Final Report

Energy Flexibility for Water Corporations

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Acknowledgement of Country

The authors of this report would like to respectfully acknowledge the Traditional Owners of the ancestral lands throughout Australia and their connection to land, sea and community. We recognise their continuing connection to the land, waters and culture and pay our respects to them, their cultures and to their Elders past, present, and emerging.

What is RACE for 2030?

RACE for 2030 CRC is a 10-year co-operative research centre with AUD350 million of resources to fund research towards a reliable, affordable, and clean energy future. https://www.racefor2030.com.au

Executive Summary

The transition to renewable energy depends on high-energy users, who can significantly reduce carbon emissions and operational costs while enhancing grid stability. This research explores energy flexibility strategies—including load management and energy trading—to support the renewable transition and improve efficiency in the water sector.

Focusing on water corporations targeting net-zero emissions by 2030, the study examines demand-side management (DSM), frequency control ancillary services (FCAS), wholesale demand response (WDR), network support services, and peer-to-peer (P2P) energy trading. Australian water utilities, such as Coliban Water, have already invested in onsite renewables and emission reduction initiatives. However, further research is needed to develop scalable, financially viable load flexibility and energy trading strategies.

A case study on Coliban Water evaluates the economic, technical, and environmental feasibility of energy flexibility measures, revealing key insights:

- **Limited Benefits from Load Shifting**: Aerator flexibility is constrained by operational requirements.
- **Photovoltaics (PV) & Battery Energy Storage Systems (BESS) Drive Cost Reductions**: Large systems enhance self-consumption, lower energy costs, and improve energy security.
- **FCAS & Wholesale Demand Resources (WDR) Offer the Largest Savings**: These services generate revenue while stabilising the grid.
- **Spot Market Arbitrage Outperforms Retail Tariffs**: Purchasing energy at low prices and selling at peak times maximises savings.
- **Optimised Load Profiles via Flexibility & Trading**: Aligning demand with market prices reduces grid constraints.
- **Grid Impact Considerations**: DSM ensures stable power flows, while P2P trading introduces variability, requiring advanced control measures.
- **Smaller Water/Wastewater Utilities**: Rochester, Echuca, and Kyneton have limited wholesale access but can still achieve significant savings through PV self-consumption and FCAS aggregation.

The study assesses multiple demand response strategies and the co-optimisation of energy flexibility, ensuring operational constraints are met while maximising distributed energy resources (DER) hosting capacity. The findings help quantify potential cost savings, carbon reductions, and revenue opportunities for water corporations and surrounding energy users.

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1 Introduction

1.1 Background and motivations

The role of high-energy users is central to the renewable energy transition. These users have significant potential to reduce both carbon emissions and operational costs when transitioning to clean energy. Additionally, they can play a crucial role in addressing challenges and uncertainties associated with renewable integration, including potential adverse impacts on the electricity grid. A key avenue for maximising these benefits is the adoption of effective and practical load management strategies.

This research project aims to investigate load management and energy trading (energy flexibility) strategies that can support the renewable transition and enhance energy efficiency for high-energy users while also benefiting the electricity grid. These strategies, in turn, provide advantages for surrounding communities that share the electricity network. The proposed energy flexibility mechanisms include demand-side management through load shifting, Frequency Control Ancillary Services (FCAS) demand response, wholesale demand response, demand response for network support services, and peer-to-peer (P2P) renewable energy trading.

The research specifically focuses on water corporations, which are among the major energy consumers, with annual electricity demands exceeding 8,760 MWh. This high energy consumption results in substantial electricity costs (exceeding AUD 1 million per annum) and considerable carbon emissions (more than 7,000 kt CO_{2e} annually). In response to these challenges, state governments have established strategic targets for carbon emissions reduction. Water corporations across New South Wales (NSW) and Victoria, for instance, have committed to achieving net-zero carbon emissions by 2050 at the latest. Some organisations, such as Sydney Water and Coliban Water, have taken proactive steps by investing in renewable energy. Sydney Water, for example, currently generates 20% of its annual energy demand from renewable sources, while Coliban Water has committed to reducing its carbon emissions by 13% by 2025, equating to 4,300 tonnes of CO_2 reduction per year.

This project seeks to support water corporations in achieving their net-zero targets by exploring the potential of load management and energy trading strategies. The study will assess the energy and cost efficiency benefits of fixed-time and adaptive load-shifting approaches, along with the integration of onsite renewable generation and storage solutions (including self-owned, third-party agreements, and community energy models).

The analysis will focus on three primary load categories:

- Onsite loads of Coliban Water,

- Residential and commercial loads within the neighbouring electricity network,
- Local distributed energy resources (DERs) and battery storage systems.

A techno-economic analysis will be conducted to ensure network operational constraints are preserved while maximising DER hosting capacity. Co-optimisation will be performed across five load management strategies:

- Load shifting,
- FCAS demand response,
- Wholesale demand response,
- Demand response for network support services,
- Emergency demand response.

The outputs will identify and quantify revenue opportunities for Coliban Water and similar large regional commercial and industrial consumers while ensuring the network's operational limits are maintained and DER hosting capacity is optimised. These value streams hold significant potential for financial savings and carbon reduction by leveraging renewable energy sources and optimal load management strategies. Additionally, these strategies may benefit surrounding customers by lowering network costs and creating new energy business models that engage local communities.

1.2 Aim and objectives

Despite the promising opportunities, water corporations require a deeper understanding of energy flexibility strategies to mitigate risks. Key uncertainties that must be addressed include:

- Financial viability of proposed strategies,
- Carbon emissions reduction potential,
- Electricity offset options,
- Benefits to all customers, including prosumers,
- Potential impacts on the electricity grid.

This research aims to systematically evaluate these uncertainties by assessing various energy flexibility strategies both in isolation and in combination. The study aligns with RACE for 2030’s research theme BT1 (Digitalising industry) by identifying business opportunities for water corporations to increase renewable energy penetration while enhancing demand flexibility to maximise economic value and minimise network impact. The project will also contribute to RACE for 2030’s themes NT6 (Developing local grid solutions) and ET9 (Incorporating end users in whole-of-system design).

The objectives of this research project are as follows:

1. Assess the availability of load flexibility, renewable energy resources, and demand response programmes in water corporations to enhance the renewable transition and improve the

efficiency of water and wastewater treatment and distribution operations.

2. Develop modelling systems to simulate the electricity energy dynamics of water utilities and their energy exchanges with neighbouring communities, quantifying the economic, environmental, and technical impacts of demand response and energy trading.
3. Develop and validate renewable energy and load management (RE-LM) strategies that optimise operations under various infrastructure configurations, trading policies, and demand response programmes while adhering to operational constraints.
4. Evaluate the power system impacts of the RE-LM strategies.
5. Provide recommendations to water corporations and distribution network service providers (DNSPs) to support their renewable energy transition decision-making.

1.3 Expected contributions and impacts

The short-term impacts of this research will support high-energy users, particularly water corporations, in their decision-making by:

- Identifying practical load management approaches, such as fixed-time and adaptive load-shifting, to reduce electricity costs and improve energy efficiency,
- Identifying optimal renewable energy strategies, including trading through the National Electricity Market (NEM) and peer-to-peer trading, to support renewable energy transition targets,
- Informing strategic planning for load management and transitioning to renewable-powered business models,
- Optimising budgetary planning through feasibility studies aligned with organisational carbon reduction targets.

For DNSPs, the study will provide insights into the opportunities and challenges associated with adopting energy flexibility strategies, enabling them to adjust operational strategies to facilitate the renewable energy transition. In the long term, the findings will empower water corporations and high-energy users to implement optimal strategies with improved feasibility understanding. Moreover, DNSPs will be better equipped to plan their operational strategies to support renewable energy generation, retail, and trading effectively.

This research also aims to serve as a model for governments and regulatory authorities by demonstrating the benefits of energy transition within local communities. The study contributes to RACE for 2030's impact metrics by:

1. Reducing energy costs for Australian households,
2. Reducing energy costs for Australian businesses,
3. Lowering Australia's overall carbon emissions.

2 Literature review

In addressing the pressing challenges of climate change, Australia established strategic carbon emissions reduction targets, committing to reduce greenhouse gas emissions to 43% below 2005 levels by 2030 [DCCEEW 2022] and achieving net zero by 2050 [DISER 2021].

Within Australia, extensive decarbonisation efforts and relevant renewable policy have been made, leading to a significantly increased penetration of renewable energy sources in the energy mix. In the last five years, the maximum renewable penetration rate has doubled from 30.2% in 2018 to 64% in 2023 [AEMO 2023a]. Consequently, in a rich intermittent renewable generation power system, the generators are often remarkably comprised of renewable energy resources in some hours, while non-renewable generation is predominant when solar and wind power outputs are temporarily diminished. This phenomenon poses a challenge to the power system in a more frequent imbalance between supply and demand, but it also presents opportunities for large energy users to reduce carbon emissions and energy costs while contributing to grid stability.

Modern water utilities were mostly developed in the last century, when the energy supply was dominated by fossil fuels and carbon emissions were not as serious as today [Sowby 2023]. The priority for water utilities from the past was always delivering affordable and unintermittent water services to the populations, on the fundamentals of reliable and affordable electricity generated from fossil fuels. In dealing with the challenges raised by the increasing intermittent renewable generation, contemporary power systems are more dynamic and urge support from large energy users. As such, demand response (DR), as an effective method to maintain the balance between supply and demand for electricity, has been widely discussed and researched for decades. It can be defined as the changes in electricity consumption patterns by electricity end users in response to variations in electricity prices or to any other indications related to operational concerns of the power system [Albadi and El-Saadany 2008, Qdr 2006].

