

Imperial College London
Department of Chemical Engineering

Operational and technological energy efficiency and
decarbonisation potential of supply chains

Solomos Georgiou

Supervised by Prof Christos N. Markides and Prof Nilay Shah

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Doctor of Philosophy

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Statement of Originality

I hereby certify that, to the best of my knowledge, the content of this thesis is original and the result of my own work. All of the assistance I received and the sources I used have been properly acknowledged.

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Publications

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Abstract

Supply chains can be energy intensive and present significant challenges towards their improvement in efficiency across multiple stages. The present work presents a modelling framework for identifying the stages and processes along supply chains which can offer the greatest potential in achieving savings in energy consumption. The identified stages in the present study are: production, transportation and storage/retail. To quantify and assess the potential for improvement in each of these three stages/processes, modelling frameworks are developed, tested and showcased.

The modelling framework developed for the production stage shows the importance of glasshouses' thermal envelope properties, operational parameters, as well as the impact of location and temporal variability on their energy performance. The transport stage is analysed while optimising the allocation and distribution of products in multi-echelon multi-period supply chains. Modelling frameworks employing deterministic and heuristic approaches are developed for this purpose. The addition of processing stages to these modelling frameworks show their ability to contribute towards better performance, particularly at higher vehicle capacities and for small stores. The retail/storage stage is found to be dominated by electricity consumption, particularly in the case of refrigerated products. The novel approach of electricity storage technologies as solutions towards savings is considered through the thermo-economic modelling of newly proposed thermo-mechanical systems. Their potential as energy solutions is found to be affected by both internal (e.g. roundtrip efficiency, capital costs) and external (e.g. renewable technologies present, electricity prices) factors.

The ability to quantify and assess supply chains using standardised approaches can be a way towards mapping energy consumption, carbon emissions and energy costs. Analyses of outputs from such investigations can offer pathways for improvement as well as contribute to the development of strategies for setting and meeting environmental targets. Findings from this work present potential opportunities through the utilisation of the modelling frameworks developed.

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Nomenclature

Main symbols:

A – area

b – binary decision variable for product from depots to large stores

B – annual benefit

c – specific heat, or carbon factor

C – vehicle capacity, or specific waste cold, or cost

CE – carbon emission per unit distance

CEX – heat exchanger cost

CF – cost factor

CL – cost per unit of volume of fuel

cs – potential for carbon savings

CV – “C-Value” cost

d – demand, or discount rate

D – distance, or diameter

e – vapour pressure

$\dot{E}$ – electricity

E – energy consumption per unit distance travelled, or capacity/size

ED – energy density

EE – emission per unit of energy

EL – emissions per litre

f – factor

F – flow rate

FC – fuel consumption

g – heat leakage factor

h – binary decision variable for product from depots to small stores, or specific enthalpy

I – radiation, or index

$KPIF$ – key performance indicator factor

l – losses

L – loss ratio

LC – lifecycle cost

$\dot{m}$ – mass production rate or flow rate

M – mass

n – number

N – infiltration rate

p – pressure, or pressure ratio

P – energy requirement, or production capacity

PE – peak electricity price

PF – penalty factor

q – continuous decision variable for product from depots to small stores, or discount factor

Q – heat

r – slack variable

R – gas constant, or cost constants

R – route

Ra – radius

s – specific entropy

S – storage capacity

SFP – specific fan power

t – time

T – temperature

u – ration of curtailed electricity to renewables generation

U – overall heat transfer coefficient, or error

v – continuous decision variable for product from depots to large stores, or specific volume

V – volume

w – specific work

W – humidity ratio or work

$\dot{W}$ – power capacity

x – air diversion ratio

Subscripts:

a – actual

amb – ambient

B – base

c – cover, or charge, or compressor, or cold

cp – cryogenic pump

ct – cryogenic turbine

d – discharge, or day

dew – dew point

e – evaporation, or expander

f – floor

fg – latent heat of vaporisation

h – hot

H – height

i – internal, or supplier

j – depot

k – large store, or key performance indicator

l – liquefaction

L – liquid air

m – mean

nor – normalised

o – outside

p – past time

p – pressure, or primary weather station

pr – present time

pr – pressure

r – region

r – roundtrip, or recoverable

rad – radiation

s – system, or secondary station, or storage

t – time period

t – turbine

T – tank

te – temperature

ts – turbine stages

u – small store

v – ventilation, or vapour

w – weather data set

y – year

Greek symbols:

β – solar radiation ratio

Δ – difference

ε – void ratio

η – efficiency

θ – latitude

μ – mean

ρ – density

σ – standard deviation

φ – longitude

ω – temperate ratio

Abbreviations:

BC – base case

BP – buy price

CAES – compressed air energy storage

CAPEX – capital expenditure

COG – centre of gravity

DSR – demand side response

ICOG – initial centre of gravity

KPI – key performance indicator

LAES – liquid air energy storage

LCA – life-cycle assessment

LCOE – levelised cost of electricity

LCOS – levelised cost of storage

MFA – modelling framework A

MFB – modelling framework B

MILP – mixed integer linear programming

MOD – modified

NPV – net present value

OPEX – operational expenditure

PHES – pumped hydro energy storage

PTES – pumped thermal electricity storage

SP – sell price

STB – sell to buy ratio

TRL – technology readiness level

TSP – travelling salesman problem

VRP – vehicle routing problem

WeSIM - Whole-electricity System Investment Model

Any other symbols and abbreviations used are as defined in the text.

Chapter 1

1 Introduction

1.1 Supply chains

A supply chain usually involves multiple stages and processes, and therefore can be considered a system as a whole as well as multiple sub-systems. Therefore, their comprehensive analysis can be multidisciplinary and involve the modelling and study of several research fields. With the expansion of trade horizons, increase in demand, and the development of fast logistics, supply chains have become larger, more complex and more dynamic. Consequently, their analysis and mapping of efficiency of their activities can be a challenge. Food supply chains have their own unique challenges and future projections indicate some that will have to be faced. It is expected that food demand will increase significantly due to population increase (FAO, 2011). To satisfy this growth in demand, global food production will need to increase by about 70% by 2050 (FAO, 2011), thus potentially creating a substantial demand for resources and worsening the environmental footprint of products. Consequentially, this could also negatively affect carbon emissions and climate change.

Furthermore, reports by DEFRA and National Statistics (2013a) and DECC et al. (2015) showed that emissions associated with the UK domestic food sector were responsible for about 30% of the UK's greenhouse gas emissions. In terms of energy, the UK food chain is accountable for about 18% of UK's primary energy use (Tassou, 2014). Also, following the ambitious targets set by organisations and governments for the reduction of carbon emissions (DECC et al., 2015), it is of great interest to seek ways of improvement in efficiency and carbon emissions in order to minimise (or even eliminate) the impact of current and future supply chains.

Estimates, by DEFRA and National Statistics (2013a), of energy consumption and emissions associated with food supply chains highlight the importance of addressing multiple stages for an overall improvement. This is particularly important along supply chains which can have high energy intensity and carbon emissions across multiple stages, even if the stages are not operated by the same stakeholder.

1.2 Emissions

In a supply chain there can be direct and indirect emissions associated with the operations of a company. Direct emissions are defined here as the emissions occurred as a result of the activities of a company by emitting carbon or by consuming electricity with an associated carbon factor (i.e. Scope 1 and 2 emissions) (WRI, 2015). Indirect emissions are defined as the emissions arising from the activities of suppliers of a company (i.e. Scope 3 emissions) (WRI, 2015). Carbon Trust (2011) showed indirect emissions, such as the supply chain of a company, can make up to 80% of its total emissions. A large retailer in the UK estimated that its supply chain emissions can be 10 times the direct emissions of its operations (Tesco Plc, 2010).

A significant challenge is expected in quantifying indirect emissions as there are currently no obligations on reporting those emissions. Nevertheless, studies in literature, such as Downie and Stubbs (2013) and Tidy et al. (2014), indicated the importance of upstream emissions on the environmental impact of products. Estimates presented for products' carbon footprint associated with upstream activities were up to 75-90%. Therefore, ways of mapping, quantifying and assessing the most important upstream activities in terms of energy and emissions can be of interest. This acted as a stirring factor for the focus of the present study.

On the other hand, considering direct emissions can be equally important since for a company it can be a performance metric that is reported, perhaps even for legislation and social responsibility reasons. Also, challenging commitments in the improvement of environmental sustainability can be an additional motivation for considering the direct emissions as well. Therefore, it is clear that energy consumption along with the consequential direct and indirect emissions can be important for a supply chain.

Commonly considered greenhouse gas emissions in supply chains include carbon dioxide, methane and nitrous oxide (Scholz et al., 2015). Their environmental impact is typically correlated by the amount emitted as well as their global warming potential. To consider a single metric for their impact on global warming, emissions are typically expressed in terms of carbon dioxide equivalent (shown as CO₂e) based on their global warming factors. Besides the emissions associated with energy consumption, an additional source of emissions is the refrigerant leakages from refrigeration systems. These leakages can be significant mostly due to their very high global warming potential. This is interesting especially for perishable products requiring refrigeration through their journey in the supply chain.

1.3 Fresh product supply chains

Fresh product supply chains can be particularly interesting in terms of energy consumption and carbon emissions due to their usual refrigeration needs. Cold food supply chains are expected to be associated with an increased energy consumption and carbon emissions in comparison to similar ambient products, particularly at the transportation and storage/retail stages. This is due to the additional energy required to drive the refrigeration systems as well as the leakage of refrigerants with high global warming potential (Birmingham Energy Institute, 2015; Carbon Trust, 2012). An example was presented in Audsley et al. (2009) which showed the greater specific emissions associated with chilled products at the depot and retail stages. This is a characteristic of fresh products which makes them an interesting category of product to study.

Fresh products are also usually associated with fast logistic networks due to their perishability. As a result, frequent deliveries are typically required and can contribute to greater annual travel distances and fuel consumption. There is also the possibility of low vehicle capacity utilisation factors due to the requirements of frequent deliveries and the risk associated with storage over long periods due to their perishability. Furthermore, the common practice of just-in-time depots (Jones, 2002) contributes to the requirement of supply chains operating at a high pace and the importance of maintaining a smooth operation with the ability to accommodate unforeseen variations in supply or demand. These variations can be a result of several factors such as uncertainties in production yields at the supply end, and weather conditions at the demand end. Therefore, the development of allocation and distribution networks in a standardised (and potentially optimal) approach while studying the impact of relevant parameters can be of particular interest.

Fast logistics in combination with refrigeration have contributed to the growth of a market for all-year-round demand for fresh products (Jones, 2002). This typically requires out-of-season production through protected heated production or the importation of products from distant origins. Both options are expected to be associated with greater energy consumption and carbon emissions; protected heated production mainly due to heat requirements and imports mainly due to the additional travel distance and associated fuel consumption (Carlsson-Kanyama, 1997). A debate has been long existed in literature about the impacts of the two approaches and the most environmentally friendly approach to obtain out-of-season products (Carlsson-Kanyama, 1998, 1997; Garnett, 2008a; Jones, 2002; Payen et al., 2015; Shi et al., 2018). The answer is expected to be case specific but when considering similar systems, it can be safely assumed that most likely both approaches will have a greater footprint than products grown at close proximity to demand and in-season. Multiple studies have indicated the great impact (and sometimes dominance) of heating requirements during production on global warming and overall energy consumption in the lifecycle of a product (e.g. Payen et al. (2015), Cellura et al. (2012), Ntinis et al. (2017)). Therefore, the seasonality associated with products can be another aspect of interest that contributes to the environmental footprint of the supply chain.

1.4 Energy consumption

Along supply chains, typically energy is generated and/or consumed in various forms while originating from various sources. These can be broadly categorised into conventional fossil fuels and renewables. Fossil fuels, including electricity generated from them, clearly dominate across the supply chain (Gowreesunker and Tassou, 2015). In 2008 it was estimated by Garnett (2008a) that renewables accounted for as low as 5% of the primary energy consumption for agriculture. This penetration was close to overall renewables penetration in the UK in terms of

primary energy fuel and electricity generation (National Statistics, 2019). Over the past decade a significant improvement was achieved by increasing renewables' penetration with their presence in electricity generation (in 2018 being >30%) increasing at a considerably higher rate than in total energy consumption (in 2018 being <15%) (National Statistics, 2019). As a result, depending on the food sector, the renewables penetration could vary. Nevertheless, there is still significant dependency of the food sector on fossil fuels and improvements in the efficiency of the system can potentially improve food security and decrease the influence of fuel prices on the cost of food.

Moreover, decentralised power generation is an upcoming common practice in an attempt to improve energy efficiency, for example through renewable energy generation, and therefore decrease carbon emissions. Examples of power generating technologies include biomass boilers, solar photovoltaics, and combined heat and power generation (Gowreesunker and Tassou, 2014; J Sainsbury Plc, 2014; Mariaud et al., 2017; Mitie, 2011; Tassou, 2014). Improvement in energy efficiency through decentralised power generation can be achieved, for example, through the use of combined heat and power (CHP) plants when heat and electricity demand coexist. This approach could potentially enhance the overall efficiency of heat and electricity supply. Also, decentralised renewables which do not suffer from thermal efficiency losses could also provide some benefits in the correct setting. Also, another category of systems involving power generation is the electricity storage systems. While batteries have been studied as a technology solution (Mariaud et al., 2017), the adoption of medium to large scale electricity storage systems with long lifespans has not been extensively studied in literature.

Costs associated with improvement measures, either capital or operational, can act as barriers for implementation. A recent common example in which cost acted as a barrier for the

application of environmentally friendly technologies was the introduction of renewable technologies, more specifically their capital expenditure. However, it can be observed that with their matureness and deployment typically specific costs decrease thus promoting even more capacity deployment. Therefore, emerging technologies can sometimes offer impactful future opportunities for solutions. However, their analysis and comparison against existing technologies can be a significant challenge due to the lack of data and/or knowledge. Nevertheless, feasibility analyses based on models integrating technical performance and economic competitiveness can provide an initial indication of the attractiveness of the systems. Interesting performance indicators include technical performance, such as efficiency, as well as economic ones, such as capital costs, operational costs, and net present values (Lumby, 1994).

While heating requirements typically dominate the production stage and transport fuel typically dominates the distribution stage, electricity usually dominates storage and retail stages (Spyrou et al., 2014) (especially when focusing on chilled products). Therefore, novel and effective ways to improve energy efficiency and carbon footprint in electricity consumption are interesting to study. Since electrical energy storage has been found to be of such great value in terms of economics, emissions, support to renewables' penetration, and meeting future demands (Strbac et al., 2012), its implementation in a commercial and high renewables penetration setting is interesting to investigate as a solution.

1.5 Structure of report

The aim of this work is to present methods for addressing the most impactful stages and processes in supply chains involving energy intensive products associated with seasonality, extensive and fast logistic networks, and refrigeration requirements. The remainder of this

report is structured in the following order: i) background, initially giving a high level introduction to studies focusing on supply chains and then focusing on the main subject areas of interest; ii) methodology separated into three sections, one for each subject area; iii) three chapters of results, one for each of the subject areas, with a highlights subsection in each one summarising the main findings; and iv) the conclusion summarising the main findings of this work and bringing everything together.

Chapter 2*

2 Background

In this section a general overview of supply chain analysis is given initially and thereafter a more specific literature review is presented focusing on the main areas of interest in this work.

Supply chain and modelling approaches presented in literature typically vary in terms of supply chain stages and processes incorporated. For example, the main stages of food supply chains for energy flows presented in the review papers of Tassou (2014) and Gowreesunker and Tassou (2015) were agriculture, processing, distribution, packaging, retail, households, and waste disposal. Common supply chain stages from literature are shown in Fig. 2.1. Jones (2002), however, who focused on the case study of dessert apples and the environmental impact of their supply chain, considered less stages excluding the agricultural, household and waste

*Parts of this chapter were presented earlier in Georgiou et al. (2019, 2018c, 2018b, 2018d, 2018a, 2017b, 2017a).

disposal stages. Similarly, Carlson (1997) focused on the greenhouse gas emissions of carrots and tomatoes while including the agricultural and transportation stages along with aspects such as fuel, refrigerants and fertilisers. However, it did not consider the retail, household and waste disposal stages.

Furthermore, Michalský and Hooda (2015) focused on the comparison of greenhouse gas emissions associated mainly with the production and transportation stages for imported and locally produced products, while excluding stages that were considered important in other studies. Another example includes Hospido et al. (2009) which considered the production and distribution of materials associated with the environmental impact of lettuce consumption while excluding the stages of retail, household and waste. Even more stages, such as waste utilisation, can be included as Goula and Lazarides (2015) and Scholz et al. (2015) presented.

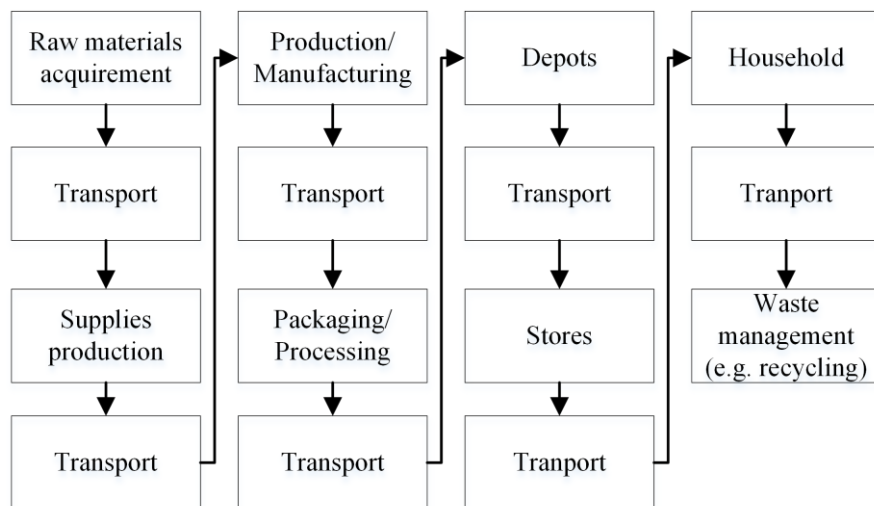


Figure 2.1. Common stages/processes in supply chains from literature.

Nevertheless, these variations are justified due to the difference in the purpose of each study along with the supply chain characteristics and scope of interest. For example, different emphasis is expected to be given on stages and processes when a study focuses on energy rather than addressing sustainability in a more general sense. Likewise, specific performance indicators are expected to drive a study towards a focus and analysis of particular areas. For instance, differences are expected between studies focusing on energy compared to ones focusing on waste.

In terms of modelling approaches, considerable attention has been given on the manufacturing and logistic oriented supply chains but much less on supply chains focusing on food production, distribution and retail (Mehdizadeh et al., 2012). Papageorgiou (2009) listed the main decisions typically considered in supply chains to be: i) production planning and scheduling, ii) interrelations between stakeholders, iii) transport, iv) inventory control, and v) characteristics of facilities such as location, number, and size. Furthermore, Papageorgiou (2009) stressed the importance of modelling approaches to consider for future challenges, including sustainability. The same study also stressed the need for the development of frameworks integrating environmental and economic aspects for supply chains. Some of the main challenges identified in Papageorgiou (2009) was the lack of detail in the representation of processes in the supply chain and the incorporation of assessment criteria besides economic ones. Therefore, an incentive in analysing supply chains by focusing on the key impact stages in more detail while considering both economic and environmental aspects emerges.

The use of optimisation models to consider the economic and environmental performance was studied in literature (e.g. Frota Neto et al. (2008), Hugo and Pistikopoulos (2005), Paksoy et al. (2011), Wang et al. (2011)). Hugo and Pistikopoulos (2005) proposed the integration of life-

cycle assessment (LCA) with multi-objective models for the design of sustainable supply chains. An example found in literature employing this approach was You et al. (2012). A multi-objective mixed-integer linear programming model integrated with LCA and input-output analysis was presented for the design of sustainable cellulosic biofuel (You et al., 2012).

The other aspect associated with the analysis of supply chains is the decisions' timeframe and purpose. A significant attention in literature falls on the design of supply chains. For example, Wang et al. (2011) used mixed integer optimisation for the design of the supply chain network. Also, Chaabane et al. (2012) presented a linear programming optimisation model used for the design of the supply chain showing particular attention to the impact of legislations and schemes (e.g. emission trading scheme).

The logistics aspect of supply chains is another area that has been extensively studied in literature. Examples include the study of Ubeda et al. (2011) which presented a logistic model for a food distribution company while considering the environmental impact through CO₂ emissions. Similarly, Frota Neto et al (2008) modelled the logistics network of pulp and paper. Furthermore, Validi et al. (2014) studied the distribution system of milk through the minimisation of CO₂ emissions. Lampropoulos (2014) developed a model for optimising the transportation of strawberries in the supply chain while also focusing on waste.

Interestingly, some studies considered the environmental sustainability in terms of greenhouse gas emissions but in the context of the cost/benefits associated with emissions and by obeying environmental regulations. Chaabane et al. (2011) proposed a linear optimisation model considering the costs and regulations associated with the carbon emissions of various activities. The main performance indicators were the carbon emissions and logistics' costs. Similarly,

Abdallah et al. (2012) considered, through a mixed integer program, the impact of carbon trading and the potential costs or benefits that a company might have from carbon emissions.

Another interesting approach for improving the environmental sustainability of supply chains was proposed by Yeh and Chuang (2011). In that study, the selection of partners was based on their green appraisal score through a mathematical model (Yeh and Chuang, 2011). This approach can be potentially applied in a wide range of supply chains. However, environmental certificates/scores based on standardised procedure for a fair assessment could be vital. Therefore, the development of models that can potentially map, benchmark and assess suppliers based on their environmental footprint can be of significant interest.

Focusing on supply chains involving fresh products, Soto-silva et al. (2016) presented a review study of operational research models focusing on fresh fruit supply chains. One of the main findings was the lack of holistic approaches/models for fresh fruit supply chains. Therefore, there was an opportunity to study this kind of supply chains in a way that has not been studied extensively in literature. This was an interesting observation as fresh products may differ from other products in several ways, such as perishability, delivery frequency requirements, refrigeration needs, seasonality and more. Interestingly, Soto-silva et al. (2016) noted the lack of carbon footprint and environmental sustainability as one of the main objectives for improvement while identifying the most common objectives to be profit, net present value and net revenue (e.g. Catalá et al. (2013), González-Araya et al. (2015), Nadal-Roig and Plà-Aragonés (2015)).

The origin of products and their environmental impact have also been studied in literature (e.g. Jones (2002), Carlsson-Kanyama (1998)). The impact of origin can have an effect on transportation distance as well as production. Studies have focused on the impact of transport

distance on the carbon footprint of products compared to locally sourced options. For example, Sim et al. (2006) studied the importance of transport with regards to sustainability when sourcing food while using LCA.

The modes of transport in literature can be categorised either in terms of type of surface used to travel on: land, air and water; or in terms of technology used: road transport vehicles, train, sea freight and air freight. It is widely accepted that air freight is the most energy and carbon intensive mode of transport (Garnett, 2006; Jones, 2002). However, the amount of fresh products currently being transported by air to the UK is small (Garnett, 2006). In terms of movement in the UK, 98% of food commodities are transported by road, something that proves the food system's dependency on this mode of transport and its infrastructure (Jones, 2002). This represents a challenge for decarbonising the transport stage but also shows the potential for finding solutions specific to this mode of transport.

However, besides the transportation distance, other factors can have an influence. More specifically, Carlson (1997) and Sim et al. (2006) showed the impact of producing products at proximate locations can sometimes involve high energy requirements and carbon emissions due to external conditions. This is particularly important when there is out-of-season demand and protected heated production is required to produce the product locally. Studies in literature, such as Torrellas et al. (2012), Dias et al. (2017), Ntinis et al. (2017), showed the dominance of the production stage in terms of energy requirements when it involves heating as well as its impact on global warming. Therefore, production of fresh products under auxiliary heating represents another interesting area for further investigation.

Moreover, fresh products are typically associated with refrigeration requirements due to their perishability. The main purpose of refrigeration is the preservation of safety and quality of the

product along the supply chain in order to satisfy regulations (Panozzo and Cortella, 2008) as well as to meet customer quality expectations. As mentioned earlier, the ability to maintain products at low temperature due to refrigeration can sometimes allow the transportation of products from long distanced origins; hence potentially contributing to an all-year-round demand of products. Refrigeration can have an impact on the energy and carbon footprint of a product due to the additional energy required to drive the refrigeration along with any emissions due to the leakage of refrigerants with high global warming potential. Nevertheless, the energy requirements can be considered the main focus here mainly due to two reasons: i) about 75% of refrigeration emissions contributing to global warming are typically due to energy consumption (Panozzo and Cortella, 2008), and ii) regulations are already in place to eliminate the use of refrigerants with high global warming potential that contribute to emissions (EU, 2016).

Refrigeration along the supply chain is typically found in transport and storage, including display at retail stage. At the retail stage, in some cases up to 50% of the electricity consumption can correspond to refrigeration (Zhang, 2006) whereas estimates for penalty in energy consumption of vehicles at the transport stage were found to be in the range of 14-25% (MacRae et al., 2013; Scholz et al., 2015; Tassou et al., 2009, 2008). Therefore, addressing the energy consumption associated with refrigeration at the retail stage through a centralised approach can potentially contribute to greater savings. Improvements in the refrigeration systems at the retail stages have been extensively studied and proposed by Carbon Trust (2012). It was noted that no single solution can decarbonise refrigeration and that refrigeration will most likely depend on fossil fuel energy in the short and medium terms (Carbon Trust, 2012). Even though refrigeration is usually the greatest single electricity consumer at retail stage, other services such as lighting, space heating, space cooling, and ventilation can also contribute

significantly to the overall energy requirements (Spyrou et al., 2014; Tassou, 2014). Nevertheless, electricity usually clearly dominates the energy consumption at retail stage with a rough ratio of electricity to heat consumption of about four (Spyrou et al., 2014).

Since fresh products requiring refrigeration are of main interest in this work, their allocated footprints at the retail/storage stage are expected to be higher than ambient products due to their additional electricity consumption. Therefore, addressing electricity consumption at these supply chain stages can potentially provide an effective way of improving the performance and footprint of the product in terms of energy, emissions and energy costs.

To sum up, the three main supply chain stages and processes identified to have the potential for an impactful improvement as well as for further investigation in the context of this work were: i) the heating requirements at the production stage for protected heated production, ii) the allocation and distribution of product through logistics networks based road transportation, and iii) the electricity consumption at the retail/storage stage.

Interestingly, the energy requirements along the supply chain can be categorised similar to the energy requirements of most typical organisations or even countries; that is in heat, transport and electricity. Looking at the different supply chain stages of interest in this work, it can be observed that: heat requirements are expected to dominate the production stage, transport fuel requirements to dominate the distribution of the product, and electricity requirements to dominate the storage (including depots) and retail stages. The rest of this chapter will focus on relevant literature and background of these three areas.

2.1 Heat – Production stage[†]

The share of energy consumption, and therefore carbon emissions and energy costs, associated with production is expected to be affected by the characteristics of the production system such as technologies used, energy sources, location, and products (Carlson, 1997). For instance, open field production is expected to require considerably less energy for production but typically it can only be applied when the environmental conditions allow. Therefore, with the expectation of product supply out-of-season, protected heated production can be significant. Nevertheless, the specific system of interest needs to be studied in more detail in order to be able to quantify its energy requirements.

A 70% increase in global food production is expected by 2050 (FAO, 2011). As it is common with most sectors on a global and UK scale, the UK food sector is heavily depended on fossil fuels while ambitious future targets for reduction in carbon emissions have already been set (DECC et al., 2015). In parallel, retailers were observed to increase their interest in mapping their carbon footprints as well as setting challenging reduction targets (ASDA, 2017; Sainsbury's, 2017; Tesco plc, 2017). To satisfy this growth in demand, additional resources or significant efficiency improvements will most likely be required. Subsequently, reducing absolute carbon emission while satisfying extra demand can be a significant challenge.

Estimates provided by DEFRA and National Statistics (2013a) and DEEC and National Statistics (2015) identified the UK domestic food section to be responsible for about 30% of the UK's greenhouse gas emissions. This is a significant share and therefore variations in the

[†] Parts of this section were presented earlier in Georgiou et al. (2018a, 2017a).

footprint of this sector can possibly influence the potential for achieving the country's emissions targets set. Similarly, Tassou (2014) estimated the energy consumption associated with UK food chains to be around 18% of the total primary energy use of the country. Therefore, reducing the energy needs of this sector can potentially increase energy security and reduce uncertainty in energy requirements. For food retailers, the improvement in energy efficiency can result in more resilient and robust supply chains from which they can benefit in the long term.

Furthermore, developments in the transport sector have contributed to the creation of an out-of-season market for fresh products (Jones, 2002). However, to produce out-of-season products locally, a protected and controlled environment is usually needed. Therefore, heated glasshouse food production is an approach that can contribute (in addition to imports) to the satisfaction of out-of-season demand. On the other hand, to maintain an internal space (like a glasshouse) at some set conditions required for production, typically imposes additional energy requirements. As a result, a debate about the energy intensity of imports against heated local production exists in literature (Carlsson-Kanyama, 1998, 1997; Garnett, 2008a; Jones, 2002). The main reason of the competitiveness of imports from distant origins against heated production in terms of energy requirements is due to the energy intensity of maintaining the glasshouse at the ideal conditions (Carlsson-Kanyama, 1997). Nevertheless, the energy requirements associated with glasshouse production are expected to be affected by several factors such as weather conditions, technologies used, energy sources, locations, and production targets (Carlsson-Kanyama, 1997), as well as the production system in general. Since so many factors can have an impact, quantifying, assessing, benchmarking, and comparing energy requirements can be challenging.

The energy requirements of glasshouse production have been explored previously in literature, for instance in studies such as Luo et al. (2005), ASABE (2008), Gupta and Chandra (2002), Wass and Barrie (1984), Chalabi et al. (2002), Moreton and Rowley (2012), Ozkan et al. (2011a), Ozkan et al. (2011b), Mariani et al. (2016), Papadopoulos and Hao (1997), and Subić et al. (2015). Papadopoulos and Hao (1997) studied the influence of glasshouse cover material in three tomato glasshouses with focus on productivity, yields, and energy requirements. Gupta and Chandra (2002) focused on the impact of a glasshouse's design in India on its energy consumption, particularly with respect to its shape and orientation. Chalabi et al. (2002) considered strategies of carbon dioxide enrichment in glasshouses while extending to the development of an energy balance model. Furthermore, the American Society of Agricultural and Biological Engineers (ASABE, 2008) proposed engineering practices for designing heating and cooling systems for glasshouses.

A model focused on the energy requirements of glasshouses with attention to temperature regimes, dimensions and weather variations was also presented in Wass and Barrie (1984). Also, Mariani et al. (2016) examined 56 sites located in Europe and Mediterranean with respect to glasshouse heating requirements, while focusing on time and space variability. It considered long times and very wide geographical territories while showing a particular interest on the impact of climate change. To acquire the data required for the model, the study used an interesting approach which employed only maximum and minimum daily temperatures to create hourly temperature and radiation data. This technique can be advantageous particularly for areas with very limited meteorological weather data where macroscale analyses are of interest. On the downside, real weather data can provide a more granular analysis while considering the effect of real weather variations as well as their unpredictability. Moreover, Ozkan et al. (2011a) and Ozkan et al. (2011b) studied specifically single and double crop

tomato production in terms of energy requirements. In addition to the direct energy consumption due to fuel and electricity, these two papers also considered indirect consumption as a result of manure and fertiliser usage.

In terms of energy sources and energy supplying technologies, Subić et al. (2015) studied the use of geothermal waters as an energy source for flowers (roses, gerbera, and cella) and vegetables (pepper, tomato, and cucumber) production in glasshouses. The production of tomatoes and roses using this technique were found to be the most promising in terms of economic benefits. Furthermore, Moreton and Rowley (2012) studied the potential of biomass combined heat and power (CHP) in glasshouses to satisfy the energy requirements from a techno-economic perspective. The study also examined the potential carbon savings from such approach. Findings showed the importance of the biomass CHP's heat-to-power ratio in matching the demand profiles of the glasshouse for the feasibility of their implementation in such setting to achieve carbon reductions.

Vanthoor et al. (2011) considered glasshouses from a slightly different perspective, the estimation of the glasshouse's internal environmental parameters. It proposed a method for describing the effects of glasshouse design parameters and weather while focusing on the prediction of parameters such as CO₂ concentration, temperature, and vapour pressure. In a similar manner, the impact of internal set temperature on crop mass production and energy requirements was studied by Luo et al. (2005) while focusing on the prediction of the microclimate conditions in the glasshouse for winter and summer periods in China.

Another approach that environmental impact of glasshouse food production was studied in literature is through life-cycle assessments (LCA) (Cellura et al., 2012; Dias et al., 2017; Ntinis et al., 2017; Payen et al., 2015; Torrellas et al., 2012). These assessments can identify hot spots

in the lifecycle of a product that can be potentially addressed in more detail to achieve savings. To start with, Payen et al. (2015) compared tomatoes imports against tomatoes locally grown in France from an environmental perspective. It concluded that tomatoes grown in heated glasshouses were accountable for greater energy use and global warming than the equivalent product grown without heating in Morocco, even when accounting for transportation. Similarly, Cellura et al. (2012) studied the energy and environmental performance in Southern and Northern Europe of various products; namely melons, tomatoes, cherry tomatoes, and zucchini. Once again, the requirement of heating in Northern Europe was found to be responsible for greater energy requirements and global warming than Southern Europe where heating requirements are typically not necessary.

Furthermore, Torrellas et al. (2013) presented an environmental impact calculator for glasshouse food production and results showed the significance of heating in the energy requirements, especially due to its dominance in the central Europe case. Likewise, Ntinis et al. (2017) pointed out the importance of fuel consumption due to heating requirements in heated glasshouses by considering carbon emissions and energy demand for open field and glasshouse tomato production in central and southern Europe. Dias et al. (2017) examined the sustainability of glasshouse tomato production in Ontario through an LCA analysis. Once more, heating using fossil fuels was found to dominate the global warming and cumulative energy demand. Torrellas et al. (2012) examined protected production of crops for four different cases. Based on cases of three European locations and two crops, the study found the reduction of fossil fuel consumption required for heating and electricity to be the highest priority for improvement in glasshouses sited in cold climates in terms of both environmental and economic metrics. Following the aforementioned studies, the importance of heating requirements on the sustainability and environmental footprint of heated production operating

on fossil fuels was noted. Interestingly, apart from the production system, Page et al. (2012) stressed the importance of seasonality and growing schedules on the carbon emissions of glasshouses.

LCA studies can be very insightful and assist in the identification of influential processes for the sustainability of a product. Nevertheless, it is common in such studies to obtain energy input information from questionnaires or surveys and to base the analyses on either specific production systems or on annual average performances (Cellura et al., 2012; Dias et al., 2017; Ntinis et al., 2017; Page et al., 2012; Payen et al., 2015; Torrellas et al., 2013). Therefore, their purpose is different from the work presented here. As noted earlier, energy requirements associated with heated glasshouse production can dominate the environmental sustainability of a product and can also present the greatest potential for improvement. In addition, the impact of different elements for improvement can vary between production systems (Torrellas et al., 2012).

A lack of generic energy associated tools for glasshouses which focus on the UK and require limited inputs as well as consider a wide variety of factors, including glasshouse design, operating conditions, geographical locations, varying weather and climate patterns, and growing schedules, was noted. Also, studies found in literature typically focus on specific aspects, such as locations, time periods, production systems, products, and glasshouse design. As a result, they typically require detailed input parameters which can sometimes be unknown or require considerable effort, time and cost to acquire. Generic modelling frameworks with limited input requirements can facilitate preliminary analyses for the identification of impactful parameters through parametric analyses. Also, they can act as a tool for performance benchmarking and energy efficiency assessment of a large portfolio of suppliers based on a

standardised approach. Therefore, there was an interest to generalise glasshouse production while integrating vital aspects for the development of a model. Nevertheless, the generalisation of models can sometimes come at the expense of accuracy, but a balance between highly technical models and high level macroscale models can be highly valuable in offering reasonable estimates under specific conditions.

Furthermore, LCA studies were found to be of interest in literature and provide great insights of the environmental impact of products/processes. However, they sometimes lack the impact of potential future improvement measures from a quantitative perspective. Since auxiliary heating in glasshouse (where applied) was identified as one of the most significant contributors in energy consumption and global warming, it was of great interest to identify and quantify the impact of improvement measures. Therefore, a tool that can simulate the energy consuming (heating/cooling) processes of glasshouse production can potentially provide hypothetical inputs into LCA studies and assess different hypothetical production systems (e.g. energy sources, products, location, operational and technical characteristics) from an LCA viewpoint.

Finally, a potentially valuable contribution to literature includes the development of a model in the form of a decision support tool intended for the UK, and the testing and showcasing of the model through a UK case study analysis. The case study could consider both performance and operational parameters associated with the glasshouse energy requirements, energy costs, and carbon footprint. Additionally, the spatial and temporal (both daily and annual) variations while quantifying the impacts expected and uncertainty introduced due to meteorological variations was found to be of interest. This was because the minimisation of uncertainty along with the improvement in robustness/stability of glasshouses and their stakeholders can be pursued.

In addition to the potential contributions from such model/tool mentioned above, such modelling framework could also attempt to integrate several areas including data analytics (comprising real meteorological data), data visualisation, modelling (for energy, carbon and energy costs), and decision support tool development. Also, this could be particularly interesting when performed in an overall generic modelling framework for one of the most energy intensive process of production while having simplicity and broad applicability as an objective.

2.2 Transport – Distribution stages

The efficiency and sustainability of supply chains usually incorporates the important effect of transportation of products to and from different stages/stakeholders (Jones, 2002; MacRae et al., 2013). A potential reason for this becoming continuously more relevant is the dependency of transport technologies on fossil fuels in combination with the development of these technologies to enable the fast and safe transportation of products both locally and internationally (Garnett, 2008b; Michalský and Hooda, 2015). Therefore, the interest in emissions and costs involved in this process of supply chains have been continuously growing.

It is usual for the different types of travel surfaces (land, air and water) or technologies (road transport vehicles, sea freight, air freight, and trains) to be used to categorise the available modes of transport. Energy consumption and carbon emissions associated with the different options can significantly vary and it is therefore a factor that needs to be accounted for when studying the impact of goods' transportation. DECC and DEFRA (2016) presented a comprehensive library of emission factors for different technologies, scenarios and fuels. These factors are also used in the UK for company reporting purposes.

It is interesting to note the dominance of the road transport mode for food commodities in the UK. Eighty eight per cent of food commodities are transported by road and this highlights the dependency of the food system on this mode of transport and its corresponding infrastructure (Jones, 2002). Jones (2002) explained this as mainly being a result of depots located close to motorway networks in combination with their usual just-in-time operation; consequently making them relying highly on motorways. This dependency in combination with an existing infrastructure network in place can act as constraints for both optimising the distribution networks as well as shifting to less carbon intensive modes of transport. Furthermore, heavy good vehicles were found to be accountable for about 80% of food freight in the UK, thus making them particularly interesting to study for improvement solutions (Tassou, 2014).

Tassou et al. (2008) categorised food distribution by road into primary, secondary and tertiary. The different categories correspond to: from suppliers to depots, from depots to demand nodes, and wholesale depots to independent retailers, respectively. Tertiary distribution is considered here as out of scope due to the main area of focus being large supply chains of organisations. Also, primary and secondary distributions are mainly dominated by articulated vehicles (~80%) in terms of total ton-km goods movement in the UK (Tassou et al., 2009). Therefore, they are considered here as the potentially most impactful categories for road transport.

Following from the arguments made above regarding the current system and modes of transport, improvements involving the immediate shift to alternative less carbon intensive modes of transport can be challenging in the short- to medium- terms. Subsequently, improvements associated with the improvement of the current mode of transport, instead of its replacement, can be more relevant and achievable at this stage. Improvements have been

studied and achieved in logistics over the past years. Examples of improvement measured included vehicles efficiency improvements and the use of dual-fuel vehicles with the use of bio-fuels (Business Green, 2014; J Sainsbury Plc, 2018; Tesco, 2018). Nevertheless, fossil fuels in most cases are still dominating the transport sector.

Besides technological improvements and shifts, the minimisation of travel distance and time of transportation are also potential aspects for achieving savings. Decrease in travel distance is beneficial for obvious reasons while decrease in time per unit of distance travelled can be beneficial in terms of refrigeration requirements and/or waste. However, this should not be done at the expense of energy efficiency due to higher speeds in the same mode of transport. Furthermore, the utilisation of empty trips can also contribute to a lower footprint of a product, whether that specific product is used in the empty trips or not. Tassou et al. (2008) considered the effect of empty trips on energy consumption by assuming a decrease of 30% across all weight categories when vehicles travelled empty. Common approaches followed by retailers included the training of drivers for the adoption of an optimal driving behaviour for the reduction in fuel consumption as well as the use of double decked vehicles (IGD, n.d.; J Sainsbury plc, 2011; Tesco Plc, 2010).

Even when considering national supply chains, it is very usual to include imports of goods from abroad. For instance, DEFRA and National Statistics (2013b) showed that large volumes of fruits and vegetables are imported in the UK. The comparison of environmental impact between local/national production and import has attracted to interest of literature impact (e.g. Jones (2002), MacRae et al. (2013), Michalský and Hooda (2015), Sim et al. (2006)). The debate around this subject is considered out of scope here. Nevertheless, the fulfilment of demand requirements usually necessitates the source of products from a variety of origins. In

a modelling exercise involving optimisation, this flexibility and diversity ensure the feasibility of the model without the violation of production capacity and demand related constraints.

The transportation of goods along supply chains in the form of logistics models is a field which has been widely studied in literature. Examples include the study of Ubeda et al. (2011) which considered the case study of a food distribution company while optimising for environmental impact through the consideration of carbon emissions. Furthermore, a method focusing on food quality in combination with production and distribution planning while using a mixed-integer linear programming model was proposed by Rong et al. (2011). Likewise, Lampropoulos (2014) considered the decarbonisation of a strawberry supply chain in the UK while focusing on the transport stages and waste. Moreover, a multi-objective optimisation approach considering costs and carbon emissions from logistics for a milk supply chain was presented by Validi et al. (2014). Similarly, Frota Neto et al. (2008) modelled the logistics of a pulp and paper supply chain.

Park (2005) considered in its analysis both production and distribution systems in an integrated optimisation approach. It considered a variety of products, retailers, periods, and production plants. The benefits from following an integrated technique considering both production and distribution in a heuristic computational model were highlighted. Nevertheless, it also pointed out the challenges arising from such mathematical models when they scale to a large number of agents; more specifically the possibility of becoming computationally unsolvable. Such approach can be very useful, especially for supply chains involving products whose production can be controlled. However, this can be challenging and sometimes its applicability limited for fresh products whose growth is greatly affected by seasonality.

Another extensively studied area in literature concerns the design of logistics networks. Nevertheless, Eskandarpour et al. (2015) concluded that generic sustainable supply chain network design exercises were not a primary focus in literature. According to the same study, decisions emerging from such exercises can have a great effect on the operational performance of supply chains. A study focusing on the strategic design optimisation of supply chains while considering environmental as well as cost aspects is Wang et al. (2011). Similarly, Tsiakis et al. (2001) optimised the design of a multi-product, multi-echelon supply chain network through an MILP. The model assumed fixed customer and manufacturing locations whereas depots and warehouse locations were to be determined.

Literature has also showed some interest in reverse logistics (e.g. Ramos et al. (2014)). Ramos et al. (2014) presented a multi-objective vehicle routing problem involving objectives associated with social, environmental and economic aspects. Lee et al. (2010) considered forward and reverse logistic operations through a deterministic MILP for the development of sustainable networks. The model was then expanded to a two-stage stochastic model.

Furthermore, routing problems have been a research area on their own in literature (e.g. (Brackers et al., 2016; Dondo and Cerdá, 2007; Erdoğan and Miller-Hooks, 2012; Hadjiconstantinou and Baldacci, 1998)). Given their heavy interest and relativity, several algorithms and methods for solving them have been proposed and analysed. The general vehicle routing problem (VRP) represents one of the challenging combinatorial problems and it has been a pivotal subject of interest in the field of operations research (Hadjiconstantinou and Baldacci, 1998). The challenging nature and practical applicability of VRP resulted in an increased interest in literature and is widely accepted as one of the challenging problems of combinatorial optimisation (Dondo and Cerdá, 2007). Unfortunately, its computational

difficulty to solve to optimality has made it a significant challenge to apply in real life cases (Dondo and Cerdá, 2007; Erdoğan and Miller-Hooks, 2012). Subsequently, heuristic methods have also been studied extensively for solving such problems. Braekers et al. (2016) pointed out that exact algorithms are usually applied in small problems due to the difficulty in implementing them in large ones. Therefore, it is common for heuristics and metaheuristics to be employed in real life scenarios which are considered large with several characteristics (Braekers et al., 2016).

Studies sometimes present and compare exact and heuristic approaches as well as variants of the VRP. For example, Dondo and Cerdá (2007) presented both exact and hybrid (heuristic) techniques for the VRP while having time windows. The hybrid technique could solve an instance with 100 nodes whereas the exact approach was limited to a single depots and 25 nodes (Dondo and Cerdá, 2007). The hybrid method proposed involved the “cluster-first-route-second” approach. Through clustering, a more compact version of the problem is formed in order to be solvable by the exact algorithm, and afterwards to perform scheduling and routing (Dondo and Cerdá, 2007). An example of a variant of the VRP, described as the “Green Vehicle Routing Problem”, was investigated by Erdoğan and Miller-Hooks (2012). This version considered the impact of trucks refuelling while in routes with the flexibility of visiting a fuel station more than ones or not at all.

Another variant of the VRP is the multi-depot VRP. Most exact methods used for solving VRP are usually difficult to be used for solving multi-depot VRPs as noted by Montoya-Torres et al. (2015). According to Montoya-Torres et al. (2015), heuristic or meta-heuristic approaches were used by 75% of the studies considered in their review for multi-depot VRPs. For example, Hadjiconstantinou and Baldacci (1998) used a heuristic method to solve a multi-depot period

VRP with the objective of determining the areas allocated to each depot, the nodes each depot serves and the routing. This challenging problem was addressed using a multi-level approach while using the travelling salesman problem (TSP) for the routing.

The study of retail intense supply chains with large multi-echelon multi-period problems affected by seasonality and sustainability factors while integrating allocation, distribution and routing problems were found to have not been studied extensively in literature. Furthermore, the significance of perishable products and their associated just-in-time depots/logistics acted as another motivation for the creation of modelling frameworks that could enable the study of impactful parameters on the supply chain's performance based on various KPIs. Also, it was important to study the impact of both import requirements and national production as a result of the seasonality commonly associated with fresh products in combination with the expectation of supply throughout the year.

The modelling frameworks proposed in this work integrate variants of the VRP and large scale supply chain models. Therefore, through this approach it is sought to look at decisions at multiple levels, including for example the strategic, tactical and operational levels. Nonetheless, for products with significant variability in demand and/or supply and which are associated with seasonality, the resulting dynamics make the short-term (in year) allocation and network design and analysis more relevant.

It is also common for studies to present models which are case-specific whose adaptation to variants of the problem is difficult (Braekers et al., 2016). This is absolutely reasonable due to the usual complexity of the problem. Nevertheless, the development and presentation of modelling frameworks which are generic and easy to understand along with having the ability to be adapted and employed by variants of the problem was of interest. To pursue this, a hybrid

method of employing deterministic and heuristic techniques was developed. This was expected to provide the model with the necessary flexibility to be utilised in supply chains of different characteristics and sizes at a reasonably little computational expense. Given that the methods employed involve heuristics, it was foreseen that results obtained would be suboptimal. Nonetheless, the comparison between modelling frameworks can still offer insights on their performance as well as assist in the investigation of impactful parameters on the system's performance.

To fulfil this objective two modelling frameworks are presented and compared in terms of performance based on indicators such as travel distance and vehicle capacity utilisation. The impact of characteristics usually associated with demand nodes is also studied through the frameworks. It is expected that discrepancies between the types of demand nodes will arise as a result of the dominant differences. Furthermore, seasonality related to products is also captured by the frameworks, primarily by adopting a sufficient frequency of periods and defining appropriate parameters for each time step. On the other hand, high frequency of time steps can result to demand uncertainties whereas if data are aggregated into annual mean values it is usually easier for models to handle short-term variations implicitly (Tsiakis et al., 2001). However, in the case of products susceptible to seasonality in terms of either demand or supply variations, it is vital to capture these fluctuations using a reasonably high frequency. In this way, their effect on the system's operation and performance can be studied and seek ways of potential improvement. To study the impact of demand uncertainty a demand factor was employed in the model in the attempt to perform a scenario planning approach through the execution of the model under several scenarios (Tsiakis et al., 2001).

High efficiency and smooth operation are usually desirable attributes for supply chains. Therefore, a simulation model that can facilitate modelling and improvement of supply chain in that sense can be valuable. Considering the case of large supply chains with high numbers in nodes associated with supply, storage, distribution, and demand, each of them having diverse characteristics, it is very useful to have a standardised modelling approach that is easily adaptable and computationally inexpensive. Due to the commonly frequent transportation requirements (usually on daily basis) of products, particularly perishable goods, the model should be able to adapt and provide outputs based on this frequency. In addition, the modelling framework should also be able to address important practical and operation factors associated with the supply chain. Examples of factors include: demand requirements, production capacities, imports, fuel costs, carbon factors, and vehicle capacities. To address these aspects, modelling frameworks using deterministic and heuristic approaches for the allocation and distribution in supply chains were developed and presented.

2.3 Electricity –Retail and storage stages[‡]

The facilities where a product is kept along the supply chain, whether in depots for handling or stores for stock availability or display for sale, contribute to the allocated energy consumption, carbon footprint and costs associated with the product. Products produced and supplied by producers, especially when they require refrigeration, are expected to have an energy consumption at these storage stages which is dominated by electricity requirements. Depending on the facilities and their technologies, the distribution between electricity consumers can vary. For example, Tassou (2014) and Spyrou et al. (2014) showed a typical distribution of electricity

[‡] Parts of this section were presented earlier in Georgiou et al. (2019, 2018c, 2018d, 2018b, 2017b).

consuming categories at the retail stage while presenting the dominance of refrigeration. This can be vital for fresh products which can usually be considered as one of the main groups which are accountable for the energy, emissions and costs associated with refrigeration.

A common approach for improvement is the replacement or upgrading of technologies. That is very useful but reaches a saturation point and in some cases can be capital intensive as well as disruptive. Another approach is employing energy efficiency of the facilities or energy savings techniques. The former can also be capital intensive and invasive (for example improving the thermal envelope of the building) and the latter typically requires behaviour change. All of these approaches, of course, typically provide benefits and should be pursued whenever possible. Nevertheless, in addition to the aforementioned approaches (which have generally been studied in literature), an additional measure that can contribute to energy efficiency, carbon savings and energy cost savings can be the use of electricity storage.

Since electricity can be distributed in a relatively easy and efficient way as well as be converted into other forms of energy very efficiently, appropriate processes and technologies storing or generating electrical energy in the interest of decreasing the carbon footprint of a system can be attractive solutions. Also, the ability to take advantage of the existing electricity infrastructure enhances the applicability of such technologies in both temporal and spatial terms.

Benefits of employing electricity storage include the link to large scale on-site renewable systems which cannot be connected to the grid due to restrictions. An electricity storage system can take advantage of potential curtailed energy to provide savings. In addition, electricity storage systems can also provide benefits to the electricity grid due to flexibility provision as well as contributing in the reduction of peak demands. Furthermore, an electricity storage

system can use off-peak low carbon low cost electricity to charge and therefore, once again, provide carbon and cost savings (or even potentially profits when exported to the grid at the correct setting) (Morgan et al., 2015). Furthermore, low carbon low cost electricity provided by the storage system can be used by all energy consumers regardless of consuming technology. Therefore, a single technology system can potentially help in reducing the carbon footprint of every electricity consuming technology in such facility. Additionally, given the efficient conversion of electrical energy to other forms, heat consuming processes or technologies can also benefit from an efficient electricity storage system. Finally, the easy and efficient distribution of electricity makes the spatial positioning of the system flexible. In other words, space or site restrictions, usually associated with alternative solutions, do not necessarily act as barriers for the application of electricity storage. Therefore, the concept of offsetting carbon emissions can also be used.

Over the last decades an increase in the interest and value of electricity storage has been noted, particularly with the increasing penetration of intermittent renewable technologies (Morgan et al., 2015) and the potential benefits mentioned above. This increasing penetration of renewables was facilitated by several factors such as supporting policies (e.g. incentives), and the reduction in technology costs (Bird et al., 2016; Markides, 2013). Due to the intermittency associated with typical renewable technologies, their deployment and independence of conventional power generation can be a significant challenge. Difficulties in the integration of renewables with the grid can sometimes result in the curtailment of energy. Studies have focused on the reasons of curtailment of energy which include transmission limitations and balancing issues (e.g. Bird et al. (2016)). In addition, future projections show the potential for the increase in value of storage (Strbac et al., 2012). Therefore, affordable, efficient and long-

lasting electricity storage systems are interesting to investigate as one of the solutions towards a more sustainable supply chain.

Bulk electricity storage technologies with some commercialisation maturity and readiness include the pumped hydro energy storage (PHES) and compressed air energy storage (CAES), whereas emerging ones include the newly proposed pumped thermal electricity storage (PTES) and liquid-air energy storage (LAES). Due to the constraints typically associated with PHES and underground CAES, especially as a result of their geographical and geological requirements, their association to the supply chain can be considered as not so relevant; therefore, they were not considered as potential solutions here. Also, PHES and CAES were studied more extensively in literature than PTES and LAES (see e.g. Chen et al. (2009)). Nevertheless, existing and commercial energy storage solutions were compared against PTES and LAES which are the main technologies of interest here in order to assess their competitiveness. To compare and assess technologies, besides their technical characteristics and performance, it is imperative to study their economic competitiveness as well.

The present work focuses on LAES and PTES, two recently proposed medium- to large- scale thermo-mechanical electricity storage technologies. The two technologies are currently under development or demonstration but they differ in terms of technology readiness levels (TRLs) (Georgiou et al., 2017b), with LAES being considered as more mature due its proven operation at pilot plant scale (Morgan et al., 2015).

The LAES pilot plant has a power and energy capacity of 350 kW and 2.5 MWh respectively (Morgan et al., 2015; Sciacovelli et al., 2016). It has been in operation for several years and has been observed to achieve roundtrip efficiencies of 7-12% depending on operational parameters (Centre for Low Carbon Futures, 2013; Morgan et al., 2015). The potential for

significantly much higher roundtrip efficiencies at larger scales and optimised operational parameters has been proposed in literature (Centre for Low Carbon Futures, 2013; Morgan et al., 2015; Sciacovelli et al., 2017, 2016). The performance and operation of the LAES pilot plant as well as the potential of LAES system have also been studied in Morgan et al. (2015) and Sciacovelli et al. (2016).

LAES system has been developed by Highview Power Storage (Highview Power Storage, 2016) and its operation is based on the storage of energy in the form of liquid air. The system is charged by liquefying air using electricity before its storage at near atmospheric pressure in insulated storage tanks. Thereafter, when feasible to discharge, the liquid air is withdrawn from the storage vessels, pressurised, heated to ambient or higher temperatures when possible due to waste heat sources, and expanded through a turbine to generate power (Morgan et al., 2015).

The cyclic operation of LAES consists mainly of three sub-processes; namely charging, storage and discharging. During charging, liquid air is supplied for storage. The liquid air can be either supplied from an on-site liquefaction plant or a third party supplier. During storage, the system can be considered as idle and liquid air is stored in low temperature low pressure storage vessels (Centre for Low Carbon Futures, 2013). Finally, during discharging, the liquid is passed through the power generation unit to generate power (Centre for Low Carbon Futures, 2013). Furthermore, the additional component of waste cold storage can be added to the storage process (Centre for Low Carbon Futures, 2013). This component stores waste cold recovered during the discharging process from the evaporation of liquid air in the form of sensible heat. The cold energy stored can then be used in the next charging cycle in order to enhance the energy efficiency of the liquefaction process (Centre for Low Carbon Futures, 2013). Furthermore, another potential roundtrip efficiency enhancer is the utilisation of waste heat in

the discharging cycle to increase the temperature of the evaporated air to higher than ambient (Centre for Low Carbon Futures, 2013).

A conceptual representation of LAES as commonly described in literature is presented in Fig. 2.2. Similarly, the configuration considered in this study uses an on-site liquefaction plant for the supply of liquid air, waste heat is supplied by an over-the-fence supplier assumed to be always available, and waste cold is recovered from the power generation unit in order to be stored and used in the charging cycle. LAES possesses the advantage of potential rapid development due to its essential components required for basic operation being readily available (Centre for Low Carbon Futures, 2013).

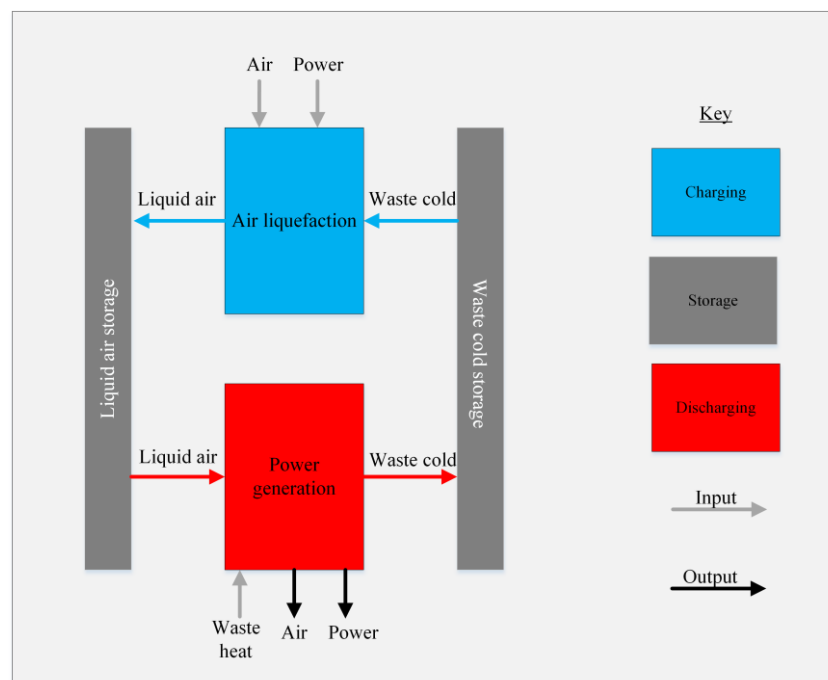


Figure 2.2. System representation and energy/material flows for liquid-air energy storage (as commonly described in literature).

PTES is the other recently proposed technology that is of interest here. This electricity storage technology stores energy in the form of sensible heat in reservoirs filled with a suitable storage medium, such as a packed bed of gravel or pebbles (White et al., 2013). As with most electricity storage devices, the cyclic operation of this technology involves a charging cycle, a storage period and a discharging cycle. A conceptual representation of PTES is presented in Fig. 2.3. As shown, the main principle involves the use of an engine to charge the system by creating a substantial temperature difference between two mediums, and to generate power by taking advantage of the temperature difference when discharging.

The configuration of PTES considered in the present study was based on the system studied in White et al. (2013). The main elements of that system are two compression/expansion devices, two heat exchangers to accommodate for the irreversibilities in the system by rejecting heat, and two reservoirs aimed to be at significantly different pressures and temperature when charged (White et al., 2013). When charging, heat is removed from the cold reservoir and supplied to the hot reservoir by using electricity. When discharging, the differences in temperature and pressure between the two reservoirs are used to drive a heat engine based on the Joule-Brayton cycle and generate power (McTigue et al., 2015; White et al., 2013). The flow direction of the working fluid (considered here to be argon as per previous studies (McTigue et al., 2015; White et al., 2013, 2016)) is opposite for the charge and discharge cycles. No operational pilot plant for this system has been found in literature. Based on this observation it can be assumed that PTES is at lower TRL than LAES which has been tested at pilot plant scale.

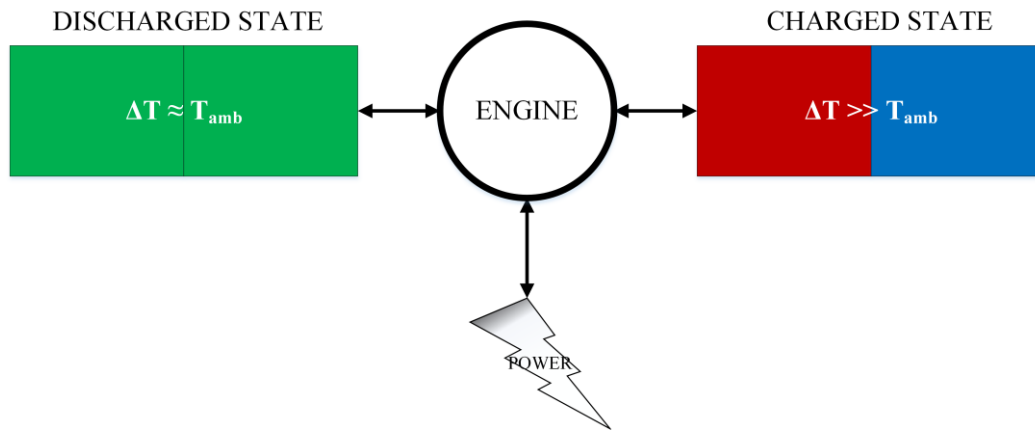


Figure 2.3. Conceptual system representation of pumped thermal electricity storage (as commonly described in literature).

PTES, in the configuration described above, was modelled and studied in other studies in literature (McTigue et al., 2015; White et al., 2014, 2013, 2016). A PTES based system, but with some vital differences, was proposed in Frate et al. (2017). In that study, the system used a vapour compression heat pump for the charge cycle and a heat engine of an organic Rankine cycle (ORC) for the discharge cycle. Interestingly, the study considered the use of low grade heat to boost the system's roundtrip efficiency to greater than one. Similarly, Roskosch and Atakan (2017) also studied a configuration of PTES which involved the use of a compression heat pump and an ORC. The study showed particular interest in the working fluid requirements for employing an ORC engine in such system.

Theoretical maximum performance analyses of thermally driven electricity storage systems has also attracted some attention in literature. For example, Guo et al. (2016) and Thess (2013) investigated the theoretical maximum performance and comparison between pumped cryogenic and pumped thermal electricity storage systems; the theories underlying the

operation of LAES and PTES respectively. The analysis was based on Carnot heat engines and Carnot heat pumps or refrigeration. Findings from Guo et al. (2016) showed the greater overall performance achievable by pumped thermal.

In terms of the economic characteristics and performance of electricity storage systems, earlier studies performed comparisons between different technologies (Luo et al., 2014). In Luo et al. (2014), a broad range of technologies was considered while thermal storage systems being a generic category and LAES mentioned briefly. Furthermore, economic metrics of several technologies at different capacities and applications were also presented in the interesting study of Sandria National Laboratories (2013). LAES was referenced as an emerging technology but no economic metrics associated with it were presented. Similarly, Obi et al. (2017) presented the levelised cost of technologies including compressed air, batteries, and pumped hydro. Also, Jülch (2016) considered the technologies of compressed air, pumped hydro, power-to-gas storage, and several battery systems while focusing on their levelised cost of storage. While economic analyses based on common metrics have been conducted in literature for energy storage technologies, detailed costing and economic feasibility analysis and comparison for PTES and LAES were found to be lacking.

A direct comparison of LAES and PTES (in the configurations proposed in literature for their development) based on a combination of aspects including the expected performance in an industrial setting while considering components' performance and influential parameters, capital costing, economic feasibility, and competitiveness, has not been found. Therefore, such analysis and comparison was interesting for further investigation. A modelling and thermo-economic assessment framework was commonly created for both technologies to assist in the direct comparison between the two. The framework comprises of both thermodynamic models

and economic models (including costing and economic feasibility models). Important metrics of interest include the thermodynamic performance, particularly in terms of roundtrip efficiency, as well as the economic viability of the two systems. Economic factors expected to be impactful on the competitiveness of each technology include electricity markets (peak and off-peak demand electricity prices and operating points), discount rates, capital costs (absolute, power and energy), net present values (NPVs), levelised cost of stage (LCOS), and buy-to-sell ratios.

Furthermore, the potential role of LAES and PTES in a low carbon electricity system with high renewables penetration has also been found to be lacking from literature. Therefore, this was considered another area for potential further investigation under different scenarios. To perform such analysis, the thermo-economic frameworks can be used to generate the technical and economic performance indicators for the two systems in order to be implemented in an electricity network system and assess their feasibility and competitiveness.

Additionally, another potential area of interest that was not found to be studied in literature was the quantification of the potential of carbon savings from the application of LAES and PTES and the associated costs under different scenarios. Factors such as curtailments levels and electricity carbon factors as well as technical and economic performances of the two systems are expected to have an effect on the competitiveness for potential carbon savings. Once again, the thermo-economic models can be used to obtain the necessary performance indicators for the two technologies.

2.4 Background conclusion

The literature firstly helped to identify some of the key energy consuming stages/processes along a supply chain as well as the lack of holistic approaches for supply chains, specifically involving fresh products affected by seasonality. It is common in literature for supply chains or products to be addressed from a specific viewpoint, such as logistics, LCA approaches, or retailing. Therefore, the development of a framework and methods to identify and improve the most impactful processes along the whole supply chain regardless of the form in which energy consumed was found to be of interest. In addition, the parallel consideration of both operational and technological improvement approaches was also an aspect that could be explored further for the determination of the best approach for improvement. This allows the analysis of the supply chain from multiple decision levels, including strategic, tactical and operational. In this way, opportunities associated with the supply chain as a whole as well as independently for some processes are expected to be identified.

Furthermore, the potential for further investigation on fresh products associated with seasonality was also noted. Seasonality affects the whole supply chain, especially in terms of operational efficiency and energy requirements in the production and distribution stages. Therefore, the case studies and performance indicators incorporated should account for the effect of seasonality. Also, fresh products typically require fast logistics with frequent deliveries as well as refrigeration, especially at the storage and retail stages. This makes the efficient distribution and storage (at appropriate conditions) of a product important; another aspect making fresh products an interesting case study.

The main forms of energy consumed were concluded to be fuel used for heat, transport fuel and electricity. For fresh product supply chains the areas with great opportunity were found to

be the production, transport and storage/retail stages. These were associated with heat requirements, transport fuel requirements, and electricity requirements, respectively. Also, methods for standardising and automating the assessment and decision making of supply chains while improving environmental and economic sustainability were found to lack from literature. Therefore, modelling frameworks that could facilitate the quantification of potential benefits from efficiency improvements and carbon curbing approaches for those energy consumers were of great interest.

The application and practicality of the approaches studied or proposed were always of primary interest to allow for their accessible implementation in an industrial setting. Also, both the improvement of existing technologies and their replacement (either gradual or immediate), where applicable, were considered as a way towards energy, carbon and energy cost savings.

Furthermore, the research gaps and potential areas interesting to investigate, as discussed in detail for each of the sub-sections above, are summarised here. To start with, heat requirements at the production stage were found to be significant for heated glasshouse production. The lack of generic glasshouse modelling frameworks and tools focusing on the UK heated production while considering a wide variety of factors mentioned above presented an opportunity for further investigation. Outputs from such models could contribute to both academic literature (such as through LCA studies) and industry (e.g. benchmarking, assessing, quantifying energy, carbon and energy costs). Secondly, for the distribution stages and transport requirements, contributions can be made through the development of modelling frameworks and the insights they can provide. The modelling frameworks contribute in the integration of allocation, distribution and vehicle routing problems for large multi-period multi-echelon systems with numerous constraints, characteristics and sustainability considerations. Finally, the

storage/retail stages involving significant electricity consumption were addressed from a novel angle by considering the application of emerging medium to large scale electricity storage systems for the provision of savings in energy, carbon emissions and energy costs. The decomposition of the supply chain into key stages and processes was also achieved through a higher level framework as way to address the whole supply chain, and thereafter concentrate on the aspects that could potentially satisfy both savings and novelty.

