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Original article

Investigating trade-offs between the operating cost and green house gas emissions from water distribution systems

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ABSTRACT

For electricity grids with an increasing share of intermittent renewables, the power generation mix can have significant daily variations. This leads to time-dependent emission intensities and volatile electricity prices in the day-ahead and spot market tariffs that can be better utilised by energy intensive industries such as water supply utilities. A multi-objective optimisation method for scheduling the operation of pumps is investigated in this paper for the reduction of both electricity costs and greenhouse gas emissions for a benchmark water distribution system. A set of energy supply scenarios has been formulated based on future projections from National Grid plc (UK) in order to investigate the range of cost savings and emission reductions that could be possibly achieved. Pump scheduling options with fixed time-of-use and day ahead market tariffs are analysed in order to compare potential reduction tradeoffs for both electricity costs and greenhouse gas emissions using Pareto optimality. The presented analysis concludes that the explicit inclusion of greenhouse gas emission reductions in optimising the scheduling of pumps operation in water distribution systems could provide considerable benefits; however, more compelling fiscal and regulatory incentives are needed.
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1. Introduction

The water industry is a large consumer of energy and an emitter of carbon, much of which is associated with the electricity it uses [1]. Although the UK water industry is expected to substantially contribute towards the emissions reduction targets established under the Climate Change Act (34% by 2020 and 80% by 2050) [2], there are currently no clear targets of what emissions reductions the water industry should be aiming for and within what time-frame. In anticipation of pending regulatory targets and fiscal incentives, and also water resources and assets management challenges associated with climate change, some UK water utilities are working towards carbon neutrality by 2050 [3,4], delivered through a combination of operational efficiency, renewable energy generation and the purchase of low-carbon grid electricity.

The majority of the electrical power utilised by water companies (65–80%) is for operating pump motors in order to deliver potable water from sources to customers [5,6]. Pumps in water distribution systems (WDS) operate with control schedules that satisfy flow and pressure head requirements in order to guarantee a supply of water while minimising the cost of operation. This minimisation is achieved by making use of time periods with a low-price electricity tariff to fill tanks and reservoirs and minimise the operation of pumps during periods of high-price electricity [7].

As intermittent renewables are projected to generate a large share of grid electricity, energy storage technologies and variable pricing models are becoming increasingly important to support the load management and grid stability [8]. As a result, water utilities could pro-actively use pump scheduling to participate in demand side response schemes to reduce both their electricity costs and GHG emissions, and contribute to grid stability [9].

Greenhouse gas emissions of the pump operation can also be minimised by changing the optimisation problem to specifically minimise GHG emissions and make use of the diurnal fluctuations of GHG emissions of the electricity supply [10,11]. To best assess GHG emission reductions and cost minimisation from pump scheduling, the problem is formulated as a multi-objective optimisation problem. To ensure the resulting schedules and operating cost, in terms of financial cost and GHG emissions, can be compared, a mathematical optimisation procedure that can quantify the optimality gap is applied. Different pump operating schedules are compared within a set of electricity supply scenarios for a benchmark water supply network. These scenarios are derived

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from the Future Energy Scenarios provided by National Grid plc (UK) [12] in order to examine plausible changes in the utilisation of intermittent renewables. In addition, various electricity purchasing options for water utilities are considered such as time-of-use (TOU) and day-ahead market (DAM) tariffs. A mathematical multi-objective Pareto optimality method is then applied to determine the optimal electricity costs and GHG emissions for the operation of pumps under future energy supply scenarios and various tariff structures.

2. Methodology and analysis

The reduction in both electricity costs and GHG emissions through optimising the operation of pumps in WDS under different energy supply scenarios has been carried out in two stages.

Firstly, future energy supply scenarios were defined as the *Green* and *No-Progress* scenarios for year 2035 based on analysis by National Grid plc [12]. These scenarios reflect expected changes in power generation technologies and fuel supply in the UK. Details of formulating the future energy supply scenarios are described in Section 2.1. The pump schedules are then optimised to reduce the electricity costs for a WDS operating with either a fixed time-of-use (TOU) tariff with peak pricing as commonly used by UK water utilities or variable electricity tariffs using day-ahead-market (DAM) tariffs. Secondly, optimal pump schedules and their associated electricity costs and GHG emissions were derived and compared using a branch and bound algorithm [13] that also includes the quantification of an optimality gap. The applied multi-objective global optimisation method is explained in Section 2.2.

The operating cost and GHG emissions resulting from the operation optimised for different objectives in different energy scenarios are compared by analysing the operation of the WDS on selected operating days.

2.1. Energy supply scenarios

Future energy supply scenarios vary significantly in their projections for the penetration rate of renewable energy in the UK [12]. An analysis of a wide range of future energy scenarios confirms that high penetration rates of renewables are feasible [14]. To ensure the applicability of our results and conclusions to many scenarios the operation in a broad range of scenarios is considered. Energy scenarios or software packages modelling energy scenarios or energy-water scenarios, that could be used to construct future operating scenarios cannot consider the hourly variance observed in the energy supply [15].

In this analysis, the assumed energy supply scenarios take both mean and extreme values from projections made by National Grid plc (UK) [16]. However, these energy supply scenarios do not consider the hourly variance observed in a diurnal energy supply [15]. Therefore, the energy supply scenarios were modified based on time series describing the electricity generation mix in terms of fuel type and total supplied energy, in order to provide half-hour time estimates. Technology specific Emission Factors (EFs), for each power generation type including the interconnections that supply the UK grid, were taken into account to derive GHG emissions time series with the required temporal resolution. The pricing data, which were used to compute the operating costs of the benchmark WDS, is based upon electricity tariffs used by three UK water utilities and spot market prices for 2014 [17]. The GHG emissions for a benchmark WDS has been investigated under four different grid (fuel mix) scenarios: the 2014 grid and three possible future scenarios which are defined as *No-Progress, Green* and *Green** (based upon information presented in [16]).

2.1.1. No-Progress energy supply scenario

This scenario assumes that the UK's renewable energy target of 15% for 2035 [2] is not met. Sustainability and decarbonisation of the energy sector are not policy priorities, which results in more emphasis on Combined Cycle Gas Turbines (CCGTs) over nuclear and renewables [16]. The fuel combination for this scenario in 2035 assumes that the contribution of natural gas increases to 47% while coal is reduced to 1% of the generation output. Renewables moderately change by 2035 with photovoltaics contributing 2%, wind energy increases to 19% and the generation from biomass contributes 5% [16].

2.1.2. Green energy supply scenario

The *Green* scenario assumes that the renewable energy target of 15% for 2035 is met. In addition, new European renewable energy targets are set to stipulate 23% energy supply from renewables by 2030 and 39% by 2050 [16]. It is assumed that the UK government adopts these recommendations and meets the targets for renewable energy production. Decarbonisation efforts are strengthened which lead to significant changes in the electricity supply with a high penetration of renewable energy. The most significant change to the fuel mix of the electrical energy supply would be the reduction of coal from 32% to 6% by 2035, which will be further coupled with carbon capture and storage (CCS) technologies. Consequently, the EF from coal is reduced from 870 to 220 g CO_2-e/kW h. Furthermore, the contribution from wind energy is expected to rise to 40% in 2035. Biomass fuel and other renewables such as photovoltaic generation will increase their contributions to 6% and 4% respectively by 2035 [16].

2.1.3. Green* energy supply scenario

An alternative *Green** energy supply scenario has also been formulated due to technical, institutional and economic uncertainties associated with CCS [18]. In this case, the GHG emissions under the *Green* scenario are recalculated for the same fuel combination; however, the emissions intensity reduction through CCS are deduced.

