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Hybrid Reinforcement Learning (RL) and Social Network Community Detection Framework for Optimal Management and Redesign of Urban Water Network

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A B S T R A C T

This study presents a novel framework for water network sectorization that integrates reinforcement learning (Proximal Policy Optimization), social network search algorithms, and multi-objective optimization to simultaneously address water quality monitoring, hydraulic performance, and topological efficiency. Tested on the Thi-Qar, Iraq water distribution network, the proposed approach achieved substantial improvements: resilience deviation index dropped by 70%, balance index reached near-perfect uniformity (1.01), modularity improved by 9.7%, and average path length shortened by 11.9% while its deviation decreased by 43.5%. Critically, the framework fills a key literature gap by explicitly incorporating water quality objectives—minimizing detection time and contaminated volume while maximizing detection likelihood—alongside traditional energy and topological metrics. Results demonstrate that reinforcement learning-enhanced optimization effectively balances multiple competing objectives, offering water utilities a powerful decision-support tool for designing resilient, monitorable, and operationally efficient distribution systems, particularly valuable for developing regions where infrastructure investments require optimal allocation.

Keywords: *Water Network Sectorization, District Metered Areas (DMAs), Community Detection, Reinforcement Learning, Multi-Objective Optimization.*

1. Introduction

Urban water distribution networks (WDNs) constitute one of the most critical classes of civil infrastructure because they must continuously deliver adequate quantities of safe water under spatially and temporally variable demand while maintaining acceptable pressure, hydraulic reliability, water quality, and operational efficiency. The increasing scale and complexity of urban water systems, aging infrastructure, leakage, energy consumption, contamination risks, population growth, and limited financial and technical resources have intensified the need for intelligent and computationally efficient management strategies. These challenges are particularly important in rapidly developing urban regions, where network expansion often occurs incrementally and where monitoring and control infrastructure may not develop at the same pace as physical distribution assets. From a sustainability perspective, the performance of a water supply system cannot therefore be evaluated solely in terms of hydraulic adequacy; reliability, environmental performance, operational robustness, and the capacity to detect and respond to abnormal conditions must also be considered simultaneously (Jojozi et al., 2025; Mondal et al., 2023). Consequently, contemporary water-network management is increasingly being formulated as a multi-objective decision problem in which hydraulic, topological, monitoring, energy, and water-quality objectives must be reconciled rather than optimized independently.

One of the most widely investigated strategies for improving the manageability of large WDNs is Water Network Partitioning or Water Network Sectorization, through which an interconnected distribution system is divided into smaller operational sectors, commonly termed District Metered Areas (DMAs). Sectorization facilitates localized flow monitoring, leakage identification, pressure management, abnormal-event isolation, maintenance planning, and more efficient interpretation of network behavior. Nevertheless, introducing DMA boundaries generally requires the closure, control, or metering of selected pipes, and these interventions can modify the original hydraulic connectivity and redundancy of the system. An effective partition must therefore achieve meaningful structural separation without causing unacceptable losses in pressure, resilience, or connectivity. Early applications of social-network concepts to WDNs demonstrated that the topology of a pipe system can be represented as a graph in which junctions correspond to nodes and pipes to edges, allowing methods originally developed for social and complex networks to identify structurally coherent groups within hydraulic systems (Campbell et al., 2015; Di Nardo et al., 2015). Subsequent case-based investigations have reinforced the usefulness of complex-network representations for practical sectorization, showing that graph-based partitions can provide meaningful operational zones while retaining important hydraulic properties (Spizzo et al., 2023).

Graph-theoretic representation is particularly attractive because WDN sectorization is fundamentally related to the identification of communities, bridges, central nodes, and structurally significant links. Social Network Analysis provides a rich family of measures—including degree, centrality, betweenness, shortest paths, clustering, and community structure—that quantify the role of individual nodes and edges within a network (Arif, 2015). Among these measures, edge betweenness is especially relevant for sectorization because pipes connecting otherwise cohesive regions frequently lie on a large number of shortest paths and can therefore represent suitable candidates for community boundaries. Community-detection procedures can use such structural information to expose naturally connected subgraphs without imposing arbitrary spatial divisions. More generally, graph-partitioning problems seek to divide a graph into balanced components while minimizing interactions or cuts between them, a class of problems extensively studied in computational graph systems because of their implications for complexity, scalability, and efficient distributed computation (Ayall et al., 2022). In water infrastructure, however, a topologically satisfactory partition does not automatically guarantee hydraulic or operational suitability, making the integration of graph metrics with engineering criteria indispensable.

This requirement has motivated hybrid approaches that combine community detection with optimization. Brentan et al. demonstrated that social-network community detection can be integrated with hybrid optimization to divide water supply systems into DMAs, establishing an important methodological connection between network topology and engineering optimization (Brentan et al., 2018). More refined methods have subsequently attempted to improve the physical realism of detected communities. In particular, Creaco et al. proposed an improved community-detection strategy based on a dual topology involving network segments and valves, thereby addressing the practical relationship between mathematically detected communities and the hydraulic components required for implementing partition boundaries (Creaco et al., 2023). Graph and community analyses have also demonstrated that pipe-network structure is influenced by the morphology and development pattern of the urban environment. Comparative analysis of pipeline configurations in Kisumu and Kigali, for example, revealed meaningful differences in network organization and vulnerability across urban contexts, emphasizing that community structure should be interpreted not merely as a mathematical property but also as an expression of infrastructure development and spatial inequality (Deng et al., 2025). Accordingly, robust sectorization methods must accommodate heterogeneous network geometries and should remain useful even where infrastructure information is incomplete or systems have evolved under constrained planning conditions.

The transition from purely topological sectorization toward multi-objective design reflects the fact that no single performance metric is sufficient for determining an optimal DMA configuration. Sectorization may improve monitoring and leakage management while simultaneously increasing head loss, reducing redundancy, or modifying flow paths and water residence times. Recent optimization studies therefore evaluate competing objectives and constraints simultaneously. Caetano et al. approached WDN sectorization through a multi-objective evolutionary framework, illustrating the suitability of population-based optimization for searching among alternative network configurations under conflicting criteria (Caetano et al., 2025). Zhang et al. further emphasized the importance of incorporating multiple hydraulic performance indicators into optimal DMA design, demonstrating that boundary decisions should be evaluated against hydraulic consequences rather than being determined solely from graph structure (Zhang et al., 2025). The importance of structural reliability has likewise encouraged approaches that assess the accessibility and significance of critical infrastructure nodes. The landmark-node concept proposed by Herrera et al. provides a graph-oriented means of evaluating reliability by examining paths toward strategically important nodes, thereby creating a bridge between topological analysis and infrastructure functionality (Herrera et al., 2025). These developments indicate that effective WDN partitioning increasingly requires a unified framework capable of reasoning across topology, hydraulics, reliability, and operational objectives.

