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The influence of temporal variability and reservoir management on demand-response in the water sector

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ABSTRACT

Urban water systems can be highly energy intensive. Yet, they are also excellent candidates for demand-response since they possess readily controllable operations and large amounts of storage. However, real-worlds trials have delivered mixed results, which implies the need to understand the underlying mechanisms of flexibility in water operations. This paper studies the potential to shift energy demand in an urban water system located in the River Thames basin, a region encompassing the city of London, England. Results show that the system could theoretically shift up to 20.1% of its annual energy demand for pumping (2.1 GWh), saving the local water utility around £5.6 million in electricity costs. However, the water system's flexibility is shown to be highly variable due to the variability in water demands and electricity prices, in-turn affecting the financial returns from demand-response. Sensitivity analysis reveals that factors such as the seasonal reservoir control strategies and total storage capacity are key determinants of system flexibility. A relationship between water storage capacity and flexibility is also derived, which could be used to estimate water sector flexibility in other regions.

1. Introduction

Energy systems are undergoing a period of rapid transition. Conventional modes of power generation, such as coal and gas fired power plants, are being replaced by relatively lower carbon electricity systems such as solar photovoltaics and wind turbines. Whilst this transition is essential for decarbonisation, the increased production from renewable energy is also introducing more complexity to the energy grid [1]. Output from wind and solar are inherently variable, depending upon stochastic weather processes (wind speed and solar irradiance), and so their electrical output is only partially predictable and not necessarily matched to variation in demand. Therefore, increased penetrations of renewables into the energy system is highly disruptive to grid-balancing activities, the act of continuously matching consumer demand to energy supply. A number of approaches will be important in managing this volatility, one of which is demand-side response [2].

1.1. Demand-side response

Electricity utilities across the world are actively deploying demand-side response (DSR) schemes. DSR is broadly defined as short-term changes in a user's normal electricity use in order to better match demand with available supplies [3]. The availability of supplies, relative to demand, may be signalled by the spot prices of electricity (units: monetary cost per unit electricity consumption). When considered alongside local generation, energy loads, and storage capacity, DSR will play a pivotal role in the widespread uptake of renewable energy supplies by allowing the energy system to shed energy demand during periods of insufficient supply and vice versa. There are three categories of DSR as noted by Albadi et al. [3]:

(1) **Curtailment:** Customer responds to high electricity prices by reducing their usage. This is an on–off operation and is usually associated with a short-term loss of service.
(2) **Substitution:** Customer responds to high electricity prices by switching to a different energy source (*e.g.* onsite generation). This is an on–off operation and service is maintained.
(3) **Shifting:** Customer shifts the 'flexible' portion of their energy demand from peak to off-peak periods. This is suitable for storage-type customers and service is maintained.

Ideas surrounding DSR mechanisms have existed for many years [4], but they are only now starting to be deployed as the energy sector modernises its information systems. It has long been understood that

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Nomenclature

Variables and parameters

$\check{q}$	Minimum flow rate along an arc (m^3/s)
$\check{v}$	Minimum storage reservoir volume (m^3)
$\hat{q}$	Maximum flow rate along an arc (m^3/s)
$\hat{v}$	Maximum storage reservoir volume (m^3)
f	Fractional component indicating the minimum raw water storage (%)
k	Fractional component indicating the minimum refill of service reservoirs (%)
q	Volumetric flow rate (m^3/s)
S	Water supply or demand (ML)
v	Storage reservoir volume (m^3)
Y	Time series data of wholesale electricity prices (£/kWh)
z_b	Bins for time-of-use tariff where $b \in \{1,\ldots,4\}$
η	Pumping efficiency (%)
C	Total cost of electricity (£)
ρ	Density of water (kg/m^3)
$\mathbf{F}*$	Flexibility index
$\mathbf{F}$	Flexible energy demand (kWh)
$\mathbf{P}_{\mathrm{BAS}}$	Load curve of scenarios without demand response
$\mathbf{P}_{\mathrm{DR}}$	Load curve of scenarios with demand response
c	Cost of electricity (£/kWh)
g	Acceleration of gravity constant (m/s^2)
h	Pumping head (m)

Indices

i	Start node
j	End node
m	Month
n	Node
t	Timestep

Sets

$\mathcal{A}$	Arcs
$\mathcal{G}$	Directed graph
$\mathcal{M}$	Months of the year
$\mathcal{N}$	Nodes
L	Time steps in which service reservoirs are refilled
n_{res}	Water storage nodes
n_{rw}	Raw water reservoir nodes
n_{sr}	Service water reservoir nodes
T	Time steps

Abbreviations

BAS	Baseline scenario
CDF	Cumulative density function
DSR	Demand-side response
GHG	Greenhouse gas
LP	Linear programme
ML	Megalitre
RA	Risk averse
RN	Risk neutral
RTP	Real-time price
TOU	Time-of-use
UK	United Kingdom

large industries—normally the biggest consumers of electricity within a country—are the best initial targets for DSR since these processes contain large controllable loads and a relatively low cost per control point [5]. Industries such as agriculture, manufacturing, waste management, and digital and telecommunications could bring substantial economic benefits whilst facilitating sustainable development [6]. For example, Papadaskalopoulos et al. [7] estimate that flexible industrial demand could lower generation and transmission costs in Europe by up to €4.3 billion per annum. Meanwhile, the owner and operator of the high voltage transmission network in the United Kingdom (UK), National Grid, recently quoted that DSR will save the UK economy an additional £17–40 billion up to 2050 [8]. The water sector is one such industry that is regularly touted as an excellent candidate for DSR.

1.2. Flexible operations in the water sector

The water industry is responsible for sourcing, cleaning, and delivering water to consumers on-demand. Fig. 1 shows a simplified representation of a typical urban water supply system. Raw water is pumped into impounding storage reservoirs before being further pumped for treatment. Treated water is then conveyed through transmission mains to service reservoirs or water towers at elevation near to population centres. Finally, water is delivered to the service area through distributional mains, where sufficient pressure is generated through gravitation.

Pumped water supply networks can provide DSR through a mechanism that is generally analogous to pumped hydro storage schemes. Pumps are activated during times of abundant renewable output or cheaper tariffs, and vice versa. The operations of large centrally owned pumps are interruptible and discrete. These pumps do not necessarily need to operate round the clock, but rather in relation to defined operational control curves set by network managers. There is a high degree of flexibility in the system since pumps can be dynamically controlled and both raw and treated water can be stored.

The benefits from DSR in the water industry could be substantial in terms of both the load shifted and costs saved. Pumps can account for around 70%–80% of the total electricity consumption in the sector [9], while costs associated with electricity are the dominant operational expense for water companies [10].

There is a growing but still scarce body of literature exploring the benefits of flexibility from pumped water supply systems. These studies have provided numerous insights. Firstly, a number of previous works have shown load shifting in water pumping schemes can yield substantial economic benefits for water operators. Van Staden et al. [11] demonstrated this in a water pumping scheme from a water purification plant in the Tshwane municipality, South Africa. This study showed the plant could lower its electricity costs by 5.8% by dynamically altering its load relative to a price signal. Several studies have followed to demonstrate the benefits of optimal pump scheduling in water systems located in areas such as Ireland [12], France [13], and the United States [14]. These works have reported varying monetary and environmental benefits from DSR in water systems, which is likely due to regional differences in climate, geography, market conditions and engineering practices [15].

