Multi-objective optimization of energy and greenhouse gas emissions in water pumping and treatment

Iliana Cardenes, Afreen Siddiqi, Mohammad Mortazavi Naeini and Jim W. Hall

ABSTRACT

A large part of operating costs in urban water supply networks is usually due to energy use, mostly in the form of electricity consumption. There is growing pressure to reduce energy use to help save operational costs and reduce carbon emissions. However, in practice, reducing these costs has proved to be challenging because of the complexity of the systems. Indeed, many water utilities have concluded that they cannot practically achieve further energy savings in the operation of their water supply systems. This study shows how a hybrid linear and multi-objective optimization approach can be used to identify key energy consumption elements in a water supply system, and then evaluate the amount of investment needed to achieve significant operational gains at those points in the supply network. In application to the water supply system for the city of London, the method has shown that up to 18% savings in daily energy consumption are achievable. The optimal results are sensitive to discount rate and the financial value placed on greenhouse gas emissions. Valuation of greenhouse gas emissions is necessary to incentivise high levels of energy efficiency. The methodology can be used to inform planning and investment decisions, with specific focus on reducing energy consumption, for existing urban water supply systems.

Key words | energy efficiency, energy intensity, energy operations, optimization, urban infrastructure, water-energy nexus

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HIGHLIGHTS

- A hybrid linear and multi-objective optimization approach is used to evaluate investment costs within an existing water supply network to identify operational savings, finding that, for the city of London, up to 18%% savings in daily energy consumption can be made through this method.
- There are persisting constraints, including security of supply and water quality, in operating and upgrading legacy water supply infrastructure for new objectives of reduction of energy and emissions.

INTRODUCTION

Urban water supply networks have high energy costs (usually electricity) associated with their operation, and high associated greenhouse gas (GHG) emissions (Brandt *et al.* 2011). Around the world, the total energy consumption and energy intensity (energy used per unit volume of water) in urban water supply systems has been steadily increasing over the last decade (Water UK 2006, 2008, 2009, 2012; Rothausen & Conway 2011; Kenway 2013; Siddiqi & de Weck 2013; Spang & Loge 2015). As growing urban populations and climate change place greater strains on existing systems to provide more, better quality water without increasing associated costs or harmful environmental impacts, there are increasing

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requirements for existing supply systems to upgrade and adapt to new conditions. However, there are typically few cost-effective options available for improving large urban supply networks operating with legacy systems.

The question of energy efficiency in water use has attracted growing attention, though for the time being the focus has been on abating water (and energy) demand by installing high efficiency appliances in homes. New tools have been developed for creating cost abatement curves which have informed demand-side management for addressing the water-energy nexus challenge (Chini *et al.* 2016). From the supply side, however, there has been limited work on developing practical approaches to determine optimal strategies for improving existing large-scale urban water systems. This study aims to address this gap and develops a multi-objective optimisation approach for informing investment decisions for reducing energy consumption in existing water supply systems. The methodology is demonstrated for London's water supply system within a context of future uncertain energy prices and GHG emission costs.

This work offers two distinct contributions: First, it demonstrates a computationally tractable modelling and optimization approach (through system aggregation and bi-level optimization) for analysing large complex urban supply systems such that optimal options for operational energy reduction can be identified by evaluating trade-offs between capital expenditure (CAPEX), operating expenditure (OPEX) and GHG emissions. While optimization techniques have been extensively used for studying water networks' operation, the emphasis has largely been on improving pumping operations for cost savings from multi-pattern electric tariffs (Schaake & Lai 1969; Ulanicki & Kennedy 1994; Broad *et al.* 2010; Perelman *et al.* 2013; Puleo *et al.* 2014; Ghaddar *et al.* 2015; Sarbu 2016). Operational optimization of the whole supply system (that includes pumping and water treatment) has not received as much attention (Ulanicki & Kennedy 1994). Here, the focus of optimization is expanded to include key elements in water supply networks. This enables a more holistic view of the energy consumption hotspots and allows for identifying a wider variety of options for increasing energy efficiency.

Second, the method is applied on a very large real-world network of the city of London. This is an important distinguishing feature of the work as most published studies use theoretical networks in optimization analysis and therefore have had limited adoption in practice (Marques *et al.* 2012; Maier *et al.* 2014, 2015). In addition, there are often practical limitations to the implementation of solutions that are derived from optimisation studies. By using a real-world network, we are able to provide insights into the practical limitations that may constrain realization of theoretical energy savings.

The approach developed and demonstrated here can be used by water providers and public-sector decision makers to identify optimal strategies for operational cost savings (by reducing energy costs), and to investigate the relationship of GHG emission costs that can have important implications on feasibility of capital investments. It is also of relevance to researchers by pushing the limits of optimisation of water supply system operation, whilst validating the feasibility of the results in the context of a practical system.

BACKGROUND

Existing water supply networks have high operating energy costs. Previous studies have found that direct consumption accounts for the largest proportion of electricity use, upwards of 87% (Parsons & Marcet 2012). It is therefore in the interest of utilities to consider options for reducing energy consumption. Furthermore, with emerging regulations and growing awareness of the need to curb emissions, there are two additional incentives converging: there may be carbon emission costs that the utilities may directly or indirectly bear, and to be better stewards of the environment, energy consumption should be reduced. While there is extensive research taking place on developing new technologies (Cook *et al.* 2012; Kartalidis *et al.* 2015; Napoli & Rioux 2015), such as desalination or more efficient pumping, this paper considers the case of action in large-scale water-supply legacy systems where radical changes are expensive, and there is a need to identify opportunities for improvement with strategic cost effective interventions and investments.

Water utilities are responsible for planning and investing to achieve reliable supplies of water. Uncertainties abound in water resources management with pressures from climate change, urbanization, population growth and increasing demand (Roach *et al.* 2016). Water planners and agencies are thus under pressure to make water resources planning decisions that can meet demand while ensuring affordability, and which will be reasonably robust and adaptable to future uncertainties. When investments are needed to enhance security of supply, there is a trade-off between affordability for the customers, who ultimately pay for investment via their water bills, and security of supply.

Traditionally, water infrastructure costs are dealt with in whole life terms; that is, costs are estimated as discounted capital expenditure (CAPEX), as well discounted operational expenditure (OPEX), though the operational costs have tended to be dealt with rather crudely. Given the very different energy implications of alternative infrastructure options, there is a strong case for a more sophisticated treatment of energy costs in decision-making processes. Requirements to consider greenhouse gas emissions associated with energy use in the water sector are a further motivating consideration of energy efficiency.

