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RESEARCH ARTICLE
10.1029/2023WR035246

Dynamic Pricing Framework for Water Demand Management Using Advanced Metering Infrastructure Data

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Key Points:

- A dynamic pricing strategy for water can lower peak water demands, peak energy, and energy cost of water distribution systems
- Advanced metering infrastructure data and hydraulic models are used to apply and assess dynamic pricing models
- Potential growth in water demand can be accommodated by existing infrastructure capacity through dynamic pricing

Supporting Information:

Supporting Information may be found in the online version of this article.

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Citation:

Alghamdi, F. M., Edwards, E. C., & Berglund, E. Z. (2024). Dynamic pricing framework for water demand management using advanced metering infrastructure data. *Water Resources Research*, *60*, e2023WR035246. https://doi.org/10.1029/2023WR035246

Received 2 MAY 2023
Accepted 18 AUG 2024

Abstract This research investigates dynamic pricing as a demand management tool to reduce cost and increase the lifespan of water distribution systems by reducing peak hour demand. Individual consumer responses to changes in hourly water price are simulated using advanced metering infrastructure (AMI) data. Demand profiles are used as input to a hydraulic simulation model to evaluate the effects of changing demands on flows and in-network metrics. The framework is applied to Lakewood City, California, using a model of the pipe network and AMI data collected at nearly 20,000 accounts. Four dynamic pricing policies are applied to the model to show that reductions in morning peak demand ranging from 6% to 25% reduce peak energy demands up to 14%. These small changes in overall energy demand, up to a 1.7% reduction, lead to relatively larger overall reductions in energy cost, up to 5.5%. The results demonstrate the importance of dynamic pricing as a demand-side strategy for infrastructure management and highlight the potential to accommodate demand growth without additional infrastructure investments.

1. Introduction

Water distribution systems (WDSs) across the United States are in need of upgrades to meet current and projected demands (ASCE, 2021), and new management approaches are needed to address the challenges of aging infrastructure and population growth. Reducing peak demand is a demand-side management approach that can conserve water and energy resources, reduce the cost of providing drinking water, and extend the life of existing infrastructure. Peak hour demand is a key determinant of fixed investment and variable operating costs in designing and managing WDSs (Cole et al., 2012; Rougé et al., 2018). Managing peak demands can also extend the life of existing infrastructure by reducing the magnitude of high-stress peak loading events and mitigating the need for system expansion to meet new demands associated with urban growth (Rougé et al., 2018).

Pumping is the most energy-intensive operation in a WDS (Carlson & Walburger, 2007), and high demands at peak periods of the day require that pumps are active to supplement water that flows from water storage tanks. Peak hour demand drives the cost of energy for pumping because the cost of electricity varies diurnally, although the marginal volumetric cost of water is generally invariant on hourly or sub-daily scales (Pabi et al., 2013). Transmission charges create an additional dynamic in cost calculations by applying a penalty based on the highest energy demand, measured in sub-hourly (e.g., 15-min) periods over the billing cycle, which is typically a 1-month period (Taylor & Schwarz, 1990). During especially high peak demand periods, additional pumps may be turned on, and this spike in energy consumption results in high transmission charges. As a result, energy can account for up to 40% of operating costs for drinking water systems (US EPA, 2020). Flattening peak-hour water demand can reduce the magnitude of peak energy consumption and the cost of distributing water.

Peak water demands can be managed through the rates offered to consumers because higher prices lead to reductions in use (Nataraj & Hanemann, 2011; Wichman, 2014). Conventionally, the cost of water does not reflect the diurnal pattern of marginal cost resulting increased pumping in periods of high demand. Instead, rate schedules are based on the aggregate volume consumed and billed on monthly or bi-monthly periods (Marzano et al., 2020). Dynamic pricing, which allows water rates to vary during peak hours (Rougé et al., 2018), provides an incentive for consumers to shift their water use to sub-daily off-peak periods (Marzano et al., 2018; Sahin et al., 2017). Dynamic pricing policies have been widely researched and implemented at some utilities within the electricity market (Hao et al., 2024). Interest in consumer response to time-varying energy pricing has been accelerated by broad adoption of smart metering for electricity and increased adoption of intermittent renewable sources (Harding & Sexton, 2017; da Silva et al., 2020). Dynamic pricing for water, on the other hand, has not been implemented by water utilities to the best of our knowledge and has been researched by a limited number of studies (Cole et al., 2012; Karrenberg et al., 2024; Lamolla et al., 2022; Marzano et al., 2020; Rougé et al., 2018; Vašak et al., 2014). Until recently, utilities could not bill for hourly water consumption because water consumption was recorded at the account level only on monthly, bi-monthly, or quarterly intervals. With the advent of smart city technologies, water utilities across the world have begun to adopt advanced metering infrastructure (AMI), which reports water consumption in hourly or sub-hourly intervals at individual accounts and can be used to bill customers for hourly water use (Cominola et al., 2015).

While the emergence of AMI and infrastructure requirements for peak demand management have generated interest in dynamic water pricing, research to date has not fully developed the required knowledge and tools to convince utility managers to adopt dynamic pricing (Marzano et al., 2021). Specifically, research has not estimated the magnitude of cost savings that could be achieved through dynamic pricing because nonlinear relationships between demand response, peak flows, pumping energy, and energy costs require complex modeling.

1.1. Existing State-Of-The-Art in Dynamic Pricing for Water

Existing research has explored consumer response to price through an online game to test how residential water consumers shorten the length of showers in response to sudden price changes (Marzano et al., 2020). Results demonstrated that dynamic price changes caused larger decreases in demand than expected, but further research is needed to quantify the response into elasticity estimates that capture behavioral response to high frequency pricing for different water end uses. Another study explored policies to target reductions in outdoor water use and developed three tariff models that apply a fee for discretionary consumption (water use exceeding 600 L/hr) (a) during peak hours, (b) during all hours except off-peak hours, and (c) across all hours of the day (Cole et al., 2012). While the work discusses the components of equitable dynamic pricing policies, it does not simulate or forecast how demands would change, or how those changes would translate into infrastructure performance.

A small number of research studies have simulated changes in water demands in response to dynamic pricing (Karrenberg et al., 2024; Lamolla et al., 2022; Rougé et al., 2018; Vašak et al., 2014). These studies simulated dynamic pricing policies as sub-daily price schedules, or time-of-use-tariffs, where two or more fixed rates are applied at different times of day, such as peak and off-peak rates (Rougé et al., 2018). Lamolla et al. (2022) developed an agent-based modeling framework to simulate the response of individual households based on sociodemographic characteristics. Demand changes were calculated for households based on characteristics of the household that represent belief systems behind household water consumption decisions. Karrenberg et al. (2024) extended the agent-based modeling framework to show via simulation that low-income households are limited in their ability to shift demands and, as a result, pay higher costs for water under dynamic pricing policies, when compared to high-income households. These studies did not explore how changes in water demands translated to infrastructure impacts and cost savings.

In contrast to work completed by Lamolla et al. (2022) and Karrenberg et al. (2024), Vašak et al. (2014), and Rougé et al. (2018) use elasticity to simulate changes in demand and apply commonly accepted values for price elasticity of water to total community demand. These studies also assessed changes to the cost of maintaining infrastructure, but did not fully evaluate how shifted demand patterns affect infrastructure performance and the cost of energy because changes in demand were simulated on an aggregated community scale. Rougé et al. (2018) calculated cost savings based on reduced costs for expanding the pipe system to meet new demands, but they did not simulate the hydraulics of a pipe system to assess changes in the cost of operations due to reduced energy consumption. Vašak et al. (2014) estimated utility cost savings as a linear function of the water use profile to represent cost savings that accompany reductions in peak demands. However, the linear function is based on estimated values and does evaluate realistic changes in network hydraulics and energy consumption due to new demand profiles.

1.2. Research Gap and Objectives

The structure of electricity prices creates a cost function for water delivery that is nonlinear in the timing of water demands and the magnitude of peak demands. Previous studies have evaluated only the reduction in aggregate peak demand and did not include the geospatial impact of demand changes on peak flows, network hydraulics, and energy costs of a pipe network. New research is needed to demonstrate the viability of dynamic pricing using infrastructure models and real-world consumption data collected at the account level. New frameworks are needed that can be applied to evaluate dynamic pricing policies based on their performance in reducing peak flows, pumping, and the cost of energy.

