

Emitting less without curbing usage? Exploring greenhouse gas mitigation strategies in the water industry through load shifting

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HIGHLIGHTS

- CO₂ benefits of demand response strategies in the water sector were analyzed.
- CAISO's hourly CO₂ intensity was used to inform load shifting in the water sector.
- Daily reductions in emissions depended on power demand and renewables availability.
- Emissions benefits from load shifting were largest in summer and winter months.
- Opportunities and challenges for load management in the water sector are discussed.

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ABSTRACT

Growing interest in greenhouse gas mitigation strategies to address global climate change has resulted in the rapid expansion of renewable electricity sources. However, increasing power generation from variable renewable electricity sources, such as solar photovoltaics and wind turbines, has made balancing electricity supply and demand across the power grid more challenging. In some regions, high penetrations of variable renewables have also created electricity supply systems where electricity is significantly cleaner in hours when renewable energy is abundant, in comparison with peak demand hours when fossil fuel-based generation is often dominant. In the absence of cost-effective, utility-scale batteries, demand response strategies that leverage flexibility in electricity consumption have gained interest as readily available resources to address the temporal mismatch between renewable energy availability and high energy demand periods. The water industry (i.e., water supply and wastewater systems) includes industrial customers that are particularly attractive in terms of demand response potential as they can offer flexibility through large interruptible pumping loads, large water storage capacities, and energy generation potential. This study explores flexibility strategies in the water sector motivated primarily by the goal of reducing emissions, rather than cost. We present an illustrative case study demonstrating that strategically shifting 5% of the total daily average electricity load of a cluster of 97 water-supply electricity consumers in California across the year can reduce annual carbon dioxide emissions by 2–5%. In the end, important future research directions are discussed to support the implementation of flexibility measures in the water industry.

1. Introduction

Decarbonization policies and falling costs have resulted in large increases in variable renewable energy generation in many regional power grids. Large penetrations of solar photovoltaic (PV) and wind generators have created grid conditions in which generator fleets are composed largely of renewable energy sources in some hours and of non-renewable generators (mostly fossil fuel-based) in other hours of the day when solar

and wind resources are diminished. These large swings in net load (i.e., the difference between load and available electricity production from solar and wind generation resources) cause operational challenges for the grid. For example, in California a phenomenon called the “Duck Curve” occurs when high fractions of solar energy create large disparities between mid-day net load and evening net load, when solar generators go offline. These conditions create two major challenges: (1) the risk for oversupply during high solar penetration hours and (2) the large

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ramping requirements of dispatchable generators that must come online in the early evening period when diminishing solar generation coincides with peaking electricity demand.

These challenges can be mitigated through supply-side solutions, such as long-distance transmission, battery storage, and flexible power generators, which can be deployed to ramp up when variable electricity sources go offline [1]. However, they can also be mitigated through demand-side resources that offer flexibility by modifying electricity consumption patterns to better match grid conditions. For example, non-essential electric loads can be shifted from hours when renewable energy generation is low (typically when wholesale electricity market prices are high) to hours when there is a surplus of renewable generation (and low wholesale electricity market prices) [2]. In this respect, water and wastewater utilities are particularly attractive options for providing demand-side management services because of their significant energy needs, large water storage capacities, and advancements in water control systems and digitalization that can help coordinate electric and water utility operation [3–5]. Thus, water utilities can serve as important allies to electricity utilities because, while electrons must be balanced in real-time, water can be treated asynchronously and stored for later use.

Municipal drinking water supply and wastewater management systems (collectively referred to as the “water industry” in this paper) represent a considerable share of total energy use and greenhouse gas emissions, particularly in cities, making them a prime target for demand response load-shedding and load-shifting programs [6]. Nationally, the water industry represents about 2% of annual US electricity consumption [7]; from a CO₂ emissions perspective, in 2005, about 85 million metric tons of CO₂ were emitted from activities related to the public water supply, wastewater treatment and supplying irrigation water, respectively [8,9]. Energy is consumed in the water industry for sourcing, conveying, treating and distributing water to consumers, as well as for managing wastewater and water recycling [10,11]. Consequently, energy costs are typically significant operational costs to water utilities, often only behind labor cost [12]. Peak electricity usage in water systems typically occurs in the morning and evening hours with higher peaks in summer months reflecting water consumption behavior [13]; these periods often coincide with peak electricity consumption periods in the evening across the electric grid. Thus, energy management solutions, such as improving energy efficiency, recovering energy, and self-generating energy from distributed renewable sources, are of high interest in this industry.

Some of the major load flexibility opportunities in the water sector that we identified in our recent literature review on the topic [6] are summarized below.

- **Leveraging water pumping and water storage capacity:** Water storage tanks embedded in water systems can operate as energy storage capacity, since the ability to store water in storage tanks enables flexibility in the operation of pumps. Pumping water to fill a reservoir at times when renewable energy is abundant can support the curtailment of pumping load during hours when the electric grid is less clean (i.e., has a high emissions intensity), which generally coincide with times when electricity prices are more expensive. Sufficient storage capacities can support longer interruptions of pumping with less adverse effects on the system [14]. Advanced process monitoring and control systems in water facilities can be programmed to satisfy operational constraints and facilitate faster response to grid needs. For example, variable-speed-drive pumps can adjust their motor speed and water flow rates continuously, and therefore, they support flexible operation when water storage capacities and grid conditions are aligned to support baseload and peak load management, as well as water system requirements [15].
- **Controlling operational load:** Water treatment facilities are typically equipped with central control systems to manage treatment processes and water quality. These control systems can help maintain