2.1.4. Formulation of representative operating days

A previous analysis by [10] proposed a future electricity supply by increasing the wind power generation and reducing coal power generation accordingly. In comparison, the energy supply scenarios applied in this analysis were formulated using grid data obtained from the Balancing Mechanism Reporting System [23] and APX Power UK [17]. Based on the proposed modelling method, a future scenario will have different overall energy supply, but weather, price and consumption patterns will preserve the variation and volatility of the energy supply from data for a benchmark year (e.g. 2014). The presented analysis focuses on relative changes between different operating conditions that arise from the short-term fluctuations in the emission intensities and electricity prices. These fluctuations cannot be represented accurately in an aggregated model. The emission intensity (EI) of the energy supply for a given time is given by:

$$EI_{s,t} = \frac{1}{1 - T_{loss}} \frac{\sum_{f=1}^{f=n} E_{f,t} \times EF_f}{\sum_{f=1}^{f=n} E_{f,t}} \tag{1}$$

where $EI_{s,t}$ is the emission intensity (EI) of scenario s at time t. The electricity source EI factors are summarised in Table 1. $E_{f,t}$ is the power generated at time t by fuel type f and EF_f is the emission factor for fuel type $f \in \{1, n\}$. The transmission and distribution losses T_{loss} are assumed constant (7.6%) for all energy supply scenarios [24].

Table 1
EI factors by electricity source. *Sources:* [1]EDF [19] [2]Intergovernmental Panel on Climate Change [20] [3]DECC [21] [4]Defra et al. [22].

Fuel type	Factor $\left(\frac{gCO_2e}{kWh}\right)$	Fuel type	Factor $\left(\frac{gCO_2e}{kWh}\right)$	Fuel type	Factor $\left(\frac{gCO_2e}{kWh}\right)$
Coal	870[1]	Wind	11[2]	Interconnections	
Coal-CCS	220[2]	Solar	72[2]	French-ICT	65[4]
Nuclear	12[2]	Biomass	230[2]	French-ICT	65[4]
Gas	487[1]	Hydro		Irish-ICT	462[4]
Gas-CCS	170[2]	Pumped storage	30[1]	EastWest-ICT	462[4]
Oil	650[1]	Non-pumped storage	10[1]	Other	770[3]

The large number of operating days (14,600) across all energy supply scenarios precludes their complete enumeration. Monte Carlo simulations were considered to select operating days to ensure a good representation of energy supply scenarios and operating conditions; however, the number of independent variables lead to a large set of operating days for the multi-objective optimisation problem.

In order to explore the operation of WDS within a wide range of grid states, the operating conditions were clustered by the dominant fossil fuel and renewable source. In the *Green* scenarios, there is no dominant fossil fuel; and therefore, the two dominant renewable sources are used to characterise the energy supply. A decision tree template was developed and applied to derive four representative operating days for each of the four energy supply scenarios (Fig. 1). As an example, Fig. 2 describes the calculated representative operating days for the 2035 *Green* scenario with daily fluctuations in electricity costs and GHG emissions. The 2035 scenarios were also clustered based upon the dominant fuel types as shown in Table 2. For each energy supply scenario, different representative operating days were selected to model the operation of a benchmark WDS. This selection aims to encapsulate the significant variations in diurnal EI fluctuations caused by differences between the energy supply scenarios and individual operating days (Fig. 2). A day with a fuel distribution closest to the groups median is selected that results in different days for each scenario with specific DAM tariffs and diurnal EIs.

The sixteen representative operating days are summarised in Table 3. These days are utilised in the pump scheduling analysis for all investigated energy supply scenarios, EI characteristics and various pricing models. The correlation between EI and DAM tariffs differ significantly for the operating days while the correlation between the EI and TOU tariffs remains relatively constant. The correlation between the GHG EI and the DAM tariff for 2014 is 0.44 while the correlation between the TOU and GHG emissions is 0.20 (Table 3). The standard deviation of the normalised DAM tariffs ranges from 0.15 to 0.29 for all considered energy supply scenarios. The standard deviation of EI in 2014 is small (0.02–0.09) and it depends upon the day in the *No-Progress* and *Green* scenarios (0.06–0.17). In comparison, the standard deviation for the *Green** energy supply scenario is considerably larger (0.09–0.29).

2.2. Optimisation of pumping schedules

The optimisation of pumping schedule in WDS is a computationally challenging problem as underlying fundamental system equations are non-linear and the description of pump or flow states involves binary variables. In mathematical optimisation, the problem can be posed as a mixed integer problem (MIP) and solved using branch and bound methods [25–27]. By using a piecewise linear approximation of the hydraulic systems, as described in [26], the operating electricity costs and resulting GHG emissions for a benchmark WDS have been computed in different electricity pricing models and GHG emission scenarios. A background review on optimisation methods for the operation of water distribution networks is provided in [28].

The optimisation problem in this analysis is formulated as a mixed integer quadratic problem (MIQP) with linear constraints and solved using a branch and bound method. The optimisation problem for the optimal WDS pump schedule is described as:

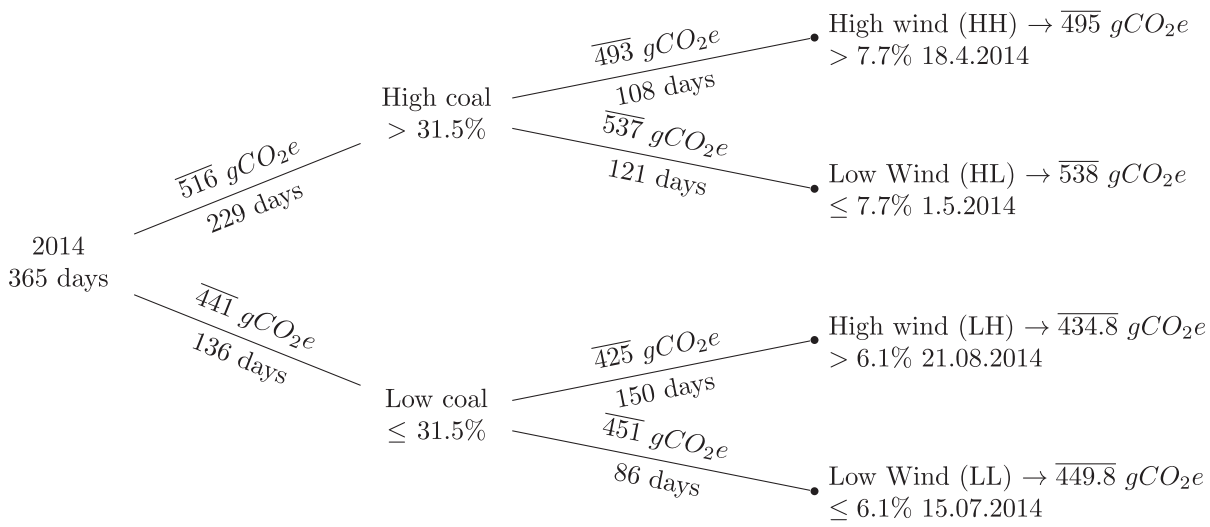


Fig. 1. A decision tree template for the construction of operating days for each energy supply scenario (based on data from 2014).

