Decomposition of Water Demand Patterns Using Skewed Gaussian Distributions: A Peak-Preserving Approach

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# Abstract

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# Introduction

Water distribution systems are essential for providing safe drinking water. Characterizing and modeling water demand patterns are crucial for their effective design, operation, and management (Blokker et al., 2017). Temporal variations in water demand influence system pressure, water quality, energy consumption, and overall reliability (Billings and Jones, 2008; Herrera et al., 2010). Therefore, developing precise mathematical representations of these time-dependent patterns is essential for a wide range of applications, from hydraulic simulation to real-time control systems. Water demand patterns exhibit complex temporal structures characterized by recurring cycles, irregular peaks, and stochastic variations that pose significant challenges for water utilities in operational decision-making and infrastructure planning (Billings and Jones, 2008). While extensive research has been conducted on water demand forecasting (Alvisi et al., 2024; Donkor et al., 2014; Ghalehkhondabi et al., 2017; Pacchin et al., 2019; Romano and Kapelan, 2014), less attention has been given to decomposing these patterns into their constituent components, most studies focuses on household-level demand patterns (Cominola et al., 2023; Di Mauro et al., 2020; Gargano et al., 2016; Herrera et al., 2010; Pesantez et al., 2020; Worthington and Hoffman, 2008). However, generating realistic daily demand profiles using a few descriptive parameters through top-down decomposition is a vital approach, particularly when data is scarce, confidential, or needed for simulating extreme or future scenarios (Cominola et al., 2023; Niknam et al., 2022). Furthermore, the creation of synthetic daily demand patterns that preserve key statistical properties and capture inherent dynamics is crucial for accurate water demand modeling (Avni et al.,2015). Therefore, this study addresses this need by employing Skewed Gaussian Distributions (SGD) to analyze water demand data, specifically decomposing it into peak events to facilitate the generation of realistic synthetic demand patterns. Early approaches to characterizing daily water demand used simple statistical measures and descriptive analysis(Shvartser et al., 1993). More advanced methods have employed time series analysis techniques, such as ARIMA models, Fourier analysis, wavelet transforms, neural networks, and other methods, as detailed in Alvisi et al. (2024), successively capturing the temporal dependencies in daily demand data.

Creaco et al. (2021) developed a two-step methodology for stochastically generating peak demand scenarios in water distribution networks, using a beta probability distribution to model nodal demands while preserving mean, standard deviation, and skewness. Their approach captures demand variability at both nodal and network scales, addressing correlations across nodes. This seminal article is significant because it employs mathematical expressions to define demand patterns (Di) using the beta density function . The beta function and positive shape parameters B, α, and β, where a ≥ 0 and b > a represent the lower and upper bounds, respectively, can approximate the behavior of demand, reflecting real-world usage patterns. The Demand mean (Dmean) and standard deviation (σ) of Di can be aligned by adjusting these parameters to match the observed statistical properties of the demand data, ensuring the model corresponds with the empirical distribution.

This research aims to further classify different usage behaviors in the demand pattern based on amplitude, width, and skewness, representing the characteristics of the individual predicted peaks. This paper introduces a methodology for decomposing real-world water demand data and generating synthetic daily water demand patterns. The components are modeled using SGD. Unlike traditional symmetric Gaussian models, skewed Gaussian functions include a skewness parameter that allows for flexible representation of asymmetric peak shapes, effectively capturing the rapid rises and gradual declines typical of daily water consumption cycles. This method enables the decomposition of complex daily demand patterns into a sum of interpretable skewed components, each characterized by location, scale, amplitude, and skewness parameters, and the generation of synthetic demand series that maintain essential peak characteristics, including timing, magnitude, and asymmetry. The peak-preserving feature is important for realistic hydraulic simulations, stress-testing of water distribution networks, and evaluation of operational strategies under extreme demand scenarios. As an example, this approach was applied to six diverse water demand datasets extracted from published research studies. To our knowledge, this approach offers a notable contribution to the field of water demand analysis.

# Methodology

This section describes the methodology employed for decomposing time-based demand patterns into a combination of SGD, with an emphasis on peak preservation. The approach enables accurate modeling of demand patterns while maintaining physically meaningful components that correspond to real-world usage behaviors.