treatment and pumping processes to operate closer to the facility’s full operational capacity during hours when electricity is cleaner. Control systems can also schedule delays in treatment or switch to low operational modes at times when electricity is dirtier [16]. This type of load management may utilize flow equalizers and storage tank capacity, in addition to the individual components of a treatment process. Aeration units are often the largest energy consumers in wastewater treatment facilities with secondary treatment, accounting for 45–75% of total energy costs [17,18]. They can be operated intermittently to control the load. However, advanced energy and water quality management systems are necessary for the water industry to determine an optimal daily plan for operating water systems, while ensuring that load management will not compromise water utilities’ services [19]. Some components of a wastewater treatment plant can be turned off for a few minutes up to a few hours [20]. Pumping systems can typically be interrupted for longer periods than treatment systems depending on the system characteristics and water delivery constraints [21]. Some water utilities already manage their electricity use to limit consumption during expensive time-of-use rates (that typically reflect higher wholesale electricity generation costs). For instance, Irvine Ranch Water District reduced significant amounts of its electrical load during peak-pricing periods on summer weekdays, primarily (but not solely) through limiting the operation of its groundwater and drinking water pumps [22].

- **Utilizing on-site generation and storage resources:** The primary goal of running on-site generation resources is to reduce electricity purchases. Engaging on-site generation resources in load shifting strategies at a water facility might not minimize its overall electricity purchases from the grid, but strategies that reduce overall load on the electric grid when electricity is generated from dirtier resources can result in environmental and grid management benefits. Aside from large hydropower generation plants located within some large water transfer projects (whose generated electricity is often sold to the electric utility, and is thus, generally decoupled from urban water systems), there are several other energy generation opportunities. Some technologies can help recover small amounts of energy from pressurized water systems such as in-pipe hydro turbine and pump-as-turbine technologies [23,24]. These energy generation resources are attractive for improving flexibility capabilities when they are coupled with energy storage technologies. Anaerobic digestion units can recover larger amounts of energy generated from organic materials in the form of biogas from wastewater. Biogas can be burned as a fuel in power generation units, such as internal combustion engines, micro-turbines, gas combustion turbines, and fuel cells [25,26]. Typically wastewater treatment facilities with influent flow rates of 5 million gallons per day or greater are more cost-effective to produce biogas in quantities adequate for power generation [26]. This large source of energy generation potential has enabled some wastewater treatment facilities to operate as net-zero energy and even energy positive facilities [27,28]. Case studies analyzed in [29] showed that six out of 20 conventional wastewater treatment plants in China could export excess energy while others could achieve a partial or full net-zero energy consumption, reducing the cost and energy consumption associated with sludge treatment and disposal. Moreover, an installed biogas storage tank in a wastewater treatment plant can be leveraged for providing additional source of flexibility [30]. Battery storage technologies have applications for flexibility by decoupling the temporal relationship between energy generation and energy consumption. For example, Irvine Ranch Water District worked with its electric utility, Southern California Edison, to deploy a 6.25 MW/ 35.7MWh network of battery arrays at its water facilities, which include six water treatment, water recycling, and pumping facilities. This battery system allows the water utility to buy and store energy during cheap electricity rate periods and consume stored energy to power its operations during periods when electricity

rates are high. In addition, battery storage systems provide a source of stored power for Southern California Edison to depend on when the electric grid constrained or during demand response events [31].

While demand-side management strategies can benefit both water and electricity utilities to better manage their energy supply and cost priorities, coordinating water and electricity utility operation could be leveraged to derive better environmental outcomes. Demand-side flexibility can be an environmental tool to support mitigating greenhouse gas emissions as the timing of electricity demand affects the emissions footprint of each unit of energy consumed. Since the fleet of generators producing electricity for the grid changes throughout the day as a function of dynamic demand, renewable resource availability, and market dynamics, the grid's real-time emissions intensity (defined here as kg of CO₂ emitted per unit of electricity consumed) fluctuates considerably throughout the day. In California, the grid generally has low emissions intensities in the middle of day and higher intensities in the high-demand evening hours, as solar resources go offline. Thus, reducing electricity consumption at water and wastewater utilities via demand-side energy management strategies during hours with high fossil fuel generation can result in emissions benefits. While these diurnal trends are not unique to the case of California, they are more pronounced in electric grids with high penetrations of renewable energy.

Many studies have used energy management solutions in the water industry to reduce electricity consumption costs based on electricity rate tariffs without incorporating the electric grid's real-time supply dynamics [32–34]. Studies that do consider the electric grid's dynamics generally use wholesale energy market prices and electricity supply costs to prescribe the needs for flexible resources or provide signals for demand response [30,35–37]. For a wastewater treatment plant in Santa Rosa, California, Musabandesu and Loge performed a cost-benefit analysis based on 2018 real-time locational marginal prices within California Independent System Operator (CAISO) and time-of-use (TOU) pricing. They estimated that the facility could potentially save \$8,015 up to \$68,344 annually (i.e., up to 4.8% of the total annual electricity cost of the facility), depending on the duration of the facility's participation in demand response and type of assets utilized for load shifting [34]. These cost savings were reached through revenues from demand response participation and projected savings based on TOU pricing [34]. Kernan et al. used genetic algorithms to minimize the cost of two different water supply systems and found that using the marginal price of the electricity supply effectively aligns the electricity consumption patterns of water pumping operations with intermittent renewable generation profiles [38]. In another study in Germany, load shifting in wastewater treatment plants was managed by on-site combined heat and power generation units to minimize electricity purchase costs based on forecasted electricity wholesale price signals in year 2030 [30]. The results of this analysis showed that load shifting in the studied wastewater treatment plants could avoid the curtailment of about 120 MW of surplus renewable generation across the electric grid [30]. Another study formulated a mixed-integer optimization model for a pump scheduling problem, based on the demand response mechanisms available in the United Kingdom [39]. This study confirmed that, in addition to financial benefits for the water utilities from demand response participation, these programs were also effective in achieving grid-related greenhouse gas emissions reductions, in many cases, greater than competing reserve energy technologies (e.g., internal combustion diesel, gas turbines, and hydro pump storage) [39].

