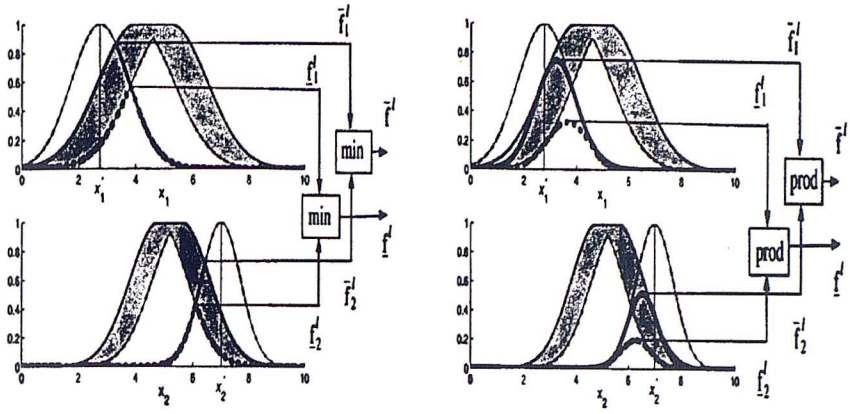


Figure 2.15 Input and antecedent operations for a type-2 non-singleton FIS

(source: Mendel 2001)

Finally, a combination of Figures 2.12 and 2.13 describes the antecedent operations in type-2 non-singleton FIS. The consequent operations in this case are the same as in Figure 2.14.

2.2.11 Mamdani inference

As discussed, an inference system translates an antecedent value to some inferred consequent value through an inference procedure. Different types of FIS are proposed in the literature (see Mizumoto and Zimmermann, 1982), which differ mainly in the exact formulation of this inference procedure and the extent to which this procedure can accurately mimic human reasoning (Leung, 1997). It has been empirically demonstrated (Leung, 1997) that most of the procedures proposed (including procedures by Zadeh (1975b)), although mathematically sound, are not really intuitively correct and do not imitate commonsense human reasoning. The simplest procedure for mapping fuzzy set A to fuzzy set B (extensively used for application purposes) was proposed by Mamdani (1977) and will be described in detail for the various FIS developed in Chapter 3. It must be noted, however, that there is a trade-off between readability and precision. If a precise solution is not needed or is not possible, while the main focus of the modelling (function approximation) effort is the ability to interpret the solution in logical terms, then the Mamdani-type FIS (i.e. a FIS whose consequents are fuzzy sets[1] such as the ones described so far) present the dominant alternative (Leung, 1997; Mendel, 2001). According to Mathworks (2000), the Mamdani procedure is intuitive, has widespread

[1] Other FIS such as for example Sugeno-type FIS use *functions* as consequents of a rule (Takagi and Sugeno, 1985).

acceptance and is well suited to human input. These premises led to the adoption of the Mamdani inference procedure as the main inference mechanism in the prototype SDSS developed in this thesis.

2.2.12 Universal Approximators

The question of the extent to which a FIS can adequately approximate an unknown function was answered by Wand and Mendel (1992), as well as by Kosko (1992). They proved that for a number of specific FIS could uniformly approximate any real continuous non-linear function to arbitrary degree of accuracy. A universal approximation theorem is an existence theorem. It implies that by using *enough* input and output fuzzy membership functions, and with *enough* rules, *correctly* tuned, any function can be approximated. It does not however explain how to build such a FIS (Mendel 2001). In the cases presented in this thesis, as experimental data to train the FIS were not available, the design made use of linguistic variables (low, medium, high), with a degree of uncertainty as to the exact design parameters of their fmfs incorporated in type-2 fuzzy membership functions.

2.2.13 Training a fuzzy inference system

Normally, fuzzy inference systems are designed by experts in the particular application field, based on their knowledge and experiences (Shi and Mizumoto, 2000). This implies that the fuzzy membership functions for both antecedent and consequent sets, as well as the rules are chosen by a process of trial and error (Nauck and Kruse, 1999). When the decision environment to be modelled is complex, the uncertainty and ambiguity of the sets and the rules combining them are increasingly affecting the - limited - human ability to design such a system intuitively. In 1992, three research groups independently reached the same conclusion as to the possibilities of tuning the parameters of a fuzzy inference system in a more systematic and rigorous way. Horikowa *et al.* (1992), Wang and Mendel, (1992) and Jang (1992), presented computational techniques using back-propagation algorithms of neural networks to tune optimal fuzzy inference systems for a set of input-output training pairs. The resulting systems are known as "neuro-fuzzy" and have widespread applications in data analysis, decision support, engineering, signal processing and control (Nauck and Kruse, 1999; Mendel, 2001; Kim and Kasabov, 1999). Although many different neuro-fuzzy approaches can be found in the literature, this research adopts the general definition provided by Nauck and Kruse (1999) and the back

propagation learning technique proposed by Mendel (2001) for reasons of clarity and computational efficiency. In general, designing a FIS can be viewed as approximating a function or fitting a complex surface in a multi-dimensional space (Mendel and Mouzouris, 1997). The following five points, as stated by Nauck and Kruse (1999), summarize this research's view on neuro-fuzzy systems.

1. A neuro-fuzzy system is a fuzzy inference system trained by a learning algorithm derived from neural network theory. The learning process is not knowledge based but data driven and relies solely on locally provided data sets, for which the system is trained.
2. A neuro-fuzzy system can be viewed as a special case of 3-layer feed forward neural network. The first layer represents input variables, the middle layer (which is hidden) represents fuzzy rules and the third represents output variables. Fuzzy sets are encoded in the system as connection weights.
3. A neuro-fuzzy system is a system of fuzzy rules. Therefore, it can be created from scratch using input-output training pairs or be created with prior knowledge embedded in fuzzy rules and then modified to account for the data structure. This second approach is the one used in this research.
4. The learning process takes into account the semantic properties of the underlying fuzzy system, therefore resulting in a number of constraints as to the type and extent of possible modifications.
5. A neuro-fuzzy system approximates an n-dimensional unknown function and the fuzzy rules embedded in it should be thought of as vague prototypes of training data and not as a kind of expert system.

Neuro-fuzzy systems, in this research, are primarily used to illustrate the possibilities existing in using adaptive techniques to enhance decision making in the urban water management environment. The knowledge that neuro-fuzzy systems incorporate is provided to them by the user in the form of examples of "correct" input and output elements. It has to be noted that both neural networks and fuzzy inference systems are universal approximators and could thus, in principle, be used interchangeably. It is accepted, however (Nauck and Kruse, 1999), that neural networks are used when the function to be approximated is completely unknown and there are enough data to drive the learning process. Fuzzy inference systems are used when the relationship between input and output can be (to some extent) expressed linguistically. The issue of training

the particular FIS created in this SDSS, as well as the issue of obtaining input-output training pairs for urban water management applications, is discussed in following chapters.

2.2.14 Genetic Algorithms and Evolutionary Programming

2.2.14.1 The concept of Genetic Algorithms

Genetic algorithms (GAs), whose theoretical basis was first discussed in Holland (1975), are a class of optimisation techniques used for complex large-scale combinatorial optimisation problems. They are stochastic algorithms whose search methods model some natural phenomena: genetic inheritance and Darwinian mechanisms of survival (Michalewicz, 1996). Natural species evolve by developing characteristics that allowing them to adapt in a particular environment. These characteristics are incorporated in their genes and the best ones survive through the process of natural selection, from one generation to the next. The metaphor is conceptually a powerful one: Darwinian natural selection and survival can be considered as one of the most complex and demanding "optimisation" problems ever encountered. Evolution is a natural process and is only "natural" that a mathematical equivalent would be used for some of our own complex optimisation problems.

Genetic algorithms use a vocabulary borrowed by natural genetics. A *population* includes a number of *individuals* each one of which contains a *chromosome* that is made up of a number of *genes*. In terms of optimisation problems, each individual is a potential solution to a problem. The solution is described in the chromosome by a succession of genes, each one of which represents one characteristic of that solution. GAs have been used successfully, over the past decade, in a number of complex optimisation problems including image-processing, VLSI (very large system integration) electronic chip layouts, robotics, water networks, control, transportation problems and database query optimisation (e.g. Michalewicz, 1996; Savic and Walters, 1997; Atkinson *et al.*, 1998; Coley, 1999).

2.2.14.2 GAs and EP

GAs are a domain-independent class of algorithms that follow a set of rules as to representation of any particular problem (e.g. the genes of the individuals are of binary form (0-1)) and its solution (e.g. changes in the population occur by crossover and

mutation operations only), without the possibility of incorporating problem specific knowledge. This increases the overall applicability of GAs as a tool but decreases its performance in situations where the inclusion of problem specific knowledge could lead to quicker and more accurate results (Michalewicz, 1996). To resolve this problem, various non-standard implementations of GAs have been developed including various other operators, richer data structures (e.g. non-binary strings or matrices) or inclusion of fuzzy rules (IF-THEN) (see for example Krzanowski and Raper, 1999; Chang and Wei, 2000; Brookes, 2001). This gave rise to a family of optimisation techniques (known as Evolution Programming (EP)), based on the same main principles of evolution but incorporating domain specific knowledge which require altering the algorithm to fit the specific problem at hand, rather than the other way round as was the case in GAs. Since GAs are a subset of EP, and since it is with the incorporation of domain-specific knowledge that GAs are used in this work, the rest of the discussion will be focused on EP in general. *The term GAs will be used interchangeably with EP in the context of this work without the strict implications of representation structures and operators that classical GAs require.*

2.2.14.3 How do GAs work?

All EPs are probabilistic in nature and maintain a population of individuals $P(t)$ for iteration t. Each individual in the population is a potential solution of the problem and is evaluated against a measure of *fitness*. Typically, fitness is related to the objective function to be optimised. In the next iteration $t+1$, a new population is formed by selecting the fitter individuals from the initial population and allows them to undergo transformations through a set of genetic *operators*. There are broadly two types of operator: unary (*mutation* type) operators which affect a single individual by changing one or more of its genes through probabilistic procedure and higher order (*crossover* type) which affect a number of individuals by combining parts of two or more initial individuals to create a new one. This way, the best individuals in a population have more *offsprings*, therefore the better solutions they represent become more dominant in successive iterations (*generations*). After a number of generations (subject to a convergence criterion) it is hoped[1] that the best individual represents a near optimum solution. The general procedure of an evolution algorithm is as follows:

---

[1] For a detailed explanation of the theoretical background of GA convergence properties through natural selection (based on the *Schema* Theorem) the reader is referred to various introductory textbooks on GAs and EP (for example Mitchell (1996) or Michalewicz (1996)).

```
begin
    t ← 0
    initialise P(t)
    evaluate P(t)
    while (not termination-condition) do
    begin
        t ← t+1
        select P(t) from P(t-1)
        alter P(t)
        evaluate P(t)
    end
end
```

2.2.14.4 Issues with GAs

- **Constraints** within the optimisation problem can be taken into account as penalty functions, reducing the fitness of an individual that under-performs with respect to a constraint (Coley, 1999). Typically, the penalty is designed to increase as a function of the extent of the constraint's violation. The "hard" alternative of setting the fitness function of an individual violating a constraint to zero, is not considered practical as it restricts the capability of the population to explore the solution space. In the beginning of a search this may be impractical, as the objective is to include a large variety of solutions to allow for a greater sampling of the solution space. At the end of the search, however, the penalties towards infeasible solutions could increase to make certain that all solutions offered in the long run are feasible. Various methods are used to establish penalty functions for (*single-objective*) GAs (including Homaifar et al., 1994 and Michalewicz, 1996). The issue of *multi-objective* GAs (which is an alternative to using constraints in various problems) will be discussed separately, as such GAs were used in the course of this thesis.
- **Population size** is another important issue in developing GA solutions. If the population size is too small, the GA may converge too quickly; if it is too large convergence might become too slow. The two most important aspects in a successful GA application is population diversity and selective pressure and these are both influenced by the population size. Goldberg (1989a) provided a theoretical analysis of population size and its effect on population fitness and algorithm convergence.

Other researchers (Michalewicz, 1996) discuss the possibility of using a population of variable size by introducing the concept of *age* in the chromosomes. In practical applications, the population size would, in principle, depend on the problem at hand. Self-tuning of the population size according to the GA needs is considered, under the circumstances, a good (heuristic) solution to this problem.

- **Operators** (selection, crossover, mutation and new population formation). An ever increasing scientific literature includes a multitude of alternatives for these operators depending on the problem size and type, the form of the solution space, computation capabilities etc. Unfortunately it can be said that knowledge about the proper selection of GA parameters and operators is still fragmentary and based on a largely empirical background (Michalewicz, 1996). A description of the GA operators used in this work is included in Chapter 3.
- **Super-individuals and premature convergence.** As discussed in the literature (e.g. in Witley (1989), Mathews et al., (1999), Kapelan (2002)), the existence of an individual with high fitness in the initial generations is a problem leading to premature convergence of the algorithm to local-optimal solutions, since the offsprings of the super-individual would soon dominate the next generations. Rank based selection, fitness scaling, population size increasing, introduction of number of non-random individuals in initial population, and mutation probability increasing can constitute solutions to this problem.
- **Multiobjective GAs.** The issue of multiple constraints and/or objectives can be addressed either by a composite objective (possibly a weighted average of the multiple objectives) together with penalty functions as discussed above, or by including in the GAs a Pareto optimality concept. This technique was proposed by Goldberg (1989b) and can be described as follows: Before selection is performed, the population is ranked on the basis of non-domination. All non-dominated (pareto-optimal) solutions are classified into one category and given a dummy fitness value. Then that group of solutions is ignored and another layer of non-dominated solutions is considered. The process continues until all individuals are classified. Fig. 2.16 illustrates the process.

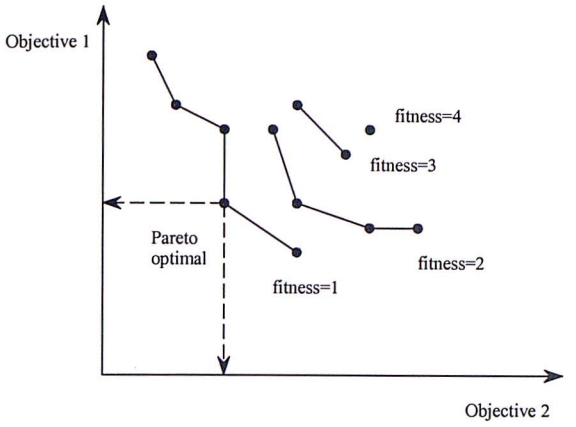


Figure 2.16 Assigning dummy fitness values in GA solutions based on pareto-optimality

- **Fitness sharing in multiobjective GAs**. The main problem of this process is that although all non-dominated individuals (correctly) share the same fitness, the lack of differentiation between individuals that arises makes the uniform sampling of pareto-optimal individuals problematic. The algorithm cannot distinguish between pareto-optimal solutions and thus there is no guarantee that the next generation will include enough different optimal solution offsprings. Fitness sharing methods were developed (Goldberg, 1989b; Fonseca and Fleming, 1993), to solve this problem: The initial fitness value, based on the pareto ranking, is reduced if other individuals exist in the *neighbourhood* of the analysed individual (Kapelan, 2002). This implicitly guarantees that the selected individuals will be more scattered along the pareto optimal line. Consequently, the size of the neighbourhood and the distance (usually Euclidean) defining whether an individual is in a neighbourhood or not have to be defined. Fitness sharing methods lead to the formation of *niches* and *speciation* among species. As stated in Kapelan (2002), speciation is the process by which a single species differentiates itself by occupying different niches. An alternative approach to that of fitness sharing is the introduction of a *crowding factor* (Deb et al., 2000), which allows the estimation of the density of solutions surrounding a particular solution in the population (Fig. 2.17). The crowding factor is calculated as the size of the largest cuboid enclosing the i^{th} solution without enclosing any other solution in the population. The crowding factor is used to differentiate between solutions of the same pareto set.

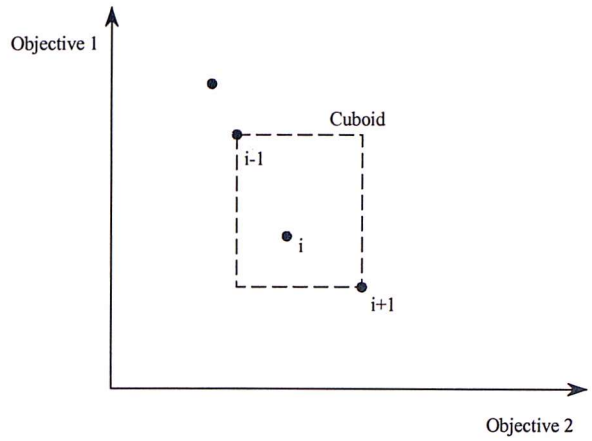


Figure 2.17. Schematic of the crowding distance calculation

A discussion on the use of GAs in the particular domain of spatial decision support systems for urban water management is included in Chapter 3. The details of its application on the WDM problem are included in Chapter 4.

2.3 Decision Support Theory

2.3.1 Introduction

This section will focus on clarifying the concepts of multi-criteria decision support and its spatial equivalent. Multi-objective versus multi-attribute decision structures will be discussed and the process of creating evaluation criteria, decision alternatives and weighting factors will be investigated. Furthermore the section will focus on sensitivity analysis and error propagation in the various stages of a multi-criteria spatial decision process. This section clarifies the decision-making framework in which our SDSS was developed.

2.3.2 Decision problem: structure and elements

Based on the work by Simon (1960), which is widely recognised by recent research (Malczewski, 1999; Bender and Simonovic, 1995) decision problems are analysed into three distinct phases: Intelligence, design and choice. As these phases are central to the structure of the solving process, a brief description of their individual characteristics is included in our discussion with particular focus on the spatial aspects of the process.

Intelligence: This is the initial phase of every decision problem, where real world situations (raw data) are selected, formatted, filtered and turned into decisional input within a geographic database. It is at this stage that the problems are identified and the relevant information outlining them is collected. Currently GIS software is more than capable of providing for this phase, being able to integrate vast spatial information from diverse sources and organise them in such a way as to maximise the information within the data.

Design: The design phase involves construction of alternatives (solutions) to the problems identified in the intelligence phase. Models – as an abstraction of reality – are applied to assist the decision maker in determining the set of alternatives relative to the particular problem. Currently, GIS software has a number of built-in functions to assist the design phase (location- allocation modelling, spatial autocorrelation, optimisation routines), but these tend to be specific to the problem the particular GIS was designed to address, rather than generic.

Choice: The alternatives generated in the design phase are evaluated and a particular course of action is selected. A specified decision rule is used to rank alternatives according to the decision maker's preferences (Eastman, 1997). The key aspect in this phase is the ability of the process to incorporate and evaluate conflicting objectives. A summary of the ongoing discussion on the role of GIS in conflict resolution can be found in Obermeyer and Pinto, (1994). Obermeyer and Pinto argued that providing more information is not necessarily positive to cognitive conflicts and in some cases it could have a negative role by aggravating the dispute fuelled by the additional facts.

2.3.3 Multi-Criteria Decision Problems

Multi-criteria decision-making (MCDM), involves a set of alternatives that are evaluated on the basis of conflicting criteria. The term criterion includes both objectives and attributes. An objective is a statement about the desired state of a spatial system. In order to conceptualise objectives and work with them, a number of attributes has to be assigned to them. The following figure summarises the structure of a multi-criteria problem.

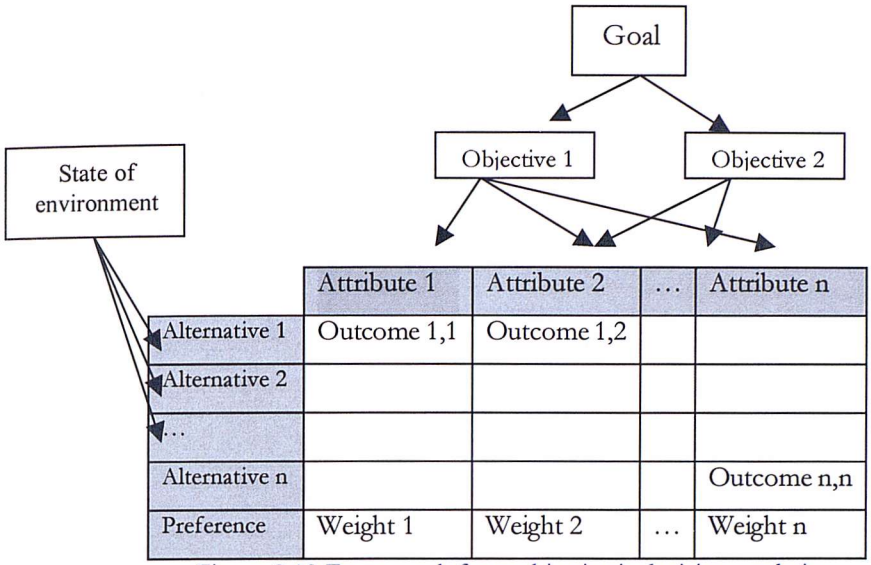


Figure 2.18 Framework for multi-criteria decision analysis

(after Malczewski, 1999)

In Fig. 2.18 "state of the environment" is any situation, which is outside the decision makers control (rain, drought, illiteracy, inflation). The possible states of nature (considered independent) reflect the degree of uncertainty about the consequences of the outcome of the decision. Each alternative yields one possible outcome per state of environment considered. The alternative is reflected upon the objectives (adding up to the overall goal) as a change in a number of attributes. The importance of each attribute to the decision maker(s) is included in the problem structure by a corresponding set of weights. In order to solve the particular problem, there is need to rank the outcomes so that the best alternative can be identified. There is yet another way to view the matter of target definition in terms of objectives and corresponding attributes, particular to fuzzy logic, which is the primary tool used for the analysis in this research. This way is to conceptualise the objective as a complex ill defined set and decompose it to better-defined ones, whose membership functions can be identified both more easily and safely. After identifying the individual membership functions for the components, an aggregation method is employed to construct the combined set's membership function. This was the approach adopted in the course of this research and its various elements (including aggregation operators) will be discussed in detail in following chapters.

2.3.4 Evaluation Criteria

Evaluation criteria (both as attributes and objectives) have to be identified in order to measure the performance of a decision. Objectives are linked to attributes, which are standardised in order to be comparable and allow for an indication of the degree that the objective has been achieved. The following paragraphs discuss these procedures.

2.3.4.1 Selection of evaluation criteria

There is no particular mechanism for defining attributes (as indicators of the achievement of an objective). To be able to accurately define all aspects of the decision problem, there is need for a large number of indicators that are generally unavailable from a data point of view. On the other hand, choosing a small number of indicators might result in oversimplifications (Young *et al*, 1996). Keeny and Raiffa (1976) identified a number of properties of a set of indicators (attributes). They claim that each attribute must be comprehensive and measurable and the set must be complete (cover all aspects of the problem), operational (meaningful in analysis), decomposable (broken into parts to simplify the process), non redundant (avoid double counting) and minimal. Although these properties are crucial to the choice of attributes, they can be considered as a rough checklist rather than a guide to criterion selection. The properties "complete" and "minimal" bring the discussion back to where it begun: to William of Occam and the principles of modelling in general. The selection process thus will have to be particular to the problem at hand and depend on the characteristics of the system that is analysed. A detailed observation of the system (and possibly the formulation of a simulation model representing it together with the relative sensitivity analysis) will lead to a better understanding of the processes involved, their interactions and the importance of different sets to the model performance and accuracy, leading in turn to the adoption of an appropriate set.

2.3.4.2 Criterion maps

After establishing a set of evaluation criteria (attributes) to measure the decision objectives, the attributes should be presented in the form of information layers (maps). Eastman (1993) makes a distinction between criterion maps and constraint maps. A criterion map is a representation of the spatial distribution of attributes, while a constraint map is a map of the feasible regions of the decision space. To be able to utilise attributes and their spatial representation, they should be associated with a – common –

scale of measurement. Scales of measurements are divided into two main categories (Keeney and Raiffa, 1976): objectives scales, that do not involve judgment or interpretation and are generally accepted (e.g. proximity in kilometres) and subjective scales that do involve judgement (e.g. aesthetic impact). A further sub-division proposed by Malczewski (1999), is the one between direct and proxy scales, as a distinction that allow direct or indirect measurement of the objective's level of achievement. These distinctions however cannot be considered strict, as in reality scales of measurement range between the two extremes mentioned above. There seldom is a purely objective, proxy scale or a purely subjective direct one or any other combination. In most cases, the scales actually used can be found somewhere in-between. A distinction that is of more importance to decision making, however, is the one between deterministic, probabilistic and fuzzy measurement scales. The process of translating the various inputs of a decision problem to a common scale, to allow for comparison, analysis and synthesis is termed standardisation. Deterministic scales are standardised either with linear scale transformations (Voogd, 1983; Massam, 1988) or value/utility functions (Hwang and Yoon, 1981; Hepner, 1984). Probabilistic scales are standardised based on subjective, objective and revised probabilities (Thomas and Huggert, 1980) and fuzzy scales are standardised using fuzzy membership functions (Klir and Yuan, 1995; Eastman, 1993; Eastman 1997; Ross, 1995). The following discussion focuses on the third case (fuzzy scales) and their standardisation, which are then applied in the case of spatial analysis in later chapters of this thesis.

2.3.4.3 Standardisation using fuzzy membership functions

A fuzzy number, as discussed earlier, is a fuzzy set defined on the domain of real numbers (Klir and Yuan, 1995). Fuzzy numbers have the property of normality in the sense that a maximum membership of a set is 1. It can be shown that a fuzzy set is a family of crisp sets (Klir and Yuan, 1995; Ross, 1995). Thus, arithmetic and algebraic operations can be defined in analogy to crisp sets, through the "extension principle". The main concepts of fuzzy set operations were summarised in section 2. The concept of fuzzy numbers can provide not only a standardisation tool (to enable comparability of attributes measured in different scales) but as a scale for defining and incorporating linguistic variables into the design process. Fuzzy numbers are actually a representation of linguistic variables (i.e. soil type: aggressive, very aggressive etc), through a base variable, which is a variable in a conventional sense (i.e. pH values). Figure 2.19 is an

example of such a standardisation of a conventional variable (slope) to a steep slope membership criterion.

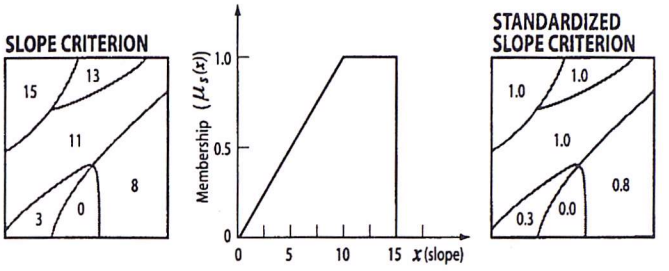


Figure 2.19 Generating standardised criterion maps

(after Malczewski, 1999)

In principle, the standardisation process is a fuzzification of the crisp set (the conventional variable). A number of fuzzification methods are discussed in literature. A summary list of these methods can be found in Ross (1995) and include: intuition, inference, rank ordering, angular fuzzy sets, neural networks, genetic algorithms, inductive reasoning, soft partitioning, meta rules and fuzzy statistics.

2.3.4.4 Weighting

Criteria that are taken into account in the decision process are generally not equally important to the expected outcome. The relative importance of these criteria should therefore be identified and the criteria should be prioritised – typically through the application of a weighting scheme. Weights should be considered to be an expression of decision maker's choices or experience (Tkash and Simonovic, 1997) and can illustrate conflicts of interest where multiple decision-makers are involved. Weights are not a measure of the general importance of an evaluation criterion, but are heavily dependent on the criterion range. They can be perceived as the relative gain when a criterion outcome changes from the lower value of its range to the higher value as compared to the same change in the other criteria (Kirkwood, 1997; Belton and Gear 1997).

A variety of methods is available in the literature for the assignment of weights, from the simplest ones involving direct ranking of criteria, to rating, involving predetermined scales, to pair wise comparison (Saaty, 1980), and trade-off analysis. The following table summarises the main elements of these methods and refers to GIS and software applications (n is the number of criteria under consideration and therefore the number of weights to be assessed).

Table 2.1 Summary of methods for assessing weights

(source: Pitz and McKillip, 1984 and Malczewski, 1999)

	Method			
	Ranking	**Rating**	**Pairwise Comparison**	**Trade-off Analysis**
Number of judgements	n	n	n(n-1)/2	<n
Hierarchical	Possible	Possible	Yes	Yes
Underlying theory	None	None	Statistical/heuristic	Axiomatic/deductive
Ease of use	Very easy	Very easy	Easy	Difficult
Trustworthiness	Low	High	High	Medium
Precision	Approximations	Not precise	Quite precise	Quite precise
Software availability	Spreadsheets	Spreadsheets	Expert Choice™	Logical Decisions™
Use in GIS	Weights can be imported	Weights can be imported	Component of IDRISI™ GIS	Weights can be imported

If multiple decision makers are involved in the weighting process (i.e. different interest groups), the weights can be calculated for each homogenous group separately and then aggregated (Jankowski *et al.*, 1997). In any case, weight assignment can play a significant role in identifying the nature and extent of the disagreement between the decision makers as well as the impact of these disagreements in the final decision outcome.

2.3.5 Alternatives and Constraints

2.3.5.1 Constraints

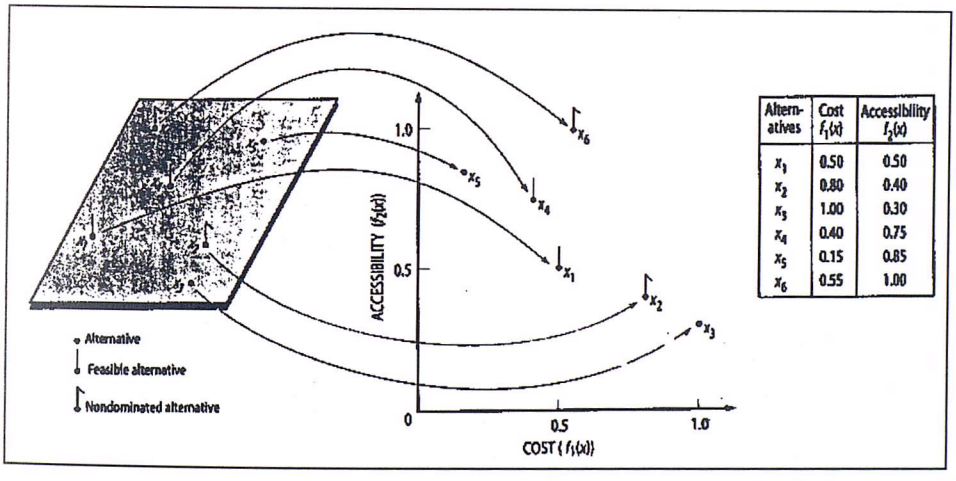
Constraints are limitations that do not permit certain actions to be taken (Keeny, 1980). They are imposed on decision alternatives dividing them into feasible and infeasible. According to Rosenthal (1985) and Eastman (1993), there are two basic types of constraints: Boolean (or logical) and target constraints[1]. In the first case, the (spatial) limitation is coded as 0 or 1 as a distinction between an infeasible and a feasible alternative (cell) respectively. In the second case, the constraint will be expressed as a characteristic, which the decision set must possess (Eastman, 1997). An example of the first case would be that the feasible alternatives (cells) are situated within a certain area. For the second case an example would be that the suitable area would be no less than 100km. Constraints separate the decision space (the set of decision alternatives) into two areas: feasible and infeasible alternatives. The process of this separation is called screening. In the case of spatial decision making and in particular raster based analysis, a

[1] Boolean constraints are also thought of as non-compensatory constraints (i.e. ignoring value trade-offs) whereas target constraints can be considered compensatory (i.e. taking into account the trade-offs between criteria) (Keeny, 1980).

large number of alternatives is involved as all the cells of the map layer can be considered alternatives (Malczewski, 1999). Site and land suitability problems are problems of this kind. When many alternatives are present, there is scope for narrowing the problem down by eliminating dominated alternatives and therefore concentrate on efficient solutions

2.3.5.2 *Non-dominated or pareto-optimal solutions*

After eliminating infeasible solutions with the application of constraints, the feasible solutions can be further divided into dominated (non-efficient) and non-dominated (efficient or non-inferior or pareto-optimal) solutions. Non-dominated solutions are those that are at least as desirable on all criteria when compared with inefficient solutions and more desirable on at least one. Figure 2.20 illustrates the distinction. In this case the six alternatives involved are evaluated through two criteria: cost and accessibility, and their relevant positions in the decision outcome space indicates that alternatives x_2 and x_6 are efficient. Note that although x_2 is less desirable than some of the dominated alternatives (x_1 and x_4) on the accessibility criterion, the fact that it is more desirable in at least one criterion (cost) makes it an efficient solution.



Alternatives	Cost $f_1(x)$	Accessibility $f_2(x)$
x_1	0.50	0.50
x_2	0.80	0.40
x_3	1.00	0.30
x_4	0.40	0.75
x_5	0.15	0.85
x_6	0.55	1.00

Figure 2.20 Decision space and criterion outcome space

(after Malczewski, 1999)

Although pareto optimality and its related concepts are widely used in the literature, this use is not always consistent and the understanding of the terms not always clear (Van Veldhuizen and Lamont, 2000). The following set of definitions is intended to provide a consistent basis for the use of these terms within this thesis.

Definition 1: Multi-Objective Problem (MOP)

A MOP minimises an evaluation function given as a vector $F(\vec{x}) = (f_1(\vec{x}), f_2(\vec{x}), ..., f_k(\vec{x}))$ subject to $g_i(\vec{x}) \leq 0$, i=1,...m, constraints where $\vec{x}$ is a n-dimensional decision variable vector from a universe of discourse, $\vec{x} \in \Omega$. The evaluation function is therefore a mapping from the decision space Ω to the objective function space Λ.

Definition 2: Pareto Dominance

A solution vector $\vec{u} = (u_1, u_2, ..., u_k)$ dominates a vector $\vec{v} = (v_1, v_2, ..., v_k)$ if and only if u is partially better than v, i.e. $\forall i \in \{1,...k\}, \vec{u_i} \leq \vec{v_i} \wedge \exists i \in \{1,...k\} : u_i < v_i$. Pareto dominance of u over v is denoted as $u \prec v$.

Definition 3: Pareto Optimality

A solution x of a decision space Ω is said to be pareto optimal with respect to Ω if and only if there is no x' in Ω, for which $\vec{u}$ =F(x') dominates $\vec{u}$ = F(x).

Definition 4: Pareto Optimal Set.

For a given F(x) the pareto optimal set (P^*) is defined as: $P^* := \{x \in \Omega \mid \neg \exists x' \in \Omega : F(x') \prec F(x)\}$

Definition 5: Pareto Front

For a given F(x) and pareto optimal set P^*, the pareto front PF^*, is defined as:

$PF^* := \{\vec{u} = F(x) = (f_1(x), ..., f_k(x)) \mid x \in P^*\}$

The pareto optimal set (which represents the global optimum of a multi-objective problem (Van Veldhuizen and Lamont, 2000)) contains all of the "better" solutions and no further distinction can be made between them without a compromise between the objectives, through a subjective decision making process. The reliability of the decision maker's choice is dependent on the extent to which the pareto optimal set presented to him (which is a model of a real life situation) is representative of the true pareto set (which represents real life's infinite choices). In complex multi-objective problems, it is generally impossible to derive an analytical determination of the true pareto set, thus

making even an approximation, through the abstraction of mathematical modeling, difficult.

2.4 Reaching decisions

The process by which the alternatives are ordered, integrating data (attributes) and decision preferences (weights) is termed "decision rule" (Chankong and Haimes, 1983). It involves identifying the outcomes (consequences) of the alternatives and measures them against the criteria. Criteria, as mentioned before, can be divided into attributes and objectives and the decision rules can be categorised based on that distinction. In the first case, attributes are considered both decision variables and objectives. In the second case there is a distinction between these two and there are objective functions relating the one to the other.

2.4.1 Multi-attribute decision rules

A variety of rules from simple additive weighting to ideal point methods can be found in the literature (Keeny and Raiffa, 1976; Keeny, 1980; Pitz and McKillip, 1984; Bender and Simonovic, 1996; Despic and Simonovic, 1997). Depending on the nature of the alternatives and the information (attributes), the rules can be applied in a deterministic, probabilistic or fuzzy context.

Simple additive methods: These are the most often used methods in spatial decision-making, although not necessarily the most accurate. Eastman (1997) describes these methods as weighted linear combination (WLC), explaining that they require the decision maker to directly specify the number of constraints and the weights (preferences) to be applied to the attributes. The aggregation result is calculated for each cell (i), by the following equation:

$$R_i = \sum_j w_j x_{ij} \qquad \textbf{Eq. 2.25}$$

Where x_{ij} is the value of cell (i) for the attribute j and w_j is the weight of that attribute. The reason why this is the most frequently used technique lies in the fact that Eq. 2.25 can be applied through any GIS with fundamental overlay capabilities. Lai and Hopkins (1989) as well as Eastman (1997) and Malczewski (1999), emphasise that WLC implies

the acceptance of two assumptions: linearity and additivity. Linearity implies that the benefit from more input of an attribute is constant and independent of the characteristics of the problem, and additivity implies independency between the variables (attributes). In practice, these assumptions are generally not valid. Furthermore, direct weight assignment, although reflecting the experience of the decision maker (Makropoulos, 1997), can be misleading.

Value-Utility methods: The concept was introduced by Keeny and Raiffa (1976) and can be divided into two sub-methods: Value rules assume determinism in the decision process and are relative risk-neutral. In Utility rules on the other hand, risk is incorporated in the assessment of the single attribute utility function and the process is probabilistic[1]. The procedure involved in both cases has two distinct steps: a (utility/value) function that transforms the attribute values into an interval (utility/value) scale and a trade-off analysis for defining the weights. By multiplying the utilities by the weights, the trade-offs among the attributes are taken into account in the multiattribute (utility/value) function. The overall utility/value is a weighted average of the individual utilities/values. Two conditions need to hold for the application of this method: utility independency (i.e. the utility function in one attribute doesn't depend on the others) and preferential independence (i.e. changes in one attribute will not affect the preference of another) (Malczewski, 1999). If there is complete independency between criteria, Equation 2.25 can be applied substituting attribute values with utility values. If there is some interaction between criteria, the following equation proposed by Zeleny (1982) can be applied.

$$V_i = \frac{\prod_j \left(1 + k w_j v_{ij}\right) - 1}{k} \qquad \textbf{Eq. 2.26}$$

Where k is a scaling constant determined so that value v_{ij} ranges from 0 to 1. Note that utility/value preferences are very subjective and not necessarily intuitive for the decision maker while they demand of him/her considerable information processing load. They would tend to vary between decision makers, vary with time for the same decision maker

[1] The term "value" function refers to a utility in the context of a deterministic criterion whereas utility function is restricted to a probabilistic criterion. Utility can be a value but the opposite does not apply (Hwang and Yoon, 1981).

and even vary spatially, as preference could be guided by the particular conditions the decision maker is in at any specific time.

Analytic Hierarchy Process (AHP): The process was developed by Saaty (1980) and is based on three principles: decomposition, comparative judgement and synthesis of priorities. The problem is decomposed into a hierarchy that describes its basic elements (Figure 2.21). The top level is the ultimate goal descending to more specific objectives that are decomposed to attributes. Attributes are rated and the composite alternatives are ranked. Relative importance between alternatives is performed by pairwise comparison, reducing the complexity of the information processing that is demanded of the decision maker. A comparison matrix is calculated, weights are estimated of the matrix and a consistency ratio is computed to validate the procedure. The consistency ratio (CR) is calculated based on the assumption that the decision maker is generally not consistent when making a preference statement. For a detailed description of the weights calculation procedure for the consistency ratio calculation procedure, the reader is referred to Saaty (1980) and Malczewski (1999) for a general application or Kirkwood (1997) for a spreadsheet application and Eastman (1997) for a GIS integrated application.

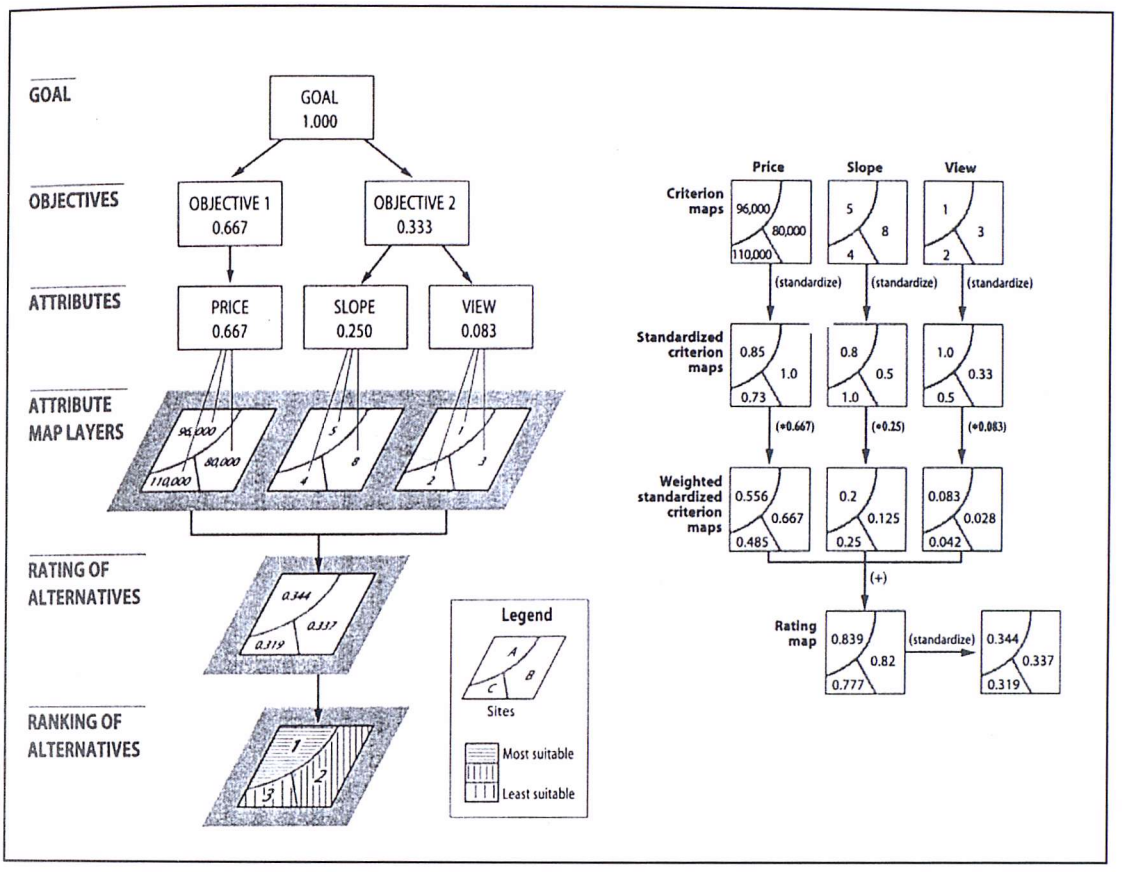


Figure 2.21 Analytical Hierarchy Process

(after Malczewski, 1999)

The final stage is to aggregate the relative weights to produce composite weights. This is achieved by a means of a sequence of multiplications of the matrices of relative weights at each level of the hierarchy. The composite weights serve as a measure of the effectiveness of each alternative in achieving the goal. The total score R_i for the i^{th} alternative (or cell in raster analysis), is given by Eq. 2.27.

$$R_i = \sum_k w_k r_{ik} \qquad \textbf{Eq. 2.27}$$

Where w_k is the vector of priorities (weights) associated with the k^{th} element (i.e. attribute) of the hierarchy and r_{ik} is the vector of priorities. The best alternative is selected as the maximum value of R. AHP has been extensively used in spatial decision support (Eastman, 1997), fuzzy decision making (Xiang *et al.*, 1992), as well as in conjunction with linear programming (Dyer and Forman, 1991). Criticism of the method focuses on the meaning of relative importance of one element of the hierarchy in comparison with the

other, particularly in large problems (Goodwin and Wright, 1998). There seems to be a reasoning problem if the decision maker, once asked to state the degree of preference of one element over the other, is not provided with some indication of the "quantities" of the two alternatives actually involved.

Fuzzy decomposition and aggregation:

One way to deal with a complex decision problem, within a fuzzy set framework, is to consider it as an ill-defined set (say: A), and decompose it into several less complex components (the components will also be ill-defined sets, say: B_1, B_2, B_3,...)(Despic and Simonovic, 1997). The decomposition process is continued until all of the ill-defined sets in the final level of decomposition allow reliable construction of the corresponding membership functions. The final stage is to find an appropriate aggregation method that combines the membership functions of the simple components into the membership function μ_A of the ill-defined set A. This is a three-step process:

> **Step 1.** Decomposition of the complex fuzzy information (an ill-defined set A) into less complex components (ill-defined sets B_i). If any of the ill-defined sets B_i is still too complex, repeat step 1.
>
> **Step 2.** Construction of the fuzzy sets B_i, representing the components B_i, by one of the existing methods for membership evaluation (see section 2).
>
> **Step 3.** Aggregation of fuzzy sets B_i into a fuzzy set A .

Each of the three steps is important and has to be worked out carefully. For step 1, some input from experts in the subject area of the ill-defined set A is usually necessary. In step 2, one has to choose a suitable method for membership evaluation. The main condition that a proper decomposition procedure should satisfy is that the components B_i must provide substantially complete information about the set A.

As mentioned earlier, the decomposition process does not have to stop on one level. If components B_i still contain complex information, we can perform further decomposition of B_i into its components C_{ij} and so on (Figure 2.22). For each decomposition, we have to ensure that the completeness condition is respected.

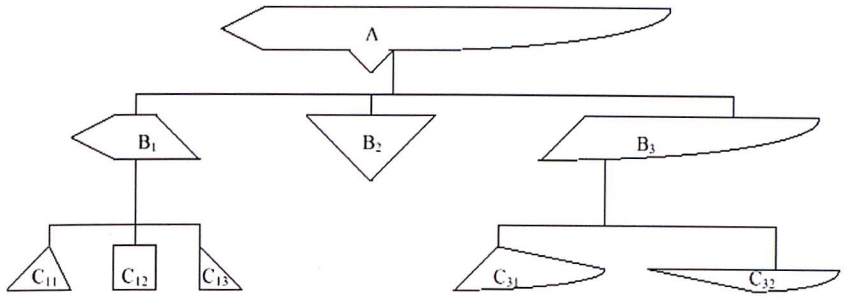


Figure 2.22. Decomposition of an ill-defined set A into its less complex components

(source: Despic and Simonovic, 1997)

For an easier aggregation process (step 3), it is a good practice to decompose the set A into more levels with fewer components as opposed to fewer levels with many components. Of course, the overall decomposition should be intuitively clear in order to provide effective evaluation of membership values in step 2. In other words, if enough attention is given to the decomposition process, the complexity enveloping steps 2 and 3 can be significantly reduced. The second step is performed on those components that are not further decomposed. (In Figure 2.22, these components are: C_{11}, C_{12}, C_{13}, B_2, C_{31} and C_{32}.) The evaluation of the membership function for these sets should be intuitively clearer (and easier) than the evaluation of the membership function for the initial ill-defined set A. Using already described methods for membership estimation, we can choose the most suitable ones for particular ill-defined sets. In some cases, many of these components can be crisp sets, as well. Rules by which membership functions $\mu_{B_i}(x)$ are aggregated into membership function $\mu_A(x)$ are the subject discussed in the remaining part of this paragraph.

Bellman and Zadeh (1970), suggested that the best decision alternative would emerge from the intersection of both criteria and constraints. Bellman and Zadeh identified this intersection to be the MIN operator of possibility theory. This operator, however, is only one of a large number of possible *aggregation* mechanisms that combine fuzzy criteria into a single composite fuzzy set. This combined set represents an overall estimation of the spatial performance of all the attributes of the problem taken into account. There are three main categories of aggregation operator: Intersection operators, union operators and averaging operators. Yager (1988), introduced an aggregation technique which is a combination of the three: ordered weighted averaging (OWA). This technique is

extensively used in the development of the SDSS due to the ability of these operators to provide the decision maker with a better insight into decision-making under ignorance[1].

Ordered Weighted Averaging provides a continuum of fuzzy operators between the logical AND (fuzzy intersection) and the logical OR (fuzzy union). OWA is a weighted sum, with ordered evaluation criteria. The order weights allow for control of the degree of trade-off among criteria, thus providing control of the degree of optimism (risk), allowed into the planning process (Malczewski, 1999). Weighting factors are not applied initially to a specific criterion, but are in fact ordered so that the highest criterion value is assigned the first weighting factor. The next highest value is assigned to the second weighting factor etc. Therefore the coefficients are not associated directly with a particular attribute but rather with an ordered position (Yager, 1988). If $[w_1,w_2,\ldots,w_n]$ is the set of ordered weighting factors (also viewed as a weighting vector), then the elements of the set can be assigned values ranging from [1,0,...,0] which is the MIN fuzzy operator (the logical AND), to [0,0,...,1], which is the MAX fuzzy operator (the logical OR). In the first extreme case, the criteria are compared for each point and the largest value is selected as the composite value. The rest of the criteria are given a value of 0. This constitutes an optimistic approach, thus incorporating maximum risk[2]. At the other extreme, the lowest criterion value is selected as the composite value. This is evidently a pessimistic (low risk) approach. Both these extreme cases involve no trade-off among criterion scores. In between, there exists a large number of alternative ordering sets with varying degrees of trade-off. A special case is when the set is [1/n, 1/n,...,1/n], where n is the number of criteria to be considered. This case results in maximum trade-off between criterion values. A high value (score) in one would compensate for a low value (score) in another criterion in the same point (x, y). A measure of ANDness, ORness and TRADE-OFF, associated with a particular set of weights can be obtained by the following equations (Yager, 1988; Malczewski, 1999).

---

[1] In decision making under ignorance it is assumed that we have no knowledge about the state of nature. In this environment, the decision maker replaces knowledge about the environment by assuming some particular "decision making attitude"(Yager, 1995). This attitude is represented here by the level of risk, the decision maker is prepared to take when evaluating the alternatives (i.e. aggregating the criterion maps).

[2] The risk associated with either ANDness or ORness is dependent on the way the criterion scores are correlated with positive or negative results and thus by the structure of the decision problem itself. In this paragraph, it is assumed that the outcome (aggregation) is positively correlated with suitability. Thus the AND operator would result in more areas being classified as suitable: an optimistic approach, involving higher risk. In the case where the outcome is positively correlated with vulnerability (i.e. to leakage) the opposite is true.

$$ANDness(w) = \frac{1}{n-1} \cdot \sum_r (n-r)w_r \qquad \textbf{Eq. 2.28}$$

$$ORness(w) = 1 - ANDness \qquad \textbf{Eq. 2.29}$$

$$TRADE - OFF(w) = 1 - \sqrt{\left[\frac{n\sum_r (w_r - \frac{1}{n})^2}{n-1}\right]} \qquad \textbf{Eq. 2.30}$$

Where n is the number of criteria, r is the order of criterion and w_r is the weight for the criterion of the r^{th} order. The measures range from 1 to 0. OWA is used as the main aggregation operator due to its advantage to lie between OR and AND operators, thus expressing quantifiers between the two extreme (binary logic) cases: "there exists" and "for all" (i.e. linguistic quantifiers such as "few", "many" etc) (Zadeh, 1983). The main properties of these mean-like operators (R) have been identified by Yager (1988) to be:

R: $I^n \rightarrow I$, such that:

a. R satisfies symmetry (generalised cumulativity)

$R(a_1,a_2,\ldots,a_n) = R(b_1,b_2,\ldots,b_n) \Leftrightarrow (a_1,a_2,\ldots,a_n) = (b_1,b_2,\ldots,b_n)$

b. R is monotonic

$R(a_1,a_2,\ldots,a_n) \leq R(b_1,b_2,\ldots,b_n)$ if $a_i \leq b_i$, $\forall i$

c. R is idem potent

$\forall i \in I$: $R(a, a,\ldots,a) = a$

Based on these properties we can prove that the R operators (OWA) are in between AND and OR operators as a theorem. The mathematical formulation of our theorem is:

$\min(a_1,a_2,\ldots,a_n) \leq R(a_1,a_2,\ldots,a_n) \leq \max(a_1,a_2,\ldots,a_n)$

let $b = \min(a_1,a_2,\ldots,a_n)$

from property $c \rightarrow R(b,\ldots b)=b$

but, $\forall i \in I$: $b \leq a_i$

from property $a \rightarrow b \leq R(b,\ldots b) \leq R(a_1,a_2,\ldots,a_n) \Rightarrow \min(a_1,a_2,\ldots,a_n) \leq R(a_1,a_2,\ldots,a_n)$

the second part follows in a similar manner.

Note that implicit in this methodology is that the criteria is of equal importance to the decision-maker, as the weighting refers to the aggregation operator's position in the

continuum between AND and OR and not to decision-maker's preference. The inclusion of preference in the overall decision function is, however, possible and feasible ways have been suggested in the literature (Yager, 1978; 1988). The procedure provided here, as an option to the user of the SDSS, is a linear weighting procedure prior to the application of the OWA operators.

Yager (1992), suggests that the OWA weighting vector has the same properties as a probability distribution, namely $w_i \in [0,1]$ and $\sum_i w_i = 1$ and therefore can be viewed as such. In this probability distribution, w_i corresponds to the probability that the i^{th} best alternative will happen. Extending this notion, we can argue that $w_1 = 1$ (pure optimism) supposes the probability of occurrence of the best outcome to be equal with one. In this view, where w_i is considered the probability of occurrence of the i^{th} best outcome, the OWA aggregation $\sum_i w_i b_i$, (where b_i is the value of the i^{th} best outcome) can be viewed as an **expected value** (Yager, 1995). This notion is very important to this work and will be used as an indication of expected value of water saved in the water demand management SDSS system development. Viewing the weighting vector as a kind of probability distribution enables us to introduce a measure of entropy (H) (Eq. 2.31), analogous to Shannon's entropy, to calculate the amount of information in the arguments, which is used during an aggregation based on the weighting vector (Filev and Yager, 1998).

$$H(w) = -\sum_i w_i \ln w_i \qquad \textbf{Eq. 2.31}$$

Another aggregation model is known as **Zimmerman's γ-family of aggregation operators**: the model for membership aggregation in Zimmerman (1987) is developed in the first place to provide good empirical fit, while at the same time it satisfies basic mathematical requirements for easy computation. Zimmermann (1987) emphasizes the importance of selecting appropriate operators by which two or more membership functions are to be aggregated. In this respect, he also gives a list of rules how to select the 'best' operator. From experimental observations, it has been concluded that for different phenomena we need different operators in order to build adequate models. To clarify this, let us suppose that we have the following situation: An ill-defined set A is decomposed into two components $B=\{B_1, B_2\}$, and the membership values $\mu_{B1}(x)$ and $\mu_{B2}(x)$ of an element $x \in X$ are 0.2 and 0.8, respectively. Depending on the nature of the

ill-defined set A and its components B_1 and B_2, the resulting membership value $\mu_A(x)$ can take any value from the interval [0.2, 0.8] and sometimes even outside this interval. There is an infinite number of operators that can be used to describe a certain model, and many of them have been generalized through t-norms and s-norms. However, even within one decomposition, depending on particular context, we might have to change operator again and again. Instead of formulating a new operator every time, Zimmermann suggests the use of a family of operators determined by a single parameter γ. When applied to membership aggregation, this family of operators is defined in the following way:

$$\mu_A(x) = \left(\prod_{i=1}^{n} \mu_{B_i}(x)\right)^{1-\gamma} \cdot \left(1 - \prod_{i=1}^{n} (1 - \mu_{B_i}(x))\right)^{\gamma}, \quad 0 \le \gamma \le 1 \qquad \textbf{Eq. 2.32}$$

Changing the value of γ from 0 to 1, the membership value $\mu_A(x)$ ranges from $\mu_A(x) = \prod_{i=1}^{n} \mu_{B_i}(x)$, to $\mu_A(x) = 1 - \prod_{i=1}^{n} (1 - \mu_{B_i}(x))$. For $\gamma = 0$ we have product operator, and for $\gamma = 1$ algebraic sum. If the product operator and algebraic sum are considered as two external operators representing non compensatory 'AND' and full compensatory 'OR', respectively, then parameter γ can be interpreted as a *grade of compensation.* Each value of γ from the interval [0, 1] represents a different operator and according to Zimmermann can successfully model empirical results of membership aggregation. Further modification of Eq. 2.32, is necessary if components B_i are not of equal importance with respect to the decomposed set A. This is achieved by assigning weights for each of sets B_i, and then Eq. 2.32 becomes:

$$\mu_A(x) = \left(\left(\prod_{i=1}^{n} \mu_{B_i}(x)\right)^{wi}\right)^{1-\gamma} \cdot \left(\left(1 - \prod_{i=1}^{n} (1 - \mu_{B_i}(x))\right)^{wi}\right)^{\gamma}, \quad 0 \le \gamma \le 1, \sum w_i = n \qquad \textbf{Eq. 2.33}$$

To preserve the structure of the model, the weights w_i should add up to the total number of components n within a single decomposition. These weights w_i can be determined by direct estimation or using relative preference method (Saaty) as described earlier and then results normalized to satisfy condition $\sum wi = n$. Unlike the weights w_i, parameter γ is much less intuitively clear for direct estimation unless decomposition of A contains only two sets B_1 and B_2. Even in this case the best way to obtain γ is through experimentally

obtained membership values for some selected elements x. For each selected object x_j, we can find γ_j solving the Eq. 2.34:

$$\gamma_j = \frac{\log \mu_A(xj) - \log \prod_{i=1}^{n} (\mu_{Bi}(xj))^{wi}}{\log\left(1 - \prod_{i=1}^{n} (1 - \mu_{Bi}(xj))^{wi}\right) - \log \prod_{i=1}^{n} (\mu_{Bi}(xj))^{wi}} \qquad \textbf{Eq. 2.34}$$

and then use the average value as the desired parameter:

$$\gamma = \frac{1}{m} \sum_{j=1}^{m} \gamma_j \qquad \textbf{Eq. 2.35}$$

where m is the number of objects x_j for which membership values $\mu_{Bi}(x_j)$ and $\mu_A(x_j)$ have been experimentally determined. One of the limitations of using this model is that the components B_i within a single decomposition B should have approximately equal "compensation strength" compared to the other components from B. Only in this case can we have satisfying results for any combination of membership values $\mu_{Bi}(x)$. Another important limitation is that γ -operator does not give any compensation if any of the components within the decomposition is estimated to be zero. Thus, before we decide to use this method for aggregation, we have to make sure that the zero membership value of any sub-criterion B_i logically leads to the zero membership value of the criterion A, regardless of the membership values of the other sub-criteria. Only after this is approved, can we start with assigning relative weights and calculating parameter γ from the empirical results.