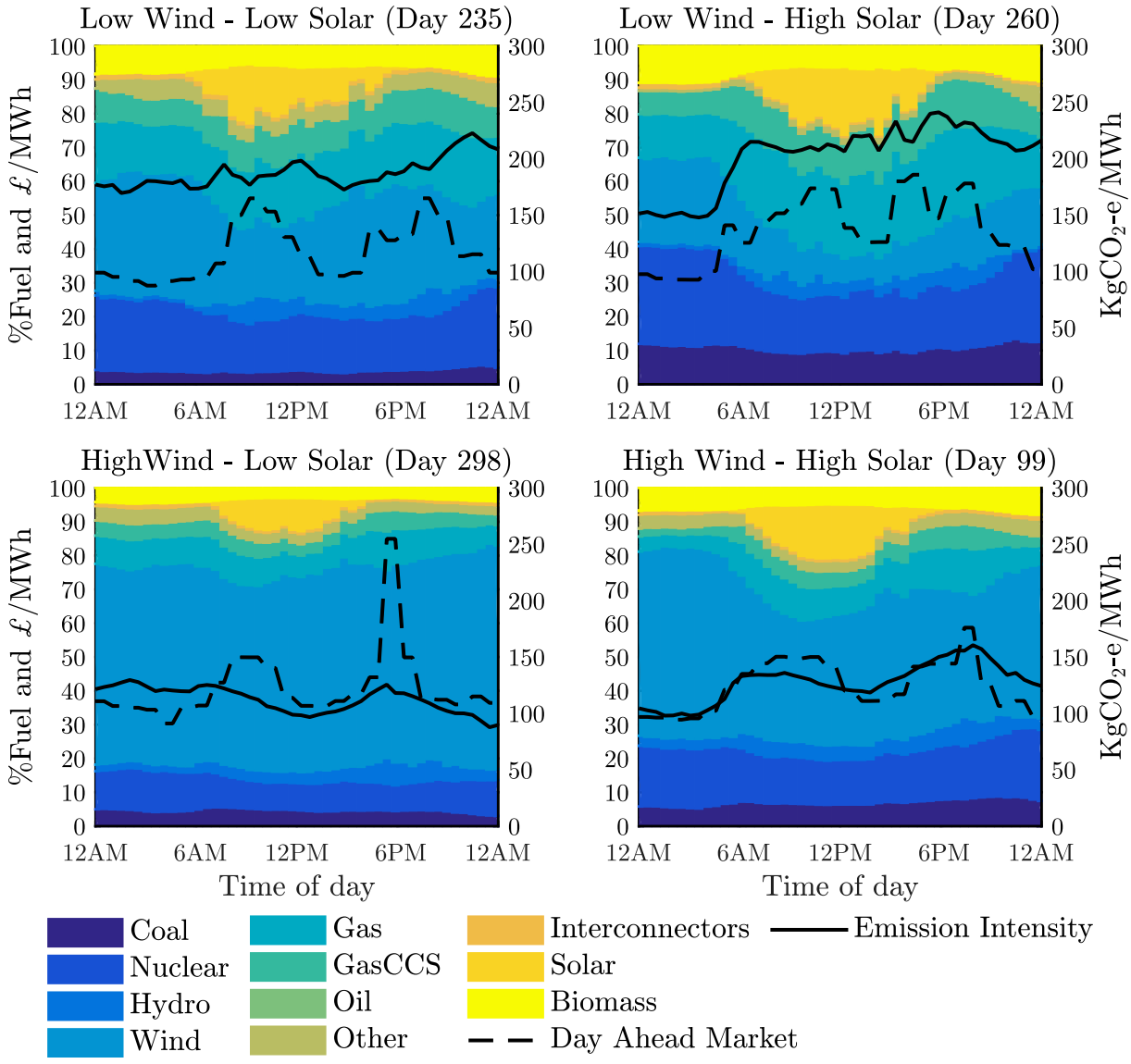


Fig. 2. Fuel mix share and electricity prices for the selected days of the 2035 Green (UK) scenario. The left y-axis shows fuel mix share and spot market prices, the right y-axis represents the emission intensity.

Table 2
An application of the decision tree template for the various energy supply scenarios. The separation is based on the dominating fuel types. Note: the Green and Green* scenario have the same fuel usage.

Scenario	Fuel	Fuel contribution average			
2014	Coal	$> \overline{31.5}\%$ (229 days)		$\leqslant \overline{31.5}\%$ (136 days)	
	Wind	$> \overline{7.7}\%$ (108 days)	$\leqslant \overline{7.7}\%$ (121 days)	$> \overline{6.1}\%$ (50 days)	$\leqslant \overline{6.1}\%$ (86 days)
2035	Wind	$> \overline{36.5}\%$ (181 days)		$\leqslant \overline{36.5}\%$ (184 days)	
Green	Solar	$> \overline{4.9}\%$ (92 days)	$\leqslant \overline{4.9}\%$ (92 days)	$> \overline{2.7}\%$ (75 days)	$\leqslant \overline{2.7}\%$ (106 days)
2035	Wind	$> \overline{36.5}\%$ (181 days)		$\leqslant \overline{36.5}\%$ (184 days)	
Green*	Solar	$> \overline{4.9}\%$ (92 days)	$\leqslant \overline{4.9}\%$ (92 days)	$> \overline{2.7}\%$ (75 days)	$\leqslant \overline{2.7}\%$ (106 days)
2035 No	Gas	$> \overline{45.3}\%$ (196 days)		$\leqslant \overline{45.3}\%$ (169 days)	
Progress	Wind	$> \overline{28.7}\%$ (85 days)	$\leqslant \overline{28.7}\%$ (85 days)	$> \overline{11.2}\%$ (87 days)	$\leqslant \overline{11.2}\%$ (109 days)

$$\begin{aligned} &\textit{minimise}: && \text{Pump operating costs and GHG emissions,} \\ &\textit{subject to}: && \text{Hydraulic constraints of components,} \\ & && \text{Mass balance of the system.} \end{aligned} \tag{2}$$

2.2.1. Objective function

The decision variable in scheduling the operation of a fixed speed pump is the pump's state, ON or OFF, here described by $T_{i_p j} \in \{0, 1\}$ for pump i_p at time step $j \in [0, N]$. With the power rating of the pump assumed fixed (i.e. independent of flow conditions for a fixed speed pump), the energy consumption by each pump during a 24hr period and the associated energy cost are calculated by a linear function:

$$f_1(\cdot) := \sum_{i_p=1}^{i_p=N_p} \sum_{j=1}^{j=N} T_{i_p j} \times \left(\lambda P^E_{i_p j} + (1-\lambda) P^{GHG}_{i_p j} \right) \tag{3}$$

Table 3
Summary of the properties of the operating days for each energy supply scenario. The table also includes the variability in the energy intensity and electricity tariffs, and the correlation between DAM, TOU and the energy intensity. The operating days are described by their fuel types. For example, 2014: LH represents low coal and high wind.

Scenario	2014				2035 No progress				2035 Green				2035 Green*			
Day	LL	LH	HL	HH	LL	LH	HL	HH	LL	LH	HL	HH	LL	LH	HL	HH
Max GHG	487	462	566	524	318	312	421	380	223	241	130	161	300	339	236	300
Mean GHG	450	435	538	495	294	244	385	343	188	202	112	127	257	276	188	202
Min GHG	376	385	521	449	246	166	311	279	170	148	88	98	211	226	137	138
EI $\sigma*$	0.09	0.06	0.02	0.04	0.06	0.17	0.06	0.11	0.07	0.14	0.10	0.14	0.12	0.09	0.15	0.29
DAM $\sigma*$	0.17	0.17	0.24	0.26	0.14	0.22	0.18	0.2	0.21	0.22	0.26	0.18	0.16	0.15	0.25	0.29
(DAM-TOU) $r^{\dagger}$	0.63	0.37	0.73	0.76	0.59	0.31	0.38	0.31	0.26	0.62	0.60	0.35	0.05	0.33	0.76	0.78
(DAM-EI) $r\dagger$	0.87	0.73	−0.42	0.56	0.27	0.47	0.62	0.60	0.25	0.73	0.18	0.75	−0.04	0.23	0.47	0.35

† Correlation between prices.
* Standard deviation of prices.

where $P^{E}_{i_p,j}$ represents the cost of energy of having pump i_p ON at time j, $P^{GHG}_{i_p,j}$ represents the GHG emissions associated with having pump i_p ON at time j. The vectors describing the cost $\mathbf{P}^{E}$ and $\mathbf{P}^{GHG}$ are normalised such that $\overline{\mathbf{P}^{E}} = 1$ and $\overline{\mathbf{P}^{GHG}} = 1$, and the factor $\lambda \in [0, 1]$ generates a weighted sum of the normalised components of costs and GHG emissions [29].