Studies have also shown that DSR from pumped water networks provide benefits wider than merely economic savings for water utilities. In a series of studies from the UK, Menke et al. [16–18] studied the financial and environmental benefits of DSR from water pumps. Their analyses showed that the greenhouse gases (GHG) generated from

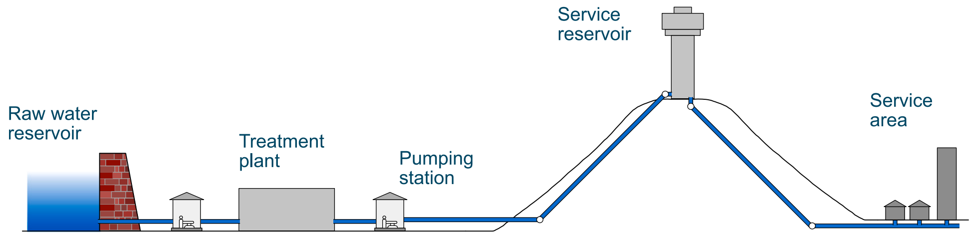

Fig. 1. An illustration of a typical urban water supply system. The direction of flow is from left to right.

water sector DSR (470–571 gCO2e/kWh) were much lower than alternative reserve technologies such as open-cycle gas turbines (480–575 gCO2e/kWh) and internal combustion diesel (520–700 gCO2e/kWh). Zohrabian and Sanders [19] also studied the GHG benefits from water system DSR. The paper presented an illustrative case-study that considered a 5% shift in the total daily average electricity load of 97 water-supply utilities in California. Their simulations demonstrated a substantial reduction in annual carbon dioxide emissions of 2%–5%. Meanwhile, Meschede [20] showed that pumped domestic water storage systems can increase the uptake of renewable energies in a small remote-island infrastructure system by providing DSR. Thus water system DSR does not only provide water operators financial rewards, but also delivers mutual benefits for energy managers by shaving peak-demand curves at a lower carbon-intensity than competing technologies.

Most of the studies to date have used electricity prices as a market signal for optimising pumping schedules. However, the tariff structure has differed between studies. Some works [21,22] adopted time-of-use (hereinafter TOU) style tariffs in which the price curve is usually split into no more than four discrete intervals. Such price regimes generally incentivise pumping overnight during off-peak hours for energy operations. Other studies [23–25] have adopted wholesale real-time pricing (hereinafter RTP) tariffs and hence incorporate the real-time dynamics of energy markets. Kernan et al. [12] used RTP tariffs to demonstrate DSR in a water network from Belfast, Northern Ireland, reporting 3%–13% reductions in operational costs. The paper argued that RTP tariffs can be more profitable than TOU structures as they comprise a higher level of volatility that can be exploited. However, the study did not directly compare the benefits from RTP and TOU price profiles.

Though hardly acknowledged in the literature so far, water system DSR is not without its risks. For example, Mkireb et al. [13] optimised pumping schedules in an urban water system relative to RTP signals under a French DSR mechanism. The paper adopted scenario analysis to study the influence of water demand uncertainty on the economic benefits from DSR. Their findings demonstrated that water-related DSR is less profitable if demand uncertainties are not adequately incorporated.

There remain substantial gaps in the literature on water system DSR. The following gaps were identified for this paper, which to the best of the authors' knowledge have not previously been studied:

- **The influence of temporal variability in water demands on DSR:** Municipal water demands exhibit significant variability in both the short and long term. Contributing factors to seasonal and random variability include household sizes, income, social status, and climate [26]. Studies to date have either assumed water demands to remain fixed [20] or adopt a short temporal horizon for the study [13]. There is a need to understand how long-term variability in water demands can influence water system flexibility.
- **Comparison of TOU and RTP tariffs:** TOU and RTP style tariffs have not yet been directly compared despite some arguing that RTP is much more profitable [12]. This is an important factor to consider given that RTP pricing entails a greater level of risk since the consumer is exposed to more market volatility.
- **Trade-off between operational risk and financial benefits from DSR:** Water storages (impounding and service reservoirs) follow strict operational curves, which vary seasonally based on the risk attitudes of operators. Running reservoirs to lower levels provides more flexible potential for DSR. Yet, running at a low level risks not being able to supply unexpected demand or vulnerability to droughts. This trade-off so far remains explored.
- **Identification of key parameters influencing water system flexibility:** Most studies to date have been devoid of sensitivity analyses. As such, the key parameters that have the most impact on water system flexibility have not been investigated. This study explores the influence of parameters such as water storage, pump capacity and tariff structure on DSR potential in water networks.

1.3. Paper scope and contribution

In light of the knowledge gaps discussed above, the aim of this paper is to address the following questions: (1) How does temporal variability in the water system influence its DSR potential? (2) Can water systems provide more flexibility under an RTP tariff when compared with a TOU tariff? If so, are the economic returns worth the greater operational risk? (3) What are the key parameters influencing water system flexibility?

To answer the questions above, this paper adopts a system-level approach to explore the potential for demand-side response in a real-world urban water supply network under temporal variability. An open-source simulation model is developed to conduct scenario analysis. The water supply system from the River Thames basin is studied, a region encompassing the mega-city of London, England. The energy flexibility in the local water system is quantified subject to the strict reservoir control strategies of the local water utility, as well as seasonal and random variability in water demands.

The main contributions of this paper can be summarised as follows:

(1) Water system DSR is shown to be beneficial in terms of economic savings for water companies and increased energy grid flexibility, but these gains are highly variable, a fact that may deter decision-making investors.
(2) Through scenario and sensitivity analyses, a trade-off between operational risk and DSR benefits is presented, providing water managers a framework for navigating these trade-offs.
(3) A generalised relationship between water system storage and flexibility is derived for the first time, which can enable an estimation of water system flexibility beyond the case-study region.

The remainder of this paper is structured as follows: Section 2 introduces the mathematical formulation of the simulation model. Section 3 describes the Thames basin in detail, as well as the setup for the scenario and sensitivity analyses. Section 4 presents the results, discussion, limitations and area for future work. Section 5 concludes the paper.

2. Mathematical framework

This section outlines the mathematical and software setup of the simulation model developed to study DSR potential in water networks.

2.1. Simulation model overview

Simulation models are commonly used in water resources engineering. A simulation model is a representation of a system that is used to predict the behaviour of the system under a given set of conditions. It allows for exhaustive explorations of '*what-if*' scenarios [27]. A common approach to model water systems is to use linear programming (LP) [28]. For example, Meschede [20] developed a mixed-integer LP to simulate optimised dispatch from pumps in a water supply system on a remote island. Moreover, LP-based models have also been used in a number of previous works that have studied DSR in industrial water systems. As such, this study also uses LP, where the model can generally be described as:

minimise : Cost of pumped flow
subject to : (1) Conservation of mass flow
(2) Supply and demand constraints
(3) System operational rules

The proceeding subsections outline the mathematical setup of the simulation model. The objective function, decision variables, and constraints of the optimisation model are described.

2.2. General formulation

The water supply system is considered as a directed network $\mathcal{G} = (\mathcal{N}, \mathcal{A})$, where $\mathcal{N}$ and $\mathcal{A}$ denote a set of nodes ($n \in \mathcal{N}$) and arcs ($(i,j) \in \mathcal{A}$). Arcs in the network carry the flow of water q_{ij} between nodes i and j. Nodes represent supply nodes if the supply S is $S_{i,t} > 0$; a sink node if $S_{i,t} < 0$; and a junction node if $S_{i,t} = 0$. Junction nodes have neither supply nor demand and instead serve as either storage units or to join or split arcs. For example, reservoirs are classified as junction nodes, as are channels that merge flows of water.

