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Scheduling Pressure Reducing Valves for Reducing Water-Leakage in Urban Networks Using K-Means Algorithm

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Abstract

Water losses are a vital problem to sustainable water management in urban water distribution networks. This study presents an approach using K-Means clustering algorithm to reduce water losses and leakages through programming of pressure reducing valves (PRVs). The research uses 24-hour water network pressure and flowrate data obtained from a supervisory control and data acquisition (SCADA) system monitoring a district metered area (DMA) located in a metropolitan municipality in the Central Anatolia Region of Türkiye. The proposed methodology divides the temporal flowrate data into 12 different time periods. This is achieved by applying K-means clustering to a dataset that maps the flow data to the time of day. Then, the optimal pressure setting values are determined for each time period by mapping the lowest and highest flow values at the obtained cluster centers to the user-defined minimum and maximum desired network operating pressures. Simulation studies were performed using the K-means algorithm both the squared euclidean (dSE) and city block distance (dCB) metrics over 50 runs. Performance was evaluated against an error metric that combines the flow rate and hourly mean absolute error. The results revealed that the dCB distance metric outperformed the dSE metric in terms of mean and best error values. Clustering successfully identified distinct daily flow patterns and provided a dynamic pressure management strategy: lower pressures (e.g. 3.0 bar) were assigned during low demand periods, while higher pressures (up to 5.0 bar) were set during peak consumption times. This data-driven PRV scheduling significantly demonstrates the potential to reduce water leakage and optimize energy consumption in water distribution systems, thus increasing operational efficiency and sustainability while ensuring adequate service levels.

Keywords: Leakage reduction, PRV scheduling, K-means algorithm

1. INTRODUCTION

Reducing water losses in urban water networks is critical for sustainable urban development, environmental conservation, and economic efficiency. Water losses, often termed non-revenue water (NRW), arise mainly from leakage, inaccurate metering, unauthorized consumption, and inefficient operational practices. Economically, excessive water loss translates into increased operational costs and revenue shortfalls, diminishing funds available for infrastructure maintenance and expansion. Additionally, effective reduction of water losses enhances system reliability and service quality, benefiting both utilities and consumers. Technological approaches such as smart sensors, Internet of Things (IoT), supervisory control and data acquisition (SCADA) systems, and advanced leakage detection methods, coupled with systematic maintenance programs, have demonstrated substantial reductions in water losses globally, highlighting their indispensable role in achieving sustainable water resource management. NRW indicates inefficiencies within water distribution systems and poses obstacles to sustainable urban water management [1–3].

A critical aspect of the NRW challenge is its diverse causes. Several studies have identified factors such as unmetered consumption, technical losses due to aging infrastructure, illegal water use, and administrative shortcomings as primary drivers [1, 2, 4]. For instance, Kamani et al. [2] emphasize the importance of water balance to effectively isolate technical and commercial losses, while Karadirek [4] discusses the operational challenges exacerbating water losses in Turkey. Similarly, González-Gómez et al. [3] highlight the paradox of significant NRW volumes in cities despite increasing awareness of water scarcity, suggesting that infrastructural inefficiencies and outdated operational practices are central to the problem. These findings collectively reveal that the complexity of NRW is rooted in both physical system deficiencies and systemic management challenges.

Methodologically, various innovative approaches have been employed to address NRW reduction. Geographic information systems (GIS) have proven useful; Zahor and Mromba [5] applied GIS to map water distribution networks and identify critical loss zones. Benchmarking, as done by Marques et al. [6], provides a systematic approach to comparing water utilities' performance, encouraging improvements through performance-based targets. Additionally, water audit systems, such as the one developed by Sharma et al. [7], offer a structured framework for assessing water flows and categorizing losses, enabling the prioritization of corrective measures. These technical interventions underline the necessity of advanced data-driven methods for diagnosing and mitigating NRW.

Operational reforms have also been highlighted in literature. Enhanced metering technologies and prepaid systems, explored by Hanjahanja and Omuto [1], can help reduce administrative losses and enhance billing accuracy, thereby improving revenue recovery. Perera et al. [8] document the implementation of water management systems in Sri Lanka that systematically address distinct loss categories through targeted interventions. Additionally, empirical research in urban India, conducted by Mukherjee et al. [9], advocates for cost recovery frameworks that not only reduce NRW but also enhance the financial sustainability of water utilities. Such operational improvements, in conjunction with transparent regulatory oversight and community engagement, create a comprehensive strategy for NRW reduction.