In this paper, we develop a modeling framework to simulate and evaluate the effect of dynamic pricing strategies on peak flows, utility revenue, energy costs, and infrastructure performance. The approach simulates a general policy increasing the hourly price of water in proportion to the difference between hourly demand and average hourly demand. This generalized result is compared to baseline (non-dynamic) pricing and three additional dynamic pricing policies, which were developed to explore practical assumptions about utility pricing decisions and water consumer behavior. The implementation of dynamic pricing is modeled to affect water demand at the account level via a price elasticity of demand parameter. This approach simulates shifting of demand to off-peak periods, rather than merely lowering overall demands. The resulting account-level water demands are integrated within a hydraulic simulation model through a modeling framework that simulates changes in flows, energy consumption, and energy costs as a result of demand changes.

The dynamic pricing framework is applied for an illustrative case study, the City of Lakewood, California, which has an existing AMI data set and an interest in reducing peak water use. Single family home account data are used in this research, based on the assumption that residential accounts are more likely to respond to incremental price changes and have the ability to shift some uses to off-peak hours, compared to non-residential consumers or multi-family homes. New insight generated by this research reveals that electricity cost is decreased more than electricity use, and quantifies these changes. Results indicate that pricing to address peak water demand can have outsized and nonlinear economic benefits, with relatively small changes in price during peak periods (6%–25%) generally reducing overall energy costs (3%–4%), while overall energy demand is reduced by less than 1%. Changes in peak demands and utility revenue vary seasonally even though the same pricing policy is implemented. Dynamic pricing policies were also shown via simulation to accommodate new demands associated with economic growth without needing to expand existing infrastructure. The framework developed in this research can be applied to AMI data sets and WDS simulation models to explore reductions in energy consumption and cost of operations associated with peak demand management.

2. Methods

This research applies a modeling approach to develop and evaluate dynamic pricing policies. The approach is grounded in the assumption that consumers change demand in response to price based on a price elasticity parameter. A demand change equation is described that uses new hourly prices and elasticity values to update demands (Section 2.1). Dynamic pricing policies are created based on the difference between the total hourly demand and the total average hourly demand (Section 2.2). To simulate the performance of dynamic pricing policies a modeling framework is developed that downloads, aggregates, and integrates AMI data within a hydraulic simulation model (Section 2.3). Performance metrics are applied to evaluate dynamic pricing policies based on changes in demands, hydraulic performance of the infrastructure, and energy cost (Section 2.4).

2.1. Demand Change Equations

Price elasticity of demand, or elasticity, is the percentage change in quantity demanded induced by a percentage change in price and is used to quantify consumer response to price. Prior work has documented water elasticity as inelastic, with mean values ranging from −0.37 to −0.51 in prior meta-analyses (Dalhuisen et al., 2003; Espey et al., 1997; Marzano et al., 2018; Sebri, 2014). In recent work, Marzano et al. (2018) reported that the average demand elasticity of water is −0.4, based on a meta-analysis of 124 studies from 1963 to 2013, and we adopt this value as the baseline behavioral response in this work. Research has not been conducted to explore how the price elasticity of water varies diurnally or at sub-daily scales, and, as a result, fine temporal elasticity estimates are not available for water. Similarly, while dynamic pricing has been researched and implemented for electricity markets, existing studies have not identified intraday elasticities for electricity. In the model described here, we assume that elasticity is uniform across accounts. Future research can explore elasticity values that vary temporally and in response to demographics, such as income, for example,

The change in demand that accompanies a dynamic pricing policy is calculated as follows, where ΔDr_h is the change in demand at hour, h, after the implementation of dynamic pricing:

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Table 1
Dynamic Pricing Scenarios

Scenario	Elasticity	Cap on price change	Number of blocks
Base-case	0	NA	NA
Hourly	−0.4	NA	24 blocks
Hourly-cap	−0.4	25%	24 blocks
3block	−0.4, −0.36, −0.32	NA	3 blocks
2block	−0.4, −0.36, −0.32	NA	3 blocks (2 active blocks)

$$\Delta Dr_h = e * \Delta Pn_h = e * \left(\frac{Pn_h - P}{P}\right) \tag{1}$$

The elasticity of demand is e and the new dynamic price is Pn_h. The original price (non-dynamic) is P, where the h subscript has been dropped because the original pricing policy does not vary with time. The new demand at h is:

$$Dn_h = D_h * (1 + \Delta Dr_h) \tag{2}$$

where D_h was the demand at hour h at price P.

2.2. Developing Dynamic Pricing Policies

Four dynamic pricing policy scenarios were developed and compared with a base-case scenario, which specifies no dynamic pricing policy. Each policy scenario specifies a price schedule as the price of water at each hour of the day (Table 1). The dynamic pricing policies begin with the assumption that changes in price are proportional to the deviation in demand from the hourly mean. The price change $(\Delta \mathrm{Pr}_h)$ for any hour is defined as:

$$\Delta \mathrm{Pr}_h \equiv \frac{D_h - \overline{D_h}}{\overline{D_h}} \tag{3}$$

where D_h is the demand at h, and $\overline{D_h}$ is the average demand across all hours. Using this ratio allows us to meet two objectives in setting dynamic prices. First, it increases prices the most where demand is highest, creating a pricing policy for shaving peak demands. Second, it allows the shifting of demand to off-peak periods, rather than merely lowering overall demand. This allows us to create and compare scenarios that have similar volumes of total water use. For example, deviation of the hourly demand from the mean for a sample set of data is shown in Figure 1.

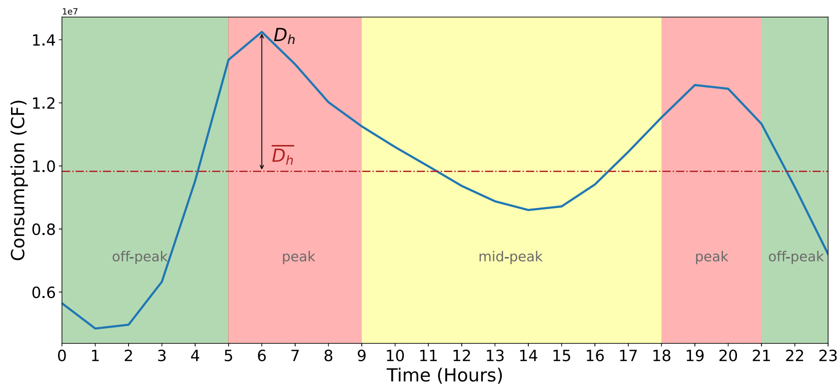

Figure 1. Sum of demands across accounts at each hour for the case study, Lakewood, CA during the period 1 July 2018–30 June 2019. Hourly prices for dynamic pricing are proportional to the difference between the demand at hour h (D_h) and the average demand across all hours $(\overline{D_h})$. Peak, off-peak, and mid-peak periods are identified through visual inspection.

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The new dynamic price becomes:

$$Pn_h = P * (1 + \Delta \mathrm{Pr}_h) \tag{4}$$

The *hourly* scenario in Table 1 was created by applying Equations 3 and 4 for 1-hr data. Other scenarios were created to test more realistic dynamic pricing policies. The first alternative policy is labeled *hourly-cap* and assumes a utility implements a 25% cap on price schedule from the hourly scenario. This price cap represents a utility's potential reticence to impose large changes in hourly price. For hourly and hourly-cap scenarios, the elasticity of water does not change diurnally (i.e., is always −0.4) and the price of water is changed every hour.

The *3block* scenario allows only three price changes (for mid-peak, on-peak, and off-peak hours) while the *2block* scenario allows price changes during peak and mid-peak hours but not during the off-peak period. For the 3block and 2block scenarios, we also use variable elasticity values, corresponding to off-peak, mid-peak, and peak periods. These changes are based on the assumption that water demand may be more elastic during peak hours. Previous studies identified that the demand during peak hours, which consists of several end-uses such as tap, toilet, shower, washing machine, dishwasher, and irrigation, may not be time-sensitive, and end uses such as washing machines, dishwashers, and irrigation can be shifted to mid-peak or off-peak hours (Beal & Stewart, 2014; Josey & Gong, 2023). Changes in elasticity in these scenarios lead to different consumer responses compared with other scenarios.