2.4.2 Decision under uncertainty

One of the main aspects of decision-making that will be addressed in this research is decision under uncertainty. Various types of decisional uncertainty and methods of quantifying to a certain extent will be summarised here to provide a framework for the mathematical development in following chapters. In summary it can be stated that two basic types of uncertainty can be identified in any decision process (Ross, 1995): (a). Uncertainty due to lack of information about the decision situation and (b). Uncertainty associated with imprecision in the description of events or statements (i.e. preferences). If the uncertainty is introduced in the decision problem by randomness, it can be handled by probability theory. If the events themselves are ambiguous, the problem can be

restructured in order to define the degree to which the event belongs to a certain class. This type of uncertainty is handled by fuzzy set theory, as discussed in previous paragraphs.

Multicriteria analysis (MCA) in particular is subject to four major types of uncertainty: method uncertainty (Voogd, 1983), problem definition, data uncertainty and accessibility. An appreciation of these four problem areas cannot be overstated as they may well influence the decision options produced through the use of MCA.

Method uncertainty takes a number of forms including overall uncertainty in the scores and priorities attached to the criteria and how they will interact to affect the decision options as well as uncertainty about how changes in the priority of an individual criteria will affect the decision option and concern over how the choice of one decision rule over another might affect the decision option.

The uncertainty associated with *problem definition* is concerned with whether all the relevant criteria have been taken into account and that the criteria properly reflect the overall policy objectives. In addition, there may well be uncertainty about the relevance of certain criteria (Janssen, 1992).

The confidence that people and organisations place in the quality of their basic information is often unsubstantiated. The topic of *data quality*, particularly in a GIS context, has received considerable attention in the literature (for example Goodchild, 1991; Malczewski, 1999; Yoon, 1989) and there is no reason to restate these arguments here. However, these should not be overlooked when considering the validity of MCA in a SDSS context.

One of the main drawbacks of many of the MCA methods is their *accessibility* (user friendliness). Saaty's analytical hierarchy process (Saaty, 1980; Banai, 1993) is a good example. Despite the concept being relatively straightforward to understand, many decision makers would not have the appropriate background in mathematics to have a complete appreciation of what is happening. This becomes particularly important when a decision maker may be called upon to justify a decision rule, which produces a set of less. than perfect decisions.

Any computer environment for applying MCA should ideally provide a mechanism for communicating the influence these four types of problems have on the outcome of the decision option.

A variety of different procedures exists for dealing with method uncertainty. These can loosely be described as sensitivity analysis and take many different forms. Carver (1991) suggests the use of a tally technique where the number of times a site is chosen through the use of a range of MCA techniques is recorded. Other techniques, such as Monte Carlo simulation have been used (Janssen, 1993) to investigate sensitivity to changes in the importance of criteria within the decision rule. To improve comparison between MCA techniques ideally more than one method should be implemented in the same system. This would also, as Carver (1991) suggests permit subjective comparison methods to be carried out by the decision makers themselves, which would permit them to explore the sensitivity of their own models. This approach, in which the decision maker varies the importance and selection of the criteria in a manual interactive way, has a number of distinct advantages. First, no complex statistical methods, which may be off-putting to the decision maker, are used. Second, the technique permits the decision maker to interact with the decision rule so that he/she has a better appreciation of how changes in weights and scores will influence the decision outcome.

Uncertainty in data quality and problem definition are much more difficult problems to tackle and in many ways are outside the remit of an SDSS as they involve the use of *a priori* knowledge which is often only gained through experience. In this context all that the system can hope to provide is a memory aid to the decision maker, which informs him/her of the quality or value of a given piece of information. It is then up to the decision maker to use these in a subjective manner to change the scoring and weighting of criteria used in the decision rule. It may well be possible to develop more formal methods for dealing with uncertainty in problem definition and data quality (Aspinal and Pearson, 1993) but these remain somewhat abstract and inaccessible for most decision makers. The use of fuzzy logic within this particular research falls within this context of addressing some of these more abstract problems in a more formal way.

2.4.3 Decision problem structure and DSS

Any decision problem falls inside the continuum between fully structured and fully unstructured decisions[1]. In a structured situation, the participants can identify coherently all aspects of the situation. The structured decisions are referred to as programmed tasks (Malczewski, 1999), as they can be programmed and solved by a computer without the need for a human decision maker. The decision maker will take over from the computer in interpreting the outputs rather than in the decision process itself. At the other end of the continuum, an unstructured problem implies non-repetitiveness and an ill defined decision structure. It also probably implies that the conditions applicable to each phase of the problem are so different that no general model can be developed as the basis for programming. In this case, the decision maker should employ heuristics and experience of similar problems without the assistance of a computer. In real world situations, there are very few examples of the extreme cases. The decision problems encountered daily, are mainly somewhere in between: this is the area of semi-structured decision making. It is within this arena, where a decision problem can be solved by a decision maker with the help of a computer based system, that decision support systems (DSS) come into their own. Figure 2.23 illustrates the degree of a problem structure and the corresponding decision making process. According to Sprague and Watson (1996), the key issue in a successful DSS is the choice of a system that corresponds to the problem's structure. A discussion on DSS and in particular SDSS and their use in environmental planning is included in following paragraphs.

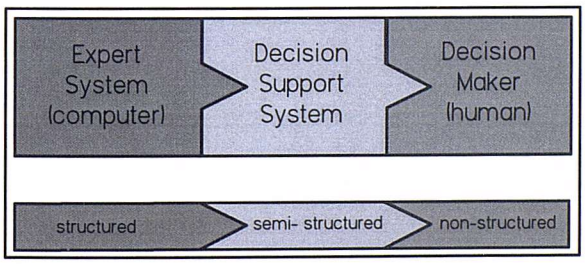


Figure 2.23 Decision problem structure and corresponding decision process

2.4.4 Error Assessment

Multi-criteria spatial decision problems are prone to considerable errors and uncertainties. In most applications these errors tend to be considered as negligible, but

[1] For a full discussion between structured and unstructured decisions, the reader is referred to Simon (1960) whose work has been central to the discussion of Decision Support Systems and more recently to Sprague and Watson (1996).

research has been challenging the veracity of this assumption (Yoon, 1989). Furthermore, these particular decision problems are subject to two levels of uncertainty: Criterion map uncertainty and preference uncertainty.

2.4.4.1 *Criterion map uncertainty*

There are two broad categories of error in spatial analysis: errors of measurement and category errors. Errors of measurement are defined as the difference between the real and the observed value. The best known measure of these errors is the root mean square error (RMS), defined as: $RMS = \sqrt{\left[\frac{\sum (x_i - x_{i(true)})^2}{n}\right]}$ where x_i and $x_{i(true)}$ are the measurement and the true value respectively. The category errors are primarily errors in reporting or classification of attribute values in sample locations. The best-known description of this kind of uncertainty is the "confusion matrix". And the best-known measure of a confusion matrix is the Kappa statistic (ranging from 0 to 1) which signifies the agreement between a predicted spatial pattern and an observed one (Congalton, 1991).

2.4.4.2 *Preference uncertainty*

Further to the classic data-set errors, the decision making process is subject to judgment and therefore the uncertainty involved in it. The most common way this uncertainty manifests itself is through uncertainty in weights portraying decision makers' priorities. Particularly where a number of decision makers are involved in the same decision process, the preciseness of their judgement (through compromise procedures) may decrease even further. Fuzzy inference systems, as seen in previous paragraphs, can incorporate uncertainty both in rules and input data (especially type-2 FIS).

2.4.5 Error propagation

Error propagation analysis (or sensitivity analysis) is the theory which deals with the way input errors (either in data sets or preference) affect the final outcome (Malczewski, 1999). Both analytical (Hevelink *et al.*, 1989) and Monte Carlo simulations (Openshaw, 1989; Openshaw *et al.*, 1991), can be used as tools for error propagation analysis within the context of spatial decision making. Openshaw *et al.*, (1991) provides a detailed description of the use of Monte Carlo simulation in error analysis in choosing sites for storing radioactive material in Britain.

2.5 Spatial Decision Support Systems

2.5.1 Introduction

This section focuses on clarifying the concept, framework of use and applications of spatial decision support systems drawing from, a relevantly scarce, available literature. Research in different fields (both engineering and non-engineering) is mentioned as means of example for the widespread applicability of these techniques. Furthermore, the background study identifies past and current applications of SDSS in our particular field of interest, namely the environmental planning field. The aim is to familiarise the reader with the terms and concepts used within this research and discuss the extent of their application in the environmental planning field. This will further illustrate the research's incentives and its applicability to this and other similar problems. Part of the discussion that follows was also included in the introduction but is included again here for reasons of completeness.

2.5.2 Decision support systems: the superset

As mentioned in the introduction, the core concept of decision support systems (DSS) was introduced in 1960 by Simon (Simon, 1960), with his work on structured versus unstructured systems. In the case of structured problems, the decision maker knows all relevant information on the system and its rules in advance. The solution to the problem is then scaled-down to a series of programmed tasks, which can be essentially solved by a computer program (Malczewski, 1999). In contrast, ill-defined problems, with no programmable/repetitive solution are termed unstructured. The experience of the decision maker is the key factor determining the solution process of the problem. Computers can be of no significant help to this type of problems. In real life situations however, problem are seldom in within the domain of these two extremes. The intermediate type of problem, termed semi-structured (Harris and Batty, 1992; Hopkins, 1984; Malczewski, 1999). This is the domain of application of decision support systems. Geoffrion's (1983) six characteristics of a DSS (discussed in Densham (1991)) which were stated in the introduction provide a general framework for this research. Modelling for decision support, or model based decision support systems for environmental and resource management problems, have been discussed and advocated for some time (Fedra, 1996; Jamieson and Fedra, 1996; Krysanova *et al.*, 1998). Success stories of actual use in the public debate and policy-making process are somewhat rarer, in particular at the societal rather than commercial end of the spectrum of possible applications.

Sprague and Watson (1996), indicate that the route to success of a DSS is to form the system in a way that best reflects the problem's degree of structure. In this respect they identify four major elements of problem solving: data as a representation of reality, procedures as a methodology for solving the problem, goals as indicators of success or failure and strategies indicating which methodology to use to achieve the goals. Consequently, four types of problems can be identified (Sprague and Watson, 1996):

1. Problems that are fully structured, in the sense that all four elements are clearly identifiable. These can be tackled with **data processing systems.**
2. Problems that are semi-structured (according to the definition given above) and can be solved with **decision support systems.** These systems leave the full control of the strategies applied to the user.
3. Problems where all relevant knowledge can be encoded and can be solved with an **expert system.**
4. Problems that are semi-structured and knowledge can be encoded to a certain degree and can be solved by **expert support systems.** The user interacts with the system in all levels including the strategies.

2.5.3 Spatial Decision Support Systems: the subset

These definitions give rise to the corresponding four spatial systems, when the character of the problem is highly spatial. These can thus be considered a subset of the broader set of decision support systems. From these, we will concentrate on the spatial analogue of the systems solving a type 2 problem: spatial decision support systems. Densham (1991), suggests that the additional capabilities and functions of spatial decision support systems, are to:

- Provide mechanisms for the input of spatial data
- Allow representation of the spatial relations and structures
- Include the analytical techniques of spatial and geographical analysis
- Provide output in a variety of spatial forms, including maps.

Spatial decision support systems have been covered in the literature in the last decade (Craig and Moyer, 1991; Densham, 1991; Moon, 1992; NCGIA, 1992; Leung, 1997). The need for using such systems comes from situations in which complex spatial problems are semi-structured and decision makers cannot define their problem or fully articulate

their objectives. The decision making process adopted to solve semi-structured spatial problems is often perceived as unsatisfactory by decision makers. What they really need is a flexible, problem-solving environment in which the problem can be explored (through modelling techniques and development scenarios), understood and redefined, trade-offs between conflicting objectives investigated and priority actions set.

The structure of a typical SDSS includes three generic components: (a) a database management system (DBMS) together with a spatial database, (b) a model-based management system (MBMS) together with a model base and (c) a user interface and dialogue/scenario generation system.

Applications range from water resources planning and management to habitat restoration, to site-selection and regional risk management. Negahban *et al.*, 1995 describe a regional planning SDSS for managing agricultural practices to solve an eutrophication problem in a number of lakes. Mailhot *et al.*, (1997) as well as Krysanova *et al.*, (1997), developed models, which although not explicitly stated as SDSS, include all the aspects of an SDSS to deal with surface water quality management. Bender and Simonovic (1995; 1996) developed a system for sustainable collaborative water resource planning at the University of Manitoba in Canada. Carver and Openshaw (1992) developed an Internet based system for site-selection of radioactive waste disposal in the UK. Gheorghe *et al.*, (2000) developed an SDSS framework and application for regional risk assessment and safety management including various models and decisions support techniques (i.e. multi-criteria ranking). The use of the term SDSS in the context of the above-mentioned examples is quite diverse and although the main concepts and elements of the system (as identified previously) are there, the details of the system's structure, process and uses are completely different. In view of the recent emergence of both the terms used and the associated field this cannot be considered an inconsistency, but rather an indication of the ongoing efforts to evolve these systems and the notions of integrated planning that go with them.

The very development of the area and scope of application of SDSS has brought about considerable discussion. Cooke (in Goodchild and Densham, 1990) questions the desirability or the near-term possibility of creating a general SDSS while Anselin (in Goodchild and Densham, 1990) advances, as a research priority, the development of

"spatial" models of decision making for a range of different decision situations, e.g. single decision maker, multiple decision makers with common goals, conflicting interest groups, etc. He even questions the need for such spatial models rather than just applying known techniques like AHP to spatial decision situations. Other experts are more optimistic about the possibilities for developing SDSS by loose or tight coupling of GIS tools with tools for modelling, simulation, statistical analysis, image processing, temporal and volumetric visualization and expert reasoning (Davidson, 1992). Davidson outlines strategies for implementing "open-systems" frameworks in which application-specific tools may be configured into a scalable, extensible and inter-operable application environment.

Further to the subject of applications and possibilities of development, the discussion on SDSS has also included the actual efficiency of these systems as decision support tools. As mentioned in Chapter 1, Crossland *et al.* (1995), has conducted series of laboratory experiments to investigate the effects on decision maker performance of using geographic information system technology, such as SDSS. In that study, which was based on Image Theory, the (volunteer) subjects' performance was operationalised as elapsed time and accuracy. The study found unequivocal evidence that addition of GIS technology to the decision environment for a spatially referenced decision task reduced the decision time and increased the accuracy of individual decision makers (Crossland *et al.*, 1995), due to, mainly, a better understanding of the task to be solved in accordance with Image Theory. The reverse approach has been adopted by Pettit and Pullar (1999), proposing a decision support system for urban planning applications, based on customising the interface for particular user groups. This is achieved by surveys among the users to identify the way the expert user reaches decisions without a decision support system and then customise the system to support this process.

2.5.4 A framework for model integration in SDSS

Predictive simulation models, embedding representations of real-world processes, are usually designed as stand-alone computer packages, each able to answer specific questions. The integration of a number of such models within the framework of an SDSS, in order to answer a variety of different questions is therefore essential. This integration gives rise to two major problems: The development of an architecture that will enable an efficient integration of the models (Abel *et al.*, 1994) and the extent to

which these models can co-exist and co-operate within a particular framework, given the fact that they were originally created for different problems and spatio-temporal scales (Taylor *et al.*, 1999).

2.5.5 System architecture considerations

In viewing a SDSS as a suite of tools for solving a class of problems there is usually the assumption that the end-user analyst will have the ability and knowledge to decompose the problem into sub-problems that can be manipulated by the tools and to recombine the results into a coherent fashion to answer the original problem. This assumption is unrealistic (Taylor *et al.*, 1999) as it requires the analyst to have a sound scientific knowledge of a variety of domains and an operational knowledge of a variety of purpose built models. Although the models built to answer environmental problems are constrained by a number of situational constraints (including scale, initial conditions, geographical location etc.), the problems themselves are not (Taylor *et al.*, 1999). The fact that there is already a vast number of mathematical models answering all types of questions[1], makes it almost useless to reprogram everything once a new complex problem comes into being. The effort of recasting such models (termed "legacy" models (Taylor *et al.*, 1999)) might be prohibitive and therefore the toolbox approach to model integration within an SDSS, followed by a large number of researchers (Djokic *et al.*, 1996; Taylor *et al.*, 1999; Abel *et al.*, 1994; Libelli *et al.*, 2000) seems more appropriate. The way this toolbox is actually created, is quite different among researchers, ranging from data transfer between models (Djokic *et al.* 1996; Ho Sham *et al.*, 1995) to the development of a central model manager interacting with a series of communication interface modules in the case of Abel *et al.*, (1994), Pascoe and Penny (1995) and Taylor *et al.*, (1999). In Taylor *et al.* (1996), the term "solver" is used for the individual mathematical models included in the SDSS toolbox, to minimise confusion from the over-use of the term "model".

2.5.6 Testing model integration in SDSS: an issue of model cooperation

The toolbox approach to modelling, within the framework of an SDSS as described earlier, is subject to the inherent problem of using individual process-based models with conflicting assumptions (e.g. spatial or temporal scale differences). This "semantic" error

[1] This is especially true in the environmental domain. Maidment (1993) identified hundreds of different systems for water resources management.

cannot be predicted prior to simulation as it emerges through the interaction of sub-models applied to specific data sets (Mackay and Robinson, 2000). Sensitivity, predictability and synchronicity of the model response variables can serve as a measure of uncertainty and error propagation (Mackay and Robinson, 2000). This in its turn will result in lessening the danger identified by Beven (1989), who states that the very theoretical rigor underlying the models may result in uncritical belief in their predictions. Model agreement is defined as the degree to which the semantic errors in model linkage affect the model outcome. This approach assumes that semantic error is directly linked with the violation of one or more underlying assumptions of the solvers used and that this error propagates through the overall model structure. Authors like Jamieson and Fedra (1996) and Robinson and Mackay, (1996), applied knowledge based modelling to improve model agreement. Several model description languages have also been used to formalise some human description processes associated with model development (Wesseling *et al.*, 1996; Rozenblit and Jankowski (1991); Keller *et al.*, 1994). The use of fuzzy logic in estimating model agreement is further discussed in Mackay and Robinson (2000). It has to be noted that although, when using a small number of solvers, the propagating uncertainty is not very important, it remains one of the major points when considering overall system performance. Model integration is a major issue in SDSS development and as such it is mentioned in this discussion. However, due to the limited use of solvers in this research, such a problem was not formally further explored.

2.6 Conclusions

Chapter 2, presented and discussed the theoretical background need for the development of the SDSS covering three main subjects: Elements of Soft Engineering (including Fuzzy Logic, Neurofuzzy Systems and Genetic Algorithms), elements of Decision Theory and elements of Decision Support Systems in general and Spatial Decision Support Systems in particular. The discussion presented the state of the art and the general principles of these scientific areas and was included because it was felt that these subjects which are central to the development of this work, do not fall under the mainstream civil and environmental engineering field and should aid the reader in the process of understanding not just the system as a software but also the underlying assumptions and principles of its use.

3. Mathematical Development

"So far as the laws of mathematics refer to reality, they are not certain.
And so far as they are certain, they do not refer to reality"

Albert Einstein

3.1. Overview

A spatial decision support system is developed in the Matlab mathematical environment using ArcGIS as a pre and post-processing tool. GIS and Matlab are used to access and analyse a variety of attributes, linked to the specified objectives of the urban water management problem at hand. The spatial model used is a classic *raster-based* model, as this resembles the structure of matrices in Matlab. Both hard and soft information are combined to allow for a comprehensive overview of the situation and fuzzy inference systems have been used to standardise the information (linguistic, probabilistic and fuzzy) in a common decisional base. **Type-1 and type-2 FIS** are programmed and are accessible to the user through user-friendly graphical user interfaces (GUI). The FIS utilise both crisp and fuzzy number input dependent on the nature of information processed. Depending on the availability of information (either field measurements or expert judgement) the user is given the option to tune the FIS to correctly respond to sets of training data. This is possible through the development of **neuro-fuzzy systems** using back-propagation algorithms to adjust the parameters of the original FIS. Aggregation techniques are then applied to compose the membership function of the initial ill-defined set from the component membership functions. A choice of such techniques, including linear summation, Ordered Weighted Averaging and Spatial Ordered Weighted Averaging are available to the user. Finally, optimisation procedures (including conventional and evolutionary programming algorithms) are used to help the user decide on a composite strategy synthesising the preferential applicability maps for the strategies taken into account.

3.2. System Architecture

The system's loose coupling principle of software integration (Malczewski 1999) allows for an increased flexibility in the development of components. A conceptual diagram of the proposed architecture can be seen in Figure 3.1. The diagram identifies both the structure of the specific system developed as well as the possibilities for modular extensions. In the terminology adopted in the following paragraphs, "modules" deal with a specific part of the analytical process (i.e. fuzzy inference, aggregation or optimisation), and are included within an "application system" which is defined as the analytical engine supporting a specific application in urban water management. One or more "application

systems" are included within the boundaries of the "overall system" which also includes the core Geographic Information and Database Management Systems as well as a Data Exchange System that allows the communication between the different system components.

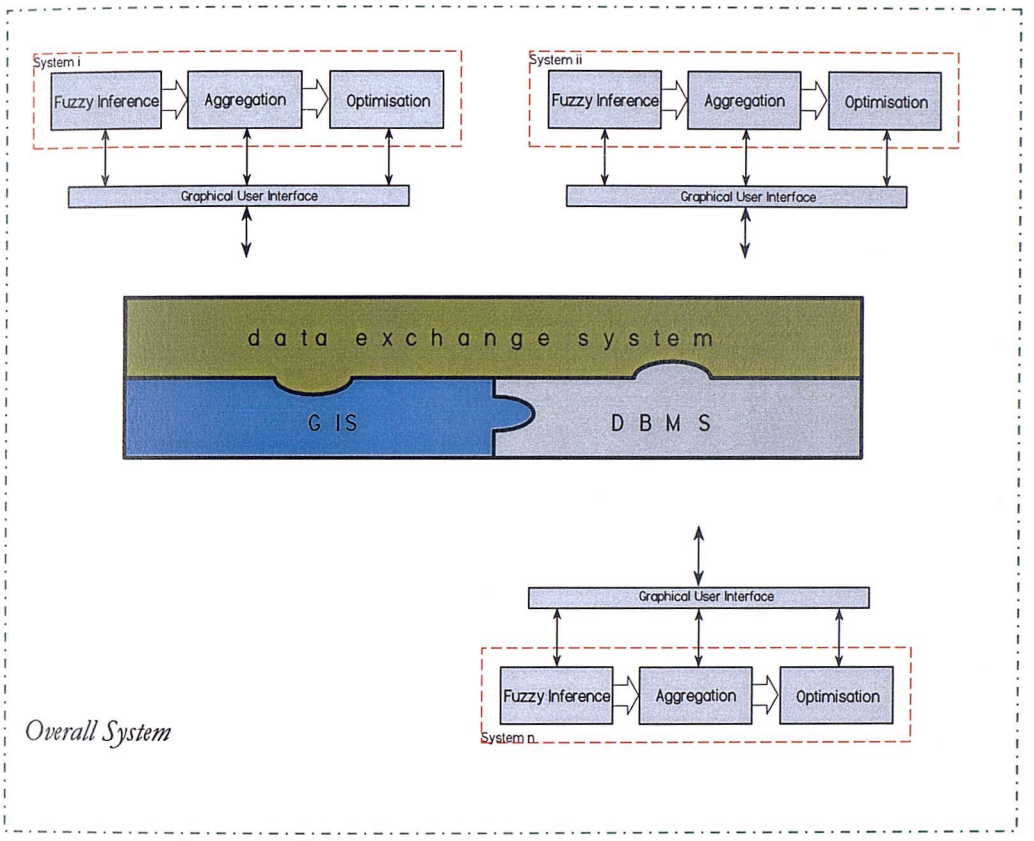


Figure 3.1 Modular System Architecture

Although the system is modular at the present state of development, the interaction is purely of a radial type. Each new application system added could interact with the database and the GIS through the general decision-making process described in following paragraphs and a common data format (exchanging ASCII files), sharing information with the rest, but there is currently no provision for investigating the interactions between the systems through a central analytical engine. This is considered a major area for further development of this research and the issues and possibilities arising from such a development are further discussed in the final chapters of this thesis.

We will now take a closer look at the system developed within this research, namely the Water Demand Management application system. All the field data are stored in the form

of GIS layers within ArcGIS. Although the initial information is stored mainly in a vector format, (to minimise space requirements) the analysis is performed outside ArcGIS using a raster format through the exchange of ASCII files between the GIS and Matlab. The extensive matrix manipulation capabilities of Matlab make it an ideal platform for analysing spatial information taking into account the particular characteristics of each application domain and programming customised spatial analysis and decision support tools that far exceed any mathematical capabilities a multi-purpose GIS can possibly have. A schematic of the system is given in Figure 3.2. As mentioned earlier, the analytical environment is comprised of three modules: an attribute standardisation module using fuzzy inference, an attribute aggregation module using a variety of weighting techniques including ordered weighted averaging and an optimisation module proposing composite strategies for a user defined investment. The interaction between the user and the system is performed through windows-type graphical user interfaces (GUI) also developed in Matlab. To increase computational efficiency the modules developed in Matlab are compiled in C (dll format) and run through the user interfaces. A specific decision making process was developed to guide the interaction between the user and the system. This process is discussed in the following paragraph.

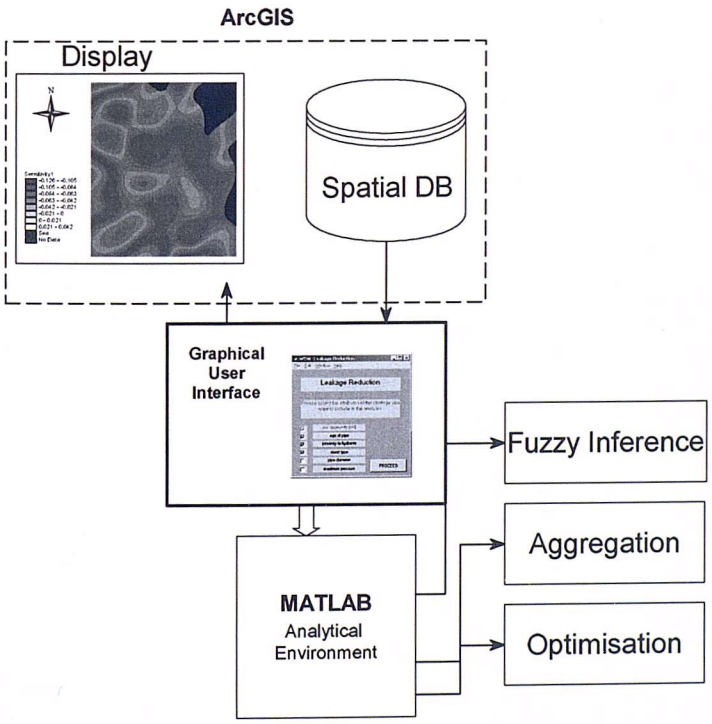


Figure 3.2 Schematic of System Structure

3.3. Decision-making Process

The general decision-making process that is supported by the system will be summarised below. A detailed description of this process, as applied to the particular case of Water Demand Management will be provided in the following chapter.

STEP 1: The user chooses which urban water management strategies he/she wishes to take into account.

STEP 2: Each strategy is broken down into a number of attributes, which directly influence its applicability into a given location. This decomposition to less complex elementary components whose affect on the suitability of the strategy's application is easier and safer to define, can be thought of as a good example of defining fuzzy membership functions for complex ill defined sets (Despic and Simonovic 1997). The conceptual basis for this decomposition and the consequent aggregation described in step 4 is provided by Kolmogorov's Theorem on approximating complex functions as a superposition of simple ones (for a detailed discussion of this theorem and its relevance to approximate reasoning the reader is referred to Nguyen and Kreinovich (1997)). The user chooses the attributes he/she wishes to take into account. In practical situations the attributes chosen will, in principle, be those linked with available data sets. This scalar approach tackles to a certain degree the problem of having to make decisions under various levels of data availability.

STEP 3: Each selected attribute is imported into the system as a raster GIS layer and is then transformed into a suitability map for the relevant strategy to the extent that the attribute influences the strategy's applicability. For example the population density attribute map of the Grey-Water Recycling strategy is transformed into a Grey-Water Recycling suitability map due to population density. As the output is now homogenous (suitability maps in a [0,1] scale), the results of heterogeneous input are now comparable. The process is performed through fuzzy inference systems (both type-1 and type-2), which can analyse both singleton and non-singleton input (Mendel, 2001). A discussion on fuzzy inference systems is included later in this chapter.

STEP 4: The standardised suitability maps for each attribute of a given strategy are then aggregated to provide one all-inclusive suitability map for the strategy's application. The user is presented with different options of aggregation including simple additive weighting (with direct weights assignment) and ordered weighted averaging. The later enables the incorporation of the decision maker's attitude towards risk in the outcome in

the aggregation process. The optimism or pessimism of the decision maker (expressed as a degree of risk aversion) is provided to the system as a user input and appropriate weights are calculated to convey this level of risk aversion into the aggregation outcome. The output strategy suitability maps for all strategies are then imported in the optimisation module.

STEP 5: Optimisation includes a number of user input parameters depending on the specific application (i.e. for the WDM application system this would include, but not be restricted to overall desired investment cost, per capita water consumption, cost for network rehabilitation per meter of network, cost for grey water recycling scheme introduction per household and cost of introducing metering per household). The optimisation maximises an objective function (which is typically integer, insofar that the result identifies number of cells suitable for application, and non-linear) using overall investment cost as a constraint. The result is a combined strategy in the form of a detailed proposed Urban Water Management application map (master-plan) on a house-by-house level indicating the optimal location for intervention.

The three main modules (fuzzy inference, aggregation and optimisation) will be discussed in some detail from a mathematical viewpoint in the following paragraphs due to their importance in the overall system development. Prior to this description, however, we will highlight the main conceptual issues encountered in this research and the solutions proposed.

3.4. Conceptual Development Issues

The issue of defining the preferential applicability of each water demand management strategy has been dealt with as a textbook case of defining membership functions for complex ill defined sets[1] (Despic and Simonovic, 1997). Systems with complex informational fuzziness require a large amount of data to be taken into account simultaneously in order to identify their membership functions. Estimation of the membership function for this kind of fuzziness can be very inaccurate and is subject to uncertainty, exponentially increasing with complexity. The way this problem was addressed was by decomposition to less complex elementary components whose membership functions of the target property are easier (and safer) to define. The three water demand management strategies (leakage reduction, metering and grey-water

[1] An extended discussion on both ill set decomposition and aggregation techniques is included in Appendix 1.

recycling) are considered ill-defined fuzzy sets and they are decomposed into simpler sets.

The issue of data uncertainty (in the case where real data were available) is dealt with by handling input values not as crisp numbers but as fuzzy numbers with a Gaussian distribution around an expected value (the initial crisp value) and a predefined standard deviation. The choice of fuzzy membership function (fmf) is made between the two most common symmetrical fmfs in the literature, namely triangular and Gaussian (Mendel, 2001). The standard deviation of the possible data values with varying degree of probability would depend, in principle, on the type of measurement error and the availability of control points and could be calculated outside the SDSS (i.e. through a Root Mean Square (RMS) procedure). Therefore, this is not considered here, nor was such a technique programmed in this SDSS. In the SDSS, the standard deviation is considered a user input.

The issue of linking antecedent to consequent[1], through an unknown function[2] was dealt with through the function approximation potential of FIS. The question of the extent to which a FIS can adequately approximate an unknown function was answered by Wand and Mendel (1992), as well as by Kosko (1992). They proved (for a number of specific FIS) that they could uniformly approximate any real continuous non-linear function to arbitrary degree of accuracy[3]. In this case, as experimental data to train the FIS were not available, the design made use of linguistic variables (low, medium, high) with a degree of uncertainty incorporated in type-2 fuzzy membership functions. Linguistic variables and their calculus have been the subject of on going research actually since Zadeh's 1975 paper on approximate reasoning (Zadeh, 1975) and it is outside the scope of this research to report this discussion. In summary, it can be stated that although "words mean different things to different people" (Mendel, 2001), there is a general agreement as to their approximate meaning and the degree of uncertainty associated with this difference in meaning can be taken into account. In this particular case, due to the expert knowledge needed to assign numerical values (i.e. for input data) to linguistic variables, the system can be thought of as designed for use by a decision maker and an expert

[1] Which serves as a criterion standardisation process.
[2] Deterministic relationships for this kind of linking do not exist in the literature. Probabilistic relationships which can sometimes be found in the literature are heavily dependant on calibration parameters for specific test data. Most of these relationships, whenever they exist, present few fundamental similarities.
[3] See discussion on universal approximators (paragraph 2.2.12).

"facilitator". The actual (default) values used at this stage were selected by the author from acceptable values found in relevant literature. The uncertainty associated with these values is modelled by enabling the user to choose between different FIS, including type-2 FIS.

The problem of aggregating the resulting criterion maps for each objective's attributes is dealt with as decision-making under ignorance (Yager, 1995). OWA is used under a variety of user options including direct weights assignment for linear summation, direct OWA assignment and identification of degree of risk (optimism-pessimism of the decision maker). In this case, weights are calculated to either comply with the user defined degree of risk and trade-off or by a maximum entropy criterion. The optimisation procedure used will be described in the following paragraphs. Composite suitability maps are derived for each strategy. The process provides insight into the strategies' applicability and is transparent in the sense that it provides the planner with the full range of aggregation possibilities and is up to the planner to identify the degree of optimism (and corresponding risk) with which the planning process will be conducted.

The issue of identifying (proposing) an optimal composite strategy, for a fixed (user-defined) investment, was dealt with through non-linear constrained optimisation specifically formulated to take into account the spatial characteristics of the problem (i.e. the location where the optimal solution should be implemented). The problem is therefore referred to hereafter as a spatial optimisation problem. Three forms of optimisation have been used and their results compared: sequential quadratic programming (e.g. Coleman et al., 1999), single and multiple objective genetic algorithms (e.g. Savic and Walters, 1997; Kapelan, 2002).

A detailed description of the mathematical development behind the three analytical modules (criterion standardisation, aggregation and optimisation) is presented in section 3.5

3.5. Mathematical Development

3.5.1. Criterion standardisation and inference

Standardisation[1] was performed by constructing fuzzy inference systems (FIS) in Matlab, by using both the Fuzzy Logic Toolbox (created by Mathworks Inc.), for the Type-1 Singleton FIS and by programming Type-2 and Type-1 non-singleton FIS based on the recommendations of Mendel (2001). All the FIS are comprised of three parts: the input membership functions, the set of logical rules (in an a rule base of IF-THEN form) and a set of output membership functions. In the end, a defuzzification[2] process is used to convert the fuzzy set into a crisp number result. In this case, the resulting scale is a 0-1 scale, positively correlating the input values to each strategy's installation suitability (1 indicating very suitable). The fuzzy criterion approach enabled a range of heterogeneous input to be taken into account, for which the literature presented diverse quantification methods (from probabilistic (probability distributions) to deterministic (linear curve fitting) to linguistic (important, not so important etc)).

It must be noted, however, that when designing a FIS there are numerous possibilities open to the developer. The kind of fuzzification (singleton or non singleton), the shape of the fuzzy membership function (trapezoid, triangular, Gaussian, Gambel etc) and their parameters (mean, variance etc), composition (max-min, or max-product), the number of rules and the defuzzifier (centroid, centre of sums, height etc) result in alternative FIS designs. There is no such thing as an *optimum* design of a FIS, although clearly some designs would be more efficient computationally or simpler or more adaptive in nature than others. Lin and Lee (1996) discuss a variety of (heuristic) methods for designing FIS. The design discussed and adopted here is not the only one possible for the application in question and was based on considerations of computational efficiency rather than domain-specificity. Future research could use for example evolutionary programming to address several of these specific design issues (such as, for example, selection of domain specific (to some extent) fuzzy membership function shapes, (Mendel, 2001)) but such a selection was not performed here. The fundamental mathematical principles behind the different FIS used and the relevant computational

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[1] Standardisation in this context is defined as the construction of the individual membership functions of the desired property for the components of the ill defined complex set of each strategy

[2] A number of defuzzification procedures are discussed in earlier Chapters. For this application, a "centre of gravity" technique was used. In the type-2 the defuzzification process is preceded by an analogous procedure termed type-reduction.

procedures under specific assumptions necessary for enhancing computational efficiency[1] are described next.

The graphical representation of the inference procedure described here can be seen in Figures 2.11-2.17.

As mentioned in the previous chapter, the core analytical procedure in any FIS is the **fuzzy inference engine**. A fuzzy inference engine is the way fuzzy logic is applied to combine fuzzy rules into a mapping from input to output fuzzy sets. The general form of the L^{th} rule in a FIS is: IF x_1 is F_1^L and x_2 is F_2^L and ...THEN y is G^L, where $F_1^L \ldots F_p^L = A^L$. Therefore the rule can re-expressed as $A^L \rightarrow G^L$ or using membership function notation $\mu_{A^L \rightarrow G^L}(x,y)$. It can be stated that:

$$\mu_{A^L \rightarrow G^L}(x,y) = [T\mu_F(x_i)] \bullet \mu_G(y) \qquad \textbf{Eq. 3.1}$$

where T and • denote a t-norm (i.e. product or minimum). These implications (t-norms) are called *Mamdani* implications[2]. An input of the general form $\mu_A(x)$ of set A, will be mapped to the output set B as $\mu_B(y)$, by passing through the rule:

$$\mu_B(y) = \sup[\mu_A(x) \bullet \mu_{A^L \rightarrow G^L}(x,y)] = \sup\{[T\, \mu_A(x) \bullet \mu_F(x_i)] \bullet \mu_G(y)\} \qquad \textbf{Eq. 3.2}$$

Note that in discreet universes the supremum operation is substituted by a t-conorm (i.e. a maximum operator). Eq. 3.2 is adapted to account for the specific characteristics of the type of FIS used. The following paragraphs explain how adaptation was performed in the four types of FIS used in this research.

3.5.1.1. Type-1 Singleton FIS

In the case of singleton fuzzification Eq. 3.2 is straightforward to compute, as $\mu_A(x)$ is non zero and equal to 1 at only one point (the input point). Hence, for minimum and product t-norms:

$$\mu_B(y) = [\mu_F(x_1) \bullet \ldots \bullet \mu_F(x_p)] \bullet \mu_G(y) \qquad \textbf{Eq. 3.3}$$

The term in the brackets is referred to as *firing level* (Mendel, 2001). The result of Eq. 3.3 is used together with the centroid defuzzification concept (introduced in Chapter 2) to derive the crisp output $y_c(x)$. The final equation produced is Eq. 3.4.

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[1] For a detailed discussion on the effect of Gaussian fmfs on the efficiency of max-min or max product type of implications in the non-singleton case, the reader is referred to Mendel (2001).

[2] These implications have nothing to do with implication in traditional propositional logic.

$$y_c(x)=\sum(y\ \mu_B(y))/\sum\mu_B(y) \qquad \textbf{Eq. 3.4}$$

Eq. 3.4 was programmed in Matlab through its built-in fuzzy rule editor. Note that the built-in fuzzy rule editor can only deal with type-1 singleton FIS.

3.5.1.2. Type-1 Non-Singleton FIS

In the case of non-singleton fuzzification, as $\mu_A(x)$ is non zero and equal to 1 at more than one point, the calculation of Eq. 3.2 is not as simple as in the case of a singleton FIS. For $\mu_A(x) \bullet \mu_F(x_k) \equiv \mu_Q(x)$ and $x_{k,,max}$ the value of x_k at which the supremum of $\mu_Q(x_k)$ occurs is:

$$\mu_B(y) = [T\mu_Q(x_{k,,max})] \bullet \mu_G(y) \qquad \textbf{Eq. 3.5}$$

The term in brackets is referred to as the *firing level* for non-singleton type-1 FIS (Mendel, 2001). To derive an analytical function for Eq. 3.5 there are a number of assumptions that have to be made by the FIS designer prior to the interaction with the user. Assumptions about the shape of the fmf, or the t-norm used for example, can greatly simplify the operations involved. So, if both membership functions and input fuzzy number have a Gaussian shaped membership, all inputs have the same level of uncertainty (and thus standard deviation) and product is used for a t-norm:

$$x_{k,\max} = \frac{\sigma_x^2 m_F + \sigma_F^2 m_k}{\sigma_x^2 + \sigma_F^2} \qquad \textbf{Eq. 3.6}$$

Where m is the mean of the Gaussian distribution.

From Eq. 3.6 it follows that:

$$\mu_Q(x_{k,\max}) = e^{-\frac{1}{2}\frac{(x_k - m_F)^2}{\sigma_x^2 + \sigma_F^2}} \qquad \textbf{Eq. 3.7}$$

The result of Eq. 3.7 is introduced in Eq. 3.5 and is used together with the height defuzzification concept (similar to Eq. 3.3) to derive the crisp output $y_c(x)$. The final equation produced is Eq. 3.8.

$$y_c(x)=\sum(y \prod \mu_Q(x_{k,max}))/ \sum(\prod \mu_Q(x_{k,max})) \qquad \textbf{Eq. 3.8}$$

Eq. 3.8 was programmed in Matlab through a new interface based on the recommendations of Mendel (2001).

3.5.1.3. Type-2 Singleton FIS

As discussed, in type-1 FIS the inference engine combines rules and gives a mapping from input type-1 fuzzy sets to output type 1 fuzzy sets. Multiple antecedents in rules are connected by the t-norm. The membership grades in the input sets are combined with those in the output sets using a max-min or a max-product composition. Multiple rules may be combined using the t-conorm operation. Type-2 uses a very similar process: The inference engine combines rules and gives a mapping from input type-2 to output type-2 fuzzy sets. To perform this operation, the unions and intersections of type-2 sets need to be computed, as well as the compositions of type-2 relations (Mendel, 2001). To go directly from type-1 results to type-2 results one must substitute type-1 fmf with type-2, the sup function (Eq. 3.2) with the *join* operation (Eq. 3.10) and the t-norm operation (minimum or product) with the *meet* operation (Eq. 3.11).

$$\mu_{B\cup C}(x)=\mu_B(x) \oplus \mu_C(x)= \iint f_x(u)\bullet f_x(w)/u\cup w \qquad \textbf{Eq. 3.9}$$

$$\mu_{B\cap C}(x)=\mu_B(x) \otimes \mu_C(x)= \iint f_x(u)\bullet f_x(w)/u\cap w \qquad \textbf{Eq. 3.10}$$

where B and C are type-2 fuzzy sets, with secondary membership functions of u and w respectively. One must keep in mind that in this case the membership of x in a type-2 fuzzy set ~F, denoted as $\mu_{\sim F}(x,u)$, (where $\sim F = \int \mu_{\sim F}(x)/x = \int [\int f(u)/u]/x$, where u is the secondary membership function) is a function and not a crisp number. By using the same basic fact used in singleton type-1 FIS: that $\mu_{\sim B}(x)$ is non-zero (and equal to 1) for only one value, we can re-write Eq. 3.2 by replaced the *sup* operation with the *join* operation and the *t-norm* operation with the *meet* operation. Hence similar to Eq. 3.3:

$$\mu_{\sim B}(y) = \mu_{\sim G}(y) \otimes \left[\otimes_{i=1}^{p} \mu_{\sim F}(x_i) \right] \qquad \textbf{Eq. 3.11}$$

The term in the brackets is referred to as *firing set* (analogous to the firing level of Eq. 3.3) (Mendel, 2001). Inference is followed by type reduction (from type-2 to type-1). In the specific case of interval type-2 sets (i.e. type-2 sets whose secondary membership function is an interval), the type reduced set is also an interval set (type-1) of the structure $Y_{TR}=[y_l, y_r]$. In every case, the procedure is similar: the firing level results in output sets, which are combined to obtain a single set (i.e. through a maximum operation). A specific defuzzification method is then applied to provide a crisp output as the centroid of the combined set. For example, a "centre of sets" defuzzification replaces each rule consequent set by a singleton situated at its centroid and then finds the centroid of the type-1 set of these singletons. First, the centroid (c^l) of the type-2 consequent set is calculated through an iterative procedure (see Mendel, 2001) and a weighted average of

these centroids is derived. The weight corresponding to the l^{th} centroid is the degree of firing corresponding to the l^{th} rule. The following equation is applied to calculate the crisp output:

$$y(x) = \frac{\sum c^l T \mu_{F_i}(x_i)}{\sum T \mu_{F_i}} \qquad \textbf{Eq. 3.12}$$

where T indicates the chosen t-norm. To ease computational burden, the chosen t-norm in this SDSS is the product operation, while all fmfs are Gaussian. Furthermore, all type-2 sets used are interval sets.

3.5.1.4. Type-2 Non-singleton FIS

In this particular application, only type-1 non-singleton type-2 FIS were developed. This means that the input values are type-1 fuzzy numbers although, in principle, they could be type-2. This latter type of FIS was considered too computationally demanding, resulting in excessive computational times, which would be impractical for a decision support system. The inference engine for the system developed here can be described by the Eq. 3.13.

$$\mu_{\sim B}(y) = [F^l(x)] \blacksquare \mu_{\sim G}(y)\} \qquad \textbf{Eq. 3.13}$$

Where $F^l(x)$ is the firing *set* (instead of a firing *level* as in singleton tpe-2 FIS) for rule l and x is a fuzzy number. $F^l(x)$ is an interval type-1 set of the form $F^l(x)=[f_{lower}, f_{upper}]=[f_, f^-)$. For the particular case of Gaussian fmfs (for antecedent, consequent and input sets) with uncertain means (lying in an interval [m1, m2]) and product t-norm, the computation is simplified but still requires the calculation of the supremum of the product of the two Gaussians (type-1 firing set and type-2 consequent set). The value of x_k where the supremum occurs is dependent on the relative position of x to m1 and m2 (see Fig. 3.3: m1 and m2 are not explicitly marked on each figure but follow the notation of Fig. 2.7). Depending on this relative position we can calculate the firing set for each of the 5 cases described in Fig. 3.3.

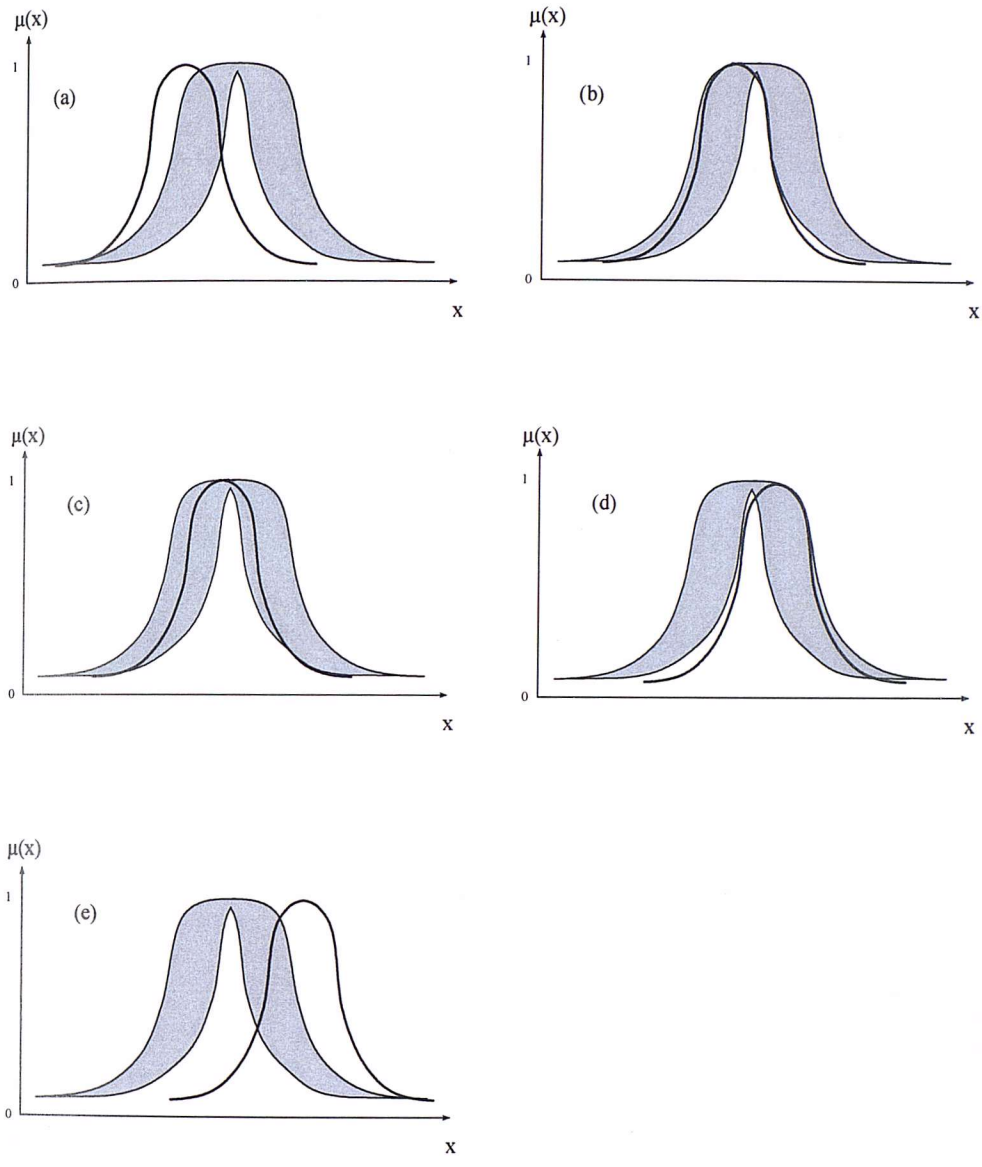


Figure 3.3. Different locations of input fuzzy number in relation to the antecedent type-2 fuzzy set.

In Fig. 3.3(a), the input value (x'_k) is less than the minimum mean of the antecedent fuzzy set (m^1_{k1}). In Fig. 3.3 (b)-(d), x'_k is between the maximum and minimum means, and in Fig. 3.3 (e), x'_k is larger than the maximum mean (m^1_{k2}). The results for a particular application (Gaussian fmfs with uncertain means and product implication) can be seen in Table 3.1.

Table 3.1 Summary of analytical expressions depending on input parameters

State	$\mu_(x^l_{k_,max})$	$\mu^-(x^{l-}_{k,max})$
a	$\exp[-\frac{1}{2}(m^l_{k2}-x'_k)^2/(\sigma^2_{x_k}-\sigma'^2_\kappa)]$	$\exp[-\frac{1}{2}(m^l_{k1}-x'_k)^2/(\sigma^2_{x_k}-\sigma'^2_\kappa)]$
b	$\exp[-\frac{1}{2}(m^l_{k2}-x'_k)^2/(\sigma^2_{x_k}-\sigma'^2_\kappa)]$	1
c	$\exp[-\frac{1}{2}(m^l_{k2}+m^l_{k1}-2x'_k)^2/4\sigma^2_{x_k}$ $-\frac{1}{2}(m^l_{k2}-m^l_{k1})/4\sigma'^2_\kappa)]$	1
d	$\exp[-\frac{1}{2}(m^l_{k1}-x'_k)^2/(\sigma^2_{x_k}-\sigma'^2_\kappa)]$	1
e	$\exp[-\frac{1}{2}(m^l_{k1}-x'_k)^2/(\sigma^2_{x_k}-\sigma'^2_\kappa)]$	$\exp[-\frac{1}{2}(m^l_{k2}-x'_k)^2/(\sigma^2_{x_k}-\sigma'^2_\kappa)]$

Where: x'_k is the central value of the input fuzzy number,

m^l_{k1} and m^l_{k2} define the interval within which lie the (uncertain) means of the antecedent type-2 fuzzy set

σ'_k is the standard deviation of the antecedent fuzzy set

σ'_{x_k} is the standard deviation of the input fuzzy number

$\mu_(x^l_{k_,max})$ is the lower boundary of the firing level (equal to $\underline{f}^l_1$ in Fig. 2.15 (right column))

$\mu^-(x^{l-}_{k,max})$ is the upper boundary of the firing level (equal to $\overline{f}^l_1$ in Fig. 2.15 (right column))

3.5.2. Training the FIS

3.5.2.1. Neurofuzzy Systems

A neurofuzzy systems approach has been utilised to tune the parameters of the FIS (i.e. to *train* the FIS). As described in Chapter 2, the knowledge that neuro-fuzzy systems incorporate is provided to them by the user in the form of examples of "correct" input and output elements. To avoid repetition, we will describe the method used to train the most complex FIS (i.e. the Non Singleton Type-2 FIS) based on Mendel (2001). This procedure can be thought of as including the remaining cases (Singleton and Non

Singleton Type-1 and Singleton Type-2 FIS) as it requires the tuning of all possible parameters encountered in the FIS.

In the case of a FIS with IF-THEN rules, as the ones described above, each rule is of the general form: IF x_1 is F_1^l and x_2 is F_2^l and ...THEN y is G^l, as explained in previous paragraphs. F_x^l is a (Type-2) fuzzy set described by a Gaussian (in all cases presented here) fmf, whose shape is given by the following equation:

$$\mu^l{}_i(x_i) = e^{-\frac{1}{2}\left(\frac{(x_i - m^l{}_i)}{\sigma_i^l}\right)^2}, \; m_i^l \in [m^l{}_{i1}, m^l{}_{i2}] \qquad \textbf{Eq. 3.14}$$

where i=1,...p (antecedents) and l=1,...M (rules) and the consequent sets are also Gaussian primary membership functions with uncertain mean and interval secondary membership function. They are therefore of the type:

$$\mu^j(y) = e^{-\frac{1}{2}\left(\frac{(y - m^j)}{\sigma^j}\right)^2}, \; m^j \in [m^j{}_1, m^j{}_2] \qquad \textbf{Eq. 3.15}$$

where the centroid of each $\mu^j(y)$, (C_j) is an interval type-1 set $(C_j=[y_L{}^j, y_R{}^j])$. Input to the FIS is also in the form of Gaussian fuzzy numbers.

The aim of the training procedure is to adjust the parameters of these functions for the antecedent and consequent fuzzy sets, using *input-output training pairs (**x**, y)*, where **x** is a vector input and *y* is a scalar output. Note that the exact shape of the fmfs, as well as the parameters to be tuned depend on the type of the system and would vary in the case of Type 1 Singleton FIS, Type-2 Singleton FIS, according to the discussion in the previous paragraphs.

The method used in this research to solve this problem is the *back-propagation* algorithm, also known as *steepest descent* method (Wang and Mendel, 1992).

For n input/output training pairs (**x**, y) the process updates all design parameters using as objective function to be minimised the following error function:

$$e^t = \tfrac{1}{2}[f_{ns2\text{-}1}(\mathbf{x}^{(t)}) - y^{(t)}]^2, \quad t=1...n \qquad \textbf{Eq. 3.16}$$

The error function has to be minimized within E training epochs, where an epoch is defined as an optimization run that takes into account all training pairs. The method is comprised of 11 steps and will be presented here for reasons of completeness:

Step 1 Choose the means of the Gaussian fuzzy numbers to be centred at the measurements.

Step 2 Set the counter, C(epoch), of the training epoch to 0.

Step 3 Set the counter, C(train), of the training data to 0.

Step 4 Use input $\mathbf{x}^{(t)}$ in the FIS to be trained, and compute the firing interval $[f^i_-, f^{i-}]$ for each rule and each antecedent (i=1,...,p), where $f^i_-=\mu_{1-}\bullet\ldots\bullet\mu_{p-}$ and $f^{i-}=\mu_1^-\bullet\ldots\bullet\mu_p^-$. There is, of course, a difference in the equations used for computing the firing interval when the input value is a crisp or a fuzzy number, but the general principle remains the same (see Figures 2.25-2.31).

Step 5 Compute y_l and y_r using the following procedure (the procedure described, refers only to y_r. The computation of y_l is identical). This iterative procedure has been proven to converge in a maximum of M iterations (Mendel, 2001).

Step 5.1 Set $f_r^i=(f^i_- +f^{i-})/2$ for i=1,...M (i.e. for all rules). Let $y'_r=y_r$

Step 5.2 Find R (rule) where $(1\le R<M-1)$ such that $y_r^R\le y'_r\le y_r^{R+1}$

Step 5.3 Compute $y_r=\dfrac{\sum_{i=1}^{M} f_r^i y_r^i}{f_r^i}$, with $f^i_r=f^i_-$ for $i \le R$ and $f^i_r=f^{i-}$ for $i > R$.

Then let $y_r=y''_r$

Step 5.4 If $y''_r \neq y'_r$ then go to step 5.5, else stop and set $y_r= y''_r$

Step 5.5 Set $y'_r = y''_r$ and go to step 5.2

Step 6 Compute the defuzzified output $f_{ns2\text{-}1}(\mathbf{x}^{(t)})=[y_l(\mathbf{x}(t))+y_r(\mathbf{x}(t))]/2$

Step 7 Determine the dependence of y_l and y_r on membership functions. R obtained in step 5 (and similarly L for y_l) will change during the iterative procedure. The general form $f^i_-=\mu_{1-}\bullet\ldots\bullet\mu_{p-}$ can be written as $f^i_-= T_{k=1 \text{ to } p}\,(\mu_-(x^i{}_{k,,max}))$ as first mentioned in Eq. 3.5. We can compute therefore that $y_r=\dfrac{\sum_{i=1}^{M} f_r^i y_r^i}{f_r^i}$ as being a function of $y_r[T_{k=1 \text{ to } p}\,(\mu_-(x^1{}_{k,,max})), \ldots$ $T_{k=1 \text{ to } p}\,(\mu_-(x^R{}_{k,,max}))$, $T_{k=1 \text{ to } p}\,(\mu^-(x^{R+1}{}_{k,,max}))$, $\ldots$ $T_{k=1 \text{ to } p}\,(\mu^-(x^M{}_{k,,max}))$, $y_r^1, \ldots, y_r^M)$. Similarly we can identify the dependencies for y_l.

Step 8 Test each element of $x^{(t)}$ to determine what is the analytical expression describing y_l and y_r as functions of the membership function parameters.

For example, in the case of Gaussian antecedent fmfs with uncertain means $[m_{k1}, m_{k2}]$, and input in the form of Gaussian type-1 fuzzy numbers (centered at x'_k), there are 5 possible specific analytical expressions depending on the input parameters. The 5 possible differentiations can be seen in Fig. 3.3:

Table 3.1 summarizes the analytical expressions resulting from this differentiation.

Step 9 Tune the parameters of the appropriate state from step 8, using a steepest descent algorithm for the error function. Partial derivatives of $\mu_{_}(x^l_{k_,\,max})$ and $\mu^-(x^{l-}_{k,\,max})$ will have to be computed with respect to the specific design parameters to be tuned.