Water utilities have vast load flexibility to participate in DR programs by curtailing their large loads during fuel-based hours or shifting loads to renewable-rich hours when purchasing electricity to make the overall energy consumption cleaner while reducing electricity bills, as electricity prices in renewable-rich hours are often cheaper than fossil fuel-based energy-rich hours. Additional on-site generation and energy storage capacity, such as PV installation + battery or pumped hydroelectric storage, which serve as both renewable energy and flexibility options, is also a promising approach for water utilities to increase renewable penetration and energy flexibility. Moreover, utilising distributed energy resources (DERs) in local energy communities presents another option for water utilities to increase their energy flexibility. Residential customers typically engage with energy retailers in fixed or time-of-use pricing schemes, water while utilities have opportunities to participate in real-time price markets, such as the NEM spot market. Exposure to the spot market enables water utilities to incentivise DERs by trading cleaner energy, especially when spot prices exceed the DERs' existing electricity arrangements.

In the context of Australian power systems, there are various demand response programs for water utilities to participate in, such as load shifting in time-of-use contracts and spot markets, or incentive-based DR programs in NEM. Incorporating these programs with flexible load management, additional on-site generation, and neighbouring DERs, it difficult for water utilities to make the best decision(s) to achieve cost and carbon emission reduction without affecting water service delivery. Decision-making can become even more complex and difficult when participating in multiple DR programs at the same time. Therefore, a holistic decision-making tool is necessary for water utilities to optimise their operation in real-time, considering DR mechanisms and leveraging their load flexibility and renewable energy options.

2.1 Classification of demand response

Demand response program settings may vary in different areas worldwide. Based on voluntariness, demand response can be generally subdivided to price-based demand response (PBDR) and Incentive-based demand response programs (IBDR) [Albadi and El-Saadany 2008, Qdr 2006]. PBDR indicates energy users voluntarily choose to change their electricity load based on electricity price variations. IBDR is a series programs that incentivise and pay the end-users who offering demand response services during critical periods or events. IBDR programs are generally designed and issued by third parties such as policy makers, electricity grids operators, and electricity retailers. Load shifting and load shedding as commonly used DR strategies in demand-side management (Figure 1). Additionally, on-site generation with energy storage management can also offer DR services by altering the diurnal load profile of water utilities to cater the generation profile of on-site renewable energy [Zohrabian and Sanders 2021].

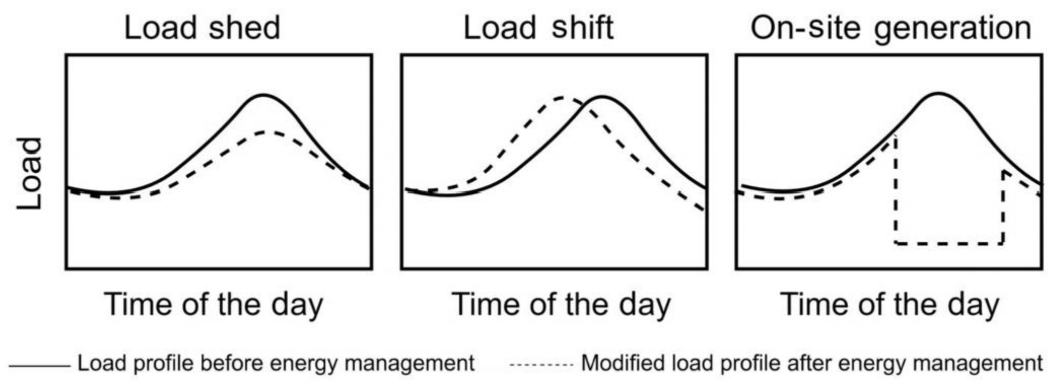

Figure 1 Demand response strategies [Zohrabian and Sanders 2021]

2.1.1 Price-based demand response strategies

The time-varying retail tariffs, namely price-based demand response, include real-time pricing (RTP), time-of-use (RTP) and critical peak pricing (CPP) rates. The key difference among them is degree of electricity price variability, with the order being RTP > CPP > TOU. In the context of Australia, energy retailers typically offer time-of-use or flat electricity price to customers while real-time pricing electricity scheme typically exits at wholesale market, where only large energy users can participate in. There is scarcely critical peak pricing option existing at Australian electricity markets or retailers offers.

2.1.1.1 Real-time-pricing

Real-time pricing (RTP) refers to a pricing scheme in which the cost of electricity fluctuates in at regular intervals aligning with the instant electricity supply and demand surplus in wholesale electricity markets [Qdr 2006]. The RTP demand response opportunities for water utilities in Australia mainly exists in the electricity wholesale spot markets. The Australia power systems along with electricity markets have three main parts: the NEM (for New South Wales, the Australian Capital Territory, Queensland, South Australia, Victoria and Tasmania), the WEM (for Western Australia), the NTESMO (for Northern Territory). They are operated as spot markets and update electricity price every 5 minutes in NEM, 30 minutes in WEM and NTESMO.

Generally, only large electricity users are eligible to register as a market customer, purchasing electricity in the Australia NEM based on spot electricity price. Hence, water utilities who wants to directly participate RTP electricity market, must register in the spot market local zone power system as market customers under relevant clauses of NER (National Electricity Rules) or NER-NT (National Electricity Rules – Northern Territory).

In a short term, exposure to high-resolution time-varying prices could incentivise energy customers to optimise their electricity consumptions with more economical efficiency [Schweppe, Caramanis 2013]. Higher-resolution time-varying prices can better reflect the real-time renewable electricity proportion in the energy supply [Zohrabian and Sanders 2021]. Thus, curtailing load on high price periods or shifting load to low price periods can not only facilitate water utilities to save cost on their energy bills but also make overall energy consumption cleaner. In longer term, the participation of RTP demand response also brings a number of benefits to the electricity market, such as mitigating the price manipulation from large electricity producers [O'Connell and Pinson 2014], reduction in average wholesale prices, and stability of peak prices [Qdr 2006].

2.1.1.2 Time-of-use

Time-of-use refers to a pricing scheme in which electricity rates vary during different blocks of time, such as peak, off-peak, and shoulder, usually in a 24-hour day basis [Qdr 2006]. It reflects the average cost of electricity during different periods of a day. In Australia, electricity retailers commonly offer TOU plans to customers. Some water utilities, especially those with restricted operational flexibility, may prefer to enter hedging contracts with retailers, opting for TOU or Flat rates to mitigate the risks of exposure to spot markets. The requirements for entering TOU contracts can vary, depending on the negotiation with different retailers. Similar to the RTP demand response, curtailing load on peak hours or shifting usage to off-peak hours could help water utilities reduce their electricity bills.

2.1.2 Incentive-based demand response

2.1.2.1 Wholesale Demand Response

Wholesale Demand Response (WDR) in the Australia NEM encourages large electricity customers to bid into the spot market with willingness to provide load reductions at what prices and amounts at each interval of the next day [AEMO 2020]. When the market price goes above the biding price, the Australian Energy Market Operator (AEMO), the operator of NEM, will send dispatch signal to participants on the biding volume. After events, participants will get paid based on the settlement by identifying the actual dispatch against a baseline load, calculated using a series of baseline models.

Only large electricity customers are eligible to participate in WDR directly. The threshold for being a large customer may vary across different states, depending on the annual electricity consumption. Besides, WDR services providers must also has at least one Wholesale Demand Response Unit (WDRU). A WDRU is an electricity import connection point with at least 1 MW (the dispatch resolution of electricity in NEM) flexible load that can response to load reduction targets within 5 minutes (the dispatch interval of NEM). The flexible load is also called the Maximum Responsive Component (MRC). Thus, large customer(s), with at least one classified WDRU and passing a series communication facility requirements and tests, can register as or aggregate to DRSP(s) (Demand Response Service Providers) to participate in WDR.

Table 1. Large energy customers threshold in different states

States	Minimum annual consumption (MWh)
Australian Central Territory	100
New South Wales	100
Queensland	100
South Australia	160
Tasmania	150
Victoria	160

Through WDR programs, participants will get paid by providing WDR service, where the payment amount is determined by reduction in consumption against a baseline and spot price during the event activation. It noted that baseline is determined by historical load with adjusted windows using a series of baseline models. From the power system point of view, WDR programs can enhance stability and transparency of the electricity market by encouraging large customers to bid their prices that they are willing to curtail load and thus mitigating the price surge caused by significant demand and supply imbalances.

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2.1.2.2 Ancillary services

Ancillary services can be defined as a set of products separated from energy production, which are related to security and reliability of a power system. There are various ancillary services in the power systems of Australia managing the gird security and reliability by maintaining the frequency and voltage, network loading, and system restart processes [AEMO 2023b].

FREQUENCY CONTROL ANCILLARY SERVICES (FCAS)

FCAS is a series of programs in NEM aiming to maintain the grid frequency around 50 Hz. It can be subdivided into regulation FCAS and contingency FCAS depending on the degree of the system frequency deviation caused by generation and demand imbalance [AEMO 2023b].

When the supply and demand are balanced, the system frequency remains constant at 50 Hz. If demand exceeds supply, the frequency will fall below 50 Hz, and vice versa. Regulation FCAS aims to mitigate subtle system frequency deviation, provided by generators on Automatic Generation Control (AGC) system. AEMO uses AGC to continually monitor the system frequency and transmit signals to generators to provide regulation that maintains the system frequency within the normal operating frequency band (NOFB) (for example, between 49.85Hz to 50.15Hz).