No study to the authors' knowledge has explored the potential for load shifting strategies designed primarily to mitigate greenhouse gas emissions in the water sector. Here we execute a case study based on a cluster of 97 water industry-related consumers in California to investigate a novel approach that uses the hourly emissions intensity of CAISO's electric grid as the main load shifting trigger. Thus, in this analysis, we provide a new perspective for demand response by altering the

motivation for load shifting from solely economic towards reducing greenhouse gases. Although these two viewpoints overlap to a great extent as more zero-production-cost and zero-emissions technologies of solar and wind are being integrated to the grid, we specifically analyze how shifting electricity consumption as a function of hourly variations in carbon intensity of the grid can derive emissions benefits, and potentially reduce renewable energy curtailment using a case study of water industry end users. We then comment on existing technical and regulatory challenges that provide barriers to the water sector taking a more active role in supporting the evolving electric grid through demand-side management.

2. Data and methods

Here we simulate a series of load shifting scenarios to investigate the emissions benefits of shifting electricity load consumption from the hours with the most polluting fleet of electricity generators to the hours with the highest penetrations of renewable energy generators, using load profiles from a cluster of water utilities operating in California. The analysis utilized load data released as a supplement to California's Demand Response Potential Study [5], which details the hourly aggregated load of 97 water supply-related accounts with loads greater than 200 kW within Pacific Gas and Electric (PG&E) utility balancing authority in the year 2014 (the data is accessible at [40]). The dataset also catalogs hourly electricity uses across the cluster into three categories: pumping, treatment and other, which represented 50%, 25% and 25% of overall load, respectively. This cluster of water facilities collectively consumed about 85,000 MWh of electricity in 2014 [40]. (Note that this load only represents a small fraction of PG&E's total annual load of approximately 123,000 GWh in that year [41]).

3. Simulating electricity load shifting scenario

First, we created twelve representative load profiles for each month in 2014. Each monthly profile consisted of 24-hourly load averages, representing the averaged load for each respective hour of day, across all days in each month. (For example, hour 1 of the January profile represented the average load between 12:00 and 1:00 am for all days in January 2014.) These twelve profiles were used as the monthly baseline scenarios for each month (shown with solid black lines in load panels of Fig. 3).

We assumed that each monthly electric load shifting scenario allowed 5% of total daily average electricity load to be shiftable over six hours (Eq. (1)), meaning that hourly electricity increased in 6 hours of 24-hour period (Eq. (2)), when compared to the baseline. In order to prevent creating a higher peak load (in magnitude) after load shifting, the amount of load increase in each hour was capped at a value equal to the highest hourly peak demand within each baseline profile prior to shifting (Eq. (3)–(4)); thus, in some months the total amount of shiftable load was less than 5% of total averaged daily electricity consumption. In other words, the magnitude of shiftable load within each month was determined by two factors: the magnitude of the total average-day electricity load and peak hourly electricity usage within the baseline diurnal profile. The additional amount of load shifted to the 6 cleanest hours was distributed evenly across the six dirtiest hours so that daily electricity consumption in the baseline and load shift scenarios remained equal. Thus, the total amount of load reduced in any of the 6 dirtiest hours was kept equal (Eq. (5)). The hourly electricity loads outside of the 12 load shifting hours remained equal to the baseline load (Eq. (6)). Months that had total daily load shifting below 5% of total daily load are illustrated in Fig. 1 by orange bars that fall below each red dot.

In Eq. (1), LS_j is the targeted amount hourly electricity consumption to be shifted in month j , where $BL_{i,j}$ is the baseline electricity load for hour $i = 1, 2, \dots, 24$ in an average day of month j .

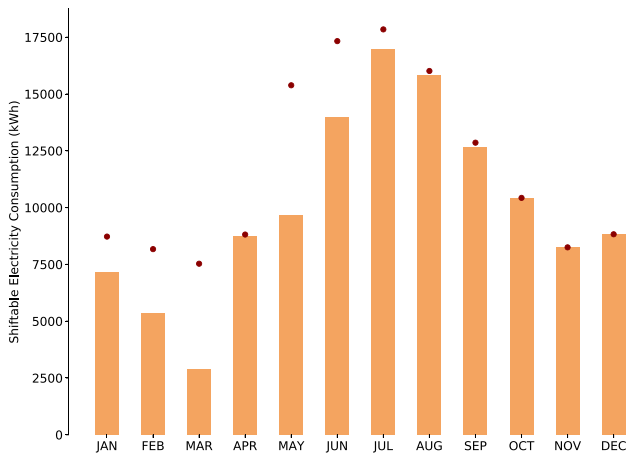


Fig. 1. Shiftable electricity consumption in each month after applying the daily load shift scenario. Red dots represent the maximum monthly load shift which was capped at 5% of daily electricity consumption for each averaged day in the month. (Monthly totals were calculated by multiplying average daily load shifts in each month by the number of days in each month.)

$$LS_j = \frac{0.05 \times \sum_{i=1}^{24} BL_{i,j}}{6}, \quad j = \text{January, February, } \dots, \text{December} \quad (1)$$

In Eq. (2), $ML_{k,j}$ is the targeted hourly electricity load for each of the six cleanest hours, k , for $k = 1, 2, \dots, 6$, in each load shifting scenario, before the peak load constraint was applied:

$$ML_{k,j} = BL_{k,j} + LS_j, \quad \text{for any of } k = 1, 2, \dots, 6 \quad (2)$$

In Eqs. (3) and (4), $ML_{k,j}$ is the modified hourly electricity load in each of the six cleanest hours, k , in each load shift scenario, after the peak load constraint is applied. $Max(BL_{i,j})$ is the hourly peak electricity consumption in each baseline profile in month j .

