Estimating Residential Outdoor Water Use with Smart Water Meter Data

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ABSTRACT

Water demand management is crucial for ensuring the efficient use of water resources. Smart water meters have emerged as a valuable tool for managing water usage in residential areas. Smart water meter data analysis can provide valuable insights for informing water resource management strategies and policy decisions. Using hourly AMI data for water demand management provides more accurate and frequent estimates of water use compared to using billing data, which can lead to more effective and targeted policies for demand management. In this study, we used hourly demand data from smart water meters in 18,000 residential accounts in Lakewood, CA, over two years to estimate the volume and timing of outdoor water use. We used the minimum day method-network level (MDM-N), minimum day method-account level (MDM-A), and minimum hour method network level (MHM-N) to develop estimates of indoor water use, which we used to calculate outdoor water use patterns. Our findings indicate that, on average, outdoor water use ranges from 31% to 41% of total demand using the MDM-N, MDM-A, and MHMN. Our study highlights the potential of smart water meter data analysis as a valuable tool for water demand management. The ability to estimate and understand outdoor water use patterns can help policymakers develop more effective water demand policies and inform water resource management strategies to ensure the efficient use of water resources. Smart water meters and new modeling methods can help optimize water demand management strategies by providing a more accurate and detailed picture of outdoor water usage.

1 INTRODUCTION

Managing water resources effectively is essential for sustainable development. Residential outdoor water use is a significant contributor to water demand, particularly in urban areas where outdoor irrigation accounts for a substantial portion of total water consumption. For example, several studies have estimated outdoor use in California to be more than 50% based on water use data and remote sensing (Mini et al., 2014; Johnson & Belitz, 2012; Deoreo et al., 2011). Methods for estimating residential outdoor water consumption include, for example, ordinary least squares multiple regression and spatial regression methods, which use sociodemographic data and other factors such as lot size and the presence of swimming pools to estimate outdoor water consumption (House-Peters et al., 2010). Other approaches survey residents to gauge the perceived importance of outdoor water use (Sadalla et al., 2014) or leverage price elasticities to study the effects of pricing changes on water consumption (Mansur & Olmstead, 2012). Technology has enabled the use of remote sensing-based approaches, aerial imagery, and cadastral data to estimate water consumption for varied land uses, offering deeper granularity in understanding outdoor water use (Llaus`as et al., 2019). Process models that incorporate the variability among fixture end uses and irrigable areas have also been introduced as effective methods to estimate residential water consumption (Friedman et al., 2014). Because climate change is a crucial factor in future water scarcity issues, statistical models have been developed to estimate the impact of climate change on residential water use (Makwiza et al., 2018).

Smart water meters have emerged as a valuable tool for monitoring and managing water usage in residential areas. Smart meters provide accurate and frequent data on water consumption patterns, making it easier for policymakers to develop effective water demand policies and inform water resource management strategies (Pesantez et al., 2022; Cominola et al., 2015). While smart meters offer advanced monitoring capabilities, estimating outdoor water use through smart meter data presents its challenges, primarily due to the inability of these devices to directly measure outdoor water use (CardellOliver, 2013). Various strategies have emerged to bridge this gap. For instance, using water use signature patterns offers a means to identify relevant consumption patterns through medium-resolution meter data (Cardell-Oliver, 2013). Some researchers classify water use events based on medium-resolution meter data, as well, to distinguish indoor from outdoor usage (Meyer et al., 2021). Furthermore, an intriguing insight lies in the pattern of leading digits from smart water meters; deviations in the first digit of a number can be indicative of abnormal water use (Sowby et al., 2023). Real-time communication of water use readings is an added advantage of smart water meters, forming an integral part of the broader Internet of Things (IoT) architecture that spans across water, electricity, and gas metering (March et al., 2017; Lloret et al., 2016). However, the vast trove of data these devices offer is not without challenges. The detailed insights that smart meters provide about water consumption can play a pivotal role in influencing consumers' intention to adopt them (Madias et al., 2022), but to fully extract meaningful insights from this data, data often need to be complemented with other datasets such as water fixture inventory data and survey data (Cominola et al., 2019).