However, credible contingency event may occur caused by significant supply and demand imbalance, such as generator failures or transmission line faults, which may result in considerable system frequency variation. During these events, AEMO will activate/dispatch different types of contingency FCAS, distinguished by response time, to work together to recover the system frequency back to NOFB and facilitate regulation FCAS to maintain the frequency stability. At various phases, very fast (1 second), fast (5 seconds), slower (60 seconds) and delayed (5 minutes) contingency FCAS will be activated consecutively. As shown in Table 2, the Australian NEM has 10 FCAS programs accessible to the market, characterised by raise/lower and response time.

To participate in FCAS programs, energy customers/generators must register as or aggregate to DRSP(s). As a prerequisite, DRSP(s) must have at least one ancillary service load (ASL) that meets the requirements of proposed FCAS programs. Once registered, DRSP(s) are obligated to submit their bids a day ahead of time, containing their FCAS availability and the prices they are willing to accept for providing FCAS services during each time interval, along with other technical parameters. Based on a series of enabling optimisations from the standpoint of the power system, NEM dispatch engine determines and publishes the clearing prices for each FCAS market at each time interval. Notably, enabled contingency FCAS availability is only activated during credible contingency events. However, participants are still paid for the standby of enabled FCAS availability at each interval, irrespective of whether a contingency event occurs.

Table 2. FCAS market in NEM

Type	Market	Response time
Contingency	Very fast raise (Commenced on 9th of Oct 2023)	1 seconds
	Very fast lower (Commenced on 9th of Oct 2023)	1 seconds
	Fast raise	6 seconds
	Fast lower	6 seconds
	Slow raise	60 seconds
	Slow lower	60 seconds
	Delayed raise	5 minutes
	Delayed lower	5 minutes
Regulation	Regulating raise	-
	Regulating lower	-

Water utilities with adequate load flexibility have the potential to engage in contingency events. Regulation FCAS programs are typically favoured by traditional generators, due to their ease of scheduling, monitoring, and manipulation by AGC from the supply side. In contrast, raise contingency FCAS programs tend to be better suited for water utilities to take advantage of their huge potential for load reduction.

OTHER ANCILLARY SERVICES

In addition to FCAS, there are plenty of other ancillary services existing in NEM, WEM and NETSMO across different states, as displayed in Table 3. However, these ancillary services programs are not available to the market, and some of them focus on the supply side or network facility/component solutions. Energy customers like water utilities are unlikely to participate in these ancillary services.

Table 3. Other ancillary services

Power system	State coverage	Ancillary services	Sub-classification	Target
NEM	Australian Central Territory, New South Wales, Queensland, South Australia, Tasmania, Victoria	Network Support and Control Ancillary Services	Voltage Control Ancillary Service	Reactive power
			Network Loading Control Ancillary Service	Inter-connectors
			Transient and Oscillatory Stability Ancillary Service	Generator rotating mass
		System Restart Ancillary Services	-	Power system
WEM	Western Australia	Load Following Service	-	Ramping capability
		Spinning Reserve Service	-	
		Load Rejection Reserve Service	-	
		Dispatch Support Service	-	
		System Restart Service	-	
NETSMO	Northern territory	Voltage control services	-	Reactive power
		Frequency control services	-	Power System Controller
		Black start services	-	Power System Controller

2.1.2.3 Reliability and Emergency Reserve Trader (RERT)

The Reliability and Emergency Reserve Trader (RERT) is a series of program in NEM to maintain power system reliability by utilising load reduction or reserved generations [Panel 2020]. In Australian NEM, AEMO consistently forecasts and schedules both electricity generation and demand to ensure they remain balanced. However, certain extreme condition, such as natural disasters or severe hot weathers, can significantly disrupt the levels of electricity generators. Consequently, the cost of raise generation level dramatically increases, seriously jeopardising the system reliability. When the quantification of the system reliability is out of the reliability standard, the RERT programs will then be called to increase the system reliability.

Typically, RERT reserves can be unscheduled large or aggregated small loads reduction, or unscheduled generation (such as standby diesels and BESS) which means they are not scheduled in any other arrangement within NEM, such as WDR and FCAS. Even without any forecasted shortfall, AEMO always maintains a number of RERT panels who can provide RERT reserves under specific technical and legal requirements just in case for needs. When there were forecasted generation shortfalls, AEMO would inform RERT panels and negotiate reserve notice contracts. During the projected generation shortfall events, the RERT reserves will be activated to maintain the system reliability.

Distinguished by the reserve-notice length, RERT can be subdivided into Short Notice RERT, Medium Notice RERT, and Interim Reliability Reserve. The criteria of directly engage in RERT through NEM is often excessive for most of energy customers even for many large users, including most water utilities. For example, the requirement of 10 WM minimum reserve capacity is far beyond the flexible capacity of typical water utilities. Hence, it is more viable for water utilities to enter contracts with energy retailers who are qualified to aggregate smaller customers into RERT reserves.

As summarised in Table 4, the payment for RERT reserves mainly consists of three parts: availability (excluding Short Notice reserves), pre-activation, and activation, where availability and pre-activation payments are based the reserve capacity covering contracts and events respectively, while activation payment is based on reduced energy usage during each event.

Table 4. RERT payment scheme

RERT type	Reserve-notice length	Payment structure and price unit
Short Notice RERT	3 hours to 7 days	Pre-activation payment: $/ MW/ event + Activation payment: $/ MWh
Medium Notice RERT	7 days to 10 weeks	Availability payment: $/ MW/ year (reserve contract periods) + Pre-activation payment: $/ MW/ event +

		Activation payment: $/ MWh
Interim Reliability Reserve	Over 10 weeks	Availability payment: $/ MW/ year (reserve contract periods) + Pre-activation payment: $/ MW/ event + Activation payment: $/ MWh

2.2 Water utilities and load flexibility

Drinking water systems [Mkireb and Dembélé 2019], including water treatment plant, storage, connection facilities, and pumps stations, are designed to extract, treat, and distribute water from various sources to consumers on demand.

2.2.1 Load flexibility in drinking water system

Drinking water systems or water supply systems, generally starts from collecting raw water to be treated in water treatment plant or water desalination plants [Majid and van Zyl 2022]. The water production is then transported/pumped to the service reservoirs or tanks at higher elevation. Finally, water is distributed to customers on demand by using gravity. The elevated position of the reservoir ensures adequate hydraulic pressure for gravity-driven distribution. There are often impounding reservoirs or storage tanks in between of these utilities as buffers to bridge the temporal discrepancies between water supply and demand.

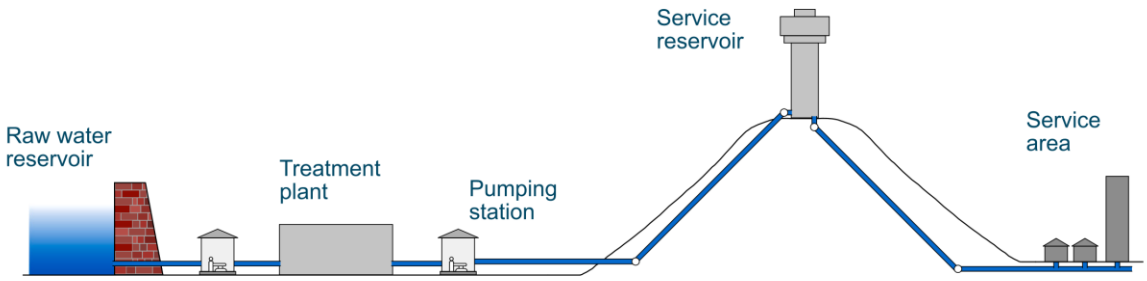

Figure 2 drink water supply system components [Majid, van Zyl 2022]

2.2.1.1 Water storage pumping

Water pumping operations can be identified as one of flexible operations in the drinking water systems. The flexibility of water pumping mainly inherits from the nature water storage capacity. Reservoirs are typically operated in a range between the minimum and maximum water storage levels [Mala-Jetmarova an Sultanova 2017]. As transporting water from service reservoirs to end users is fed by gravity, [Zohrabian and Plata 2021] drinking water systems only need to monitor the water level of service reservoirs within the operational range to sustain the system pressure. Thus, the water pumping is operated on-demand instead of continuously, so that the pumping loads can be broadly classified as interruptible loads [Kernan and Liu 2017]. In water pumping systems, variable speed drive (VSD) pumps are widely used. These pumps possess the capability to modulate their pumping speed from full capacity down to completely off. The adaptability not only allows for precise control over water flow but also increases the system's energy flexibility.

From the perspective of energy consumption, water pumping normally constitutes a significant proportion of energy consumption within water supply systems, especially when water needs to be transported over long distances or pumped against the force of gravity. In Australia, for example, [Kenway and Priestley 2009, Radcliffe and Page 2020] Adelaide has very high-water supply pumping energy consumptions during drought conditions due to the needs of pumping water from the Murray River over Adelaide Hills to fill metropolitan reservoirs. Similarly, water utilities in Sydney needed to pump water from the Shoalhaven River to urban area, during the millennium drought in 2000s. However, it is noted that not all the water supply systems' water pumping accounts for a large portion of their energy consumption. Comparing to other Australian capital cities, Melbourne [Kenway and Priestley 2009] has relatively low energy consumptions for water pumping because of the gravity-fed water supply systems sourced from mountain catchment storage. Thus, given these energy-intensive requirements and energy flexibility, water pumping in the systems with significant energy magnification have potential in participating in providing demand response services.