There are many variations of a steepest descent (back propagation) algorithm. The simplest implementation of back propagation, which was used here, updates the parameters in the direction in which the performance function decreases most rapidly (the negative of the gradient). An iteration of this algorithm can be written as:

$$\theta_{t+1} = \theta_t - a \cdot grad[J(\theta)]_t \qquad \textbf{Eq. 3.17}$$

where θ_t is a vector of current design parameters, grad is the gradient of the function we want to minimize $J(\theta)$ (in this case the error function (e^t)), and a is a (positive) learning rate.

Step 10 Set C(train)=C(train)+1. If C(train)>N, go to step 11, else go to step 4.

Step 11 Set C(epoch)=C(epoch)+1. If C(epoch)=E, stop, else go to step 3. As discussed, in each epoch, all training pairs are used once. The optimization is performed taking into account Eq. 3.17, which depends on only one point at a time. To be able to take into account the error from all points and minimize it, the training pairs are used over multiple epochs, each epoch producing a new improved overall error, until convergence occurs. The overall error minimized in our procedure is the RMS (root mean squared error). Eq. 3.18 calculates the RMS for one epoch of n training pairs.

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - f(x_i)\right)^2} \qquad \textbf{Eq. 3.18}$$

The RMS from this epoch is compared with the RMS from the previous epoch. If there is no significantly change (an arbitrarily low threshold is used to ensure this), the algorithm is considered to have converged to the final solution. C(epoch) is set to E and the new FIS design parameters are proposed by the SDSS.

Note that, to apply this procedure, it is essential to be able to derive the closed forms of the equations for $\mu_{-}(x^{l}_{k,\,max})$ and $\mu^{-}(x^{l-}_{k,\,max})$. If this is not possible, then the partial derivatives in step 9 cannot be computed and the steepest descent algorithm cannot be implemented.

3.5.2.2. On obtaining input-output training pairs

The input-output pairs used to train the neuro-fuzzy systems can originate from a number of possible sources. In most cases presented here, a direct measurement is not possible due to the nature of the consequent sets (i.e. suitability). In other words, it is generally impossible to evaluate the suitability for application of a specific urban water management strategy to a specific location using anything other than (subjective) expert judgement. The SDSS developed here takes into account multiple experts judgment in the form of possible input (attribute value) – expected output (suitability value) pairs provided by the experts through, for example, a questionnaire. The pairs specified by the expert(s) serve as a direct input to the neurofuzzy module, which is then tuned as described in the previous paragraph. If, however, a direct measurement of an attributes impact to suitability for application is possible then such a measure can be imported into the neurofuzzy module allowing more objective tuning of the fuzzy inference modules. A specific case of such data being available is water mains burst records. These records can be used to train the fuzzy inference module dealing with leakage reduction.

A Bayesian statistics module is included in the SDSS to allow the pre-processing of field data to a form that is usable from the neurofuzzy system described above. The module, accepts data in the form of a vector $[c_1,c_2,\ldots,c_n]$. Each vector is considered an instance (for example a failure) associated with characteristics c_1, c_2, ... c_n and Bayes formula (Eq. 3.19) is used to calculate the probability of an instance occurring, given a characteristic c_i.

$$p(f/c)=\frac{p(c/f)\cdot P_f}{p(c/f)\cdot P_f + p(c/nf)(1-P_f)} \qquad \textbf{Eq. 3.19}$$

where:

(a) P_f is the system-wide failure frequency

(b) p(c/f) is the probability of observing the specified characteristic on pipe lengths that showed a failure in a given year and

(c) p(c/nf) is the probability of observing the specified characteristic on pipes with no failure history on record.

The technique presupposes that the records (instances) are grouped into ranges of characteristics, and the resulting probability refers to a specific characteristic's range (for example: pipes with diameter < 300mm have P probability of failure). In general, these ranges are selected arbitrarily by the analyst but although some researchers have the expertise to decide on best ranges (e.g. Fenner and Sweeting (1998)), the average end-user cannot be expected to be able to decide which grouping of the data suits better the analysis. The technique employed here to overcome this issue is *fuzzy c-means clustering* (Bezdek, 1981). Faced with a data set, the technique starts with an initial guess of the cluster centres, which are intended to mark the mean location of each cluster. The initial guess for these cluster centres is most likely incorrect. Additionally, it assigns every data point a membership grade for each cluster. By iteratively updating the cluster centres and the membership grades for each data point, it iteratively moves the cluster centres to the "right" location within a data set. This iteration is based on minimizing an objective function that represents the distance from any given data point to a cluster centre weighted by that data point's membership grade. In case the analyst does not have a clear idea of how many clusters there should be for a given set of data, *subtractive clustering* (Chiu, 1994) provides a fast, one-pass algorithm for estimating the number of clusters and the cluster centres in the data set. The method assumes each data point is a potential cluster centre and calculates a measure of the likelihood that each data point would define the cluster centre, based on the density of surrounding data points. The algorithm:

1. Selects the data point with the highest potential to be the first cluster centre
2. Removes all data points in the vicinity of the first cluster centre (as determined by a user defined radius), in order to determine the next data cluster and its centre location

3. Iterates on this process until all of the data is within the radius of a cluster centre

The cluster estimates obtained from the technique can be used to initialise the fuzzy c-means clustering technique. For a more detailed discussion of the above techniques, the reader is referred to Chiu, (1994), Bezdek, (1981) and Mathworks (2000). In applying these techniques, the SDSS makes use of functions developed by Mathworks for MATLAB. Details of the Bayesian module applied to the case of WDM are presented in Chapter 4.

3.5.3. Aggregation

As described in step 4 of the decision-making process, the output from the fuzzy inference module needs to be aggregated to produce a final *suitability for application* map for each specific strategy taking into account all attributes. Two types of weighted aggregation have been applied in this SDSS. The first is simple weighted averaging (SWA) and the second is ordered weighted averaging (OWA) (Yager 1988; 1997). SWA can be considered a subset of OWA, being a special case of including *importance* in OWA operators, as discussed by Yager (1997). SWA is included separately in the interface to provide the average system user with a simple (intuitive) aggregation tool which utilises weights directly assigned by the user and then performs a standardisation to achieve $\sum w_i=1$. The OWA, is a more complex technique but provides the experienced user with better control of the aggregation's results. This SDSS has three options for calculating ordered weights:

A. **Direct weights assignment** (as user input) in the form $[w_1,\ldots,w_n]$, where w_n is the weight assigned to the attribute of the n^{th} rank. As discussed in Chapter 2, Ordered Weighted Averaging provides a continuum of fuzzy operators between the logical AND (fuzzy intersection) and the logical OR (fuzzy union). OWA is a weighted sum, with ordered evaluation criteria. If $[w_1,w_2,\ldots,w_n]$, is the set of ordered weighting factors (also viewed as a weighting vector), then they can be assigned values ranging from [1,0,...,0] which is the MIN fuzzy operator (the logical AND), to [0,0,...,1], which is the MAX fuzzy operator (the logical OR). As in the context of spatial decision support, each cell is considered a decision alternative (Malczewski 1999), in the sense that the decision will be applicable (or not) in the particular location (cell), a vector including all criterion scores is calculated for each point (x, y) prior to aggregation. The number of vectors is equal to

the number of cells in each layer[1] and contains elements equal to the number of criteria used. Each vector is ranked from higher to lower values prior to the application of the ordered weights.

B. **User input of the acceptable level of risk** (associated with ANDness) and trade off. The set of weights that is applied to the ordered alternatives is calculated to satisfy the trade-off and level of risk introduced by the user. A measure of ANDness, ORness and TRADE-OFF, associated with a particular set of weights is obtained by Eq. 2.28, 2.29, 2.90 (Yager, 1988; 1997; Malczewski 1999). The measures range from 1 to 0. OWA is used as the main aggregation operator due to its advantage to lie between OR and AND operators, thus expressing quantifiers between the two extreme (binary logic) cases: "there exists" and "for all" (i.e. linguistic quantifiers such as "few", "many" etc) (Zadeh 1983).

C. **User input of level of "degree of risk aversion" and use of a maximum entropy method**. From the Eq. 2.28 to 2.29 it is evident that for a particular value of risk (ANDness), there is more than one set of weights associated with it. The approach selected here to formalise the selection of weights using a single metric (risk aversion) supplied by the user is *maximum entropy*. Viewing the weighting vector as a form of probability distribution enables us to introduce a measure of entropy (H) (Eq. 2.31), analogous to Shannon's entropy, to calculate the amount of information in the arguments, which is used during an aggregation based on the weighting vector (Filev and Yager 1998).

If entropy is high, meaning the arguments are similarly weighted, then the information used is high. If entropy is low, meaning the arguments are unevenly weighted, some of the arguments are actually ignored, therefore the overall information used is low. It can be observed that the entirely optimistic and completely pessimistic attitudes have zero entropy as they ignore all the information but that of one argument. Maximum entropy is achieved for equal weights ([1/n,...1/n]). A given degree of risk aversion (pessimism) can be modelled through a number of alternative weight sets with varying degree of entropy. The problem of selecting a specific set of weights is transformed into an

[1] All layers have the same number of cells.

optimisation problem which was first identified by O' Hagan (1988) and which can be stated as:

$$\text{Maximise:} \quad H = \sum w_i \ln w_i \qquad \textbf{Eq. 3.20}$$

subject to:

$$\frac{1}{n-1} \cdot \sum_r (n-r) w_r = user_input$$

and

$$\sum w_i = 1, \qquad \textbf{Eq. 3.21}$$

where: $w_i \in [0,1]$ are the ordered weights

i=1 to n indicates the position (order) of the weight w_i in the weighting vector which contains n weights

w_r is the weight of the r^{th} order

user_input is the user specified ANDness

This conceptually guarantees the maximisation of the degree of information used in the aggregation for a given degree of acceptable risk. The optimisation is solved using sequential quadratic programming (SQP) in Matlab (Matlab, 1999) and the resulting weight set is applied to the ordered attribute values.

However, a question arises at this point: Is there a structured way of changing the risk aversive attitude according to objective characteristics of the decision to be taken? In this case, is there a way to select an "appropriate' risk-aversive attitude that would make sense when considering a particular urban water management strategy? As each cell in the study area is considered an alternative in the decision-making process, the answer is that we could assign a different risk-aversive attitude to each cell if there was a reason to justify our choice. This technique, which will be referred to as **Spatial OWA** *(SOWA)*, has been developed here to allow for the spatial variability of the risk-aversive attitude of the decision maker and therefore of the weights used in the aggregation procedure. To the author's knowledge, this is the first time this technique has been used[1]. The technique involves the following steps:

[1] However, it should be noted that the concept behind SOWA has similarities to the concept of spatial compromise programming introduced by Tkach and Simonovic (1997). In that research Tkash and

1. Identification of risk-aversive value (***R***) associated with each cell (an example of such a risk aversion variation will be provided in the next chapter in the case of prioritising water mains replacement).
2. For each cell in the study area, Eq. 3.20 is solved with the constraints introduced in Eq.3.21 , where the "*user_input*" variable is set to ***R***.
3. A different set of ordered weights is assigned to each cell and the aggregation resulting to the final overall value for the cell is performed with this set of ordered weights.

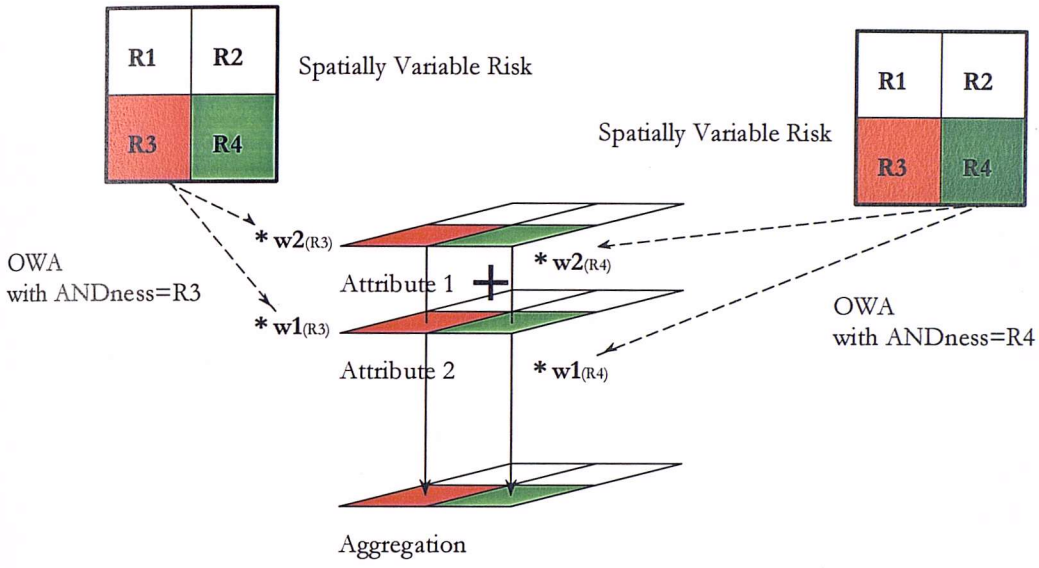


Figure 3.4 An example of the application of SOWA in aggregating two attributes

The result is an aggregation which takes into account not only the fact that the decision maker may need to express his risk-aversive attitude and thus influence the final result, but also that this risk-aversive attitude may be a spatially variable one. A module allowing aggregation with spatially variable risk inputs has been developed for the SDSS. A schematic of the process can be seen in Figure 3.4. A discussion on the physical meaning of this spatially variable attitude to risk for the particular case of WDM is included in Chapter 4.

Simonovic decided to use different criteria for different cells in an effort to define an optimal flood protection scheme. In our case, we use different weights per cell, to indicate our prioritisation.

3.5.4. Optimisation

3.5.4.1. Spatial optimisation

The final part of the decision process is to identify a composite scenario, taking into account the spatially distributed suitability ratings of each strategy. This scenario would represent a balanced approach that would be closer to a strategy adopted in a "real life" situation. This is a spatial optimisation problem: the result should identify the proportion of each strategy's implementation as part of the composite scheme based on economic and performance considerations whilst at the same time identify the exact location where each strategy will be implemented to obtain best results based on additional factors such as acceptability, increased benefits etc. This is a particularly complex planning problem and raises a number of challenging issues: In real life a site is a continuous domain, but in a raster model such as the one used in this research, a site is the aggregation of individual cells. Therefore, from an optimisation point of view the problem is to identify, among numerous possible cell aggregations, the set of cells that best meet the criteria at hand (Cova and Church, 2000). This type of problem is referred to as site selection (Han and Kim, 1989) or site allocation (Brookes, 1998). An important question to be answered prior to determining the approach for programming the spatial optimisation algorithm is whether the site we need to specify is contiguous or not (Cova and Church, 2000). A site is contiguous if it is possible to walk from any point of the site to any other without leaving the site. If contiguity is not an issue then the problem is simplified. The latter is the case in siting WDM strategies that are included in our SDSS, because in this case, locations for intervention need not be situated in neighbouring cells, but could, in principle, be dispersed throughout the site area.

3.5.4.2. Stating the problem

In our particular case, the spatial optimisation (non-contiguous) problem can take two distinct forms:

A. Identify the optimal composite strategy of urban water management, using a number of strategies alone or in combination ***to maximise a user-defined benefit*** *(for example water saving in the case of WDM),* ***subject to a user defined overall investment****. The choice of strategies' application is influenced by the fact that specific spatial suitability ratings have been assigned to each strategy.*

B. *Identify the optimal composite strategy of urban water management, using a number of strategies alone or in combination* ***to minimise the overall investment, subject to a user defined water management target*** *(for example a desired water reduction in the case of WDM). The choice of strategies' application is influenced by the fact that specific spatial suitability ratings have been assigned to each strategy.*

Three approaches have been developed in this work to address the problem:

- A *conventional* method (Sequential Quadratic Programming) whereby a hybrid algorithm was developed using suitability ratings to change the objective function combined with a random search (Monte Carlo) to identify an optimal initial search location.
- A hybrid algorithm which utilises the evolution properties of genetic algorithms to solve a single objective problem of selecting a number of application sites for the various strategies (sorted by suitability) using either the water management target or the investment as penalty function.
- A multiobjective GA utilising all three elements of the problem (suitability, investment and water management target) as separate objectives and identifying non-dominated optimal surfaces.

These approaches will be analysed and discussed next.

3.5.4.3. The conventional approach

To address the synthesis of a composite scenario as **an optimisation problem,** there is need to take into account the spatial variability dimension, introduced by the suitability ratings. The approach suggested here to incorporate this variability is to consider it as a weighting rather than an optimisation parameter. Consider the conceptual meaning of the rating $\mathbf{r_{i,j}}$ of the cell $\mathbf{(i,j)}$. It is a measure of the degree of suitability of the particular cell for application of the particular strategy. It is thus related to the perceived benefit in the particular location.

Let $\mathbf{W^{(k)}(n \times m) = [w^{(k)}_{i,j}]}$, be the matrix of weights (suitability ratings), where $\mathbf{0<w^{(k)}_{i,j}<1}$ is the value of cell $\mathbf{(i,j)}$, $\mathbf{k}$ is the index associated with the alternative strategies we are exploring and where $\mathbf{n}$ and $\mathbf{m}$ are the number of lines and columns of

the matrix respectively. For simplicity, let us assume that we have three alternative strategies (max($\mathbf{k}$)=3).

Let $\mathbf{S^{(k)}(n \times m) = [s_{i,j}]}$ be the matrix of benefits (for example the volume of water saved) per day on intervention using the strategy $\mathbf{k}$, $\mathbf{s_{i,j}}$ is the water saved with an intervention in the cell $\mathbf{(i,j)}$ per day.

The weighted indicator of benefit (e.g. water saved) is:

$$WS^{(k)} = \left[w_{i,j}^{(k)} \right] \bullet \left[s_{i,j} \right] \qquad \textbf{Eq. 3.22}$$

Where • ≡ overlay multiplication operation (element by element). Therefore, each grid cell is multiplied with one weight.

$\mathbf{WS^{(k)}}$ is then rearranged as a $(\mathbf{n \times m}) \times 1$ vector in decreasing order of suitability.

If the weighted benefit of Eq. 3.22 describes an actual decrease in expected benefit due to lower suitability (e.g. if a low suitability network cell is replaced to reduce leakage) then the result of Eq. 3.22 is used directly in Eq. 3.23. If, however, the weighted benefit is associated with an aggregation between a number of criteria that may not be directly related to the perceived benefit (i.e. education level is not directly related with water consumption reduction in the case of metering introduction as a WDM strategy), then once the vectors are ordered (with the weights taken into account), the order defined can be used to form the "true" vector of water savings, i.e. the un-weighted benefit per cell that will then be used in Eq. 3.23. This overcomes the problem of underestimating the benefit that would otherwise occur with the weights decreasing the total benefit while at the same time keeping the advantage of choosing the more "attractive" option in terms of both benefit and suitability ratings.

Forming the objective functions and the associated constraints is different for the two forms of the optimisation problem stated above:

Addressing optimisation problem A:

The objective function to be maximised is:

$$f = \sum_{q=1}^{k} \sum_{r=1}^{X^{(q)}} WS_r^{(q)} \qquad \textbf{Eq. 3.23}$$

Subject to:

$$\sum_{s=1}^{k} \left(X^{(s)} * (COST(s)) \right) = I \qquad \textbf{Eq. 3.24}$$

where the variables $\{\mathbf{X^{(s)}}\} \in \mathbf{N^+}$ (s=1 to **k**), are the number of cells (and therefore positive integers or zero) selected for strategy (**k**) application, $\mathbf{COST(s)}_{\mathbf{s=1\ to\ k}}$ is the cost per cell where an intervention is taking place in each of the **k** strategies and **I** is the desired investment.

For example, if according to Eq. 3.23, an optimum scenario would require intervention in 100 cells for strategy 1, 50 cells for strategy 2 and 10 cells for strategy 3, Eq.3.24 would have to make sure that 100 (=$\mathbf{X^1}$) times the cost of intervention per cell for strategy 1 plus 50 (=$\mathbf{X^2}$) times the cost of intervention per cell for strategy 2 plus 10 (=$\mathbf{X^3}$) times the cost of intervention per cell for strategy 3 is equal to or lower than the specified investment (=**I**)

Addressing Optimisation problem B:

The objective function to be minimised is:

$$f = \sum_{s=1}^{k} \left(X^{(s)} * (COST(s)) \right) \qquad \textbf{Eq. 3.25}$$

Subject to:

$$\sum_{q=1}^{k} \sum_{r=1}^{X^{(q)}} WS_r^{(q)} \geq \mathrm{T} \qquad \textbf{Eq. 3.26}$$

where the variables $\{\mathbf{X^{(s)}}\} \in \mathbf{N^+}$ (s=1 to **k**), are the number of cells (and therefore positive integers or zero) selected for strategy (**k**) application, $\mathbf{COST(s)}_{\mathbf{s=1\ to\ k}}$ is the

cost per cell where an intervention is taking place in each of the **k** strategies and **T** is the Industry's water management target .

Eq. 3.25 represents, for example, the total investment needed for intervening in $X^{(1)}$ cells of strategy 1, $X^{(2)}$ cells of strategy 2 and $X^{(3)}$ cells of strategy 3 and Eq. 3.26 calculates the water saved with interventions in these cells and keeps the quantity above or equal to industry targets.

In both cases, the physical meaning of the cost functions dictates the way to solve the optimisation problem. An example of solution given to the problem of WDM is given in the Chapter 4.

3.5.4.4. The single-objective GA

A GA procedure was developed based on the literature but without making use of existing GA libraries due to the heuristic approach adopted to solve this object location problem. The spatial variability of the suitability for application of a strategy is taken into account, this time explicitly, by forming a number of matrices equal with the number of strategies taken into account. The matrices are sorted by suitability and include the cumulative effect of the application of strategy i (for example ∑Water_Target) to the first n_i cells of the matrix (as specified by a pointer i) as well as the associated cumulative cost (for example ∑Investment). Figure 3.5, is an example of such a matrix.

$M_i =$

Cell_Row	Cell_Column	Suitability	∑Water_Target	∑Investment
10	20	0.7	50	100
5	158	0.68	80	200
...	...	...	...	...
120	79	0.001	20,450	100,000

Pointer i ←

Figure 3.5. An example of a matrix of a water management strategy

The column of the expected benefit can be multiplied by the suitability weighting or not, depending on the physical meaning of the suitability in the case of intervention in a particular cell, as discussed in paragraph 3.5.4.3. For example, if the strategy in question is leakage reduction, then the suitability ratings are assumed to affect the actual water saved, and should be used to decrease the expected water saved by an intervention in a specific cell. If, however, the strategy is metering introduction, then the suitability ratings

do not refer to actual decrease in water savings but to a decision maker's preference which may be linked for example to social policy. In that case, the column of expected benefit (column 4, Figure 3.5) should not be multiplied by the suitability weighting.

The objective here is to identify the vector of pointers [pointer 1, pointer 2, ..., pointer n] associated with all strategies that would either provide the water management target with the minimum investment ("water target" being the objective function and "investment" the constraint) as in problem A, or vice versa as in problem B.

The process followed by the GA to identify an optimal pointer vector can be summarised as follows:

Step 1: Initialisation

The initial GA population includes individuals of the type $pointer_i$= [pointer 1, pointer 2, ..., pointer n] which are created at random.

Step 2: Fitness

The fitness (**eval**($pointer_i$)) of each individual is calculated as proportionate to either a water target (jn the case of water saved in a WDM application) or the inverse of the investment needed, depending on the problem type (A or B). A penalty function decreases this fitness value whenever the relevant constraint is violated. At the beginning of the process, an individual that does not respect the target is not excluded, but given a low probability of reproduction, inversely proportional to the violation; at the end of the process such individuals are completely excluded.

Step 3: Selection Process

Two methods, widely used in the literature, were used to select individuals for mating. The "roulette wheel" proposed by Holland (1975) and the "stochastic universal sampling" proposed by Baker (1987). These selection methods are only two of a large number of selection methods quoted in the literature. As is generally the case in GAs, there are no rigorous guidelines for deciding which selection method to use for which problem (Mitchell, 1996). These two selection methods were chosen because of their widespread application. Their performance in dealing with the particular problem at hand will be discussed in Chapters 4 and 5. A brief discussion of these two methods follows:

(a) Roulette Wheel

The total population fitness (F) is calculated and the probability of selection of each individual is calculated as p_i =**eval**(*pointer*$_i$)/F. The cumulative probability is then calculated as $q_i = \sum_{j=1}^{i} p_j$. The individuals are mapped into continuous segments of a line from zero to q_i such that each individual's segment is equal in size to its fitness. A random number is generated and the individual whose segment spans the random number is selected. The process is repeated until the desired number of individuals is obtained. This technique is analogous to a roulette wheel with each slice proportional in size to the fitness (Figure 3.6).

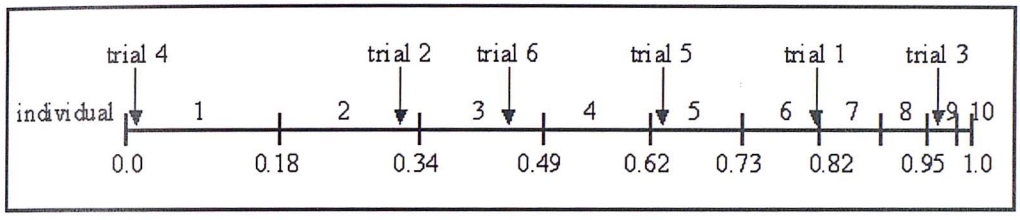


Figure 3.6 Roulette-wheel selection

Some individuals (presumably those with better fitness) will be selected more than once thus producing more offsprings. However, with the small population numbers typically used in GAs the actual individuals selected are not necessarily the expected ones. An extremely unlikely series of *n* "roulette spins" could even result in the selection of the worst individual in the population *n* times (Mitchell, 1996). To overcome this problem, Baker (1987) introduced the "stochastic universal sampling" selection process.

(b) Stochastic universal sampling

The individuals are mapped to continuous segments of a line, such that each individual's segment is equal in size to its fitness exactly as in roulette-wheel selection. Here equally spaced pointers are placed over the line as many as there are individuals to be selected. Consider *NPointer* the number of individuals to be selected, then the distance between the pointers are 1/*NPointer* and the position of the first pointer is given by a randomly generated number in the range [0, 1/*NPointer*].

For n individuals to be selected, the distance between the pointers is q_i/n Figure 3.7 shows an example of such a selection.

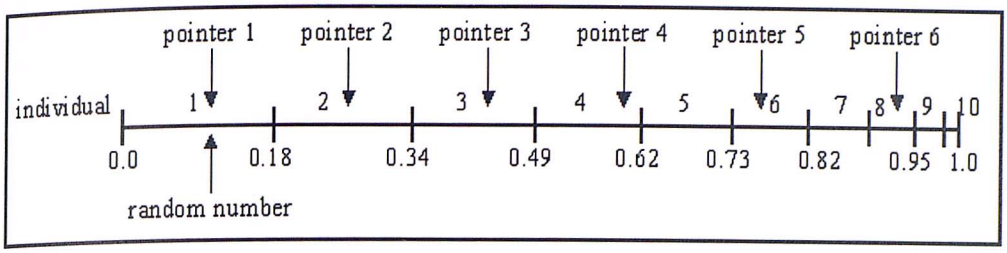


Figure 3.7 Stochastic universal sampling

Step 4: Crossover

A probability of crossover (p_c) is selected by the user. A random number **r** (between 0 and 1) is generated for each of the individuals. If $r<p_c$ the individual is selected for crossover. A random number between 1 and the length of vector *pointer*$_i$ is generated to indicate the point of crossover. The two parents exchange genetic material and are replaced by their offsprings as seen in Fig. 3.8

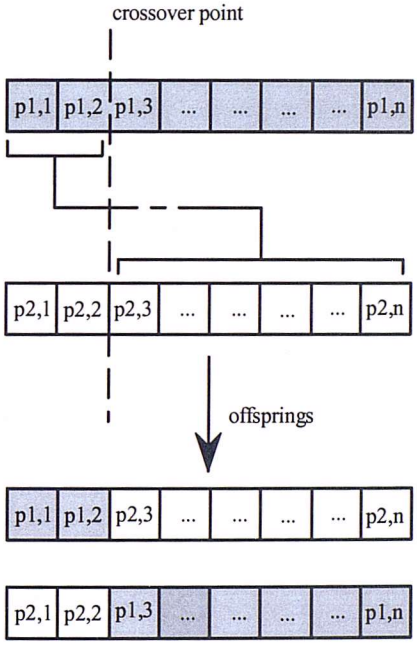


Figure 3.8. A crossover operation between two *pointer* vectors

Step 5: Mutation

A probability of mutation (p_m) is selected by the user. A random number **r** (between 0 and 1) is generated for each of the individuals. If $r<p_m$ the individual is selected for mutation. One gene of the selected individual is randomly changed.

Step 6: New population

A new population is generated after crossover and mutation and the process returns to step 2 to re-evaluate the new population.

Step 7: Stop

The algorithm is stopped after a fixed number of generations (or if a convergence criterion is reached).

The overall fitness of the population is increased in the course of these runs and the best individual of the final population is the proposed solution. This is guaranteed by an *elitist* strategy included in this algorithm, whereby the best individual of each population is transferred to next population unchanged. The problems of premature convergence, which this elitist strategy could cause, are dealt with by increasing the mutation rate. The domain specific operations and parameters used in this work will be described in Chapter 4. Results will be presented and discussed in Chapter 5.

3.5.4.5. The multi-objective GA

The last methodological alternative for spatial optimisation examined in this work is the development and use of a multi-objective GA optimisation module[1]. This approach addresses the issues of maximising (or minimising) multiple objective functions and allows the explicit inclusion of the suitability ratings in their proper spatial variable sense into the optimisation process. The process, however, is much more complex computationally and naturally results in increased computation times. The problem structure and the proposed solution algorithm are described below.

Step 1: Initialisation

A matrix (M_i) of legal individuals for each strategy is created to provide the pool from which the solution will be formed. This avoids the computationally intensive process of checking each solution for illegal individuals at every generation. The matrix (M_i) for each strategy (i) is of the form:

[1] Again, the particular nature and structure of the object location problem suggested that the development of a completely new algorithm (without using existing GA libraries) was a more convenient option.

$M_i =$

Cell_Row	Cell_Column	Suitability	Water_Target	Investment	Application
10	20	0.7	50	100	1
5	158	0.68	20	70	0
...	...	...	...	...	
120	79	0.001	40	90	1

where "cell row" and "column" are the indexes of the GIS maps of the area, identifying the physical location of the strategy's application, "suitability" is the value of the aggregated suitability maps for an application in that particular location, "water target" is the expected benefit from the application[1] and "investment" is the expected cost. Illegal individuals would have a suitability rating equal to zero and these are excluded from the matrix. The last column determines if indeed an application at that particular site will (application=1) or will not (application=0) take place. This flag can be turned on (1) or off (0) within the algorithm thus including more locations to the solution without changing the length of matrix of the individual solution.

A number of rows of each strategy matrix are selected at random and included in a new matrix I_j, which is termed "individual". Each individual represents one possible solution to the overall combined problem and its structure is as follows:

$I_j =$

Cell_Row	Cell_Column	Suitability	Water_Target	Investment	Application	
10	20	0.7	50	100	1	Strategy1
5	158	0.68	20	70	0	
...	...	...	...	...	...	
124	16	0.5	35	80	1	Strategy2
90	38	0.3	100	20	0	
120	79	0.001	40	90	1	

The number of rows of matrix I (j=1: population size) belonging to interventions of each strategy is fixed within one *epoch*. The analysis runs for a number of epochs, (defined as the part of the analysis within which the length of I remains fixed). After the end of an epoch, the length of I is increased by a small percentage (here 10%). A number of generations are allowed to evolve within each epoch. The reason behind this dual

[1] Multiplied or not with the suitability ratings depending on their physical meaning (see also discussion in paragraphs 3.5.4.3 and 3.5.4.4).

evolution process is the fact that the analyst does not know in advance the optimum length of a solution and therefore the maximum number of interventions allowed to take place for all strategies in combination. The length is thus allowed to increase progressively and the outcome monitored to see the performance of the solution against the objective functions.

Step 2: Fitness

An objective function matrix (ObjFun) is created whose rows represent the evaluation of each individual in the population through a number of objective functions. For example: $ObjFun = [index \quad objfun1 \quad objfun2 \quad objfun3]$, where index is the association between the particular row and the evaluated individual.

Step 3: Pareto-Optimality

After identifying the value of the objective functions for each individual, there is a need to derive the non-dominated sets. The procedure used here is an adaptation of the algorithm proposed by Deb *et al.* (2000), namely NSGA-II. The reason for this choice was that NSGA-II is a fast and elitist multi-objective algorithm specifically designed to reduce computational complexity (which is a key concern in a problem of this magnitude and mathematical and physical complexity). Furthermore, the NSGA-II algorithm uses a simple way to address the problem of speciation (as mentioned in earlier chapters) that will be described in step 4. The NSGA-II is an improved version of the NSGA algorithm, which is one of the five algorithms, recommended for use in multi-objective GA problems by the state-of-the-art overview of such algorithms provided by Van Veldhuizen and Lamont (2000). Briefly the non-dominated sorting algorithm can describe as:

P′=find-nondominated_front(P)
P′= {1}
for each $p \in P \wedge p \notin P'$
    $P'=P' \cup \{p\}$
    for each $q \in P' \wedge q \neq p$
        if $p \prec q \Rightarrow P'=P'$-remove $\{q\}$
        else if $q \prec p \Rightarrow P'=P'$-remove $\{p\}$

The first solution from the population is kept in a set P'. Each solution p is compared with all members of the set P'. If a solution is found to dominate any member q of the P' set, then the solution q is removed from the set. If the solution p is dominated by any member of the set, it is ignored, if it is not, then it is included in the set P'. At the end of the algorithm, the first non-dominated front is identified. The set P' is saved and the procedure begins again searching through the remaining solutions to identify the other non-dominated fronts.

Step 4: Crowding Factor

As mentioned earlier, the identification of the non-dominated fronts alone is not adequate to guarantee a good spread of solutions in the final solution set. The algorithm needs to avoid selecting elements of the same non-dominated front that represent solutions which are close together as this reduces the exploration capabilities of the algorithm. A standard way of solving this problem is through a sharing function (Deb and Goldberg, 1989; Goldberg, 1989b; Fonseca and Fleming, 1993). This requires setting a parameter (σ_{share}) determining the largest value of the distance metric within which any two solutions share its others fitness. This parameter is usually user-defined and thus introduces an element of subjectivity and is ultimately dependent on the analyst's experience of the problem at hand. Additionally since each solution is compared with every other, the overall complexity increases. Deb et al., (2000) propose a low complexity solution, which addresses effectively the issue of subjectivity in parameters assignment. The estimation of density of the solutions surrounding a particular solution in a specific non-dominated front is performed by calculating the distance between two points on either side of the solution along each objective (Figure 2.17). The *crowding factor* computation requires a sorting of the population according to each objective function value in ascending magnitude. The boundary solutions are assigned an arbitrarily large value while all the intermediate solutions are assigned a distance value equal to the absolute difference in the function values between the two adjacent solutions. The crowding factor of a specific solution is thus identified as the sum of the individual distance values corresponding to each objective. The algorithm can be briefly described as follows:

For a non-dominated set P

for each solution i set $P(i)_{distance} = 0$

for each objective m

P=sort(P,m)

$P(first)_{distance} = P(last)_{distance} = \infty$

for i=2:lengthP-1

$P(i)_{distance} = P(i)_{distance} + abs(P(i+1)_m - P(i-1)_m)$

Step 5: Formation of a parent population

The parent population is half the size of the original population. The new parent population is formed by selecting members of the best non-dominated front, then the second best etc. When the size of a non-dominated front is larger than the remaining positions in the parent population, the individuals with the highest crowding factor are selected.

Step 6: Selection

A 1-1 tournament selection process (see for example Krzanowski and Raper 1999; Michalewicz, Z., 1996) is used to identify the mating part of the new parent population. The tournament selection process selects two individuals from the parent population, compares them and selects the best one for the mating population. An individual can be selected more than once by using this method. There are two variations of the method used in this work: with and without explicit constraint handling.

Step 6.1: Without explicit Constraint handling

In the comparison process, individuals are selected when they have better non-dominated rank (i.e. if they belong to a better non-dominated front) or when the rank is the same by larger crowding factor (indicating increased exploration potential).

Step 6.2: With explicit Constraint handling

If constraints are explicitly taken into account, there are three possible situations:

- If both selected individuals fulfil the constraint requirements then the selection is performed as in step 6.1.
- If one individual fulfils the constraint requirements and the other does not, then the one that does is selected.

- If both individuals do not fulfil the constraint requirements then the individual with the smallest constraint violation is selected for inclusion in the mating population.

Step 7: Operators

The operators used include crossover, uniform mutation and complete substitution. The percent of the population subject to the operators is governed by a *Temperature* component, decreasing with each generation (similar to simulated annealing).

Crossover: Two individuals selected at random from the mating population exchange part of the solution they represent. The procedure requires two crossover points (selected at random by a start and stop pointer) as the crossover is performed within each strategy (Fig. 3.9). Only the first of the two individuals created is kept within the offspring population.

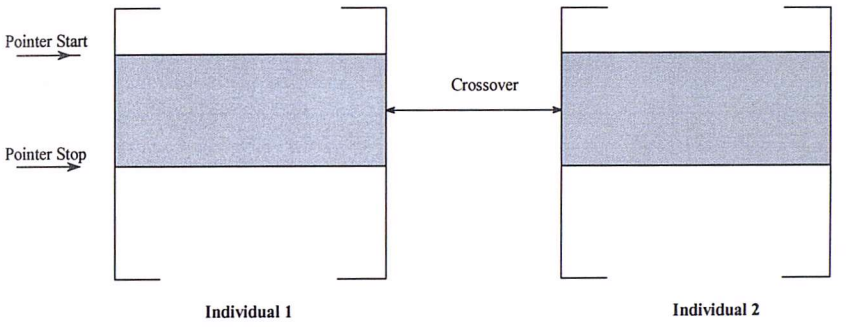


Figure 3.9. Crossover operator

Mutation: A part of the selected individual (selected at random by a beginning and an ending pointer) changes application status at random (Fig. 3.10). This mutation approach ensures that none of the new individuals created are illegal.

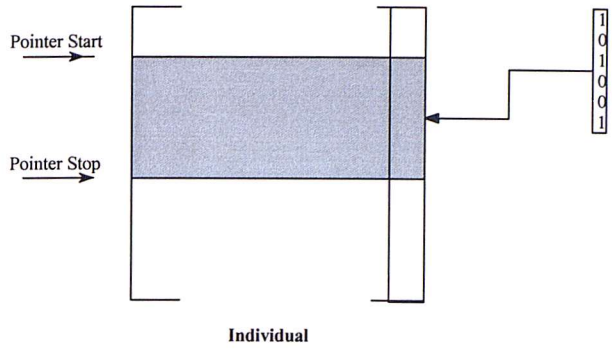


Figure 3.10. Mutation of the application status

Complete substitution: Two approaches were developed at this stage dependent on the progress of the generations within each epoch.

1. Early stages: A complete substitution of a (random) number of individuals occurs. These new individuals are created using the same procedure as that used for creating the initial individual population.
2. Later stages: A local search algorithm is used to investigate the possibility of finding individuals with better characteristics close to the existing individuals. A local, deterministic, hill-climbing algorithm (Krzanowski and Raper, 1999), was adapted to the spatial multi-objective problem at hand to assess the changes in the objective function space by local, spatial, changes in the parameter space.

The algorithm can be briefly described as follows:

The algorithm selects a location where a strategy application has taken place and searches the nearby (legal) locations for a better sitting of the same application. When a suitable location is found within the distance specified by a step, the algorithm calculates the objective function for the new solution. If it is found to be better than the original, the new solution is kept. Otherwise, the old one is kept and the search continues until all points are checked for all steps and directions. The main problem in the application of this local search spatial optimisation algorithm is that in this case the objective function is not one number but many, which makes the comparison of solutions difficult. The number of alternative solutions created in the process of this local search algorithm makes it impractical to rank the solutions based on non-domination. A more simple weighting procedure has therefore been used to speed up the comparison between alternatives within this operator. The objective function evaluations for each strategy are

divided by their respective best scores to achieve standardisation and the resulting values for each strategy are summed to derive a composite (weighted) objective function evaluation. This evaluation is then used for comparison purposes. Although this process clearly allows the multi-objective problem to collapse to a single objective one, this should not affect the overall multi-objective character of the solution, as the new solutions generated from this process undergo themselves ranking based on non-domination as part of the new population of individuals.

Step 8: Forming the new population

The offspring population derived from the application of the operators described above is merged with the initial parent population derived from the non-dominated and crowding factor ranking thus ensuring elitism. The new population is in turn allowed to evolve and the process is resumed from step 2.

Step 9: Stop

For each epoch, the algorithm retains the best non-dominated set and the corresponding individual solutions. The algorithm stops when the maximum number of generations is reached for the maximum number of epochs.

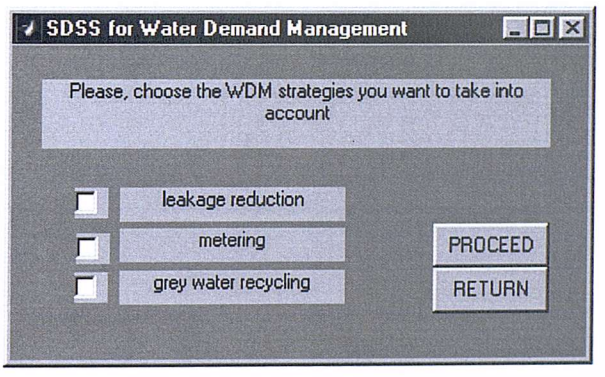
The decision-maker is then presented with a set of alternative solutions and is asked to state an *a posteriori* preference, which is effectively a compromise between the solutions included in the (known) Pareto-front computed by the algorithm. The quality of the final decision reached is influenced by the degree to which the known Pareto front accurately represents the real Pareto front of the problem at hand.

3.6. Conclusions

Chapter 3 presented the mathematical framework used to develop the spatial decision support system and the system's architecture. The system is developed in the Matlab mathematical environment using ArcGIS as a pre and post-processing tool. GIS and Matlab are used to access and analyse a variety of attributes, linked to the specified objectives the urban water management problem at hand. The spatial model used is a classic *raster-based* model, as this resembles the structure of matrices in Matlab. Both hard and soft information are combined to allow for a comprehensive overview of the situation and fuzzy inference systems have been used to standardise the information

(linguistic, probabilistic and fuzzy) in a common decisional base. Type-1 and type-2 FIS are programmed and are accessible to the user through user-friendly graphical user interfaces (GUI). The FIS utilise both crisp and fuzzy number input dependent on the nature of information processed. Depending on the availability of information (either field measurements or expert judgement) the user is given the option to tune the FIS to correctly respond to sets of training data. This is possible through the development of neuro-fuzzy systems using back-propagation algorithms to adjust the parameters of the original FIS. Aggregation techniques are then applied to compose the membership function of the initial ill-defined set from the component membership functions. A choice of such techniques, including linear summation, Ordered Weighted Averaging and Spatial Ordered Weighted Averaging are available to the user. Finally, optimisation procedures are used to help the user decide on a composite strategy synthesising the preferential applicability maps for the strategies taken into account. For this purpose, three new optimisation algorithms: one based on SQP and two based on evolutionary programming (EP) were developed within this research. Especially for the EP it must be noted that the mathematical development presented here and the coding that followed, is a novel contribution of this work to the relevant literature, as it made no use of existing GA libraries. The reason behind developing an entirely new, customised algorithm was that the specific problem was assumed to benefit from the largely heuristic approach described above.

4 Application in WDM



4.1 Introduction

Following the detailed discussion of the mathematical framework on which this SDSS was based, Chapter 4 provides concrete examples of applying the mathematical tools described in Chapter 3, to the specific problem of Water Demand Management (WDM).

The analysis undertaken here is a tool for Water Service Providers to:

(a) Compare different water demand reducing scenarios,

(b) Plan the site-specific implementation of these scenarios and

(c) Assess the investment needed to achieve a desired reduction or

(d) Identify the best composite scenario dependent on a desired investment scheme

Chapter 4 discusses the case studies, data availability and data format issues and provides an overview of the decision-making process (presented in Chapter 3) applied in the case of WDM through fuzzy inference, aggregation and optimisation. The results from the case studies and their discussion are included in Chapters 5 and 6 respectively.

4.2 Case studies description

Two case studies have been developed within the course of this work:

Case study I is based exclusively on data from two UK settlements and was developed to illustrate the capabilities and to validate specific processes within the SDSS that can indeed be validated in a quantitative sense, e.g. the leakage reduction module and the data-driven training module.

Case study II is semi-hypothetical, based on data from a city in Western Georgia, USA. This case study was used to present and discuss the capabilities and limitations of the overall SDSS procedure and model. Where data were not available they were hypothesised following the structure and ranges real data would have had.

Due to the nature of the decisions supported by the SDSS there can be little validation in most parts of the model development (as discussed also in paragraph 3.5.2.2) apart from validation derived indirectly through expert judgement. A composite water demand management scheme proposed by the SDSS cannot really be validated against real life metrics as in reality only one such scheme would have been implemented thus no

comparison data can possibly exist. This is, however, not the case in leakage reduction strategies, where pipe prioritisation schemes can - to some extent - be validated through past burst records. Such records were identified for two networks in the UK and used to validate the rule-based analysis process as well as to demonstrate the use and usefulness of the training modules when data is available.

4.2.1 Case study I

Databases (in MS Access™) containing real data of water mains characteristics and burst records were used to form the second case study, which is based on two water supply networks in the UK. Approximately fifty years of burst records were available for the analysis. The databases link the assets (water mains and burst records) to Ordinance Survey (OS) coordinates and were processed to derive the shape of the corresponding networks in GIS. Apart from the characteristics of the pipes (age, material and diameter) the derived network was used to calculate the spatial distribution of the pipe density, while additional data on the road network for the specific sites were used to identify the type of road traffic the water supply network pipes were subjected to. The five resulting data sets (age of pipe, material, diameter, pipe density and road type) were used in the same way as the corresponding data sets of case study I. In this case *only real-world data were used* to provide an example of the applicability of the tool under situations of data scarcity, similar to those encountered in practice. Input to the Bayesian training module was extracted from the burst records of the upper network (Fig. 4.1) and used to train the SDSS to assess leakage vulnerability of both the upper and the lower network in order to avoid issues of data fitting. The resulting GIS layers, which served as input to the SDSS, can be seen in Figures 4.2-4.6.

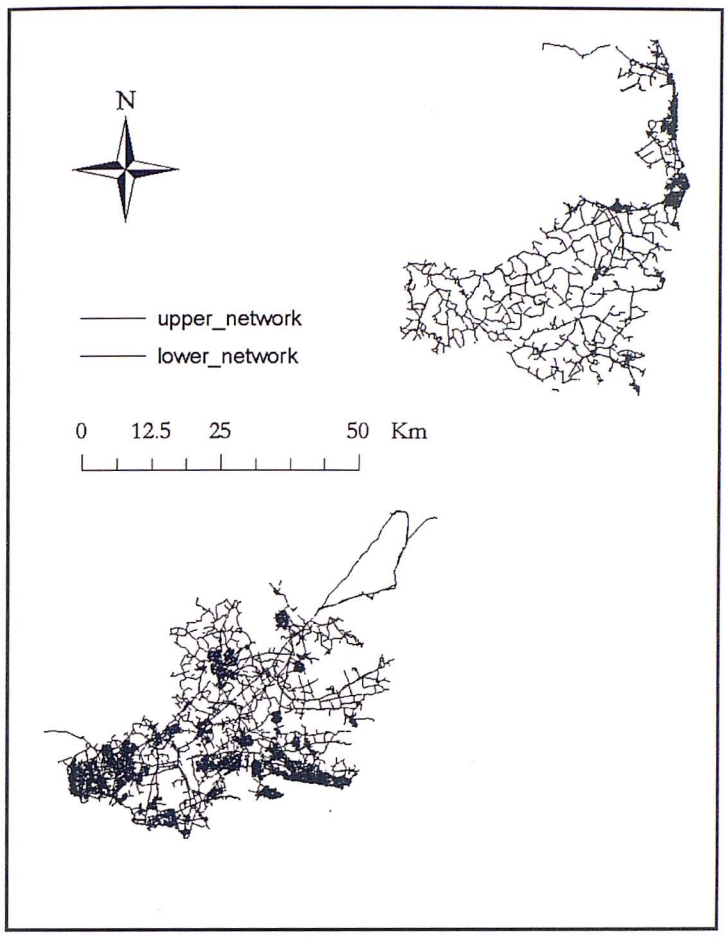


Figure 4.1 Case study I: Two Water Supply networks in UK settlements

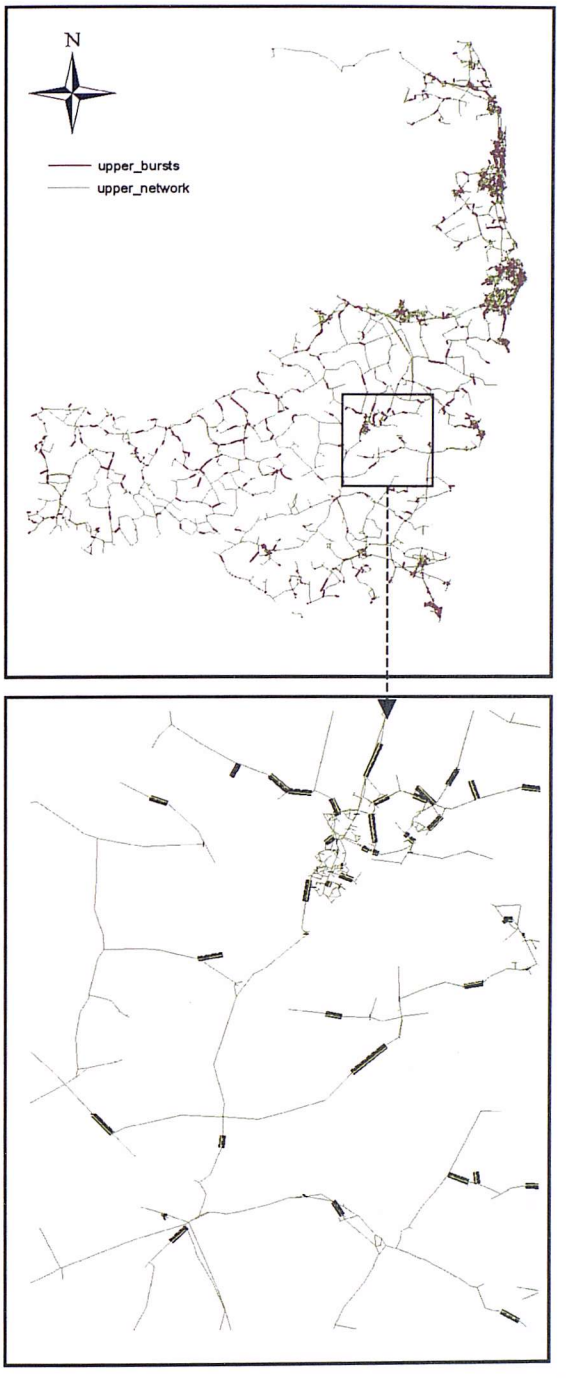


Figure 4.2 Burst locations

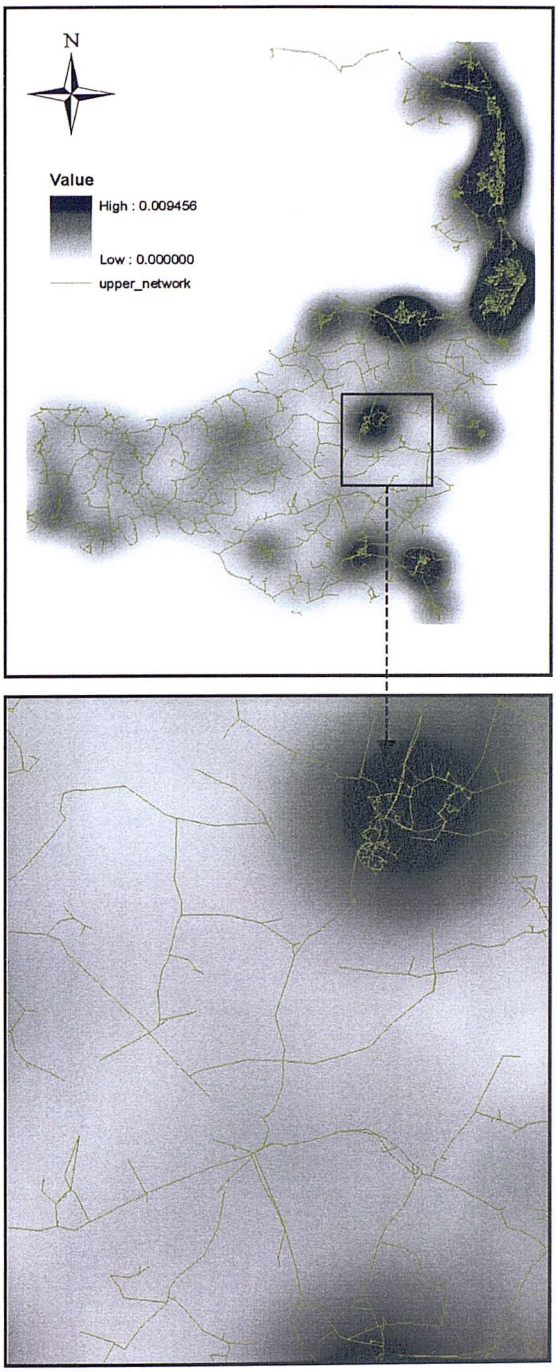


Figure 4.3 Pipe density (network cells/m^2)

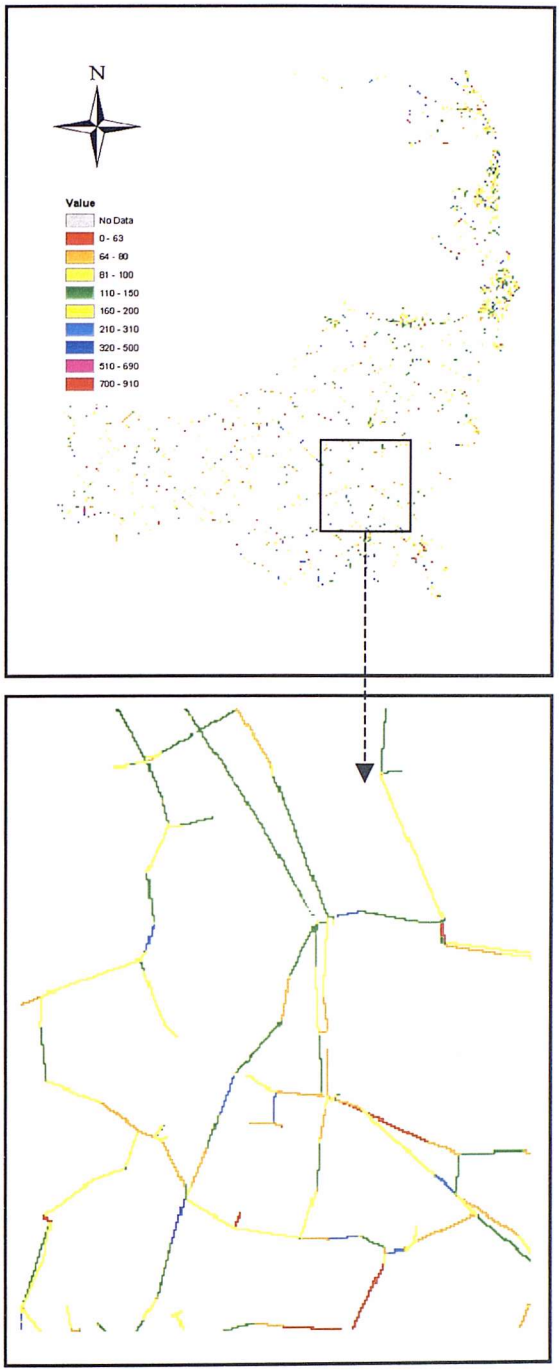


Figure 4.4 Pipe diameter (mm)

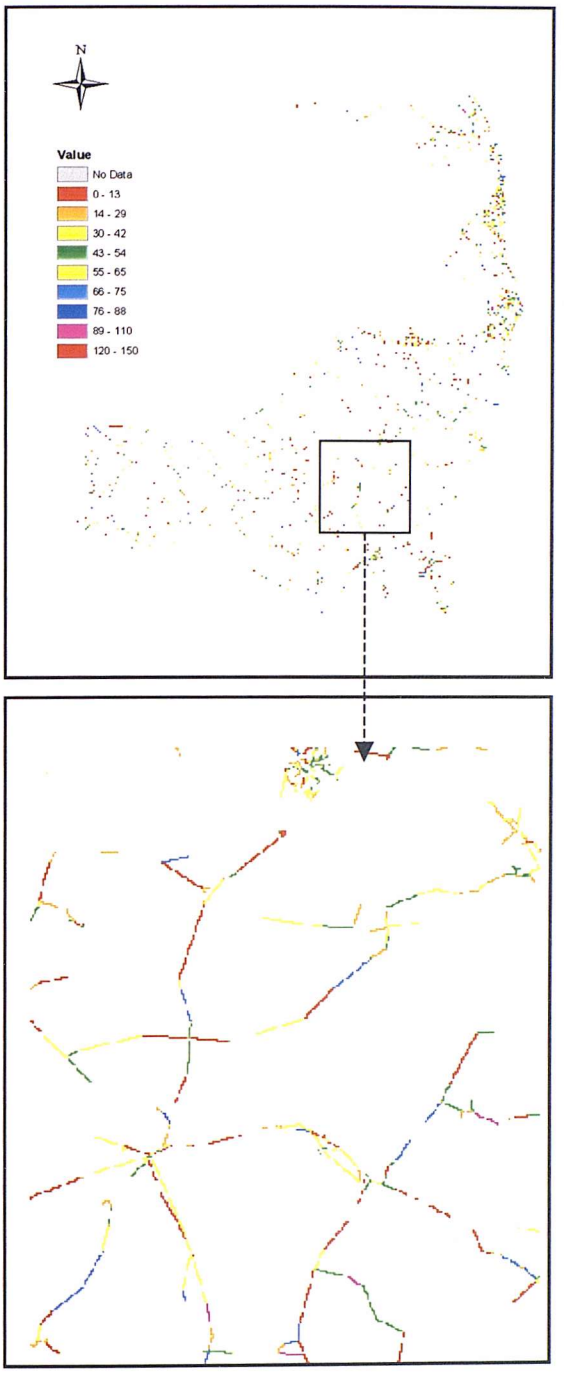


Figure 4.5 Pipe age (years)

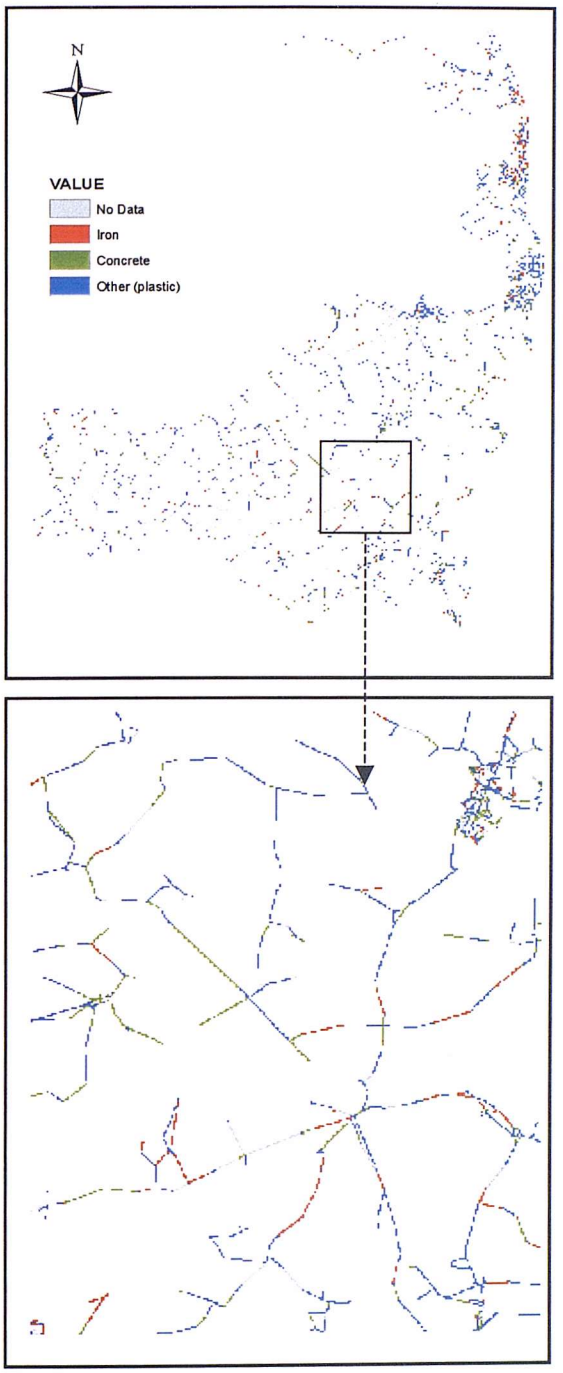


Figure 4.6 Pipe material

4.2.2 Case study II

The second case study is a city of 50,000 inhabitants located in a closed valley adjacent to a coastal zone, where a commercial harbour is situated. Data include:

- A digital elevation model (DEM). The entire area is divided into 250×211 cells, with a cell size of 30m.
- A road network with 3 road types:
  - Category 1: secondary street
  - Category 2: highway
  - Category 3: streets where a change of use from lighter to heavier traffic has been recorded
- A water distribution network, which was hypothesised using the generally valid practical assumption that it follows the road pattern. The network database contains information for:
  - The pipe diameter (between 200 and 1000 mm)
  - The pipe class (main and secondary pipes)
  - The pipe age created using a random distribution of ages
  - The pipe material. Materials used are:
    - 1-Cast iron
    - 2- Reinforced Concrete
    - 3-Plastic (uPVC)
  - Fire hydrant locations
  - Soil properties: pH distribution (created as a random set of values from the Normal distribution between values 4 and 9, in 62 random sample points. The resulting continuous image is the interpolation of these values by the *spline* method.
- Age of buildings. A zoning system was hypothesised that divides the city into 9 zone districts, under its assumption that the construction occurred during distinct well-regulated phases. This assumption, is in fact a simplification of real life situations where construction is much more arbitrary and thus far less homogeneous. This fact however is dependent on detailed information availability and can be readily incorporated in the DSS.
- Population per cell

- Type of use for the various buildings units[1]
  - industrial
  - commercial
  - residential
- Income per building unit
  - high
  - medium
  - low
- Education level per building unit
  - high
  - medium
  - low

Two additional data inputs complete the case study description:

1. The *case study water distribution network was imported into EPAnet* and a model of the hypothetical system was run for a period of 1 week. The network model and simulation performed here does not aim to investigate specific water demand scenarios, but rather serves as an example of incorporating model simulations into the SDSS. In this case, the output of the model that was imported back to the SDSS in the form of a grid layer (or a matrix in Matlab conventions) is maximum pressure in each network cell over the simulation period.
2. A *data set of pipe failures* together with the associated network characteristics for each failure in the form of a vector of attributes was also hypothesised. The data are based on the data format and availability presented in the literature (for example Cooper *et al.* (2000) and Fenner and Sweeting, (1998)). The aim was to provide the SDSS with a mechanism to enable field data to be used to increase the knowledge within the fuzzy inference systems, through mechanisms more objective than expert judgment.

