ABSTRACT

ALGHAMDI, FAISAL MOHAMMED G. A Dynamic Pricing Framework for Water Demand Management Using Advanced Metering Infrastructure Data. (Under the direction of Dr. Emily Z. Berglund).

Cities face continuous challenges in maintaining and operating reliable water supply systems. Management strategies are needed to support both water conservation and cost reduction of infrastructure operations. New pricing policies can be used as an instrument of water demand management to reduce the cost of operating, maintaining, and expanding water distribution networks. As utilities adopt advanced metering infrastructure (AMI), new data that describe water consumption at high temporal resolution and accuracy are available and can be used to evaluate demand management policies. In this research, dynamic pricing strategies are developed and evaluated as a tool to enhance the performance and life of water distribution systems (WDSs). This research investigates the performance of a dynamic pricing framework designed to flatten the daily demand curve by reducing peak demand. Demand changes reduce peak flows within the WDS to mitigate the cost of energy. Several criteria are used to evaluate the effects of dynamic pricing on drinking water infrastructure management, including the cost of water for consumers and the hydraulic performance of the network, based on water loss, peak flow, energy consumption, energy cost, and water age. AMI data collected at nearly 20,000 accounts at Lakewood City in California are used to develop a model of expected water use and simulate changes in consumption and in-network metrics. This research developed four dynamic pricing policies with different parameters and levels of constraints to test the model. Analysis is conducted to explore reductions in the peak demand, reduction in total water demands, and hydraulic performance. Results demonstrate that reductions in peak demand ranging from 8% to 20% lead to a 40% reduction in peak energy demands and a 10-11% reduction in total energy, with a maximum of 13% reduction in energy cost. Cost savings reflect the importance of dynamic pricing as a demand-side strategy to manage infrastructure. Operational costs can be lowered without new infrastructure investment or expansion, while continuing to meet urban water demands.

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

by
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DEDICATION

To my late mother, Ghaliyah, and my father, Moahmmed, the most loving encouraging and supportive in my life.

To Rashidah, Aljowharah, Rasheed, Ameerah, Fahad, Malak, and Sultan, who have been always there when I needed.

To my wife, Somya, for always being supportive, encouraging, and patient with me.

To my friend, Abdulrahman, for his unlimited support.

BIOGRAPHY

Faisal Alghamdi was born in Taif, Saudi Arabia. He graduated with a BS in Civil Engineering from King Abdulaziz University (KAU), Jeddah, Saudi Arabia, in 2015. During his undergraduate studies, he worked as a project management assistant at TWARD, a construction company. As an intern he worked on the Grand Mosque Expansion. He was also a co-founder and president of the Civil Engineering Students Club. After graduation he joined Saudi Aramco as a civil engineer in the Engineering Division. In 2017, he joined King Abdulaziz University as a Teaching Assistant in the water resources engineering group. In 2019, he joined NCSU to pursue his master's degree in water resources engineering. He is passionate is about the use of new infrastructure systems such as Advanced Metering Infrastructure to apply and develop water distribution management strategies.

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CHAPTER 1: INTRODUCTION

Management of urban water resources is challenged by a number of factors, including climate change, population growth, land use change, and ageing infrastructure (Bhatkoti et al., 2018; Garrone et al., 2019; Sahin et al., 2017). New management strategies are needed to conserve water resources and reduce the cost of supplying and distributing water (Bhatkoti et al., 2018). Water distribution systems are critical infrastructure and distribute water to meet residential, industrial, and commercial demands over large geographic areas. Water demand management provides important mechanisms to conserve water and energy and reduce the cost of natural resources. Water pricing methods are an effective water demand management strategy. Pricing policies can reduce the cost of water and the cost of operating, maintaining, and expanding water distribution networks. The adoption of Advanced metering infrastructure (AMI) within the water industry provides access to new datasets that report high-resolution readings of water consumption at the account level. Observations of sub-hourly and hourly demands enable dynamic pricing as a new strategy to reduce peak water demands by adjusting intraday water prices on an hourly or sub-hourly basis. This research develops a dynamic pricing framework (DPF) as a tool to enhance hydraulic performance for water distribution systems (WDSs) (Rougé et al., 2018; Vašak et al., 2014). This research presents the application of a dynamic water pricing framework and its effects on the water distribution systems, based on reductions in the cost of energy. In this work, dynamic pricing strategies focus on reducing peak-hour demands. Peak-hour demands pose a challenge for managing water distribution infrastructure. Peak demands lead to high energy costs needed to pump water due to transmission charges, which are applied to the highest energy consumption during any (typically 15-minute) interval in a billing period. Minimizing the peak demand or flattening the demand curve can lead to improvements in WDS management, energy costs, and

infrastructure integrity. The DPF applies changes to the water price to reflect the demand change during the day as an incentive to the consumers to shift water use from peak-hours to non-peak-hours (Rougé et al., 2018). Consumers respond to dynamic prices based on the price elasticity of demand. The effects of the DPF are measured by several metrics falling under three main categories, namely water demand, hydraulic performance, and energy and energy cost.

This research develops a DPF to simulate and evaluate dynamic pricing strategies. First, dynamic pricing policies are developed based on diurnal demand patterns and peak water demands. Changes in water demands are simulated based on elasticity values. Changes in water demands are coupled with a hydraulic simulation model to simulate changes in flows, energy consumption, and energy costs due to demand changes. The DPF is applied for an illustrative network that serves Lakewood, CA. AMI data of water consumption is used to apply the proposed DPF framework for four scenarios of pricing that explore changes in elasticity and price as they affect the performance of dynamic pricing. Results demonstrate that dynamic pricing can change peak energy demands by up to 40% under the assumptions of intraday water elasticity. This research develops a new understanding for water managers about the application of dynamic pricing to achieve management goals. The DPF can be applied to explore and develop new dynamic pricing strategies for utilities interested in reducing costs of energy.

CHAPTER 2: BACKGROUND

The global population is estimated to grow by two billion in the next three decades and to reach 11 billion by 2100 (United Nations, n.d.), while water available for human consumption is not expected to increase during that time. Drinking water that is safely managed is not accessible by almost 2.2 billion people around the world, or more than a quarter of the global population (WHO, n.d.). In the United States, the Environmental Protection Agency reported in 2018 that almost half a trillion dollars should be invested in the water system infrastructure over the next 20 years (US EPA, 2018). This amount does not include the funds needed for EPA's compliance with the Lead and Copper Rule, which is currently estimated at more than $400 million and increasing. The American Society of Civil Engineers reports that drinking water infrastructure has a grade of C- based on their recent report card of America's Infrastructure (ASCE's 2021 Infrastructure Report Card, 2021). Those global and national challenges increasingly impose stresses on water distribution systems. Efforts to address such challenges are of critical importance and include water conservation, water resources management, and water demand management.

Water demand management includes several strategies and methods to reduce total demands or shift demands from peak periods. Peak daily demands are critical to the design of water distribution systems and drive the design of infrastructure expansion. Utilities that can reduce peak demand may find significant cost savings. Savings may come from the offset or delay of capital investment in expanding the system or direct savings to the cost of the pumping energy to satisfy the peak demand (Cole et al., 2012; Rougé et al., 2018). According to the EPA, 40% of operating costs for drinking water systems are applied to energy costs (US EPA, 2020). Energy rates are structured based on the monthly peak energy, time of use, and total energy used. The cost of energy can be reduced by reducing the peak demand.

Water pricing methods are one set of water demand management strategies. Conventionally, water tariffs are fixed by a volume–unit price that is billed monthly or bi-monthly. This basic method of estimating water price does not take into consideration several factors of variability. For example, water scarcity, the production cost of water (especially related to changes in the cost of energy), and water demand variability during different temporal scales (peak demand) can affect the value of water. Typically, water prices are not changed to reflect the changing value of water. Dynamic pricing strategies can be applied to change the price of water for sub-daily time steps (Rougé et al., 2018). Dynamic pricing provides an incentive to consumers to change or shift their water use patterns (Sahin et al., 2017). Dynamic pricing policies specify the policy, or schedule of price changes, based on utility costs and price elasticity (Marzano et al., 2018a; Rougé et al., 2018). The pattern of the daily water demand of residential consumers has two peaks around 7:00 AM and 7:00 PM, and in times such as after midnight and in the afternoon, the demand is less than the average. Dynamic water pricing can be used to encourage consumers to redistribute their consumption toward low-demand hours (Marzano et al., 2018a).

A dynamic pricing framework was developed by Vašak et al., (2014). Their framework consists of two main systems. The first system is a data management platform that stores the collected data of consumption via smart meters and other data such as weather, utility parameters, and a day-ahead predicted demand. The second system is an optimization approach to develop the dynamic pricing policy. The goal of the optimization process is to minimize the operational cost for the utility by proposing a day-ahead hourly price, under the constraints that the revenues must be equal to or greater than the cost, the unit hourly price is limited by minimum and maximum price settings, and the water demand at any hour is equal to or greater than zero. Results

demonstrate that using a dynamic pricing system can reduce the costs of utility's operation by 5.28% and consumers' bills by 3.98 % (Vašak et al., 2014).

Rougé et al., (2018) proposed a dynamic pricing policy that shifts and reduces peak demand to reduce the investment needed for infrastructure expansion. Results demonstrate that increasing the price of water during the peak demand hours leads to demand reduction and operational savings. Rougé et al. reported that significant savings can be found in the operation and maintenance of infrastructure in addition to delaying expansion projects. Their framework also explored and evaluated scarcity pricing across a shared water basin. They found that using scarcity pricing, which increases the cost of water during longer (e.g., seasonal) periods of water shortage, can lead to savings to other systems beyond drinking water distribution (Rougé et al., 2018).

Demand management of water use depends on the consumer who adopts voluntary actions to change demands, responds to incentives and rewards, or complies with regulations and laws. Consumer response to dynamic pricing is unknown, and, existing studies estimate how price change might affect water demand under conventional price strategies that do not have intraday changes. Most studies evaluate demand elasticity, which is the proportion of demand change to the proportion of price change. The majority of research on demand elasticity estimation found that, in the short term, the absolute value is less than 1.0, implying that that the demand could be considered inelastic. Even a small value of elasticity can cause a considerable impact on the total demand of a district metered area or at the utility level (Garrone et al., 2019; Marzano et al., 2018b; Pesantez et al., 2019), however, and studies have estimated the demand elasticity of water, despite on-going debates that water demand is inelastic. An average from 24 studies indicates that water elasticity is -0.51 (Espey et al., 1997). Another study reported water demand elasticity as –0.41 (Dalhuisen et al., 2003), based on a meta-regression of 296 observations from 51 studies. Sebri

(Sebri, 2014) also reported a value of -0.365 using meta-regression, where 638 observations ranging from -0.3054 to -0.002 were identified from 100 studies. In recent work, Marzano et al. (Marzano et al., 2018b), reported that the demand elasticity of water on average is -0.4, based on a meta-analysis of 124 studies from 1963 to 2013. The value reported by Marzano et al. is adopted in this work.