2.2.1. Objective function

The objective of the LP optimisation routine is to minimise the total cost of electricity C across the simulation period such that:

$$\min \ C = \sum_{t=1}^{T} c_t P_t \tag{1}$$

where c_t represents the cost of electricity (£/kWh) at time $t \in T$ and P represents the energy requirements of the pump (kWh). The energy consumption P at node i is calculated as:

$$P_i = \frac{q_{ij,t} \rho g h_{ij}}{\eta} \quad \forall \ (i,j) \in \mathcal{A} \text{ and } t \in T \tag{2}$$

where q is the volumetric flowrate (m^3/s) from node i to j and is the decision variable within the optimisation programme. The terms ρ and g are constants representing the density of water (assumed as 1000 kg/m^3) and acceleration due to gravity (assumed as 9.81 m/s^2), respectively. Meanwhile, the term h_{ij} is the total head gain between i and j, where as η is the pumping efficiency (%) (Table 1).

2.2.2. Pumping constraints

A number of constraints are observed as with all optimisation models. Firstly, pumping stations in the network have capacity constraints in that their total outflow must be below a maximum value $\hat{q}$ and above a minimum value $\check{q}$. This is defined as Eq. (3):

$$\check{q}_{ij} \le q_{ij} \le \hat{q}_{ij} \quad \forall \ (i,j) \in \mathcal{A} \tag{3}$$

The number of pump switches per day were not constrained as no data were available on these at a system-scale. Modern pumping stations can handle numerous switches each day without significantly altering the maintenance costs [29], and so these costs were ignored here. However, excessive pump switching can have an adverse effect on the system as dynamic loads could cause fatigue or transient related failures [17]. Therefore, the number of pump switches are tracked and reported in the results.

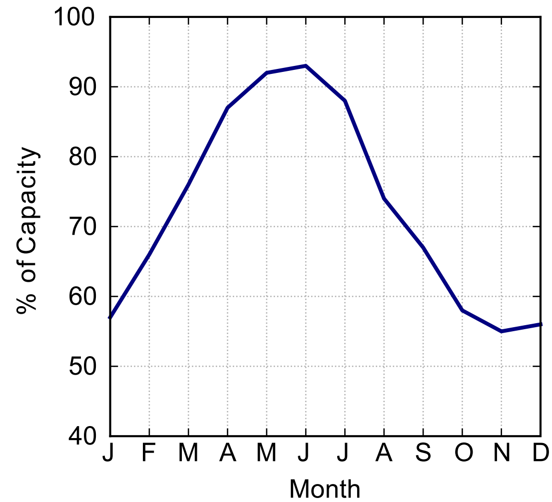

Fig. 2. Storage reservoir control curve in the River Thames basin [30].

2.2.3. Conservation constraints

Conservation of mass is observed throughout the network such that:

$$\sum_{j:ij\in\mathcal{A}} q_{ij,t} - \sum_{j:ij\in\mathcal{A}} q_{ji,t} = S_i \quad \forall \ i \in \mathcal{N} \text{ and } t \in T \tag{4}$$

The constraint shown by Eq. (4) ensures that supply and demand is met throughout the network at each time step. The mass balance constraint at storage reservoir nodes $n_{res} \in \mathcal{N}$ is defined as:

$$v_{i,t} = v_{i,t-1} + \sum_{j:ij\in\mathcal{A}} q_{ij,t} - \sum_{j:ij\in\mathcal{A}} q_{ji,t} \quad \forall \ i \in n_{res} \text{ and } t \in T \tag{5}$$

$$\check{v}_i \le v_{i,t} \le \hat{v}_i \quad \forall \ i \in n_{res} \text{ and } t \in T \tag{6}$$

where v refers to the storage reservoir volume (m^3) at a given time step, $\check{v}$ is the minimum reservoir level to be maintained, and $\hat{v}$ is the storage capacity. Storage losses as a result of evaporation and leakage were neglected.

2.2.4. Impounding reservoir control

Raw water storage reservoirs ($n_{rw} \in \mathcal{N}$) assume a seasonal control curve, such as that shown by Fig. 2. The curve defines the minimum storage levels to maintain in each month ($m \in \mathcal{M}$) through the year. This operational feature is constrained as:

$$v_{i,t} \ge f_m \hat{v}_i \quad \forall \ i \in n_{rw} \text{ and } m \in \mathcal{M} \tag{7}$$

where $f \in [0.0, 1.0]$ denotes a fractional component and $\hat{v}_i$ is the capacity of raw water storage node i. A unique f value is inferred for each month based on the seasonal control curve.

2.2.5. Service reservoir control

The control strategy of service reservoirs ($n_{sr} \in \mathcal{N}$) differs from that of raw water reservoirs. Service reservoirs are typically built to hold twice the average annual water demand [26]. A standard operational strategy is to recharge the reservoir to capacity once per day, normally overnight in preparation for the following day of service. This was the assumed operational strategy in the simulation model and constrained as:

$$v_{i,t} = k\hat{v}_i \quad \forall \ i \in n_{sr} \text{ and } t \in L \tag{8}$$

where $L \subset T$ and denotes the time steps in which service reservoir nodes are refilled. The variable $k \in [0.0, 1.0]$ is a fractional component representing the percentage of capacity to which the reservoir i is refilled to. The influence of parameter k on the system's flexibility potential is explored through scenario and sensitivity analysis (described in the proceeding sections).

2.3. Sensitivity analysis

A global sensitivity analysis was carried out to capture the uncertainty in the model output and characterise the key parameters in the optimisation. This technique was preferred over local methodologies for sensitivity analyses as it is more suited to complex systems such as water networks [31]. Moreover, it can facilitate the understanding of interactions between model parameters and their influence on the objective function.

The following parameters were evaluated: (i) reservoir operational capacity $\hat{v}$, (ii) pumping station capacity q_{ij}, (iii) fractional recharge parameter k, and (iv) recharge times $t \in L$. For each of these parameters, a set of values were generated within respective parameter bounds using the Morris sampling approach [32]. This allows for optimal distribution of parameter values between the bounds. The model was then iteratively ran for each of the parameter sets generated and the objective function was evaluated. Further details regarding this methodology can be found in Morris [32] and Herman et al. [33].

2.4. Software carpentry

The model developed here is formulated entirely in Python, an interpreted high-level programming language that emphasises code-readability and can support numerous important programming paradigms such as object-orientation, functionality, and procedural [34]. The LP optimisation model is formulated using the GurobiPy package for Python, which is a popular library used to formulate optimisation problems [35]. The optimisation problem is solved using the Gurobi solver [35]. The open-source SALib library was used for the global sensitivity analysis. All of the software used in this work, as well as the sub-dependent libraries, are free to download and use for academic purposes. The model developed and applied in this work is openly available [36].

3. Case-study: Thames basin, England

The model described in Section 2 was applied in a case-study from the River Thames basin, which is located in South East England and encompasses the region of Greater London. Fig. 3 shows a map of the River Thames basin, as well as a schematic of the local water supply network as modelled in this study. This section describes the water supply system in the Thames region and the model setup.