Despite the growing use of smart meters by utilities, the availability of fine-resolution data, which is needed to classify end-uses, is rare, therefore, and methods to use hourly Advanced Metering Infrastructure (AMI) data are needed to classify indoor and outdoor uses. This study addresses this gap by utilizing hourly demand data from smart water meters in Lakewood, CA over a two-year period to estimate the volume and timing of outdoor water use. Specifically, we use the minimum day method (MDM) and minimum hour method (MHM) at both the network and account levels to develop estimates of indoor water use, which we use to calculate outdoor water use patterns. Previous research has used similar methods to estimate outdoor use but is limited to monthly billing data (Mini et al., 2014; Deoreo et al., 2011). In this research, we use AMI hourly data to assess minimum day and minimum hour use for a precise estimation of the volume of the outdoor use. Minimum day and minimum hour water use is applied to estimate indoor use and generate diurnal outdoor use patterns. The purpose of this research is to provide policymakers and water managers with accurate and frequent estimates of outdoor water use, which can promote more efficient use of water resources. This study is a step to fill the gap in our understanding of residential outdoor water use patterns by utilizing hourly smart water meter data analysis. The results of this study will provide valuable insights for informing water resource management strategies and policy decisions.

2 DATA AND METHODS

2.1 Data

The research analyzes hourly demand data from smart water meters in 18,000 residential accounts in Lakewood, CA, over a two-year period. The study area, Lakewood, CA, is an urban area with a population of over 80,000 people, located in Los Angeles County, California. This study covers a period from 2018 to 2020, during which time outdoor water use restrictions were proposed but not enforced to limit the frequency and hours of outdoor water use. The smart water meter data provides hourly demand data, which will be used to estimate indoor water use. This study utilized hourly demand data from smart water meters in 18,000 single-family home (SFH) accounts in Lakewood, CA over a two-year period starting from July 2018 to June 2020. Accounts with no demands or negative demands were excluded and considered as readings from defective meters. Additionally, precipitation data of Lakewood for the same time period were obtained to identify dry periods.

2.2 Methods

The minimum month method, which was used by Mini et al., 2014, is used here for the purpose of comparison. The study utilized the minimum day method (MDM) and minimum hour method (MHM) to estimate the volume and timing of outdoor water use at both the network (-N) and account (-A) levels. The MDM and MHM were also used to develop estimates of indoor water use, which were then used to calculate outdoor water use patterns.

2.2.1 Minimum Month Method-Network (MMM-N)

In this method, the month with minimum use throughout the dataset is identified and considered as indoor use only, under the assumption that indoor use is consistent for each month. The outdoor water use is calculated as a ratio for each month based on the total residual consumption volume.

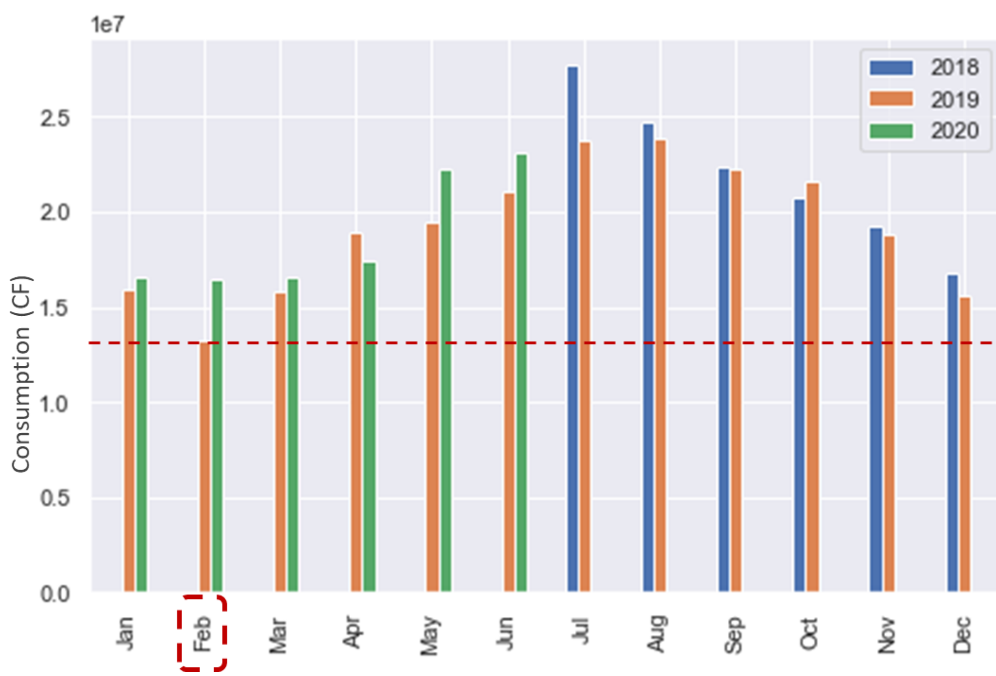

Figure 1. The month of Feb. 2019 was identified as the minimum month.