The resulting GIS layers, which were used as input to the SDSS, are presented in the following figures (Fig 4.7-4.13).

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[1] Building Units: due to available detail of information, the buildings were not considered on an one-by-one basis. The unit is comprised of a small number of buildings where land use and other information are considered homogenous.

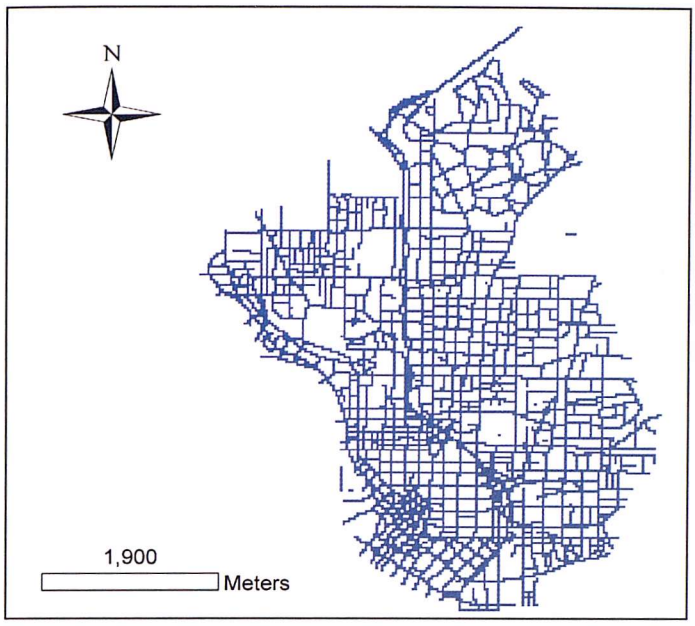


Figure 4.7. The water supply network in case study II

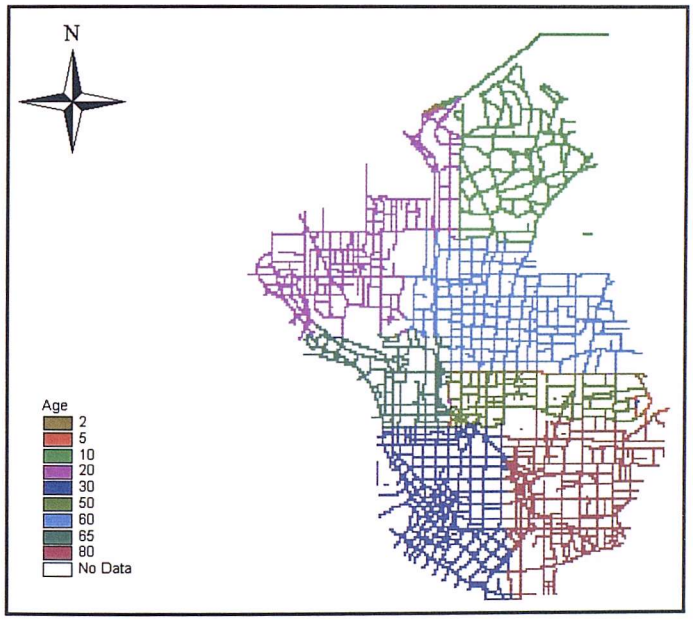


Figure 4.8 Network age (years)

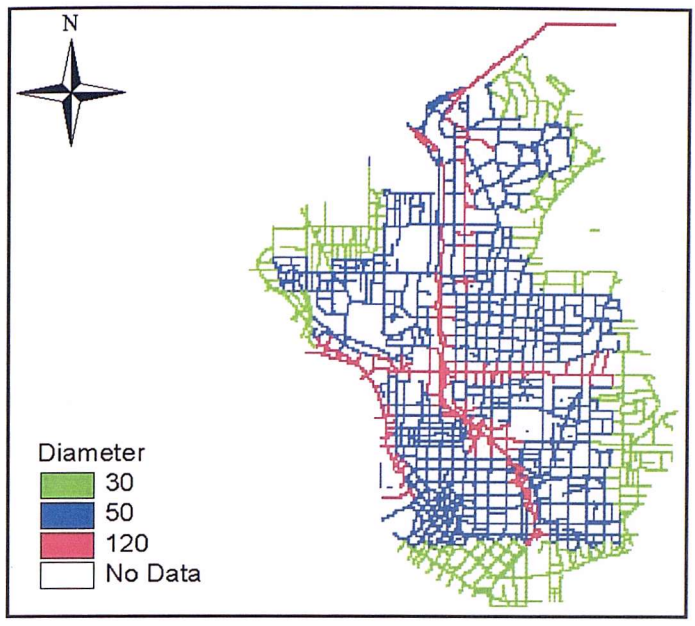


Figure 4.9 Network diameter (cm)

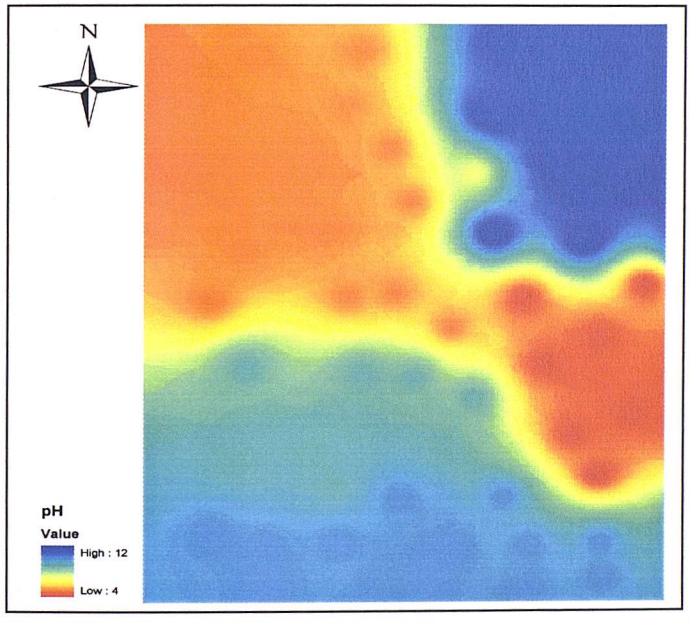


Figure 4.10 Soil pH

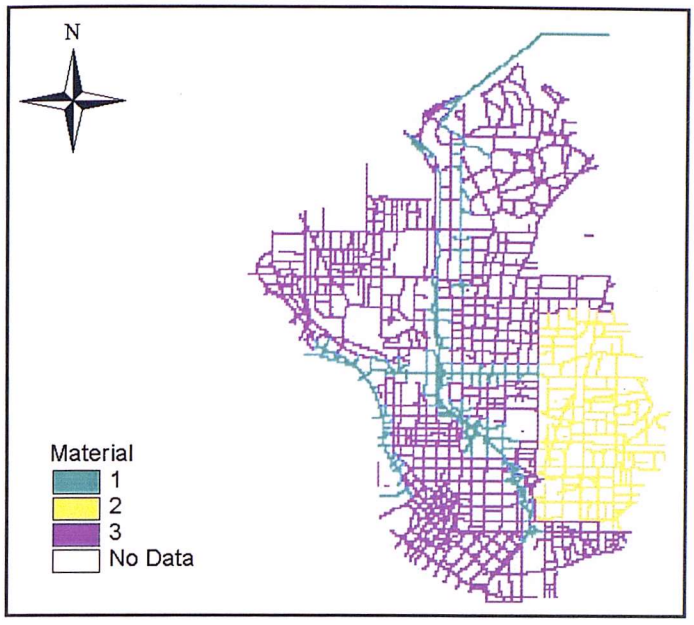


Figure 4.11 Network material (1-Cast iron, 2- Reinforced Concrete, 3-Plastic)

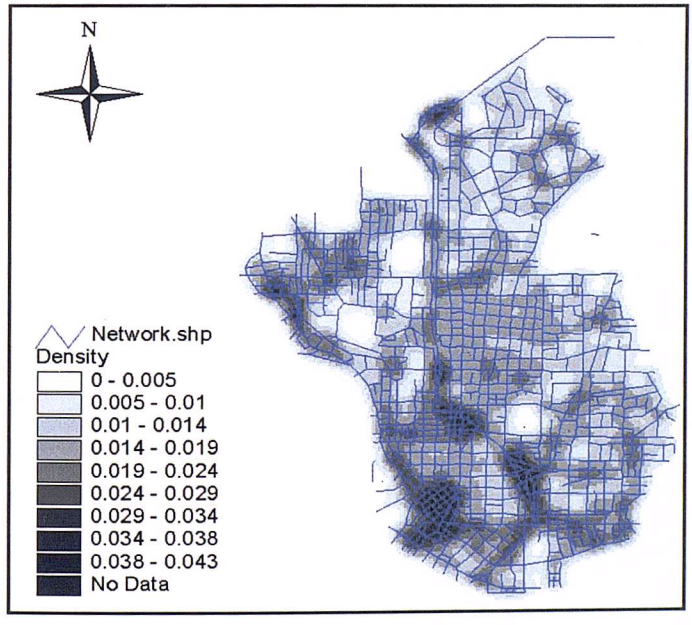


Figure 4.12 Network density (network cells/m^2)

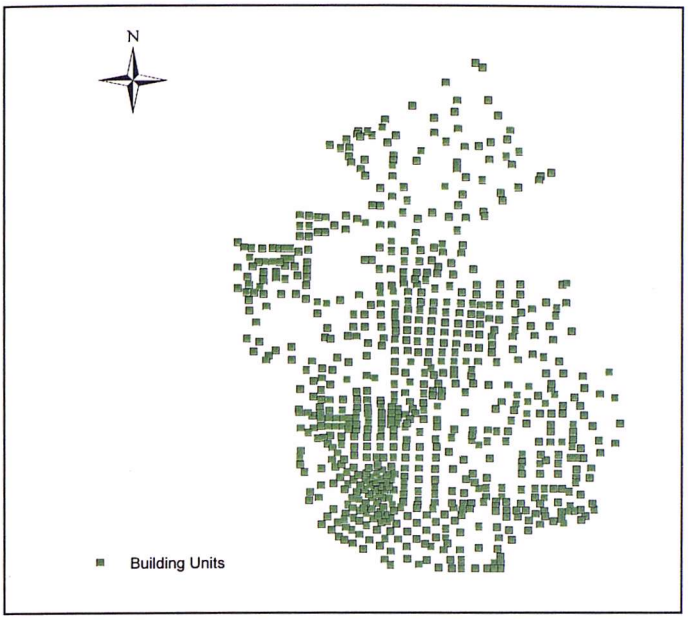


Figure 4.13 Social and financial information on a building unit level

4.3 Decision-making Process

Following the general decision-making process supported by the system (as discussed in previous chapters), we next provide a detailed application of the process to the particular case of Water Demand Management:

STEP 1: The user chooses which water demand management strategies he/she wishes to take into account. Three management strategies were taken into account while developing the SDSS (in accordance with Foxon *et al.*, (2000)): *Grey-water recycling, water metering and leakage reduction.* These strategies can be thought of as examples of all three WDM options (i.e. positive incentives, negative incentives and quota regulations) as discussed in the introduction.

STEP 2: Each strategy is broken down into a number of attributes, which directly influence its applicability in a given location. The user chooses the attributes he/she wishes to take into account. Note that in real life situations the attributes chosen will, in principle, be those linked with available data sets. This scalar approach tackles to a certain degree the problem of having to make decisions under various levels of data availability. Details of how the strategies were broken down to specific attributes are included in the paragraph 4.4.1 on set decomposition.

STEP 3: Each selected attribute is imported into the system as a raster GIS layer and is transformed into a suitability map for the relevant strategy to the extent that the attribute influences the strategy's applicability. For example the population density attribute map of the Grey-Water Recycling strategy is transformed into a Grey-Water Recycling suitability map due to population density. As the output is now homogenous (suitability maps in a [0,1] scale), the results of heterogeneous input are made comparable. The process is performed through fuzzy inference systems (both type-1 and type-2), which can analyse both singleton and non-singleton input (Mendel, 2001). The fuzzy inference systems were initially programmed based on general cause-effect relationships between attributes and suitability for application, identified in the literature. These general relationships, which served as the principle assumptions for structuring the FIS, are discussed in paragraph 4.4.2 on linking attributes and objectives. To reduce the subjectivity of these assumptions, whenever possible, the SDSS is equipped with a neurofuzzy training module, which uses input-output training pairs to modify the structure of the FIS, to suit the data available. The process of creating input-output training pairs from raw data on water mains burst records using Bayesian statistics is discussed in the paragraph 4.4.4 on training the Fuzzy Inference Systems.

STEP 4: The standardised suitability maps for each attribute of a WDM strategy are then aggregated to provide one all-inclusive suitability map for the strategy's application. The user is presented with different options of aggregation including simple additive weighting (with direct weights assignment) and ordered weighted averaging. The later enables the incorporation of the decision maker's attitude towards risk in the outcome in the aggregation process. The degree of risk aversion of the decision maker is provided to the system as a user input and appropriate weights are calculated to convey this level of risk aversion into the aggregation outcome.

For the particular case of leakage or burst reduction, identified as one of our WDM strategies, a form of spatially distributed risk aversion is introduced to take into account the potential consequences of flooding (due to bursts) in an urban area. These consequences are spatially variable and are a function of mean rateable value, insurance data and occurrence (or not) of a basement (Cooper *et al.*, (2000)). This application is

presented in paragraph 4.5.2. The output strategy suitability maps for all three strategies are then imported into the optimisation module.

STEP 5: Optimisation includes a number of user input parameters including but not restricted to, overall desired investment cost, per capita water consumption, cost for network rehabilitation per metre of network, cost for grey water recycling scheme introduction per household and cost of introducing metering per household. The spatial optimisation problem solved at this stage takes two forms: (a) Maximise water savings for a desired investment and (b) minimising investment required for a specific target water reduction. Three approaches were used in solving this problem: sequential quadratic programming, single-objective genetic algorithms and multi-objective genetic algorithms. The structure and form of the objective functions and constraints, as well as the difficulties in this particular application are discussed in the paragraph 4.6. The result is a combined strategy in the form of a detailed proposed Water Demand Management application scheme (master-plan) on a building unit -by - building unit level indicating the optimal location for intervention.

The specific issues arising from the use of the three main modules (fuzzy inference, aggregation and optimisation) for WDM will be discussed in sections 4.4 – 4.6 following.

4.4 Applying Fuzzy Inference

4.4.1 Set decomposition

The three major water demand management strategies were considered ill-defined fuzzy sets and were decomposed into their elementary attributes. Alternatively, this decomposition can be thought of as identification of parameters affecting the suitability of strategy application. Although the list of parameters taken into account here can be considered adequate for the analytical and demonstrative purposes of this research, in principle, other similar parameters affecting the application of these strategies can be added[1] subject to data availability. Table 4.1 summarises the attributes taken into account for each strategy.

[1] Similarly some of the parameters in the list could be subtracted if it was felt that there are not enough data to take support them.

Table 4.1 Attributes of WDM strategies

Strategy	Leakage Reduction	Metering	Grey and Rainwater RC
Attributes	1. Soil aggressivity	1. Population Density	1. Population Density
	2. Age + Material	2. Income	2. Income
	3. Traffic Type	3. Education	3. Education
	4. Diameter		4. Renovation Status
			5. Roof Characteristics
	5. Distance to Fire Hydrants		
	6. Pipe Density		
	7. Max Pressure (EPAnet simulation)		

(Data for the attributes in **bold** were available in case study I)

4.4.2 Linking attributes and objectives

Developing the FIS to link the input attributes (as seen in table 4.1) to each strategy's suitability for application requires setting up the initial sets (antecedent and consequent) and rules in such a way that incorporates expert judgement. In this case expert judgment was substituted for by an extensive literature review, identifying the state-of-the-art knowledge on cause and effect relationships between the attributes and the suitability for application of the associated WDM strategies. The results of the literature review used in setting up the initial structure of the FIS are summarised below. A user has the possibility of altering the structure by training the FIS with available data. This procedure is described in the following paragraphs.

4.4.2.1 Leakage reduction

The relevant literature is extensive, but the results of numerous case studies do not generally converge. The broad definition of leakage, used by Goulter and Kazemi (1989) has been adopted. According to this definition leaks, failures and breaks are all grouped as failures requiring repair. This definition has the advantage that it could be applied to almost every historical pipe record (Wengstrom, 1993) and is suitable for reliability analysis. The following parameters were taken into account in deriving the plan for leakage reduction priority areas and thus constructing the attribute value distribution maps. These parameters are also in accordance with Cooper *et al.* (2000) and their

research on leakage risk in the London Water Supply Area, on behalf of Thames Water Utilities Limited (TWUL). The list, however, is not all-inclusive: other parameters such as, for example, soil moisture or land use have also been mentioned in the literature (e.g. Savic and Walters, 1999), and could be included in the system in a similar way.

Age of the system

In a literature survey by Gulter and Kazemi (1988), there seem to be two prevailing opinions on the "age of pipe" effect on leakage. The first states that there is a positive correlation between age and break rate (Goulter and Kettler, 1985), and the second argues that there are several equally important factors (O'Day, 1982; Andreou *et al.*, 1987). The view adopted in this research, is that of Hertz (1996), which claims ageing is linked to a deterioration phenomenon, but it should be seen with respect to its material, diameter, bedding, external and internal stress, as age alone is an "unsatisfactory indicator of the actual pipeline condition" (Hertz, 1996). In the same study, Hertz proposes a probabilistic approach, based on "ageing distribution" functions. The proposed distribution (F) (Eq. 4.1) has been specifically developed for ageing of pipelines and allows failure rate to increase with age exponentially at the first part of the curve, then more gradually and finally asymptotically to a boundary value.

$$1 - F(t \le c) = 1$$
$$1 - F(t > c) = \frac{a+1}{a + e^{[b(t-c)]}} \qquad \textbf{Eq. 4.1}$$
$$1 - F(t = \infty) = 0$$

where: **a** is the ageing factor; no ageing takes place if a=0

b is the failure factor; the final maximum failure rate

c is the resistance time, up to which no major rehabilitation work takes place.

t is the age of the pipe

The distribution was then solved for F(t) to derive the membership function[1] for leakage vulnerability as a function of age and material (Eq. 4.2)

[1] In this case the membership function that is derived is interpreted as a likelihood function and is then viewed in terms of a conditional uncertainty measure, here a probability, in accordance to Dubois and Prade (1993). The probability function given by Hertz is not, therefore, used directly as probability, but as a measure of the likelihood of a pipe of specific characteristics to be categorised as susceptible to leakage. No direct link between possibility and probability measures is implied here.

$$F(t \le c) = 0$$

$$F(t > c) = 1 - \frac{a+1}{a + e^{[b(t-c)]}} \qquad \textbf{Eq. 4.2}$$

$$F(t = \infty) = 1$$

The shape of the membership function can be seen in figure 4.14.

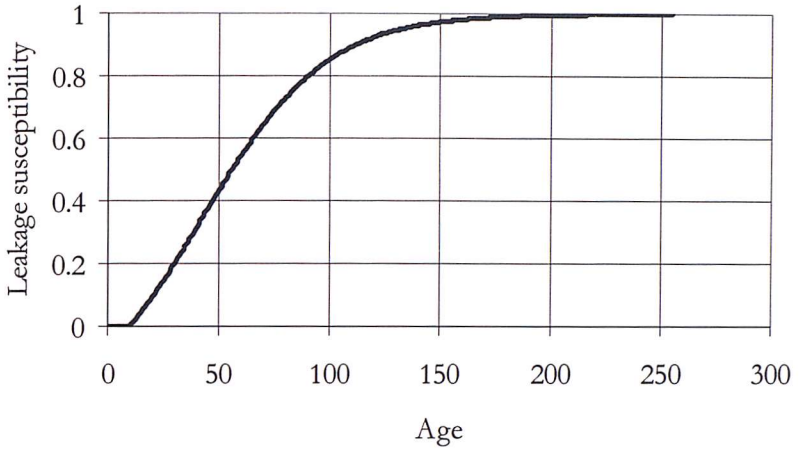


Figure 4.14. Schematic illustrating the shape of the Hertz membership function

The values used for c, a, b are in accordance with Hertz (1996). The specific values for cast iron, concrete and plastic, which were used here, can be seen in Table 4.2.

Table 4.2. Parameters for the Hertz membership function

(based on Hertz, 1996)

Material	c [yr]	a	b
Cast iron (>150mm)	60	2.5	0.032
Concrete	45	3	0.07
Plastic	42	1.57	0.05

A "two antecedents – one consequent" FIS based on Hertz's research was developed to link age of pipes and material with leakage vulnerability. The results of the Hertz functions presented above were used to provide a "two input - one output" training sets for the neuro-fuzzy system that tunes the parameters of the FIS. The FIS is therefore

acting as a function approximator of Eq. 4.2. There are three main reasons for developing this FIS instead of using directly Eq. 4.2:

- Consistency of the suitability/vulnerability maps generation procedure through FIS.
- Development of a 2 antecedents – 1 consequent FIS to demonstrate its structure and discuss its usefulness.
- Development of a training module for a 2 antecedents – 1 consequent FIS to demonstrate its function when training data are available (here through either the deterministic function of Eq. 4.2 or real burst record through the Bayesian process described in previous chapters).

System induced pressure

Sudden pressure changes imposed on distribution networks can have severe consequences on the formation of pipeline breaks (List, 1994). Rapid changes in the flow rate produce a sudden change of pressure that propagates through the system as a high-speed wave (water -hammer) and can be provoked by operational fire hydrants, acting as the equivalent to a rapid valve operation (List, 1994). There seems, however, to be no deterministic or probabilistic modes which would allow leakage vulnerability to be expressed as a function of proximity to fire hydrants. This is more so because fire hydrants can only cause damage to the system when they are operated and thus a record of uses would have to be compared with leakage data over a long period to establish some relationship. In this case, the effect of hydrants was introduced linguistically, based on the assumption that proximity to fire hydrants is a cause of deterioration to the system and that the effect is a regional one. In fact as a second assumption the impact of proximity to fire hydrants is included in the identification process for parts of the network closer than 500m. The layer of proximity to fire hydrants is introduced in the FIS based on the above assumptions and the result is standardised to a 0-1 interval. A correlation between leakage and past records of hydrant proximity and use would be valuable in better tuning the FIS parameters.

Additional system-induced (internal) pressure is incorporated as a result of network simulation (EPAnet), identifying high pressure areas based on water demand and consumption patterns (Carmi, 1997). A model of the water distribution network was

built based on an image of the GIS-stored network imported into EPAnet. The system has 236 nodes and the simulation was run for the period of 1 week under normal consumption patterns. Maximum pressure for each node was exported to the GIS and a surface was interpolated for use as a Matlab matrix. The result was imported to Matlab as an ASCII file.

Soil aggressivity

Soil parameters are a common input to "break prediction" models. Doleac, Bratton and Lackey (1980) model corrosion rates using soil resistivity, soil aeration/redox potential and pH. McMullen (1986) correlates actual break numbers to pH, redox potential and saturated resistivity. An essential problem, however, is that corrosion is not commonly recorded as a break type, thus the data available are generally insufficient for attaining a good correlation (Wengstrom, 1993). Poulton *et al.*, (1999) use a more descriptive approach in their measurements, categorising the soil types encountered into 9 categories (from non-aggressive to most aggressive) and observe an increase in burst rates from 0.09 bursts/km per year to 0.35 bursts/km per year. Soil corrosivity is also taken into account by water utilities: Cooper *et al.* (2000), quote an internal report for TWUL by Jarvis *et al.* (1997), which considers corrosivity and fracture potential of the soil surrounding a main as having considerable impact on its longevity. It has been observed (Cooper *et al.*, 2000) that soil fracture potential has a similar distribution to soil corrosivity class, and therefore these two variables could be merged into one for simplicity. In the current study, soil pH was used as a general indicator of soil aggressivity. The FIS was programmed under the additional assumption that very alkaline environments are also deleterious for the pipes.

External Loading

Externally induced stress is seldom used in comparative pipe record analysis although the surrounding environment is believed to be related to infrastructure behaviour (Wengstrom, 1993). In O'Day *et al.*, (1987) several external factors (including land use) were summarised. There seems, however, to be no deterministic analysis for their incorporation in actual pipe leakage forecasting. In Poulton *et al.*, (1999) burst rates were examined for a period of 8 years against various surface types. Four road classification types were identified (from major to minor). Although major roads were found to have a

slight negative effect due to heavier loading, the most significant negative effect was observed in the case of minor roads subjected to unusual heavy loads or increased traffic. This is in accordance with Cooper *et al.* (2000) who discuss the effect of changes in traffic loading for a given road design. Block paved surfaces were also found to have a negative effect probably because of parking practices and vibration from nearby traffic. This latter category was not taken into account in the present study, due to the scale of data it involves.

Three road categories have been identified, as seen in the case study description. The FIS was programmed based on the assumption that major roads exert more stress on the system than minor, but roads that are under-designed for their current loads (constructed as minor and are used as major, or as diversion routes for heavy vehicles) have the most negative effect (Poulton *et al.*, 1999; Cooper *et al.* 2000).

Pipe diameter

In a literature review from 1960 to 1985 by Goulter and Kettler (1985), break rate was found to increase with decreasing diameter for pipes equal to or less than 300mm. A number of reports seem to agree with this result (Newport, 1981; Walski *et al.*, 1987). The explanation proposed is that smaller pipes have less strength and thinner walls that are susceptible to corrosion. This hypothesis combined with the long lengths prevalent in pipes of these diameters might account for their vulnerability to breaks. In this study, the FIS is programmed under the assumption that, for pipes with diameters <300mm, vulnerability to leakage increases with decreasing diameter and that for pipes with diameters >300mm the effect of diameter change is very small. This agrees with Walski *et al.*, (1987) and the Goulter and Kettler study (1985).

The membership functions are constructed in such a way as to agree with the basic hypothesis (sharp increase of vulnerability for diameters<300mm and graduate decrease for increasing diameters). The small diameter effect is incorporated by the use of a larger weight associated with this rule (1 instead of 0.8 for the other two rules).

Pipe Density

The fact that data is generally scarce when analysing the effect of attributes to pipe vulnerability, implies the need to represent some factors indirectly through easily measurable quantities. Cooper *et al.* (2000), in their analysis of pipe failure records for Thames Water Utilities Limited, suggested that pipe density can act as an indirect measurement of the effects of other mains such as disturbance from excavation or operational procedure. They have found that pipe density is one of the four[1] major attributes that explained most of the distribution of mains failures on their records.

4.4.2.2 Metering

Utility meters are considered the "gateway technology" through which energy and water services are delivered to the home (Marvin and Guy, 1997). Currently they are being transformed from simple measurement devices to complex socio-technical systems enhanced by the addition of new informational and communication capabilities (Marvin *et al.*, 1999). In the context of this research, interest will be focused on the introduction of compulsory metering for specific types of customers at different penetration levels. Type of use (industrial, commercial or residential) and income differences are taken into account as an indicator of water consumption levels under the assumption that industrial and commercial uses have to be metered and regulated and higher income population groups tend to use more water than lower income groups (Butler and Davies, 2000; Russac *et al.*, 1991; Thackray *et al.*, 1978). The existence of gardens with sprinkler systems is considered an indicator of increased consumption (Butler and Davies, 2000), and education levels are taken into account as an indicator of metering acceptability as a water conservation strategy. The concept of selective metering based on household characteristics and types of use is well within the approach proposed by OFWAT (as reported in Marvin *et al.*, 1999), which whilst advising against universal compulsory metering, recommends selected metering for some households (using sprinklers etc.). It is also in accordance with the concerns expressed by the National Consumers Council (as reported in Marvin *et al.*, 1999), which urges caution in the metering of lower income households focusing on social rather than demand management objectives, which indeed should be taken into account in the water management planning process.

[1] The other three parameters were: number of buses (as a measure of traffic load or road type), pipe diameter and soil aggressivity class (Cooper *et al.*, 2000)

Type of use

Three major types of use were identified: industrial (1), commercial (2) and residential (3). The underlying assumption for the incorporation of variability into the planning process is that industrial and commercial activities should be regulated as a priority due to larger consumption rates and inapplicability of statistically defined consumption values for predicting that consumption. Industrial and commercial activities were excluded from the analysis as they are subject to process-specific water demand management procedures.

Population Density

The primary data on population were transformed to population density information. The resulting layer was rated under the assumption that metering areas with higher population density would result in metering a larger percentage of the consumption with lower installation costs as the metering installation would be performed in a single building rather than a number of individual dwellings. There are two points to be considered at this stage of analysis. The first is that increased population density would not result in increased per capita consumption but rather the opposite (Butler 1996). The total consumption would however be larger and that is what metering needs to monitor and reduce. The population density criterion is in principle contradictory to the high-income criterion, as population groups with higher income can afford to live in low-density areas and vice versa. The degree of trade off between these criteria will have to be observed in the aggregation process and is subject to political rather than engineering concepts.

Income

It has been extensively argued that the greater the affluence or economic capabilities of a community, the greater the water use tends to be (Butler and Davies, 2000). Russac *et al.* (1991), working with UK data has confirmed Thackray' s argument (Thackray *et al.*, 1978), that economic indicators (such as dwelling rateable value and income) influence water consumption. It is speculated (Butler and Davies, 2000) that this can be attributed to greater ownership and use of domestic appliances, which utilise large water volumes (i.e. washing machines). This assumption of a positive correlation between income and water consumption, together with the concepts of metering the high consumers first and allowing low income groups to continue using water at a "politically determined" price,

are the underlying elements for the use of income indicators in this decision support scheme. The income data for each (residential) building unit were introduced in a FIS programmed according to the principles mentioned above. The output rated image has suitability values for metering between 0 and 1.

Education

Water conservation and demand management is more than just a water consumption issue. Above all, it is a strategy promoting efficient and wise use of scarce resources (Arlosoroff, 1998). In this respect, social acceptability is essential for the successful implementation of the strategy as it represents the response of the individual client and of the local community to the proposed strategy. Measures are socially acceptable if they are adopted by the community in which they are proposed (Opitz and Dziegielewski, 1998). Unlike technical feasibility, however, the degree of social acceptability cannot be predicted with a high level of accuracy. In this decision support framework, it has been assumed that education plays an important role in the ability of clients to understand and accept the introduction of water metering as a tool to achieve resource minimisation and provide the water supplier with investment potential, representative of the actual consumption needs. The education data for each (residential) building unit were introduced in FIS programmed according to the principles mentioned above. The output image assigns suitability for metering values from 0 to 1.

4.4.2.3 *Water recycling systems: grey water recycling, rainwater use and combined grey water and rain water systems*

Water recycling (including grey water recycling, rainwater use and combined grey water and rain water systems) is a means to reduce consumption of water in households and commercial activities such as hotels and laundries. In households, each of these practices may reduce water consumption between 25% and 50% (Opitz and Dziegielewski, 1998; CIRIA 2000; BSRIA, 2001).

In the case of grey water, the concept is to redirect wastewater from hand-wash basins, baths, showers and clothes washing machines (but not normally kitchen wastes and never WCs), through a detention/treatment system, back into "consumption" in the form of WC waste flushing and sometimes irrigation (BSRIA, 2001). The latter is particularly the

case with rainwater use that can be directed to irrigation without significant treatment, particularly when it is collected from roofs (CIRIA, 2000).

There appears to be a psychological barrier in accepting the use of secondary quality water for uses, which do not require water of drinking quality (Opitz and Dziegielewski, 1998), although in cases where water recycling has been extensively practiced over a period of years (e.g. in Japan where water recycling has been in practice for over 50 years (Stephenson *et al.*, 2000)), public perception appears to be in favour of water recycling and reuse as a result of familiarity with the systems. Quality and health issues that can potentially arise from the (often variable) quality of recycled water can be addressed by on-site treatment (including disinfection, filtration and bio-reactors) in accordance with BSRIA recommendations (2001).

The main obstacle to this method is the need to install a water recycling system, which incurs installation and capital costs. In new buildings and buildings that will undergo large scale restoration, the additional cost of installing a water recycling system is not significant. Several criteria affecting household[1] suitability for water recycling were taken into account in the programming of the decision support scheme as described below. Depending on the specific water recycling scheme investigated (grey water recycling, rainwater use or combined systems) the criteria influence differently the final outcome.

Population density

The same analysis, as in the case of water metering, was used based on the assumption that cost of installation drops when the water distribution system of an entire building with many occupants is changed rather than of individual households. Increased population density is also used as an indicator of increased water consumption[2] from the same system due to the increase in the number of users. The density criterion has a different effect depending on the water recycling scheme investigated: The close match between arising of grey water and demand for (recycled) water for toilet flushing and their relation to occupancy make grey water recycling more preferable than rainwater use

[1] Industrial and commercial buildings were not taken into account as recycling of water in these cases is a process-specific option that can be much more complicated than household grey-water recycling.
[2] Note that the assumption refers to total water consumption per household and not per capita consumption, which can be shown to decrease with increased occupancy (Butler and Davies, 2000).

systems for high-density areas. This is because the fact that more flushing water is needed in high-density areas is counterbalanced by the fact that in high-density areas more grey water is actually produced, therefore a small storage volume is required relative to that required for rainwater systems (CIRIA, 2000). Low-density areas favour rainwater collection and use systems for yet another reason: rainwater use is ideal for irrigation purposes as, in that case, it generally does not require treatment (BSRIA, 2001). The analysis makes the assumption that low-density areas are more probably associated with the existence of gardens thus with an increased need for irrigation.

Income

As in the case of water metering, high income was used as an indicator of increased consumption. The reader is referred to the paragraph on income as an attribute in metering suitability for a discussion of its effect on consumption as well as the fuzzification – standardisation of the input variables. In addition to the arguments presented there, it must be mentioned that operating and maintenance costs for grey water recycling schemes are not insignificant (including chemicals for disinfection, maintenance checks in pumps etc and electricity operating costs (BSRIA, 2001)) and therefore the user should have the financial ability to support the scheme even in cases where the actual financial benefits from water savings (including drinking and disposal of sewerage costs) are less than the incurred costs. The income criterion's impact on the water recycling alternatives is slightly different as rainwater recycling is considered less costly than grey water recycling, requiring less maintenance (particularly due to lower treatment requirements (BSRIA, 2001)) and can thus be supported by lower income users.

Education

Education was used as a common indicator of acceptability of all water recycling schemes both as a way of paying less in the water bill and as a water resources conservation method. Ecological conscience is considered a main driver for users for installing such systems (CIRIA, 2000) and this is associated with education. Education also accounts for the ability of the householder to overcome the psychological barrier of the reuse of wastewater. The fuzzification – standardisation was performed as in the case of education as a water metering criterion.

Renovation Status

As discussed earlier, the cost of the installation of the water recycling system can be significantly reduced if it is directly installed in new construction and major renovations. The former is outside the scope of our demand management decision support tool, as we focus on the current state of the city. The renovations however refer to the current state and were introduced to the database and the FIS. The way the fuzzification – standardisation process was accomplished resembles the case of gardens in the water metering suitability assessment. The input variable is a Boolean constraint (1 in the case of an eminent restoration and 0 otherwise). In the case of grey water or combined system a high suitability value is assigned for restoration and a low value otherwise. This criterion is not so stringent in a rainwater collection system installation.

Roof Characteristics

A criterion particular to the rainwater collection and combined systems is the one dependent on the characteristics of the roofs. Non-retentive roof surfaces, such as glass, glazed tiles and metal roofing sheets reduce moss and algae growth that would inhibit water quality and block the filters used in the treatment process (CIRIA, 2000). Flat roofs encourage moss growth and water retention acting as a source of debris and bacterial contamination. When uncoated copper, lead and zinc are used as roof surfaces the rainwater collected can includes significant concentrations of heavy metals and should be no be used for drinking water purposes (Forster 1999; CIRIA, 2000; ICON, 2001). The roof characteristics criterion is used instead of the renovation status criterion when exploring the possibility of installing rainwater or combined systems. The roof criterion is translated into three roof characteristics categories: type 1, which is the least favourable, is a flat gravelled roof. Type 2 is a roof of uncoated copper, zinc or lead but of sufficient slope and type 3, which is considered the most suitable is a roof with a non-retentive surface and a sufficient slope. The criteria chosen serve as an example of taking into account diverse roof characteristics and do not represent a definitive list of everything that affects rainwater collection. Other characteristics such as, for example, exposure direction and roof inclination (Wallinder *et al.*, 2000) or pervious-to- impervious area ratios (Makropoulos *et al.*, 1999) would also affect the quality and quantity of the roof runoff and therefore the performance of the system.

4.4.3 Membership functions for the FIS

All fuzzy membership functions used throughout the analysis are of Gaussian shape. This is purely for computational efficiency purposes because the Gaussian membership function (being closed form) facilitates mathematical computations. The effect of such an assumption cannot be considered significant for two reasons:

- Due to the complex fuzzification-defuzzification procedures, the effect of the actual shape of the input and output fmfs on the crisp result is insignificant (Mendel, 2001). In principle, the same input-output relationships could be approximated using any of the widely used fmfs (Triagonal, Gaussian, Bell shaped etc) if these functions are correctly tuned. A comparison between triangular, bell shaped and Gaussian fmfs is included in paragraph 5.3.1. A more detailed discussion on the effect of shape in type-1 and type-2 FIS is included in Chapter 5.
- Data are not sufficient in this case to dictate a specific shape for either input or output fmfs, although in principle, the nature of the problem (the unknown function which the FIS tries to approximate) might favour some particular shape.

Three antecedent and three consequent sets are included in each FIS to model the linguistic terms [low], [medium], [high]. The shape of the consequent sets identifying leakage vulnerability in the type-1 FIS can be seen in Fig. 4.15.

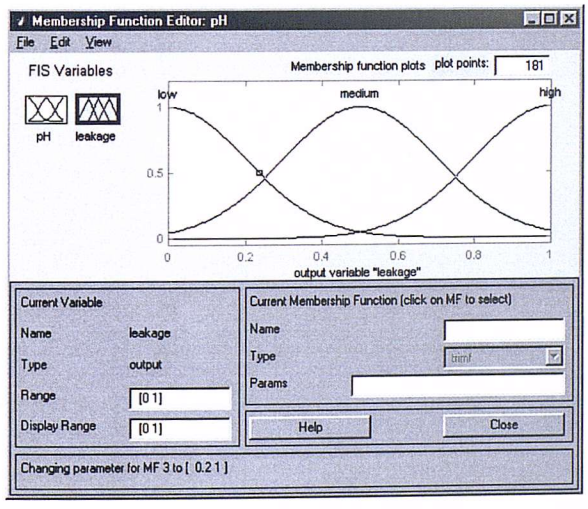


Figure 4.15. Consequent fuzzy membership functions for the type-1 FIS

4.4.4 Training the Fuzzy Inference Systems

As described in previous chapters, the training of the FIS was performed via a neurofuzzy approach, which makes extensive use of input-output training data. The input-output pairs used to train the neuro-fuzzy systems can originate from a number of possible sources. In most cases presented here, a direct measurement is not possible due to the nature of the consequent sets (i.e. suitability). In other words, it is generally impossible to evaluate the suitability for application of a specific urban water management strategy to a specific location using anything other than (subjective) expert judgement.

This is the case for the grey water recycling and the metering introduction strategies, where such input-output training pairs are provided in the form of expected suitability for application of either the water recycling scheme or the metering introduction scheme for a range of randomly selected values of the input attributes (income and education level, population density, renovation status etc). This process allows the participation of multiple experts, each contributing their personal opinion. The neuro-fuzzy system takes into account all the values, using the process described in Chapter 3, and thus takes into account all the expert views. Of course, if the input values are significantly different between different values, the system's tuning will result in a compromise solution, which might not be appropriate. In case of significant differences, the expert input values should be further pre-processed to provide a meaningful input to the training routine. This type of pre-processing tool has not been developed here. For further discussion on the subject the reader is referred, for example, to Kingston *et al.*, 2000, Sarjakoski, 1998 or Nyerges *et al.*, 1997.

In the case, however, of a leakage reduction strategy for water demand management, burst records can, in principle, be obtained, together with characteristics of the network in both the location of the burst and elsewhere. Examples of the processing of historical data linking location attributes and network failure can be found in Cooper *et al.* (2000) for the case of water distribution networks as well as in Fenner and Sweeting (1998) for the case of sewer networks. These data sets cannot be directly used in the neurofuzzy training system discussed above but have to be pre-processed to obtain a measure of probability of failure (f) of a pipe with a specific characteristic (c) (i.e P(f/c)), from the event records and use (c, P(f/c)) as the training pair for the appropriate inference system.

A tool to pre-process this kind of data has been developed within this research project, based on Bayesian statistics. The approach adopted is in accordance with techniques presented in Fenner and Sweeting (1998) as well as in Fenner *et al.* (2000), for the case of sewer network rehabilitation. According to Bayes theorem, the probability of failure (p(f)) of a pipe of a characteristic c is given by:

$$p(f/c) = \frac{p(c/f) \cdot P_f}{p(c/f) \cdot P_f + p(c/nf)(1-P_f)} \qquad \textbf{Eq. 4.3}$$

where:

(a) P_f is the system wide failure frequency, given by:

$$P_f = \frac{\sum_{i=1}^{n} \text{total number of pipes failing in year i}}{\sum_{i=1}^{n} \text{total number of pipes in year i}} \qquad \textbf{Eq. 4.4}$$

and n is the number of years in record.

(b) $p(c/f)$ is the probability of observing the specified characteristic on pipe lengths that showed a failure in a given year and

(c) $p(c/nf)$ is the probability of observing the specified characteristic on pipes with no failure history on record.

This approach allows the vulnerability of a pipe to be quantified (expressed here as probability of failure), for a range of values of a given attribute (for example, soil aggressivity) thus creating the input-output training pairs needed for training the single-antecedent FIS. This is also facilitated by the fact that both the probability measures and our fuzzy output vulnerability measures accept[1] values from 0 to 1.

[1] Although a [0-1] scale is obligatory for probabilities, it is not necessarily so for fuzzy set outputs. In this case the FIS were deliberately designed on a [0-1] scale to allow probabilistic measures to be used, whenever possible, in linking antecedents to consequents.

To compute Eq.4.3, we need to specify two probabilities: *P(c/f)*, i.e. the probability of observing the characteristic c, in pipes that have failed, and *P(c/nf)*, which is the probability of observing the same characteristic in pipes that have not. These probabilities are calculated with the following equations:

$$P(c/f) = \frac{\text{number of failed pipes with c}}{\text{total number of failed pipes}} \qquad \textbf{Eq. 4.5}$$

$$P(c/nf) = \frac{\text{total number of pipes with c - number of failed pipes with c}}{\text{total number of pipes - total number of failed pipes}} \qquad \textbf{Eq. 4.6}$$

The input values associated with the aforementioned analytical process are a series of vectors each one of the form $[c_1,c_2,\ldots,c_n]$ representing a failure event. As discussed in Chapter 3, the Bayesian statistical process requires the grouping of the failure records in characteristics' ranges.

The input is required prior to the model run:

- Six characteristics (soil, age, pipe density, street type, diameter, maximum pressure, pipe material) of the recorded failure for all failures. The characteristics should be either provided in a separate file or can be extracted by the system using a *burst record mask* layer to identify locations of bursts and their associated characteristics.
- The number of years on record (as a direct user input).
- The number of network cells (segments) either as direct input or extracted using a *network mask* layer.
- The number of segments of any specified category (the categories are specified by the program using fuzzy c-means clustering (see Chapter 3)). Again, these can be either provided by the user as a direct input or can be calculated using a network mask layer to extract the characteristics from the raster input files.

After calculating the Bayesian probability of failure for a pipe with characteristic c_i within a range $[c_{lower}, c_{upper}]$, the module randomly generates values within these ranges and matches them with the appropriate Bayesian probability value to create input-output training pairs for the neuro-fuzzy system. For example, we might conclude that p(failure/pipes with diameter <300mm) = 0.6. In that case, due to the neurofuzzy

system's need for input-output values rather than sets, random values from the set are selected and paired with the output probability of failure to act as training pairs. The final output is a set of six ASCII files with 500 records for each value range for training the FIS. The resulting probability is not treated as a specific probability assignment, but rather as an indication of relative risk of failure. The actual resulting probability values are generally rather small (see also Fenner and Sweeting, 1998), and have to be standardised to be consistent with the 0-1 scale of the output vulnerability index from the FIS. This is realised by assigning (arbitrarily) as maximum vulnerability (=1) the larger of two values: the maximum probability assignment of the data set or 10*Average probability of the network, under the assumption that a characteristic that causes a pipe to have a probability of failure larger than 10 time the average probability of the network can indeed be rated as a very high risk characteristic.

Additionally, Bayesian probability models imply independent variables (which is in accordance with our set-decomposition approach) and therefore no interdependency of characteristics can be computed with this method, even if we compute a combined probability. For example, the "street type" criterion might in practice change the way the "diameter" criterion would affect the probability of failure under specific circumstances: smaller pipes might be more resilient than larger ones in smaller rather than larger roads. Calculating the combined probability (using a combinatorial Bayes formula) of a failure given characteristic "street type"=A and "diameter"=B, will not reveal such an interaction and is nothing more than a specific way of aggregating independent probabilities. Such a combinatorial approach of Bayes formula was not, therefore, developed.

For the specific example of *pipe age - material FIS* which requires a 2-antecedent 1-consequent training set (see discussion in paragraph 4.4.2.1), the age and material output of the Bayesian module can be combined using either a probabilistic approach (multiplication of the two independent probabilities for age and material) or a conservative aggregation approach (maximum of the two ratings). The later, although not accurate in probability terms was found to be more intuitive as it assumes that the worse characteristic is what determines the final outcome. It has to be noted that the values produced from this module will not be used as probabilities but as vulnerability ratings and therefore both approaches are scientifically valid. An alternative module for deriving

training sets for the pipe age-material FIS was also developed using the Hertz equations. The resulting sets and their effect to the training of the FIS are compared in later chapters.

4.5 Applying Aggregation

4.5.1 WDM as a case for applying SOWA

Aggregation, in the WDM application of our SDSS allows the user to include both the perceived differences in importance between the criteria (by way of direct weights assignment), as well as to include his risk-aversive attitude towards a particular combined result. There are, however, cases where there is need to include a spatially variable measure of this risk-taking attitude and for this reason the SDSS uses a SOWA (Spatial Ordered Weighted Averaging) technique discussed in Chapter 3. This is particularly the case in the first WDM strategy (leakage reduction), which proposes a prioritisation scheme for changing water mains. The FIS link individual attributes contributing to a main's vulnerability to leakage (as discussed above), to a [0-1] vulnerability index and the resulting aggregation proposes a prioritisation scheme based on all parameters taken into account. The decision-maker can increase or decrease the number of pipes above a threshold by accepting a lower or a higher level of risk aversion for his result respectively. A leak or burst, however, may have a significant impact (economic, environmental and social) if viewed as one of the main causes of *urban floods*. In the WDM SDSS, a module assessing the effect of flooding due to water mains bursts is used to derive a flood consequences map that is then used by the SOWA developed in this research, to derive a spatially variable aversion to risk for aggregation. The elements of the flood consequences assessment module will be discussed in section 4.5.2.

4.5.2 Urban floods as a spatially variable risk-aversive index

The consequence of possible failure is the main driver behind most network rehabilitation efforts, from water mains (Cooper *et al.*, 2000) to sewer maintenance (Fenner *et al.*, 2000). Several algorithms have been proposed for computing the consequences of a pipe failing in a particular location as a function of the characteristics of that location. Fenner *et al.*, (2000) propose a simple algorithm, which is to calculate a consequence factor, taking into account the road length, number of pollution events in the power of two, burst events and the repeatability. Cooper *et al.*, (2000) propose a differentiation between domestic and commercial properties, with a different

consequences model applied to each case. They further mention the possibility of including other categories into the model, such as key customers, sensitive customers (hospitals etc), tourist attractions and main arterial roads. The approach adopted here is a FIS assessment of the consequences of flooding, based on the following attributes:

- Domestic property value
- Category of road
- Probability of basement existence
- Proximity to sensitive customers (e.g. hospitals)

The FIS developed here is a singleton type-1 FIS although, in principle, depending on the type and the extent of the uncertainty involved, other more complex types of FIS could be used. The attributes included in the analysis do not represent an exhaustive list of attributes affecting flood consequence, but rather a list of the most important attributes for which information can be more easily obtained by users. In particular:

Domestic property value can be assessed through a combination of mean rateable value and amount for which a property was insured. The assumption is that houses with higher values will cost more to be repaired. *Road categories* are included as a means to take into account the flood effect from the interruption of major transportation and commercial activities. *Basements* represent the types of property most vulnerable to flooding. If specific information on existence or not of a basement is available this could be included in the analysis. Otherwise a probability can be developed based on the age of the building. For example, Cooper *et al.* (2000) present the following table for the London Water Supply zone.

Table 4.3 Relation between age of house and existence of basement

Property Age band	Basement probability
Pre 1920	0.60
1920-1945	0.20
1946-1979	0.10
Post 1980	0.10

The final attribute included in the analysis is the proximity to sensitive customers. This attribute allows the user to include social as well as economic objectives by including as sensitive customers, hospitals, government buildings, commercial centres and the like.

The final flood consequences map is a simple aggregation of the flood consequences maps resulting from the four attributes. Each cell is assigned the value of the sum of the values of the cell in the four single attribute maps rescaled to fit a [0,1] interval. This is in recognition of the fact that the nature of the attributes listed above is cumulative (i.e. a low score in road importance would not reduce a high score in the same cell for being very near a major hospital).

The maximum value of the flood consequences index is selected to be one (1) to allow for direct input to the SOWA procedure, where one (1) indicates maximum risk aversion (see discussion in Chapter 3). After the completion of the analysis, the final flood consequences map is imported to the main aggregation module to be used as a spatially variable indicator of risk aversion. Each network cell is therefore treated with a different level of associated risk aversion depending on the impact of a possible flood at that point (taking into account the impact related four attributes discussed above).

For each network cell the optimisation problem of Eq. 3.20 subject to Eq. 3.21 is solved and a different set of weights is derived. These weights are then used to aggregate all the cells of the different attributes of the leakage reduction strategy in that particular location. The resulting aggregation (spatial ordered weighted averaging) indicates pipe replacement prioritisation, taking into account, not only the various attributes leading to susceptibility to leakage, but also the effect of a possible urban flood at the particular location in terms of damage to domestic property, disruption of road traffic and problems caused to sensitive customers (for example hospitals). Figure 4.16 is a schematic of the process and provides an example of using SOWA to aggregate two attributes of the leakage reduction strategy, using flood impact as a spatially variable risk-aversion index.

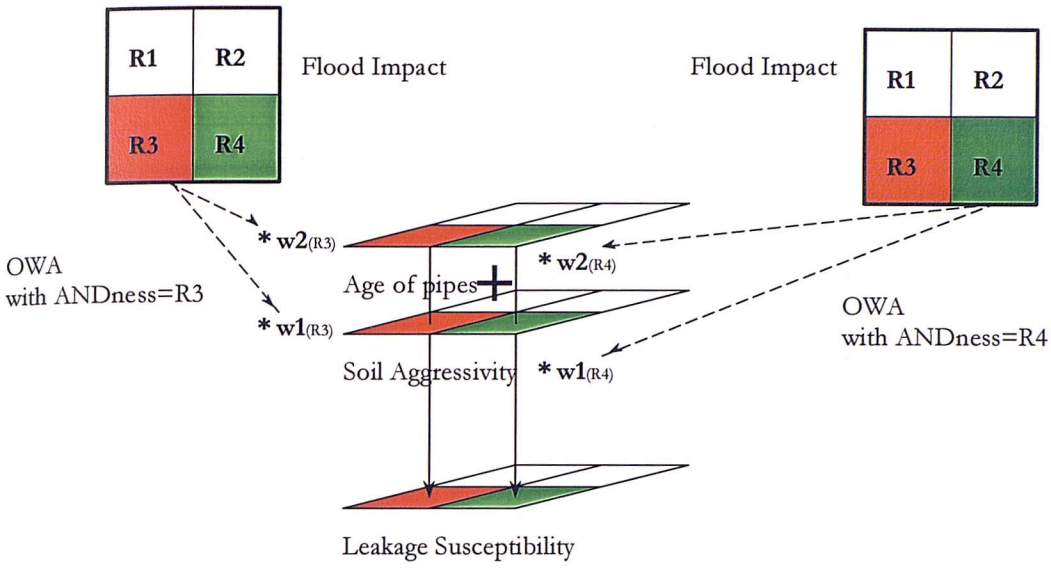


Figure 4.16 A schematic of the application of SOWA in leakage reduction using flood impact as a determinant of risk aversion

In the schematic of Fig. 4.16, two of the cells of the *flood impact* map (R3, R4) are used as an example to provide two risk indexes subsequently used to define the (ordered) weights used to aggregate the corresponding cells of the *age of pipes* and *soil aggressivity* layers (w1(R3), w2(R3) and w1(R4), w2(R4)) resulting to a *leakage vulnerability* layer which takes into account the spatial variability of risk. Examples of the results of the application of this technique in the case study area are included in Chapter 5.

4.6 Applying Optimisation

4.6.1 Solving the "Conventional" Optimisation Problem for WDM

As discussed in Chapter 3, the objective function to be maximised is given by Eq. 3.23 subject to Eq. 3.24 for the problem of *maximising water savings for a given investment* and Eq. 3.25 subject to Eq. 3.26, *for the problem of minimising investment for a given water reduction target.*

We will now describe an example of the physical meaning of these functions in the case of WDM and three intervention strategies promoting it (leakage reduction, grey water recycling and compulsory metering introduction). Cost1(leakage) is constant for each cell (and independent of the exact cell being changed). Cost2 and 3 (metering and grey-water recycling) on the other hand are of the type:

$$Cost(2or3) = \sum selected\ cells \qquad \textbf{Eq. 4.7}$$

and are therefore non-linear themselves, as the cost of introducing metering or grey-water recycling in a particular cell is a function of the number of households present in the cell. This time the cells are not ranked in any way but correspond to the ranking that took place for the suitability.