Machine learning has expanded this methodological landscape by enabling nonlinear relationships between graph characteristics and engineering performance to be learned from data. Bahrami Chegeni et al. developed machine-learning models for the optimal design of WDNs using graph-theory-based features, illustrating that topological and hydraulic descriptors can jointly provide informative representations for design optimization (Bahrami Chegeni et al., 2025). Such approaches are particularly significant because exhaustive hydraulic optimization over all possible network partitions can become computationally prohibitive as network size and decision dimensionality increase. Learning-based representations can potentially identify promising configurations, reduce the search space, or approximate relationships that would otherwise require repeated simulation. More broadly, community detection itself has been addressed using evolutionary computation; genetic approaches based on structural concepts such as k-cliques demonstrate that community identification can be treated as a combinatorial optimization problem rather than as a purely deterministic graph-processing operation (Ma & Fan, 2020). These developments support a broader shift toward adaptive sectorization methodologies in which graph structure supplies physically meaningful features while learning and optimization algorithms determine how those features should be exploited.

Monitoring-point and sensor-placement research further illustrates the value of combining graph representations with learning algorithms. Water-quality and pressure monitoring are constrained by the fact that installing sensors at every node is economically and operationally unrealistic. The design problem is consequently to identify a limited set of highly informative locations. Peng et al. employed graph neural network clustering for pressure sensor placement, demonstrating that graph-based learning can support the formation of monitoring zones and improve the spatial organization of sensor locations (Peng et al., 2022). More recently, Sun et al. proposed an adaptive attributed-graph clustering method designed to reduce dependence on fully specified hydraulic models, an important advantage where calibrated models are unavailable, uncertain, or costly to maintain (X. Sun et al., 2025). Similarly, unsupervised graph-based deep clustering has been applied to the optimal placement of monitoring points in urban drainage networks, showing that graph learning can uncover useful structural representations even when explicit class labels are unavailable (Qi et al., 2025). Collectively, these studies suggest that graph-based intelligence is becoming increasingly important for infrastructure monitoring; however, sensor placement and network partitioning are often considered as separate optimization tasks even though they are operationally interdependent.

This separation becomes especially problematic when water quality is considered. A sectorization arrangement that performs well according to modularity, balance, pressure, or resilience may still be undesirable if it delays contamination detection, increases the volume of contaminated water consumed before detection, or produces monitoring blind spots. Water-quality monitoring is intrinsically linked to the topology of the network because contamination propagates along hydraulically determined pathways, while the effectiveness of a sensor depends on its location relative to possible contamination events and demand patterns. Therefore, DMA design and water-quality sensor placement should ideally be coordinated within a unified decision framework rather than optimized sequentially using unrelated criteria. The manuscript underlying the present study explicitly treats expected detection time, expected contaminated-water volume, and detection likelihood as core monitoring objectives alongside hydraulic and topological performance, thereby extending sectorization beyond conventional structural optimization. Such a formulation creates a highly constrained and nonconvex search problem in which improvements in one objective may degrade another, making adaptive multi-objective optimization particularly relevant.

Metaheuristic algorithms offer one route for addressing these complex search spaces. Social Network Search (SNS), for example, is a population-based global optimization method inspired by patterns of interaction within social networks and models search behavior through mechanisms analogous to imitation, conversation, disputation, and innovation (Talatahari et al., 2021). The appeal of SNS for infrastructure design lies in its ability to alternate between exploitation of promising regions and exploration of new candidate solutions without relying on problem-specific gradients. Yet conventional metaheuristics generally use fixed update mechanisms and parameter structures, which may limit their ability to adapt to changing search conditions or differently weighted engineering objectives. Recent research has consequently explored the integration of reinforcement learning (RL) with population-based multi-objective optimization. Peng et al. proposed a reinforcement-learning-enhanced multi-objective SNS algorithm for engineering design problems, illustrating how an adaptive learning component can guide search behavior and improve decision making within complex optimization landscapes (Peng et al., 2025). This integration is particularly relevant to WDN sectorization, where the relative importance of hydraulic resilience, topological quality, sensor effectiveness, and operational efficiency can vary substantially among candidate partitions.

Reinforcement learning differs fundamentally from static optimization because an agent improves its policy through repeated interaction with an environment, receiving rewards that reflect the quality of its decisions. This architecture is suitable for sequential and adaptive engineering problems in which the consequences of an action depend on the current system state. Context-based representations in multi-task reinforcement learning have shown how policies can incorporate task-specific information and learn across related environments, providing a conceptual basis for adaptive optimization under heterogeneous operating conditions (Sodhani et al., 2021). RL has also demonstrated broader potential in complex networked infrastructure systems. For example, its use in multi-regional economic dispatch and demand-response optimization in smart grids shows that reinforcement learning can coordinate decisions under interacting technical and economic objectives across spatially distributed systems (Q. Sun et al., 2025). In graph-partitioning research, deep reinforcement-learning architectures have similarly been applied to social-network graph partitioning, indicating that learned policies can contribute directly to the division of complex graphs rather than merely serving as post-processing components (Cao et al., 2025). These studies collectively provide a strong methodological rationale for embedding RL within the WDN sectorization process.

Despite these advances, an important research gap persists at the intersection of community detection, multi-objective sectorization, reinforcement learning, and water-quality monitoring. Existing graph-based WDN studies have established the effectiveness of community detection for identifying coherent network sectors, while optimization studies have improved hydraulic and topological performance, and machine-learning studies have advanced sensor placement and design prediction. Nevertheless, comparatively limited attention has been devoted to architectures in which reinforcement learning adaptively guides a social-network-inspired search while water-quality objectives are explicitly optimized together with hydraulic and topological performance. This gap is important because real-world infrastructure management cannot be reduced to a single static criterion: a partition that minimizes edge cuts may be hydraulically vulnerable; a hydraulically robust partition may be poorly balanced; a structurally efficient partition may provide inadequate contamination detection; and a highly sensitive sensor network may be costly or incompatible with feasible DMA boundaries. The optimization challenge is therefore not simply to locate a mathematically superior partition, but to identify a practically defensible compromise among multiple competing dimensions of system performance.

Such integration is particularly valuable for networks in developing regions, where monitoring resources and infrastructure investments must often be allocated selectively. Optimization from the supply-side perspective already demonstrates the difficulty of balancing infrastructure constraints, resource availability, service requirements, and system efficiency (Jojozi et al., 2025). A hybrid framework capable of exploiting graph structure, learning from iterative interactions, and evaluating several hydraulic, topological, and water-quality objectives can consequently function as a decision-support mechanism rather than merely as a clustering algorithm. By preserving the interpretability of graph-based communities while introducing adaptive RL-guided search, such a framework can potentially improve DMA balance, modularity, path efficiency, pressure consistency, resilience, and contamination-monitoring performance simultaneously. This is consistent with the broader evolution of infrastructure analytics toward data-driven yet structurally informed optimization, in which machine learning complements rather than replaces domain-specific physical and network knowledge.

Accordingly, the aim of this study is to develop and evaluate a hybrid reinforcement-learning and social-network community-detection framework, integrating Proximal Policy Optimization, Social Network Search, edge-betweenness-based community partitioning, and multi-objective optimization, for the optimal sectorization, monitoring, and redesign of the Thi-Qar urban water distribution network while simultaneously improving water-quality detection, hydraulic performance, and topological efficiency.