The research interests and approach followed in this work were unavoidably multidisciplinary. Therefore, this research can contribute to multiple fields, including supply chain assessments, supply chains modelling and optimisation, and process and technology modelling (see Fig. 2.4). Based on findings from literature, heat, transport and electricity could be investigated from the perspective of each of those fields, respectively, to achieve an impactful improvement in efficiency, carbon emissions, and costs.

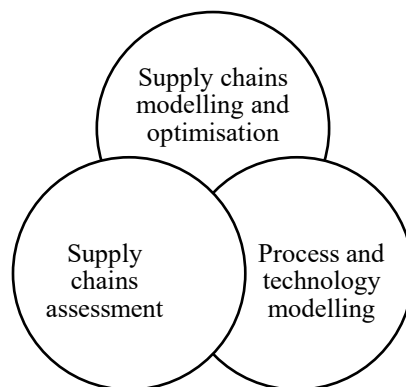


Figure 2.4. Research fields Venn diagram.

In summary, the contributions of this work were aimed to be fulfilled by satisfying the following aims and objectives:

- General:
 - Develop a framework for identifying and addressing the most impactful stages and processes in a supply chain along with their needs in terms of energy source/requirements.
- Heat requirements:
 - Develop a modelling framework for quantifying energy requirements for heated glasshouse production.
 - Identify influential operational and technological parameters on energy, carbon and energy costs.
 - Showcase the model using a case study and note the benefits associated with using such model.
- Transport fuel requirements:
 - Develop a modelling framework integrating allocation, distribution and routing of large scale multi-period multi-echelon supply chains.
 - Test and compare the models based on a case study, and identify potential benefits from varying influential parameters.
- Electricity requirements:
 - Develop a thermo-economic modelling framework for novel electricity storage systems, namely LAES and PTES.
 - Analyse and compare the two technologies based on technical performance and economic competitiveness, as well as against other existing electricity storage solutions.

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- Explore the potential and viability of emerging electricity storage systems for contributing towards carbon savings at a local level as well as at an electricity system level.

Chapter 3[§]

3 Methodology

It is common for studies concerned with the energy intensity of processes to focus on one aspect of potential improvement. That can be for example in terms of a supply chain echelon, a technology, operational or technological measures for improvement. Improving the performance of the whole system was of primary interest here. To achieve that, a variety of solutions which involve several aspects were considered while focus was given on the most energy intensive ones. Besides the reduction in energy intensity, the reduction of uncertainty and the smooth operation of the supply chain was among the objectives for improvement. Also, the development of methods that could be transformed into systematic or decision support tools applicable in industry was pursued. Therefore, practicality and scalability of these models to

[§] Parts of this chapter were presented earlier in Georgiou et al. (2018c, 2018b, 2018d, 2018a, 2017b, 2017a).

accommodate the need for large scale models applicable to the real world was also one of the objectives of this work.

As mentioned earlier, the energy intensity along the supply chain and the energy category in which it can be categorised varies depending on the stage of the supply chain. Therefore, it was of value to study the supply chain stages and identify the dominant energy resources at each stage. This then allowed to seek for methods to improve the overall performance of the supply chain by focusing on the most impactful activities while also potentially enabling the identification of synergies between the different solutions. The generic framework developed and used in the present study with the overriding objective of reducing the energy intensity, carbon emissions and energy costs is presented in Fig. 3.1. The framework was then translated into the modelling framework specifically for the supply chain system used in this study (see Fig. 3.2). Also, the potential for performance improvement through technological approaches and operational efficiency approaches was identified.

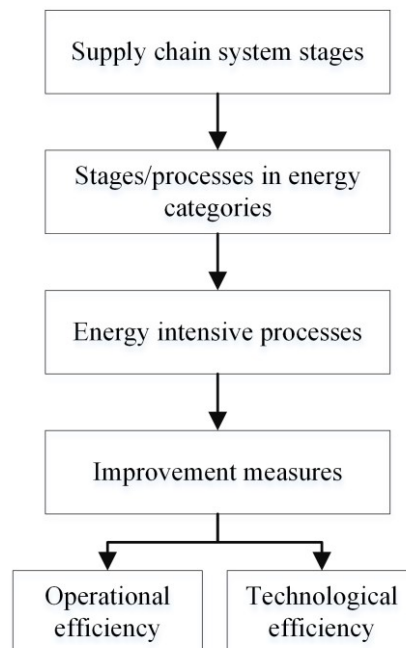


Figure 3.1. Generic supply chain energy intensity framework.

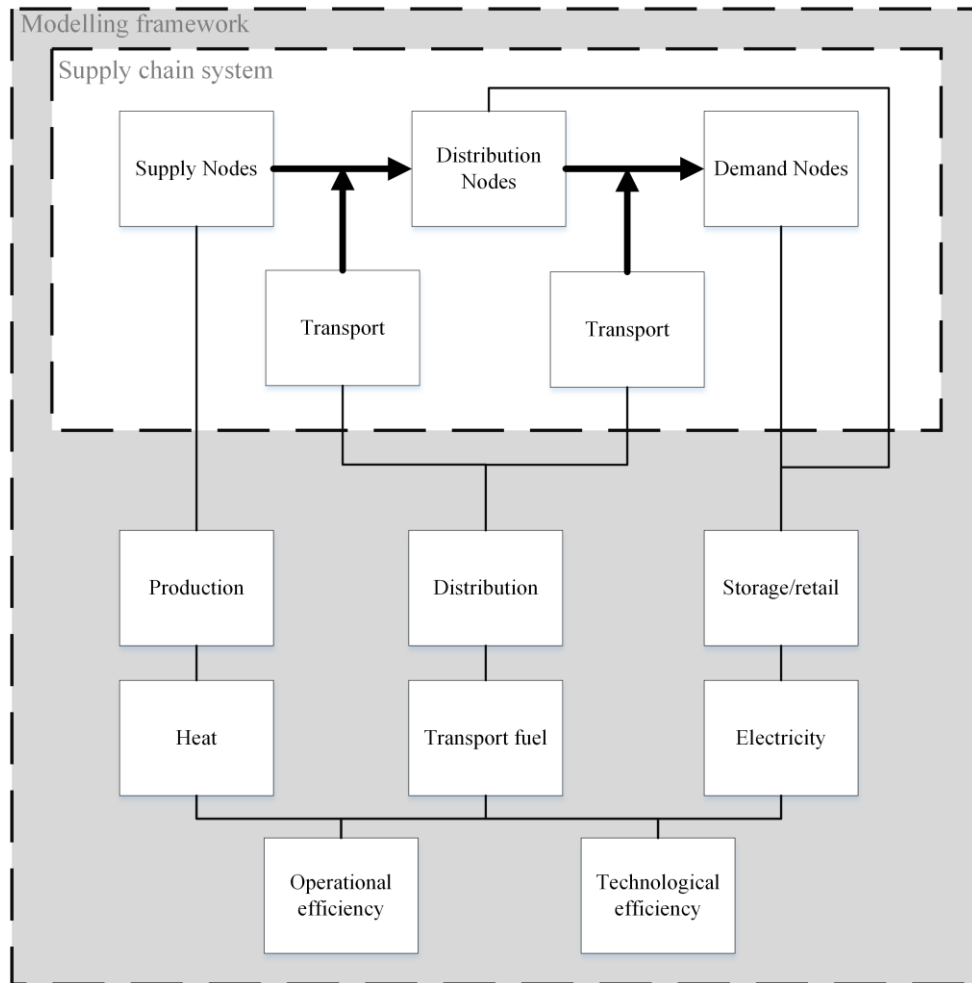


Figure 3.2. High level energy intensity modelling framework.

Stages and processes in supply chains with the highest footprints can vary and depend on various factors. Nevertheless, for the fresh product category several studies indicated the importance of heat requirements at the production stage. For example, Payen et al. (2015) concluded that heating required for growing tomatoes in heated glasshouses resulted to increasing energy use and global warming enough to have a greater footprint than products

transported over longer distances. Similarly, Cellura et al. (2012) identified the requirement of heating in northern Europe to be responsible for greater energy requirements and global warming than southern Europe where heating requirements are typically not necessary. Furthermore, Torrellas et al. (2013) showed the significance of heating in energy requirements, particularly in central Europe. Fuel consumption required for heating in heated glasshouse was also pointed out to be important by Ntinis et al. (2017) for the production of tomatoes in central and southern Europe. Moreover, while considering several scenarios, Torrellas et al. (2012) pointed out the importance of prioritising the reduction in fossil fuel consumption for heating and electricity in glasshouses located in cold climates from an environmental perspective. Therefore, heat provision at the production stage can be considered as an important aspect to study in a supply chain with the aim of improving energy consumption and carbon emissions. Furthermore, transportation of products from stage to stage along the supply chain is inevitably a vital and necessary process in most cases. Therefore, finding ways to improve this process could potentially contribute to the overall performance of the supply chain. In the UK, the dominant mode of transport for food transportation has traditionally been on the road with a very high proportion of food commodities depending on it and its infrastructure (Jones, 2002). In addition, about 80% of food freight in the UK is transported by heavy good vehicles (Tassou, 2014), and according to Tassou et al. (2009) primary and secondary distributions are mainly dominated by articulated vehicles in terms of total ton-km. Since transport is usually considered a challenging sector to decarbonise, this process category also presents an interesting and potentially impactful aspect to study. The next process of interest in the supply chain can be considered to be the storage of products, either at depots or stores. Electricity consumption requirement for this process can be very important for products requiring refrigeration. The dominance of refrigeration at the retail stage was pointed out by Tassou (2014) and Spyrou et al. (2014). This can be particularly important for fresh products which can usually be

considered as one of the main categories accountable for the energy, emissions and costs associated with refrigeration.

Following from the framework above, three processes were the main focus: i) production, ii) distribution, and iii) storage/retail. For each of the three processes there was a dominant energy form: i) heat, ii) transport fuel, and iii) electricity, respectively. Therefore, the objective was to find ways (novel when possible) through operational efficiency or technological efficiency improvements to reduce the energy intensity, carbon emissions or energy costs at each level. This improvement is expected to be translated into carbon emissions and energy costs as a function of energy consumption.

To quantify and assess the impact of variables at each stage, a variety of models were developed, including thermodynamic models, spatial and temporal models, optimisation models, and thermo-economic models. The need for each type of modelling approach depended on the process being modelled. Each stage's models are discussed in detail in the following sections.

This chapter consists of three main sections representing the most important energy forms that can be improved along the supply chain; namely heat, transport, and electricity. Each subsection is focused on the reduction of energy consumed in each corresponding form through either technological approaches or operational approaches or both. Therefore, the structure of remaining sections of this chapter is: i) heat requirements at the production stage, ii) transport fuel for the distribution of product between the echelons of the supply chain, and iii) electricity consumption at the storage and retail stages through the use of electricity storage systems.

3.1 Heat – Production stage^{**}

Heat is one of the main forms of energy consumption in a food supply chain. More specifically, as discussed above, in a supply chain involving food growth/production the heat requirements can dominate the energy requirements and/or carbon footprint of the product's lifecycle when produced under auxiliary heating. Furthermore, the availability of fresh fruits and vegetables in the UK has been significantly extended over the past decades with out-of-season products becoming more widely available (Jones, 2002). The expectation of society for out-of-season products can increase the requirement for implementation of production techniques that could increase the energy consumption and carbon emissions of a product. These aspects acted as motives for developing a modelling framework that could allow the quantification of heating and cooling requirements associated with glasshouse while accounting for important parameters such as characteristics of the glasshouse, weather patterns, the spatial and temporal aspects, operational parameters, and technological parameters. Therefore, in this section the modelling approach for quantifying the energy requirements for heated food production in glasshouses is discussed.

Also, this modelling framework was transformed into a decision support tool with a graphical user interface to promote its use to the glasshouse operators and potentially increase stakeholder engagement.

^{**} Parts of this section were presented earlier in Georgiou et al. (2018a, 2017a).

3.1.1 Thermodynamic model

The energy inputs and outputs required for maintenance of the glasshouse internal set conditions are quantified through the evaluation of the key heat gain and heat loss mechanisms. The heat loss mechanisms considered here are conduction losses, convection losses and radiation losses as well as latent and sensible heat losses due to air infiltration. The heat gain mechanisms are the equivalent with the addition of solar radiation. The energy balance (Eq. (3.1)) is used for the evaluation of the necessary heat rate input and output ($\dot{Q}$).

$$\dot{Q} = \rho \cdot N \cdot V \cdot \left(c_p \cdot (T_i - T_o) + h_{fg} \cdot (W_i - W_o) \right) + U \cdot A_c \cdot (T_i - T_o) - \beta \cdot I \cdot A_f \quad (3.1)$$

where ρ is the air density assumed to be constant at 1.29 kg/m^3 , N is the air infiltration rate in s^{-1} , V is the glasshouse's inside volume, and c_p is the specific heat of air assumed to be constant at 1.005 kJ/kg . T_i and T_o are the internal and external temperatures respectively, h_{fg} is the latent heat of vaporization of water, and W_i and W_o are the humidity ratios in $\text{kg}_{\text{vap}}/\text{kg}_{\text{air}}$ of the internal and external air respectively. Also, U is the overall heat transfer coefficient of the glasshouse cover, A_c is the glasshouse cover's surface area, β is the ratio of solar radiation per unit of area (I) absorbed by the glasshouse and A_f is the floor area. Similar energy balance equations were presented in ASABE (2008), Chalabi et al. (2002), and Wass and Barrie (1984).

When heating is required (i.e. $\dot{Q}$ is positive), to convert require heat input rate from the energy balance to energy consumption rate as delivered by the heating system (e.g. boiler), the system's efficiency (η_s) is accounted for and the outcome is given as thermal power. Any type of fuel will supply the same amount of energy. However, alternative fuels are expected to have

different carbon and economic footprints depending on their corresponding carbon and cost factors. Hence, the thermal power input from the heating system ($\dot{Q}_s$) can be determined as:

$$\dot{Q}_s = \frac{1}{\eta_s} \dot{Q} \quad (3.2)$$

When cooling is required (i.e. $\dot{Q}$ is negative), the required heat output rate needs to be translated into energy consumption based on the cooling system. Cooling in glasshouses is usually provided using mechanical ventilation systems or natural ventilation. Here, the ventilation rate is estimated in terms of unit of air volume extracted per unit of time to maintain the internal set conditions. Combining the energy balance equation (Eq. (3.1)) with the impact of external air interaction through air extraction depending on the external and internal temperatures, the following equation is derived:

$$\rho \cdot N \cdot V \cdot \left(c_p \cdot (T_i - T_o) + h_{fg} \cdot (W_i - W_o) \right) + U \cdot A_c \cdot (T_i - T_o) - \beta \cdot I \cdot A_f = \frac{-F \cdot A_f \cdot c_p}{v_i} (T_i - T_o) \quad (3.3)$$

where v_i is the specific volume of the internal air and F is the air flow rate through the ventilation per unit of area. A similar expression for the approximation of cooling using ventilation is presented in ASABE (2008). When mechanical ventilation is present, the required ventilation rate can be converted into electrical power consumption ($\dot{E}_v$) by using the Specific Fan Power (SFP) variable. This variable gives the electrical power required per unit of volume of air supplied or extracted per second (see Eq. (3.4)).

$$\dot{E}_v = SFP \cdot (F \cdot A_f) \quad (3.4)$$

To obtain the energy consumption associated with heating and cooling, $\dot{Q}_s$ and $\dot{E}_v$ can be integrated over the time period (t) of interest while assuming steady state conditions using:

$$Q_s = \int_0^t \dot{Q}_s dt \quad (3.5)$$

$$E_v = \int_0^t \dot{E}_v dt \quad (3.6)$$

To estimate the total energy requirements over continuous consecutive periods considering discrete time steps ($t_i - t_{i-1}$) depending on the available data, the following equations can be used:

$$Q_s = \sum_{i=1}^n \int_{t_{i-1}}^{t_i} \dot{Q}_{s(i)} dt \quad (3.7)$$

$$E_v = \sum_{i=1}^n \int_{t_{i-1}}^{t_i} \dot{E}_{v(i)} dt \quad (3.8)$$

When the time steps (t_s) considered are equal in duration, the average values of all variables obtained from the data sets over the corresponding time step are used to determine the energy requirements. Therefore, both heating and cooling evaluations simply become:

$$Q_s = \sum_{i=1}^n \dot{Q}_{s(i)} \cdot t_s \quad (3.9)$$

$$E_v = \sum_{i=1}^n \dot{E}_{v(i)} \cdot t_s \quad (3.10)$$

It is also important to consider the aspect of seasonality in the model. Therefore, depending on the growing schedules selected, the quantification of the metrics above is adjusted accordingly so that energy requirements are evaluated only during production/heating/cooling periods. It is noteworthy that depending on the product and variety the growing schedules and ideal

conditions might differ. To accommodate for this, the model accepts inputs that define these aspects and consequently there are periods throughout the year in which thermal energy supply is purposely set to zero by the model. The model can therefore quantify the impact of growing schedules and the benefits/costs of producing alternative products or varieties.

3.1.2 Spatial model

The weather station for the provision of meteorological data is selected by the model following a standardised approach based on the distance proximity from the glasshouse. The data are important for the evaluations and outputs of the model; therefore, to ensure the best possible allocation, each data set is selected from the best available weather station. The distance proximity (D) between the two points of interest is calculated based on their coordinates using the commonly used law of cosine as follows:

$$D = Ra \cdot \arccos(\sin \theta_1 \cdot \sin \theta_2 + \cos \theta_1 \cdot \cos \theta_2 \cos(\Delta\phi)) \quad (3.11)$$

where Ra is the Earth's radius, $\Delta\phi$ is the difference in geographical longitude between the two points, and θ_1 and θ_2 are the geographical latitudes in radians. In the UK, it is common for locations of facilities to be defined in the form of a postcode. Therefore, in order to make the parameter input process more convenient and reduce the risk of error for large organisations with large portfolios of suppliers, the additional feature of accepting the locations of the facilities in terms of postcodes was incorporated in the tool. This is employed by using a UK postcode database (based on data from Free Map Tools (2016)) to identify the coordinates assigned to the glasshouse and the program is then executed.

Furthermore, to allow for a better visualisation of the spatial aspect of the outputs, the model is capable of developing UK maps with distinct regions based on postcodes areas highlighting key performance indicators such as heating and cooling requirements, total energy use, carbon emissions and energy costs. Also, following the same principles, the tool can quantify and map the temporal variability for all regions with the objective of identifying the competitiveness of different locations in terms of both performance and robustness against external conditions. This evaluation is categorised based on postcodes registered in the UK (Free Map Tools, 2016). By taking a sample of the available location options (at least one point for each postcode area), each simulation's outputs are assigned to the corresponding postcode area polygon as formed in Opendoorlogistics Ltd (<http://www.opendoorlogistics.com>) (2015). Thereafter, based on these, maps can also be created (as shown in Chapter 4). The benefits associated with better spatial and temporal performance can be passed to organisations operating both the production facilities and the supply chain operators (e.g. retailers). Therefore, the outputs can act as an indication of efficiency, sustainability and robustness of production, and as a result potentially identify the most attractive partners to form long term partnerships with.

3.1.3 Meteorological data model

Data such as temperature data and solar radiation data, provided by and acquired from Centre for environmental data analysis and Met Office Integrated Data Archive System (MIDAS) (2012), are available in units that can be used by the model after filtering and processing. For humidity ratio, however, that is not always the case. Some weather stations might report direct humidity data. Since having a large number of stations available for the model to select from is fundamental for sourcing the meteorological data, the most commonly available approach for obtaining the humidity ratio (W) as defined in the energy balance (Eq. (3.1)) is used.

Therefore, W is calculated based on the widely used method presented by Allen et al. (1998) in combination with the ideal gas law as follows:

$$W = \frac{\frac{e_a \cdot R_d}{R_v \cdot (p - e_a)}}{1 + \frac{e_a \cdot R_d}{R_v \cdot (p - e_a)}} \quad (3.12)$$

where p is the atmospheric pressure, R_v and R_d are the gas constants for vapour and air respectively, and e_a is the actual vapour pressure which can be calculated when the dew point temperature (T_{dew}) is available by using Eq. (3.13).

$$e_a = P \cdot \exp\left(\frac{A \cdot T_{\text{dew}}}{T_{\text{dew}} + 237.3}\right) \quad (3.13)$$

where P is a constant with value 0.6108 kPa, T_{dew} is in °C, and A is a dimensionless constant that takes the value 17.27 (Allen et al., 1998).

3.1.4 Information process flow and main algorithms

The model incorporates several elements such as databases, models and outputs. The information process flow with its fundamental elements is presented in Fig. 3.3. The modelling framework comprises mainly three databases, three models and three outputs that are concentrated in the “Tool Outputs” label. A feedback loop has been introduced into the model to allow for the execution of multiple scenarios with the overriding aim of facilitating parametric variations and analyses.

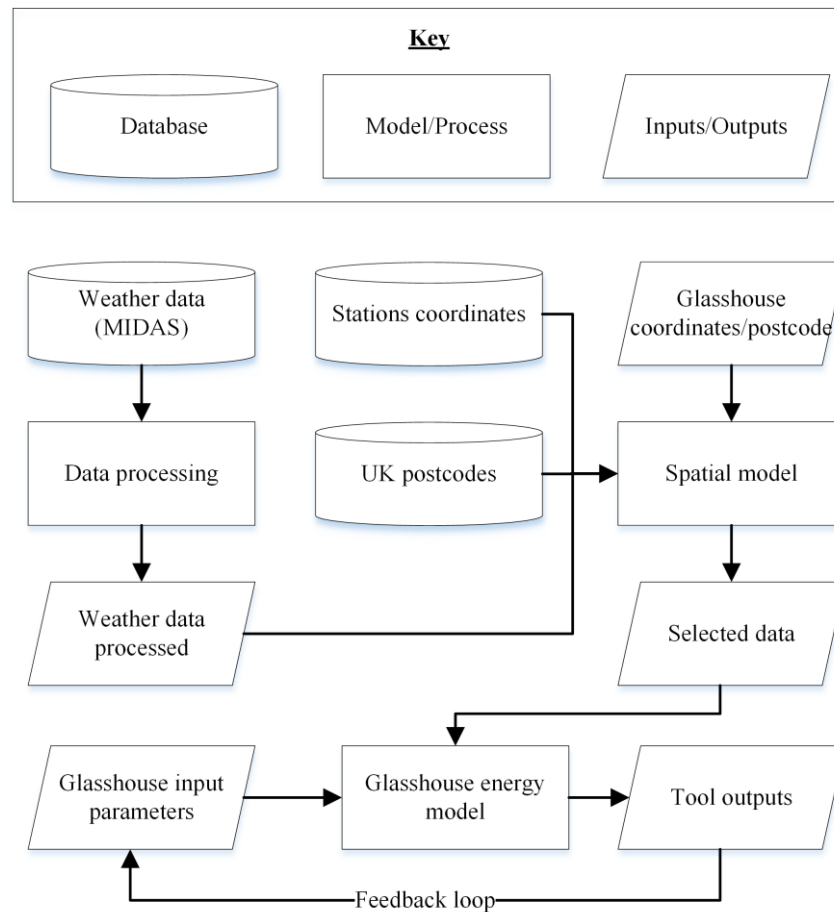


Figure 3.3. Modelling framework process flow diagram.

Each of the main models consists of sub-models and algorithms of which the most relevant ones are shown in Figs 3.4-3.6. More specifically, the energy model process flow diagram (see Fig. 3.4) shows the algorithm for performing the energy related queries based on the input parameters and exporting outputs essential for the tool's evaluations. The spatial model process flow diagram (Fig. 3.5) presents the algorithm employed within the spatial model for the acquirement of the data required by the energy model. In this algorithm the UK postcode and weather stations databases along with the facility's postcode are used for the acquirements of the datasets required by the energy model. Lastly, the weather data processing model process

flow diagram (see Fig. 3.6) shows the procedure used for processing and exporting the raw meteorological data in a form that can be utilised in the other modules of the tool.

Therefore, the tool attempts to integrate all of the aforementioned modules and data through a generic tool which focuses on metrics including energy, heating and cooling requirements, carbon emissions and energy costs associated with heated production in the UK. All the models are written and executed utilising Python programming language while in some occasions Python libraries such as Pandas, Matplotlib, TkInter and NumPy are used.

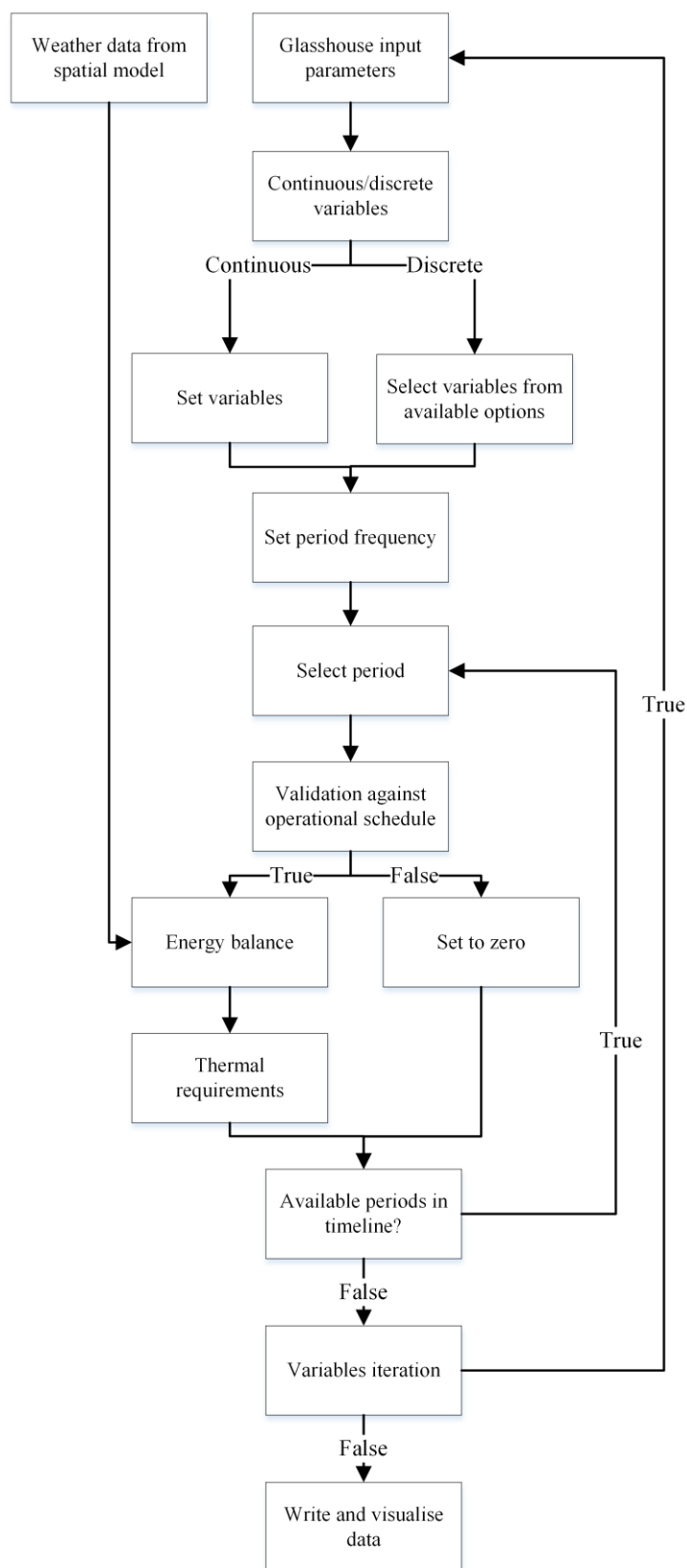


Figure 3.4. Modelling framework for energy model.

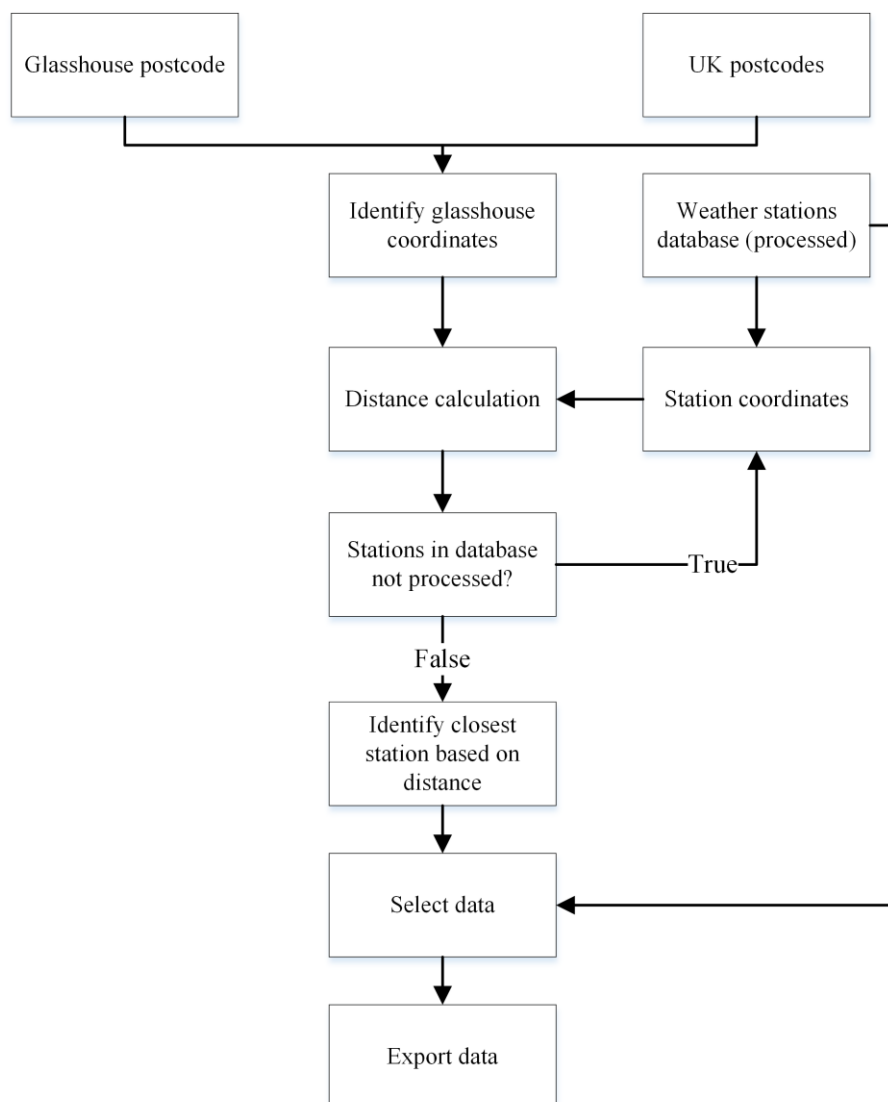


Figure 3.5. Modelling framework for spatial model.

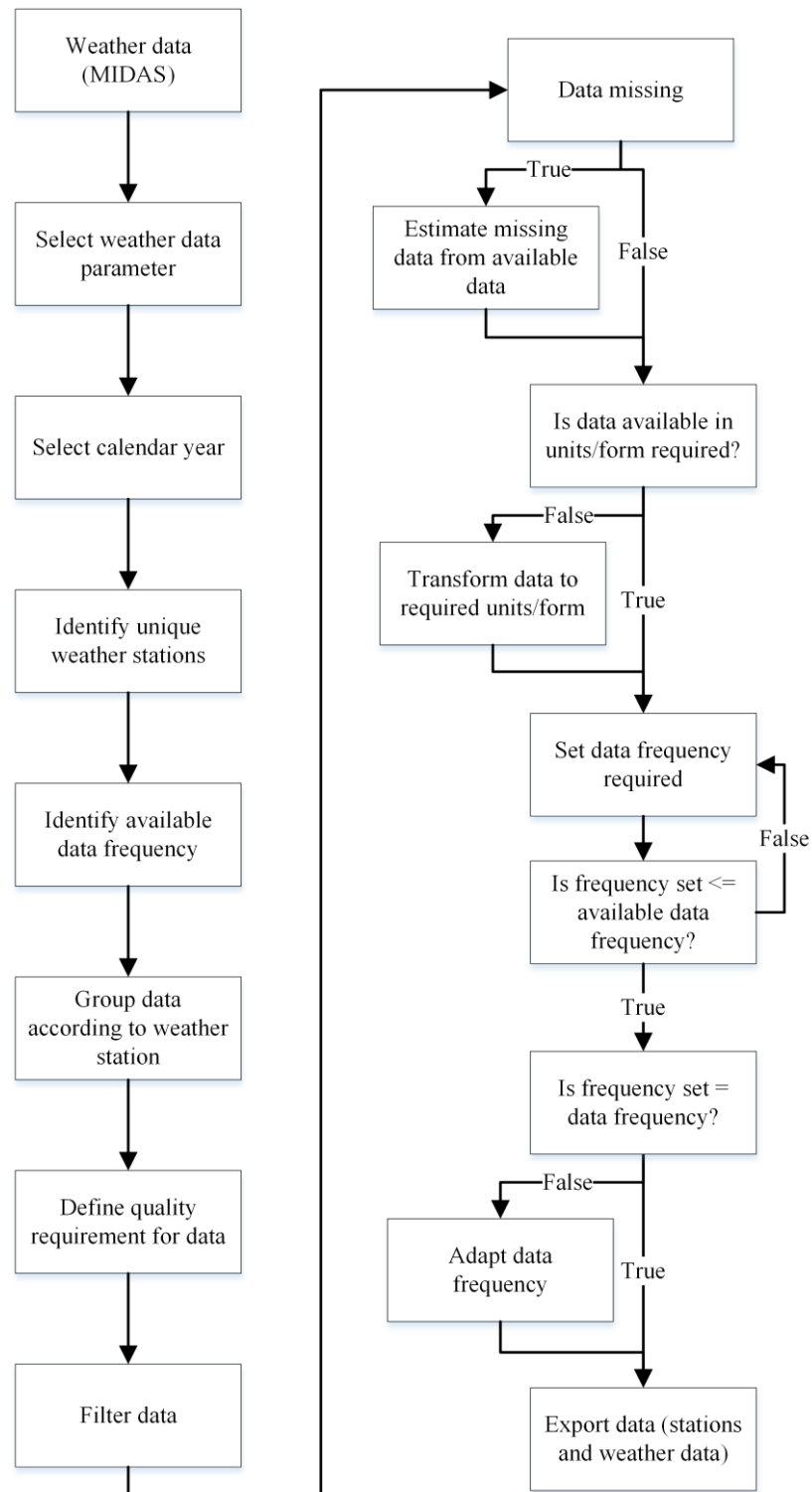


Figure 3.6. Modelling framework for weather data processing model.

3.1.5 Expected error estimation

The approach followed by the modelling framework (and essentially the tool) was aimed to provide good estimations in the quantification of different energy related key performance indicators (KPIs) while using as little data input as possible from the user. This means that the model relies heavily on meteorological data obtained from weather stations. As expected, unless the facility has a weather station in-situ, there is an expected source of error due to distance from the data source (i.e. weather station) to the facility. Unfortunately, the magnitude of this error was unknown since it is expected to vary depending on each weather station and dataset acquired. For example, the effect of acquiring atmospheric pressure data from a distant location might not introduce the same error as obtaining temperature data from a station with an equivalent distance difference. Similarly, the same can apply to the other datasets acquired. Also, some stations might have significantly different conditions due several reasons such as dissimilar landscape. It is therefore useful to have a sense of the error introduced by obtaining a specific dataset from a specific weather station. The model was therefore designed to be able to quantify this expected source of error by identifying the weather station from which each dataset is obtained and performing an evaluation based on the distance from the facility.

A relationship of distance with expected error is required for the model to be able to give an estimation of the error magnitude. Therefore, an analytical way to approach this is to compare results from the station of interest against results from certain distance intervals and observe the resulting error. In a perfect world, this would mean all data required at each of those distance intervals are available. To overcome this, two approaches can be followed: i) using exogenous data or ii) endogenous data. Here, by exogenous data it is meant that energy consumption data (i.e. equivalent expected outputs from the model) are acquired from a large

number of facilities and compared against the outputs of the model to derive the error introduced based on the distance from the weather station to the facility, assuming that distance is the only source of error. The endogenous data approach would involve using data already available to the model for the simulation of the model based on hypothetical facilities with exactly the same characteristics located at distance intervals from the ‘primary weather station’ (i.e. weather station analysed). To follow this approach, these hypothetical facilities which are situated at the locations of all the secondary weather stations are used. Due to practicality, time consumption, and cost related reasons associated with acquiring data from operating facilities along with the wide availability of weather stations being able to produce a larger sample and therefore a stronger statistical inference, the latter approach was chosen.

Referring back to the estimation of energy requirements discussed in Section 3.1.1, the energy requirement (P) with respect to either heating or cooling can be translated into a key performance indicator using:

$$E_t = P \cdot KPIF_k \quad (3.14)$$

where E_t is the periodic evaluation, $KPIF$ is the key performance indicator factor and P is the energy requirement. If the key performance indicator is in energy terms, then $KPIF$ takes a unit value. Otherwise, the appropriate factor is applied; for example, in terms of energy cost or carbon emissions.

The expected error (U) can be quantified based on either periodic or annual evaluations (E). The periodic evaluation is based on the lowest resolution of the calculation in the model whereas the annual evaluation is based on the error derived from the summation of the periodic evaluations. Furthermore, the error is expected to vary depending on the specific data set (w)

and on the KPI (k) evaluated. The following equation shows the simple definition of expected error based on periodic evaluations (in this case daily):

$$U_{y,d,p,w,k,s} = \frac{E_{y,d,p,w,k} - E_{y,d,s,w,k}}{E_{y,d,p,w,k}} \quad \forall y \in Y, \forall d \in D, \forall p \in P, \forall s \in S, \forall w \in W, \forall k \in K \quad (3.15)$$

where y is the calendar year, d is the day within the year, p refers to the primary station and s to the secondary station. The corresponding capitalised letter represents the population of each set. Assuming that the expected error data within each calendar year follow a normal distribution, the daily error for each station can be determined using the mean for each dataset and for each KPI using the following expression:

$$\bar{U}_{p,w,k,s}^{\text{Dly}} = \frac{\sum_y \sum_d \frac{E_{d,p,w,k} - E_{d,s,w,k}}{E_{d,p,w,k}}}{|Y| * |D|} \quad \forall p \in P, \forall w \in W, \forall k \in K \quad (3.16)$$

Similar to the daily analysis, the annual expected error can be determined as follows:

$$U_{y,p,w,k,s} = \frac{\sum_d E_{y,d,p,w,k} - \sum_d E_{y,d,s,w,k}}{\sum_d E_{y,d,p,w,k}} \quad \forall y \in Y, \forall p \in P, \forall s \in S, \forall w \in W, \forall k \in K \quad (3.17)$$

where all the symbols are as defined above. This leads to the annual expected error for each station for each data set and for each KPI shown on Table 3.1. The mean annual expected error can also be evaluated using the following equation:

$$\bar{U}_{p,w,k,s}^{\text{Yly}} = \frac{\sum_y \frac{\sum_d E_{y,d,p,w,k} - \sum_d E_{y,d,s,w,k}}{\sum_d E_{y,d,p,w,k}}}{|Y|} \quad \forall p \in P, \forall s \in S, \forall w \in W, \forall k \in K \quad (3.18)$$

Table 3.1. Sets and variants considered in uncertainty/error analysis.

Set	Y	P and S	W	K
Variants	1996-2016	All weather stations in database	Air temperature Dew temperature Solar radiation Atmospheric pressure	Energy Heating Cooling Energy cost Heating cost Cooling cost Energy carbon Heating carbon Cooling carbon

Once the evaluations of daily and annual expected errors are obtained for each weather station for each dataset and for each KPI, they are plotted against the distance separating the primary weather station and the corresponding secondary weather station. Given the range of years and number of stations originally considered, a rich sample of data points is usually acquired. These data points can then be used in a regression analysis to determine a fit function of expected error against distance for each case. Naturally, the y-intercept is set to zero given the assumption that the only source of error is the distance and therefore the error is null if the simulation is performed at the primary station itself. Distance between each point is determined using the spatial analysis model and Eq. (3.11) as shown in Section 3.1.2. It is of course recognised that additional factors other than distance might affect the difference between the simulations. Factors introducing additional sources of error might include the specific landscape and vegetation. However, to derive a quantitative and easily comparable metric distance has been considered as the main driver for error. Figure 3.7 gives an overview of the method followed.

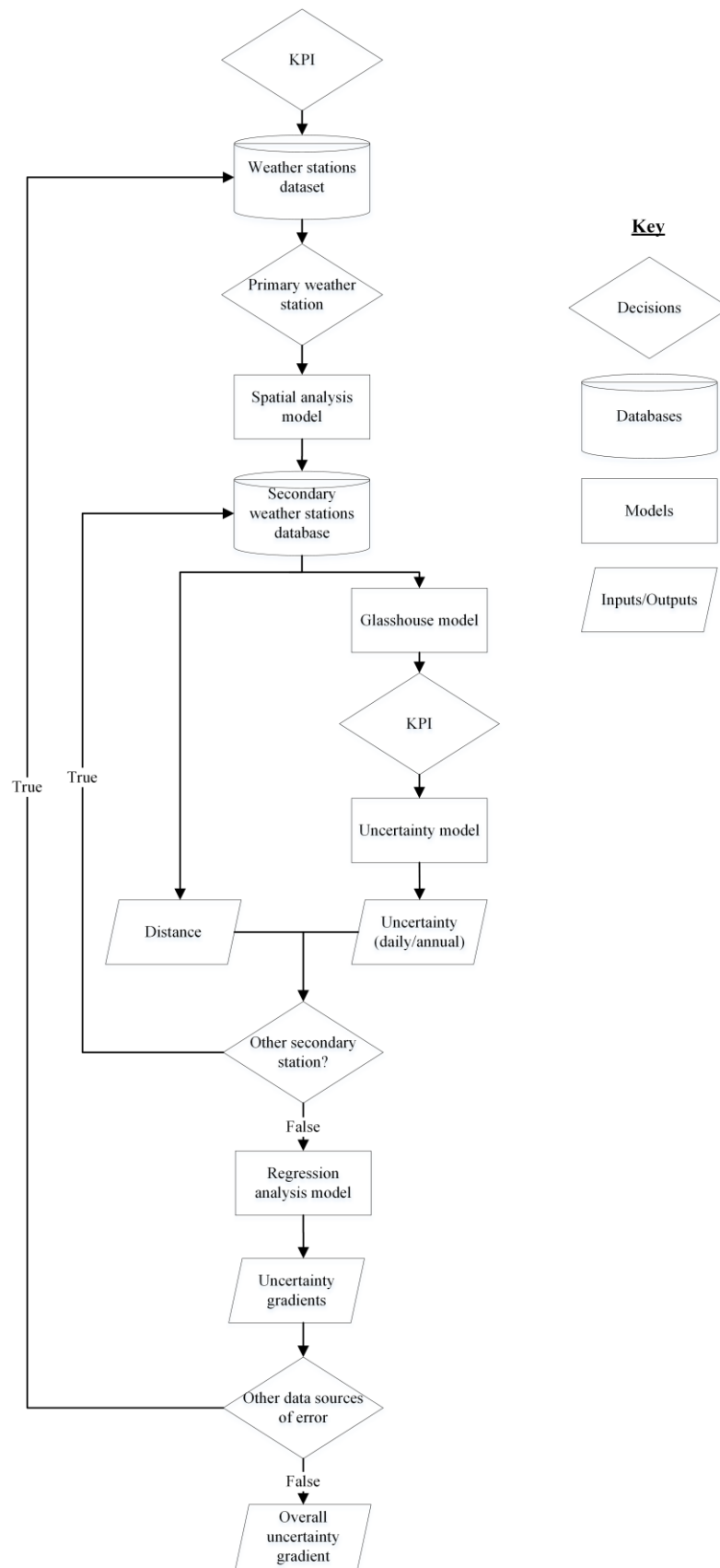


Figure 3.7. Expected error quantification algorithm.

Thereafter, expected error functions are derived for each of the cases mentioned earlier. As mentioned in Section 3.1.3, for any simulation of the model weather datasets might be sourced from multiple weather stations. Therefore, the overall error corresponding to each simulation might consist of more than one error value. Therefore, in order to get an approximate expected error associated with each case, either the average errors (Eqs 3.19 and 3.20) or, to be more conservative, the maximum errors (Eqs 3.21 and 3.22), are assigned.

$$\bar{U}_k^{o,Dly} = \bar{U}_{p',te,k}^{Dly} + \bar{U}_{p',rad,k}^{Dly} + \bar{U}_{p',pr,k}^{Dly} + \bar{U}_{p',dew,k}^{Dly} / 4 \quad \forall k \in K \quad (3.19)$$

$$\bar{U}_k^{o,Yly} = \bar{U}_{p',te,k}^{Yly} + \bar{U}_{p',rad,k}^{Yly} + \bar{U}_{p',pr,k}^{Yly} + \bar{U}_{p',dew,k}^{Yly} / 4 \quad \forall k \in K \quad (3.20)$$

$$\hat{U}_k^{o,Dly} = \max\{\bar{U}_{p',te,k}^{Dly}, \bar{U}_{p',rad,k}^{Dly}, \bar{U}_{p',pr,k}^{Dly}, \bar{U}_{p',dew,k}^{Dly}\} \quad \forall k \in K \quad (3.21)$$

$$\hat{U}_k^{o,Yly} = \max\{\bar{U}_{p',te,k}^{Yly}, \bar{U}_{p',rad,k}^{Yly}, \bar{U}_{p',pr,k}^{Yly}, \bar{U}_{p',dew,k}^{Yly}\} \quad \forall k \in K \quad (3.22)$$

where $\bar{U}_{p',k}^{o,Dly}$ and $\bar{U}_{p',k}^{o,Yly}$ are the mean overall daily and yearly expected error factors based on the selected stations and their uncertainty functions, respectively. Similarly, $\hat{U}_{p',k}^{o,Dly}$ and $\hat{U}_{p',k}^{o,Yly}$ represent the maximum overall daily and yearly expected error factors, respectively. The subscripts in the locational position of the set W represent the data sets acting as the main source of error (*te* as the air temperature, *rad* as the solar radiation, *pr* as the atmospheric pressure, and *dew* as the dew temperature).

3.2 Transport – Distribution stages

Transportation of goods can be one of the most energy and carbon intensive processes in a supply chain system. Hence finding ways to improve the performance of this process in terms of operational efficiency as well as technologically, is of interest. In the present work, one of the main objectives is to develop a systematic and standardised method which addresses allocation and distribution in supply chains in an automated way. Through this approach, the evaluation of impact of influential parameters on the performance of the system should be a capability.

This section describes the methodology for solving a challenging problem comprising of multiple echelons, multiple periods, multiple depots, and a large pool of supply and demand nodes. As discussed in Chapter 2, the vehicle routing problem (VRP) is a difficult problem to solve exactly to optimality, even without the additional complexity of multiple depots or echelons. Outputs from the modelling framework can provide some insight to long-term decisions and planning. Nevertheless, due to the variability of supply and demand typically associated with fresh products, the short term planning and design of networks become more relevant. Also, the easy alteration of parameters is also an aspect of interest here. To fulfil these objectives while addressing the difficulty and computational expense of such problem, a simplification of the problem is desired. Essentially this simplification results to a supply chain problem consisting of multiple single depot VRP at the last echelon. A combination of deterministic and heuristic approaches is used to develop the appropriate modelling frameworks to address this problem. The former is employed for the allocation of nodes, either supply, distribution or demand, between the different stages of the supply chain. The heuristic

approaches and combinatorial optimisation are used for the construction of distribution networks and routing sequences from depots to demand nodes.

The same problem is solved by employing two different modelling frameworks, both of which use hybrid approaches of deterministic and heuristic optimisation techniques. They differ in simplicity, complexity and minor computation expense. The one attempts to enhance the system performance by employing more processing steps and algorithms, as well as combinatorial optimisation.

This section initially describes the allocation optimisation models which is the higher level of the problem. These optimisation models are utilised in the modelling frameworks described thereafter. Finally, the two modelling frameworks are described in detail including the methodology used for the distribution networks' development, routing sequences, and derivation of key performance indicator factors.

3.2.1 Allocation optimisation models

The allocation optimisation is executed using two methods: (i) a continuous linear optimisation model, and (ii) a mixed-integer linear programming (MILP) optimisation model. Both methods are utilised in the modelling frameworks and they are implemented in a way to accommodate the practicality aspects of the problem. The continuous optimisation model comprises only continuous decision variables, thus resulting to an allocation system with greater flexibility by allowing multiple nodes at adjacent echelons to create links (see Fig. 3.8). The MILP model, however, incorporates continuous as well as integer variables. Therefore, the model is naturally more constrained in terms of allocation links between the second and third echelons where the integer (binary) variables are applied (see Fig. 3.9). This approach is followed to ensure the

formation of discrete distribution networks for each depot at each step by allowing demand nodes to be allocated to a maximum of one distribution node. The use of this tactic could potentially be a practical approach in an industrial setting. Although the end result is an output from the MILP, the continuous optimisation model is still vital for the modelling frameworks, especially when clustering of large numbers of demand nodes is performed. This is to reduce the risk of lost opportunities or insights through exceptionally large clusters.

In addition, a slack variable is introduced in both models to address any potential infeasibility in the balance of supply and demand as a result of scarce national production. This variable can be interpreted as the requirement for imports at the corresponding time steps. Nevertheless, to ensure maximum national production utilisation, possibly based on agreements with suppliers, a penalty factor is assigned to the slack variable. The factor can vary depending on the time step and the desired priority level to national production. In this way, the penalty factor can be substituted with a cost (or any other KPI) coefficient to characterise the variance from an equivalent national supplier.

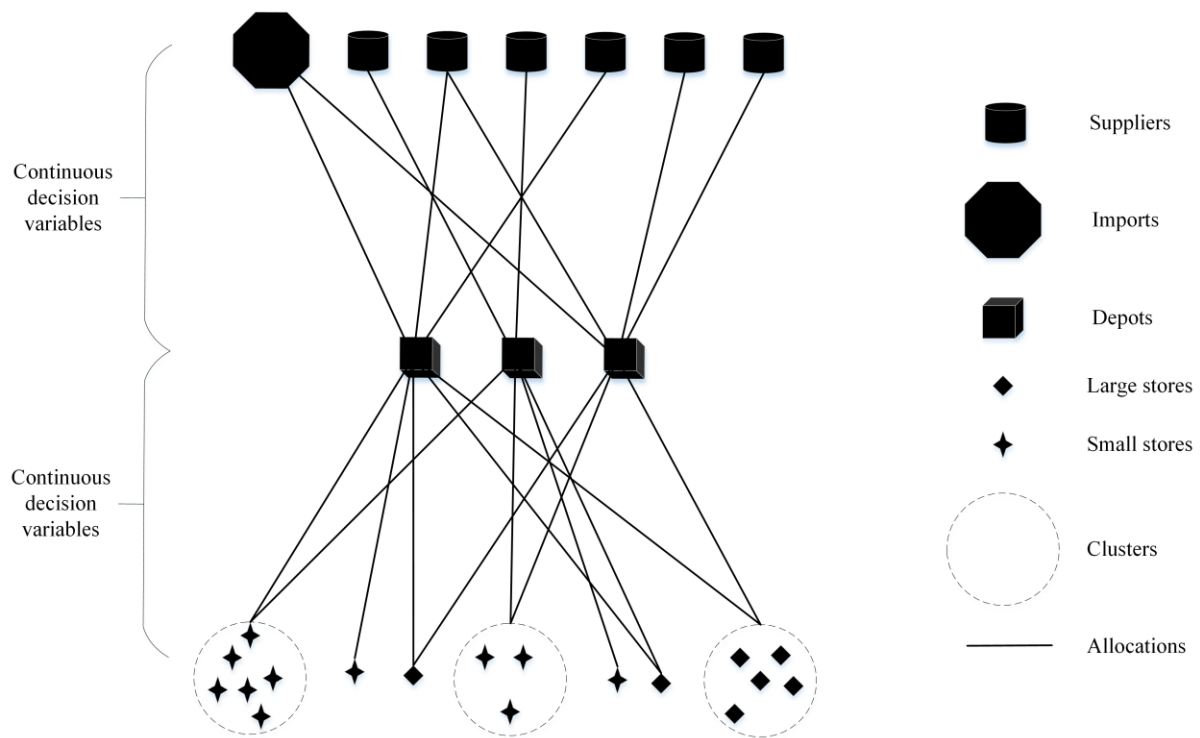


Figure 3.8. Schematic for the continuous optimisation allocation approach.

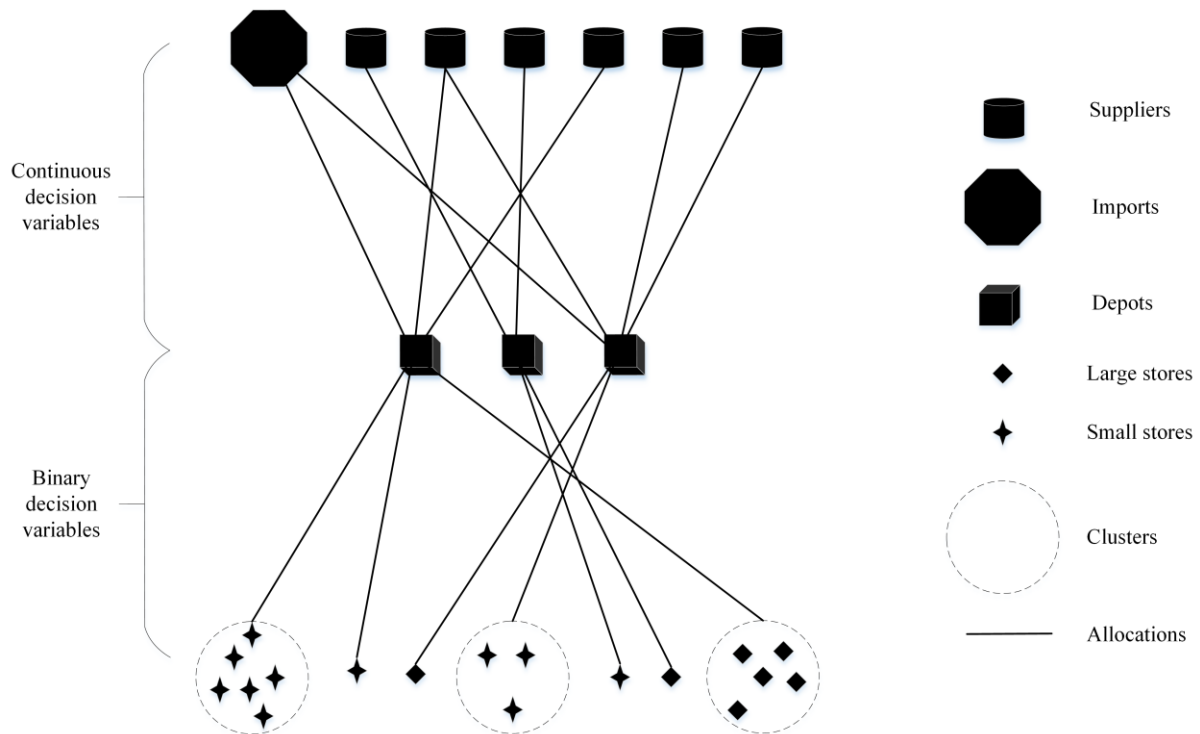


Figure 3.9. Schematic for the mixed integer optimisation programming allocation approach.

3.2.1.1 Continuous optimisation model

The objective function of the continuous optimisation problem is the minimisation of travel distance in conjunction with the amount of product transported over that distance. Therefore, the objective function is as represented by Eq. (3.23).

$$\min \sum_{i,j,t}^{|I|,|J|,|T|} z_{i,j,t} D_{i,j} + \sum_{j,t}^{|J|,|T|} r_{j,t} PF + \sum_{j,u,t}^{|J|,|U|,|T|} q_{j,u,t} D_{j,u} + \sum_{j,k,t}^{|J|,|K|,|T|} v_{j,k,t} D_{j,k} \quad (3.23)$$

where set indexes i, j, k, u and t represent the suppliers, depots, large stores, small stores and periods, respectively. Parameters $D_{m,n}$ are the distance between nodes m and n as presented in the corresponding indexes. Parameter PF represents the imports factor which is enforced either when the suppliers' production capacity is insufficient for satisfying demand at the stores echelon, and subsequently makes the continuous decision variable r to act as a slack variable, or when the objective function equates to a lower value when imports are used instead of national production. More specifically, $r_{j,t}$ is the amount of product imported to depot j at time step t . However, the supply chain capacity in handling the product (for example: depot handling capacity, storage capacity, fleet capacity) has still to be within limits in order for the problem to be feasible. This can be a reasonable assumption in practice since if the infrastructure supporting the supply chain cannot cope with outstanding demand in short periods of time, then demand satisfaction is assumed to be capped by the capabilities of the supply chain. Nevertheless, this is not expected to be the case here as it is assumed that supply chain infrastructure in place is able to cope with the necessary demand. Also, demand at demand nodes is usually expected to be forecasted while taking into consideration the capabilities of the supply chain and making sure that the supply chain can deal with the asked demand.

The decision variables z , q and v are continuous variables defining the amount of product transported between two nodes at adjacent levels of the supply chain at each time step. More specifically, $z_{i,j,t}$ is the amount of product allocated from supplier i to depot j at time step t ; $q_{j,u,t}$ is the amount of product allocated from depot j to small store u at time step t ; and $v_{j,k,t}$ is the amount of product allocated from depot j to large store k at time step t .

For simplicity as well as for maintaining consistency between the models in this work, the distance between nodes (either at different echelons or within this same echelon) is considered to be a straight line over the surface of the Earth. This is estimated using the nodes' coordinates and the commonly used law of cosine, as shown in Eq. (3.24):

$$D_{m,n} = Ra \cdot \arccos(\sin \theta_m \cdot \sin \theta_n + \cos \theta_m \cdot \cos \theta_n \cos(\Delta\varphi)) \quad (3.24)$$

where Ra is the Earth's radius, θ_m and θ_n are the geographical latitudes of the two nodes in radians, and $\Delta\varphi$ is the difference in geographical longitude between them.

The optimisation problem is subject to constraints including production capacities, demand requirements, storage capacities, and mass balances. At the production stage, the following constraint (Eq. (3.25)) maintains the feasibility of the system by ensuring that the production capacity of each supplier at each time step is not exceeded.

$$\sum_j^{|J|} z_{i,j,t} \leq P_{i,t} \quad \forall i \in I, \forall t \in T \quad (3.25)$$

where $P_{i,t}$ is the production capacity of supplier i at time step t . For the storage capacity (sometimes also seen as handling capacity) of depots, constraint Eq. (3.26) ensures that the

allocated total amount of product handled by each depot remains within the limits of its capacity, while accounting for both small and large stores.

$$\sum_u^{|U|} q_{j,u,t} + \sum_k^{|K|} v_{j,k,t} \leq S_{j,t} \quad \forall j \in J, \forall t \in T \quad (3.26)$$

where $S_{j,t}$ is the storage capacity of depot j at time step t . Since the food category of interest here is that of fresh products, it is assumed that due to their perishability and the fact that usually depots in the UK operate on just-in-time basis (Jones, 2002), that stock accumulation or depletion between periods in the model does not exist. As a result, the capacity of the depot is assumed to be limited by the amount of product it can handle at each period. It is worth mentioning that storage (or handling) capacity can also be converted into each depot's vehicle fleet capacity. Therefore, transport capacity in terms of vehicles availability can be captured by the depot capacity constraint. In other words, this depot related constraint can represent the bottleneck in the capability of a depot handling a certain volume of product, whether that is in terms of space, personnel, fleet, or possibly something else. It is also noteworthy that the fleet capacity could also be translated into the type of vehicle and the fuel it uses by considering alternative types of fuels; for example, ethanol, biodiesel, electricity and LNG. For the main part of the analysis, it is assumed that current deployment levels of alternative fuel driven vehicles is negligible and therefore vehicles are fuelled by conventional diesel. However, the impact of replacing fleet vehicles to alternative fuels is also considered in the analysis.

For demand requirements, considering again both small and large stores, constraints represented in Eqs (3.27, 3.28) ensure that allocated product volumes are satisfactory at each time step.

$$\sum_j^{|J|} q_{j,u,t} \geq d_{u,t} \quad \forall u \in U, \forall t \in T \quad (3.27)$$

$$\sum_j^{|J|} v \geq d_{k,t} \quad \forall k \in K, \forall t \in T \quad (3.28)$$

where $d_{u,t}$ is the demand of small store u at time step t , and $d_{k,t}$ is the demand of large store k at time step t . To ensure the feasibility of the system, a mass balance constraint (shown in Eq. (3.29)) for the three echelons of the supply chain is also introduced.

$$\sum_i^{|I|} z_{i,j,t} + r_{j,t} = \sum_u^{|U|} q_{j,u,t} + \sum_k^{|K|} v_{j,k,t} \quad \forall j \in J, \forall t \in T \quad (3.29)$$

It is worth mentioning that the model assumes perfect foresight of demand and therefore there is no dependency between different time steps. If no perfect foresight was considered, then accumulation or depletion of stock at different time steps would have been a possibility given the potential difference between sales and demand. However, as noted above, since the product type considered here is of perishable fresh products with short shelf-life along with the common just-in-time operation nature of depots, no accumulation or depletion is assumed. Nevertheless, as a potential avenue for future work, the model could be further developed to accommodate the dependency between time steps in order to accommodate this aspect for supply chains which have strong dependency on stock.

Lastly, the decision variables are constrained to only positive values by constraints Eqs (3.30-3.33).

$$z_{i,j,t} \geq 0 \quad (3.30)$$

$$r_{j,t} \geq 0 \quad (3.31)$$

$$q_{j,u,t} \geq 0 \quad (3.32)$$

$$v_{j,k,t} \geq 0 \quad (3.33)$$

where $z_{i,j,t}$ is the amount of product allocated from supplier i to depot j at time step t ; $q_{j,u,t}$ is the amount of product allocated from depot j to small store u at time step t ; and $v_{j,k,t}$ is the amount of product allocated from depot j to large store k at time step t .

3.2.1.2 Mixed integer linear programming optimisation model

Similar to the continuous optimisation problem above, the objective function of the mixed integer optimisation problem (MILP) is the minimisation of travel distance in conjunction with the amount of product transported over that distance. The objective function (Eq. (3.34)) is:

$$\begin{aligned} \min \sum_{i,j,t}^{|I|,|J|,|T|} z_{i,j,t} D_{i,j} + \sum_{j,t}^{|J|,|T|} r_{j,t} PF + \sum_{j,k,t}^{|J|,|K|,|T|} b_{j,k,t} D_{j,k} d_{k,t} + \\ \sum_{j,u,t}^{|J|,|U|,|T|} h_{j,u,t} D_{j,u} d_{u,t} \end{aligned} \quad (3.34)$$

where the sets and parameters are as defined earlier in the continuous optimisation section (3.2.1.1). Likewise, the decision variables associated with the amount of product allocated from suppliers to depots ($z_{i,j,t}$) and imports ($r_{j,t}$) are continuous. However, the decision variables related to the allocation of small stores ($h_{j,u,t}$) and large stores ($b_{j,k,t}$) are binary variables.

The MILP optimisation problem is subject to several constraints as well. These consider production capacities, demand requirements, storage capacities, mass balances, and also allocation constraints. Firstly, the production capacity limit of suppliers is fulfilled by constraint Eq. (3.25).

$$\sum_j^{|J|} z_{i,j,t} \leq P_{i,t} \quad \forall i \in I, \forall t \in T \quad (3.35)$$

The storage (or handling) capacity limit of depots is satisfied by the following constraint Eq. (3.36):

$$\sum_u^{|U|} h_{j,u,t} d_{u,t} + \sum_k^{|K|} b_{j,k,t} d_{k,t} \leq S_{j,t} \quad \forall j \in J, \forall t \in T \quad (3.36)$$

Like in the continuous optimisation model, in the case of capacity limit being the fleet capacity, it is assumed that current deployment levels of alternative fuel driven vehicles is negligible and therefore vehicles are fuelled by conventional diesel.

The demand nodes allocation at the third echelon is constrained to exactly one distribution node. This condition is satisfied for both small and large stores using constraints Eqs (3.37, 3.38), respectively.

$$\sum_j^{|J|} b_{j,k,t} = 1 \quad \forall k \in K, \forall t \in T \quad (3.37)$$

$$\sum_j^{|J|} h_{j,u,t} = 1 \quad \forall u \in U, \forall t \in T \quad (3.38)$$

Also, to ensure feasibility of mass flow in the supply chain, a mass balance constraint Eq. (3.39) is imposed to the system.

$$\sum_i^{|I|} z_{i,j,t} + r_{j,t} = \sum_u^{|U|} h_{j,u,t} d_{u,t} + \sum_k^{|K|} b_{j,k,t} d_{k,t} \quad \forall j \in J, \forall t \in T \quad (3.39)$$

Lastly, decision variables associated with the allocation of supplies to depots ($z_{i,j,t}$) and imports to depots ($r_{j,t}$) are continuous variables and constrained to positive values (Eqs (3.40, 3.41)). Contrariwise, decision variables associated with the allocation of third echelon nodes, $h_{j,u,t}$ and $b_{j,k,t}$ for small and large stores respectively, to distribution nodes are binary variables (see

Eqs (3.42, 3.43)). These variables take the value of 1 when depot j is connected with a store at time step t .

$$z_{i,j,t} \geq 0 \quad (3.40)$$

$$r_{j,t} \geq 0 \quad (3.41)$$

$$h_{j,u,t} = \begin{cases} 1 & \text{when } j \text{ is linked with } u \text{ at } t, \\ 0 & \text{otherwise} \end{cases} \quad (3.42)$$

$$b_{j,k,t} = \begin{cases} 1 & \text{when } j \text{ is linked with } k \text{ at } t, \\ 0 & \text{otherwise} \end{cases} \quad (3.43)$$

3.2.2 Modelling frameworks

3.2.2.1 Basic deterministic and heuristic modelling framework: A

The supply chain system considered here involves three echelons connected by two transportation stages. In addition to the spatial dimension, there is also the temporal dimension of the problem which introduces an interesting dynamic. In the present work, a systematic approach for managing supply and demand of large supply chains through the consideration of both spatial and temporal aspects is developed. The temporal aspect is considered by addressing multiple periods in the problem while taking into account possible variations in characteristics between the different periods. In this way, time related parameters, such as seasonality, are captured and studied. Primary objectives of this approach also include the quantification of KPIs, improvement of operational efficiency, and smooth operation.

Modelling framework A (MFA), described briefly in Fig. 3.10, starts initially with the three echelons of the supply chain; namely suppliers, depots and stores for each time step in the

timeframe. Based on data defining the parameters associated with each one at each time step, the MILP optimisation model is used for the allocation process as discussed in Section 3.2.1. Outputs from this process include the decision variables associated with the allocation of suppliers and stores to depots. The main difference between the allocation at the two transportation stages is the exclusivity of stores to depots in the second stage. In other words, in the first echelon nodes are not exclusively allocated to one depot whereas in the last echelon they are.