When $ML_{k,j} \leq Max(BL_{i,j})$, for any of $k = 1, 2, \dots, 6$:

$$ML_{k,j} = BL_{k,j} + LS_j \quad (3)$$

When $ML_{k,j} > Max(BL_{i,j})$, for any of $k = 1, 2, \dots, 6$:

$$ML_{k,j} = Max(BL_{i,j}) \quad (4)$$

In Eq. (5), $ML_{r,j}$ represents the modified hourly electricity load in each of six dirtiest hours, r , for each load shift scenario. $BL_{i,j}$, LS_j , $ML_{k,j}$, $ML_{k,j}$, $ML_{r,j}$ are all in kilowatt hours (kWh).

$$ML_{r,j} = BL_{r,j} - \frac{\sum_{k=1}^6 (ML_{k,j} - BL_{k,j})}{6}, \quad \text{for } r = 1, 2, \dots, 6 \quad (5)$$

$$ML_{i,j} = BL_{i,j}, \quad \text{for all } i \text{ not in } k \text{ or } r \quad (6)$$

3.1. Identifying the Cleanest and Dirtiest Hours of the Electric Grid

We assume that the amount of shiftable load in each load shifting scenario would be shifted from the six “dirtiest hours” (i.e., hours with the highest CO₂ emissions intensity due to high shares of fossil fuels) to the six “cleanest hours” (i.e., hours with the lowest CO₂ emissions intensity due to high shares of clean electricity generation sources) within the same 24-hour average day of each monthly baseline profile. In some months, the “dirtiest” and “cleanest” hours were not consecutive (e.g., in May, load is shifted from the dirtiest hours between 6:00–7:00 and 20:00–23:00, to the cleanest hours between 12:00–17:00). The six dirtiest and six cleanest hours were determined based on the emissions intensity values of hours 1 through 24, respectively.

Twenty-four hourly emissions intensities were estimated to represent an average day for each month using the linear regression model

described in Eq. (7). In this equation, the independent variable is hourly electricity consumption in CAISO region ($D_{i,j}$ in MWh), the dependent variable is total hourly CO₂ emissions ($E_{i,j}$ in kg), and the coefficient factor is average CO₂ emissions intensity ($AEF_{i,j}$ in kg CO₂/MWh) at hour i within each month (i.e., what we seek to estimate for this analysis). Hourly electricity demand data, $D_{i,j}$, and hourly CO₂ emissions data, $E_{i,j}$, are available on the CAISO Today's Outlook website [42]. The regression model was evaluated with data for each hour, i , within each month, j , to derive 24 hourly emissions factors representing an average day for each monthly scenario, thus assuming all days of each month are similar.

$$E_{i,j} = AEF_{i,j} \times D_{i,j} \quad (7)$$

The results of the regressed CO₂ emissions intensities are displayed in Fig. 2 and show a wide range of values between 100 and 362 kgCO₂/MWh, where cleaner hours tend to be in the sunniest hours of the day, particularly in spring months when more hydropower, in addition to solar generation, is available, and dirtier hours tend to be in the early evening after the sun goes down and demand is high.

Once average hourly emissions intensities were calculated for each month, the hourly CO₂ emissions associated with each hour of electricity consumed by the aggregated cluster of water industry accounts were estimated for the following three scenarios:

- (1) Baseline Scenario: Uses the average 24-hour daily load profile of the cluster for each month (using historical data as described above) and emissions intensity assumptions estimated by the regression model.
- (2) Load Shift Scenario 1, No Renewable Oversupply: Reflects load shifting assumptions for each month described above and emissions intensity assumptions estimated by the regression model.
- (3) Load Shift Scenario 2, Renewable Oversupply: This scenario is equivalent to Load Shift Scenario 1 except that we apply a second emissions assumption applied to electricity load after it is shifted to the cleanest hours, assuming that a curtailment of renewables occurs and that accommodating all shifted load during the clean hours in the middle of day incurs zero additional emissions in order to simulate days when there is excess emissions-free solar energy available. (Note that in CAISO, the average daily renewable curtailments due to oversupply were over 670 and 370 MWh in May and November 2019 [43], respectively, which were much greater in magnitude than the amount of shiftable load explored in this case study).

The daily avoided CO₂ emissions due to load shifting across the average day in each month were calculated as the sum of hourly differences between the emissions associated with the aggregated electricity load of the cluster of water utility accounts before ($E_{i,j,bef}$ in kg CO₂) and after load shifting ($E_{i,j,aft}$ in kg CO₂) at each respective hour i . Additionally, an avoided emissions metric (A_j in kg CO₂ per MWh daily shifted load) was defined in Eq. (8) where the daily avoided CO₂ emissions in one day was divided by the total daily shifted load for each month to inform the effectiveness of load shifting scenarios in reducing greenhouse gas emissions.

$$A_j = \frac{\sum_{i=1}^{24} (E_{i,j,bef} - E_{i,j,aft})}{\sum_{k=1}^6 (ML_{k,j} - BL_{k,j})} \quad (8)$$

4. Results and discussion

This analysis evaluates the CO₂ emissions reductions that follow a load shifting strategy that shifts up to 5% of the total daily load across a cluster of 97 water industry end users from 6 hours when the grid is relatively carbon-intensive to another 6 hours when the grid is relatively carbon-lean. Hence, while most demand response strategies are motivated by economic factors, this analysis evaluates a case study driven