2.2.1.2 Excess capacity

Modifying operational load on water treatment plants and water desalination plants is another flexible operation in drinking water systems. Depending on the water source, water treatment plants often use a series of water treatment steps that may include operations of coagulation, flocculation, sedimentation, filtration, and disinfection to produce drinking water for consumers. With increasing concerns over freshwater scarcity and unpredictability, desalination has emerged as an important method for generating freshwater in coastal regions [Elimelech and Phillip 2011]. Water desalination plants remove salts and minerals from saline water by using a series of steps including pre-treatment, filtration, Reverse Osmosis (the most widely used technology for desalination), post-treatment, and brine disposal.

The flexibility of the modifying operational load stems from two primary factors:

1) the treatment/desalination capacity of water treatment/desalination plants is design based on the maximum daily water demand in the service areas [Hughes 1980].

2) Water treatment facilities are commonly equipped with central control systems, such as SCADA, to manage treatment processes and monitor water quality.

Thus, water treatment plants are frequently operated below the capacity in a year, which enables certain energy flexibility by optimising the facility operation [Liu and Mauter 2020], based on the electricity price variation or demand response signals without deteriorating water quality. Leading water treatment plants worldwide, including a few Australia water utilities, have also implemented advanced energy and water quality management systems (EWQMS) for daily optimisation and planning of the system considering energy and water priorities [Cherchi and Badruzzaman 2015]. EWQMSs can mitigate water quality concerns when facilitate operational flexibility in water treatment plants. However, they are still in the early phase of adoption and the integration with demand response services need further development [Zohrabian and Plata 2021].

2.2.1.3 Demand response research in water supply system

To facilitate the optimisation of the control strategies and energy management under demand response schemes, there have been research investigating decision support tools in water supply systems, aiming at enhancing the efficiency of water supply systems [Doorn 2021]. However, decision-making on operation and control strategies for water supply systems in very short notice or in near-real-time is typically difficult [Reis, Lopes 2023]. In Figure 3, [Reis and Lopes 2023] described that a decision-support tools typically rely on the information exchange between SCADA systems, which are the control and information systems widely used in water utilities. It integrates the functions of hydraulic modelling, water demand forecasting, and control strategy optimisation. The decision-support tools conventionally aim for water quality monitoring and network facility maintenance. In recent years, there's been a growing interest in leveraging the decision-support tool to address energy and cost optimisation, concerning DR in water supply systems [Doorn 2021].

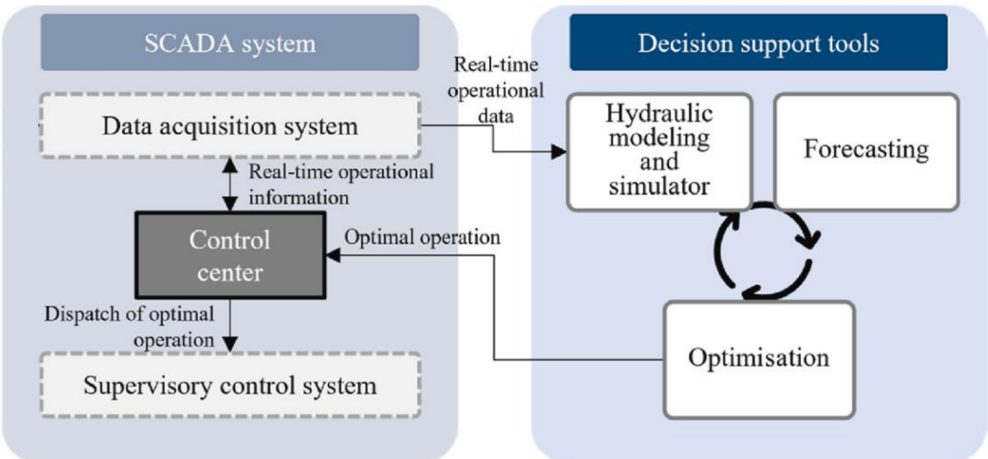

Figure 3 Decision supporting tool concepts [Reis, Lopes 2023]

Except decision support applications, there are also existing research targeting on pumping scheduling for the optimal energy cost under DR schemes are summarised in Table 5. DR participation in studies [Kernan andd Liu 2017, Luna and Ribau 2019, Abiodun and Ismail 2013, Cimorelli and D’Aniello 2020, Van Staden and Zhang 2011, Menke and Abraham 2016] primarily focused on Time-of-Use (TOU) and Real-Time Pricing (RTP) schemes. A few also considered the day-ahead wholesale market [Mkireb, Dembélé 2019], the ancillary service of frequency control (capacity reserve and rapid response) [Menke and Abraham 2016, Menke and Abraham 2017], and DR programs through aggregators [Tadokoro and Koibuchi 2020]. In the literature, the physical, hydraulic, operational, and DR mechanism constraints were considered. The optimisation algorithms typically consist of metaheuristic algorithms (evolutionary algorithms and PSO) and different solvers for MILP problems. The optimisation constraints often include physical, hydraulic, operational, and DR mechanism constraints. However, existing studies do not adequately address the real-time decision-making on control strategies considering energy management under DR programs. To address the research gap, this project will investigate potential solutions of developing a real-time or near-real-time decision-making tool to optimise operation scheduling in a more stochastic environment.

Table 5. Methods of existing research on pumping optimisation under DR

Characteristics	Method/content/objective
DR programs	-TOU [Van Staden and Zhang 2011] -RTP [Menke and Abraham 2016] -Day-ahead WDR [Mkireb and Dembélé 2019] -Ancillary services [Menke and Abraham 2016, Menke and Abraham 2017] -Third party DR [Tadokoro and Koibuchi 2020]
Optimisation algorithms	-Evolutionary Algorithms [Mkireb and Dembélé 2019, Barán and Von Lücken 2005, Coelho and Tavares 2012] -Genetic Algorithm [Luna and Ribau 2019, Cimorelli and D’Aniello 2020, Coelho and Tavares 2012, Wu and Simpson 2008, Kernan and Liu 2016, Alvisi and Franchini 2016] -PSO Algorithms [Tang and Zheng 2014] -MILP [Menke and Abraham 2016, Menke and Abraham 2017, Costa and de Athayde Prata 2016, Liu and Barrows 2020] -min-max optimisation [Takahashi and Koibuchi 2017]
Constraints	-Physical (e.g., water tank levels and flow rate), -Hydraulic (e.g., mass conservation, energy conservation, satisfy water demand) -Operational (e.g., pump switches) -DR mechanisms (e.g., load reduction MW, and load shift duration)

2.2.2 Load flexibility in wastewater treatment systems

After water consumption, the used water, characterised as wastewater, is channelled to wastewater treatment plants (WWTPs) through networks of sewer pipes. Wastewater treatment is an energy-intensive process that essentially accelerates the natural degradation process to efficiently remove contaminants from wastewater. The treatment process can be subdivided into four major steps: preliminary, primary, secondary, and tertiary treatment including disinfection [Thompson and Song 2008]. Specifically, preliminary treatment uses screening and grinders to remove large solid debris. Primary treatment employs sedimentation to eliminate suspended solids and organic matter.

Secondary treatment oxygenates the wastewater and accelerates microorganism growth to degrade organic matter. With primary and secondary treatment processes, there are often sludge treatment process by recycling activated sludge or generating biogas energy and beneficial fertiliser. Tertiary treatment, which is optional and varies depending on the industry, further purifies water by resolving nutrients, toxins, and remaining organic materials. Before discharging or reusing the treated water, the treatment process concludes with disinfection using chemical methods such as chlorination or physical methods such as ultraviolet (UV) light.

2.2.2.1 Aeration

In wastewater treatment facilities, the secondary treatment is often extremely energy intensive, mainly due to the high energy requirements of aeration units [Rosso and Larson 2008]. These units are responsible for supplying dissolved oxygen (DO) to facilitate the microbial breakdown of organic materials in the wastewater. [Kirchem and Lynch 2020] stated that aeration process is usually the most energy intensive load in WWTPs.

Based on existing case studies, the maximum switch-off time for aeration without significant effects to the effluent quality could range from 15 minutes to 120 minutes, based on site conditions. The case of [Schäfer and Hobus 2017] suggested the maximum switch-off duration for aeration is 60 minutes without significant effluent quality change, while the case of [Berger and Eisenhut 2013] confirmed that the maximum shut-down duration for aeration is within 15 minutes. [Müller and Möst 2018] reported the possible load shedding duration for aeration is 30 minutes during daytime and 2 hours at night. [Thompson and Song 2008] demonstrated the safe aerator switch-off could be 2 hours without significant drop in effluent quality. [Thompson and Song 2008] also experimented with the load shifting operation in the aeration process, namely over-oxygenation. The mechanism is to blow excessive oxygen into the wastewater ahead of the DR events. However, the load shifting operation may lead to an increase in effluent turbidity to some extent. In [Brdjanovic and Slamet 1998], the efficiency of the aerator may also be contaminated by excessive aeration, while limited dissolved oxygen may sustain the flexibility potential. In contrast, the water may only dissolve a small amount of oxygen which even makes adverse effects to the flexibility of load shifting [Tchobanoglus and Burton 2003]. [Kirchem and Lynch 2020] also reported that there were limited studies to support the feasibility of over-oxygen operations. Hence, the load shifting of aeration must be monitored and operated within a safe operational range to avoid effluent quality deterioration caused by prolonged detention time and aeration intensity decreasing [Giberti and Dereli 2019].