The problem is essentially a **non-linear integer programming** problem and is solved by restructuring it so that the sums from i to x, y, z are expressed as a polynomial function of x, y and z respectively. Five polynomials have been calculated (three for the water savings sums and two for the cost sums). The problem is solved as a non-linear problem with integer constraints using Sequential Quadratic Programming (SQP) in the Matlab environment. Initially, the 3 weight maps and the two cost maps are imported to Matlab. A 4th order polynomial function is computed for the best fit in a least squares sense for each ranked vector that is produced as described above.

From an optimisation perspective, the problem has three complicating features:

- The variables are integers (no. of cells)
- The objective function is non-linear and non-convex
- The constraints are non-linear (cost function)

Together, these features render the identification of global optima unrealistic using traditional optimisation techniques. A heuristic approach is therefore utilised to identify good initial points to enable the optimisation routine to identify global optima. Reeves (1993), defines heuristic as "*a technique which seeks good (i.e. near optimal) solutions of an optimisation problem at a reasonable computational cost without being able to guarantee optimality*". Lee and Ellis (1996) discuss a number of heuristic techniques and conclude that these techniques are much more effective than traditional optimisation techniques at solving constrained, integer, non-linear optimisation problems (such as the one presented above).

In this particular case, a random search algorithm was used to identify the best[1] starting point (X,Y,Z) for the optimisation out of 100000 possible points created using a normal distribution. The result of the algorithm generally proves to be very close to the final optimal point. The integer constraint is not used until the end where real values are rounded to the closest integer. This is considered a small deviation from optimal solution due to the nature of the problem. As indicated before there is no real proof that the point selected is actually the global optimal point. However a Monte-Carlo type of approach, running the random generating algorithm for 100 times with varying means of normal distribution indicates initial points very close to each other, which always converges to the same point after the convergence of the optimisation algorithm.

4.6.2 Solving the single-objective GA optimisation problem

Three matrices, one for each of the three WDM strategies taken into account here, are constructed as follows[2]:

$M_{\text{leakage reduction}} =$

Intervention Cell Row	Intervention Cell Column	Leakage Vulnerability	$\sum$ Water_Saved/day	$\sum$ Investment
10	20	0.7	10	15
5	158	0.68	20	30
...	...	...	...	...
120	79	0.001	10,000	50,000

$M_{\text{metering}} =$

Intervention Cell Row	Intervention Cell Column	Metering Suitability	$\sum$ Water_Saved/day	$\sum$ Investment
10	20	0.7	50	100
5	158	0.68	80	200
...	...	...	...	...
120	79	0.001	20,450	100,000

$M_{\text{greywater recycling}} =$

Intervention Cell Row	Intervention Cell Column	Greywater Suitability	$\sum$ Water_Saved/day	$\sum$ Investment
10	20	0.7	100	500
5	158	0.68	200	1000
...	...	...	...	...
120	79	0.001	50,000	1,000,000

Column 1 and 2 of each matrix are integers associated with the row and column of the cell where the intervention will take place, thus fully describing its location within the case study grid. The matrices are sorted from higher to lower suitability for intervention (column 3) under the assumption that if one and only one cell is to be "changed" (e.g. if

[1] "Best" in the sense that it yields the maximum value for the objective function without violating any constraints.

[2] The numbers used in the following matrices are rand om and are used as an example.

metering is to be introduced in one cell in the case study area) the cell should be the one with the highest suitability score. Columns 4 and 5 at each row state the cumulative water saved and related investment needed for intervention to all cell prior to and including that row.

Following the GA procedure described in Chapter 3, the solution to the problem of either minimising investment needed to achieve a water target or maximising water saved for a desired investment can be reduced to finding (in this case) three "pointers', identifying how many cells of each strategy (matrix) will be "changed". The total water saved is the sum of the cells of the three matrices of row as specified by pointers 1, 2 and 3 and column 4. Similarly, the total investment needed is the sum of the cells of the three matrices of row as specified by pointers 1, 2 and 3 and column 5.

The procedure followed and the operators and parameters used in this particular case are described next:

Step 1: Initialisation

The initial GA population includes individuals of the type $pointer_i$= [pointer 1, pointer 2, pointer 3] which are created at random. The initial population has to be large enough to allow for variation but not excessive as this would significantly slow down the procedure and would not allow the algorithm to run for a sufficiently large number of generations. A trial-and-error process was used with initial population numbers ranging from 100-700 individuals. The runs showed that populations of the order of 100-200 performed better and allowed enough variation to be introduced.

Step 2: Fitness

The fitness (eval($pointer_i$)) of each individual is calculated as proportionate to either the water target (in the case of water saved in a WDM application) or the inverse of the investment needed, depending on the problem type[1] (A or B). A penalty function decreases this fitness value whenever the relevant constraint is violated. The penalty function calculates the fitness value as either $\frac{\text{water saved with solution i}}{\text{target water saving}}$ or $\frac{\text{desired investement}}{\text{investment required by solution i}}$. The penalty is therefore proportionate to the violation of the

[1] For a definition of these problems see paragraph 3.5.4.2.

constraint. After a number of generations (set at 1/5 of the maximum number of generations after a trial-and-error procedure), the penalty's calculation is changed and the new penalty sets the fitness value to zero thus excluding illegal individuals from the calculation. This is developed, in accordance with the recommendation of Michalewicz (1996) to enable exploration of the solution space at the initial stages and avoidance of illegal individuals at the later stages when the algorithm is closer to a solution.

Step 3: Selection process

Between the two selection processes which have been implemented and assessed in this work, as discussed in Chapter 3, the "stochastic universal sampling" (SUS) proposed by Baker (1987) was identified as the best due to its stability and superior performance. It was observed that, in a series of runs, the individuals selected using this method were on average better than the individuals selected using the "roulette wheel" selection method (Holland, 1975). SUS will thus be described in more detail as this was selected for inclusion in the core SDSS. The roulette wheel, is also available its performance is not judged as optimal.

Initially, the probability of selection is calculated. It was recognised that the selection pressure needed for optimal performance of the algorithm had to vary as a function of time. For example, in the initial stages, less fit individuals could be allowed to reproduce to enhance the variation of the population (thus increase the exploration of the solution space). In the later stages though, fit individuals have to be promoted to allow for a more concentrated search near optimal areas of the solution space (exploitation of the good candidate solutions identified). The approach used here is "Boltzmann selection" which is similar to *simulated annealing*, where a continuously varying *temperature* (T) controls the rate of selection. As the generations progress, the temperature drops and thus the selection pressure increases, favouring the fitter individuals (Lozano et al. 1999). The following equation was used to calculate the value affecting selection of individual I, at time T:

$$Value(i,t) = \frac{e^{f(i)/T}}{\left\langle e^{f(i)/T} \right\rangle_t} \qquad \textbf{Eq. 4.8}$$

where T is the temperature and is a inversely proportional to the generation counter,
f(i) is the fitness of individual,
$\langle\ \rangle$ is the average over the population.

The individuals are mapped to continuous segments of a line, such that each individual *i* at time *t* is assigned a segment equal in size to *Value(i,t)*. Equally spaced pointers are placed over the line, as many as there are individuals to be selected. In this case the selected individuals equal the initial population. The position of the first pointer is given by a randomly generated number in the range [0, 1/population_size]. If a pointer's position is within a segment assigned to an individual, that individual is selected for mating. Using this method, although the fitter individuals are selected by more pointers (subject to temperature decrease), less fit individuals are also selected (at least at the initial stages) thus avoiding premature convergence. Furthermore, as the pointers are spread out across the individuals' segments they are forced to choose a number of different individuals at once rather than being allowed to select one random individual per turn. This minimises the risk of selection (in extreme cases) of only low fitness individuals due to the purely stochastic nature of the selection process.

Step 4: Crossover

Initial Stages. A probability of crossover (p_c) is selected by the user and is kept constant throughout the process. A random number **r** (between 0 and 1) is generated for each of the individuals. If $r<p_c$ the individual is selected for crossover. A random number between 1 and the length of vector $pointer_i$ is generated to indicate the point of crossover. The two parents exchange (swap) one pointer thus producing two offsprings with similar characteristics (i.e. each offspring shares 1 gene (pointer) with the one and 2 genes (pointers) with the other parent. The offsprings replaced their parents irrespective of fitness in the new population to increase diversity.

Step 5: Mutation

An initial probability of mutation (p_m) is selected by the user. This probability is very high (0.7-0.9) guaranteeing that almost all selected individuals will undergo random changes. A random number **r** (between 0 and 1) is generated for each of the individuals. If $r<p_m$ the individual is selected for mutation. One gene (pointer) of the selected individual is substituted with a randomly selected integer within a predefined range. The objective of

this mutation operator is to explore the solution space and randomly select individuals with large fitness values scattered across the solution space.

Intermediate stages: When the generation count exceeds a certain threshold (defined here, after a trial –and-error procedure, as ½ of the maximum number of generations) the original (random) mutation operator is changed and another operator begins the process of fine-tuning: Each time an individual is selected for mutation (still at the original high p_m), all of its genes are changed by adding a small random number $\mathbf{\Delta v}$ (here between 1-20) to one of the genes (pointers), selected at random, and subtracting $\mathbf{\Delta v}$ from the other two genes (pointers). This process enables the algorithm to investigate the solution space close to individual solutions with high fitness values and to identify optima close to the solutions selected that would otherwise be overlooked with a purely random mutation process. This procedure is in accordance with Grefenstette (1987) who observes that " ... *GAs change the distribution of high performance superstructures in the overall population; individual structures are not the focus of attention. Once the high performance regions of the search space are identified by a GA, it may be useful to invoke a local search routine to optimise the members of the final population...*"

Final stages: At the last stage of the algorithm (selected here as the final 1/5 of the maximum population), the probability of mutation is allowed to decrease as a function of time leading to virtually zero probability of mutation towards the end of the process. This feature is included under the assumption that mutation at the final stages would destroy good individuals, already present in the population, and it allows the evolution process to be driven by crossover almost exclusively and exploit the full potential already present in the final solution populations. The time differentiation of the probability for mutation is given by multiplying the original mutation probability with a function $\Delta_{Mutation}$ given by Eq. 4.9.

$$\Delta_{Mutation} = 1 - r^{\left(1 - \frac{\text{generation counter}}{\text{max number of generations}}\right)^2} \qquad \textbf{Eq. 4.9}$$

where **r** is a random number between 0 and 1

This equation is selected for its property to return values between 0 and 1, such that the probability of $\Delta_{Mutation}$ to be close to 0 increases as the *generation counter* reaches *max number*

of generations. The probability of mutation (p_m) is therefore varied though time according to Fig. 4.17.

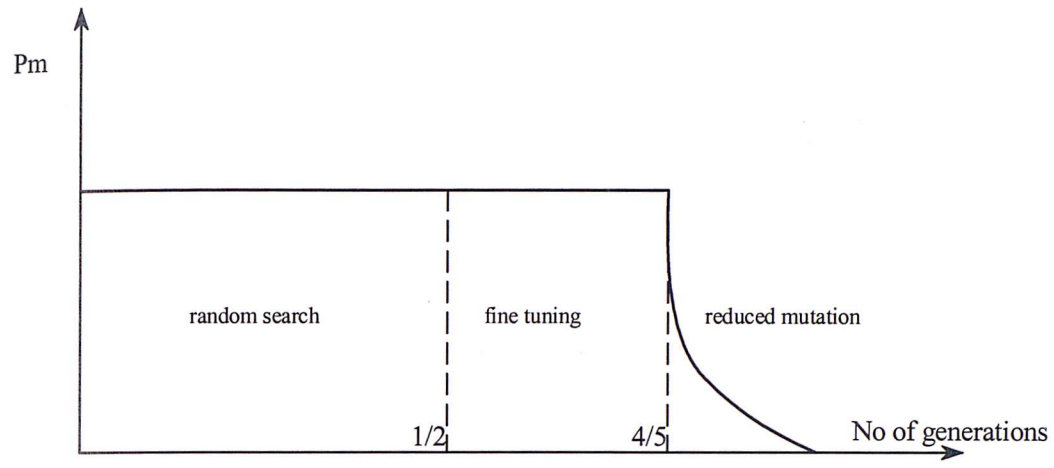


Figure 4.17. Variable mutation operator as a function of progression of generations

Step 6: New population

A new population is generated after crossover and mutation and the process returns to step 2 to re-evaluate the new population. In each new population, the best individual of the past generation is also included (according to the *elitist* model).

Step 7: Stop

The algorithm is stopped after a number of generations. It was found that 3,000 generations were sufficient for the algorithm to converge successfully, particularly after the modification of the penalty function and the inclusion of the variable mutation operator. It has to be noted that prior to these changes, and by using classic uniform mutation, the same results required at least 100,000 generations to reach similar results.

4.6.3 Solving the multi-objective GA optimisation problem

In the case of the multi-objective approach to the WDM problem at hand, all the decision elements are handled as objective functions. In particular, suitability for application of each WDM technique, water saved and associated cost form the three objective functions for the problem at hand. By treating both cost and water saved as objective functions in their own right this approach does not distinguish between the two problems (A and B) addressed separately in the previous paragraphs. An advantage of

this optimisation solution is therefore that the two problems are addressed with the same algorithm at the same time. A disadvantage is that the problem is highly complex (particularly due to its spatial nature) and thus computational efficiency is an issue that had to be addressed throughout the development of the algorithm. The application of the mathematical framework described in Chapter 3 to the WDM problem is presented next.

Step 1: Initialisation

Three matrices (one for each of the strategies taken into account) are constructed using the suitability maps derived earlier, and information on cost per application and expected reduction based on user input values.

$M_{leakage} =$

Intervention Cell_Row	Intervention Cell_Column	Leakage Suitability	Water_Reduction	Cost per intervention	Application (yes/no)
10	20	0.7	50	100	1
5	158	0.68	20	70	0
...	...	...	...	...	
120	79	0.001	40	90	1

$M_{metering} =$

Intervention Cell_Row	Intervention Cell_Column	Metering Suitability	Water_Reduction	Cost per intervention	Application (yes/no)
10	20	0.7	50	100	1
5	158	0.68	20	70	0
...	...	...	...	...	
120	79	0.001	40	90	1

$M_{greywater\ recycling} =$

Intervention Cell_Row	Intervention Cell_Column	Greywater RC Suitability	Water_Reduction	Cost per intervention	Application (yes/no)
10	20	0.7	50	100	1
5	158	0.68	20	70	0
...	...	...	...	...	
120	79	0.001	40	90	1

These matrices - after excluding all cells that have zero suitability - represent the set of the legal solutions to the problem and serve as a pool from which new individuals are selected, thus avoiding the computationally expensive process to scan each new individual for illegal applications. In this sense, illegal applications would be assigning a strategy (i.e. leakage reduction) to a cell where such an application has no meaning (i.e. a non-network cell).

The algorithm then identifies, randomly, the maximum number of applications allowed for each strategy within one epoch. This is included in the process as the number of rows of each individual that correspond to each strategy.

For each epoch, the maximum number of applications is increased by 10% to account for the fact that the analyst does not know this parameter *a priori*. The reason why more applications are introduced gradually instead of assigning the actual maximum number of applications from the beginning is computational efficiency and convergence speed. Indeed if, for example, the full number of network cells was allowed to be eligible for leakage reduction actions that would increase dramatically both the computational burden of the algorithm and reduce the probability of convergence within a reasonable time scale. Instead, the maximum number of network cells eligible for leakage reduction actions is set to be small at the beginning and progressively allowed to increase. Dependent on the problem at hand it may be that a much smaller number of cells than the overall maximum is sufficient to achieve the water reduction or investment objectives. Fig. 4.18 is a schematic of such a stepwise approach to increasing the problem's size (and complexity).

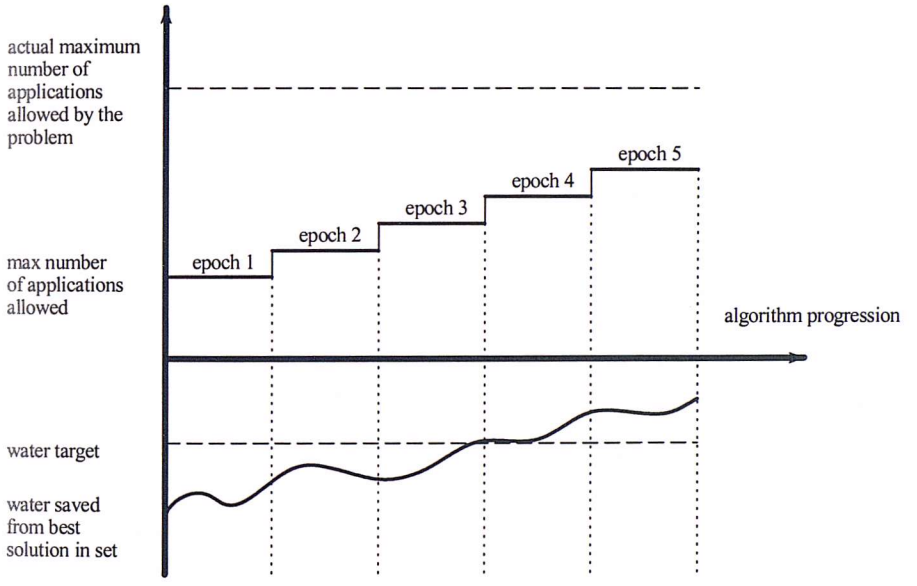


Figure 4.18. A schematic example of how the water target objective can be reached with reduced computational burden using a stepwise increase algorithm with multiple epochs.

Each individual represents a composite solution of three water management strategies combined to achieve maximum water savings with minimum investment, while selecting cells where these strategies have maximum suitability. An example of an individual is presented below.

$I_j =$

Cell_Row	Cell_Column	Suitability	Water_Saved	Investment	Application	
10	20	0.7	50	100	1	Leakage
5	158	0.68	20	70	0	
...	...	...	...	...	...	
124	16	0.5	35	80	1	Metering
90	38	0.3	100	20	0	
120	79	0.001	40	90	1	
...	...	...	...	...	...	Grey Water Recycling
180	23	0.9	190	150	0	
202	122	0.4	250	300	1	

The individuals are then checked for duplicate solutions (i.e. more than one intervention per cell per strategy).

Step 2: Fitness

The objective function vector is of the form:

$$ObjFun = \left[i \quad 1/\sum \text{suitability} \quad 1/\sum \text{water_saved} \quad \sum \text{cost} \right],$$

where i is a pointer connecting the objective functions vector with the corresponding individual, while $1/\sum \text{suitability}$, $1/\sum \text{water_saved}$ and $\sum \text{cost}$ are derived from the sum of columns 3,4 and 5 of the individual i, after multiplying each line with the appropriate line of column 6. The problem is thus transformed into a minimisation problem to reduce algorithm complexity and support a visual understanding of the final solution in a 3D space.

Step 3: Pareto-Optimality

After evaluating the objective functions for each individual in the population the individuals are ranked, based on non-domination[1]. The algorithm used was described in Chapter 3 and is an adaptation of the algorithm proposed by Deb *et al.* (2000), namely NSGA-II. The individuals are grouped based on non-domination with the members of the groups with lower ranks dominating the members of the groups of higher ranks. The rank of each individual is appended as a 5th column in the objective function matrix.

[1] For a discussion on non-domination in multi-objective GAs please see paragraph 2.2.14.4

Step 4: Crowding factor

The crowding factor estimation (Deb et al., 2000) was used instead of the conventional fitness sharing methods of niche formation (Goldberg and Richardson, 1987; Deb and Goldberg, 1989) to reduce both computational complexity and uncertainty[1] in the setting of the niche size (σ_{share}). The algorithm, described in Chapter 3, identifies the size of the largest cuboid that contains only the evaluated solution and uses this size as an indication of the number of other similar solutions that are included in the specific non-dominated front. The crowding factor is appended as a 6th column in the objective function matrix and is used to distinguish between solutions of the same non-dominated rank in the tournament selection phase.

Step 5: Formation of a parent population

The parent population is half the size of the original population. The new parent population is formed by selecting members of the best non-dominated front, then the second best etc. When the size of a non-dominated front is larger than the remaining positions in the parent population, the individuals with the highest crowding factor are selected (Fig. 4.19).

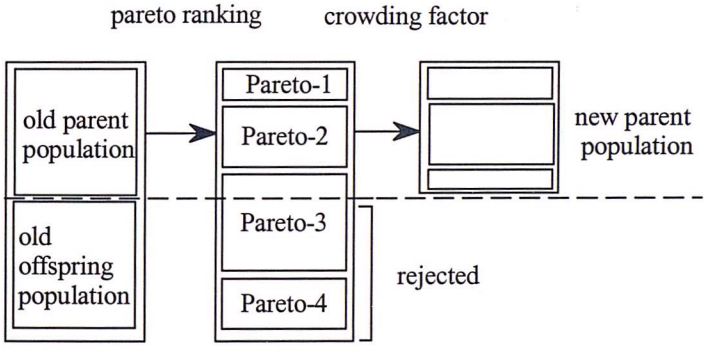


Figure 4.19. Forming a new parent population in the NSGA-II algorithm (Deb et al., 2000).

Step 6: Selection

From the parent population, formed in the previous step, some individuals (whose number is equal with the parent population) are chosen to mate. The selection procedure is this time a tournament 1-1 selection where two individuals are selected at random and

[1] For a discussion on methods for choosing σ_{share} see Fonseca and Fleming (1993).

then compared. The two selection procedures used in the single-objective algorithm (roulette and stochastic universal sampling) are not applicable in this situation due to the existence of multiple objective functions. As described in Chapter 3, there is a possibility of using either explicit constraint handling or not. The difference lies in the use or not of the constraint in the comparison process between the two solutions. The explicit constraint handling method is the only one that introduced an element of differentiation between problems A and B as described earlier in this chapter (namely maximisation of water saved for a fixed investment or minimisation of investment to achieve a desired water target). The results presented here as examples of the application of the algorithm assume that the constraint is a desired water reduction target. The following steps are described also in Chapter 3 but are included here for completeness.

Step 6.1: Without explicit Constraint handling

In the comparison process, individuals are selected when they have a better non-dominated rank (i.e. if they belong to a better non-dominated front) or if the rank is the same by larger crowding factor (indicating increased decision space exploration potential).

Step 6.2: With explicit Constraint handling

If constraints are explicitly taken into account, there are three possible situations:

- If both selected individuals fulfil the constraint requirements (either water reduction target or investment target) then the selection is performed as in step 6.1.
- If one individual fulfils the constraint requirements and the other does not, then the one that does is selected.
- If both individuals do not fulfil the constraint requirements then the individual with the smallest constraint violation is selected for inclusion in the mating population.

Step 7: Operators

Crossover, mutation and complete substitution (with or without local search) are used to introduce variability into the population and increase exploration of the decision space as described in Chapter 3. The local search algorithm is particularly developed for spatial optimisation problems in that the locations searched are selected based on physical

proximity. This is similar to the approach used by Krzanowski and Raper (1999), in their study of site selection for transmitters in wireless networks but differs from it in that the local search in the case of the DWM SDSS is severely limited by physical constraints within the urban environment (i.e. network and house locations and characteristics). The new location identified by the proximity search had therefore to take into account these constraints and to eliminate illegal applications before the evaluation of the new overall solution. This resulted in increased computation times towards the end of the analysis when the local search algorithm is brought into play.

Step 8: Forming the new population

The offspring population derived from the application of the operators is merged with the initial parent population derived from the non-dominated and crowding factor ranking thus ensuring elitism. The new population is in turn allowed to evolve and the process is resumed from step 2.

Step 9: Stop

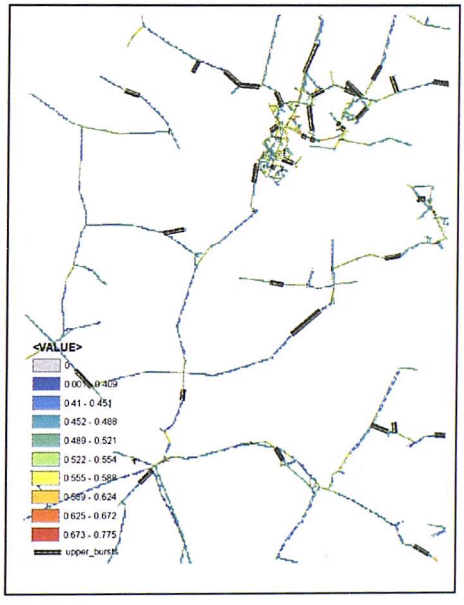
For each epoch the algorithm retains the best non-dominated set and the corresponding individual solutions. The algorithm stops when the maximum number of generations is reached for the maximum number of epochs.

A presentation of the results of the algorithms discussed here for spatial optimisation is included in the following chapter.

4.7 Conclusions

Chapter 4 described the application of the SDSS, presented in Chapter 3 to the specific domain of WDM. The end product developed is a tool for Water Service Providers to compare different water demand reducing scenarios, plan the site-specific implementation of these scenarios and assess the investment needed to achieve a desired reduction or identify the best composite scenario dependent on a desired investment scheme. Chapter 4 discussed the case studies, data availability and data format issues and provided an overview of the decision-making process (presented in Chapter 3) applied in the case of WDM through fuzzy inference, aggregation and optimisation.

5 Results


<VALUE>
0
0.41 - 0.451
0.452 - 0.488
0.489 - 0.521
0.522 - 0.554
0.555 - 0.588
0.589 - 0.624
0.625 - 0.672
0.673 - 0.775
upper_bursts

5.1 Result presentation structure

The SDSS allows significant user control over the analytical processes used and thus increased degrees of freedom in the results. This chapter does not represent an exhaustive account of all possible combinations of options and relevant processes (from a sensitivity analysis perspective) but rather presents the main outputs that indicate the differences of the results depending on the procedures and control options used. The chapter focuses particularly on the uncertainty handling capabilities of the SDSS critically discussing its implications and significance in the decision making process.

The results of the two case studies are presented separately: Issues of training and validation are addressed in case study I where real data were available and where validation of the results could take a quantitative form (leakage reduction strategy). The rest of the WDM strategies (metering and recycling) are presented in case study II together with issues of aggregation and composite strategy generation (optimisation). These results cannot be explicitly validated for reasons discussed in previous chapters, and are used to demonstrate the analytical processes incorporated in the SDSS as well as the uncertainty propagation through this decision support system. Furthermore case study II is used to discuss differences in results stemming from user – system interactions, including but not restricted to, choices of processes used, risk aversive attitudes, confidence in expert judgement and so on.

5.2 Results from case study I

Results from the first case study are organised into two stages. Stage 1 presents examples of the use of the system including rules and aggregation methods and demonstrates the effect of alternative risk aversion levels to the final result. Stage 2 addresses the issue of training the system with real data and quantifies its impact to the improvement of the leakage vulnerability assessment. Both datasets from the network analysed and a neighbouring one were used for training and their results are compared and discussed.

5.2.1 Stage 1

The analysis was performed taking into account data from two UK settlements. As discussed in Chapter 4, where the two case studies were presented, the available

attributes used to assess the leakage reduction strategy (represented as network vulnerability to leakage) can be seen in table 5.1

Table 5.1. Attributes used in case study I

Primary data:	age of pipes, material and diameter
Derived data:	pipe density and road type

These attributes were selected from the full list of attributes that can be analysed by the SDSS (table 4.1) to be used for assessing the leakage vulnerability of the particular networks. Each of the two networks was analysed separately for two reasons: (a) to ease computational burden and thus facilitate the use of high spatial resolution and (b) to allow training datasets derived from burst records of the one network to be used to train the modules used to assess leakage vulnerability in the other network thus avoiding data fitting issues. The corresponding raster data models used for the analysis (Figures 4.1-4.6) were of a 30m cell-size (within which all information is aggregated), which should be considered reasonably detailed. However the analysis resolution is only limited, in principle, by data availability (and reliability) and hardware specifications. The software developed has no particular size limitations although run times could eventually become an issue especially when alternative scenarios are investigated using computationally intensive procedures such as the genetic algorithms module.

Type 1 singleton fuzzy inference was used both with and without training for the two networks. The choice of the FIS was governed by computational intensity as it represents the simpler form of inference. Each (raster) layer, representing one attribute was imported into the inference system and an equal number of leakage vulnerability maps was calculated. The resulting maps were then aggregated using a user input, risk aversion level to compute the ordered weights through a maximum entropy method of weights assignment. The actual variables used for fuzzy inference in the case of the "two antecedents – one consequent" FIS assessing the (combined) effect of age and material to water supply networks leakage vulnerability can be seen in Tables 5.2-5.4 as an example of the procedure followed. In all cases presented here, the membership functions used are of a Gaussian shape, described by two parameters (the mean and the standard deviation) as discussed in Chapter 3.

Table 5.2. Antecedent Parameters

Age of pipes (in years)				
Mean of Antecedent fmfs	10	30	50	80
Standard deviation of antecedent fmfs	5	5	5	5

Table 5.3. Antecedent Parameters

Material of pipes (1: Iron, 2: Concrete, 3: Other (primarily plastic))			
Mean of Antecedent fmfs	1	2	3
Standard deviation of antecedent fmfs	1	1	1

Table 5.4. Consequent Parameters

Centre of sets of (combined) consequent fmfs	0.2	0.4	0.6	0.8

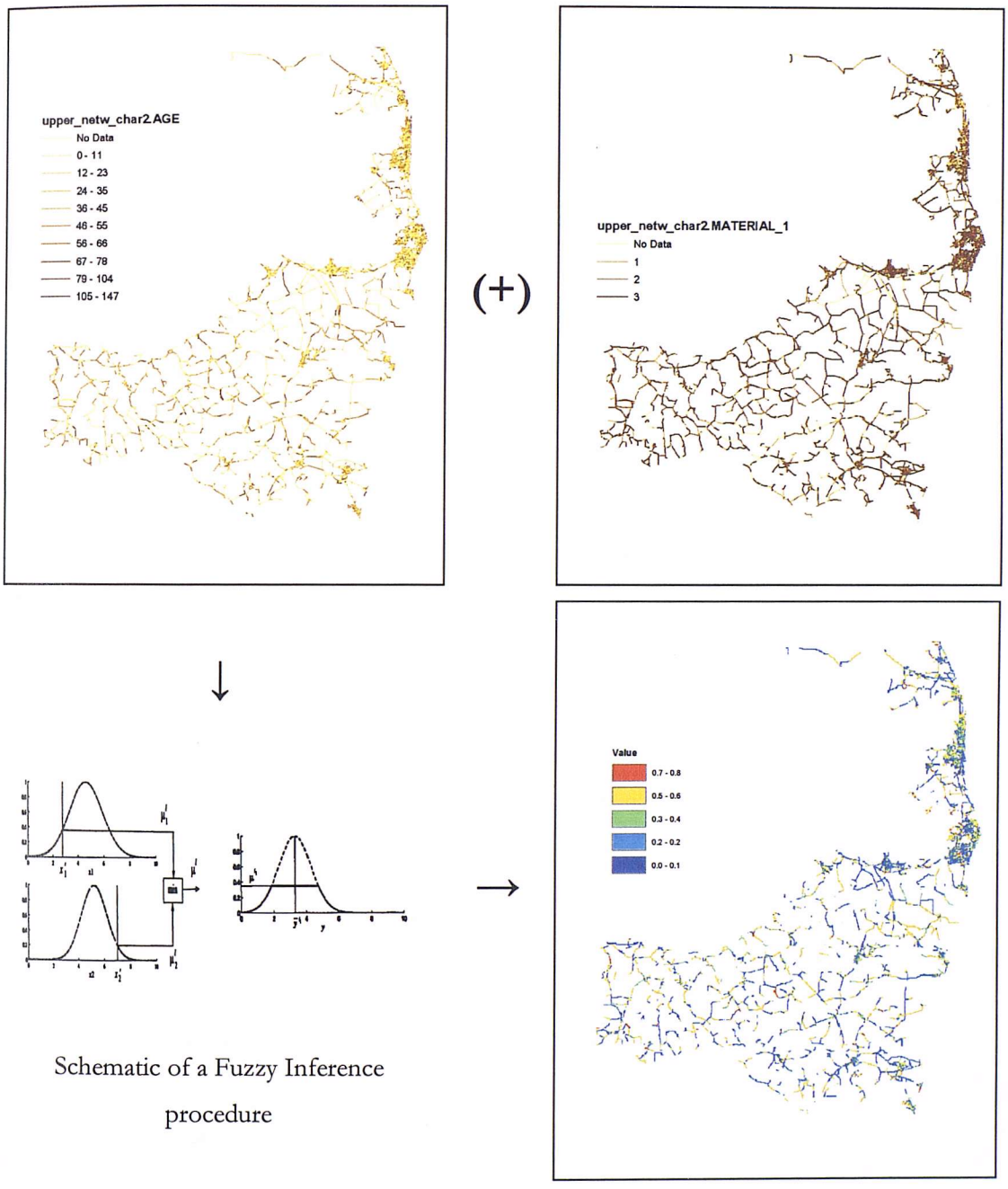
These parameters were used within the "two antecedents – one consequent" FIS developed for this purpose, with rules described in Table 5.5.

Table 5.5. Rules used in the age + material FIS

Rules		
Age	Material	Vulnerability
1	1	1
1	2	1
1	3	1
2	1	1
2	2	2
2	3	2
3	1	2
3	2	3
3	3	3
4	1	4
4	2	4
4	3	3

The indexes in the age and material column of Table 5.4, refer to the membership functions that dictate the belonging of a particular cell of the network to in the age and material sets, which are specified in Tables 5.1 and 5.2, while the indexes in the vulnerability column refer to the membership functions of the leakage vulnerability sets

which are specified in Table 5.3. For example row one of Table 5.4 states (in linguistic terms) that if a network cell belongs to the age set 1 (a new pipe: mean age 10 years with standard deviation 5) and is of material 1 (an iron pipe) then it belongs to the vulnerability set 1 (low vulnerability: centre of set 0.2). The two antecedents and one consequent map can be seen in Figure 5.1.



Schematic of a Fuzzy Inference procedure

Figure 5.1. The two antecedent GIS layers and the result of the fuzzy inference procedure

Similar outputs were derived for all attributes and the resulting vulnerability maps were imported into the aggregation module. The underlying assumptions for linking antecedent to consequents have been discussed in Chapter 4. The aggregation procedure used was ordered weighted averaging where all input attributes were considered equivalent and a range of risk aversion factors from 0.4 to 0.7 (with maximum risk aversion factor = 1.0) were used to order the weights. Low risk aversion factors result in decreased leakage vulnerability ratings, and therefore decreased the number of pipes that are identified for replacement.

The resulting layer can be seen in Figure 5.2, where the leakage vulnerability layer has been overlaid with the layer of the actual burst locations from the database indicating the extent of the accuracy of the prediction. As data were available only for the current state of the network, while burst records sometimes preceded the time when the actual main was set in place, only bursts occurring after the year the current main was laid were used for validation purposes.

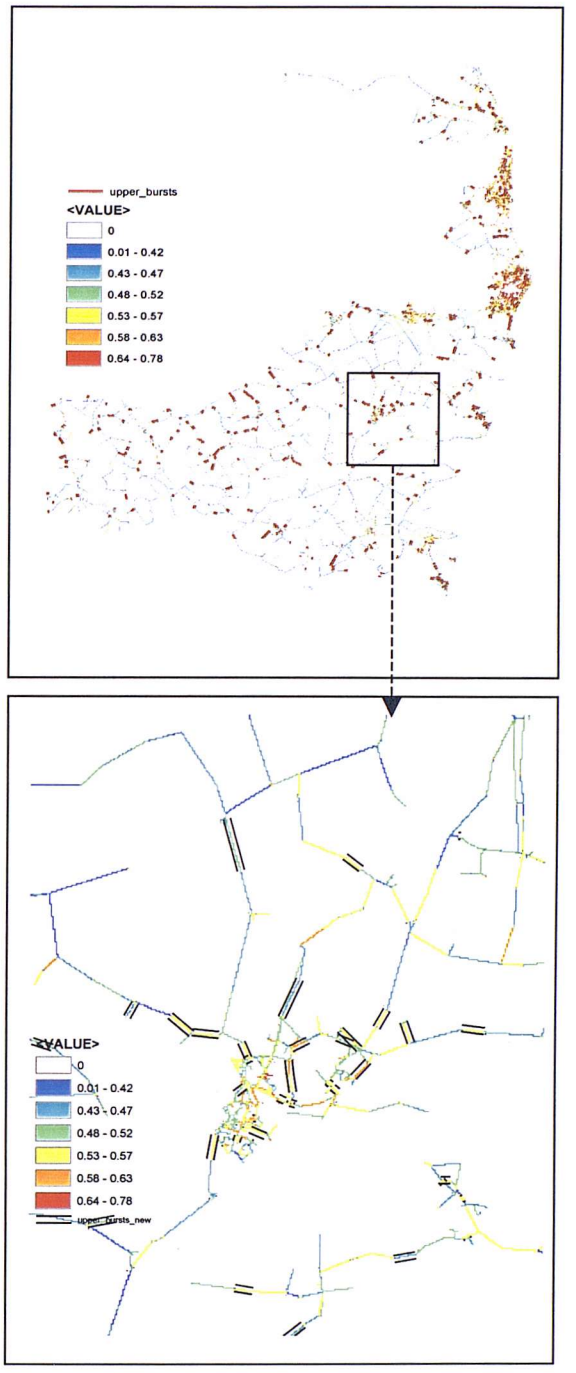


Figure 5.2. The leakage vulnerability map overlaid with the actual burst locations

Figure 5.3 presents the quantification of the extent to which the prediction of the location of the recorded bursts was successful for a range of risk aversion levels. The values are the percentage of cells with vulnerability ratings over a threshold (X axis) where burst have actually been recorded in the database.

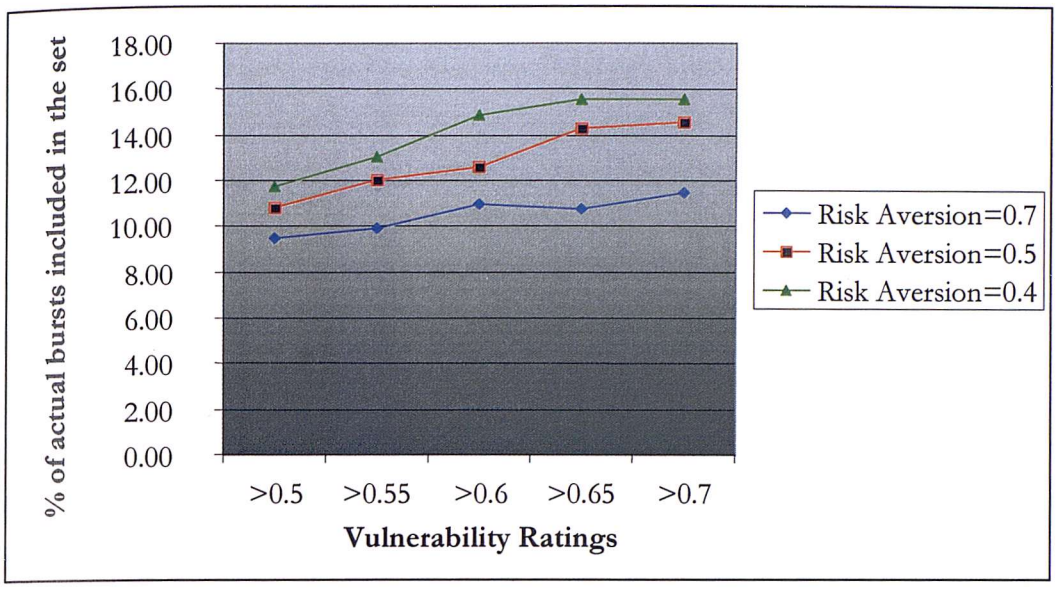


Figure 5.3. Percent of cells marked as vulnerable where actual burst had been recorded (lower network)

The results indicate that when risk aversion is decreased, the tool limits the suggestion of pipe replacements to the most vulnerable pipes. This is confirmed by the associated increase in the percent of pipes that actually have a burst records within the sets suggested by the system. In that respect the decrease in risk aversion turns the tool towards a more predictive role (i.e. towards a "physical modelling" role) and identifies a number of pipes that have presented in the past or will shortly present problems) rather than a long term planning one (i.e. a "decision making" modelling role), which is the main scope of the system. In any case, the decision maker can steer the desired role of the tool between these two extremes by defining the risk aversion attitude of the analysis. Furthermore, the fact that the accuracy of the prediction increases as vulnerability ratings increase signifies that higher ratings also allow for more confidence in the accuracy of the results. This can be explained by the fact that higher vulnerability ratings signify the coexistence of multiple (negative) attributes in the given cell, which increases the probability of a burst having been recorded there in the past. Note that this is not the main aim of the tool's design, which is to assess the overall vulnerability of the pipes rather than predict exact burst locations. The increase in prediction accuracy and the corresponding increase in confidence level of the resulting analysis should be considered as added value to the tool's use.

5.2.2 Stage 2

Consequently the system was run using the training module (see discussion in Chapter 3). Training data were prepared using the Bayesian probabilities procedure described in Chapter 4 and data from actual bursts within the network for a period of 50 years. The Bayesian probabilities procedure identifies clusters within the data using a c-means clustering technique and assigns a probability of failure for the members each cluster. In this case, the number of rules used in the FIS is based on the number of clusters found in the data. An example of such a clustering and associated probability of failure for the case of the attribute "pipe diameter" is presented in Table 5.6.

Table 5.6. Bayesian Probabilities for pipe diameter

From (mm)	To (mm)	Pipe cells	P(f/c)
-999	-999[1]	4140	0.1917
6	127	48000	0.2183
150	305	21391	0.2170
355	610	3460	0.8279
864	864	197	0.2773

Data from both the upper and lower networks were used for training purposes. Each network was analysed with and without training the FIS, with data derived from its own bursts as well as with data derived from the other network to provided insight into issues of data fitting in the training process.

Figures 5.4-5.7 present the convergence of the optimisation algorithm minimising the RMS error in the training procedure for the four FIS types available in the system. As was to be expected, the convergence is faster in the simpler systems (singleton input systems) and slower in the complex (non-singleton systems). A further observation is that convergence in the type-2 (highly non-linear) systems is generally less stable than in the case of the simpler type-1 FIS.

[1] The value -999 signifies no data available.

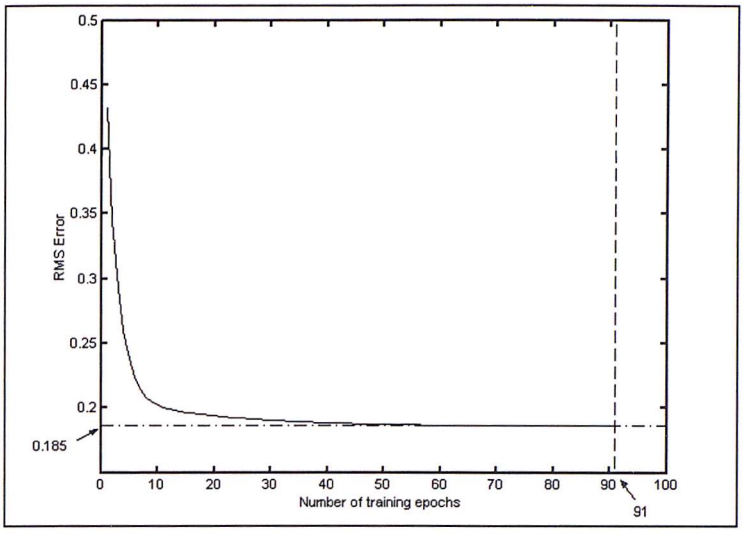


Figure 5.4. Example of convergence of the training algorithm for s-type-1 FIS

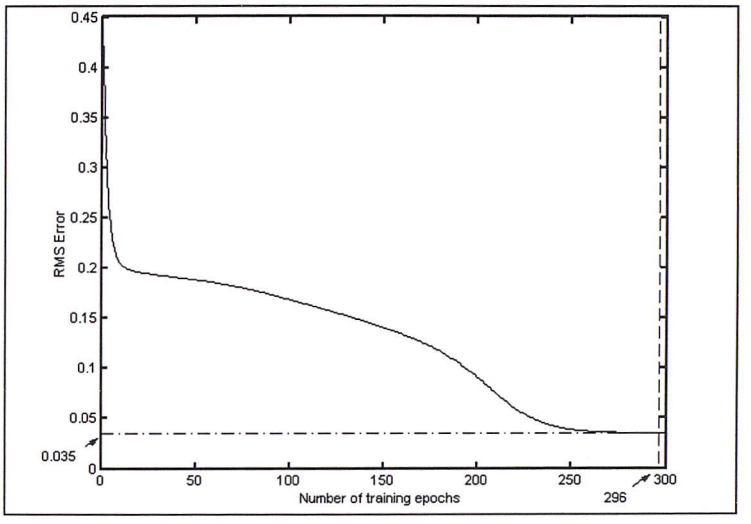


Figure 5.5. Example of convergence of the training algorithm for ns-type-1 FIS

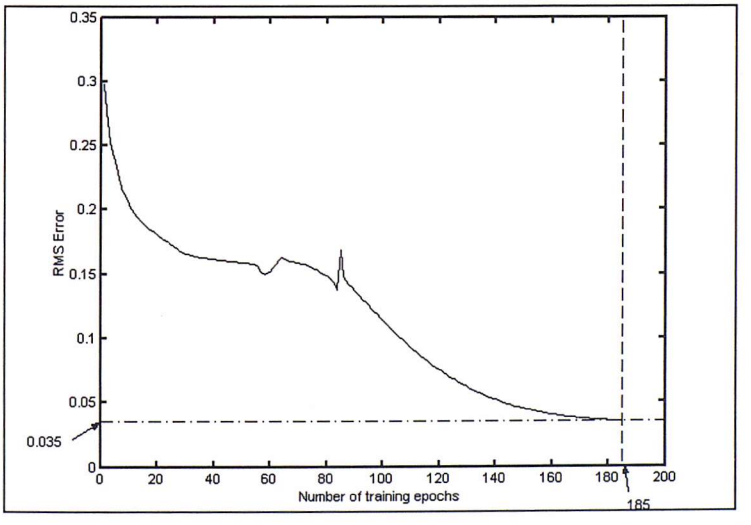


Figure 5.6. Example of convergence of the training algorithm for s-type-2 FIS

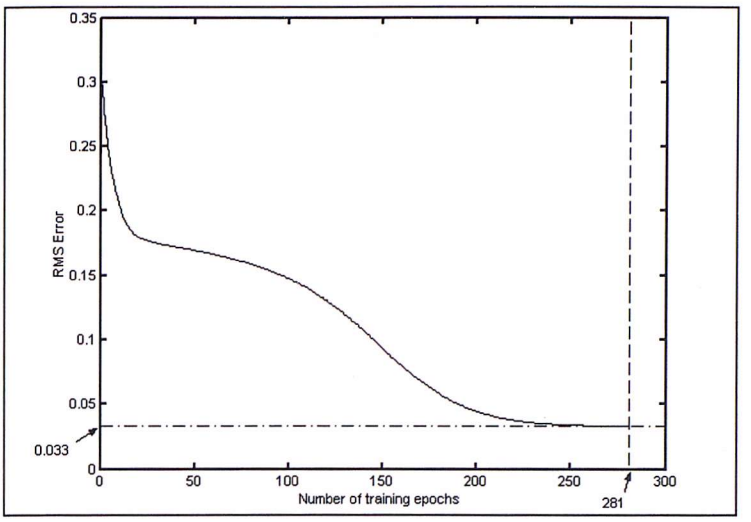


Figure 5.7. Example of convergence of the training algorithm for ns-type-2 FIS

The resulting vulnerability maps for each attribute were aggregated using the maximum entropy OWA procedure with range of risk aversion factors. One of the resulting composite vulnerability maps for risk aversion level = 0.7 can be seen in Figure 5.8. The layer of recorded bursts developed from the original geo-referenced database was overlaid on the leakage vulnerability layer to facilitate comparisons of the performance of the algorithm. Figure 5.9 presents a quantification of the effect of risk aversion to the percentage of pipes identified as vulnerable for which real burst records existed.

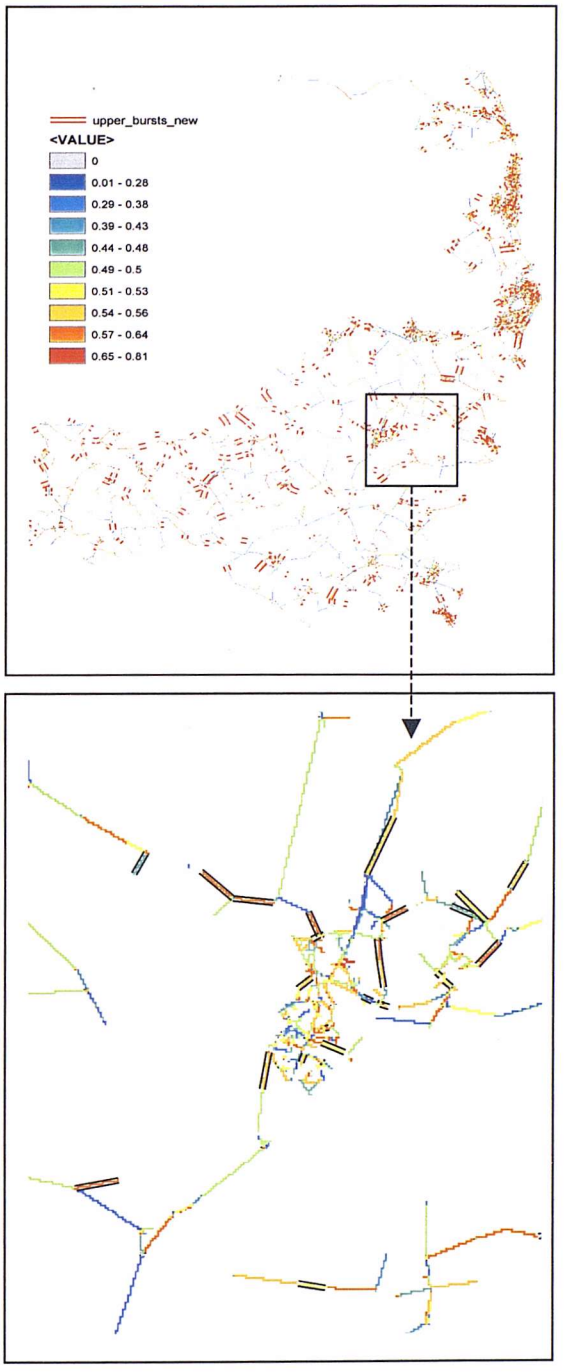


Figure 5.8. The leakage vulnerability map of the upper network overlaid with the actual burst locations (after the training procedure)

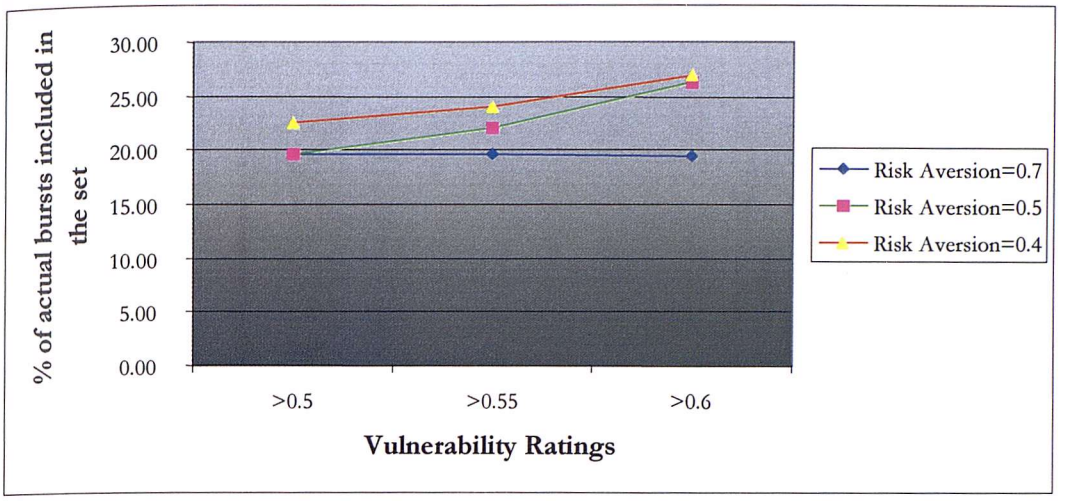


Figure 5.9. Percent of cells marked as vulnerable where actual burst had been recorded

The results indicate that the trained system has a similar behaviour with the untrained system, including an upward trend as vulnerability ratings increase and increase of accuracy as risk aversion decreases. The actual accuracy however, in terms of % of cells identified as vulnerable where a burst records actually exists, is substantially increased.

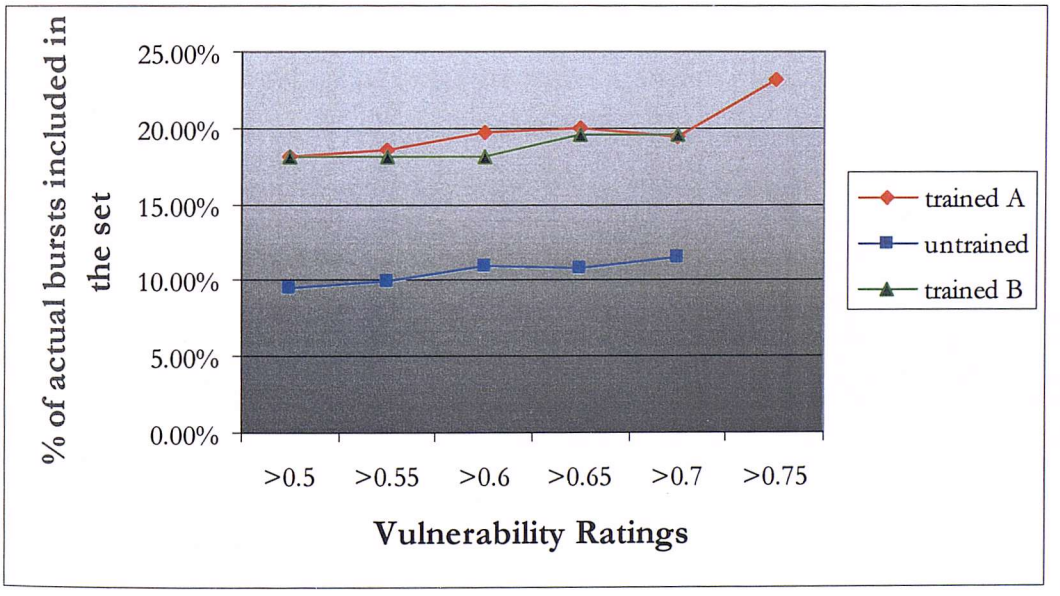
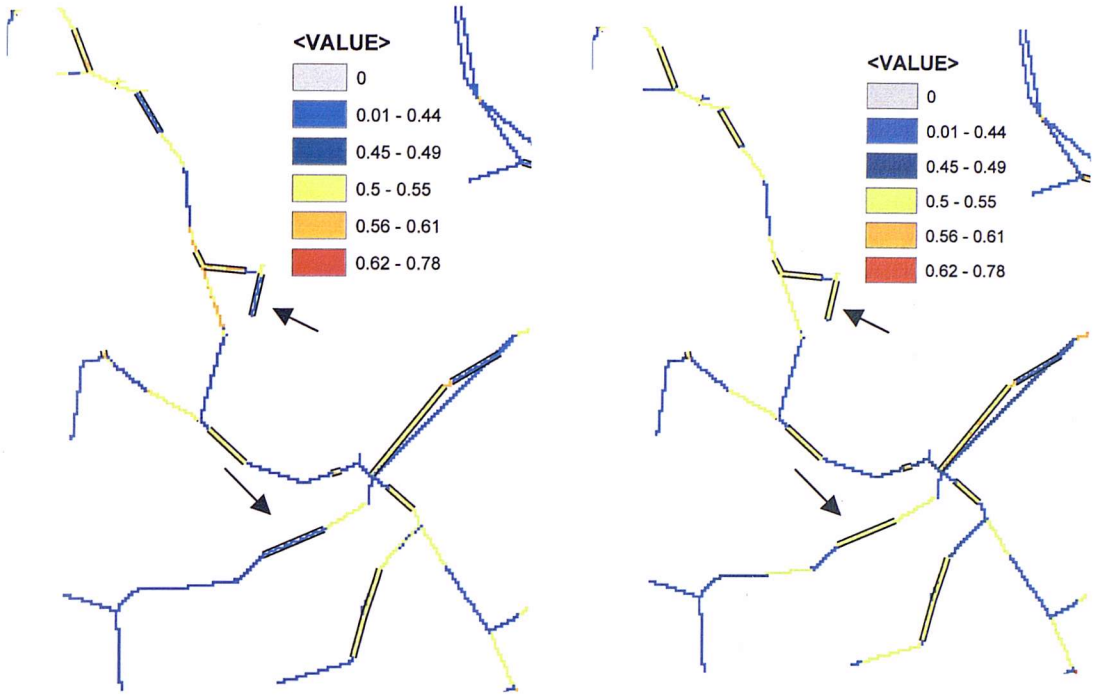


Figure 5.10. A comparison of performance of the system with and without training (lower network)

Figure 5.10 presents a comparison of the results obtained with and without training for the lower network of case study 1. The risk aversion level was constant and equal to 0.7 as an example. Two sets of training pairs were used: Training set A, where data used for training were derived from the same network that was analysed and training set B where training data were derived from another network (in this case training data from the upper network were used to analyse the lower network). The results from both trained systems include a higher percentage of pipes with burst records in the set of vulnerable cells, indicating that the performance of the algorithm has indeed been significantly improved. This fact is slightly more pronounced in the case where data from the same network that was analysed were used for training (set A) but the difference is not significant. This suggests (based on this limited evidence) that training data sets could be used to a certain extent interchangeably between networks with similar characteristics, thus increasing the applicability of the tool in data scarce areas. Figure 5.11 is a network detail from the resulting leakage vulnerability maps from the trained and non-trained FIS with equal direct weights and risk aversion level = 0.7. The actual burst locations are also included in the figure for comparison purposes. It can be observed that even though vulnerability was correctly estimated using exclusively the (untrained) rule base, the training procedure significantly increases the system's performance.



(a) (b)

Figure 5.11. The resulting vulnerability map without training (a) and with training (b). The arrows indicate areas of improvement. The lines parallel to the network indicate network segments where a burst has been recorded.