3.1. System description

The River Thames basin area covers around 16,200 km^2. Water is supplied from a combination of groundwater and surface waters, as well as from one desalination plant [30]. There are approximately 15 million customers supplied with water every day and the mean water usage is around 160 L/person/day [30]. Regional water supply infrastructure includes 32,000 km of water mains, 97 water treatment works, 26 raw water service reservoirs, 308 clean water pumping stations and 235 clean water service reservoirs, all of which can consume around 556 GWh per annum [10]. Moreover, pumping for water supply accounts for approximately 56% of total electricity usage in the water system.

The network model developed here is a highly simplified representation of the real system in the basin. The system is represented as a network comprised of 32 nodes and 40 arcs (Fig. 3). There are seven impounding storage reservoirs and six service reservoirs with a combined capacity of 216,650 ML and 10,000 ML, respectively. Raw water storage reservoirs observe the control curve shown by Fig. 2. The control curve was provided by the local water utility and is based on their internal analyses of water shortage risks [30]. At each time step in the simulation, the term f_m is inferred from the curve shown by the figure. For instance, an $f = 0.92$ is assumed for all time steps that fall within May. Meanwhile, a combination of service reservoir strategies are evaluated through scenario analysis, which reflect different operational risk appetites (discussed later in Section 3.4).

Table 1
Parameters and assumptions related to the case-study system.

Variable	Value	Units
Mean daily demand	3	GL
Raw water storage	216	GL
Service reservoir capacity	10	GL
Service reservoir recharge time	02:00	–
Pumping capacity	3800	ML/h
Assumed pumping efficiency	80	%

The operational rules and constraints within the system model were implemented with reference to the local water utility's water models and have previously been validated with good agreement [37]. The assumed parameters within the case-study system are shown by Table 1.

3.2. Electricity prices

A historical record of electricity spot prices was used following previous studies [12]. Price data was obtained from the N2EX market database, which comprises data related to the power exchange market in Great Britain and is managed by the Nord Pool group [38]. The price data is a time series Y_t of wholesale electricity prices (£/kWh) at an hourly resolution (Fig. 4a). Two peaks in the daily median prices were observed (Fig. 4b): (i) 0.13 p/kWh at 10:00 and (ii) 0.24 p/kWh at 20:00. Electricity prices exhibit seasonal variations, though random effects are much more pronounced as compared with water demand profiles [39].

Three price tariffs were tested in the case-study: (i) fixed-price, (ii) time-of-use, and (iii) real-time pricing. These tariffs are taken to be the market signal for demand-response. In other words, pump schedules are optimised on the basis of these price tariffs, where the price signal incentivises pump switching.

In the first case, a fixed-price electricity tariff was assumed, which is a common tariff structure for many water companies. The fixed-price tariff was calculated as the mean of the wholesale price record Y_t. Since this price signal does not exhibit any variation, this case represents a scenario without demand-response and is hence referred to as the baseline scenario (hereinafter BAS).

A time-of-use tariff splits the price curve into usually no more than four discrete intervals and is commonly used by water utilities [40]. Yet, TOU tariffs vary between customers and regions, and data on these can be difficult to obtain due to their commercial sensitivity. Therefore, following previous works [41], in this study the TOU curve was computed by averaging the wholesale price data Y_t based on four discrete time bins. The four bins z_b ($b \in \{1, \dots, 4\}$) are as follows: (1) an early morning off-peak at 01:00–06:00, (2) morning to late afternoon mid-peak at 07:00–17:00, (3) evening peak at 18:00–21:00, and (4) late evening off-peak at 22:00–00:00. Each element in the series Y_t was binned into z_i based on the hour of the observation. For example, all elements in Y_t that were observed at 18:00 were placed into z_3. The tariff for each of the four TOU periods was then calculated by averaging all elements within that bin, which produced four discrete prices for the TOU curve (e.g., Fig. 5b). This case is henceforth referred to as the TOU scenario.

The final price tariff assumed the real-time price of electricity as given by Y_t (Fig. 4a). This represents the most volatile pricing scenario for a water utility. It is noted that this does not represent the actual cost a utility may pay in such a case but this data is not published. This case is henceforth referred to as the RTP scenario.

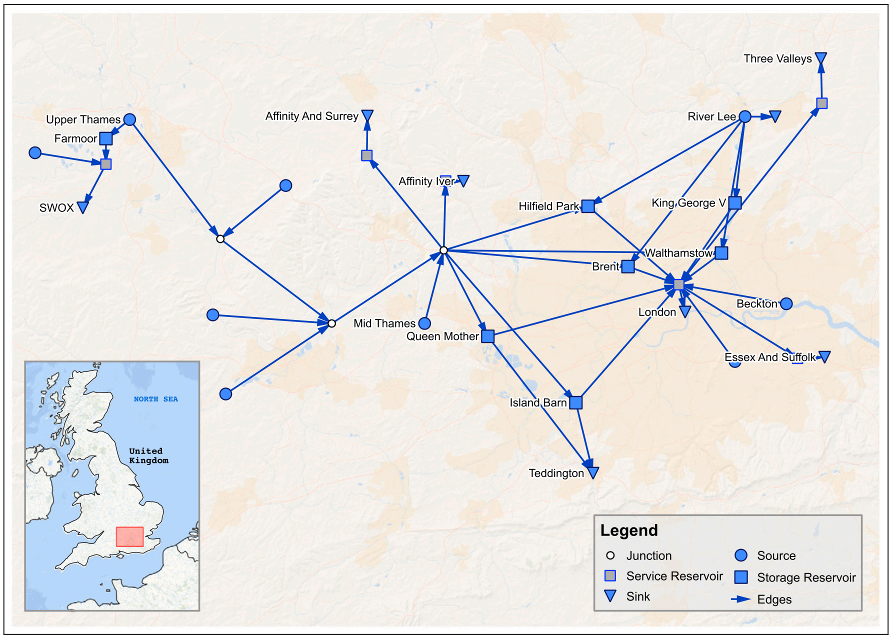

Fig. 3. Schematic of a simplified network model of the water supply system in the River Thames basin in South East England.

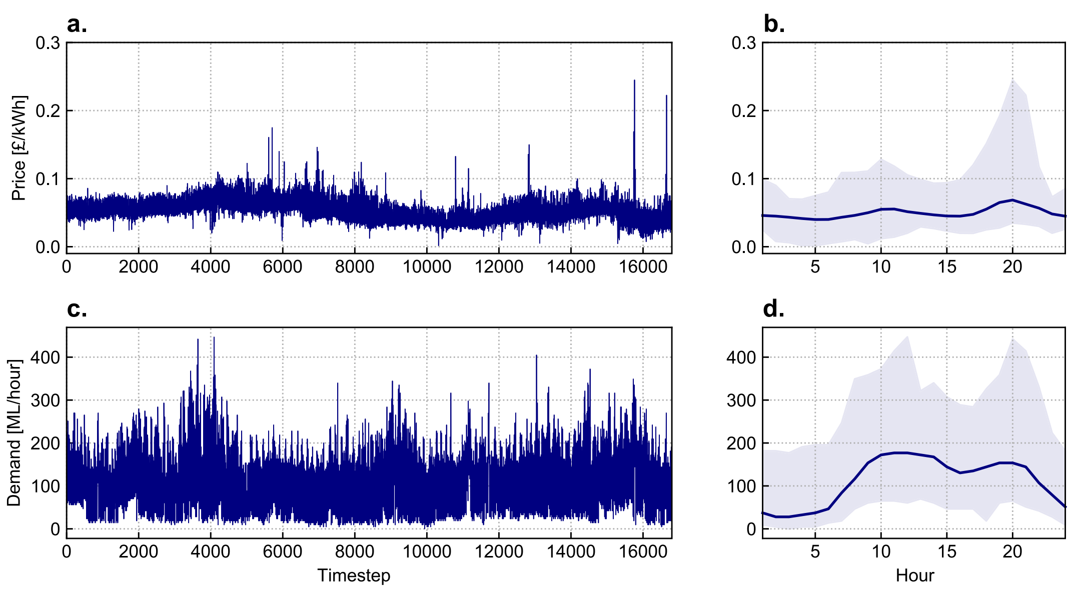

Fig. 4. Electricity price and water demand data. Panel plots (a) and (c) show time series of prices and demands, respectively. Panel plots (b) and (d) show hourly medians of the price and water demands, where the shaded area shows the minimum and maximum observation for each hour.

