Efficient pathways to zero-carbon energy use by water supply utilities: an example from London, UK

Aman Majid, Mohammad Mortazavi-Naeini and Jim W Hall

Environmental Change Institute, University of Oxford, Oxford, United Kingdom

* Author to whom any correspondence should be addressed.

E-mail: aman.majid@new.ox.ac.uk

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Abstract

Urban water utilities are increasing their use of energy-intensive technologies such as desalination and long-distanced pumped transfers. Under pressure to reduce their energy-related carbon emissions to zero, water utilities have devised a variety of energy management strategies, including the purchase of renewable energy and self-generation of electricity using locally installed renewables. These strategies will incur different costs for the utility, whilst some may have implications for the reliability of water supply systems. Yet the trade-offs between costs, water security and energy sustainability remain unexplored. Here, we present a regional scale analysis to test competing energy strategies, mapping pathways to zero carbon energy and water security. Results from a case-study of the London water system show a balanced approach that allows for some energy self-generation, using biogas, solar and wind, while also purchasing green energy credits from the electricity supply grid can best navigate this trade-off. Balanced investment plans can accommodate energy-intensive water supply techniques such as long-distance transfers, desalination and effluent reuse while meeting energy targets. By becoming energy generators and also adopting more flexible arrangements for energy use, water utilities could become significant players in energy markets.

1. Introduction

The water sector faces enormous challenges from climate change, population growth, and over-exploited freshwater resources [1]. Water utilities operate a diverse portfolio of infrastructure that is responsible for conveying, treating, and delivering clean water to consumers through complex networks [2]. These systems need to be continuously expanded or changed in order to adapt to ever-changing external conditions.

Water infrastructure are also closely linked with energy systems [3]. Substantial quantities of electricity are consumed by water utilities for processes such as pumping and treatment [4], which are in a period of rapid change [5, 6]. Utilities are swiftly augmenting supplies to combat the challenges posed by climate change and demand growth. Technologies such as desalination, which can be highly energy-intensive, are becoming more prevalent [7]. Such water sources are being explored to reduce the environmental impacts of over-exploitation of groundwater and surface water resources [8]. Yet, this is causing electricity use by the water sector to grow sharply [9]. This brings increased operational costs, and, unless electricity supplies are from zero-carbon sources, make a large contribution to the sector’s carbon footprint.

There exist several opportunities to reduce energy use by water utilities. Ageing units within networks can be rehabilitated or replaced to enhance their energy efficiency and drive down their energy-intensiveness [10]. Reducing water leakage from pipes and water use will also decrease the sector’s energy use since this reduces the amount of water that needs to be conveyed and treated [11]. Sometimes incentivised by government renewable energy subsidies, water utilities have also begun to invest in local installations of renewable energy systems (RES) (e.g. solar,
wind, and biogas). In combination, adoption of these technologies mean that water utilities are increasingly becoming energy prosumers (combined consumers and producers of energy). Some water companies may even become entirely energy self-sufficient whilst exporting electricity back to the grid [12]. This raises a number of questions: which RES options should utilities invest in? How much RES capacity might be needed? What are the trade-offs between water security and carbon emissions reduction? What are the costs to the utilities (and hence its customers) of these varying energy strategies? How could the uncertain future costs of RES, along with electricity price volatility, influence potential costs and benefits of such strategies? As of yet, these questions remain unanswered in the context of deeply uncertain future conditions, such as climate change, population growth, and changing electricity prices. We argue it is essential to address these questions to unravel the costs and benefits of water-related energy goals, as well as to identify the key trade-offs between water and energy.

Infrastructure planning methodologies that can capture the linkages between water and energy could help answer the questions posed above. Models that serve such purposes, often referred to as ‘integrated energy-water nexus models’, are being deployed widely for cross-sector planning [see reviews by 13–16]. Multi-sector planning strategies have been shown to derive plans that are not only more economical, but also yield a greater level of sustainability [e.g. 17–20]. Yet, most of the analyses to date have been at a national or global scale, which inevitably entails approximations, whilst water sector decisions are actually made at a more local scale, for which there is a dearth of methodologies and analysis [21, 22]. Whilst the trade-offs between water system resilience, cost, and energy-related carbon emissions have been illustrated previously [e.g. 23–25], water sector planning methods need to enhance integration of energy systems to better capture water-energy interactions, such as the role of an energy prosuming water industry. Such developments are needed to link hydrological variability in the water system (e.g. reservoir dynamics) with volatility in the local energy system from stochastic weather processes (e.g. variable solar output), thus facilitating water managers to plan a water sector that is reliable, energy sustainable, and robust to uncertainties. This study provides such a methodological advance.