In the energy sector, many studies report values of residential price elasticity of electricity demand, and these studies find elasticity values that are slightly higher than those reported for water. A study in China reported a value of 0.3 (He et al., 2010), and, in another study, a range of -0.56 to -0.53 for the long-run and -1.01 to -0.75 for the short run were reported for consumers in the European Union (Csereklyei, 2020). In South Korea, the long-run elasticity was reported as -0.048 and 0.066 for the short run (Kwon et al., 2016). Another study in Canada reported the long-run elasticity as -1.2 (Feehan, 2018). In the United States, an analysis (Burke & Abayasekara, 2018) covering the years from 2003 to 2015 found that the long-run elasticity is around –1.0 and the short-run is close to -0.1. Existing studies have not been conducted to identify intraday elasticities for electricity, though dynamic pricing has been applied for electricity markets.

CHAPTER 3: METHODOLOGY

3.1 Overview

To conduct this research, a dynamic pricing model was developed based on the assumption that the price change ratio at hour *t* is equal to the distance between the consumer demand at time *t* from the average demand of the system. This research applies the model for single-family home (SFH) accounts. The output of the model is used as input to a wrapper that aggregates the consumer demand to nodes of the WDS based on the k-nearest neighbor algorithm (KNN) and writes a new input file for a hydraulic model. The hydraulic model simulates several scenarios to analyze and compare the performance of the dynamic pricing policy. The metrics used to compare scenarios are in two stages. First, the demand is analyzed as the total demand difference, the total revenue of the utility, and the difference on the two daily peaks. The hydraulic performance of the WDS is evaluated based on the total water loss of the WDS, the peak flow, and the water age. The other key analysis in this research is the energy consumed by the WDS and the energy cost to the utility. The research approach is visualized in Figure 1.

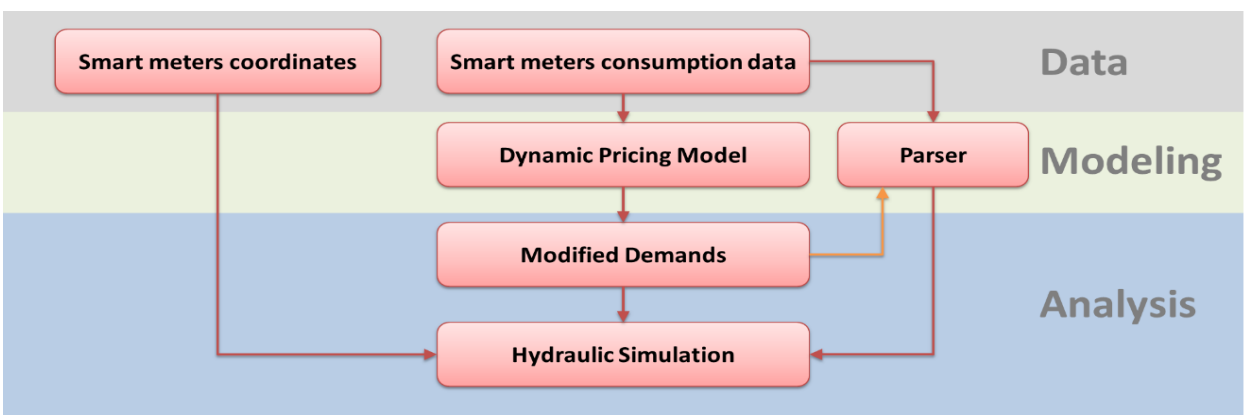

Figure 1. Methodology Schematic

3.2 Dynamic Pricing Model

The model is developed to calculate the price change ratio per hour (Δpr_h), as shown in Equation 1. The model calculates that the ratio in which the hourly price will be changed is equal to the difference of the demand at a certain hour and the average demand of the system (Figure 2). Using the price elasticity (e) with multiple values (Equation 2) described by Rouge et al. (2018), the actual demand (Dn_h) will be modified with the demand change ratio (ΔDr_h) as shown in Equation 2. The new price (Pn) is calculated based on the new hourly price change ratio (ΔPr) (Equation 5).

The modelling work as follows separately for each scenario:

Price change ratio (Δpr) is determined using Equation 1. This model has not been explored in other research for developing dynamic pricing schedules.

$$\Delta pr_h = \frac{D_h - \overline{D_h}}{\overline{D_h}} \qquad Eq.(1)$$

The demand change ratio (ΔDr) is calculated using Equation 3. Elasticity values are explored for different scenarios.

$$e = \frac{\Delta Dr_{\ h}}{\Delta pr_h} = \frac{\Delta D/_D}{\Delta p/_p} \qquad Eq.(2)$$

$$\Delta Dr_{\ h} = e * \Delta pr_h \qquad Eq.(3)$$

The new demand at each hour h is calculated using Equation 4 for every SFH consumer.

$$Dn_h = D_h * (1 + \Delta Dr_h) \qquad Eq.(4)$$

The new price per hour is calculated using Equation 5.

$$Pn_h = P_h * (1 + \Delta Pr_h) \qquad Eq.(5)$$

where D is demand, ΔD is demand change, P is the original unit price of water per 100 CF, and Δp is price change.

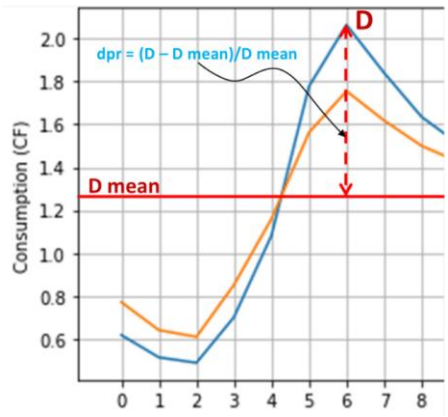

Figure 2. Proposed Price Change Ratio Calculation Method

3.2.1 Wrapper

The AMI dataset is housed in a data frame, where each column represents a smart meter account, and each row is a time step of one hour. An aggregating process is used to incorporate data across accounts and transform AMI data into nodal demand patterns. A wrapper was developed in previous research and applied for this model (Pesantez, 2021). The wrapper inputs are the 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 KNN 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 are 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 all the original features in addition to the updated demand patterns. The period of the demand patterns (number of hours included) depends on the input consumption data.

CHAPTER 4: CASE STUDY: LAKEWOOD, CA

4.1 Data

This research uses a dataset gathered from more than 20,000 smart meters reporting water consumption during two fiscal years, from July 1, 2018 to June 30, 2020. The data set used is provided by Neptune Inc. for Lakewood in California, United States. The dataset consists of the water consumption in cubic feet at hourly time steps for each meter and includes the location in terms of longitude and latitude for each smart meter.

The data was uploaded originally to an Application Programming Interface (API) by the utility's partner (Neptune). To download the data, a script on Python was developed to request the data. The request includes the start and end times, the interval, whether monthly, daily, or hourly. A temporary token is requested to access the API prior to downloading. The data is downloaded in XML format. For this case, each month of the two years of data was downloaded separately due to the computational limitations, since each file is approximately two gigabytes in size. The total size of the data is approximately 48 gigabytes. The next step was to parse the dataset from XML format to CSV, reducing the size of the file to 2.48 gigabytes.

The City of Lakewood is located in southern Los Angeles County. The city includes three zip code areas, and this study includes two zip codes: 90712 and 90713. The population of those two areas is estimated to be 59,419 (United States Census Bureau, 2019). The Lakewood WDS infrastructure and location of smart meters are shown in Figure 3.

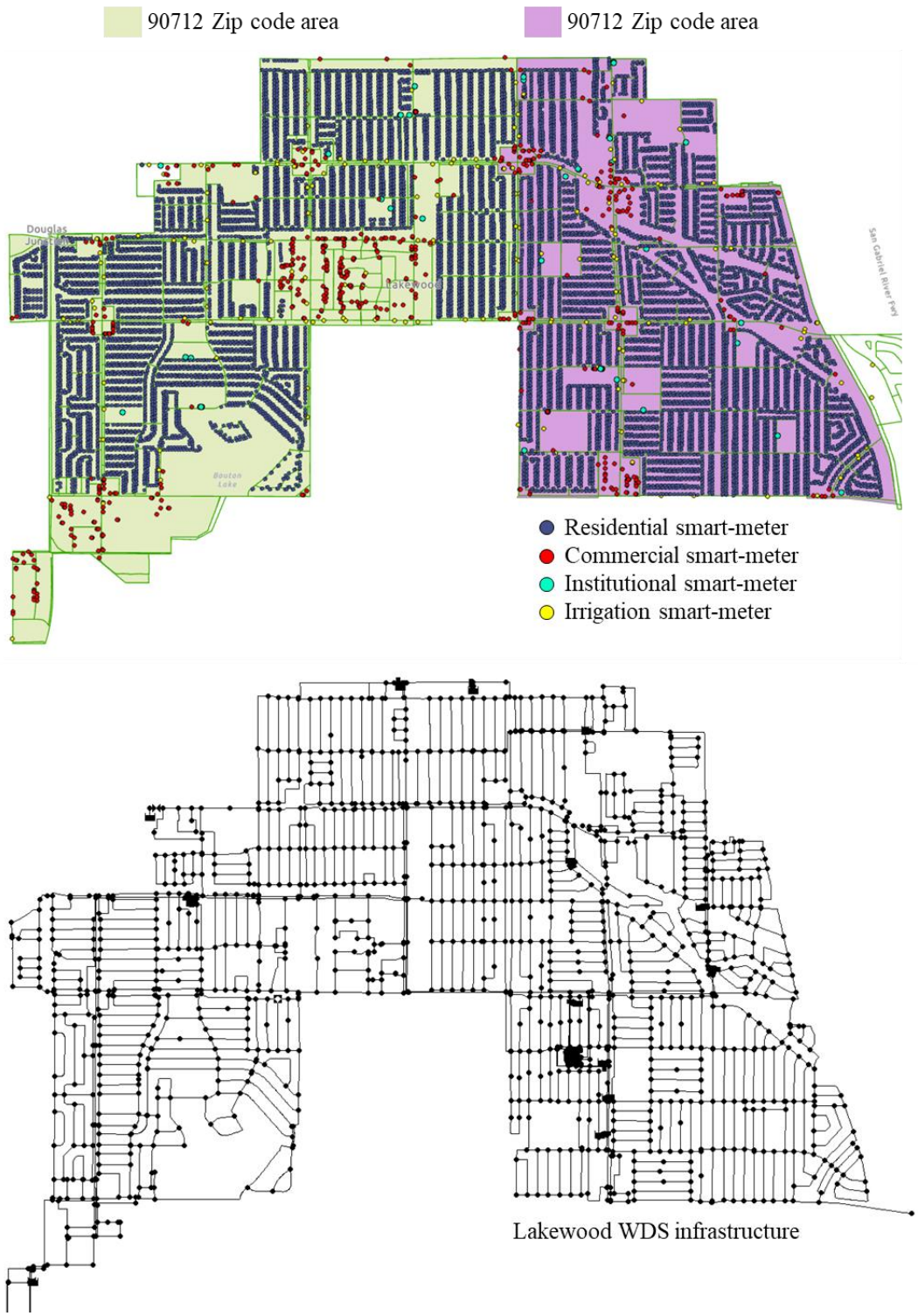

Figure 3. Lakewood city and WDS map

Since the data provided were direct logs of the meters, some records were missing for unforeseen reasons. Data were cleaned and prepared by eliminating all accounts with incomplete consumption logs. The data were checked for outliers in the readings. Eighty-five accounts recorded zeros for the entire period of observation, and seven accounts reported negative demands. These records are considered a malfunction of the smart meters and were removed from the dataset. Cleaning resulted in a total of 19,985 smart meter accounts, reduced from 20,286. The data set also reports the use type of the accounts, such as residential, commercial, institutional, or irrigation. Sub-types are also reported, such as single-family homes, restaurants, and high schools. The average hourly consumption over all single-family homes (SFH) is reported in Figure 4. SFH accounts are used to apply the DP framework, based on the assumption that SFHs are more likely to respond to price change and have the ability to shift some uses to off peak hours, compared to non-residential consumers or multi-family homes.