Alongside technology and operations, the role of policy, regulation, and stakeholder participation is crucial. Legislative frameworks, as noted by Karadirek [4], significantly influence water utility performance by enforcing standards and penalties for losses. The interplay between tariff structures and water consumption patterns, discussed in complementary studies [7], [9], illustrates that economic incentives can motivate both utilities and consumers to conserve water. Yilmaz et al. aim to develop an innovative model using ant lion optimizer (ALO), mountaineering team-based optimization (MTBO), and grey wolf optimizer (GWO) algorithms to minimize water losses in networks, considering status, economic, and technical capacities, and thereby determine the most appropriate network management plans for water loss management (WLM) [10].

The optimization and scheduling of pressure regulation valves (PRVs) in water distribution networks has emerged as a key research topic in recent years. This interest is driven by the need to reduce leakages, minimize energy consumption, and ensure appropriate pressures throughout urban networks. An extensive body of literature addresses both the strategic placement and operational scheduling of PRVs as part of a comprehensive approach to water network optimization [11–13]. A central theme in the literature is the joint scheduling of pumps and PRVs to mitigate leakage and energy losses. Shao et al. [11] demonstrate that simultaneously managing pump operations and PRV settings can dissipate excess hydraulic head, thereby reducing leakages and improving energy efficiency. Complementary findings by Laspidou et al. [12] reinforce that a carefully coordinated pressure regulation strategy through single- or multi-feed control via PRVs, in conjunction with a network divided into district metered areas (DMAs), yields significant benefits in leakage reduction. These studies underscore the importance of synchronizing valve operations with the overall hydraulic management strategy, which is critical in urban water networks.

Several researchers have developed optimization methods to improve the placement and operation of PRVs. Mamizadeh et al. [14] investigated various placement scenarios using calibration techniques on an urban network, proposing that PRV locations significantly influence system performance. Similarly, Quiñones et al. [15] combined dynamic pressure management and energy recovery strategies to highlight how spatial valve optimization can reduce leakage volumes. In parallel, digital twin methodologies have been applied to provide rapid detection of leakages and optimally set pressure control valves, as evidenced by Ramos et al. [16]. These contributions indicate that combining real-time data analytics with advanced optimization algorithms is a promising avenue for enhancing network performance.

Optimization frameworks that incorporate multi-objective strategies have been widely proposed to address the inherent trade-offs among leakage minimization, energy savings, and maintenance costs. Research by Gupta et al. [17] utilized nodal matrix analysis to determine the optimal positioning of PRVs, while others have demonstrated that algorithms such as non-dominated sorting genetic algorithm-II (NSGA-II) and nondominated sorting differential evolution (NSDE) can effectively generate optimal scheduling strategies [18], [19]. Furthermore, penalty and relaxation methods have been employed to achieve optimal control valve installation and operation, indicating that mathematical programming techniques are a vital component in the optimization process [20]. These methodologies not only optimize the number and locations of PRVs but also inform real-time scheduling decisions based on dynamic network conditions.

The integration of scheduling with dynamic control strategies further enhances the adaptability of water networks. Pressure management strategies that incorporate time-modulated PRVs, as discussed by Mahardini and Tangahu [21], work effectively when integrated with real-time control algorithms. In addition, real-time pressure control algorithms based on piston-actuated PRVs [22] and nonlinear model predictive control (MPC) [23] have been proposed to dynamically adjust valve settings in response to changing hydraulic conditions. Such approaches are also supported by work on coupled electric and hydraulic control systems [24], and adaptive systems that leverage dynamically reconfigurable network topologies [25, 26]. These contributions are critical for achieving robust network performance under variable demand and supply conditions. Moreover, multi-objective optimization studies have specifically targeted leakage reduction through pressure management. Gupta et al. [27] and Li et al. [28] have demonstrated that an integrated optimization of valve locations and control settings results in significant economic and operational benefits. Additional efforts in the formulation of knowledge-based optimization models have further refined the approaches to control valve placement in water networks [28]. Assessments of virtual pressure management projects [29] and case studies such as those in Nagpur [30] affirm that the integration of these optimized scheduling strategies into real-world networks can generate substantial improvements in water loss reduction and energy efficiency.