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Jan	318	317	317	316	314	314	316	314	274	242	228	220	221	222	231	255	298	320	325	325	327	330	328	323
Feb	294	293	294	293	291	290	297	280	228	202	187	186	186	188	194	211	250	293	310	309	308	308	302	298
Mar	262	258	255	253	252	255	267	259	203	158	137	128	124	126	127	136	159	201	258	287	288	281	274	268
Apr	225	220	218	216	217	230	249	218	155	123	109	103	100	101	101	108	123	149	212	265	276	263	249	235
May	215	214	213	214	213	222	225	186	148	132	122	114	108	108	109	112	119	137	183	235	251	245	232	221
Jun	241	235	233	233	236	242	233	188	153	142	139	138	136	139	142	154	163	180	215	259	275	272	260	248
Jul	279	274	269	266	264	266	262	225	189	177	173	173	174	180	185	194	204	219	251	293	306	306	299	292
Aug	317	310	305	302	300	300	305	271	221	201	195	195	199	207	216	227	238	257	298	333	339	338	335	326
Sep	337	333	331	328	324	321	329	310	250	218	211	211	213	220	227	238	253	284	332	351	354	356	355	343
Oct	346	343	341	340	337	331	335	330	266	214	200	195	194	197	198	203	247	311	354	362	360	358	356	350
Nov	346	343	341	340	337	331	335	330	266	214	200	195	194	197	198	203	247	311	354	362	360	358	356	350
Dec	340	340	339	336	332	327	329	326	296	273	265	260	259	263	272	291	315	332	335	335	336	339	341	340

Fig. 2. Hourly CO₂ emissions intensity profiles for each month representing electricity consumed in the CAISO region (kgCO₂/MWh) based on a linear regression analysis of 2019 hourly CO₂ emissions and electricity demand data from CAISO [42].

primarily by the priority to reduce greenhouse gas emissions.

4.1. Load shifting potential

The load profiles of the aggregated water-industry cluster before and after load shifting are summarized for all twelve months in Fig. 3. A few trends are worth highlighting in the baseline electricity use profiles (i.e., before load shifting). The electricity use patterns of water facilities are generally very different from month to month, due to differences in water demand and time-varying electricity pricing (See Fig. 3). For example, from a seasonal perspective, more energy was consumed for water services during hot summer months (i.e., June, July and August), across which there tended to be significant hourly variation, as compared to electricity use profiles in winter months (i.e., January and February), which had a flatter load curve.

In summer months, the aggregated loads associated with the studied cluster of water end users show a diurnal trend that reflects TOU electricity rates. The industrial TOU rates in PG&E in year 2014 (the year that the electricity use data were collected) included two-period pricing from November to April (partial-peak period from 8:30 am to 9:30 pm on weekdays, and off-peak period from 9:30 pm to 8:30 am on weekdays and all-day weekends and holidays), and a three-period pricing from May to October (peak period from noon to 6:00 pm on weekdays, partial-peak period from 8:30 am to noon and from 6:00 pm to 9:30 pm on weekdays, and off-peak period from 9:30 pm to 8:30 am on weekdays and all-day weekends and holidays) [44]. It is important to note the conflict between the peak period defined in the PG&E's industrial TOU rates and CAISO's true system-wide peak electricity demand period. In 2019, CAISO's system-wide electricity demand generally peaked between 4:00 pm to 9:00 pm in summer months [45], while the TOU tariffs charged the most for electricity between noon to 6:00 pm. Reducing electricity consumption during peak demand periods, especially in the evening, is important from an emissions perspective, because dirtier generators come online to meet the electricity demand, as solar diminishes in the evening, so this conflict is problematic from both cost and emissions reduction standpoints. As of March 2021, PG&E still defines its industrial peak pricing period between noon to 6:00 pm from May to October [44]. In addition, PG&E's 2014 demand charges (i.e., fees applied to electric bills based on the highest amount of electric power usage that occurred during the billing period) were higher in summer and peak periods compared to winter and off-peak periods [44].

In response to these electricity price signals (peak and partial-peak periods being about twice and 20–40% more expensive than off-peak

periods), water facilities in the studied cluster consumed more electricity during evening hours and less during morning hours (see load profiles in Fig. 3). With more aggressive time-varying electricity rates (e.g., real-time pricing), the electricity rate structures will become more reflective of the renewable electricity supply availability, and therefore, better align with reducing the CO₂ emissions intensity of the electricity consumption as variable renewable penetrations increase.

More load was shifted during months that had higher electricity consumption and larger gaps between the peak and midday electricity use (i.e., May through October), creating a daytime peaking period of electricity use. In these months, the electricity load profiles after load shifting created a new daytime peak period (albeit equal to or lower than the original highest peaking hour because of our analysis's constraint) and a new valley in the evening. In other months (i.e., from January to April and from November to December), the electricity load profiles after load shifting became flatter with an extended period of electricity load reaching the daily peak load level. From the electric grid's operational perspective, reshaping electricity consumption patterns such that there is higher daytime usage helps accommodate more midday renewable energy utilization, reduce the need for dirtier generators to supply the evening electricity load, and alleviate the need for expensive ramping resources.