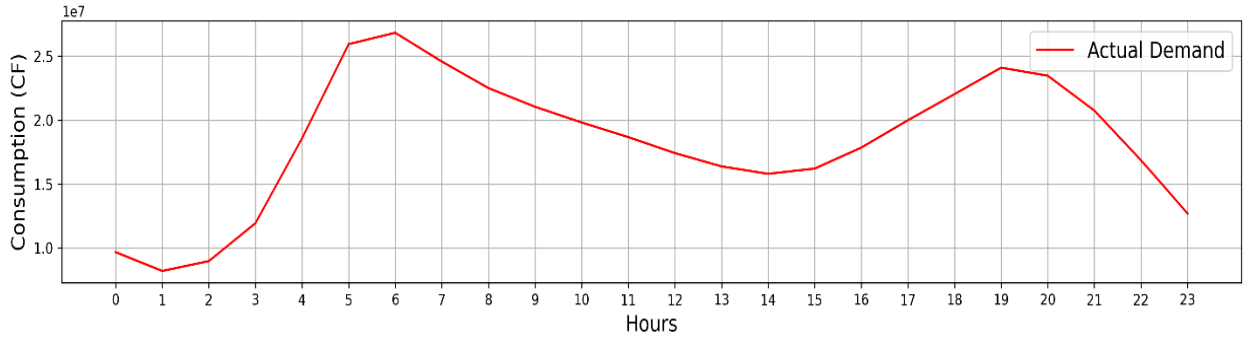

Figure 4. Average hourly consumption over-all single-family homes accounts, calculated from July 2018-July 2019

4.2 Modeling Scenarios

The dynamic pricing model was tested using four scenarios. Price change ratios are calculated for four scenarios based on the demand and distance to average demand, shown in Figure 2. The value of demand elasticity used in this model is selected to be -0.4 based on the

meta-analysis done by Marzano et al in 2018. The first two scenarios, S1 and S2 have a fixed value of demand elasticity of -0.4. Scenario S3 has a varying elasticity value based on the peak demand hours to reflect the relationship between the peak demand hours and elasticity. In scenarios S2 and S3, a 25% cap is used to limit the price change ratio, which should lead to policies that may be more feasible for utilities and customers. Scenario S4 uses a 3-block rate policy with a varied elasticity value and no price change cap. Scenarios are described in Table 1. Based on the average hourly demand shown in Figure 4, the dynamic pricing policy and price change schedule are calculated using Equation 1. Hourly price change ratios are shown in Table 2 and Figure 5.

Table 1. Dynamic Pricing Proposed Scenarios

SCENARIO #	ELASTICITY	CAP ON PRICE CHANGE	NUMBER OF BLOCKS
Scenario 1 (fixE-noc-24b)	-0.4	NA	24-blocks
Scenario 2 (fixE-25c-24b)	-0.4	25%	24-blocks
Scenario 3 (varE-25c-24b)	-0.4 to -0.32	25%	24-blocks
Scenario 4 (varE-noc-03b)	-0.4 to -0.32	NA	3-blocks

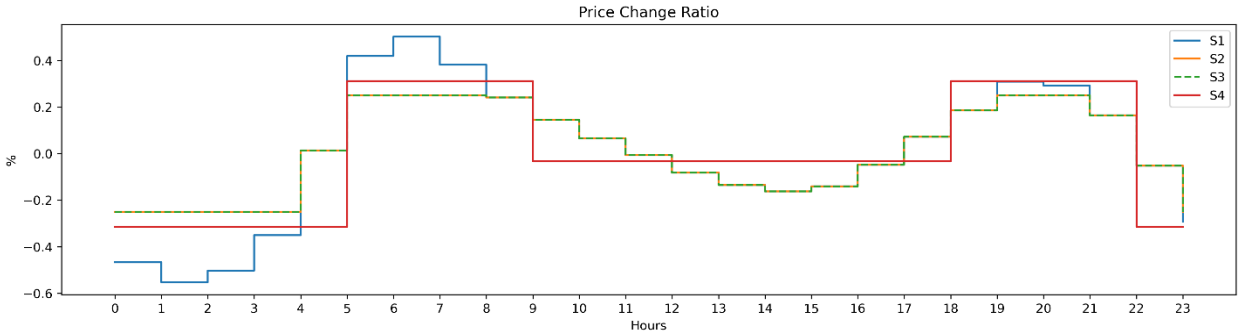

Figure 5. Price Change Ratio for the Proposed Scenarios

Table 2. Calculated Price Change Ratio for the Proposed Scenarios

TIME (HOURS)	Δpr(S1)	Δpr(S2)	Δpr(S3)	Δpr(S4)
12:00 AM	-0.47	-0.25	-0.25	-31%
1:00 AM	-0.55	-0.25	-0.25	
2:00 AM	-0.5	-0.25	-0.25	
3:00 AM	-0.35	-0.25	-0.25	
4:00 AM	0.01	0.01	0.01	
5:00 AM	0.42	0.25	0.25	31%
6:00 AM	0.5	0.25	0.25	
7:00 AM	0.38	0.25	0.25	
8:00 AM	0.24	0.24	0.24	
9:00 AM	0.15	0.15	0.15	-3%
10:00 AM	0.07	0.07	0.07	
11:00 AM	-0.01	-0.01	-0.01	
12:00 PM	-0.08	-0.08	-0.08	
1:00 PM	-0.14	-0.14	-0.14	
2:00 PM	-0.16	-0.16	-0.16	
3:00 PM	-0.14	-0.14	-0.14	
4:00 PM	-0.05	-0.05	-0.05	
5:00 PM	0.07	0.07	0.07	
6:00 PM	0.19	0.19	0.19	31%
7:00 PM	0.31	0.25	0.25	
8:00 PM	0.29	0.25	0.25	
9:00 PM	0.16	0.16	0.16	
10:00 PM	-0.05	-0.05	-0.05	-31%
11:00 PM	-0.29	-0.25	-0.25	

CHAPTER 5: RESULTS

The four scenarios described in Table 1 were simulated to explore how dynamic pricing performs based on changes in water demand, hydraulic performance, energy, and energy cost.

5.1 Water Demand Analysis

The dynamic pricing model was applied to derive the demand change ratios based on the price change ratio for each scenario using Equation 3. Demand change ratios are listed in Table 3 and shown graphically in Figure 6. In Scenario S1 (fixE-noc-24b), the demand change ratio values follow the same shape of the demand because the price is not restricted and the elasticity value is fixed for all hours of the day. Scenario S2 (fixE-25c-24b), however, has less variability to the demand change ratio because a 25% cap is applied to the price. Scenario S2 results in changes that are higher than Scenario S3 (varE-25c-24b) on mid and off-peak hours, where the value of elasticity is reduced to simulate that people respond less to price changes during off peak hours. On the other hand, Scenario S4 (varE-noc-03b), which uses three blocks of price, has three values for the demand change ratio: 10% increase for off peak hours, 1% increase for mid-peak hours, and 12% decrease for peak hours. The similarity between S2 and S4 in the early morning off-peak hours (12 am to 4 am) occurs due to the calculations. Since S2 has, at those hours, a Δpr of –25% and e equal to -0.4, there is a 10% increase in ΔDr. In S4, at the same hours, Δpr is -31%, and e is -0.32%, which yields around 10% increase in ΔDr. The values of ΔDr for both S2 and S3 at the peak hours are the same, because values of Δpr and e are the same on those hours.

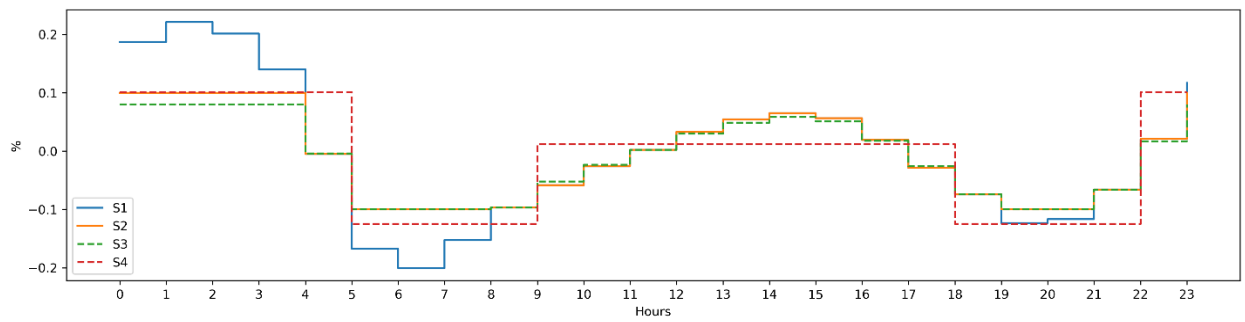

Figure 6. Demand Change Ratio for the Proposed Scenarios

Table 3. Calculated Demand Change Ratio for the Proposed Scenarios

TIME (HOURS)	ΔDR			
	S1 (FIXE-NOC-24B)	**S2 (FIXE-25C-24B)**	**S3 (VARE-25C-24B)**	**S4 (varE-noc-03b)**
12:00 AM	0.19	0.10	0.08	0.10
1:00 AM	0.22	0.10	0.08	0.10
2:00 AM	0.20	0.10	0.08	0.10
3:00 AM	0.14	0.10	0.08	0.10
4:00 AM	-0.01	-0.01	0.00	0.10
5:00 AM	-0.17	-0.10	-0.10	-0.12
6:00 AM	-0.20	-0.10	-0.10	-0.12
7:00 AM	-0.15	-0.10	-0.10	-0.12
8:00 AM	-0.10	-0.10	-0.10	-0.12
9:00 AM	-0.06	-0.06	-0.05	0.01
10:00 AM	-0.03	-0.03	-0.02	0.01
11:00 AM	0.00	0.00	0.00	0.01
12:00 PM	0.03	0.03	0.03	0.01
1:00 PM	0.05	0.05	0.05	0.01
2:00 PM	0.06	0.06	0.06	0.01
3:00 PM	0.06	0.06	0.05	0.01
4:00 PM	0.02	0.02	0.02	0.01
5:00 PM	-0.03	-0.03	-0.03	0.01
6:00 PM	-0.07	-0.07	-0.07	-0.12
7:00 PM	-0.12	-0.10	-0.10	-0.12
8:00 PM	-0.12	-0.10	-0.10	-0.12
9:00 PM	-0.07	-0.07	-0.07	-0.12
10:00 PM	0.02	0.02	0.02	0.10
11:00 PM	0.12	0.10	0.08	0.10