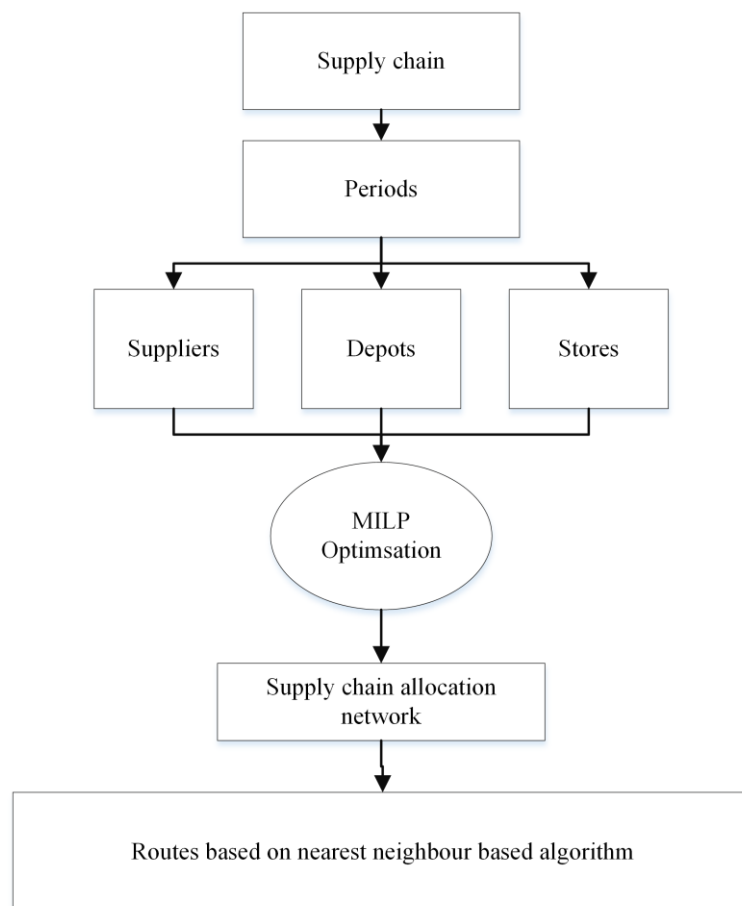


Figure 3.10. Process flow diagram for modelling framework A (MFA).

The next step involves the construction of distribution networks for each depot at each time step. Once again, some of the dominant parameters for solving this problem include the demand of each store along with the vehicle capacity. Outputs are then used to treat each depot as a discrete distribution problem for each period. Therefore, in this way the multi-depot problem is reduced into a much easier to solve single-depot problem. Each distribution problem is then solved using the nearest neighbour based algorithm presented in Fig. 3.11. In summary, in the algorithm presented in Fig. 3.11 a route for each depot for each time step has to be formed while satisfying demand at all demand nodes. As each route is constructed, nodes are added while making sure that constraints such as vehicle capacity are not violated. When all routes are formed and no outstanding demand is present, the algorithm stops.

In summary, this algorithm is driven by demand requirements and the corresponding data feed from the allocation optimisation model. After defining vehicles' transportation capacity, the development of the distribution networks is performed using a constructive search approach. In this approach, each network is developed constructively until the remaining vehicle capacity is not sufficient to serve the next demand node, at which point returns to its route starting point (i.e. depot). Furthermore, it is possible for the full capacity of a vehicle to not be able to satisfy the demand of a single store; something which the model was designed to accommodate for. The end output of this algorithm in the modelling framework is the distribution networks for each depot for each time step as well as the routing sequence of multi-drop routes.

Advantages of this nearest neighbour based approach include its simplicity, low computational expense and therefore fast solving times, and the lack of requiring optimisation solvers. On the downside, outputs obtained from it are expected to be suboptimal. As the name implies, this

algorithm is based on the famous nearest neighbour technique which was extensively studied and presented in literature (e.g. Bellmore and Nemhauser (1968), Hougardy and Wilde (2015)).

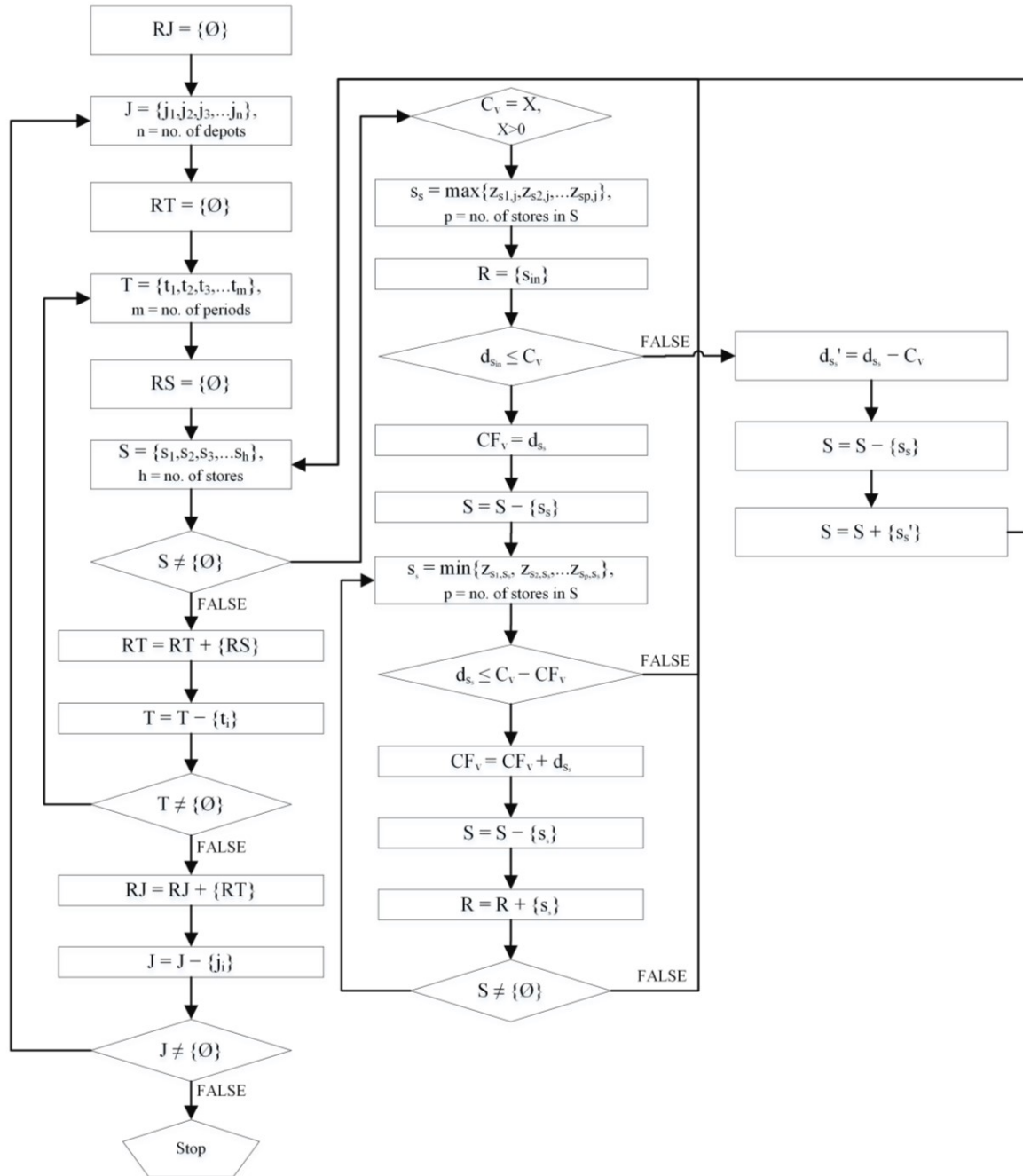


Figure 3.11. Algorithm based on the nearest neighbour approach for the development of distribution networks.

3.2.2.2 *Cluster based deterministic and heuristic modelling framework: B*

Following the same motives followed for MFA, modelling framework B (MFB) is also developed to solve this challenging problem while having the same objectives. In MFB, summarised in Fig. 3.12, the three echelons of the supply chain and their corresponding stakeholders are firstly considered; namely suppliers, depots and stores. After acquiring and processing the required data, a clustering step is performed. This step involves a clustering algorithm inspired by and based on the famous k-mean clustering technique (e.g. Celebi et al. (2013), Everitt et al. (2001), Peña et al. (1999)). It is used to form clusters of demand nodes of the same type which are at close proximity. The aim of this step is to improve the allocation optimisation through the consideration of not only the distance between nodes at different echelons but also the distance between nodes at the same echelon.

The clustering algorithm's initiation requires the input of initial number of cluster centres along with the random definition of those centres' initial coordinates. The selection of initial number of clusters should be treated with caution to avoid potential loss of opportunities as a result of clustering to either a much greater or a much lower degree than appropriate. As a result of the clustering algorithm's initial randomisation, outputs from simulations or iterations of the same problem are expected to slightly differ. The impact of this aspect on the overall outputs from the modelling frameworks is investigated and discussed in Chapter 5.

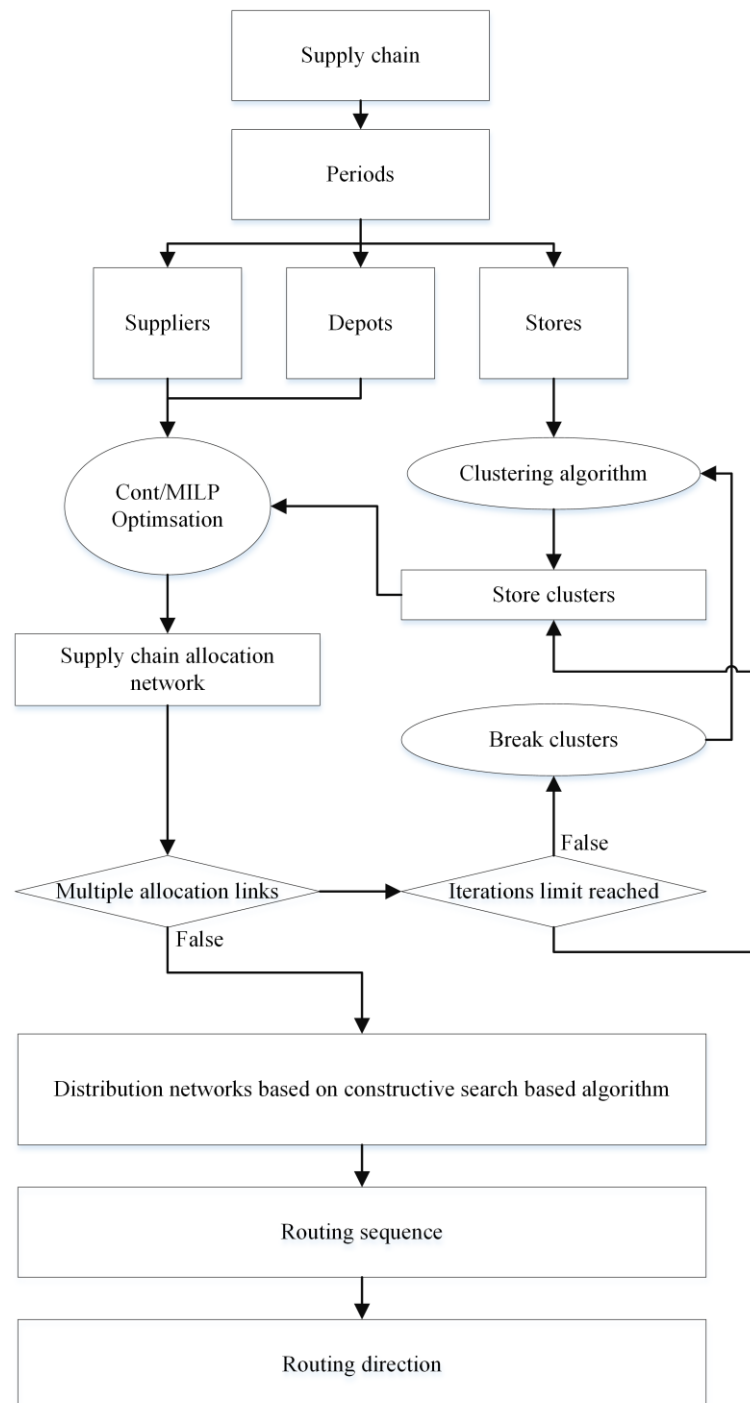


Figure 3.12. Process flow diagram for modelling framework B (MFB).

After data associated with each node of each of the supply chain stages for all time periods in the timeline are acquired, the allocation is initially executed using the continuous optimisation model described in Section 3.2.1. Based on decision variables derived using this model, allocation of suppliers and stores to depots is performed. Outputs from the continuous optimisation model are then analysed and tested against the conditions set. Conditions include, for example, the iterations limit and the allocation of clusters to more than one depot. When the model indicates that optimality is reached when some clusters are allocated to more than one depot, those clusters are broken into smaller clusters and are inputted into the continuous optimisation model to be executed again. This iteration loop is executed until limit conditions are met. If the iteration limit is met before exclusivity of store clusters to depots, then the last iteration's results are used to run the MILP optimisation. The output of MILP is the allocation of suppliers to depots (not necessarily exclusively) and the allocation of clusters to depots (exclusively). In this way, each depot's distribution network is developed. Using these outputs, each depot can now be solved as an independent VRP for each time step. Before solving each problem by forming discrete networks, all clusters are broken down into individual stores while holding their allocation identity. Even after the decomposition of the problem into smaller independent problems, as Rardin (2017) highlights, the VRP is a non-linear problem and particularly at large sizes it can be a difficult problem to solve to optimality using exact methods. Subsequently, a constrictive search algorithm is used to solve the problem. This algorithm is based on a similar approach proposed in Rardin (2017) and described specifically for the problem in this study in Fig. 3.13.

In summary, the algorithm presented in Fig. 3.13 a route for each depot for each time step has to be formed while satisfying demand at all demand nodes. As each route is constructed, nodes are added while making sure that constraints such as vehicle capacity are not violated. With

addition of nodes to each route the new centre of gravity of the route is calculated and the decision of the next addition is based on that. When all routes are formed and no outstanding demand is present, the algorithm stops.

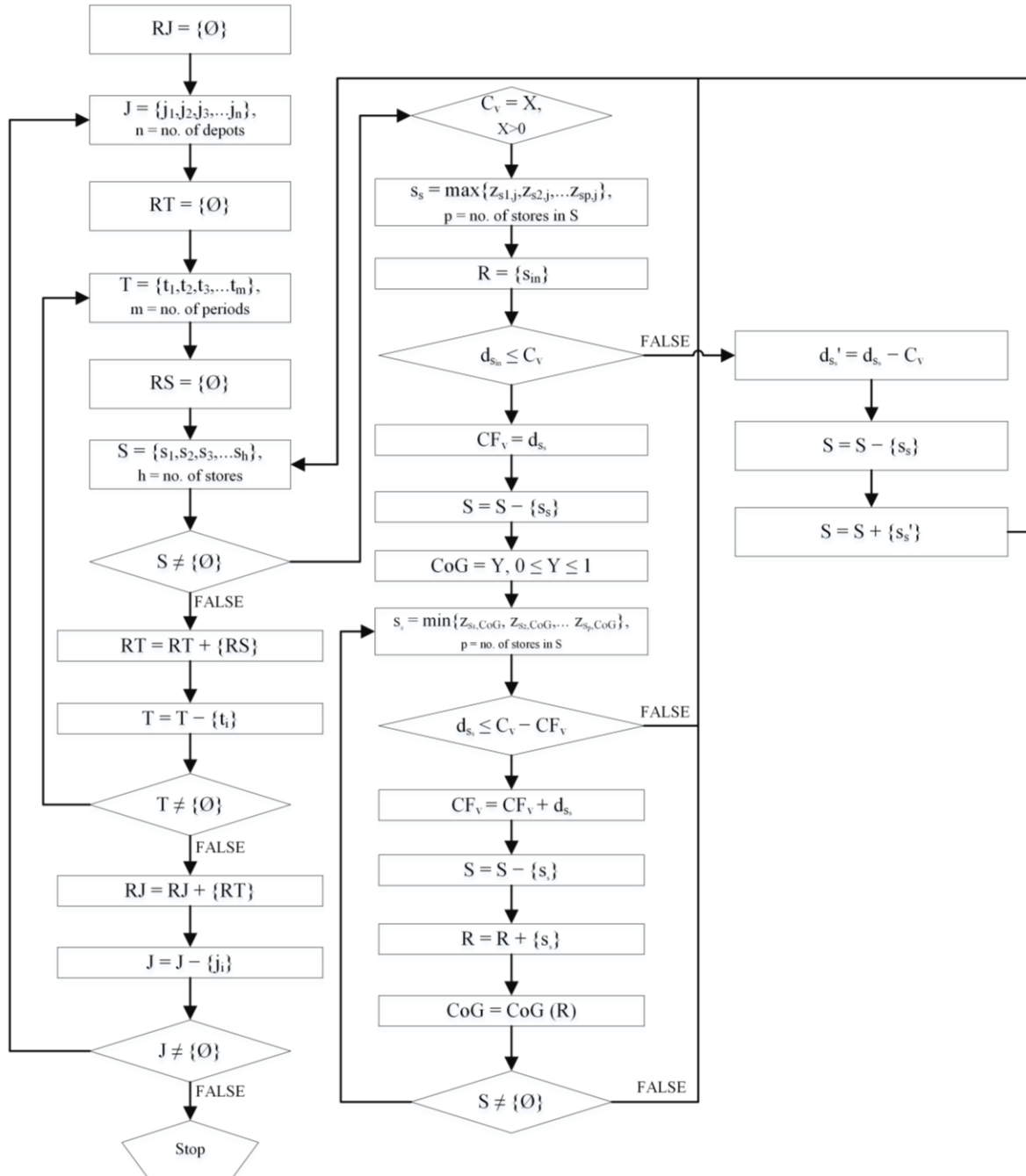


Figure 3.13. Algorithm based on constructive search approach for the development of distribution networks.

Once again, advantages of this algorithm include its simplicity, low computational expense and therefore fast solving times, and the lack of requiring optimisation solvers. On the downside, outputs obtained from it are again expected to be suboptimal. However, it is expected to perform better in terms of outputs compared to the constructive search approach employed in MFA. The algorithm is driven by demand data for the formation of the distribution networks while considering vehicle capacity. This form of constructive search designs distribution networks in which each route is built until the available vehicle capacity is not sufficient to satisfy the demand of the next store, and therefore returns to its base depot. As in MFA, the model accommodates for the possibility of a whole vehicle capacity being insufficient to satisfy the demand of a single demand node. The key difference of this algorithm from the nearest neighbour based one used in MFA is in the selection of each consecutive node in a route. Here, the selection is based on the centre of gravity (based on geographical coordinates) of the route up to the last selected node, rather than selecting the closest in proximity to the last node. This approach aims to develop more compact routes, like clusters, and therefore potentially avoid the expansion of networks to greater distances (see illustration in Fig. 3.14). The output of this algorithm is the distribution networks of each depot for each time step. In this modelling framework, however, the routing sequence and travel direction are not given directly by the constructive search algorithm. Instead, some additional processing steps are employed in an attempt to improve the performance of the model.

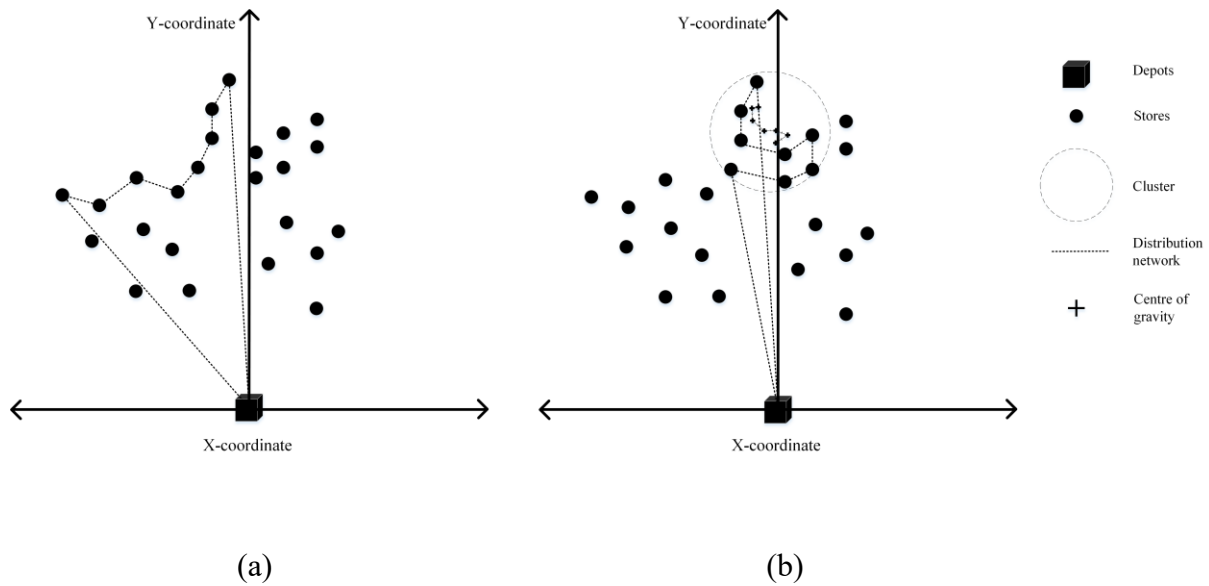


Figure 3.14. Schematic illustrating the potential benefit of using (b) centre of gravity based constructive algorithm against (a) the basic nearest neighbour based algorithm.

To develop the routing sequence of every multi-drop route while minimising the distance travelled and satisfying all the relevant constraints, the famous combinatorial optimisation problem of Travelling Salesman Problem (TSP) is solved for each route of each depot for each time step. The problem is assumed to be symmetric, meaning that distance between nodes is equal in both directions of travel. The TSP is solved based on the approach presented in Gurobi Optimization (2018) while using a feature offered by Gurobi solver called “lazy constraints”. In summary, this technique solves the problem iteratively by the addition of subtour elimination constraints retrospectively until the optimum route without subtours is formed.

Following the assumption of a symmetric problem, the minimum total travel distance in each route is the same in both travel directions. As a result, in a simplified scenario and under the assumption of equal stop durations and travel speeds in both directions, the total travel time in

each route is also expected to be equal. However, if the fact that the last trip in every route is a return trip is considered, then the total travel time to deliver to all demand nodes might differ depending on the direction of travel. The effect of this possibility is presented in an illustrative example in Fig. 3.15. Using this approach and selecting the optimum direction, the product potentially travels less distance and spends less time in vehicles before demand is satisfied at all nodes in the route.

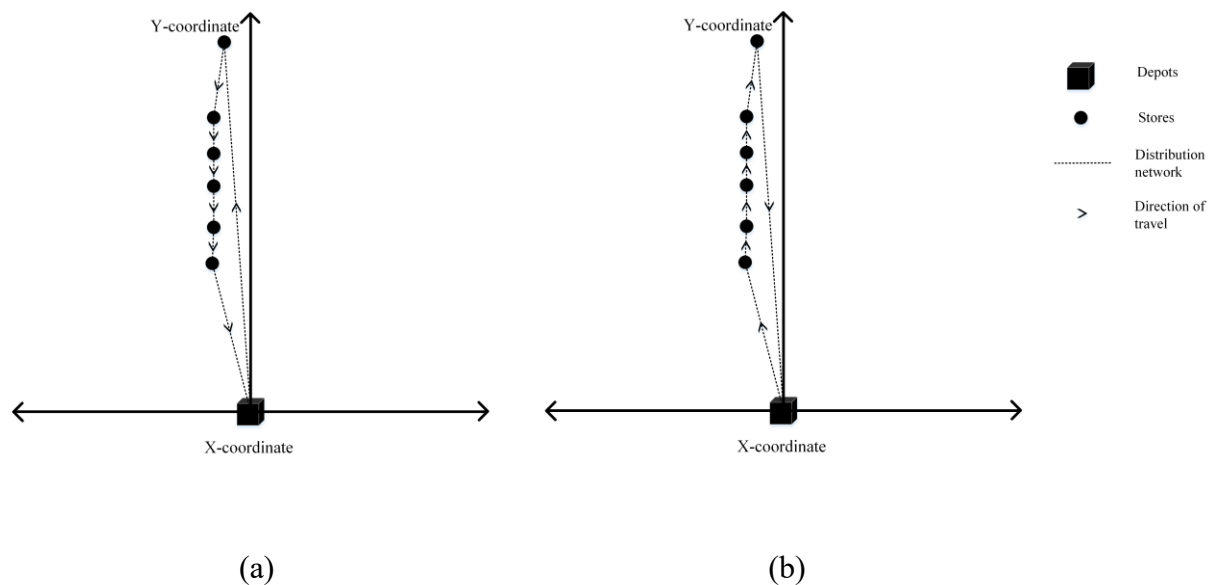


Figure 3.15. Schematic illustrating the potential total distance and total time differences for delivery of product depending on direction of travel (sub-figure (a) shows longer and sub-figure (b) shows shorter distance and time).

The travel distance and time for delivery of product (instead of completion of the route) can be of particular interest, for example, in cases when the quality of the product is affected by time,

delivery time slots have to be satisfied as well as when considering the impact of vehicles travelling with greater loads over longer distances.

3.2.2.3 Carbon factors

Firstly, the average fuel consumption per unit of distance is calculated using Eq. (3.44).

$$FC = \frac{\text{Total litres consumed}}{\text{Total distance travelled}} \quad (3.44)$$

Since one of the objectives of this exercise is to examine the impact of using alternative fuels and each fuel has its own energy density, it is required to calculate the energy consumed per distance travelled. This can then be used as the baseline for all fuels considered, assuming that the thermal efficiency of all engines is the same regardless of the fuel used. To calculate the energy consumption per unit of distance travelled (E), Eq. (3.45) is used:

$$E = FC \cdot ED \quad (3.45)$$

where FC is the average fuel consumption per unit of distance and ED is the energy density of each fuel obtained from DECC and DEFRA (2016).

To calculate the carbon factors per unit of distance for all fuels, two methods can be used depending on the units of the data available. The first approach can be used when the carbon emissions are given per unit of volume of fuel. The following equation can be used to calculate the carbon emissions per unit of distance (CE):

$$CE = \frac{E}{\rho \cdot ED} \cdot EL \quad (3.46)$$

where E is the energy consumption per unit of distance travelled, ρ is the density of the fuel, ED is the specific energy of the fuel, and EL is the emissions per litre of fuel. The second approach can be used when carbon emissions are given per unit of energy in the fuel. In this case the following equation can be used to calculate CE :

$$CE = EE \cdot E \quad (3.47)$$

where EE is the emissions per unit of energy in the fuel.

3.2.2.4 Cost factors

Similar to the carbon factors, the energy consumption per unit of distance travelled calculated from data is used as the baseline for the calculation of the cost factors. Following from that estimation, the cost factor (CF) for each fuel can be calculated using:

$$CF = \frac{E}{\rho \cdot ED} \cdot CL \quad (3.48)$$

where E is the energy consumption per unit of distance travelled, ρ is the density of the fuel, ED is the specific energy of the fuel, and CL is the cost per unit of volume of the fuel.

3.2.2.5 Application of KPI factors

Since the main objective of the modelling frameworks is to minimise the transport distance while satisfying the all constraints and requirements associated with the supply chain, one of the main outputs of the model is in terms of distance travelled. In order to translate the distance travelled to other metrics, such as the carbon emissions and fuel costs, it is required to use key performance indicator (KPI) factors which are normalised based on distance travelled.

Furthermore, another aspect of interest for analysis is the impact of the truck capacity on the performance of the system. Nevertheless, to study the impact of vehicle capacity beyond the distance travelled, it is worth considering the effect of KPI factors' variation as a function of capacity. Based on data obtained from DECC and DEFRA (2016) for diesel fuel, Fig. 3.16 shows the linear regression relationships constructed at different percentages of laden. A positive linear relation is observed for all laden percentages. These relationships can be used to estimate the impact of varying the vehicles capacity on the carbon factors used to estimate the carbon emissions of the system.

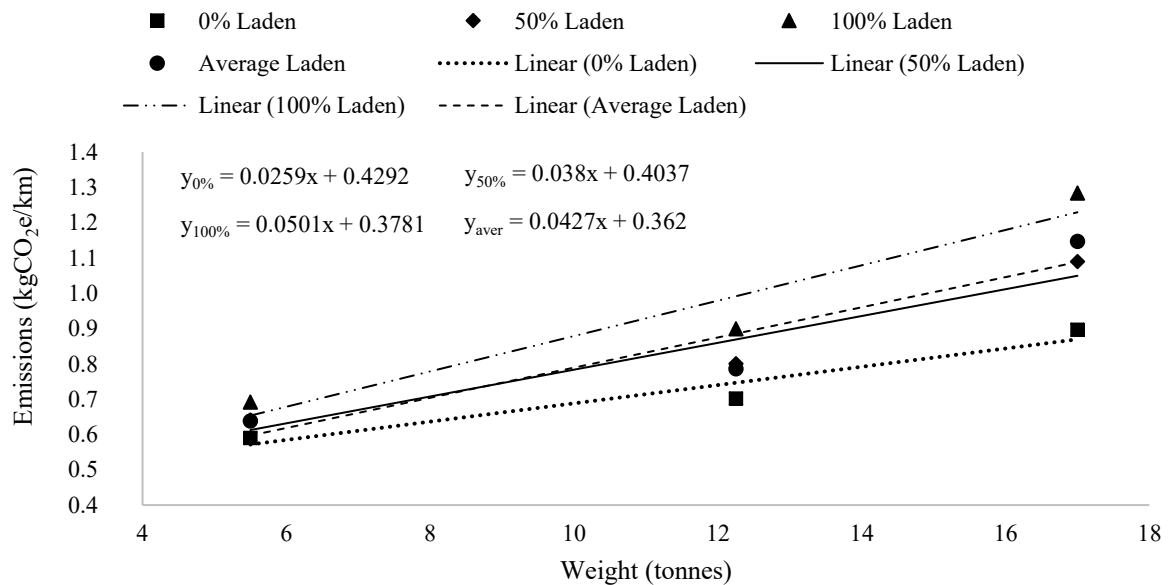


Figure 3.16. Vehicle capacity and emissions relation at different percentages of laden.

Assuming that emissions are directly proportional to fuel consumption, the impact of vehicles capacity on the cost factors (CF) can be estimated as well. This can be done using the following equation:

$$CF = \frac{CE}{EL} \cdot CL \quad (3.49)$$

where CE is the emissions per unit of distance travelled, EL is the emissions per litre of fuel, and CL is the cost of fuel per unit of volume. Considering diesel as fuel, the relationships presented in Fig. 3.17 were determined. Similar to the carbon factors, a linear positive relationship between vehicle capacity and cost of fuel per unit of distance travelled was observed. Nevertheless, the gradients of the regression lines are smaller than the carbon factors showing that the impact of vehicle capacity variation on carbon factors is expected to be greater than that on cost factors.

Also, some variation on the calculated carbon and cost factors was observed due to the effect of laden. This variation can be captured by performing a simulation at different laden percentages and studying the impact on the corresponding KPI.

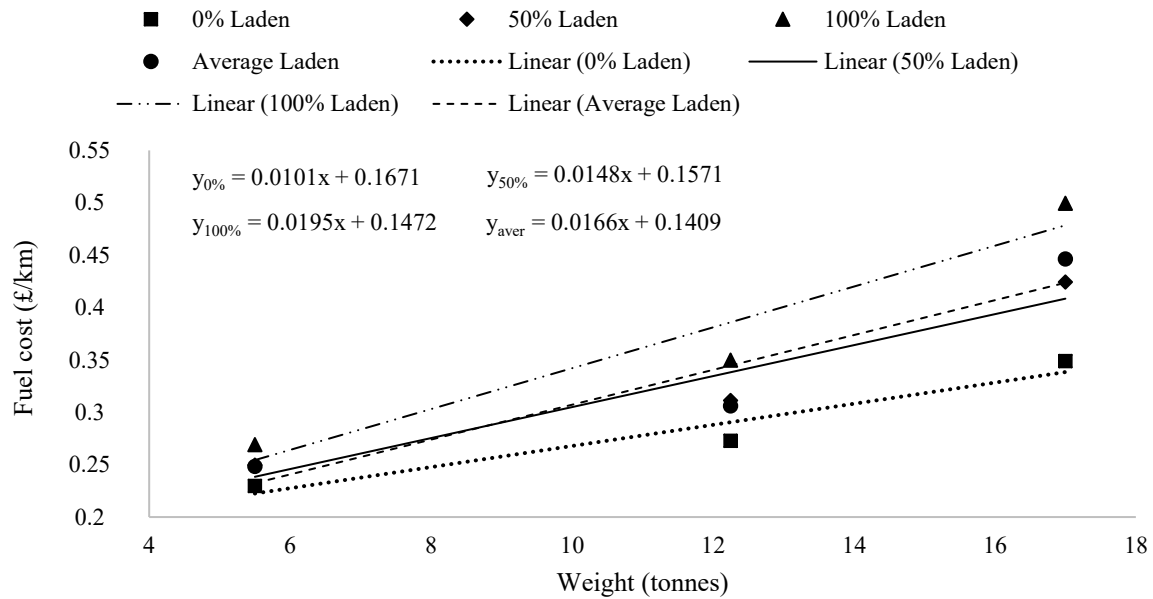


Figure 3.17. Vehicle capacity and cost of fuel relation at different percentages of laden.

3.3 Electricity – Retail and storage stages^{††}

Electricity is, as expected, a significant form of energy consumed in a supply chain, especially dominating in the stages involving retail and storage activities. This is due to the typical processes involved in these activities such as lighting, refrigeration, and ventilation. Therefore, it was of interest to find novel ways of reducing the carbon intensity associated with electricity consumption while ensuring that it is within the limits of commercial competitiveness.

Various ways were studied in literature and have already been implemented, to some extent, in industry. In the UK, these ways are sometimes dominated by the installation of renewable

^{††} Parts of this section were presented earlier in Georgiou et al. (2019, 2018c, 2018d, 2018b, 2017b).

technologies, such as solar PV, onshore wind and offshore wind. However, these technologies suffer from intermittency and since they are not dispatchable their deployment and integration to the grid might be limited. Therefore, while renewables provide an efficient and in most cases affordable way of reducing Scope 1 and 2 emissions of an organisation, their installation can sometimes be limited and economically infeasible.

It was interesting to identify novel ways/technologies which were not widely studied/compared in literature and are not widely implemented in industry; thus having the potential to contribute towards the improvement in carbon footprint. A way to achieve this can be the use of electricity storage systems. Electricity storage systems can assist in both the deployment of renewables and the use of low carbon electricity generated during low demand periods. Also, they can potentially contribute towards an economic benefit by taking advantage of the difference in electricity prices between peak and off-peak electricity demand periods. These aspects were of interest and were studied for two newly proposed medium to large scale electricity storage systems; namely the liquid-air energy storage (LAES) system and the pumped thermal electricity storage (PTES) system.

Both systems were studied in terms of technical and economic competitiveness against each other as well as against other technologies available in the marketplace. Besides the novelty of studying and comparing these technologies, they were also of interest due to their expected operational capacity range and competitive characteristics as discussed in Section 2.3. The following subsections present the methodology for quantifying and assessing their performance.

3.3.1 Thermodynamic models

3.3.1.1 Liquid-air energy storage (LAES)

The LAES system's configuration and operation was discussed in Section 2.3 and Fig. 2.2. Based on the underlying operation and thermodynamic principles of the system a thermodynamic model was developed with the most important performance indicator being the system's roundtrip efficiency (η_r). Here, η_r is defined as the ratio of net work output (W_d) during discharging to net work input (W_c) during charging, as expressed in Eq. (3.50).

$$\eta_r = \frac{W_d}{W_c} \quad (3.50)$$

The thermophysical properties used in the model evaluations were obtained from Lemmon et al. (2010). To evaluate W_c for a full charge cycle, the mass storage capacity of the liquid air storage vessels (M_L) along with the specific work input required for air liquefaction (w_l) are used as follows:

$$W_c = M_L w_l \quad (3.51)$$

The ideal w_l can be determined through the consideration of the famous Claude (Fig. 3.18) liquefaction cycle (see for example Perry et al. (1997)) while also considering the additional thermal energy sourced in the form of cold recovered from the power generation plant during the discharge cycle when liquid air is evaporated:

$$w_l = \frac{[(T_{in,c}(s_{in,c}-s_{out,c})-(h_{in,c}-h_{out,c})) - x(h_{in,e}-h_{out,e})][(h_{in,c}-h_f)-C_r(1-L)]}{x(h_{in,e}-h_{out,e})+(h_{in,e}-h_{out,e})} \quad (3.52)$$

where for all applicable symbols subscripts ‘c’ and ‘e’ refer to the compressor and expander respectively, and subscripts ‘in’ and ‘out’ refer to the inlet and outlet respectively. Also, variables T , h and s refer to the temperatures, specific enthalpies and specific entropies respectively. Also, h_f refers to the specific enthalpy of air at saturated liquid state at atmospheric pressure. Moreover, term x refers to the ratio of mass of air diverted for expansion to the total mass flow rate of the compressed air. The expression $(1 - L)$ represents the fraction of the recovered waste cold from the power generation cycle delivered to the charging cycle. Finally, C_r is the specific waste cold available through the complete evaporation of liquid air.

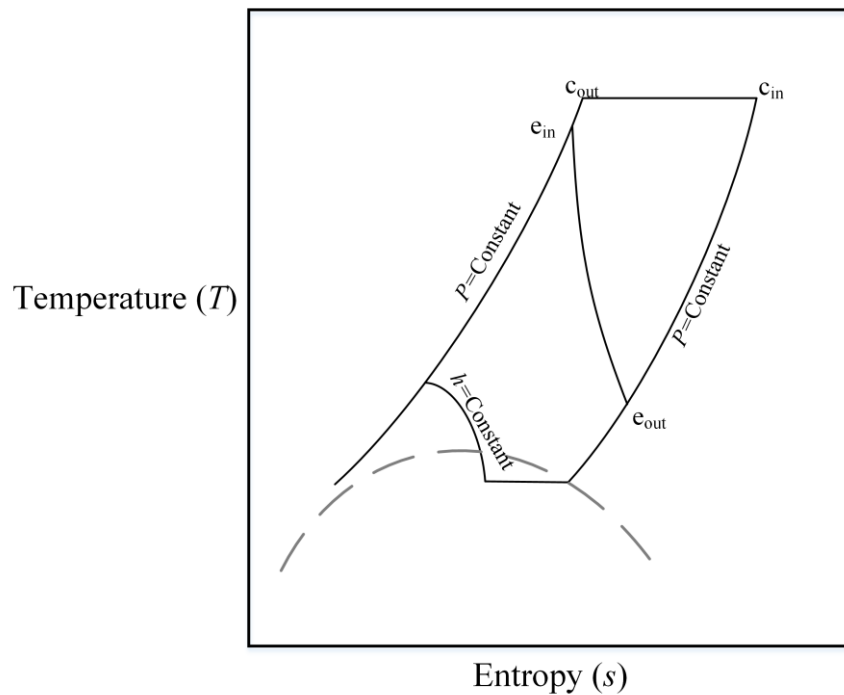


Figure 3.18. LAES liquefaction (Claude Cycle) T - s diagram (as commonly described in literature).

The recoverable C_r during the discharge period can be determined by evaluating the difference in the specific enthalpy between the fully evaporated air at ambient temperature and at the outlet of the cryogenic pump in the discharge cycle. It is also of interest to evaluate the power capacity ($\dot{W}_c$) necessary for a specified liquid air mass production rate ($\dot{m}_L$) in the charging cycle; this is given by Eq. (3.53).

$$\dot{W}_c = \dot{m}_L w_1 \quad (3.53)$$

Furthermore, the required volume of the liquid air storage vessel is determined by dividing the mass storage capacity of the vessel by the liquid air's density at storage conditions. Similarly, the required volume of the waste cold storage vessel (V_c) is calculated by considering the required mass of storage medium (M_c) which is assumed to be magnetite (Fe_3O_4), the density of the storage medium (ρ_w) taken for be 5175 kg/m^3 (McTigue et al., 2015), the void ratio in the storage vessel (ε) and the recovered waste cold:

$$V_c = \frac{M_c}{\rho_c(1-\varepsilon)} \quad (3.54)$$

$\dot{W}_d$ for the discharge cycle is calculated based on the net power output ($\dot{W}_d$) and the discharge duration (t_d) by assuming steady-state conditions. To evaluate the net power output ($\dot{W}_d$) the difference in power between the power input in the cryogenic pump ($\dot{W}_{cp}$) to pressurise the liquid air and the total of power outputs ($\dot{W}_t$) from the turbine expansion stages (N_{ts}) is calculated as shown in Eq. (3.55). Also, reheating to a higher than ambient temperature, where a waste heat source is available, is considered.

$$\dot{W}_d = \sum_{i=1}^{N_{ts}} \dot{W}_{t,(i)} - \dot{W}_{cp} \quad (3.55)$$

The evaporation losses (l_e) during idle time (t_i) due to heat gain from the ambient environment (Q_h) are also estimated and accounted for in the roundtrip efficiency of the system. To evaluate Q_h the following expression can be used:

$$Q_h = U(T_a - T_L) \left[\pi H_T D_T + \frac{\pi D_T^2}{2} \right] \quad (3.56)$$

where U is the overall heat transfer coefficient, T_a and T_L are the ambient and liquid air storage temperatures, and H_T and D_T are the height and diameter of the liquid air storage vessel respectively. Thereafter, l_e can be calculated assuming a fully charged system based on:

$$l_e = \frac{\frac{Q_h t_i}{h_f}}{M_L} \quad (3.57)$$

Finally, the maximum t_d for the system from full storage capacity is simply determined from $\dot{m}_L$ and M_L .

3.3.1.2 Pumped-Thermal Electricity Storage (PTES)

The approach for modelling the PTES system here is mainly based on the thermodynamic model proposed in McTigue et al. (2015) with some aspects proposed in White et al. (2013), White et al. (2016) and White et al. (2014). The system configuration and working principles of the system considered in this work are described in Section 2.3. Studies presenting this system in more detail include White et al. (2013) and McTigue et al. (2015).

Similar to the LAES system, the most important technical performance indicator for this study is the roundtrip efficiency. As defined earlier (Eq. 3.50), that is the net work output during the discharge cycle divided by the net work input during the charge cycle. The most influential

thermodynamic losses for this system, as proposed by McTigue et al. (2015), are due to heat transfer and pressure in the thermal vessels and the expansion and compression components. To maintain the simplicity of the model in this study, the exit losses as a result of the thermal fronts approaching the outlets of the reservoirs are assumed to be negligible.

An effective approach proposed by McTigue et al. (2015) to model the compression and expansion devices, which for this system are considered to be reciprocating machines, by accounting for both heat leakage and irreversibility is used in this model. This approach segregates irreversibility and heat leakage by considering a polytropic efficiency (η) for the expansion and compression machines and a heat leakage factor (g). The heat leakage factor is defined as the ratio of instantaneous heat to work transfer (McTigue et al., 2015). Based on this approach, the compression processes are evaluated based on:

$$\omega_c = p_c^{\vartheta_c} \quad (3.58)$$

where

$$\vartheta_c = \frac{\gamma-1}{\gamma} \left(\frac{1-g_c}{\eta_c} \right) \quad (3.59)$$

Similarly, the expansion processes are characterised by:

$$\omega_e = p_e^{\vartheta_e} \quad (3.60)$$

where:

$$\vartheta_e = \frac{\gamma-1}{\gamma} (1 - g_e) \eta_e \quad (3.61)$$

where ω_c , ω_e are the temperature ratios across the compressor and expander respectively. Also, p_c and p_e refer to the pressure ratios across the compressor and expander respectively. For η and g nominal values of 2% were used, as estimated in McTigue et al. (2015).

It is also expected that pressure losses in the two thermal reservoirs will result in a reduced pressure ratio across the expander compared to the pressure ratio across the compressor (McTigue et al., 2015). To account for the impact of these pressure losses, the relations discussed above are adapted to consider a pressure loss factor (f_p) as follows:

$$\omega_e = (1 - f_p) p_e^{\gamma_e} \quad (3.62)$$

Thereafter, the power input to the compressor and the power output from the expander are evaluated. For example, to calculate the power input to the compressor during the charge cycle, the following expression can be used:

$$\dot{W}_c = \frac{\dot{m} c_p T_{in,c} (\omega_c - 1)}{1 - g_c} \quad (3.63)$$

where c_p is the specific heat capacity, $\dot{m}$ is the mass flow rate of the working fluid, and $T_{in,c}$ is the temperature at the compressor inlet during the charge cycle. Equivalent equations are employed for the discharge period as well as for the expander for both charging and discharging. Thereafter, the work input and output for a complete cycle can be calculated by integrating the power inputs and outputs over the charge and discharge periods.

Furthermore, another loss of the system that is accounted for in this model is the thermal irreversibility in the two reservoirs. This loss arises as a result of the heat transfer across solid and gas (McTigue et al., 2015; White et al., 2013; White, 2011). Due to these losses there is

entropy generation in the two reservoirs during charge and discharge periods. The entropy generation rates can be approximated using the method proposed in White et al. (2016) which was proven to give reliable results. More details on this approach can be found in White et al. (2016).

Other interesting metrics that are evaluated are the required mass and volumes for the cold and hot vessels. For example, the volume (V) for each of the two reservoirs can be calculated by:

$$V = \frac{M}{\rho_s(1-\varepsilon)} \quad (3.64)$$

where M is the mass of the storage medium, ρ_s is the density of the storage medium and ε is the void ratio in the reservoir.

The nominal energy (E) stored in the system can be acquired by accounting for the difference in internal energies between the hot and the cold storage vessels (McTigue et al., 2015). Therefore, E can be calculated considering the nominal temperature points for of the vessels by:

$$E = (T_{h,2} - T_{h,1} - T_{c,1} + T_{c,2})M_h c_h \quad (3.65)$$

where the T variables represent the temperatures at the nominal operational points (states) of the hot and cold reservoirs, M_h is the storage medium's mass in the hot reservoir, and c_h is the average specific heat capacity of the storage medium in that reservoir. If the required nominal energy storage capacity is set, M_h can be calculated and thereafter the required mass for the cold storage vessel can be calculated as well.

3.3.2 Economic and cost estimates

3.3.2.1 *General approach*

Emerging technologies can be significantly difficult to cost due to the lack of case studies and cost data associated with them. Therefore, it is also expected that most cost estimates determined before the technology being commercially deployed to involve significant uncertainties. Usually tenders from manufacturers are required to obtain more accurate costs. Unfortunately, this can also be challenging especially when such technologies are still at low technology readiness level (TRL). Here, it is of interest to obtain preliminary estimations of the costs of such systems and the expected uncertainty in those costs derived from different costing methods. Also, an economic feasibility analysis is performed to compare the two technologies against each other and assess their competitiveness in a marketplace.

The general approach followed for this costing exercise is based on the evaluation of the most important equipment of each system individually while also attempting to consider installation costs where possible. Thenceforth, the estimated cost of the whole system is obtained by summing all the costs. The components costed here include compressors, expanders/turbines, generators, pumps, storage vessels, and heat exchangers.

Due to the uncertainty and variability associated with costing equipment based on different methods, a variety of costing methods available in literature are employed in order to get the relevant uncertainty ranges derived from the maximum and minimum cost values as well as the expected mean cost estimates. The accuracy of the different methods is currently unknown and therefore the same weight is given to all of them. Also, in this exercise it is assumed that the standard cost correlations available in each costing method can provide accurate cost information for all the components analysed in each system.

In addition to the cost estimates being converted to the relevant currency (currency rates used were: 1.39 \$/£ and 1.24 €/£ for GBP (£) to USD (\$) and EUR (€) to USD (\$), respectively), the costs need to be adjusted to current prices. This is because cost data used in the equipment costing methods are based on past data. Therefore, to adjust them to current costs based on the industry economic conditions and inflation, composite cost indexes are used as commonly done literature. To calculate the cost at the present time (C_{pr}) the following expression is used:

$$C_{cp} = C_p \left(\frac{I_p}{I_{pr}} \right) \quad (3.66)$$

where C_p is the cost at data collection time as available in the cost correlations, and I_{pr} and I_p are the cost indexes at base and present year respectively. Here, the cost indexes used are based on the Chemical Engineering Plant Cost Index (CEPCI) (Jenkins, 2016).

The remaining of parts of this section present a summary of each costing method used for the different components of the systems. The complete methodology for each method can be found in the sources provided.

3.3.2.2 Main components: Compressors, expanders/turbines, pumps and storage vessels

The selected methods were chosen because in most cases they comprehensively account for a variety of cost factors including manufacturing materials, operating conditions, type of component, and additional costs related to installation.

One of the methods used to provide estimates of the component costs of compressors, pumps, storage vessels, and expanders/turbines was the equipment module technique approach (Turton

et al., 2012). In this method the base cost of component (C_B), which is given in USD (\$), is calculated by using an expression of the following form:

$$\log C_B = R_1 + R_2 \log (E) + R_3 [\log (E)]^2 \quad (3.67)$$

where E represents the size or capacity, depending on the equipment, of the component, and factors R_1 , R_2 and R_3 are derived from the cost correlation plots provided in Turton et al. (2012) for each equipment. This base cost is based on the assumptions of carbon steel used for manufacturing material and operating conditions being at or near ambient pressure.

Thereafter, the effect on cost of elements as a result of divergence from the base case conditions are incorporated by applying multiplication factors (e.g. for material, pressure) in order to give a more specific cost estimate. In addition to direct costs, the bare module cost also includes indirect costs, such as installation and commissioning costs, where applicable.

The other costing methods used, Couper et al. (2010) and Seider et al. (2010), follow a similar approach to the method described above. In other words, they cost different equipment individually while accounting for impactful factors (and indirect costs where applicable) for each equipment type that might affect its cost. However, the way that different components are costed and the parameters used based on cost correlations in each of these approaches differ. Thus, the cost estimations obtained from each method are expected to provide additional and independent estimations for the costing of the systems. All costs below are in USD (\$). Similar to the method above, most of the equipment costed here using these approaches are based on expressions such as the following:

$$C_B = \exp\{R_1 + R_2 [\ln(E)] + R_3 [\ln(E)]^2\} \quad (3.68)$$

$$C_B = R_1 E^{R_2} \quad (3.69)$$

3.3.2.3 Other equipment

Since the cost correlations required to estimate the base cost (C_B) of the generators while following a similar approach to the ones mentioned above were not found in literature, the capacity exponent factor method is used instead as follows (Lemmens, 2016):

$$C_B = 1.85 \cdot 10^6 \left(\frac{\dot{W}}{1.18 \cdot 10^4} \right)^v \quad (3.70)$$

where C_B is found in EUR (€), $\dot{W}$ represents the power output in kW, and v is the exponent factor assumed here to be 0.94 (Lemmens, 2016). No correction factors were used for the costing of this component given that operational conditions such as pressure are not considered relevant.

Furthermore, the cost of storage material used in the packed bed thermal stores of the systems (PTES for the two thermal reservoirs and LAES for the waste-cold storage vessel) is estimated based on the assumption that magnetite is used and its specific cost is £100/t (White et al., 2016). It is noteworthy that the waste-cold thermal store used in LAES is not yet a commercially available component (Sciacovelli et al., 2016) but for the purpose of this costing exercise it is assumed to be a simple packed bed thermal store as the ones used in PTES.

Finally, in the case of heat exchangers it is usual to estimate the cost based on the area requirement for heat transfer. This can be determined from:

$$A = \frac{\dot{Q}}{U \cdot \Delta T_m} \quad (3.71)$$

where $\dot{Q}$ is the duty of the heat exchanger, U is the overall heat transfer coefficient and ΔT_m is a suitable mean temperature difference. However, determining the area of several heat exchangers can be complex and out of the scope of this costing exercise. Therefore, it is also common for approximate costing exercises to use an alternative costing approach, the “C value” method. This method can oftentimes be more suitable for high level analysis and potentially provide a more intuitive costing for comparison (Hewitt and Pugh, 2007). The “C value” method provides the “C value” cost (CV) in terms the mean temperature difference (ΔT_m), which is the available driving force, and the heat exchanger duty ($\dot{Q}$); thus CV is provided per unit of $\dot{Q}/\Delta T_m$ and is obtained from data in literature such as in Hewitt and Pugh (2007). To obtain the specific cost of a value, logarithmic interpolation of the available tabulated CV values is employed. Finally, the heat exchanged cost (CEX) is estimated by:

$$CEX = CV \cdot \frac{\dot{Q}}{\Delta T_m} \quad (3.72)$$

The “C value” method was observed to generally overestimate the cost associated with heat exchangers in comparison to the other methods, such as in Turton et al. (2012), Seider et al. (2010) and Couper et al. (2010) that rely on the knowledge of the heat transfer area. Preliminary cost estimates showed the small share of heat exchangers’ cost out of the total system costs for the LAES and PTES systems. Therefore, the difference from using a more approximate method is not expected to significantly affect the overall cost of the systems for the purpose of this exercise.

3.3.2.4 Economic indicators

A useful economic metric for assessing the competitiveness of electricity storage systems is the Levelised Cost of Storage (LCOS). This metric is similar/equivalent to the common metric

used for electricity generation systems Levelised Cost of Electricity (LCOE). These metrics quantify the cost per unit of electricity generated while accounting for costs discounting for the system under consideration. LCOE is also usually associated with renewable energy technologies and therefore oftentimes operational costs do not significantly contribute to this value. LCOS, however, can sometimes involve substantial operational energy costs due to the energy required to charge the system. Consequently, the LCOS can depend heavily on the cost of imported energy, and therefore the electricity generating technology when directly coupled with one, as well as all the other variables such as technical performance, discount rates, and other costs.

To determine LCOS while assuming equal annual electricity outputs, the following widely used expression can be used (Luo et al., 2014):

$$LCOS = \frac{LC}{E \cdot q} \quad (3.73)$$

where E refers to the system's annual electricity output, q is the discount factor, and LC represents the system's total lifecycle cost. To calculate q , the discount rate (d) and lifetime of the system in years (n) are considered in the following common expression:

$$q = \frac{(1+d)^n - 1}{d \cdot (1+d)^n} \quad (3.74)$$

Furthermore, another commonly used economic metric used for assessing the economic feasibility of a technology is the net present value (NPV). Similar to the LCOS and LCOE, NPV also accounts for cost discounting, the lifetime of the system, the costs, and the performance of the system over its lifetime. Assuming equal annual benefits, NPV can be calculated from the commonly used equation:

$$NPV = -C + B_i q \quad (3.75)$$

where C represents the initial capital expenditure of the system, B_i is the annual benefit from using the system, and q is the discounting factor as defined earlier. For a system to be considered as economically feasible, the NPV should be calculated as a positive value. Here, to calculate the required operating spread in electricity prices between charging and discharging cycles for the system to be economically feasible, the NPV is considered to be equal to or greater than zero.

To determine the parameters required for the estimation of these economic metrics, both technical performance indicators and economic evaluations are essential, and they are obtained using the methodology discussed earlier in this section.

3.3.3 Carbon savings as decentralised storage systems

The end user can use electricity by importing directly from the electricity grid, a renewable energy generator or an electricity storage system, as shown in Fig. 3.19. It is common for generation from intermittent renewables not to be in synchronisation with the demand requirements profile. Therefore, sometimes, especially in the case of high capacity systems, the energy generated is curtailed and therefore the capacity of the system is not utilised fully over a year. By employing an electricity storage system to store this energy and smoothen the mismatch between supply and demand carbon savings can be potentially achieved.

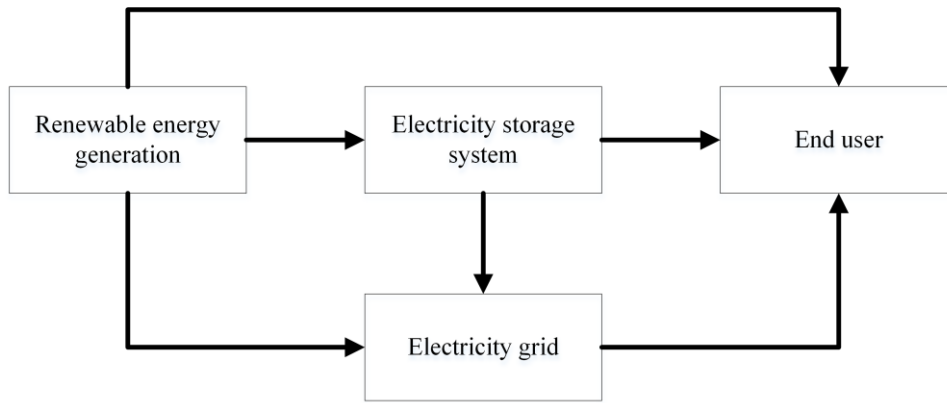


Figure 3.19. Interaction of electricity storage systems with power generation technologies, the electricity system and end users.

Carbon savings from the electricity storage system are achieved based on the assumptions that electricity from the storage system can be used in lieu of using electricity from the grid and that energy from renewables is carbon free. To estimate the potential for carbon savings, the following aspects are considered: the ratio of curtailed electricity to the electricity generated from renewables (u), the grid's carbon factor (c) (which is considered as business-as-usual), and the electricity storage system's roundtrip efficiency (η_r) as defined earlier. Therefore, the potential carbon savings (cs) can be estimated by:

$$cs = c \cdot u \cdot \eta_r \quad (3.76)$$

The above expression shows the potential carbon savings through the utilisation of curtailed renewable energy by using an electricity storage system. Nevertheless, to estimate the carbon savings per unit of electricity generated by the storage system during the discharge cycle (cs_s), the grid's electricity factor is simply considered. This is because the grid electricity is considered here as the baseline and therefore carbon savings are benchmarked against that.

Besides the benefits in terms of carbon savings through the use of electricity storage systems, the economic implications associated with these savings are also of great interest. This is particularly important considering the possible alternative options. The economic implications are expected to vary depending on the economic conditions associated with the specific case. Factors expected to have an impact include for example the location, the cost of electricity, and policies, and incentives. For example, if direct use of electricity from a renewable technology by the electricity storage system is considered, the cost of energy to the storage device can be expected to be proportional to the generator's LCOE. On the other hand, there is the argument that energy that would have been curtailed can be considered as valueless (unless a compensation policy exists) and consequently the energy cost to the storage system can be assumed to be negligible. Therefore, to accommodate some of the possibilities a few pivotal scenarios are considered as summarised below (also see Fig. 3.20). It is also assumed that curtailed energy is readily available to the electricity storage system based on a scenario in which a renewables dominated system has sufficient curtailed energy available to fulfil the capacity of the storage system.

Scenario 1 – No electricity cost imposed. The operational energy cost to the electricity storage system is assumed to be zero based on the assumption that the value of curtailed electricity is also zero and both generation and storage systems are potentially operated by the same stakeholder. Also, the following two sub-scenarios are considered:

- a) cost savings considered by avoiding peak electricity prices, and
- b) no cost savings considered as a result of avoiding peak electricity prices.

Scenario 2 – Electricity cost imposed. The operational energy cost to the electricity storage system is considered to be equal to the LCOE of the renewable energy generation technology.

Also, the following two sub-scenarios are considered:

- a) cost savings considered by avoiding peak electricity prices, and
- b) no cost savings considered as a result of avoiding peak electricity prices.

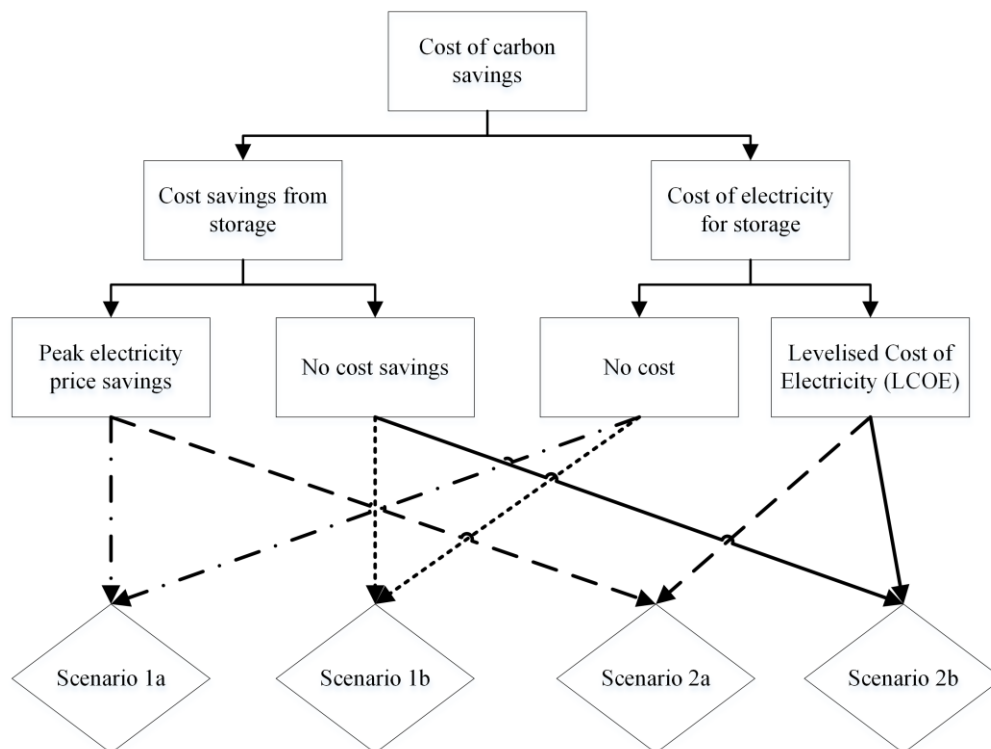


Figure 3.20. Scenarios considered for costing carbon savings.

For the two scenarios which assume cost savings by avoiding peak electricity prices, the cost of carbon savings (CS) can be estimated by the following expression:

$$CS = \frac{LCOS - PE}{cs_s} \quad (3.77)$$

where $LCOS$ is the levelised cost of storage calculated based on each technology and electricity cost, PE refers to the peak electricity price, and cs_s are the carbon savings from utilising the electricity storage system. For the two scenarios which do not consider any cost savings as a result of avoiding peak electricity prices, CS can be estimated from the following expression:

$$CS = \frac{LCOS}{cs_s} \quad (3.78)$$

The expressions above do not explicitly include the technical performance of the storage system (i.e. its roundtrip efficiency). Therefore, the effect of utilising the maximum possible curtailed energy is also not explicitly comprised since for both technologies the carbon factor is the same. However, the technical characteristic and performance of each system is implicitly accounted for in the calculation of its LCOS; thus it is considered in the analysis.

3.3.4 Deployment of LAES and PTES in low-carbon systems

Besides the independent analysis and comparison of the electricity storage systems it is also interesting to see how they behave and their value within a larger system with a high penetration of low carbon technologies. To study LAES and PTES in that context, the thermo-economic models described above in combination with the Whole-electricity System Investment Model (WeSIM) presented in Pudjianto et al. (2014) are used.

Very briefly, the WeSIM ensures security of supply while optimising investments in generation, network and/or energy storage. A detailed example of the WeSIM was presented in Strbac et al. (2017) and further details about the model can be found in Pudjianto et al. (2014) and Georgiou et al. (2019, 2018b). The work associated with this exercise was done in collaboration with the co-authors of Georgiou et al. (2019, 2018b) from another research group (Marko Aunedi and Goran Strbac), while the WeSIM model was operated by the collaborators.

As shown in Fig. 3.21, the outputs from the thermo-economic models of LAES and PTES and their corresponding characteristics, are used in the WeSIM to assess the value of these technologies in several scenarios. Scenarios considered include different locations, carbon emission targets, and Demand Side Response (DSR) uptake (Georgiou et al., 2018b).

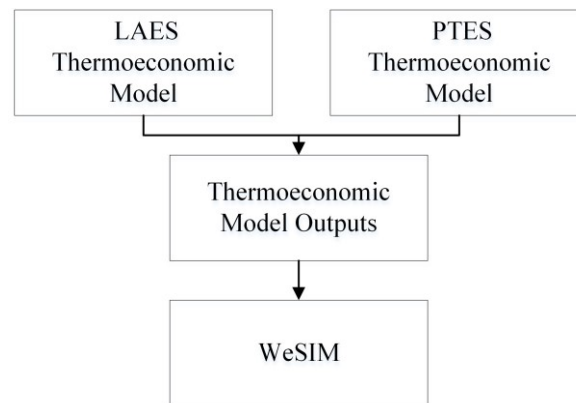


Figure 3.21. LAES and PTES thermo-economic model outputs used in WeSIM model.

Chapter 4^{‡‡}

4 Heat – Production stage

This chapter focuses on the heat requirements in the supply chain and more specifically at the production stage which, as discussed earlier, can be the most energy intensive stage for products grown under auxiliary heating. This chapter consists of i) the validation of the model discussed in Section 3.1, ii) a parametric analysis identifying influential technological and operational variables to energy performance, iii) the evaluation of energy requirements based on daily and annual terms, iv) the fluctuations in energy requirements due to weather variations, v) the effect of energy sources on carbon emissions and energy costs, and vi) a spatial analysis of the UK while in some cases also considering the impact of temporal weather variability.

To start with, the model was validated using a case study considering both monthly and annual heating requirements. The case study's development used here was supported by a UK retailer

^{‡‡} Parts of this chapter were presented earlier in Georgiou et al. (2018a, 2017a).

and its suppliers for a production farm. For the simulation of the model, dominant variables included an infiltration rate of $1.5 \times 10^{-4} \text{ s}^{-1}$, annual mean internal temperature of 14°C . The comparison between the case study and the model simulation is presented in Fig. 4.1. Significant variations were observed throughout the year with winter, spring and autumn months (February, March, April, October, November, December) showing the greatest heating requirements. Summer periods showed significantly lower heating requirements potentially due to higher external temperature and higher solar radiation levels contributing to the maintenance of the internal conditions required. Also, the impact of heating supply can be observed through the decrease in heating requirement particularly during the early year months (January). As expected, a small difference between the plots was observed. This difference can be due to several factors such as the distance difference from the weather station selected by the model and the farm. Nonetheless, for the purpose of this high-level model which is based on a relatively small number of inputs, the trends of the two plots showed very good correlation and small difference between the points.

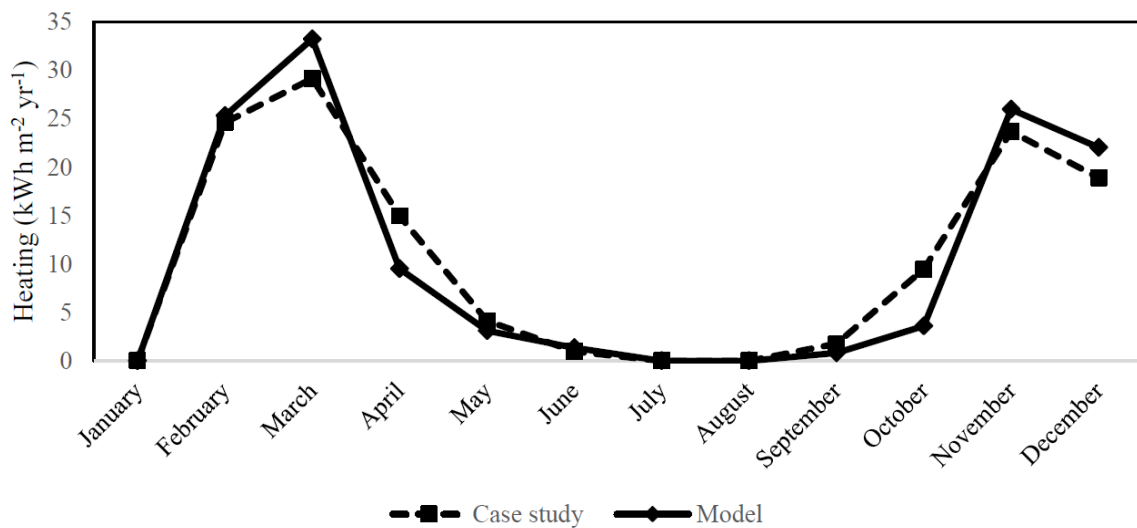


Figure 4.1. Model validation on normalised monthly basis (Georgiou et al., 2018a).