4.2. CO₂ emissions reduction potential due to load shifting

The CO₂ emissions associated with electricity use depend on the magnitude of load and the electric grid's emissions intensity in each hour. Thus, the load shifting strategy explored here helps avoid high emissions during evening hours when the electric grid is dirtier, typically with only a small daytime penalty of increased emissions during the daytime, as illustrated in Fig. 3. The diurnal CO₂ emissions profiles typically follow the same pattern as the electricity use profiles with the exception of in daytime hours when it diverges into a deeper valley because of the grid's lower emissions intensity. From seasonal perspective, emissions were higher in months of June to October when both the magnitude of the electricity load and the electric grid's evening-time emissions intensity were higher than other months (i.e., from January to April, and from November to December). Thus, the outcome was that more emissions were avoided in summer and winter months compared to spring months (see Fig. 4), when hydropower and wind power are more abundant across much of the day and demand is relatively low due to mild weather [46]. Although the electricity load of the aggregated water utilities was nearly the same in March and

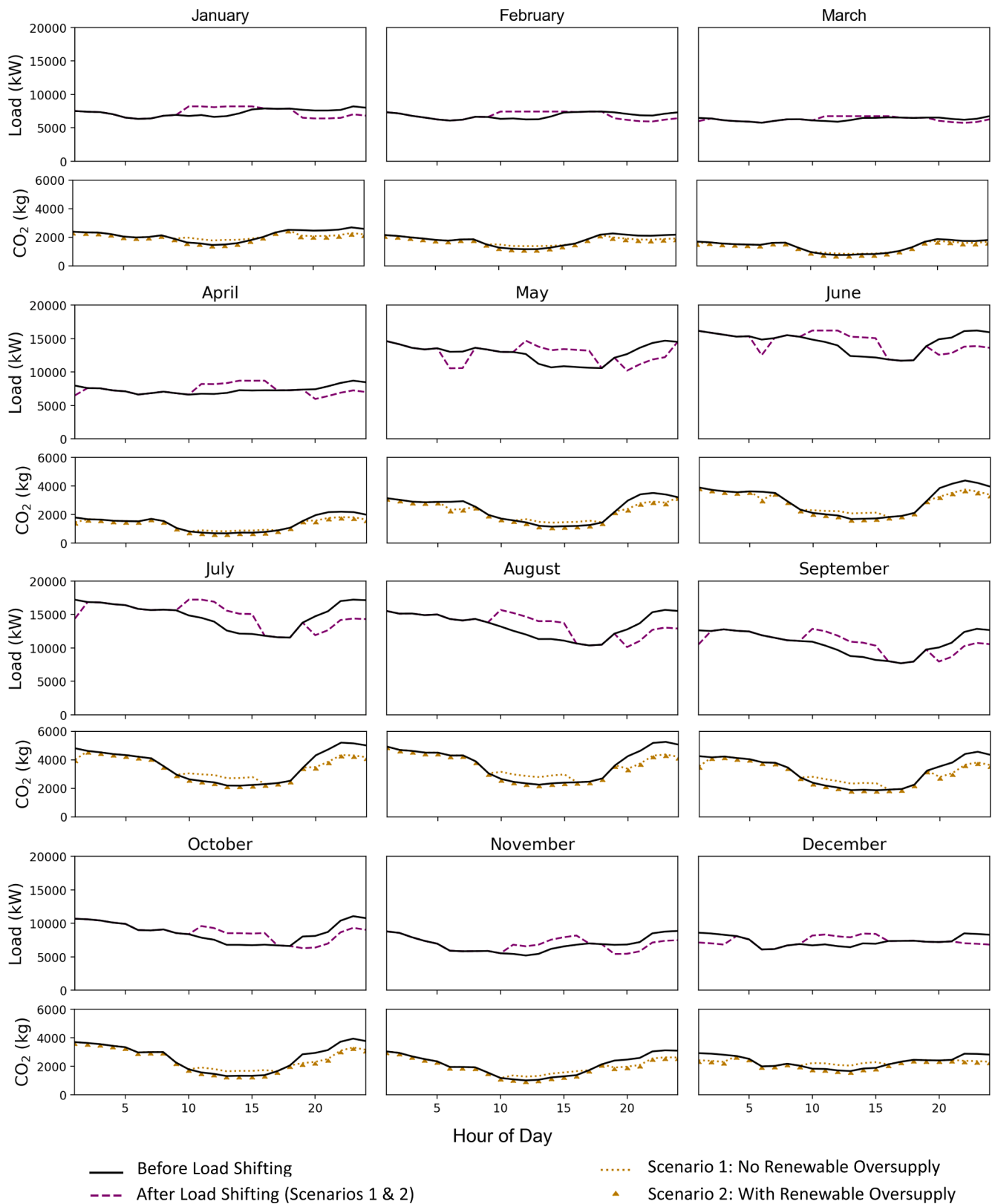


Fig. 3. Top within each month: Diurnal profiles for the aggregated electricity use of the 97 electricity accounts associated with the water industry, before and after load shifting. Bottom within each month: Diurnal profiles for the CO₂ emissions from the aggregated cluster, before and after Load Shifting Scenarios 1 (No Renewable Oversupply) and 2 (With Renewable Oversupply).

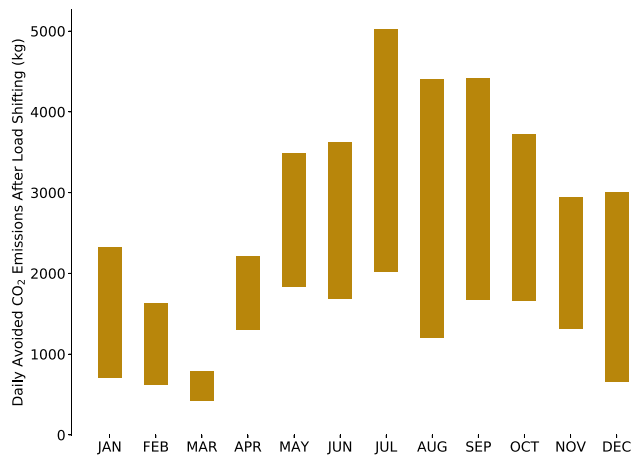


Fig. 4. Range of daily avoided CO₂ emissions in each month due to load shifting in the studied cluster of water-industry accounts. The upper and lower values of the bars illustrate results in load shifting scenario 2 (with renewable oversupply) versus load shifting scenario 1 (no renewable oversupply), respectively.