5.1.1 Change in Demands

To evaluate each scenario, the total demand exerted by residential consumers is inspected based on peak demands at 6:00 AM and 7:00 PM and off-peak demands at 1:00 AM. Changes are shown as the hourly total demand over one billing cycle covering July and August of 2019 (July 1, 2019 – August 31, 2019). Scenario S1 is compared with a policy that uses no dynamic pricing, referred to as S0. Scenario S1 reduces the morning peak by 20% and the evening peak by 12% (Figure 7). The off-peak demand increases by 22%. To assess how the demand curve is flattened, the standard deviation of the average demands across the 24-hour period is evaluated. For Scenario S1, the standard deviation is reduced by 34%, indicating a flattened curve when compared with no dynamic pricing. The total demand is reduced by 3.64%, indicating that consumers use overall less water. Scenario S2 applies a 25% cap on the price change. Due to smaller changes in price, there is less variation in demand when compared with Scenario S1 (Figure 7). The peak demand is reduced by 10% at 6:00 AM and 7:00 PM and increases by 10% at 1:00 AM. The standard deviation is reduced by 22%, and the total demand of this cycle is lowered by 2.76%. Scenario S3 results in lower changes in demand, due to the cap on the price change and the change in elasticity. Demands change at 6:00 AM and 7:00 PM by 8%. This is expected, since the third scenario has lower demand elasticity values at the mid-peak and off-peak hours. The standard deviation at 18% is also less than the standard deviation for Scenarios S1 and S2. For Scenario S4, the price change is limited to three periods in a day and produces changes in demand that are similar to Scenario S2. The peak demands at 6:00 AM and 7:00PM are reduced by almost 10%, and the peak demand at 1:00AM increases by 10%. There is no cap on price change, and these prices vary more than Scenario S3. The change in the standard deviation is 21%, indicating a flattened curve.

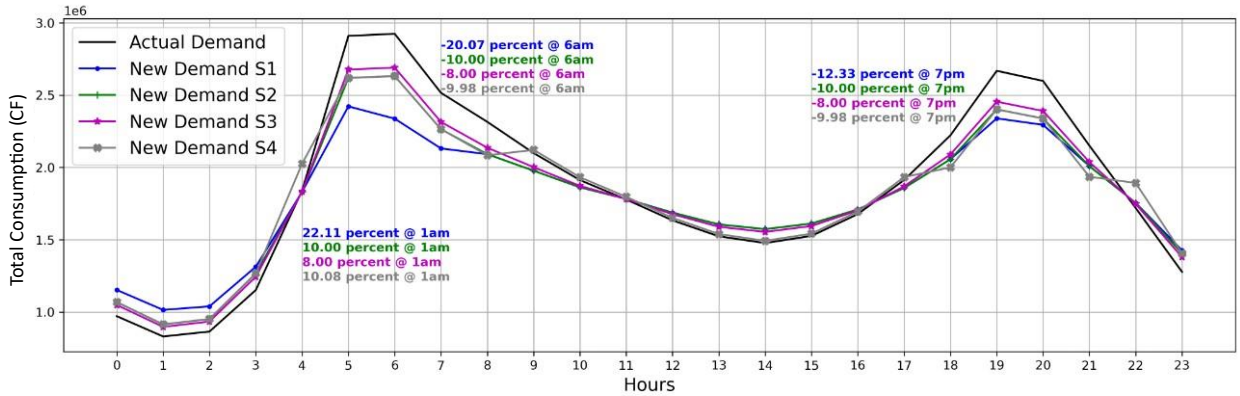

Figure 7. Hourly Total Demand Change of The DP Model

Total changes in demands are summarized in Figure 8. Total demands are summed over a one-year period (August 1, 2018 – July 31, 2019) and compared with no dynamic pricing policy. The total demand does not change significantly for the four scenarios. This indicates that these dynamic pricing policies do not significantly change the amount of water that consumers use, but they will only change the timing of use. This is important for issues of equity, to ensure that populations are able to access the resources that they need and want. However, these results are based on assumed elasticity values that are applied throughout the 24-hour period. For example, it is not realistic to assume that demands at 1:00 AM 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. For the time being, data does not exist to support a better understanding of intraday water elasticity values.

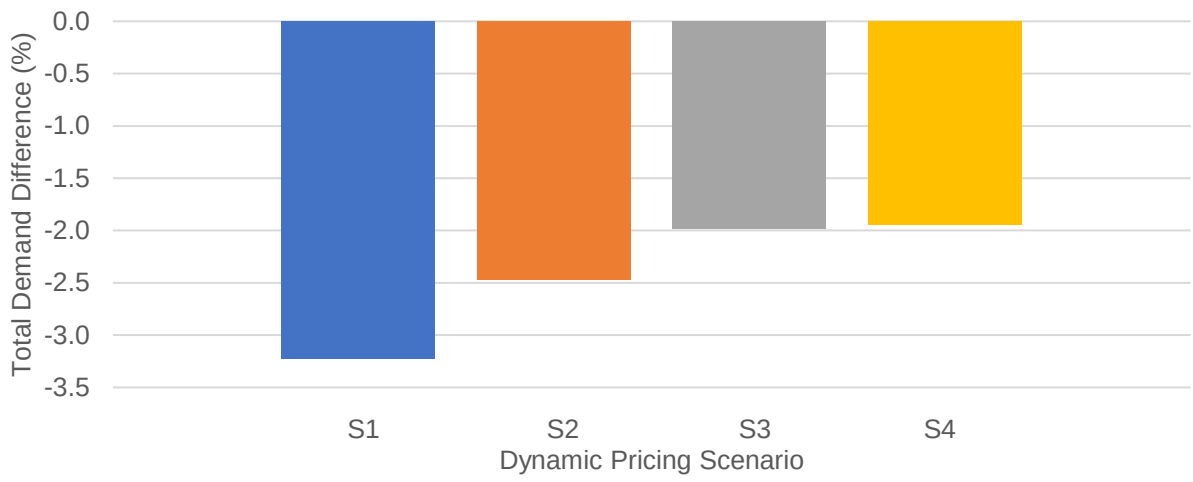

Figure 8. Total Demand Difference for All DP Scenarios for One Year Period

5.1.2 Change in Revenue

Lakewood's billing structure is a bimonthly billing policy with two tiers of residential consumers and a minimum service charge of $17.69. The consumers that use less than 400 cubic feet per billing cycle are charged only with the minimum service charge. Consumers that use more than 400 cubic feet are charged for additional water at a rate of $3.50 per 100 cubic feet. This structure is only for the period of study, and Lakewood pricing policies were updated in 2019.

The billing structure was altered to apply and explore a dynamic pricing policy. In this modeling framework, the base policy with no dynamic pricing applies a minimum fee to every household and applies a rate of $3.00 per 100 cubic feet for all water consumed. Dynamic pricing policies apply the minimum fee and vary prices around $3.00 per 100 cubic foot as a base rate. The hourly price of water is calculated using price change ratios in Table 1 and Equation 5 and is shown in Figure 9.

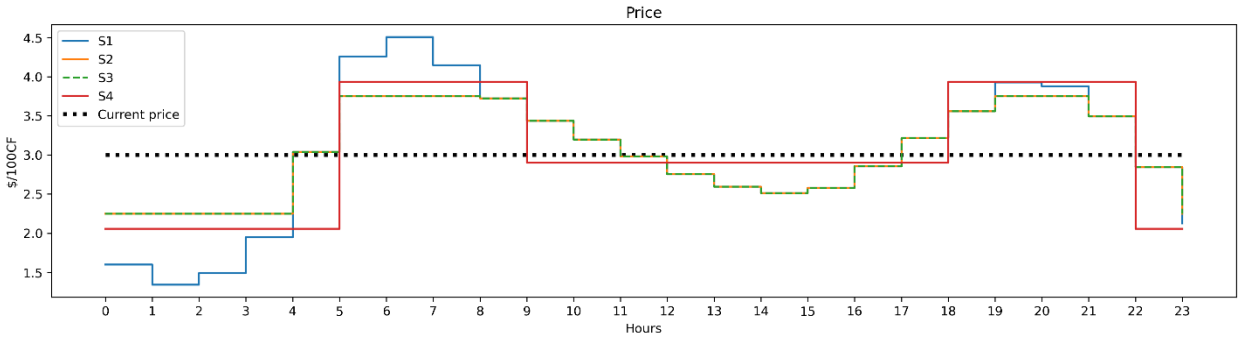

Figure 9. Hourly Unit Price per 100 CF for dynamic pricing policies

Dynamic pricing scenarios are compared with no dynamic pricing based on total revenue (Figure 10). Total revenue increases by 3-4% for each Scenario, representing a minimal change in total revenue. Utilities may wish to maintain revenue neutrality to avoid profit gain or loss of revenue, and these results demonstrate that dynamic pricing can be designed to lead to small changes in total revenue. In this research, the base rate was adjusted to identify a value that would lead to little change in total revenue, and further research can explore optimization approaches to further minimize change in total revenue. Scenario S1 shows the least amount of change, and this is because prices can vary widely. Limits on the amount of variation in price lead to higher total revenue changes. Scenario S1 may be impractical due to wide changes in price, and other scenarios explore more practical policies. However, further restrictions on the way prices can change, as seen in Scenarios S2-S4, lead to higher changes in total revenue. Scenarios with more restrictions on how price can change, compared with S1, lead to lower volumes of shifted peak demand in hours when the hourly price is the highest. On the other hand, for S1, demand shifting is not restricted, and higher volume of demand can be shifted to periods when price is lower. This is also the case when comparing S4 with S3. Because S3 has a 25% price change cap, there is smaller change in the demand change at peak hours, or higher consumption of water during peak hours when price is high.

A new scenario is introduced, S4e0, to explore the effects of dynamic pricing on consumer bills. In S4e0, the price change is simulated as the three-block rate shown for S4. In this scenario, consumers do not respond to the dynamic pricing policy and consume water using the same timing as shown in the original AMI data. It is assumed that demand elasticity (*e*) is equal to 0.0. For Scenario S4e0, utility revenue increases, nearly doubling the change in revenue, when compared with S4 (Figure 10).

Figure 10. Total Utility's Revenue Difference for All DP Scenarios for One Year Period

The distribution of water bills over one cycle (July 1, 2019 – August 31, 2019) is explored for Scenarios S4 and S4e0 (Figures 11 and 12). As shown in Figure 11, the average bill for Scenario S4 is $91.30, with a standard deviation of $42.90. For S4e0, the average bill increases by $3.00 over a two-month period, when the dynamic pricing policy is applied, and consumers do not respond (Figure 12). This change is consistent across 25, 50 and 75 percentiles, with increases of approximately $3.00 for each percentile. Utility managers may wish to consider the effects of dynamic pricing on bills when consumers are not able or unwilling to respond to changing prices or do not have the necessary information about the relationship between the timing of water use and energy costs. These results demonstrate that changes in water prices would be marginal for

many users. Further research can explore policies that tailor pricing policies to allow marginalized groups to continue to use water in typical diurnal patterns while mitigating hydraulic performance and energy costs.