2.2.2 Minimum Day Method-Network (MDM-N)

To apply MDM-N, the day with the least total consumption across the network across the two years of data was identified as the minimum use day of February 14, 2019. Figure 2 shows an illustration of selecting this specific day, which was the day with the highest precipitation amount during the data period. Water use on this day is considered as the typical indoor use on any other day, as shown in equation (2), where all residual demands are considered as total network outdoor use. Any residual of the demand compared to the minimum day demand was considered outdoor use. The outdoor ratio is calculated as shown in equation (3), where $D_{n,d}$ is the Demand of network n at any day d, and a refers to the account or customer. The ratio of outdoor water use from is used to calculate the network outdoor water use on any day as modeled in equation (4).

$$D_{n,d} = \sum_{a=1}^{18000} D_{a,\ d} \tag{1}$$

$$Indoor\ d_{n,d} = D_{n,\ Feb14,2019} \tag{2}$$

$$Outdoor\ Ratio_{MDM-N} = \frac{D_{n,d} - Indoor\ D_{n,d}}{D_{n,d}} \tag{3}$$

$$Outdoor\ D_{a,d} = D_{a,d} \times Outdoor\ Ratio_{MDM-N} \tag{4}$$

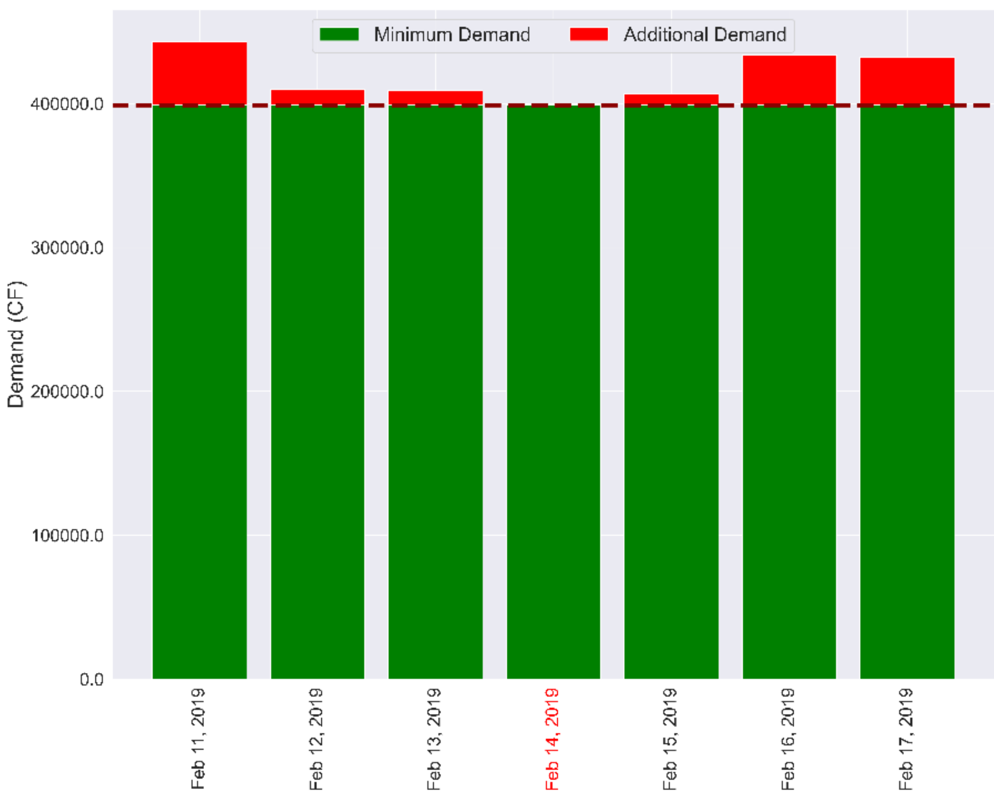

Figure 2. Feb 14, 2019, was selected as the minimum use day for the MDM-N and MDM-A approaches. Additional demand beyond the minimum use is identified as outdoor demand.