The discussion on the efficiency of the training algorithm deserves one last important remark. The training process and the comparisons discussed above made use of all burst records available in the database. This, however, is considered a simplification of the actual problem, as there are types of bursts that would not be associated with the site-specific attributes used in the FIS. A selection of the burst records used on the training process depending on the description of the burst type as well as an exclusion of these non site-specific bursts from the comparison set would yield more pronounced results. Such a filtering process was abandoned in favour of a more simplified, but at the same time more general, process of including all records available for various reasons: the burst records database that was available for training and comparison purposes contained a large number of unidentified burst types (labelled "other") that may or may not be associated with site-specific characteristics. There was no possibility to validate the uncertainty involved in the burst type characterisation within the database and therefore the extent this characterisation was accurately portraying the actual type of the burst. Most of the descriptions were too general to assess whether or not the burst was really

influenced by site-specific attributes (e.g. "contractor damage", "ring crack") and the records that clearly identified for example "corrosion" as the cause, were too few to drive the training process. It was therefore decided that since the aim of this work was not to solve a particular problem but rather to present and discuss a methodology for assisting decision making, the training process should be kept as general and as simple as possible. This also accounts for real-life situations within the water industry where training data is scarce and to a large degree uncertain. The results suggest that although the process is simple and thus easy to use by the industry it significantly improves the performance of the analysis.

5.3 Results from case study II

Case study I provided the opportunity to validate the methodology used to derive the leakage reduction strategy within the SDSS, which is the only part of the system that can be validated in the true sense of the word. The remaining parts of the system, dealing with grey and rain water recycling or the introduction of compulsory metering and their combination into a composite WDM strategy cannot be validated through any other process apart from expert opinion, as the process modelled is not physical that can be confirmed, to some extent, through observation but rather decision-making. To illustrate and discuss the applicability and full functionality of the system in supporting decision-making, the second case study was developed based on semi-hypothetical data. This case study (case study II, described in detail in Chapter 4) is used as a means to discuss all other functions of the SDSS and its application to WDM, apart from training the FIS which was covered in case study I. The presentation of case study II is organised in three stages, following the structure of the decision-making process the system is designed to support (see paragraph 4.3); namely inference, aggregation and optimisation.

5.3.1 Stage 1: Inference

Stage 1 consists of an assessment of the sensitivity of the results of the FIS to changes in parameters of the systems themselves: changes in the mean and variance of the input and output fuzzy sets, comparison between the results of type-1 and type-2 FIS as well as between singleton and non-singleton FIS is undertaken at this stage. The aim of the following examples is to explore the uncertainty handling capabilities of the system and the propagation of that uncertainty throughout the decision-making modelling process.

In all cases presented here the shape of the fuzzy membership functions is Gaussian (and in the case of Type-2 sets, Gaussian primary membership functions with interval secondary membership functions) and the output fmfs are identical to allow for results comparability.

As discussed in Chapter 5, the use of Gaussian fmfs is adopted purely for computational efficiency purposes because the Gaussian membership function (being closed form) facilitates mathematical computations (integration, differentiation etc). The use of interval secondary membership functions is justified by the significant reduction in complexity it achieves. As mentioned in Chapter 5, due to the complex fuzzification, defuzzification procedures the effect of the actual shape of the input and output fmfs on the crisp result is insignificant (Mendel, 2001). A comparison between triangular, bell shaped and Gaussian fmfs in Type-1 FIS is included in the following paragraph. As far as Type-2 FIS are concerned, it should be remembered that conceptually Type-2 FIS could be thought of as a large number of embedded Type-1 FIS (as discussed in paragraph 2.2.10.2). Within the boundaries of an antecedent or consequent fmf therefore all possible shapes of fmfs are in fact approximated. The effect of the actual shape of these boundaries to the results of the analysis is discussed in the following paragraph. Furthermore, data are not sufficient in this case to dictate a specific shape for either input or output fmfs, although in principle, the nature of the problem (the unknown function which the FIS tries to approximate) might favour some particular shape. The same is true for secondary fmfs. Karnik and Mendel (1999) also support the argument that "interval sets are very useful when we have no other a priori knowledge about membership function uncertainties".

In these examples the consequent fmfs have means and standard deviations of [0, 0.2], [0.5, 0.2], [1, 0.2] respectively and represent the linguistic variables low, medium and high suitability in the case of metering and recycling strategies (or vulnerability in the case of the leakage reduction strategy).

(a) Uncertainty in the shape of the fuzzy membership functions

The following examples of assessing the sensitivity of the inference procedure to the parameters of the FIS is from the soil aggressivity attribute (soil pH) of the leakage reduction strategy. A set of simple linguistic rules were modelled as an example:

IF x Acidic THEN leakage vulnerability High

IF x Neutral THEN leakage vulnerability Low

IF x Alkaline THEN leakage vulnerability Medium

The effect of the selection of a fuzzy membership function shape to the output leakage vulnerability map was assessed following the claim that the specific shape is not particularly significant. Figure 5.12, quantifies the effect of three (commonly used) shapes of antecedent and consequent fmfs: Gaussian, Bell-shaped and Triangular. Table 5.7 includes the parameters used to specify the shapes of the fmfs for each FIS.

Table 5.7. Parameters used to define the 3 fmfs of Figure 5.12

	Antecedent fmfs	**Consequent fmfs**
Triangular [a,b,c]: $f(x;a,b,c)=\begin{cases}0, & x\le a\\ \frac{x-a}{b-a} & a\le x\le b\\ \frac{c-x}{c-b} & b\le x\le c\\ 0, & c\le x\end{cases}$	Acidic: [-7,0,7] Neutral: [4.5,7,9.5] Alkaline [7,14,21]	Low: [-0.47,0,0.47] Medium: [0.02,0.5,0.98] High: [0.52,1,1.47]
Generalised Bell [a,b,c]: $f(x;a,b,c)=\frac{1}{1+\left\lvert\frac{x-c}{a}\right\rvert^{2b}}$	Acidic: [3.5,2.5,0] Neutral: [1.17,2.5,7] Alkaline [3.5, 2.5, 14]	Low: [2.36, 2.5, 0] Medium: [2.36, 2.5, 0.5] High: [2.36, 2.5, 1]
Gaussian [σ,m]: $f(x;\sigma,m)=e^{-\frac{(x-c)^2}{2\sigma^2}}$	Acidic: [3,0] Neutral: [1,7] Alkaline [3,14]	Low: [0.2, 0] Medium: [0.2, 0] High: [0.2, 0]

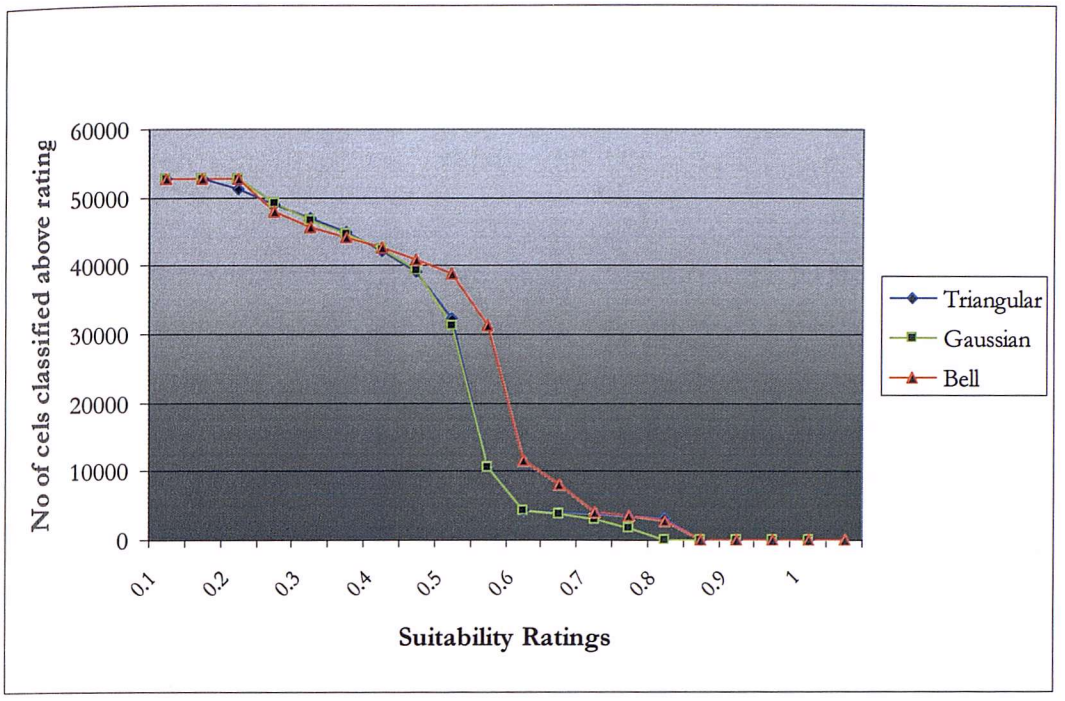


Figure 5.12. Differences between FIS using different shapes of fmfs

The results obtained support the relevant literature (e.g. Mendel, 2001) claiming that the differences in the analysis caused by the shape of the fmf are not really significant (this seems to be particularly the case between the two most commonly used fmfs: the triangular and the Gaussian). In the absence of specific reasons for selection of a shape, the designer is therefore to some extent free to select a shape that is most easily handled by the computational tools available. The fact that Gaussian fmfs ensure a smooth transition between membership and non-membership, they are of closed form and therefore computationally easier to handle and they are non-zero for all input values make them the most attractive of the three. As mentioned above Gaussian fmfs will be used throughout this work. Figure 5.13 presents the actual outputs of the three FIS as GIS layers of vulnerability to leakage due to soil aggressivity.

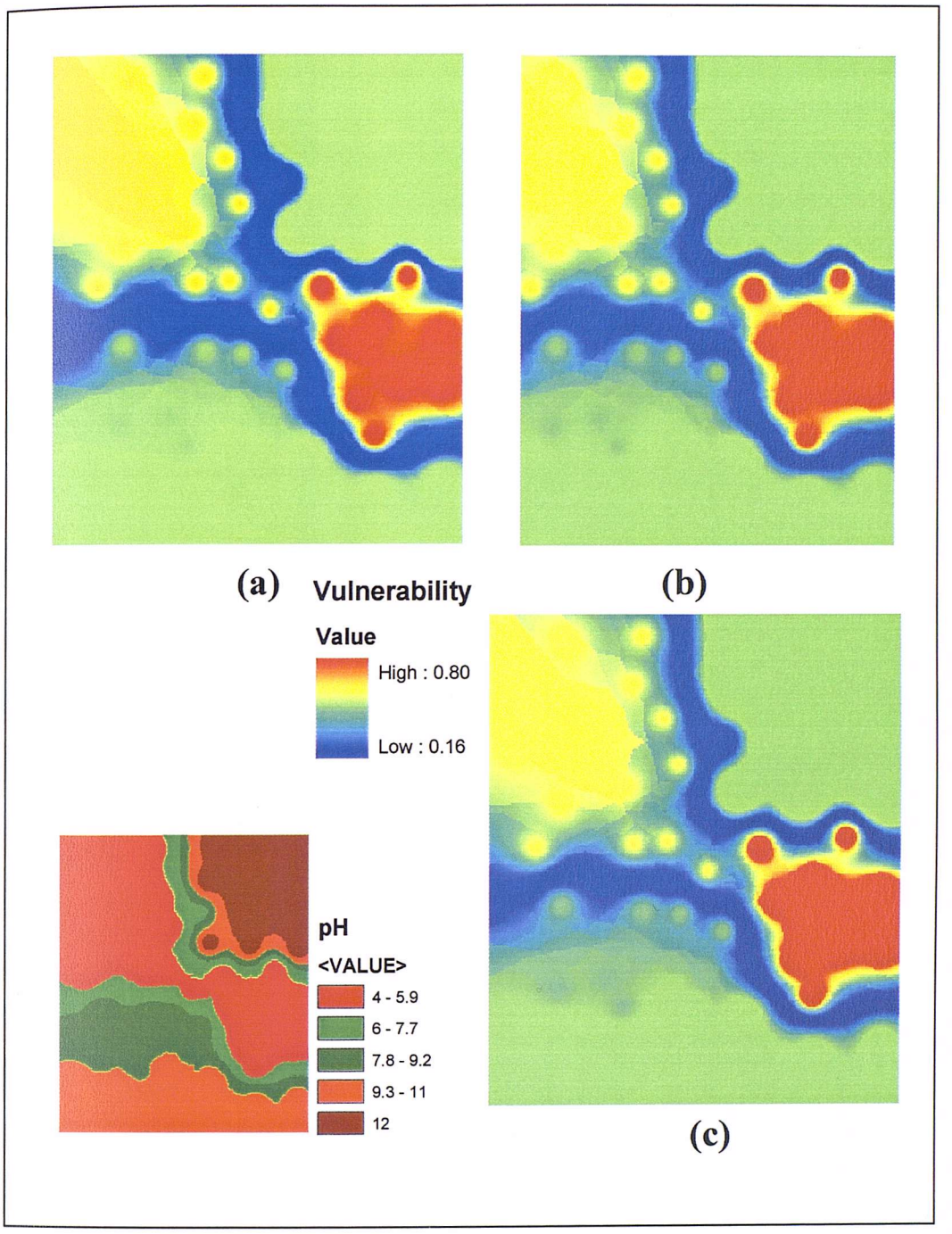


Figure 5.13. The soil pH attribute (lower left) and the resulting vulnerability layers from the same FIS using: (a) bell-shaped (b) Gaussian and (c) Triangular fmfs.

Figure 5.13 is a visual representation of the effect of the linguistic rules and the associated fmfs linking acidic, neutral and alkaline soil pH to pipe vulnerability to leakage. The clear advantage of this visualisation is the ability of the decision maker to visually quantify the impact of the rules on the result as well as to visualise the effect of the attribute to the problem in question based on these rules. In the example that follows, we

use the simple form of IF-THEN rules mentioned above in order to investigate the effect of the standard deviation of the fmfs, the standard deviation of the input data (in the case of non-singleton FIS) and the footprint of uncertainty allowed by the type 2 FIS. The three antecedent sets (the linguistic variables: acidic, neutral and alkaline) were modelled with Gaussian fmfs for two sets of parameters (see Table 5.8) and the resulting suitability ratings can be observed in Figure 5.14.

Table 5.8. Parameters for antecedent sets in soil pH

Antecedent sets	Mean	St.D (1)	St.D (1)	St.D (2)
Acidic	2	1	2	3
Neutral	7	1	2	3
Alkaline	10	1	2	3

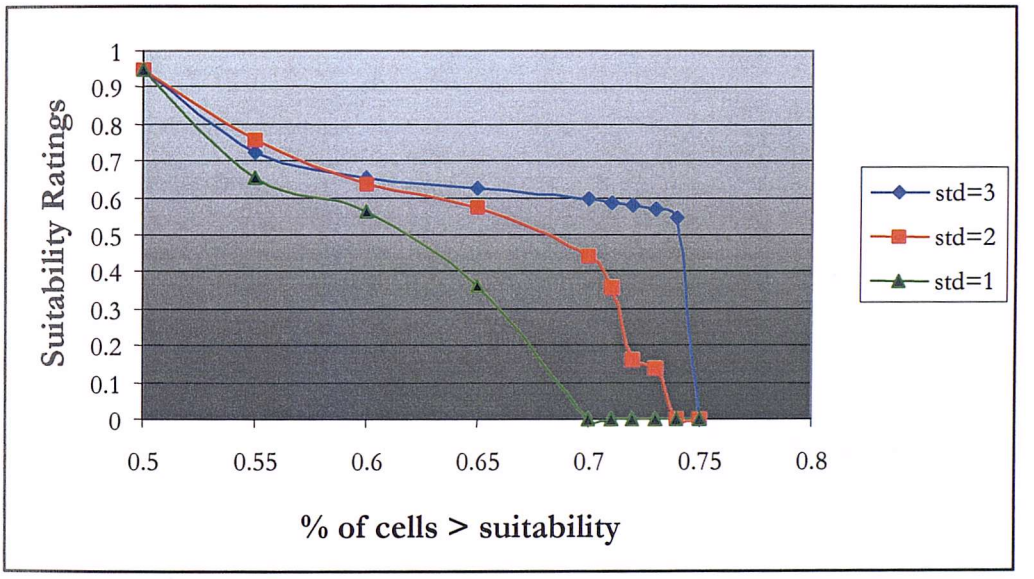


Figure 5.14. Cumulative graph of % of cells with suitability (vulnerability) ratings over a specified value

The increase in standard deviation, corresponding to an increase in uncertainty as to the relative extents of the sets has one specific effect. It increases the number of input points receiving high scores in all three consequent sets. The reason is that by increasing the standard deviation of the antecedent fmfs, there is a tacit acknowledgement of uncertainty as to which set a specific input value belongs. For example it is not possible to clarify whether an income ***a*** is *medium* or *high*. Due to that fact, ***a*** is assigned a high membership in more than one set, and the defuzzification procedure (in this case a

centroid defuzzification) results in a more neutral response, with values for all inputs closer to a medium value. This is why the increase is more pronounced in low-to-medium vulnerability ratings while high vulnerability ratings have in fact been slightly decreased. The physical meaning of this result is that higher design uncertainty results in more "indifferent" system generated suggestions. Figure 5.14 displays this overall increase in medium range vulnerability values due to the change of the shape of the antecedent Gaussian fmf. Figure 5.15, displays two layers of leakage vulnerability due to soil aggressivity (pH) corresponding to antecedent fuzzy membership functions' standard deviations of 1 and 2. It also provides an example of the output of the fuzzy inference module of the SDSS. The difference between the two outcomes is generally small (maximum difference $\approx$ 10%) but its spatial variation provides the decision maker with a visual quantification of the uncertainty and its effect in site-specific planning.

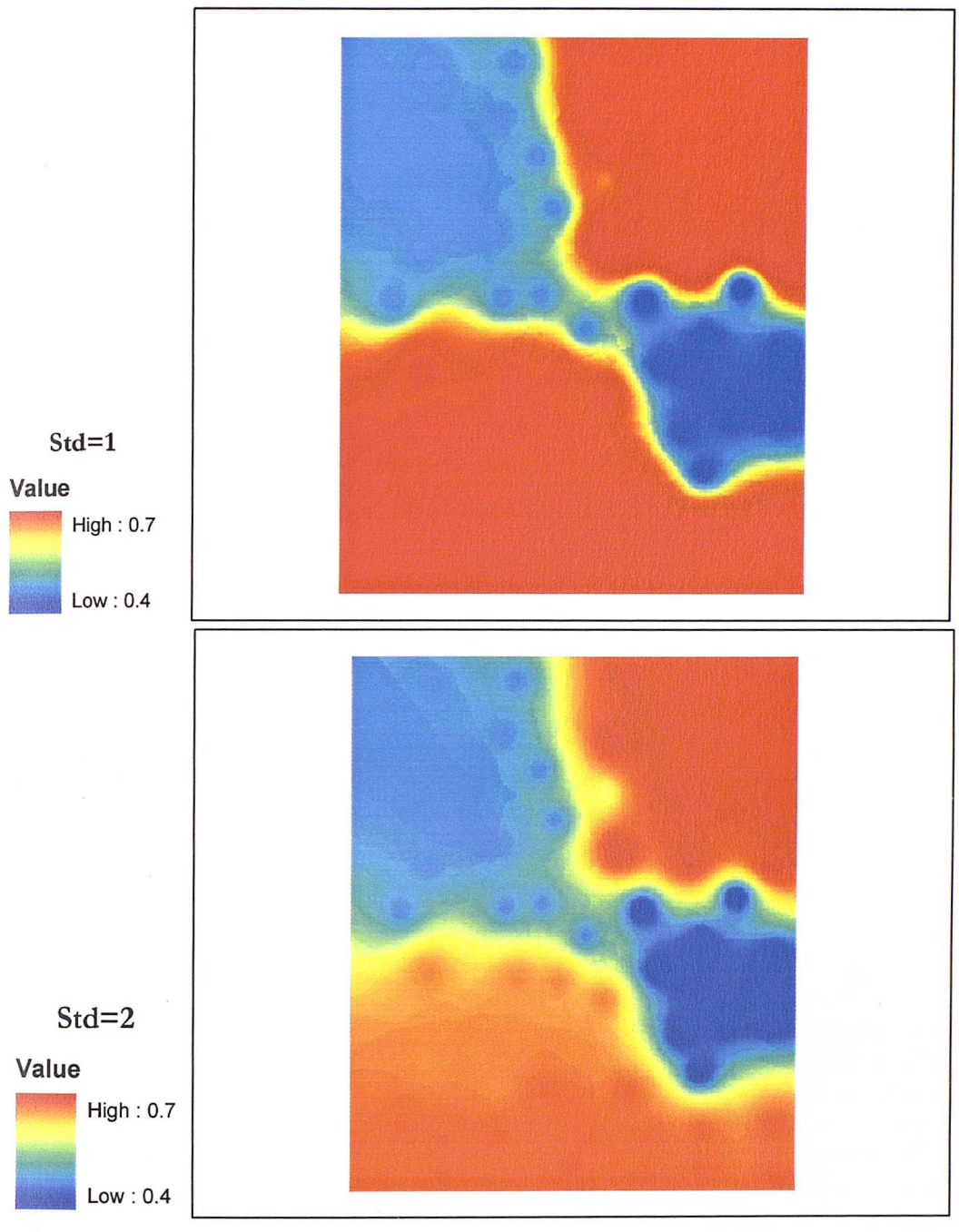


Figure 5.15. The soil aggressivity vulnerability layers corresponding to standard deviations of 1 and 2

It should be noted that due to the parameters used in this example (summarised in Table5.8) the resulting layers in Figure 5.15 are quite different from the ones produced by the inference procedure in Figure 5.13. This is because the standard deviations of the Gaussian functions used in Figure 5.15 are not sufficiently large to allow for an adequate overlapping between the fuzzy sets needed to correctly model the inference rules. In this case, pH=4 is clearly an acidic but the set "acidic" has a mean of 2 and a standard deviation of 1 and 2 for the upper and lower maps of Figure 5.15 and therefore 4 has a very low membership in set "acidic". The example serves two purposes: it illustrates the sensitivity of the system to changes in parameters affecting the shape of the fmfs and stresses the importance of parameters that adequately cover the variables' space and allow for a meaningful (in terms of the rule base) overlapping of both the antecedent and consequent fuzzy sets.

(b) Uncertainty in the data

The proposed approach acknowledges the fact that data input to the FIS are uncertain as well. For example if pH data are not collected for each and every point in the network but are a result of interpolation from point measurements (as is generally the case), there is considerable uncertainty as to the exact value in any specific point depending for example on the interpolation procedure (e.g. spline, kriging, inverse distance weighting), and the distance to a control point (to name but a few possible factors affecting data accuracy). Data uncertainty has been taken into account by treating data not as a single number (a *singleton* input) but as a fuzzy number, with -in this case- Gaussian membership function, where the mean (and therefore most probable value) is the value of the original data measurement and the standard deviation is specified by the user and applied to all inputs based on a belief about the measurement accuracy (Figure 5.16). This practically means that there is a "most probable" value for the data input (equal to the measurement) but there is also a (lower) possibility of the value being somewhat lower or higher.

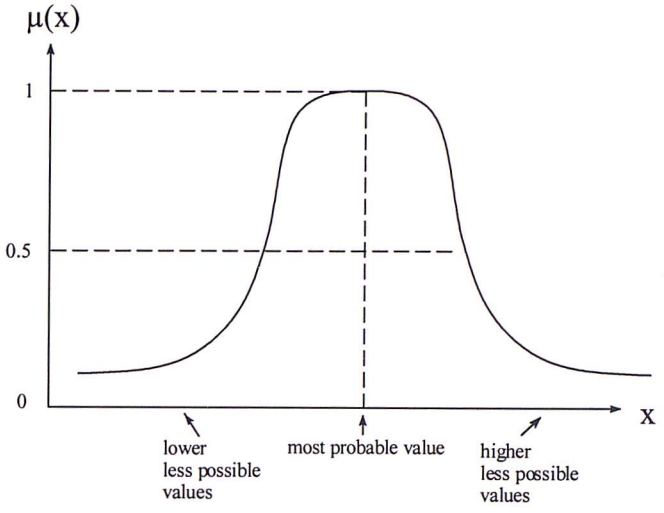


Figure 5.16. A fuzzy number quantifying data uncertainty (where μ(x) is the membership value of x)

The analysis quantified differences resulting from *non-singleton inputs of varying standard deviations*. The results (Figure 5.17) indicate that with increasing standard deviation of the input measurements (and thus increasing uncertainty) the numbers of cells with high vulnerability ratings decrease, while the number of cells with medium vulnerability ratings increase. The values of standard deviation used are 1, 3 and 5. The antecedent sets standard deviation was always equal to 1.

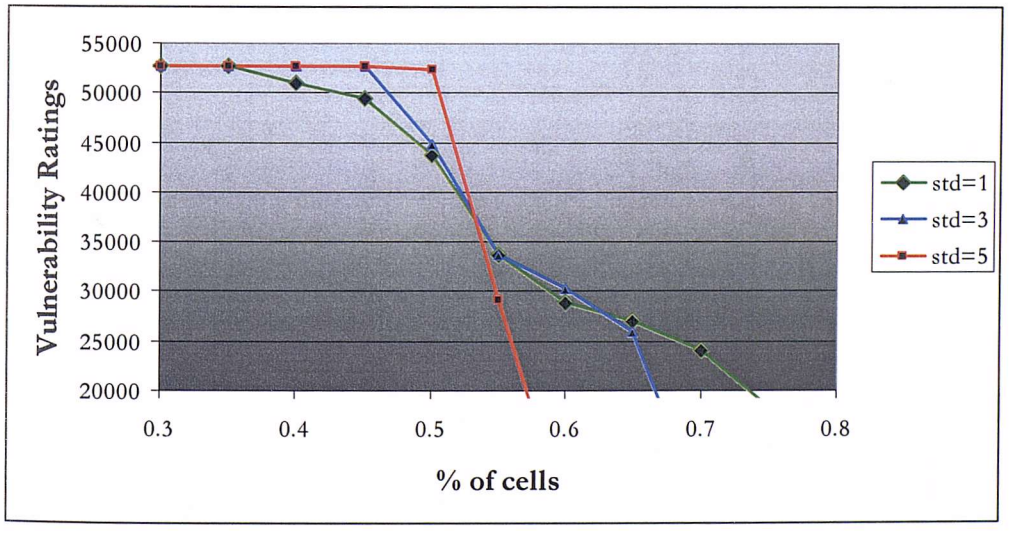


Figure 5.17. Cumulative graph displaying the effect of increased data input uncertainty (through changes in standard deviation)

The reason for this effect of increased standard deviation (and thus increased uncertainty) can be observed in the schematic of Figure 5.18.

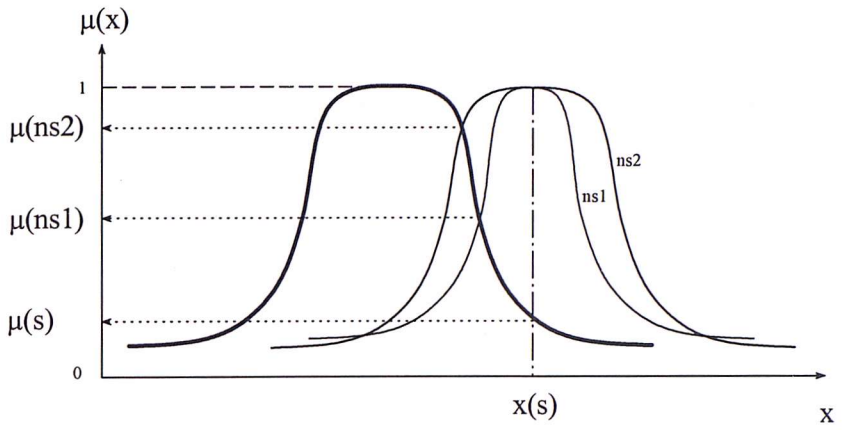


Figure 5.18. Fuzzification of two fuzzy numbers (ns1 and ns2) both with x(s) as their most probable value but different standard deviations (st.d of ns2 > st.d of ns1)

The effect of uncertainty in the input data represented here by increased standard deviation of the input fuzzy number is that the input value is associated with a progressively larger membership value to the antecedent set (the left most set in Figure 5.18). This is in recognition of the fact that more values are associated with the input value (although with a smaller possibility[1]), and these values are bound to have larger memberships than the "most probable" one in any antecedent set. The more uncertain a fuzzy number is (i.e. the larger its standard deviation) the larger its membership value is to all antecedent sets. The defuzzification procedure (a centroid defuzzifier) calculates the crisp output as the value associated with the centroid of the consequent set resulting from the application of all relevant rules. If the result from the singleton input was a neutral one (i.e. a medium suitability associated with the middle one of three consequent sets) the effect of this increase is not significant. If however the result was a small or large suitability, the increase in all sets shifts the new result towards the middle, producing more "indifferent" results as was to be expected from a physical viewpoint. This increase of medium suitability ratings at the expense of the high suitability ratings explains the shape of Figure 5.17.

[1] The term *possibility* is used here as the *grade of membership* of an input value to a fuzzy set.

(c) Uncertainty in the rules

Another interesting example of the WDM-SDSS results is the output of the type-2 FIS where the user is able to incorporate his perception of uncertainty in the rules as well. This is programmed by using, as antecedent and consequent set fmfs, Gaussian functions with uncertain means, which are assumed to lie in an interval [m1, m2] and a common standard deviation. The example given below, uses the type-2 singleton FIS to assign suitability ratings for metering introduction based on population density. The user specifies the intervals [m1, m2] for both antecedent and consequent fmfs and the standard deviations (one for each of 3 antecedent and 3 consequent fmfs). The output is in the form of 3 maps containing the mean value of the outcome as well as the minimum and maximum values for the same locations. This approach can provide a transparent estimation of the effect of rule uncertainty to the final proposed composite scenario. The analysis (Figure 5.19) was performed for antecedent fmf with the parameters shown in Table 5.9. Figure 5.19 shows three output suitability layers for the same input [max: (upper map), mean: (centre map) min: (lower map)], of a type-2 FIS, indicating the level of analysis uncertainty associated with rule uncertainty. The mean (centre map) result coincides with the result obtained by the equivalent Type-1 FIS with non-fuzzy antecedent fmfs whose defining parameters (in this case the mean) are given by the mean of the values of the interval presented for each function in Table 5.7. For example the "medium" population density fmf of the equivalent Type-1 FIS has a mean of 100 and a standard deviation of 20). The advantage is in the fact that specifying the (rule) uncertainty as an interval in the Type-2 FIS allows the result of the analysis to vary accordingly (Figure 5.19). The visualisation of the uncertainty propagation within the FIS is one of the most interesting characteristics of the use of Type-2 FIS within an SDSS.

Table 5.9. Parameters used in the Type-2 FIS resulting in Figure 5.19 outputs

Fuzzy membership function	**Antecedent sets (Population density in inhabitants/km²)**	**Consequent sets (Suitability to metering introduction)**
Low	(mean:[-20,20],st.d.:20)	(mean:[-0.15,0.15],st.d.:0.2)
Medium	(mean:[80,120],st.d.:20)	(mean:[0.35,0.65],st.d.:0.2)
High	(mean:[180,220],st.d.:20)	(mean:[0.85, 1.15],st.d.:0.2)

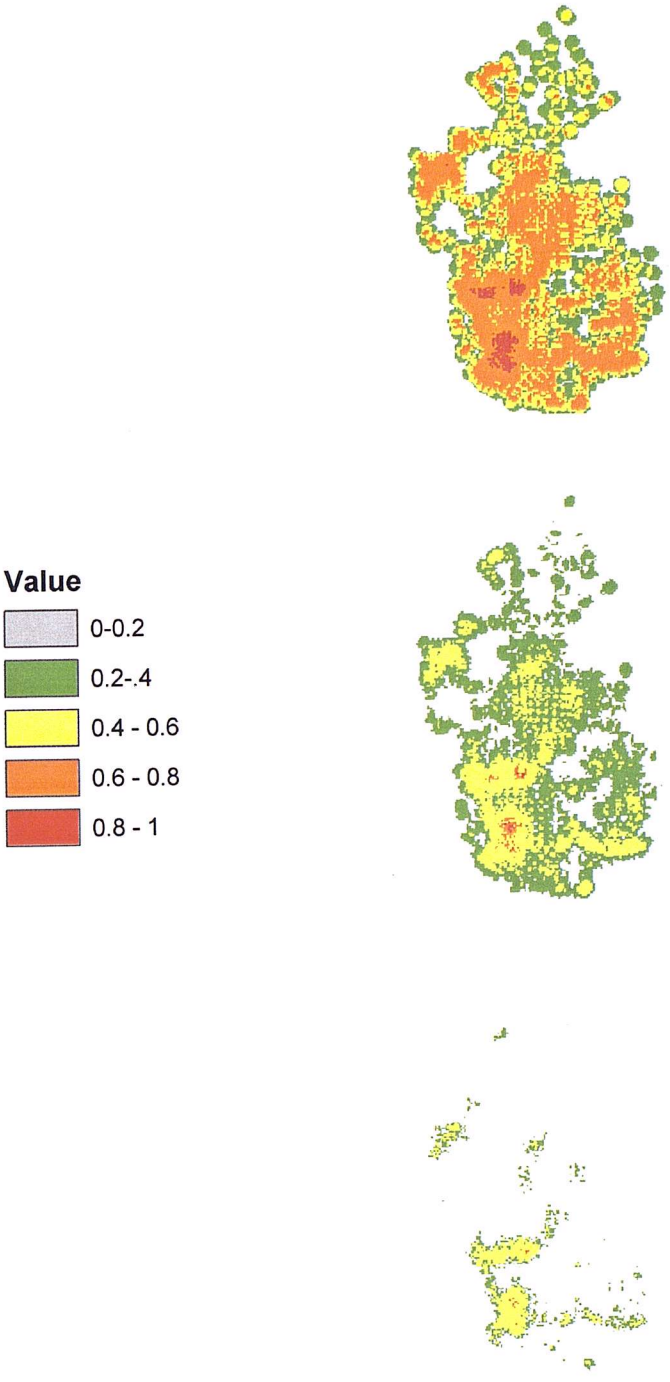


Figure 5.19. Three output suitability layers for the same input of a type-2 FIS, indicating the level of analysis uncertainty associated with rule uncertainty [max: (upper map), mean: (centre map) min: (lower map)].

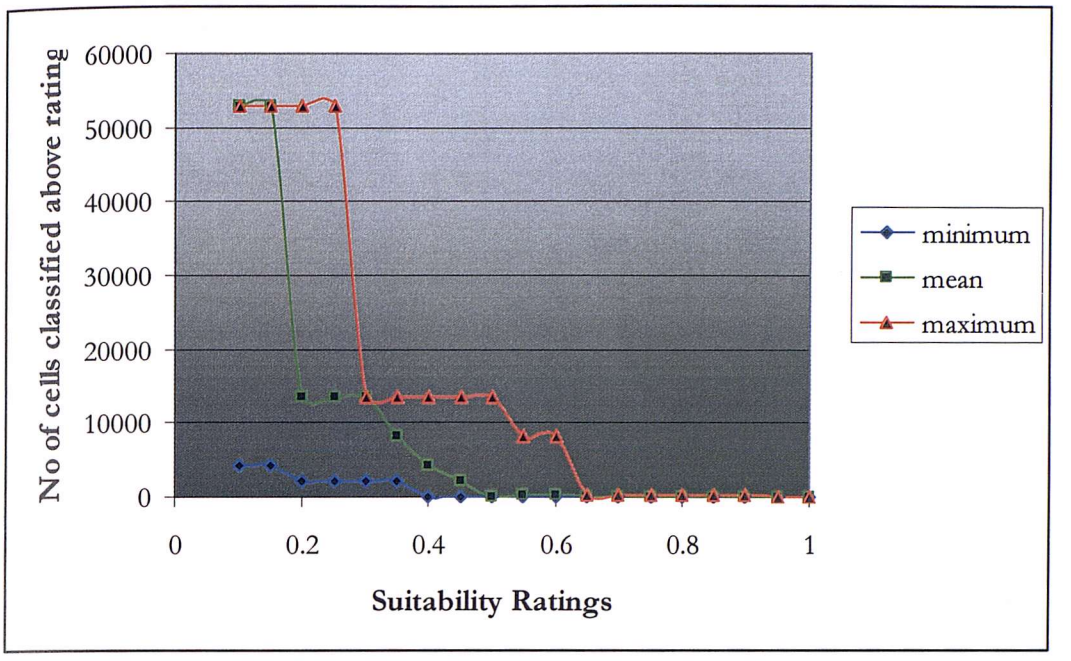


Figure 5.20. Cumulative graph comparing the suitability ratings of the three outputs for the case of population density attribute of metering introduction as a WDM strategy.

Figure 5.20 illustrates the envelope of uncertainty (between the maximum and minimum value) incorporated in the three layers of Figure 5.19, by identifying the changes in the suitability ratings for households considered for metering introduction. This provides the decision maker with an understanding of the uncertainty propagation through the decision making process, thus allowing for more informed decisions. By identifying the elements causing greater variations in the end result, the decision maker can identify information or knowledge gaps crucial to the analysis and thus better manage the resources for collecting them.

The result is presented through the GUI as three layers (Figure 5.21), the middle containing the mean value of the outcome (corresponding to the centre of the interval type-reduced centroid) and the lower and upper are the min and max values (corresponding to the $[y_l, y_r]$ of the type-reduced centroid) for the same locations. Higher suitability values are plotted as higher lines. The reason why this figure is not continuous is that this refers only to individual (discrete) housing cells rather than being a continuum over a surface. The actual suitability values cannot be observed from this schematic but all three outputs are saved and can be used for further analysis (aggregation and optimisation) enabling the user to develop a range of scenarios from best to worst-case

by using three layers which identify the extend of rule uncertainty propagation through the FIS. This approach can provide a transparent estimation of the effect of rule uncertainty to the final proposed composite scenario.

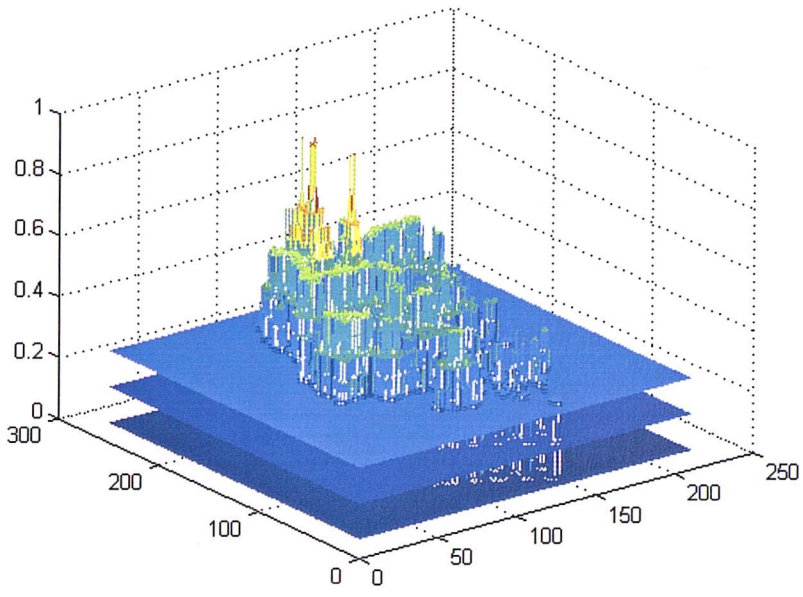


Figure 5.21. Schematic of the three output suitability layers [max, mean, min] of a type-2 FIS. X and Y-axis represent latitude and longitude of the case study site while the Z-axis represents suitability.

5.3.2 Stage 2: Aggregation

Stage 2 consists of comparisons between results from different aggregation procedures and will investigate the effect of the level of risk accepted by the user to the aggregation outcome. This issue is partly covered by the results presented in case study I but some will be repeated here for completeness. Furthermore, issues of aggregation associated with spatially variable levels of risk (Spatial Ordered Weighted Averaging procedure) will be investigated and results presented.

(a) Level of risk

As mentioned earlier, the user is presented with a number of weighting techniques including OWA. For a number of attributes standardised through the same inference procedure (in this case type-1 singleton) the user can incorporate his/her decision-making attitude towards the problem, by specifying an acceptable level of risk and associated decision making optimism. The analysis specifies a set of weights

corresponding to either user-specified degrees of risk and trade-off or to user-specified degree of risk and maximum entropy (O' Hagan, 1988). In the examples given below, the later approach has been used. Specifically, the leakage vulnerability map was derived from its attributes, for a number of user specified degrees of acceptable risk. Figures 5.22-5.25 are the results from equal direct weighting (the attributes are considered of equal importance) for a degree of acceptable risk varying from 0 to 1. Note that **values of risk closer to 1 indicate risk aversion as they will increase the weights assigned to the first ranked alternatives** (cells in this case) **and thus increase the number of cells classified as vulnerable**. A risk aversion attitude will result in a conservative approach to leakage repair (i.e. aim to repair the largest number of cells under suspicion).

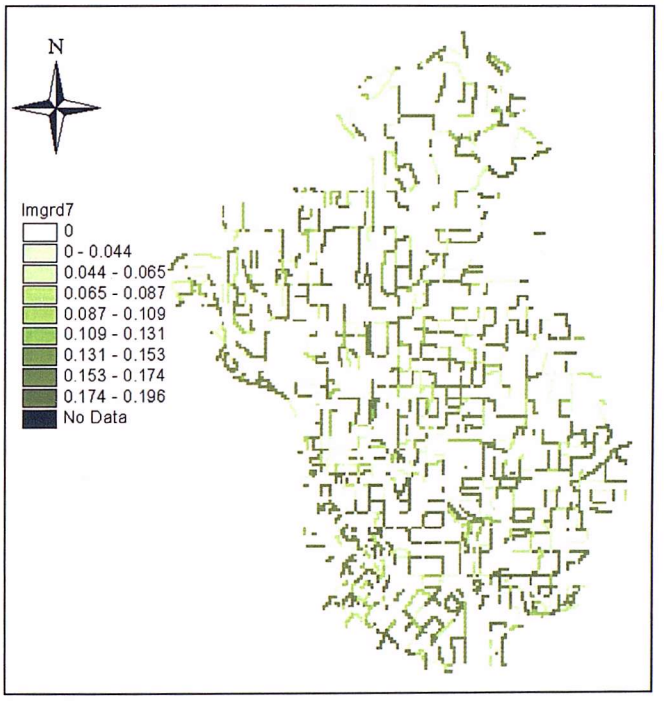


Figure 5.22. Leakage vulnerability for level of risk aversion= 0

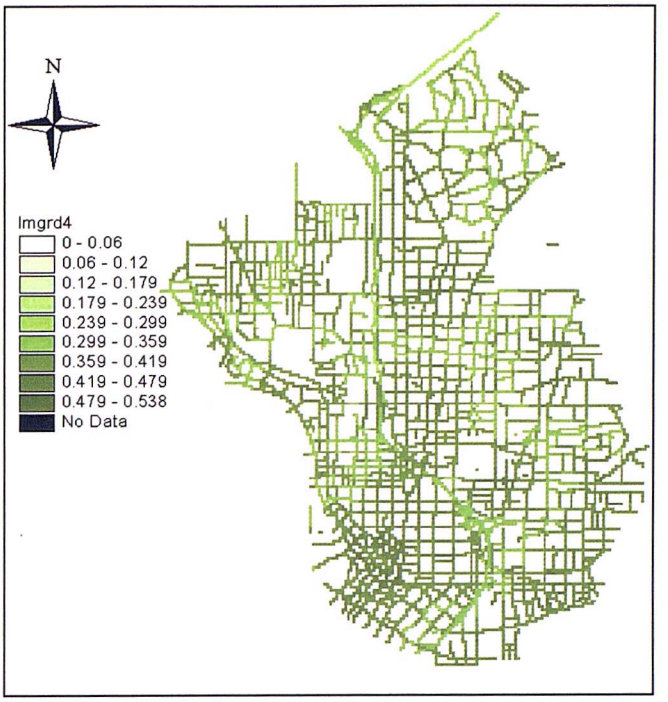


Figure 5.23. Leakage vulnerability for level of risk aversion = 0.6



Figure 5.24. Leakage vulnerability for level of risk aversion= 0.8

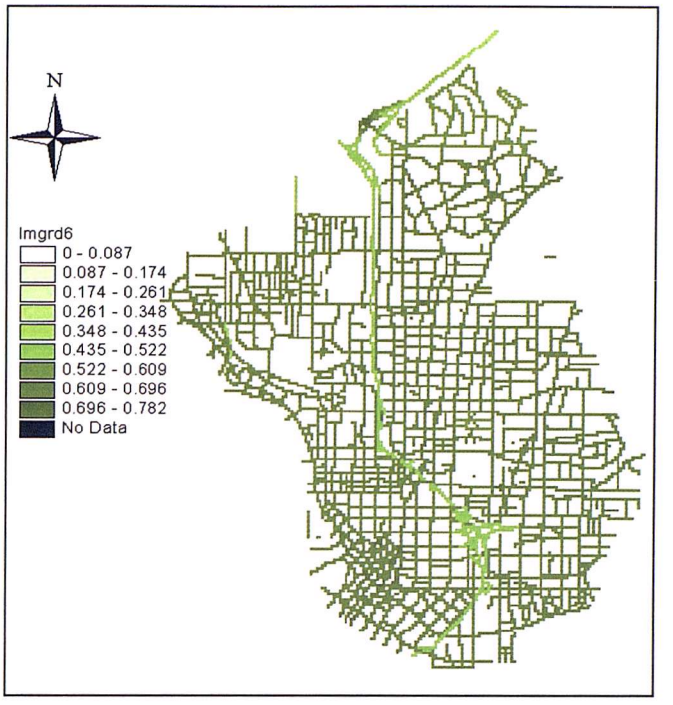


Figure 5.25. Leakage vulnerability for level of risk aversion= 1.0

The increase in cells labelled as vulnerable under the maximum risk aversion decision attitude is not surprising considering the fact that this represents the synthesis of the worse case for each attribute cell, and can be viewed as the upper limit of the decision alternative's space. Similarly, the maximum risk-taking scenario (R=0) can be viewed as the lower limit with all intermediate attitudes lying in between.

(b) Spatially variable risk

As discussed in Chapter 4, a novel aggregation technique was developed for the purposes of this work to enable the inclusion of spatially variable risk aversive attitude within the decision making process. The technique allows the decision maker to import the spatially variable measure of risk as a GIS layer and use it to perform OWA on a cell-by-cell resolution. One of the main forms of spatially variable risk relevant to urban water management, namely urban flood risk was used here as an example of this technique. The SDSS allows the user to derive the urban flood risk map using the following GIS layers as attributes:

- Domestic property value
- Category of road

- Probability of existence of basement
- Proximity to sensitive customers (e.g. hospitals)

The attributes are passed though a FIS where the user can associate them with flood risk according to his/her (risk) perceptions and priorities. Figure 5.26, is an example of the composite flood risk map derived using data for all four attributes. As observed in the figure, individual housing units are categorised (based on property value and existence of basements), zones around sensitive customers (e.g. hospitals) are identified as areas of high risk and major roads are assigned a higher flood risk value.

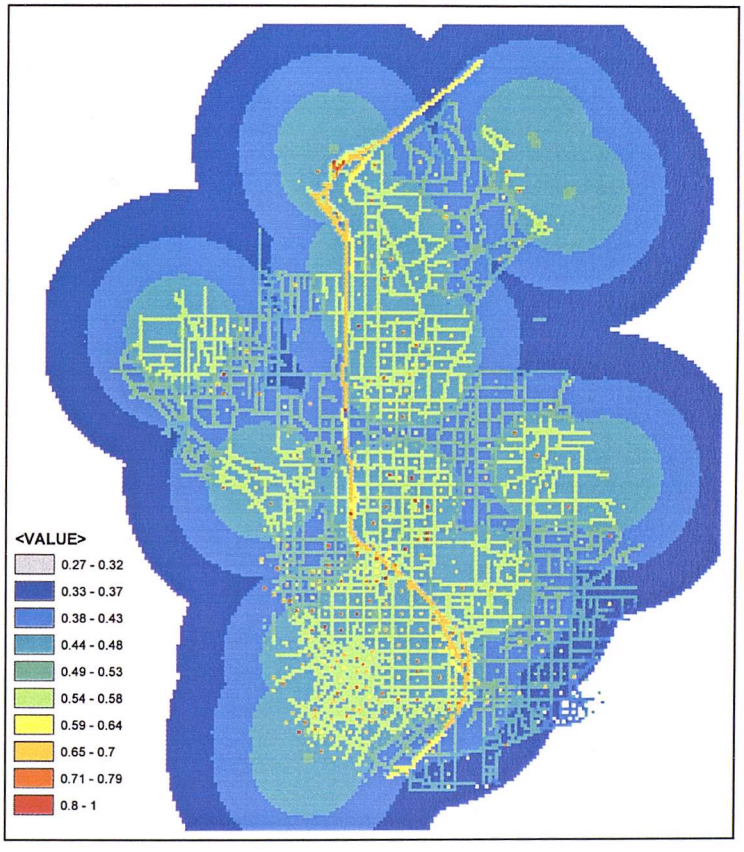


Figure 5.26. Detail of the composite map of flood risk

The assumptions and linguistic rules used to associate the attributes to flood risk are explained in Chapter 4. The flood risk layer was used as a spatially variable risk aversion matrix to produce the composite leakage vulnerability map of Figure 5.27.

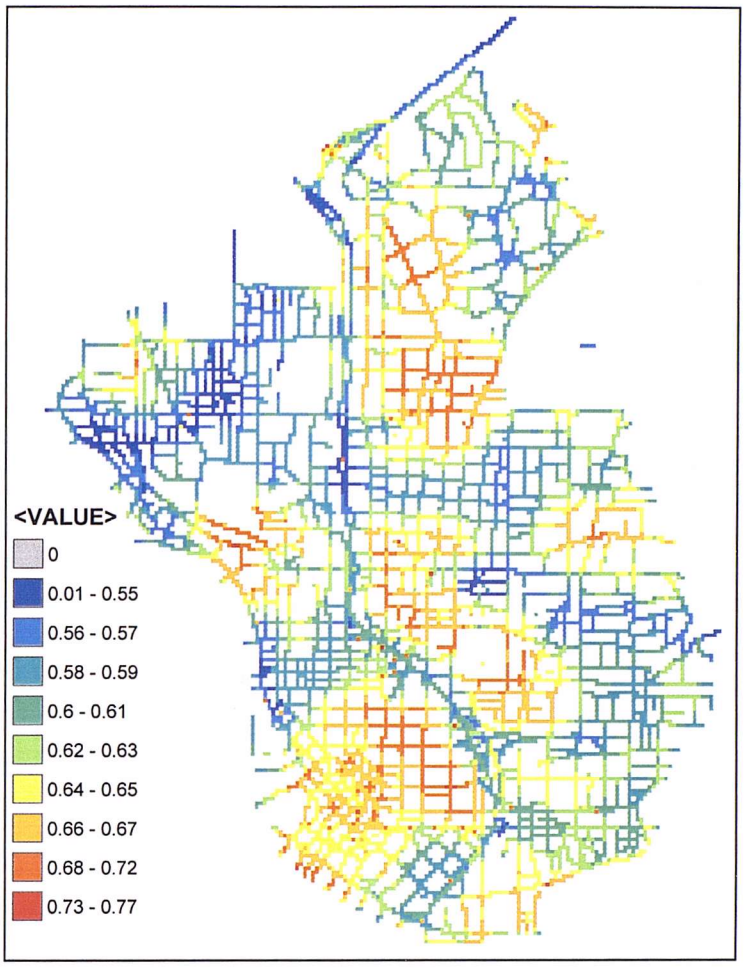


Figure 5.27. The leakage vulnerability map (SOWA procedure)

The effect of the weighting matrix derived from the spatially distributed risk aversion attitude to the result of the aggregation procedure is clearly observable in Figure 5.27. The SOWA procedure, based on flood risk, represents a more objective way for decision makers to specify their risk aversion attitude towards the attribute composition in the aggregation process. Depending on the priorities of the decision maker the flood risk layer can incorporate more or less attributes and thus influence the pipe prioritisation process to tae into account social, environmental and purely financial costs.

5.3.3 Stage 3: Optimisation

Stage 3 will compare the results of the same initial input suitability maps to the spatial optimisation routines under varying optimisation techniques, user input scenarios, including changes in investment, cost of application of strategies and expected water savings.

There are three optimisation procedures available to the user in the SDSS to solve the spatial problem discussed in Chapter 4: A "conventional" non-linear constraint optimisation technique and two genetic algorithms procedures (a single objective and a multi-objective one).

(a) The non-linear constraint optimisation procedure

A number of scenarios were investigated to assess the effect of changes in investment and cost of installation on the actual composite scenario proposed by the SDSS. Composite scenarios resulting from input suitability maps aggregated under varying levels of risk-aversion were also developed to assess the effect of the decision maker's "attitude" to the overall plan.

The actual optimisation problem is based on a number of assumptions, both in costs and water savings in the various scenarios discussed. The assumptions closely follow the average values given by the water industry in the OFWAT 98-99 Reports (OFWAT 1998; OFWAT 1999) and should be thought of as estimates rather than exact deterministic predictions. They will be outlined next, classified by water demand strategy.

Leakage Reduction

The initial average value given in the OFWAT report is 11.2 m^3/km/d and the industry's target is 4 m^3/km/d, which is a 75% reduction. It was assumed that by repairing/changing a part of the network, a reduction of 75% could be achieved for that particular part. This can be considered a realistic estimate. The average cost for repairing/changing a metre of water pipe varies depending on practices, wages, and particular contracts. An average value of £15/m was used in this model.

Compulsory Metering

An average reduction of 10% between metered and non-metered households is assumed (as indicated in Foxon *et al.*(2000) together with £160 cost per household for installation (NRA 1995).

Grey Water Recycling

OFWAT (1997-98) assumes a 33% reduction in water consumption and Opitz and Dziegielewski (1998) discuss possible savings of up to 50%. In this case an average of

40% reduction was assumed, which can be considered optimistic and is actually an effort to promote the strategy, which would otherwise be completely outweighed by its installation price (£1000 per household) in the optimisation process.

General water consumption assumptions

An average consumption of 200 l/inhabitant/day and an average occupancy of 3 inhabitants/household were assumed in accordance with conservative UK estimates (Russak et al, 1991; Butler and Davis, 2000).

The results of 5 scenarios evaluating variations of the prices of metering and recycling installation can be seen in Table 5.10. The results are in no particular order and all result from investment of £2.7M while the acceptable risk level for all strategies was fixed at 0.5. Results indicate that the actual cost of installation plays an important role in determining the preferential applicability of the strategies. Thus, the outcome is sensitive to technological changes (new cost effective devices for recycling and metering with lower installation costs or new improved cost effective techniques for leakage repair). Due to the investment associated with the installation of grey water recycling systems in individual houses, the technique only becomes attractive after a significant reduction in price, when, due to its significant estimated reduction per household, it tends to dominate the proposed composite plan. This suggests two main conclusions: the installation of grey water recycling systems can only be considered a viable strategy when the consumption is particularly high. Therefore, with the current installation price it can only be considered for large public or private buildings (offices, schools etc) rather than individual dwellings. Secondly, if the price of the installation drops significantly, either by technology change or financial promotion, it can become a primary strategy due to its ability to decrease water demand without actually decreasing consumption.

Table 5.10. Scenarios and results for various installation prices

(Investment = £2.7M, Risk Level = 0.5)

Scenario	**1**	**2**	**3**	**4**	**5**
Cost for leakage repair (GBP/m)	15	15	15	15	15
Cost metering installation (GBP/household)	160	160	160	160	180
Cost g/w recycling installation (GBP/household)	1000	500	700	800	700
Length of network repaired (km)	140	19	100	135	100
No. metering installations	3650	3600	3650	3600	5
No. g/w recycling installations	5	3650	875	103	1710
Water saved (m^3/d)	963	1206	977	964	958

A composite scenario can be seen in Figure 5.28. The system indicates the exact locations of the most vulnerable parts of the network as well as the preferential locations for the installation of grey water recycling and compulsory metering. The final product is a master plan for the site-specific implementation of the combined strategy for water demand management. The master plan can be derived at a strategic level as well as at an application level depending on the resolution of the spatial information available.

Although metering and recycling schemes can be installed in either individual houses or entire blocks with no particular difference in terms of economy of scale, pipe replacement is an operation that benefits (financially) from economies of scale. Depending on the pipe replacement policy of the water company in charge of the network, decisions can be taken based on the composite result as to the desired pipe replacement scheme. The company may opt for replacing the specific pipes identified by the SDSS if the pipes to be replaced are close enough to make the replacement feasible from an operational/logistics point of view (as is, for example, the case in Figure 5.28), or a decision for a more grouped pipe replacement scheme can be taken, based on either a statistic derived from the vulnerability ratings of the leakage vulnerability map (for example a district chosen for complete pipe replacement can be identified as the one with the higher mean vulnerability value) or based on the number of pipes to be identified as replaceable from the composite scheme map (for example a district including the largest number of pipes identified for replacement would receive top priority). In Figure 5.29, the case study area is aggregated into intervention areas. In this

specific example the areas are 700x700m but they could also follow DMU patterns or indeed any other area size the company and its contractors find easy to work with. The information used to prioritise the intervention at these larger 700x700m areas, in Figure 5.29, is the mean of vulnerability values of all pipes in each area. The assumption is that areas with higher mean vulnerability should be replaced prior to those with lower.