The flexibility of aeration load may also be influenced by seasonal rainfall level and temperature. As the energy consumption of aeration is closely related to the biological oxygen demand (BOD) and dissolved oxygen concentration [Aghajanzadeh and Wray 2015], hot seasons may incur more oxygen demand, leading to higher energy demand [Tchobanoglus and Burton 2003]. On the other hand, in dry seasons, the sewage intake volume is usually lower than in a rainy season, so that the aeration load in WWTPs can be lower in drier seasons [Lekov and Thompson 2009].

2.2.2.2 Wastewater storage and pumping

Another possible flexibility operation in wastewater treatment is from wastewater storage and pumping. Depending on the wastewater topography and the texture of the sewage, energy usage of wastewater pumping can significantly vary [Thompson and Song 2008]. For example, some wastewater transport and collection are gravity fed, while others use pumps to lift and transport wastewater, which consumes higher electricity energy. Some WWTPs may have extra capacity in wastewater tanks or sewers serving as a buffer between the influent pumping and treatment facilities, which allows them to temporarily retain untreated or partially treated wastewater. This enables the pumps to be flexibly operated based on the demand response signals. For example, [Thompson and Song 2008] reported that the equalisation basins may perform a similar role as wastewater storage, which may potentially be used for demand response. However, the study [Olsen and Goli 2012] argued that switch-off inlet pumps may decrease the safety margin because redundant sewer capacity was originally designed to mitigate the risks of weather, such as heavy rain, which may further stress heavily loaded sewers.

Except sewage intake pumping, [Schäfer and Hobus 2017] also demonstrated the possibility of load shedding on sludge recycle pumps, where the switch-off duration was up to 2 hours. The author also stated that small WWTPs usually have more redundancy of treatment than large WWTPs, as large sites are often designed based on the optimal treatment processes while some small WWTPs are under optimised due to insufficient monitoring facilities.

In other cases, multiple studies [Kirchem and Lynch 2020, Chang and Chang 2012, Zhang and Zeng 2012, Olszewski 2016, Torregrossa and Hansen 2017] investigated the optimal energy consumption for wastewater pumping in WWTPs using different optimisation methods, but the potential of demand response was not clearly addressed.

2.2.2.3 Demand response research in wastewater treatment

The industrial process models for DR evaluation typically take the energy prices, process inputs, or regulation standards as inputs to yield DR potential indicators, such as optimal control strategy, GHG, and energy consumption. In [Kirchem and Lynch 2020], the industrial modelling approaches integrating DR can be classified into model-based and data-driven models.

Table 6. Industrial process modelling approaches

Model-Based Approaches	Data-driven Approaches

Simulation - Simulation approaches are designed to represent fundamental physical processes and typically involve a set of controllers.

Optimisation - Optimisation models use mathematical models such as LP or MILP method to abstract physical details and relevant electricity demand to find the optimal process schedule.

Data-driven models - Data-driven models normally utilise regression models, such as machine learning algorithms, to infer relationships between input and output variables without explicit knowledge of the physical processes.

There are model-based and data-driven approaches have been utilised in relevant literature of wastewater treatment plants optimisation considering DR. Model-based simulation approaches were adopted in the case study of [Póvoa and Oehmen 2017, Emami and Sobhani 2018, Aymerich and Rieger 2015, Giberti and Dereli 2020], primarily including Activated Sludge Model 1 (ASM1) and Benchmark Simulation Model 1 (BSM1) models and sub-models. The ASM1 describes the biochemical processes in the secondary treatment by 8 processes and 13 state variables, while BSM1 model focuses on the full-scale wastewater treatment. The [Póvoa and Oehmen 2017] combined the ASM1 model and an energy consumption model to investigate the cost effectiveness of control strategies of aeration operations under RTP demand response scheme.[Emami and Sobhani 2018] developed a model based on Biokinetic model and aeration sub-model to examine the impacts of fluctuations in influent on energy cost of aeration processes and related GHG emission. However, the load-shifting under TOU was not considered due to the effluent quality incompatibility. [Aymerich and Rieger 2015] modelled a WWTP based on the ASM1 in BSM1 model that simulates the biokinetic processes of second treatment in aeration tank to investigate the effects of electricity price schemes to energy cost efficiency. The results suggested that flat energy rate may lead to biased operation strategy selection. [Giberti and Dereli 2020] employed a customised version of BSM1 model to investigate the impacts of load shedding on pollutant removal condition of aeration tanks.

In terms of the data-driven models in wastewater treatment, [Asadi and Verma 2017] trained an aeration model by comparing multiple supervised learning methods to established relationships between influent and effluent variables. The optimisation results by using the trained model can significantly reduce the dissolved oxygen concentration level, reflecting energy consumption, without contaminating the effluent quality. However, due to the limitation of the input data resolution, the model exhibited a certain degree of noise outputs.

In [Torregrossa and Leopold 2018], the energy cost modelling of the WWTP was also constructed by training a supervised learning regression model. The training dataset includes energy price, influent volume, effluent pollutant loads, and plant sizes as input attributes, and energy consumption cost as output. However, the research did not take different energy price scheme into account and the results suggested that the energy price has subtle impacts on the energy cost.

In comparison, the model-based methods may yield more accurate impacts of wastewater treatment operation rescheduling on effluent quality but may require more state-variable inputs and process details. The wastewater treatment processes are often simulated in commercial simulators with pre-defined WWTP paradigms. However, the model-based simulation requires high quality data including large array of input attributes related wastewater parameters and strict calibration between the model and WWPTs. In contrast, data-driven methods typically need fewer input features and can hide physical or biological details inside models. However, the accuracy of the data-driven model may largely depend on the size of the dataset.

2.2.3 Energy flexibility of on-site generation in water utilities

In water utilities, some treatment processes and facilities can produce electricity to directly offset the on-site electricity consumption. Normally, the direct utilisation of the on-site electricity generation is considered as an energy efficiency strategy. To provide demand response services, the intermittent renewable energy resource, such as wind and solar power, can also be integrated with energy storage systems to counteract the intermittency nature [Ayodele and Ogunjuyigbe 2015, Park and Schäfer 2013, Korpås and Greiner 2008]. Therefore, on-site generation resources can provide flexibility to water sites to enable demand response services if they are connected to energy storage, such as pumped hydroelectric storage (PHS) or battery devices [Zohrabian and Plata 2021]. However, despite the huge demand response potential in hydroelectric generation, there are also challenges in the implementation of energy storage systems. [Bloetscher and Sham 2014] conducted a survey on over 200 underground hydroelectricity storage and recovery sites, water utility operators raised concerns about the water recovery quality and efficiency as one of the potential operational challenges.

In wastewater treatment plants, anaerobic digesters are increasingly being considered for demand response services due to their capacity for energy generation. The byproduct of anaerobic digestion, namely biogas, can be burned and produce electricity using various power generation technologies. These include combined heat and power engines (CHPs), internal combustion engines, micro-turbines, gas combustion turbines, and even microbial fuel cells [Gude 2015]. In [Gude 2015, Shen and Linville 2015], the biogas generation from sludge process can potentially enable 50% to 100% self-sufficient WWTPs and even surplus energy production. [Seier and Schebek 2017] indicated that a German WWTP can potentially produce 120 MW of extra electric power from the anaerobic digestion production. However, this potential must be balanced against the initial investment and ongoing maintenance costs. According to [Schäfer and Hobus 2017], the switch off duration for digestion tank in four Europe WWTPs can range from 2 hours to over 4 hours. Thus, water utilities can take the advantage of the flexibility of digestion tank by shifting the sludge processing to the high electricity price hours to offset the electricity import from the grid. Additionally, wastewater treatment facilities can also generate hydroelectric power by installing small-scale hydro turbines on-site, enabling energy recovery [Bousquet and Samora 2017, Chae and Kang 2013, Corcoran and Coughlan 2013].

Beyond water sector-specific technologies, water utility sites can also integrate renewable energy systems like solar PV and wind turbines [Helal and Ghoneim 2013, Gu and Li 2017, Mo and Zhang 2013]. [Okampo and Nwulu 2021] reviewed the state-of-the-art desalination technology and integration with renewable energy sources, indicating that RES-RO (renewable energy source - reverse osmosis), such as PV-RO (photovoltaics - reverse osmosis), is the most studied application due to the wide acceptance of RO technology. When integrated with energy storage technologies, RES can significantly enhance the energy flexibility of the site so that the renewable generation can be stored for later use as a means of demand response.

3 Methodology

In this project, an extensive literature review was undertaken, revealing four key findings: (1) the prevailing demand-side management (DSM) technologies and initiatives in Australia and other global regions; (2) the existing opportunities for load shifting within water utilities; (3) current optimisation methodologies applied to DSM in the water sector; and (4) the advantages of employing a reinforcement learning (RL) framework to address complex optimisation problems with robust performance.

Building on these findings, this section details the methodology developed to model the renewable energy (RE) and load management (LM) system from two principal perspectives: (1) mechanisms for demand-side management and (2) corresponding interactions with load flexibility and renewable energy utilisation. These elements jointly represent the two dimensions of the proposed techno-economic assessment matrix, as depicted in Figure 4.

Figure 4 Techno-economic assessment matrix

Additionally, a simplified DO-BOD-Load model was integrated into the broader framework to accommodate the effects of load shifting on wastewater treatment quality. The primary aims of this model are twofold: first, to assess how different DSM strategies and potential distributed energy resource (DER) facilities can benefit water corporations, and second, to ensure minimal disturbances to the grid. In establishing the RE-LM model, certain trade-offs were made by excluding direct coupling of electrical and biological processes, thereby preventing excessive complexity and computational overhead. Instead, the electric load and battery simulations were conducted under idealised conditions, and a series of predefined functions was developed to capture the approximate relationships between biological treatment and electric loads.