December, greater amounts of emissions could be avoided in December because the emissions intensity of electricity was generally higher across all hours in December as compared to March. Similarly, more evening electricity consumption could be avoided in May as compared to November, and as a result, load shifting in May lead to more avoided emissions.

About 1–7% of CO₂ emissions could be avoided in each month with the load shifting scenarios compared to baseline monthly emissions. The height of the top and bottom bars in Fig. 4 show the emissions avoided of Load Shifting Scenario 2 (overgeneration) versus Load Shifting Scenario 1 (no overgeneration), respectively, with Scenario 2 incurring the most emissions reduction benefits when shifted load was moved to hours when emissions-free renewable energy would have otherwise been curtailed due to solar oversupply, which tends to be exacerbated in the spring months of March to June in CAISO [47]. (CAISO's renewable oversupply rose from 10 GWh to 223 GWh from May of 2014 to May of 2019 [48], so in the absence of substantial investments of utility-scale storage, the importance of load flexibility strategies to leverage this resource is growing.) Annually, the emissions benefits of the investigated load shifting scenarios were equivalent to emissions benefits of reducing 2–5% of the baseline electricity load from this cluster of water end users, despite the fact that total electricity usage was held constant across all scenarios. This amount of avoided annual emissions is equivalent to reducing about 2,400–6,000 MWh of electricity in California assuming an average emissions intensity of 420.4 lbCO₂/MWh (190.8 kgCO₂/MWh) based on CAISO's average eGRID emissions rates for the year 2018 [49].

In terms of avoided emissions per unit of shifted load (Fig. 5), we observed values ranging between 75 and 350 kgCO₂/MWh, with greater benefits of reducing electricity incurred in September, October and November. Overall, the variation in avoided emissions per unit of shifted electricity suggests that the value of load shifting in terms of avoiding emissions varies significantly depending on the range of daytime and evening-time CO₂ emissions intensities of the electric grid, and the potential of load shifting. In this analysis, the duration of load shifting was kept constant (spanning an aggregated timespan of 6-hours per day), but it should be mentioned that shorter load shifting durations will generally lead to greater emissions benefits per unit of shifted load because the emissions reduction potential of shifting load is the highest when the load is shifted from the dirtiest hour, in terms of the grid's generation mix, to the cleanest hour of the day, since there is more of a difference between the hourly emissions intensities.

Since emissions benefits were quantified based on the electric grid's

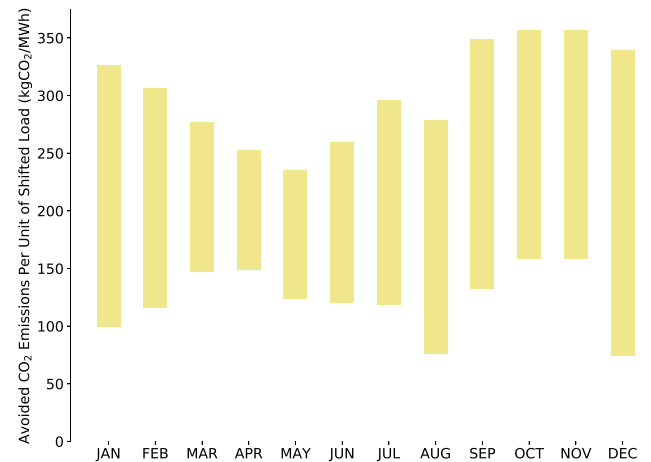


Fig. 5. Range of avoided CO₂ emissions per unit of shifted load in each month due to load shifting in the studied cluster of water-industry accounts. The upper and lower values of the bars illustrate results in load shifting scenario 2 (with renewable oversupply) versus load shifting scenario 1 (no renewable oversupply), respectively.

average hourly emissions intensities, these benefits represent rather conservative estimates. Average hourly emissions factors represent emissions averaged across all generators producing electricity across the hour while changes in electricity demand (in this case, load shifting) affects only a fraction of the generators operating at margin that respond and adjust their output to accommodate changes in demand. Thus, when electricity load is reduced during evening hours (when fossil-fuel fired power plants operate at the margin), the emissions associated with decreasing load will be much higher than when considering the average suite of electricity generators at any given hour (when the electricity being supplied is from a combination of fossil fuel, nuclear, hydro and renewable generators). In the future, we plan to quantify the marginal emissions factors of CAISO and reassess the emissions benefits of the load shifting.

4.3. Technical and regulatory factors

Some of the underlying assumptions regarding ground facts were simplified in this analysis as there is still information lacking about the scale of potential disruptable load, especially given that not every facility is equipped with technologies that can help manage load shifting and policies and market structures are not effective enough to incentivize load shifting. Other technological limitations could impact overall load shifting potential in water systems, particularly access to control and communication technologies. For example, upgrading water pumps that are still controlled manually with control technologies or adopting variable frequency drive pumps could pose an important economic barrier for achieving reliable electricity load shifting [5,50]. We acknowledge that the operation scheduling limitations vary depending on factors such as system design (both at the facility-scale and policy-scale) and water quality regulations, and therefore, we designed our analysis based on a conservative assumption that only 5% of total daily average electricity load can be shifted across the aggregate cluster (which serves as a good proxy for the water industry at large).