Here we introduce a highly resolved coupled system modelling approach to inform cross-sectoral decision-making at a regional scale. We harmonise water-energy systems in stochastic simulations, which allows us to examine in detail the effects of variability, on a day-to-day basis, in energy use by the water utility and renewable energy supplies and prices. We explicitly model the risk of insufficient energy supplies and the impact that this has on security of water supplies. Use of multi-objective optimisation enables us to elucidate the trade-offs between cost (combining operation and capital costs) and security of water supply, subject to a constraint of transitioning to carbon-free electricity supplies.

To illustrate our methods, we turn our attention to the Thames basin, England, where local water systems face chronic pressures from climate change and population growth, while the energy footprint of water infrastructure is increasing rapidly [9]. The local water utility, Thames Water Utilities Ltd (TWUL), has invested in a desalination plant and plans to invest in large-scale indirect wastewater reuse, which may further add to energy costs. At the same time, TWUL has ambitious plans to achieve net-zero energy consumption by 2030. We apply our methodological framework to derive infrastructure investment strategies that can balance the trade-offs between water and energy, while also ensuring plans robust to uncertainties in the climate, water demands and electricity price fluctuation.

2. Case-study

The Thames basin is located in South East England (figure 1) and is considered to be ‘seriously water stressed’ [26]. The region is the most densely populated in the country and it comprises one of the largest mega-cities in the world, London.

TWUL faces a number of challenges. Average urban water demand of 15 million persons is currently estimated at 160 L/person/day and total water demands are projected to increase by 0.25%–0.75% per year with regional population growth [27]. Climate projections predict warming across the Thames basin [28], which is expected to result in more uncertain and stressed water resources [29, 30]. In order to meet increasing water demands and adapt to predicted climatic changes, TWUL needs to expand its water supply capacities in the future. However, because the aquatic environment is already stressed, there is practically no scope for extracting more water from natural surface and groundwater bodies within the Thames basin, so attention is shifting to energy-intensive non-conventional water sources or to long-distance water transfers.

The utility’s rising electricity use is also a significant concern. Between 2009 and 2014, electricity consumption by TWUL grew by 10% per year due to changing treatment standards and growth in service demands [31]. Current system consumption stands at around 941 GWh per annum and makes up the largest carbon source and operational cost for TWUL [32]. The utility self-generates around 23% of its total energy demand using local installations of solar, wind, and bio-gas generation. TWUL plans on growing this self-generation capacity to eventually obtain all of its energy from renewable sources. This is with the aim of realising net-zero carbon emissions...
by 2030, as set by water utilities across England and Wales [33]. We conduct a water and energy infrastructure planning study for the TWUL system to 2035, mapping efficient pathways to water system resilience whilst achieving net-zero energy use by 2030. We consider 13 supply-side water and energy expansion options (table 1). The upper bounds for feasible capacities are based on TWUL's management plans [27] and the options are discretised to reduce the complexity of the decision space. Based on these options, water supplies could be augmented through desalination and inter-basin water transfers using existing or new pipelines, as well as indirect effluent reuse schemes in which treated wastewater could be pumped into storage reservoirs during periods of drought [27]. Figure 1 illustrates the proposed transfer schemes, some of which involve transporting water over hundreds of kilometres.

Three energy supply expansion options are considered: solar PV, wind, and biogas. It is assumed that for the portion of electricity not generated by TWUL (i.e. difference between consumption and self-generation), green energy credits will be purchased from the grid operator to meet TWUL’s net-zero ambitions. As TWUL is a combined water and wastewater utility, biogas was considered in the planning problem given that it is touted as a significant opportunity for self-generation. However, our study does not incorporate the wastewater cycle of TWUL’s business and the limitations of this are discussed later in this paper.