2.2.3 Minimum Day Method-Account (MDM-A)

On the account level, the demand of the minimum use day (February 14, 2019) for each account a is considered the typical indoor water use for the specific account on any day of the year. The 24 hourly demand values of this day were subtracted from the demand of each day, and the residual was considered the outdoor demand of this account, where $D_{a,d}$ is the demand at account a at day d.

$$Indoor\ D_{a,d} = D_{a,\,Feb14,2019} \tag{5}$$

$$Outdoor\ Ratio_{MDM-A_a} = \frac{D_{(a,d)} - Indoor\ D_{a,d}}{D_{a,d}} \tag{6}$$

$$Outdoor\ D_{a,d} = D_{a,d} \times Outdoor\ Ratio_{MDM-A_a} \tag{7}$$

2.2.4 Minimum Hour Method-Network (MHM-N)

To apply the MHM, the minimum total demand at each hour of a 24-hour period was identified and identified as the minimum use hour. Equation (8) shows this step for the first hour, MH-00. This step was repeated for each hour of the day to create values for MH-00, MH-01, ..., MH-23, as shown in equation (9). This list of 24 minimum hours was considered the indoor use at any day across the network. For the network level, the list of MH values was subtracted from every day and the residual was identified as the outdoor use, as shown in equations (10) and (11). This process is illustrated in Figure 3.

$$D_{n,\,h_{00}} = min\left[D_{n,0,\,h_{00}}, D_{n,1,\,h_{00}}, \dots, D_{n,729,\,h_{00}}\right] \tag{8}$$

$$Indoor\ D_{n,\,d} = \left[D_{n,\,h_{01}}, D_{n,\,h_{02}}, \dots, D_{n,\,h_{23}}\right] \tag{9}$$

$$Outdoor\ Ratio_{MHM-N} = \frac{D_{n,d} - Indoor\ D_{n,d}}{D_{n,d}} \tag{10}$$

$$Outdoor\ D_{a,d} = D_{a,d} \times Outdoor\ Ratio_{MHM-N} \tag{11}$$

Using the minimum hour approach at the account level was not applicable, as most of the accounts have hours of approximately zero demands that would result in a 99% outdoor use of that specific hour.

2.2.1 Estimating Outdoor Water Use Profiles

The timing of outdoor use is estimated by generating hourly ratios of outdoor use to total use using the MDM and MHM output. These ratios were multiplied by the total demands of the network or the account to create outdoor use patterns.

3 RESULTS

The study utilized three different methods, the MMM-N, MDM-N, MDM-A, and MHM-N methods, to estimate the volume and timing of outdoor water use using smart water meter data in

18,000 single-family homes in Lakewood, CA. Using the MMM-N, the average outdoor water use ratio was 25%. This value is compared with 27%, which was calculated by Mini et al., 2014 using the same method for another utility in California. The outdoor average daily use ratio was 38% using the MDM-A method, 31% using the MDM-N method, and 42% using the MHM-N method. These results found that outdoor water use in residential areas is significant and that managing outdoor use effectively can lead to freshwater savings.