3.3. Water demands

An intra-annual demand curve was obtained from the regional water utility [30] and combined with patterns of hourly water demands from [26]. This process generated a two-year time series of hourly water demands (ML/hour) (Fig. 4c). The figure shows significant temporal variation over the two-year period. Hourly water demands can be as low as 3 ML/hour and upper values are observed in excess of 100 ML/hour during the summer months. At the daily scale, median water demands show two clear peaks between: (1) 08:00–14:00 and (2) 16:00–21:00 (Fig. 4d). It is noted that the water demand data shown here are only for municipal water demands as the majority of water use within the Thames basin is for public supply [30].

3.4. Scenarios tested

As described previously in Section 3.2, three scenarios of electricity price tariffs were assumed: (i) BAS, (ii) TOU, and (iii) RTP. In addition to these, two service reservoir control strategies were also incorporated into the scenario analysis. The first is a risk-averse (RA) strategy, where service reservoirs are charged to capacity once per day. The second control strategy does not impose such a condition on the system and is known as the risk-neutral (RN) state. The RA and RN operations reflect the two extremes of an operator's risk attitudes and as such allows for the bounds of flexibility from service reservoirs to be explored.

Therefore, a total of six scenarios were evaluated and these are outlined in Table 2. Scenarios in which a fixed-price electricity tariff was assumed (RA-BAS and RN-BAS) are non-optimised solutions and represent reference cases. Whereas under the TOU and RTP price

Table 2
Experimental setup for the scenario analysis. The Boolean operator indicates whether service reservoirs are constrained to be recharged at least once per day for a given scenario.

Scenario	Price tariff	Daily refill
RA-BAS	Fixed-price	True
RA-TOU	Time-of-use	True
RA-RTP	Real-time price	True
RN-BAS	Fixed-price	False
RN-TOU	Time-of-use	False
RN-RTP	Real-time price	False

schemes, pump schedules are optimised to minimise the total expenditure associated with pumping. The operational costs and load shifted under the TOU and RTP cases were then compared with the BAS scenarios. Further, the sensitivity of the derived results to key model parameters was also evaluated.

3.5. Computing flexibility

Flexibility is computed using the reference profile method following Meschede [20]. The flexible energy demand $\mathbf{F}$ (kWh) is calculated as the difference between the load curve of the non-optimised scenarios ($\mathbf{P}_{\mathrm{BAS}}$) and scenarios with demand-response ($\mathbf{P}_{\mathrm{DR}}$), where the area under the curve gives the flexible potential such that:

$$\mathbf{F} = \int_a^b (\mathbf{P}_{\mathrm{BAS}} - \mathbf{P}_{\mathrm{DR}})\, dt \tag{9}$$

In Eq. (9), $\mathbf{P}_{\mathrm{BAS}}$ represent the load profiles of scenarios with fixed-price tariffs (i.e. RA-BAS and RN-BAS), whereas $\mathbf{P}_{\mathrm{DR}}$ are the load curves of scenarios with dynamic prices. The integral is computed over the whole time series ($a = 1$ and $b = 17{,}520$) with respect to time.

3.6. Computational requirements

The water system simulation was computed over two-year period at an hourly time resolution, making a total of 17,520 time steps. The GurobiPy optimisation routine converged to a solution in approximately 10–15 seconds on a PC with a 2.9 GHz Dual-Core Intel i5 processor and 16GB of installed RAM.

4. Results and discussion

4.1. Optimal pumping schedules

Fig. 5 shows a two-day sample of the simulated hydraulic profiles from the RN-TOU and RN-RTP scenarios. The panel plots show the: (a) water demand curve, (b) RTP and TOU price profiles, (c) service reservoir volumes, and (d) pumping rate into the service reservoir under the two price profiles. The hydraulic curves under both price regimes are similar. The majority of pumping occurred in the early morning hours with a midday top-up ahead of the second peak in water demand. In both cases, pumps were most active in the periods with the cheapest tariffs. However, under RTP pricing, the hydraulic curve shifted to the right, and a greater frequency in pumping was also observed.

Results from the six scenarios are outlined in Table 3. The total load for pumping under the RN and RA control strategies was measured as 10.5 GWh/year and 10.7 GWh/year. These model estimates were benchmarked against previously reported data [10] and showed good agreement. The difference in the pumping load between the two operations is due to the increased daily pumping required (+2 ML/h) to recharge service reservoirs under the RA strategy. This is also highlighted by the average service reservoir volumes, which were observed to be higher under the RA strategy across all price structures.

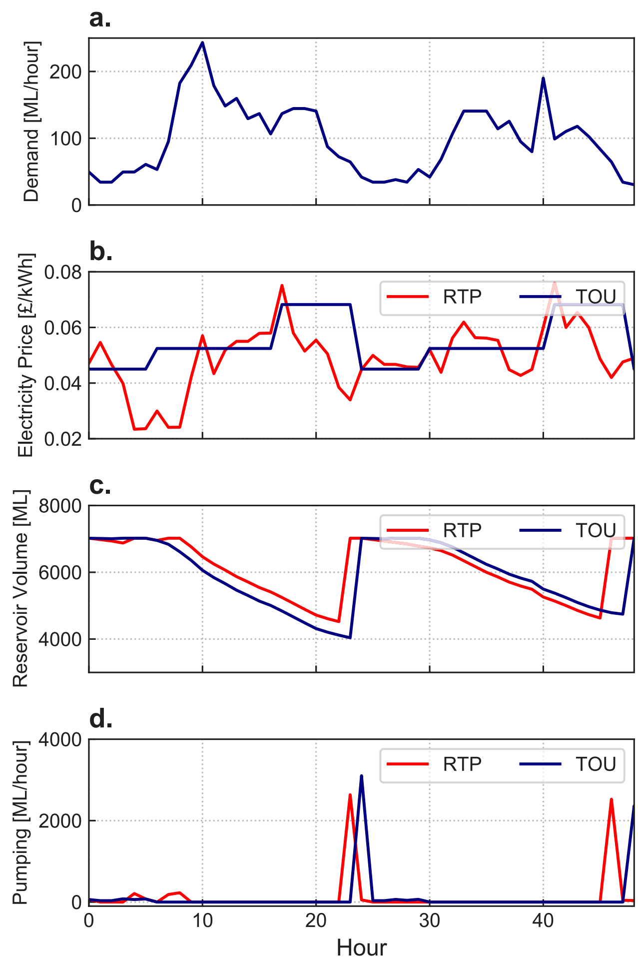

Fig. 5. A two-day sample of hydraulic behaviour in a system operating under the risk-neutral (RN) reservoir control strategy. The panel plots show the: (a) water demand, (b) RTP and TOU prices, (c) operational storage volume under the RTP and TOU prices, and (d) pumping rates under RTP and TOU prices. In plots b–d, RTP and TOU prices are shown in red and blue, respectively.