2. Methods and Materials

Building on the methodological framework established for network partitioning, the subsequent challenge lies in designing an effective water quality sensor network within the created districts. To evaluate sensor network performance, this study considers 3 established criteria: (1) expected time to detection, (2) expected volume of contaminated water consumed before detection, and (3) the detection likelihood, or reliability, of the sensor configuration. As noted in the literature, the population affected is inherently correlated with both the contaminated volume and the detection time—larger contamination volumes and slower detection times inevitably lead to a larger affected population, and vice versa. Minimize the expected detection time (f_1) have been showed in equation (1).

$$f_1 = Minimize\{\frac{1}{N_s}\sum_{s=1}^{N_s} t_d^s(X)\} \tag{1}$$

Where N_s is the number of contamination events, X is the decision vector and defined as $X = [x_1, x_2, x_3, \ldots, x_n]$, xi is an integer parameter which takes on values of 1 or 0 depending on the presence of a sensor at the junction i, n is the number of candidate junctions, t_d^s is the detection time of the contamination event s using decision vector X which is defined as $t_d^s(X) = \text{Min}\{t_d(x_i)\}$, $t_d(x_i)$ is the detection $x_i = 1$ time at candidate junction i. Minimize the expected contaminated water volume (f_2) have been showed in equation (2).

$$f_2 = Minimize\{\frac{1}{N_s}\sum_{s=1}^{N_s}\sum_{i=1}^{N}\sum_{t=t_s^{in}}^{t^s{}_d} V_i^s(t)\} \tag{2}$$

Where N is the number of junctions in the system, $V_i^s(t)$ is the water volume contaminated in junction i in time step t for the contamination event s, as estimated by

$$V_i^s(t) = \begin{cases} 0 & if \quad C_{is}(t) < C_{\min} \\ q_i(t)\Delta t & if \quad C_{is}(t) \geq C_{\min} \end{cases} \tag{3}$$

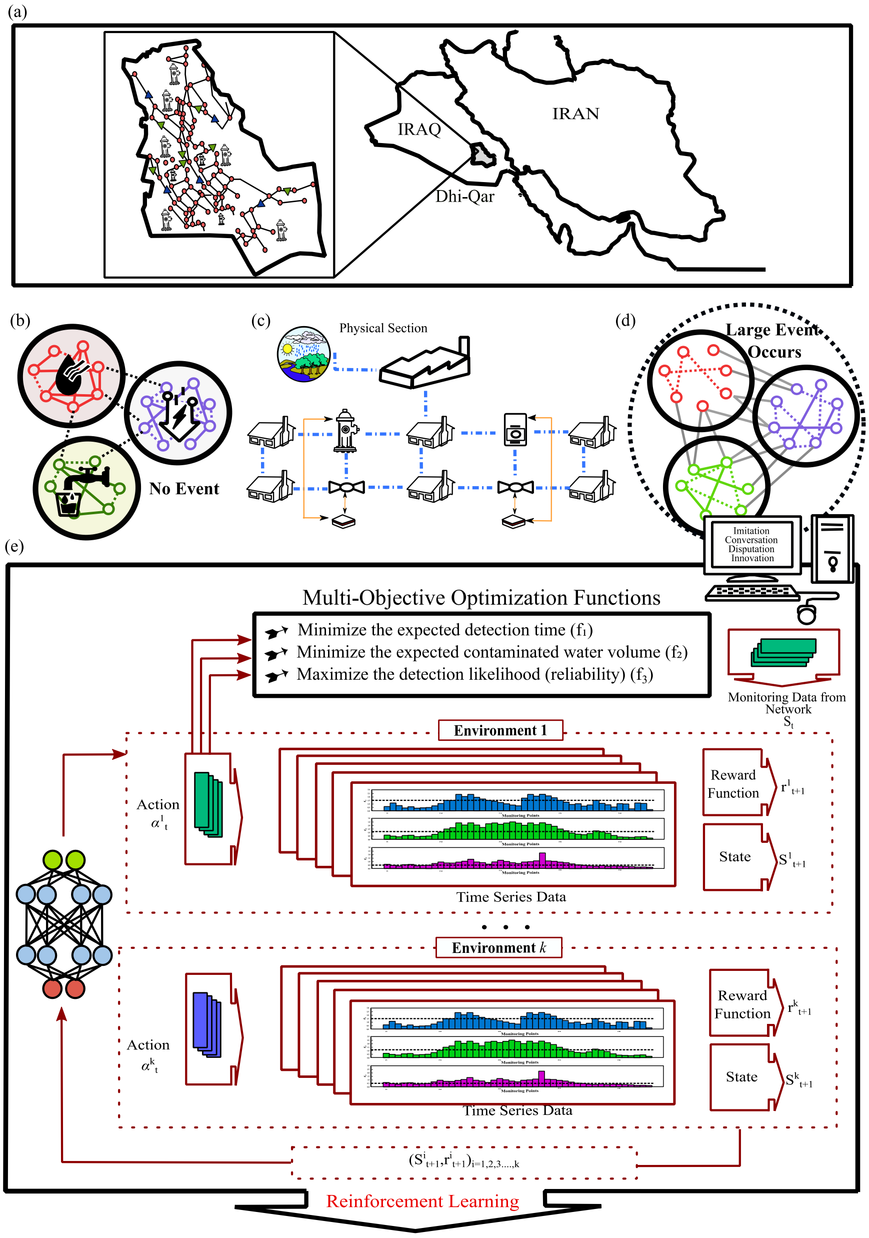
Where qi(t) is the actual water demand at junction i at time step t, Δt is the time step interval, $C_{\min}$ is a predefined threshold hazard concentration in the water distribution system. Maximizing the detection likelihood is expressed by equation (4).

$$f_3 = Maximize\{\frac{1}{N_s}\sum_{s=1}^{N_s} d_s(X)\} \tag{4}$$

Where $d_s = 1$ if the contamination event s is detected using decision vector X, and zero otherwise. The detection likelihood is an important measure and directly reflects the reliability of the system. When the number of sensors placed in the system is specified as M, the decision variable should satisfy the constraint, $\sum x_i = M$. Equations (1) through (4) can be used to construct the multi-objective optimization problem for the design of water sensor network in the water distribution system.

Figure 1

Concept of Present Work; (a) location of applied model on its water network named thi Qar city in Iraq, (b) schematic view of no event of social network, (c) schematic view of water network based on sources, (d) occurring event inside the social network, (e) schematic view of RL based optimizer for multi objective assessment of social network.



2.1. Reinforcement learning as Optimizer

Having established the necessity of a robust methodology for simultaneous valve placement and water quality monitoring, the subsequent phase of this study addresses the sensor placement sub-problem within the partitioned network. To achieve this, a multi objective optimization framework is developed. First, a roulette wheel selection method, weighted by nodal water demands, is employed to generate an initial sub-domain of candidate junction nodes for sensor placement. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) then operates on this sub-domain to evolve a Pareto-optimal front of sensor configurations. In an iterative refinement process, junctions appearing on the new

Pareto front are automatically carried over to the next generation, while the roulette wheel method probabilistically fills the remaining slots in the sub-domain. This cycle repeats, progressively refining the solution space and efficiently providing the necessary hydraulic and water quality data for all evaluated scenarios. The objective of this hybrid approach is to identify an optimal set of sensor placements more efficiently than standard, full-network optimization methods. In this paper, we introduce a novel approach that synergistically combines a social network-inspired algorithm with reinforcement learning, implemented within a behavior tree framework to enhance decision-making structure. Proximal Policy Optimization (PPO) serves as the core reinforcement learning algorithm, enabling an agent to improve its decision-making through iterative interaction with the environment, guided by a system of rewards and penalties. PPO achieves stable and efficient policy updates by employing a clipping parameter in its objective function, which prevents destructively large policy shifts and maintains learning consistency. The primary objective of PPO is to converge upon the optimal policy that maximizes the expected cumulative reward, formalized as a stochastic optimization problem.