In this paper, an optimal operational schedule for PRVs has been developed using the K-means clustering algorithm. The research utilizes network pressure and flow data obtained from the SCADA software that monitors DMA stations.

2. MATERIAL AND METHOD

In this section, the dataset used in experimental studies, clustering algorithm K-means and the proposed scheduling method are explained.

2.1. Dataset

The dataset for this study was acquired from a DMA station located within a metropolitan municipality in the Central Anatolia region of Turkey. Data collection spanned from February 12, 2025, at 13:00, to February 13, 2025, at 13:00. As depicted in Figure 1, the average flow rate was recorded as 25.9 m^3/h, and the average pressure was 5.96 bar. During the 24-hour period, the minimum and maximum pressure values observed were 5.64 bar and 6.15 bar, respectively, while the minimum and maximum flow rates were 5.88 m^3/h and 48.21 m^3/h.

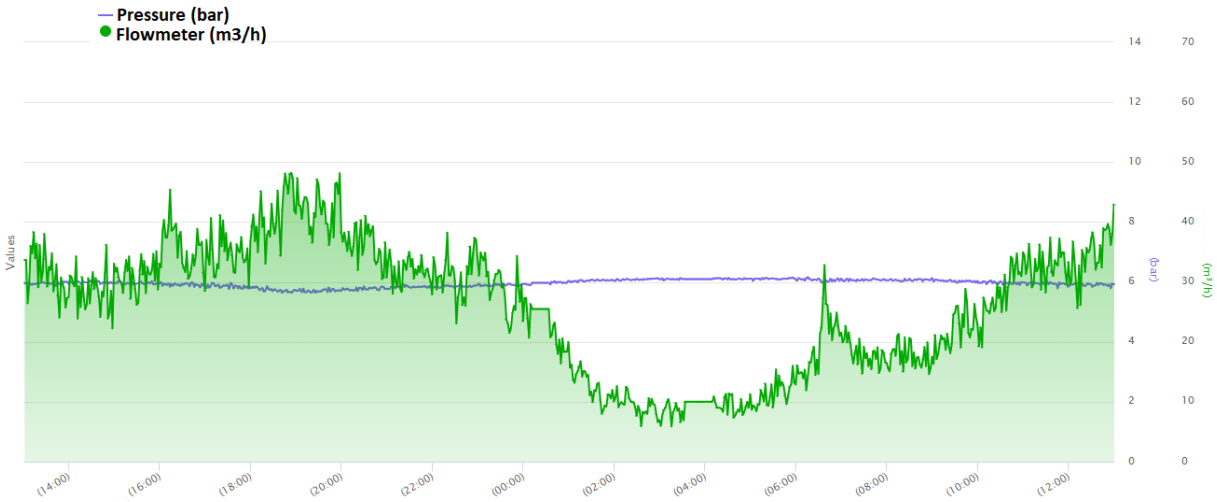


Figure 1. Dataset: Pressure and flow graph for 24-hour period

2.2. K-Means Algorithm

The K-means clustering algorithm is a prominent unsupervised learning method used for partitioning a dataset into a pre-determined number of *k* distinct, non-overlapping subgroups (clusters). The primary objective of this iterative algorithm is to minimize the within-cluster sum of squares (i.e., variance), effectively assigning each data point to the cluster whose centroid (mean) is nearest.

The K-means algorithm proceeds iteratively through the following fundamental steps:

i. *k* initial cluster centroids are selected, either randomly from the dataset or using a more sophisticated heuristic.
ii. Each data point in the dataset is assigned to the nearest cluster centroid. This proximity is typically determined using a distance metric.
iii. The centroids of each cluster are recalculated by taking the mean of all data points assigned to that respective cluster.
iv. The assignment and update steps are repeated iteratively until the cluster assignments no longer change significantly, or a predefined number of iterations is reached, indicating that the algorithm has converged.

Distance metrics are crucial in K-means as they quantify the similarity or dissimilarity between data points, and between data points and cluster centroids. The choice of metric can significantly influence the shape and composition of the resulting clusters. Two commonly employed metrics are the squared euclidean distance (dSE) and the cityblock distance (dCB) (also known as manhattan distance).