The price change for the 3block scenario is calculated at the three periods, peak, mid-peak, and off-peak using Equation 5:

$$\Delta Pr3block_h = \begin{cases} \dfrac{\overline{D_{ph}} - \overline{D_h}}{\overline{D_h}}, & \text{at peak demand hours} \\ \dfrac{\overline{D_{mh}} - \overline{D_h}}{\overline{D_h}}, & \text{at mid-peak demand hours} \\ \dfrac{\overline{D_{oh}} - \overline{D_h}}{\overline{D_h}}, & \text{at off-peak demand hours} \end{cases} \tag{5}$$

where $\overline{D_{ph}}$ is the average demand during peak hours; $\overline{D_{mh}}$ is the average demand during mid-peak hours; and $\overline{D_{oh}}$ is the average demand during off-peak hours.

The 2block scenario does not change the price during off-peak hours because it is expected that consumers are not likely or may not be able to shift high volumes of water demands to the night. Changes in price during peak and mid-peak periods are calculated based on demands during those periods alone and stimulate shifts in demand from peak periods to mid-peak periods (Equation 6), without considering demands during the off-peak period. However, this calculation yields smaller price changes for peak and mid-peak periods, compared with other scenarios. A correction factor, f, shown in Equation 7, is used to create larger price changes in peak and mid-peak periods that will yield demand changes that are in the same range, based on the volume of demand change, when compared with other policies. The correction factor increases the price during peak hours and decreases the price during mid-peak hours, while the price during off-peak hours remains fixed.

$$\Delta Pr2Block_h = \begin{cases} \dfrac{\overline{D_{ph}} - \overline{D_{ph+mh}}}{\overline{D_{ph+mh}}} + |f|, & \text{at peak demand hours} \\ \dfrac{\overline{D_{mh}} - \overline{D_{ph+mh}}}{\overline{D_{ph+mh}}} - |f|, & \text{at mid-peak demand hours} \\ 0, & \text{at off-peak demand hours} \end{cases} \tag{6}$$

where $\overline{D_{ph+mh}}$ is the average demand during peak and mid-peak hours.

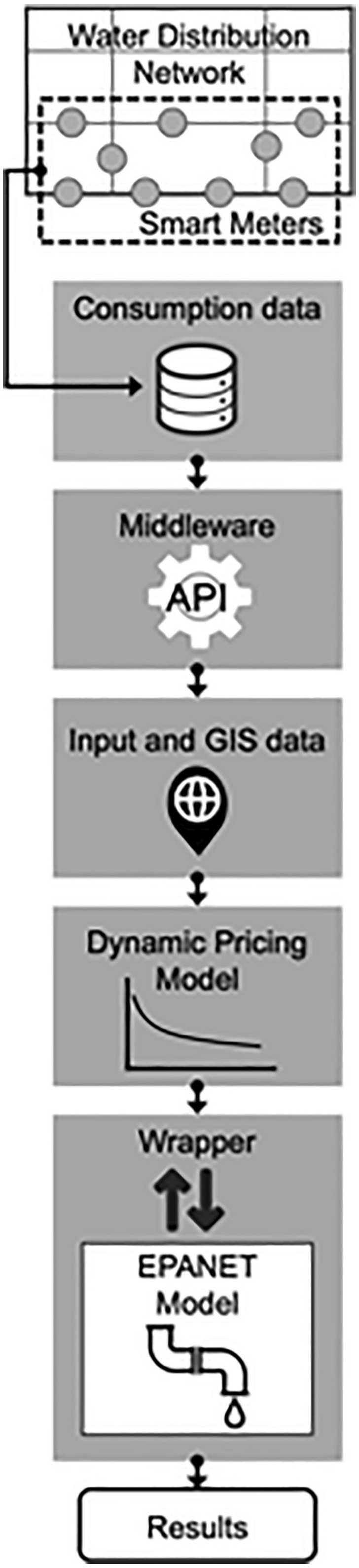

Figure 2. Modeling framework couples smart meter data with a hydraulic model to simulate dynamic pricing policies. API: application programming interface.

$$f = \frac{\sum_{n=t_{oh}}^{t_{oh}+N_{oh}} \Delta \mathrm{Pr}_h D_h}{N_{ph} + N_{mh}} \tag{7}$$

where t_{oh} is the first hour of the off peak period; N_{oh} is the number of hours in the off-peak period; N_{ph} is the number of hours in the peak period; and N_{mh} is the number of hours in the mid-peak period.

2.3. Dynamic Pricing Modeling Framework

A modeling framework was developed to simulate and evaluate dynamic pricing policies for households using water and the infrastructure system that delivers water (Figure 2). A digital twin was developed by Pesantez et al. (2022) and is updated in this research to include a new module that calculates changes in hourly demands using the demand change equation. While Pesantez et al. (2022) presented the modeling framework as a digital twin based on its ability to couple real-time water demand data with infrastructure modeling, this research does not simulate real-time flows and applies the modeling framework for analysis of proposed policies.

The data were uploaded originally to an application programming interface (API). To download the data, a script on Python was developed to request the data. The request includes the start and end times, and the interval, whether monthly, daily, or hourly. A temporary token was used to request access to the API prior to downloading. The data were downloaded in XML format. For this case, each month of the 1 year of data was downloaded separately due to computational limitations, since each file is approximately two gigabytes in size. The total size of the data is approximately 48 gigabytes. The next step parsed the data set from XML format to CSV, reducing the size of the file to 2.48 gigabytes.

The AMI data set is housed in a data frame, where each column represents a smart meter account, and each row is a time step of 1 hr. The dynamic pricing model was applied to each account, by applying the demand change equations (Equations 1 and 2) at each account to transform AMI data and calculate a time series of new demands.

A wrapper was used to aggregate AMI data into nodal demand patterns (Pesantez et al., 2022). The wrapper inputs are the transformed AMI data, the original hydraulic model, and the coordinates of the smart meters. The coordinates are converted to x and y coordinates, consistent with the nodes of the hydraulic model. The K-nearest neighbor algorithm is applied to search for smart meters that are neighbors to the nodes of the WDN. The sum of the demand patterns of each cluster of smart meters is calculated and assigned to a corresponding node in the hydraulic model. Each node is assigned a unique demand pattern, and this process produces a new hydraulic model input file, with the original features in addition to the updated demand patterns. The period of the demand patterns (number of hours that were simulated) varies based on the input consumption data. The new input file was used to execute the EPANET model and calculate flows and pressures throughout the network at hourly time steps.

2.4. Performance Metrics

Performance metrics evaluate the total demand difference, the total revenue of the utility, and the reduction of peak demands; in addition, dynamic pricing policies are evaluated based on the hydraulic performance of the WDS. Hydraulic performance is analyzed using five metrics introduced by Zhuang and Sela (2020): peak flow, total pumping energy, peak energy, water age, and total background leakage. The median peak flow, calculated over all pipes in the network, is used to represent peak flow. The peak energy is the maximum pump energy at any hour. The water age is the average water age at all nodes at the final step of the simulation, which is calculated by the simulation EPANET.

Background leakage is calculated using Equation 8. In this analysis, it is assumed that every pipe is associated with a leakage flow value. This calculation is based on the pressure difference between the two end nodes, the pipe condition (represented by parameter beta), and the hole size. The estimated volume of leakage can be verified in future studies by comparing the simulation results to utility data. For this study, the water lost to leakages provides a baseline for comparing the four proposed scenarios to the original one.

$$Q_{leak} = \sum_{k=1}^{k=N_P} \beta * L_k * P_k^{\alpha} \tag{8}$$

where Q_{leak} is the estimated leak flow associated with all (N_P) pipes, and L_k is the length of pipe k. The parameter P_k is the average pressure across pipe k, calculated as the average of the pressures at the beginning and end nodes for pipe k. The pipe degradation parameter is β, assumed equal to 10E−7; and α is the parameter of the area of the hole and is assumed to be equal to 0.5 (A. Berglund et al., 2017; Giustolisi et al., 2008; Zhuang & Sela, 2020).