Since switching the pumps operation could have a negative impact on the maintenance cost of a system due to the resulting pressure variations and fatigue related failures, penalties for the pump switching could be introduced to reduce this negative impact [30,31]. A penalty function that approximates the switching costs was added to the objective function to lower maintenance costs. By penalising ON-to-OFF and OFF-to-ON states equally, this function is defined as:

$$\begin{aligned} f_2(\cdot) \quad &:= \sum_{i_p=1}^{i_p=N_p} P_s \sum_{j=1}^{j=N} |T_{i_p,j} - T_{i_p,j-1}| \\ &= \sum_{i_p=1}^{i_p=N_p} P_s \sum_{j=1}^{j=N} \left(T_{i_p,j} - T_{i_p,j-1}\right)^2 \end{aligned} \tag{4}$$

where P_s is an approximation of the costs for switching a pump (adapted from [30]). While the electricity costs and GHG emissions are difficult to estimate as a function of the number of pumps switches, a well designed and maintained surge protection coupled with continuous high-frequency pressure monitoring [32] can ensure that such additional operating costs are kept to a minimum and are several orders of magnitude smaller than the considered electricity and GHG emission costs [33]. In fact, the electrical energy expended for pumping is the most significant GHG emission source during the life cycle of a pump [6]. The inclusion of f_2 in the multi-objective optimisation could be used to reduce the number of pumps switches; however, it is not included here since the exact cost and environmental impact are not known and the additional costs from frequent pumps switches are assumed negligible in this work. For a WDS without adequate surge protection and continuous pressure monitoring, the pumps switches may be a major contributing factor for a cumulative pressure induced stress and pipe failures that result in considerable extra costs.

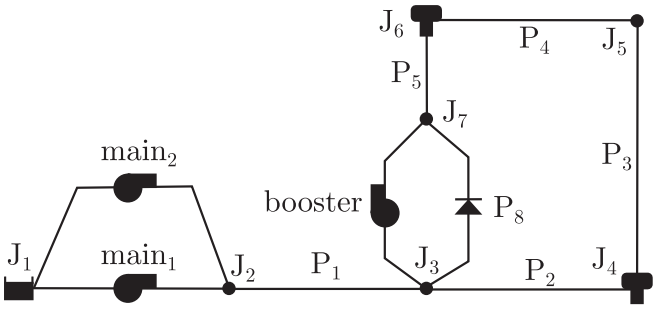


Fig. 3. Benchmark case study adopted from [33].

2.2.2. Hydraulic energy conservation

The head difference across a pump is given by a set of linear constraints. These constraints describe a convex set that approximates the characteristic curve. For the benchmark network resented in Fig. 3, the hydraulic constraints at a given time step for a pump i_p connecting nodes $J1$ and $J2$ are:

$$h_{J1} - h_{J2} \leqslant \begin{cases} m^{p}_{i_p,1} q_{i_p} + c^{p}_{i_p,1} T_{i_p} & \text{and} \\ m^{p}_{i_p,2} q_{i_p} + c^{p}_{i_p,2} T_{i_p} & \text{and} \\ \quad \vdots & \\ m^{p}_{i_p,5} q_{i_p} + c^{p}_{i_p,5} T_{i_p} & \text{if} : T_{i_p} = 1 \\ \Delta h_{ub},\ q_{i_p} = 0 & \text{if} : T_{i_p} = 0 \end{cases} \tag{5}$$

where $m_{i_p,1} \ldots m_{i_p,5}$and $c_{i_p} \ldots c_{i_p,5}$ are the linear coefficients. Δh_{ub} is an upper bound on the head difference across the pump. The constraints are enforced using a big-M method and the symmetry of pump schedules is defined by:

$$T_1 \geqslant T_2 \ldots \geqslant T_{n_p-1} \geqslant T_{n_p} \tag{6}$$

The hydraulic balance for the pipes is done using a piecewise linear approximation of the head losses in pipes as given by the Hazen-William or Darcy–Weisbach equations [25]. For a pipe $P2$, which connects nodes $J3$ and $J4$, this can be approximated using a set of piecewise linear equations (five pieces were applied in this case):

$$h_{J3} - h_{J4} = \begin{cases} q_{P2} m^{c}_{P2,1} + c^{c}_{P2,1}, & \text{if } q_{lim1} \leqslant q_{P2} \leqslant q_{lim2} \\ q_{P2} m^{c}_{P2,2} + c^{c}_{P2,2}, & \text{if } q_{lim2} \leqslant q_{P2} \leqslant q_{lim3} \\ \quad \vdots & \\ q_{P2} m^{c}_{P2,5} + c^{c}_{P2,5}, & \text{if } q_{lim5} \leqslant q_{P2} \leqslant q_{lim6} \end{cases} \tag{7}$$

where the linear sections are given by $m_{P2,1} q_{P2} + c_{P2,1} \ldots m_{P2,5} q_{P2} + c_{P2,5}$. The linear sections are bound by q_{limk} and q_{limk+1}, where k is the number of the section. These are implemented using linear big-M constraints as detailed in [26] and [25].

2.2.3. Mass balance at network nodes

The flow of water in pipes is considered incompressible and for a network node with demand d_j, and incident components $P_1, P_2, \cdots P_n$, the conservation of mass flow at each time step j is:

$$q_{P1,j} + q_{P2,j} + \cdots + q_{Pn,j} = d_j. \tag{8}$$

Demand at network nodes must be met to obtain hydraulically feasible solutions. To ensure further feasibility requirements of the solutions, a minimum hydraulic head could be enforced at specific (critical) nodes in the network.

Tanks provide buffer storage in a network to meet water demand when the supply from the pumps is less than the demand. For a tank J with flows q_{in} and q_{out} the mass balance for time steps $j = 1 \ldots N-1$ is given by:

$$q_{in,j} + q_{out,j} = \left(h_{J,j+1} - h_{J,j}\right) \times A_J, \tag{9}$$

where the surface area of the tank is given by A_J. Since diurnal demand patterns are relatively similar, the pump schedules are repeatable by enforcing a constraint that the final levels in tanks do not differ notably from their initial conditions:

$$\begin{aligned} \left(h_{J,1} - h_{J,N}\right) \times A_J &\leqslant \delta_V \\ \left(h_{J,1} - h_{J,N}\right) \times A_J &\geqslant \delta_V, \end{aligned} \tag{10}$$

where δ_V defines the volumetric difference. This removes the requirement to specify the final or initial tank levels as input data, which would limit the feasible search space and could potentially lead to a sub-optimal final solution. A similar approach is adopted by [34].

2.2.4. Summary of the optimisation problem

The pump schedule optimisation problem for fixed-speed pumps is given by:

$$\begin{aligned} &\min: \quad f_1(\cdot) \\ &\text{s.t.}: \quad (5), (6), (7), (9), (8), (10). \end{aligned} \tag{11}$$

The MIQP problem in (11) has been implemented in MATLAB and solved with CPLEX. The formulation as a branch and bound problem provides solutions with certifiable optimality, which enables a comparison between objectives with small differences in value. By varying the factor λ in small increments, a weighted sum multi-objective optimisation was carried out.