Across all scenarios, the mean flexible load was measured to be in the range of 0.3–2.1 GWh per annum. Further, the flexible load was substantially higher under RN operations when compared with the RA strategy. The model results showed between 10.5%–20.1% of the annual load was shifted under RN, while only 2.5%–5.6% could be shifted under RA. This is because RA operations require service reservoirs to be recharged at least once per day, which substantially hampers the system's flexible potential. The price structure was observed to impact the system's flexibility, where the network exhibited greater flexibility under RTP pricing in comparison to TOU. RTP tariffs show greater variations in prices, which increase the opportunity for pumps to capitalise on cheaper rates and hence increase the flexible load.

Overall, scenarios with demand-response showed substantial reductions in electricity costs. When compared with the BAS case, the four scenarios with demand-response exhibited operational cost reductions of 16.5%–33.2%, equivalent to around £2.8–5.6 million assuming the price profiles used in this study. Thus demonstrating that water sector DSR is not only beneficial to regional energy systems, but could also be profitable for water utilities.

The benefits from DSR observed here are higher than those reported in previous studies. For example, one previous study found DSR based on TOU pricing from a small water pumping scheme in South Africa lowered operating costs by around 5.8% [11]. Meanwhile, a study from

Table 3
Summary of results from the six scenarios.

Mean values	Units	Baseline (BAS)	Time-of-use (TOU)	Real-time pricing (RTP)
RA				
Load for pumping	GWh/year	10.7	10.7	10.7
Pumped flow	ML/hour	120.9	120.9	120.9
Service reservoir volume	ML/hour	6,913	5,941	6,291
Total pump switch-offs	ℕ	11,288	14,271	15,683
Flexible load	GWh/year	–	0.3 (2.5%)[b]	0.6 (5.9%)[b]
Total operational cost	£ million	17.0	14.2 (−16.5%)[a]	13.9 (−18.2%)[a]
RN				
Annual load for pumping	GWh	10.5	10.5	10.5
Pumped flow	ML/hour	120.7	120.7	120.7
Service reservoir volume	ML/hour	2,249	5,769	3,422
Total pump switch-offs	ℕ	9,315	14,393	17,977
Flexible load	GWh/year	–	1.1 (10.5%)[b]	2.1 (20.1%)[b]
Total operational cost	£ million	16.9	14.1 (−16.6%)[a]	11.3 (−33.2%)[a]

[a]Percentage change computed relative to BAS value.
[b]Percentage calculated relative to the annual load for pumping.

Ireland showed RTP pricing could lower costs by up to 13% [12]. There are several explanations for the differences in reported data. Firstly, water systems differ significantly between regions in terms of their service demands, operational configurations, engineering design and climate, among other factors [15]. Such regional variability would clearly impact the flexible potential of water system. This highlights the need to conduct region-specific analyses when designing a energy management programme for a water system in order to maximise the efficiency of the scheme [42,43]. A second reason for the differences between reported data in the literature relates to the modelling scale and assumption. Most previous studies have used short temporal horizons (*e.g.* hours to days) and assumed water demands to remain fixed. Such model simplifications neglect important features of a water system such as seasonal variability, which significantly impact model estimates of flexibility (discussed in the proceeding sections).

4.2. Temporal analysis of flexibility

The quantity of load shifted under the four scenarios with demand-response was analysed temporally. Fig. 6 shows the median load shifted by month under the (a) RA and (b) RN control strategies. The shaded regions show the 75% confidence interval. The figure shows again that the energy shifted under RN exceeds that in the RA case, with median observations ranging between 4–21 MWh/month and 0.3–6.8 MWh/month, respectively. Further, a greater load was shifted under the RTP price regime when compared with TOU.

The temporal analysis reveals that the load shifted varied seasonally. Across all scenarios, the shifted load was at its lowest during the autumn months of September–November and peaked around spring. Whilst it had previously been hypothesised that water system DSR would peak during months with the lowest water demands [13], this current study found the opposite to be true. Water demands were found to correlate with: (1) total load shifted and (2) frequency of demand-response events (not shown). This is because lower water demands reduces the pumping in the network and hence its energy load profile, which lowers the flexible potential.

All four scenarios with demand-response showed significant variations in the energy load shifted. This finding has practical implications. Variability in the water system's load shifting capability will result in uncertainty in the financial returns from demand-response. This uncertainty is further compounded by the fact that profits from DSR are inherently tied to local energy markets, which are continuously changing in the modern decarbonisation era. For example, recent changes in the UK frequency response scheme lowered the overall profits from DSR for clients in the water industry [44]. These factors could be concerning for decision-making investors in the water sector, who may instead opt for investments that could guarantee a more stable payback. For instance, water managers may prefer to invest in upgrading older assets with more energy efficient technologies. Many water networks were constructed decades ago, so repairing and renewing equipment such as pumps and pipelines can substantially reduce energy bills [10,45]. Other options include installing stand-alone wind or solar energy generation to power water pumping systems. This is advantageous as it can partially decouple a water utility from the energy grid and hence reduce their vulnerability to price shocks [46]. Overall, for DSR to be an economically attractive proposition to water managers, it will be important to understand the variability in its financial returns.

Table 4
Parameters studied in the sensitivity analysis and their ranges.

Parameter	Ranges
Reservoir operational capacity	[−50%, + 50%]
Pump capacity	[−50%, + 50%]
Reservoir recharge quantity	[0%, 100%]
Reservoir recharge time	[00:00, 23:00]

4.3. Global sensitivity analysis

A global sensitivity analysis was carried out to capture the uncertainty in the model output and to characterise the key parameters in the optimisation model. The influence of the following parameters was tested: (i) reservoir operational capacity, (ii) pumping capacity, (iii) proportion of service reservoirs recharged daily, and (iv) the time at which reservoirs must be recharged. An overview of each of these parameters and their ranges are presented in Table 4. Note that the sensitivity analysis sought to understand the influence of variables on theid] total load that could be *shifted* rather than the absolute load itself. Hence, operational assumptions such as pumping efficiency were not tested as these impact the total system load rather than flexibility.

The distribution of estimated load shifted (GWh/year) under the RTP and TOU price regimes is shown by Fig. 7a. This distribution was generated by running the model assuming the sets of parameters generated by the Morris sampling. In the box plot, the bar shows the median value, while the box shows the interquartile range (25th and 75th percentiles). The whiskers extend to the minimum and maximum values in the data sample. Extreme values (beyond the 95th percentile) were removed and are hence not shown. The annual flexible load was observed between 0.1–2.4 GWh and 0.08–1.52 GWh in the RTP and TOU scenarios, respectively. Meanwhile, median values were observed at 1.0 GWh and 0.6 GWh for the two price profiles, respectively.