## Mathematical Model

### Skewed Gaussian Function

To model asymmetric peaks commonly observed in demand patterns, we employed SGD, Eq.1 (Wolfram Research, 2016) defined as:

Eq.1

Where:

* *A* is the amplitude
* *µ* is the location parameter (peak position)
* *σ* is the width parameter (standard deviation)
* *α* is the skewness parameter
* *erf* is the error function, implemented using SciPy (Virtanen et al., 2020)

### Composite Model

The complete demand pattern model (Eq.2) was constructed as a sum of multiple skewed Gaussian components plus a base demand level:

Eq.2

Where *Cbase* represents the minimum or base demand level, and each component *i* represents a distinct demand peak with its own parameters.

## Peak Detection Algorithm

Significant peaks in the demand patterns were identified using a differential approach that analyzes temporal changes in flow rates. The algorithm extracts hourly data from timestamps and computes the first flow derivative to identify directional changes. Points where the derivative transitions from positive to negative (direction changes from increasing to decreasing) are classified as potential peaks. Special handling is applied to endpoints, where the first point is marked as a peak if its value exceeds the subsequent measurement, and the last point is identified as a peak if it surpasses the penultimate value. The method applies a dynamic threshold to account for plateaus - periods where flow remains constant across multiple timepoints—by marking plateau regions spanning multiple hours as significant peaks. This approach ensures accurate identification of both sharp demand spikes and sustained high- demand periods.

## Constrained Optimization Approach

A key innovation in our methodology is the use of constrained optimization to ensure the fitted curve passes exactly through all identified peaks while maintaining a smooth overall fit. This was implemented using Sequential Least Squares Programming (SLSQP) algorithm (Kraft D, 1988) implemented using SciPy’s optimization module(Virtanen et al., 2020)

### Objective Function

The objective function Eq.3 aims to minimize the sum of the Mean Squared Error (MSE) and regularization terms (R1 and R2 were set to 2 and 0.01 respectively). Mathematically, it can be represented as:

Eq.3

### Constraints

Equality constraints (Eq.4) were defined to ensure the model passes exactly through all identified peaks:

### Parameter Bounds

To ensure physically meaningful results, bounds were applied to all parameters: *Cbase* was constrained between 0 and the maximum demand value, the amplitude (A) was bounded between 0 and 20% more than the maximum hourly demand value, the width (σ) was limited between 0.1 to 10, and the skewness (α) was restricted between -5 and 5.

### Multi-start Optimization

To avoid local minima, multiple starting points were used for width and skewness parameters:

*σ starts* = [1*.*0*,*2*.*0*,*3*.*0], *α* *starts* = [−1*.*0*,*0*.*0*,*1*.*0]

Each combination was optimized using SciPy(Virtanen et al., 2020) with the SLSQP method, and the best result was selected based on the objective function value.

## Model Validation

The fitted models were validated using multiple error metrics: (i) Root Mean Square Error (RMSE); (ii) MAE; and (iii) Maximum Error: max . Additionally, we ensured the total volume (integral) of the predicted pattern matched the actual data by applying a scaling factor. This step ensures conservation of total demand volume over the analysis period.

## Evaluation of Methodology on Water Demand Patterns

To evaluate the proposed methodology, six distinct hourly time-series water demand datasets were analyzed, capturing diverse demand patterns: (i) Two patterns identified by Nemati et al. (2023) from a Northern California water utility, representing periods during (June 2015 to May 2016) and after (June 2016 to May 2019) the 2015–2016 California drought conservation mandate; (ii) Two patterns reported by Abu-Bakar et al. (2021) during the COVID-19 lockdown in East England, from January to May 2020; (iii) Two patterns documented by Plantak et al. (2022) for a settlement with a daily water demand of 2440 m³/day. These patterns, used to evaluate the methodology, are indexed (Pattern ID) in Table 1.

Table 1: Pattern Index and Source

|  |  |  |
| --- | --- | --- |
| Pattern ID | Units | Source |
| P1a | Gallons/h | (Nemati et al., 2023) |
| P1b | Gallons/h | (Nemati et al., 2023) |
| P2a | m³/h | (Abu-Bakar et al., 2021) |
| P2b | m³/h | (Abu-Bakar et al., 2021) |
| P3a | m³/h | (Plantak et al., 2022) |
| P3b | m³/h | (Plantak et al., 2022) |

# Results

The time-based demand pattern decomposition methodology was applied over the extracted demand patterns (Table 1). This section presents the outcomes of this decomposition process, highlighting the performance of the SGD approach in capturing complex demand behaviors.