There is also growing recognition of the need to address uncertainty and its impact on water infrastructure planning (Ray & Brown 2015), which has led to increasing uptake of various methods for decision-analysis under uncertainty (Lempert 2003; Ben-Haim 2006; Brown 2011; Groves *et al.* 2013; Matrosov *et al.* 2013). Optimization studies have focused on deterministic approaches to optimizing both the design and operation of water networks (Perelman *et al.* 2013), thus providing limited applicability to real-world network where there is usually uncertainty in the data and parameters. Recent studies have highlighted that uncertainty in model parameters has rarely been incorporated into water network optimization studies (D'Ambrosio *et al.* 2015), and so remains a research challenge for the field (Mala-Jetmarova *et al.* 2017). Developing a further understanding on how energy consumption looks like for water infrastructure systems, and its associated uncertainties, will provide more insight to the water sector, as it seeks to both to supply more affordable water to customers and to do so in a more sustainable way.

MATERIALS AND METHODS

The data used for this study, including the source and details of datasets can be found in the Supporting Information (section 1). The method consists of creating three main analytical components: First, the supply system is modelled as a network, for which a linear optimization problem is formulated. The decision variables represent flows over each edge (link or pipeline), and capacity constraints and conservation constraints are applied. The objective of the optimization problem is to find daily flow rates that minimise total energy costs in the network, whilst meeting demand. While the linear program (LP) formulation guarantees an optimal solution (Broad *et al.* 2010), it requires some simplification for tractability. The linear optimization model determines the optimal routing (in volumetric flow rates) for distributing the water through the supply network at minimum cost.

The second component consists of another (second) level of optimization based on a multi-objective evolutionary algorithm (MOEA), in which optimal investment strategies are identified. To do this, 'bottlenecks' are identified using the upper Lagrange multipliers from the optimal solution in the LP. A MOEA is run that aims to meet water demand whilst minimizing total expenditure costs for a set of investments that are identified based on the Lagrange multipliers obtained from the LP.

The third component is of uncertainty analysis in which changes in population, per capita and industrial water demand, water available for supply, discount rates, energy prices and carbon prices are stochastically modelled and provided as inputs. Several network investment strategies are then evaluated to determine if any of these configuration changes improve the optimal solution enough to warrant investment. The final target is to identify a strategy with the lowest energy consumption that best meets water demand under uncertainty for a given budget.

Mathematical formulation of linear model

The problem addressed in this study can be stated as follows:

Let $G = (T, P)$ be a directed network with n nodes and m arcs, where T is the set of nodes that represent a source (such as a river) or a storage element (such as a reservoir or water treatment works (WTW)) and P is the set of arcs (representing a set of network pipes). Each arc represents a pipe $(i, j) \in P$, *with* a cost c_{ij} that denotes the energy cost in kilowatt hours (kWh) of a unit of water flowing in the pipe. Researchers have previously approximated the energy consumed by pumps as a linear function of the pumping station water flow, and comparisons with more complex hydraulic models have demonstrated that they are capable of solving real-life pumping problems in a comparable and more computationally efficient manner (Giacomello *et al.* 2013; Puleo *et al.* 2014). Each P are also associated with an amount of x_{ij} water flow in meters cubed (m^3) per day. Each element of T and P are associated with a lower bound l_{ij} and an upper bound u_{ij} of the flow; b_i represents the available amount of supply or demand of water.

$$Minimize\ J = \sum_{(i,j)\in P} c_{ij}x_{ij}, \tag{1}$$

Subject to:

$$\sum_{j:(i,j)\in P} x_{ij} - \sum_{j:(i,k)\in P} x_{jk} = b_i \qquad \textit{for all } i \in T, \tag{2}$$

Flow capacities in pipelines:

$$l_{ij} \le x_{ij} \le u_{ij}\,, \qquad \textit{for all } (i,\ j) \in P. \tag{3}$$

The first equation is for the objective function J, where the objective is to minimise the total daily operational energy costs in the network. The second equation is a constraint that assures that the summation of supply and demand around each demand node is zero. The third equation is a constraint imposed to assure that there are no negative water volumes and to establish the capacities of each water source, reservoir and treatment works. Following other studies (Puleo *et al.* 2014), this LP formulation assumes that the network hydraulics are embedded in the empirical energy consumption relationship and are represented in the cost coefficients c_{ij} for each pipeline.

Implementation of multi-objective evolutionary algorithm

The MOEA is implemented to evaluate a set of investment options. In water supply systems (as in many other infrastructure systems) there are typically a finite and discrete set of options (such as upgrades, retrofits and expansion) that can be considered for investment decisions. Here, using the city of London as a case, a set of 12 options was considered (outlined in Table 1). As the MOEA searches for the optimal solution, it uses the LP to obtain optimal flow volumes in the distribution network for each case. Figure 1 illustrates the computational setup.

The optimization is carried out using a multi-objective evolutionary algorithm that evaluates trade-offs between the objectives of capital expenditure and operational expenditure and builds a 'Pareto approximate set', which is the best-known approximation to the Pareto optimal set (Kasprzyk *et al.* 2013). An ϵ-dominance multi-objective evolutionary algorithm (ϵMOEA) was used, which has been applied to water resources problems in the past (Mortazavi *et al.* 2012; Mortazavi-Naeini *et al.* 2014, 2015; Borgomeo *et al.* 2016). ϵMOEA uses the ϵ-dominance concept to divide the objective space into hyper boxes of size ϵ and allows only one non-dominated solution to reside in each

Table 1 | Short-term investment strategies derived from optimal LP model

	Type of investment	Location of investment in network	Capacity (m^3/day)	Investment details	CAPEX (£000 s)	OPEX (kWh/m^3)
1	Capacity upgrade	Chingford WTW	27,300	Expand up to 32,760 m^3/d	278[a]	0.68
2	Energy efficiency improvement	Walton WTW	85,900	Use new technology to increase efficiency. Reliability factor associated to the technology included	160[b]	2.57 – improved up to 1.7
3	Capacity upgrade	Hornsey Reservoir and WTW	30,000	Increase the capacity of reservoir and WTW up to 33,000 m^3/day	303[a]	0.15
4	Capacity upgrade	Ashford WTW	682,700	Expand up to 750,970 m^3/day	4,723[a]	0.12
5	Energy efficiency improvement	Groundwater pumps	286,600	Groundwater pump replacement results in a 2–10% gain in the energy intensity of groundwater pumping[c], there are 31 stations.	Thames Water process model	1.02 – improved by up to 10%
6–12	Energy efficiency improvement	Main distribution pumps in system	NA	Improve pumping energy use by 2%: variable speed drives (VSDs) increasing the efficiency of the pumps in the water distribution system implemented, improving the energy intensity from 0.117 kWh/m^3 to 0.116 kWh/m^3	Thames Water Process model	0.167–0.105 improved by up to 10%

[a]Estimated from plant capacity construction cost curve for existing plants; originally established by Hinomoto (1977).
[b]Estimated from the capital cost of installing an efficient UV technology in a medium sized water treatment (WT) plant (National Research Council 1999).
[c]From Nogueira Vilanova & Perrella Balestieri (2014).