The dSE is the square of the standard Euclidean distance between two points. For two points $P=\left(p_1,p_2,...,p_n\right)$ and $Q=\left(q_1,q_2,...,q_n\right)$ in an *n*-dimensional space, the dSE is formulated as:

$$d_{SE}\left(P,Q\right)=\sum_{i=1}^{n}\left(p_i-q_i\right)^2 \tag{1}$$

This metric tends to emphasize larger distances more heavily due to the squaring of the differences. It aligns well with the K-means objective of minimizing intra-cluster variance.

The dCB, or manhattan distance, measures the distance between two points by summing the absolute differences of their coordinates along each dimension. This is analogous to navigating a grid-like street layout, where movement is restricted to horizontal and vertical paths. For points $P=\left(p_1,p_2,...,p_n\right)$ and $Q=\left(q_1,q_2,...,q_n\right)$ in an *n*-dimensional space, the dCB is given by:

$$d_{CB}\left(P,Q\right)=\sum_{i=1}^{n}\left|p_i-q_i\right| \tag{2}$$

The dSE calculates the sum of the squared differences between the coordinates of two points, effectively penalizing larger distances more significantly. This often leads to the formation of more spherical (or hyperspherical in higher dimensions) clusters. In contrast, the dCB computes the sum of the absolute differences between coordinates. This means it measures distance along axes at right angles. Consequently, dCB is generally less sensitive to outliers than dSE because it does not square the differences, thereby giving less weight to extreme values. While dSE relates directly to minimizing variance and assumes clusters are somewhat isotropic, dCB can sometimes be more appropriate for higher dimensional data or when the underlying cluster shapes are not necessarily spherical.

The K-means algorithm offers several advantages, including its simplicity in implementation and interpretation, making it a go-to algorithm for initial data exploration. It is also computationally efficient and scales well to large datasets, which is a significant benefit in big data applications.

2.3. Proposed Method

The amount of water leaking from existing cracks, holes or weak connections in pipelines is directly proportional to the pressure. As the pressure increases, it is inevitable that more water will leak out of these openings at a higher rate. Studies have shown that a certain increase in pressure can increase the leakage rate exponentially [31, 32]. For example, increasing the pressure from 1.5 bar to 5 bar can increase the amount of leakage by 2-3 times. This relationship is usually expressed with a potential equation such as the following:

$$Q=C\times P^n \tag{3}$$

where *Q* is the leakage flow rate, *C* is the leakage coefficient (depending on the hole geometry, pipe material, etc.), *P* is the pressure, *n* is the leakage exponent (usually takes a value between 0.5 and 2.5, depending on the type of hole and the elasticity of the pipe material). While *n*=0.5 is theoretically expected for a fixed hole geometry, in practice this value can often be above 1 due to the flexibility of the pipe material and the ability of cracks to expand under pressure.

For this reason, adjusting the network pressure is very important. Reducing the network pressure during low-use hours allows for the reduction of losses and leakages. Determining what the pressure should be at which time zone is a very difficult problem. Water companies want to operate the network by using the PRVs at the lowest pressure value that will not cause complaints from the customer.

The steps of the method suggested to solve this problem are as follows (also shown in Figure 2):

i. Obtain the last 24-hour flow and pressure data of the DMA to be pressure regulated.
ii. Create the dataset by matching the flow data with the time (hour + minute) of day.
iii. Divide the dataset into 12 clusters with K-means (since the SCADA and IoT system that provides PRV control used in the field supports max.12 time zones)
iv. Request the highest and lowest pressure values desired for the operation of the network from the user.
v. Calculate the pressure required for each time zone by mapping the lowest and highest flow values from the obtained cluster centers with the lowest and highest-pressure values.
vi. Create the time schedule and pressure set values and send the data to the IoT device via SCADA.