## Decomposition Analysis

The methodology decomposed the six hourly water demand patterns (P1a, P1b, P2a, P2b, P3a, P3b) into individual predicted peaks using SGD, with the predicted profiles formed by their superposition. Figure 1 compares the actual and predicted profiles, highlighting the predicted peaks (dashed lines) and their components. Table 2 details the model parameters, including the number of significant peaks (N peaks) and their characteristics, revealing differences in peak timing and visibility compared to the actual data.

Table 2: Model Parameters for Skewed Gaussian Decomposition (SGD) of Water Demand Patterns. Summary of the decomposition results for each pattern, including the number of predicted significant peaks (N peaks), Cbase and the flow range. The table also provides the ranges for the SGD parameters: Amplitude Range, width (Range), and skewness (Range), reflecting the characteristics of the individual predicted peaks.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Pattern ID | N peaks | Cbase | Flow Range | Amplitude Range | Sigma Range | Alpha Range |
| P1a | 5 | 8.48 | (11.7, 23.2) | (0.0, 14.57) | (0.73, 2.18) | (-0.37, 0.64) |
| P1b | 3 | 6.16 | (9.0, 14.8) | (2.74, 7.97) | (1.02, 3.18) | (-0.85, 0.39) |
| P2a | 5 | 0 | (4.0, 108.0) | (1.7, 107.64) | (1.15, 4.18) | (-2.04, 0.62) |
| P2b | 6 | 0 | (2.0, 34.0) | (0.0, 25.67) | (1.75, 3.71) | (-1.01, 0.94) |
| P3a | 9 | 24.68 | (24.4, 170.8) | (0.0, 100.2) | (0.31, 4.35) | (-3.16, 0.2) |
| P3b | 9 | 1.48 | (12.2, 256.2) | (3.61, 179.96) | (0.46, 4.57) | (-3.06, 4.71) |

For P1a, the model identified 5 significant peaks, predicting dominant peaks at 06:00 and 21:00. The superposition aligned closely with actual peaks. P1b, with 3 peaks, predicted dominant peaks at 07:00 and 23:00, matching the actual timings with minimal deviation. In P2a, the model’s 5 peaks predicted demand aligned closely with actual peaks. P2b’s 6 peaks, 10:00 and 15:00 predicted peak lagged by ~1 hour, and 21:00 peak appeared ~2 hours later than the actual peak reflecting the influence of overlapping components. The maximum decomposed components amplitude of 25.67 (Table 2) is only slightly higher than the actual mean of 20.75 (Table 3). Notably, P3a and P3b each identified 9 significant peaks, reflecting a high diversity in the model’s decomposition (see ranges in Table 2). However, Figure 1 shows only 3 distinct peaks for P3a (e.g., around 7:00, 14:00, 22:00) and 2 for P3b (e.g., around 07:00, 23:00), as the superposition of smaller components merged several peaks. For both P3a and P3b the predicted peak aligned with the actual, but in most cases the component was less pronounced in the figure due to overlap.