4.1 Parametric and temporal analyses

The energy balance, and therefore the energy requirements, is influenced by variables that can be controlled and variables that cannot be controlled. For example, external environmental variables affected by weather, such as radiation, external humidity and external temperature, cannot be controlled at a specific location. On the other hand, there are operational and technological variables that can influence the energy balance and can also be controlled. Technological variables include equipment performance characteristics while operational variables include decisions on the internal glasshouse conditions and heating schedules.

To explore the impact of controllable variables, a parametric analysis was performed to observe the effect of each one in terms of annual heating requirements while keeping all remaining variables at nominal values. Among the technological variables studied, the infiltration rate (N) and the overall heat transfer coefficient (U) were observed to have the greatest impact (Fig. 4.2) over their respective ranges applied according to values given in ASABE (2008) (1.40×10^{-4} – $11.10 \times 10^{-4} \text{ s}^{-1}$ for N and 0.57 – $6.20 \text{ W m}^{-2} \text{ K}^{-1}$ for U).

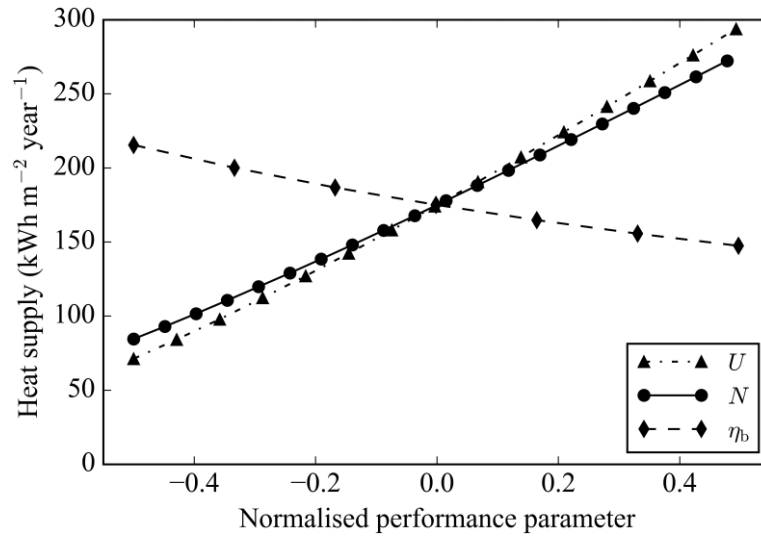


Figure 4.2. Annual heat requirements per square metre against normalised ($y_{\text{nor}} = (y - \bar{y}) / (y_{\text{max}} - y_{\text{min}})$) performance parameters.

Also, with respect to the operational variables, heating requirements were found to be greatly affected by the internal temperature set. As shown in Fig 4.3, the variation depending on internal temperature over the range examined (12-16 °C) is significant and shows the potential for achieving energy consumption reductions by adapting the internal temperature when possible. Also, the flexibility in internal temperature allowed by different products, or even varieties of the same product, demonstrates the potential benefit from choosing alternative products to produce.

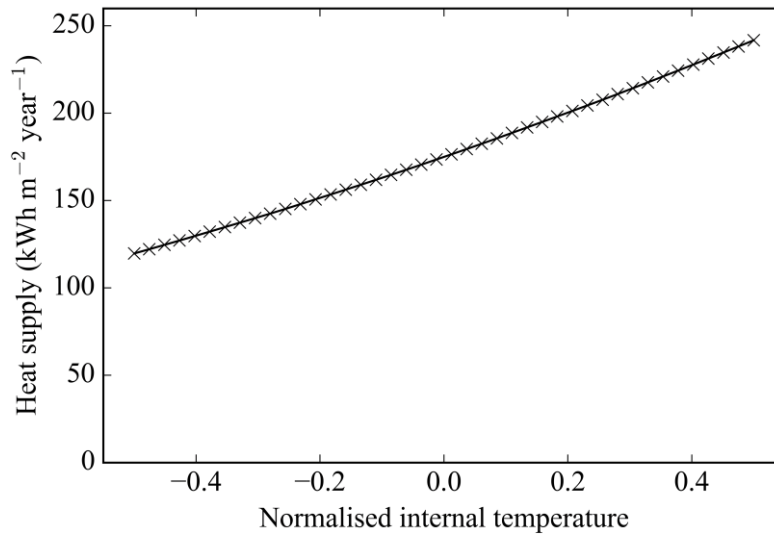


Figure 4.3. Annual heat requirements per square metre against normalised ($y_{\text{nor}} = (y - \bar{y})/(y_{\text{max}} - y_{\text{min}})$) internal temperature.

Therefore, considering the design and operational parameters of the glasshouse along with the weather conditions associated with its location, the model can quantify the costs or benefits from producing an alternative product. Also, variation in internal temperature can sometimes give some control over the production yields. As a result, the model can also quantify the economic perspective from employing such techniques using its daily analysis capability. For example, the additional energy requirements and the corresponding additional cost in fuel can be benchmarked against the extra incomes from the prospective increased product yields. Even though this is expected to be a rough estimation, it can potentially still provide a sense of the costs and benefits as well as a comparison between different techniques. More accurate estimates can theoretically be acquired by using weather data directly from the glasshouse when available. However, this introduces an additional level of input requirements and data processing due to the need to add the glasshouse weather station into the databases.

Following from the aforementioned observation of the impact of infiltration rate and overall transfer coefficient, the impact on heating and cooling requirements in terms of both annual and daily requirements was studied (see Figs 4.4 and 4.5 respectively). This analysis was based on a hypothetical case study of a glasshouse taken here to be the base case. This glasshouse was assumed to have an infiltration rate of $5.6 \times 10^{-4} \text{ s}^{-1}$ (ASABE, 2008), a single glass sealed cover with overall heat transfer coefficient of $6.2 \text{ W m}^{-2} \text{ K}^{-1}$ (ASABE, 2008), and mechanical ventilation for the provision of cooling. The effect of improvement of these parameters was tested by improving the infiltration rate to $2.8 \times 10^{-4} \text{ s}^{-1}$ (ASABE, 2008) and its cover to double glass sealed with an overall heat transfer coefficient of $3.7 \text{ W m}^{-2} \text{ K}^{-1}$ (ASABE, 2008). Hence, this allowed the estimation of potential energy savings associated with the improvement of these thermal properties.

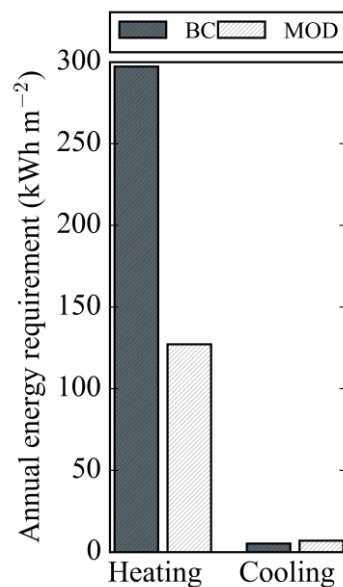


Figure 4.4. Annual energy requirements in terms of heating and cooling for the base case and a modified scenario with changed infiltration rate and cover (BC: base case, MOD: modified).

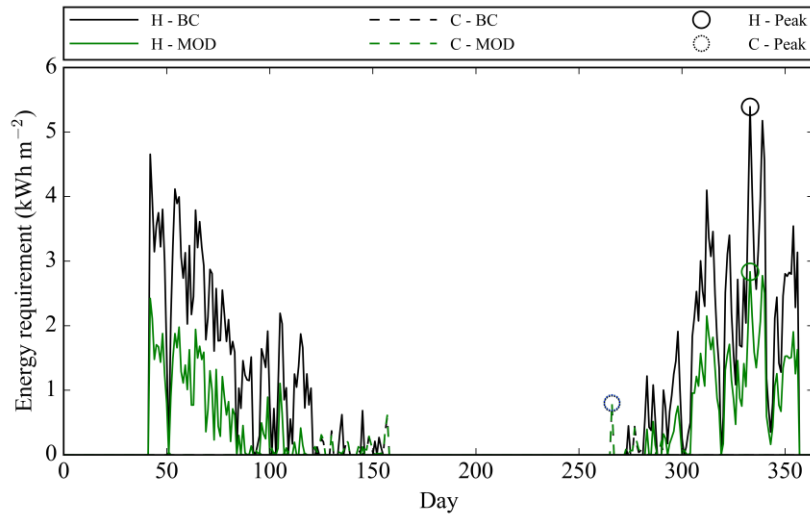


Figure 4.5. Daily energy requirements for one year in terms of heating and cooling for the base case and the modified scenario with changed infiltration rate and cover (H-BC: heating base case, C-BC: cooling base case, H-MOD: heating modified, C-MOD: cooling modified).

In terms of annual heating requirements, an improvement of 57% was observed whereas cooling experienced a slight increase (Fig. 4.4). Focusing on daily energy requirements (Fig. 4.5), besides the significant decrease in energy requirements achieved in the modified case, a large number of days was observed to have zero heating and cooling requirements. This indicates the ability of the model to account for growing schedules; in other words, account for periods in which the glasshouses climate controls are not operational. Furthermore, peak heating or cooling requirements were noted throughout the year indicating the impact of extreme weather conditions on the daily energy requirements. Comparing the base case with the modified case, it was clear that a significant decrease in those peaks was achieved in the modified case. A reduction of 57% on the annual peak heating requirement was achieved. Thus, improving these properties of the glasshouse can result in shaving those peak days and

therefore allowing for the downsizing of the heating system. In addition to the capital and operational cost savings that are possible by downsizing the heating system, energy efficiency improvement can also be achieved as a result of operating the system closer to its nominal capacity for more time in a year (Intelligent Energy Europe, 2012). Furthermore, reducing the peak levels of heating or cooling requirements indicate a more resilient system to external conditions and possibly a lower risk of quality degradation during extreme events. An equivalent exercise was performed for a sample of location sites across the whole UK to get an overview of the potential range in energy savings. The range of improvement for peak daily and annual heating demands were 44-50% and 51-57% respectively depending on the location. Therefore, a significant improvement was noted for all the locations considered in this exercise.

The impact of the improvement in infiltration rate and overall heat transfer coefficient on the cooling requirements while assuming a Specific Fan Power (*SFP*) of $0.5 \text{ kW m}^{-3} \text{ s}^{-1}$ was observed to be significantly less than heating. An insignificant increase in both daily peak and annual requirements was noted. Nevertheless, the much greater effect in reducing heating requirements through these changes resulted in an overall significant improvement in the energy requirements of the glasshouse.

Also, a shift from heating days to cooling days was noted with a difference of 30 days. The negative effect on cooling requirements, even though small in this case, showed that modifications should be treated with caution while considering both the effect on heating and cooling to avoid negative consequences on either one.

The impact on energy efficiency is also expected to be reflected in terms of carbon emissions, embodied carbon of the product, and production costs. The level of impact on these indicators is expected to depend on the energy source as discussed in Section 3.1.

Moreover, a multi-year daily simulation from 1996 to 2016 was executed for the case study analysed above while considering the same modifications for improvement. A consistent reduction in annual heating requirements was observed resulting to a mean (μ) decrease of 158 kWh m⁻² year⁻¹, representing a 56% improvement in comparison to the base case (see Fig. 4.6). In addition, a significant reduction in the variance of annual heating requirements over the timeline was noted. The standard deviation (σ) was found to decrease by 25.4 kWh m⁻² year⁻¹.

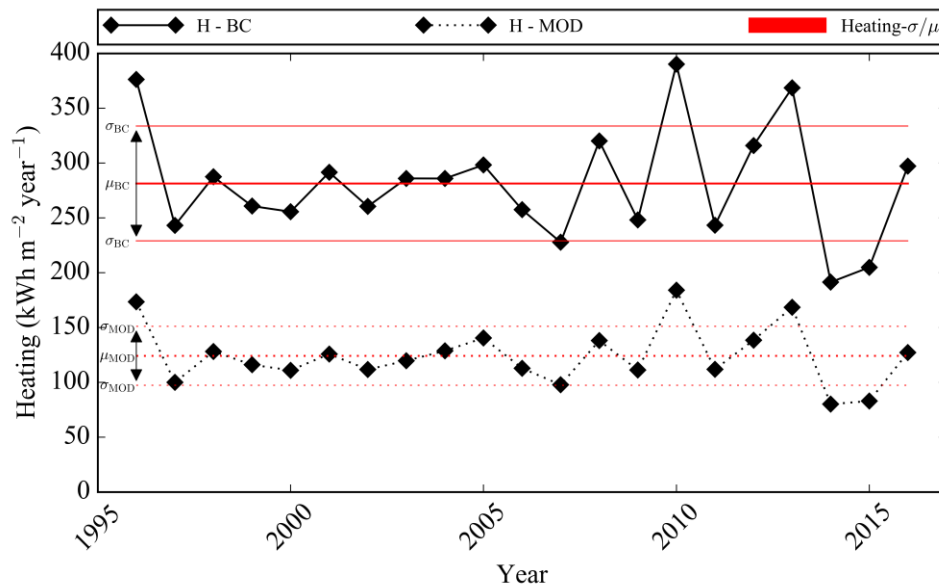


Figure 4.6. Variation in annual heating requirements per unit area (σ : standard deviation; μ : mean) (H: heating, C: cooling, BC: base case, MOD: modified).

Similarly, the same analysis was performed in terms of cooling demand (see Fig. 4.7). For the base case, cooling's requirements and variability were noted to be significantly lower compared to heating. However, the impact of the improvement modifications on cooling was found to be

marginal in terms of both mean (μ) annual requirements and variance. Nevertheless, other improvement measures could possibly introduce a more noticeable impact on cooling requirements.

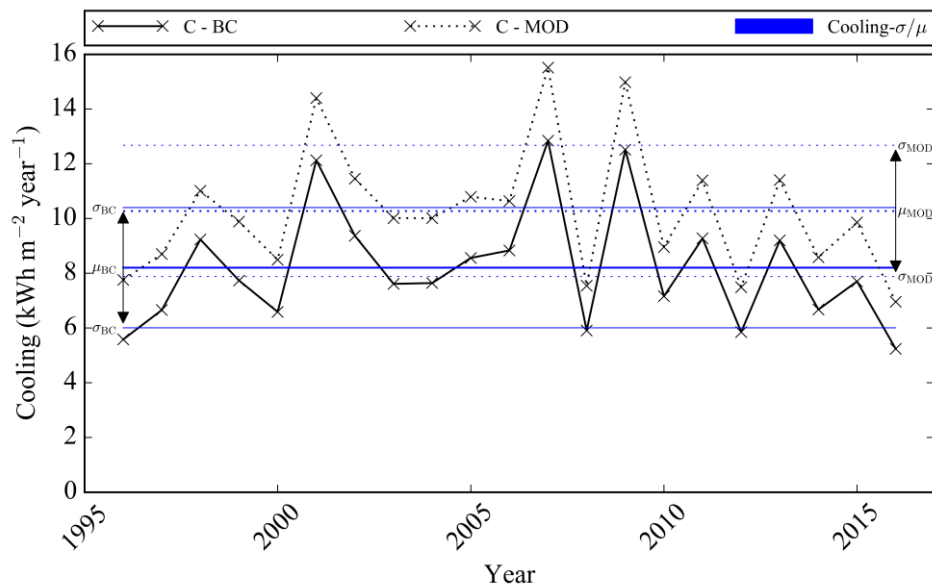


Figure 4.7. Variation in annual cooling requirements per unit area (σ : standard deviation; μ : mean) (H: heating, C: cooling, BC: base case, MOD: modified).

The variance and therefore the standard deviation in annual energy requirements can represent an uncertainty over the energy costs and carbon emissions, as well as vulnerability to extreme weather events. Therefore, minimising this variability can potentially increase the robustness of the glasshouse against external weather variations along with possibly providing a more confident carbon and cost budgeting ability. Hence, this can be beneficial for both suppliers and buyers.

4.2 Spatial analysis

Up to this point, only controllable technological and operational parameters were considered and analysed to quantify their influence. Weather conditions at a location, however, are out of the control of the stakeholders. Nonetheless, some control over the weather conditions can sometimes be claimed through the spatial aspect. Therefore, the spatial capabilities of the model are showcased here while observing the impact of the spatial aspect on the energy requirements of the glasshouse. As mentioned earlier, impacts on energy requirements are expected to be reflected on the carbon emissions and energy costs associated with production. For conciseness, only heating and cooling are analysed in this section while assuming the expectation of a relatively similar distribution in terms of emissions and energy costs.

Once again a multi-year daily simulation, for a 21-year period, was performed while considering the operational and technological characteristics of the modified case discussed above. The analysis is focused on annual heating and cooling requirements and their corresponding variability over the timeline.

The location and its associated characteristics was observed to significantly affect the heating requirements of the glasshouse. They were found to range from less than $100 \text{ kWh m}^{-2} \text{ yr}^{-1}$ in the south to more than $275 \text{ kWh m}^{-2} \text{ yr}^{-1}$ in the north (see Fig. 4.8a). A similar observation was noted for cooling but in reverse; in other words, greater cooling requirements in the south and less in the north (see Fig 4.8b). However, the range noted for the different regions of the UK was much smaller, from about 3 to $13 \text{ kWh m}^{-2} \text{ yr}^{-1}$, than in heating.

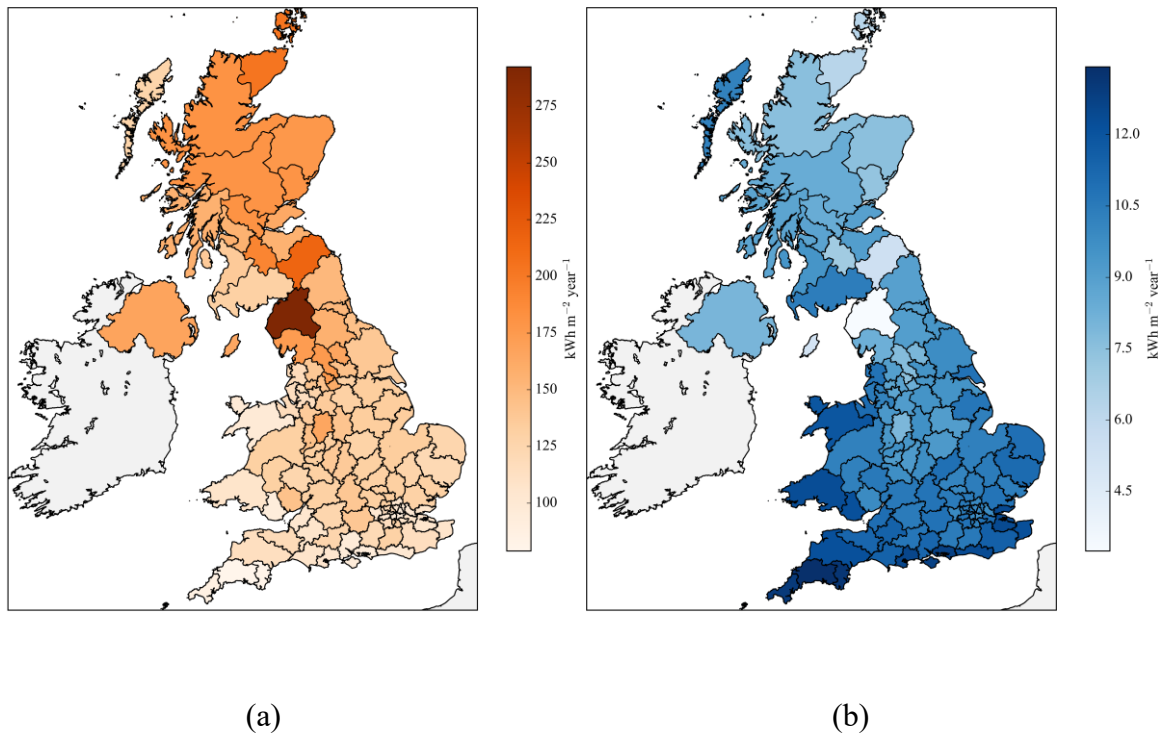


Figure 4.8. UK maps for annual (a) heating and (b) cooling requirements per unit area for the modified case based on a 21-year daily simulation (Georgiou et al., 2018a).

Regarding the annual variability of heating and cooling requirements, the location generally was not found to have a great influence with the exception of a few regions as shown in Fig. 4.9. For example, some areas that were found to have lower than usual variability included some areas in the East Midlands of England and some areas with higher than usual variability included some areas in the South West Wales. Interestingly, variability was observed to be greater for cooling than heating due to a more obvious difference between the north and south of the UK (Fig. 4.9b). As discussed earlier, the variability can sometimes be associated with uncertainty and vulnerability to external weather conditions. Thus, its minimisation can be associated with several benefits, potentially for both suppliers and buyers.

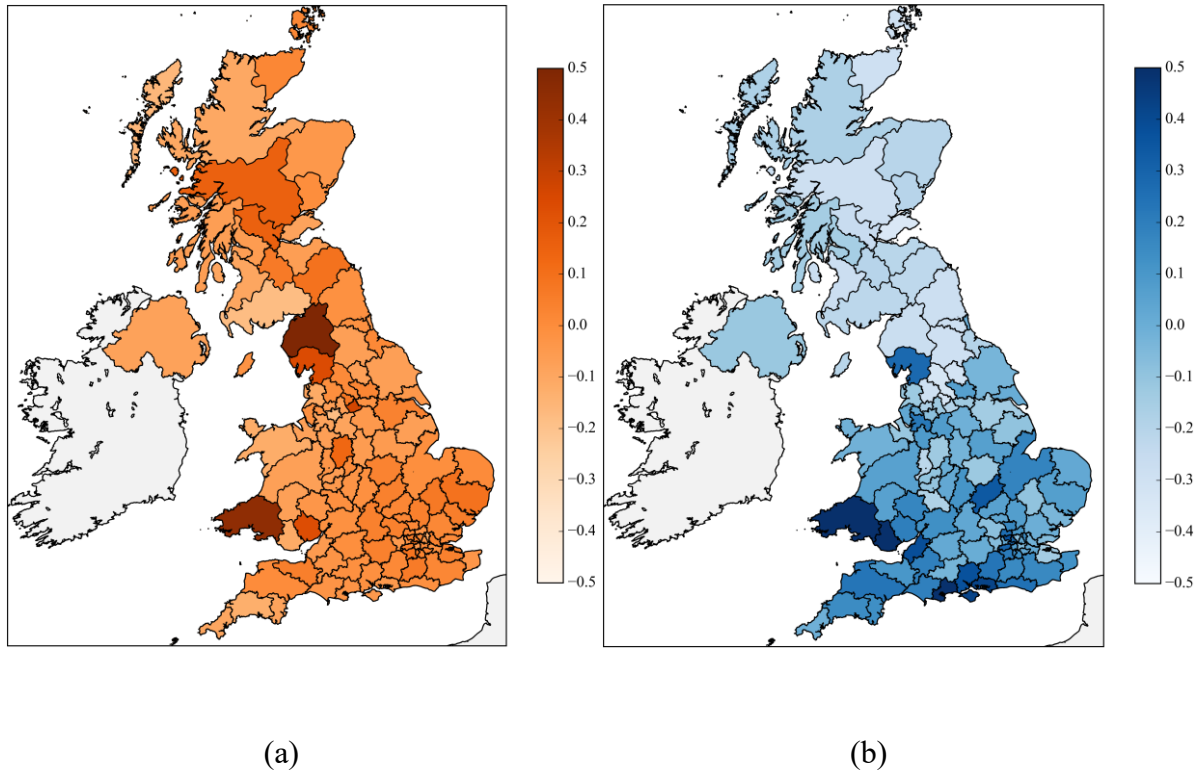


Figure 4.9. UK maps for the normalised ($y_{\text{nor}} = (y - \bar{y}) / (y_{\text{max}} - y_{\text{min}})$) variability in terms of standard deviation in annual (a) heating and (b) cooling requirements (Georgiou et al., 2018a).

Similarly, the impact of location was studied with regards to peak daily heating and cooling consumption to determine the impact of location based on daily extremes. Here, the peak daily requirements were found to vary depending on the region with the north in some cases showing more than 50% greater requirements than southern regions (Fig. 4.10a). In terms of cooling, it was again very close to the reverse of heating requirements (Fig. 4.10b). Nevertheless, as noted in the annual requirements, the range observed across the regions was significantly greater for heating, therefore showing its dominance over the overall energy requirements.

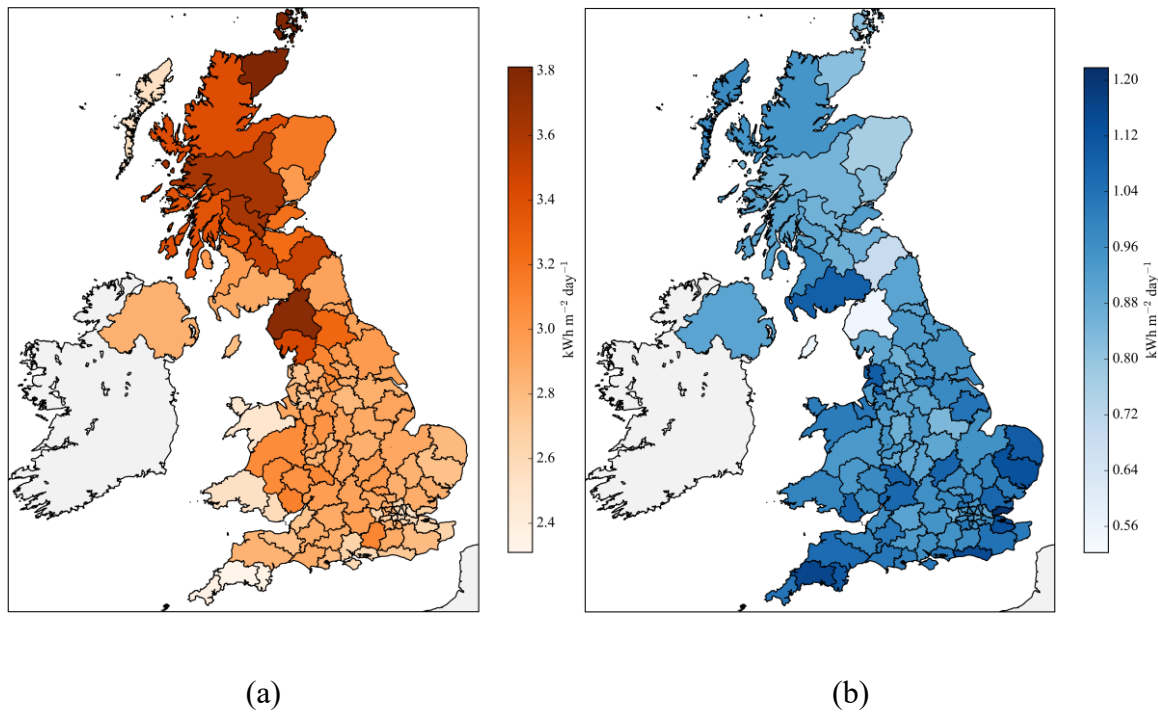


Figure 4.10. UK maps of the peak daily (a) heating and (b) cooling requirements per unit area for the modified case based on a 21-year daily simulation (Georgiou et al., 2018a).

These peak requirements can be considered as the maximum demand requirements over a year which can be used to determine the size of the heating and cooling systems. Therefore, it was important to consider these over multiple years to minimise the chance of miscalculating the required capacity. Also, a reduction in these peaks, and the resulting allowance in downsizing the support systems, can potentially increase the running energy efficiency of the systems due to their operation closer to their nominal capacities (Intelligent Energy Europe, 2012).

Moreover, similar to the annual demand variance, the annual peak daily variance over the 21-year period was investigated to see how the daily peaks can vary based on the spatial aspect

(see Fig. 4.11). This, once again, is a potential indication of the potential for the glasshouse to be exposed to extreme weather events that can have a negative impact on production due to the risk of the support systems being unable to cope with demand.

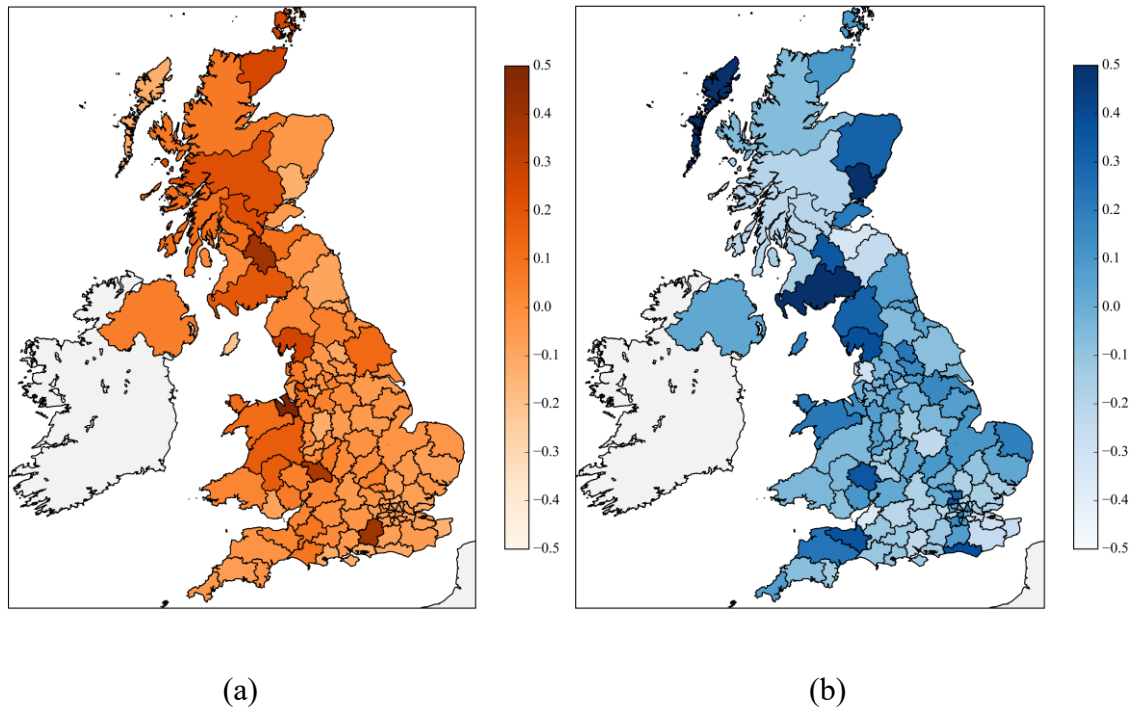


Figure 4.11. UK maps of the normalised dimensionless ($y_{\text{nor}} = (y - \bar{y}) / (y_{\text{max}} - y_{\text{min}})$) variability in terms of standard deviation in peak daily (a) heating and (b) cooling requirements (Georgiou et al., 2018a).

Equivalent analyses can be performed for glasshouses with different characteristics to observe the impact of the spatial aspect on them and identify locations with greater potential for a better performance, considering both energy requirements and variability. This can be applicable to both new glasshouses and existing glasshouses which can be relocated.

The spatial aspect was found to have significant impacts in both annual demand and daily peak demands. Interestingly, in some cases the difference between locations can be greater than the difference achieved from significant improvement measures, both technological and operational. Subsequently, a more energy efficient glasshouse can be found to require more energy than a less efficient one due to its location.

In terms of variance, with the exception of a few regions, the effect of location was found to be less significant than the improvement noted through modifications on other parameters studied earlier, such as the overall transfer coefficient of the cover and the infiltration rate. Hence, this shows the need for a holistic approach towards the improvement of all indicators.

4.3 Carbon and cost analysis

In this section the impact of the improvement measures considered above as well as the energy source is studied in terms of carbon emissions and energy costs. This can be considered as an attempt to quantify the difference in potential for reducing carbon or costs between improvement measures and energy sources used. The energy sources considered here include for heating: oil, natural gas and biomass, and for cooling: electricity. The emission factor for electricity assumed here was the UK wide standard electricity factor of $0.41205 \text{ kgCO}_2\text{e/kWh}$ in accordance with the UK government GHG conversion factors for company reporting (DECC and DEFRA, 2016). This analysis considered once again mean annual demands and variance (standard deviation) with respect to a 21-year period of day-frequency simulations.

The first thing noted through this exercise was the significant reduction in carbon emissions and energy costs for all heating related energy sources by introducing the improvement measures (see Fig. 4.12a). The magnitude of improvement, however, depended heavily on the

energy source considered. Interestingly, in some cases the improvement that can be achieved by considering a different energy source was greater than the improvement achieved from modifying the thermal properties of the glasshouse. Looking at some of those examples, the carbon savings achieved from switching from natural gas or oil to biomass were found to be significantly more than the savings through the improvement measures of the thermal properties.

Likewise, the variability in carbon emissions, expressed here in terms of standard deviation, was also found to vary depending on the energy source (see Fig. 4.12b). Also, the standard deviation was observed to significantly decrease for all heating energy sources considered in the modified case showing the impact of the glasshouse's thermal properties on this aspect. Nevertheless, the magnitude of improvement was affected by both energy source and glasshouse properties; thus indicating the importance of considering both.

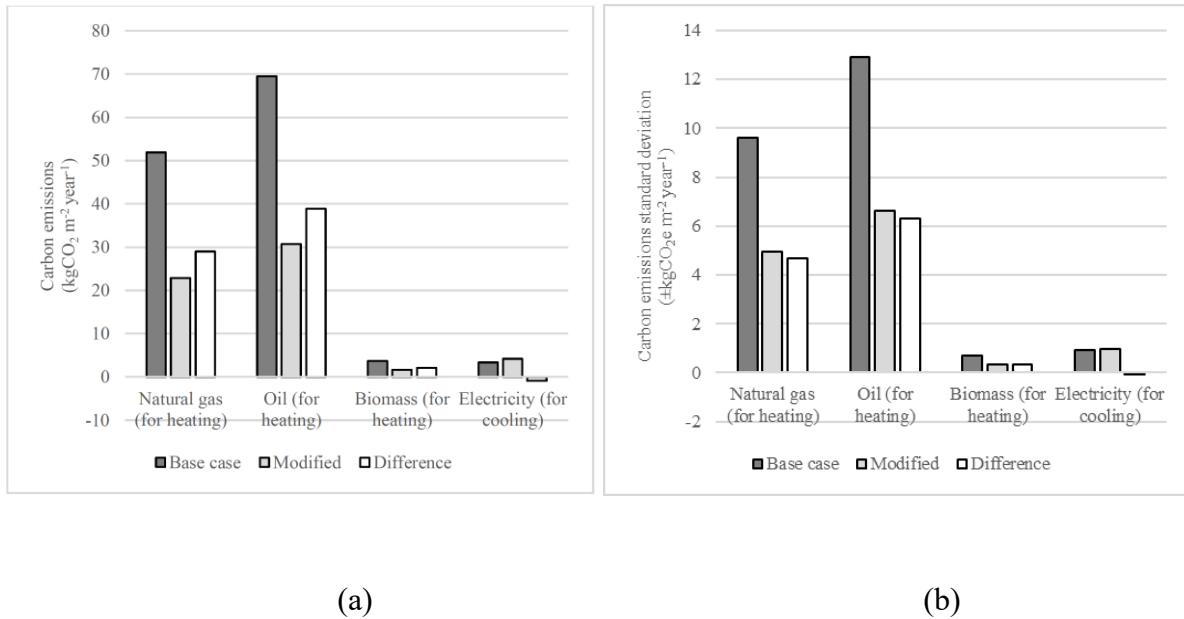
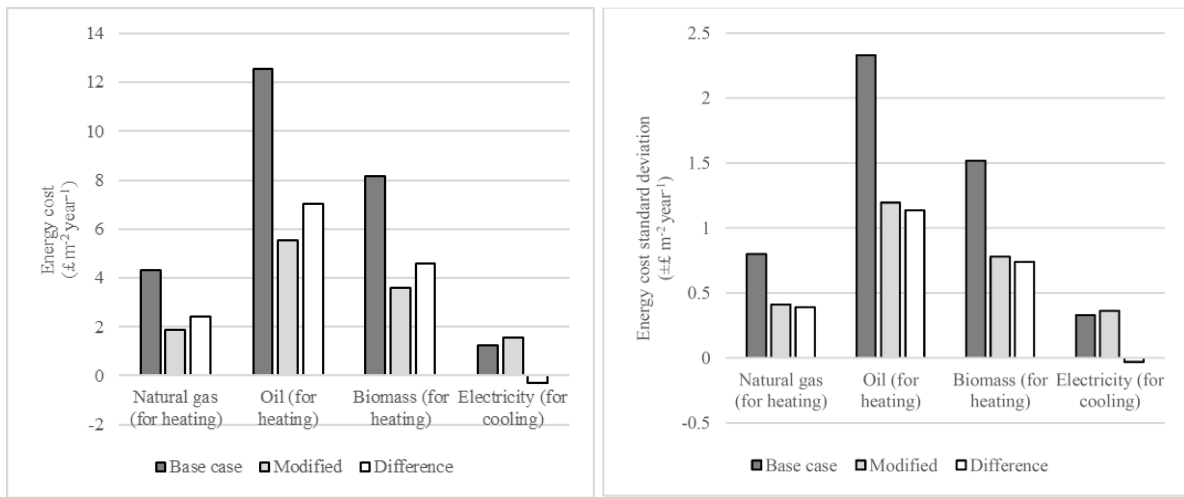


Figure 4.12. (a) Carbon emissions with its (b) variability for different energy sources under for the base case and modified case.

Similarly, the energy cost savings and their variability were greatly affected by both the glasshouse properties and the energy source to the support systems (see Figs 4.13a and 4.13b respectively). However, while energy cost savings (for heating) were correlated with carbon savings for improvement measures, this was not always true when considering energy sources. In other words, while some energy sources might provide better carbon savings they might not provide better energy cost savings as well. An example of this was biomass which provided the greatest carbon savings but not the greatest energy cost savings. Hence, a trade-off between costs and carbon emissions was noted when considering energy sources as a measure of improvement.



(a)

(b)

Figure 4.13. (a) Energy cost and its (b) variability for different energy sources under the base and modified scenarios.

Therefore, it can be good practice to consider both thermal properties improvements as well as change of energy source. Since it was noted that in some cases savings achieved through the change of energy source were comparable to that of improvement of thermal properties, when considering other factors such as capital costs and required downtime for implementation, the most beneficial approach might be affected.

The variability, and therefore standard deviation, in energy requirements was of interest in this analysis because of the great uncertainty weather patterns can introduce on the production stage and its associated carbon footprint and energy costs. Also, the potential robustness of the glasshouse against extreme weather conditions resulting from climate change can be observed. The minimisation of this variability can possibly provide more accurate cost forecasting and

budgeting as well as more stable energy costs and carbon emissions. These aspects can be beneficial for both suppliers and buyers.

Buyers can benefit from long term relationships/partnerships with suppliers who have more stable supply prices and less carbon emissions; something that can potentially assist in the development of stronger and more environmentally friendly supply chains. A reduction in the suppliers' carbon emissions also means a reduction in Scope 3 emissions for the buyers. Also, in the case of a carbon tax this variability might impose an additional uncertainty level in costs. Besides the risk of this additional cost uncertainty, social commitments of both suppliers and retailers to environmental targets might be at risk, or at least be more difficult to commit to, with greater variability expectations. Hence, minimising this variability can potentially provide several benefits.

4.4 Expected error analysis

As discussed in Section 3.1, since the model heavily depends on data from weather stations which might be at a distance from the site of interest, an additional error is expected as a result of this distance difference.

To indicate the relationship of uncertainty against distance, some selected examples which showed a good correlation are presented in this section. The plots shown in Fig. 4.14 represent the uncertainty derived for a case study of a weather station. This weather station is located in a region where it is possible for heated glasshouses in the UK to be situated. The example presented below is for heating based on daily uncertainty. Each plot represents one dataset out of the four main datasets required by the model.

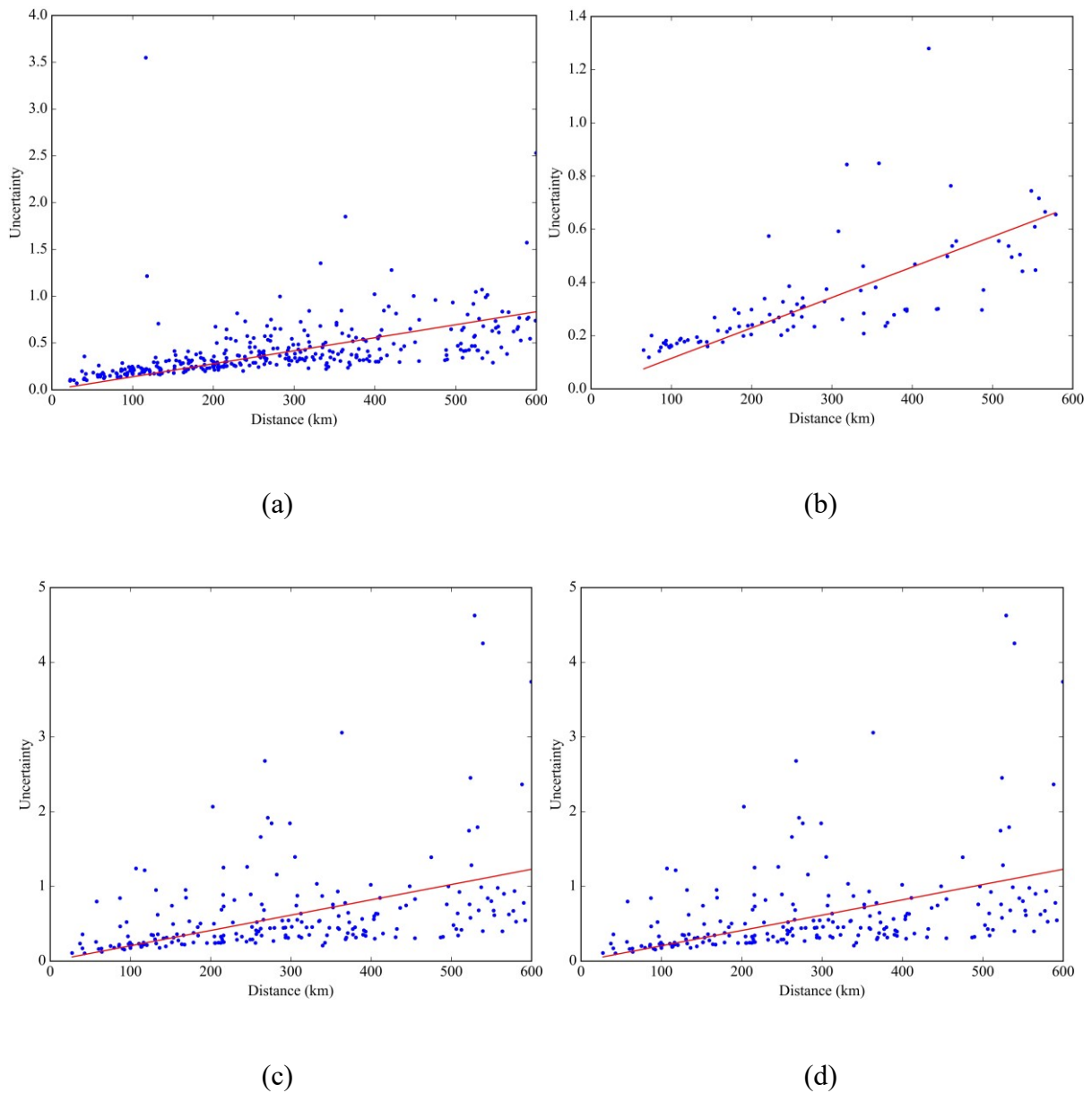


Figure 4.14. Uncertainty against distance from weather station (at a common place for production) based on: (a) temperature, (b) radiation, (c) atmospheric pressure, and (d) dew temperature.

The gradients from the regression lines were found to be 0.0014, 0.0011, 0.0020 and 0.0020 for temperature, solar radiation, atmospheric pressure and dew temperature respectively. The gradients of atmospheric pressure and dew temperature in this case, being the highest, represent

the dominant/driving data sets for uncertainty whereas the lowest represents the opposite. Therefore, this can act as an error indicator which depends on where the glasshouse is acquiring its data from as well as for considering the possibility of collecting the appropriate datasets on site. For example, if atmospheric pressure and dew temperature data are acquired from this station and one would like to improve the simulation accuracy, it can be of interest to install a data collection point on site to collect the necessary data. In such case, preference is given to the datasets dominating the uncertainty.

Different key performance indicator (KPI) are expected to have different uncertainty correlations from heating. Therefore, it is important to derive separate error/uncertainty factors depending on the KPI. The same applies for different weather stations as well. For instance, correlations of a weather station located further north in the UK are expected to differ from a weather station in south UK. For example, looking at another weather station, the uncertainty gradients for heating were found to be 0.0015, 0.0017, 0.0013 and 0.0013 for temperature, radiation, atmospheric pressure and dew temperature respectively (Fig. 4.15). These factors are different from the previous case in terms of both values and order of importance. In this case, the radiation dataset becomes the one associated with the greatest risk.

This shows again the importance of having uncertainty factors corresponding to each weather station. Nevertheless, it was observed that, for this case, under 100 km the uncertainty is not expected to exceed 0.2 for both weather stations (see Figs 4.14 and 4.15). Given the large number of weather stations in the UK, it is unlikely that the distance from the closest weather station to the glasshouse will be greater. Therefore, the uncertainty is expected in most cases to be within that limit. This is of course purely based on the uncertainty associated with the distance separating the glasshouse and the weather station it acquires the data from.

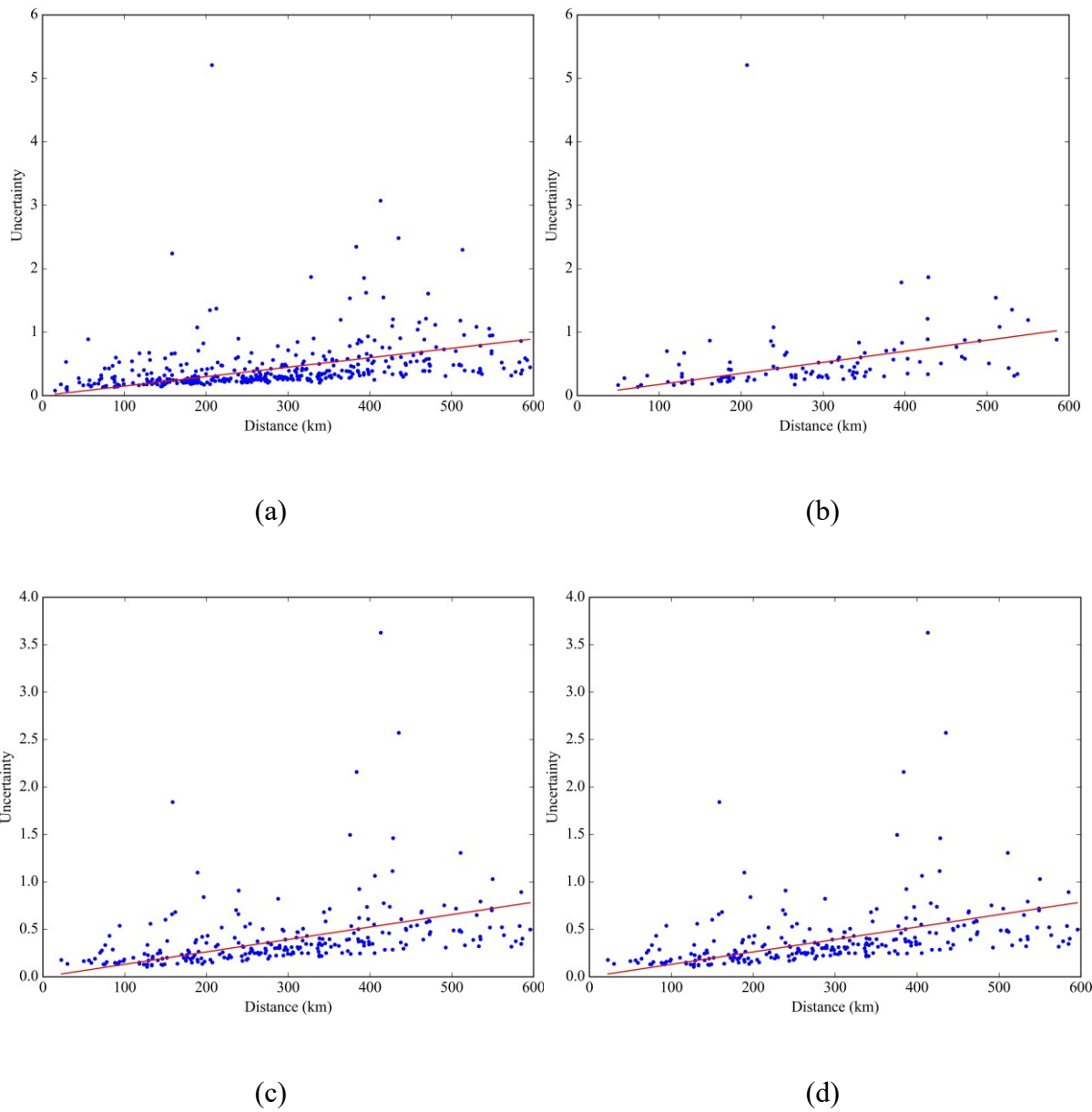


Figure 4.15. Uncertainty against distance from weather station (in north UK) based on: (a) temperature, (b) radiation, (c) atmospheric pressure, and (d) dew temperature.

This analysis was done for all weather stations in the database for all the cases based on historical data as mentioned in the methodology section, thus creating a portfolio from which the model can quickly withdraw data and based on simple calculations give the expected uncertainty/error associated with the outputs of each simulation.

4.5 Summary

The importance of energy requirements at production stage when auxiliary support systems are used led to the interest in developing a model/tool which can be used to quantify and analyse this supply chain process. The model was showcased and its capabilities were highlighted based on some case studies. Based on the comparison of the model outputs and a case study, the model was found to provide reasonable estimates of the energy requirements. The model was developed in such way that it requires minimum input from the user and allows for its easy application. Hence, this contributed to the model being generic enough to enable its broad application. However, this makes the model data-focused and therefore makes the quality and relevance of data a factor of its accuracy. To capture some of the expected error from the data, the model was developed with the capability to quantify the expected uncertainty for each simulation. The integration of several elements, including specific lower level models, databases, and visualisation packages, enabled the development of the model. The model can be used for different purposes such as benchmarking, parametric analyses, spatial analyses, temporal analyses, and development of energy, carbon and cost reduction strategies. Its outputs showed the potential for addressing different cases and offer insights, including:

Operational performance:

- energy performance assessment of existing glasshouses;

- portfolio creation of multiple glasshouses' energy performance based on a standardised approach;
- daily and peak demand energy requirements estimation in year or season;
- annual energy requirements estimation;
- energy requirements analysis for products and their corresponding required conditions and growing schedules;
- cost-benefit analysis for strategies used to control product yields;
- estimating the potential impact of climate change and weather variability on energy requirements;
- energy costs quantification and cost reduction options analysis;
- carbon emissions quantification and curtailment options analysis.

Long term impact analysis and high-level design:

- spatial and temporal analyses and impact on energy requirements;
- identification of potential improvement measures, both through independent modification and combinations;
- analysis of expected variation in energy requirements and identification of potential approaches for their minimisation.

The parametric analysis results showed the great impact of the glasshouse's characteristics as well as the spatial and temporal aspects (which were more associated with the weather data) on the performance of the glasshouse. Analysis showed the potential for energy savings through the improvement of performance and operational parameters of the glasshouse. More specifically, for performance parameters the infiltration rate and overall heat transfer coefficient were observed to have the greatest impact. Similarly, the internal temperature as

well as the heating schedules were found to affect significantly the energy requirements. Through improvement measures a significant reduction in heating, in terms of annual and peak daily, was achieved while cooling showed a slight increase. Nevertheless, due the significantly greater reduction in the magnitude of heating compared to cooling, the overall energy requirements still decreased significantly.

The temporal analysis indicated the variation that can be expected on annual terms and the impact of the glasshouse design parameters on it. A significant decrease in both mean annual energy requirements and variation in annual energy requirements was noted as a result of the improvement measures introduced. The energy improvements were again found to be driven by the significant improvement in heating.

Furthermore, the spatial analysis showed that even though the relative range of improvement from the measures introduced was not very large for both annual heating and peak daily heating requirements, location still has a great effect on the absolute energy requirements. The magnitude at some northern areas was found to be around three times the requirements of some southern areas. This observation was noted for both annual and daily peak requirements. This shows that more efficient glasshouses in some areas may have greater energy requirements than poor performing ones because of their location. On the other hand, with the exception of a few areas, the variability was found to be relatively evenly distributed across the UK and therefore showing some irrelevance to the spatial aspect. Nevertheless, the analysis indicated that in some cases regions can be ideal in terms of absolute energy requirements but suffer from greater uncertainty due to greater weather fluctuations.

The analysis on carbon emissions and energy costs showed again the impact of improvement measures as well as the impact of the energy source. The energy source, in some cases, was

found to be more influential than improvement measures; thus when considering other aspects such capital costs and downtime requirements it might be a more attractive approach towards improvement. Nevertheless, carbon emissions and energy costs were observed to not be mutual when considering different energy sources. Therefore, a trade-off analysis between the two can provide more insight in the most competitive energy source. However, in the case of improvement measures, the carbon and cost savings are expected to be mutual.

Both controllable and non-controllable parameters were found to have a great influence on the performance of the glasshouse. Factors observed in this chapter to have the potential to contribute to the improvement of glasshouses' performance include:

- improvement of the thermal envelope properties;
- improvement of performance of heating and cooling systems;
- adjustment of growing (heating) schedules;
- adjustment of internal set conditions;
- selection of products and/or varieties;
- selection of location; and,
- change of energy source (heating fuel and electricity source).

The improvement in annual energy requirements, peak daily requirements, and their associated expected variabilities can introduce several benefits to different stakeholders. These benefits may include:

- reduction in energy consumption, energy costs and carbon emissions;
- downsizing the support systems and potentially operating at higher efficiency;
- more resilience to external weather conditions;

- better cost forecasting and budgeting;
- more stable energy consumption, energy costs and carbon emissions; and,
- setting more confident environmental targets.

Moreover, the model was also tested against the expected error/uncertainty associated with the distance difference between the source of weather data (i.e. the weather station) and the glasshouse. In the attempt to quantify this uncertainty, it was found that in certain cases the weather stations can give very precise estimations whereas in other cases using data from distant weather stations can lead to significantly different outcomes. In the case studies analysed here, the uncertainty level below 100 km distance from a weather station was observed to be less than 20% based on the overall uncertainty of the timeline considered. Considering the UK as an example, given its large number of weather stations collecting and providing data, it is expected that relative distances between glasshouses and stations will be relatively small and therefore not contribute to the significant increase of uncertainty.

Temperature was observed in most cases to be the greatest source of uncertainty. Therefore, it can be concluded that this approach also indicates the most appropriate dataset (for each case of supplier considering from where it gathers its data from) to be collected on site if that would be an option. For example, since in the aforementioned case the temperature was found to be responsible for the greatest share of overall uncertainty, a simple approach to improve the accuracy of the model's simulation would be to collect temperature data on site. In this way the tool provides an indication of how confident the user should be with the outputs of the model depending on the source of data.

As discussed in Chapter 2, several studies in literature have considered the energy requirements of glasshouses (e.g. Luo et al. (2005), ASABE (2008), Gupta and Chandra (2002), Subić et al.

(2015)). The modelling framework presented in this work aimed to contribute towards the further development of tools focusing on the UK and requiring a limited set of inputs to run while considering factors such as location, time, design parameters, operational parameters, weather conditions from data at the required frequency as well as the potential impact on several key performance indicators. Outputs from the analysis performed in the present study also indicated the importance of considering such aspects and the impact they could have in some cases as well as contributed towards understanding better the drivers of energy requirements and carbon emissions. Therefore, outputs from this work could also contribute towards acquiring further knowledge from a quantitative perspective for potential future improvements suggested in LCA studies. Finally, the development of the modelling framework through the use of multiple modules could contribute towards the integration of areas such as data analytics (including real meteorological data), data visualisation, and modelling (for energy, carbon and energy costs) for studying the requirements of glasshouse production.

Finally, there are some limitations of the model that can represent avenues of future work. For example, as noted earlier, the model depends on weather data from distant weather stations which potentially introduces an additional source of error. In regions with limited weather stations availability or dissimilar site characteristics, this error should be taken into consideration and possibly assess the potential for installing a weather station on site. Furthermore, more case studies could be considered in the future in order to observe the performance of the model. Also, more parameters can be incorporated into the model to potentially improve its accuracy, but that option can affect one of the main objectives of the model which was simplicity and minimal requirement of inputs. More examples regarding some limitations and potential future work are discussed in Section 7.2.

4.6 Highlights

- A model for quantifying energy requirements of glasshouse production was developed while showcasing the capabilities of the model through parametric analysis, spatial and temporal analysis, and energy costs and emissions analyses. This contributes to the lack of tools for glasshouses focusing on the UK while requiring limited inputs as well as consider a wide variety of factors, including operating conditions, glasshouse design parameters, growing schedules, geographical regions, varying weather conditions from high frequency weather data, and analyses on energy requirements, carbon and energy cost.
- The parametric analysis indicated that the overall transfer coefficient and infiltration rate could have a significant impact on the performance of the glasshouse. A similar outcome was observed in terms of operational parameters for the internal temperature set.
- Carbon and cost savings were found not to be mutual when considering different energy source; thus trade-offs between the two might exist. However, in the case of thermal envelope improvements, carbon and energy cost savings are not expected to compete against each other.

Chapter 5

5 Transport – Distribution stages

This chapter focuses on the implementation of the methods discussed in Section 3.2 to: i) identify and define influential parameters required for the execution of the modelling framework (MFB), ii) compare the results from the two modelling frameworks, iii) perform an analysis based on different scenarios, and iv) showcase the potential outputs from the models.

There are two main transportation stages in the model; namely one from the supplier nodes to the depots and one from the depots to the demand nodes. Initially, the first transportation stage was analysed while considering different UK supply regions and the requirements for imports to satisfy demand. Then, the second transportation stage was analysed based on the transport requirements between depots and demand nodes. It is worth mentioning though that the allocation optimisation of the second transportation stage is affected by the decisions taken for the first transportation stage. This is because the allocation optimisation takes into account both transportation stages by considering characteristics and constraints from both stages, as described in Section 3.2. For example, production capacities affect the decision on where the

product is sourced from for depots while at the same time demand requirements at demand nodes affect the decision of the which depots are allocated to them.

Also, the difference between two main categories of demand nodes (i.e. stores) was studied; namely large and small stores. These two categories differ mainly in size, demand, location and spatial concentration. As the name indicates, large stores usually have larger sales floor area and greater demand. Also, they are usually more disperse in location whereas small stores are usually located in higher spatial concentrations within cities/towns. These characteristics are expected to introduce differences in the allocation and distribution networks (e.g. length of routes and nodes in each route) associated with each type of store.

5.1 Case study analysis

It was important to study the demographics of the data used to gain a better understanding of the problem in hand. The following data were normalised to provide a comparative analysis.

Since distance travelled (used also as a proxy for fuel consumption) was one of the main key performance indicators in the analysis, the spatial orientation of the supply chain stakeholders was of interest. Concentration of some stakeholders in certain areas was noted, particularly for supply and demand nodes. More specifically, the concentration of small stores in several areas was obvious, especially within cities. On the other hand, large stores seemed to be more evenly spread in the whole of the UK. Similar to small stores, suppliers were also located in some distinct areas while it was clear that there was a considerable share of suppliers located far away from most of the demand nodes. Since depots were not externally driven by spatially oriented supply and demand, they appeared to be distributed in a way that they could satisfy demand. Normalised distances between depots and large store nodes, and depots and small

store nodes are shown in Figs 5.1 and 5.2 respectively. Similarly, normalised distances from supply nodes to depot nodes are shown in Fig. 5.3. These relations are expected to help interpret the outputs from the modelling frameworks in the later sections.

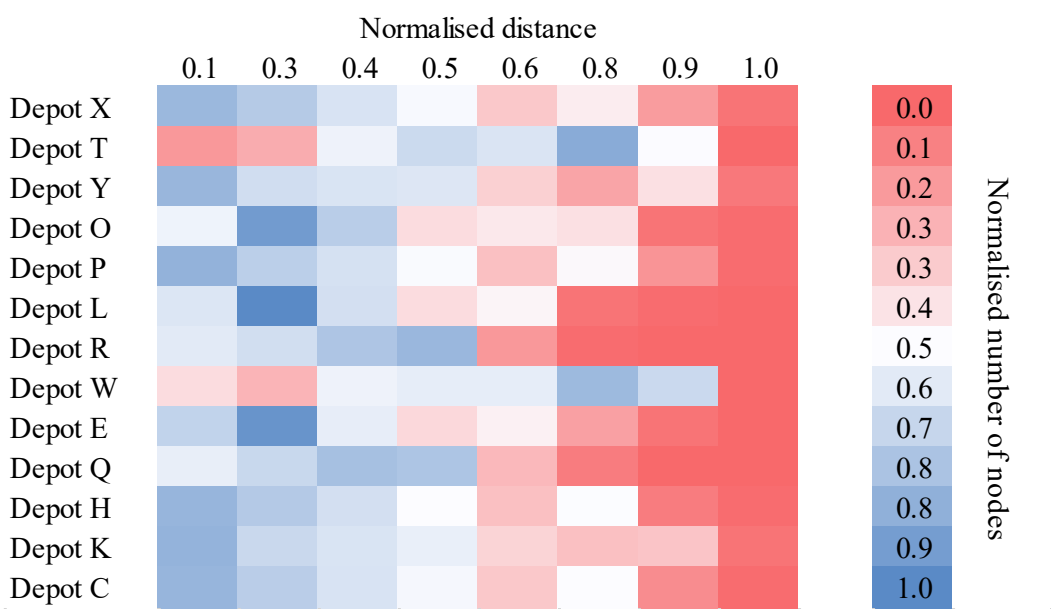


Figure 5.1. Normalised distance from depots to large store demand nodes.

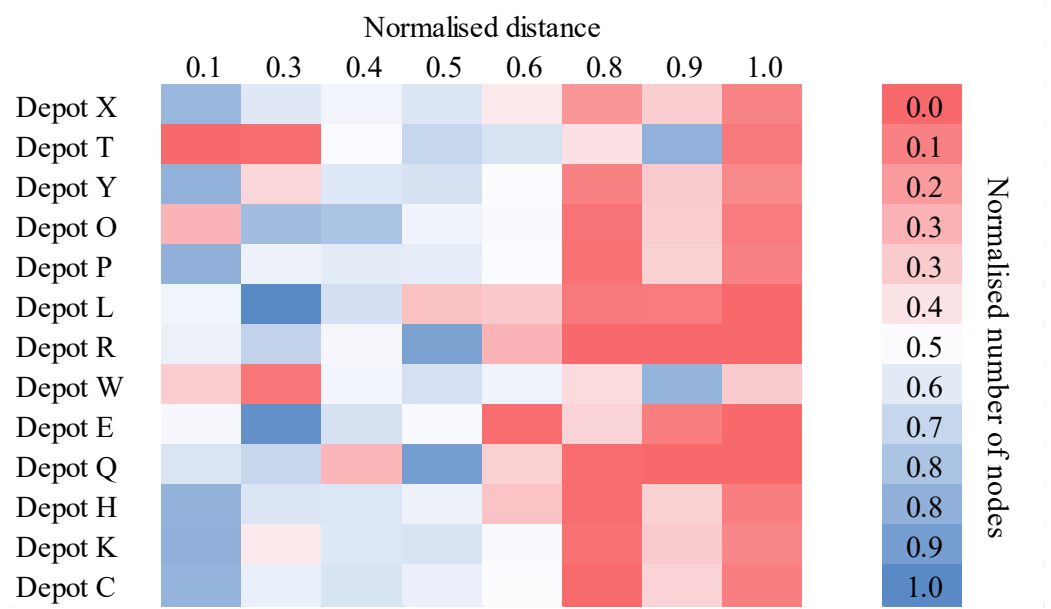


Figure 5.2. Normalised distance from depots to small store demand nodes.

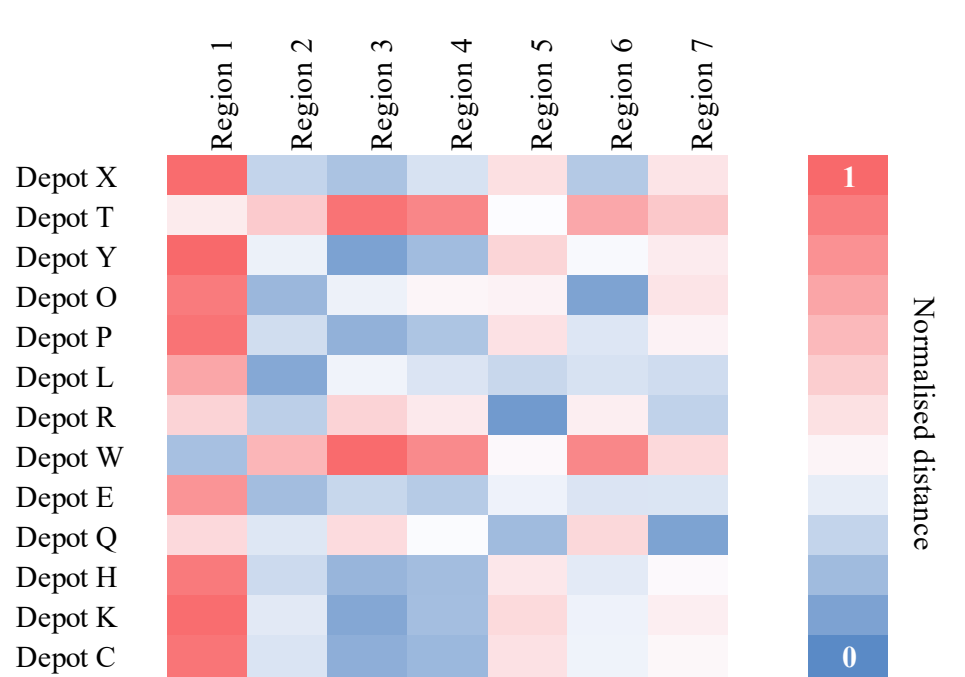


Figure 5.3. Normalised distance from supply nodes to depot nodes.

Besides the spatial representation of the data, it was important to consider the temporal aspect as well. More specifically, it was interesting how the total demand at stores varied through the year (represented by the top line of the chart in Fig. 5.4), how supply varied through the year, both in terms of imports and national supply (Fig. 5.4), and how supply varied through the year depending on the geographical region (Figs 5.5 and 5.6).

The total UK demand peaked in the middle of the calendar year (June, July) with significantly lower demand in winter periods. Also, demand was satisfied mostly by imports in the early and late months of the year when demand was lower, and mainly by national production during most of the high demand periods. It was interesting to note the significantly higher national production in the autumn period in comparison to the spring period. Also, a mass balance

between supply and demand was assumed, meaning that the sum of imports and national production supply was equal to the demand.