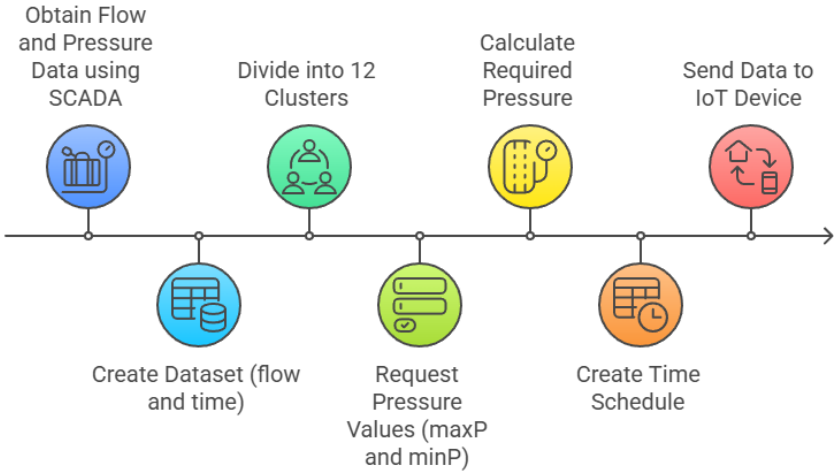


Figure 2. Proposed method pipeline

3. EXPERIMENTAL RESULTS

Simulation studies were performed on a computer powered by an Intel Core i7 processor, with 16GB of RAM, and in MATLAB 2022b version.

The 24-hour temporal flow rate data was partitioned into 12 clusters using the K-means algorithm. dSE and dCB were utilized as distance metrics. If a cluster became empty during the process, a new cluster was formed consisting of the data point furthest from its previous centroid. The default value of 100 was used for the maximum number of iterations (MaxIter). The clustering process was repeated 5 times, each with new initial cluster centroid positions. For the initial seeding, *k* seeds were selected for cluster center initialization. The overall error value was calculated as the Euclidean distance between the mean absolute error (MAE) of the flow rate and the MAE of the hour.

$$E = \sqrt{MAE_{flow}^2 + MAE_{hour}^2} \tag{4}$$

Experiments were repeated 50 times with random seeds. Table 1 shows the euclidean distance between the MAE of the flow rate and the MAE of the hour features. Lower values indicate better results. dCB performed slightly better than dSB in terms of average and best values.

Table 1. Comparison of distance metrics

	Average	Standard Dev.	Best
K-Means (dSE)	1.820	0.015	1.790
K-Means (dCB)	1.807	0.029	1.759

Table 2 shows the cluster centers and calculated timetable. These values were calculated by using the best run of dCB distance metric. Hour + minute is the decimal combination of HH:MM format, it is equal to HH+MM/60. The middle points between hour + minute cluster centers are used as the start and end time zones. The lowest flow cluster center is mapped to lowest set pressure value (9.81 m3/h => 3 bars) and the highest flow cluster center is mapped to the highest set pressure value (44.44 m3/h => 5 bars). The timetable with start and end timings and associated set pressure values are also given in Table 2.

Table 2. Numerical results: (a) Cluster centers and (b) pressure timetable for PRV

	(a)		(b)		
	Flow (m3h)	Hour + Minute	Start Time	End Time	Set Pressure (bar)
1	25.49	0.48	01:58	04:45	3.00
2	9.81	3.48	04:45	07:05	3.30
3	14.93	6.02	07:05	09:07	3.54
4	19.09	8.17	09:07	10:59	3.88
5	25.05	10.08	10:59	13:00	4.39
6	33.85	11.90	13:00	15:23	4.12
7	29.24	14.12	15:23	17:23	4.34
8	33.05	16.65	17:23	18:36	4.66
9	38.60	18.15	18:36	20:15	5.00
10	44.44	19.07	20:15	22:02	4.41
11	34.14	21.43	22:02	23:33	4.17
12	30.00	22.65	23:33	01:58	3.91

The analysis of Figure 3 reveals a successful application of clustering to 24-hour temporal flow rate data, partitioning it into 12 distinct periods, each characterized by a specific flow range and an assigned pressure set value. The visualization depicts a typical diurnal flow pattern with low overnight demand, a morning increase, sustained daytime consumption, a pronounced evening peak, and a subsequent decline. Crucially, a linear mapping is observed between the average flow rate within these identified time periods and their corresponding pressure set values: higher pressures are generally set during high-demand periods (notably setting up to 5.0 bar during the evening peak), while lower pressures (e.g., 3.0 bar) are applied during low-flow intervals. This approach strongly suggests a dynamic pressure management strategy aimed at optimizing water distribution system operation by potentially reducing water leakage and energy consumption, while maintaining adequate service levels across varying demand conditions.