A commonly applied benchmark network (Fig. 3), which was presented by [33], has been chosen for this study. In order to make a comparison of the energy consumption of the benchmark network using different pump configurations and flows, the water demand has been redefined in terms of the pump capacity of the network. The water demand allocated to a node is described by a time dependent demand pattern and a constant base demand [33]. The network has one source reservoir and the hydraulic conditions in the network such as demand and pressure are maintained by the pumping station with pumps $main_1$ and $main_2$. For the purpose of this analysis, the pump utilisation of the network is described as a ratio of the average demand versus the flow rate at the best efficiency point (BEP) of one of the identical parallel pumps. The initial demand d_o is 14 ML/day. The total demand in the simulation is d_s and $\frac{d_s}{d_o}$ is the pump utilisation rate. To define d_o, the water demand was modified for the benchmark network (Fig. 3) with the base water demand set to the BEP flow rate of $main_1$. A low pump utilisation factor suggests that a large pump supplies a network, while a higher utilisation factor indicates that several smaller pumps supply the network. The proportion of time that pumps are operational, which is a measure of their utilisation rate, can vary by a factor of two over a period of one year as shown in [35]. The pump utilisation rate affects the ability of a WDS to alter its pumping schedules, and consequently, it has an impact on the potential GHG emissions reduction. This is further discussed in the following section.

3. Results

The optimisation of pumps operation has provided a control schedule and a corresponding system response. The system response was verified for its hydraulic feasibility in a hydraulic simulation using a sparse null-space hydraulic solver [36]. An example of a calculated pumps schedule and electricity tariffs, for which the schedule was optimised for, is shown in Fig. 4.

The performed investigation aims to compare different operating strategies for the various energy supply scenarios. As a result, the optimal pump schedules and the corresponding electricity costs and GHG emissions were determined for each operating day from the considered energy supply scenarios and for different values of the trade-off term λ (described in Section 2.2.1).

The variations in operating costs and GHG emissions depend on the pump utilisation rate, the ability to alter pump schedules and the electricity tariffs (e.g. switching from a TOU tariff to a DAM tariff) as demonstrated in Fig. 5. A significant reduction in GHG emissions was achieved for the benchmark WDS for a pump utilisation rate of $d_s/d_o = 0.5$ versus other utilisation rates. For example, GHG emissions have been reduced within 0–11% for the considered 2035 scenarios and for pump utilisation rates greater than 0.5 (Fig. 5). For 2014, GHG emission reductions of around 8% were obtained, while the operation costs increased in all scenarios for which the pricing plans were switched from TOU to DAM tariffs.

A comparison of the future *Green* scenarios against the 2014 and 2035 *No Progress* scenarios demonstrates that the GHG emission reductions from pump scheduling is most significant for the *Green** scenario, followed by the *Green* scenario and the other two scenarios. A greater variation of the emission intensity in the *Green** scenario enables a greater reduction. The variations in operating costs and GHG emissions, as a result of optimising different objectives, are summarised in Tables 4 and 5. These results indicate that depending on the pump utilisation rate, significant reductions in GHG emissions can also be achieved when switching from TOU to DAM tariffs. These reductions were up to 35% for $\frac{d_s}{d_o} = 0.5$, and 5–10% for $\frac{d_s}{d_o} = 0.7$. For $\frac{d_s}{d_o} = 1$, reductions between 2 and 5% were achieved on most operating days, and no reductions were realised with $\frac{d_s}{d_o} = 1.3$. Switching from DAM to GHG emissions reduces only

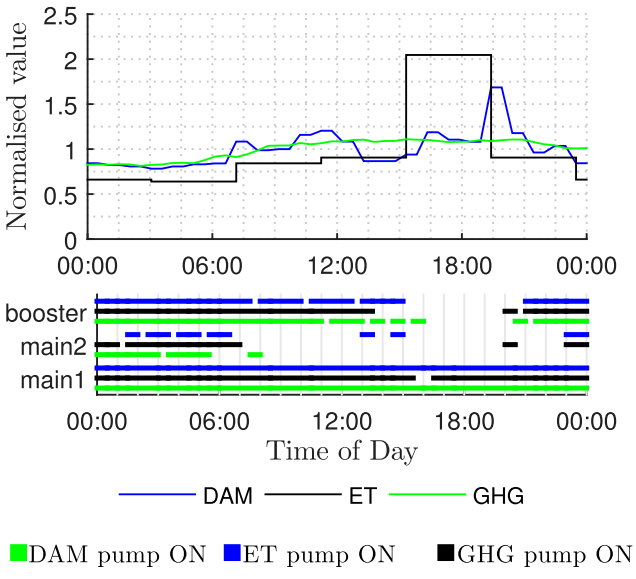


Fig. 4. Calculated pump schedules that take into consideration the various electricity tariffs, green house gas emissions and the day-ahead market prices. The inputs are normalised to have a mean of 1.