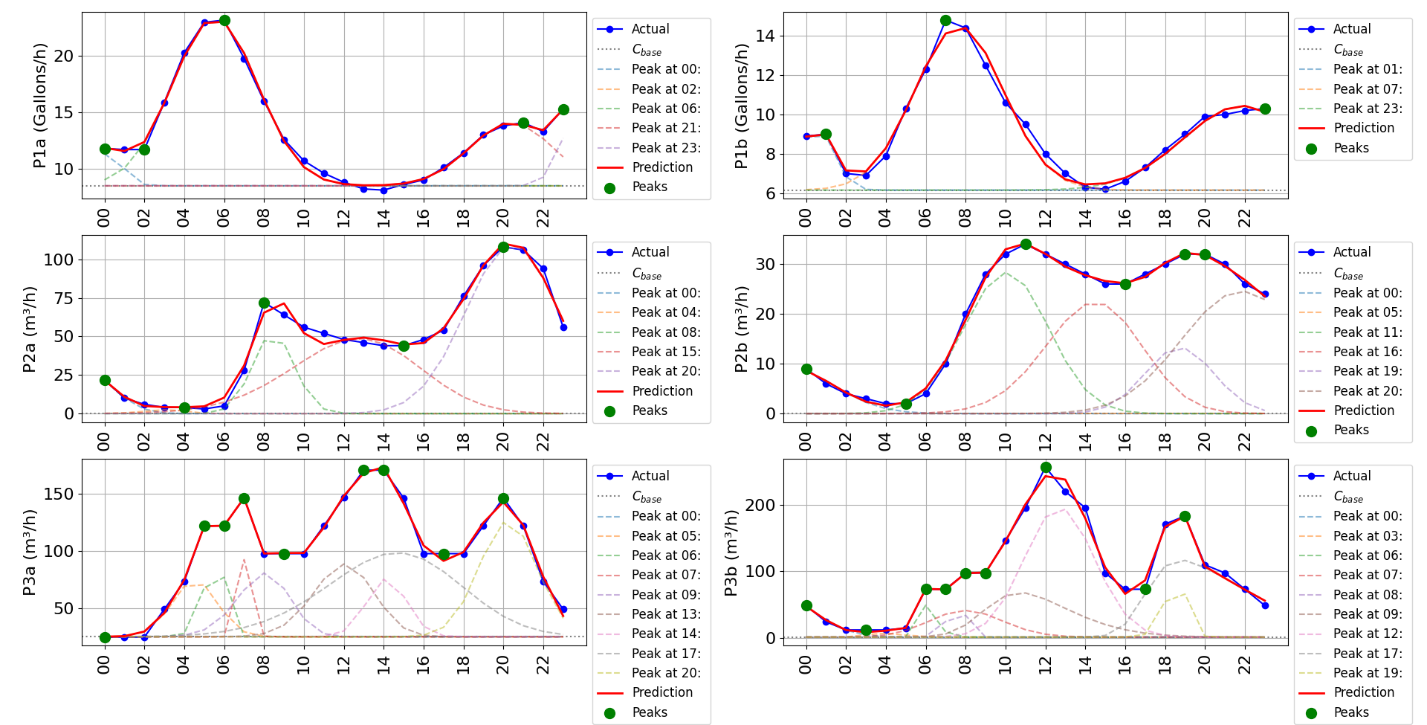


Figure 1. Actual vs. Predicted Patterns and SGD Model Components. Visualization of the fitted model for the different demand patterns. The actual data (blue lines) alongside the predicted model (dashed red lines) for each pattern, with detected significant peaks marked, highlighting the contribution of each peak to the composite model. Time is represented in hours (00:00 to 23:00) on the x-axis, and the y-axis shows the pattern flow rate.

Performance metrics (Table 3) indicate an average RMSE of 4.33% of the mean flow, with higher values in P3b (7.16%) and P2a (7.40%), reflecting sensitivity to timing mismatches and overlapping peaks. The average MAE was 3.23% of the mean (~1.8 units/hour, ranging from 0.22 gallons/hour for P1a to 4.77 m³/hour for P3b), showing consistent accuracy in most predictions.

Table 3: Model Performance Metrics. Summary of the six hourly water demand patterns analyzed to evaluate the proposed methodology. The table includes model performance metrics for each pattern, with Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values indicating the accuracy of the fitted model compared to the actual data.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Pattern ID | Mean flow | RMSE | RMSE as % of mean | MAE | MAE as % of mean | Max Error |
| P1a | 13.33 | 0.28 | 2.14 | 0.22 | 1.61 | 0.68 |
| P1b | 9.3 | 0.32 | 3.41 | 0.25 | 2.73 | 0.69 |
| P2a | 47.75 | 3.54 | 7.4 | 2.68 | 5.61 | 7.15 |
| P2b | 20.75 | 0.57 | 2.74 | 0.48 | 2.32 | 1.21 |
| P3a | 101.68 | 3.21 | 3.15 | 2.38 | 2.34 | 6.98 |
| P3b | 100.25 | 7.17 | 7.16 | 4.77 | 4.76 | 18.48 |
| Average |  |  | 4.33 |  | 3.23 |  |

## Skewness Analysis

The skewness parameter (*α*) proved particularly valuable in characterizing different usage behaviors. Table 2 (Range) illustrates the distribution of skewness values across all identified components. Skewness values ranged from highly negative (-3.16 in P3a) to extremely positive (4.71 in P3b) highlights the necessity of using skewed rather than symmetric Gaussian distributions to accurately model demand patterns.