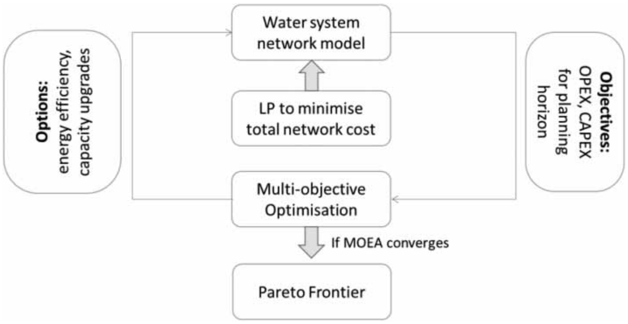

Figure 1 | Relationship of two-stage LP-MOEA optimization.

box (Laumanns *et al.* 2002). Inclusion of this concept in an evolutionary algorithm produces a method capable of maintaining a diverse and well-distributed set of solutions with a small algorithmic computational cost (Deb *et al.* 2003).

Pareto efficient solution

The final pareto efficient solution of each pareto approximation curve was calculated by dividing the change in operational energy costs over the change in capital investment cost, where the maximum E is the pareto efficient solution for a given multi-objective trade-off:

$$E = MAX\left\{\frac{-\Delta OPEX}{\Delta CAPEX}\right\} \quad (4)$$

This is the point on the pareto curve at which the capital expenditure provides the largest operational saving per unit of capital investment. It is important to note that OPEX usually includes more than energy costs such as staff costs, maintenance costs, insurance, vehicles and others which are not included in the model. In this study, OPEX is used to represent operational energy cost, as the largest operational cost for utilities, usually upwards of 87%. Furthermore, within OPEX, energy costs are variable (depending on the price of electricity), while other costs (such as salaries) are largely fixed.

Application: London water supply system

To demonstrate the proposed method, the model was applied to the London urban water supply system, located in the Thames River Basin in the South East of England, and operated by Thames Water Utilities. The region is under serious water stress and climate change is projected to result in a decrease of water availability (Environment Agency 2008; Burt *et al.* 2016). The area is also known as the London Water Resource Zone (WRZ). A WRZ is the standard geographical unit for water resources planning and is defined by the UK Environment Agency (2009) as: 'The largest possible zone in which all resources, including external transfers, can be shared, and hence the zone in which all customers experience the same risk of supply failure from a resource shortfall.' It is thus an appropriate regional scale at which to make management decisions for the daily operations of the water network. The WRZ is mostly supplied by surface water abstractions from the river Thames via pump storage reservoirs, and by some groundwater abstractions, delivering clean water to approximately 7 million people every day (Thames Water 2015). Water abstractions are subject to limits to maintain environmental flows. A previous study (Borgomeo *et al.* 2014) identified population growth and abstraction allowance reductions as two of the major uncertain factors posing the greatest pressures on the supply system.

The London WRZ has the challenge of continuing to supply water to growing populations while ensuring affordability. Because it is in a heavily urbanised and densely populated area, the opportunities for operational improvement lie mostly in making the operation of the system more efficient, and in investments at key network points that can reduce the energy consumption of the system.

Figure 2 shows the London WRZ. The ovals over the reservoirs shows how they have been grouped in the model. The yellow diamonds show the water treatment works and how they are connected to the reservoirs and the ring main, all of which are represented in the model. A simplified representation of how the model is connected can be found in the Supporting Information (section 2). The optimisation model uses an aggregated (simplified) representation of the actual network in order to reduce the number of nodes and reduce the computational burden for optimization (following a similar approach from other studies) (Mala-Jetmarova *et al.* 2017). The treatment works included in the model represent all surface water treatment works in London. The groundwater treatment work (GWTWs) is a conglomerate of all the groundwater treatment works, in which the capacity of all the groundwater treatment works has been summed and an average cost of abstraction used. The groundwater sources have a minimum daily supply requirement of at least 40% of their capacity. This was incorporated after discussions with Thames Water modelling experts to represent the system more accurately, as some London demand must be met through groundwater sources. The x## numbers represent the

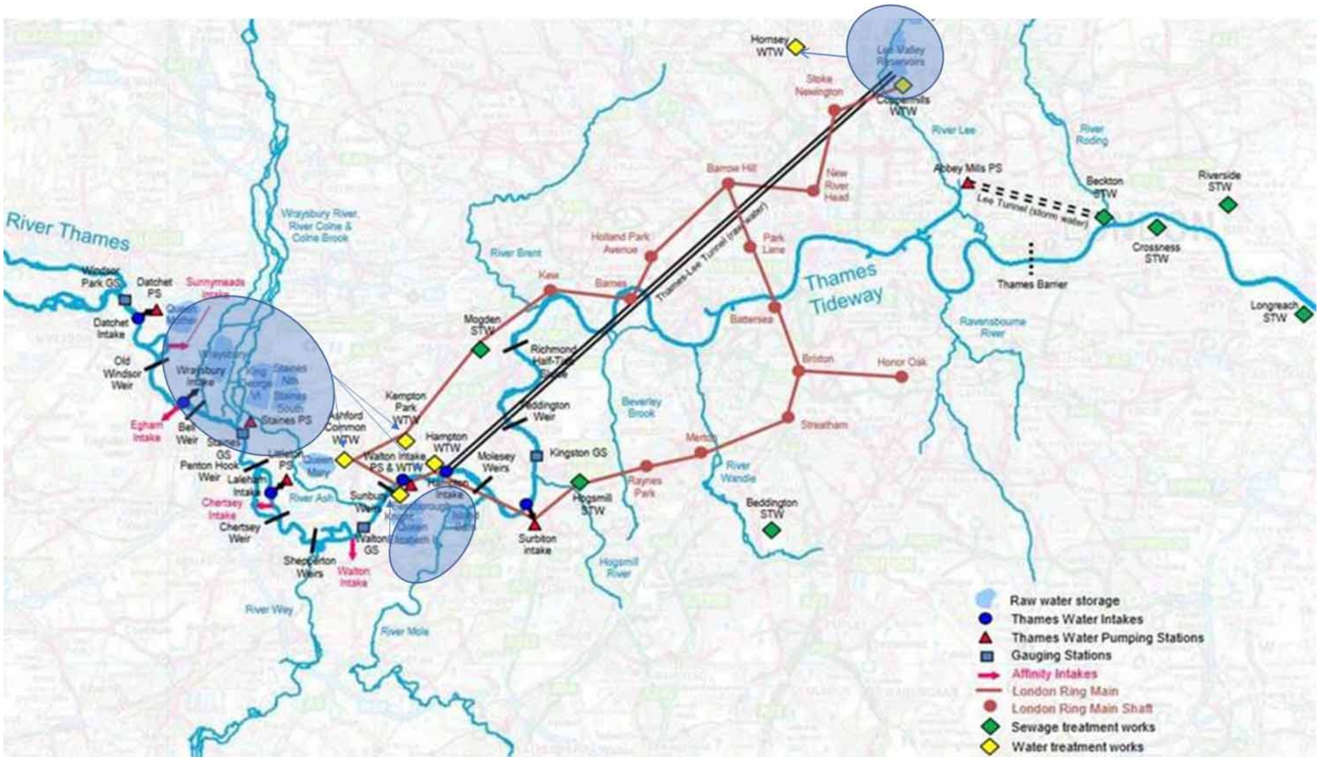

Figure 2 | The London Water Resource Zone and simulation model (Thames Water 2014).

assigned names for the optimization for each node and arc of the network. This configuration was used to illustrate the ability of the modelling technique to provide useful investment solutions.