Total pump energy (E_p) for each pump p is calculated as the sum of energy as follows:

$$E_p = \sum_{t=1}^{T} E_{p,t} = \sum_{t=1}^{T} \frac{1000 * 9.81 * HL_{p,t} * Q_{p,t} * \Delta t}{\eta} \tag{9}$$

where the head loss, $HL_{p,t}$, and flow rate, $Q_{p,t}$, are associated with each pump p at timestep t, and the timestep (Δt) is equal to 1 hr. The total number of timesteps that are simulated is denoted as T. The efficiency, η is assumed to be 70% across all pumps. The head loss for each pump p is calculated as the difference in head (H) between the end node, n_j, and start node, n_i, of the pipe where the pump is located.

$$HL_p = H_{n_j} - H_{n_i} \tag{10}$$

The peak energy is reported as the maximum pump energy $(E_{p,t})$ at any hour (A. Berglund et al., 2017; Giustolisi et al., 2008; Zhuang & Sela, 2020).

3. Case Study: Lakewood, California

The City of Lakewood is located in southern Los Angeles County, California. The city includes three zip code areas, and this study focuses on two zip code areas (90,712 and 90,713) that are served by the City of Lakewood water utility. The Lakewood WDS infrastructure and location of smart meters are shown in Figure 3. The population served by the distribution system is estimated as 59,419 (United States Census Bureau & Bureau, 2019).

A data set was collected at 20,286 smart meters reporting water consumption at single-family homes (SFH) during a fiscal year, from 1 July 2018, to 30 June 2019, at accounts in Lakewood, California. The data were downloaded using the API provided by the utility's partner, Neptune. The data set reports water consumption in cubic feet at hourly time steps and the longitude and latitude for each smart meter. Water consumption data were provided as direct logs of the meters. Data were cleaned and prepared by eliminating all accounts with incomplete consumption logs, leading to a set of 18,807 SFH smart meter accounts (Figure 3). Peak, off-peak, and mid-peak periods are used in 3block and 2block scenarios, and the demand periods were determined through visual inspection of the demands and the slope of the demand curve across all accounts for the period of data collection (Figure 5). The hydraulic model for the Lakewood WDS was developed in EPANET by the utility and shared with the research team to conduct this research.

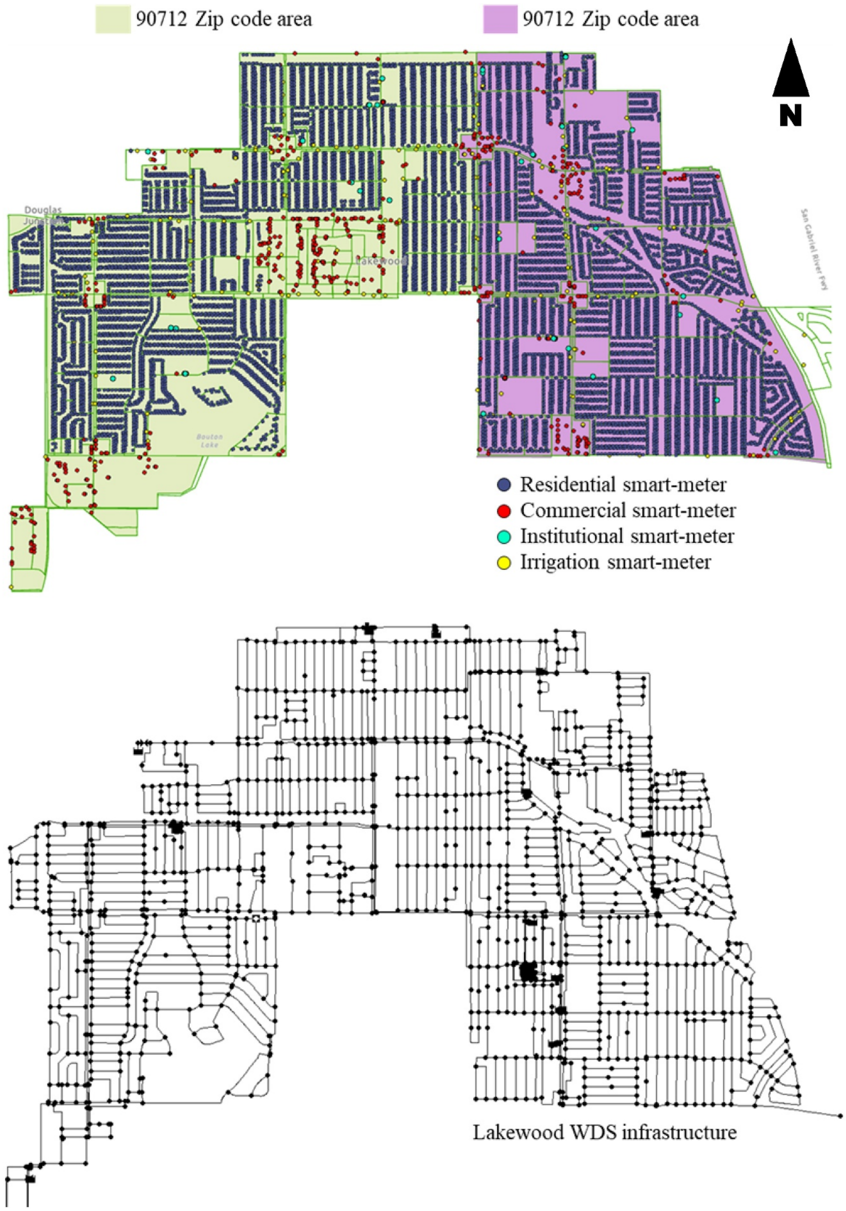

Figure 3. Smart meters and water distribution system infrastructure in the City of Lakewood, CA.

Lakewood's billing structure is a bi-monthly billing policy with two tiers of residential consumers and a minimum service charge of \$17.69. Accounts using less than 400 ft^3 (11.3 m^3) per billing cycle are charged only with the minimum service charge. Customers that use more than 400 ft^3 are charged for additional water at a rate of \$3.50 per 100 ft^3.

3.1. Energy Costs

The Lakewood WDS uses 21 pumps at wells and at pump stations in the network. The price of electricity for pumping varies based on the hour of the day, day of the week, season, and specific pump. The time of the day is classified as super off-peak, off-peak, mid-peak, and on-peak hours. Seasons are classified as winter (October 1–May 31) or summer (June 1–September 30), and pumps are classified within groups. Weekdays are classified differently than weekends. Weekdays generally have higher rates during day time hours when compared with weekends, and in most cases, holidays are treated as weekends. For illustration purposes, Figure 4 shows the

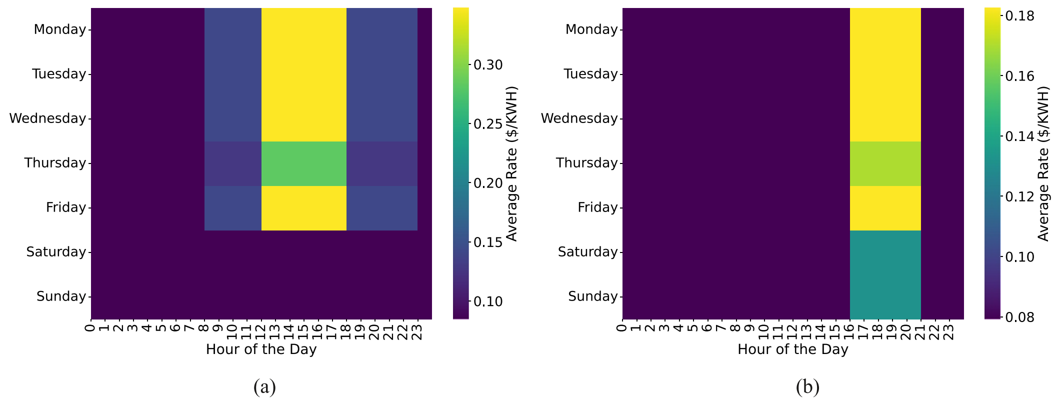

Figure 4. Average hourly rate ($/KWH) of energy for the period of July 2019, shown for (a) Group 1 pumps and (b) Group 2 pumps.

variation in the cost of energy for two pump groups, Group 1 and Group 2, for the month of July 2019, as an example. Thursday, 4 July, was a holiday, which reduces the average rates across Thursdays in July, as shown in Figure 4.