The relative influence (%) on the load shifted from each of the four parameters is shown by Fig. 7b. It shows that the reservoir capacity (42%) and the daily refill rate (40%) are the two most influential variables that affect system flexibility. There is also a strong interaction between these two parameters. In comparison, the influence of the

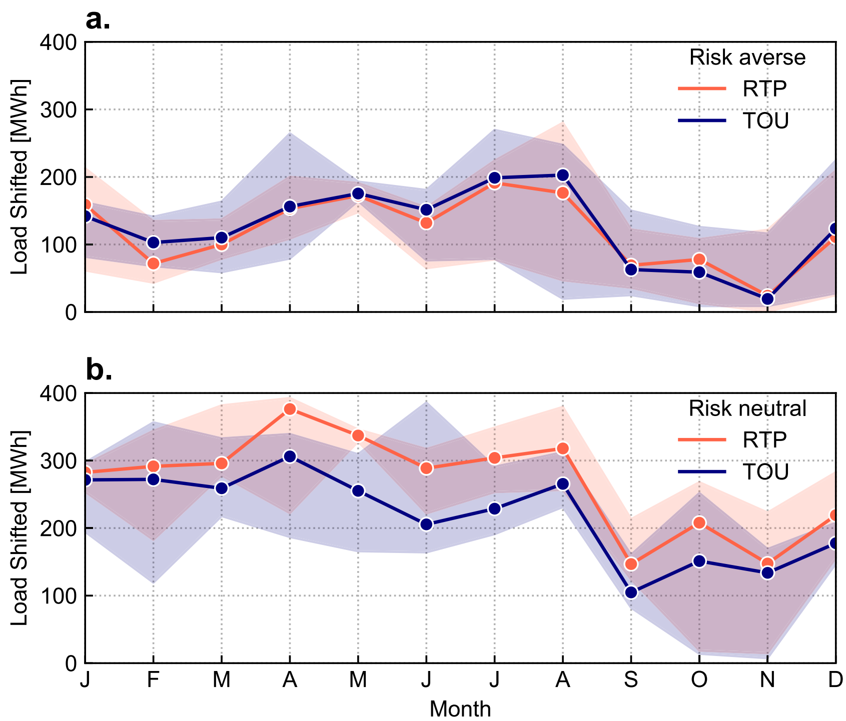

Fig. 6. Median load shifted per month under each scenario. Shaded regions represent the 75% confidence interval.

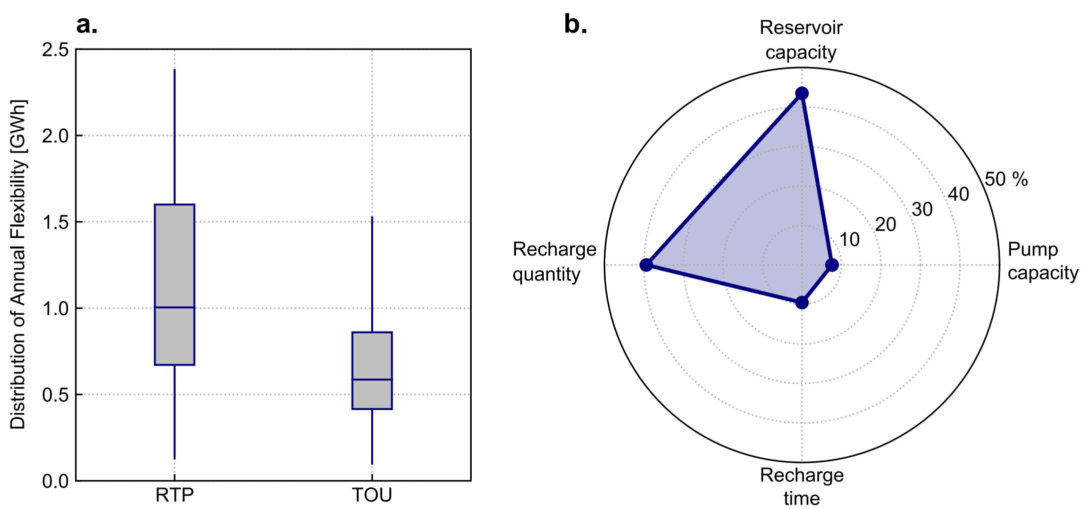

Fig. 7. Results from the global sensitivity analysis showing (a) the distribution of annual flexibility (GWh/year) under the time-of-use and real-time price tariffs relative to the baseline scenario and (b) the relative influence (%) on the flexibility from the four parameters listed.

service reservoir refill time (10%) and the pump capacity (8%) was relatively lower. These parameters influence the system flexibility as follows:

- **Reservoir capacity:** The reservoir capacity significantly affects the system flexibility as it relates to the network's capability to delay pumping, whilst observing reservoir control curves. Hence, increasing the storage yields a greater demand-response potential, where the flexible potential would plateau at the point where total pumping capacity becomes a limiting factor.
- **Recharge quantity:** The daily refill rate of reservoirs strongly impacts the total system flexibility. Increasing the recharge rate negatively influences the flexible portion of the energy demand.
- **Recharge time:** The time by which the daily recharge must be completed has a relatively minor affect on the total flexibility. This factor negatively influences the flexible potential if the recharge times are constrained to peak-price periods.
- **Pumping capacity:** Increasing the pump capacity facilitates the system in deferring a larger amount of pumping to a period with cheaper tariffs. However, the reservoir capacity, operational rules, and water demands constrain the overall flexibility pumps can provide. Hence, this factor had the lowest influence to the model output.

Overall the results from the sensitivity analysis demonstrate that the quantity of water storage in the system, as well as their control configurations, are the two most important factors in dictating the flexible potential of a pumped water network. The results also highlight a key trade-off between risk and reward. Allowing reservoirs to run at lower levels increases the flexible potential of the system. Yet, it raises the risk of being unable to meet unexpected demands.

In practice, reservoirs typically observe strict control protocols set by operators. Implementing DSR into water systems will require substantial changes to these protocols. Furthermore, assets and software will need to be upgraded in order to optimise DSR strategies. Such measures could ensure robust control strategies that can navigate the trade-offs between the profits from DSR and operational risk. Yet, it is also important to recognise that implementing these changes will challenge legacy operational practices and cultures. This could pose a significant practical barrier to wider adoption.

4.4. Relating water storage and flexibility

As observed in the sensitivity analysis, water storage capacity and operational risk thresholds were found to be key determinants of the flexible potential in an urban water system. Hence, the relationship between water storage, operational risk, and energy flexibility could serve as a meaningful indicator in gauging the flexible potential of other water systems.. Fig. 8 shows the following plots for this purpose: (a) a cumulative distribution function (CDF) of a flexibility index $\mathbf{F}^*$; and (b) a linear regression between median monthly capacity and load shifted. In Fig. 8a, $\mathbf{F}^*$ was taken as the ratio between the shifted energy consumption $\mathbf{F}$ (kWh/month) and the total system water storage V (ML), such that:

$$\mathbf{F}^* \text{ (Flexibility Index)} = \frac{\mathbf{F}}{V} \tag{10}$$

In both plots, the functions are computed by averaging the results across all price structures for RA and RN operations. As such, the RA and RN series shown represent a lower and upper bound of the expected load shifting under two extreme operational strategies. For example, in Fig. 8a, it can be observed that an $\mathbf{F}^*$ value of 0.9 and 2.3 was computed for 60% (P[x] = 0.6) of the data points in the RA and RN case, respectively. Assuming a storage capacity of 100 GL, this would correspond to an average load shifting between 0.09–0.21 GWh/month. The regression models shown by Fig. 8b show a similar estimate.