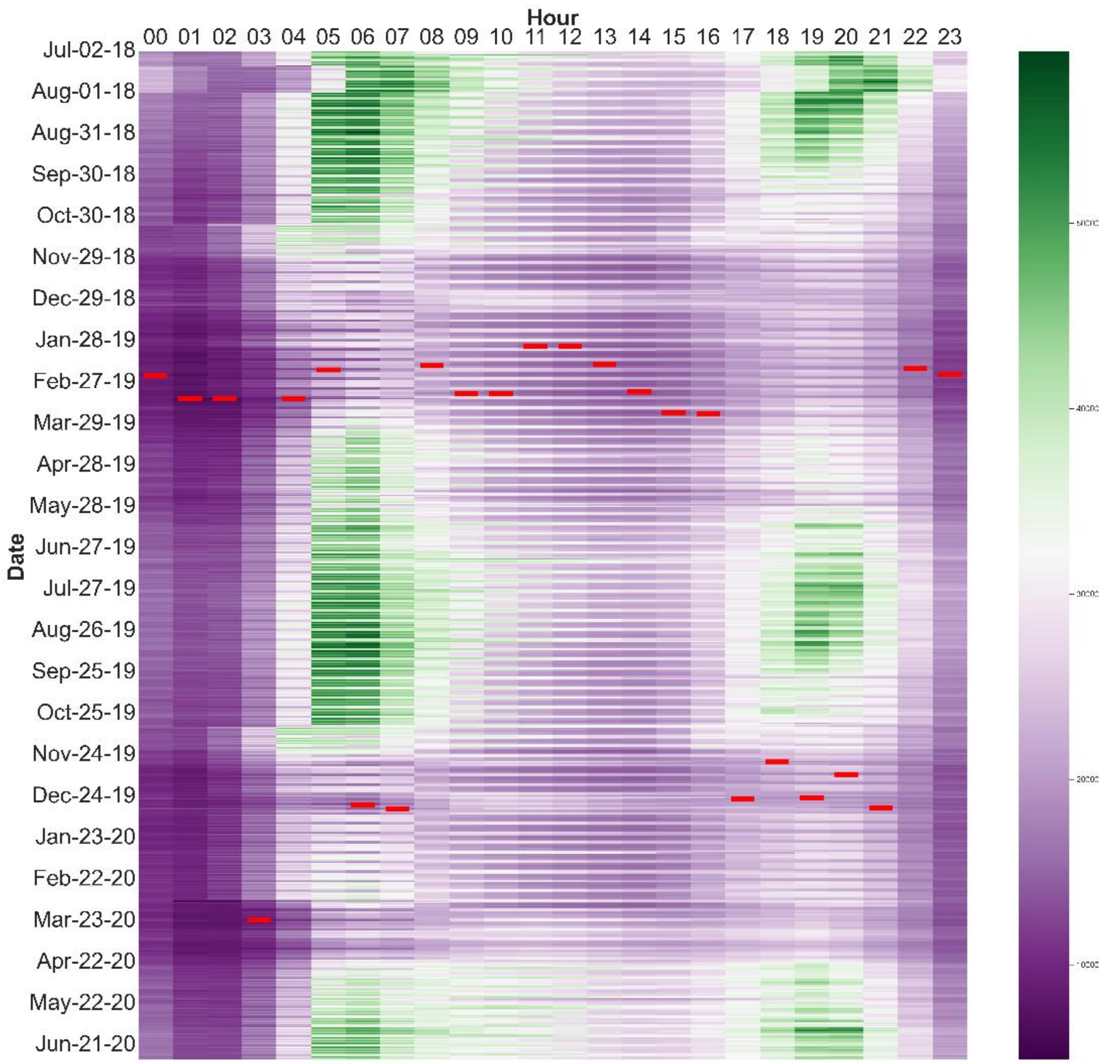

Figure 3. The MHM-N approach identifies the minimum hour use at each of 24 hours based on the minimum use at each hour across the dataset.

3.1 Daily Outdoor Water Use Ratio: Diurnal Pattern

The timing of water use is essential information for water distribution systems managers. Knowledge of consumer water use time and volume allows managers to operate the system and design rules and operational practices for all of its components. Understanding the outdoor water use time facilitates the design of the demand management policies.

The methods developed in this study estimate the timing of outdoor water use, as shown in Figure 4. The MDM-N approach finds the peak outdoor water use in the morning hours starting from 4 am up to 11 am, with a notable decline at 7 am. This pattern shows outdoor water use with a range of 22% at 2 a.m. and 38% at 5 am. This method uses the minimum day of the aggregated demands of the systems to construct the outdoor water use ratio, which dissolves some of the granularity of the data or account behavior. The MDM-A calculations show the peaks occur between 9 am and 2 pm with a maximum ratio of 42% at 10 am and a minimum outdoor water use ratio of 32% at 6 am, as shown in Figure 3. Finally, the MHM-N approach shows the peaks occur in the early morning hours between 1 am and 6 am, which was not expected, with the maximum ratio of 60% found at 6 am and the minimum ratio of 30% at 5 pm, shown in Figure 3. This unexpected time of use is because, in this method, outdoor water use ratios are constructed based on minimum hours across the system which were identified in cold months, January, February, March, and December.