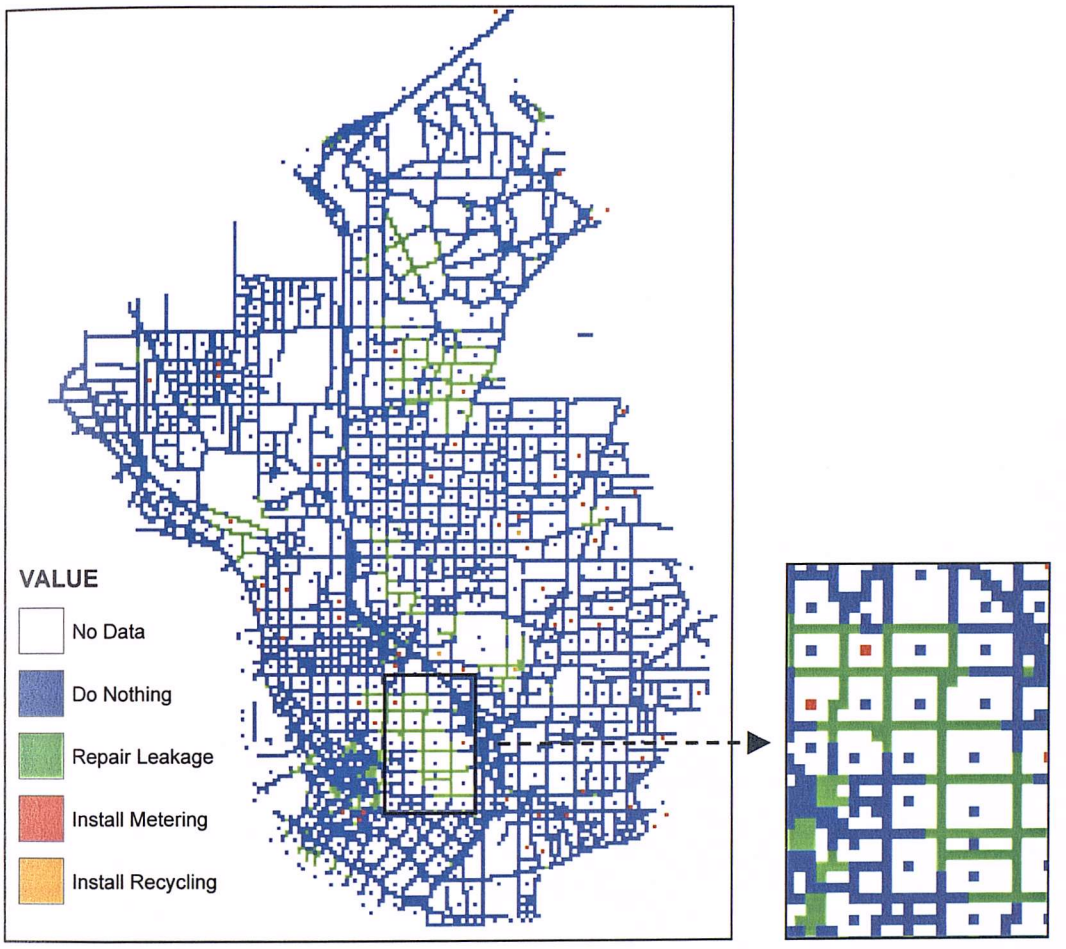


Figure 5.28. An example of the optimisation module output (non-linear optimisation method) for an investment of £500,000

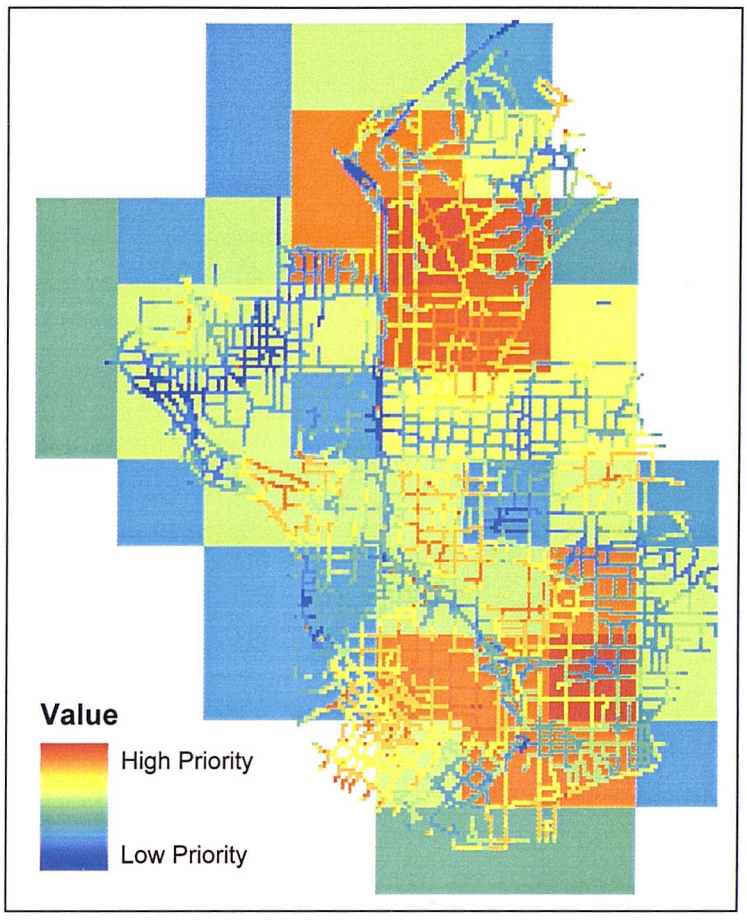


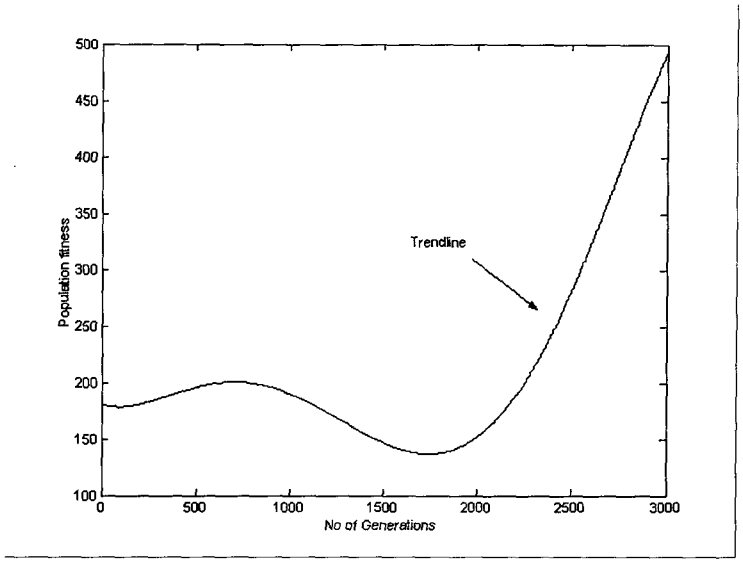
Figure 5.29. Prioritisation of pipe replacement at a larger area scale

The result presented in Figure 5.29 is far less site-specific, but may be more practically useful to the water companies. Due to the range of available policy options as well as the uncertainty within the water industry itself as to what constitutes the best intervention policy in terms of its financial implications, the further customisation of the tool towards some particular policy was considered to be outside the scope of this work. In any case, the current SDSS results can serve as a basis for a variety of prioritisation and intervention schemes, depending on company policy, with minimum effort on behalf of the decision maker.

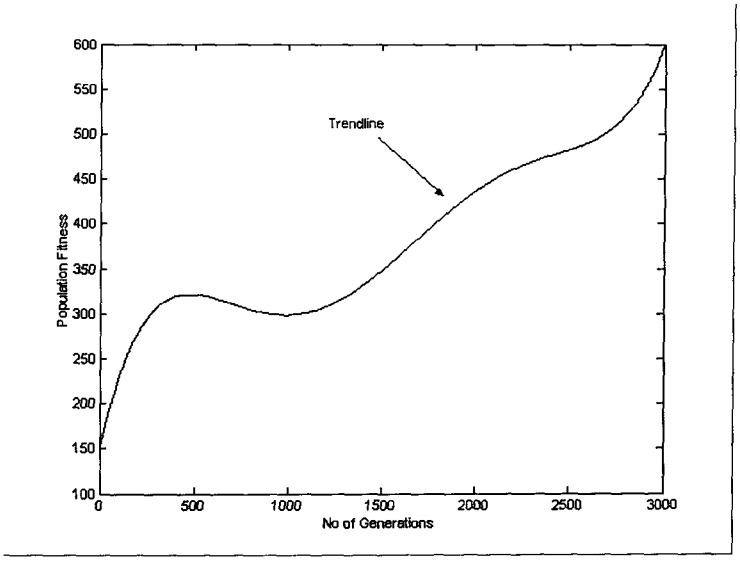
(b) The single objective genetic algorithm optimisation method

The next issue addressed is the performance of the single criterion genetic algorithm optimisation process. The following figures show examples of the convergence of the algorithm. Figures 5.30 (a) and (b) are examples of the use of a roulette wheel selection process, while (c) is an example of the stochastic universal sampling process. The latter outperforms the first two models both in terms of fitness achieved and time needed to

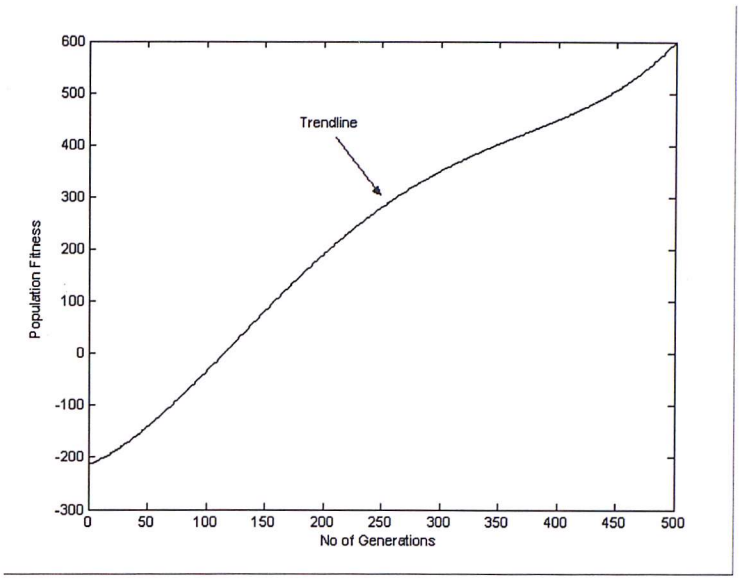
achieve convergence (indicated here by the number of generations needed). The trendline is an interpolation through the total fitness values of the populations at each generation.



(a)



(b)



(c)

Figure 5.30. Examples of the convergence of the genetic algorithm for a range of selection procedures

A common problem was set-up for both the single objective genetic algorithm (SOGA) and the conventional sequential quadratic programming algorithm (SQP). The same input layers for leakage, metering and recycling suitability were used in both optimisation procedures and the analysis was performed for a target water reduction of 200 m^3/day (Table 5.11). The optimisation is performed with cost as the function to be minimised.

Table 5.11 Comparison between SQP and SOGA (target reduction=200m^3/d)

	SQP	**SOGA**
Cost for leakage repair (£/m)	15	15
Cost metering installation (£/household)	160	160
Cost g/w recycling installation (£/household)	640	640
Length of network repaired (km)	19	17.6
No. metering installations	28	143
No. g/w recycling installations	371	375
Cost (£)	527,400	526,800

The differences between the two solutions are (arguably) not significant, although multiple runs have indicated that the GA algorithm always slightly outperforms the SQP algorithm in terms of (minimising) total investment cost. The differences observed in

Table 5.11 are attributed to the fact that SQP is not actually solving the specific problem at hand (specific installations in specific location at a housing unit level), but rather an approximation of that problem as defined by the interpolation through the values of installation cells as a function of suitability, cost and achieved water consumption reduction. The polynomial function used for the approximation, although achieving a good fit (differences between actual and simulated values of the order of 10^{-10}), does not correspond exactly to the actual characteristics of the case study and the result is given by rounding up the (non-integer) solution retrieved by the optimisation algorithm. The solution given by the SOGA does not experience these problems, and accurately addresses the integer optimisation problem at hand.

Table 5.12 Comparison between SQP and SOGA (target investment: £530,000)

	SQP	**SOGA**
Cost for leakage repair (£/m)	15	15
Cost metering installation (£/household)	160	160
Cost g/w recycling installation (£/household)	640	640
Length of network repaired (km)	19.0	17.6
No. metering installations	75	150
No. g/w recycling installations	364	378
Water saved (m^3/d)	201.1	203.0

Table 5.12 summarised the results of the SQP and SOGA algorithms applied to the problem of maximising water saved for a fixed investment. The investment was chosen to be similar to the resulting investment proposed by the algorithms for the cost minimisation problem (Table 5.11) and the installation price assumptions were kept the same for comparison purposes. The main differences are observed between the results of the SQP algorithms and are clearly attributable to the inaccuracy of the fit of the polynomial used in both cases and therefore the indirect way the SQP algorithm is used to solve the spatial non-integer optimisation problem. The GA algorithms, which address the problem directly (rather than addressing a model of the problem by way of a function approximation), yield very similar results for both optimisation problems.

The convergence of the SOGA for the solution given in Table 5.11 can be seen in Figure 5.31. The population of solutions starts with high price composite strategies and the

algorithm forces the population to evolve into suggesting less costly composite strategies to achieve the same water target.

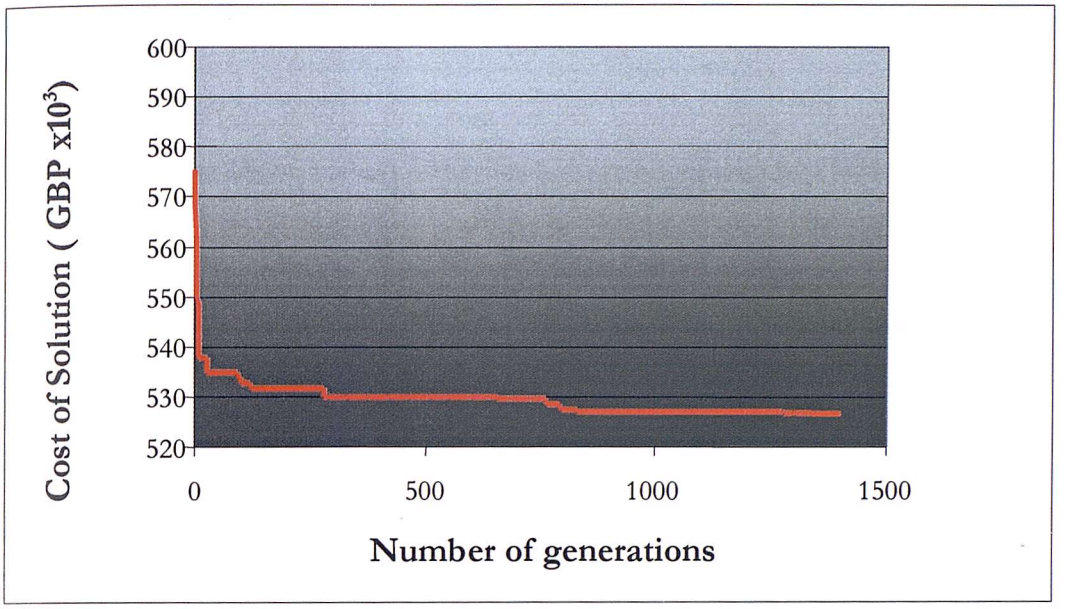


Figure 5.31. The convergence of the genetic algorithm procedure (best individual of every generation plotted against the number of generations)

The initial population is randomly selected from the overall population of viable solutions and the algorithm is allowed to run (in this example) for 1400 generations with a population size of 100. Figure 5.32 presents a comparison between genetic algorithms run for different population sizes. It can be observed that larger population sizes do not yield necessarily better results. On the contrary, convergence in large population sizes is faster in the beginning as there is increased probability of a better solution to be present in the initial generations, but then slows down considerably. In the cases presented in Figure 5.32, as an example, the best individual after convergence for the largest populations is slightly inferior to the best individuals of smaller populations. This is caused by the elitism of the selection strategy used, which keeps the best individual of each generation within the next generation: in small population sizes, the best individual has increased probability of being selected for mating and thus increased probability of contributing to the formation of a better individual[1]. In larger population sizes, the opposite is true.

[1] The premature convergence problems associated with elitist strategies are handled by a series of measures, including "temperature" controlled mutation rate (as discussed in Chapters 3 and 4).

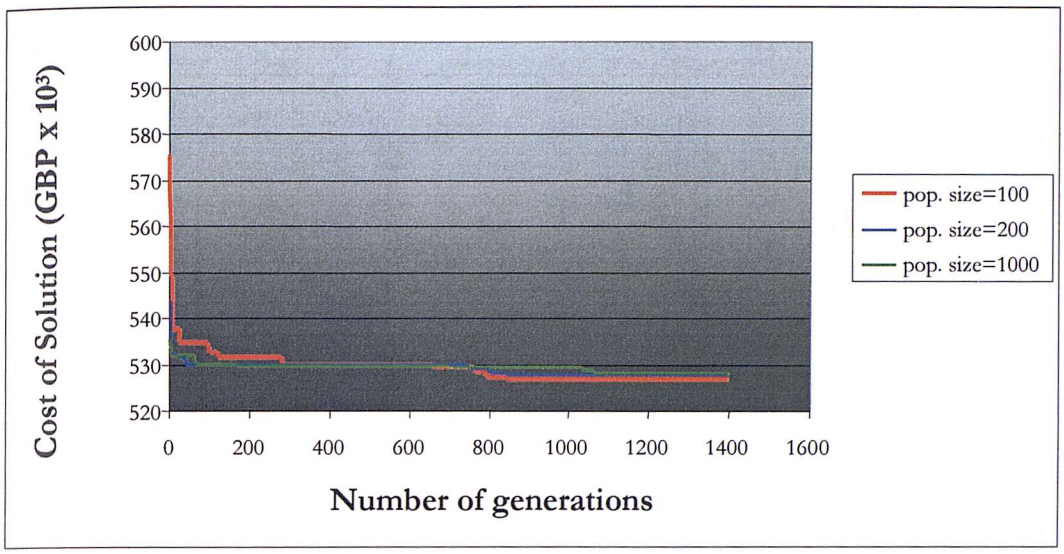


Figure 5.32. Comparison between GAs with varying population size.

As the matrix, from which the cells are selected to be included in the composite solution, is the same in both the SQP and SOGA procedures (all cells ordered by decreasing suitability), this means practically that if, for example, 100 network cells are selected for pipe replacement in both optimisation procedures, those cells will be the same 100 cells in both cases. There is therefore no reason to compare the final composite WDM maps resulting from these two procedures. Only the exact number of interventions suggested is of importance (Table 5.9). This is not the case however in the final optimisation procedure available to the user, which is conceptually quite different from the previous two: the case of multi-objective genetic algorithms. The results from this algorithm, and their role in the WDM decision process will be presented in the next paragraph.

(c) The multiple objective genetic algorithm optimisation method

The incorporation of a multi-objective approach to the composite strategy generation enables the decision maker to try to attain simultaneously three goals: minimise the cost, maximise the water savings and maximise the suitability of the cells selected for intervention. In this case, the problem is treated as a spatial optimisation one directly rather than being simplified through the use of suitability ratings as weights, while hill-climbing techniques are used for local search in a spatial sense. At the end of the process the specific constraint handling comes into place excluding large constraint violations.

Several system runs were performed to increase understanding of how the algorithm handled the specific problem and identify a set of parameters (number of epochs, number of generations within an epoch, mutation, crossover and substitution rates and rate of increase of population within from epoch to epoch) that could better tackle the problem.

In the examples presented below, the algorithm was run for a population size that started with 30 individuals and was allowed to increase by 10% from epoch to epoch for 5 epochs. Each epoch consisted of 100 generations within which the individuals were allowed to mate, mutate or be completely substituted at time-decreasing rates, starting with relatively high probabilities: 0.5 for the mutation operator, 0.45 for the crossover operator and 0.05 for the substitution operator. The water target was again set at $200m^3/d$ for comparison purposes. At each generation, the pareto set of the best (non-dominated) individuals was kept in a separate matrix.

The pareto set of the final generation of the 4th epoch, contained solutions that were very close to the set water target. Beyond the 4^{th} epoch the solutions became more expensive and achieved a larger water reduction than needed. The solutions presented are non-dominated solutions and therefore there is no predefined way to choose between them. The choice of a particular solution would be dependent upon the specific priorities of the end user and the situation at hand. A 3D plot of the solutions included in the pareto set, achieving the three objectives to a different extent, can be observed in Figure 5.33. Each solution is represented by the dot at the upper end of each line. The line itself has no physical meaning but is plotted to assist the 3D visualisation of the figure.

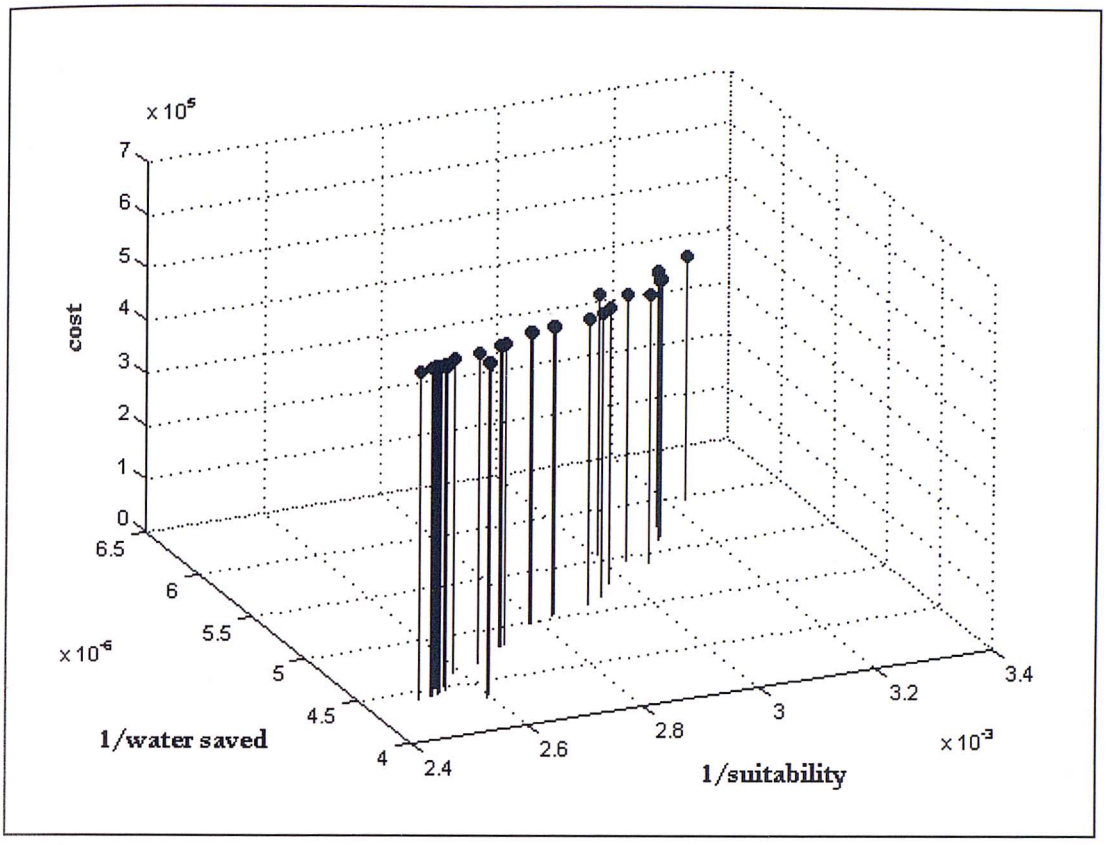


Figure 5.33. The solutions of the pareto set plotted against the three objectives pursued.

Figures 5.34-5.36 present each objective plotted against all others to better visualise the level of achievement of the three objectives for each solution.

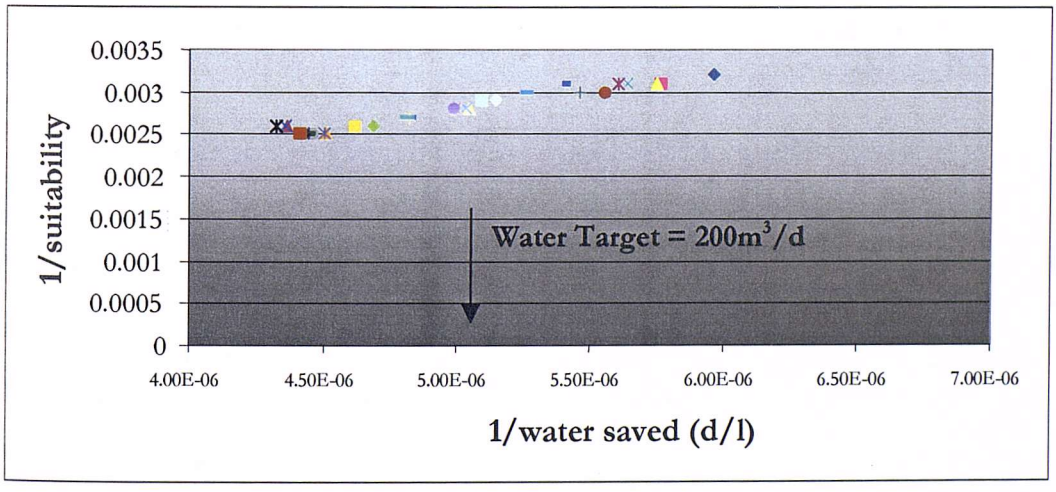


Figure 5.34. The pareto set (a)

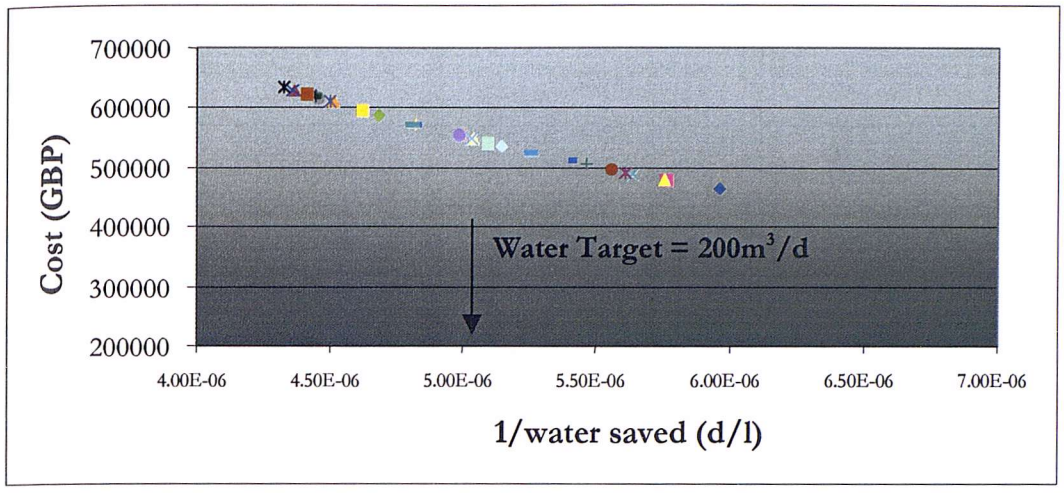


Figure 5.35. The pareto set (b)

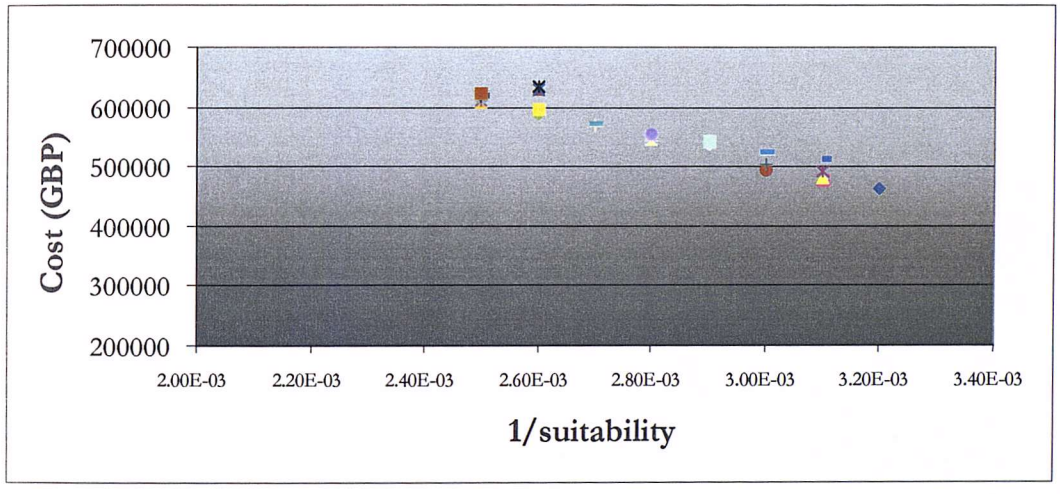


Figure 5.36. The pareto set (c)

In all of the above figures, the best solutions are closer to the beginning of the axis. As this is the pareto set, more than one choice (with associated pros and cons) is available to the user. The SDSS does not further prioritise the solutions, as this would decrease the flexibility of choices available to the decision maker, which would negate the main purpose for using multi-objective optimisation. Figure 5.37 is a plot of two of the most obviously associated objectives: cost and water saved and is presented here to assist the understanding of the decision space available to the decision maker in this particular problem.

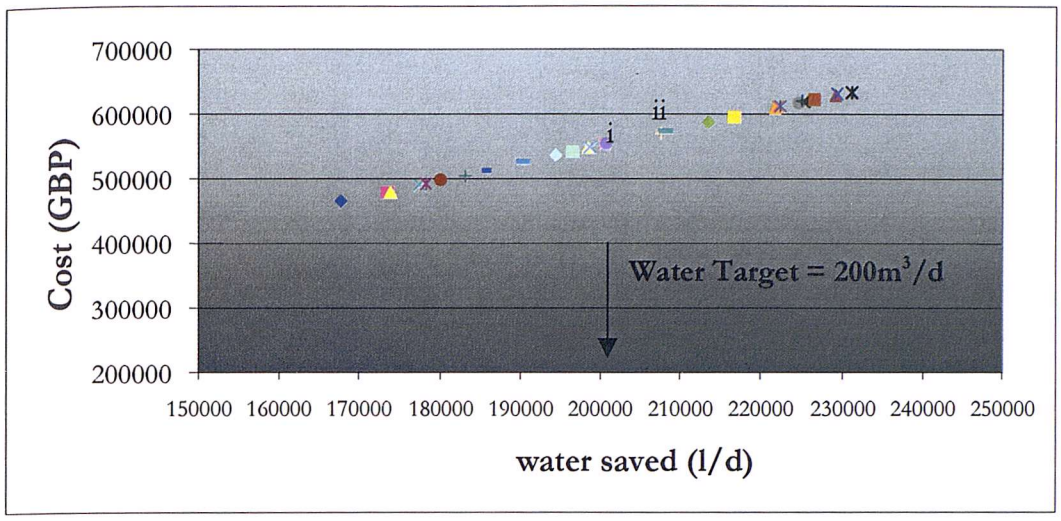


Figure 5.37. The solutions included in the pareto set of the last epoch (cost in £, water savings in l/d).

As expected, more expensive solutions achieve better water savings, but the fact that all the pareto solutions are available to the decision-maker with the trade-off between them clearly identifiable, allows for more flexible decisions, not possible under the single criterion optimisation processes discussed above (both SQP and SOGA). For example, between solutions *i* and *ii* identified in Figure 5.37, there is a step increase in investment resulting in a substantial increase in water savings. A single criterion optimisation procedure running for either a water target of 200m^3/d or an investment of £540,000 would ignore solution *ii* which provides around 210m^3/d for £570,000, although, in principle, there would be situations where solution *ii* might be the most favourable for a decision maker.

It can be further observed (from Figures 5.34-5.37), that the effect of the introduction of a crowding factor to favour solutions of the same pareto rank, that better explore the solution space (i.e. are not close to other solutions), has produced a final set of solutions that are evenly spread over the decision space, rather than being concentrated on a specific area, thus increasing the number of meaningful alternatives. Table 5.13 presents all solutions of the final pareto set, with their crowding factors and the number of suggested WDM interventions.

Table 5.13. The pareto set of the last epoch and suggested interventions per solution

1/suitability	1/water saved (d/l) ($x10^{-6}$)	Cost (GBP)	Crowding Factor	Network Repair (km)	Metering Applications	Recycling Applications
0.0032	5.96	462650	300	12.39	130	400
0.0031	5.76	478170	0.0032	12.66	108	423
0.0031	5.75	478970	0.0016	12.66	113	423
0.0031	5.64	488570	0.0018	12.66	113	438
0.0031	5.61	490970	0.0017	12.66	128	438
0.003	5.56	496130	0.0024	13.2	130	433
0.003	5.46	504100	0.0025	13.02	130	450
0.0031	5.4	511220	0.0034	13.05	105	467
0.003	5.25	524320	0.0037	13.23	143	473
0.0029	5.14	535530	0.0027	13.32	145	488
0.0029	5.09	540980	0.0024	13.47	145	493
0.0028	5.04	546550	0.0016	13.77	125	500
0.0028	5.03	547350	0.0012	13.77	130	500
0.0028	4.99	552100	0.0012	13.98	140	500
0.0028	4.98	552900	0.0029	13.98	145	500
0.0027	4.82	570020	0.003	14.25	113	528
0.0027	4.81	570920	0.0004	14.31	113	528
0.0027	4.81	571720	0.0024	14.31	118	528
0.0026	4.69	586880	0.0036	14.61	138	540
0.0026	4.62	595830	0.0028	14.94	143	545
0.0025	4.51	609200	0.002	15.12	143	562
0.0025	4.5	610550	0.0003	15.21	143	562
0.0025	4.5	611000	0.0007	15.24	143	562
0.0025	4.46	616750	0.0009	15.09	153	572
0.0025	4.45	618100	0.0003	15.18	153	572
0.0025	4.44	618550	0.0004	15.21	153	572
0.0025	4.43	619900	0.0004	15.3	153	572
0.0025	4.43	620700	0.0006	15.3	158	572
0.0025	4.41	623050	100.0008	15.51	153	572
0.0026	4.36	628670	0.0011	14.64	150	602
0.0026	4.36	629470	0.0007	14.64	155	602
0.0026	4.33	634270	200.0002	14.64	165	607

The solutions marked in red in Table 5.13, are the ones closest to the water target set in the simulation ($200m^3/d$). The solutions of the MOGA process are similar but not identical to those of the SQP and SOGA processes, due to the fact that in, this case, the algorithm is not forced to maximise the suitability value of the solution using some

predefined sorting method. The existence of three objectives makes the solution space much more complex and thus the algorithm has reached slightly less optimal solutions in terms of cost (of the order of £20,000 for the solution proposed to achieve water savings of 200m^3/d). The clear advantage is that the decision maker is presented with a range of alternatives whose differences in achieving the objectives are clearly identifiable. The main drawback of this optimisation method is that longer processing times are needed to reach a result due to the complex nature of the problem. This is, however, not considered to be a limitation of the method, as the increase in processing power available to engineers in the past few decades is much greater than the increase in the complexity of the problems they handle.

The algorithms were run under a range of both user parameters and input values (GIS layers). The most important characteristic accounting for differences in results between the optimisation algorithms was identified as the input data resolution. The difference in solutions proposed by the MOGA, the SOGA and the SQP algorithms increase with decreasing resolution, as the level of integration of households into one "housing unit" affects both the fit of the function formed within the SQP procedure and the attractiveness of the housing cells to the introduction of metering or recycling schemes. If the households to be integrated are numerous (i.e. low resolution) then the differences in intervention costs between a densely populated cell and a scarcely populated one are significant. It was found that this cost makes the introduction of (for example) metering in one more (costly, but with high water saving capacity) cell, less attractive than the repair of one more (relatively inexpensive but with lower water saving capacity) network cell. It was therefore found that when input data is of low resolution, the algorithms (with the exception of MOGA) tend to favour leakage repair against all other strategies. At a high resolution up to a house-by-house level, the results are similar (as shown in Table 5.11) and the proposed solution more balanced. Thus the outcome should be considered more dependable.

Figure 5.38, is a comparison between the first solution marked in red in Table 5.13 and the solution for the same water target given by the SOGA algorithm as described in Table 5.11.

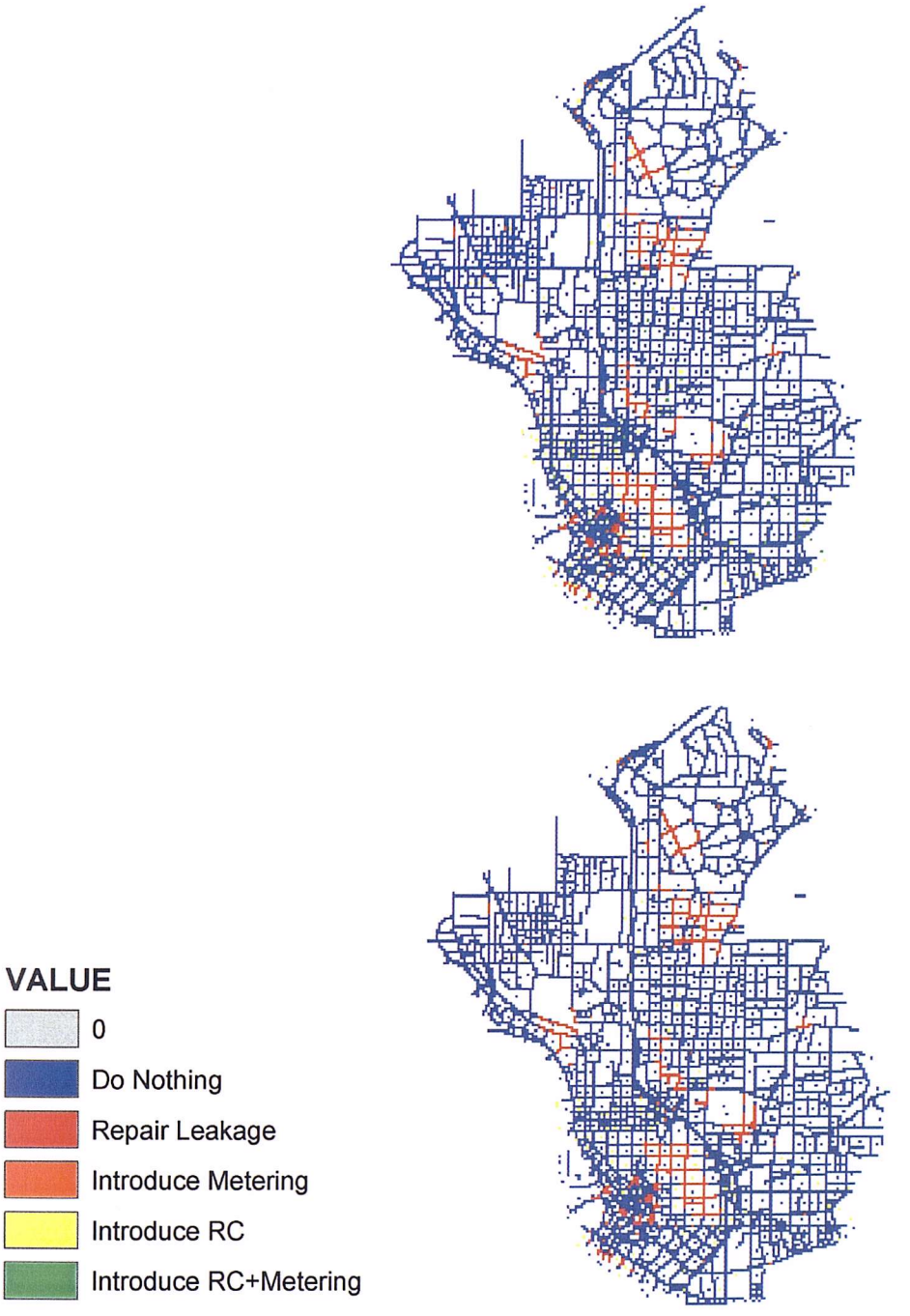


Figure 5.38. The composite map resulting from the SOGA optimisation process (upper map) and the MOGA optimisation process (lower map)

Differences in locations of intervention sites are not significant between the optimisation results even though the MOGA algorithm does not predefine the priority of intervention of the cells within each strategy. This is considered a very positive result increasing the confidence in the MOGA results.

5.4 Conclusions

The SDSS was run under various user-defined assumptions and for a range of control options to investigate the uncertainty quantification potential of the SDSS and present an overview of the sensitivity of results to the concept of uncertainty and risk of the decision maker. Alternative optimisation techniques were used and their results compared and discussed. The system's performance supports the assumption that the decision making potential for planning WDM schemes is greatly increased by the use of the SDSS as a tool for site-specific planning under user-defined or estimated levels of risk aversion and explicit uncertainty handling.

6. Discussion

"The purpose of scientific method is to select a single truth from among many hypothetical truths. But historically, science has done exactly the opposite. Through multiplication of facts, information, theories, hypotheses, it is science itself that is leading mankind from single, absolute truths to multiple indeterminate, relative ones. The major producer of social chaos, the indeterminacy of thought and values that rational knowledge is supposed to eliminate, is none other than science itself"

Robert M. Pirsig: "Zen and the art of motorcycle maintenance"

6.1 Preamble

A detailed discussion on the development of a Spatial Decision Support System for urban water management, with reference to its underlying concepts, development framework and application possibilities will be undertaken in this chapter. The author will seek to identify the main points of interest of the overall development and research process, as well as the strengths and weaknesses of decision support in general and the WDM SDSS developed in particular. The relevance of the work presented both to the (academic) research environment and the water industry will be analysed from a critical viewpoint.

6.2 Discussing the concept: Supporting Complex Decisions in the Urban Environment

Urban environmental planning is currently burdened with the task of creating a sustainable urban environment (Vlachos and Braga, 2001). But what exactly does this entail? Following the discussion on the urban "ecological footprint" (Wackernagel and Rees, 1996), a sustainable urban environment is one that minimises the city's dual role in a catchment's fragile equilibrium: the role of sink for resources and source for pollution. Concentrating on the concurrent role of water as a key resource and a pollution transport vehicle, it can be stated that the two main inputs of water into the urban environment are water supply and rainfall. Strategies for minimising fresh water demand for public as well as private use within the city in the form of Water Demand Management (WDM) can result in minimising water resource consumption, thus attaining the first minimisation goal. The same strategies coupled with minimising rainfall-runoff entering the drainage system (for example using Sustainable Urban Drainage Systems (SUDS) strategies (e.g. D'Arcy and Frost, 2001)) could result in less wastewater generation, improving treatment costs and attaining the second minimisation goal. Waste minimisation by itself, however useful, should also be coupled with research into the effect of these minimisation strategies on wastewater quality: either directly (through the purification capabilities of methods used for minimisation e.g. grass swales in rainfall runoff source control, gully pots viewed as reactors (Memon and Butler, 2002)) or indirectly (through the effect the minimised and more concentrated wastewater volumes will have in treatment plants from an engineering and cost-effectiveness point of view). The essence of urban sustainability and the extent to which strategies such as WDM or SUDS are truly sustainable at various

spatial or temporal scales is still, to a large extent, open to discussion. This issue is not tackled by the work presented here, which focuses on the application of WDM rather than it's in depth, critical assessment. WDM is a broad domain and, as discussed in previous chapters, the variety of methods that could be included to promote it range from economic incentives and legal regulations to technical measures. Only three technical strategies can be supported at this stage of the SDSS development although the same processes and methodologies presented here could be used to include various other strategies within the same framework. The list of strategies and the attributes associated with each strategy discussed in this work are not exhaustive but are presented as examples rather than as a "complete" solution. Other technical strategies as well as other methods to achieve water reduction within the same strategies are available to the planner but were not included due to time and space limitations. For example, issues related to pressure and leakage reduction (e.g. Savic and Walters, 1995) have not been fully addressed although maximum pressure (as resulting from EPA-net simulations) has been included as an attribute to the leakage reduction strategy.

The issues that are addressed here stem from the fact that the application of urban water management is a complex problem of a highly spatial nature (Larsen and Gujer, 1997; Seder et al., 2000). *Each location* within the city boundaries has its own properties and its own set of constraints (social, economic and engineering). The decision maker in urban areas asks for higher quality information, including intelligent decision support for time and investment-critical planning. The view adopted in this work is that taking into account these site-specific characteristics, rather than drawing a black box around the cities, results in more realistic and therefore more applicable planning. The environmental planner in the urban environment is thus in need of tools that can address the following issues (Seder et al., 2000):

- Integrate and coordinate information on a domain-oriented scale
- Support analysis, observation, valuation and forecast of environmental systems and their conditions
- Support decisions as a balance between economic and ecological objectives based on expert knowledge
- Use an information system which is intuitive to the user and which offers transparency without requiring knowledge of some computer language.

The stated requirements imply that the tools (or decision support systems) should in principle, integrate knowledge and reasoning as an essential part of the system's functionality while dealing with the inherent ambiguities and uncertainties of any reasoning/decision making process. An example of such a decision support system, based on fuzzy inference, was developed within this work to assist and support decision-making in the urban water environment in general and water demand management in particular. Although, clearly, the system developed is only one possible design of a WDM SDSS, it is felt that it introduces and innovatively combines a variety of state-of-the-art concepts and methodologies and is therefore an important contribution to the on-going process of evolving tools for decision making within the urban water environment. Some of these concepts will be summarised next.

6.3 Discussing the framework: Fuzzy Inference and Evolutionary Programming

Complexity, naturally occurring in real life, is transformed into uncertainty when building an abstraction of the real world: a model. If a system is fairly simple, and therefore little uncertainty is inherent in the associated model, closed form mathematical expressions can be used to provide insight in the way the system functions. For more complex systems for which significant data exist, model-free methods (such as neural networks) provide a methodology for dealing with uncertainty through learning, based on patterns in available data (Ross, 1995). Finally, for more complex systems where scarce data exist and where only ambiguous or imprecise information is available (a widely appreciated fact in urban water management), fuzzy logic provides a framework for handling and formally expressing this uncertainty, assisting the understanding of the system's functions. Therefore, the imprecision in fuzzy systems is generally high. It is thus evident that the successful application of fuzzy logic, apart from the knowledge of the theory involved, is dependent on the correct identification of the type of uncertainty involved in the system's structure. Despic and Simonovic (1997), identify two basic forms of uncertainty in environmental modelling: Uncertainty caused by inherent stochastic variability and uncertainty due to fundamental lack of knowledge (including model structure and model parameters). Intuitively, the second form can be more readily modelled by fuzzy sets, particularly if there is need for quantification of qualitative criteria and synthesis of non-homogeneous information (technical, economical, political etc), where lack of knowledge is coupled with scarce available data and ambiguous cause-

effect relationships. This is the reason why fuzzy inference was selected as the preferred computational framework for the decision support system discussed in paragraph 6.2. The choice is justified by the significant uncertainty present in real data (when) available in the water industry, the lack of precise cause-effect relationships linking site attributes to site-specific suitability for application of WDM strategies, as well as by the ambiguity of the expert rules used by decision-makers to plan WDM interventions in practice. The need to provide a structured representation of knowledge so that processing elements can correspond to meaningful concepts and inference can be traced and explained, together with the data scarce nature of the problems addressed, led to the exclusion of neural networks as a viable alternative to fuzzy logic as an inference procedure (Leung, 1997).

The highly complex, non-linear form of the relevant decision synthesis problems stemming from this uncertainty and ambiguity (referred to in this work as optimisation for simplicity) justifies the choice of evolutionary programming (referred to in this work as GAs for simplicity) to solve single and multi-objective object location problems. The results presented in Chapter 5 and the comparison between these techniques and more conventional ones, reveal that evolutionary programming is a robust and powerful tool adaptable to the diverse problems of the urban water environment, able to directly address spatial problems, while facilitating the exploration of the decision space through optimisation of multiple objectives (Savic and Walters, 1999).

The following paragraph discusses the role and performance of each of the three main modules of the system developed within the fuzzy inference and evolutionary programming framework discussed above.

6.4 Discussing Development: The modules

6.4.1 Inference

The use of rule based FIS presents a solution to the issue of linking *antecedent* (field data) to *consequent* (suitability for WDM strategy application), such as linking overhead traffic with leakage vulnerability of the water distribution pipes below, through an unknown

function[1]. Using fuzzy inference systems to assign suitability values to spatial data makes use of the function approximation capabilities of these systems and urban water management is a textbook example of a case where the function linking antecedents to consequents is not predetermined. As discussed in Chapter 2, the question of the extent to which a FIS can adequately approximate an unknown function was answered by Wand and Mendel (1992), as well as by Kosko (1992). They proved (for a number of specific FIS) a universal approximation theorem, in other words that FIS could uniformly approximate any real continuous non-linear function to an arbitrary degree of accuracy. A universal approximation theorem is an existence theorem. As mentioned in Chapter 2, it does not explain how to build such a FIS (Mendel, 2001). The designs presented and discussed within this work are not the only possible solutions to the problem of building a linguistic rule based fuzzy inference system. Other design options (including the kind of fuzzification (singleton or non singleton), the shape of the fuzzy membership function (trapezoid, triangular, Gaussian, Gambel etc) and their parameters (mean, variance etc), composition (max-min, or max-product), the number of rules and the defuzzifier (centroid, centre of sums, height etc)) can all result in alternative - equally valid - FIS designs. The design adopted was based on considerations of computational efficiency rather than domain-specificity. Further research could possibly focus on the selection of alternative design variables towards the specific domain of urban water management although currently no particular heuristic rules for such a selection can be found in the literature. Evolutionary programming can be used to address several of these issues (such as, for example, selection of domain specific (to some extent) fuzzy membership function shapes, (Mendel, 2001)). Even at this stage of development however alternative designs of the FIS within the SDSS remain within the possibilities open to the user.

The use of both Type-1 and Type-2 FIS within the WDM SDSS is considered an interesting application of FIS in the environmental planning domain and a useful add-in to an SDSS from a decision support point of view. The thesis does not advocate the use of type-2 FIS instead of Type-1, but simply explores their potential in quantifying to a larger extent uncertainty associated with both data and the rules. The premise on which this discussion of Type-2 sets was based is that when there is ambiguity or uncertainty about the exact value of some decisional attribute, we use fuzzy instead of crisp sets. Yet,

[1] Deterministic relationships for this kind of linking do not exist in the literature. Probabilistic relationships, which can sometimes be found in the literature, are heavily dependant on calibration parameters for specific test data. Most of these relationships, whenever they exist, present few fundamental similarities.

in Type-1 sets, we are asked to determine the fuzzy membership function of that value to some (fuzzy) set *exactly* which seems counter intuitive considering we are not even able to determine its value (Mendel, 2001) and thus even less able to determine its membership in a set. In real life, when rules are collected by experts, if we first query the experts about the locations and spreads of the fuzzy sets associated with antecedent and consequent terms, it is very likely that we will get different answers from each expert (Karnik *et al.*, 1999). This leads to uncertainty about locations and spreads of antecedent and consequent fuzzy sets. Such uncertainties can be incorporated into the descriptions of these sets using type-2 membership functions (as seen in Chapter 5).

Naturally, the same problem exists with Type-2 sets and the secondary membership function, which is in its turn a crisp function. In principle, to be able to capture uncertainty completely one should work with Type-∞ fuzzy sets. This is of course impossible for practical purposes. Higher order fuzzy sets are more complex and thus a trade-off between complexity and quantified uncertainty has to be reached. This research argues that Type-2 (singleton and non-singleton) FIS are able to incorporate, to some extent, rule uncertainty in the decision making process while still be practically applicable for large scale problems without significant computational burden. The fact that the SDSS used their output in a GIS context to visualise the result in the form of maps assists in the quantification of the spatially variable effect of the uncertainty to urban water management problems of the object location type. Additionally the results indicate that the use of fuzzy numbers instead of crisp data points (non-singleton inputs) in a FIS increases the ability of the system to address problems of high data uncertainty and ambiguity.

6.4.2 Training

The incorporation of neuro-fuzzy processes to allow the decision maker to tune the FIS parameters (in this case the means and variances of antecedent and consequent sets) by training the original FIS is also considered a significant advantage of the proposed SDSS. This enables the subjectivity in the design of a FIS to be considerably reduced and partly answers the questions about optimal design put forward above. Such an approach requires input-output training data and changes the parameters of the FIS by a back-propagation procedure, usually a steepest descend algorithm. There is, however, a clear problem associated with this methodology in our particular application, and that is lack

of training data. This lack can be explained by the following two factors: (a) Water company records are scarce (at least in the public domain) and of unspecified reliability. Information on all of the identified attributes for the same network is even scarcer. (b) The suitability rating is not always a measurable quantity. The case of suitability for compulsory metering introduction dependent on the financial level of the occupants is a good example of this problem. This does not mean, however, that the technique is not potentially useful: computerised data of acceptable resolution and accuracy are becoming more and more available and should, in principle, continue to do so in the future and an expert rating could take the place of actual measurements when the rating itself is not a measurable quantity. In this case, the FIS would not model reality but the decision making process of the expert(s). There are of course cases where data exist and can be processed to create input-output training pairs, as is the case of pipe prioritisation for leakage reduction presented in Chapter 5. The results presented support the claim that training significantly improves the overall performance of the system even if the training data have not been extracted form the network in question, but from another network of similar characteristics.

Some important issues should, however, be stressed at this point. The fuzzy inference systems developed in this work have a relatively simple structure as the number of rules within the rule base is kept constant and is pre-defined by the user. This reduces the FIS design complexity by significantly reducing the degrees of freedom allowed to be altered by the training algorithm. The advantage of this design is that the system can be trained with less data in less time but it loses some of its ability to perform detailed modelling of input-output relationships. The choice of the number of rules and their overlap is, to a large extent, a domain-specific heuristic process and thus presupposes a firm understanding of the domain-specific problems by the main user (for example a facilitator operating the SDSS on behalf of a group of non-specialist decision makers). A good initial choice of the number of rules and associated fmfs would allow the training algorithms to provide meaningful results as to the optimum[1] set of tuning parameters (mean and variance of the Gaussian antecedent and consequent fmfs). If, for example, too few rules are programmed, then the system is not able to correctly model the variability of the input-output options at its full extent and thus the training algorithm cannot produce meaningful results. On the other hand, the clustering technique used to

[1] In terms of the parameters providing the best fit to the data.

produce the input-output training pairs, is producing an indication of the number of rules that would best represent the data in question, by identifying the actual number of clusters present in the data. The user has to make a (subjective to some extent) decision on how many of these clusters have true physical meaning and how many are just dataset-specific, representing some characteristic of the particular system that would not be general enough to be useful in a non-system-specific learning process. Due to the inclusion of this stage of interaction between the SDSS and the user, as well as due to the need of allowing the user to have complete control over the FIS when data is not available, the process of defining the number of rules was not automated. It is, however, acknowledged that this is a possible area of improvement of the current system. In particular it would be interesting to include data mining techniques (as advocated, for example, in Savic and Walters, 1999) to extract rules for the FIS from available data sets. GAs have been applied in recent years for similar purposes by selected researchers in the urban water management field (e.g. Leung, 1997; Keedwell *et al.*, 2000).

6.4.3 Aggregation

The system includes a number of techniques to achieve the integration of the results obtained from the FIS on the various attributes of each strategy into one combined, suitability rating's map per strategy. Standard techniques such as simple weighted averaging with direct weights assignment were programmed and included in the system. The problem these techniques present is that they require an *a priori* statement from the user as to the relative importance of the various attributes (used here as criteria to assign suitability). This statement may or may not be justifiable in terms of expert judgement and past experience. There is also no possibility to incorporate *risk* as a critical factor in planning urban water management strategies although there is clearly an advantage to doing so. The solution offered in this thesis is the development and programming of two alternative aggregation techniques: ordered weighted averaging and spatial ordered weighted averaging. The first (described in detail in Chapters 3 and 4) enables the user to define a level of risk aversion to be associated with the decision as well as an acceptable trade off level, either explicitly or implicitly, through a process that maximises the entropy within the set of weights, and therefore the information each criterion contributes to the overall decision.

The second addresses the issue of finding and incorporating a structured way of changing the risk aversive attitude according to objective characteristics of the decision to be taken. In this case, to select an "appropriate' risk-aversive attitude that would make sense when considering a particular urban water management strategy. As each cell in the study area is considered an alternative in the decision-making process, the technique assigns a different risk-aversive attitude to each cell based on spatially variable risk index. The risk index used in the context of decision-making for WDM is urban flood risk and an appropriate module to calculate such a risk index by including site-specific characteristics (e.g. proximity to sensitive clients, property value etc) and incorporate this risk index into the SOWA process was developed and tested. The risk-dependent aggregation techniques included in the SDSS and their use to solve spatial aggregation problems is a novel approach for synthesis of spatial information and the inclusion of spatially variable risk is a new research development, which is considered valuable to spatial planning both within the urban water management environment as well as within the broader risk management environment.

6.4.4 Optimisation

The development of three distinct optimisation procedures to solve the complex object location problem of identifying and planning an optimal WDM scheme in terms of water saved, cost and site-specific suitability for application enabled the exploration of various alternative options to address such problems, taking into account the spatially variable suitability indexes (and thus the site characteristics) both implicitly and explicitly. Both state-of-the-art in nonlinear programming methods (SQP) and evolutionary programming have been used to address this issue. The object location problem is generally little explored in the context of WDM although several attempts to solve varieties of it can be found in the literature for a range of problems (for example Krzanowski and Raper (1999) or Chang and Wei, 2000). The optimisation procedures and the novel alternative formulations of the problem proposed in this work provide three alternative options to address this class of problems within the urban water management environment in specific as well as within the broader environment of environmental planning. It was found that the SQP type of algorithms can address the spatial problem implicitly to the extent the polynomials constructed to model the problem accurately depict the problems characteristics. This was found to be easier when high-resolution data were available. In cases where the resolution decreased, formation of

the problem the SQP algorithm was attempting to solve was somewhat diverged from the actual problem. Evolutionary programming, (in the form of both single and multi-objective hybrid genetic algorithms) was extensively used to address the spatial optimisation problem both implicitly (but without the polynomial approximation limitations of the SQP procedure) and explicitly. Two novel, hybrid genetic algorithms were developed and tailored to address WDM object location problem, while keeping the process as generic as possible to facilitate the use of the algorithm in other object location problems in the future (e.g. for locating SUDS). The performance of the algorithms suggest that evolutionary programming for spatial optimisation purposes is able to handle the multiple constraints and highly complex nature of these type of problems. It was found that intimate knowledge of the particular characteristics of the domain specific problem improves the performance of the algorithm both in terms of achieving fitter solutions and in terms of time required to achieve these solutions.

6.5 Discussing Results: On system's performance

Subject to the limitations on the scope and current development stage of the SDSS discussed in previous paragraphs, it is felt that the SDSS results can be viewed as a useful and fast exploration of possible strategic action plans at a city level (or indeed on a much smaller one – dependent on data availability and resolution), allowing the decision maker to assess alternative WDM scenarios and plan their site-specific implementation. The results are however associated with a degree of uncertainty in data input, antecedent and consequent fmfs, inference rules, aggregation and optimisation. In the case of multi-objective optimisation, there is also uncertainty in the final decision taken after the completion of the analysis due to the multiple solutions proposed. The questions arising from recognising this fact are two:

(a) Is this uncertainty sufficiently taken into account in the decision making process and is the decision maker aware of the degree of uncertainty associated with the decisions?

(b) To what extent can the results of the system be validated and to the extent this is not possible, are the decisions taken under this uncertainty informed and useful enough?

As far as the first question is concerned, the incorporation of data uncertainty through fuzzy number inputs, the incorporation of rule uncertainty through the development and application of type-2 FIS and the incorporation of aggregation-decisional uncertainty through OWA techniques and a user specified degree of risk, based on both personal choice (as is usually the case in everyday decision-making) or indeed based on objective parameters such as risk of flooding through the new SOWA techniques developed within this research, provides a rigorous framework for handling a number of different facets of uncertainty to a significant degree. The decision uncertainty is *transparent* throughout the decision process and the system assists the user to transform linguistic criteria and rules used in everyday decision making into a mathematically sound, robust and consistent algorithm. Throughout the decision process the system supports rather than substitutes the decision maker by making sure that the results of the analysis are reproducible, coherent and consistent with decision makers logic. The fact remains that the results of the inference systems are only as good as the expert judgement used to derive the rules and are limited by the quality and availability of the data used to adjust these rules. They however score highly in allowing logically structured, consistent conclusions to be drawn each time and transparently portray the uncertainty involved in the process. The fuzzy inference process incorporates (and is limited by) the perception of the user but improves the user's analytical capabilities in the face of large and complex data sets that should be assessed simultaneously. This last point brings us to the issue raised by the second question.