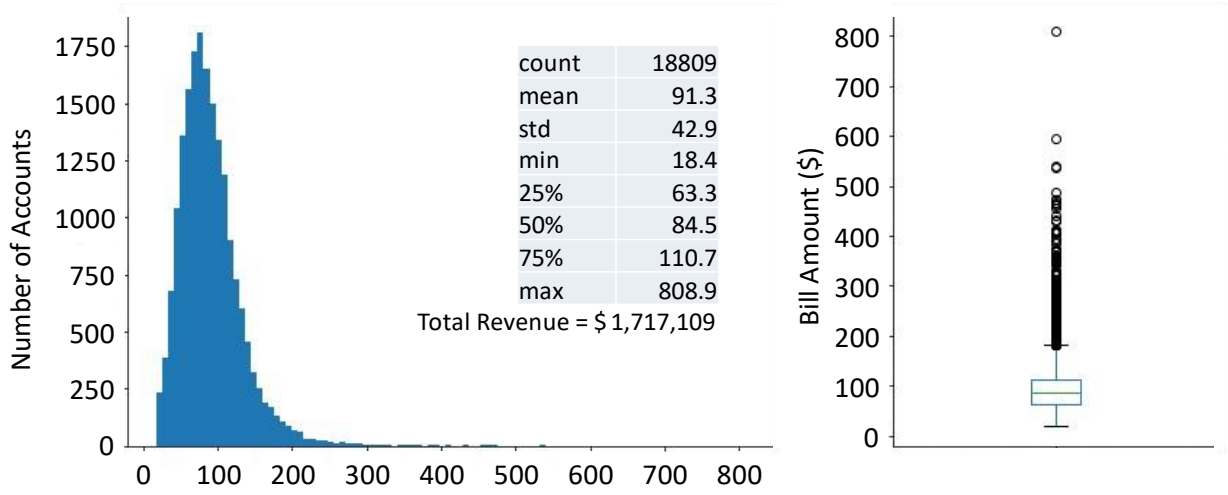

Figure 11. Distribution of Billing Amount for S4 Over Consumers for One Billing Cycle (Jul-Aug 2019).

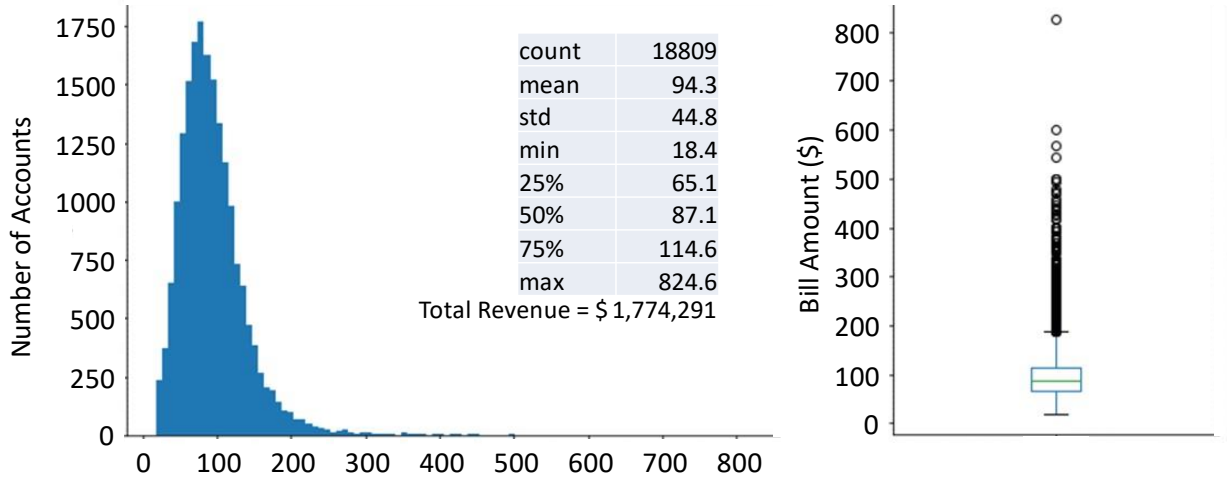

Figure 12. Distribution of Billing Amount for S4e0 Over Consumers for One Billing Cycle (Jul-Aug 2019).

5.2 Hydraulic Performance Analysis

Hydraulic performance is analyzed using five metrics introduced by Zhuang and Sela (Zhuang & Sela, 2020), which includes peak flow, total pumping energy, peak energy, water age, and total background leakage. Scenarios S1-S4 are simulated using the wrapper, described above, that translates demands to EPANET within WNTR (K.A. Klise et al., 2017; Katherine A. Klise et al., 2017; Rossman et al., 2020). The Lakewood WDS and location of smart meters are shown in Figure 13. The median peak flow, calculated over all pipes in the network is used to represent peak flow. Total pump energy is calculated as the sum of energy at each pump calculated as follows:

$$E = \frac{1000 * 9.81 * headloss * flowrate}{efficiency} \times timestep \quad (6)$$

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. Background leakage is calculated using Equation 7. 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 base line for comparing the four proposed scenarios to the original one.

$$Qleak = \sum \beta * link\ length * link\ average\ pressure^{\alpha} \quad (7)$$

where *alpha* is the parameter of the area of the hole and assumed to be 0.5, and *beta* represents the pipe degradation parameter and assumed as 10E-7 (Berglund et al., 2017; Giustolisi et al., 2008; Zhuang & Sela, 2020).

Dynamic pricing scenarios are simulated for one month (July 1, 2019 – July 31, 2019) and compared to a one-month simulation of no dynamic pricing policy. Results demonstrate that peak pipe flow considering all pipes at all timesteps is reduced significantly, by approximately 50% for Scenarios S1-S4 (Figure 13). Water age, however, increases for all scenarios, from 7.81 hours to values around 24 hours (Figure 14). Both peak demand and velocity of water decreases, leading to longer residence time in the network.

Analysis demonstrates that background leakage increases for dynamic pricing scenarios, as shown in Figure 15. The volume of water lost to leaks increases by approximately 8% for each of the scenarios. Due to decreases in demands, pressure increases throughout the system, which leads to increased water lost through cracks and breaks. As pressure may be more uniform across a day due to dynamic pricing, pressure management can be used to control leaks by adjusting pump and tank operations.

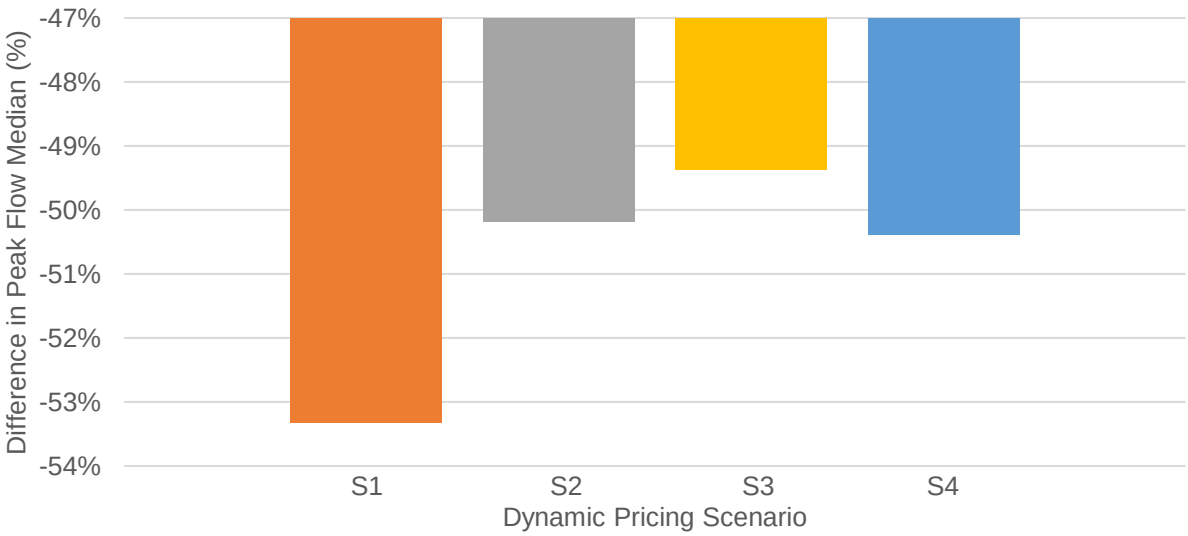

Figure 13. Median of Peak Flow for DP Scenarios for One Month Period, July 2019

Figure 14. Water Age for DP Scenarios at the End of One Month Simulation, July 2019

Figure 15. Total Estimated Background Leakage for DP Scenarios at the End of One Month Simulation, July 2019

5.3 Energy Analysis

Total pumping energy, *E*, is calculated as the sum of energy at each pump, calculated as follows:

$$E = \sum \frac{1000 * 9.81 * headloss * flowrate}{efficiency} \times timestep \quad (6)$$

Where the headloss and flowrate are associated with each pump for every timestep (hour), and the efficiency is assumed to be 70% across all pumps. The headloss for each pump is calculated as in Equation 7.

$$Headloss = head_{end\ node} - head_{start\ node} \quad (7)$$

The peak energy is the maximum pump energy at any hour (Berglund et al., 2017; Giustolisi et al., 2008; Zhuang & Sela, 2020).

Dynamic pricing scenarios lead to reductions in the total energy consumed at pumps and peak energy consumption. Energy consumption across the system decreases by approximately 10% for each scenario, and the peak energy decreases by 40% over one month of simulation (Figure 16). This result is consistent with the assumption that flattening the demand curve (shifting demand to lower demand peaks) will result in lowered energy peaks. This could result in a considerable saving of energy costs for the water utility.

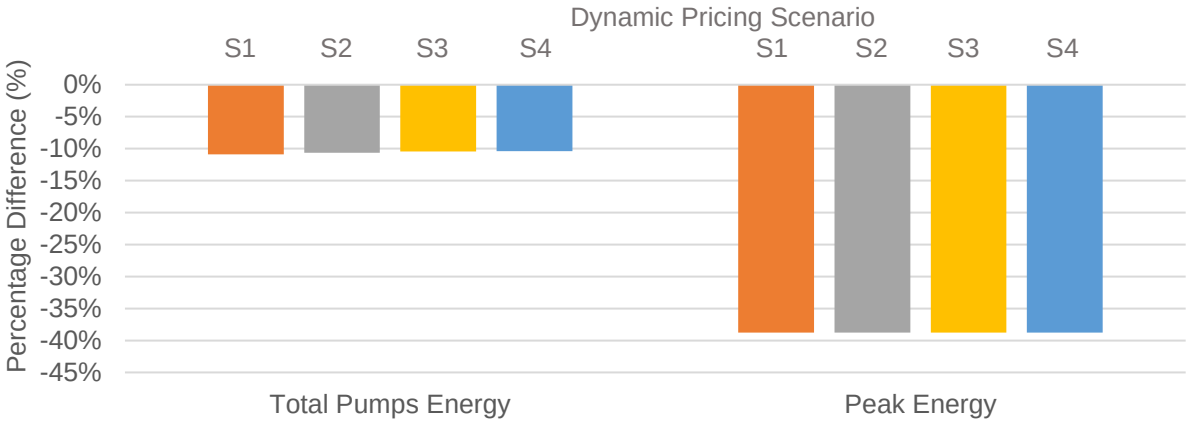

Figure 16. Total Peak Pumping Energy for All DP Scenarios at the End of One Month Simulation, July 2019

The energy consumed by pumps is averaged over hours of the day to visualize the average change of peak energy (Figure 17). The overall total energy reduction is clear from the curves of all four scenarios compared to the original energy consumption (S0). Scenario S1 reduces the two peaks most significantly. Scenarios S2 and S3 performed similarly, however, Scenario S4 has slightly different trends at hours 9 am, 2 pm, 5 pm, 6 pm, and 11 pm. Overall, the trend for each scenario is similar, and there is a uniform reduction in energy at each hour of the day. This is because flows at pumps are only minorly different at most pumps when the demand is shifted. The peak energy of each pump for no dynamic pricing and S4 are inspected to further explore changes in the peak energy consumption. For no dynamic pricing, the highest energy peak is identified at pump 3 at plant 4, at 135 kWh. Two pumps at well 13 and well 17 consume 85 kWh as shown in Figure 18. For scenario S4, the highest energy peak is 85 kWh for pumps at well 13 and well 17, while the peak of pump 3 of plant 4 is reduced to 73 kWh, as shown in Figure 18. For each of the four scenarios, pump 3 at plant 4 is used significantly less throughout the month, and is shut off for most of the simulation, leading to the uniform reduction of energy shown in Figure 17.