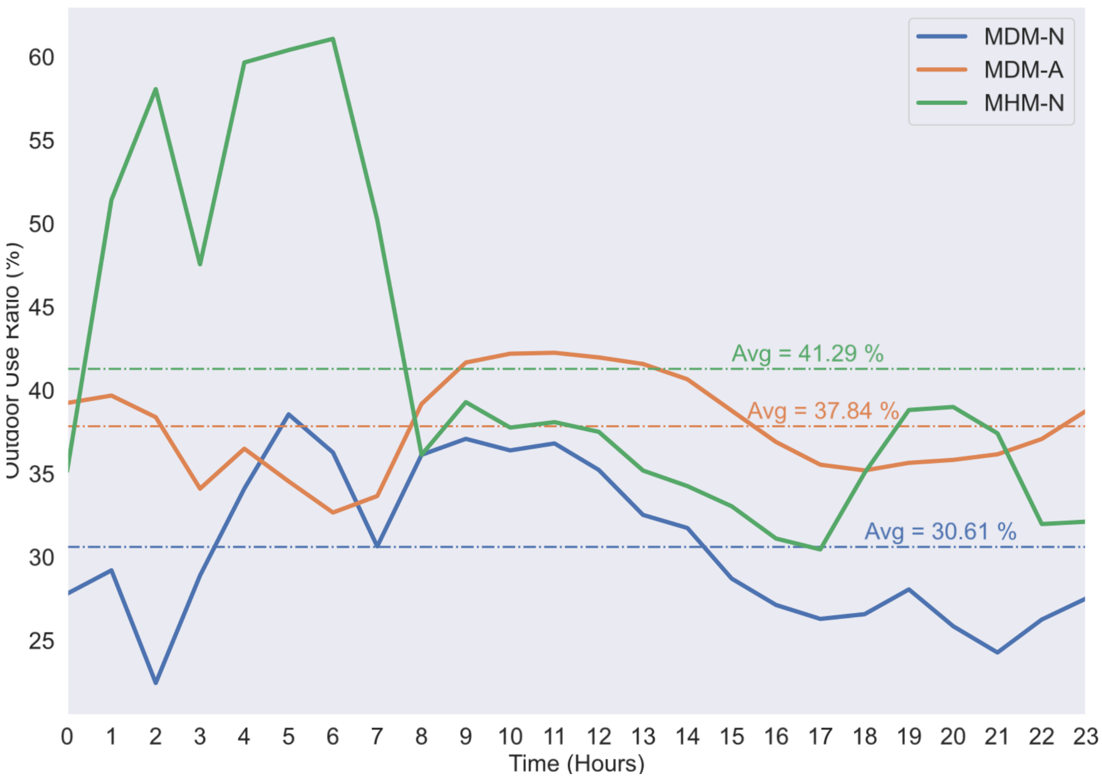

Figure 4. Average diurnal pattern of outdoor demand ratio is calculated using the MDM-N approach (blue line), MDM-A approach (orange line), and MHM-N approach (green line).

3.2 Weekly Outdoor Water Use

The three methods were applied to each SFH account within the system to estimate the account outdoor water use and then averaged over the system (Figure 5). These figures illustrate the weekly pattern using each method. Blue lines represent the average actual total demand, and the green lines represent the average estimated outdoor water use. The selected week is a dry week in August to reduce the possibility of demand change due of rainfall. Higher outdoor use peaks occurred across all weekdays in the morning using the three methods, with use ranging from 1 to 1.7 CF/hour on average. In contrast, on the weekend days, those peaks range between 0.8 to 1.4 CF/hour. This pattern follows the total actual demand pattern. An exception is noted for the MHM-N method because the peaks of outdoor water use are estimated in the early morning hours. In all cases, the outdoor use peaks are estimated at the same hour aligned with the peak of the total demand. This indicates that there is an opportunity for lowering the peak demands of the system by managing the peak outdoor water use. Lowering the peak demands of the system can save energy and cost for the utility. Each day of the week has a unique pattern, but a few days have some similarities. The maximum outdoor water use of 1.1 CF/hour occurred on the early morning peak on Monday, Wednesday, and Friday, using the MDM-N estimation. When using the estimates of MDM-A and MHM-N, the highest estimated outdoor use also occurred on the same three days of the week but with higher values reaching above 1.5 CF/hour and 1.7 CF/hour, respectively.