3. Methods

We adopt a multi-objective robust decision (MORDM) framework to map pathways towards a resilient and energy-sustainable water sector (figure 2). The conceptual framework, first introduced by Kasprzyk et al [34], has been applied for planning the TWUL system in a number of previous studies [e.g. 24, 25], and is embedded within the contemporary literature on water resources planning under uncertainty. Whilst there exist several methodological variants, robust decision frameworks generally emphasize: (a) recognition of critical uncertainties in the planning problem and extensive stress-testing of infrastructure alternatives to reveal key vulnerabilities [35–38]; (b) identification of solutions that are robust to uncertainties in that they perform acceptably well under a wide range of future conditions [39–41]; and (c) multi-objective framing of the planning problem to allow decision-makers to trade-off competing objectives under uncertainty [42–44]. Similarly, we develop and apply an MORDM framework to conduct integrated water-energy planning under a wide range of uncertainties to derive robust plans. This section describes that three-part framework with references to supplementary

![Figure 1. Map of the Thames basin in South England. The nodes show major water storage reservoirs (blue), cities (grey) and options (red). Red arrows indicate proposed water transfer schemes by means of new pipelines and inter-basin transfers.](image-url)
Table 1. Infrastructure alternatives considered in the case-study with their meta-variables. The sets show the capacities possible for each option.

| No. | Name | Capacity (ML or MW) | Capital cost (£k year\(^{-1}\)) | Start |
|-----|------|---------------------|---------------------------------|-------|
| **Water** | | | | |
| 1 | 48 km pipeline from Deerhurst to Cricklade | \([0,100,300,600]\) | 0–47000 | 2027 |
| 2 | 58 km pipeline from Deerhurst to Radcot | \([0,100,300,600]\) | 0–40000 | 2027 |
| 3 | 87 km pipeline from Lechlade to Culham | \([0,300]\) | 0–17000 | 2027 |
| 4 | Indirect effluent reuse scheme | \([0,100,150,200,300]\)† | 0–40000 | 2021 |
| 5 | Brackish desalination at Beckton | \([0,150]\) | 0–2275 | 2024 |
| 6 | Seawater desalination at Beckton | \([0,150,300]\) | 0–32000 | 2024 |
| 7 | 21 km transfer from Draycote | \([0,25]\) | 0 | 2027 |
| 8 | 40 km transfer from Minworth | \([0,88]\) | 0 | 2027 |
| 9 | 5 km transfer from Mythe | \([0,15]\) | 0 | 2027 |
| 10 | 170 km transfer from Lake Vyrnwy | \([0,180]\) | 0 | 2023 |
| **Energy** | | | | |
| 11 | Solar PV | \([0,20,40,60,80,100]\) | 0–5847 | 2024 |
| 12 | Wind turbines | \([0,10,20,30,40,50,55]\) | 0–8430 | 2024 |
| 13 | Biogas | \([0,20,40,60,80,100]\) | 0–45000 | 2025 |

†The maximum possible capacity for this option (300 MLD) represents approximately 12% of average daily drinking water demand in the basin.

3.1. Scenario generation

Our analysis incorporates aleatory uncertainties via stochastic simulation, whilst also exploring sensitivity and robustness to epistemic uncertainties about future changes in population and technology.

First, the weather@home2 (w@h) climate model was used to generate large sets of weather sequences [45, 46]. The w@h platform is based on the HadAM3P Global Circulation Model (GCM), which has been downscaled with the HadRM3P Regional Climate Model (RCM) by the UK Met Office Hadley Centre model [47]. It can be used to generate high-resolution (25 km) RCM weather sequences across Europe, which have been demonstrated to well represent extreme events [45]. Synthetic weather sequences of rainfall \(P\) (mm), temperature \(T\) (K), wind speed \(W\) (m s\(^{-1}\)), and solar irradiance \(I\) (W m\(^{-2}\)) were simulated at a daily time-resolution over the Thames region assuming two climate scenarios. The first uses historic climatic conditions and is referred to as the Baseline (BL) scenario, whereas the second assumes the Representative Concentration Pathway 8.5 (RCP 8.5)—a pathway with high greenhouse gas emissions and greater overall warming [48]—and is referred to as the Near-Future (NF) scenario. These two scenarios represent the lower and upper bounds of the projected global emissions scenarios and hence capture the climatic variability under uncertain decarbonisation pathways. In total, 100 synthetic realisations were derived for each emissions scenario (200 in total), each of a length of 15 years.

Time series of rainfall \(P\) and temperature \(T\) generated by w@h were used to simulate river flows using the DECIPHeR hydrological model [49]. DECIPHeR explicitly characterises connectivity and fluxes across landscapes using a flexible modelling framework and has demonstrated good performance in replicating hydrological behaviour across Great Britain. A more detailed account of the DECIPHeR methodology can be found in previous works [49], as well as the process of simulating rainfall-runoff dynamics historical and future naturalised flows across England and Wales [50]. Figure A.8 shows the flow-duration curves of the total simulated river flows under the BL and NF scenarios. Perturbations in groundwater availability induced by the climate sequences were not considered in this work and are instead held constant at the dry year annual average following the methodology developed by previous work [51].