2.2. State-Action Model

Each agent operates within a standard Markov Decision Process (MDP) loop, defined by the tuple (s_t, a_t, r_t, s_{t+1}). The state s_t comprises the agent's positional information, relevant task features, and a representation of the environmental map. From this state, the agent selects an action a_t intended to maximize the action-value function Q(s_t, a_t). Its policy π(s_t, j), which defines the probability distribution over possible actions, is optimized through reinforcement learning. The reward r_t is computed as a weighted function incorporating task importance, completion effectiveness, and collaborative efficiency among agents. Following the execution of action a_t, the environment transitions to a new state s_{t+1}. Learning is achieved using an Actor-Critic framework. The Critic evaluates the desirability of states by learning the value function V(s_t). Specifically, within the Proximal Policy Optimization (PPO) algorithm, the advantage of a given action A(s_t, a_t) is calculated using Generalized Advantage Estimation (GAE). This advantage estimate, derived from the temporal difference error Δ_i, is also used to iteratively update the Critic's value function. This continuous cycle of evaluation and policy refinement enables the agent swarm to maximize cumulative rewards for efficient and coordinated task execution.

2.3. Social Network Search (SNS) Algorithm Clustering by Edge betweenness community (EBC)

The Social Network Search (SNS) algorithm provides a conceptual representation of how nodes interact on these platforms. Within social networks, nodes routinely affect each other's attributes by exchanging parameters and insights—a phenomenon that can be interpreted as an optimization process, since each node naturally strives to enhance its influence and popularity across the network. To produce novel solutions for optimization challenges, the SNS algorithm emulates four key behavioral patterns observed in social networks: imitation, conversation, disputation, and innovation. These modes are mathematically detailed below, and together they form a population-based search mechanism that serves as a complementary approach to the gradient-based policy optimization used in reinforcement learning. Specifically, the algorithm employs Imitation for local exploitation of the best solutions, Conversation for global exploration, Disputation for balancing through averaging, and Innovation for injecting randomness. Meanwhile, network rules impose feasibility constraints and manage selection, collectively replicating the evolving dynamics of opinions within a social network to effectively locate the global optimum. We calculate the social network's imitation mood using the equations below:

$$x_{inew} = x_j + rand(-1,1) \times R \qquad (5)$$
$$R = rand(0,1) \times r$$
$$r = x_i - x_j$$

During the imitation mood, individual nodes mimic the popular characteristics of their peers to enhance their own visibility. This behavior is formally represented by Equation (5). Here, x_i and x_j denote the feature vectors of nodes i and j, respectively, where i is distinct from j. The terms rand(-1, 1) and rand(0, 1) stand for random vectors uniformly distributed over the intervals [-1, 1] and [0, 1]. Additionally, R defines the shock radius of the imitation space, while r corresponds to the popularity radius associated with node j. We calculate the social network's Conversation mood using the equations below:

$$x_{inew} = x_k + R \qquad (6)$$
$$R = rand(0,1) \times D$$

$$D = sign(f_i - f_j) \times (x_j - x_i)$$

In the conversation mood, nodes exchange a variety of parameters to produce new ones, as expressed by Equation (6) [24]. In this equation, x_k and x_j represent two randomly chosen nodes, while D denotes the difference in their feature vectors. Here, x_i refers to the features of the current i-th node, with i, j, and k being distinct indices. The directional factor sign(f_i - f_j) governs the movement trajectory of x_k. Importantly, this formulation highlights that a node's features evolve through conversational exchange with node j. We calculate the social network's Disputation mood using the equations below:

$$x_{inew} = x_i + rand(0,1) \times (M - AF \times x_i) \quad (7)$$

$$M = \frac{\sum_{t}^{Nr} x_t}{N_r}$$

$$AF = 1 + round(rand)$$

In the disputation mood, a node justifies its newly generated parameters, with the resulting updated parameters or nodes calculated using Equation (7). In this context, M represents the average feature values of the parameters belonging to the nodes involved in the evaluation, while the function round maps its input to the closest integer. Additionally, Nr denotes the total number of parameters under consideration. We calculate the social network's Innovation mood using the equations below:

$$x_{inew}^{d} = tx_j^d + (1-t) \times n_{new}^{d} \quad (8)$$

$$n_{new}^{d} = LB^d + rand(0,1) \times (UB^d - LB^d)$$

$$t = rand(0,1)$$

During the innovation mood, nodes share specific parameters to converge toward an optimal solution, thereby generating novel nodes. This mechanism is captured mathematically by Equation (8). In this equation, the index d refers to the d-th variable (or dimension) within the feature vectors of the nodes, while $U_B{}^d$ and $L_B{}^d$ represent the upper and lower bounds for that dimension, respectively. The term $n_{new}{}^d$ denotes a new idea introduced in the d-th dimension, and $x_j{}^d$ corresponds to the d-th dimension of node j's feature vector (where i ≠ j). The updated feature, $x_{i,new}{}^d$, is formed by combining an existing idea $x_j{}^d$ with the novel feature $n_{new}{}^d$. Any modification in a given dimension indicates an overall shift in the graph's parameters with respect to that event.

$$x_{inew}^{d} = \min(x_{inew}^{d}, UB^d) \quad (9)$$

$$x_{inew}^{d} = \max(x_{inew}^{d}, LB^d)$$

Social networks impose certain rules that optimized nodes must observe when sharing their features. These constraints are specified as boundary conditions, as given in Equation (9), where d ranges from 1 to the total feature dimensions and i ranges from 1 to the total number of nodes. In each subsequent iteration, one of the four moods is chosen at random to update a node's features, and the resultant parameters must comply with these predefined network rules.