4. CONCLUSION

In this study, an optimal operational program was developed using the K-means clustering algorithm for PRVs in water networks. Network pressure and flow data obtained from the SCADA system monitoring the DMA stations in a metropolitan municipality in Türkiye were used. The proposed method includes obtaining the last 24-hour flow and pressure data, creating a dataset by matching the flow data with the time of day, dividing this dataset into 12 clusters with the K-means algorithm (since the SCADA and IoT system providing PRV control used in the field supports a maximum of 12 time zones), requesting the highest and lowest pressure values desired for the operation of the network from the user, and matching the lowest and highest flow values in the obtained cluster centers with these lowest and highest pressure values and calculating the required pressure for each time zone. Finally, the created time schedule and pressure setting values will be sent to the IoT device via SCADA.

Experimental results show that the K-means clustering algorithm successfully segments the 24-h temporal flow data into 12 different periods, and each period is characterized by a specific flow range and an assigned pressure setpoint. A linear mapping is realized between the average flow rates in the defined time periods and the corresponding pressure setpoints; higher pressures are set during high demand periods (especially up to 5.0 bar during evening peak hours), while lower pressures (e.g., 3.0 bar) are applied during low flow intervals. This approach strongly suggests a dynamic pressure management strategy that aims to optimize water distribution system operation by potentially reducing water losses and energy consumption and maintaining adequate service levels under changing demand conditions. In the comparison of distance metrics, the dCB slightly outperformed the dSE in terms of mean and best error values.

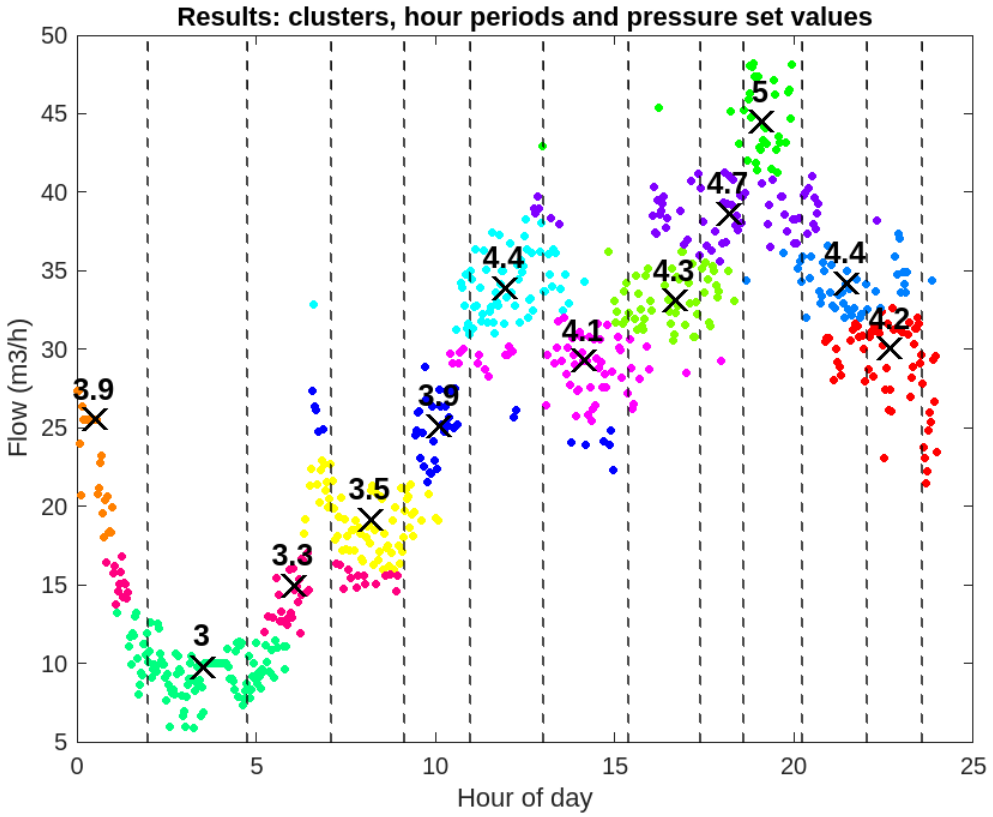


Figure 3. Visual results of 12 time periods and the set pressure values (each cluster is visualized by a different color, cluster centers are marked by X and pressure values are also above the markers)

For future studies, it is aimed to apply the pressure setting values obtained in this study in DMA under real world conditions and observe their long-term effects. Evaluating the real effects of this application on water loss reduction and energy consumption will reveal the practical benefits of the proposed method.

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