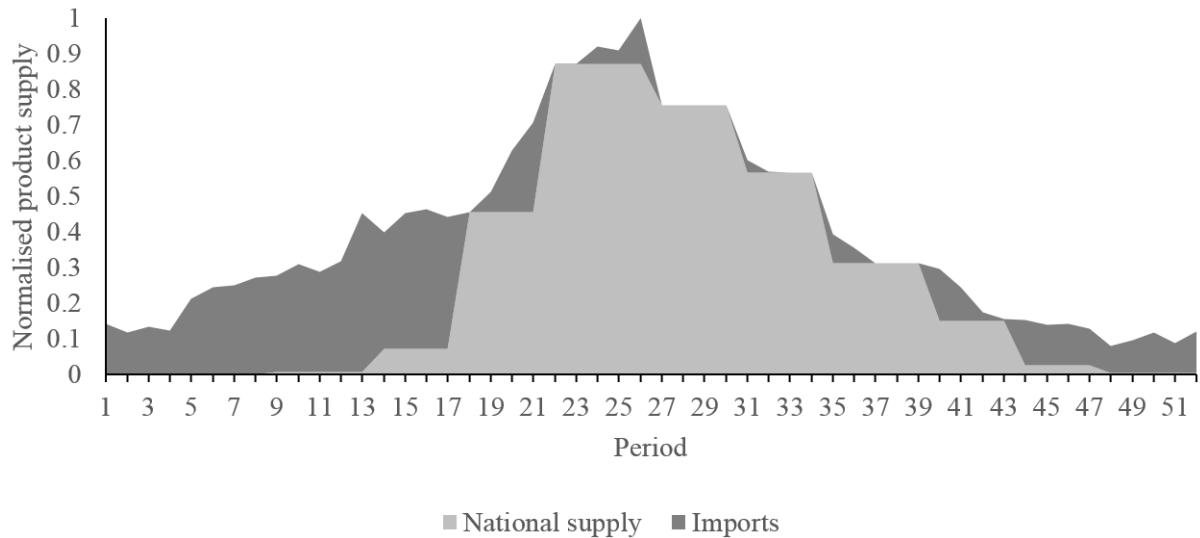


Figure 5.4. Normalised product supply ($s_{\text{nor}(t)} = \frac{s_t}{d_{\text{max}}} \forall t \in T$) segregated into national supply and imports for the UK supply chain of the case study considered.

Figure 5.5 shows how each region's product supply varies throughout the year. It was clear that depending on the region the production profile changed. For instance, Region 7 was observed to peak in mid to late spring, then significantly dropping in early summer and finally picking up again to almost 60% of its peak supply in late summer. Region 4, Region 2 and Region 3 followed a similar trend with a gradual increase starting from spring, peaking in summer and gradually falling in autumn. This trend was similar to the total demand profile during the late spring, summer and autumn periods. Furthermore, Region 1 followed a similar trend as Region 4, Region 2 and Region 3 but with a forward shift of about a month. Most

interestingly, Region 5 followed a considerably different trend with its peak being in late autumn and minimum supply in summer, thus not sharing a similar trend with the overall demand profile. Nevertheless, since demand is present throughout the year, diversity in production and supply can be important for the satisfaction of demand by national producers.

In addition, it was useful to see the product supply profile from each region in comparison to the total supply at each period (see Fig. 5.6). Region 1 clearly dominated the peak supply with Region 3 following second. This gives a different insight from the Fig. 5.5 as it shows the importance and dominance of supply from certain regions with respect to volume of product supplied. This is expected to have an impact on the allocation optimisation and the transport distance allocated to each region.

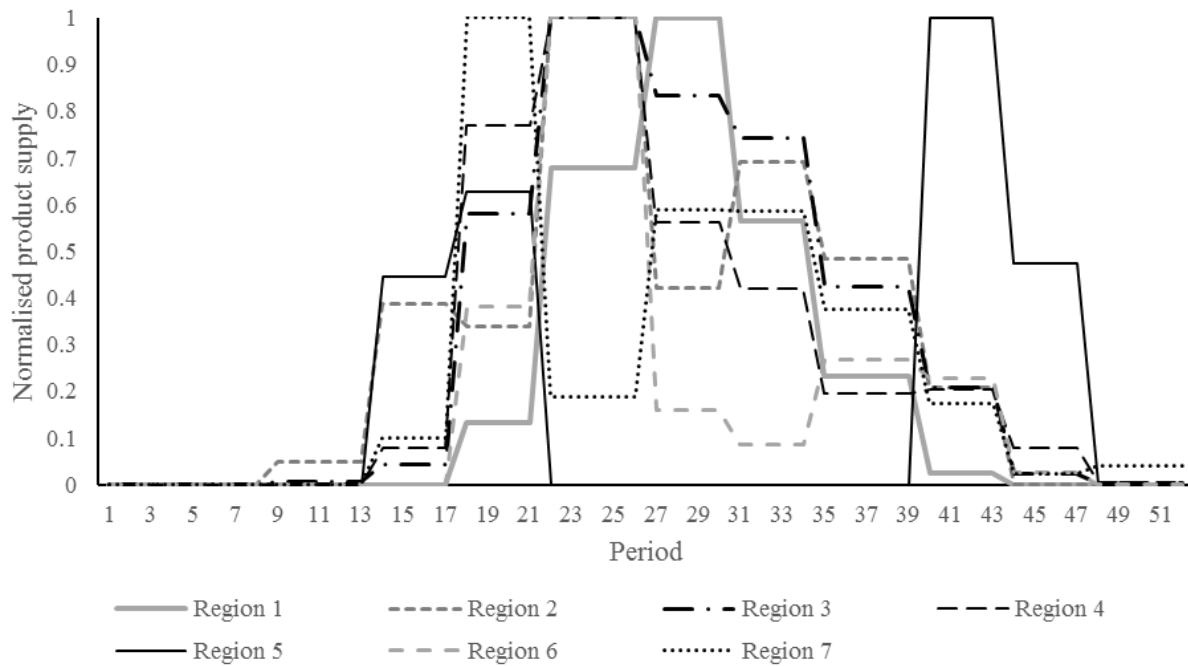


Figure 5.5. Regionally normalised product supply ($s_{\text{nor}(r,t)} = \frac{s_{r,t}}{s_{r,\text{max}}} \forall t \in T, \forall r \in R$) for the supply chain.

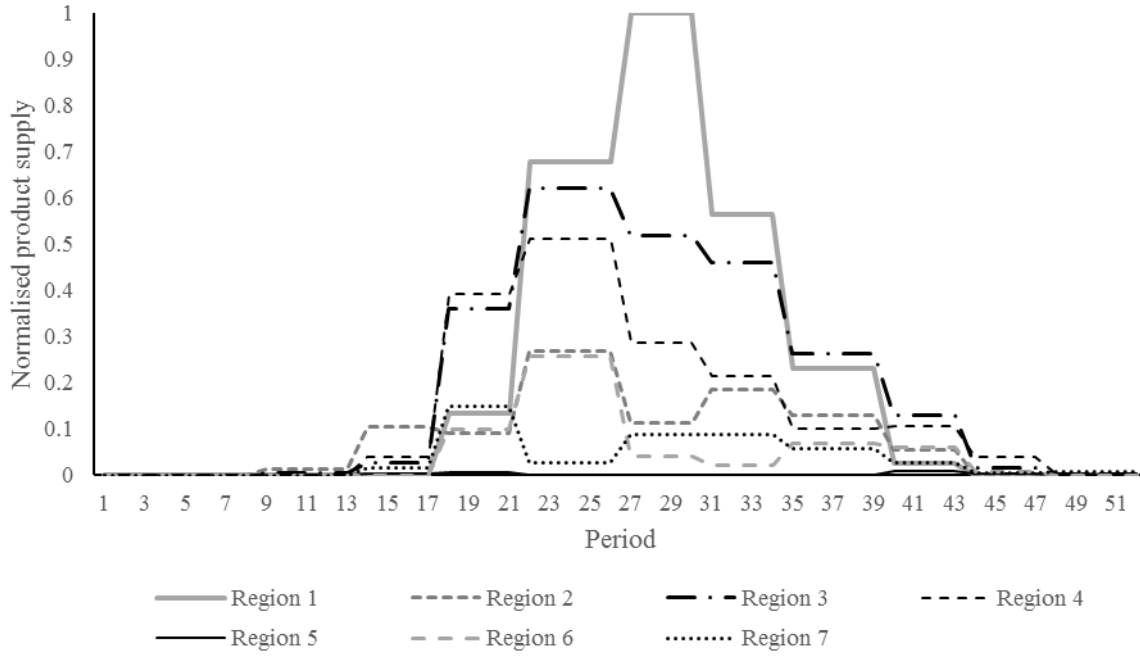
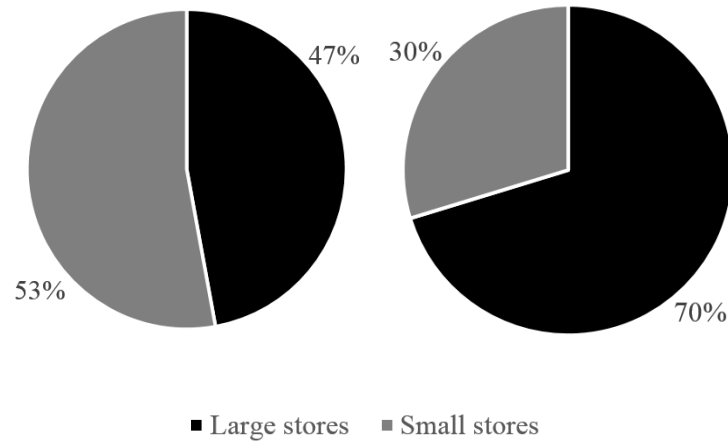


Figure 5.6. Normalised product supply ($s_{\text{nor}(r,t)} = \frac{s_{r,t}}{s_{\text{max}}} \forall t \in T$) by region for the supply chain.

Comparing large and small stores in terms of a) number of stores and b) share of product demand, shows that there was no clear relation between these two metrics (see Figs 5.7a and 5.7b). For instance, while the number of small stores was greater than large stores, the demand of small stores were accountable for a significantly smaller share (30%). Similarly, in terms of temporal demand variation, Fig. 5.8 shows the dominance of large stores. Nevertheless, given the perishability of the products and the fact that deliveries have to take place daily, the number of stores might have a greater impact on the travel distance associated with each type of store. Therefore, even if some stores have much lower requirements, they will still need to have at least one delivery per period which will make the vehicle travel that distance whatever the demand is. Therefore, an efficient multi-drop system is imperative.



(a)

(b)

Figure 5.7. Comparison between large and small stores in terms of: a) number of stores and b) total demand.

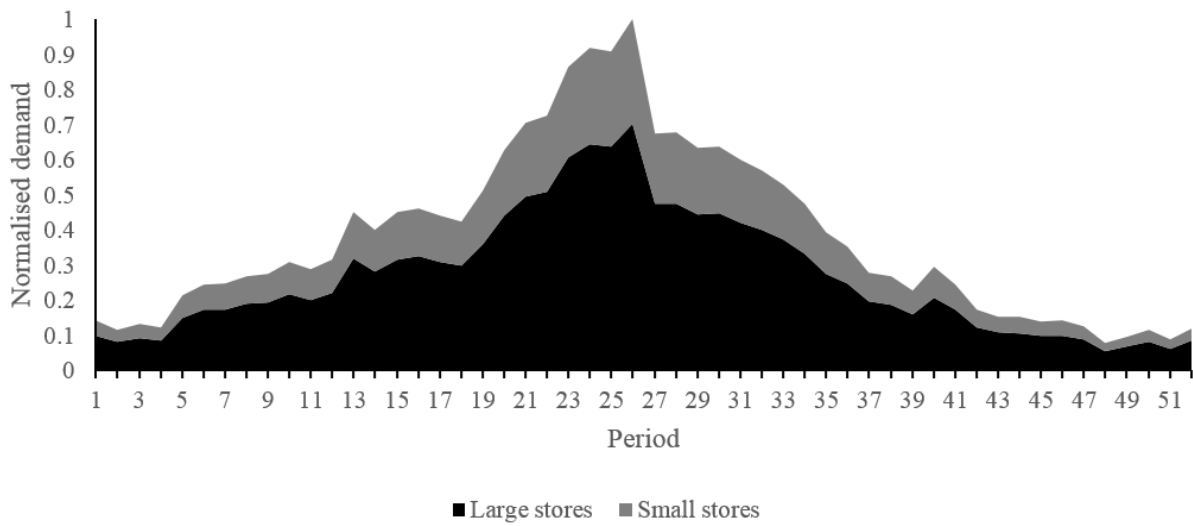


Figure 5.8. Normalised product demand ($d_{\text{nor}(t)} = \frac{d_t}{d_{\text{max}}} \forall t \in T$) segregated into large and small stores' demands for the supply chain.

5.2 First echelon analysis – allocation optimisation

This section focuses on the results from the allocation optimisation based on part of the modelling framework presented in Fig.3.12 in Section 3.2.2. The results presented here mainly focus on the first echelon of the supply chain, although the whole supply chain was considered for the allocation decisions.

Travel distance between suppliers and depots was based on the assumption of one delivery per supplier per depot per day in each time period, where an allocation link was decided by the model. Region 1 was found to account for the greatest share of total annual distance travelled with 43% (Fig. 5.9a). Nevertheless, it was important to also observe the share of product supplied by each region (see Fig. 5.9b). The regions with the greatest share of product supply were noted to be Region 1 and Region 3. Since production capacity of the different regions was in large part fully utilised, this is expected to be primarily driven by the regions' supply capacity as indicated in Fig. 5.6. Distance travelled was in some cases disproportionate to the product delivered by each region. While some regions showed close correlation between distance travelled and product supply (e.g. Region 4, Region 7), others showed great difference between the two (e.g. Region 1, Region 3). Even though this was an optimised scenario (operationally), it still showed the impact of distance between supply points and depots along the supply chain. Therefore, the impact on sustainability through distance travelled was illustrated, something that can be translated into fuel consumption, emissions and fuel costs. The determination of higher ratio of distance travelled to product supplied can act as an indicator for prioritising or targeting improvement measures with a potentially greater impact on overall performance.

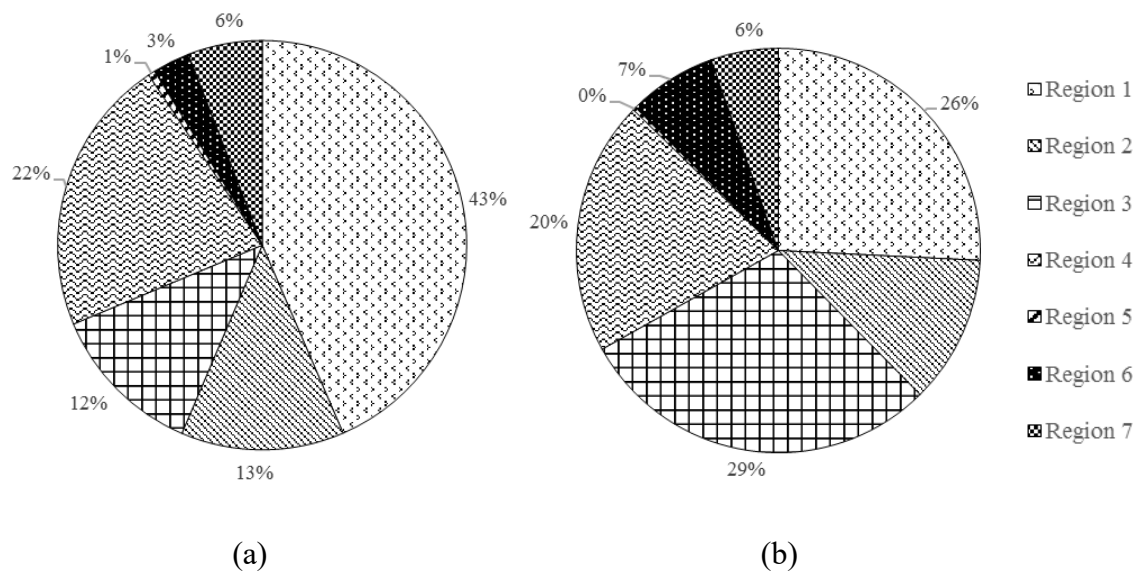
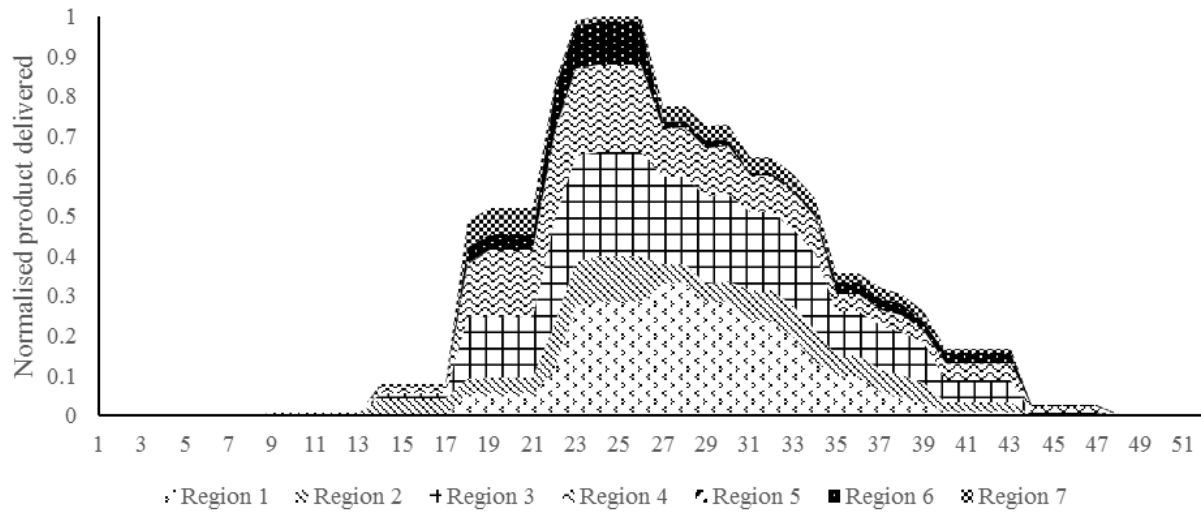


Figure 5.9. (a) Travel distance at first echelon and (b) product supply by the different national regions to depots.

It was also interesting to see how the allocation model selected regions at each time period. Figures 5.10a and 5.10b show how the normalised national supply from each region varied along the timeline based on cumulative supply and percentage share for each region, respectively. The dominance of different regions at different periods was noted. For example, Region 1 was found to contribute significantly to the supply during most of the peak periods as well as some during off-peak periods. On the other hand, Region 3 was observed to be associated with more constant contributions along the timeline. Once again, since production capacity is in large part fully utilised throughout the year, this is expected to be mainly due to the supply capacity available from the different regions. As a way of validating and justifying this observation, Figs 5.4 and 5.6 (showing the total demand and supply capacity considered for the different regions, respectively) were used to compare against the case study characteristics. More importantly, the dependence of retailers on a less diverse portfolio of regions in some periods might indicate an increased risk on product shortage and price increase as a result of social, environmental or economic factors that can be specific to a region (e.g. extreme weather conditions). The same can apply when considering imports from specific regions. For the case study considered here (see Fig. 5.10b), a good diversity of supply regions was noted along the timeline, with the exception of the very last periods. However, the amount of product in absolute terms was insignificant in those periods (see Fig. 5.10a), therefore its impact is expected to be minor.

a)



b)

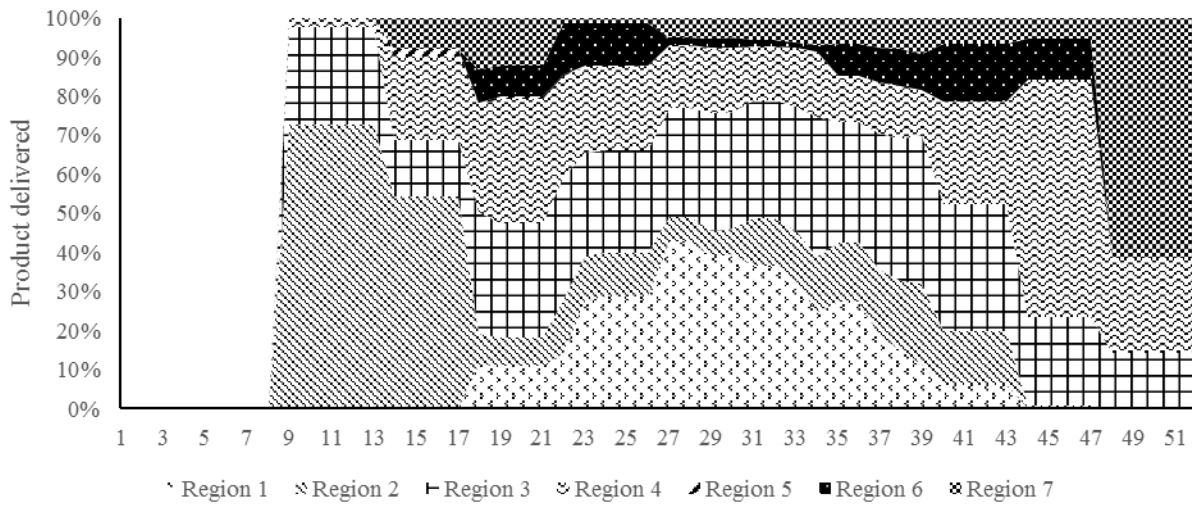
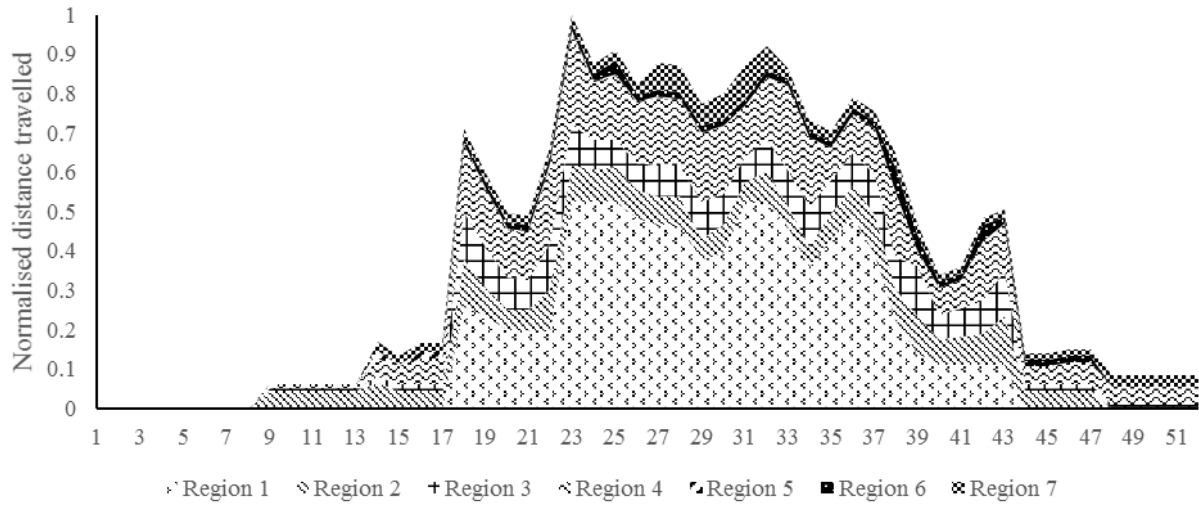


Figure 5.10. (a) Aggregate normalised national production delivered each period ($s_{\text{nor}(r,t)} = \frac{s_{r,t}}{s_{\text{max}}} \forall r \in R, \forall t \in T$) by suppliers' region and (b) national production delivery share by suppliers' region.

Similarly, Figs 5.11a and 5.11b show the normalised distance from national regions to depots in each period based on cumulative distance and percentage share by region, respectively. The dominance of Region 1 was noted during periods in which supply was provided. Region 1's dominance in terms of distance travelled was observed to be more obvious relevant to its product supply.

Comparing the product supply and distance travelled, both similarities and differences in trends and shares were noticed (Figs. 5.10 and 5.11). In addition to Region 1's difference noted above, a main difference was in the trend of total product supply and distance travelled. The total distance was found to be close to the peak for more periods than in the case of product supply. This indicated that total product supply and distance travelled were not strongly correlated. Also, greater fluctuations were seen in mileage, especially during high demand periods. Ways to reduce these fluctuations are of interest in order to create a smoother curve. Another difference was noted when focusing on the tails of the curves (i.e. the very first and very last periods in which national supply exists). During those periods, even though the total product volume supplied was barely visible (periods 8-13 and 49-52), the distance travelled was observed to be substantially more noticeable. Therefore, distance travelled per product delivered is expected to be greater, thus potentially indicating greater specific footprints (e.g. emissions, cost and fuel) associated with the product. In terms of similarities, both product supply and distance travelled were found to be shared among the different regions with relatively similar proportions (with the exception of Region 1).

a)



b)

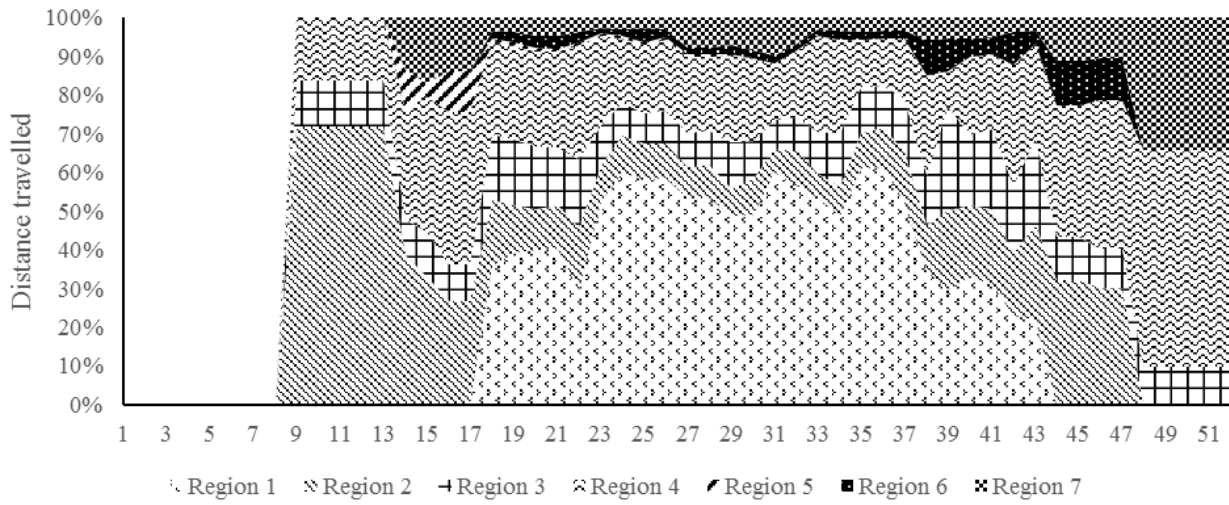


Figure 5.11. (a) Normalised national distance travelled each period ($D_{\text{nor}(r,t)} = \frac{D_{r,t}}{D_{\text{max}}} \forall r \in R, \forall t \in T$)

by suppliers' region and (b) national production delivery share by suppliers' region.

Considering the allocated product to each depot, a significant difference between depots was observed (see Fig. 5.12a), possibly due to the difference in demand nodes and their proximity to depots (i.e. the potential demand each depot has) as well as the distance between supply nodes and depots (i.e. the production capacity at close proximity). The difference between demand nodes and depots can be observed in Figs 5.1 and 5.2 for large and small stores respectively. As shown in those figures, the difference in number of demand nodes between depots can be significant and therefore could have an impact on the allocated product to each depot, particularly in a distance minimisation driven optimisation. This was assuming the capacity of each depot was not a limiting factor and all depots could be used by any supply node. Similarly, the proportion of national production supplied by different regions to each depot was found to greatly vary (see Fig. 5.13). Some depots were served fully by a specific region (e.g. Depot W by Region 1) while others were served by up to four regions (e.g. Depot Q). This could be explained by comparing the distance between depots and supply nodes shown in Fig. 5.3, from which the number of supply regions at close proximity to some depots is obvious whereas for others limited, while also having in mind the production capacity of the proximate supply regions shown in Fig 5.5.

The dependence of depots solely on a single region can mean the sole dependence on imports during periods of no national production in those regions. Also, less diversity can result to limitations, such as on product varieties and risk of no supply due to hazards or other external factors. Nevertheless, in terms of fuel consumption, emissions and cost, it could be the optimal option. Furthermore, additional savings opportunities with respect to energy consumption, emissions and costs might arise by having depots served mostly by one region. Examples can include change in mode of transport (e.g. train) or increasing the capacity of trucks to reduce transportation distance. For instance, when depots are primarily dependent on a specific region

and that region is very distant, then alternative options which might have lower carbon footprint, such as train transport, might worth considering; particularly when economies of scale are possible. It is worth mentioning though that this analysis was not in the scope of this work but could be an interesting avenue for future work.

The transport distance allocated to each depot was also observed to significantly vary between depots (see Fig. 5.12b). Interestingly, once again product supplied and transport distance were observed to not correlate in some cases. For example, Depot Y accounted for 15% of the total national product supply while accounting for a less than half share (7%) of the total transport distance. Also, comparing the depots against each other, the difference in share between the national product delivered and the distance travelled was in some cases very obvious. An example was Depot Y which handled about 107% the amount of Depot W but had an allocated distance travelled of only 47% that of Depot W. This is potentially due to the supply region of each depot. In this case for example, Depot W received all of its product from Region 1 and therefore all its distance travelled was allocated to Region 1 which is one of the most distant region from most depots (as shown in Fig. 5.3). Once again, this effect could be justified by considering this distance difference along with the product availability from different regions (as shown in Figs. 5.5 and 5.6) and the demand each depot has to serve under an optimal configuration.

Furthermore, it was interesting to compare the proportion of national production delivered from each region against the distance travelled from each region for each depot (see Figs 5.13 and 5.14). It was clear that again in some cases the two metrics were disproportional. For example, Depot Q handled 52% of its products from Region 1 and 43% from Region 7. However, in terms of distance, 63% was allocated to Region 1 and only 25% to Region 7. This is due to the

significant difference in distance from the depot to the two regions. As shown in Fig. 5.3, Depot Q is considerably closer to Region 7 than Region 1. Furthermore, since Region 1 is one of the main contributing regions during some periods (see Fig. 5.5), it could still be the optimal selection to satisfy demand.

Consequently, the correlation of product and transport distance is expected to depend on the supply region. Noticeable disproportionalities in product supply and allocated transport distance might indicate the potential for further investigation in those cases as well as opportunities for relocation of depots. Nevertheless, this should be treated with caution in order to avoid any consequential worsening of the other supply chain transport stages. To examine this in more detail, spatial optimisation of the supply chain identifying the optimal placement of depots might be required. This however is a different type of problem and is considered out of scope here as it is assumed that only existing infrastructure can be used. Nevertheless, this aspect can be an interesting avenue for future work.

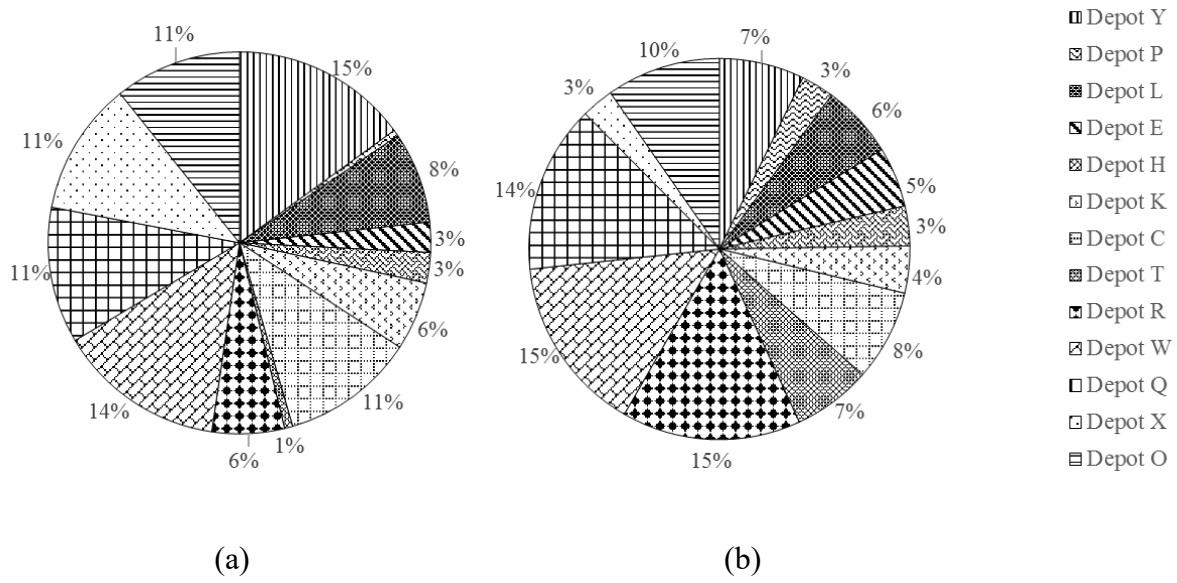


Figure 5.12. (a) National product volume handled by depots and (b) travel distance from national suppliers to depots.

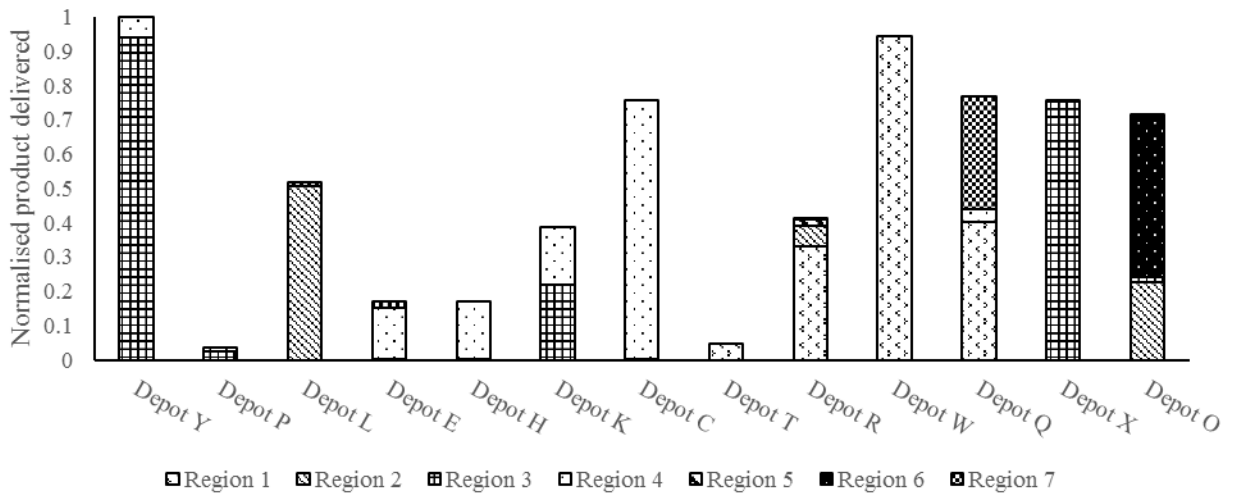


Figure 5.13. Allocated normalised national production volume ($s_{\text{nor}(d)} = \sum \frac{s_{r,d}}{d_{\text{max}}} \forall d \in D, \forall r \in R$) to depots from the different UK regions.

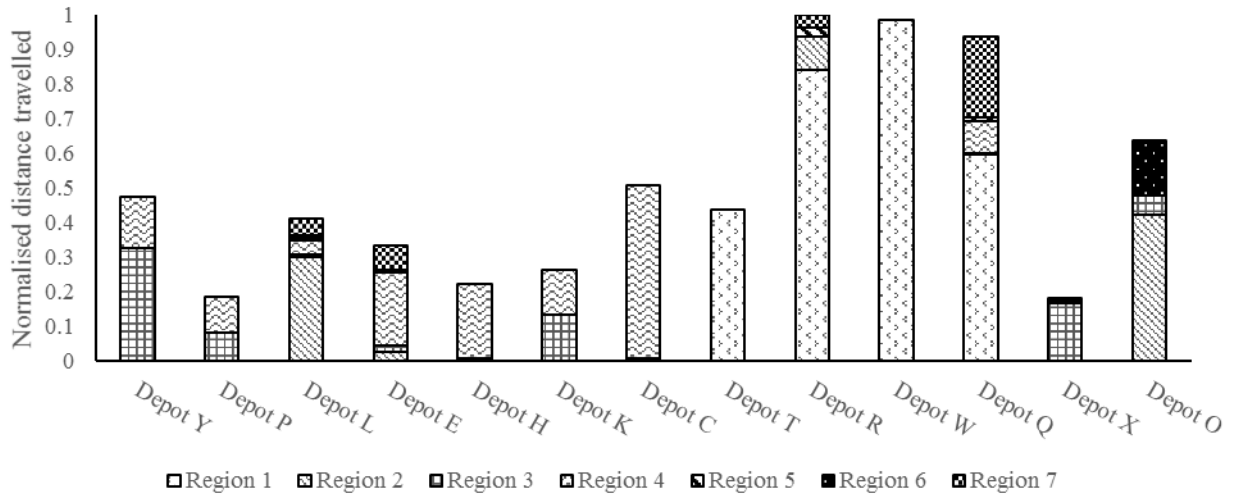


Figure 5.14. Normalised distance travelled ($t_{\text{nor}(d)} = \sum \frac{t_{r,d}}{t_{\text{max}}} \forall d \in D, \forall r \in R$) from suppliers to depots for the different UK regions.

Imports against national production supply were found to vary significantly through the year with the late spring, summer and autumn being dominated by national production (see Figs 5.15 and 5.16). Even though the supply volume greatly varied depending on the period (see Fig. 5.15), during off-peak periods supply was provided almost solely by imports whereas during high demand periods almost solely by national production. Also, the intermediate periods show a transition from imports to national production during spring and from national production to imports during early winter (see Fig. 5.16). This can be explained and justified by considering product availability as discussed in Section 5.1 and Fig. 5.4.

It is important to note though that cultivation periods and supply periods are not necessarily the same. Therefore, even if there is no national production supply, the glasshouses supported by heat might still require significant amounts of energy during those periods, thus still making heated production an important factor in the overall performance of the supply chain. This can

be illustrated for the scenario considered in Chapter 4 in Fig. 5.15 in comparison to Fig. 5.16 in which distance travelled is analysed. As noted above, if distance travelled is treated as a proxy for fuel consumption and energy consumption, there is a clear difference between the trends in energy requirements between the production stage and the transport stage from supply nodes to depots. Assuming that the majority of energy requirements at supply points is attributed to heated glasshouse production, this shows that temporal variation in energy requirements at supply nodes might not necessarily coincide with the temporal variation in energy requirements for transporting the product from those nodes to depots. It should be mentioned though that this is only an example and in different cases other profiles might occur. Furthermore, the temporal variation for the next transportation stage is discussed in the next sections while for the retail and the storage stages the temporal variation could be close to the demand profile under the assumption that energy requirements are proportional to the amount of product being stored. This, however, could depend on various aspects (e.g. refrigeration requirements, stored temperature, etc.), something that was out of scope here but could be studied further in combination with the findings of this work in the future.

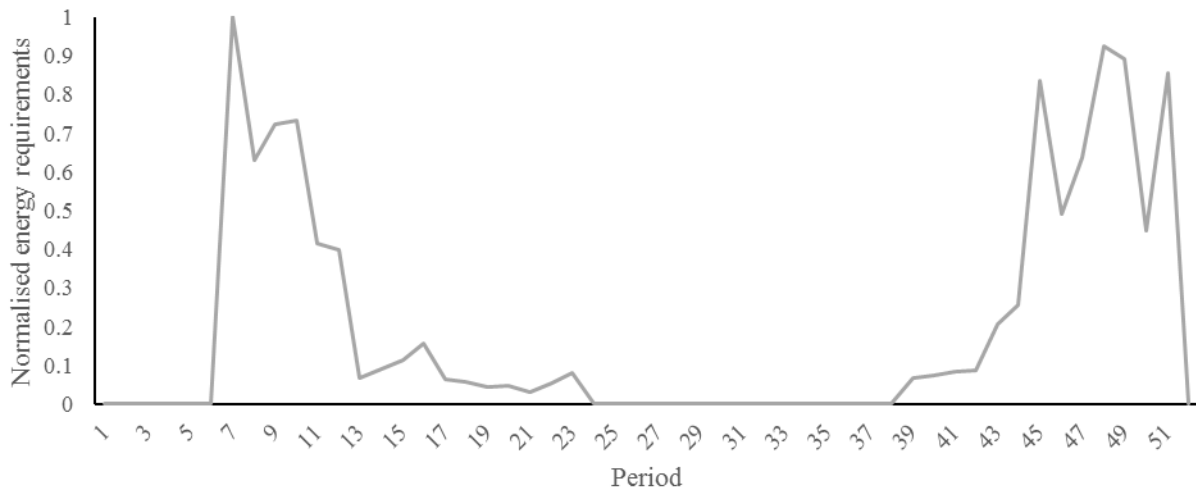


Figure 5.15. Normalised energy requirements ($E_{\text{nor}(t)} = \frac{E_t}{E_{\text{max}}} \forall t \in T$) from heated glasshouse production based on scenario considered in Chapter 4.

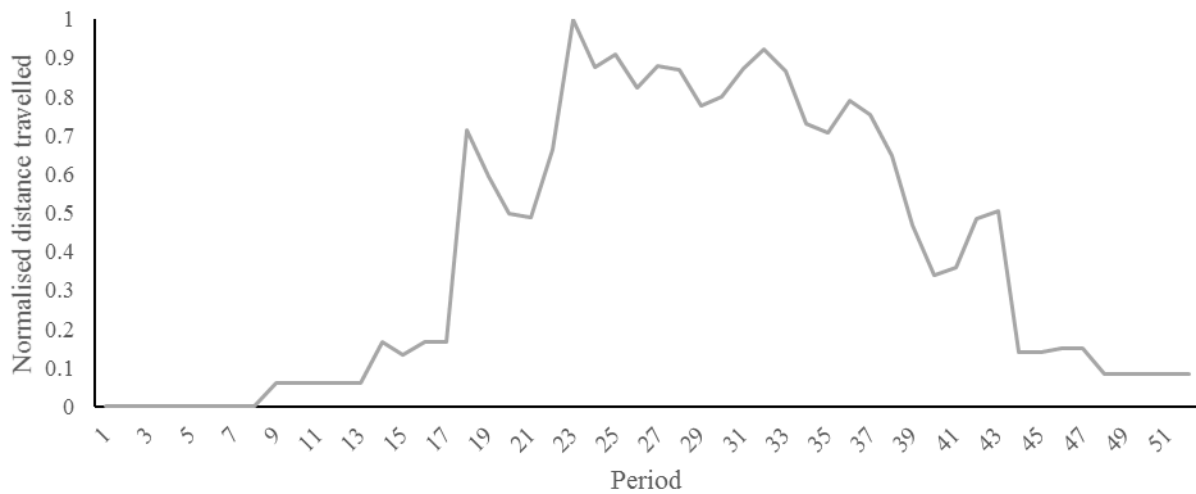


Figure 5.16. Normalised distance travelled ($D_{\text{nor}(t)} = \frac{D_t}{D_{\text{max}}} \forall t \in T$) from supply points to depots.

Comparing the results obtained from the model with the case study characteristics discussed in Section 5.1 can provide some validation of the transport model. More specifically, as discussed above and shown in Figs 5.17 and 5.18, the results observed here show greatest availability of national production during peak periods while imports to contribute mostly during off-peak periods; both of which are line with the case study shown in Fig. 5.4. In addition, further validation of the model could be attained by considering the production capacity available from the different regions of the case study (see Figs 5.5 and 5.6) and compare them against the model outputs in terms of product supply determined by the model. For example, it can be seen that supply from Region 1 selected by the model (Fig. 5.11) is in line with the production capacity of the region mostly being during peak demand periods (Fig. 5.6). Similarly, considering a region with a significantly different availability profile, Region 2, it can be seen that product supply allocated by the model has the greatest contribution earlier in the year which is again in line with the outputs from the model. Furthermore, another validation of the model outputs can be considered the allocation of distance travelled to supply regions for specific depots by the model (see Fig. 5.14) while also comparing the relative distance difference between the depots and supply regions shown in Fig. 5.3. For example, as mentioned above, Depot Q handled 52% of its products from Region 1 and 43% from Region 7. However, in terms of distance travelled, 63% was allocated to Region 1 and only 25% to Region 7. Comparing this result along with their relative distances shown in Fig. 5.3, Depot Q can be seen that is considerably closer to Region 7 than Region 1, thus providing another validation point for the model outputs.

Furthermore, it is noteworthy to mention that supply profiles of other products might differ from the product considered in this work. For example, a product with a different supply and/or demand profile might have a different share between imports and exports. This is also expected

to be affected to a certain degree by other factors such as the geographical location which is analysed and its ability to produce the product required for demand. In addition, the correlation of national production capacity and demand curves could also be an aspect that could affect the distribution of product. Nevertheless, assuming that other products' supply chains share similar characteristic to the supply chain considered here, the modelling framework could be adjusted and applied. This could also be considered as potential future work.

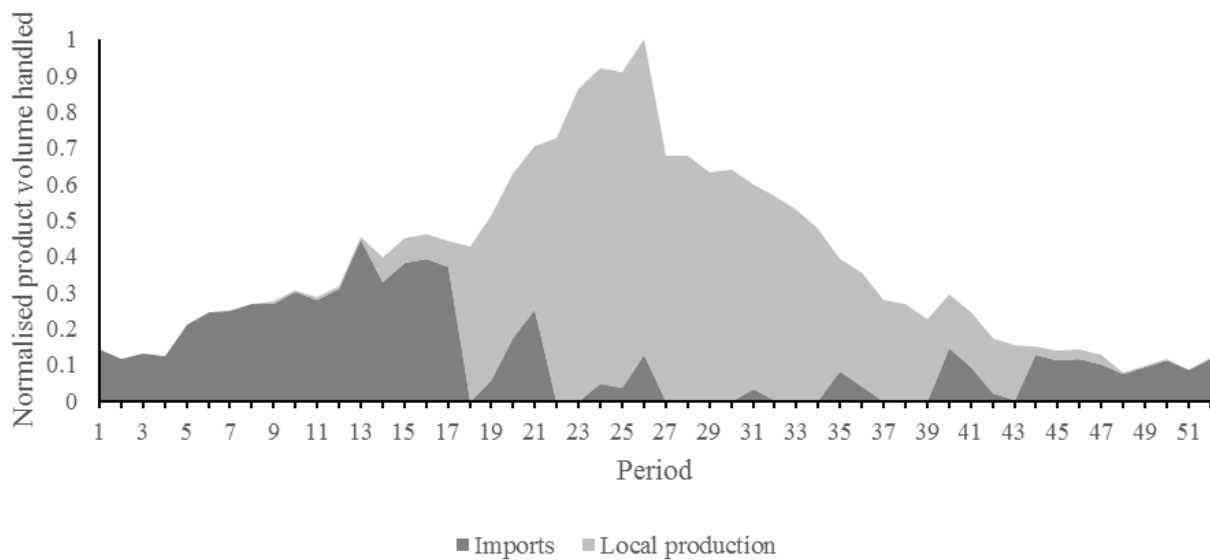


Figure 5.17. Normalised product handled ($s_{\text{nor}(t)} = \frac{s_{t,l} + s_{t,i}}{s_{\text{max}}} \forall t \in T$) by depots for each period on the year separated into national production and imports.

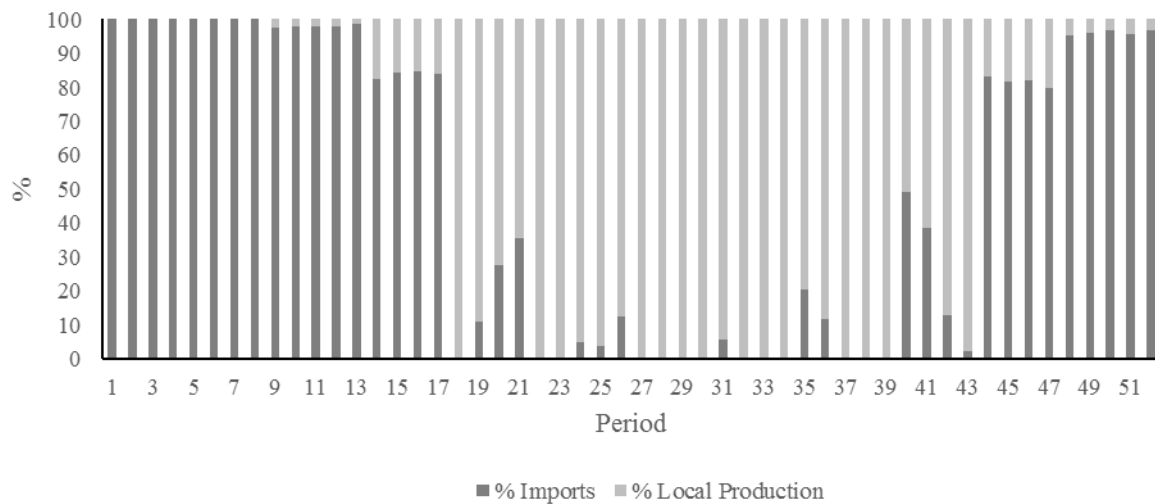


Figure 5.18. Share of national production supply and imports for each period.

Moreover, it was interesting to see which depots were allocated mostly imports or national production. As shown in Figs 5.19 and 5.20, all depots' handling volume consisted of both national production and imports. However, it is clear that in some cases the imports dominated (e.g. Depot P) whereas in other cases national production dominated (e.g. Depot W). This is expected to be partly driven by the difference in distance between supply points. The arguments made earlier regarding the benefits of diversifying supply origins are expected to apply here as well. One limitation of this analysis is that the distance from the import locations to the depots was not considered and it is something that might have had an impact on the share between the two. This is because the allocation of specific overseas suppliers to depots was out of the scope of this study. Nevertheless, the expected impact if distances from import origins were considered is expected to be insignificant since those origins are expected to be at a greater distance than national production anyway.

It is noteworthy that, here, the allocation optimisation was set up in such way that the local production was always given preference over imports. Further work could include factors for national production and imports to see whether or not imports are chosen over national production in certain periods in terms of key performance indicators. However, this would mean that factors should be assigned for each period as national production in season without heating will probably have a significantly different factor than heated production in terms of energy requirements. An interesting question is whether the ratios of imports to national production supply would change when performance factors are assigned to each option. Nevertheless, such analysis is expected to differ depending on the type of performance indicators, some of which can be difficult to quantify (e.g. social).

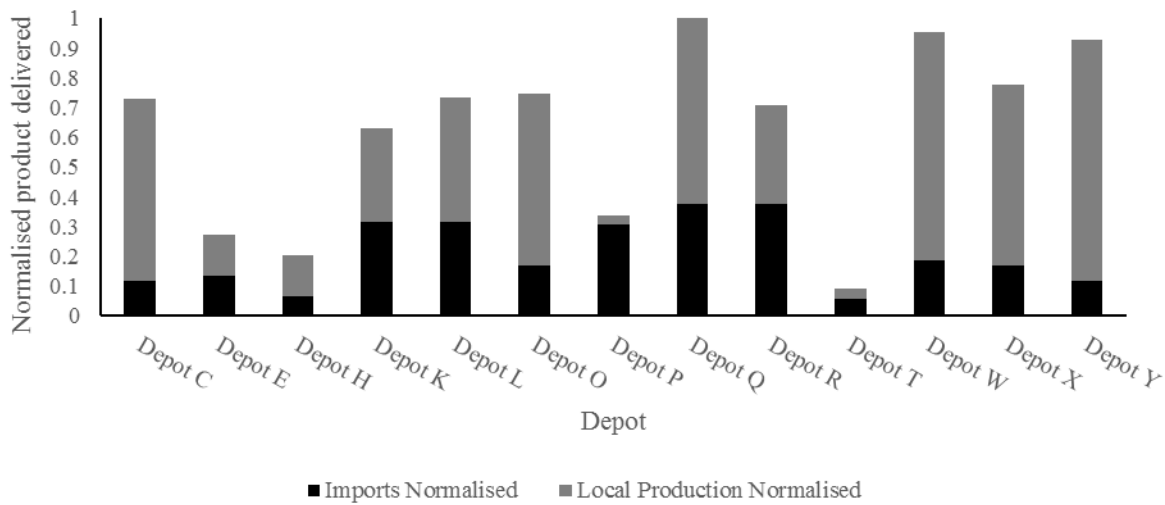


Figure 5.19. Normalised product handled ($s_{nor(j)} = \frac{s_{j,l} + s_{j,i}}{s_{max}} \forall j \in J$) by each depot separated into national production and imports.

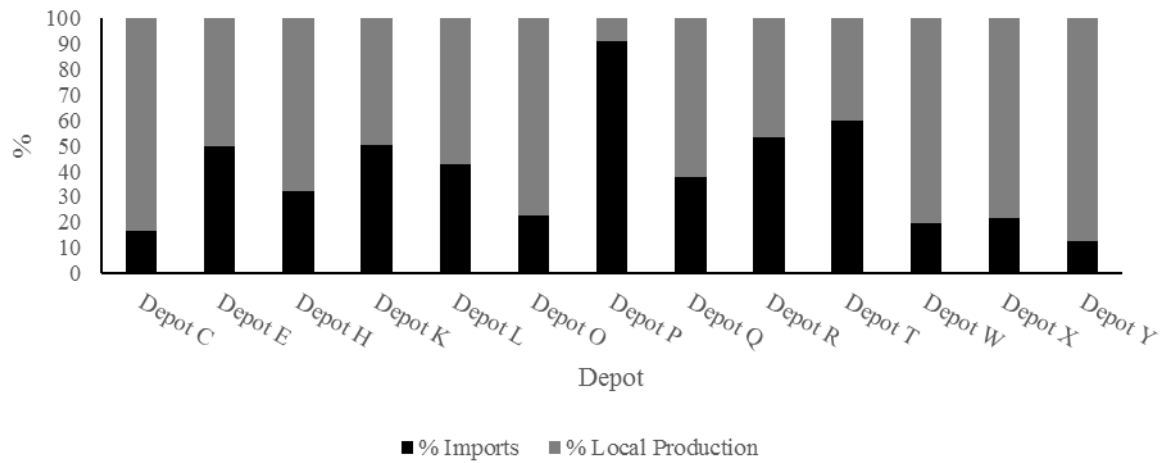


Figure 5.20. Share of national production supply and imports for each depot.

5.3 Modelling framework B: method analysis

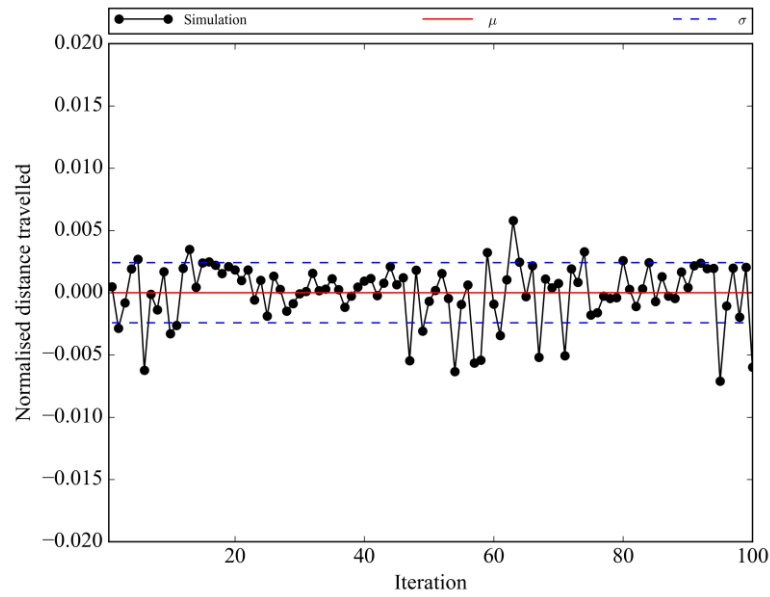
This section focuses on analysing the techniques employed in MFB and the impact of parameters and characteristics associated with this approach. Parameters associated with this framework mostly affected the outputs related with the second transport stage; namely from depots to stores. This is expected to be due to multiple trips and multi-drop requirements usually relevant to this stage, as opposed to the first transport stage from supply nodes to distribution nodes. Therefore, even though decisions made by the model account for the whole supply chain, the results discussed in this section focus on the second transportation stage.

As part of this analysis, aspects investigated include: the effect of initial randomisation employed in the clustering step, the effect of selection criteria of first node in the constructive search step, the impact and definition of the optimum initial centre of gravity for the formation of routes, and the effect of direction of travel on the total time required for demand satisfaction of all stores in a route.

As discussed in Chapter 3, MFB has the limitation of relying on the random initialisation of clustering centroids. As a result, a level of uncertainty is introduced as well as the probability of ending up with inexact outputs from different simulations. Therefore, the impact and quantification of this random initialisation on the results was important to investigate. A minimal variation between runs could potentially indicate the robustness of the framework against this randomness. To examine this, the same problem was simulated for several times using identical parameters while observing the variation in total annual travel distance for the two types of demand nodes independently (see Figs 5.21a and 5.21b). Even though a slight variation in the results is observed, the variation can be considered negligible relative to the absolute mean value. It is worth mentioning that travel distance is used in this work as a proxy for energy/fuel consumption. This might not be accurate for all cases and the study of the correlation between distance travelled and fuel consumed for the different route options presents a potential avenue for future work.

To study this effect more closely and quantify the variation between runs for both small and large stores, the simulation was performed 100 times (see Fig. 5.21). The plots in Fig. 5.21 show the output values in terms of normalised travel distance and the standard deviation based on the mean. The percentage of standard deviation to mean was determined to be 0.30% and 0.24% for small and large stores respectively; thus showing a very similar variability associated with both types of demand nodes. Furthermore, in this run no simulations resulted in a variation of equal to or greater than 1% from the mean in the cases of both small and large stores. It can therefore be concluded that the random initialisation of cluster centroids is expected to have an insignificant effect on the end results as generally consistent outputs were noted through the different simulations for both types of stores.

(a)



(b)

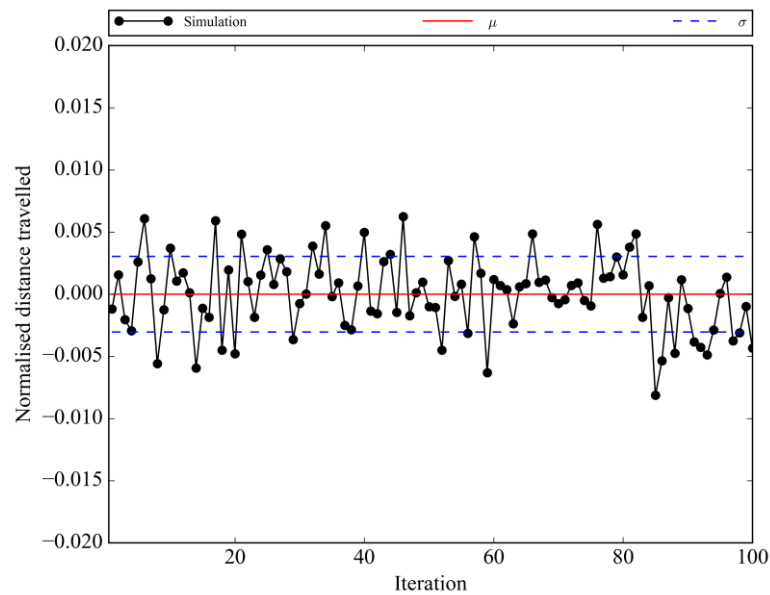


Figure 5.21. Initial randomisation's effect on end results in terms of normalised travel distance and standard deviation (σ) for (a) large and (b) small stores. Normalisation: $y_{\text{nor}} = y/\bar{y} - 1$, μ : mean.

Moreover, in MFB the initiation of constructive search for the development of route networks starts with the selection of the furthest free demand node from the depot. To ensure that selection of the furthest is better than the closest, the constructive search algorithm was executed using both scenarios again while using exactly the same problem. Although the results observed were close, the algorithm selecting the furthest node was found to perform better with the difference in performance to be greater for small stores (see Fig. 5.22).

The outcome of better performance associated with the selection of the furthest node approach is potentially because of the remaining store outliers of a depot being at closer distance proximity to each other when they are clustered in one route. If the starting point is the closest one, the risk of the last ones left unvisited being at a greater relative distance is higher. This is a result of being at a greater radius from the depot compared to what it would have been if all the remaining unvisited ones were also the ones closest to the depot. The greater difference in small stores was potentially due to their lower demand and therefore the probability of more than one node being included in each route.

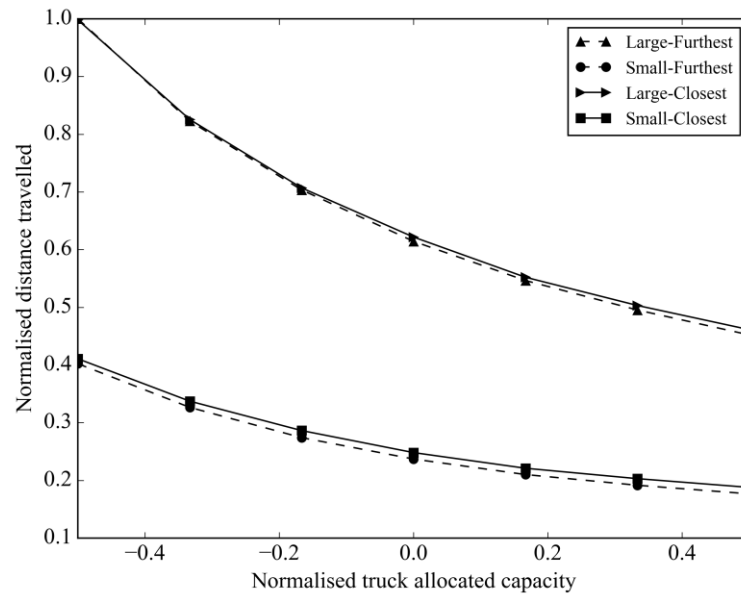


Figure 5.22. Normalised distance travelled ($y_{\text{nor}} = y/y_{\max\{K,U\}}$) against truck capacity for small and large stores using closest and furthest node for initiation of distribution network development.

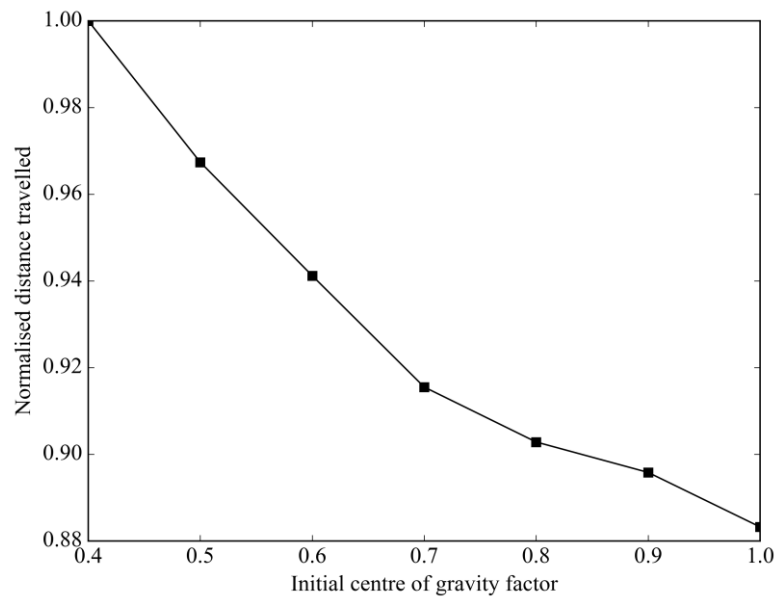
The constructive search algorithm in MFB also relies on the arbitrary input of initial centre of gravity factor ($ICOG$) which is necessary for determining the initial centre of gravity ($COG = ICOG \cdot (x, y)$) for each route construction (see Fig. 3.14). Since this factor is expected to have an impact on the outputs, the algorithm was tested against different values to study its impact through the quantification of the variation in results. Also, the outcome of this analysis can provide the most appropriate value for the specific problem. This is expected to vary between systems and case studies, therefore it can be a good practice to do this exercise prior to main optimisation and analysis.

This exercise indicated the improvement in system performance for both types of stores as $ICOG$ approached one (see Figs 5.23a and 5.23b for large and small stores respectively).

Interestingly, a greater gradient was observed from low to medium *ICOG* values; thus showing greater incremental improvement. Although both cases showed a monotonous decreasing trend, the effect on small stores was noted to be overall greater as they approached the value of one. For small stores an improvement of almost 30% was achieved whereas for large stores the maximum improvement noted was about 12%. This is potentially due to the greater spatial concentration typically associated with small stores and the fact that they are closer to each other as opposed to large stores which are usually more spread out. Therefore, an opportunity to form more compact route clusters when *ICOG* approaches one arises.

Following the observation of optimal *ICOG* being one, this value was used for the simulations and analysis in the present work. It is worth noting that this is still significantly different from selecting the closest second node as with every iteration a new node is added to the route and therefore the centre of gravity on which the next selection is based on changes.

(a)



(b)

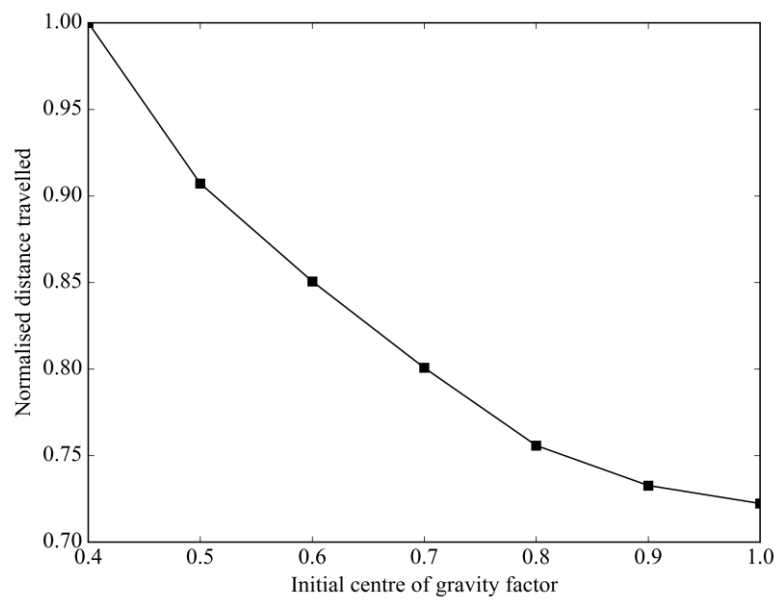


Figure 5.23. Initial centre of gravity factor ($COG = ICOG \cdot (x, y)$) and normalised annual distance travelled ($y_{nor} = y/y_{max}$) relation for (a) large and (b) small stores.

Lastly, as discussed in Chapter 3, the total travel distance and delivery time required for the satisfaction of all demand nodes in a route can be affected by the direction of travel. While considering again the same problem and parameters, the difference between optimal and worst direction of travel was examined against different travel speeds (see Fig. 5.24); stops at each node were assumed to last one hour. Benefits in total time from using the optimal route for each route at each time step were obvious for both types of stores at all travel speeds. This indicates the benefits in considering the direction of travel even in a symmetric problem. Furthermore, the difference between the two directions of travel was noted to be significantly affected by the speed of travel, particularly at lower speeds. Interestingly, the benefit of small stores was observed to be marginally greater than large stores at all speeds.