A widely adopted method for identifying network communities employs a divisive algorithm that utilizes edge betweenness as a metric to locate community boundaries. Edge betweenness, $c_B(l)$, is defined as the sum, over all pairs of vertices, of the fraction of shortest paths (geodesics) between those pairs that pass-through edge l. This is formally expressed as:

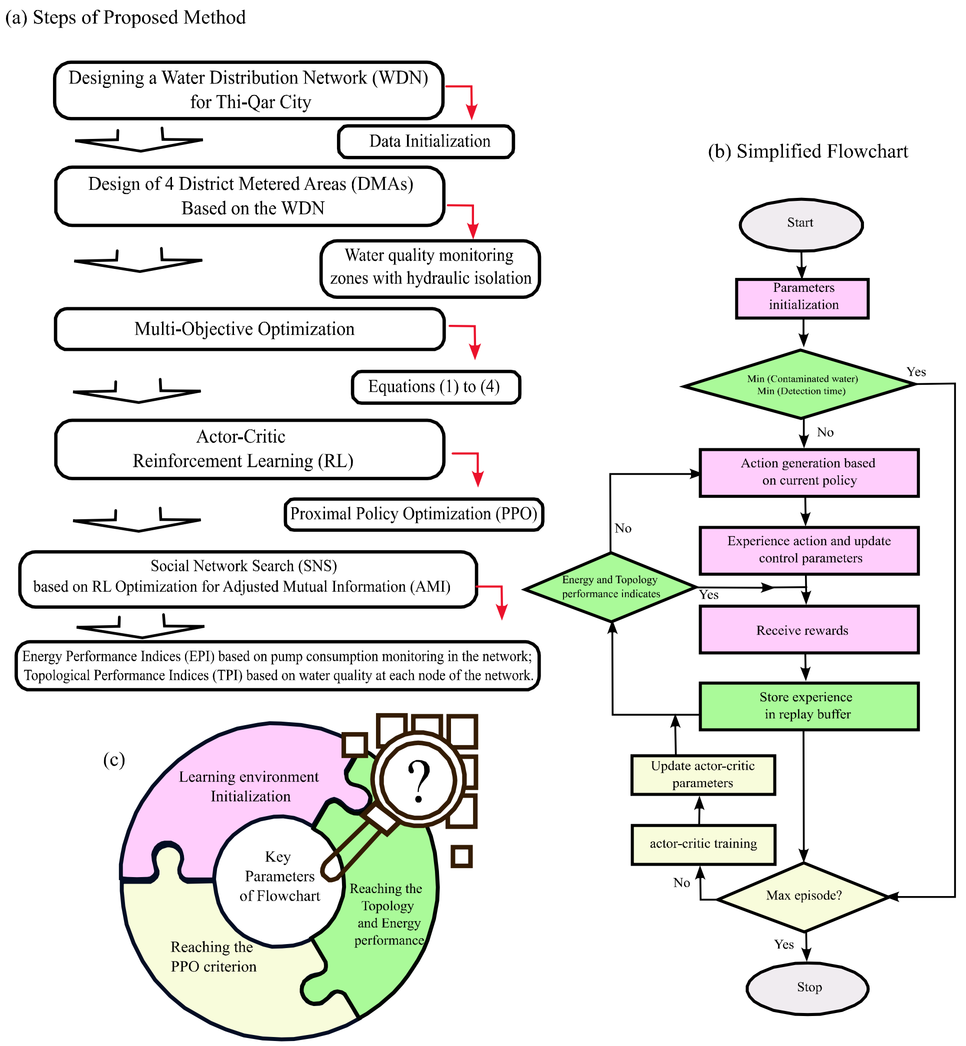
1. $$c_B(l) = \sum_{s,t \in V} \frac{\sigma(s,t|l)}{\sigma(s,t)} \quad (10)$$

Where V is the set of nodes, σ(s, t) is the total number of shortest paths from node s to node t, and σ(s, t|l) is the number of those paths traversing edge l. This metric effectively extends Freeman's concept of betweenness centrality from nodes to edges, quantifying how often an edge acts as a bridge in the network's shortest-path structure. The underlying principle of the algorithm proposed by Girvan and Newman is that the edges connecting distinct communities—those lying between them—naturally exhibit high betweenness scores. Therefore, instead of building communities by adding strong connections, the algorithm iteratively removes the edges with the highest betweenness, progressively isolating the communities. After each removal, the betweenness scores for all remaining edges are recalculated. This process repeats until no edges remain, and its hierarchical sequence can be visualized as a dendrogram. In summary, the Girvan-Newman algorithm is characterized by three key features: (1) it is a divisive method that removes edges, contrasting with agglomerative techniques; (2) edge selection for removal is based on betweenness scores; and (3) these scores are dynamically recomputed after each edge removal to reflect the evolving network structure.

Figure 2(a) illustrates the steps of the proposed Water Network Sectorization model, which accounts for both water quality and energy consumption. Based on this framework, the water network of Thi-Qar city is designed according to the locations of its essential components, after which four zones are delineated using similar water sources and matching water quality criteria for each DMA. The design enforces identical network topology and hydraulically isolated conditions across zones. Subsequently, the three functions from equations (1) to (4) are applied as a multi-objective optimization, enhanced by an actor-critic reinforcement learning mechanism using Proximal Policy Optimization (PPO). This RL agent adaptively guides the optimization by tuning objective weights and refining solutions to balance the three key goals. The SNS algorithm, which employs edge-betweenness community (EBC) clustering, is used to evaluate water quality within each DMA zone, assess energy consumption from pump operations, and extract the appropriate topology according to the multi-objective criteria. This smart system enables rapid water-quality monitoring, estimates the volume of potential contamination, and maximizes detection likelihood through the PPO iterative algorithm. A simplified flowchart of the proposed method appears in Figure 2(b), with its essential parameters color-coded in Figure 2(c). The case study focuses on the Thi-Qar network in Iraq, a densely populated area in the southwest with 650,000 inhabitants, supplied by the Euphrates River and the Al-Gharraf stream (a Tigris branch). The network features multiple main loops, a uniform design pressure of $h_i = 20$ m at each node, $k = 7$ DMAs, and Nfm = 10 flow meters installed accordingly, with only the main flow pipes considered in this analysis.

Figure 2

Schematic view of algorithm and pseudocode



3. Findings and Results

3.1. Performance Indices

Table 1 showed the obtained results with k = 7 clusters (or DMAs) for without Reinforcement Learning and with Reinforcement Learning. For minimum node pressure, the RL-enhanced algorithm showed higher values compared to the non-using RL. Likewise, mean and maximum node pressures remained within acceptable ranges.

Table 1

Energy Performance Indices (EPI).

EPI	Network	Without Reinforcement Learning	With Reinforcement Learning
Minimum node pressure (h_{min})	21.31	21.25	21.57
Mean node pressure (h_{mean})	31.05	30.78	31.01
Maximum node pressure (h_{max})	50.57	50.44	50.87
Standard deviation node pressure (h_{SD})	5.69	5.72	5.12
Resilience index (I_R)	0.347	0.355	0.354
Resilience deviation index (I_{RD})	-	8.69	2.60

The RL-based optimization yields clear improvements across key metrics: the minimum node pressure (h_{min}) rises from 21.25 m to 21.57 m, a modest yet positive gain of about 1.5%, while the mean pressure (h_{mean}) recovers from 30.78 m to 31.01 m, improving by 0.75%. More notably, the standard deviation of nodal pressures (h_{SD}) drops significantly from 5.72 to 5.12, representing a substantial 10.5% reduction, which indicates a far more uniform pressure distribution throughout the system. The resilience index (I_R) remains practically stable, decreasing negligibly from 0.355 to 0.354 (a mere 0.3% change), confirming that hydraulic robustness is fully preserved. Most strikingly, the resilience deviation index (I_{RD}) plummets from 8.69 to 2.60, an extraordinary 70% reduction, demonstrating that the RL agent profoundly minimizes pressure deviations from ideal resilience conditions. Although the maximum node pressure (h_{max}) sees a slight rise of about 0.85% to 50.87 m, the overall trade-offs are overwhelmingly positive, proving that the PPO-based RL mechanism effectively enhances pressure uniformity and overall network resilience while maintaining stable and reliable operational performance.