Each reservoir has abstraction pumping costs (River to Res connections in network diagram). All treatment works also have transmission pumping costs that are equal for all stations (WTW to demand centre connections). It is assumed that the water pressure in the system is constant and there are no flow variations due to pressure differences. Operational water pressure for the Thames Water (TW) network was not available, so the effect of head loss is not included in the model. It is assumed that the pressure variations are captured in the empirical cost numbers used in the model. Each treatment work has a unique cost per unit of water treated, which is representative of the average cost to treat each unit of water in these treatment works in London. Reservoirs are assumed to have daily capacities matching daily demand unless otherwise stated. Reservoir 4 has a lower capacity than the others (30,000 m^3/d), while the others have virtually unlimited capacity. This was due to lack of data for daily capacities of reservoirs. Discussions with Thames Water experts highlighted that this was not a problem for modelling of daily supply because service reservoirs have capacities far in excess of daily demands. Each treatment work has a capacity which matches the real capacity in these treatment works in London.

Uncertainty modelling

A number of different input parameters are varied in Monte Carlo simulations (20,000 runs) to ascertain how changes in different factors would influence the operational costs. The parameters, represented by a set of distributions, were:

1. Water demand: change in total water demand, which is a combination of change in per capita demand and change in population
2. Electricity prices (£/kWh)
3. Carbon prices (£/tCO_2e)
4. Discount rates: the rate at which the value of investment is discounted over time.

According to the Thames Water Resources Management Plan (WRMP), the average demand for the London WRZ is approximately 2,035 megalitres per day (ML/d). The mean total demand in the optimization was thus 2,035 ML/d (which is broken down into a multiplication of the population with the per capita demand plus the industrial and commercial demand for London). Per capita demand was generated from a normal distribution, with a mean of 160 L/p/d, which was the average Thames Region per capita demand, and a standard deviation of 1 L/p/d to capture small variations over the 5-year period under investigation. The 5-year period was deemed as a useful time-frame as it matched the water sector's price review time periods. This is the period over which the regulator, Ofwat, assesses each company's ability to finance its activities (National Audit Office 2015; Ofwat 2017). Gaussian distribution probability distributions are commonly used for Monte Carlo simulations of water demand where relatively accurate estimations of demands for a region can be made (Babayan *et al.* 2005). A right skew Pearson distribution (skew: −0.75, kurtosis: 3.4) was applied to population, as population was expected to increase in the basin. This was done so that the distribution of resulting simulations included a larger number of higher than average demand figures than lower than average, as demand was expected to increase, and thus the uncertainty was rightly skewed. Other population forecast studies have traditionally used rightly skewed distributions to represent the probability that the population will increase (Alho 1997). Demand was calculated as follows:

$$D_T = (P * PC_D) + I_D + C_D \tag{5}$$

where D_T represents total demand, P represents the population, and PC_D, I_D and C_D represent, per capita demand, industrial demand and commercial demand respectively.

The water available for use (WAFU) was derived from the maximum abstraction allowed for the London WRZ published in the TW WRMP of 2,385 ML/d. The availability in the LP was generated from a normal distribution with $\mu =$ 2,385 ML/d and $sd = 10$ ML/d. The LP was optimized to meet London's daily demand, and to not exceed the maximum abstraction available for the region. The LP was run for each of the 20,000 simulations.

Electricity prices were derived from forecasted figures for the next 5-year horizon from the UK Government (DECC 2016). The electricity price was thus generated from a normal distribution with $\mu = 0.125$ £/kWh and $sd = 0.01$ £/kWh. It is important to note that electricity prices are not just uncertain, but also variable on short timescales, and that is why an uncertainty analysis around electricity price changes was carried out.

Greenhouse gas emissions

The operational greenhouse gases were calculated by multiplying the daily kWh consumed by a unit rate (emissions factor) to generate a tCO_2e from a kWh. The emissions factor was varied in the Monte Carlo simulations to assess the impact of a decarbonising grid, with a mean of 0.212 $kgCO_2e$/kwh and a standard deviation of 0.05, to incorporate higher end emissions factors closer to today's rates (around 0.4) and projected changes of down to 0.1. Capital investment embodied greenhouse gases were calculated from Thames Water's 2017 driven rates for embodied carbon of proposed capital investment options in tCO_2e/£, provided by the utility. Carbon prices were also used to calculate the monetary cost of greenhouse gas emissions. These were derived from the UK government's carbon price values used for UK public policy appraisal (DECC 2015). They published three scenarios: low, central and high, with approximate values of 4, 21 and 46 £/tCO_2e. The starting multi-objective optimization was carried out with the central value.

Investment strategies

For the ϵMOEA optimization, several investment strategies were tested to evaluate potential operational energy savings. A pareto approximation cost curve was derived that gives an indication of how much capital investment would be needed to warrant specific operational gains. These results can be used to evaluate the costs of different technologies or capacity expansions versus the potential savings that such technologies may provide, for a given budget.

Opportunities for improving the performance of the system were identified with the outputs from the LP, using the Lagrange multipliers. The optimal LP solution was used as a basis to identify strategic options for CAPEX investment solutions. The Lagrange multipliers show how much the optimal (minimum) cost value would change if a constraint of capacity is relaxed. They show the elements of the network where if the constrains are relaxed, the solution can be further improved. This is a rigorous systematic approach to identifying potential for cost reduction, which has traditionally been done through expert knowledge. The investment options were first identified based on values of the Lagrange multipliers, and were then discussed with the utility experts to determine the feasibility of the options, which were then refined and are listed in Table 1.

The capital costs for proposed investments that included pumping were derived from Thames Water's in-house process model for pumping stations. The final capital costs in the model depend on the ML/d required to be pumped, for which the total associated cost was provided by Thames Water from output from their inhouse model. The costs depend on the type of pump, as abstraction pumps (e.g. river to reservoir) have a different cost curve to pressurized distribution pumps.

These investment options are by no means exhaustive, and some may not be feasible due to other external constraints, such as land limitations; but they illustrate the capacity of this model set-up to provide an indication of where costs can be saved within a water distribution and treatment network, and provide a cost trade-off for each investment option. The cost of the investments was calculated for a five-year return on investment period, following current water industry regulation, and industry discount rate of 3.5%.