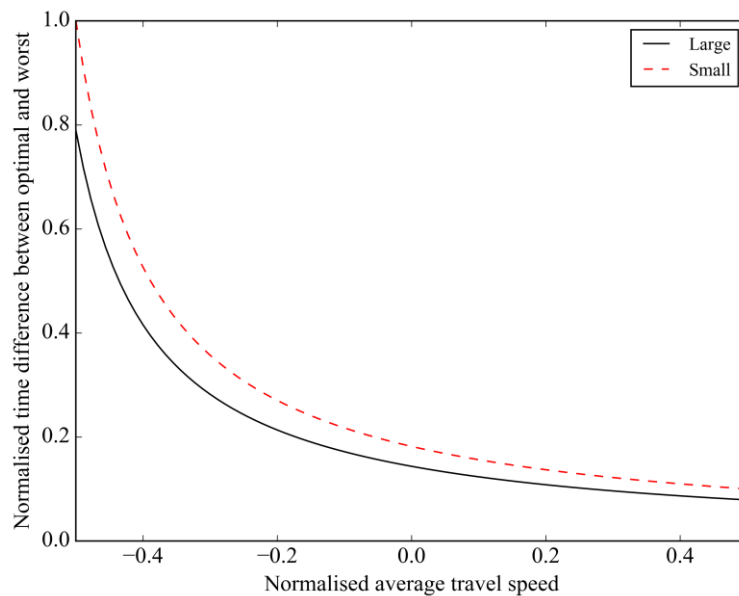


Figure 5.24. Effect of choosing time optimal route against worst route on the normalised average ($y_{\text{nor}} = y/y_{\max\{K,U\}}$) time difference for delivery to last node in route for small and large stores.

5.4 Comparison of modelling frameworks

Modelling frameworks A (MFA) and B (MFB), described in Chapter 3, were compared in terms of performance. This was a useful exercise to gain a better understanding of potential benefits associated with more complicated frameworks, such as MFB, which employ more processing stages.

The comparison was based on average annual travel distance at different allocated vehicle capacities for each type of stores, small and large (see Fig. 5.25). Interestingly, the results showed that the relative difference between the frameworks varied depending on the allocated vehicle capacity. More specifically, at low capacities both models showed similar results while their difference was observed to grow as capacity increased. Furthermore, at low capacities a steep negative slope was observed for both types of stores for both frameworks. This indicates the potential benefits in annual mileage by increasing vehicle capacities, especially along the low to medium range.

A monotonous decrease in average annual travel distance was observed for both small and large stores in framework MFB. However, in the case of small stores, framework MFA showed an increase in annual travel distance with the increase in vehicle capacity over the +ve deviation from the nominal. For large stores, the effect was found to diminish over the equivalent capacities.

Generally, the two frameworks showed similar performance in low vehicle capacities. Towards the medium to high end range, however, MFB's better performance was clearly distinguishable with the performance difference growing as capacity increased. This is potentially as a result of the greater number of nodes in routes as capacity increases. Subsequently, there is greater

opportunity for taking advantage of the benefits associated with features of MFB, including the clustering technique for the allocation optimisation, the centre of gravity approach for the constructive search for route development, and the travelling salesman problem combinatorial optimisation for routing sequence.

Furthermore, emissions and fuel costs are expected to be proportional to distance travelled (not necessarily directly proportional). Therefore, the comparison between the two frameworks is expected to be similar in terms of those performance indicators.

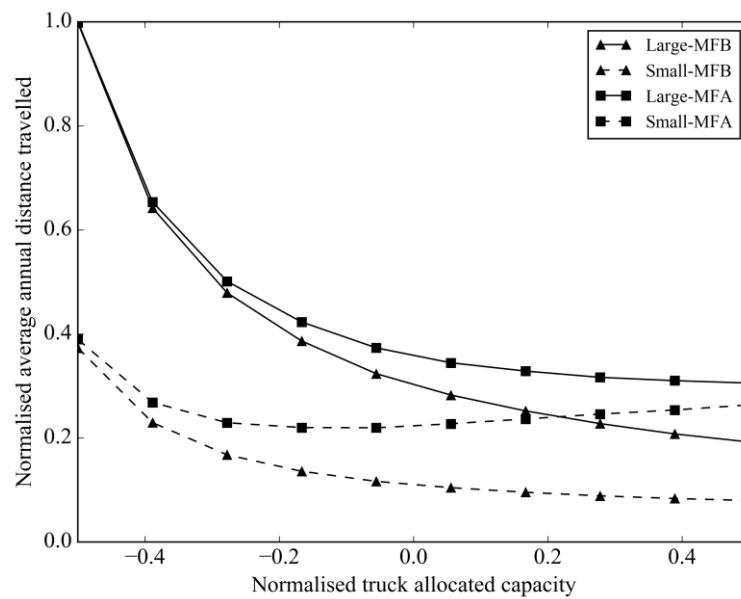


Figure 5.25. Normalised average annual travel distance ($y_{\text{nor}} = y/y_{\max\{K,U\}}$) against truck capacity for small and large stores using the two modelling frameworks. MFA: modelling framework A, MFB: modelling framework B.

Another important performance indicator expected to be affected by the vehicle capacity is the capacity utilisation. Thus, it can also be used in assessing and comparing the performance of the two modelling frameworks. Examining this relationship for small and large stores showed the performance similarity between the two frameworks (see Fig. 5.26). Therefore, superiority of any of the frameworks with respect to utilisation capacity was not observed.

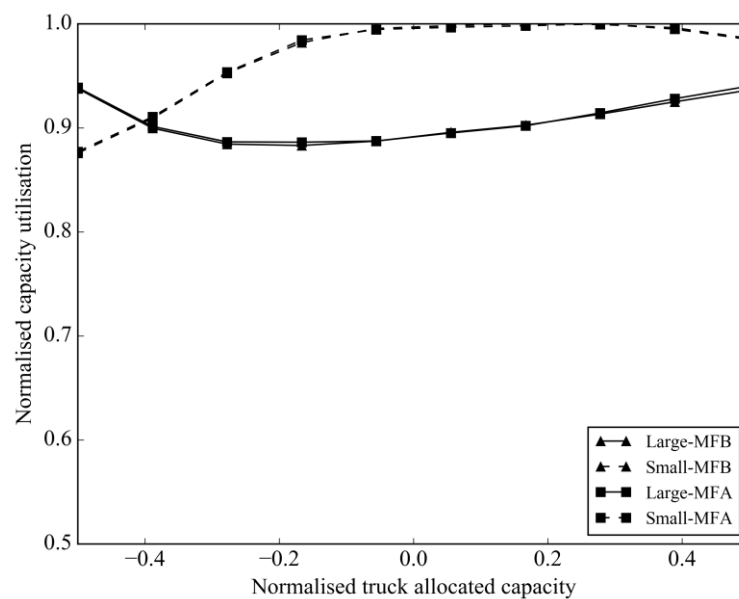


Figure 5.26. Normalised average vehicle capacity utilisation ($y_{\text{nor}} = y/y_{\max\{K,U\}}$) against truck capacity for large and small stores using the two frameworks. MFA: Modelling framework A, MFB: Modelling framework B.

Following the above results it was concluded for this problem that MFB was able to achieve a better outcome than MFA, particularly as flexibility in capacity of vehicles increased, while

not being disadvantageous in terms of capacity utilisation. Therefore, the following sections mainly focus on the application of MFB and analysis based on its outputs.

5.5 Temporal analysis

Logistic networks and their requirements in supply chains can also be affected by seasonality and the demand associated with it when relevant. Even when demand exists throughout the year, its magnitude can still vary depending on the season or even on shorter periods of time. Besides variation in demand, there can also be variation in supply due to seasonality. As a result, an additional dynamic is introduced in the allocation and distribution along supply chains, thus making their smooth operation with minimal temporal variations a challenge. Therefore, it was interesting to study the influence of seasonality on distance travelled, and also identify any potential for improvement at different time steps as well as decreasing the variability between consecutive periods. Achieving these can provide a smoother time series and therefore potentially improve the robustness of the system as well as support a smoother operation. Once again, the performance indicator of travel distance was examined against the impactful parameter of vehicle capacity for each time step in the timeframe.

This temporal analysis involved primarily two aspects relevant to travel distance: (i) the peaks in distance travelled along the timeline, usually associated with high demand periods, and (ii) the difference in travel distance between consecutive time steps. At the low capacity vehicle option, a great variability was noted along the timeline as well as between consecutive time steps for both types of stores (see Fig. 5.27 for small stores and Fig. 5.28 for large stores). The rise in distance travelled in the year mainly occurs during high demand periods which result to less number of demand nodes being included in each route. This shows the potential usefulness of tools and modelling frameworks, like the ones presented here, to be able to anticipate

variations in resource requirements and plan accordingly while accounting for the overall system performance. As mentioned earlier, the minimisation of variations, both in absolute and relative terms, can be desirable for enhancing the system's stability.

As a result of the increase in vehicle capacity the following were noted: (i) overall move of travel distance curves to a lower range, (ii) the elimination of extreme points along the timeline which typically occurred at peak demand periods, and (iii) the reduction in variation between consecutive time steps. Therefore, the potential for achieving a smother distribution network in terms of product transportation while minimising the impact of seasonality was noted.

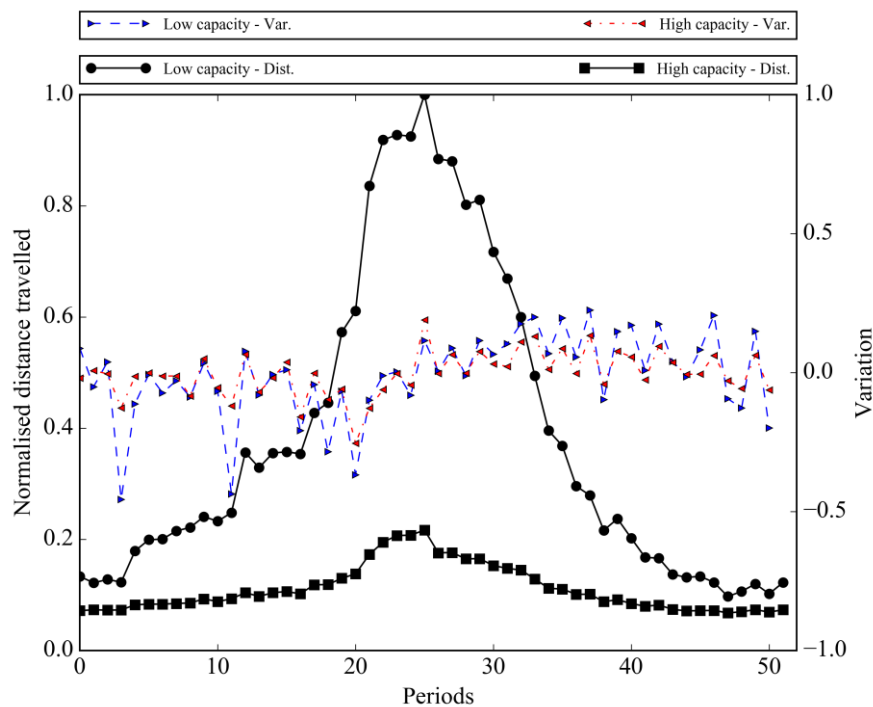


Figure 5.27. Small stores: temporal variation of, and the effect of vehicle capacity on, normalised ($y_{\text{nor}} = y/y_{\text{max}}$) average annual distance travelled for each period and variation in travel distance between consecutive periods.

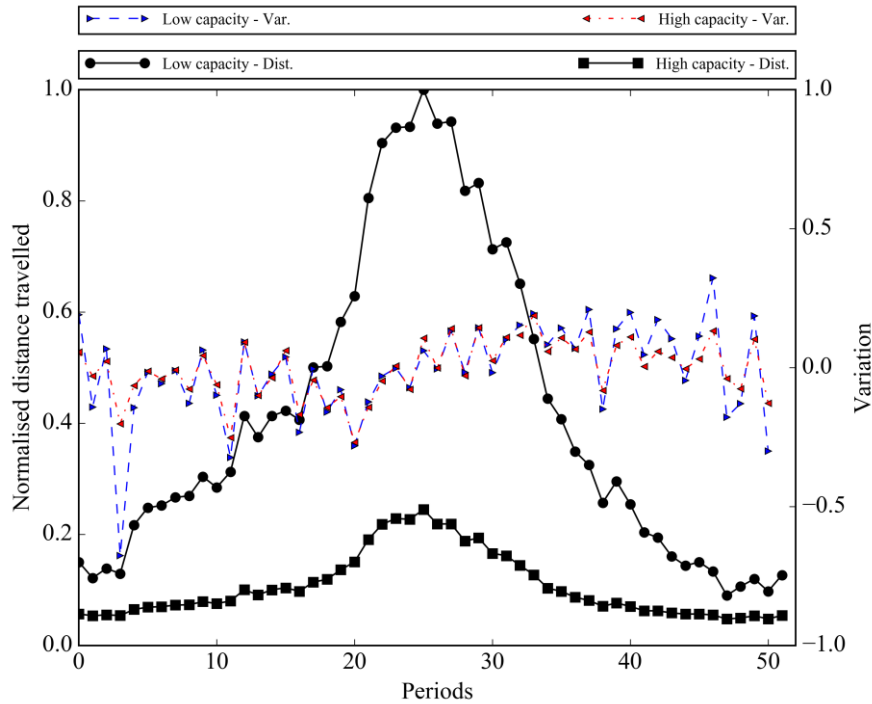


Figure 5.28. Large stores: temporal variation of, and the effect of vehicle capacity on, normalised ($y_{\text{nor}} = y/y_{\text{max}}$) average annual distance travelled for each period and variation in distance travel between consecutive periods.

Furthermore, seasonality might affect the performance of the system in terms of vehicle capacity utilisation. Therefore, it was vital to assess the risk of negatively impacting the capacity utilisation when vehicle capacity was increased, particularly at low demand periods. Results from the same problem as above indicated an increase in capacity utilisation during most periods along the timeline when vehicle capacity increased for small stores (see Fig. 5.29). On the other hand, there were occasions, mostly during low demand periods, when utilisation dropped. Interestingly, for large stores, an almost reverse situation from the small stores was

observed (Fig. 5.30). In other words, capacity utilisation during most of periods increased while a decrease was noted during peak demand periods. A potential explanation to this might be the better match of demand associated with individual demand nodes. Also, for both small and large stores an increase in the temporal mean utilisation was observed with the increase in vehicle capacity, while the improvement was more obvious for large stores.

Following the above findings and their indication of the benefits in terms of distance travelled and capacity utilisation for both small and large stores, the conclusion that these performance indicators are not mutually exclusive can be drawn. Therefore, both metrics can be potentially improved by increasing vehicle capacity.

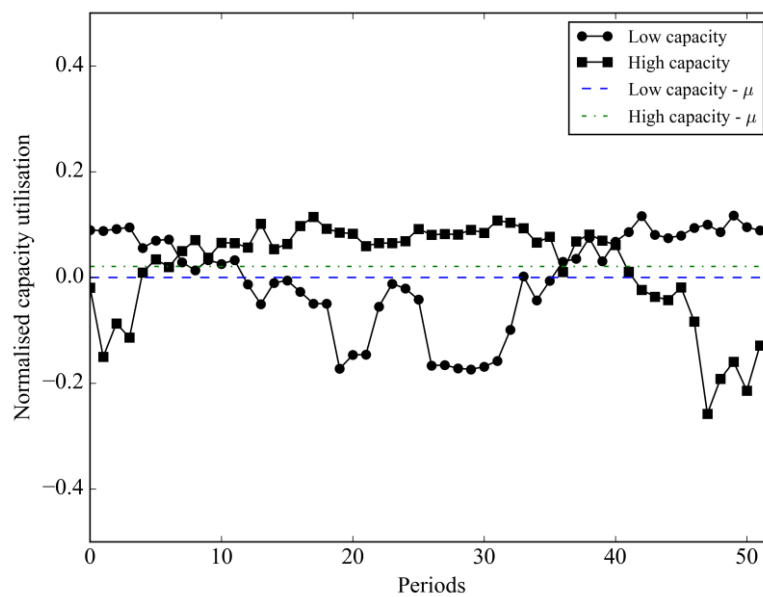


Figure 5.29. Small stores: temporal variation of, and the effect of vehicle capacity on, normalised ($y_{\text{nor}} = y/y_{\text{max}}$) average capacity utilisation for each period and the annual mean (μ) capacity utilisation.

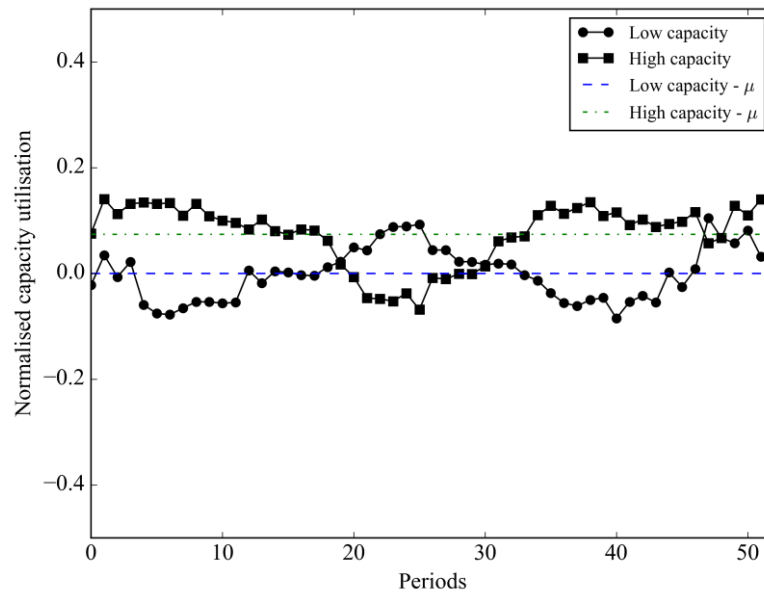


Figure 5.30. Large stores: temporal variation of, and the effect of vehicle capacity on, normalised ($y_{\text{nor}} = y/y_{\text{max}}$) average capacity utilisation for each period and the annual mean (μ) capacity for large stores.

5.6 Demand uncertainty

Although demand forecasts can be based on historical data, various aspects (e.g. weather) are expected to influence demand and result to necessary adaptations to the system operation. As highlighted by Tsiakis et al. (2001), demand can be a source of uncertainty in supply chains. In the case of products associated with seasonality and frequent fluctuations in demand due to uncontrollable external factors, this uncertainty can be of particular interest. Therefore, the design of distribution networks while considering the effect of inevitable variations in demand and aspects that can minimise its impact on performance was interesting to explore. The

reduction of demand influence can potentially improve the robustness of the system. Subsequently, the impact of demand on the overall performance of the system was examined. In order for the model to accommodate this, it was designed to allow the input of a demand factor which can be employed to alter demand levels when needed; thus enabling a sensitivity analysis capability. In this exercise, demands were modified by using this capability of the model with the overriding aim of performing a scenario planning approach (Tsiakis et al., 2001).

This exercise involved the variation of demand to a positive (double) and negative (half) from the nominal demand while observing the effect on annual travel distance for both types of stores (see Fig. 5.31). Large stores were found to be impacted to much a greater degree than small stores, something that can be observed by the corresponding curves' gradients. Interestingly, these gradients can be significantly reduced for both small and large stores through the increase of vehicle capacity. Consequently, travel distance was impacted more by demand variations when vehicle capacity was lower. When capacity was higher, however, besides having substantially lower travel distance, the influence of the demand factor was weakened. Therefore, a more resilient system in terms of transportation requirements against demand variations can be potentially achieved by increasing the capacity of vehicles.

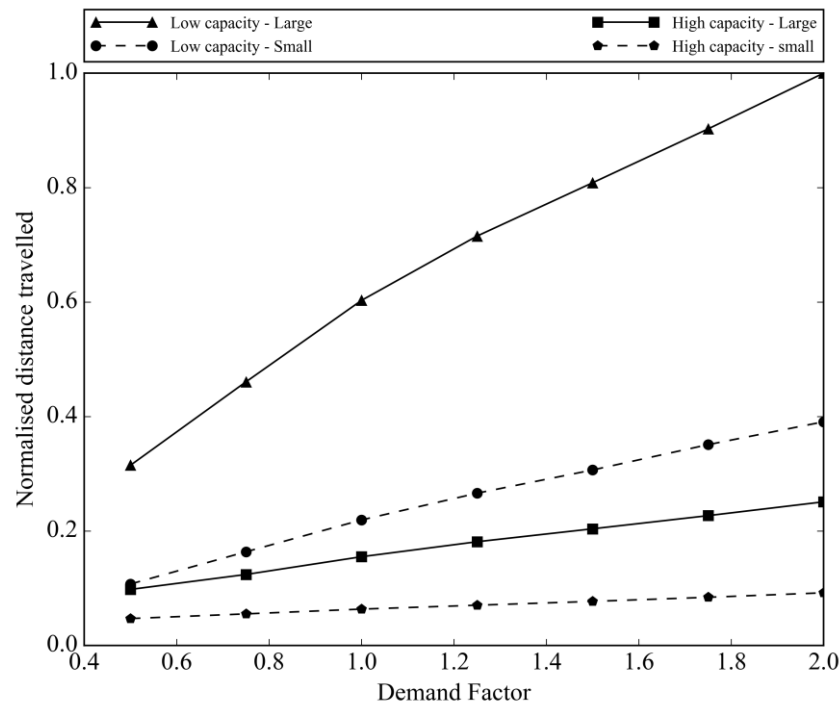


Figure 5.31. Effect of demand variation on annual average distance travelled at different vehicle capacities for small and large stores.

5.7 Number of stops and delivery time

Another important factor in a routing problem is the number of stops as it can represent the number of stores visited along with the additional emissions usually associated with multiple drops. An analysis of the system for a timeframe of one year showed that small stores, in most cases (of time steps), involve a greater average number of stops than large stores (Fig. 5.32). Additionally, a much greater variation in average number of stops over different seasons was noted for small stores whereas large stores were found to be considerably more stable throughout the year.

In terms of total number of stops for each time step (Fig. 5.33), small stores were associated with less stops than large stores. This can be a result of the greater demand and the cases in which more than one trip is required by large stores to satisfy their needs, particularly at peak demand periods. In contrast to the average number of stops, the total number was observed to be considerably more stable along the timeline for small stores. Therefore, in this way, small stores can be more resilient against demand profiles and seasonality as opposed to large stores which showed greater variability towards the temporal aspect.

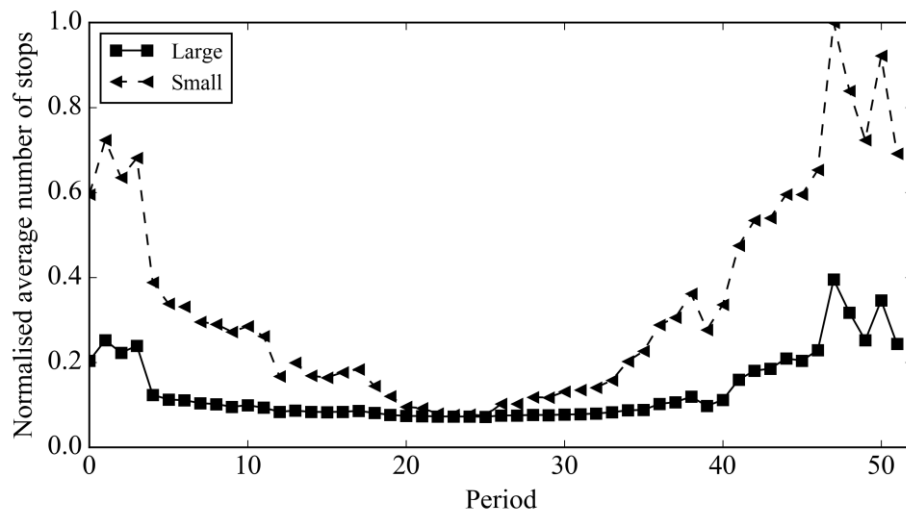


Figure 5.32. Normalised ($y_{\text{nor}} = y/y_{\max\{k,u\}}$) average number of stops in routes for each period for small and large stores.

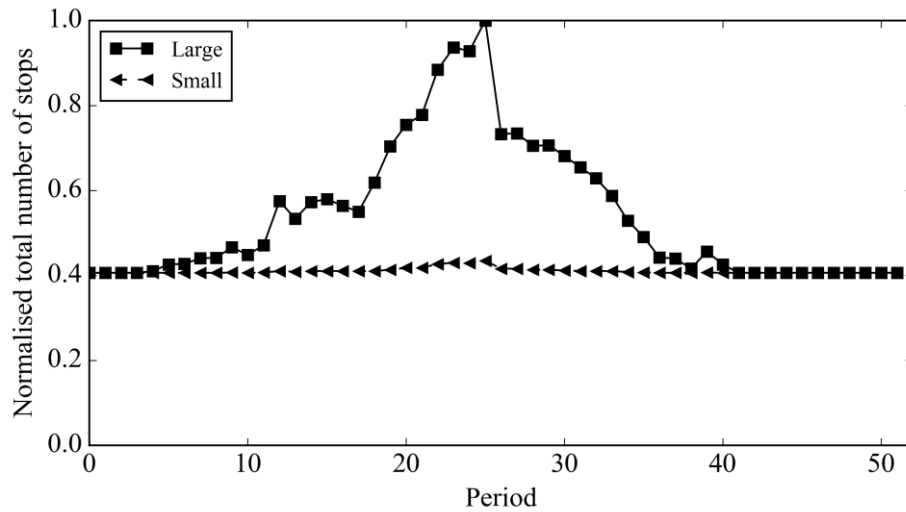


Figure 5.33. Normalised ($y_{\text{nor}} = y/y_{\max\{K,U\}}$) total number of stops for each period for small and large stores.

In terms of average number of stops associated with each depot in the supply chain, a significant difference between the depots was observed, specifically in the case of small stores (see Fig. 5.34). This is expected to be partly due to the spatial orientation and demand of the stores that each depot is selected by the model to serve. Also, a difference between the two types of stores was noted for each depot while some showed significant dependence on one of the two types and others showed relatively similar distribution.

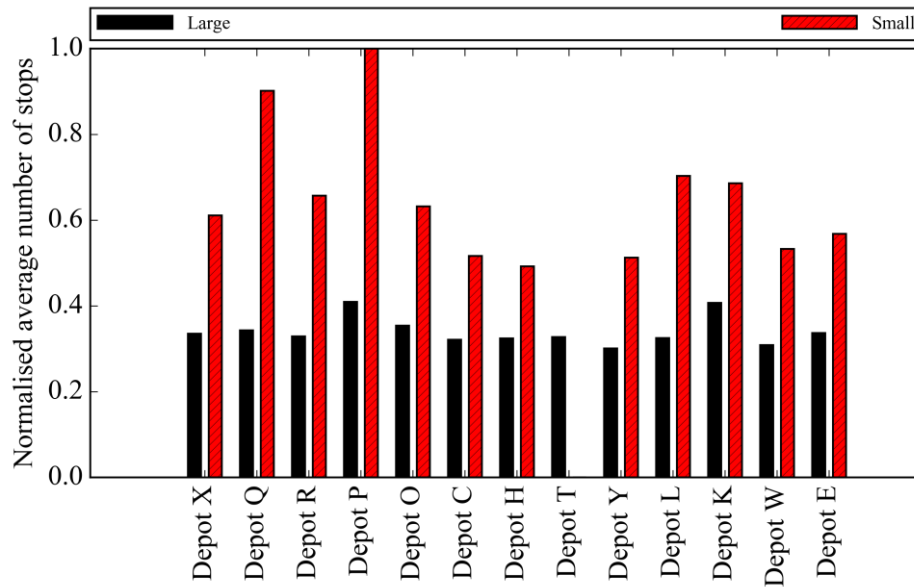


Figure 5.34. Normalised ($y_{\text{nor}} = y/y_{\max\{K,U\}}$) average number of stops in routes for each depot for small and large stores.

With respect to total number of stops, a different distribution to the average number of stops was observed (see Fig. 5.35). Here, the large stores in most cases dominated the number of stops as opposed to the average number of stops. Also, the difference between the depots was in this case greater than in the average case; thus showing the impact of product volume distributed by the different depots.

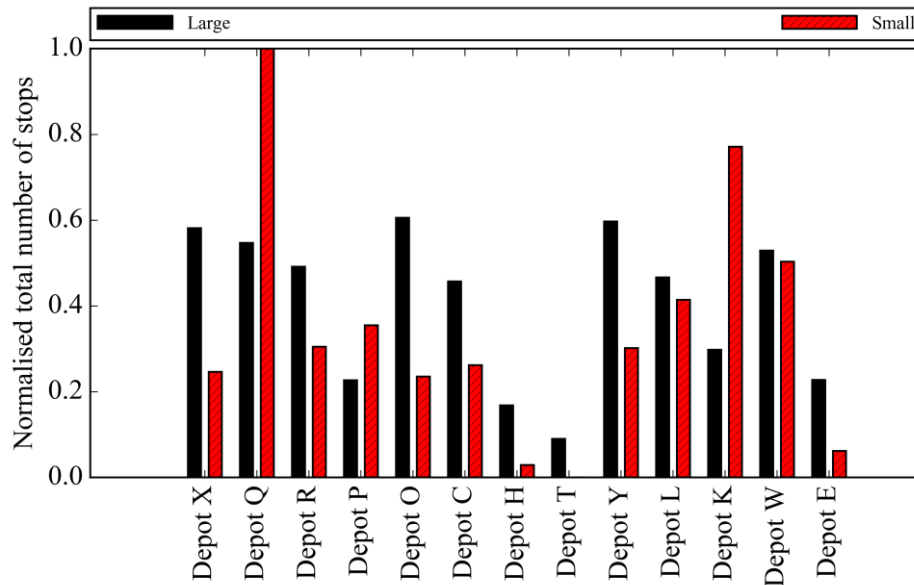


Figure 5.35. Normalised ($y_{\text{nor}} = y/y_{\max\{K,U\}}$) total number of stops for each depot for small and large stores.

In terms of average travel time, an analysis for each route of each depot and each period was performed. Furthermore, an analysis in terms of total travel time in a year again for each depot and each period for both types of stores was conducted. Both of these metrics can be insightful, particularly when the impact of delivery time on the quality of the product and the minimisation of waste are of interest. In addition, these indicators can have an impact on system performance due to economic reasons associated with aspects such as labour cost, resources requirements and satisfying delivery time slots.

The average time for each route was found to greatly vary depending on the depot while in most cases small stores were found to be associated with longer times. Regarding the variation between periods, a similar situation to the one observed above for the average number of stops

(i.e. greater variation for small stores and therefore greater dependency of the product's demand profile curve) was observed (see Fig. 5.36).

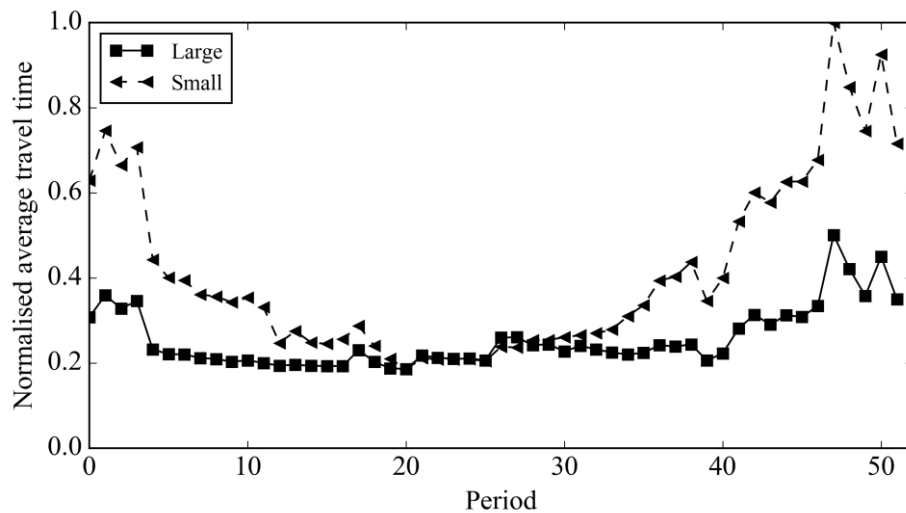


Figure 5.36. Normalised ($y_{\text{nor}} = y/y_{\max\{K,U\}}$) average travel time in routes for each period for small and large stores.

Likewise, the total time associated with different periods was found to greatly vary while in most periods greater values were associated with large stores (see Fig. 5.37). Also, large stores showed greater variability correlating more to the product's demand profile than small stores. Nevertheless, small stores were still found to be affected by the temporal aspect more than what was observed in terms of total number of stops (see Fig. 5.38).

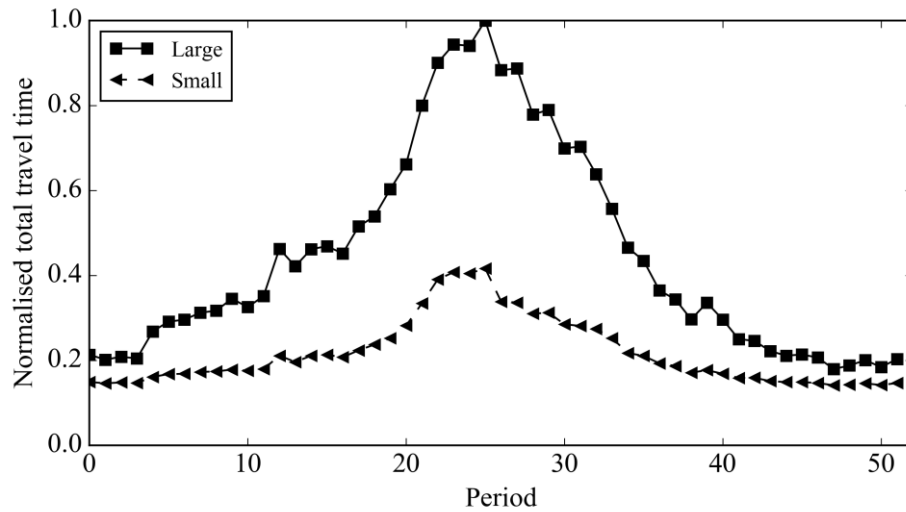


Figure 5.37. Normalised ($y_{\text{nor}} = y/y_{\max\{K,U\}}$) total travel time in routes for each period for small and large stores.

In the case of average time for each depot, similar to the number of stops, a difference was noted between the depots (Fig. 5.38); especially when looking some cases in the upper and lower limits. However, in this case, the difference observed between small and large stores was significantly smaller in most cases. Hence, a more equal share in terms of time resources between the two types of stores was noted.

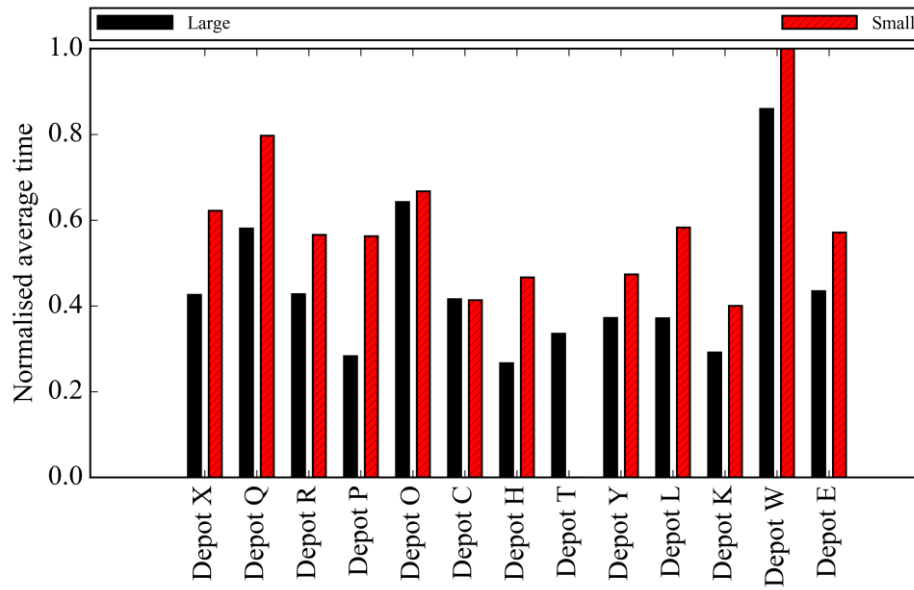


Figure 5.38. Normalised ($y_{\text{nor}} = y/y_{\max\{K,U\}}$) average travel time in routes for each depot for small and large stores.

Interestingly, in terms of total time the difference between different depots as well as between types of stores was observed to increase significantly in most cases (Fig. 5.39). This, once again is expected to be due to the difference in distribution volumes allocated to the different depots based on their location.

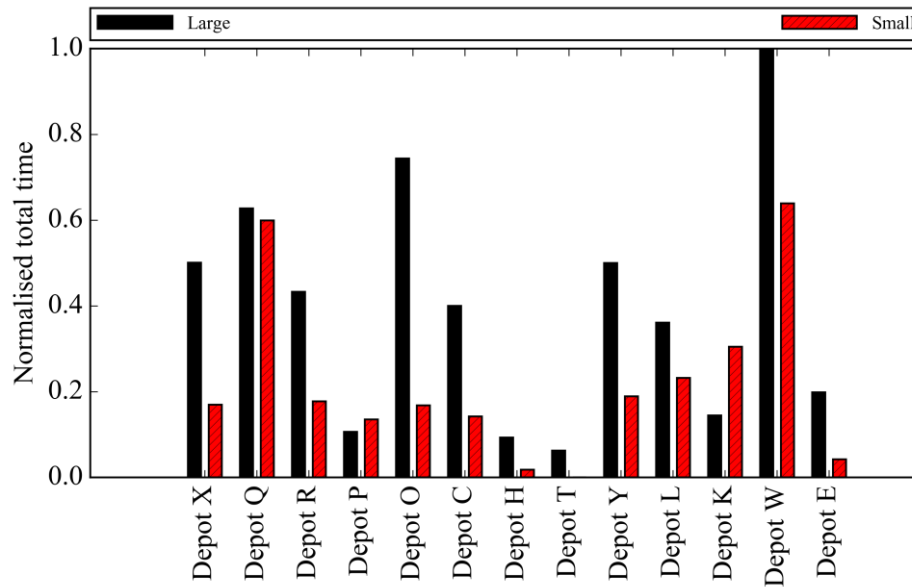


Figure 5.39. Normalised ($y_{\text{nor}} = y/y_{\max\{K,U\}}$) total travel time in routes for each depot for small and large stores.

The sources of the major differences between the depots as well as between stops and time (both average and total) would be interesting to investigate as future work and try to find ways to create a more even distribution or decrease the values of outliers. For example, a way might be to introduce additional depots in key areas if that would decrease the requirements in time resources, stops and distance travelled.

5.8 Depots analysis

This section focuses on the analysis of depots for the second echelon in terms of associated travel distance, volume of product distributed, impact of vehicle capacity, and the difference between the different types of stores. Outcomes of this analysis can contribute to understanding

better the role of different depots in the supply chain and potentially identify opportunities for impactful improvements.

Outputs from MFB for the second echelon showed substantial difference in allocated distance travelled between the different depots (see Fig. 5.40b). However, in terms of product distributed by each depot (see Fig. 5.40a), the distribution was found to be more uniform, resulting to a disproportionality between distance travelled and product handled. A distinctive example was Depot W with 12% of total product allocation and a share of allocated distance travelled more than double (27%). This does not necessarily mean that a depot was performing poorly since the type of demand points, their demand, and their spatial distribution might cause this disproportionality.

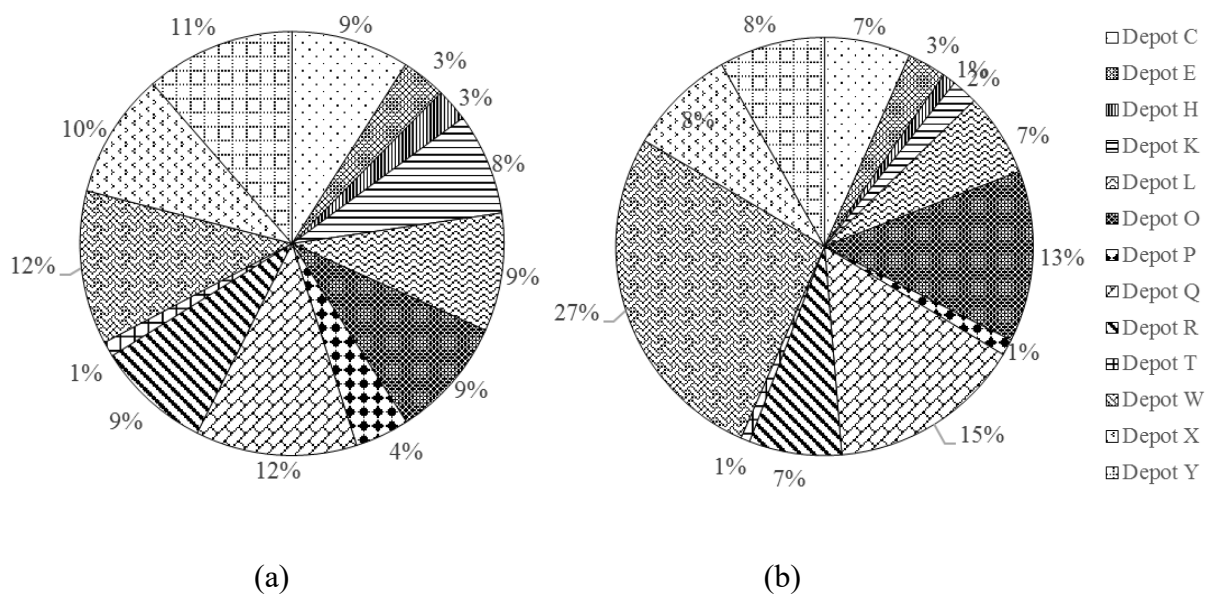


Figure 5.40. (a) Total product volume handled by depots and (b) travel distance from depots to demand nodes.

A clear dominance of some depots in terms of distance travelled was observed (see Fig. 5.40b). This insight can be useful when considering the conversion of the fleet to more sustainable options. However, the distinction between the two types of stores was not shown and therefore, it is possible for that factor to contribute to the observed difference. In other words, some depots might be serving more small stores than large stores (or vice versa) and that can have an impact on the overall share in distance travelled against product volume handled.

Therefore, it was also interesting to see the breakdown of each depot in terms of type of stores it served (Fig. 5.41). This is particularly interesting when decisions depending on the type of stores have to be made. For example, there can be vehicle specification requirements, such as size limitations, which can introduce an additional aspect for consideration. Thus, choosing where to place each type of truck is expected to affect the decision if aspects such as the ones mentioned become relevant.

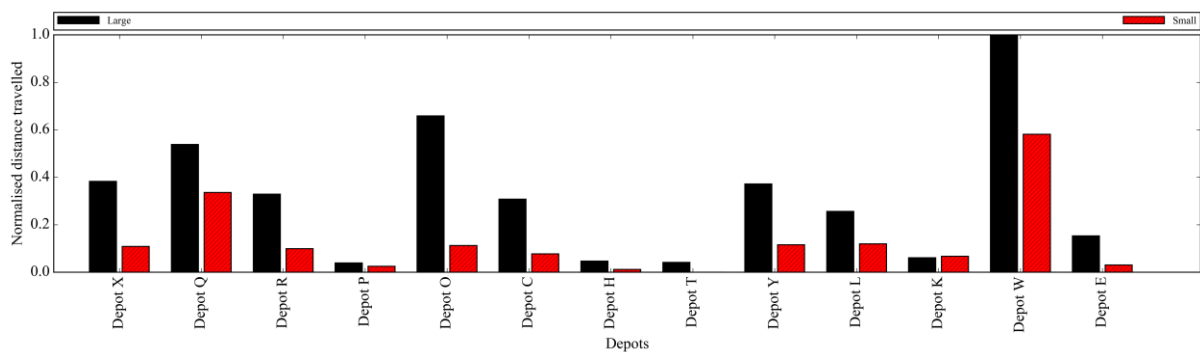


Figure 5.41. Normalised ($y_{\text{nor}} = y/y_{\max\{K,U\}}$) total distance travelled for each depot for each store type.

Once again, the impact of increasing the capacity of vehicles was noted, but this time on each depot for small and large stores (see Figs 5.42 and 5.43 respectively). Interestingly, the impact of increasing the capacity of the vehicles was different between large and small stores for some of the depots. For example, Depot O showed considerably greater improvement in the case of large stores compared to small stores. In general, depots' distribution networks associated with large stores were found to benefit more from the increase of vehicle capacity than the equivalent networks of small stores. This can act as a driver for prioritising distribution networks and/or vehicle fleet sections which could be addressed to achieve a more impactful improvement.

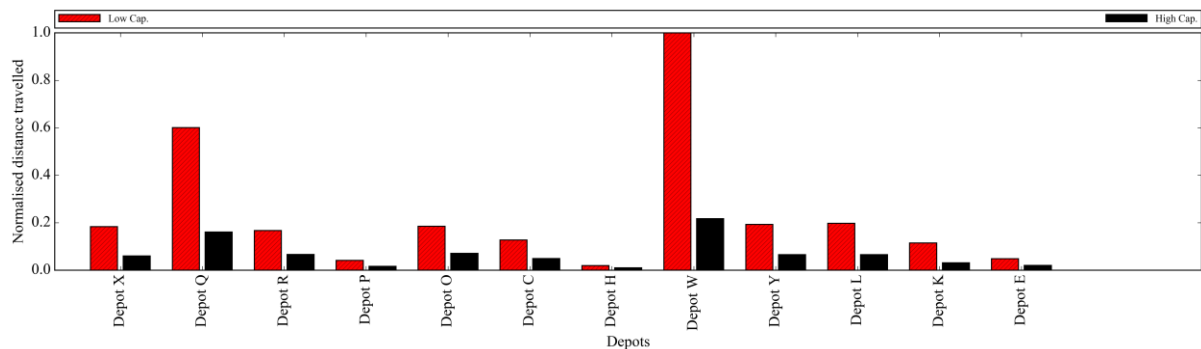


Figure 5.42. Normalised ($y_{\text{nor}} = y/y_{\max\{K,U\}}$) total distance travelled for each depot for small stores at low and high vehicle capacities.

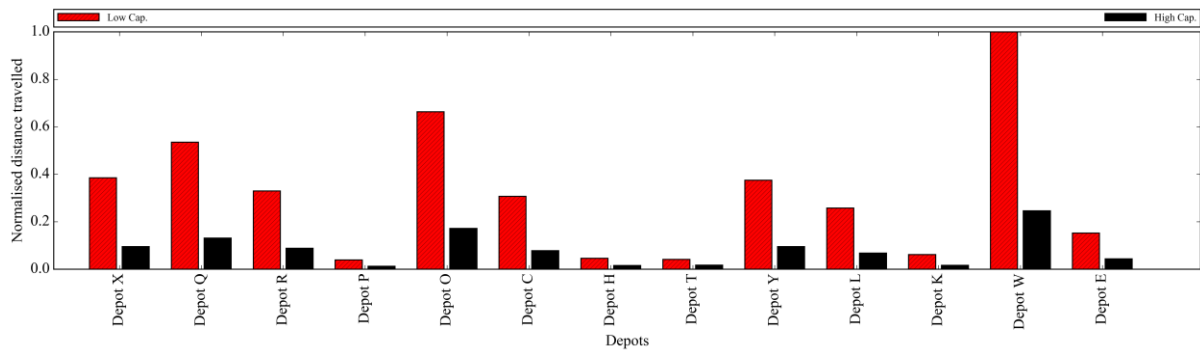


Figure 5.43. Normalised ($y_{\text{nor}} = y/y_{\text{max}\{K,U\}}$) total distance travelled for each depot for large stores at low and high vehicle capacities.

5.9 Carbon emissions and fuel cost analysis

Literature and industry have been increasingly interested in the environmental impact of supply chains. Some potential benefits that could be attained by increasing vehicle capacity were highlighted in the previous sections. However, emission factors provided by DECC and DEFRA (2016) show the possibility of absolute emissions increasing as a result of higher emission factors introduced due to increased weight. It was, therefore, interesting to examine the trade-off between potential emission savings due to decrease in travel distance and emissions increase due to increased carbon factors resulting from greater weight.

Results from the model indicated the significant decrease in carbon emissions in spite of the increased carbon factors (Fig. 5.44). The trend followed by the curves in Fig. 5.44 share a similar trend to the one observed when the independent variable was annual mileage. Therefore, benefits of the reduction in travel distance clearly dominated. This indicated that increase in carbon factors as a result of greater weight can have a minor negative impact relative

to the improvement that can be achieved by optimising the system based on a greater vehicle capacity.

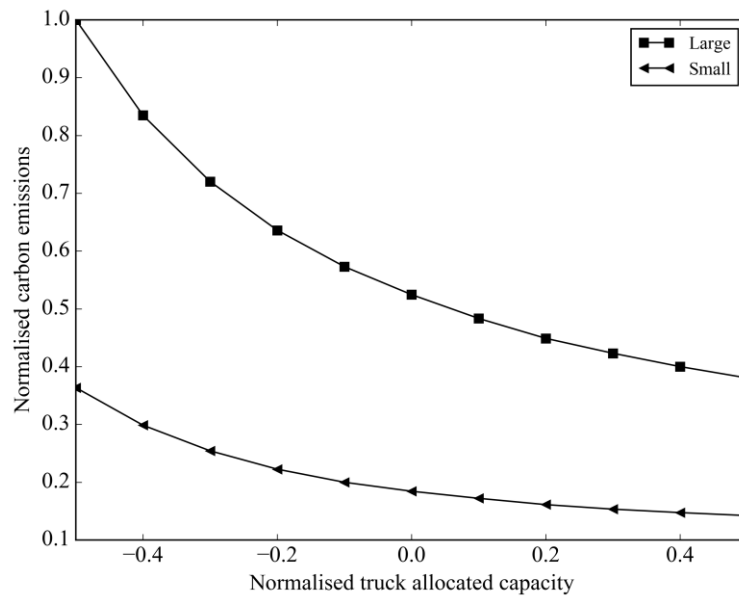


Figure 5.44. Normalised average carbon emissions ($y_{\text{nor}} = y/y_{\max\{K,U\}}$) against truck capacity for small and large stores using modelling framework B (MFB).

If it is assumed that the variation in emissions with respect to vehicle capacity is directly proportional to fuel consumption, the relationship between fuel cost and vehicle capacity can be evaluated as well.

The immediate and entire conversion of a fleet to an alternative technology or fuel is very uncommon. A more realistic and practical scenario in an industrial setting would be the gradual shift of the fleet while matching the end of vehicles' lifetime. Therefore, here, the effect of

such gradual replacement while assuming a hypothetical replacement rate of 20% was tested for this transportation stage (see Figs 5.45 and 5.46 for emissions and fuel costs respectively). The factors used for the key performance indicators associated with each fuel and technology were derived based on the carbon factors available in DECC and DEFRA (2016) for carbon emissions, and cost factors available in Clean Cities U.S. Department of Energy (2018) for fuel costs.

In terms of carbon emissions, the most effective options were found to be the replacement of diesel fuelled vehicles with ethanol (E85) or biodiesel (see Fig. 5.45). Over the period of 10 years, with about 90% of the total fleet replaced, a reduction of around 70% and almost 90% was observed for ethanol (E85) and biodiesel respectively. LNG also showed potential for significant emissions savings but at a considerably lower level and rate, showing a possible reduction of slightly more than 20% in the 10-year period. This analysis assumes constant carbon factors over the timeline. An extension of this analysis could be the study of how possible changes in carbon factors can affect the outcomes and potential for carbon savings.

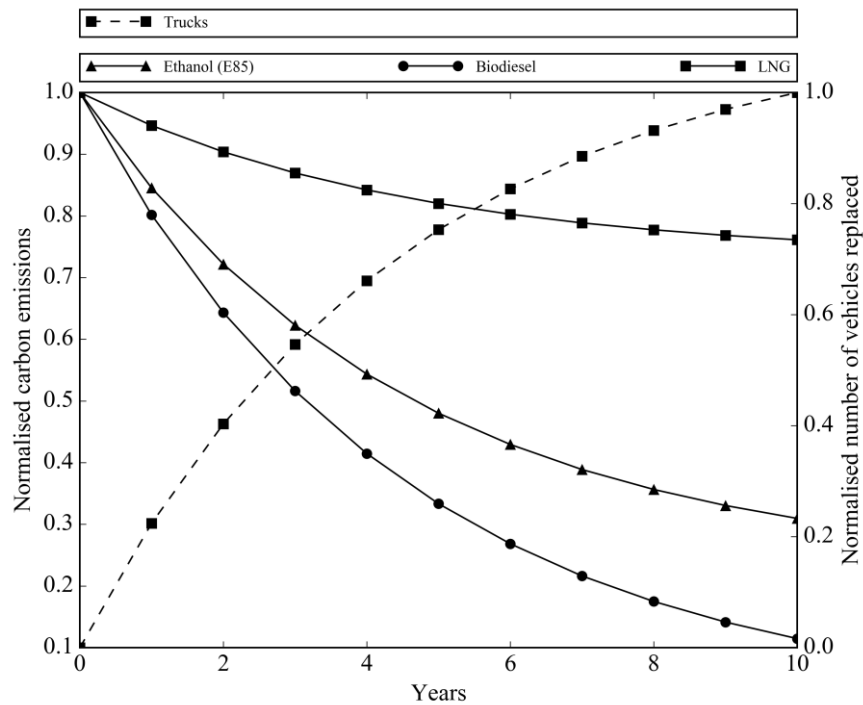


Figure 5.45. Normalised annual carbon emissions with gradual replacement of vehicles in fleet from diesel fuel to alternative fuels (biodiesel, ethanol (E85), LNG) at a rate of 20% of remaining fleet per year, and number of vehicles replaced.

The equivalent analysis was also done with respect to transport fuel costs. Similar to the emissions analysis, constant fuel prices were assumed over the timeline (Fig. 5.46). This is supported by: (i) the assumption that the relative difference between fuel prices will not change significantly over the years, and (ii) the fact that the primary interest here was the relative difference between the options. Nevertheless, drastic changes in policy or other external factors might have an impact on fuel prices. However, such predictions are very difficult to make and are out of scope of the present study. Outputs from this exercise showed a slight increase in fuel costs as vehicles switched from diesel to ethanol (E85) while biodiesel showed a more

rapid increase. LNG, however, was found to monotonically decrease as the vehicles gradually switched to this option.

A combination of the findings from the emissions and fuel costs analysis indicated ethanol (E85) to be most competitive solution as it achieved significant carbon reductions without incurring a substantial increase in fuel costs. It is worth noting that in this analysis other costs that might be associated with the transition to alternative technologies and fuels were not considered.

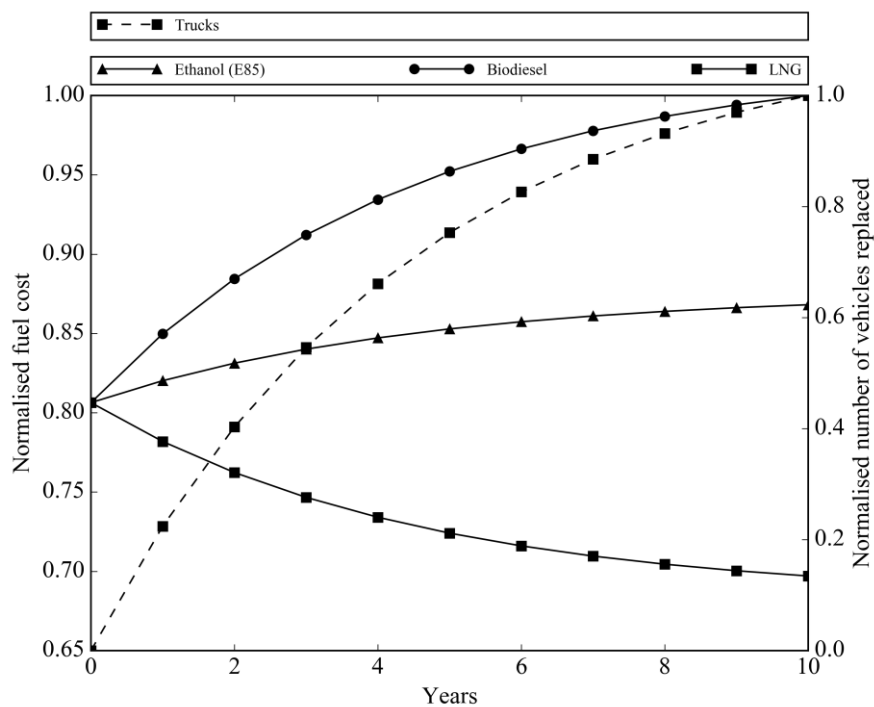


Figure 5.46. Normalised annual fuel cost with gradual replacement of vehicles in fleet from diesel fuel to alternative fuels (biodiesel, ethanol (E85), LNG) at a rate of 20% of remaining fleet per year, and number of vehicles replaced.

5.10 Summary

This chapter studied the optimisation of multi-echelon supply chains through modelling frameworks which use hybrid approaches employing deterministic and heuristic techniques. Two modelling frameworks were presented and compared while most of the results were focused on the one found to have a better performance. The frameworks initially design the supply chain network through deterministic optimisation in order to allocate/assign supply nodes and demand nodes to depots. Thereafter, a series of stages involving heuristic approaches, and in some cases combinatorial optimisation techniques, are used to develop the distribution networks and routing sequences over the time steps for the satisfaction of demand at the different types of stores.

The modelling frameworks can be used as a tool for designing the allocation and distribution of supply chains through a systematic and standardised way while also managing supply and demand. One of the main objectives of the approach was to be kept as generic as possible in order to be applicable to a broad range of supply chains. On the other hand, very specific characteristics associated with some supply chains are not expected to be captured by this method, but perhaps some adaptations to the model can make it possible.

To showcase and study the performance of the frameworks, a case study was used. Main characteristics of the case study that were of interest included the relation of national production and imports, and the temporal and spatial variations of supply/demand throughout the year. The overall demand was observed to vary depending on seasons with a considerably higher demand during the summer periods. The demand was noted to be satisfied by both national production and imports for most of the year. Their distributions, however, were observed to vary seasonally with imports dominating the winter/cold periods and national

production the summer periods. Spatially, it was observed that supply contributions from different regions vary throughout the year. Some regions loosely followed the demand profile while others peaked outside the high demand periods. Furthermore, the (i) number of, and (ii) demand of the different types of stores were seen to be disproportional, with small stores being greater in number but having a lower share in demand.

Initially results from the model for the first transport stage (i.e. transport from suppliers to depots) were studied. The distance travelled and product transported were found to be disproportional for the different regions and depots. This indicates the potential for prioritising efficiency measures where it is expected to have the greatest impact. For example, priority to transport improvements might be given to links associated with greater allocated distance and low volumes whereas facility improvements might be applied to facilities with greater product volume. Furthermore, a great variation on the reliance of depots on different supply regions was noted. While some were found to depend only on a single area, others were found to source their product from up to four regions. This indicates the potential for adopting methods specifically applicable to one region, but also the risks introduced due to low diversity of sources. Similarly, the transport distance corresponding to the fleet of each depot was found to vary significantly based on the supply region. Finally, once again the variation in distribution between national production and imports during different periods was noted. The share between the two was also studied in terms of depots. Interestingly, some depots were chosen by the model to source their product primarily from national production while others from imports, even when the penalty factor associated with imports was equal for all depots. Nevertheless, all depots were found to be associated with some national production and some imports; thus showing the need for both sources. This is due to the demand being present when

no national supply exists as well as when total supply being provided by national production is not sufficient.

Considering the difference in performance between the two modelling frameworks, they were observed to perform similarly at low vehicle capacities. However, as vehicle capacity increased modelling framework B (MFB) was noted to perform substantially better in terms of average annual mileage. Interestingly, this effect was more obvious for small stores.

As discussed above, MFB relies on some arbitrary input decisions. Therefore, an analysis of the effect of these inputs on the outputs from the model was performed along with the derivation of the best values for the specific problem. Findings from this exercise indicated the insignificant effect of the initial randomisation required for the execution of the model as relatively stable results were obtained from a large number of simulations. The initial centre of gravity, however, was found to greatly affect the outputs from the model. Therefore, the importance of testing and training the model to select the most suitable value for the problem in hand was noted.

Furthermore, the effect of vehicle capacity on distance travelled, capacity utilisation, temporal variability, and uncertainty in demand was studied. In addition, the number stops and duration of travel in both average and total terms were evaluated over the temporal dimension. It is worth noting that an increase in capacity does not necessarily equates to an increase the physical size of vehicles, as techniques such as double decked trucks can be used. Various interesting insights were observed from this analysis but, in summary, generally benefits were associated with the increase in vehicle capacity. A reason for this is potentially due to the additional flexibility in the route construction with the increase of vehicle capacity since there

was a lower possibility of a vehicle not being able to accommodate the demand of the next demand node.

Another interesting aspect studied was the difference between the two types of demand nodes in the system, particularly the effect of system parameters on them. Interestingly, results from them were usually significantly different and affected differently by variables. Therefore, it is important in some cases to differentiate the demand notes, especially when characteristics such as demand profiles, demographics, clustering, location relative to each other, and location relative to depots, differ substantially.

In terms of the key performance indicators of fuel costs and carbon emissions associated with the transport stage from depots to stores, MFB was used to quantify the potential for decarbonisation approaches. Firstly, the trade-off between increased weight and reduced mileage was evaluated. It was found that benefits from reducing mileage by increasing vehicle capacity clearly outweighed the effect of increased carbon factors due to increased weight. Furthermore, the potential of decarbonisation was considered through a gradual shift to alternative technologies and transport fuels while considering a hypothetical fleet determined based on the logistical requirements of the system. The relative differences between the solutions considered were in most cases substantial with some being more competitive in terms of fuel costs while others on emissions. Based on the KPI factors assumed in this work, Ethanol (E85) was found to provide a good balance between the two metrics by showing the potential for emissions savings without incurring a significant increase in transport fuel cost.

Contributions from this work include the study of retail intense supply chains with large multi-echelon multi-period problems which are influenced by seasonality and sustainability factors while integrating allocation, distribution and routing problems. Extensive research has been

performed in literature on problems such as VRP (e.g. (Braekers et al., 2016; Dondo and Cerdá, 2007; Erdoğan and Miller-Hooks, 2012; Hadjiconstantinou and Baldacci, 1998)) and several algorithms and methods for solving such problems have been proposed and analysed. They are considered as some of the challenging problems of combinatorial optimisation (Dondo and Cerdá, 2007) and their computational difficulty to solve usually make them very challenging in large problems. Therefore, heuristic approaches are sometimes used to approach them. Heuristic approaches, however, can sometimes significantly vary in terms of accuracy and computational expense (i.e. solving time and required resources). Therefore, the present work aimed to better understand the potential difference in performance between heuristic approaches of different complexity. In addition, several studies have focused on the design of logistic networks while considering aspects such as manufacturing locations (e.g. Tsiakis et al. (2001)). Through the development and study of modelling frameworks and case studies, this work aimed to contribute by bringing together important aspects from different areas such as supply chains' design, supply chains' operation, vehicle routing problems, energy efficiency and decarbonisation. Furthermore, it is also common for studies to present models which are case-specific whose adaptation to variants of the problem is difficult (Braekers et al., 2016). This is absolutely reasonable due to the usual complexity of the problem. Nonetheless, it was useful in the present work to approach the problem with the aim of simplifying and generalising to a certain degree the development and presentation of modelling frameworks in order to be generic and possibly have the ability to be adapted and employed by variants of the problem. This of source comes with several limitations as discussed further later.

The modelling frameworks and methods discussed in this chapter, as expected, have some limitations and the potential for extension is future works. For example, the addition of multi-objective optimisation techniques can expand the capabilities of the frameworks to optimally

address trade-offs between other KPIs. Furthermore, the consideration of inventory control and the associated dynamics can be another interesting avenue for future work. Also, extension of the decarbonisation approaches through the gradual replacement of the fleets to consider other cost factors in addition to fuel cost is another potential work for future studies. Moreover, distance travelled is used in this study as a proxy for fuel consumption which might not always be the case. A study around the correlation between the two could be another interesting avenue for future work. Finally, results presented here are based on a specific problem and its characteristics. Therefore, findings might differ for other problems; thus, the testing of the frameworks on other cases and the comparison between them can be an interesting exercise. Further discussion on some of the limitations of the models and potential avenues for future work can be found in Section 7.2.

5.11 Highlights

- Modelling frameworks were developed as a tool for the systematic design of both allocation and distribution networks of supply chains while being generic enough to allow their application to similar supply chains. The approach followed aimed to contribute in the better understanding of the integration of allocation and distribution along supply chains while incorporating the impact of influential parameters (e.g. vehicle capacity, seasonality) on distance travelled, fuel consumption and carbon emissions.
- The more complex modelling framework B (MFB) showed significantly better performance in minimising travel distance, specifically with the increase in vehicle capacity when delivering to small stores.
- Increasing vehicle capacity was found to have a generally positive effect on travel distance, temporal variability, demand uncertainty, number of stops and travel time. A

neutral effect was observed on the vehicle utilisation capacity showing the absence of significant trade-offs.

- The impact of parameters was found to vary based on the type of store. Therefore, there can be a benefit in differentiating between types of stores when their characteristics are dissimilar; for example, demand profiles, locations, and concentration in areas.
- Annual carbon emissions showed a decrease with the increase in vehicle capacities, even when considering the increase in carbon emissions per unit of distance travelled due to increased weight.

Chapter 6^{§§}

6 Electricity – Retail and storage stages

Electricity is expected to be consumed in most stages of the supply chain. In the case study analysed here, the electricity consumption was mostly associated with the storage and retail stages. Nevertheless, the approach of electricity storage to improve energy efficiency, carbon emissions and energy costs, can be used in most cases and it is therefore widely applicable. It can even be the case that electricity storage is not situated in the operators' existing facilities; thus offsetting energy consumption from existing facilities with new electricity facilities placed in more suitable or advantageous locations. This is particularly useful in terms of practical factors, such as space availability, as well as energy efficiency and economic conditions, such as coupling with renewables or implementation within a supporting marketplace.

^{§§} Parts of this chapter were presented earlier in Georgiou et al. (2019, 2018c, 2018d, 2018b, 2017b).

This chapter focuses on two newly proposed medium to large scale electricity storage systems, the liquid-air energy storage (LAES) and pumped thermal electricity storage (PTES). The analysis is oriented around thermodynamic and economic analyses while employing thermo-economic models of the two systems.

Initially a thermodynamic performance analysis is performed on the two systems validating the LAES model and identifying impactful variables in the systems' technical performance. Then, a thermo-economic analysis follows for both systems both at their intended capacities and at equal capacities. Finally, the potential of carbon savings and the costs expected from achieving those savings from the deployment of the technologies is examined.

6.1 Thermodynamic analysis

The LAES system has been demonstrated at pilot plant scale in the UK at power and energy capacities of 350 KW and 2.5 MWh. Data from the operation of the pilot plant available in literature (Centre for Low Carbon Futures, 2013; Morgan et al., 2015) were used in comparison to the model predictions in this study to validate the thermodynamic model developed. Uncertainties in operational and performance parameters required as model inputs exist. Therefore, these uncertainties were quantified in terms of lower and upper bounds of the outputs from the model. The overall uncertainty was determined from Eq. (6.1) (Holman, 2012).

$$u_R = \left[\left(\frac{\partial R}{\partial x_1} u_1 \right)^2 + \left(\frac{\partial R}{\partial x_2} u_2 \right)^2 + \dots + \left(\frac{\partial R}{\partial x_n} u_n \right)^2 \right]^{1/2} \quad (6.1)$$

Here, $u_1, u_2, \dots, u_n$ represent the uncertainties associated with the n independent input variables used in the model to evaluate u_R which is the overall uncertainty in a specific output.