Three water demand scenarios were used, referred to as the low, medium, and high growth scenarios. Each case assumes a growth of 0.25%, 0.50%, and 0.75% per annum, using the TWUL supplied intra-annual demand curve shown by figure A.9. These scenarios are based on regional modelling of future population and socioeconomic status by TWUL [27]. We used water demands at monthly temporal resolution as more granular data were not available. Hence, the results presented here may underestimate the water shortage risks given that the influence of daily variability is not incorporated.
Figure 2. Illustration of the three-part integrated water-energy modelling framework. In the first part, stakeholders define future scenarios in the climate and local water system, as well as infrastructure alternative options. Next, a water-energy model exhaustively simulates various option combinations under the scenario set, where spatio-temporal dynamics of energy are tracked. Finally, a risk profile is derived for stakeholders to assess potential pathways to achieve their targets.

Finally, we used three scenarios of average annual electricity prices, which are based on forecasts from the UK Department for Business, Energy, and Industrial Strategy (BEIS) [52]. These scenarios assume an annual rate of change of 0.69%, 1.06%, and 1.4% respectively, where the growth rate is applied to a baseline price of 13.1 p/kWh for renewable electricity from the grid. We incorporated only the grid price for renewable energy since TWUL intends to source all of its electricity from zero-carbon sources. For instances within the modelling where TWUL can produce more energy than it consumes, we assumed the energy is sold back to the grid for a feed-in tariff (FIT) of 5.24 p/kWh, which was adjusted annually by an RPI of 1.2%. The baseline electricity price and FIT were both derived from TWUL’s current power purchase agreement for renewable energy [53]. We did not model the influence of weather or climate change on electricity prices as others have done previously [e.g. 54, 55]. This is because water utilities typically operate off fixed-price contracts agreed to by energy utilities and hence are not as vulnerable to climate-driven risks within dynamic day-ahead electricity markets.

3.2. Simulation model
The system simulation model, known as TWmod, formulates the TWUL system as a set of nodes and edges and runs between 2020 and 2035. TWmod incorporates sociological, hydrological, and environmental parameters to represent the TWUL system. The model aggregates processes based on six water resource zones (WRZs) as shown by figure C.10. For example, a single node captures all groundwater abstractions in the SWOX WRZ (figure C.10, top-left). Similarly, all water storages within this WRZ are also aggregated into one reservoir node. This methodology to 'lump' operation is common in water resources modelling but represents a highly simplistic model of the real-world system. Yet, it ensures fast computation times and model tractability, as well as the ability to publish materials without compromising privacy or national security [56]. However, due to the simplicity of this approach, the results here should be treated as a preliminary screening that ought to be evaluated with further analysis. Nonetheless, TWmod was developed in extensive partnership with the local water utility and was calibrated and validated against the company’s own models as
described previously [57]. Further, TWmod has been deployed in a number of studies of the Thames basin [e.g. 51, 57].

TWmod incorporates the processes shown by figure 3. Based on the inflows produced by rainfall-runoff modelling, TWmod uses network linear programming (NLP) (C.1) to simulate and optimise supply allocation to demand nodes at a daily timestep. The NLP is subject to several constraints as outlined by the equations in sections C.1 and C.2. Numerous operational and environmental constraints are implemented including but not limited to: (a) reservoir releases are constrained subject to the control curve shown in figure D.11, (b) maximum daily to weekly abstractions from surface water resources as set by the water regulator, and (c) essential environmental releases to preserve downstream water quality. Due to a lack of information related to the wastewater system, TWUL’s wastewater operations were not included in the modelling process, which represents a significant limitation that is discussed later in the paper.

Following Porse et al [58], each edge carrying water is assigned a unique energy-intensity value ($e_i$, kWh ML$^{-1}$) depending on the process or technologies associated with the given edge. The assumed $e_i$ values are outlined by table C.4. For example, an edge carrying groundwater to a water treatment plant over a distance of 10 km would be assigned an $e_i = 300$ kWh ML$^{-1} + (5$ kWh ML$^{-1}$ km$^{-1} \times 10$ km). The modelled energy consumption was benchmarked against previously reported empirical data and showed reasonable agreement [9]. However, it is acknowledged that this is a significantly simplified method to compute energy use in the water system given that it neglects the actual topology and hydraulics of the system. The total electricity consumption by the water system ($E_C$) was computed as the sum of usage by each of these edges.