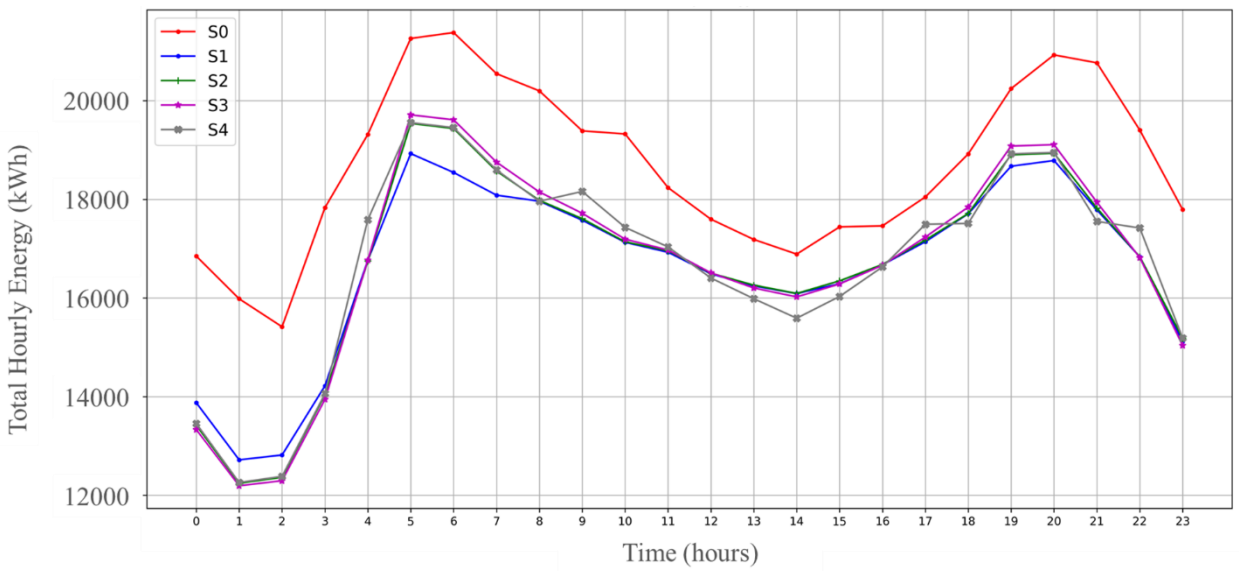

Figure 17. Hourly Average Pumping Energy for All DP Scenarios at the End of One Month Simulation, July 2019

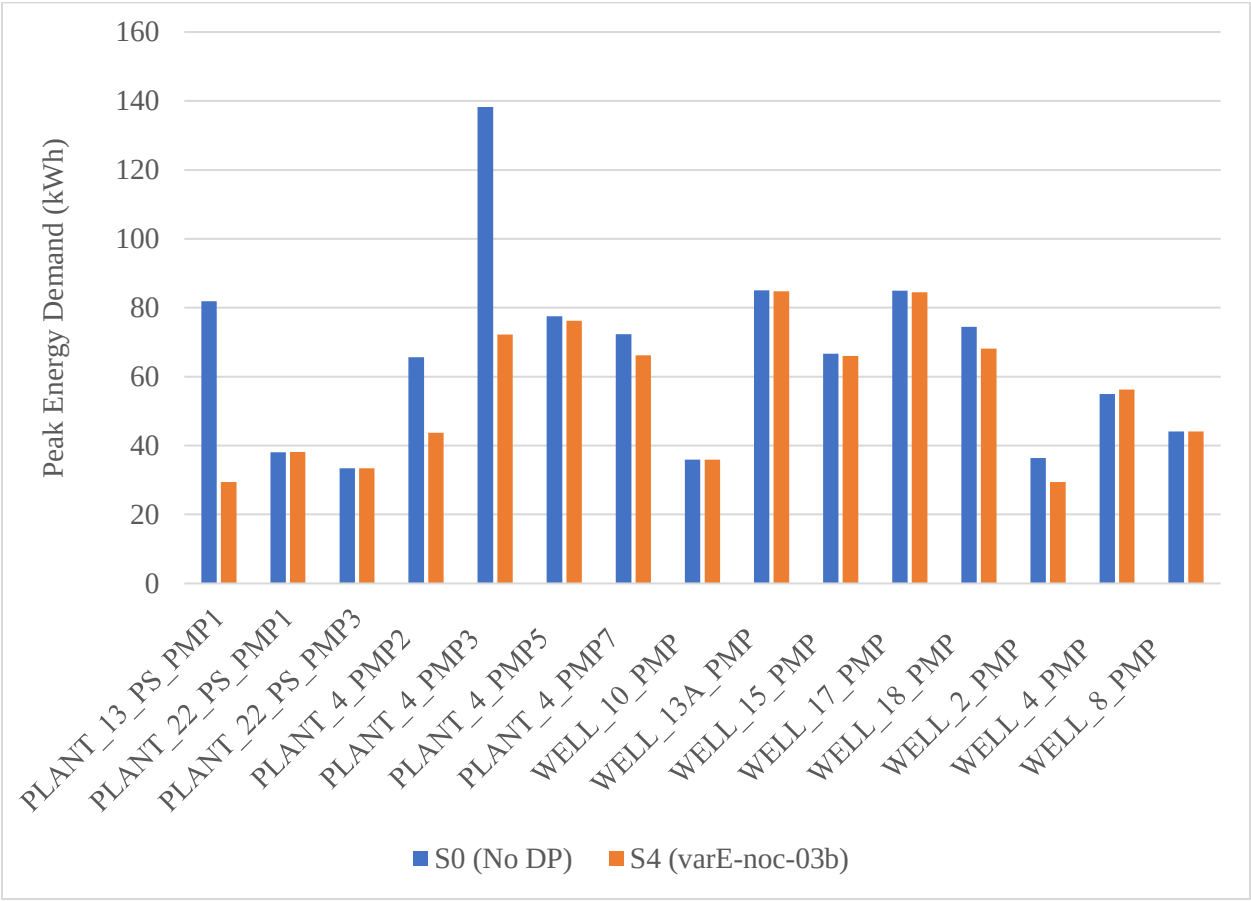

Figure 18. Peak Energy for Each Pump at the End of One Month Simulation, July 2019

5.3.1 Energy Cost

The cost of pumping energy is calculated based on utility bills provided by The City of Lakewood to approximate actual rates. The rate structure varies over pumps, time of day (peak and off-peak hours), and time of year as summarized in Tables 4-6.

Table 4. Energy Rates of Pumps in Winter Season

	WINTER (OCT 1 TO MAY 31)			
	Mid Peak	**Off Peak**	**Super Off Peak**	**Winter Demand**
WELL 2A	$ 0.101	$ 0.085	$ 0.076	$ 11.56
WELL 4	$ 0.101	$ 0.085	$ 0.076	$ 11.56
WELL 8	$ 0.118	$ 0.076	NA	$ 7.90
WELL 10	$ 0.125	$ 0.104	$ 0.091	$ 7.90
WELL 13A	$ 0.118	$ 0.076	NA	$ 7.90
WELL 15	$ 0.118	$ 0.076	NA	$ 7.90
WELL 17	$ 0.101	$ 0.085	$ 0.076	$ 11.56
WELL 18	$ 0.101	$ 0.085	$ 0.076	$ 11.56
WELL 22	$ 0.125	$ 0.104	$ 0.091	$ 7.90
WELL 27	$ 0.125	$ 0.104	$ 0.091	$ 7.90
PLANT 13	$ 0.101	$ 0.085	$ 0.076	$ 14.19
PLANT 4	$ 0.101	$ 0.085	$ 0.076	$ 11.99

Table 5. Energy Rates of Pumps in Summer Season

	SUMMER (JUNE 1 TO SEPTEMBER)			
	On Peak	**Mid Peak**	**Off Peak**	**Summer Demand**
WELL 2A	$ 0.137	$ 0.129	$ 0.078	$ 23.82
WELL 4	$ 0.137	$ 0.129	$ 0.078	$ 23.82
WELL 8	$ 0.348	$ 0.142	$ 0.085	$ 7.42
WELL 10	$ 0.408	$ 0.147	$ 0.085	$ 7.42
WELL 13A	$ 0.348	$ 0.142	$ 0.085	$ 7.42
WELL 15	$ 0.348	$ 0.142	$ 0.085	$ 7.42
WELL 17	$ 0.137	$ 0.129	$ 0.078	$ 21.19
WELL 18	$ 0.137	$ 0.129	$ 0.078	$ 23.82
WELL 22	$ 0.408	$ 0.147	$ 0.085	$ 7.42
WELL 27	$ 0.408	$ 0.147	$ 0.085	$ 7.42
PLANT 13	$ 0.137	$ 0.129	$ 0.078	$ 23.82
PLANT 4	$ 0.137	$ 0.129	$ 0.078	$ 24.41

Table 6. Time of Day Variations

WINTER	WELLS 8, 13,15***	WELLS 2, 4, 10, 17, 18, 22, 27, P13, P4
MID PEAK	8a - 9p	4p to 9 p
OFF PEAK	9p - 8a	9p to 8am
SUPER OFF PEAK		8a to 4 p
***OFF PEAK RATES ALL WEEKEND AND HOLIDAY**		

SUMMER	WELLS 8, 13,15**	WELLS 2, 4, 10, 17, 18, 22, 27, P13
ON PEAK	12p-6 p	4p-9pm
MID PEAK	8a - 12 p 6p-11p	*4p-9pm**
OFF PEAK	12a - 8a 11p-12a	9p-4pm
***WEEKEND & HOLIDAYS**		
** ALL WEEKENDS ARE OFF-PEAK RATES**		

The cost of pumping energy is calculated for one month (July 2019) for all scenarios to compare the cost savings as shown in Table 7. Reductions in the cost of energy range from 12% to 14% for Scenarios S1-S4.