The pilot plant considered here was the first of a kind (FOAK) and was also tested under varying conditions. Therefore, its modules are expected to have been performing sub-optimally affecting the overall performance of the system. The model was tested based on nominal ('best' guess) values (see Table 6.1) against data from the pilot plant. The system was analysed with respect to: i) the liquefier specific work input against specific cold recycled, ii) system roundtrip efficiency against specific cold recycled, and iii) the gross motor power against temperature at the inlet of the turbine (see Figs 6.1a, 6.1b, 6.1c respectively). The good correlation of the model outputs and the data from the pilot plant operation provided some validation of the model for the conditions tested while also providing some confidence in some of the model outputs when considering variables outside the pilot plant operational conditions range.

Table 6.1. Nominal ('best' guess) values for the LAES pilot plant (350 kW, 2.5 MWh) and nominal values for parametric analysis for LAES plant (12 MW, 50 MWh) model.

Parameter	η_{ct} <i>Cryogenic turbine isentropic efficiency</i>	η_p <i>Cryogenic pump isentropic efficiency</i>	$C_r(1-L)$ <i>Specific waste-cold utilisation (kJ/kg)</i>	η_t <i>Turbine isentropic efficiency</i>	η_c <i>Compressor efficiency</i>	l_p <i>Pressure losses</i>	$P_{p,out}$ <i>Pump outlet pressure (bar)</i>	$T_{t,in}$ <i>Turbine inlet temperatu re (K)</i>
Nominal ('best' guess) values for pilot plant	0.80	0.60	-	0.60	0.80	10%	56	337
Nominal values for parametric analysis	0.85	0.85	170	0.85	0.85	10%	170	393

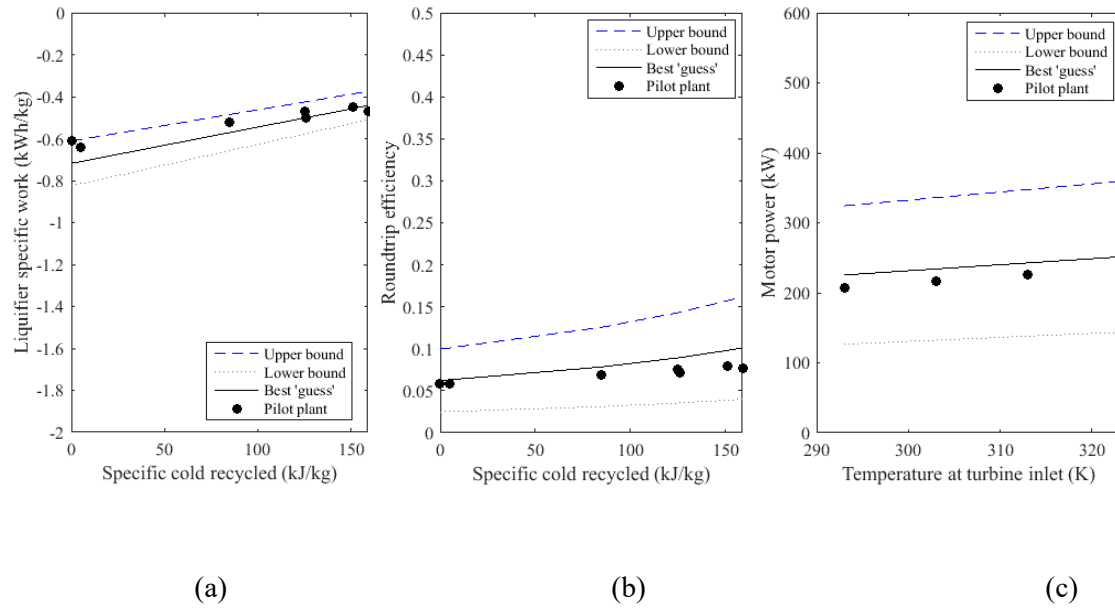
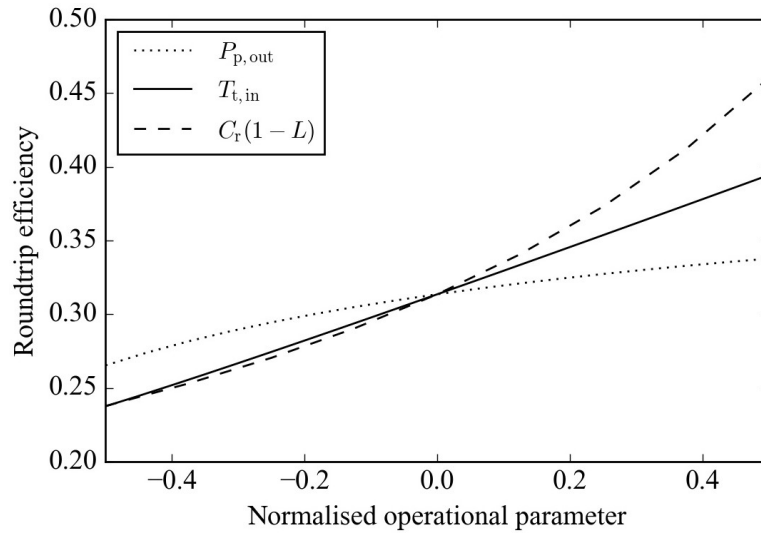


Figure 6.1. Comparison of LAES model outputs against pilot-plant data: (a) liquifier specific work against specific cold recycled, (b) roundtrip efficiency against specific cold recycled (per kg of processed liquid air), (c) gross motor power against temperature at the turbine inlet; based on the model parameters and variables in Table 6.1.

The observed roundtrip efficiency of the LAES pilot plant was low and as mentioned earlier this is expected to be a result of its varying operating conditions and for being FOAK. Nevertheless, the expected roundtrip efficiency can be improved by altering the operational conditions as well as improving the components' performance. Operational conditions can include the cold utilised in the air liquefaction process ($C_r(1 - L)$), the pressure at the outlet of the pump ($P_{p,out}$), and the temperature at the turbine inlet ($T_{t,in}$). Improving the components' performance can include the employment of larger scale and more efficient equipment which operate at their designed conditions. The impact of these aspects on roundtrip efficiency is

presented in Figs 6.2a and 6.2b when varying the tested variable while keeping all the others at their nominal values.

(a)



(b)

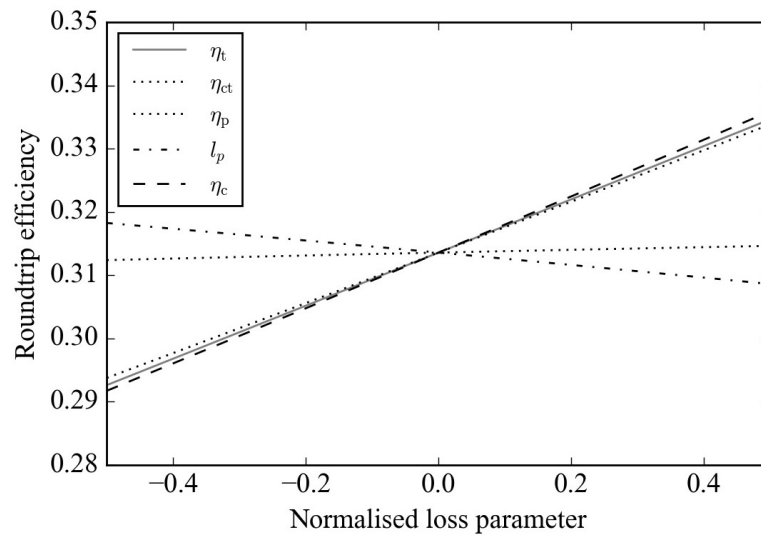


Figure 6.2. LAES roundtrip efficiency against: (a) normalised operational parameters $(y - \bar{y})/(y_{\max} - y_{\min})$, and (b) normalised loss parameters; based on the model parameters and variables in Table 6.1.

In terms of important operational parameters, interestingly, the impact of some parameters was found not to be the same for the positive and the negative deviations from nominal values. More specifically, the parametric analysis presented the dominance of the amount of cold recycled and utilised in the positive deviation from the nominal values. In the negative range, the waste cold and turbine inlet temperature were found to be of great importance and have similar effect on the roundtrip efficiency. The increase of the pump outlet pressure was also found to contribute to higher roundtrip efficiencies but less so.

In terms of performance parameters, the most impactful parameters on the roundtrip efficiency were found to be the compressor's efficiency, the turbine's efficiency in the power generation unit and the efficiency of the cryogenic turbine in the air liquefaction unit. A positive, linear relationship between the efficiencies of these components and the roundtrip efficiency of the system was noted.

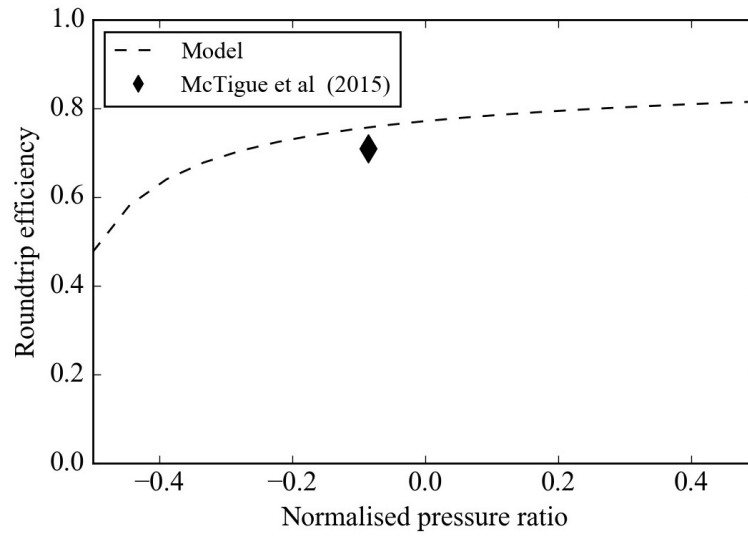
Similar to LAES, the PTES system's roundtrip efficiency is expected to be affected by both operational and loss parameters. Important loss parameters of this technology were studied extensively and presented in literature (see for example McTigue et al. (2015)). A parametric analysis based on nominal values presented on Table 6.2 was performed for PTES as well.

Table 6.2. Nominal PTES plant (2 MW, 11.5 MWh) model values used in the analysis.

Parameter	T_h <i>Hot reservoir discharged state temperature (K)</i>	T_c <i>Cold reservoir discharged state temperatur e (K)</i>	η <i>Compressi on/expansi on devices polytropic efficiency</i>	p <i>Pressure ratio</i>	f_p <i>Pressure losses</i>	g <i>Heat leakage factor</i>
Nominal values	310	310	0.98	11.5	0.02	0.02

An interesting parameter observed through model simulations to be of great influence on the system's performance was the pressure ratio between the two reservoirs. Expectations obtained from the model in terms of net power input and net power output during charge and discharge periods respectively presented a monotonic increase as the pressure ratio increased over the range considered (2.9, 11.5, and 20.0 for minimum, nominal and maximum respectively) (see Fig. 6.3b). Considering also the effect on roundtrip efficiency (Fig. 6.3a), even though the difference between power inputs and output increases with the increase in pressure ratio, the roundtrip efficiency was still noted to increase monotonically with the increase in pressure ratio. Nonetheless, the effect of pressure ratio was found to significantly differ between the negative and positive deviation from the nominal. The benefit of increasing the pressure ratio in the negative range was found to be substantially greater with the effect of pressure ratio diminishing at the higher end. More specifically, the greatest benefit was noted in the extreme negative end with an expected relative increase in roundtrip efficiency of about 50% (around 20% absolute) by increasing the normalised pressure ratio by just 0.17. Therefore, the benefit in increasing the pressure ratio over some level might be offset by other factors, such as material strength requirements and additional costs involved, that need to be considered in a cost-benefit optimisation exercise.

(a)



(b)

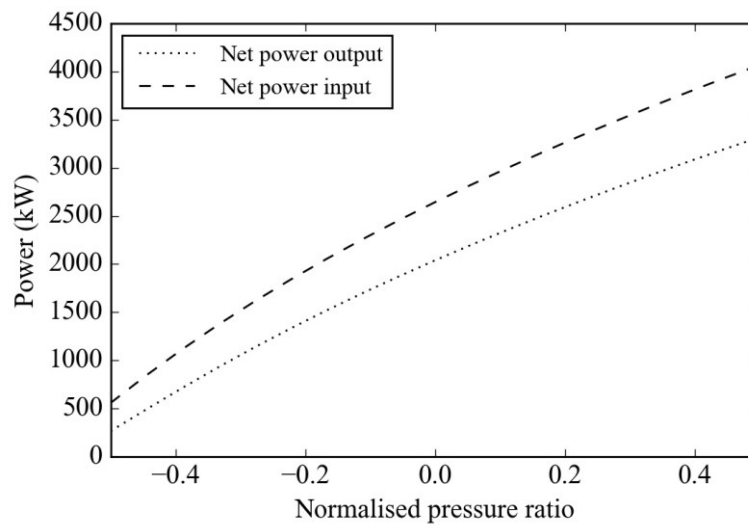


Figure 6.3. PTES: (a) roundtrip efficiency against normalised pressure ratio from the model (also showing a comparison to a result from McTigue et al (2015)), (b) net power input and net power output against normalised pressure ratio, $(y - \bar{y})/(y_{\max} - y_{\min})$; based on the model parameters and variables in Table 6.2.

The roundtrip efficiency of this system was found to be very promising, reaching efficiencies of up to ~80% at high pressure ratios. Nevertheless, these estimates assume the use of component and performances of those components that need to be developed and proven in an industrial setting (McTigue et al., 2015). Also, in a more sophisticated model more losses that might contribute to a lower roundtrip efficiency can be accounted for, such as heat losses to the environment due to prolonged storage times. This was not considered in this model under the assumption that these losses can be negligible with sufficient insulation (McTigue et al., 2015) and operation on frequent basis.

To sum up, in terms of technical performance the PTES system was generally found to achieve a higher theoretical roundtrip efficiency exceeding 75% at the right operating conditions. On the other hand, the LAES system was found to have the potential for significantly improving its roundtrip efficiency from its nominal design considered here through the appropriate recovery and utilisation of waste cold and heat. The combination of these two parameters was observed to contribute in the improvement of LAES's efficiency achieving more than 55%.

6.2 Thermo-economic analysis

In this section, a thermo-economic analysis of LAES and PTES systems is presented. The main focus of the analysis is the systems at their intended capacities but a brief comparison at equal capacities is also performed. This is to provide a like-for-like comparison and observe the potential impact of capacity on the competitiveness of the two technologies against each other.

Metrics of interest here include the power capital cost (defined here as the capital cost divided by the rated power output capacity) and energy capital cost (defined here as the capital cost divided by the rated energy output capacity). These were estimated while assuming overnight

purchase and construction of the systems. Also, economic feasibility metrics including the levelised cost of storage (LCOS), net present value (NPV), and the sell-to-buy ratio (STB) were considered. The LCOS and NPV were used as defined in Section 3.3.

The additional economic metric of STB discussed here can be an insightful metric specific for electricity storage devices seeking to take advantage of the difference in peak demand (sell price – SP) and low demand (buy price – BP) electricity prices to generate profits. This metric was analysed for both systems to determine the minimum required STB for the system to be economically feasible over its lifetime. This minimum required STB was determined on the basis that the system breaks even at the end of its lifecycle by having an NPV equal to zero. Therefore, the profile of the required STB against a range of BP was examined where any point over the curve can be considered as an economically feasible operating point. These economic metrics were used to assess the economic feasibility of the two systems over their lifetime while considering their operating conditions as well as initial capital expenses, discount rates, operational energy costs, and maintenance costs.

The lifetime of both systems was assumed to be 30 years without component degradation. Also, daily cycling operation (365 cycles per year) was considered. Furthermore, since both technologies are considered emerging and lack existing mature commercial scale plans, they are expected to possess uncertainties on economic parameters such as maintenance costs, discount rates and energy costs. These parameters are not expected to be affected only by the technology but also by the marketplace (e.g. location, fuel prices, policies). Therefore, to capture some of the expected uncertainties, a range of those parameters was considered. The resulting uncertainty in the outputs of the model and therefore the sensitivity of each system to

these uncertainties was captured by the error bars/bounds presented in the figures below as well as the range in outputs discussed.

For maintenance costs, an annual cost in the range of 1.5-3.0% (Centre for Low Carbon Futures, 2013) of initial capital costs was assumed. For discount rates, a slightly higher rate was assumed for PTES than for LAES to account for its lower maturity and the consequential higher risk of investment (Steinbach and Staniaszek, 2015). The range of rates considered here were 9-15% and 6-12% for PTES and LAES respectively. Finally, in terms of energy costs the range of off-peak electricity prices considered for charging the system was 0.02-0.06 £/kWh (Energy Solutions, 2016).

In terms of operational and performance parameters, the LAES and PTES systems were assumed to operate at the nominal design values used earlier, except for the amount of waste cold utilised in LAES which was taken to be 250 kJ/kg. This assumption was made due to the importance of waste cold utilisation identified earlier and the feasibility of this quantity in a commercial plant (Morgan et al., 2015). Also, the waste heat utilisation at 393 K for LAES was assumed not to involve additional costs. The cost of this element is expected to be case specific and to depend on various aspects which are out of scope of this exercise. The impact of the additional cost on the overall cost of the system, if applicable, is expected to have a proportional effect to its unit cost and can be added accordingly.

6.2.1 Analysis at intended capacities

In this section, a thermo-economic analysis at the intended capacities of the LAES and PTES systems is presented along with their competitiveness in the market against other technologies.

The PTES system was analysed based on rated power and energy storage capacities of 2 MW and 11.5 MWh respectively. The system at this scale was studied in literature and found to be viable (e.g. McTigue et al. (2015), White et al. (2016)). Further development and maturity of the system might allow for its scalability to bigger sizes, something that can be considered as an avenue for further investigation in the future.

Similarly, the LAES system was analysed based on rated power and energy storage capacities of 12 MW and 50 MWh respectively. This system size is obviously larger than the operating pilot plant and its power to energy storage ratio is closer to what is proposed in literature (Centre for Low Carbon Futures, 2013) for commercial scale plants. Similar to the PTES, this system size was considered in literature (Centre for Low Carbon Futures, 2013) to be viable for implementation.

In terms of power capital cost, the range obtained for LAES, 0.98-1.88 £K/kW, was found to be lower than the range of PTES, 2.07-4.22 £K/kW (see Fig. 6.4a). In terms of energy storage capacity, again LAES was found to have a lower range than PTES with ranges of 0.24-0.46 £K/kWh and 0.37-0.75 £K/kWh respectively (see Fig. 6.4b). However, the relative difference observed in the energy capital costs between the two systems was considerably less than the equivalent in power capital costs. The smaller difference can probably be due to PTES having a higher energy storage capacity to power capacity ratio. Observing that shows that at different scales or energy to power ratios the technologies' economics might change. This is something that is analysed in the next section in which the systems are considered at equal capacities.

Furthermore, the uncertainty associated with the PTES's determined values was considerably greater than LAES's (see Figs 6.4a and 6.4b), especially in the case of power capital cost where they differ by about a factor of two. The uncertainty in these two plots was dominated by the

estimates obtained by the different costing methods; thus showing the importance of considering multiple methods. It is expected that the greater uncertainty noted for PTES was associated with the variation in costing of compression and expansion devices which were the main costs of the system. Even though both technologies use compression and expansion devices, the PTES system employed here reciprocating machines (McTigue et al., 2015) whereas LAES employed turbomachinery. Also, given the smaller capacity of PTES, a small variation in the absolute values is expected to have a great effect on the specific costs.

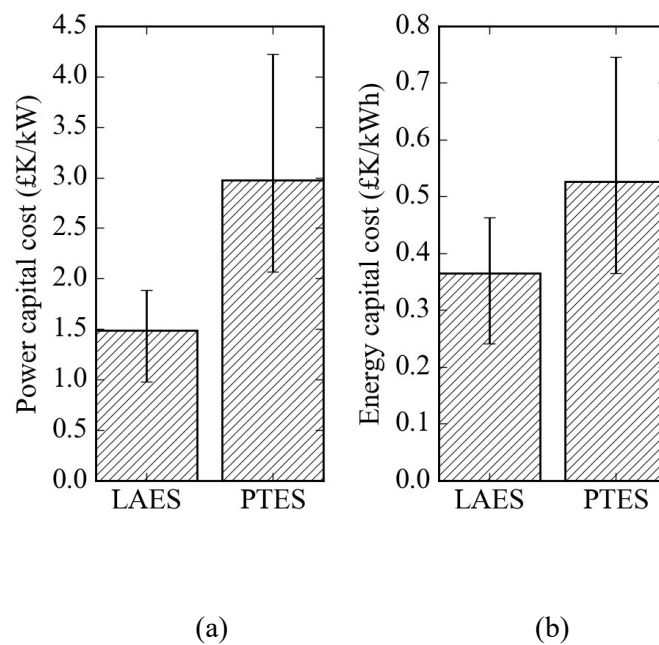


Figure 6.4. (a) Power capital cost and (b) energy capital cost of LAES and PTES. The error bars indicate the variations (min-max) obtained by the different costing methods in Chapter 3.

Following from the estimations above, it was interesting to break them down into the allocated capital expenditure for the main components of the systems. Based on mean values, Fig. 6.5

shows the distribution of initial capital expenditure. The components associated with power consumption or generation were found to be responsible for the greatest share in capital cost for both technologies. More specifically, the air liquefaction plant and the power recovery plant were accountable for more than 70% of the capital cost of LAES. Likewise, in the PTES system the compressor/expander devices were found to be responsible for almost 80% of the cost. Interestingly, components associated with thermal storage contributed significantly less in the overall capital cost.

The dominance of the power consuming or generating devices showed once again the significance of the waste cold recycle and utilisation in LAES. This is because the marginal increase in waste cold (i.e. thermal store) is expected to contribute significantly less in the capital cost of the system as opposed to the required increase in the capacity of the compressor to achieve the equivalent liquid air yield.

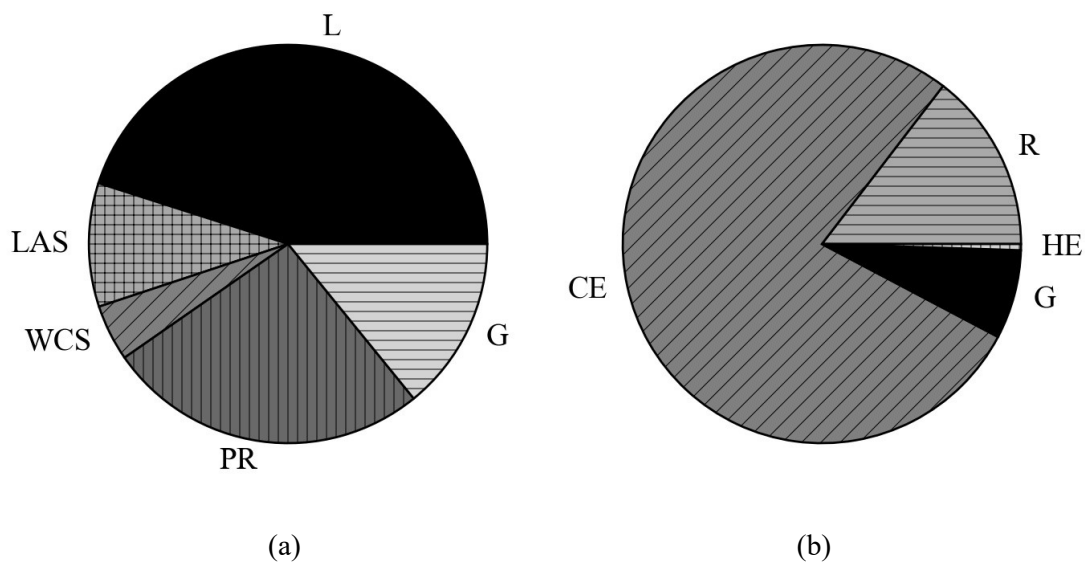


Figure 6.5. Capital cost distribution among main components of: (a) LAES (L: liquefaction plant, G: generators, LAS: liquid air storage, WCS: waste cold storage, PR: power recovery), and (b) PTES (R: reservoirs, CE: compressors/expanders, G: generators, HE: heat exchangers).

The distribution of capital expenses was also evaluated in terms of absolute costs, power output, and energy capacity (see Figs 6.6. and 6.7 for PTES and LAES respectively). For PTES, the compression/expansion devices were found to dominate the cost in all three distributions as well as showing the highest uncertainty range. Likewise, for LAES the liquefaction plant was found to be accountable for the greatest proportion of costs with respect to all three metrics while also presenting the greatest variation. The next significant cost in the LAES system was noted to be the power recovery unit.

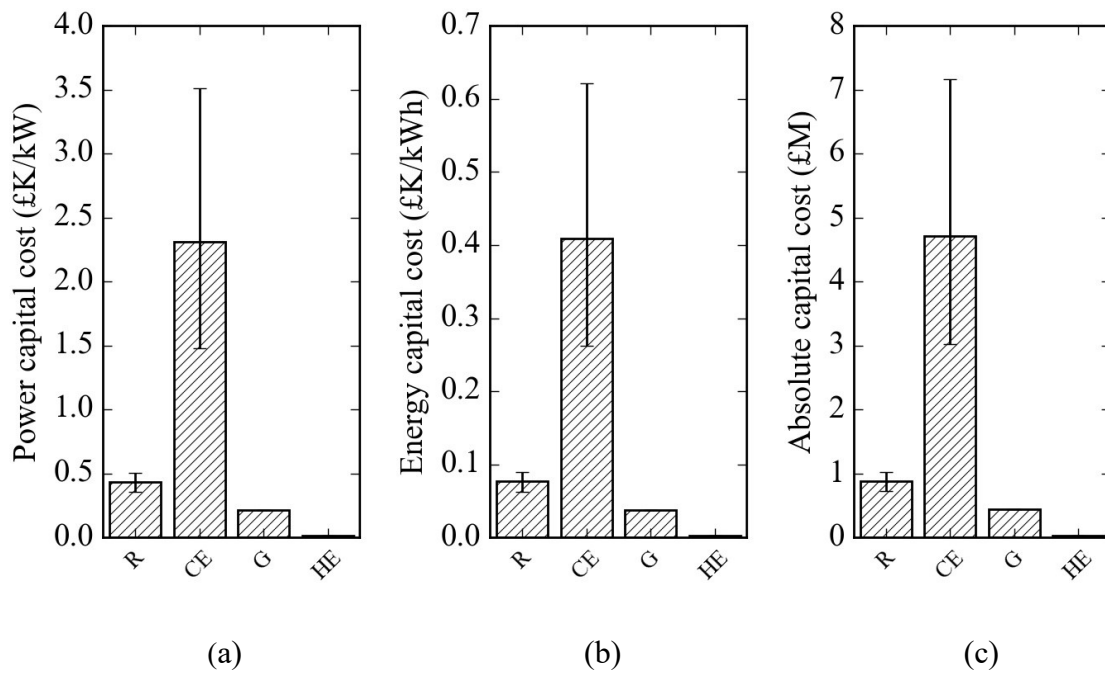


Figure 6.6. (a) Power capital cost, (b) energy capital cost, and (c) absolute capital cost distribution between the main components of PTES (R: reservoirs, CE: compressors/expanders, G: generators, HE: heat exchangers). The error bars indicate the variations (min-max) obtained by the different costing methods in Chapter 3.

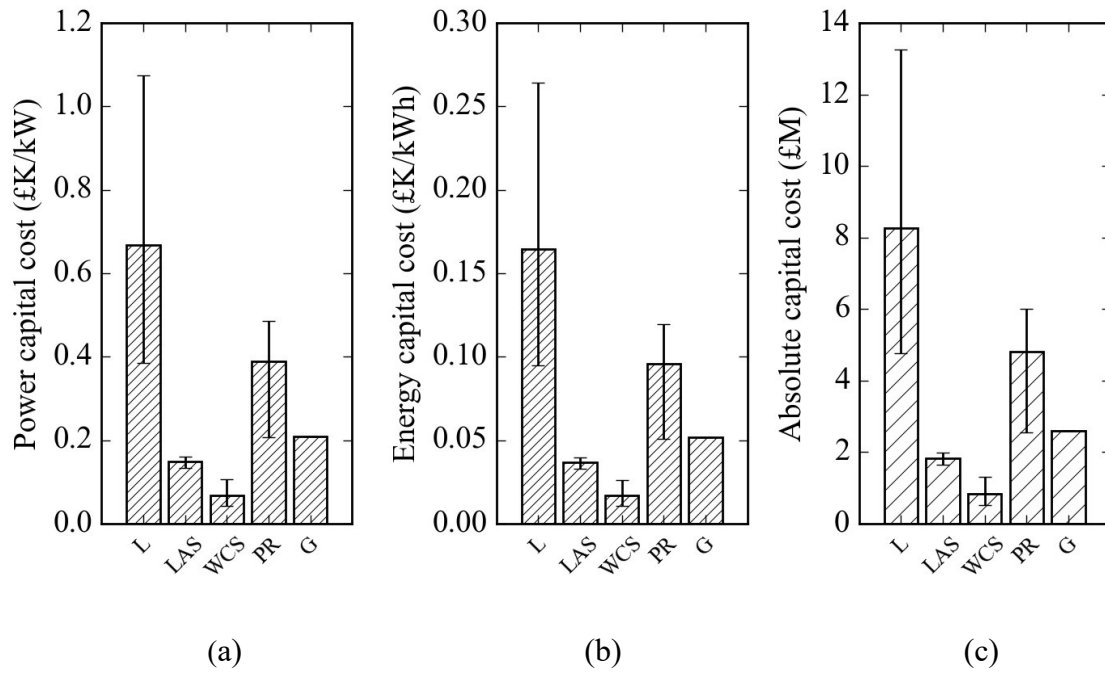


Figure 6.7. (a) Power capital cost, (b) energy capital cost, and (c) absolute capital cost distribution between the main components of LAES (L: liquefaction plant, LAS: liquid air storage, WCS: waste cold storage, PR: power recovery, G: generators). The error bars indicate the variations (min-max) obtained by the different costing methods in Chapter 3.

A scale-up of the technologies in the appropriate setting, either in energy or power output capacity, can result in greater capital expenditure but can potentially also increase economic incomes and lead to economies of scale. Following from the observation that components associated with power consumption or generation were more capital intensive, the marginal benefit from increasing the power input or output should justify the alternative option of increasing the energy capacity of the system. Within the scalability limits of each technology, ideally the minimisation of both power capital cost and energy capital cost should be pursued.

Nevertheless, this is expected to be case specific and depend on external factors, such as the electricity market, as well.

Furthermore, the levelised cost of storage (LCOS) for these technologies was evaluated and compared. The LCOS is presented here in terms of overall value (Fig. 6.8a) as well as in terms of independent cost elements (Fig. 6.8b). The expected uncertainty associated with each estimation due to the different costing methods and cost parameters was evaluated and is also presented. The average total LCOS was determined to be 0.21 £/kWh and 0.26 £/kWh with ranges of 0.10-0.33 £/kWh and 0.14-0.45 £/kWh for LAES and PTES respectively.

For PTES, the operational energy costs were estimated to be accountable for less than half of the capital expenditure for LCOS. However, in the case of LAES the operational energy costs and capital expenditure were found to be accountable for a similar share of LCOS. Also, less uncertainty was associated with the operational energy costs of PTES in comparison to LAES. This is expected to be linked with the higher roundtrip efficiency observed in PTES. On the other hand, the uncertainty noted for capital expenditure contribution to LCOS of PTES was considerably greater than its operational energy costs and the equivalent uncertainty of LAES's capital expenditure category. Therefore, this can act as a justification of the greater uncertainty observed in the total LCOS of PTES.

It noteworthy that the operational energy cost allocation to the LCOS was only affected by the energy prices. Therefore, PTES can be considered to be more flexible in terms of marketplace and potentially less vulnerable to the fluctuations of electricity prices. The opposite can be implied for LAES. This outcome is anticipated to be due to the higher energy unit input requirement per unit output as a result of the lower roundtrip efficiency observed in LAES. On the other hand, LAES was found to be more attractive in terms of its capital expenditure

allocation to LCOS and the corresponding sensitivity. This can potentially present an opportunity for a lower risk investment compared to the more capital intensive PTES.

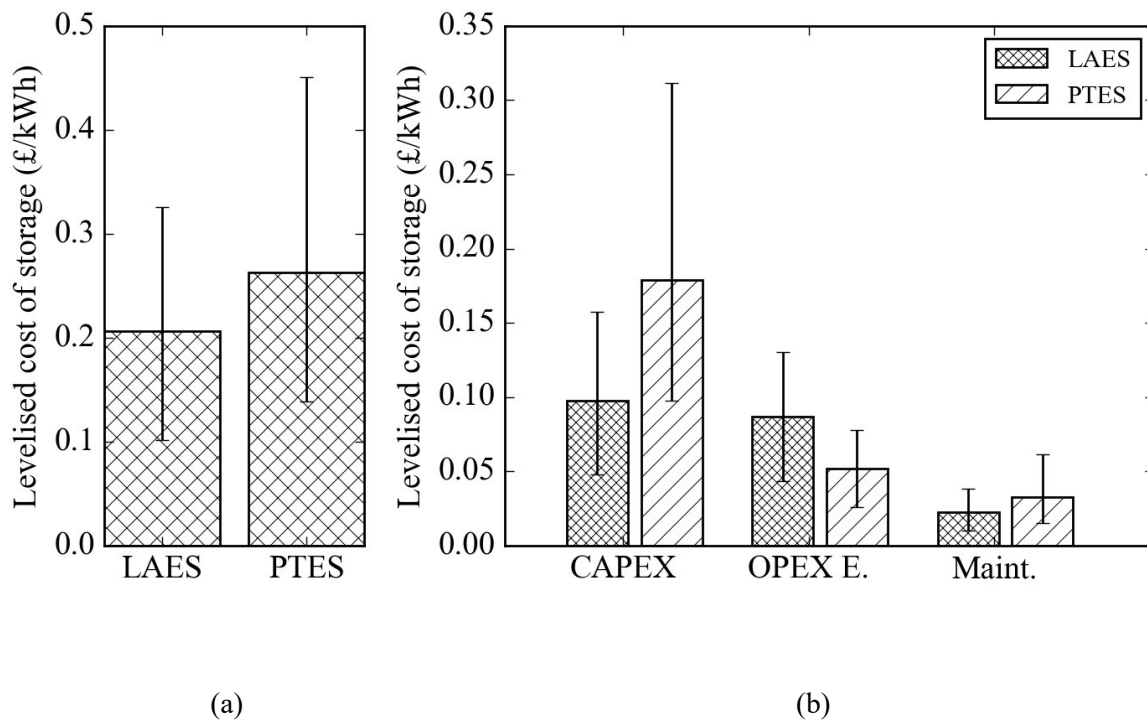


Figure 6.8. (a) Overall levelised cost of storage (LCOS) and (b) LCOS per expenditure category for LAES and PTES (CAPEX: capital expenditure, OPEX E.: operational expenditure for energy, Maint.: maintenance costs). The error bars indicate the variations (min-max) obtained by the different costing methods in Chapter 3 and the variability associated with the uncertainty factors where applicable.

Following from the observations above, an improvement in the roundtrip efficiency is expected to contribute towards to reduction of the operational energy cost element of the LCOS. However, this is not necessarily true for the two other elements; namely the capital expenditure and the maintenance costs. In fact, it can even result to the increase of these elements due to

the requirement of more expensive components and/or more extreme operating conditions; especially in cases where the benefit in roundtrip efficiency is marginal compared to the additional costs imposed.

Focusing now on the required STB ratio, both system's curves followed a similar trend showing a monotonic decrease with the increase in BP (see Fig. 6.9). A much steeper gradient was noted at the lower end of BPs while a shallow profile was observed at BPs over ~ 0.15 £/kWh. This effect is expected to be a result of the dominance of operational energy costs over capital and maintenance costs as BPs increase. Hence, the independence of the required STB ratio from capital maintenance costs with the increase of BP was noted. Consequently, as BPs increase the roundtrip efficiency of the system becomes the main driver of the required STB ratio. This is possibly the reason for PTES appearing marginally more economically competitive than LAES at BP values greater than 0.10 £/kWh, with the difference between the two growing slightly over that point and then remaining relative constant at higher prices. On the other hand, LAES which was found earlier to be less capital intensive indicated a lower required STB ratio than PTES at the lower end of BPs while the difference between them decreased with the increase in BPs.

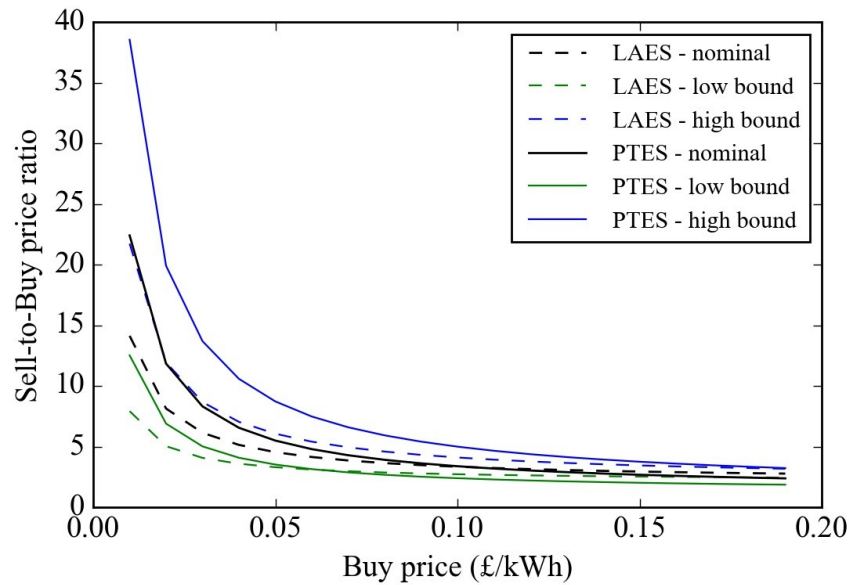


Figure 6.9. Required sell-to-buy price ratio against the electricity buying price for LAES and PTES. The high-low bounds indicate the variations (min-max) obtained by the different costing methods in Chapter 3 and the variability associated with the uncertainty factors where applicable.

Furthermore, it was also interesting to note the much greater uncertainty in the STB ratio at the low end of BPs in comparison to the uncertainty at higher BPs. This shows both systems being more resilient in the marketplace in terms of minimum STB ratio. In this analysis the energy cost was the variable in terms of BPs and therefore it did not contribute to the uncertainty bounds derived here. Therefore, the uncertainty factors reflected here, besides capital costing, are the discount rate and maintenance costs. This can act as an indication of the systems' economic vulnerability in terms of STB to those factors and the relation to BPs. Hence, due to the greater intensity in capital expenditure noted for PTES as well as the greater share of costs allocated to capital expenditure, these factors were observed to have a greater impact on the magnitude of the uncertainty bounds.

Finally, in order to observe these technologies among competing electricity storage solutions, the systems were compared in terms of power capital costs (see. Fig. 6.10). LAES was found to be more competitive than PTES as well as to be competitive against other well established technologies, such as lithium-ion batteries, PHS, hydrogen fuel cells, and sodium sulfur batteries. Also, interestingly, the power capital cost range of these technologies was noted to be greater than the range obtained for LAES.

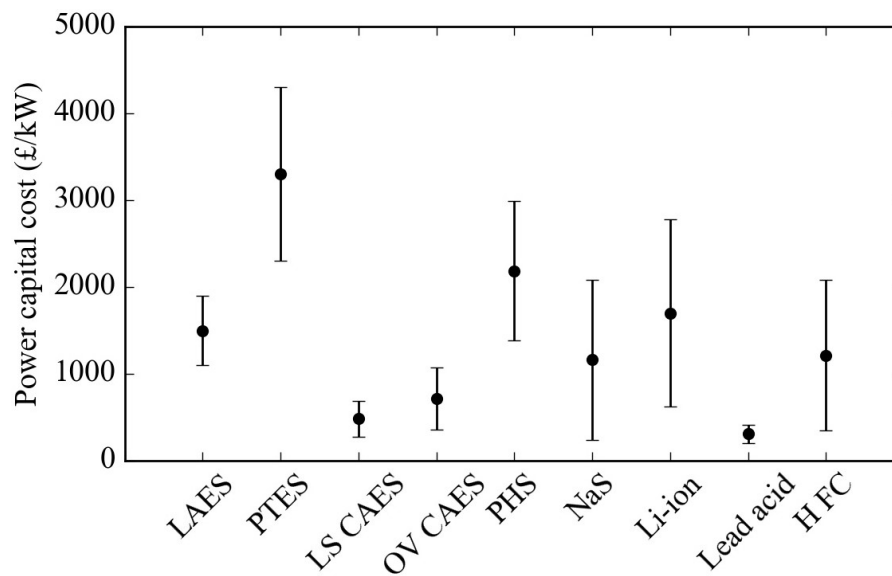


Figure 6.10. Power capital cost comparison between the two systems (LAES and PTES) and existing electricity storage technologies (PHS: pumped hydroelectricity storage, LS CAES: large scale underground compressed air electricity storage, OV CAES: over ground compressed air electricity storage, Li-ion: lithium ion batteries, NaS: sodium sulphur batteries, Lead acid: lead acid batteries, H. FC: hydrogen fuel cell) (data for all technologies except LAES and PTES were obtained from Luo et al. (2014)).

6.2.2 Analysis at equal capacities

In this section, economics of LAES and PTES systems at equal power, energy and charging capacities are studied. It was anticipated that at these capacities the comparison between the two systems might not be fair as it was not necessarily in alignment with their intended capacities and therefore might lack the potential benefits associated with economies of scale. Nevertheless, a brief comparison at equal capacities was expected to give a more like-for-like analysis.

To compare the two systems at equal capacities, the LAES system was downsized to a smaller scale to match the scale of PTES. This choice was based on the merit of being easier and more confident on the scale feasibility of the capacity considered. More specifically, the upscaling of the PTES system was considered as a less straightforward approach, especially due to the uncertainty associated with the ability to scale up components of the system such as reciprocating compression and expansion devices. Therefore, the two systems were considered at a rated power output and energy capacities of 2 MW and 11.5 MWh respectively.

LAES was found to have higher average power capital cost than PTES with 3.49 £K/kW and 2.98 £K/kW respectively (see Fig. 6.11a). Likewise, the average energy capital costs of LAES was also found to be higher than PTES with costs of 0.61 £K/kWh and 0.53 £K/kWh respectively (see Fig. 6.11b). Similarly, the average LCOS of LAES was found to be slightly higher than that PTES with values of 0.29 £/kWh and 0.26 £/kWh respectively (see Fig. 6.11c). Therefore, a significant increase in all three metrics was noted for LAES at this capacity in comparison to its intended capacity studied earlier. The resulting change in absolute value of LAES and relative difference between the two technologies in power and energy capital costs can be due to the lower capacity of LAES and the consequential lower economies of scale

compared to a higher capacity system. This increase was enough to surpass PTES values with respect to all three metrics. Nevertheless, the difference noted between the two systems was smaller than the difference observed at their intended capacities. Also, the uncertainty ranges observed for LAES in all three metrics were found to be significantly greater than their equivalent ranges at its intended capacity.

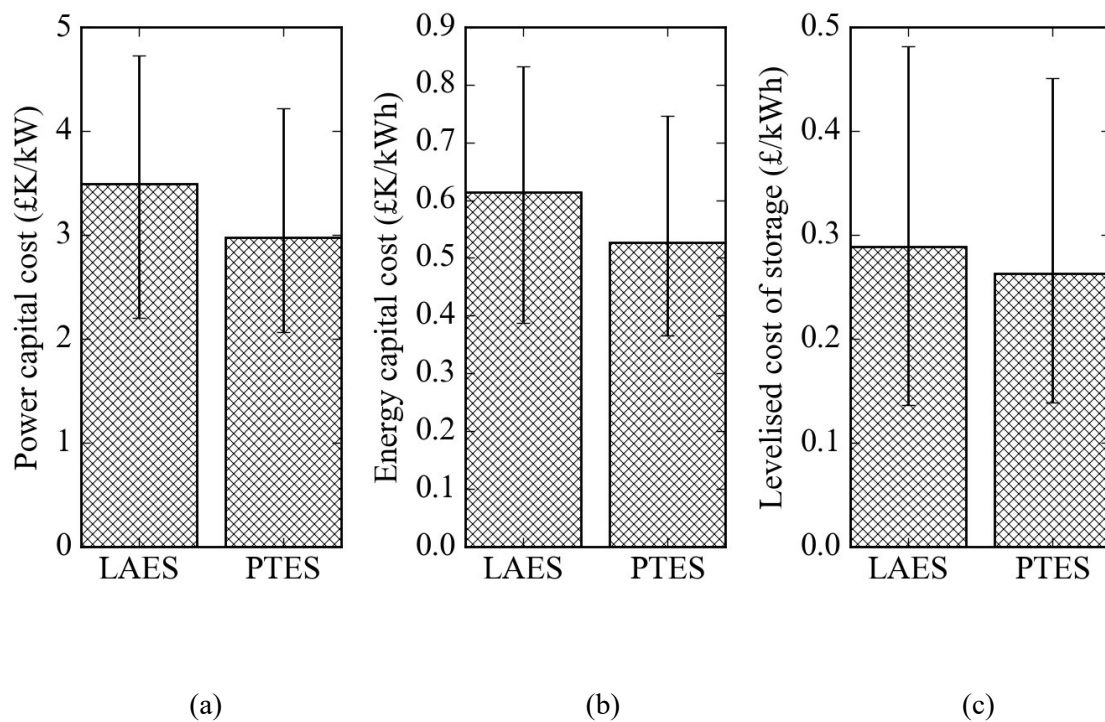


Figure 6.11. Comparison of LAES and PTES systems at equal capacities (2 MW, 11.5 MWh) in terms of (a) power capital cost, (b) energy capital cost, and (c) levelised cost of storage. The error bars indicate the variations (min-max) obtained by the different costing methods in Chapter 3 and the variability associated with the uncertainty factors where applicable.

The allocated LCOS to capital expenditure was found to remain greater for PTES than LAES as it was noted at the intended capacities. The same was noted for the LCOS allocated to operation energy costs which was found again to be greater for LAES than PTES (see Fig. 6.12). The difference between the two systems in terms of LCOS allocated to capital expenditure, however, was noted to be significantly smaller at these capacities mostly due to the increase of LAES. On the other hand, the difference in terms of allocated operational energy costs remained relatively unaffected. Consequently, this indicates the main driver of the increase in LAES's LCOS to a greater value than PTES to be the capital expenditure.

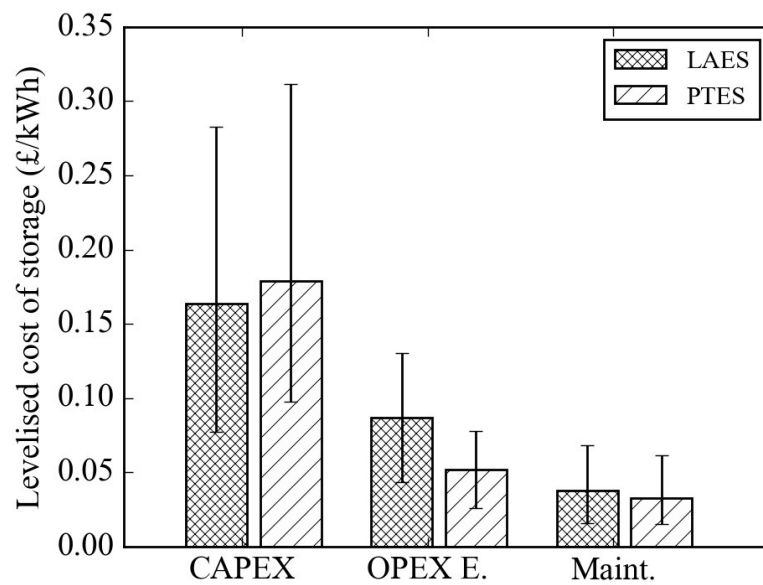


Figure 6.12. Comparison of LAES and PTES systems at equal capacities (2 MW, 11.5 MWh) for levelised cost of storage (LCOS) per expenditure category (CAPEX: capital expenditure, OPEX E.: operational expenditure for energy, Maint.: maintenance costs). The error bars and high-low bounds indicate the variations (min-max) obtained by the different costing methods in Chapter 3 and the variability associated with the uncertainty factors where applicable.

In terms of minimum required STB ratio, the two technologies showed a similar trend to the ones at intended capacities with a sharp monotonic decrease at low BPs and a shallower at mid and high BPs. However, in contrast to the results at intended capacities, the minimum STB ratio was found to be very similar for both systems at the lower end of BPs ($\sim < 0.03$ £/kWh) while at values close to ~ 0.02 £/kWh PTES was observed to become slightly more competitive than LAES (see Fig. 6.13). From prices over ~ 0.02 £/kWh the difference between LAES and PTES initially grew and then became relatively unaffected at the higher end of BPs considered. Based on the observation above about LAES's increase in LCOS mainly due to capital expenditure along with the observation in the section above about operational costs dominating the STB as BPs increase, the trends in this chart can be justified.

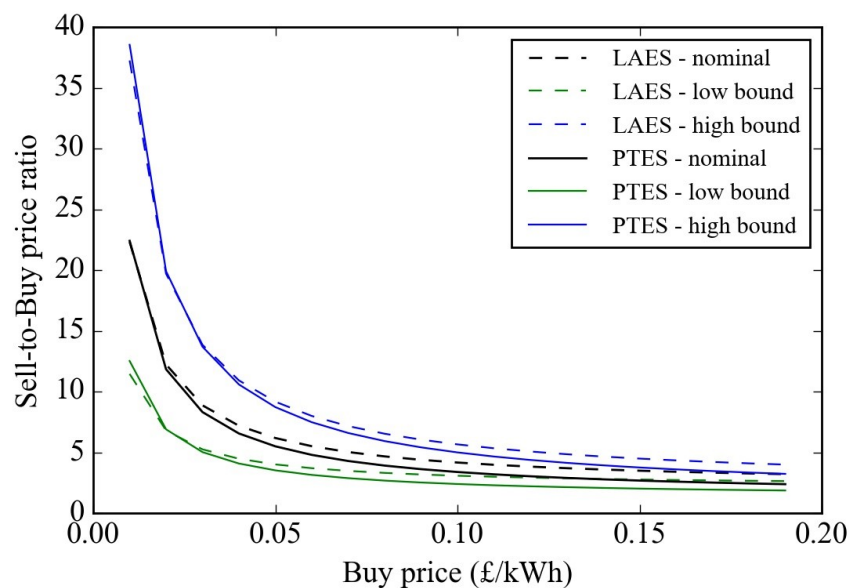


Figure 6.13. Comparison of LAES and PTES systems at equal capacities (2 MW, 11.5 MWh) in terms of required sell-to-buy price ratio against the electricity buying price. The error bars and high-low bounds indicate the variations (min-max) obtained by the different costing methods in Chapter 3 and the variability associated with the uncertainty factors where applicable.

6.3 Carbon savings as decentralised storage systems

Following from the previous section which determined the technical and economic performance/competitiveness of the two systems, this section focuses on the potential for achieving carbon savings through the use of these technologies as standalone systems and the associated costs of those savings.

In this section, various factors affecting the carbon savings from the application of these technologies are discussed. Factors considered here include: carbon factors associated with geographical locations, quantitative and qualitative potential for carbon savings, renewable energy curtailment levels, and the expected imposed costs for the potential carbon savings at various conditions.

Carbon factors are usually assigned to locations in order to reflect the carbon intensity of using energy at those places. These factors can be employed by organisations for company reporting purposes of emissions (DECC and DEFRA, 2016). The application conditions of these factors can vary depending on the activities required to be quantified. In the present analysis, electricity carbon factors that account only for the carbon intensity of electricity were used, as opposed to composite carbon factors which also account for emissions from heat generating activities (Ecometrica, 2011). Therefore, the factors considered here were acquired from Ecometrica (2011). These factors were used here in order to estimate the carbon intensity of the electricity grid at the location of interest. Thereafter, it would be possible to assess the potential for achieving carbon savings from the application of electricity storage systems when coupled with renewable energy facilities.

As mentioned in Chapter 3, the levelised cost of electricity (LCOE) is an indicator usually used for electricity generation technologies to assess the competitiveness of the technology in terms of cost per unit generated. Examples of LCOE for common renewable technologies are available in literature (e.g. U.S. Energy Information Administration (2018)). One of the main differences between renewables and conventional technologies is in the relative difference in costs allocated to capital expenditure, maintenance costs and operational costs; in the case of renewables, where the fuel is usually absent, the capital and maintenance costs dominate the LCOE. Therefore, the operational costs of renewables can sometimes be considered insignificant in comparison to the fuel cost requirements of conventional power generation.

A similar metric which is specific to electricity storage technologies is the levelised cost of storage (LCOS). LCOS can be considered more closely related to the LCOE of conventional power generation since storage technologies can too typically involve significant operational costs due to the energy requirements for charging. Therefore, if renewable energy can be used to charge an electricity storage system, the LCOE of the corresponding technology can potentially represent the energy cost element of LCOS of the storage system. It is noteworthy that the LCOE of technologies might vary depending on factors such as manufacturing material, location and technology maturity. However, for the purpose of this exercise, a single LCOE was assumed for each technology based on the assumption that variations are not significant.

Furthermore, in order to make both economic and technical sense to store electricity from renewables there needs to be a mismatch between supply and demand profiles, or other reasons that might result in the curtailment of renewable energy. Several reasons can cause the curtailment of renewable energy but in the present analysis only the cases which consistently

result in curtailment and make the implementation of storage attractive were of interest. Examples of significant wind energy curtailments were presented in Fink et al. (2009). More specifically, a case of 14% of total annual wind generation being curtailed in the USA was presented. Furthermore, the level of curtailment can be affected by the location (Bird et al., 2016; Luo et al., 2016), sometimes even within the same country. For example, China was presented to have wind energy curtailments ranging from 0 to 34.3% depending on the year and region (Bird et al., 2016; Luo et al., 2016), whereas Canada was reported to have minimal curtailments (Bird et al., 2016). Therefore, it was also of interest to study the impact of curtailment level on the potential for installation of electricity storage devices in an attempt to utilise that energy and therefore contribute to additional carbon savings from renewables.

Among the factors affecting the curtailment level can be the total renewable energy generation capacity in a system (Bird et al., 2016). Examples of this found in literature include China which in 2010 surpassed the capacity of USA's wind generation but its curtailment levels also increased reaching 3.94 million MWh in that year (Luo et al., 2016). Another example was presented in Bird et al. (2016) which did not find any solar generation curtailment but it was stated that curtailment might be more evident in areas with more installed capacity. Also, hydroelectric power is another renewable that can be important for some locations. An interesting example is China whose hydroelectric capacity is considerably higher than both solar and wind generation and it can be associated with curtailment (Li et al., 2015).

The aforementioned findings indicate that not only the location can be a significant factor on energy curtailment but also the technology (or the energy source). Hence, the curtailment level associated with a technology or location can affect significantly its economic returns and economic viability (Luo et al., 2016). Identifying utilisation solutions for this effect can be

beneficial for both generating and consuming (in this case storage) technologies (Li et al., 2015). To maintain a level of simplicity in this exercise that allows an easy comparison between the cases considered, an equal curtailment level of 20% was assumed for all locations and technologies.

To determine the thermo-economic performance of the LAES and PTES systems in this analysis, the thermo-economic models at their nominal settings described above were used. Therefore, the LAES and PTES systems were considered at their described nominal configurations and intended capacities. Also the same economic values were considered as described in the thermo-economic analysis.

6.3.1 Potential for carbon savings

Due to inevitable irreversibilities and losses associated with the electricity storage systems (as reflected on their roundtrip efficiency), the expected carbon savings by using storage systems are unavoidably lower than using the energy directly from renewables. However, as discussed above, because of the variability and intermittency typically associated with common renewables it is usual to have some curtailment of the energy generated. This curtailed energy can essentially be considered as “lost” potential of carbon savings as it does not contribute. Subsequently, utilising that energy to charge storage systems and provide that back when needed can contribute to securing a significant percentage of the otherwise “lost” carbon savings potential.

The potential carbon savings for different countries were found to vary significantly, affected both by location and technology (see Fig. 6.14). Based on the countries included in this analysis, Germany presented the greatest potential while France the lowest. Since equal

curtailment levels were assumed for all countries, the order of potential between the different locations was the same for both technologies. However, a clear difference was noted between the two technologies with PTES showing a greater potential for carbon savings in all locations. This is expected to be a result of the higher roundtrip efficiency which is therefore expected to be the driving factor for a technology's potential. Furthermore, the difference between the two technologies was found to be affected by the carbon factor of the location. In other words, an increase in the carbon factor is expected to increase the difference between the two technologies favouring the one with the highest roundtrip efficiency.

To compare against the case of the entire renewable energy used directly without storage, Fig 6.14 also shows the total potential carbon savings. The difference between the two cases represents the lost potential with PTES showing again a slightly better outcome. In a more realistic set up, different curtailments would have been considered for the different locations. However, the impact of the technologies' roundtrip efficiency and carbon factor would probably be less apparent.

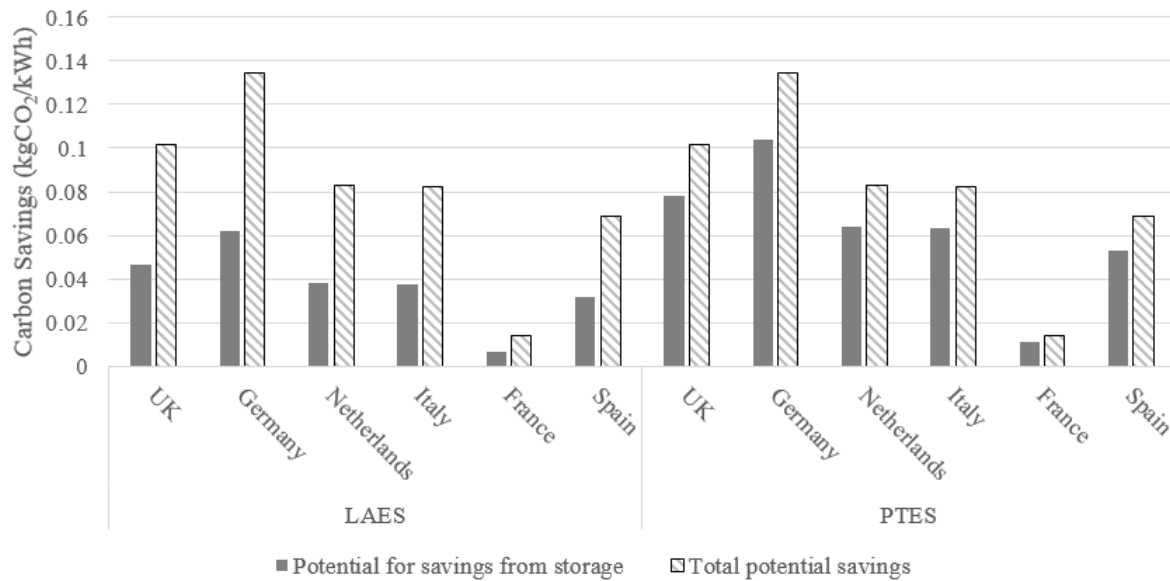


Figure 6.14. Potential for carbon savings by using LAES and PTES in comparison to total potential savings from curtailed energy at different locations.

To sum up, in a setting where renewable technologies were used in combination with electricity storage systems, the electricity carbon factor, the roundtrip efficiency of the storage technology, and the curtailment level of renewable energy were found to affect the potential for carbon emissions savings. Interesting cases can include for example a region with low electricity carbon factor because of high nuclear generation capacity and low curtailment levels due to low capacities of intermittent renewables. In this case, the implantation of electricity storage for improving the carbon footprint might not be a competitive solution. Nonetheless, electricity storage systems can still provide carbon benefits, such as through the avoidance of old inefficient or carbon intensive power generation plants used to meet peak demands.

The impact of these three factors (i.e. carbon factor, roundtrip efficiency and energy curtailment) is represented in qualitative terms in Fig. 6.15. The potential for carbon savings

risks with the increase in any of these three factors. Interestingly, the only factor controlled by and related to the storage system is the roundtrip efficiency, whereas the other two are external factors.

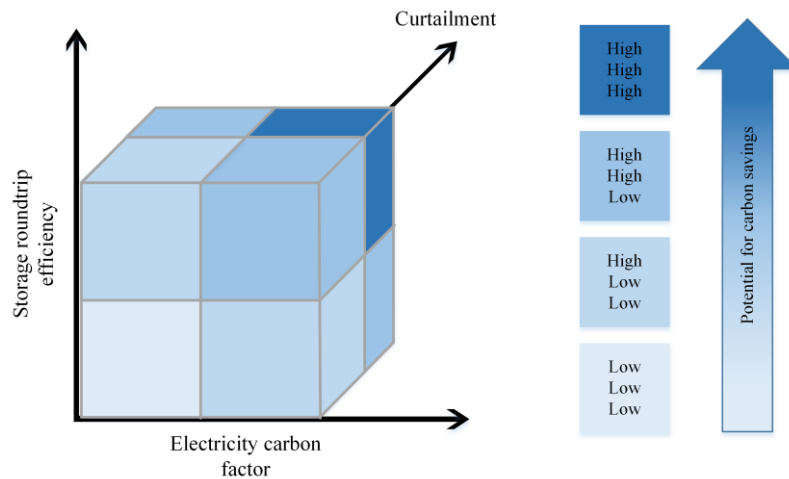


Figure 6.15. Qualitative demonstration of potential for carbon savings and the expected influential factors when using electricity storage technologies from intermittent renewable energy sources.

6.3.2 Cost of carbon savings

As mentioned above, factors affecting the potential for carbon savings include the energy curtailment levels, the carbon factor and the roundtrip efficiency of the storage system, out of which only the last one is linked to the storage technology. However, if the cost of carbon savings is to be considered, additional variables directly related to the storage technology (e.g. capital costs) as well as external (e.g. grid electricity prices) can have an impact on the economic attractiveness of a storage system for achieving carbon savings.

Considering the cost of energy for the electricity storage system to be equal to the LCOE of each renewable technology along with the outputs from the thermo-economic analysis of these systems, the cost associated with the carbon savings potentially achieved through their use was estimated. As discussed in Chapter 3, a few scenarios were considered in this analysis in order to capture some of the probable possibilities.

In Scenarios 1, no energy cost was imposed to the storage system allowing for the decoupling of the energy source and the cost of carbon savings. To make the benefits from avoiding peak electricity prices more obvious, two electricity price values were considered: 0.14 £/kWh and 0.28 £/kWh. When the former was considered in Scenario 1a, PTES presented a minor cost whereas LAES showed a negative cost. PTES showed positive costs possibly due to being unable to capitalise on its higher roundtrip efficiency in terms of economic benefits at this electricity price (see Fig. 6.16). However, when the higher electricity price was considered, negative costs were observed for both technologies signifying the potential not only for carbon savings but also for economic benefits, with higher electricity prices potentially enhancing the economic competitiveness of the technologies. Nevertheless, as shown through the electricity prices, achieving both carbon and cost savings is expected to be relying on factors such as the market conditions.

In Scenario 1b, the cost associated with both technologies was observed to be significant higher than Scenario 1a. This was due to assumption of no economic benefits from the difference in electricity prices between charging and discharging. Therefore, the importance of right market conditions was again highlighted.

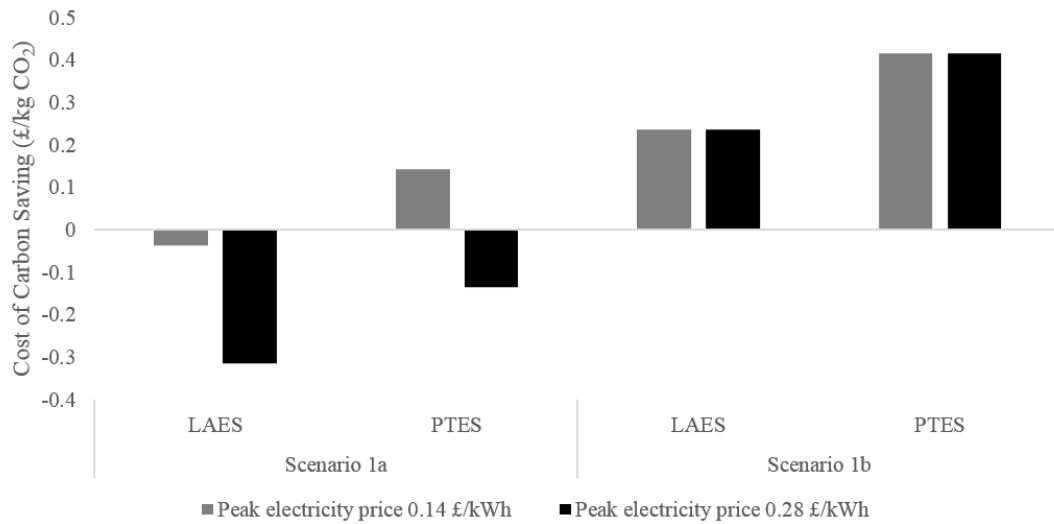


Figure 6.16. Cost of carbon savings (at different peak electricity prices) for Scenarios 1a and 1b when using LAES and PTES.

Scenarios 2 considered the effect of the cost of buying electricity to charge the system. In Scenario 2a, cost savings were considered by the possibility of avoiding high electricity prices (assumed to be 0.14 £/kWh) during peak demand when the system is discharging. In this case, offshore wind energy was found to have similar costs for both storage systems whereas onshore wind, hydroelectric and solar PV were observed to have lower cost for LAES than PTES (see Fig. 6.17). Furthermore, the energy source showed to greatly affect the difference between the two systems. For instance, offshore wind showed a percentage difference of less than 10% whereas the other technologies showed a considerably greater difference, especially onshore wind. This effect is expected to be a function of the LCOE of each technology since offshore wind was also the most expensive. Therefore, the cost associated with LAES was anticipated to grow with the increase in LCOE of the energy source, probably reaching a point which surpasses PTES. To test this theory, a hypothetical energy source with a higher LCOE (0.14

£/kWh) was considered. As anticipated, LAES was found to be associated with a higher cost than PTES. Hence, this indicates the existence of a point from where LCOE dominates over the other costs involved in the implementation and use of the storage systems.

In Scenario 2b, no cost savings were assumed due to the avoidance of peak electricity prices. As expected, the cost of carbon savings was observed to significantly increase for both storage technologies and for all energy sources (see Fig. 6.17) in comparison to Scenario 2a. Therefore, it was inferred that as electricity prices increase the costs of carbon savings decrease. Above a point at which electricity prices are equal to the LCOS, profits are expected to be possible.

Scenario 2b, like Scenario 1b, does not account for any potential of cost saving due to peak electricity prices; in contrast, Scenario 2a does. When comparing like-for-like (i.e. Scenario 1a with 2a and Scenario 1b with 2b) generally the costs for both technologies were found to be lower for Scenarios 1 due to the additional operational energy costs considered in Scenarios 2. Therefore, the market conditions, policies and electricity agreements are expected to have an impact on the attractiveness of these technologies as energy storage solutions.