4. Results

The four scenarios described in Table 1 were simulated to evaluate the performance of dynamic pricing based on changes in water demand, hydraulic performance, energy, and energy cost. Each dynamic pricing scenario is run on Python 3.7 using Spyder IDE and requires approximately 5 min of computation time. The simulation is divided into three steps, the dynamic pricing model, the wrapper, and the hydraulic simulation. The dynamic pricing model takes approximately 3 min to run for one cycle (2 months of data). The wrapper requires 60 s to generate the modified hydraulic model for one scenario. Finally, the hydraulic simulation for 1 month requires 50 s. The model is executed using a i7-6700HQ CPU @ 2.60 GHz and 32 GB of RAM.

4.1. Changes in Demand

The base-case policy and four dynamic pricing policies were simulated to assess changes in demand. To apply the dynamic policies developed in Section 2.2 and shown in Table 1, the two-tiered pricing policy that Lakewood currently uses is removed. Price change ratios were calculated for dynamic pricing policies (Table 1) to establish the price of water at each hour (Figure 5a), and price change ratios were applied to a base price of $3.00 per 100 ft^3. As a result, prices vary from approximately $1.50 to $4.50 per 100 ft^3 for the four dynamic pricing policies, and the price remains at $3.00 per 100 ft^3 for the base-case policy. In addition to the marginal cost of water, each account pays a service charge of $17.69 per billing cycle, which reflects the minimum charge that is used in Lakewood's current policy. The base price was determined through simulations to maintain revenue neutrality between the base-case policy and Lakewood's current two-tiered policy. Revenue neutrality across the dynamic pricing policies is assessed and reported in Section 4.3.1.

Demand response is reported as the demand change ratio (Figure 5b). In the hourly scenario, demand change ratio values follow the price change ratio pattern because the elasticity value does not vary across the hours of the day, and the demand change ratio ranges from 20% and −20%. Demand change ratios for the hourly-cap scenario have a similar pattern when compared with the hourly scenario. Because the 25% cap is applied to the change in price, the magnitude of demand change is limited by values that range from −10% to 10%. The 3block and 2block scenarios also range from −10% to 10% and use fewer changes to hourly price.

Demand change ratios for each scenario were applied at each account for six bi-monthly cycles, corresponding to bi-monthly billing cycles for water bills, across the period of 1 July–31 August 2018 (Figure 5c). Dynamic pricing scenarios are compared with the base-case that does not apply a dynamic pricing policy (base-case scenario in Figure 5c). Each dynamic pricing policy reduces the peak demands that occur at 6:00 a.m. and 7:00 p.m., with the hourly scenario generating the greatest reduction. The hourly scenario reduces the morning peak by 21.1% and the

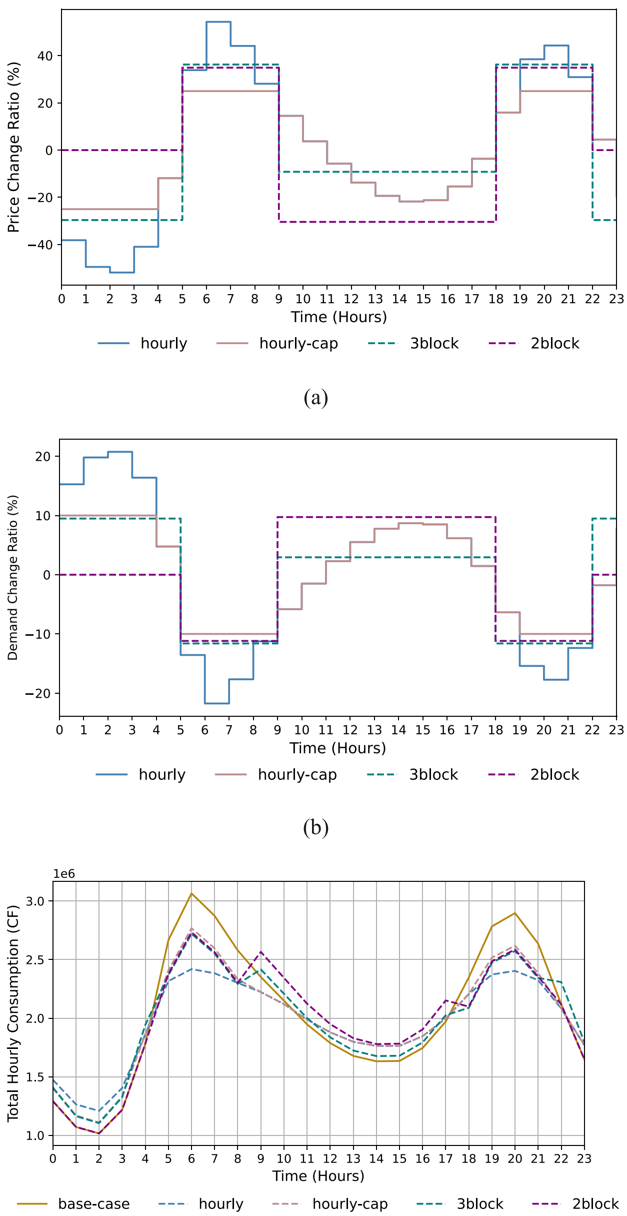

Figure 5. Dynamic pricing policies generate (a) price change ratios and (b) demand change ratios. (c) Demand change ratios are applied to each consumer account for the period of July–August 2018 and reported as the total hourly consumption across customer accounts.

evening peak by 14.8% compared with no dynamic pricing (base-case scenario). The hourly-cap, 3block, and 2block scenarios reduce the morning and evening peaks by approximately 10%. Due to smaller changes in price (Figure 5a), there is less variation in demand when compared with the hourly scenario. The standard deviation of the average demands across the 24-hr period is evaluated to further assess changes to the demand profile. For the hourly scenario, the standard deviation is reduced by 31.6% on average, compared with the base-case scenario, indicating a flattened curve when compared with no dynamic pricing. For scenarios hourly-cap, 3block, and 2block, the standard deviation of the average hourly demand profile is reduced by 20.5%, 20.1%, and 15.2%, respectively. The 2block scenario does not lead to changes in demand at off-peak hours and is limited in its ability to flatten the demand curve. Note that peak periods were selected using one fiscal year of data, shown in Figure 1, corresponding with the results reported in Figure 5.

Demand changes that emerge due to dynamic pricing policies are inspected via heat maps for each bi-monthly billing cycle over the 12-month simulated period. The total demand reduction varies from 0.2% to 4% across all cycles and scenarios (Figure 6a). For all scenarios, reductions in the morning peak are substantially higher from March through October, and the effects are reduced from November through February. Although dynamic pricing policies modeled in this research lead to changes in the timing of water use, there is not a significant change in the amount of water that consumers use. The hourly scenario leads to the highest change in total demand, with decreases of up to 4%.

Changes in morning and evening peak demands are also inspected using heatmaps (Figures 6b and 6c). While the hourly scenario generates a maximum reduction in morning peak demands of 25.5% during the September–October billing period, the hourly-cap scenario shows a maximum decrease of 9.7% in morning peaks across billing cycles. The hourly-cap policy is limited by the 25% cap on the price change. The 3block scenario generates reductions in the morning peak up to 11.3%, and the 2block, a maximum of 10.8%. These trends are repeated for changes in the evening peak (Figure 6c). As shown in Figure 5, demand changes for the hourly-cap, 3block, and 2block scenarios report similar changes during peak times, and the largest change during the peak periods is generated by the 3block scenario, followed by the 2block scenario, and finally, the hourly-cap scenario. The lowest reduction in peak flows across times of day and scenarios are reported for the billing periods November–December and January–February. Water demand profiles during the winter months are flatter with less variation, and dynamic pricing is not as effective at shifting demands when the demand profile is relatively flat. Dynamic pricing is more effective during the summer season, instead, when the demand profile has high peaks related to outdoor irrigation.