TWUL’s own energy supply ($E_G$) was modelled as the sum of generation from their solar ($E_{PV}$), wind ($E_W$), and biogas ($E_{BG}$) assets. Biogas was included within the energy system representation despite the omission of TWUL’s wastewater treatment cycle since it constitutes a significant portion of TWUL’s energy supply portfolio. The procedure for solar, wind, and biogas modelling are described in section C.3 with equations. The difference between TWUL’s electricity consumption and self-generation is assumed to be imported from the grid ($E_{IMP}$) without constraints, such that:

$$E_{IMP} = E_C - (E_{PV} + E_W + E_{BG}) = E_C - E_G. \quad (1)$$

As described previously (section 3.1), all imports from the grids are assumed to be purchased in the form of green energy credits, while any excess electricity produced by TWUL is sold back to the grid at the FIT rate. Though studied by previous works [e.g. 59, 60], the dynamics of intra-day market trading are not incorporated here since it is still uncommon for utilities to participate in these schemes.

3.3. Decision module

The third part of the framework used $\varepsilon$-dominance multi-objective evolutionary optimisation ($\varepsilon$-MOEA), a meta-heuristic search and optimisation algorithm [61], to search the decision space to identify infrastructure combinations that best minimise overall costs, while performing adequately across the defined scenario states. This approach facilitates the evaluation of trade-offs between competing objectives and has been used widely in water resources planning and management [62]. A dual
Table 2. Experimental setup for the optimisation. Six experiments were considered based on two climate scenarios and three energy strategies. RES and GC refer to renewable energy systems and green energy credit purchases, respectively.

| Experiment | Climate scenario | Energy strategy | RES | GC | Experimental meaning |
|------------|------------------|-----------------|-----|----|-----------------------|
| BL-IMP     | Baseline (BL)    | Importer        | ✗   | ✓  | Meet energy goal with only green credits purchases under baseline (historic) climate conditions |
| BL-PRO     | Baseline (BL)    | Prosumer        | ✓   | ✗  | Meet energy goal with only self-generation under baseline (historic) climate conditions |
| BL-BAL     | Baseline (BL)    | Balanced        | ✓   | ✓  | Meet energy goal through a balanced (50:50) approach to energy imports and self-generation under baseline (historic) climate conditions |
| NF-IMP     | Near-future (NF)| Importer        | ✗   | ✓  | Meet energy goal with only green credits purchases under near-future (RCP8.5) climate conditions |
| NF-PRO     | Near-future (NF)| Prosumer        | ✓   | ✗  | Meet energy goal with only self-generation under near-future (RCP8.5) climate conditions |
| NF-BAL     | Near-future (NF)| Balanced        | ✓   | ✓  | Meet energy goal through a balanced (50:50) approach to energy imports and self-generation under near-future (RCP8.5) climate conditions |

The objective problem was formulated in which we seek to minimise: (a) total cost of operational and capital expenditure \( f_1 \) and (b) total economic costs due to restrictions on water use associated with water shortages \( f_2 \) such that:

\[
\min_{x \in \Omega} F(x) = [f_1, f_2],
\]  

where \( x = (x_i, \text{Cap}_i) \) and \( x_i \) is a binary decision variable to activate decision \( i \) at capacity \( \text{Cap}_i \), \( f_1 \) is a function of the options implemented and total electricity costs of the system, whereas \( f_2 \) is computed as a function of the total reservoir volumes, where a restriction cost penalty is imposed should the volume fall below those defined by TWUL's operational curve (figure D.11 and table D.5). These two objectives are further described in section D.1.

The ε-MOEA yields a set of solutions, where each solution is a unique intervention of infrastructure investments and considered to be Pareto optimal, in that it is non-dominated or not exceeded with respect to all objectives by any other solution. The visualisation of each Pareto optimal set with respect to their objective values generates the Pareto frontier. The ε-MOEA was configured using the parameters defined in table D.6 following previous studies [63–66]. The termination conditions for the optimisation, as well as the procedure for ensuring a complete Pareto frontier, are discussed in section D.2.