Table 2

Topological Performance Indices (TPI).

TPI	Network	Without Reinforcement Learning	With Reinforcement Learning
n_1	-	44	46
n_2	-	54	46
n_3	-	38	46
n_4	-	54	46
n_5	-	43	47
n_6	-	44	46
n_7	-	51	49
Balance index (I_B)	-	1.27	1.01
Total number of the edge-cut (N_{EC})	-	15	17
Worst number of the edge-cut (N_{WEC})	-	5	4
Modularity index (I_Q)	-	0.72	0.79
Average Path Length (I_{APL})	9.6	9.82	8.65
Average Path Length Deviation (I_{APLD})	-	12.36	6.98

Table 2 summarizes the topological performance indices, revealing that the RL-enhanced approach substantially improves the structural balance and connectivity of the sectorized network. The most striking gain is observed in the balance index (I_B), which drops from 1.27 to 1.01—a 20.5% reduction—indicating that zone sizes (n_1 to n_7) become far more uniform, shifting from a scattered distribution (ranging from 38 to 54) to a tightly clustered set (46, 46, 46, 46, 47, 49). Modularity (I_Q) rises by 9.7%, from 0.72 to 0.79, confirming stronger intra-zone connectivity and clearer community structure. Meanwhile, the average path length (I_{APL}) shortens from 9.82 to 8.65, an 11.9% improvement that enhances hydraulic efficiency, while its deviation (I_{APLD}) plunges by an impressive 43.5%, from 12.36 to 6.98, demonstrating far more consistent travel distances across all zones. The worst number of edges-cuts (N_{WEC}) also decreases by 20%, from 5 to 4, reducing the maximum cut penalty. Although the total number of edges-cuts (N_{EC}) marginally increases from 15 to 17—a 13.3% rise—this slight trade-off is largely offset by the substantial gains in balance, modularity, and path length consistency, proving that the RL agent successfully refines the network topology to achieve a more robust and operationally efficient sectorization.

3.2. Topology Evaluation

This section examines the reconfigured topology of the water network in the case study area, demonstrating that the layout produced by the RL-based approach achieves superior regularity and structural integrity compared to conventional methods. As shown in Table 2, the Balance Index (I_B) is a fundamental metric, and the RL-based method brings this value remarkably close to the optimal unity (1.01), signifying highly balanced districts with even node distribution—in stark contrast to the uneven partitions observed without RL (1.27). Similarly, the Modularity Index (I_Q) shows considerable improvement, rising to 0.79, which denotes stronger community formations and inherently cohesive network groupings, a quality effectively enhanced by the RL-driven clustering process. The Average Path Length (I_{APL}) and its Deviation (I_{APLD}) further confirm the superiority of the proposed approach, yielding substantially shorter average paths and a dramatic reduction in deviation, reflecting more uniform, efficient, and consistent connectivity across all zones. The enhanced uniformity is also evident in the node distribution across individual districts, where the RL approach produces a remarkably narrow node-count range (46 to 49), sharply contrasting with the broader spread (38 to 54) seen without it. Finally, Figure 3 illustrates the resulting District Metered Areas (DMAs) generated by the proposed method, depicting distinct pipe-community structures that successfully minimize expected detection times and contaminated water volumes while maximizing detection likelihood—all without compromising topological performance indices.

Figure 3

Various DMA for proposed method

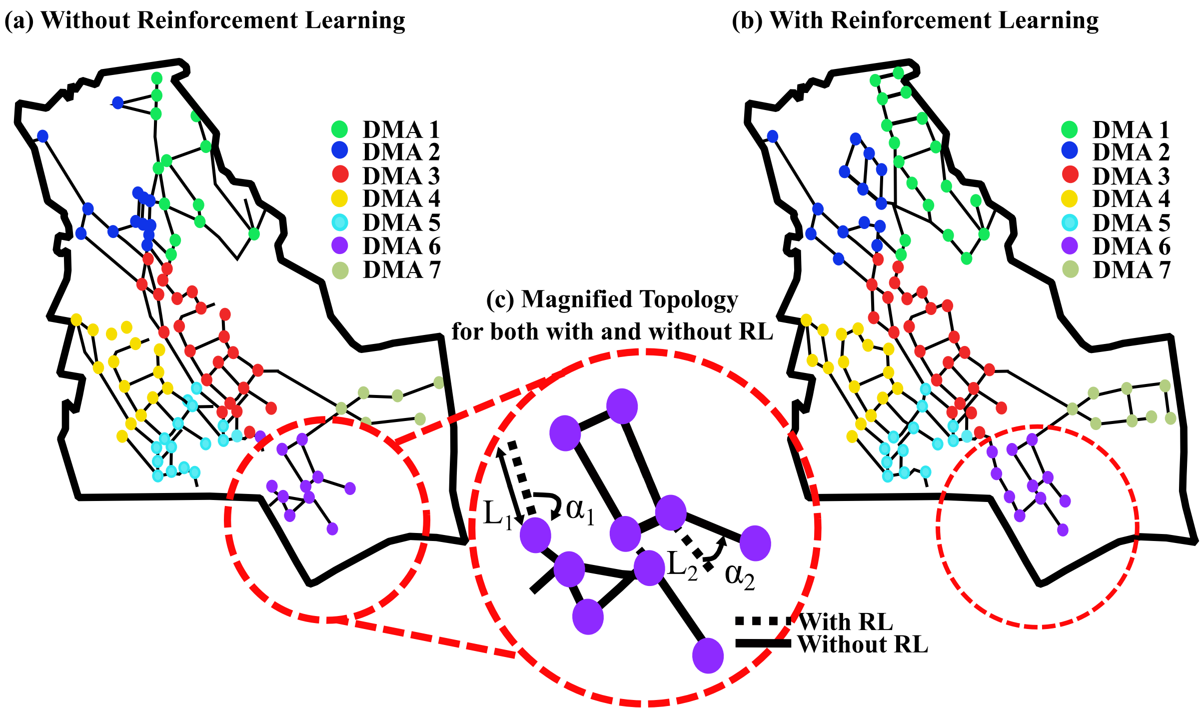


Figure 4 illustrates the optimized zones selected for the Thi-Qar water network, where four distinct zones are delineated across the seven District Metered Areas (DMAs) derived from the proposed topology. These zones are defined to maintain a consistent population distribution across the province, and for each zone, the expected detection time, expected contaminated water volume, and detection likelihood are presented as normalized values for straightforward comparison. Specifically, Zone 4—comprising DMAs 7 and 3—records an expected detection time of 0.85, reflecting strong compatibility with the objective functions, while Zone 2 (encompassing DMAs 1 and 2) achieves a contaminated water volume of 0.65. In terms of detection likelihood, Zone 4 again demonstrates robust performance, reaching a value of 0.79. Turning to Figure 5, this provides a comprehensive performance analysis of water quality detection across the entire network. As shown, the proposed algorithm effectively satisfies all three primary objectives simultaneously—minimizing expected detection time, minimizing expected contaminated water volume, and maximizing detection likelihood—while consistently maintaining all Topological Performance Indices within acceptable ranges.