3.1 Electric load model

Recent literature highlights that aeration in WWTPs can be flexibly managed for DR. This study explores on secondary treatment processes, classifying aerator loads as flexible and other loads as non-flexible.

A MATLAB handle class was developed to model load behaviour, featuring functions for setting load properties, interacting with other objects, assigning power sources (including renewables and VSP-based shedding), and calculating WDR baselines per AEMO standards. Each load is represented by a class instance within the RE–LM model to support dynamic energy management and DR optimisation.

3.2 Renewable energy sources model

WWTPs often utilise diverse renewable sources such as biogas co-generation, hydropower, and large-scale solar PV systems. This study introduces a Renewable Generation class to simulate renewable output and its interaction with electrical loads. Key functions include initialising generation parameters, managing object interfaces, and specifying energy use—whether offsetting loads, charging a BESS, or exporting to the grid. Unlike load objects, surplus energy is curtailed or dissipated, not automatically exported, to maintain grid stability.

3.3 Battery Energy Storage System model

The BESS enhances system flexibility, supports DR, and improves renewable energy utilisation. A battery class is developed to simulate key functions including safe charging/discharging based on SOC, efficiency, and system limits, as well as participation in FCAS markets. It interacts dynamically with the Electric Load and Renewable Generation classes, enabling coordinated demand-side management and real-time energy balancing.

3.4 Energy trading model

The water utility procures renewable energy from DERs using a double auction mechanism that ensures efficient and balanced energy trading. The utility sets a demand cap (Q), and DER bids are sorted by price to determine winning offers. The clearing price is based on the second-highest accepted bid plus the lower of the spot price or residential tariff.

Key principles include:

- **Trading cap**: Total accepted bids cannot exceed the utility's demand.

- **Individual rationality**: Prices must cover costs and align with tariff limits.
- **Non-cooperative game**: Bidders act independently without knowledge of others' strategies, preventing collusion.
- **Bounded rationality**: Bidders adjust their prices iteratively based on bid outcomes—lowering if rejected, raising if accepted—while responding to real-time spot price and utility pricing signals.

This framework promotes fair, dynamic, and adaptive energy trading between DERs and the water entity.

3.5 Demand side management and energy flexibility model

The **Demand-Side Management (DSM)** system functions as the central controller for real-time coordination of energy trading, load balancing, and cost optimisation. It integrates actions from DERs, batteries, and flexible/non-flexible loads, enabling dynamic power management across a water utility's operations.

Key Components:

- Traded Energy from DERs: Household DER bids are assessed using a double auction, with accepted energy dispatched to the utility.
- On-Site Generation: Includes PV, biogas, and hydro simulated via Renewable Generation objects.
- Flexible & Non-Flexible Loads: Modelled using Electric Load objects to reflect operational constraints and response capabilities.
- Battery Storage: Managed by the Battery class, enabling energy shifting and participation in ancillary services.

Demand Response (DR) Mechanisms:

The DSM model supports five DR strategies:

1. Load Shifting
   Shifts flexible loads from high- to low-price periods using batteries or direct generation. Dispatch modes include load shedding, battery use, and renewable load offsets.
2. FCAS (Frequency Control Ancillary Services)
   Enables grid frequency control via flexible loads (shed for raise) and batteries (bidirectional for raise and lower). Participation is based on market clearing prices and NEMDE dispatch signals.
3. WDR (Wholesale Demand Response)
   Water utilities submit bid prices and curtailment volumes to AEMO. If the spot price drops below the bid, committed load is reduced. A refined baseline using recent data improves

dispatch accuracy.

4. RERT (Reliability and Emergency Reserve Trader)

   A last-resort DR scheme for extended grid emergencies (4+ hours). Events are generated probabilistically, and load-shedding is triggered accordingly. Compensation includes pre-activation and activation payments.

Operational Modes:

Various DER combinations (e.g., Max Import, Max Export) allow the system to meet different objectives under changing price signals and constraints, with actions executed instantaneously or sequentially within five-minute intervals.

3.6 Wastewater treatment quality model

In wastewater treatment, monitoring effluent quality is complex due to the many interacting parameters (e.g., BOD, chemical oxygen demand (COD), mixed liquor suspended solids (MLSS)). Traditional metrics like total electric load fail to reflect treatment effectiveness, especially for BOD. To address this, a simplified water-quality model was developed to estimate chemical changes resulting from load shifting, under ideal conditions and without environmental factors like temperature or sludge activity.

The model links:

- Treatment productivity to DO (dissolved oxygen) levels,
- Treatment tasks to COD, and
- Electric load to aeration energy use.

It uses historical DO and load data to infer how load changes (e.g., turning aerators off/on) affect DO concentration. Site-specific parameters (e.g., tank size, aerator efficiency) help customise the model for different WWTPs.

BOD reduction is modelled based on DO efficiency and assumes plants are sized for peak demand. The model tracks how DO affects the BOD removal process across multiple aeration tanks, ultimately estimating final effluent quality. Although simplified, the model enables a practical evaluation of how DSM strategies influence water treatment performance.

3.7 Reinforcement learning model

This study employs a Reinforcement Learning (RL) framework to optimise load management in the Water-Energy system. The RL agent iteratively tests control actions and refines its strategy based on performance feedback.

The framework uses two neural networks:

- **Actor Network**: Proposes control actions (e.g., aeration levels, battery power, P2P trading).
- **Critic Network**: Evaluates these actions against system objectives.

With 12,000 and 6,000 nodes in the Actor and Critic networks, respectively, the model handles high system complexity and adapts to changing conditions, enabling robust and efficient real-time decision-making.

3.8 RE-LM-RL system

This study presents a Reinforcement Learning (RL)-based decision-making model to optimise control of an integrated water-energy system. The RL agent observes real-time system states—such as DO, BOD, and dynamic DR signals (e.g., energy prices)—and learns to maximise rewards reflecting cost savings and revenue, while respecting operational constraints like tank capacity and effluent standards.

The model combines:

- **Water-Energy Subsystem**: Simulates influent loads, energy-DO dynamics, DO-BOD treatment relationships, water levels, and effluent quality.
- **Load Management Subsystem**: Incorporates battery storage (with SOC tracking), DR opportunity analysis, and DER generation simulations to support energy optimisation.

Additionally, a game-theoretical energy trading mechanism enables peer-to-peer exchanges with local DER-equipped prosumers, further enhancing economic and operational efficiency.

Together, these modules create a robust, adaptive framework for holistic water-energy management under variable conditions.

3.9 Reinforcement learning training

The RL model initially faced performance issues due to the complexity of training across all scenarios, requiring over 100 million episodes and nearly two months of training. To manage this, the problem was divided into five demand response (DR) categories: ToU load shifting, Spot market shifting, FCAS, WDR, and RERT. Each category was trained separately to reduce complexity.

To accelerate training, five AWS EC2 instances (with Nvidia T4 GPUs) were used in parallel, running four sequential sessions per server. This reduced training time to about three days per instance. In total, 20 models were trained and then aggregated into a unified decision-making block.

This centralised block dynamically selects the appropriate RL model based on input configurations from the RE-LM system. It runs in Simulink, updating control policies for loads and DERs. The resulting operational profiles and import/export histories are stored for subsequent economic assessment.

Overall, the strategy of scenario splitting, cloud-based parallel training, and model aggregation significantly improved the framework's efficiency, adaptability, and real-world applicability.

4 Assessment

This section evaluates the financial impacts of implementing different load management strategies and demand response participation to align with the matrix mentioned in the methodology part. The assessment compares the BAU cost with reductions achieved through:

- Load shifting of aerators
- Spot market arbitrage using PV + BESS
- Load shifting + arbitrage
- Load shifting + arbitrage + P2P with DERs

Each scenario is further analysed under three ancillary service participation models:

- Frequency Control Ancillary Services (FCAS)
- Wholesale Demand Response (WDR)
- Reliability and Emergency Reserve Trader (RERT)

4.1 Case study Epsom

4.1.1 System Configuration

- PV Installation: 2 MW
- BESS: 1.5 MWh
- Aerator Load: 0.7 MW
- Total Load: 1.5 MW

4.1.2 Comparative Cost Analysis

BAU Cost

Based on the raw energy data input and retailer tariff from Epsom WWTP, full reliance on grid electricity.

Scenario 1: Load Shifting of Aerators

Adjusting aerator schedules to reduce costs by shifting operation to low-price periods.

Scenario 2: Arbitrage in Spot Market (PV + BESS)

Using PV + BESS to store cheap energy and discharge during peak prices.

Scenario 3: Load Shifting + Arbitrage

Combining aerator flexibility with market arbitrage for enhanced cost reductions.

Scenario 4: Load Shifting + Arbitrage + P2P with DERs

Integrating P2P trading to source cheaper local energy.

4.1.3 Key assumptions

The lifecycle cost calculation incorporates key economic parameters for the PV and BESS system. The following global parameters are defined to estimate capital expenditure (CAPEX), operational expenditure (OPEX), and system value over its lifespan:

- **Capital Costs:**
  - **PV Unit Cost:** AUD 500/kWh
  - **BESS Unit Cost:** AUD 620/kWh
  - **Installation Cost:** 20% of total equipment cost (PV + BESS)
  - **Electrical System Cost:** 5% of total equipment cost (wiring, inverter, switchbox, etc.)
- **System Performance and Lifespan:**
  - **Total Lifespan:** 30 years
  - **PV Degradation Rate:** 1% per year
  - **Maintenance Period:** Every 5 years
- **Operational and Maintenance Costs:**
  - **Maintenance Cost:** 5% of total capital cost (PV + BESS + electrical system)
  - **Salvage Value:** 10% of total capital cost recovered at the end of the system's lifespan
- **Economic Parameters:**
  - **Discount Rate:** 3.27% (inflation-adjusted)

These parameters will be used to perform Net Present Value (NPV) and Levelised Cost of Energy (LCOE) calculations, providing insights into system feasibility and long-term economic performance.