3.4. Experiments conducted

A total of six experiments were conducted (table 2), which incorporated the Baseline (BL) and Near-Future (NF) climate scenarios, in addition to three energy strategies. Each of these strategies sees TWUL obtain all of its energy from renewable sources by 2030, using a combination of self-generation and the purchase of green energy credits from the grid. The first is the Importer (IMP) strategy, in which no further expansions in RES are considered, instead the utility’s energy target is met entirely by purchasing green energy credits from the grid. The second strategy, Prosumer (PRO), represents a case in which the utility energy goal is met entirely by self-generating its energy demand using RES. Hence, the IMP and PRO scenarios represent two opposing and extreme energy strategies. Meanwhile, the Balanced (BAL) strategy is a course of action in which TWUL achieve their energy targets by combining self-generation with grid energy purchases at a 50:50 ratio.
Table 3. Results from the post-optimisation analysis of the six selected plans. The objective values for total cost $f_1$ and water use restriction costs $f_2$ are given in million Great British Pounds (GBP£). The $W$ and $R$ denote the mean reliability and robustness, respectively.

| Plan | Climate scenario | Sense          | $f_1$ (£) | $f_2$ (£) | W (%) | R(%) |
|------|------------------|----------------|----------|----------|-------|------|
| A    | Near-future      | Best water restrictions | 207.7    | 5.74     | 99.0  | 91.0 |
| B    | Near-future      | Optimal$^1$    | 160.2    | 14.65    | 95.2  | 81.9 |
| C    | Near-future      | Best cost      | 116.7    | 45.45    | 91.9  | 74.3 |
| D    | Baseline         | Best water restrictions | 211.8    | 0.15     | 99.2  | 96.3 |
| E    | Baseline         | Optimal$^1$    | 150.9    | 1.31     | 98.1  | 92.4 |
| F    | Baseline         | Best cost      | 121.2    | 4.96     | 97.6  | 88.7 |

$^1$ Optimal point in principle based on TWUL’s tolerable level of risk [51].

3.5. Post-optimisation analysis

A post-optimisation analysis was conducted on a small sample of solutions derived from the optimisation. Specifically, three solutions were selected from both the BL-BAL and NF-BAL strategies, making a total of six solutions (table 3). The selected solutions represent (1) cheapest solution, (2) best from the perspective of water security, and (3) optimal solution (in principle) where the gradient of the Pareto frontier is equivalent to 45° [51]. We compare the cost, investment composition, robustness, and reliability of each of the six solutions. We define robustness following Paton et al [23]:

$$R = \frac{T}{\Omega},$$

where $R$ is robustness, $T$ is the number of scenarios in which the solution exhibits ‘acceptable performance’ and $\Omega$ is the total number of scenarios. We define ‘acceptable performance’ in terms of reliability ($W$): ≥95% of days without restrictions and a maximum failure duration of 100 days.

4. Results

4.1. Trade-off between water security, cost, and energy sustainability

Figure 4 shows the results from the multi-objective optimisation under the NF climate scenarios for the three energy strategies evaluated. The curves depict the Pareto frontier (PF) fitted onto the non-dominated solution set for each energy strategy (see E.1). The non-dominated solutions derived for each of the six experiments are shown by figure E.12 and further described in section E.2. The IMP curve on figure 4 represents the cheapest way for TWUL to transition to zero-carbon electricity. Solutions to the right of the PRO curve are uneconomical since cheaper solutions exist that can achieve the same security of supply. Plans within the IMP and PRO range (green shaded region) are those that can balance objectives in cost and water security whilst achieving the zero-carbon electricity goal.

A distinct trade-off between total cost and water use restriction cost is observed, whereby increasing the investment lowers the risk of water use restrictions. Though the gradients of the PFs are nearly identical the PFs under the BAL and PRO strategies shift upwards relative to the IMP case, demonstrating that these two strategies are more costly. The PFs shown quantify the marginal cost of incremental increases in RES. For example, the distance between the IMP and BAL curves represents the marginal cost of shifting from 0% to 50% RES self-generation in the TWUL system. The dashed curves show linearly interpolated estimations of PFs representing plans with 25% and 75% RES self-generation, therefore allowing decision-makers to estimate the marginal cost of increasing RES capacity.

The trade-off frontiers also capture the climate sensitivity in the space of choices. For example, figure 5 shows the non-dominated Pareto optimal solution sets derived under BL and NF climate conditions (see also figure E.12). A right-shift is observed in the PF from the NF case when compared to that from the BL case. This shows that achieving a given level of water security requires substantially greater investment in water supply infrastructure to mitigate against the climate impacts of a high-emissions future.

4.2. Post-optimisation analysis

Three plans from the BL-BAL and NF-BAL experiments were selected for post-optimisation analysis. These are denoted plans A–F and are shown by figure 5. These plans represent the following: (a) the best solutions from the perspective of water security (A and D); (b) the best solutions from the perspective of cost (C and F); and (c) the optimal points in principle (B and E).