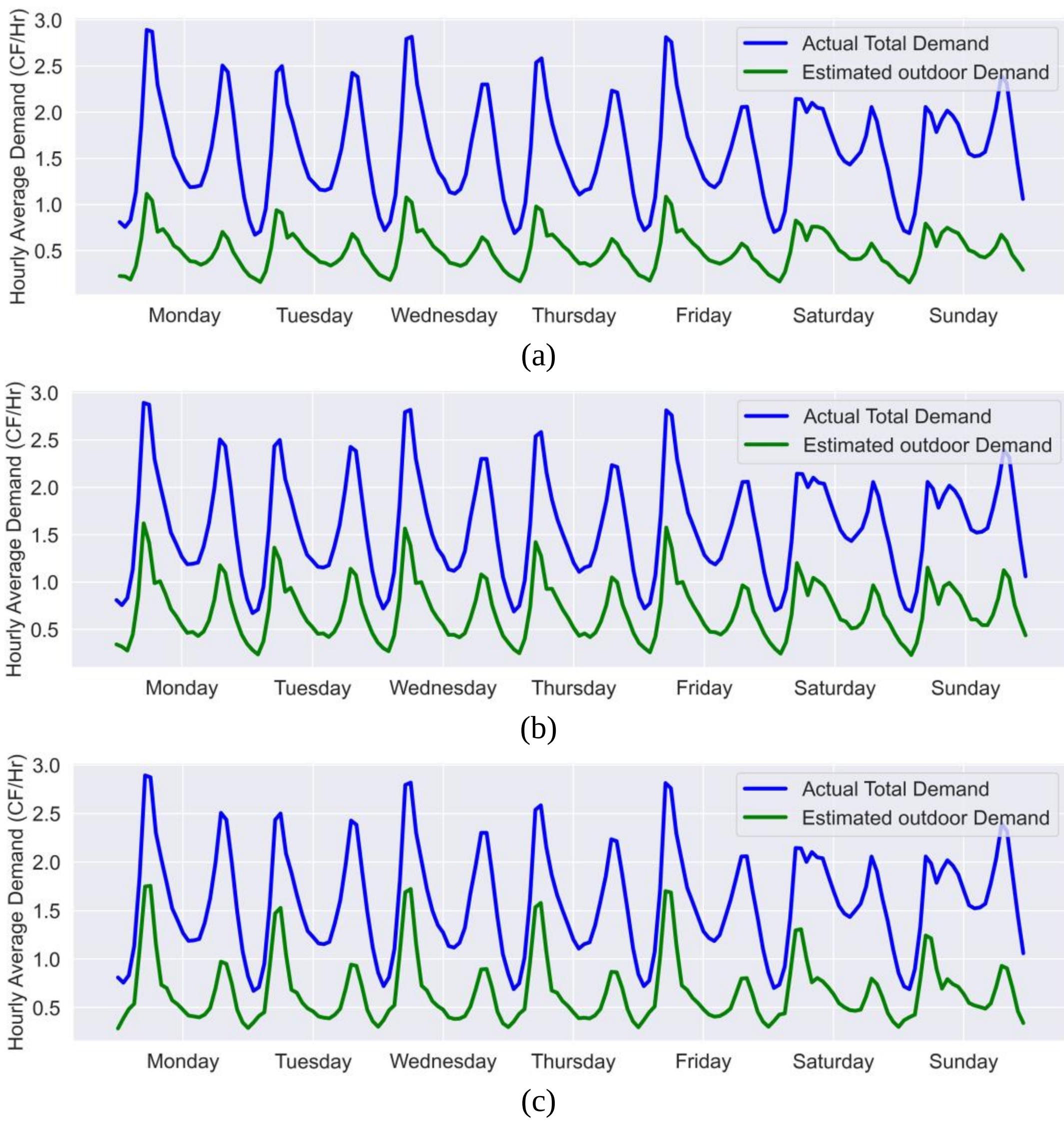

Figure 5. Average hourly pattern of outdoor demand for SFH for the week of 2019-08-05 to 2019-08-11 using (a) MDM-N method, (b) MDM-A method, and (c) MHM-N method.