Figure 4

Various optimized for selected zone of Thi-Qar

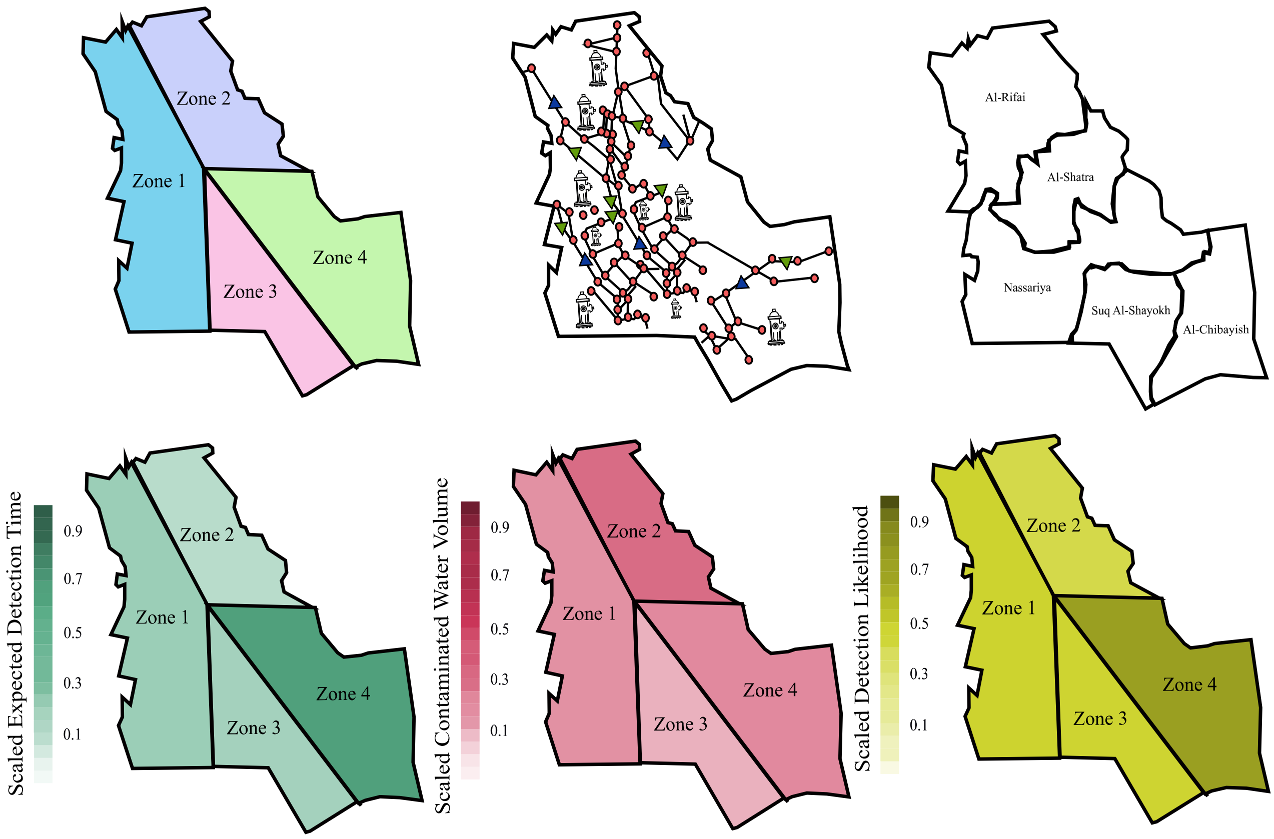
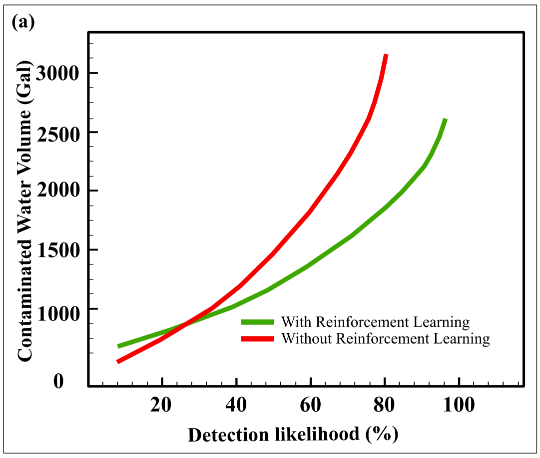
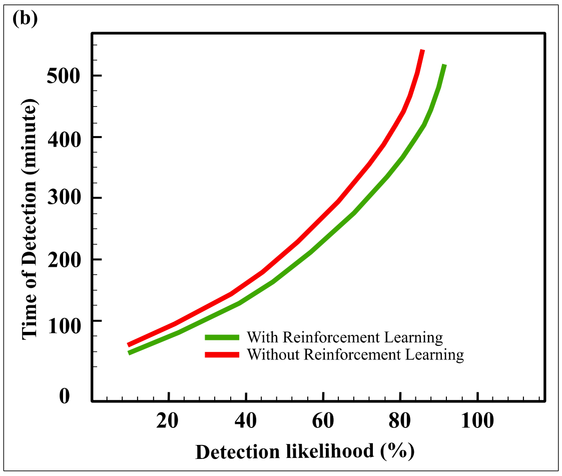


Figure 5

Performance analysis of detection of water quality



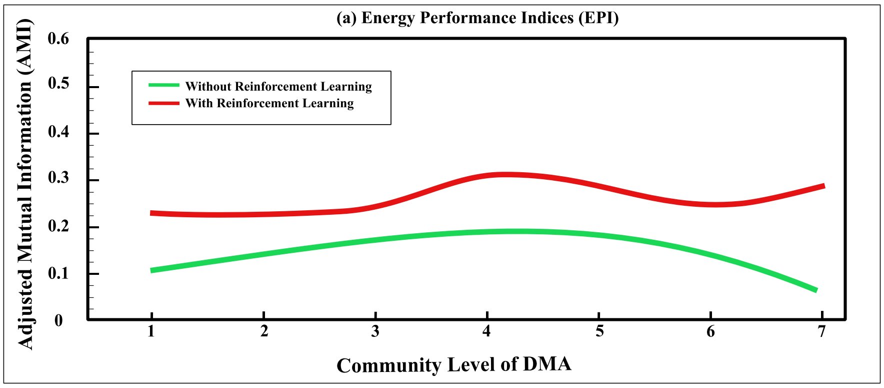


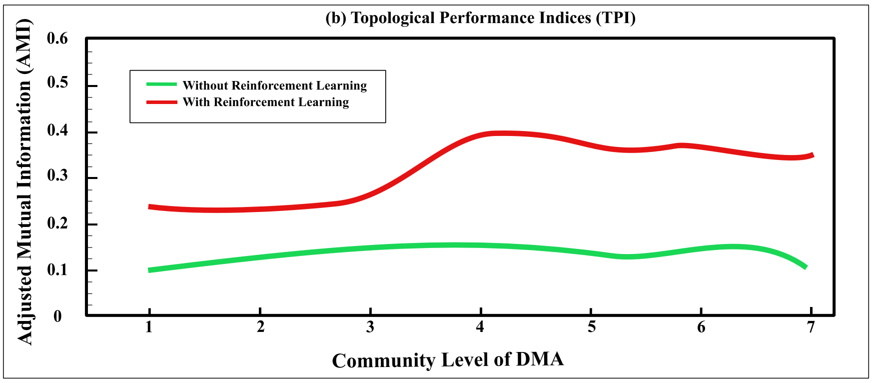
3.3. Graph Similarity and Community Partitioning Analysis