The composition of each strategic investment plan A–F is shown by figure 6. The plot shows that inter-basin transfer schemes (e.g. options 8–10) are selected with the highest frequency. On the other hand, transfer schemes that involve the construction of new pipelines (e.g. options 1–3) are chosen with relatively lesser frequency. Similarly, options such as desalination and effluent reuse were selected within fewer plans. Inter-basin transfer schemes can entail significant energy costs due to the requirement of long-distance pumping, yet they
Figure 4. Pareto frontiers (PFs) fitted onto the non-dominated solutions derived under the NF climate scenario for the IMP, BAL, and PRO energy strategies. Dashed lines are linearly interpolated curves representing the marginal cost of increasing self-generation capacity between 0% and 100%.

Figure 5. Non-dominated Pareto optimal solutions derived from the BL-BAL and NF-BAL experiments. The highlighted points (A)–(F) show the six investment plans chosen for post-optimisation analysis.
Figure 6. Composition of investment plans A–F showing the capacities of water (options 1–10 in ML) and energy (options 11–13 in MW) infrastructure implemented.

| Plan  | A | B | C | D | E | F |
|-------|---|---|---|---|---|---|
| Option 01 | 100 | 100 | 0 | 0 | 0 | 100 |
| Option 02 | 0 | 0 | 0 | 0 | 0 | 0 |
| Option 03 | 300 | 0 | 0 | 0 | 0 | 0 |
| Option 04 | 300 | 150 | 0 | 300 | 0 | 0 |
| Option 05 | 150 | 0 | 0 | 150 | 150 | 0 |
| Option 06 | 0 | 0 | 0 | 0 | 0 | 0 |
| Option 07 | 25 | 0 | 0 | 25 | 25 | 0 |
| Option 08 | 0 | 88 | 0 | 88 | 88 | 88 |
| Option 09 | 15 | 15 | 15 | 15 | 0 | 15 |
| Option 10 | 0 | 180 | 180 | 180 | 180 | 180 |
| Option 11 | 20 | 20 | 40 | 20 | 20 | 50 |
| Option 12 | 10 | 10 | 10 | 10 | 10 | 20 |
| Option 13 | 40 | 40 | 30 | 50 | 40 | 30 |

Analysis of the investment plans also shows that plans included a combination of biogas, solar, and wind supply. However, total biogas capacity is the...
highest out of all energy supply options across all plans. This is likely due to biogas plants not being subject to strong seasonal variability as wind and solar. However, as discussed in C.3, our modelling process does not capture the TWUL's wastewater system and as a result omits key feedback loops and linkages in this portion of the system boundary.

Figure 7 shows the results from the simulation across all scenarios $\Omega$ as a parallel coordinates visualisation for (a) plans A–C under the near-future climate conditions and (b) plans D–F under the baseline climate conditions. Grey lines show the output from each scenario, whereas the lines in colour represent the mean values for each plan computed across all scenarios. The plot demonstrates that there is a significant amount of variation under each scenario. Mean reliability for all plans is over 90%, yet it can be below 80% under certain scenarios, particularly under plans C and F, which undermines the overall robustness of the plans. The robustness metrics computed for each of the plans A–F are given by table 3. The results demonstrate that maximising robustness requires greater investment in supply infrastructure.

The parallel coordinates curve illustrates a number of water-energy trade-offs. Firstly, it shows that plans that deliver a higher reliability, and hence that exhibit fewer number of water use restrictions on average, are more energy consumptive on average. In other words, increasing the level of water supply reliability results in a commensurate increase in the system’s energy consumption. Secondly, whilst all plans exhibit a minimum energy self-sufficiency of >50% as constrained by the BAL strategy, the average self-sufficiency is in fact higher across all plans, reaching up to 125% of overall demand (i.e. generating excess electricity that is sold back to the grid). For example, the average self-sufficiency under Plan A is around 70%. This demonstrates that guaranteeing a minimum level of self-sufficiency involves overproduction on average to cope with the inherent variability within the water system.

5. Discussion

The utility of multi-objective optimisation to plan water supplies whilst balancing costs and water supply reliability in the face of uncertainty has been demonstrated previously [e.g. 24, 25] and this process is now recognised as an integral part of the decision-making process [67]. Yet, as demonstrated here, extending the decision framework to incorporate increasingly important energy sustainability targets has substantial effects on the decision space. Doing so allows decision-makers to balance critical water-energy trade-offs to maximise the reliability of water supply in a manner that is sustainable. This could provide practical benefits for water managers. Even within the same water organisations, decisions related to securing future water supplies and energy targets are often made within separate departments or entities [58, 68], which could lead to sub-optimal management plans. Cross-cutting decision methodologies could facilitate the integration of such entities [13, 17].