4 DISCUSSION

Water demand management in residential sectors is challenged by increasing urbanization, which causes a rise in water demand. The demand for water resources is expected to grow, which puts water distribution systems at risk of shortages and strain due to high peak demands. Thus, an understanding of the water demand patterns and uses is an important part of better managing demand and demand changes. Data collected by utilities can facilitate analysis of water demand patterns and uses. This study presented a novel approach to estimate outdoor water use in residential areas using AMI data. The basis for the proposed methods is the assumption that indoor use is the minimum use, and the residual is the outdoor use. The results derived from the analysis of smart water meter data in Lakewood, CA, shed light on outdoor water use patterns and paves the way for more informed water management strategies such as targeted water restrictions and pricing strategies.

4.1 Analysis of the Methods

This work introduced methods, MDM-N, MDM-A, and MHM-N, to estimate outdoor water use in residential single-family homes and compared these methods with the MMM-N approach. The MDM-A method estimates the outdoor water use based on the consumption behavior of individual accounts, yielding an average daily use ratio of 38%. In contrast, the MDM-N and MHM-N methods estimated outdoor water use at 31% and 42%, respectively, based on the aggregated ratios. The variations between these methods highlight the complexity involved in water consumption patterns and the importance of data analysis granularity. Previous studies found outdoor use in LA county to be more than 50% (Mini et al., 2014; Johnson & Belitz, 2012; Deoreo et al., 2011), which indicates that using the minimum hour method could result in a more accurate estimation when compared to using the minimum day or minimum month methods.

These methods also estimate the time of use that could be used to construct a pattern of outdoor water use of any individual account in the system. This advantage is useful for customized water demand management policy design. The diurnal patterns, as estimated by these methods, offer further insights. The daytime peak of the MDM-A method, between 9 am and 2 pm, may indicate that residents engaging in outdoor activities like irrigation. The early morning peaks observed in the MDM-N and MHM-N methods could be attributed to automated irrigation systems. These findings emphasize the importance of understanding consumer behavior and its impact on water demand. The methods developed in this research may be improved through considering seasonality in constructing outdoor water use profiles.

4.2 Implications for Water Infrastructure and Utility Costs

The insights derived from this study have implications for water infrastructure planning and management. Peak demands, especially during early morning hours, can exert significant pressure on water distribution systems. High flows can lead to increased deterioration of infrastructure components, which can shorten their lifespan and lead to more frequent leaks or breaks. Managing ageing infrastructure and pipe breaks requires substantial investments. Peak demands can also influence operational costs for water utilities. High demands necessitate increased pumping, which can lead to higher energy consumption and costs. By shifting portions of peak demands to non-peak demand hours or days, utilities can lower the peak demand of the system. By understanding these peak periods of demand, utilities can optimize their operations and design new demand management policies, leading to cost savings and more efficient resource allocation.

4.3 The Role of Smart Meters in Water Distribution Systems

Smart water meters, as presented in this study, are more than data collection devices to calculate accurate water bills. Smart meters are instrumental in shaping the future of water distribution systems. By providing granular and frequent records, these meters facilitate dynamic and responsive water distribution system. Utilities can leverage smart meter data to identify potential issues in the distribution network, such as leaks or pressure anomalies before they escalate into more significant problems. Using fine resolution data, utilities can design, apply, and evaluate demand management policies.

4.4 Challenges and Future Research Avenues

While this study provides a novel approach to outdoor water estimation using hourly AMI data, the methods have a few limitations. Lack of ground truth data limits the ability to verify the accuracy of these proposed methods. Availability of outdoor water use data is needed to assess the accuracy of these newly developed methods. Previous methods used the minimum use month method using monthly data (Mini et al., 2014) but did not have access to hourly data as used here. The methods developed in this study estimated the time of using outdoor water in addition to the ratio or volume of outdoor water use, and data are not available to verify these estimations. The methods introduced here compared the application of the same method over the network and on a single account level. Estimations that calculate the outdoor use ratio over the network remove the irregularities of daily indoor uses, leading to improved estimation of indoor household end uses over longer periods of time. The rainfall data reported for Lakewood over the same period was examined and was not included in the analysis approaches that were developed in this research. Future work can explore modeling methods that account for the effects of rainfall to predict outdoor water use.

The findings from this study highlight the potential of using hourly, mid-resolution, smart water meter data, to drive informed decision-making. By understanding the patterns of water demands at individual household accounts and at the network level, policymakers and utility managers can design strategies that ensure the sustainable and efficient use of water and energy.

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