4.1.4 Tariff structure:

The energy cost assessment is based on detailed inputs provided by Coliban Water, encompassing, energy cost based on two rate Time-of-Use tariff, network charges, standing charges, environmental fees, and market-related fees. These parameters are essential for calculating the total operational cost and ensuring an accurate lifecycle cost analysis. The key components are outlined below:

Category	**Parameter**	**Notes**
Market Charges	Market Fee	*Fee for retailer participating in the wholesale electricity market.*
	Ancillary Services Market Fee	*Fee for* Ancillary Services
	Market Fee FRC	*Charge for Full Retail Contestability, enabling customer choice.*

Category	Parameter	Notes
Environmental Charges	Environment Fee SREC	*Cost for Small-scale Renewable Energy Certificates under RET.*
	Environment Fee LREC	*Cost for Large-scale Renewable Energy Certificates under RET.*
	Environment Fee VEEC	*Fee for Victorian Energy Efficiency Certificates under the VEU program.*
Network Charges	Peak Network Rate	*Charge for using the electricity distribution network during peak periods*
	Off Peak Network Rate	*Charge for using the electricity distribution network during off peak periods*
Daily Charges	Metering Fee	*Daily charge for metering services.*
	Standing Fee	*Daily fixed charge for service availability.*
Rolling Energy Rate	Rolling Rate per MWh	*Variable usage-based charge.*
Energy usage rate	Peak Energy	*Rate for energy consumption during peak periods.*
	Off Peak Energy	*Rate for energy consumption during off-peak periods.*
	Spot market	*Variable rate based on the Australian National Electricity Market (NEM).*

4.1.5 Economic Analysis for Epsom

Spot Market Exposure – Risks and Opportunities

Exposure to the wholesale market offers both potential savings and significant risks for large users like Epsom WWTP. Without load flexibility, direct spot market participation would increase energy bills by 40%. While load shifting through flexible assets reduces costs via arbitrage, the net result still falls short of retailer contract savings.

Impact of PV and Battery Integration

Installing a 2 MW PV system and 1.5 MWh BESS significantly improves cost efficiency, reducing energy bills by 30–43%. When combined with flexible load shifting and P2P energy trading with neighbouring DERs, total savings can reach up to 60%.

Lifecycle Performance

From a lifecycle perspective, combining load flexibility, PV, BESS, and trading under spot market and WDR participation enables full cost recovery in as early as 13 years, with projected NPV exceeding $8 million. The greatest benefits stem from FCAS and WDR participation. Given scalability limits in energy trading, the scale-up assessment focused on PV, BESS, and flexible loads within spot and FCAS/WDR frameworks.

Scale-Up Assessment

A larger 3 MW PV and 2.25 MWh battery system could reduce energy bills by 99%, with a shortened payback period of 11 years.

In contrast, smaller sites like Rochester, Echuca, and Kyneton have limited capacity for wholesale participation, reducing their ability to leverage arbitrage. Their cost savings rely primarily on maximising PV self-consumption and aggregating FCAS revenue. TOU arbitrage offers limited value due to minor peak/off-peak price differences (e.g., 40.9 vs 29.0 AUD/MWh, 64.8 vs 46.7 AUD/MWh).

Load Profile Optimisation

Prior to implementing flexibility, the load profile remained flat, with PV output overlapping with spot price peaks—diminishing economic returns. Introducing flexible aerator load shifting improved responsiveness to price signals. Further integration of PV, BESS, and energy trading reshaped the load profile, enabling peak-to-off-peak shifting, lowering peak demand, and reducing grid constraints—resulting in optimised cost savings and operational efficiency.

4.1.6 Technical Impact Analysis for Epsom

With the modified load profile at the Epsom site, the technical impact on the grid was assessed. The local distribution network simulation model, based on the PowerCor (DNSP) setup, serves multiple key purposes:

1. **Identifying Gaps in DSM, Energy Flexibility, and Grid Impacts:** The model helps identify the gaps between the water corporation's demand-side management (DSM) strategies, energy flexibility measures, and the resulting impacts on the grid. This enables better understanding of how current practices affect grid stability and efficiency.

2. **Case Study on Integrating Renewable Energy and DSM/DR Programs:** The model also facilitates a case study by integrating local renewable energy sources with energy flexibility and DSM/DR programs specifically for Coliban Water. The focus is on the Epsom water reclamation plant, aiming to optimise the simulation model by incorporating updated data and improving its accuracy for real-world application.

The model includes household loads that are specifically aligned with the Epsom area (postcode 3551). The network analysis will explore 13 different scenarios to assess the impact of various DSM strategies, the detailed scenario classification shown in Table 7

4.1.6.1 Grid impact analysis model

The simulation result analysis is addressed to identify the grid impacts of the water corporation's energy flexibility scheme and DSM/DR program under different scenarios and provide discussion and suggestions based on the simulation result. The simulated distribution network contains 500 householders functioning as prosumers, but there is no energy trading between them. The exclusive consumer in the network is the high-demand user (MV load - Coliban Water - Epsom site) situated at the 22 kV voltage level. The network configuration comprises two voltage levels as illustrated: the 22 kV level for the high-demand users and the external grid and the 415 V for households. Also, the 22 kV level that houses the main transmission line and 22 kV - 415 V transformers and the 415 V level that links the total 1,800+ householders via the low voltage power line and 22 kV - 415 V transformer. The 1,800+ householders are scattered across 120+ buses and near 1,600 terminals. Realistic data is incorporated to simulate all network parameters, spanning from transmission line length, which is calculated based on actual geographic location, to householders' past energy usage, which is used to estimate their energy consumption.

Table 7. Network Model - Scenario Classification

Scenarios	Typical LV Load	500 digital twined LV Load	500 P2P LV Load	Water Plant Load
1	Y			Base
2.1	Y	Y		FCAS 1
2.2	Y	Y		FCAS 2
2.3	Y	Y		FCAS 3
2.4	Y	Y		LS 1
2.5	Y	Y		LS 2
2.6	Y	Y		LS 3
2.7	Y	Y		WDR 1
2.8	Y	Y		WDR 2

2.9	Y	Y		WDR 3
3.1	Y		Y	FCAS 4
3.2	Y		Y	LS 4

4.1.6.2 Analysis from HV side

For the total infeed power across 13 scenarios. P2P participation scenarios (FCAS 4, LS 4, WDR 4) exhibit the largest fluctuations, with infeed power dropping to negative values and lower average levels. In contrast, non-P2P scenarios (FCAS 1–3, LS 1–3, WDR 1–3) maintain higher, more stable infeed power with narrower variation ranges. This underscores how energy trading introduces volatility and reduces average grid infeed compared to non-energy trading consumption patterns.

For the voltage profiles at the Water Plant connection bus. P2P-enabled scenarios (FCAS 4, LS 4, WDR 4) exhibit slightly higher variability, with voltages ranging from ~0.988 to ~1.001 p.u. (average ~0.995 p.u.). In contrast, non-P2P scenarios (FCAS 1–3, LS 1–3, WDR 1–3) demonstrate tighter voltage ranges (average ~0.993–0.994 p.u.) and lower fluctuations. Despite these differences, in this case study, all scenarios maintain voltages within standard limits (0.95–1.05 p.u.), indicating that P2P energy exchange introduces marginal variability while maintaining grid stability.

For the transformer loading at the Epsom site across scenarios. The base case shows stable operations with the highest average loading (~25%) and moderate variation (max ~35%, min ~2%). In contrast, P2P-enabled scenarios (FCAS 4, LS 4, WDR 4) exhibit lower averages (~14%) but extreme volatility (min <0.1%), reflecting instability from distributed energy injections. Non-P2P-enabled consumption scenarios (FCAS 1–3, LS 1–3, WDR 1–3) demonstrate balanced loading (~15–21%) with narrower fluctuations, suggesting DSM strategies could mitigate grid stress even with P2P integration.

4.1.6.3 Analysis from the LV side

For the transformer loading at LV side. The loading patterns of a 315 kVA transformer serving 121 LV loads, including 27 P2P participants. P2P scenarios (FCAS 4, LS 4, WDR 4) exhibit lower peak loading (~54%) but extreme minimums (~0.2%), reflecting volatility from dynamic energy injections. In contrast, non-P2P scenarios (FCAS 1–3, LS 1–3, WDR 1–3) maintain stable loads (peak ~63.6%, minimum ~12%), ensuring balanced utilisation. The base historical scenario shows moderate loading (peak ~40%, minimum ~11.5%). While P2P participation reduces peak stress, it introduces variability within operational limits.

The line loading of a critical LV line under different scenarios. In P2P-enabled cases (FCAS 4, LS 4, WDR 4), peak loading decreases to ~53%, while minimum loading approaches near-zero values (0.001–0.002%), reflecting volatility from intermittent energy injections. Non-P2P scenarios (FCAS 1–3, LS 1–3, WDR 1–3) maintain stable loads, with peak values at ~61.5% and minimums around 3.5%.

This demonstrates that P2P participation reduces peak line stress but introduces significant load variability, while conventional consumption patterns sustain steadier loading.