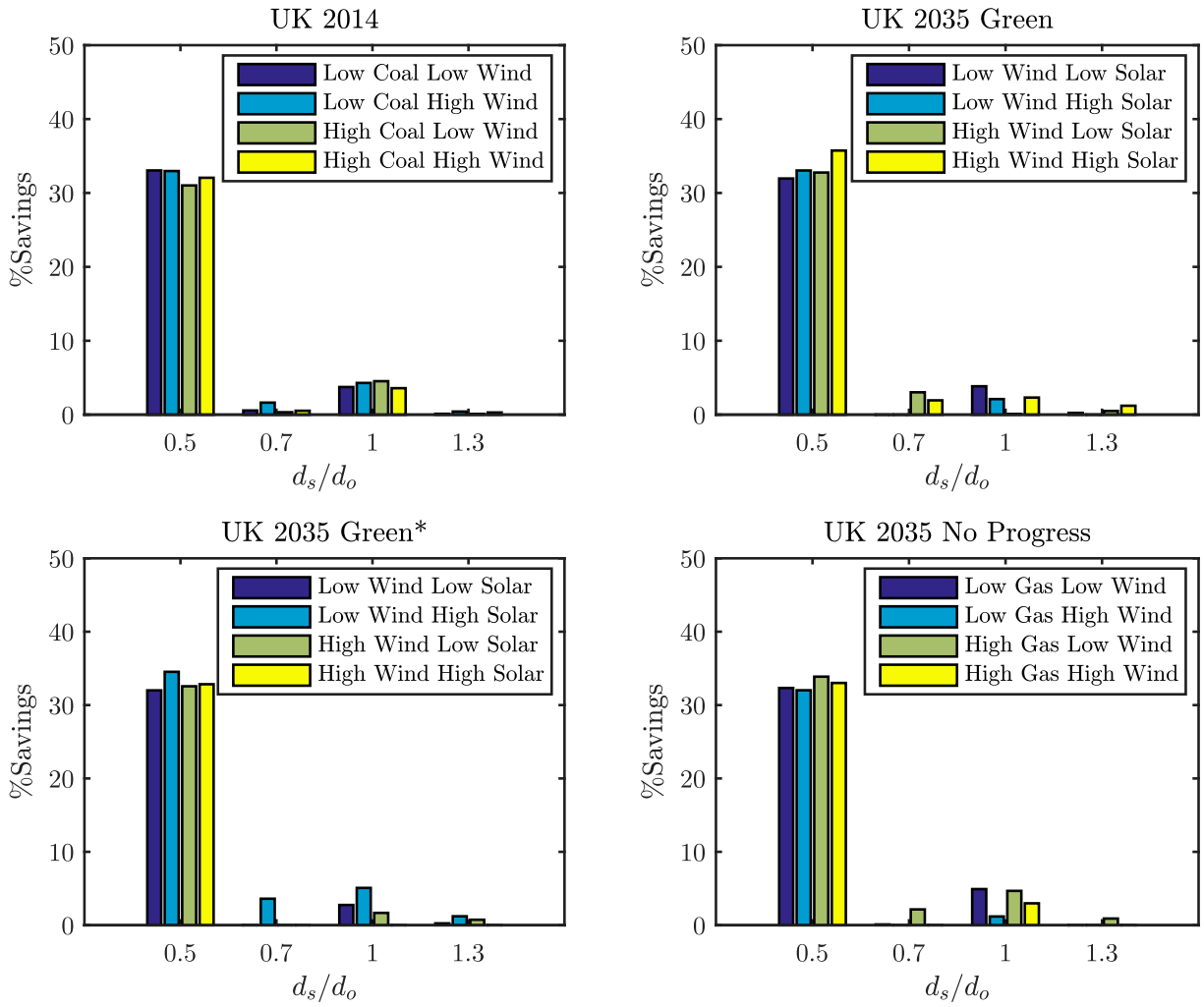


Fig. 5. Pump utilisation rate versus the reduction (savings) in GHG emissions when changing electricity tariffs from TOU to DAM for all energy supply scenarios and operating days.

Table 4
Maximum GHG emissions reduction and savings in operating costs for $d_s/d_o = 0.5$ and $d_s/d_o = 0.7$. The change is reported as a percentage decrease in the objective function value. The reported variable is displayed in brackets. E.g. The third row is the percentage-decrease in GHG emissions when switching from a TOU tariff to a DAM tariff. The fourth row shows the change in electricity costs associated with the same switch of tariffs.

Schedule change and criterion (%)	2014				2035 Green				2035 Green*				2035 No progress			
	LL	LH	HL	HH	LL	LH	HL	HH	LL	LH	HL	HH	LL	LH	HL	HH
Pump utilisation rate $d_s/d_o = 0.5$																
DAM to GHG (GHG)	−0.7	−1.0	−2.3	−0.5	−2.6	−3.6	−9.5	−1.6	0.7	3.4	6.4	12.1	3.5	5.8	1.0	1.5
TOU to GHG (GHG)	33.5	33.6	32.6	32.4	33.7	35.4	39.1	36.8	32.5	36.8	36.9	41.0	34.7	35.9	34.5	34.0
TOU to DAM (GHG)	33.1	33.0	31.0	32.1	32.0	33.0	32.8	35.7	32.0	34.5	32.6	32.8	32.3	32.0	33.9	33.0
TOU to DAM (Cost)	20.9	23.6	26.2	25.0	25.7	26.3	22.5	24.2	21.6	21.2	25.1	27.1	20.6	26.5	23.9	23.2
Pump utilization rate $d_s/d_o = 0.7$																
DAM to GHG (GHG)	1.3	3.6	7.3	0.2	7.9	2.4	6.0	2.5	6.9	5.5	4.4	10.6	6.1	4.5	4.5	2.7
TOU to GHG (GHG)	1.9	5.2	7.6	0.8	6.3	2.4	8.9	4.3	5.3	9.0	4.0	7.4	6.2	2.0	6.5	1.4
TOU to DAM (GHG)	0.6	1.6	0.3	0.5	−1.7	0.0	3.0	1.9	−1.7	3.6	−0.4	−3.5	0.1	−2.7	2.2	−1.4
TOU to DAM (Cost)	−19.3	−16.4	−12.3	−13.8	−13.7	−14.4	−14.1	−17.2	−17.5	−17.8	−14.6	−11.5	-19.0	−13.6	−15.9	−16.9

%: percentage decrease.

marginally the GHG emissions, as the observed reductions are within the margin of error for the optimisation analysis. The change in costs when switching from TOU to DAM tariffs also depends on the pump utilisation rate. For $\frac{d_s}{d_o} = 0.5$, the costs were reduced within 20–26%. In comparison, the operating costs increased by 20% for $\frac{d_s}{d_o} = 0.7$, and by up to 5% for higher pump utilisation rates.

Within the considered energy supply scenarios, operating days with a significant share of renewables and, consequently, a wide range between the diurnal maximum and minimum GHG emis-

Table 5
Maximum GHG emission savings and operating cost changes for $d_s/d_o = 1$ and $d_s/d_o = 1.3$.

Schedule change and criterion (%)	2014				2035 Green				2035 Green*				2035 no progress			
	LL	LH	HL	HH	LL	LH	HL	HH	LL	LH	HL	HH	LL	LH	HL	HH
Pump utilization rate $d_s/d_o = 1.0$																
DAM to GHG (GHG)	0.0	0.0	0.5	0.5	1.5	0.4	5.3	0.3	0.9	1.3	1.1	5.8	0.1	1.8	0.2	0.5
TOU to GHG (GHG)	3.7	4.3	5.0	4.0	5.3	2.5	5.3	2.6	3.6	6.3	2.8	4.7	5.0	2.9	4.9	3.5
TOU to DAM (GHG)	3.7	4.3	4.5	3.6	3.8	2.1	0.1	2.3	2.8	5.1	1.7	−1.2	4.9	1.2	4.7	3.0
TOU to DAM (Cost)	−5.4	−4.3	−4.6	−3.4	−3.6	−4.9	−4.4	−5.0	−3.7	−4.0	−4.9	−2.5	−5.1	−3.6	−4.2	−5.7
Pump utilization rate $d_s/d_o = 1.3$																
DAM to GHG (GHG)	0.2	0.3	0.6	0.1	0.7	1.6	3.5	1.0	0.1	1.4	1.4	4.4	1.4	2.3	0.5	1.0
TOU to GHG (GHG)	0.4	0.8	0.7	0.4	0.9	1.2	4.0	2.2	5.6	2.6	2.1	4.0	1.3	1.6	1.4	0.7
TOU to DAM (GHG)	0.1	0.4	0.1	0.3	0.2	−0.4	0.5	1.2	2.1	1.2	0.7	−0.4	−0.1	−0.7	0.9	−0.3
TOU to DAM (Cost)	−5.4	−4.7	−3.5	−3.7	−3.4	−4.1	−4.7	−4.6	−5.1	−5.2	−4.2	−2.9	−5.4	−3.6	−4.5	−4.5

%: percentage decrease.