Results are limited by modeling assumptions, such as elasticity values that are applied throughout the 24-hr period. For example, it may not be realistic to assume that demand at 1:00 a.m. will increase in response to dynamic pricing, and these values of total demand should be assessed using more realistic approximations of elasticity values when those become available. The 2block scenario was developed to account for consumers who cannot adjust their water use during off-peak hours (e.g., late night and early morning). Further research is needed to explore intraday water elasticity values and their effects on the performance of dynamic pricing policies.

Water Resources Research

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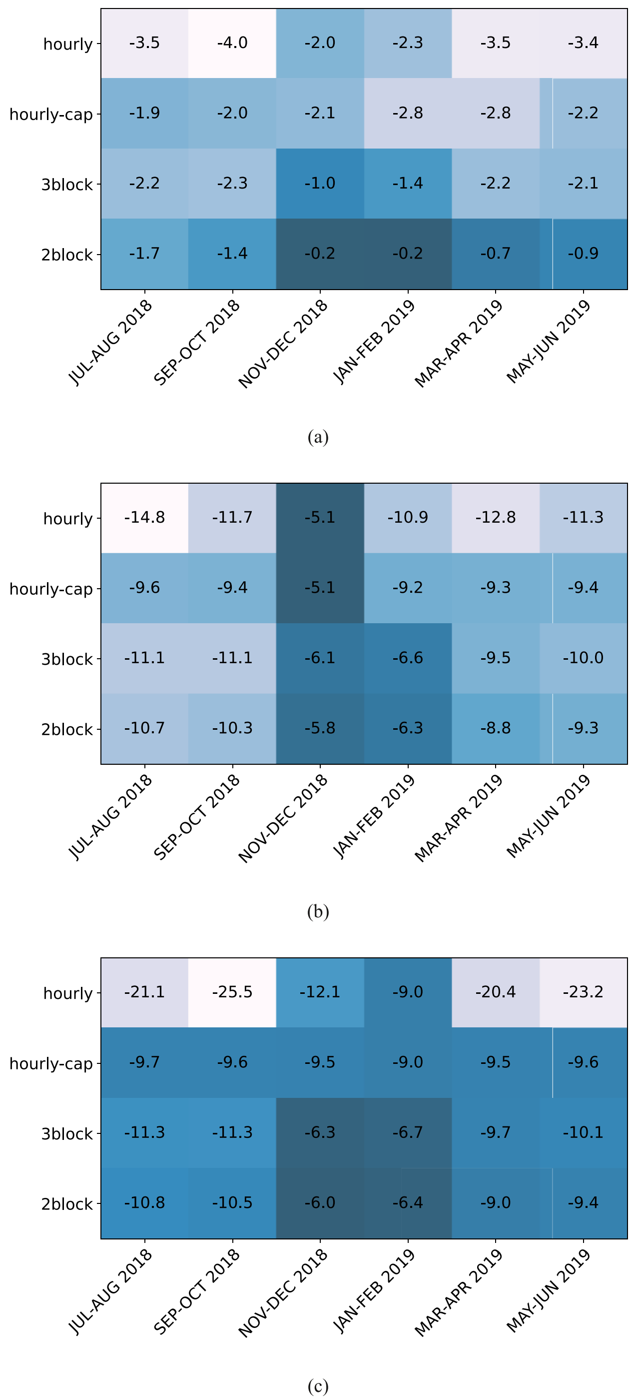

Figure 6. Changes in total and peak demands for scenarios when compared with the base-case scenario, reported for bi-monthly billing cycles as (a) change in total demand (% difference), (b) change in the morning peak demand at 6:00 a.m. (% difference), and (c) change in the evening peak demand 7:00 p.m. (% difference).

4.2. Hydraulic Performance Analysis

Hydraulic simulation is applied to model the effect of dynamic pricing scenarios for a 1-month period (July 2018), and hydraulic metrics are compared with the base-case scenario. While results above (Figures 5 and 6) are reported in bi-monthly intervals across 1 year, corresponding to the billing cycle for water, hydraulic simulation results and analysis of energy (shown below) are reported for 1 month to correspond with utility energy costs, which are billed on a monthly basis. Peak pipe flow, which is the maximum of the sum of flows in the pipe network at any hour, is reduced for each scenario (Figure 7). The hourly scenario results in the greatest reduction at approximately 16%, and the 3block scenario generates a reduction of almost 14%.

Water age increases for all scenarios, increasing 2.0–4.0 hr relative to the base-case, with the hourly scenario resulting in the highest impact (Figure 7). Increases in the water age occurred because of peak flows decreased in the system in all scenarios. The water age does not exceed 24 hr in these simulations. Increased water age in a WDS leads to a higher risk of compromised water quality and health risks. The average water age for WDSs in the United States is 31–72 hr (Kourbasis et al., 2020), and the values reported here should not introduce a significant additional risk for any of the scenarios. For other WDSs that report high water age under base-case scenarios, dynamic pricing may be expected to increase the water age and can be tested using the modeling framework and approach presented here.

Leakage is evaluated as the total volume of water lost to background leaks that may occur due to pre-existing cracks in pipes. Dynamic pricing scenarios decrease peak flows, which increases the pressure in the system and the volume of water lost through cracks and breaks in pipes. On the other hand, dynamic pricing may reduce leakage by inducing pressures that are uniform across a day. The volume of water lost to leakage increases for the hourly scenario and the 3block scenario by less than 1.2% and decreases in the hourly-cap scenario and the 2block scenario by approximately 0.2% (Figure 7). This is reported for July 2018 in Figure 7, and in other months, changes are closer to zero. While results do not demonstrate significant impacts on leakage, dynamic pricing may be explored within pressure management strategies for other WDSs to assess the effects of flattened demand curves on improving the uniformity of pressure across a network.

4.3. Energy Consumption and Cost

The energy cost of pumping is calculated based on the rate structure of energy, which varies over pumps, time of day (peak and off-peak hours), and time of year. Modeling results for the cost of energy for the base-case scenario were compared with the utility cost of energy. Calculated energy costs were similar to reported costs, and the difference in cost ranged from 0.0% to 3.7% for 20 of the pumps, and 9.7% for the last pump.

The total energy consumption across the system decreases by less than 1% for each scenario (Figure 8). For the month of July 2018, peak energy decreased by 14.8%–14.9% across scenarios because one pump that was turned on during the base-case scenario was not needed to provide extra pumping for the dynamic pricing scenarios (Figure S1 in Supporting Information S1). As shown in Figure S1 in Supporting Information S1, the four dynamic policy scenarios all generate the same reduction in peak energy each month, with no reduction in October through June. Although the policies generate variations in peak flow reduction, the energy required to provide the peak flow is uniform across scenarios because one pump is turned on (or not). The dynamic pricing policy led to a cost saving in all scenarios, ranging

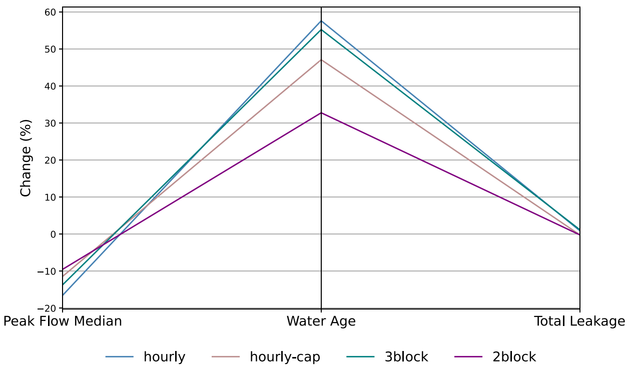

Figure 7. Parallel coordinate plot shows the change in hydraulic metrics when compared with base-case scenario, reported for July 2018 as % difference.

from 2.3% to 4.2% (Figure 8 and Figure S1 in Supporting Information S1). The reduction in energy cost is a nonlinear and discrete function of the reduction in total energy and reduction in peak energy.