RESULTS

Linear programme

The LP results show that optimizing the system based on energy cost provides an approximate 18% daily saving in energy consumption of the water distribution and treatment system, from an average daily total energy consumption of 1.15 million kWh to 939,000 kwh per day. It also provides an average optimal annual cost in pounds of approximately £42.8 million per year to run the network. Thames Water currently spends approximately £50 million per year to operate the water network in London, thus using optimising techniques for the network could provide significant annual savings. TW reports to Ofwat show that their annual average operating expenditure for water delivery for their whole region is £327 million a year (Ofwat 2010). This includes other areas outside of London, and contains other costs such as staff costs, maintenance costs, insurance, vehicles and other miscellaneous costs.

Discussions with experts within the case study utility to validate and discuss the model output place this result within the context of the daily operations of a water utility. Such savings are currently not achieved in practice due to competing needs that must be fulfilled. The first is security of supply. Even though some sources of water within the network are very costly, for example, groundwater supply, there are sections of the network that require water from these sources to meet demand, and thus they need to be used daily at a high cost. Some of these are represented in the model, such as groundwater source requirements, but not all. The second priority is ensuring high water quality. Due to the variable nature of water quality, for example, the emergence of algal blooms seasonally, some more efficient parts of the network sometimes need to be turned off to avoid contamination, thus requiring more costly areas of the network to be run. Such modifications occur on a regular basis, requiring expensive resources to be turned on often. The third is the avoidance of leakage. If an efficient section of the network suffers from increased leakage, for example, from a burst pipe, supply is drawn away from that area and more costly water supply options may be used that would not be used otherwise, to avoid water losses. The reduction in energy consumption is thus currently the fourth priority for the case study utility, and most likely for the whole sector. These priorities added together mean that, in practice, it is difficult for utilities to make large energy savings based on existing operations.

However, discussions with experts from the utility did bring out that there are opportunities for more coordination between priorities, to improve the understanding of the connections between operating goals and energy costs, and benefit from potential savings. Studies such as this one can support such coordination and contribute to cohesion between objectives by showcasing methodological approaches that could be used in conjunction with existing processes for operating networks.

Table 2 presents a comparison between the volumes of water treated in the existing system (and associated empirical operational energy costs provided by Thames Water), with the optimized results for the water treated (in m^3) in each treatment work and associated energy costs (in kWh) without any additional investments. The figures in this table are lower than the overall system results above because they focus only on the water treatment works, and the overall result also includes pumping figures.

As can be seen, even though the actual treatment works provide less water, on average, than the modelled results (around 35,000 m^3/day, most likely due to daily variations in water supplied), the total energy consumption is significantly lower for the modelled results (476,170 kWh/day) than the current system (552,798 kWh/day), but the results are highly comparable.

Multi-objective evolutionary algorithm results

Figure 3 shows the ϵMOEA trade-off between capital investment costs and operational energy costs. Each point in the figure represents a unique combination of investments.

Table 2 | Comparison of LP optimization results for the main WTWs with operational figures for validation

	Treatment works	Current average water provision (m^3/d)	Current average daily energy use (kWh/d)	Model average water provision (m^3/d)	Model average daily energy use (kWh/d)
GWTWs	GW Sources	200,800	154,104	114,000	116,394
WTW 1	Chingford WTW	7,698	7,885	0	0
WTW 2	Coppermills WTW	458,372	105,056	523,606	120,429
WTW 3	Hamptom WTW	520,377	106,134	664,300	146,146
WTW 4	Ashford WTW	617,381	75,381	682,700	81,924
WTW 5	Kempton WTW	138,688	44,224	21,176	6,776
WTW 6	Walton WTW	26,780	55,609	0	0
WTW 7	Hornsey WTW	30,000	4,404	30,000	4,500
Total	–	2,000,096	552,798	2,035,782	476,170

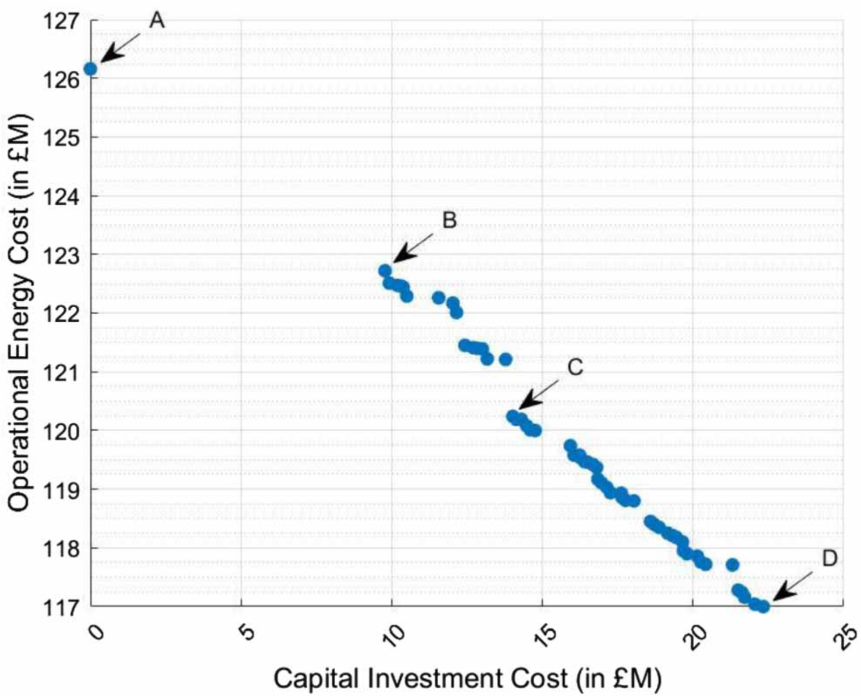

Figure 3 | Multi-objective trade-off between CAPEX and OPEX costs. Solution A represents no capital investment; Solutions B and D are the lowest and highest combination of capital investment respectively; and solution C is the pareto efficient solution. There is a gap between solution A and B because the capital investment at solution B is the minimum amount needed to reach an optimal combination of capital investment and operational energy costs.

The solution A on the x axis is the LP optimal result. The LP resulted in an optimal average 5-year discounted operating cost of approximately £126.2 million pounds. This is the single optimal solution for minimizing operational energy consumption in the network without additional investment, and for a set of specific parameters, which are later treated as uncertain – see Supporting Information (section 3) for list of parameter values. The solution C is the Pareto efficient solution in the Pareto-approximation curve, as defined in section 2.3.1. It is the point at which the relative operational energy savings are the best in relation to the capital investment. The ϵMOEA results show the trade-off between the capital costs of different combinations of investment strategies and the operational 5-year discounted costs for each of these optimal combinations. The ϵMOEA, even though computationally time-consuming, allows for a visualization of a Pareto-approximation frontier and trade-off between multiple objectives, showing how operational savings can be made with more investment. This permits a more in-depth evaluation of options to the water utility based on available investment budgets. Furthermore, it allows the water utility to calculate the recoupment period for each investment combination.