While we were not able to model the technical operations of individual water facilities to simulate load flexibility, there are several reasons why we believe shifting 5% of total daily average load across the water industry, over a duration of six hours, is a very conservative estimate compared to actual technical potential. First, pumping activities represented approximately 50% of the total electricity consumption in the analyzed cluster, with the remaining load split pretty evenly across water treatment (25%) and other activities (25%) [40]. Pumping loads are inherently flexible so long as there is enough usable storage along

the water supply chain, and these loads alone are much larger than the 5% total daily average electricity load shifted. Second, since the analysis is done on an aggregated water industry-related load, the effective 5% load shifting does not require or assume that a single facility has to curtail its electric load for the total duration of 6 hours. In practice, water utilities should schedule and prioritize their flexible resources, so that load shifting operations will have no adverse consequences, and it should be expected that while some of the 97 accounts in the aggregated cluster will likely have large load shifting potential, others may not. Third, previous studies suggest that significant load reductions have already been achieved by various water utilities in practice. For example, Irvine Ranch Water District in California successfully and continuously reduced its electricity load during expensive time-of-use rate periods in summer of 2015 to avoid costly electricity charges during noon to 6 pm [22]. It was able to consistently reduce peak-period electricity use on a typical summer day to levels 40% less than evening and morning periods. This low level of electricity use during the day was achieved by curtailing electricity from groundwater pumping, drinking water pumping and other facilities during that six-hour period [22]. Additionally, Liu and Mauter (2020) also found that most US drinking water treatment plants were theoretically capable of shifting up to 100% their business-as-usual loads, but the magnitude of load shifting varied significantly depending on the duration of load curtailments and the ratio of the maximum treatment capacity to peak-day water demand [51]. In their analysis, daily load curtailment durations of 2–8 hours were modeled for water treatment plants with a daily water production constraint that kept water production levels after load shifting to levels equivalent to baseline operations. Thus, these plants still produced enough treated water after load shifting to meet daily demand without need for multiple day water storage capacity [51].

While these factors suggest that the true technical potential of the water industry is likely much higher than our analysis assumes, factors such as electricity rates and utility programs are key drivers of flexibility decisions in practice. In some markets, optimizing flexible operations to reduce emissions, as our analysis seeks to do, might not align with operations that also minimize utility costs. However, in CAISO, wholesale electricity prices are lowest during hours of high renewable penetration and highest during the peak hours of the evening when electricity is relatively carbon-intensive [52]. Thus, our analysis, which seeks to minimize emissions through load shifting across the water industry, would also have a co-benefit of reducing total electricity costs, underscoring the economic feasibility of case study assumptions. Moreover, with higher penetrations of wind and solar, due to no marginal generation cost, are likely to further decrease the hourly wholesale electricity generation costs [53], further improving the alignment of economic and emissions mitigation load shifting operations.

The results of our analysis suggest that there is a potential for considerable emissions benefits from load shifting in water industry, but it should be noted that over the long-term, the emissions benefits of load shifting strategies are likely to decrease in electric grids that achieve high fractions of carbon-free generation during peak periods. However, demand-side management strategies will remain important resources to support the electric grid, particularly in grids that have high disparities in carbon emissions intensities across the day and grids that suffer from oversupply issues. While the ramping and renewable oversupply issues occurring in CAISO are not yet widespread, there are other markets, such as in Texas (ERCOT) [54] and in Northwest China [55], where deficits in adequate transmission capacity and storage have created similar renewable oversupply issues. Thus, as variable renewable penetrations increase, their successful integration will depend on the availability of more flexible resources, including battery storage technologies and demand-side management resources, to cope with the intermittency and variability of wind and solar photovoltaic generators and manage oversupply risks. (While quick ramping natural gas combustion turbines can also serve as backup, they can offset some of the carbon emissions benefits of renewable integration [56].) Demand

response technologies are relatively low-cost compared to battery storage technologies or large transmission capacity investments, and offer several value propositions in terms of supporting the grid's capacity needs, system reliability, market efficiency, congestion management, and market opportunities for electricity consumers (particularly large, industrial consumers) [57]. Moreover, demand response can enhance the resiliency of the electric grid, especially in face of extreme weather events such as wildfires, heat waves and winter storms [58,59,60]. These benefits will become increasingly valuable in highly decarbonized electric grid of the future facing more frequent extreme weather events.

5. Conclusion

The growth of renewable energy deployment has increased the need for flexible demand-side management resources that can help to balance the electric grid by reducing peak demand, while increasing the penetration of variable renewable energy generators to support climate change mitigation goals, especially in the absence of large-scale battery storage. This analysis illustrates that there are opportunities for coordinating water and electricity systems to derive synergistic benefits that support a diversity of economic, environmental, climate change mitigation and grid reliability priorities. Thus, it underscores the potential multi-faceted benefits that could be cost-effectively leveraged by making a paradigm shift towards more holistic energy management strategies that also emphasize non-economic priorities. However, several factors complicate active engagement of the water industry with the electric grid. Future research efforts should focus on filling some of the gaps in understanding that might delay the roll-out of such a synergistic strategy between water and electric utilities. We suggest:

- Executing more pilot experiments to help to identify and address the technical limitations of implementing flexible operation strategies to ensure that the quality of water services is not compromised.
- Building a better understanding of the holistic trade-offs and synergies across different energy management measures in the water industry, in order to maximize overall demand-side management benefits.
- Designing reasonable rate structures and demand-side management programs that better reflect the electric grid's needs and can support rational energy management decision making in water systems.
- Developing comprehensive models that integrate water and energy systems to inform the value of flexibility for the water industry, the agriculture sector and the electric utilities and guide more effective market mechanisms to incentivize the water industry to take part in electric grid services.

CRedit authorship contribution statement

Angineh Zohrabian: Conceptualization, Formal analysis, Methodology, Writing - original draft, Writing - review & editing. **Kelly T. Sanders:** Conceptualization, Methodology, Funding acquisition, Supervision, Writing - review & editing.

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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