4.3.1. Change in Revenue and Consumer Cost

Dynamic pricing scenarios are compared based on total revenue as shown in Figure 9. The average total revenue increases by 0.0%–10% for each scenario. The 2block scenario shows the least amount of change in revenue because prices during the off-peak hours are not changed. Limits on the amount of variation in price lead to higher total revenue changes. Scenarios with more restrictions on price changes lead to a lower volume of water that is shifted from peak periods to periods of lower price. In the hourly scenario, demand shifting is not restricted, and a higher volume of demand can be shifted to periods when the price is lower. Revenue increases are not necessarily desirable, as utilities may wish to maintain revenue neutrality, and these results demonstrate that dynamic pricing can be designed to result in minimal changes in total revenue. Further research can explore optimization approaches to further reduce the change in total revenue.

An additional scenario called the 2block-e0 scenario was created to examine how dynamic pricing affects consumer bills. This scenario evaluates changes in consumer water bills when a dynamic pricing policy is in place, but consumers do not respond to price changes under the assumption that elasticity is equal to 0.0. The 2block-e0 scenario uses the pricing structure that is was developed for the 2block scenario, and consumers use water at the same rate as reported in the original AMI data. In the 2block-e0 scenario, the average bi-monthly billing amount increases by less than $4 compared to the 2block scenario. The distribution of billing amounts for both scenarios is shown in Figures S2 and S3 in Supporting Information S1. For the July–August billing cycle, the average bi-monthly bill for the 2block scenario is $92.17, and the average bill for the 2block-e0 scenario increases by $3.35. For the January–February cycle, the increase in the average bill is $0.55. These results suggest that changes in water prices would have only a small impact on most users, even when they do not change their water usage behavior in response to dynamic pricing. Utility managers should consider the effects of dynamic pricing on bills when consumers are unable or unwilling to respond to changing prices or lack information about the relationship between water usage and energy costs. Future research could explore pricing policies that allow marginalized groups to use water in typical patterns while mitigating hydraulic performance and energy costs.

5. Dynamic Pricing Policies Under Demand Growth Scenarios

Additional modeling scenarios were created to evaluate the ability of dynamic pricing policies to provide additional infrastructure capacity for meeting increased water demand. Demands reported by the AMI data are

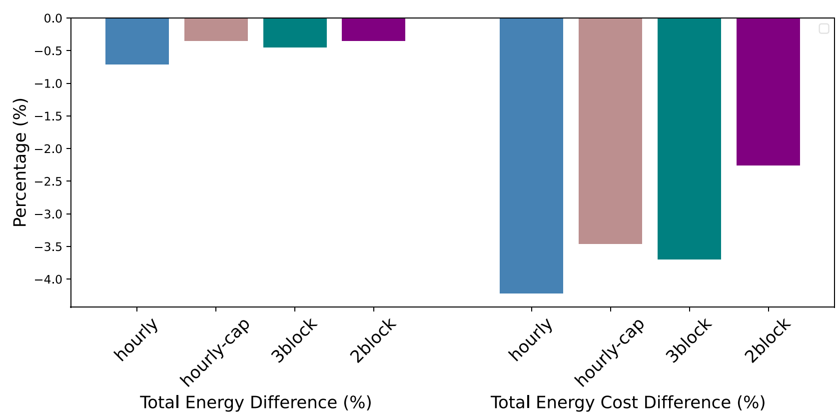

Figure 8. Change in energy consumption and energy cost when compared with base-case scenario, reported for July 2018 as % difference.

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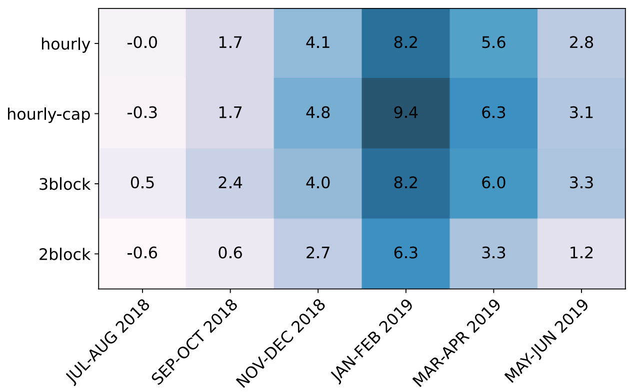

Figure 9. Change in utility revenue compared with base-case scenario, reported as percent difference.

increased in 5% increments to simulate potential increase in demands due to population growth through infill. Note that the infrastructure system is not updated. Instead, through these simulations, we assess how the existing capacity of the infrastructure can be extended to meet future demands by shifting peak demands through dynamic pricing. The performance of the system is recorded at each 5% increase to identify the maximum demand growth that the system can accommodate without any change to the infrastructure or any new investments. The average minimum pressure was assessed for each month to check for negative pressures, which indicate that the system is undersized. The system can sustain a maximum increase in demand of 25% without leading to negative pressures, when dynamic pricing is implemented (Figure S4a in Supporting Information S1). The minimum pressure under 25% increased demands is negative in August 2018 when dynamic pricing is not used (Figure S4a in Supporting Information S1), while dynamic pricing scenarios result in pressures that are positive. The hourly-cap, 3block, and 2block scenarios bring the pressure to a value that nearly meets the acceptable range of 20 psi. Low pressures occur in high-demand months of the year, June to September, and other months reported minimum pressures around 50 psi. These simulations demonstrate that dynamic pricing can offset the need for new infrastructure due to increased demands. These scenarios represent the effect of applying dynamic pricing policies in delaying the need for expansion projects.

6. Discussion

6.1. Contributions

This research applied a simulation approach to analyze AMI data and quantify the expected effects of dynamic pricing to reduce peak water demands. The framework presented in this manuscript uses water consumption collected at approximately 20,000 households and couples data with a network hydraulic model to analyze hydraulic performance, energy consumption, and energy cost. While existing frameworks to assess dynamic water pricing use predicted demands (Vašak et al., 2014) or a range of assumed price change ratios (Rougé et al., 2018), this research contributes new insight by coupling models of elasticity, time-of-day use tariffs, and water demand data with hydraulic simulation to provide a quantitative evaluation of the effects of dynamic pricing on energy costs.

Results demonstrate how dynamic pricing policies could lead to reductions in the cost of energy. It is expected that many water utilities pay transmission charges on peak energy demands similar to that modeled in this study, and, as resources become increasingly scarce, dynamic pricing may serve as an important management strategy. Managers can consider an array of metrics to measure performance to address utility-specific objectives, for instance revenue neutrality and total customer bills. Utility revenue increased by a maximum of 9.4% under all tested scenarios, but revenue changes under some policy/demand combinations were near zero. Consumer water bills were assessed through additional simulations, which identified that consumers who did not respond to price changes would pay on average 3%–4% more for water bills, when compared to water bills under no dynamic pricing policy.

Hydraulic metrics such as background leakages and pressure assess the reliability of the infrastructure under new policies; high pressures and leakage can lead to increased pipe breaks in some cases. Pressures and leakage were affected marginally by different dynamic pricing policy scenarios. This research finds that the maximum flow and average flow, in general, are lowered in all scenarios, leading to lower velocities. Lower velocities lead to higher water ages, which can allow bacterial growth in the network. For the Lakewood system, the water age does not increase to thresholds that would be considered a threat to health. Lower velocities can also lead to savings and improvements in long-term infrastructure maintenance and aging. This research does not assess the long-term effects of lower velocities, and further research is needed to develop models that can evaluate minimum velocities and quantify cost savings.

Dynamic pricing is a potential solution for averting the need for infrastructure expansion due to economic and population growth. This research tests the ability of dynamic pricing to mitigate pressure losses that accompany increased demands. Dynamic pricing can mitigate negative pressures for up to 25% increase in demands for the

Lakewood system by shifting demands and lowering peak flows. Demands were increased uniformly across the network, and further research can explore specific economic growth scenarios to explore how hotspots of demand growth may affect the performance of dynamic pricing policies.

Results reported above provide an approach to assess trade-offs among dynamic pricing policies. The hourly scenario reports the highest reductions in peak flow and energy cost with relatively small changes in utility revenue. It also generates a negligible change in leakage, but larger changes in water age and it does not lead to an infrastructure system that can support high levels of demand growth, based on pressure in the system. Other scenarios may also be more politically feasible. A 2block policy can be used to better communicate price changes to the public; it generates approximately half of the cost savings when compared with the hourly scenario, but better maintains revenue neutrality and can mitigate infrastructure failure to support high levels of demand growth.