The Pareto curve in Figure 3 appears linear, but is in fact many small Pareto curves made up of a combination of increasing capital investments which happen to assimilate a linear increment when seen together. Figure 4 shows a close-up of the location of solutions B, C and D to visualize the small Pareto curves at those locations; the Pareto efficient solutions can be seen in a different color.

It may appear that operational cost savings are not large enough when compared to capital investment. However, the figures shown only show the savings over a five-year period, but the life cycle of investments are in the range of 30–40 years, or even more. Thus, operational savings of about ~£5 million in a 5-year period for a ~£14 million investment, as seen in Figure 6. Solutions A and C can provide a large saving over the life-time period of the asset. In this case, the evaluation is 5-years because of the budget cycles in the UK, as outlined above, but water utilities also plan in longer-term frameworks.

Solutions B and D are the lowest and highest combination of capital investment, respectively, and are chosen with C (the Pareto efficient solution) to explain in detail in Table 3. Solution A has no capital investments. There is a gap between solutions A and B because the capital investment at solution B is the minimum amount needed to reach an optimal combination of capital investment and operational energy costs.

All the solutions in the Pareto-approximation curve include using groundwater pumping in the investment solution. This is because the model has a constraint where a minimum amount of water needs to be extracted from groundwater systems, as occurs in the actual system, which is a more expensive source than some surface water treatment works. All the solutions on the Pareto-approximation curve also involve investment in capacity expansion at Ashford WTW. Ashford is already a large

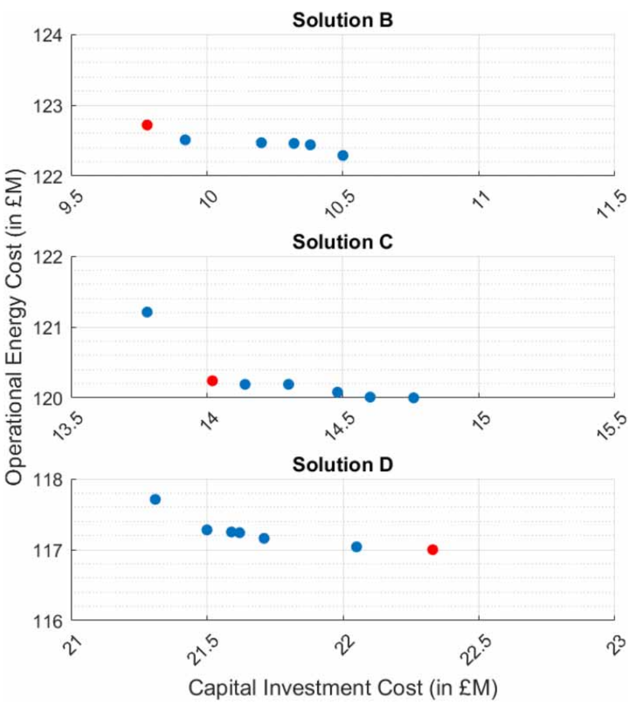

Figure 4 | Slices of Figure 3 showing the Pareto curves of specific solutions.

Table 3 | Optimal solutions showing Pareto efficient solutions (E) in the results section

Solution	Capital investment (million £)	5-year discounted operational energy (million £)	Investment solution details
A	0	126.20	NA
B	9.78	122.72	– Ashford expansion – GW pumping – 5/12 distr. pumps
C(*E*)	14.02	120.24	– Ashford expansion – GW pumping – 6/12 distr. pumps
D	22.33	117	– Ashford expansion – Walton efficiency – GW pumping – 12/12 distr. pumps
Change in discount factor			
E(*E*)	5.97	99.06	– 8/12 distr. pumps
F(*E*)	9.41	151.01	– GW pumping – 7/12 distr. pumps
Inclusion of GHG emissions			
G(*E*)	14.46	124.85	– Ashford expansion – 8/12 distr. pumps
Change in carbon price			
H(*E*)	11.45	121.67	– 9/12 distr. pumps
I(*E*)	10.5	131.27	– 8/12 distr. pumps

All solutions are presented in this table for ease of comparison. Solutions A–D are described above this table, and solutions E–I are described in subsequent text.

and efficient WTW, so re-routing more water through this location improves the energy consumption of the system significantly.

Water utility decision-makers can use this trade-off and options to evaluate whether they would be cost-effective, for example within 5-year or 10-year investments cycle. The above-optimal solution C would save £5.9 million within a 5-year investment cycle. Undoubtedly, this trade-off evaluation does not consider additional costs such as staff costs, land costs, insurance costs, capital maintenance costs and other externalities. But with more complete data-sets available in-house to the utilities, such tools could provide very useful information to improve performance of water networks at key nodes.

Discount rate

To test the sensitivity of the solution to changes in the discount rate. Two additional Pareto-approximation curves were generated with different discount rates (2% and 5%) in addition to the industry standard of 3.5%. Figure 5 shows the original trade-off curve at 3.5% and two additional Pareto-approximation curves, with their corresponding Pareto efficient solutions E and F. As can be seen, a change in the discount rate affects the costs in the trade-off curves and the optimal solution. Higher discount rates reduce the operational cost more and lower discount factors mean higher operational costs. The capital investments are unchanged as they are Net Present Value figures.

Solution E does not include the groundwater efficiency improvement (as in previous solutions), including Pareto efficient solutions C and F, which is why the capital investment is comparatively smaller (Table 3). This is probably because the investment cost of groundwater efficiency improvements is higher than the discounted operational cost of the pumps. It is interesting to point out that the 'recouping' percentage – how much of the capital investment is made back over the 5-year period – is quite different for the lower discount factor over the two other solutions. For optimal solution C it is 41%, E is 42% and F has a saving of 62% of the investment. This is most likely to do with the lower discount factor allowing for a larger saving over the 5-year period.