Table 7. Pumping Energy Cost to the Utility for the Month of July 2019

SCENARIO	ENERGY CONSUMPTION COST	CHANGE (%)	PEAK ENERGY COST	CHANGE (%)	TOTAL ENERGY COST	CHANGE (%)
S0 – NO DYNAMIC PRICING	$ 16,822	0.0%	$ 43,987	0.0%	$60,809	0.0%
S1	$ 12,873	-23%	$ 39,450	-10%	$52,323	-14%
S2	$ 13,272	-21%	$ 39,553	-10%	$52,825	-13%
S3	$ 13,749	-18%	$ 39,630	-10%	$53,379	-12%
S4	$ 13,669	-19%	$ 39,591	-10%	$53,260	-12%

5.3.2 Spatial Analysis for Energy Consumption

The effect of dynamic pricing policies and reductions in peak demands on different sections of the network is explored in this analysis. The Lakewood WDS was divided into separate tracts or districts based on pressure at the outset of the simulation (Figure 19). Tracts are separated as shown in Figure 20. For example, tract 571000 has the highest overall pressure and tract 571400 has the lowest average pressure (Figure 20). The total number of smart meters and the number of single family home smart meters in each tract are listed in Table 8.

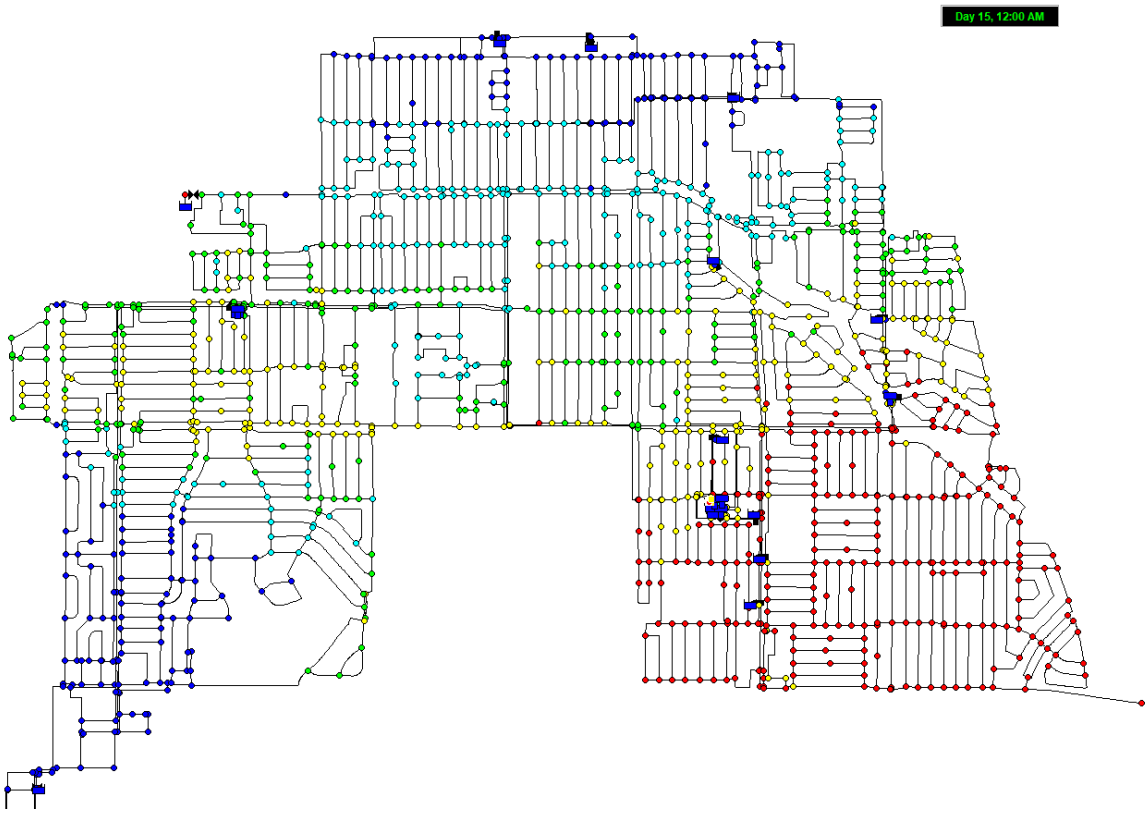

Figure 19 . WDS Pressure at the Node Level for Mid of July Simulation

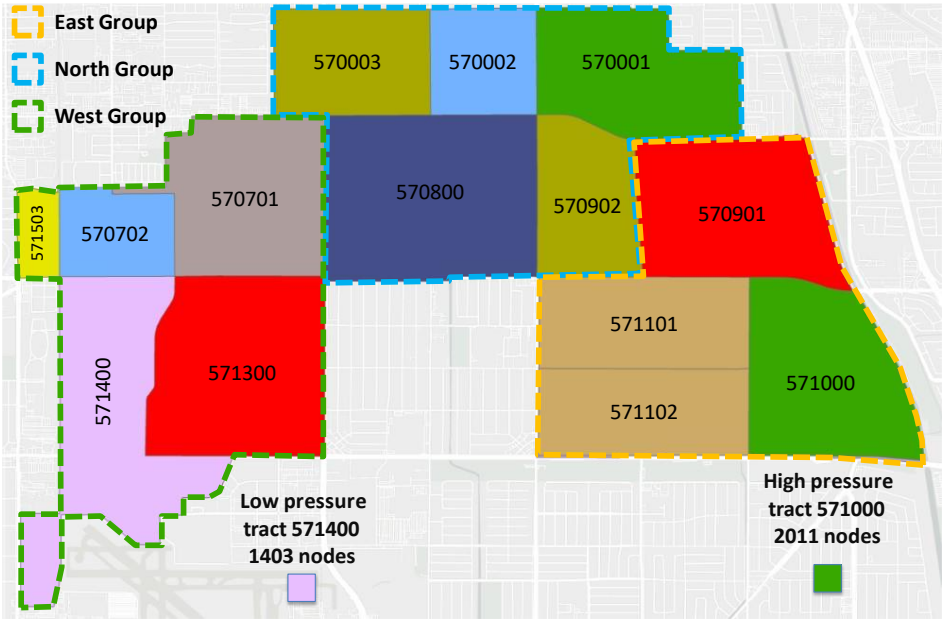

Figure 20. Tract Locations over Lakewood Map and Locations of High- and Low-Pressure Tracts

Table 8. Number of Smart-Meters and Number of Single-Family-Home at Each Tract

TRACT ID	# METERS	# SFH METERS	TOTAL SFH DEMAND JULY 2019 (CF)
571000	2038	2011	2,316,557
571400	1558	1403	1,657,924
570001	1365	1242	1,542,679
570002	903	860	1,084,730
570003	1420	1371	1,483,948
570901	1962	1905	1,538,182
570902	1178	1134	871,205
570800	2109	1819	2,096,830
570701	1642	1471	2,317,362
570702	855	833	1,350,318
571503	274	272	1,775,916
571101	1634	1591	1,542,154
571102	1424	1359	2,312,394
571300	1565	1538	322,934

To analyze spatial effects, Scenario S4 is applied to one tract individually to update single family home consumption within that tract. Demands in other tracts are not altered from the original AMI data. For the dynamic pricing policy applied in each tract, the hydraulic analysis is executed to evaluate the energy consumed by pumps. In Figure 21, the average energy consumption for individual tracts: 571400 (low pressure) and 571000 (high-pressure) is compared to Scenario S4, which applies dynamic pricing across all smart meters. The effect of individual tracts changes the total hourly energy consumption by between 5% and –5%. There is little difference between the effects of different tracts when comparing the rest of the 14 tracts, indicating that energy savings are not significantly based on the geospatial location of demand changes. Instead, energy savings are a result of reductions in demands, regardless of where the change in demand occurs. In addition, though there is a substantial difference in the number of SFH meters within each tract, the effect does not vary significantly. For example, tract 571503 has 272 single family home meters, while tract 571000 has 2011 single family home smart meters, yet the total energy difference at any hour varies within change of 0.5% from the total energy demand for scenario S4.

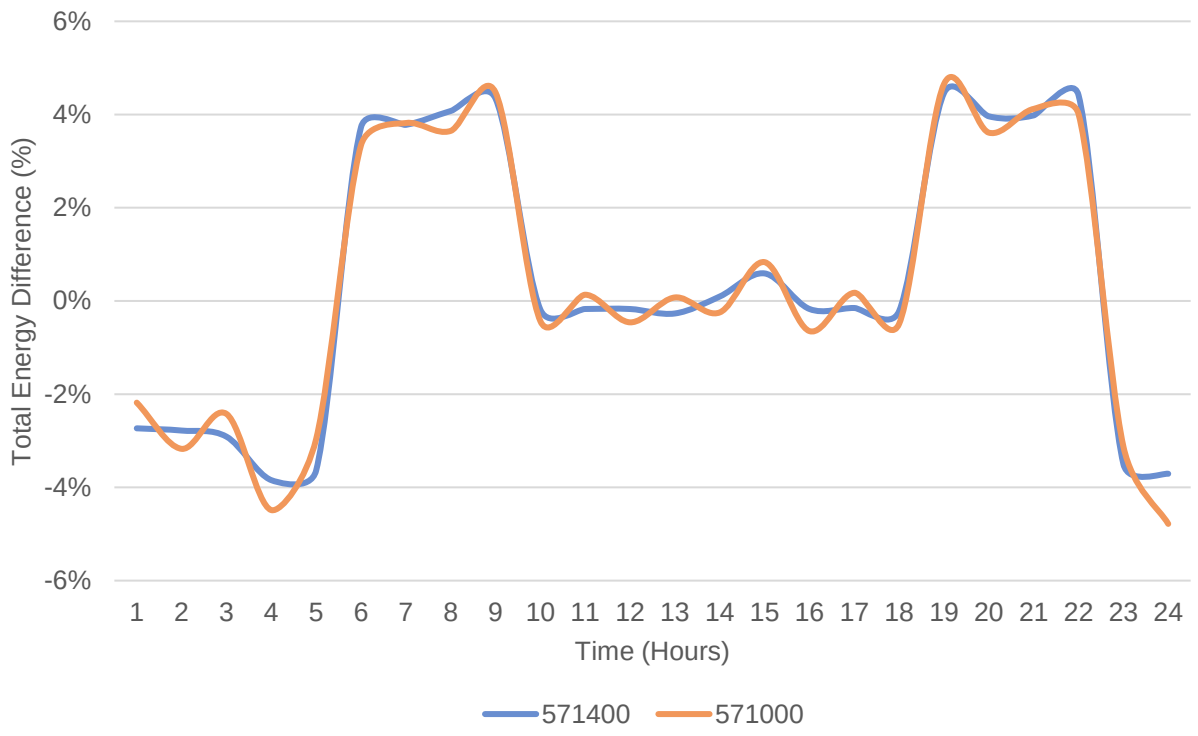

Figure 21. Average Hourly Difference of Pumping Energy if DP Applied to Tracts 571400 and 57100 Compared to DP Applied to All SFH for S4 at the End of One Month Simulation, July 2019

The tracts are grouped based on location within three groups: North, East, and West as in Figure 20. For each group, we compare the pump average energy cost for each pump (Figure 22). Each pump is affected differently by the change in the timing of demands. The cost difference is calculated as the group average of the difference in cost when dynamic pricing scenario S4 is applied to one tract at a time, compared to scenario S4 applied across all tracts. As shown in Figure 22, three pumps have a cost difference greater than 5%, indicating that energy costs are saved at those pumps for a policy that applies dynamic pricing to only one tract. Pump 2 at plant 4 has the highest cost savings, and there is some variation among tracts. Tract 571300 has the lowest effect on pump 2, and tract 571503 has the highest effect on pump 2. For pump 3 at plant 4, tracts 570003 and 570002 have a much smaller effect on cost savings, compared to the effect of other tracts on

pump 3. Similarly, for the pump at well 18, tract 571000 has the lowest effect on the energy cost at that pump, and tracts 571102 and 570003 have the highest effect. Overall, spatial analysis provides some insight into the mechanisms that result in cost savings for energy.