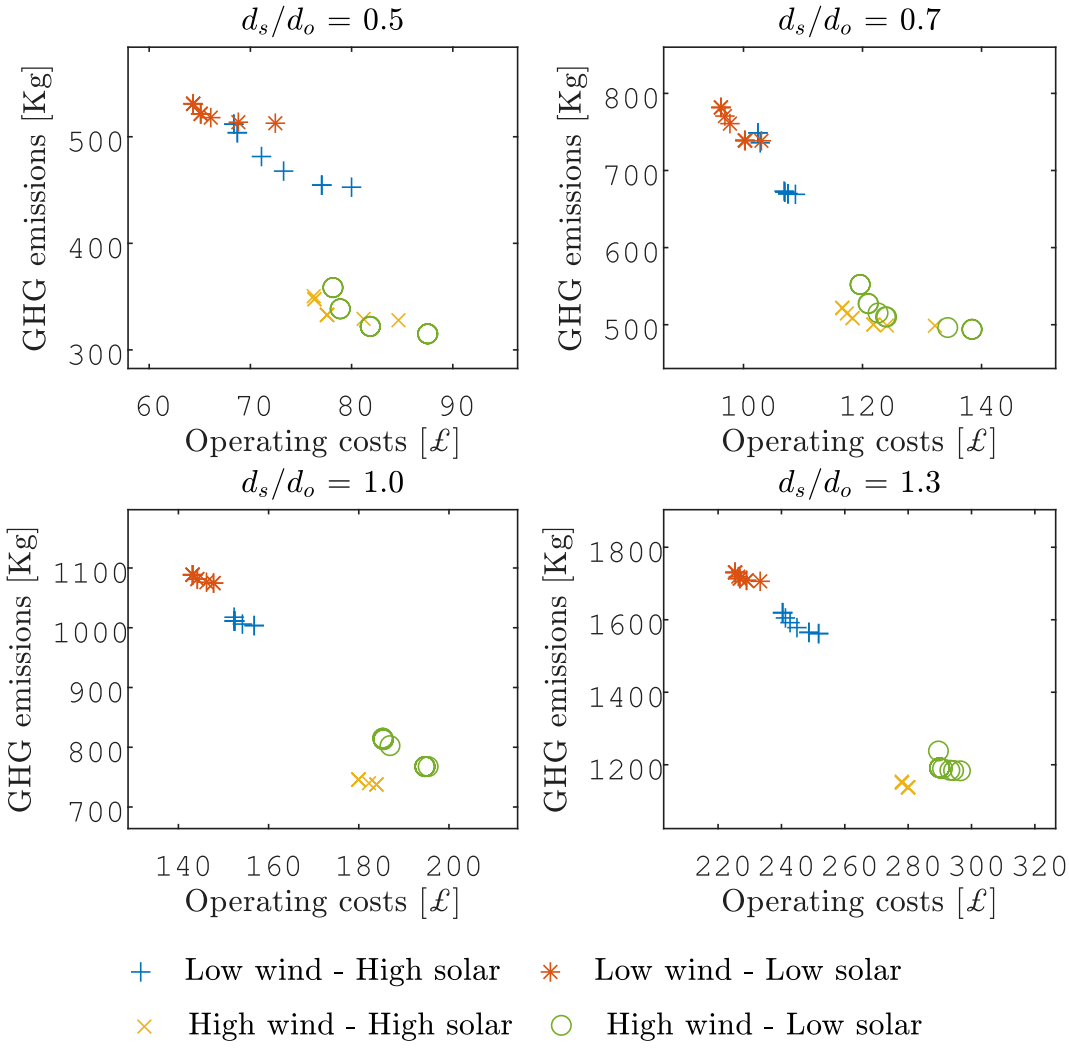


Fig. 6. Pareto fronts (*Green** scenario) that quantify the trade-offs in reducing both the operating (electricity) costs and GHG emissions based on the pump utilisation rate and energy supply scenarios.

sions, have shown considerable GHG emission reductions when optimising the pump scheduling for lower GHG emissions (e.g. the HH day in the Green* scenario). Whether these reductions can also be achieved when scheduling for minimising the electricity costs using the TOU or DAM tariffs would depend on the correlation between the electricity prices and GHG emissions as summarised in Table 3.

In order to investigate the trade-offs between optimising the pump scheduling for electricity costs and GHG emissions, a set of Pareto fronts have been derived (Fig. 6). The results indicate that pump schedules that optimise both electricity costs and GHG emissions are attainable. Significant reductions in GHG emissions could be achieved for only a small increase in operating costs. The pump utilisation rates have a significant impact on the magnitude of the

GHG emission reductions; and less on the trade-off between the multiple objectives.

4. Discussion

The presented results for a benchmark network show that a multi-objective optimisation analysis for scheduling the operation of pumps could successfully reduce both the operating costs and GHG emissions. The correlation between the emissions intensity of the fuel mix and electricity costs is a key factor which also depends on the applied tariff (e.g. TOU or DAM), the energy supply scenario and the share of renewables in the daily power generation.

The reduction in electricity costs and GHG emissions from optimally scheduling the operation of pumps depends considerably on the utilisation rate of available pumps. This is particularly evident when the benchmark network operates at the lowest pump utilisation ratio of 0.5 as there is a large number of feasible pump schedules and options to vary pumps operation. For the considered benchmark network and operating scenarios, the achieved reduction in electricity costs was within 20%, while the reduction in GHG emissions was within 30% for most operating days with low pumps utilisation rates. In comparison, a 5% increase in operating costs and no significant changes in GHG emissions were observed for operating days with high pumps utilisation rates.

The multi-objective pump scheduling analysis shows that there is a potential to reduce both electricity costs and GHG emissions for all energy supply scenarios. This potential is the largest for the two *Green* energy supply scenarios. For the *No Progress* scenario, the considerable share (approximately 50%) of natural gas and the low utilisation of renewables, has minimised the variations in the diurnal emission intensities that limit the potential reductions in both operating costs and GHG emissions. Similar results were observed for the 2014 scenario, when the energy supply was dominated by coal. The larger variations in daily emission intensities for the Green energy supply scenario, and in particular for the Green* scenario, result in greater GHG emission reduction opportunities for water utilities from optimal pump scheduling.

For tariffs with an equal average cost, a tariff with finer time steps is expected to lead to lower operating cost due to the finer schedule adjustments possible. In the energy prices used the DAM price showed significantly finer differentiation in prices across the day, but the overall variance of the price was not always larger than that of the TOU tariff. The results suggest instead, that low pump utilisation rates would provide greater flexibility and opportunities for reducing both operating costs and GHG emissions. Consequently, the pumps utilisation rate could be an important factor for the design of pumping stations given the anticipated benefits from pump scheduling and the increased operational reliability. The results suggest that with a low pump utilization rate, these savings can be achieved. The pump utilisation rate varies with seasonal demand throughout the year, by $\sim \times 2$ [35], suggesting that the WDS's ability to reduce its GHG emissions through optimised scheduling may depend on the seasons or time of year and the configuration of existing pumping stations.

The greater reduction in GHG emissions from DAM tariffs compared to TOU tariffs arises from the stronger correlation between the energy prices and corresponding time-dependent emission intensities (eg. 0.44 compared to 0.20 in 2014). This is because expensive and GHG intensive plants, such as open gas cycle turbines (OCGTs), are used for electricity generation at peak demand. However, this situation could change in the future as carbon tax might improve the correlation between energy prices and GHG emissions. Alternatively, the wider adoption of intermittent renewables or cheaper fossil fuels might weaken this correlation as renewable energy generation from wind or PV could drive spot prices down [37–39].

The Pareto fronts plotted in Fig. 6 illustrate that the tradeoffs in reducing electricity costs and GHG emissions from optimising the operation of pumps in WDS depends on the scenario days and the fuels mix that supplies the power grid. Scenario days with a higher standard deviation of the GHG emissions and electricity costs provide a greater opportunity for achieving substantial reductions in GHG emissions for only a minor increase in electricity costs. The presented analysis could also be utilised to identify (and even drive) a threshold price for GHG emissions; for example, a threshold price of $\sim$100 £/ t of CO_2, which would have a sufficient financial justification for water utilities to proactively optimise the operation of their pumping stations in order to reduce both operating costs and GHG emissions.

5. Conclusions and further work

A multi-objective optimisation method for scheduling the operation of pumps has been investigated in this paper. The derivation of pump schedules for optimally reducing both electricity costs and GHG emissions for a benchmark water supply network under different energy supply scenarios and electricity tariff structures has demonstrated considerable benefits. Further analysis on multiple operational networks is required to validate the presented results and take into account operational constraints associated with assets condition and utilisation.