# Discussion

This research aims to improve understanding of daily water demand using a peak-preserving decomposition method with SGD. It breaks down complex patterns into interpretable components with location, scale, amplitude, and skewness parameters. This approach reveals hidden insights like multiple peaks and generates synthetic demand series retaining key characteristics. The study, applied to six daily data patterns, shows the model's ability to detail consumption behaviors.

The model’s decomposition of water demand into a high number of significant peaks—such as 9 peaks for both P3a and P3b, despite only 3 and 2 visually apparent peaks in Figure 1, respectively—provides a detailed representation of underlying consumer behaviors across diverse urban settings. For P3a, peaks at 07:00, 14:00, and 20:00 likely reflect morning, noon, and evening routines, while additional peaks capture overlapping behaviors of smaller consumer groups merged in the superposed profile; similarly, P3b’s 9 peaks, with visible peaks at 12:00 and 19:00, align with typical daily routines, though timing mismatches (e.g., a ~1-hour shift for the 12:00 peak) highlight the model’s sensitivity to complex, overlapping usage patterns. In contrast, patterns with fewer peaks, such as P1a or P1b, reveal simpler, more synchronized behaviors— often correspond to commercial areas with concentrated usage during opening and closing hours, or may reflect residential areas with distinct morning, afternoon, and evening routines, offering easier predictability for conservation strategies. A notable insight from the SGD method is highlighted in the case of patterns P2a and P2b, derived from Abu-Bakar et al. (2021), which capture the demand shift during the COVID-19 lockdown. This study examined household water consumption in England using smart meter data from January to May 2020, a period marked by significant routine disruptions as people stayed home due to the lockdown starting March 23, 2020. This societal shift offers a valuable opportunity to observe its impact on residential water use within the same region. As illustrated in Figure 1, the SGD method reveals a striking transformation: the morning peak emerges as the dominant single peak, while the evening peak, previously obscured, splits into two distinct peaks, uncovering nuanced behavioral shifts that might not be fully apparent from the aggregated total demand curve alone.

This contrast between complex and simpler patterns demonstrates the methodology’s versatility in capturing a spectrum of usage behaviors, from intricate urban dynamics to uniform routines, thereby providing fine-grained insights into demand drivers that can inform targeted water management strategies.

## Physical Interpretation of Components

The decomposition of water demand into SGD components offers not only a mathematical framework but also valuable physical insights into water usage behaviors within the distribution system. The base component (Cbase), representing constant demand such as leakage, background residential usage (e.g., refrigeration units), and continuous industrial processes, varies significantly across zones—from negligible in P2a (0.00 m³/h) to substantial in P3a (24.68 m³/h)—highlighting differences in infrastructure conditions and baseline consumption needs. Complementing this, the skewness of each peak provides further behavioral context: peaks with moderate to high positive skewness (e.g., 0.5 to 1.2 in P1a, P1b) reflect rapid increases followed by gradual declines, aligning with synchronized morning routines in residential areas where households begin activities like showering simultaneously but conclude at varying times, while extreme positive skewness may indicate commercial operations starting in unison. Conversely, slightly negative to moderately positive skewness in evening patterns suggests heterogeneous usage across residential and commercial groups, and negative skewness (e.g., -0.3) points to gradual buildups and rapid declines, consistent with staged startups and abrupt shutdowns in commercial settings.