Before beginning the discussion on results' validation, we need to reiterate a distinction between modelling physical processes, and modelling decisions. In the first case, results can to some extent be confirmed through observation of the actual physical processes. A forecast of a "measurable" physical quantity (e.g. river discharge) based on some (perceived) cause and effect relationship can be "confirmed" by field observations to some degree of precision. The "only" parameter that limits our ability to effectively model a physical system is the limit of our understanding of its functions. Several conceptual problems obviously exist even in this domain due to the fact that physical systems are not closed systems (in contrast to, for example, purely mathematical structures) (Oreskes *et al.*, 1994). The non-uniqueness of any modelling outcome, i.e. the possibility that more than one model can result in the same predictions strengthen Popper's thesis (Popper, 1959, as quoted in Oreskes *et al.*, 1994) that it is to some extent

possible to prove a theory false but not even theoretically possible to prove a theory true. Within that context, it has been argued that all that physical modelling can claim to achieve in comparing model predictions to field observations is "forced empirical adequacy" (van Fraassen, 1980 as quoted in Oreskes *et al.*, 1994). Modelling decision-making is even more uncertain. This is not a weakness of the modelling process as such, but rather an intrinsic characteristic of the decision making process and the risk every decision entails. In a sense this is true for all designs, which are particular forms of decisions: Based on general principles (for example in the form of rules) the planner/decision-maker, processes field data and derives a plan (an "engineering" decision). There is no real confidence that the design (any design) is optimal to its full extent and that there aren't alternative designs that surpass the one suggested in some way. In fact the later is most commonly the case. The reason that a design cannot be validated is that it does not yet exist and its performance can only be measured by models, which are abstraction of reality and not reality itself with all the problems of non-uniqueness mentioned above. Once the design is materialised (and therefore its performance becomes a measurable quantity), then it can *de facto* no longer be compared with any alternative, as these remain non-existent. In cases where the plan is site specific (as for example in a WDM scheme of a particular city, with particular water network and population characteristics) alternative designs applied in different case studies are (to a large extent) not comparable. General rules could be drawn (and therefore incorporated into the decision making process) based on experience of performance of past designs, but there is no real guarantee that rules that worked well in a particular situation will do so again under different circumstances. Yet the fact remains: decisions are taken every day, based on the imprecise knowledge and ambiguous, linguistic IF-THEN rules of human intuition. The system developed here does not eliminate this uncertainty and imprecision. It simply provides a rigorous mathematical framework to quantify it and assess its importance in decision alternatives. Tools supporting decision-making can be validated up to a point in terms of:

- **Ability to incorporate rules from the decision maker's experience and expert judgement and correctly apply them.** In this case, the results described show how a decision maker can add rules at will, and they support the claim that the effect of the analysis is accurately depicting the concept of the rule. The decision maker can therefore assess if the result of the rule added agrees with the

result expected from past experience and thus build the rule base with increased confidence.

- **Consistency and transparency in the decision making process and its results**. The effect of the decision making process modelled by the system (in all stages discussed) was consistent with the process itself and recorded results agreed conceptually with the choices made (see Chapter 5). The results of each choice and assumption are visible and quantifiable and can be tested against perception and expert judgment.
- **Adapting to increased data availability in terms of extracting new rules from field data when these data are available.** In the case of WDM, field data have a physical meaning only in the case of leakage reduction, in terms of identifying characteristics of past pipe bursts and incorporating this information in the rule base that identifies leakage vulnerability. Of course, the tool's aim is not to predict bursts using exclusively spatial information, as that would be an oversimplification of the variety and causes of bursts in water supply networks. The aim is to provide a consistent methodology of prioritising pipe replacement (as a means to achieve WDM) by assessing spatial information through an index of vulnerability. The index provided is not an *absolute* measure of vulnerability but rather a *comparative* one: the network segment in question is measured against the other segments within the case study and the most vulnerable segments are identified for replacement prioritisation. Past burst records can only be used as an indication of the ability of the system to adapt to increasing data availability by tuning its rules accordingly. The results presented in Chapter 5 fully support this claim. The system's performance is significantly improved by using its build-in training algorithm to incorporate available data sets both from the particular network and other networks of similar characteristics.

Klir and Wierman (1998) (as reported in Mendel, 2001), suggest that "*uncertainty has a pivotal role in any efforts to maximise the usefulness of a systems model ... a slight increase in uncertainty can significantly reduce system complexity and at the same time increase the credibility of the model. Uncertainty is thus an important commodity in the modelling business, a commodity which can be traded for gains in other essential characteristics of the models*". It is this degree of (quantified and observable) uncertainty that gives to this SDSS the ability to produce quick results, which

should be accurate and dependable enough (through a user defined risk taking attitude) for strategic planning in this and other similar domains.

6.6 Discussing Application: Future Use

The SDSS developed and described in this work is a prototype system, developed for academic rather than industrial use. It is not commercial software and cannot be used from the water industry "as is". There are several reasons why this is so: primarily, the water industry is not currently actively involved in the application of WDM, at least not to the extent of alternative strategies described in this work and supported to a certain extent by the SDSS's current development stage. Leakage reduction may be currently the main focus of the water industry and OFWAT but there is still some uncertainty as to strategies and tools needed to attain the water reduction targets. Grey water and rainwater recycling schemes are not yet in the priorities list of the water companies and would, probably, remain outside until the leakage reduction has achieved what is feasible with a minimum investment or until technology improvement drives the installation and operation prices down. Metering is more of a political decision within the UK and as such is subject to parameters outside the scope of technical feasibility or even water company policy. The water industry is, however, beginning to realise the need for better data collection and management to assist a long overdue assets management programme. GIS is in the process of being introduced into the industry but is restricted for the time being to little more than a simple assets inventory. The industry's procedures for collecting data and storing them in an electronic form are in their infancy, and, in some cases, assets (e.g. water mains) and events (e.g. bursts) are not combined in relational form within databases. Information already collected by the industry is sometimes of little use due to either low resolution or inconsistency in the collection process. In short the site-specific WDM process is still in very early stages.

These facts, however, do not mean that developing tools for the water industry or the water regulators is of little importance for various reasons: The industry has realised the need for assets management and fully comprehends the importance and viability of demand management being faced with more stringent environmental regulations and the possible adverse effects of climate change. Leakage reduction, however useful, can only take reduction in water demand up to a certain point before increased investment makes it impractical as an option. Alternative techniques, such as grey and rainwater recycling

and the introduction of metering should have a increasingly important role in the near future. Technological advance in terms of data acquisition systems and processes is fast and related prices are dropping due to high competition. Parts of the system (e.g. the leakage reduction module) could currently be used by the industry for pipe prioritisation whether the industry opts for pipe replacement at a small or a large scale (as discussed in Chapter 5). The development of tools can act as a driver for the industry to collect the specific type, resolution and quality of data that the tools can readily use and thus help in focussing the efforts of the industry in terms of investment. By including more strategies and options than currently in practice, decision support tools can encourage decision makers to think about alternative and perhaps more sustainable ways of achieving their objectives while visualising the effect of composite what-if scenarios. The specific role of an SDSS in terms of handling and presenting the results in a spatial sense also increases the ability of decision makers with different backgrounds to communicate with each other and thus facilitates the overall decision process. Last but not least, it is the main function of academia to think ahead of current realities into possible futures and try to steer society and its industry into a more sustainable development pattern while providing the tools to facilitate this process. It is within this broad framework that the SDSS presented here could act as a discussion platform between experts and users to explore and actively promote and support sustainable decisions in the urban water management environment.

6.7 Conclusions

This chapter discussed the need, basic concepts, development issues, results and usefulness of a spatial decision support system for urban water management. Although the system is still a prototype, and as such open to further development, improvement and testing, it is felt that it is a promising research direction and could be of great potential benefit to the decision making process within the water industry.

7. Conclusions

"Information is not knowledge.
Knowledge is not wisdom.
Wisdom is not truth.
Truth is not beauty.
Beauty is not love."

Frank Zappa

7.1 Preamble

This thesis has discussed the development of spatial decision support system for water demand management. The underlying concepts of water demand management and the tools needed to support its site-specific implementation have been discussed in detail. A mathematical framework for the development of these tools was formed and a specific system prototype was built. The system's overall performance and results were assessed using both real and hypothetical data sets and the issues arising from the development and use of the system were critically presented. The main conclusions of the work performed, including the conclusions of all previous chapters are summarised in this (final) chapter of the thesis for reasons of completeness. Finally, the chapter will conclude with the author's recommendations on future research and development.

7.2 Conclusions by chapter

Chapter 1 introduced the main concepts of sustainable water management through the paradigm of the "tragedy of the commons" and identified the role of urban planning and urban water management as a means to minimise a city's ecological footprint. Acknowledging that this is a complex task, the discussion supported the view that the planner is in need of decision support tools of a spatial nature and identified the main function and characteristics of these tools. Furthermore, the chapter proposed a mathematical framework for developing such a tool to support water demand management (WDM). Key concepts of WDM were introduced and discussed. It is concluded that WDM is a key strategy for sustainable environmental management and one of the few viable alternatives in addressing, cost-effectively, the environmental targets set by the WFD.

Chapter 2 presented and discussed the theoretical background need for the development of the SDSS covering three main subjects: Elements of Soft Engineering (including Fuzzy Logic, Neurofuzzy Systems and Genetic Algorithms), elements of Decision Theory and elements of Decision Support Systems in general and Spatial Decision Support Systems in particular. The discussion presented the state of the art and the general principles of these scientific areas and was included because it was felt that these subjects, which were central to the development of this work, do not fall under the mainstream civil and environmental engineering field and thus the reader should be

assisted in the process of understanding not just the system as a software but also the underlying assumptions and principles of its use.

Chapter 3 presented the mathematical framework used to develop the spatial decision support system and the system's architecture. The system is developed in the Matlab mathematical environment using ArcGIS as a pre and post-processing tool. GIS and Matlab are used to access and analyse a variety of attributes, linked to the specified objectives the urban water management problem at hand. The spatial model used is a classic *raster-based* model, as this resembles the structure of matrices in Matlab. Both hard and soft information are combined to allow for a comprehensive overview of the situation and fuzzy inference systems have been used to standardise the information (linguistic, probabilistic and fuzzy) in a common decisional base. Type-1 and type-2 FIS are programmed and are accessible to the user through user-friendly graphical user interfaces (GUI). The FIS utilise both crisp and fuzzy number input dependent of the nature of information processed. Depending on the availability of information (either field measurements or expert judgement) the user is given the option to tune the FIS to correctly respond to sets of training data. This is possible through the development of neuro-fuzzy systems using back-propagation algorithms to adjust the parameters of the original FIS. Aggregation techniques are then applied to compose the membership function of the initial ill-defined set from the component membership functions. A choice of such techniques, including linear summation, Ordered Weighted Averaging and Spatial Ordered Weighted Averaging are available to the user. Finally, optimisation procedures are used to help the user decide on a composite strategy synthesising the preferential applicability maps for the strategies taken into account. For this purpose, three new optimisation algorithms: one based on SQP and two based on evolutionary programming (EP) were developed within this research. Especially for the EP it must be noted that the mathematical development presented here and the coding that followed, is a novel contribution of this work to the relevant literature, as it made no use of existing GA libraries. The reason behind developing an entirely new, customised algorithm was that the specific problem was assumed to benefit from the largely heuristic approach described in detail in Chapter 3.

Chapter 4 described the application of the SDSS presented in Chapter 3 to the specific domain of WDM. The end product developed is a tool for water service providers to: compare different water demand reducing scenarios, plan the site-specific implementation of these scenarios and assess the investment needed to achieve a desired reduction or identify the best composite scenario dependent on a desired investment scheme. Chapter 4 discusses the case studies, data availability and data format issues and provides an overview of the decision-making process (presented in Chapter 3) applied in the case of WDM through fuzzy inference, aggregation and optimisation.

Chapter 5 presented the results produced by the SDSS under various user-defined assumptions and for a range of control options to investigate the uncertainty quantification potential of the SDSS, as well as an overview of the sensitivity of results to the concept of uncertainty and risk of the decision maker. Alternative optimisation techniques were used and their results compared and discussed. The system's performance supports the assumption that the decision making potential for planning WDM schemes is greatly increased by the use of the SDSS as a tool for site-specific planning under user-defined or estimated levels of risk aversion and explicit uncertainty handling.

Chapter 6 discussed the need, basic concepts, development issues, results and usefulness of a spatial decision support system for urban water management. It was concluded that although the system is still a prototype, and as such open to further development, improvement and testing, it is a promising research direction and could be of great potential benefit to the decision making process within the water industry.

7.3 Overall Conclusions

The work presented in this thesis aimed at:

(a) *Investigating the use of different tools (including mathematical modelling, GIS, decision support techniques, spatial analysis, fuzzy inference systems and evolutionary programming) to facilitate environmental planning on an urban scale.* The results support the claim that soft computing can support the planning process within the environmental sector in general and the urban water management sector in particular, if the tools are correctly integrated within a common decisional framework.

(b) *Developing a framework for coordinating these tools (i.e. a prototype Spatial Decision Support System).* Such a system prototype has been built and the results of applying the tool to real and hypothetical data sets presented and discussed

(c) *Investigating the use of soft computing in general and fuzzy logic in particular within this framework as a means to include and process heterogeneous information (from engineering data to public perception data) and quantify the corresponding decisional uncertainty.* The results of the work suggest that fuzzy logic and evolutionary programming are indeed useful as tools for quantifying decisional and data uncertainty and incorporating it into the decision making process. It was concluded that the ability of the tool to formulate and process linguistic rules based on fuzzy inference greatly enhances its functionality and usefulness.

(d) *Identifying the extent to which the SDSS can be applied in complex urban water planning and management problems, to assist in reaching informed decisions.* The system developed addressed complex issues of planning a number of WDM strategies under a range of user inputs and levels of uncertainty. Based on the results produced by the SDSS, the discussion suggested that the SDSS developed is a flexible tool that can be adapted to the characteristics of the problem at hand, while its transparent nature greatly enhances the perception of uncertainty of the decision maker and allows the assessment of alternative what-if planning scenarios.

It is believed that the work presented here has identified and investigated a promising area of research and development within the urban water management sector, that of spatial decision support systems based on soft computing, adapted a range of existing methodologies for use in the particular domain of urban water management, developed a useful set of new tools, both in terms of programming and underlying methodology, and presented a working example of successful application of these tools in water demand management.

7.4 Future Research Directions

Two phases of further development should be identified: Development of the existing system to better support decisions for WDM and adaptation of the system's framework to other problems within the urban water environment.

As far as the first issue is concerned, future research could focus on the improvement of the inference systems in including more attributes on which each strategy is dependent. The current list of attributes is not exhaustive and while these are the most usually quoted criteria in the literature, the inclusion of other factors could increase the reliability of the systems. In particular system pressure as an element of leakage reduction has not been adequately explored within this thesis but represents a main element of leakage reduction strategies both as an indicator of vulnerability and as a water reduction strategy itself.

The system's development and its ability to correctly model the decision making process would also benefit from interviewing decision makers within government and industry to assess what they consider attributes affecting the suitability of a particular site for a particular WDM strategy and incorporate it into the SDSS.

Further development of the inference module could also include evolutionary and other data mining techniques for extracting rules from data sets (when available) as well as for assisting in the selection of domain-specific shapes or parameters for the fmfs used.

The flood risk assessment module should also be further developed (including but not restricted to attributes used and aggregation methods) as the possibilities of using the SOWA technique for spatially sensitive risk management and planning have only just been touched upon.

The system would also greatly benefit from more case studies, both within the UK and elsewhere, and it the author's is intention to apply the tool on other datasets, which the industry is starting to make available.

As far as the second issue is concerned, the obvious field for application of the methodology and tools developed here is sustainable urban drainage systems (SUDS) and urban flood risk management as they too have a distinct spatial character in application. The author has some past experience in developing GIS based applications for locating SUDS using fuzzy logic (Makropoulos et al., 1999; Makropoulos et al., 2001b) and the merging of these two application fields within a common GIS-based toolbox is considered both interesting and feasible. In particular, the inclusion of rainwater reuse in

this SDSS (in terms of WDM) can also be thought of as a rainwater detention facility (in terms of SUDS) and could serve as a link between these two applications

Current research initiatives (e.g. the WaND project of EPSRC's Sustainable Urban Environment Programme, scheduled to start in 2003) intend to investigate the use of SDSS similar to the one described in this thesis for sustainable planning and management of the urban water cycle. The author would like to believe that the work presented here has somewhat influenced the focus of these research initiatives which represent the state-of-the-art within the UK Water Research Community.

8. References

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Appendix 1: WDM SDSS Flow Chart

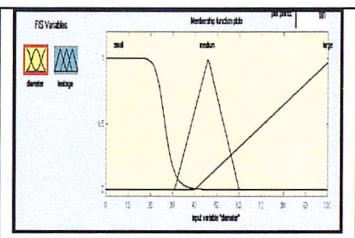
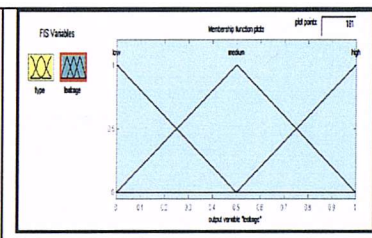
Water Demand Management

Strategy	Leakage Reduction	Metering	Grey and Rain Water Recycling
Attributes	Soil aggressivity Age + Material Traffic Type Diameter Distance to Fire Hydrants Pipe Density Max Pressure (EPAnet simulation)	Population Density Income Education	Population Density Income Education Renovation Status Roof Characteristics

A

Fuzzy inference system (type-1 & 2 using singleton and non-singleton input)

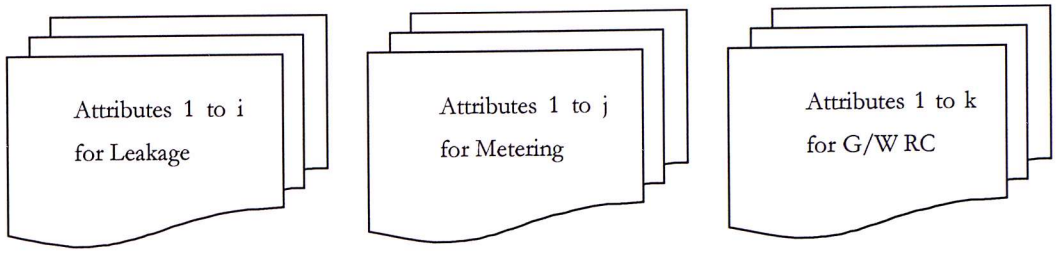
(standardisation)

Input	Rules	Output
	IF… THEN	

B

Training FIS with data or expert opinion

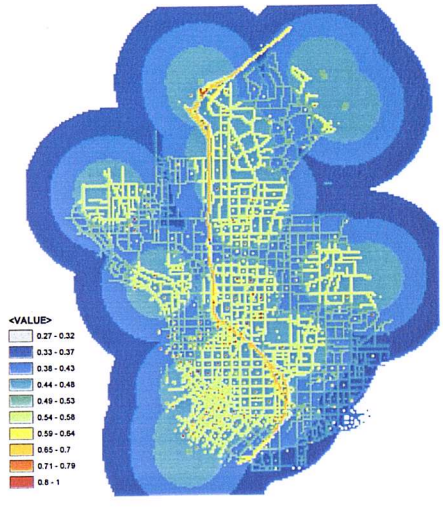
Standardised Attribute Layers for each Strategy



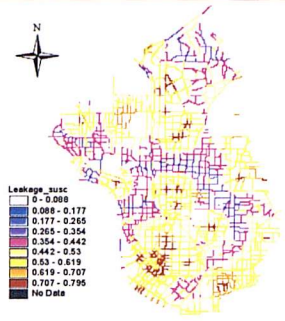
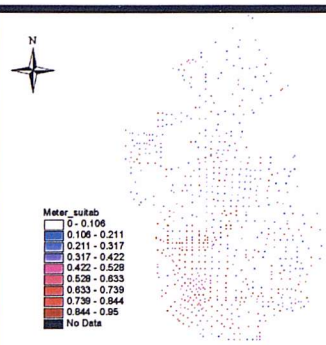
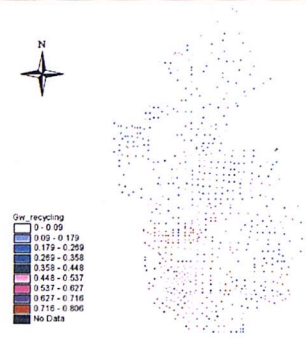
Ordered Weight Calculation using level of Risk + Entropy

Or

Spatial Ordered Weighted Averaging including flood risk



C

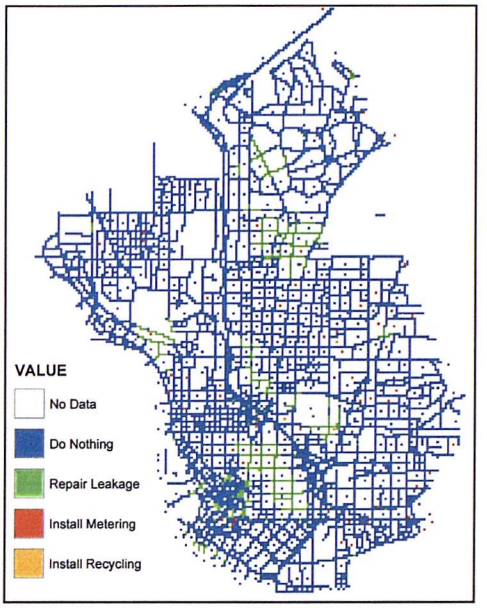
Final Suitability Map for Leakage	Final Suitability Map for Metering	Final Suitability Map for Recycling
		

Optimisation

Objectives	User Defined
Investment	consumption, leakage, cost of intervention, population per house etc
Water saved	

D

Sequential Quadratic Programming	Single Criterion Genetic Algorithm	Multi-criterion Genetic Algorithm

Composite Scenario	
• Total Cost • Total Water Saved/d • No of application of each strategy	

E

Decision Support Phases	
A	Problem Decomposition
B	Inference
C	Aggregation
D	Optimisation
E	Results

Appendix 2: Fuzzy Membership Evaluation

Direct methods for membership evaluation

To construct a fuzzy set **A**, we can take each element $x_i \in X$ and directly assign its corresponding value $\mu_A(x_i)$. This straightforward method (intuition or inference depending on the knowledge we have of the system's processes) is usually inadequate for more complex systems, and it is often difficult to avoid inconsistencies. A somewhat more consistent evaluation can be derived if we fix some value a from [0,1] and then directly assign the subset $A_a \subset X$ defined as:

$$A_a = \{ x \in X: \mu_A(x) \geq a \} \qquad \textbf{Eq. AII.1}$$

The set A_a is called the *a-cut* of A. For different values of a, the corresponding a-cuts can be estimated. Using the representation theorem stated below, we can construct the fuzzy set **A** from the a-cuts A_a. Another method of constructing fuzzy set **A** is to directly assign a mathematical expression for the membership function $\mu_A = \mu_A(x)$.

These methods and their combinations we call direct methods for the membership function estimation. They will now be further described, within the following categories:

- Statistically based methods
- Parametric function approximations
- *Ad hoc* methods and fuzzy numbers

Some real-world applications will also be indicated.

Statistically based methods

Although most of the methods for membership function estimation use statistics in some form or another, here we discuss only the methods, which rely exclusively on the statistical interpretation of the collected information.

- Horizontal methods for membership estimation:

The basic idea is to statistically obtain the grade of membership for some selected element x from X. This is done by asking a group of experts whether x belongs or does not belong to the ill-defined set A. The membership value for x is then calculated as:

$$\mu_A(x) = \text{N(belongs)/N} \qquad \textbf{Eq. AII.2}$$

where: N(belongs) is the number of experts who answered that x belongs to A, and N is the total number of experts who answered the question.

This process is then repeated for other elements in X until enough data is obtained for a reasonably accurate membership function μ_A. Note that the uncertainty of the results will be distributed along the axis representing the values of the membership function μ_A. Variations of this method can be applied at different levels of complexity. For example, one can change the spectrum of possible answers. The questions used in some experiments include more possible answers than just "yes" and "no".

- Vertical methods for membership estimation

We can think of the vertical methods as the horizontal methods with the reversed order of selection. The selected element is not from X. Rather, grade of membership, a value a is selected from the interval [0,1], and the corresponding a-cut (Eq. AII.2) is estimated through experiments. By repeating this process for different values of a, we obtain a family of nested sets. The membership function is then constructed using the representation theorem:

$$\mu_A(x) = \sup\{a \cdot f_{A_a}(x)\}, a \in [0,1] \qquad \textbf{Eq. AII.3}$$

where $f_{Aa}(x)$ is the characteristic function of the a-cut A_a . With vertical methods the uncertainty of the results is now distributed along the axis representing the universal set X.

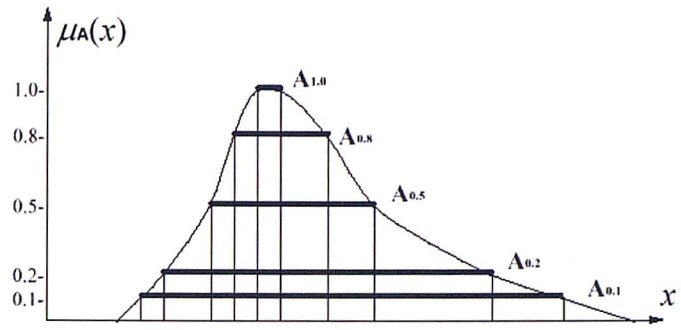


Figure AII.1 Representation of a fuzzy set by the a-cuts

Parametric function approximations

It is often possible, and natural, to think of the universal set X as a subset of an interval **I** on the real line. (**I** could be finite or infinite). In this case, it is usually suitable to construct a continuous function μ_A on the interval **I**, which can be used as a membership function for an ill-defined set A. In this section we will exclusively deal with continuous membership functions.

- S-curves and π-curves

Quite often, for convenience, membership functions are represented by standardized functions with adjustable parameters. Based on the experience with statistically obtained membership functions, we can employ various mathematical curves for the best fit of empirically obtained data. Some of the frequently used curves for this purpose are the S-curves and π-curves defined by Zadeh (1987). An S-curve is defined by:

$$S(x; a,b,c)= \begin{cases} = 0, \textit{ for } x \le a \\ = 2 \cdot \left(\dfrac{x-a}{c-a} \right)^2 \textit{ for } a \le x \le b \\ = 1 \text{ for } c \le x \end{cases} \qquad \textbf{Eq. AII.4}$$

Where this curve is used to represent a membership function μ_A, the parameters *a*, *b* and *c*, have the following meanings:

$$a = \inf\{x: x \in A_a, \mathbf{a} = 0\},$$
$$b = \inf\{x: x \in A_a, \mathbf{a} = 0.5\}, \text{ crossover point} \qquad \textbf{Eq. AII.5}$$
$$c = \inf\{x: x \in A_a, \mathbf{a} = 1\}$$

The S-curves are used to define π-curves in the following way:

$$\pi(x; m,c) = \begin{cases} S(x; c-m, c-(m/2), c) & \text{for } x \leq c \\ 1-S(x; c, c+(m/2), c+m) & \text{for } c \leq x \end{cases} \qquad \textbf{Eq. AII.6}$$

Zadeh (1987) uses S- and **p**-curves for the fuzzy description of: 'true', 'borderline' and 'false'. These fuzzy concepts are represented by membership functions μ_T, μ_B, and μ_F respectively:

$\mu_T(x) = S(x; a, b, 1)$,

$\mu_B(x) = \pi(x; m, 0.5)$,

$\mu_F(x) = 1-S(x; 0, b, c)$.

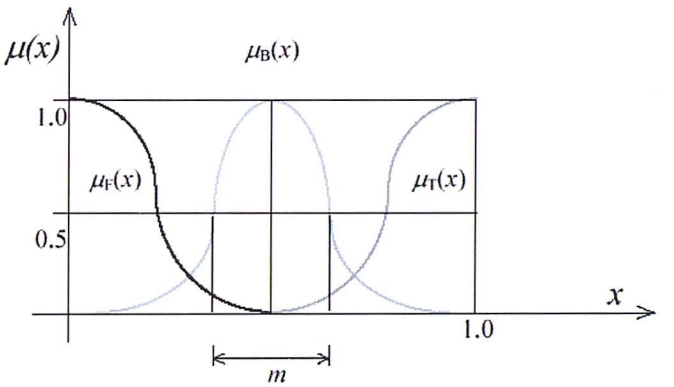


Figure AII.2. Membership functions of "true", "borderline" and "false"

- Piecewise linear membership functions

Some researchers argue that the efforts to develop a sophisticated curve of a membership function are unnecessary, since the imprecision of the empirical data already exists (Despic and Simonovic, 1997). They also consider and discuss the acceptability of approximating a non-linear shaped function by a linear shaped form. McVicar-Whelan (1978) introduced the filter function F with two parameters:

$$F(x; b,w) = \begin{cases} = 0, \textit{for } x \in (-\infty, b - \frac{w}{2}) \\ = \frac{1}{w} \cdot \left(x - b + \frac{w}{2} \right) \textit{for } x \in [b - \frac{w}{2}, b + \frac{w}{2}] \\ = 1 \text{ for } x \in (b + \frac{w}{2}, +\infty) \end{cases} \qquad \textbf{Eq. AII.7}$$

Where b is the crossover point as defined in Eq. AII.5 and w is the width of fuzziness (the smallest distance between non-membership and complete membership). Figure AII.3 gives an example of a filter function.

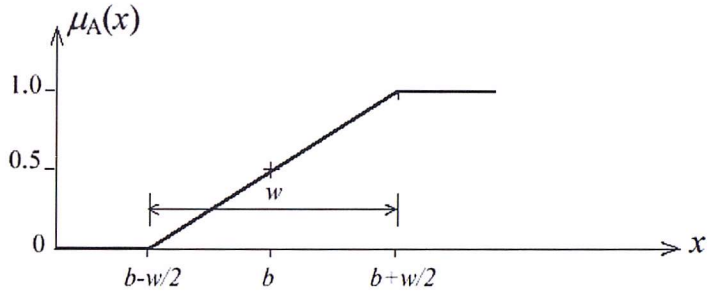


Figure AII.3. Filter function

(source: McVicar-Whelan, 1978)

In most applications of fuzzy sets one actually finds that mathematical / statistical accuracy need not be considered if one can simply "tell" an approximate shape of the membership curve (Despic and Simonovic, 1997). The membership function adopted in this way is then tested and modified for a particular application. For example, Murty and Sinha (1990) employ the S- and π-curves for a fuzzy description of different levels of bridge traffic's safety. They use a linguistic rating scale where each term is represented by an appropriate membership function. The S- and π-curves are just some, among many, that can be used with the *ad hoc* methods. Piecewise linear curves present another possibility. The simple form of these curves allows relatively easy operations on fuzzy sets.

Indirect methods of membership evaluation

Everyday life is full of examples when we make, consciously or unconsciously, some kind of comparisons. These comparisons imply an indirect evaluation. However, it is always done in one of two contextually different ways. Things are either compared relative to

one or more reference points (called prototypes) or they are compared pairwise without any reference point. Both ways, applied for membership evaluation, have some advantages and disadvantages. In this section, they are discussed as clustering methods (where objects are compared with prototype(s)) and relative preference methods (pairwise comparison).

Clustering

As mentioned above, in order to employ this type of evaluation, we assume the existence of some prototype(s), for which the membership value may and may not be known in advance. In most practical applications, however, we look for some kind of ideal prototype p with the membership value $\mu_A(p)=1$ in a set A. Another common approach is also to choose several prototypes with the known membership values in A (not necessarily equal to 1), and then compare the elements from the universal set X to these prototypes. An illustrative example, when the membership values are determined using the concept of the ideal prototype is given by Bremermann in (1976). For the comparison of the elements x_i from X with the given deformable prototype p, Bremermann uses two types of measurements: the minimal 'distance' from x_i to the prototype p and the minimal distortion 'energy' of the deformation. These two measures are combined into the dissimilarity value $D(x_i, p)$ between the element x_i and the prototype p:

$$D(x_i, p) = \min [d(x_i, p) + w\delta (x_i, p)] \qquad \textbf{Eq. AII.8}$$

where: $d(x_i, p)$ is the distance between x_i and p,
$\delta(x_i, p)$ is the distortion between x_i, and p; and
w is a weighting constant.

Since there are many possible choices for the distance between x_i and p, many possible ways of distorting p into x_i, and also many possible ways of combining these operations into some transformation from p to x_i, the minimal value is taken over all possible combinations. Once the values of $D(x, p)$ are determined for every x, the membership values are then computed in a more conventional way, by using a function that maps the values of $D(x,p)$ into the interval [0, 1]. One such function is:

$$\mu_A(x) = 1 - \frac{D(x,p)}{\max_i D(x_i,p)} \qquad \textbf{Eq. AII.9}$$

For the prototype p, we have $D(p,p) = 0$ so that $\mu_A(p) = 1$, and for the element x with the maximal dissimilarity value $\mu_A(x) = 1-1 = 0$.

Almost all clustering techniques use some kind of similarity or dissimilarity measures. Kandel (1982) gives a list of the existing methods for the selection of such measures. Some of the frequently used similarity measures are association and correlation, while dissimilarity measures are the various forms of the distance: Minkowski, Mahalanobis and weighted Euclidian distance. Kandel also discusses the most appropriate application areas for each of the listed measures by considering the properties of elements in X that are most emphasized under a particular measuring technique.

Another important class of clustering techniques is the class of algorithms of **fuzzy clustering**. These techniques, which have been used in our SDSS development, can be used even if the membership values of prototypes are initially unknown. Fuzzy ISODATA clustering algorithm is probably the most widely used algorithm in applications (particularly in pattern recognition). Any of the fuzzy clustering algorithms will allow, during the computation, that an element belongs to several clusters simultaneously with different degree of membership. After the clusters have been computed, by some of the least error criteria for classification, elements are assigned to those clusters where they show the highest degree of membership. The fuzzy ISODATA algorithm is formulated as the following minimization problem (Pedrycz, 1995):

$$\min Q = \sum_i \sum_j \mu_{Aj}^n(x_i) \cdot d(x_i, p_j), \quad n > 1 \qquad \textbf{Eq. AII.10}$$

Subject to:

1. $\sum_j \mu_{Aj}^n(x_i) = 1, \ \forall j$
2. $\sum_i \mu_{Aj}^n(x_i) > 0, \ \forall i$

where: $d(x_i,p_j)$ is a distance function between the ith element x_i and the prototype p_j of the jth cluster A_j; and $\mu_{Aj}(x)$ is a membership value of the ith element x_i in the jth cluster A_j. The formula for Q is just the fuzzy extension of the ordinary least error criterion. The

first constraint equation says that the membership values of x_i in all of the clusters should add up to 1, while the second constraint ensures that no cluster will be empty. More details on fuzzy ISODATA, and its variations can be found in Kandel (1982), Tucker (1986), Trivedi (1986), Cannon (1986), Pal and Majumder (1986) and Bezdek (1976; 1981).

Relative preference methods

In the case of a discrete universal set X with a relatively small number of elements, with no prototype for the ill-defined set A on X, the most appealing method for the membership function estimation is by pairwise comparisons. The process for membership estimation proposed by Saaty (1974) is very simple and natural. The main limitation of the method is the number of elements in X. In addition to the fact that the number of necessary comparisons, $N = \frac{n(n-1)}{2}$ increases much faster than the number of the elements n, it is also true that "...the number of elements is very critical in determining the impact of the consistency of the pairwise comparisons" (Triantaphyllou *et al*, 1990). Saaty's method begins with the selection of a suitable scale of importance. Initially, he proposed nine quantization levels using the natural numbers from 1 to 9. The higher the importance of x_i over x_j, the higher number is associated with the pair (x_i, x_j). In order to preserve consistency, the number associated with the pair (x_j, x_i) will be the reciprocal value of the number associated with the pair (x_i, x_j). The next step is to arrange these numbers in a square matrix $M=[m_{ij}]$, where m_{ij} denotes the number associated with the pair (x_i, x_j). Since the pairwise comparisons are made with respect to some ill-defined set A on X, it is natural to see the m_{ij}'s as the ratios of the respective membership values. Namely $m_{ij} = \frac{\mu_A(x_i)}{\mu_A(x_j)}$.

In the most consistent preference evaluation, the matrix **M** will be transitive. This is because:

$$m_{ij} \cdot m_{jk} = \frac{\mu_A(x_i)}{\mu_A(x_j)} \cdot \frac{\mu_A(x_j)}{\mu_A(x_k)} = m_{ik} \qquad \textbf{Eq. AII.11}$$

Note that in a perfectly consistent matrix **M** all rows are linearly dependent, and therefore rank **M** = 1. Furthermore, if we multiply **M** by the vector $\mathbf{m} = [\mu_A(x_1)\ \mu_A(x_2)\ \mu_A(x_3)\ \ldots\ \mu_A(x_n)]^T$, the result is:

$$\mathbf{M}\,\mathbf{m} = n\,\mathbf{m}, \text{ or equivalently,}$$
$$(\mathbf{M} - n\mathbf{I})\,\mathbf{m} = \mathbf{0} \qquad \textbf{Eq. AII.12}$$

Therefore n is an eigenvalue for the matrix **M**. Since rank **M** = 1, we conclude that n is the only eigenvalue of **M** different from 0, and because n>0, it is the largest eigenvalue of **M**. The corresponding eigenvectors of **M** are the scalar multiples of **m**. Thus in a perfectly consistent case, membership values are obtained as the components of an eigenvector (a solution to Eq. AII.11) normalized so that its largest component is equal to 1. In practice, the reciprocity ($m_{ij} = 1 / m_{ji}$) is kept intentionally, while the transitivity is rarely respected. However, if the judgment errors are small, the largest eigenvalue of **M** will stay close to n (the size of matrix **M**), while the remaining n-1 eigenvalues will stay close to 0. It can be shown that the desired vector **m** always corresponds to the largest eigenvalue λ of the inconsistent matrix **M**. Thus the Eq. AII.12 becomes:

$$(\mathbf{M} - \max_i\lambda_i * \mathbf{I})\,\mathbf{m} = \mathbf{0}. \qquad \textbf{Eq. AII.13}$$

If we compute all the eigenvalues of **M**, then Eq. AII.13 can be solved for n. The vector **m** is then normalized so that its largest component is 1, and so the membership values $\mu_A(x_i)$ are obtained as the components of the vector **m**. The principal question now is how to estimate the error due to inconsistencies. Saaty (1974) suggests the following method. Once max λ_i is found, we calculate the consistency index CI of the matrix **M** as

$$CI = \frac{\max_i \lambda_i - n}{n-1}$$

Note that for the consistent matrix **M** (reciprocal and transitive) CI = 0. The CI value is then compared with the random consistency index RCI, yielding the consistency ratio CR=CI/RCI. Saaty estimates RCI as the average CI for a sample of 500 reciprocal randomly generated *nxn* matrices, where the entries are taken from the scale 1/9, 1/8, ...,1/2, 1, 2,...9. The RCI value of a reciprocal matrix **M** depends only on the size of **M**. If the CR is less then 10% (CR < 0.1) then the consistency of **M** should be satisfying. Otherwise, revisions of pairwise comparisons are recommended. Some researchers have studied methods for obtaining desired membership values (vector **m**) where both pairwise comparison and an appropriate measure of inconsistency are taken into account. Triantaphyllou *et al* (1990) employ a human rationality assumption, which can be interpreted as an effort to minimize the errors of the pairwise comparisons. Under this

assumption, the problem becomes a typical least-square problem. They also discuss the consistency of the matrix **M**, by using the concept of the average residual. The average residual is described as an indicator of the effectiveness of the membership evaluation process by the pairwise comparison technique. Their finding is that the average residual can vary significantly even if the CR value is kept to less than 0.1. This has an impact on the selection of alternatives in many decision-making problems. Pairwise comparison is a very useful technique for the evaluation of small fuzzy sets. Applications of Saaty's method are seen in optimization and decision making; see Juang *et al* (1992) and Lund and Palmer (1986). The relative preference methods can take the form of pairwise comparison among subsets (clusters of elements) of X. The clusters sometimes occur quite naturally, and the assigned values will give useful information about the membership function. Evaluation of the membership values of subsets (clusters of elements) of X is also used within the frame of decomposition /aggregation methods. Some more sophisticated methods for membership evaluation, such as the construction via B-spline curve (Wang *et al*, 1995) and other techniques designed for learning membership functions, are not addressed here. They can obtain more exact representation of membership functions through the local and global tuning in a learning process (i.e. neural network and genetic algorithms).

Appendix 3: The Graphical User Interface (GUI)

Developing a GUI

The development of a GUI was considered crucial to the formation of any SDSS for the following reasons:

- The software is a decision support system and thus user and tool interaction is an important feature and an expected result of such an endeavour.
- The need for extensive user input to allow for flexibility and transparency of the procedures (rather than including hidden assumptions) dictates the need for a powerful and easy to use interface.
- The need to perform the analysis under varying scenario assumptions and analysis methods for the same scenarios demand a compact, easy to reproduce structure and procedure of the overall program. This procedure is greatly facilitated by a GUI.

Programming issues

The GUI was programmed entirely in Matlab and provides the various scripts executing the analysis with user input values. Furthermore, it provides the user with choice of preferable analysis procedures and enables the on-screen viewing of most of the results. For the purposes of this work the program and GUI are not in stand-alone mode, but require Matlab's mathematical environment. However, a procedure for compiling Matlab files to C++ code to build a dll library able to be linked with other stand alone applications has been successfully implemented for part of the code. Although the reason behind this initial experimentation was to increase computational speed, it can serve as a way to enhance the software's utility, separating the user from the obligation to have and use other software packages (i.e. Matlab).

The main GUIs

Examples of the GUI and the choices available to the user can be seen in the following figures.

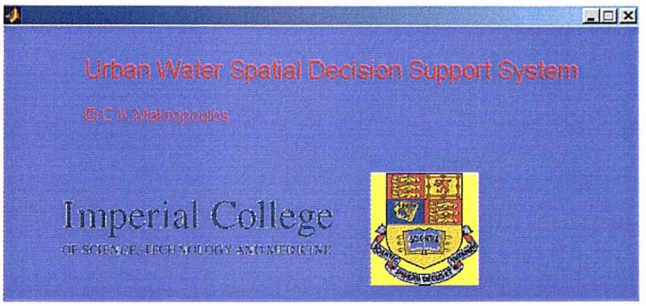


Figure AIII.1. The Urban Water SDSS

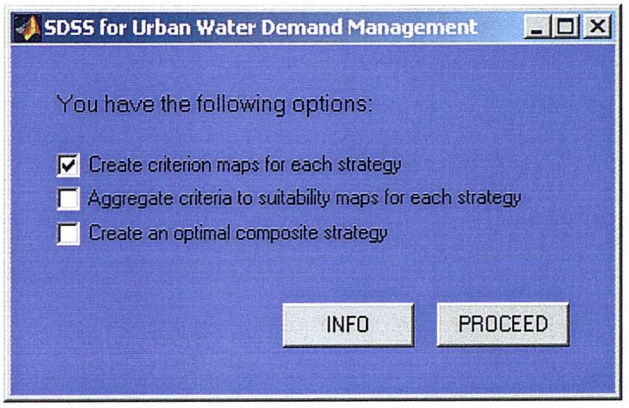


Figure AIII.2. The central interface leading the user to the three analysis phases

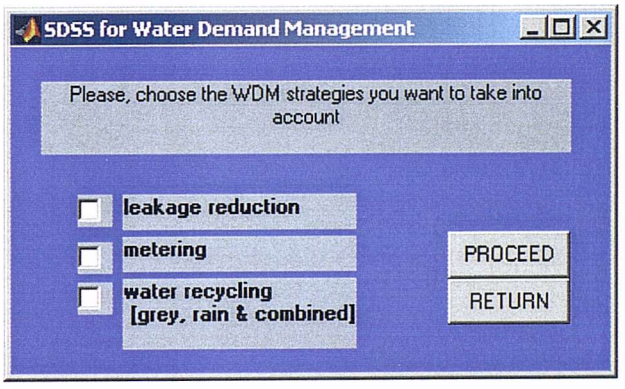


Figure AIII.3. The criterion maps creation GUI

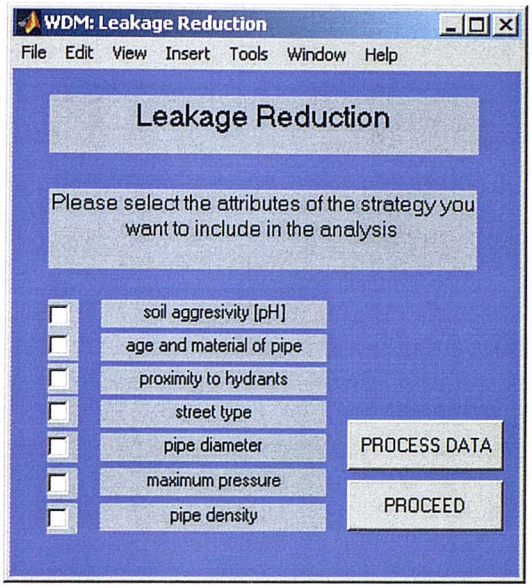


Figure AIII.4. Selection of attributes for leakage reduction criterion map creation

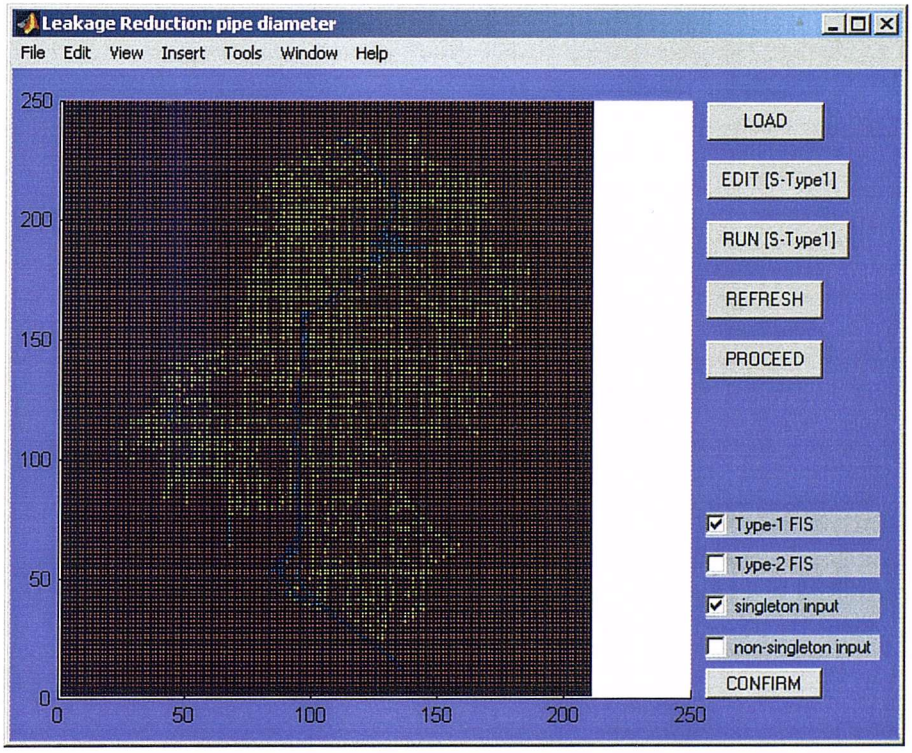


Figure AIII.5. The pipe diameter attribute module of the leakage reduction strategy. The analysis can be performed through a range of different FIS types.

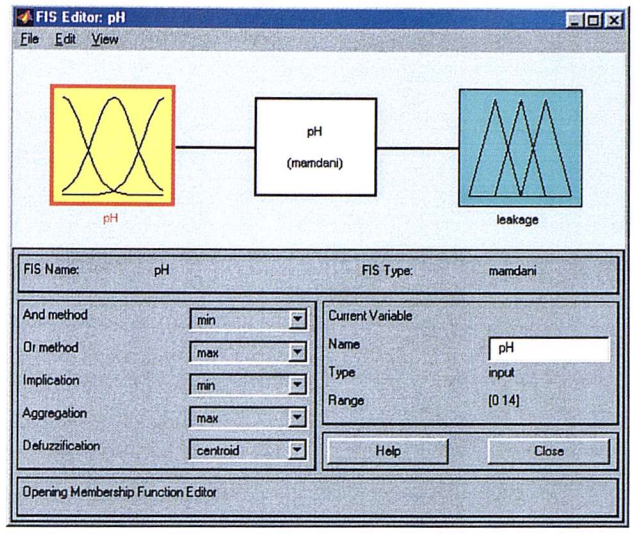


Figure AIII.6. The editor for a type-1 singleton FIS (developed by Mathworks)

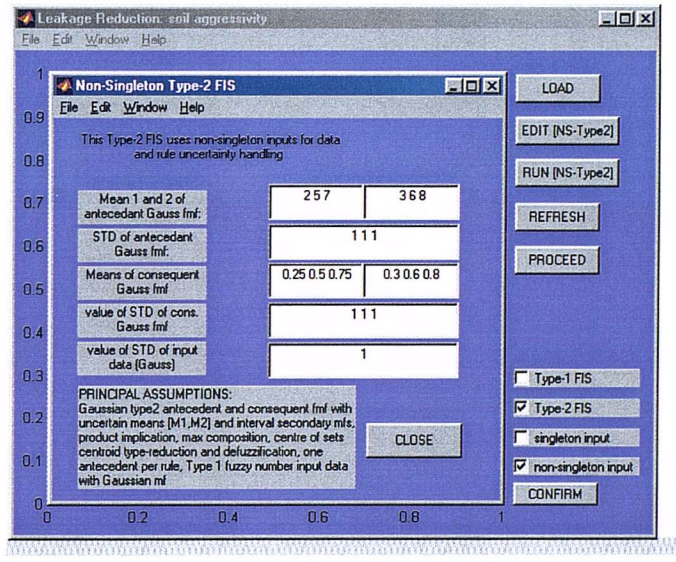


Figure AIII.7. The editor for a type-2 non-singleton FIS

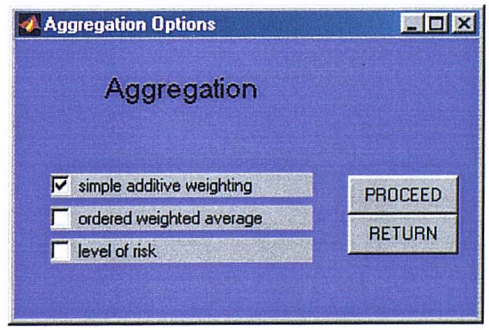


Figure AIII.9. Aggregation choices

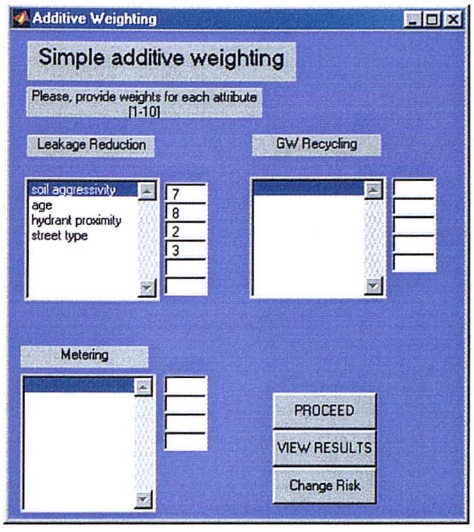


Figure AIII.8. Direct Weight assignment (alone or in combination with OWA)

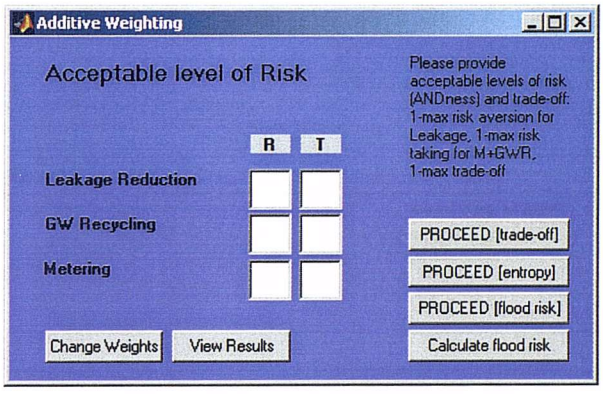


Figure AIII.9. Defining Risk and Trade off for the aggregation process. The user can choose between a trade-off, a maximum entropy and a spatial ordered weighted averaging procedure, the later taking into account flood risk.

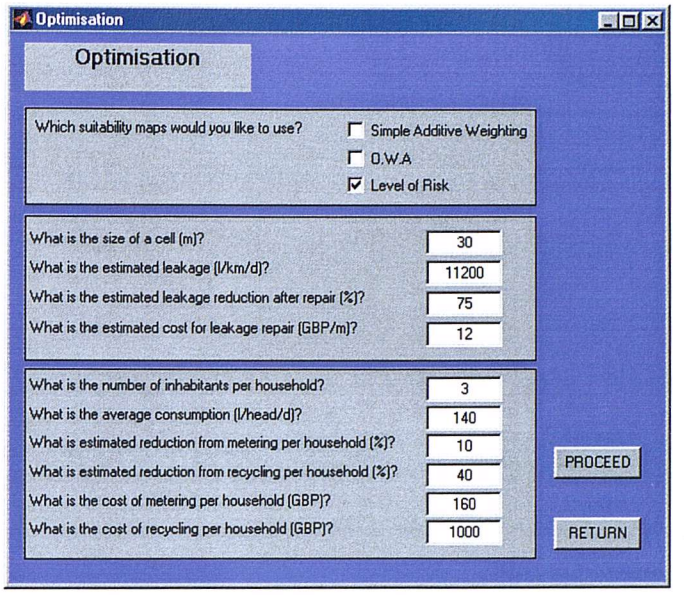


Figure AIII.10. Optimisation GUI. The user states the primary assumptions of the analysis, thus increasing the transparency of the procedure. An additional GUI is used for investment or water target specification

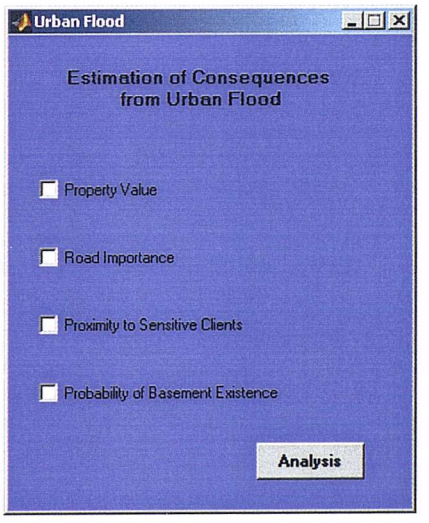


Figure AIII.11. Spatial Ordered Weighted Averaging GUI: Attributes used to calculate flood risk, which is then used to change the aggregation weights for each cell

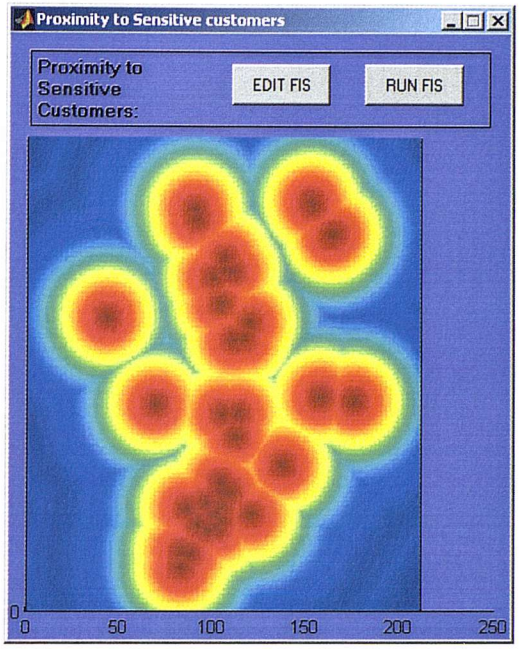


Figure AIII.12. Spatial Ordered Weighted Averaging GUI: Assessing the effect of sensitive clients attribute to the overall flood risk map

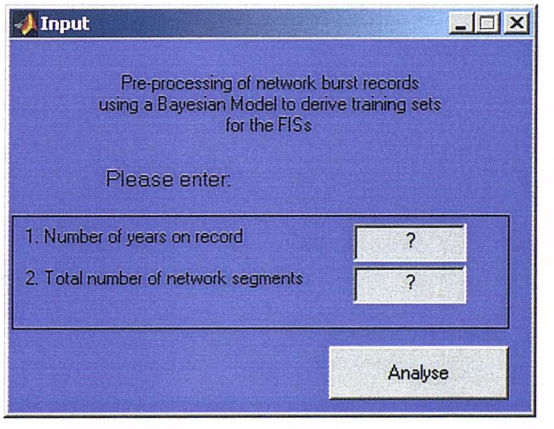


Figure AIII.13. The first interface of the Bayesian training module asking for general input from the data set.

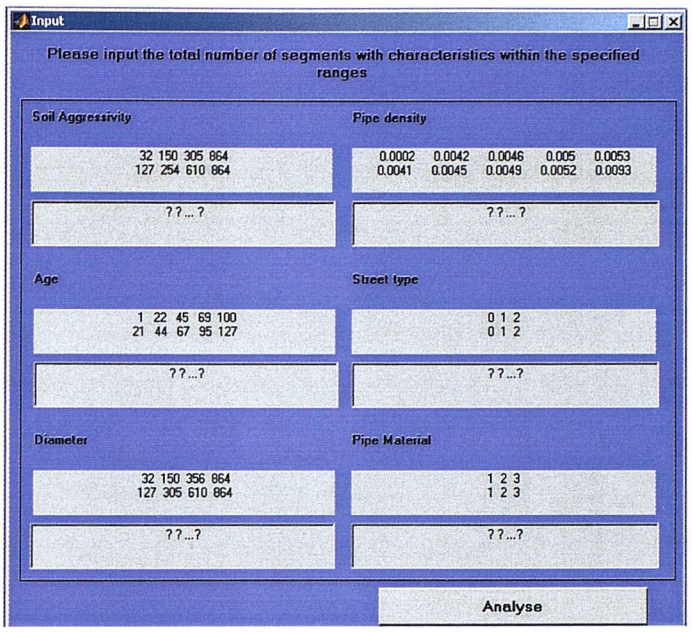


Figure AIII.14. The second interface of the Bayesian training module GUI. The user is asked to input the pipe segments corresponding to the calculated ranges.