Achieving energy targets by partially or fully self-generating energy demands was shown to be a costly proposition. It also entails the implementation of significant amounts of RES, which may be technically infeasible due to constraints on land use and storage availability. However, there are a number of strategic advantages to maximising energy self-generation. Firstly, it can partially decouple the water system from the energy grid and decrease water utilities’ vulnerability to price increases. Secondly, utilities that both possess storage and are able to dynamically alter their energy demands (e.g. a water treatment facility) have been shown to increase the utilisation of RES within local energy systems [59]. This could provide mutual benefits for the water and energy sectors in the form of lower operational expenditures and greater RES uptake respectively. Thirdly, recent studies of behavioural studies have demonstrated a shift in consumer behaviour towards green energy products [e.g. 69, 70]. In regions such as England and Wales, where water utilities operate in a privatised market, demonstrating energy sustainability may have benefits in terms of consumer confidence.

Given that the timescales to meet energy targets are short, additional synergies between water and energy systems will need to be explored to gain project financing and achieve objectives in a cost-effective manner. One of the most promising energy-water synergies is for water utilities to participate in demand-side response (DSR) programmes, schemes proposed by the energy sector to incentivise the shift of consumers’ demands to off-peak periods to alleviate grid pressures. Kernan et al [59] showed dynamically altering water-related energy demands to signals from energy systems could lower operational costs by up to 13% whilst ensuring the same level of service. This could materialise large cost savings given that energy consumption is typically the dominant portion of operational costs for water companies. The advent of high-resolution smart metering data in the water sector could facilitate such schemes without compromising supply [71]. Increasing biogas production from the water sector, which still remains under-utilised, could also enhance participation in DSR programmes as it can provide additional flexibility through the ability to store gas, whilst also exhibiting negligible variability and high ramping rates. Biogas capacity also provides the benefit of being able to export gas supplies to the grid.
and also utilising its heat energy output through combined heat and power (CHP) technologies [72]. However, it is important to recognise that the adoption of schemes such as DSR will require major cultural changes as operational practices will need to be overhauled.

As with any study that attempts to model multiple complex sectors for future planning, there are a number of important limitations in the methodology presented here. Firstly, this study did not incorporate the wastewater cycle of TWUL’s system. Though TWUL is a combined water and wastewater utility, these two operations are managed independently in practice with limited integration of models and data systems. Multi-sector approaches that can capture water and wastewater interactions have only just begun to be developed [56]. As this field advances, our efforts could be improved upon in future through a more holistic representation of water-wastewater-energy links and feedback loops. For example, the influence of variability in the wastewater system on biogas production could be incorporated, as well as the downstream impacts of effluent reuse schemes due to the removal of a stream of water. Our study also used simplistic forecasts of grid energy prices. While this is a common method for dealing with deep uncertainties [38], others have linked climate model data to create energy price forecasts [e.g. 55, 73]. Using such approaches could provide a more reliable means of studying the affects of future emissions pathways and their implications for water and energy systems. Also, whilst the models used here were validated against historical data to show good agreement, it is important to recognise that there remain uncertainties in methods to validate integrated models [74]. Finally, our case-study considered only supply-side options, whilst considerable opportunities exist to secure future water and energy supplies using demand-side management options such as leakage reduction and upgrading older assets to more energy-efficient units.

Despite these limitations, this study provides a first analysis of the achieving energy sustainability in the water sector by means of utilities transitioning into prosumers using a multi-objective robust decision-making framework. Such multi-sector approaches at a regional scale will be critical in ensuring utilities are developing in line with the sustainable development goals [13]. By unravelling the key trade-offs, we have provided a blueprint toward realising a water sector that is reliable, robust and sustainable.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

Disclaimer

The case-study presented here is illustrative and hence does not represent the views or strategic plans of Thames Water Utilities Ltd (TWUL). The authors declare no conflict of interest that could have influenced the representation and interpretation of the reported research results.

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ORCID iDs

Aman Majid  
https://orcid.org/0000-0001-5892-7181
Mohammad Mortazavi-Naeini  
https://orcid.org/0000-0002-5745-4156
Jim W Hall  
https://orcid.org/0000-0002-2024-9191

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