Implementing SGD on real-world operational data, analyzed on a weekly basis, provides a robust framework for tackling diverse water management challenges, drawing on detailed insights from actual usage patterns. For non-revenue water issues, such as leakage versus water theft, the SGD approach excels by isolating the base flow component, allowing the detection of subtle anomalies that deviate from expected weekly patterns. For instance, a consistent increase in baseline flow might indicate leakage, while irregular peak anomalies could suggest water theft, enabling targeted investigations and interventions to address these distinct issues. Weekly decomposition might reveal moderate variations in peaks driven by seasonal changes, with impacts potentially limited to specific peaks, such as those associated with garden watering or showering. Incorporating SGD components into machine learning (ML) models for peak prediction could enhance accuracy by predicting each peak individually and then aggregating the results (Eq. 2), a promising direction for future research. The incorporation of decomposed peaks into ML models is likely to improve prediction accuracy by leveraging the detailed insights gained from isolating specific behavioral components, rather than relying solely on the aggregated observed pattern. When detecting changes in individual peaks—such as those linked to garden watering or showering due to seasonal variation—the method captures nuanced shifts (e.g., increased morning peaks in summer or evening splits during lockdowns) that might be obscured in the total demand curve. This granularity allows ML models to learn distinct patterns associated with each peak, such as timing, amplitude, or skewness, which are tied to specific activities or external factors like weather or policy changes. By predicting each peak separately and then summing the results, the model can account for variability and interdependencies among these components more effectively than a holistic approach, reducing errors from averaging out localized anomalies. For instance, a sudden spike in a garden-watering peak might be misattributed in an aggregated model, whereas decomposition isolates it, enabling the ML algorithm to weigh its influence accurately. This peak-by-peak approach enhances the model’s ability to adapt to diverse contexts, such as urban vs. rural zones or drought-affected areas, ultimately leading to more precise demand forecasts and better-informed water management strategies. These insights into constant and dynamic demand components enhance the understanding of system-specific usage drivers, aiding in targeted infrastructure maintenance, peak load management strategies, and opening new research opportunities to further refine these applications

## Synergy with Established Methodologies

The SGD approach in this study provides complementary advantages over existing methods, enhancing the interpretability and efficiency of water demand pattern analysis while leveraging the strengths of prior frameworks. Unlike Fourier series(Moretti et al., 2022), time series decomposition (Shvartser et al., 1993; Zhou et al., 2002), and advanced machine learning prediction methods (Alvisi et al., 2024; Antunes et al., 2018; Villarin and Rodriguez-Galiano, 2019), which often rely on extensive historical data, our method uncovers hidden peak characteristics and infers user routines from short patterns, as evidenced by the identification of 9 peaks in P3a and P3b that reflect distinct routines. Each component in our model corresponds to a tangible usage pattern, offering clear physical interpretability—such as linking P3a’s 07:00 peak to morning activities or P3b’s 1-hour shift at 03:00 to overlapping behaviors. This granular behavioral insight aligns with Shvartser et al. (1993), who decomposed daily demand into “rising,” “oscillating,” and “falling” segments, but our approach extends their work by isolating individual peaks (e.g., 9 in P3a) for a more detailed understanding of consumer behaviors.

In bottom-up demand pattern construction, Blokker et al. (2017) introduced SIMDEUM, a stochastic model simulating drinking water demand at a 1-second, tap-level scale using physical parameters like appliance flows and consumer behavior (Blokker et al., 2010), producing realistic patterns across aggregation levels. Similarly, Creaco et al. (2021) developed a stochastic framework for generating peak demand scenarios with beta distributions, with both studies supporting a Gaussian approach to demand patterns. Complementing these, our top-down method decomposes hourly demand into skewed Gaussian components, with the decomposition adjusted to accommodate aggregation at both city-wide and small neighborhood levels, revealing behavioral peaks—such as the 9 in P3a and P3b linked to routines like morning usage—enhancing real-world data interpretability for targeted water management.

## Building Synthetic Pattern

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# Conclusions

In conclusion, the application of the skewed Gaussian decomposition (SGD) method to hourly water demand data provides a powerful tool for enhancing water management practices by uncovering detailed behavioral insights from real-world operational data. By isolating base flows and identifying distinct peaks, such as the 9 peaks in P3a and P3b reflecting diverse routines, or the morning peak dominance and evening peak splitting in P2a and P2b during the COVID-19 lockdown, the method facilitates precise leakage detection, water stilling prevention, and adaptive strategies for behavioral changes, seasonal variations, and methodological impacts. Furthermore, its integration as a feature in machine learning models enriches predictive capabilities, offering a more granular understanding of demand drivers. Ultimately, this decomposition approach complements existing frameworks, providing actionable insights that support sustainable and efficient water resource management across diverse urban contexts

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