Greenhouse gas emissions

The analysis is continued with the central discount factor (3.5%) to evaluate the difference in the optimal solution and multi-objective optimization results when the capital

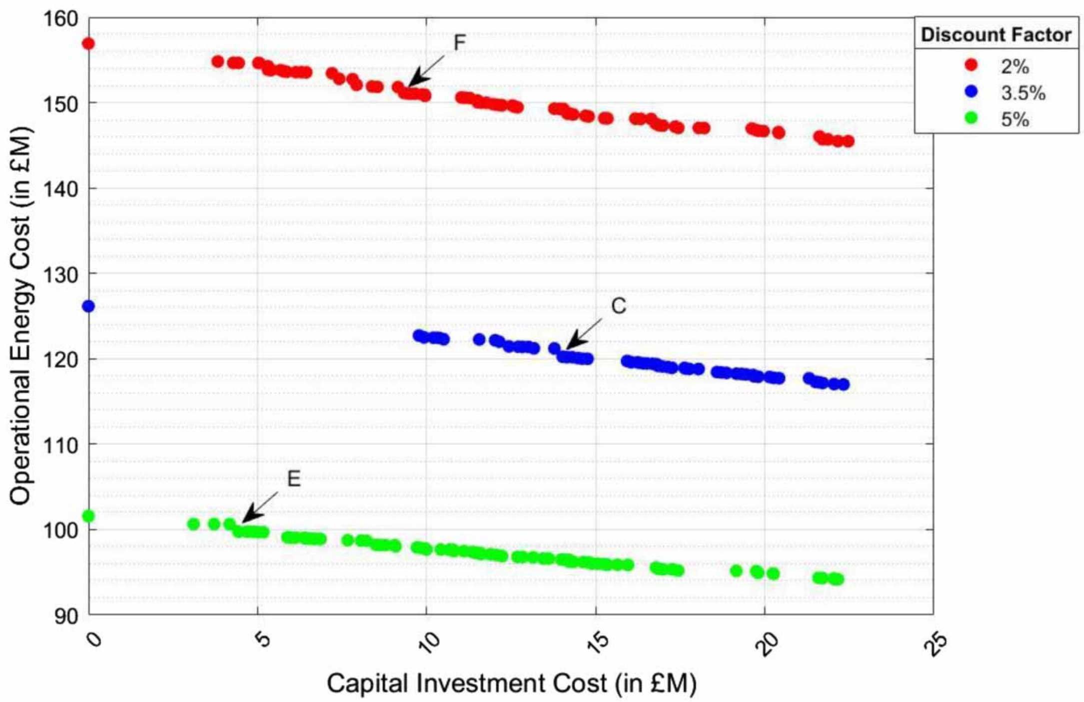

Figure 5 | Multi-objective trade-off between CAPEX and OPEX costs with different discount rates. Solutions E and F represent higher and lower discount rates respectively. Solution C remains as the original Pareto efficient solution in Figure 3.

and operational costs of greenhouse gas emissions are considered in the analysis.

Figure 6 shows the original 3.5% trade-off curve between capital investments and operational energy costs and a trade-off curve that includes capital investments costs plus the embodied capital investment costs from GHG emissions on the y axis, and operational energy costs plus operational GHG emission costs on the x axis. The two curves show the difference between just considering direct capital and operational energy costs and adding the costs of GHG emitted to the calculations. It is important to note that there are other costs involved in the building, maintaining and operating of water supply options, but this analysis aimed to investigate how the addition of GHG emissions may alter optimal solutions, particularly when considering carbon price changes. Thus, the graph includes direct capital and operational energy costs plus the greenhouse gas emission costs involved in the proposed CAPEX and the GHG emissions in the operation of the network.

Solution G is the Pareto efficient solution when GHG emissions are considered in the trade-off (Table 3). The investment in solution G is like solution C in that it also includes an expansion at Ashford WTW, but it does not include an improvement in the energy efficiency of groundwater treatment. This is probably due to the high embodied capital costs of improving so many pumps. It instead includes an upgrade in eight out of the 12 large water distribution pumps in the system, instead of the six in the original solution, denoting how an inclusion of greenhouse gas emissions changes the best investment choice. The embedded greenhouse gas costs in the capital investment are small compared to those in the energy costs but could become significant if the carbon intensity of electricity is reduced to close to zero.

Carbon price

The Pareto-approximation curve including greenhouse gas emissions costs was subjected to a sensitivity analysis to evaluate the influence of a change in carbon prices. Figure 7 shows three curves, each representing a multi-objective optimization trade-off between capital costs and embodied capital GHG emissions on the *y* axis and operational energy and GHG emissions costs on the *X* axis. The central curve is the same as the GHG emissions curve in the previous figure and has a carbon priced of 21 £/tCO2e. The other two curves represent the trade-offs with a carbon price of 4 £/tCO2e and 46 £/tCO2e and the details

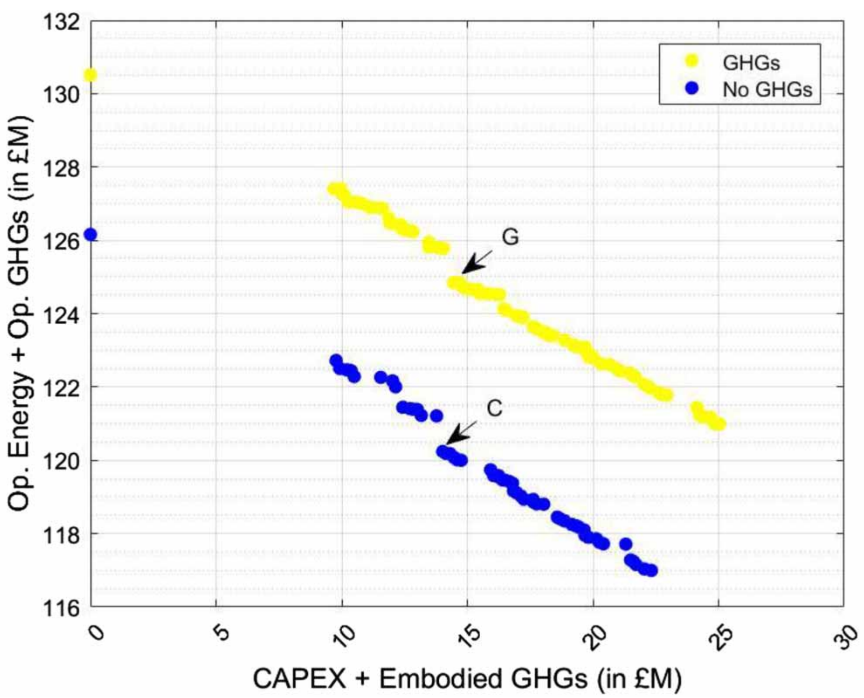

Figure 6 | Multi-objective trade-off between CAPEX and OPEX, and CAPEX and OPEX with GHGs. Solution C represents the original pareto efficient solution in Figure 3 and point G represents the pareto efficient solution when GHG emissions are considered.