For the voltage profiles at a critical network bus located at the terminal of a heavily loaded feeder at LV side. In non-P2P scenarios (FCAS 1–3, LS 1–3, WDR 1–3), voltages remain stable within 0.9600–0.9944 p.u. In contrast, energy trading scenarios (FCAS 4, LS 4, WDR 4) exhibit elevated and more variable voltages, peaking at 1.0123 p.u. and reaching a minimum of 0.9665 p.u. Despite these differences, all voltages comply with regulatory limits (0.95–1.05 p.u.), demonstrating that energy trading will affect voltage fluctuations at critical nodes, but in this case study, it is still under regulation.

4.2 Case study: Kyneton, Rochester and Echuca

Comparing to Epsom site, Rochester, Echuca, and Kyneton sites have smaller capacities for wholesale market participation, which limits their ability to capitalise on the most lucrative load management strategy—arbitrage. Cost reductions in these sites primarily rely on maximising PV self-consumption and aggregating FCAS revenue with other users, as ToU arbitrage is less profitable due to small price differences between peak and off-peak usage and network rates (40.9 vs 29.0 AUD/MWh, 64.8 vs 46.7 AUD/MWh).

Simulations of various PV and battery system combinations indicate that larger systems can significantly reduce energy bills. Kyneton, Rochester, and Echuca could reduce up to 85%, 87%, and 92% of their energy bills, respectively. However, the economic viability of these systems remains unclear, as payback periods exceed 30 years. In contrast, smaller systems, such as a 200 kW PV and 140 kWh BESS for Kyneton or a 100 kW PV and 70 kWh BESS for Rochester and Echuca, provide a more viable investment, with payback periods within 20 years. Increasing the system size beyond these configurations would significantly lengthen the payback periods.

5 Conclusions

The integration of renewable energy systems, flexible load management, and demand response strategies has provided significant insights into the operational dynamics and economic viability of the Epsom water reclamation plant, as well as the broader local distribution network. Key findings from the simulation and grid impact analysis highlight the following:

- **Limited Benefits from Load Shifting of Flexible Loads (Aerators):** The cost savings from shifting aerator loads are relatively small due to the operational constraints imposed by the water-energy model. Aerators must adhere to strict schedules to maintain treatment efficiency, limiting their ability to shift loads to off-peak periods compared to more flexible industrial loads.
- **Significant Role of PV and BESS in Load Management:** The integration of large PV systems and battery energy storage systems proves to be a critical factor in reducing energy costs. By enabling higher levels of self-consumption and allowing energy storage for later use, these systems reduce reliance on the grid, thus enhancing energy security and achieving substantial cost reductions.
- **FCAS and WDR Provide the Most Significant Cost Reductions among DR Participation:** Among various DR strategies, participation in FCAS and WDR offers the most significant cost reductions. These services enable the water plant to generate revenue by contributing to grid stability, particularly when paired with flexible load management techniques.
- **Spot Market Arbitrage Yields Greater Benefits than Retail Tariffs:** Participation in the spot market allows for energy arbitrage, purchasing energy at lower prices during off-peak periods and selling at higher rates during peak periods. This strategy significantly reduces energy bills, especially when combined with flexible load management and renewable energy systems.
- **Increasing System Size Can Further Reduce Energy Bills and Shorten the Payback Period:** Scaling up the PV and BESS systems further reduces energy bills and shortens the payback period. Larger systems support higher self-consumption rates and quicker returns on investment, with potential bill reductions up to 99% for larger setups.
- **Optimising Load Profiles with Flexibility and Energy Trading:** The load profile at the Epsom site was modified using flexible load shifting and renewable energy trading, which significantly improved alignment with the spot market price. By shifting energy demand from peak to off-peak periods, the system optimised cost savings and reduced grid constraints, helping to maintain voltage stability and prevent system overloads.
- **Grid Impact Analysis from Epsom Insights:**
  - **DSM vs. P2P Trading Impact:** Load management strategies ensure higher and more stable infeed power, while P2P trading introduces greater variability, with fluctuations exceeding 5,000 kW, affecting grid stability.
  - **Transformer and Line Loading:** P2P scenarios reduce peak transformer loading (54.3–54.32%) but cause extreme fluctuations (min 0.015%), indicating underutilisation risks. DSM-based scenarios provide higher and more stable utilisation (15.07–20.89%), optimising network performance.
  - **Voltage Variability:** P2P energy trading increases voltage fluctuations (0.0122–0.0130 p.u.), compared to DSM scenarios (0.0083–0.0114 p.u.), requiring additional voltage regulation to maintain stability.
  - **Energy Flexibility Optimisation:** A balanced mix of DSM and P2P trading is needed to maximise economic benefits while avoiding grid instability, potentially requiring advanced

grid control mechanisms.

- **Benefits for Smaller Sites:** Smaller WWTPs like those in Rochester, Echuca, and Kyneton, which have limited capacity for wholesale market participation, face challenges in exploiting arbitrage opportunities. However, even with smaller systems, these sites can still achieve significant cost reductions by maximising PV self-consumption and aggregating FCAS revenue with other users. Smaller systems, such as 100 kW PV and 70 kWh BESS, offer a more feasible investment with payback periods within 20 years, although increasing system size may lead to longer payback periods.

Overall, the findings underscore the significant potential of integrating renewable energy systems, flexible load management, and demand response programs to enhance the economic viability and technical performance of wastewater utilities. By leveraging the full potential of these technologies, water corporations can manage their energy demands more effectively, contribute to grid stability, and achieve long-term sustainability goals. This comprehensive approach not only reduces energy costs but also improves the resilience of the local distribution network, providing a model for future energy management strategies in similar high-energy demand sectors.

6 IRG and Stakeholder outcomes

6.1 First IRG meeting

The first IRG meeting, held online alongside the project kick-off on 28 March 2023, covered the project plan, activities, timeline, and data collection requirements. Discussions focused on confirming data collection priorities with project partners and IRG members, as well as planning the ethics application through the RMIT University Human Research Ethics Committee.

In June 2023, a site visit was conducted at Coliban Water's Epsom Water Reclamation Plant in Bendigo, a priority site for energy flexibility approaches. Insights into the site's operational mechanisms were provided, confirming key operational constraints, the existing FCAS agreement, and potential renewable energy capacity.

6.2 Second IRG meeting

The second IRG meeting, held in June 2023, confirmed priority site selection for Coliban Water and Sydney Water Corporation. Site selection details and general information were provided and use case and activity diagrams were developed as references for programming and modelling tasks. DNSPs (Powercor and Ausgrid) were also engaged for further data collection regarding the single-line diagram.

In July 2023, discussions on demand response from an energy retailer's perspective took place with an IRG member from Origin Energy. Insights were shared on the mechanisms of Origin Zero, risks and benefits of exposure to the NEM Spot Market, and concerns regarding deviations from original load patterns. These insights were used to refine the use case diagram, incorporating further details on retailers' roles in P2P trading, wholesale, and FCAS demand response.

In August 2023, a meeting with a power system engineer from AEMO introduced the project scope and NEM considerations within the Energy Flexibility for Water Cooperation project. Feedback was provided on AEMO's management mechanisms for FCAS and wholesale demand response, leading to the engineer joining the project as an IRG member.

6.3 Third IRG meeting

On 24 November 2023, the third IRG meeting provided project progress updates, discussed priority sites with complex scenario settings, and reviewed project engagement at APSRC 2023. The meeting also outlined the project plan leading up to the next IRG meeting.

On 5 December 2023, a project summary and interim outcomes were presented during the APSRC 2023 *Solar Energy in the Water Industry* workshop session, chaired by Professor Mikel Duke from Victoria University. Project partners and IRG members participated, and the presentation received positive feedback, generating insights for further improvements.

6.4 Fourth IRG meeting

On 28 June 2024, the fourth IRG meeting reviewed key points from the previous session, including literature review, data collection, system design, and reinforcement learning model construction. A project update covering the period from February to May highlighted improvements in reinforcement learning, interim economic assessment results for Coliban Water, and advancements in operational constraints modelling.

Discussions on DR in Coliban Water’s aeration process covered operational rules, MLSS effects, sewage inflow patterns, and autonomous control of weir levels and aeration power. A new interface for modelling, including calibration and DR scenario selection, was introduced, followed by a live demonstration of economic assessment functions and real-time DO and BOD monitoring.

The LV distribution network model was also reviewed, assessing grid impacts and simulating 4,000 households and 500 PV-battery prosumers. Additionally, potential integration with the live SCADA system was discussed, further expanding the project's scope and practical applications.

7 Knowledge sharing

The project's key findings and advancements were shared through major conferences and workshops:

- **APSRC 2023 – Solar Energy in the Water Industry Workshop (Dec 5, 2023):**
  The project summary and interim outcomes were presented during a session chaired by Professor Mikel Duke (Victoria University). Project partners and IRG members participated, and the presentation received positive feedback along with valuable insights for further improvements.

- **APSRC 2024 – Energy Trading Session (Dec 3–5, 2024):**
  Research on peer-to-peer energy trading between Coliban Water and neighbouring DERs was shared, focusing on the trading mechanism, game theory auction design, and empirical benefits for both parties. The session highlighted the potential of DER integration in rural energy communities and received highly positive feedback with suggestions for further development.

- **First International Conference on Digital Intelligence for Energy Systems (Jan 5–8, 2025):**
  The reinforcement learning-based battery automation mechanism within the RE-LM management system was presented. The session covered system design, training, and assessment results, showcasing the model's effectiveness in optimising arbitrage value from the spot market. The work was well received as a strong case study on digital intelligence integration for energy storage, with valuable feedback and insights for future refinement.

- **Public Webinar in 2Q25, after final report is published**

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