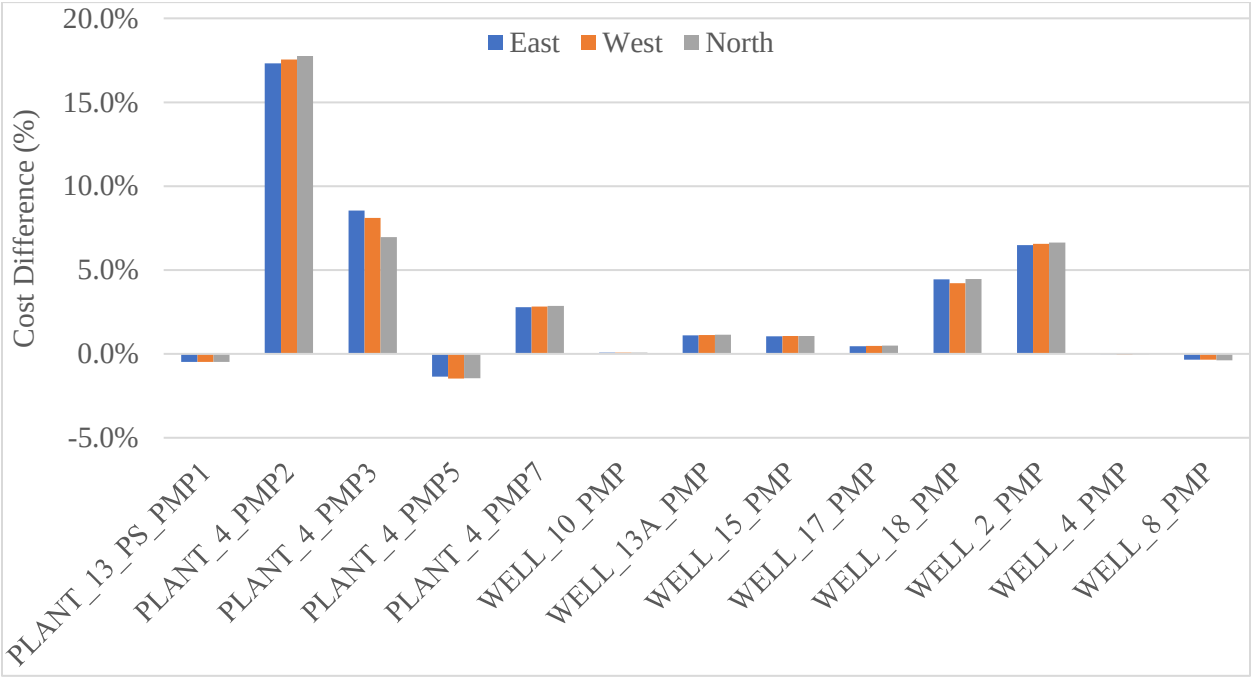

Figure 22. Change in the Cost of Energy for Each Pump for S4 when DP is applied to one tract per simulation. Difference is calculated based on the average cost across all tracts in a group (East, West, or North) less the costs of energy for the scenario S4 applied to all SFH accounts. Cost is calculated across one month of simulation, July 2019.

5.4 Computing Time

Each dynamic pricing scenario is run on Python 3.7 using Spyder IDE and requires approximately five minutes 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 three minutes to run for one cycle two months of data. The wrapper requires 60 seconds to generate the modified hydraulic model for one scenario. Finally, the hydraulic simulation for one month takes 50 seconds. This is on a system with a processor of i7-6700HQ CPU @ 2.60GHz and 32 GB of RAM.

CHAPTER 6: DISCUSSION

Results of this research demonstrate that dynamic pricing reduces the pumping energy and peak energy. Each scenario performed similarly, and reductions in peak water demands ranging from 20 to 8% led to reductions in energy consumption with a range of 11 to 10% and peak energy demands of approximately 40% for all scenarios. This research does not include analysis of required pressure or velocity within the system, which can limit the peak energy reduction. These results may be dependent on the topography and operation of the Lakewood distribution network, which utilizes pumps and tanks to satisfy the required pressure and demand. Other water distribution networks might experience different changes in energy consumption based on their unique structures.

This research assumes a uniform price elasticity of demand across all single-family-home consumers. The heterogeneity of those consumers such as the consumption tier, lot size, number of occupants, or socioeconomical status is not considered. Price elasticity values are typically developed at city-level and capture heterogeneity of the consumers and seasonality since they are based on collected observations. Further research can update the modeling approach to include the effect of demographics on elasticity values, as that information becomes available. New research is needed that would explore how information and education are needed to improve customer awareness of the interactions of the timing of water use and energy costs and how educational campaigns may change elasticity values. The model can be refined by including the characteristics of the consumers, such as the lot area or the number of residents, to better estimate demand elasticity for intraday periods. The model reports a small reduction in total demand, and though conservation is not the objective of this framework, changes to total demands and utility revenues can be further minimized thorough optimization or machine learning algorithms. This

study uses AMI data reported at hourly intervals. Higher temporal AMI data can be used to identify end uses that can be targeted with dynamic pricing, such as irrigation or laundry demands, which can be exclusively shifted to off-peak hours.

The hydraulic model of Lakewood city is not calibrated, and model error may affect the comparison among dynamic pricing scenarios. Efforts are underway to calibrate the model using SCADA data of the pumps for a one-month period. Moreover, the model can be improved through optimizing the operation practice and the controls. These efforts will improve the performance of the model and consequently the results of this research or future work on this model. Energy consumption and peak energy demand can be reduced through optimizing the pumps controls, and research is needed to evaluate effectiveness of infrastructure controls in energy consumption and energy cost savings.

Dynamic pricing policies lead to reductions in the cost of energy, because of the reduction in the peak energy demand and the total energy consumption. Both peak energy demand and the total energy consumption are elements of the energy cost for the utility. For other networks with different energy cost structures or minimal utilization of pumps, energy savings may vary. It is expected that many water utilities pay a transmission charge on peak energy demands, and, as resources become increasingly scarce, we expect that dynamic pricing may serve as an important demand management, energy management, and cost management strategy. The dynamic pricing framework should be implemented and simulated within a hydraulic model for networks of interest to explore how the reduction of water demand at peak hours affects the energy consumption by the network.

The possible positive effects of the peak hours water demand, and the savings of the energy and cost can contribute to reducing the operation and maintenance costs or reducing or delaying

any expansion investment planned. This framework uses actual data of water consumption coupled with a network hydraulic model to analyze hydraulic performance, energy consumption, and energy cost. This framework extends existing research and knowledge by coupling models of elasticity, time-of-day use tariffs, and water demand data with hydraulic simulation to provide quantitative evaluation of the effects of dynamic pricing on energy costs. Existing DP frameworks used predicted demands (Vasak et al. 2014) or a range of assumed price change ratio (Rouge et al 2018) to simulate the effects of dynamic pricing programs. These studies did not couple demand changes with hydraulic simulation of pipe networks.

Other hydraulic metrics such as background leakages and average pressure increase are evaluated for dynamic pricing policies. These values can affect the reliability of the infrastructure and lead to increased pipes beaks. This research does not simulate any changes in operations or controls, and adjusting valves or pump controls could improve pressure and reduce background leakages. This research finds that the maximum flow and flow in general are lowered significantly, leading to lower velocities. Water age is adversely affected by lower velocities, but for the Lakewood system, water age does not cross thresholds that would be considered as a threat to health. Lower velocities can lead to savings and improvements in long-term infrastructure maintenance and aging. This research does not assess long-term effects of lower velocities, and further research is needed to develop models that can quantify the associated cost savings.

The spatial analysis of the dynamic pricing based on the tracts of Lakewood city demonstrate that there are small differences on the system, based on where demands are changed. The city is primarily residential, changes in demands occur uniformly across the system. Customers are not modeled with heterogenous responses to price changes (e.g., elasticity). Variations in demand patterns among households are captured through the AMI data that is used

to initialize demands. However, the effects of different sections (tracts) of the network on the reduction in energy costs and the pumps with reduced demands are small.

CHAPTER 7: CONCLUSION

In this work a dynamic pricing model is developed to reduce and shift the peak demand of residential consumption. In this framework, the model uses the difference between a consumer use compared to average network use at the same hour to produce price change ratio for every hour of the day. This ratio is used to predict how the demand of each consumer is changed as a response to the price change at each hour under four scenarios. The modified demand of each single-family home consumer, the output of the model, is then used in hydraulic simulations to be compared with the actual demands for the four scenarios.

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. In order to limit the price increase, a price change cap of 25% is added to the second and third scenarios. Also, in an effort to reflect the fact that consumers' use is less changeable out of the peak hours, the third and fourth scenarios have two lower elasticity values for the mid and off-peak hours such as, -0.36 and -0.32, respectively. The fourth scenario is constructed as a three-block of price instead of hourly change of price, 24-block, such as the first three scenarios. 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 Lakewood city, where most of the demand is residential, with about 15% of water is distributed for commercial and institutional purposes. Dynamic pricing leads to a flattened demand curve, and the peaks are shifted and reduced to varying degrees. The differences are affected by the design of each scenario and restrictions on the price change. The model performed similarly for all four scenarios; however, and it is found that more restrictions on the price change lead to less impact of the dynamic pricing on the demand change. Hydraulics

in the network is similar across all dynamic pricing scenarios. This research calculated the utility revenue associated with different dynamic pricing scenarios and found that using a unit price of $3.00/100 cubic feet can lead to a slight increase to the total revenues, when compared to the current rate structure. In order to achieve revenue neutrality, the unit price can be adjusted.

The model estimated the possible shifting of water consumption on an hourly basis per day based on four scenarios for the Lakewood city in California. In all scenarios the diurnal demand curve was flattened. The model does not consider the actual behavior of consumers or the probability of changing their water consumption habits; however, the significance of the model results is that proving that dynamic pricing leads to a reduction in peak water demand reduces total energy, peak energy, and energy cost, reflecting the importance of this type of demand management strategy. Operational costs can be lowered without changing or expanding the current infrastructure and continuing to supply the same volume of water. The results demonstrated through this framework can be used by water utilities in designing dynamic pricing schedules that can be implemented to save energy costs. The modeling framework that is developed in this research can be implemented for other utilities to explore how dynamic pricing would perform. These outcomes address the needs of utilities that are under-funded, as they need creative approaches to sustain levels of service for customers without needed budget increases. This research also provides a toolbox for utilities to develop and explore new management strategies to protect natural resources and conserve both water and energy in urban management.

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