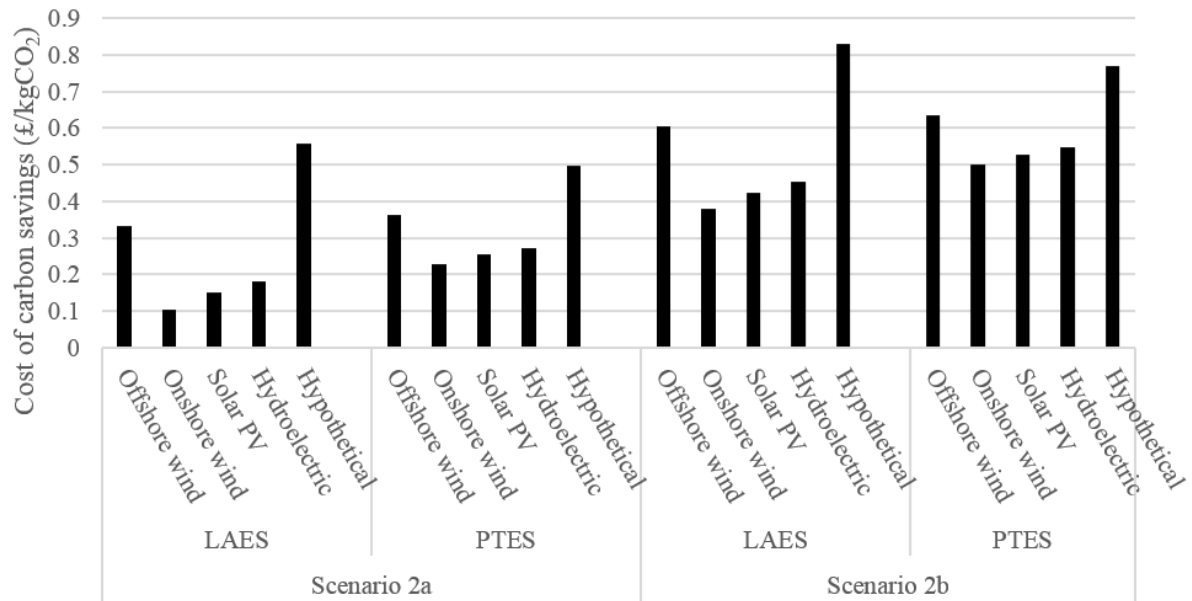


Figure 6.17. Cost of carbon savings for Scenarios 2a and 2b when LAES and PTES and utilising electricity from different sources.

6.4 Deployment of LAES and PTES in low-carbon electricity systems^{***}

The technologies can also be integrated within the electricity grid system to provide benefits associated with low carbon electricity systems and flexibility. To study LAES and PTES within that context, the thermo-economic models described above in combination with the WeSIM model presented in Pudjianto et al. (2014) were used. The work presented here was done in collaboration with the co-authors of the work presented in Georgiou et al. (2019, 2018b). More specifically, the thermo-economic models were operated and their outputs were analysed by

^{***} This section was developed in collaboration with the co-authors of Georgiou et al. (2019, 2018b).

the author of the present work. However, the WeSIM model was operated by the co-authors (Marko Aunedi and Goran Strbac) of the paper mentioned above as well as the creation and analysis of the figures from the outputs of that model.

A brief analysis of the outputs from the work of Georgiou et al. (2018b) are presented here to show the viability of the deployment of these systems in a low-carbon electricity system and their corresponding value in such system. A detailed definition and discussion of the systems can be found in Georgiou et al. (2018b).

In terms of scenarios, the locations used were north and south Europe, and the carbon targets considered were 100 g/kWh and 50 g/kWh. Firstly, the system was analysed without any energy storage (considered here as counterfactual scenarios). As Fig. 6.18 shows, the main differences in north and south scenarios involve the use of wind and PV with significant demand being satisfied by wind in the north whereas in the south PV makes a significant contribution as well. In terms of the two carbon target scenarios, the main differences lie in the use of CCGT and CCS, with the 100 g/kWh scenario having more CCGT and less CCS than the 50 g/kWh for both north and south (Georgiou et al., 2018b).

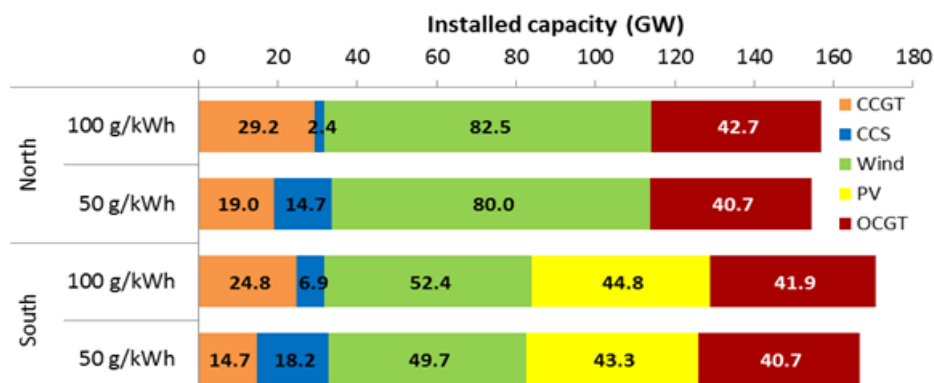


Figure 6.18. Electricity generation technology mix in baseline scenarios (i.e. without energy storage) (Georgiou et al., 2018b).

The two technologies were analysed in the system at different uptake levels under the scenarios considered (see Fig. 6.19). Firstly, the value of storage was found to decrease with the increase in cumulative storage capacity for both average and marginal (i.e. based on the previous energy storage scenario) values. Additionally, a faster decrease in marginal value than the average value was noted. In terms of carbon targets, the two scenarios were found to be relative close to each other with the lower carbon target indicating slightly higher system value. Comparing north and south scenarios, the south scenario was consistently found to give higher storage value, possibly due the greater variability associated with the PV than wind (Georgiou et al., 2018b). Therefore, once again, this shows the impact of different technologies on the potential for achieving carbon savings and cost benefits from electricity storage devices.

Comparing LAES and PTES, the value of storage obtained by employing PTES was in most cases greater than LAES. This is expected to be due to its higher roundtrip efficiency and duration (Georgiou et al., 2018b). Nevertheless, based on the thermo-economic analysis discussed earlier, PTES was also found to be more cost intensive. Therefore, in order for it to be viable, the system should also provide higher value of storage.

Also, the effect of demand side response (DSR) level was considered. DSR can provide a level of flexibility services to the system too, and therefore can act in some ways as a competitor against storage. Consequently, the system value of storage level was observed to generally decrease with the increase in DSR update levels (Georgiou et al., 2018b).

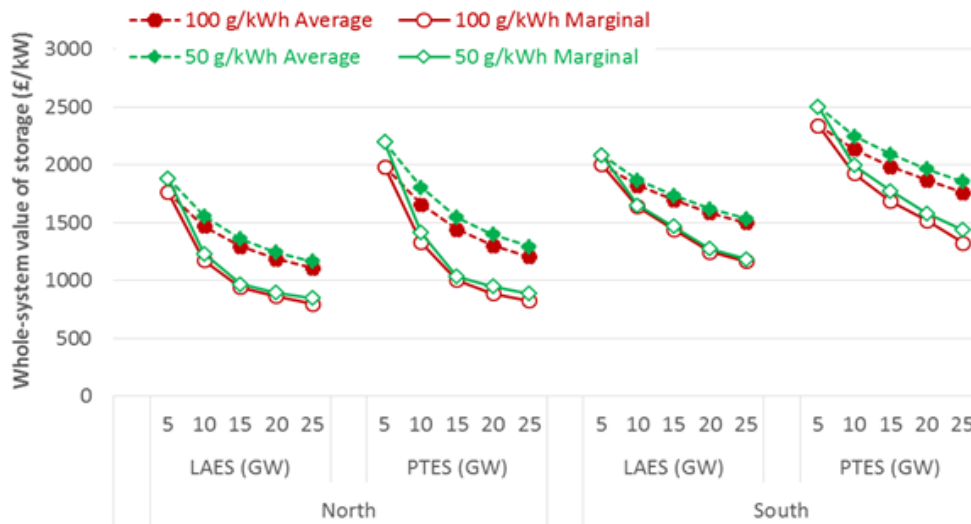


Figure 6.19. Marginal and average electricity system value of LAES and PTES technologies for North and South of Europe scenarios (Georgiou et al., 2018b).

At these storage values, the systems can be considered close to viable at the lower end of capacities installed and low DSR update levels. Nevertheless, the potential decrease in costs due to the increase in maturity and readiness levels with the increase in installed capacity was not taken into account here. Therefore, if costs decrease with the deployment of these systems, they might become more attractive at high deployment capacities as well (Georgiou et al., 2018b).

6.5 Summary

In this chapter thermo-economic models of two emerging electricity storage systems, liquid-air energy storage (LAES) and pumped thermal electricity storage (PTES), aimed for medium to large scale applications were used to perform analyses about technical performance, economic competitiveness, potential for carbon savings, and cost/benefits associated with any

carbon savings. The two systems were found to be competitive against each other in most metrics with factors affecting their absolute and relative competitiveness to include their scales, operational and performance parameters, marketplace's economic conditions, and location.

In terms of thermodynamic performance at the current conditions and configurations, PTES showed the potential for achieving higher roundtrip efficiencies than LAES, with the pressure ratio showing to have a great influence particularly at the lower end examined. Also, LAES's roundtrip efficiency was found to be greatly influenced by the amount of waste cold utilised in the charge cycle and the waste heat utilised in the discharge cycle. The sufficient use of these two element can potentially enhance the roundtrip efficiency of LAES to a level that can have a better advantage over alternative solutions.

In terms of economics at their intended capacities, LAES was found to have an overall lower power capital cost and energy capital cost than PTES. Also, the capital expenditure of both systems was dominated by components associated with power consumption or generation; such as compressors, expanders and turbines. Furthermore, the levelised cost of storage (LCOS) was noted to be similar for both technologies whereas the distribution of the cost elements compounding LCOS to be different. More specifically, the capital expenditure of PTES dominated its LCOS whereas in LAES the capital expenditure and operational energy costs were relatively close. In terms of minimum required sell-to-buy (STB) ratio, both systems were greatly affected by the electricity buy price (BP) at the lower end of BPs considered. The diminishing impact of BPs on STB ratio is expected to be due to the dominance of operational energy costs against the other cost elements of capital expenditure and maintenance costs. Comparing the two systems, LAES was found to be more competitive at low BPs with PTES becoming slightly more competitive at prices over ~ 0.10 £/kWh.

The two technologies were also analysed and compared at equal capacities by downsizing the scale of LAES. This possibly means that LAES was evaluated at a significantly smaller scale than its intended, something expected to affect its competitiveness negatively. Nevertheless, this analysis provided a like-for-like comparison as well as insights on the impact of scale. An increase in the power capital cost, energy capital cost and LCOS of LAES was noted. This increase was enough to slightly surpass the values observed for PTES, thus bringing PTES to a more advantageous position in terms of these metrics. Also, the required STB ratio at low BPs was found to be very similar for the two technologies while PTES was seen to become slightly more competitive at a lower BP than at the intended capacities.

To study the competitiveness of LAES and PTES against other electricity storage solutions, the power capital costs at the intended capacities were compared against existing technologies based on data from literature. Interestingly, LAES was observed to already be competitive against several existing storage technologies. Also, LAES has the advantage of maturity over PTES as it has already been proven at pilot plant scale and it employs equipment already available in the market. It is anticipated that both LAES and PTES might become more attractive as their maturity and readiness develop. Besides costing, it is also important to note the attractiveness of LAES and PTES in terms of other aspects/constraints (e.g. landscape requirements) that allow relatively few competing technologies to be as widely applicable.

Furthermore, the potential for carbon savings and the costs associated with those savings by using LAES and PTES were analysed. To obtain technical performance and characteristics along the economic metrics, the thermo-economic models developed for LAES and PTES were used while exploring several scenarios. The main points of interest of the scenarios included

the impact of cost savings by taking advantage of the peak demand electricity prices, the energy cost to the electricity storage system, and the electricity carbon factor at different locations.

The potential for carbon savings was observed to be affected by both the storage technology and location. In terms of cost of carbon savings, the capitalisation on peak electricity prices and the electricity cost to the storage system when charging were found to have a great influence. Therefore, both internal (e.g. characteristics of the storage technology) and external (e.g. electricity prices) factors greatly affected the costs associated with the quantified carbon savings. The impact of energy cost to the storage system was reflected through the LCOE of the different renewable energy technologies used to provide electricity for charging. Therefore, the cost competitiveness of the storage systems to achieve carbon savings can be significantly influenced by the generation technology providing electricity.

Finally, to study the potential for deployment of these technologies in a low-carbon electricity system under different conditions and requirements, an external model was employed through a collaboration. The findings from that exercise indicated the decrease in the system value of storage with the increase in deployment capacities for both technologies. PTES was generally found to be associated with higher system storage value, potentially due to its higher roundtrip efficiency and duration. However, it also requires higher values for it to be considered attractive due to its greater cost intensity observed. Also, the variability of the low-carbon technologies employed in the electricity system were found to affect the value of storage. More specifically, systems with high PV capacity were found to be associated with higher value of storage compared to wind. Lastly, demand side response (DSR) was found to act as a competitor solution to storage and therefore decreasing the value of system storage at high uptake levels.

As discussed in Chapter 2, energy storage has been of interest in literature including LAES (e.g. Morgan et al. (2015), Sciacovelli et al. (2016)) and PTES (e.g. McTigue et al. (2015), White et al. (2013)). The present work aimed to contribute in this area by providing a direct comparison of LAES and PTES (in the configurations proposed in literature for their development) while integrating the consideration of aspects including: the expected performance in an industrial setting while considering components' performance and influential parameters, capital costing, economic feasibility, competitiveness against other options, potential carbon savings from their deployment, the cost of achieving carbon savings from their deployment, and (in collaboration with another research group) the value they can provide to a low carbon electricity system.

The subject of electricity storage to pursue benefits in energy efficiency and decarbonisation in supply chains can be extended in future works to provide more insights. For example, to account for the future competitiveness of LAES and PTES at a more mature and higher readiness level, learning curves can be employed. Nevertheless, the impact of learning curves is expected to be based on the possible potential for improvement with respect to performance as well as cost. Therefore, the study of this potential can also be an avenue for future work. Also, further work could include the study of scalability of these technologies and their ability in variation of power to energy storage capacities as well as at different configurations, along with the impact on economic estimations. Finally, it should be noted that the approximate economic estimates presented here were based on simplified and generic approaches for the specific configurations under the assumption that equipment available in the correlations of those methods can be used for the development of the systems and can provide accurate estimates. More accurate figures might be obtainable from tenders and as the maturity of the technology increases more information is expected to be available in order to refine the

estimates obtained. Further discussion on some of the limitations of the models and potential future work avenues can be found in Section 7.2.

6.6 Highlights

- PTES was found to achieve higher roundtrip efficiency than LAES with the pressure ratio having a significant influence. LAES's roundtrip efficiency was observed to be greatly affected by waste cold and heat utilisation.
- At intended capacities, LAES was more competitive in terms power and energy capital costs. The two technologies had similar LCOS whereas the distribution of the costs elements of LCOS were different.
- The minimum required STB ratio was greatly affected by the electricity BPs at low BPs. Operational energy costs were found to dominate the STB at high BPs.
- The economic competitiveness comparison of the two systems was affected by changing the scales at which they are compared.
- Carbon savings through electricity storage systems were found to increase with the increase of the electricity carbon factor, energy curtailment level and roundtrip efficiency of the storage system.
- LAES generally showed lower cost of carbon savings while utilising electricity from technologies with low LCOE. However, at high LCOE PTES became more attractive than LAES.
- Deployment of LAES and PTES in low-carbon electricity systems showed the decrease in value of storage with the increase in deployment capacities. PTES was found to be generally associated with higher system storage value due to its higher roundtrip efficiency and greater duration.

Chapter 7

7 Conclusion

7.1 Main findings and conclusions

This research focused on the development of methods to analyse and identify improvement measures for energy intensive multi-echelon supply chains. The approaches were viewed from an academic viewpoint while integrating the perspective of large organisations with targets for improving the energy efficiency of their supply chain from their suppliers to their stores. This work also gave particular attention to fresh perishable products due their additional challenges such as energy intensive production, fast and frequent logistics requirements, and the necessity for refrigeration.

Multiple processes typically take place at the different stages of supply chains. Each of those processes is expected to have some energy and carbon footprint. This work's objectives included the identification of the processes whose improvement could potentially provide the greatest impact. Furthermore, a balance between novelty and industrial applicability was one

of the main objectives to be met. Given the current ambitious environmental targets set by governments and legislations imposed as well as targets set by companies, practical and novel solutions were a priority in this work.

A framework for analysing supply chains and identifying potential areas of improvement was developed and presented. The supply chain stages with the greatest potential for energy and/or carbon savings were found to be production, transport, and storage/retail. Each of these stages was found to be dominated by a process associated with a specific form of energy consumption. For production, that was heating/cooling requirements required for glasshouse production under auxiliary heating/cooling systems. For transportation, it was more obvious that fuel requirement was the dominant energy source. Nonetheless, for perishable products associated with frequent and fast logistics also affected by seasonality, transportation optimisation from both operational and technological perspectives was expected to provide even more impactful benefits. For storage/retail stage, electricity consumption was noted to be the dominant form of energy consumed, particularly in the case of products requiring refrigeration.

The development of modelling frameworks for the provision of methods for quantifying, analysing and benchmarking energy requirements, carbon emissions and energy costs, was identified as an impactful contribution to determining the potential savings of the energy intensive supply chain stages/processes through different improvement measures. Therefore, approaches for improving energy efficiency along the three main supply chain stages were identified and modelling frameworks were developed accordingly. The application of these modelling frameworks is expected to be widely applicable to similar supply chains; they were designed with this in consideration. Nevertheless, to test, showcase and identify potential savings, case studies or scenarios were used in this work.

Energy requirements associated with heat at the production stage were found in literature to usually dominate the energy requirements of products grown under support. The standardised quantification of energy requirements was therefore considered to be of great importance to allow the assessment, benchmarking and efficiency improvement at this stage of the supply chain. Therefore, the development of a model that can also act as a decision support tool was found to be useful. The development of the tool integrated different fields including data analytics, data visualisation, tool development, and modelling. The model was designed to be generic enough to be applied to different glasshouse production systems while relying only on basic input requirements from the producer/retailer. This is expected to assist in providing fast and in a straightforward way, but still reasonably accurate, estimates of energy requirements, carbon emissions and fuel costs.

The model was tested and showcased based on case studies indicating some of the influential parameters affecting the energy performance of production systems. Both operational and performance parameters were tested. The overall heat transfer coefficient and infiltration rate were found to have a great impact offering up to 57% savings in heating requirements. Similarly, lower internal temperatures were found to contribute towards significant energy savings; thus showing the potential savings that can be achieved by cultivating products (or varieties of products) which either require lower temperatures or are more flexible in their requirements. Furthermore, temporal and spatial analyses showed the importance of the glasshouses' thermal envelope properties on the resilience and uncertainty/variability of heating requirements against external weather conditions. A reduction of $25.4 \text{ kWh m}^{-2} \text{ year}^{-1}$ in the standard deviation of annual heat requirements was observed. Also, great variation in heating and cooling in terms of both annual and peak daily requirements was noted across the UK. This showed the impact of location on the energy performance of producers while

indicating the possibility of highly efficient glasshouses having greater requirements than less efficient ones due to their location.

Another effective method of reducing carbon emissions at this supply chain stage was found to be the change to alternative fuels for the heating systems. Interestingly, the impact of changing to a less carbon intensive fuel was in some cases greater than that of significant improvement measures on the thermal envelope. For example, in the case study this was observed to be the case for switching from oil to biomass. This can be particularly interesting when considering other factors such as capital cost requirements and disruption level (e.g. required downtime). However, in terms of operational energy costs, the relative difference between the measures was found to be significantly dissimilar from the carbon emissions analysis. An obvious example of this was the biomass which even though achieved great savings in emissions its cost was significantly greater. This indicated the potential trade-off between the carbon emissions and operational energy costs. This trade-off was not expected to be so strong for the operational or performance efficiency measures considered here.

Finally, due to the reliance of the model on weather data from stations (which can be located at some distance away) an expected error was anticipated. An attempt to estimate the expected error showed for some stations a good linear correlation with distance while with some not so good. Results based on cases of good correlations showed that a different error was introduced depending on the sourced data. Interestingly, the expected error was found to be relatively small for distances less than 100 km. This showed a reasonable confidence in the outputs for these cases, especially while considering the number of available weather stations in the UK.

The next stage in the supply chain identified to be important to investigate was transport while considering the allocation and distribution of products from supply points to depots and

thereafter to demand points. Modelling frameworks employing deterministic and heuristic approaches were developed for this purpose. Once again, one of the main objectives of the models was flexibility in application to different supply chains, practicality, and scalability to tackle very large systems. The allowance for the variation of parameters in the models encouraged the study of their impact on the performance of the system as well as the identification of the best performing model under different conditions. Some of the important aspects considered in the present work included the difference between types of stores, temporal variation, number of stops, delivery time, imports and national production allocation, vehicle capacity, demand uncertainty, capacity utilisation, and gradual replacement of vehicles in a fleet in terms of carbon emissions and fuel cost.

The initial analysis of the case study showed the disproportionality between number of demand points and their total demand for different types of stores. Also, the differences in the supply volumes (both absolute and relative to total) from different regions in the UK were noted. Some regions were found to dominate during some periods of the year while others were only responsible for a small share of the total supply without a significant contribution at any time of the year.

The first echelon optimisation analysis indicated the importance of both imports and national production in the satisfaction of demand throughout the year. Nevertheless, the ratio of national production to imports was found to greatly vary depending on the period of the year. Also, some depots were found to be dominated by a single supply region whereas others to have a more diverse supply including up to three regions. Advantages of greater diversity include the potentially lower risk associated with problems affecting a single region whereas disadvantages

include the potentially greater difficulty in achieving economies of scale for proposed improvement solutions.

The modelling framework which involved more processing steps (MFB) was found to perform better in terms of annual distance travelled, especially as vehicle capacity increased and in the case of small stores. As this modelling framework integrates deterministic and heuristic approaches, including continuous optimisation, mixed integer linear optimisation programming, clustering and combinatorial optimisation, it requires some arbitrary inputs. Results from this work indicated the importance of deriving those inputs according to the problem in hand for achieving good results. Furthermore, the initiation of the clustering approach used involves random initialisation which introduces a variation between iterations. The effect of this initialisation was tested and found to have minimal impact on the overall output of the model in terms of annual travel distance with small stores showing an even smaller variation than large stores.

Particular attention was given also to the impact of vehicle capacity on travel distance, utilisation capacity, and variation in required travel distance in the year as well as between consecutive periods. The increase in vehicle capacity was observed to generally have a positive effect on travel distances and their variation without negatively affecting the vehicle capacity utilisation. Also, with the increase in vehicle capacity the uncertainty associated with demand variation was observed to decrease.

Furthermore, some depots were observed to be heavily dominated by a single type of store. This introduced an interesting observation which raised the question whether depots and their fleets should be designed specifically for a type of store and introduce measures that can potentially achieve greater economies of scale. Also, the gradual replacement of the fleet to

alternative fuels was considered in order to inspect the effect on carbon emissions and fuel costs. A trade-off between emissions and fuel cost was noted in most cases while the fuel offering a balance between the two was found to be ethanol (85).

The next energy intensive stage of the supply chain was found to be the storage/retail stages which are mostly dominated by electricity consumption, especially when the products of interest require refrigeration. A novel way of improving the carbon footprint of electricity consumption at those stages was found to be through medium to large scale thermo-mechanical electricity storage systems. Besides the less attention thermo-mechanical storage systems have received in literature, they have several advantages including their long lifetime, decoupling of energy and power capacities, and scalability. In this work, the two recently proposed technologies of liquid-air energy storage (LAES) and pumped thermal electricity storage (PTES) were studied. Nevertheless, following the approach proposed here for these technologies, other technologies can be potentially studied as well.

As with most new technologies, estimates about their technical performance and economic competitiveness usually do not extensively exist or are difficult to acquire. Therefore, a framework assisting the thermo-economic analysis and comparison of these technologies can be of particular interest in order to perform a preliminary feasibility assessment. Given the usual variation in cost estimates, several costing methods with different cost correlation factors were used to obtain the expected range in cost-related estimates as well as their average for a more robust/diversified outcome. The two technologies were analysed at a capacity within their intended/proposed range as well as at equal capacities.

At their intended capacities, the LAES and PTES were found to be competitive against existing or alternative electricity storage solutions, especially when considering the constraints (e.g.

geological/landscape) sometimes associated with conventional large scale electricity storage technologies such as pumped hydro and underground compressed air. Comparing LAES and PTES, the former was found to have lower power and energy capital costs. Nevertheless, LAES was observed to be associated with higher energy operational costs primarily due to its lower roundtrip efficiency noted. LAES's roundtrip efficiency was found to be significantly enhanced through the sufficient utilisation of waste cold and heat. This improved the roundtrip efficiency of LAES and decreased operational energy costs. PTES, however, was found to be more capital intensive potentially making its initial investment a greater challenge. In both technologies, compression and expansion components were accountable for the greatest share in capital expenditure. Therefore, cost reduction techniques and advancements in those components could potentially contribute significantly to the reduction in capital expenditure required and result to the improvement in the economic competitiveness of these technologies.

Furthermore, metrics usually associated with the economic feasibility of electricity storage systems were studied while considering additional factors such as discount rates, lifetime and maintenance costs. The two technologies were found to have very similar levelised cost of storage but a breakdown analysis of this metric showed the dominating costs along the lifetime of the assets. As mentioned earlier, LAES was found to be more operationally cost intensive while PTES more capital intensive. In terms of sell-to-buy ratios, due to the greater capital intensity of PTES, it was found to require higher sell-to-buy ratios at low buying electricity prices (BPs). However, over the point of electricity buying price at which operational energy costs start to dominate the net present value, PTES was found to become slightly more competitive due to its higher roundtrip efficiency. Both LAES and PTES showed a rapid decrease in the required sell-to-buy ratio with the increase in BPs at the lower end of BPs considered. At the high end of BPs, however, the required sell-to-buy ratio stabilised.

Therefore, market conditions and electricity buying prices were found to have an impact on the economic feasibility and competitiveness of the systems.

Following the competitiveness analysis, the potential for achieving carbon savings as a decentralised system as well as a system integrated within the whole electricity grid was studied. Significant carbon savings were noted through the use of LAES and PTES by utilising intermittent renewable energy sources. The potential savings were affected mainly by three factors: the electricity carbon factors of the location, the renewable energy curtailment level, and the roundtrip efficiency of the electricity storage system. Furthermore, the cost associated with achieving carbon savings using electricity storage systems was found to be mainly affected by: the energy source used for charging and its associated levelised cost of electricity, and the potential for taking advantage of the difference in electricity prices between peak and off-peak demand (i.e. charging and discharging prices). In most cases, LAES was observed to have lower cost but the difference between LAES and PTES was affected by the energy source. Energy sources with higher levelised cost were found to be beneficial for PTES against LAES. Therefore, the selection of the most competitive technology for application is expected to depend on both internal factors (e.g. technical performance including roundtrip efficiency, power and energy capital costs, NPV, and levelised cost of storage) and external factors (e.g. energy source and its associated levelised cost of electricity, electricity carbon factor, energy curtailment level, and electricity market prices).

The value of both LAES and PTES in a large electricity grid system was found to decrease with the increase in deployment level. At the estimated prices, the two systems were found to be feasible but at relatively low penetration levels. Nevertheless, with the adoption of learning curves and the maturity of these systems, they could achieve lower costs and potentially

become even more competitive at higher deployment levels. Also, the target for carbon emissions in the grid was noted to affect their value. At the lower carbon target, the value of storage was found to be greater at all deployment levels. In addition, the energy mix, and particularly the level and type of renewable energy sources, was also another factor that contributed in the noted variation of storage value. Demand side response was found to act as a competitor against electricity storage devices as it provides a level of flexibility too. Therefore, the value of these technologies within the electricity system was found to decrease consistently with the increase in demand side response levels. Therefore, LAES and PTES were again found to be competitive in most cases for achieving carbon savings at an economically feasible cost with their competitiveness to be affected by both internal and external factors. Organisations can potentially install these technologies for achieving carbon emissions both directly or indirectly by offsetting the emissions of their activities that have yet to be decarbonised.

To summarise, the modelling frameworks were found to be useful in quantifying and identifying energy/carbon/cost savings in all three stages and their associated processes for the scenarios considered. The findings found in the scenarios in this work can act as examples of addressing ambitious targets set.

7.2 Limitations of modelling frameworks and potential future work

The present work showed the potential of the modelling frameworks and analyses presented. Nevertheless, it should be noted that several limitations of the modelling frameworks exist and potential future works could contribute to the further development of the models as well as the extension of the analysis to consider different scenarios, products and supply chain stages.

For the production stage, the modelling framework relies heavily on data from existing weather stations which gives the advantage of requiring limited inputs to get results. However, the distance difference between the weather station and the site along with other characteristic of the weather station location which might introduce an additional error to estimates present a limitation of the model. This is particularly important especially for sites with no weather stations at close proximity and similar site characteristics.

The modelling framework also considers a certain number of parameters at a certain frequency which as expected comes with the sacrifice of some accuracy if a more detailed analysis is required. Future works could include the consideration of more parameters while using a higher frequency of data. However, this is expected to introduce additional data requirements that might not be available from such large pool of weather stations. Consequently, the additional source of error due to the potentially greater distance from the weather station can be greater than the higher accuracy that could be achieved by a more detailed model. However, if a weather station is available at the production site the outcomes are expected to be better.

Furthermore, another limitation of the modelling framework is that it does not have the capability to optimise the spatial arrangement of production sites with the aim of minimising energy requirements under specific operational and performance parameters. This can also be another avenue of future work. Additionally, another point of view which is not captured by the model is the optimisation of design parameters for a specific location. This can also be interesting to study in the future.

Also, a limitation of the production stage analysis is the consideration of limited case studies and products. More case studies and comparison against different products or production systems could be performed in future studies to investigate how the impact of parameters could

affect different products. This could provide an insight into the selection of sites depending on the requirements of the products.

Finally, the impact of climate change could be further studied by considering the potential impact of rising temperatures. This analysis could be performed at different scenarios of temperature increase and at different locations to see the ones which could be more prone as well as the ones which could be more resilient to such changes.

The modelling frameworks and analysis for the transport stage also have several limitations and could be further studied in future works. For example, a limitation of the model is the lack of multi-objective optimisation techniques to optimally address potential trade-offs between different key performance indicators. This can be a potentially interesting expansion of the models.

Moreover, distance travelled is used in this study as a proxy for fuel consumption which might not always be the case. A study around the correlation between the two could be another interesting avenue for future work.

Furthermore, the cost considerations of the model are only limited to fuel costs and therefore other infrastructure and capital expenditure of potential solutions are not captured. Therefore, considering such solutions from a capital costs perspective could also be an interesting avenue for future work.

Additionally, the model does not consider inventory control and potential constraints to such requirements. In addition, the model assumes perfect demand foresight and therefore it assumed that no accumulation or depletion of product exists; thus time steps were considered

as independent to each other. This is a limitation of the model and presents a potential avenue for future work in order to expand the model to accommodate such requirements of the supply chain. Moreover, the incorporation of multiple products could also give interesting insights and is an aspect that could be considered in the future.

In addition, the production stage's modelling framework could be potentially integrated with the allocation and distribution modelling frameworks to incorporate the performance of suppliers in the allocation process. This could provide insights regarding the effects of prioritising suppliers based on their energy performance.

The model also assumes that it can only use the existing supply chain nodes and infrastructure. In other words, it does not consider the design of the supply chain (infrastructure). The optimal design of the supply chain is a different type of problem but it can potentially be another interesting perspective to consider in combination with the findings of this work in future research.

Also, the model boundary of the current modelling framework was for national production only. Therefore, the model considers the requirement of imports in the form of a slack variable and does not distinguish between the different potential points of origin. An extension of the system boundary to consider overseas production and the impact on the transport requirements could also be a useful extension of the model in future works.

Finally, the study of LAES and PTES as electricity storage solutions from a thermo-economic perspective and their deployment as decentralised systems as well as in a large low carbon electricity system also has some limitations which could be potentially studied further in future works, especially when more information is available regarding their costing and

performance in practice. This is expected to be available as the technologies mature and their readiness level increases.

Also, the investigation of scalability of these technologies can be further studied as well as the associated technical performance and economic competitiveness. This is also an area that could be studied further as the technologies mature.

Furthermore, the models in the present study currently do not consider the adoption of learning curves to provide estimates of the costing of the systems at a more mature level can be employed. The adoption of learning curves could potentially affect the cost estimates of each technology as well as their relative difference. This can be addressed through the further development of the modelling frameworks in the future and the anticipated future costs can be then applied and studied with respect to the impact on the technology itself, its competitiveness against other technologies, and its application in large electricity systems.

Finally, another interesting avenue for future work could be the application of these technologies in an electricity system grid model while considering a large variety of solutions from which the model can select the optimum options. This will potentially indicate the conditions in which these technologies are selected over others and therefore at what conditions they are most competitive and should be designed for.

References

- Abdallah, T., Farhat, A., Diabat, A., Kennedy, S., 2012. Green supply chains with carbon trading and environmental sourcing: Formulation and life cycle assessment. *Appl. Math. Model.* 36, 4271–4285. doi:10.1016/j.apm.2011.11.056
- Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop evapotranspiration: Guidelines for computing crop water requirements - FAO Irrigation and drainage paper 56, in: FAO. FAO - Food and Agriculture Organization of the United Nations, Rome, p. 300.
- ASABE, 2008. Heating, ventilating and cooling greenhouses, ANSI/ASAE. St Joseph.
- ASDA, 2017. Suppliers [WWW Document]. URL <https://sustainability.asda.com/suppliers> (accessed 9.15.17).
- Audsley, E., Brander, M., Chatterton, J., Murphy-Bokern, D., Webster, C., Williams, A., 2009. How low can we go? An assessment of the greenhouse gas emissions from the UK food system end and the scope to reduce them by 2050, November 2009. Bedford, Lohne, Edinburgh.
- Bellmore, M., Nemhauser, G.L., 1968. The traveling salesman problem: a survey. *Oper. Res.* 16, 538–558.
- Bird, L., Lew, D., Milligan, M., Carlini, E.M., Estanqueiro, A., Flynn, D., Gomez-Lazaro, E., Holttinen, H., Menemenlis, N., Orths, A., Eriksen, P.B., Smith, J.C., Soder, L., Sorensen, P., Altiparmakis, A., Yasuda, Y., Miller, J., 2016. Wind and solar energy curtailment: A review of international experience. *Renew. Sustain. Energy Rev.* 65, 577–586.

doi:<https://doi.org/10.1016/j.rser.2016.06.082>

Birmingham Energy Institute, 2015. Doing cold smarter. Birmingham.

Braekers, K., Ramaekers, K., Van Nieuwenhuyse, I., 2016. The vehicle routing problem: State of the art classification and review. *Comput. Ind. Eng.* 99, 300–313.
doi:<https://doi.org/10.1016/j.cie.2015.12.007>

Business Green, 2014. Waitrose rolls out low carbon lorries [WWW Document]. Incisive Bus. Media Ltd. URL <http://www.businessgreen.com/bg/news/2334615/waitrose-rolls-out-low-carbon-lorries> (accessed 2.1.16).

Carbon Trust, 2012. Refrigeration road map. London.

Carbon Trust, 2011. Value chain hotspotter value chain hotspotter. London.

Carlson, A., 1997. Greenhouse gas emissions in the lifecycle of carrots and tomatoes. Department of Environmental and Energy System Studies, Lund.

Carlsson-Kanyama, A., 1998. Food consumption patterns and their influence on climate change. *Ambio* 27, 528–534.

Carlsson-Kanyama, A., 1997. Greenhouse gas emissions in the life cycle of carrots and tomatoes - methods, data and results from a study of the types and amounts of carrots and tomatoes consumed in Sweden, IMES/EESS Report.

Catalá, L.P., Durand, G.A., Blanco, A.M., Alberto Bandoni, J., 2013. Mathematical model for strategic planning optimization in the pome fruit industry. *Agric. Syst.* 115, 63–71.

doi:10.1016/j.agry.2012.09.010

Celebi, M.E., Kingravi, H.A., Vela, P.A., 2013. A comparative study of efficient initialization methods for the k-means clustering algorithm. *Expert Syst. Appl.* 40, 200–210. doi:<https://doi.org/10.1016/j.eswa.2012.07.021>

Cellura, M., Longo, S., Mistretta, M., 2012. Life cycle assessment (LCA) of protected crops: an Italian case study. *J. Clean. Prod.* 28, 56–62. doi:<https://doi.org/10.1016/j.jclepro.2011.10.021>

Centre for environmental data analysis, Met Office Integrated Data Archive System (MIDAS), 2012. Land and marine surface stations data (1853-current).

Centre for Low Carbon Futures, 2013. Liquid air in the energy and transport systems: Opportunities for industry and innovation in the UK. York.

Chaabane, a., Ramudhin, a., Paquet, M., 2012. Design of sustainable supply chains under the emission trading scheme. *Int. J. Prod. Econ.* 135, 37–49. doi:10.1016/j.ijpe.2010.10.025

Chaabane, A., Ramudhin, A., Paquet, M., 2011. Designing supply chains with sustainability considerations. *Prod. Plan. Control* 22, 727–741. doi:10.1080/09537287.2010.543554

Chalabi, Z.S., Biro, A., Bailey, B.J., Aikman, D.P., Cockshull, K.E., 2002. SE—Structures and environment: Optimal control strategies for carbon dioxide enrichment in greenhouse tomato crops—Part 1: Using pure carbon dioxide. *Biosyst. Eng.* 81, 421–431. doi:<https://doi.org/10.1006/bioe.2001.0039>

Chen, H., Cong, T.N., Yang, W., Tan, C., Li, Y., Ding, Y., 2009. Progress in electrical energy

storage system: A critical review. *Prog. Nat. Sci.* 19, 291–312.
doi:10.1016/j.pnsc.2008.07.014

Clean Cities U.S. Department of Energy, 2018. Clean cities alternative fuel price report. Washington, D.C.

Couper, J.R., Penney, W.R., Fair, J.R., Walas, S.M., 2010. Chemical process equipment: selection and design., Revised Se. ed. Butterworth-Heinemann, Elsevier Inc, MA, USA.

DECC, DEFRA, 2016. UK government GHG conversion factors for company reporting. London. Contains public sector information licensed under the Open Government Licence v3.0.

DECC, DEFRA, Environment Agency, 2015. 2010 to 2015 government policy: greenhouse gas emissions. London. Contains public sector information licensed under the Open Government Licence v3.0

DEEC, National Statistics, 2015. 2013 UK greenhouse gas emissions, final figures. London. Contains public sector information licensed under the Open Government Licence v3.0

DEFRA, National Statistics, 2013a. Food statistics pocketbook 2013 in-year update. London. Contains public sector information licensed under the Open Government Licence v3.0

DEFRA, National Statistics, 2013b. Basic horticultural statistics 2013. York. Contains public sector information licensed under the Open Government Licence v3.0

Dias, G.M., Ayer, N.W., Khosla, S., Acker, R. Van, Young, S.B., Whitney, S., Hendricks, P., 2017. Life cycle perspectives on the sustainability of Ontario greenhouse tomato

- production: Benchmarking and improvement opportunities. *J. Clean. Prod.* 140, 831–839.
doi:<https://doi.org/10.1016/j.jclepro.2016.06.039>
- Dondo, R., Cerdá, J., 2007. A cluster-based optimization approach for the multi-depot heterogeneous fleet vehicle routing problem with time windows. *Eur. J. Oper. Res.* 176, 1478–1507. doi:<https://doi.org/10.1016/j.ejor.2004.07.077>
- Downie, J., Stubbs, W., 2013. Evaluation of Australian companies' scope 3 greenhouse gas emissions assessments. *J. Clean. Prod.* 56, 156–163. doi:[10.1016/j.jclepro.2011.09.010](https://doi.org/10.1016/j.jclepro.2011.09.010)
- Ecometrica, 2011. Electricity-specific emission factors for grid electricity.
- Energy Solutions, 2016. Historical electricity prices [WWW Document]. URL <http://www.energybrokers.co.uk/> (accessed 12.10.16).
- Erdoğan, S., Miller-Hooks, E., 2012. A Green Vehicle Routing Problem. *Transp. Res. Part E Logist. Transp. Rev.* 48, 100–114. doi:<https://doi.org/10.1016/j.tre.2011.08.001>
- Eskandarpour, M., Dejax, P., Miemczyk, J., Péton, O., 2015. Sustainable supply chain network design: An optimization-oriented review. *Omega* 54, 11–32. doi:<https://doi.org/10.1016/j.omega.2015.01.006>
- EU, 2016. EU legislation to control F-gases [WWW Document]. *Clim. Action*. URL http://ec.europa.eu/clima/policies/f-gas/legislation/index_en.htm (accessed 5.12.16).
- Everitt, B.S., Landau, S., Leese, M., 2001. *Cluster analysis*, 4th ed. Arnold.
- FAO, 2011. *Climate change, water and food security*, FAO Water Reports. Rome.

Fink, S., Mudd, C., Porter, K., Morgenstern, B., 2009. Wind energy curtailment case studies. Columbia, Maryland.

Frate, G.F., Antonelli, M., Desideri, U., 2017. A novel pumped thermal electricity storage (PTES) system with thermal integration. *Appl. Therm. Eng.* 121, 1051–1058. doi:<https://doi.org/10.1016/j.applthermaleng.2017.04.127>

Free Map Tools, 2016. Data: Full UK postcode latitude longitude (Contains Ordnance Survey data © Crown copyright and database right 2016, Contains Royal Mail data © Royal Mail copyright and database right 2016, Contains National Statistics data © Crown copyright and database right 2016).

Frota Neto, J.Q., Bloemhof-Ruwaard, J.M., Nunen, J.A.E.E. van, Heck, E. van, 2008. Designing and evaluating sustainable logistics networks. *Int. J. Prod. Econ.* 111, 195–208. doi:[10.1016/j.ijpe.2006.10.014](https://doi.org/10.1016/j.ijpe.2006.10.014)

Garnett, T., 2008a. Cooking up a storm: Food, greenhouse gas emissions and our changing climate, Food Climate Research Network, Centre for Environmental Strategy, University of Surrey. Surrey.

Garnett, T., 2008b. Cooking up a storm. Food, greenhouse gas emissions and our changing climate, Food Climate Research Network. Surrey.

Garnett, T., 2006. Fruit and vegetables & UK greenhouse gas emissions: exploring the relationship working paper produced as part of the work of the food climate. *Food Clim. Res. Netw.* 1–134.

-
- Georgiou, S., Acha, S., Shah, N., Markides, C.N., 2018a. A generic tool for quantifying the energy requirements of glasshouse food production. *J. Clean. Prod.* 191, 384–399. doi:<https://doi.org/10.1016/j.jclepro.2018.03.278>
- Georgiou, S., Acha, S., Shah, N., Markides, C.N., 2017a. Assessing, benchmarking and analyzing heating and cooling requirements for glasshouse food production: A design and operation modelling framework. *Energy Procedia* 123, 164–172. doi:<https://doi.org/10.1016/j.egypro.2017.07.250>
- Georgiou, S., Aunedi, M., Strbac, G., Markides, C.N., 2019. On the value of liquid-air and pumped-thermal electricity storage systems in low-carbon electricity systems. *Energy*.
- Georgiou, S., Aunedi, M., Strbac, G., Markides, C.N., 2018b. Application of liquid-air and pumped-thermal electricity storage systems in low-carbon electricity systems, in: *Heat Powered Cycles Conference*. Bayreuth, Germany.
- Georgiou, S., Mac Dowell, N., Shah, N., Markides, C.N., 2017b. Thermo-economic comparison of liquid-air and pumped-thermal electricity storage., in: *ECOS 2017: Proceedings of the 30th International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems*. San Diego, USA.
- Georgiou, S., Shah, N., Markides, C.N., 2018c. A thermo-economic analysis and comparison of pumped-thermal and liquid-air electricity storage systems. *Appl. Energy* 226, 1119–1133.
- Georgiou, S., Shah, N., Markides, C.N., 2018d. Potential for carbon savings from the deployment of liquid-air and pumped-thermal electricity storage systems, in: *Offshore*

Energy and Storage 2018.

González-Araya, M.C., Soto-Silva, W.E., Espejo, L.G.A., 2015. Harvest planning in apple orchards using an optimization model, in: Plà-Aragónés, M.L. (Ed.), *Handbook of Operations Research in Agriculture and the Agri-Food Industry*. Springer New York, New York, NY, pp. 79–105. doi:10.1007/978-1-4939-2483-7_4

Goula, A.M., Lazarides, H.N., 2015. Integrated processes can turn industrial food waste into valuable food by-products and/or ingredients: The cases of olive mill and pomegranate wastes. *J. Food Eng.* 167, 45–50. doi:10.1016/j.jfoodeng.2015.01.003

Gowreesunker, B., Tassou, S., 2015. Approaches for modelling the energy flow in food chains. *Energy. Sustain. Soc.* 5, 1–18. doi:10.1186/s13705-015-0035-y

Gowreesunker, B.L., Tassou, S.A., 2014. Energy generation potential of anaerobic digestion from the food and farming wastes of the UK food chain. *Renew. Bioresour.* 2. doi:10.7243/2052-6237-2-4

Guo, J., Cai, L., Chen, J., Zhou, Y., 2016. Performance optimization and comparison of pumped thermal and pumped cryogenic electricity storage systems. *Energy* 106, 260–269. doi:https://doi.org/10.1016/j.energy.2016.03.053

Gupta, M.J., Chandra, P., 2002. Effect of greenhouse design parameters on conservation of energy for greenhouse environmental control. *Energy* 27, 777–794. doi:https://doi.org/10.1016/S0360-5442(02)00030-0

Gurobi Optimization, L.L.C., 2018. Gurobi Optimizer Reference Manual.

- Hadjiconstantinou, E., Baldacci, R., 1998. A multi-depot period vehicle routing problem arising in the utilities sector. *J. Oper. Res. Soc.* 49, 1239–1248. doi:10.1057/palgrave.jors.2600641
- Hewitt, G.F., Pugh, S.J., 2007. Approximate design and costing methods for heat exchangers. *Heat Transf. Eng.* 28, 76–86. doi:10.1080/01457630601023229
- Highview Power Storage, 2016. Liquid air energy storage [WWW Document]. URL <http://www.highview-power.com> (accessed 2.15.16).
- Holman, J.P., 2012. *Experimental methods for engineers*, 8th ed. McGraw-Hill, New York, NY.
- Hospido, A., Milà I Canals, L., McLaren, S., Truninger, M., Edwards-Jones, G., Clift, R., 2009. The role of seasonality in lettuce consumption: A case study of environmental and social aspects. *Int. J. Life Cycle Assess.* 14, 381–391. doi:10.1007/s11367-009-0091-7
- Hougardy, S., Wilde, M., 2015. On the nearest neighbor rule for the metric traveling salesman problem. *Discret. Appl. Math.* 195, 101–103. doi:https://doi.org/10.1016/j.dam.2014.03.012
- Hugo, A., Pistikopoulos, E.N., 2005. Environmentally conscious long-range planning and design of supply chain networks. *J. Clean. Prod.* 13, 1428–1448. doi:10.1016/j.jclepro.2005.04.011
- IGD, n.d. Optimising transport modes [WWW Document]. URL <https://www.igd.com/Research/Supply-chain/Optimising-Transport-Modes/Case->

Studies/Waitrose---Multi-Temperature-Double-Deck-Trailers/ (accessed 3.2.16).

Intelligent Energy Europe, 2012. Forest. A guide to specifying biomass heating systems.

J Sainsbury plc, 2011. Logistics – our operations [WWW Document]. URL <http://www.j-sainsbury.co.uk/responsibility/case-studies/2011/logistics-our-operations/> (accessed 3.2.16).

J Sainsbury Plc, 2018. Our values make us different. UK.

J Sainsbury Plc, 2014. Sainsbury's 20x20 factsheet quarter 3 2014/15.

Jenkins, S., 2016. Chemical engineering essentials for the CPI professional [WWW Document]. Econ. Indic. CEPCI. URL <http://www.chemengonline.com/economic-indicators-cepci> (accessed 11.5.16).

Jones, A., 2002. An environmental assessment of food supply chains: a case study on dessert apples. *Environ. Manage.* 30, 560–76. doi:10.1007/s00267-002-2383-6

Jülch, V., 2016. Comparison of electricity storage options using levelized cost of storage (LCOS) method. *Appl. Energy* 183, 1594–1606. doi:<https://doi.org/10.1016/j.apenergy.2016.08.165>

Lampropoulos, S., 2014. Developing sustainable food supply chains; decarbonising the strawberry supply chain. Imperial College London.

Lee, D.-H., Dong, M., Bian, W., 2010. The design of sustainable logistics network under uncertainty. *Int. J. Prod. Econ.* 128, 159–166.

doi:<https://doi.org/10.1016/j.ijpe.2010.06.009>

- Lemmens, S., 2016. Cost engineering techniques and their applicability for cost estimation of organic rankine cycle systems. *Energies* 9.
- Lemmon, E.W., Huber, M.L., McLinden, M.O., 2010. NIST standard reference database 23: Reference fluid thermodynamic and transport properties (REFPROP), version 9.0. Phys. Chem. Prop.
- Li, C., Shi, H., Cao, Y., Wang, J., Kuang, Y., Tan, Y., Wei, J., 2015. Comprehensive review of renewable energy curtailment and avoidance: A specific example in China. *Renew. Sustain. Energy Rev.* 41, 1067–1079. doi:<https://doi.org/10.1016/j.rser.2014.09.009>
- Lumby, S., 1994. Investment appraisal and financial decisions, 5th Editio. ed. Chapman & Hall, London.
- Luo, G., Li, Y., Tang, W., Wei, X., 2016. Wind curtailment of China's wind power operation: Evolution, causes and solutions. *Renew. Sustain. Energy Rev.* 53, 1190–1201. doi:<https://doi.org/10.1016/j.rser.2015.09.075>
- Luo, W., de Zwart, H.F., Dai, J., Wang, X., Stanghellini, C., Bu, C., 2005. Simulation of greenhouse management in the subtropics, part I: model validation and scenario study for the winter season. *Biosyst. Eng.* 90, 307–318. doi:<https://doi.org/10.1016/j.biosystemseng.2004.11.008>
- Luo, X., Wang, J., Dooner, M., Clarke, J., 2014. Overview of current development in electrical energy storage technologies and the application potential in power system operation.

Appl. Energy 137, 511–536. doi:10.1016/j.apenergy.2014.09.081

MacRae, R., Cuddeford, V., Young, S.B., Matsubuchi-Shaw, M., 2013. The food system and climate change: An exploration of emerging strategies to reduce GHG emissions in canada. *Agroecol. Sustain. Food Syst.* 37, 933–963. doi:10.1080/21683565.2013.774302

Mariani, L., Cola, G., Bulgari, R., Ferrante, A., Martinetti, L., 2016. Space and time variability of heating requirements for greenhouse tomato production in the Euro-Mediterranean area. *Sci. Total Environ.* 562, 834–844. doi:https://doi.org/10.1016/j.scitotenv.2016.04.057

Mariaud, A., Acha, S., Ekins-Daukes, N., Shah, N., Markides, C.N., 2017. Integrated optimisation of photovoltaic and battery storage systems for UK commercial buildings. *Appl. Energy* 199, 466–478. doi:https://doi.org/10.1016/j.apenergy.2017.04.067

Markides, C.N., 2013. The role of pumped and waste heat technologies in a high-efficiency sustainable energy future for the UK. *Appl. Therm. Eng.* 53, 197–209. doi:https://doi.org/10.1016/j.applthermaleng.2012.02.037

McTigue, J.D., White, A.J., Markides, C.N., 2015. Parametric studies and optimisation of pumped thermal electricity storage. *Appl. Energy* 137, 800–811. doi:10.1016/j.apenergy.2014.08.039, <http://hdl.handle.net/10044/1/22196>

Mehdizadeh, A., Shah, N., Raikar, N., Bongers, P.M.M., Iftekhhar, A.K., Rajagopalan, S., 2012. An optimization of the food quality products throughout the supply chain, in: Srinivasan, I.A.K. and R. (Ed.), *Proceedings of the 11th International Symposium on Process Systems Engineering*. Elsevier B.V., Singapore. doi:http://dx.doi.org/10.1016/B978-0-444-59506-

5.50036-5

Michalský, M., Hooda, P.S., 2015. Greenhouse gas emissions of imported and locally produced fruit and vegetable commodities: A quantitative assessment. *Environ. Sci. Policy* 48, 32–43. doi:<http://dx.doi.org/10.1016/j.envsci.2014.12.018>

Mitie, 2011. A model for sustainable energy. Surrey.

Montoya-Torres, J.R., López Franco, J., Nieto Isaza, S., Felizzola Jiménez, H., Herazo-Padilla, N., 2015. A literature review on the vehicle routing problem with multiple depots. *Comput. Ind. Eng.* 79, 115–129. doi:<https://doi.org/10.1016/j.cie.2014.10.029>

Moreton, O.R., Rowley, P.N., 2012. The feasibility of biomass CHP as an energy and CO₂ source for commercial glasshouses. *Appl. Energy* 96, 339–346. doi:<https://doi.org/10.1016/j.apenergy.2012.02.023>

Morgan, R., Nemes, S., Gibson, E., Brett, G., 2015. Liquid air energy storage – Analysis and first results from a pilot scale demonstration plant. *Appl. Energy* 137, 845–853. doi:[10.1016/j.apenergy.2014.07.109](https://doi.org/10.1016/j.apenergy.2014.07.109)

Nadal-Roig, E., Plà-Aragónés, L.M., 2015. Handbook of Operations Research in Agriculture and the Agri-Food Industry. Springer New York, New York, NY. doi:[10.1007/978-1-4939-2483-7_7](https://doi.org/10.1007/978-1-4939-2483-7_7)

National Statistics, 2019. Energy trends: March 2019. London. Contains public sector information licensed under the Open Government Licence v3.0

Ntinas, G.K., Neumair, M., Tsadilas, C.D., Meyer, J., 2017. Carbon footprint and cumulative

- energy demand of greenhouse and open-field tomato cultivation systems under Southern and Central European climatic conditions. *J. Clean. Prod.* 142, 3617–3626. doi:<https://doi.org/10.1016/j.jclepro.2016.10.106>
- Obi, M., Jensen, S.M., Ferris, J.B., Bass, R.B., 2017. Calculation of levelized costs of electricity for various electrical energy storage systems. *Renew. Sustain. Energy Rev.* 67, 908–920. doi:<https://doi.org/10.1016/j.rser.2016.09.043>
- Opendoorlogistics Ltd (<http://www.opendoorlogistics.com>), 2015. Data: UK postcode boundary polygons (Contains Royal Mail data © Royal Mail copyright and database right 2015, Contains National Statistics data © Crown copyright and database right 2015).
- Ozkan, B., Ceylan, R.F., Kizilay, H., 2011a. Comparison of energy inputs in glasshouse double crop (fall and summer crops) tomato production. *Renew. Energy* 36, 1639–1644. doi:<https://doi.org/10.1016/j.renene.2010.11.022>
- Ozkan, B., Ceylan, R.F., Kizilay, H., 2011b. Energy inputs and crop yield relationships in greenhouse winter crop tomato production. *Renew. Energy* 36, 3217–3221. doi:<https://doi.org/10.1016/j.renene.2011.03.042>
- Page, G., Ridoutt, B., Bellotti, B., 2012. Carbon and water footprint tradeoffs in fresh tomato production. *J. Clean. Prod.* 32, 219–226. doi:<https://doi.org/10.1016/j.jclepro.2012.03.036>
- Paksoy, T., Özceylan, E., Weber, G.-W., 2011. A multi objective model for optimization of a green supply chain network. *Glob. J. Technol. Optim.* 51, 84–96.

Panozzo, G., Cortella, G., 2008. Standards for transport of perishable goods are still adequate?.

Connections between standards and technologies in perishable foodstuffs transport.

Trends Food Sci. Technol. 19, 432–440. doi:10.1016/j.tifs.2008.03.007

Papadopoulos, A.P., Hao, X., 1997. Effects of three greenhouse cover materials on tomato growth, productivity, and energy use. Sci. Hortic. (Amsterdam). 70, 165–178.

doi:[https://doi.org/10.1016/S0304-4238\(97\)00054-X](https://doi.org/10.1016/S0304-4238(97)00054-X)

Papageorgiou, L.G., 2009. Supply chain optimisation for the process industries: Advances and opportunities. Comput. Chem. Eng. 33, 1931–1938.

doi:10.1016/j.compchemeng.2009.06.014

Park, Y.B., 2005. An integrated approach for production and distribution planning in supply chain management. Int. J. Prod. Res. 43, 1205–1224.

doi:10.1080/00207540412331327718

Payen, S., Basset-Mens, C., Perret, S., 2015. LCA of local and imported tomato: an energy and water trade-off. J. Clean. Prod. 87, 139–148.

doi:<https://doi.org/10.1016/j.jclepro.2014.10.007>

Peña, J.M., Lozano, J.A., Larrañaga, P., 1999. An empirical comparison of four initialization methods for the K-Means algorithm. Pattern Recognit. Lett. 20, 1027–1040.

doi:[https://doi.org/10.1016/S0167-8655\(99\)00069-0](https://doi.org/10.1016/S0167-8655(99)00069-0)

Perry, R.H., Green, D.W., Maloney, J.O., 1997. Perry's chemical engineers' handbook seventh edition.

- Pudjianto, D., Aunedi, M., Djapic, P., Strbac, G., 2014. Whole-systems assessment of the value of energy storage in low-carbon electricity systems. *IEEE Trans. Smart Grid* 5, 1098–1109. doi:10.1109/TSG.2013.2282039
- Ramos, T.R.P., Gomes, M.I., Barbosa-Póvoa, A.P., 2014. Planning a sustainable reverse logistics system: Balancing costs with environmental and social concerns. *Omega* 48, 60–74. doi:<https://doi.org/10.1016/j.omega.2013.11.006>
- Rardin, R.L., 2017. *Optimization in operations research*, 2nd ed. Pearson Higher Education Inc., Hoboken, NJ.
- Rong, A., Akkerman, R., Grunow, M., 2011. An optimization approach for managing fresh food quality throughout the supply chain. *Int. J. Prod. Econ.* 131, 421–429. doi:<http://dx.doi.org/10.1016/j.ijpe.2009.11.026>
- Roskosch, D., Atakan, B., 2017. Pumped heat electricity storage: potential analysis and requirements. *Energy Procedia* 129, 1026–1033. doi:<https://doi.org/10.1016/j.egypro.2017.09.235>
- Sainsbury's, 2017. Sustainable sourcing [WWW Document]. URL <http://www.j-sainsbury.co.uk/making-a-difference/sustainable-sourcing> (accessed 9.15.17).
- Sandia National Laboratories, 2013. DOE/EPRI 2013 electricity storage handbook in collaboration with NRECA. New Mexico and California, USA.
- Scholz, K., Eriksson, M., Strid, I., 2015. Carbon footprint of supermarket food waste. *Resour. Conserv. Recycl.* 94, 56–65. doi:10.1016/j.resconrec.2014.11.016

-
- Sciacovelli, A., Smith, D., Navarro, H., Li, Y., Ding, Y., 2016. Liquid air energy storage – Operation and performance of the first pilot plant in the world, in: *The 29TH International Conference on Efficiency, Cost, Optimization, Simulation and Impact of Energy Systems*. Portoroz.
- Sciacovelli, A., Vecchi, A., Ding, Y., 2017. Liquid air energy storage (LAES) with packed bed cold thermal storage – From component to system level performance through dynamic modelling. *Appl. Energy* 190, 84–98. doi:<https://doi.org/10.1016/j.apenergy.2016.12.118>
- Seider, W.D., Seader, J.D., Lewin, D.R., Widagdo, S., 2010. *Product and design principles: synthesis analysis, and evaluation.*, 3rd Ed. ed. John Wiley & Sons (Asia) Pte Ltd., Asia.
- Shi, J., Visschers, V.H.M., Bumann, N., Siegrist, M., 2018. Consumers' climate-impact estimations of different food products. *J. Clean. Prod.* 172, 1646–1653. doi:<https://doi.org/10.1016/j.jclepro.2016.11.140>
- Sim, S., Barry, M., Clift, R., Cowell, S.J., 2006. The relative importance of transport in determining an appropriate sustainability strategy for food sourcing. *Int. J. Life Cycle Assess.* 12, 422. doi:[10.1065/lca2006.07.259](https://doi.org/10.1065/lca2006.07.259)
- Soto-silva, W.E., Nadal-roig, E., González-araya, M.C., Pla-aragones, L.M., 2016. Operational research models applied to the fresh fruit supply chain. *Eur. J. Oper. Res.* 251, 345–355. doi:[10.1016/j.ejor.2015.08.046](https://doi.org/10.1016/j.ejor.2015.08.046)
- Spyrou, M.S., Shanks, K., Cook, M.J., Pitcher, J., Lee, R., 2014. An empirical study of electricity and gas demand drivers in large food retail buildings of a national organisation. *Energy Build.* 68, 172–182. doi:[10.1016/j.enbuild.2013.09.015](https://doi.org/10.1016/j.enbuild.2013.09.015)

Steinbach, J., Staniaszek, D., 2015. Discount rates in energy system analysis.

Strbac, G., Aunedi, M., Konstantelos, I., Moreira, R., Teng, F., Moreno, R., Pudjianto, D., Laguna, A., Papadopoulos, P., 2017. Opportunities for energy storage: assessing whole-system economic benefits of energy storage in future electricity systems. *IEEE Power Energy Mag.* 15, 32–41. doi:10.1109/MPE.2017.2708858

Strbac, G., Aunedi, M., Pudjianto, D., Djapic, P., Teng, F., Sturt, A., Jackravut, D., Sansom, R., Yufit, V., Brandon, N., 2012. Strategic assessment of the role and value of energy storage systems in the UK low carbon energy future. London, UK.

Subić, J., Nastić, L., Bekić, B., 2015. Economic effects of using geothermal waters in the production of flowers and vegetables in glasshouses. *Procedia Econ. Financ.* 22, 131–140. doi:[https://doi.org/10.1016/S2212-5671\(15\)00241-5](https://doi.org/10.1016/S2212-5671(15)00241-5)

Tassou, S.A., 2014. Energy demand and reduction opportunities in the UK food chain. *Energy* 167, 162–170. doi:<http://dx.doi.org/10.1680/ener.14.00014>

Tassou, S.A., De-Lille, G., Ge, Y.T., 2009. Food transport refrigeration - Approaches to reduce energy consumption and environmental impacts of road transport. *Appl. Therm. Eng.* 29, 1467–1477. doi:10.1016/j.applthermaleng.2008.06.027

Tassou, S.A., Hadawey, A., Marriott, D., 2008. Greenhouse gas impacts of food retailing. London.

Tesco, 2018. Corporate responsibility [WWW Document]. URL <https://www.tesco.ie/corporate-responsibility/about-tesco/> (accessed 8.6.18).

- Tesco plc, 2017. Reducing our impact on the environment [WWW Document]. URL <https://www.tescopl.com/little-helps-plan/products-sourcing/reducing-our-impact-on-the-environment> (accessed 9.15.17).
- Tesco Plc, 2010. Corporate responsibility report 2010. Hertfordshire.
- Thess, A., 2013. Thermodynamic efficiency of pumped heat electricity storage. *Phys. Rev. Lett.* 111, 110602. doi:10.1103/PhysRevLett.111.110602
- Tidy, M., Wang, X., Hall, M., 2014. The role of supplier relationship management in reducing greenhouse gas emissions from food supply chains: Supplier engagement in the UK supermarket sector. *J. Clean. Prod.* 112, 3294–3305. doi:10.1016/j.jclepro.2015.10.065
- Torrellas, M., Antón, A., Montero, J.I., 2013. An environmental impact calculator for greenhouse production systems. *J. Environ. Manage.* 118, 186–195. doi:<https://doi.org/10.1016/j.jenvman.2013.01.011>
- Torrellas, M., Antón, A., Ruijs, M., Victoria, N.G., Stanghellini, C., Montero, J.I., 2012. Environmental and economic assessment of protected crops in four European scenarios. *J. Clean. Prod.* 28, 45–55. doi:<https://doi.org/10.1016/j.jclepro.2011.11.012>
- Tsiakis, P., Shah, N., Pantelides, C.C., 2001. Design of multi-echelon supply chain networks under demand uncertainty. *Ind. Eng. Chem. Res.* 40, 3585–3604. doi:10.1021/ie0100030
- Turton, R., Bailie, R.C., Whiting, W.B., Shaeiwitz, J.A., 2012. Analysis, synthesis and design of chemical processes, 4th ed. Pearson Education.
- U.S. Energy Information Administration, 2018. Levelized cost and levelized avoided cost of

new generation resources in the annual energy outlook 2018.

Ubeda, S., Arcelus, F.J., Faulin, J., 2011. Green logistics at Eroski: A case study. *Int. J. Prod. Econ.* 131, 44–51. doi:10.1016/j.ijpe.2010.04.041

Validi, S., Bhattacharya, A., Byrne, P.J., 2014. A case analysis of a sustainable food supply chain distribution system—A multi-objective approach. *Int. J. Prod. Econ.* 152, 71–87. doi:10.1016/j.ijpe.2014.02.003

Vanthoor, B.H.E., Stanghellini, C., van Henten, E.J., de Visser, P.H.B., 2011. A methodology for model-based greenhouse design: Part 1, a greenhouse climate model for a broad range of designs and climates. *Biosyst. Eng.* 110, 363–377. doi:https://doi.org/10.1016/j.biosystemseng.2011.06.001

Wang, F., Lai, X., Shi, N., 2011. A multi-objective optimization for green supply chain network design. *Decis. Support Syst.* 51, 262–269. doi:10.1016/j.dss.2010.11.020

Wass, S.N., Barrie, I.A., 1984. Application of a model for calculating glasshouse energy requirements. *Energy Agric.* 3, 99–108. doi:https://doi.org/10.1016/0167-5826(84)90012-3

White, A., McTigue, J., Markides, C., 2014. Wave propagation and thermodynamic losses in packed-bed thermal reservoirs for energy storage. *Appl. Energy* 130, 648–657. doi:10.1016/j.apenergy.2014.02.071

White, A., Parks, G., Markides, C.N., 2013. Thermodynamic analysis of pumped thermal electricity storage. *Appl. Therm. Eng.* 53, 291–298.

doi:10.1016/j.applthermaleng.2012.03.030

White, A.J., 2011. Loss analysis of thermal reservoirs for electrical energy storage schemes.

Appl. Energy 88, 4150–4159. doi:10.1016/j.apenergy.2011.04.030

White, A.J., McTigue, J.D., Markides, C.N., 2016. Analysis and optimisation of packed-bed thermal reservoirs for electricity storage applications. R. Soc. Publ.

WRI, 2015. Greenhouse gas protocol [WWW Document]. URL <http://www.wri.org/our-work/project/greenhouse-gas-protocol/online-courses#project-tabs> (accessed 11.16.15).

Yeh, W.-C., Chuang, M.-C., 2011. Using multi-objective genetic algorithm for partner selection in green supply chain problems. Expert Syst. Appl. 38, 4244–4253. doi:10.1016/j.eswa.2010.09.091

You, F.Q., Tao, L., Graziano, D.J., Snyder, S.W., 2012. Optimal design of sustainable cellulosic biofuel supply chains: Multiobjective optimization coupled with life cycle assessment and input-output analysis. Aiche J. 58, 1157–1180. doi:10.1002/aic.12637

Zhang, M., 2006. Energy analysis of various supermarket refrigeration systems, in: International Refrigeration and Air Conditioning Conference. Bridgeton.