The derived relationship could be used to estimate the flexibility in the water sector at a system scale. Increasing the adoption of water sector DSR could have significant benefits for the energy and water sectors. In an energy system with an increasing share of renewables, the amount of flexibility and storage available to grid operators will be vital for ensuring reliable operations. Whilst significant innovations have been made in battery storage technologies, pumped water storage remains the most reliable and widespread form of energy storage and provides around 95% of the total global capacity [47]. However, the potential for pumped hydro storage is limited in many regions of the world, particularly large metropolitan regions such as that in the case-study. Yet, reservoirs in water supply may be an untapped source of flexibility and storage. In the context of the case-study area, the UK water sector currently has around 7390 GL of storage capacity [48], which is likely to be augmented in the future to cope with increasing water stresses. Based on the relationships derived here (Fig. 8), this could theoretically provide a load shifting potential of 159–443 GWh per annum. Whilst this value is a nominal quantity of the national energy demand (0.04–0.12%), it could still nonetheless present an opportunity to realise mutual benefits for water utilities (lower operational costs) and electricity operators (system flexibility).

4.5. Future extensions

As with all studies that simulate complex systems, there were a number of assumptions and simplifications made in this work to constrain the scope of the study. There are several opportunities to extend this study for future research.

This current study explored priced-based demand-response in a multi-reservoir water supply system, which is just one avenue for DSR

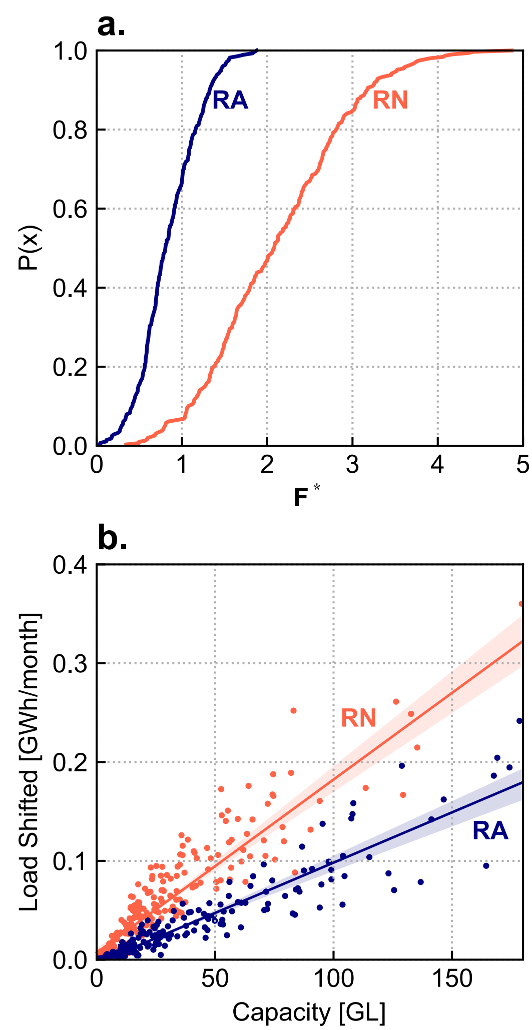

Fig. 8. Relationship between reservoir capacity and load shifted. Panel (a) shows the cumulative distribution function (CDF) of $\mathbf{F}^* = \mathbf{F}/V$. Panel (b) shows a linear regression between the two parameters under the RN and RA scenarios.

in the water sector. As highlighted by Zohrabian et al. [49], there are several mechanisms by which the water sector can provide DSR. Considerable amount of pumping also occurs downstream in the water supply chain for post-use wastewater distribution, though relatively less storage is available to these systems. There is also potential for scheduling water and wastewater treatment processes at the plant level, which was also not considered here. Further, the amount of electricity used for water-related services at the consumer level are substantial [50]. For example, Escriva-Bou et al. [51] showed that end-use of water accounted for 95% of water-related energy consumption in a Californian district. There are degrees of flexibility in how this electricity is consumed and future works could explore the potential benefits of shifting the time of water demands.

A number of assumptions were made in this work in order to keep the model setup tractable at a system scale. For example, it was assumed that all pumps in the system use variable speed drives as specific asset-level data were not available. This is not an accurate reflection of the entire water supply network in the River Thames basin. Future studies could zoom into specific areas of the Thames system and incorporate more refined asset information, as well as conduct a more detailed hydraulic analysis [25], in order to get an improved estimate for DSR potential and risks.

A distinction made in this study was between RTP and TOU price profiles in that the latter have significantly less daily variation. It is generally the case that TOU price curves exhibit no more than four changes per day [12]. Yet, in principle, these tariffs could be made significantly more complex, and as such could better incentivise the consumer to shift their energy demand, though this remains uncommon for the moment. The fundamental difference between RTP and TOU tariffs relates to the risk. Since TOU tariffs are pre-agreed contracts, the risk stays with the energy supplier. On the other hand, under an RTP tariff, the risk shifts to the consumer as their tariff is subject to the day-to-day conditions in energy markets, which could leave them vulnerable to price shocks. Given that this study considered only two forms of price regimes, future works can explore the potential for water-related DSR under uncertainties in the energy markets.

The influence of climate variability was not incorporated into this work. It is widely understood that the global water sector is highly vulnerable to climate change with extreme weather events such as droughts becoming more frequent [52]. Managing climatic risks requires careful planning of reservoir operations and management [53]. Further work could explore the trade-offs between water system flexibility and reservoir resilience under varying climate scenarios. For example, Anghileri et al. [54] developed a framework to devise robust hydropower operational strategies under uncertainties in future climate change and energy policies. Applying such a framework to design DSR strategies for water systems could facilitate water managers to balance climate and market risks with the rewards from DSR.

5. Conclusions

This study investigated the flexible potential of an urban water system located in a large metropolitan area through demand-response based on price signals. It incorporated detailed dynamics in water demand and energy markets, as well as realistic operational parameters of a pumped water network. The main conclusions of this work are as follows:

- The regional water supply system can shift 2.5–20.1% of its annual energy demand (0.3–2.1 GWh). This could theoretically decrease electricity costs associated with pumping—often the largest operational expenditure for water companies—by around £2.8–5.6 million.
- Demand-side response (DSR) based on real-time pricing structures were found to be more profitable than time-of-use style tariffs, though the former entail substantially higher amount of risk.
- The benefits from DSR for a water utility can be significant but are highly variable across the year mainly due to intra-annual variability in water demands.
- Sensitivity analysis showed that the financial returns from DSR are highly dependant upon the storage capacity within the system, as well as the control configurations of reservoirs. It is essential to balance the trade-off between the profits from DSR and operational risk in order to devise robust DSR strategies in water systems.
- This study also derived for the first time a relationship between water system storage, operational risks, and flexible potential. This could facilitate the estimation of water sector DSR potential in other regions.

Overall, this study demonstrated that the water sector could play an important role in realising a more flexible electricity grid in the transition to a low-carbon energy sector. Yet, water managers may be reluctant to invest into DSR schemes given that financial returns are volatile . Moreover, DSR at a system scale would require major cultural shifts in operations practices, an obstacle that may be difficult to surpass with network operators. Certainly, if the underlying mechanisms of demand-response in the water sector are not properly understood, a significant potential to realise societal and economic benefit might go amiss.

CRediT authorship contribution statement

A. Majid: Conceptualised the methodology, conducted the analysis and wrote the manuscript. **J.E. van Zyl:** Helped devise the methodology and edited the manuscript. **J.W. Hall:** Helped devise the methodology and edited the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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