Dynamic pricing and AMI data provide cities the ability to "smarten" infrastructure operations using real-time data and algorithms (E. Z. Berglund et al., 2020). The framework developed in this research is first of its kind to enable dynamic analysis of dynamic water pricing. For instance, utilities could explore new opportunities to induce pro-environmental behavior, such as transferring energy cost savings back to consumers to further lower prices in off-peak periods. While pricing policies simulated here provide the opportunity for cost-savings for customers—as the price of water is reduced during off-peak periods—caution is warranted. Dynamic pricing would introduce significant customer relations and political implications, and further research is needed to conduct benefit-cost analysis that includes political and social dimensions.

6.2. Limitations

6.2.1. Infrastructure Modeling

Results presented in this research are sensitive to the topography and operation of the Lakewood distribution network, which utilizes pumps and tanks to satisfy the required pressure and demand. Other WDSs would experience different changes in energy consumption based on their unique structures. Model error may affect the comparison among dynamic pricing scenarios, as many hydraulic models are not developed to run within a digital twin system that is updated for hourly demand data. On-going research is calibrating the Lakewood model to match pressures and flows to hourly Supervisory Control and Data Acquisition data when AMI data is used as input. While this research focused on demand-side management, energy savings can be further improved through optimizing pump controls and infrastructure operations. Further research is needed to evaluate the effectiveness of adjusting infrastructure controls in tandem with dynamic pricing policies to reduce energy consumption, improve energy cost savings, and mitigate high pressures and leakage.

6.2.2. Consumer Behaviors

This research assumes a uniform price elasticity of demand across all consumers. The effect of heterogeneity in consumer characteristics, such lot size, number of occupants, or socioeconomic status, on elasticity is not evaluated in this research. Further research can update the modeling approach to include the effect of demographics on elasticity values, as that information becomes available. Different elasticity values for each account can be assigned and used within this framework when those values become available, for instance if the characteristics of the consumers, such as the lot area or the number of residents, affect the elasticity for intraday periods. New research is needed that would explore how informational campaigns can both improve customer awareness of the interactions between the timing of water use, energy consumption, and energy cost and create changes in water elasticity values. Across scenarios, the model reports small reductions in total demand, and though conservation is not the objective of this framework, changes to total demands and utility revenues can be further minimized through optimization or machine learning algorithms.

This study simulates changes in demands based on the volume of demand and the time of day that water is consumed. This formulation was developed to accommodate the available data, which is AMI data reported at hourly intervals. More realistically, consumers may associate different elasticities with different end uses based on the ease of shifting the timing of showering, flushing the toilet, drinking water, preparing meals, washing dishes, irrigation, and laundering clothes. Higher temporal AMI data can be used to characterize end uses that can be more easily shifted, such as irrigation and laundry demands, and test dynamic pricing policies that target these end uses.

Although the dynamic pricing policies modeled here lead to changes in the timing of water use, there is not a significant change in the amount of water that consumers use. The hourly scenario leads to the highest reduction in the total demand, which is approximately 4%. Dynamic pricing policies can support equitable access to water as they allow consumers to continue to access water, and no large aggregate demand reductions are required. To take advantage of potential cost savings, however, consumers need to have the flexibility to shift the time that they exert demands. Some demands may be unmovable due to school and work schedules, for example. Allowing consumers to have the option to opt-out of participation in dynamic pricing may be an important characteristic of water pricing that enables equitable outcomes.

6.2.3. Equitable Policies for Dynamic Pricing

Dynamic pricing has been criticized because it can create inequities among water users and exacerbate inequities in the cost of water (Karrenberg et al., 2024; Lamolla et al., 2022; Solis & Bashar, 2022). Water customers who use water for necessary purposes alone may not be able to shift the timing of their water consumption, whereas water users who use water for discretionary purposes (e.g., irrigation and pools) may be able to shift their time of consumption and reduce their cost of water. Equity and price neutrality considerations have been explored for block rate tariffs (Lopez-Nicolas et al., 2018), in the context of monthly tariffs. New research is needed to explore how to develop intraday block rate tariffs and take into account economic efficiency, customer heterogeneity, affordability, and water conservation (Fuente, 2019). As described above, Cole et al. (2012) pose intraday block rate tariffs based on accounts that exceed an hourly water demand and evaluate impacts to water bills if consumers do not respond to price changes or change their water use behaviors. Without knowledge of intraday elasticities or demand response behaviors, it is difficult to assess equity in dynamic pricing policies. Further research is needed to explore the implications of dynamic pricing within a block rate tariff within the context of the metrics described here and the metrics introduced by Fuente (2019).

Our model is applied to a utility with a constant marginal per-unit charge for water and none of the four scenarios included billing-period block rate pricing. The implementation of dynamic pricing while retaining traditional billing-period block rates will create complex interactions in behavior that may limit the generalizability of the findings reported in this research. The framework can, however, be extended to model intra-day pricing under more complex water tariff systems in future research.

6.3. Transferability and Reproducibility

The dynamic pricing models developed here can be applied for other WDSs, based on the availability of data. Data required includes a hydraulic simulation model and hourly AMI data at the account level, specifying the account type, the coordinates of smart meters, and water consumption data. This approach is applicable to a WDS with the required data through minor modifications to the scripts. The methods developed in this research consists of several parts: a Python script that communicates with the API to download the AMI data; an *R* script to arrange data on monthly dataframes and exclude corrupted portions; a Python script to prepare all data including AMI and GIS data to filter data for the model; a Python script to apply the dynamic pricing model for each scenario; a Python script that aggregates account demands to nodal demands in EPANET input files; and a Python script that calculates the metrics and plot the result figures. The analysis of dynamic pricing policies will vary for individual WDSs, as each WDS is unique based on consumer types and number and infrastructure system, including, for example, the pipe network, tanks, and pumps. The Lakewood WDS provides water to mostly SFH accounts and relies on pumps to deliver water. Networks that are gravity-driven, for instance, will not benefit from energy reduction by applying a dynamic pricing policy. In contrast, if the system depends on pumps during high peak demands and energy costs, the dynamic pricing policy could generate significant effects, leading to energy and cost savings.

7. Conclusion

This research creates a new model to simulate consumer demands that shift in response to dynamic pricing policies based on elasticities. The model output is the modified demand of each consumer, which is aggregated as nodal demands and is used to simulate changes in network metrics, including peak demands and energy costs.

This research developed four scenarios to simulate dynamic pricing policies. In the first scenario, the price changes at each hour without restriction and with a constant value of elasticity of −0.4. To limit the price increase, a price change cap of 25% is added to the second scenario. The third and fourth scenarios have two lower elasticity values for the mid and off-peak hours as −0.36 and −0.32, respectively, in an effort to reflect consumer use being less changeable outside of peak hours. These scenarios are created to explore dynamic pricing policies that may be more realistic, more acceptable for customers, and easier for utilities to implement. The model is applied to the City of Lakewood, where most of the demand is exerted by residential consumers. Dynamic pricing leads to a flattened demand curve, and the peaks are shifted and reduced. Policy scenarios which apply restrictions on the price change, however, lead to less demand reduction. The hydraulic performance of the network is similar across all four scenarios, and utility revenue increases marginally.

The results of this research demonstrate that operational costs can be lowered through a dynamic pricing policy. In addition, dynamic pricing can lead to energy savings and support a more sustainable future. As demands continue to grow with economic and population growth, dynamic pricing can offset the need for new infrastructure. Further research is needed to develop elasticity values that reflect the ease of shifting demands based on the time of day and specific end uses. Further research can also explore how to optimize infrastructure operations and controls that will most effectively save energy costs in tandem with dynamic pricing policies. This research provides a toolbox that can be used by decision-makers to develop and explore new pricing strategies that will protect natural resources and conserve both water and energy in urban management.

Data Availability Statement

Dynamic pricing models and codes that support the findings of this study are made available by Alghamdi et al. (2023). AMI data and hydraulic models are not accessible to the public or research community due to privacy implications and are available only from the city of Lakewood by request.

Acknowledgments
The data used in this research was provided by the City of Lakewood, California. Faisal Alghamdi was funded by King Abdulaziz University, Saudi Arabia, through the Saudi Arabian Cultural Mission to the US (SACM).

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