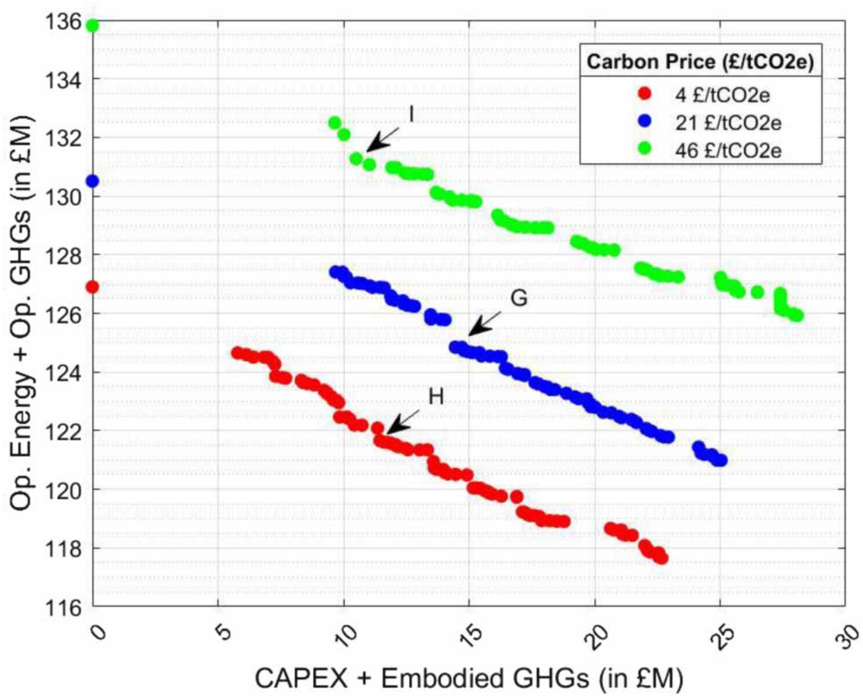

Figure 7 | Comparison of CAPEX and embodied capital GHGs with operational energy and GHG costs. Solution G is the original pareto efficient solution in Figure 6 which includes the cost of GHGs; Solutions H and I represent higher and lower carbon prices respectively.

of the Pareto efficient solutions H and I can be seen in Table 3.

As can be seen, carbon prices change the optimal investment combinations, highlighting the importance of setting a carbon price so that decision-makers can use the information to make the most efficient choices for their businesses.

Sensitivity of optimal solution

There are two additional sources of exogenous uncertainty in the model that may influence the optimal solution. As mentioned previously, electricity prices are not just uncertain, but also variable on short timescales, so an uncertainty analysis to the variability of energy prices can provide a more accurate representation of how costs in the system may vary in the short term. Figure 8 shows how optimal solution G (which includes the costs of GHG) would vary with changes in the additional two sources of uncertainty: change in water demand (made up of population change and per capita demand) on the x axis and change in energy price on the y axis. Each dot on the figure represents one scenario out of the 20,000 runs. The figure is coloured by the total 5-year discounted cost in pounds to see how the sources of uncertainty affect the change in cost.

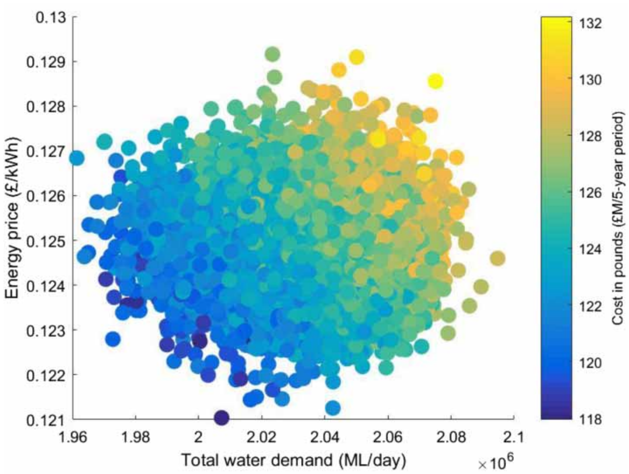

Figure 8 | Cost in pounds change with total water demand change and energy price change.

The figure shows how increases in demand raise the average operational energy costs in pounds, as does an increase in energy price. The results suggest that both small percentage changes in water demand and energy price could increase operational energy costs by between 2% and 5%. Additional simulations could be done in future work where larger uncertainty is looked at, in order to further analyse and refine the results.

CONCLUSIONS

Major cities around the world with large existing water supply systems are struggling to identify options to reduce operational energy use. In this study we have introduced a new a hybrid linear and multi-objective optimization approach. We have shown how this objective optimization approach can help to evaluate trade-offs between operational energy costs and capital investments within a water supply network. Visualizing the generated sets of Pareto-approximate optimal solutions helped to evaluate how different uncertainties (in discount rates and carbon prices) could affect projected costs and recoupment of investments within a network.

For the city of London, the optimization study shows that daily energy consumption can be reduced by up to 18% by optimally routing water distribution and treatment through the network. Other studies attempting the optimization of water networks through operational changes have achieved results in a range of 5–25% in energy cost savings (Cherchi *et al.* 2015). As well as being at the higher end of this range of efficiency savings, we have been able to incorporate a wider set of system requirements, particularly provision of high-quality water.

The case study highlights how small changes in the regulatory and planning framework, such as discount rates or carbon prices can have a significant effect on the cost of investment within water supply networks and are thus important elements to consider when evaluating the costs of possible solutions. Sensitivity analysis has demonstrated how a change in discount rates could change the daily operating costs by ∼19% (from £126 million to £151 million), that, in turn, leads to a different set of optimal investment options. GHG prices and changes in discount rates have an impact on the cost of water system operations, and there are regions at which the optimal solution for the utility changes. For example, at a 5% discount rate, investment in groundwater pump efficiency improvements as part of the efficient Pareto set of investments disappears as compared with the 3.5% discount rate set, most likely because the investment cost of groundwater efficiency improvements is higher than the discounted operational cost of the pumps. However, the 'recouping' percentage – how much of the capital investment is made back over the 5-year period – remains the same, at approximately 41%, due to the higher discounting.

Under cases where additional external costs such as GHG prices are not considered, there may not be enough of a justification to invest in higher energy saving approaches because the solutions are not cost-effective. When wider costs are included, a more realistic recoupment of investment can be evaluated and the case for higher investment made. If carbon prices are imposed in the future, this can impact investment decisions, and thus, uncertainty within this policy area can lead to inefficiencies in the economy.

The study also demonstrated how changes in water demand, including per capita use and population can have an important effect on the operational energy costs of water supply systems. Conservation measures and behavioural change are key for reducing water demand and associated energy implications. The results of this study quantified this impact for the city of London, showing that the fraction of reduction in water demand is almost one to one with the reduction in operational energy costs: 3% water demand reduction results on average in a 3% reduction in operational energy costs, including GHG emissions costs.

These results identify and highlight the persistent constraints and challenges in operating and upgrading legacy water supply infrastructure for new objectives of reduction of energy and emissions. Nonetheless, the optimisation methods we have proposed help to elucidate these constraints and thus facilitate discussions between utilities, regulators and governments about how they can be addressed.

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SUPPORTING INFORMATION

The Supporting information includes further details on:

1. Data sources
2. The simplified model
3. Starting linear programme parameters
4. Key equations

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

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