The analysis has demonstrated that the potential reductions in electricity costs and GHG emissions depend on the pump utilisation rate, the ability to alter pump schedules and the used electricity tariffs (e.g. switching from a TOU tariff to a DAM tariff). A significant reduction in GHG emissions was achieved for a benchmark WDS when a pump utilisation rate of $d_s/d_o = 0.5$ was considered versus other pump utilisation rates. For example, GHG emissions were reduced within 0–11% for the derived 2035 scenarios and for pump utilisation rates greater than 0.5. The reduction in electricity costs was close to 20%, and the reduction in GHG emissions was 30% for most operating days with low pumps utilisation rates.

The presented analysis has only focused on the reduction in electricity costs and GHG emissions from optimal pump scheduling. Optimising the operation of pumps, reservoirs and water transmission mains, which are considered the backbone of a water supply system, tend to be decoupled from the operational optimisation of water distribution networks. Water distribution networks are segregated into sectors (e.g. District Metering Areas in the UK) and the pressure management, leakage and GHG emissions associated with their operation could and should be considered in the drivers for reducing operating costs and GHG emissions in water supply systems.

The analysis has demonstrated the importance of considering the pumps utilisation rate as an additional variable in the design of pumping stations. This would have a combined impact on the pump scheduling capacity of a water supply system and its reliability of operation. The enhanced pump scheduling flexibility would be beneficial not only for optimally managing the operating costs and GHG emissions, but can enable the participation in demand response schemes to create new revenue streams for WDS.

There is an increasing interest among UK water utilities to optimise pump scheduling for reducing electricity costs. However, more compelling fiscal and regulatory incentives are needed to encourage water utilities to consider the simultaneous reduction in electricity costs and GHG emissions when deriving schedules for the operation of pumps. The presented multi-objective optimi-

sation problem formulation could be utilised to identify a threshold price for GHG emissions.

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References

[1] CIWEM, A blueprint for carbon emissions reduction in the UK water industry, Technical Report; 2013.
[2] Parliament of the United Kingdom. Climate Change Act 2008.
[3] Anglian water, Greenhouse gas emissions annual report 2016, Technical Report; 2016.
[4] Wessex water, Water – the way ahead 2015–2040. Wessex Water's long-term strategy, Technical Report; 2012.
[5] Bunn S. Reducing the GHG footprint at water and wastewater utilities in the US and the UK, Report, Derceto Inc; 2011.
[6] Grundfos Managment A/S. Pump Handbook. Bjerringbro, Denmark: Grundfos Managment A/S; 2004.
[7] Ormsbee LE, Lansey KE. Optimal control of water supply pumping systems. J. Water Resour. Plan. Manage. 1994;120:237–52.
[8] Akinyele D, Rayudu R. Review of energy storage technologies for sustainable power networks. Sustain. Energy Technol. Assessments 2014;8:74–91.
[9] Menke R, Abraham E, Parpas P, Stoianov I. Demonstrating demand response from water distribution system through pump scheduling. Appl. Energy 2016;170:377–87.
[10] Stokes CS, Maier HR, Simpson AR. Water distribution system pumping operational greenhouse gas emissions minimization by considering time-dependent emissions factors. J. Water Resour. Plan. Manage. 2015;141.
[11] Blinco L, Simpson A, Lambert M, Auricht C, Hurr N, Tiggemann S, Marchi A. Genetic algorithm optimization of operational costs and greenhouse gas emissions for water distribution systems. Proc. Eng. 2014;89:509–16.
[12] National Grid, UK Future Energy Scenarios, Tech. Report July, National Grid; 2014.
[13] Garfinkel R, Nemhauser GL. Integer Programming. New York: Wiley; 1972.
[14] Mai T, Mulcahy D, Hand MM, Baldwin SF. Envisioning a renewable electricity future for the United States. Energy 2014;65:374–86.
[15] Dale AT, Bilec MM. The Regional Energy & Water Supply Scenarios (REWSS) model, Part I: framework, procedure, and validation. Sustain. Energy Technol. Assessments 2014;7:227–36.
[16] National Grid, Operating the Electricity Transmission Networks in 2020, Report, National Grid; 2011.
[17] APX Power UK, UKPX RPD Historical Data; 2015.
[18] Kheshgi H, de Coninck H, Kessels J. Carbon dioxide capture and storage: Seven years after the IPCC special report. Mitig. Adapt. Strateg. Glob. Change 2012;17:563–7.
[19] EDF, Measuring energy's contribution to climate change; 2015.
[20] Intergovernmental Panel on Climate Change, Climate Change 2014 Mitigation of Climate Change, Annex III, Technical Report Fifth Assessment Report, Cambridge University Press, Cambridge; 2014.
[21] DECC. Fuel Mix Disclosure Data Table – 2014 Technical Report. Department of Energy and Climate Change; 2005.
[22] Defra, DECC, Ricardo-AEA, Carbon Smart, C. Smart, Greenhouse Gas Conversion Factor Repository, Technical Report, Department of Environment Food & Rural Affairs and Department of Environment & Climate Change; 2014.
[23] BMRS, neta – The New Electricity Trading Arrangements; 2015.
[24] Worldbank, Electric power transmission and distribution losses (% of output); 2011.
[25] Vigerske S, Huang W, Held H, Gleixner A. Towards globally optimal operation of water supply networks. Numer. Algebr. Control Optim. 2012;2:695–711.
[26] Menke R, Abraham E, Parpas P, Stoianov I. Approximation of system components for pump scheduling optimisation. Proc. Eng. 2015;119:1059–68.
[27] Ghaddar B, Naoum-Sawaya J, Kishimoto A, Taheri N, Eck B. A Lagrangian decomposition approach for the pump scheduling problem in water networks. Eur. J. Oper. Res. 2014;241:490–501.
[28] D'Ambrosio C, Lodi A, Wiese S, Bragalli C. Mathematical programming techniques in water network optimization. Eur. J. Oper. Res. 2015;243:774–88.
[29] Miettinen K. Nonlinear Multiobjective Optimization. International Series in Operations Research & Management Science, vol. 12. US, Boston, MA: Springer; 1998.
[30] Lansey KE, Awumah K. Optimal pump operations considering pump switches. J. Water Resour. Plan. Manage. 1994;120:17–35.
[31] Savic DA, Walters GA, Schwab M. Multiobjective genetic algorithms for pump scheduling in water supply. In: Evol. Comput.. Springer; 1997. p. 227–35.
[32] Hoskins A, Stoianov I. Infrasense: a distributed system for the continuous analysis of hydraulic transients. Proc. Eng. 2014;70:823–32.
[33] Van Zyl JJE, Savic DAD, Walters GGA. Operational optimization of water distribution systems using a hybrid genetic algorithm. J. Water Resour. Plan. Manage. 2004;130:160–70.
[34] Price E, Ostfeld A. Iterative linearization scheme for convex nonlinear equations: application to optimal operation of water distribution systems. J. Water Resour. Plan. Manage. 2013;139:299–312.
[35] Stokes CS, Simpson AR, Maier HR. A computational software tool for the minimization of costs and greenhouse gas emissions associated with water distribution systems. Environ. Model. Softw. 2015;69:452–67.
[36] Abraham E, Stoianov I. Sparse null space algorithms for hydraulic analysis of large-scale water supply networks. J. Hydraul. Eng. 2016;142:04015058.
[37] Cutler NJ, Boerema ND, MacGill IF, Outhred HR. High penetration wind generation impacts on spot prices in the Australian national electricity market. Energy Policy 2011;39:5939–49.
[38] Sijm J, Neuhoff K, Chen Y. CO2 cost pass-through and windfall profits in the power sector. Clim. Policy 2006;6:49–72.
[39] PowerSolution Energieberatung. Energiemarkt Info 03—04 2015 Technical Report. Vienna: PowerSolution Energieberatung; 2015.