Figure 6 provides critical insights into both the structural and operational performance of the proposed RL-based water network sectorization. Regarding energy performance [Figure 6(a)], the marked decline in connectivity and flow within densely populated DMA pipelines confirms their role as peripheral extensions rather than primary transmission lines, while the consistently high and uniform AMI values (0.263 and 0.289) achieved by the RL approach demonstrate its superior capability to identify meaningful community structures that align with hydraulic functionality. In terms of topological performance [Figure 6(b)], the elevated AMI values observed for DMA classifications 4, 5, and 6 indicate that these complexity levels yield the most clearly defined and internally cohesive network communities, with the refined algorithm attaining an impressive average AMI of 0.38—approaching the 0.4 threshold that signifies substantial structural correspondence. Overall, AMI values nearing unity confirm that the algorithmically identified communities accurately mirror the underlying functional and topological divisions of the pipeline infrastructure, validating the effectiveness of the proposed sectorization strategy.

Figure 6

AMI versus of community levels





4. Discussion and Conclusion

The findings of the present study demonstrate that integrating reinforcement learning (RL), specifically Proximal Policy Optimization (PPO), with Social Network Search (SNS), edge-betweenness community detection, and multi-objective optimization can substantially improve the hydraulic, topological, and water-quality monitoring performance of an urban water distribution network. In the Thi-Qar case study, the RL-enhanced sectorization produced improvements across several performance dimensions without materially compromising basic hydraulic reliability. The minimum nodal pressure increased from 21.25 m in the non-RL solution to 21.57 m under the proposed framework, while mean pressure increased from 30.78 to 31.01 m. More importantly, the standard deviation of nodal pressure decreased from 5.72 to 5.12, corresponding to an improvement of approximately 10.5% in pressure uniformity. Although the resilience index remained almost unchanged, decreasing marginally from 0.355 to 0.354, the resilience deviation index declined markedly from 8.69 to 2.60, representing an approximately 70% improvement. These results indicate that the proposed method did not simply pursue topological partition quality, but was able to generate district configurations with more homogeneous hydraulic behavior and substantially lower deviation from desirable resilience conditions. This finding is compatible with the broader direction of recent WDN optimization research, in which network partitioning is increasingly evaluated through multiple hydraulic indicators rather than solely on the basis of structural separation (Caetano et al., 2025; Zhang et al., 2025).

The improvement in pressure uniformity is particularly important because one of the principal concerns associated with District Metered Area formation is that closing or regulating boundary pipes may reduce redundancy, alter preferred flow paths, and create pressure inequalities across the system. The present results suggest that the RL agent was capable of learning partition decisions that controlled these adverse consequences while retaining the monitoring advantages of sectorization. Similar concerns have been recognized in previous social-network-based water partitioning studies. Campbell et al. showed that successful sectorization requires simultaneous consideration of social-network concepts and engineering objectives, because structurally coherent communities may not necessarily preserve acceptable hydraulic performance if implemented without optimization (Campbell et al., 2015). Likewise, Brentan et al. integrated community detection with hybrid optimization specifically to reconcile graph-derived district formation with practical hydraulic requirements (Brentan et al., 2018). The present findings extend this line of research by showing that adaptive policy learning can refine the search process beyond static graph partitioning and can identify configurations characterized by improved pressure consistency while maintaining resilience.

The topological results provide further evidence of the effectiveness of the hybrid framework. The balance index decreased from 1.27 without RL to 1.01 with RL, bringing the district structure very close to ideal uniformity. This improvement was also visible in the distribution of nodes among the seven DMAs: without RL, DMA sizes varied from 38 to 54 nodes, whereas the RL-based approach generated much more homogeneous groups of approximately 46–49 nodes. Such structural balance is operationally desirable because highly unequal districts may impose disproportionate monitoring, maintenance, and control burdens on different parts of the system. The observed improvement accords with the general principles of graph partitioning, in which balancing the size or workload of subgraphs while minimizing inter-partition connections is a fundamental optimization objective (Ayall et al., 2022). It also supports the applicability of graph-theoretical representations to water infrastructure, where balanced network communities can improve the manageability and interpretability of physical systems (Di Nardo et al., 2015; Spizzo et al., 2023).

A second major topological improvement was observed in modularity, which increased from 0.72 to 0.79, corresponding to an increase of approximately 9.7%. Higher modularity indicates stronger internal connectivity within identified communities relative to the connections between communities. From a DMA perspective, this implies that the partitioning process generated more internally cohesive sectors with clearer structural separation. This result is consistent with community-detection theory, in which measures such as betweenness and modularity are used to identify densely connected groups separated by relatively important bridging edges (Arif, 2015). It also agrees with previous applications of social-network algorithms in WDN partitioning. Di Nardo et al. demonstrated that community structures identified using social-network algorithms can reveal meaningful clusters within water distribution systems (Di Nardo et al., 2015), while Creaco et al. showed that improved community detection incorporating the practical relationship between segments and valves can create partitions that are more suitable for real-world DMA implementation (Creaco et al., 2023). The improved modularity obtained in the current study suggests that RL did not distort the underlying graph structure in pursuit of hydraulic objectives; instead, it strengthened the coherence of the identified communities.

The improvement in average path length provides complementary evidence concerning network efficiency. The average path length declined from 9.82 without RL to 8.65 under the RL-enhanced method, an improvement of approximately 11.9%, while the deviation in average path length decreased from 12.36 to 6.98, representing an approximately 43.5% reduction. Shorter and more uniform paths indicate that the final community organization retained efficient internal connectivity and reduced extreme differences in accessibility between different portions of the network. This is an important result because excessively long paths can increase hydraulic losses and may contribute to undesirable residence-time patterns. Landmark-node reliability analysis similarly emphasizes the importance of network paths and accessibility to critical nodes when assessing infrastructure robustness (Herrera et al., 2025). The present results therefore reinforce the argument that path-based measures are valuable complements to conventional pressure and resilience indices when evaluating WDN sectorization.

The increase in the total number of edge cuts from 15 to 17 represents one of the few trade-offs observed in the proposed method. However, the worst number of edge cuts decreased from 5 to 4, indicating that although the total number of boundary interventions increased slightly, their concentration in the most affected part of the network was reduced. This finding is consistent with the inherently multi-objective nature of sectorization: the configuration with the absolute minimum number of cuts is not necessarily the most balanced, resilient, hydraulically efficient, or monitorable solution. Multi-objective sectorization studies similarly emphasize that optimal designs must be interpreted as compromises among competing criteria rather than as the minimization of a single structural quantity (Caetano et al., 2025; Zhang et al., 2025). From this perspective, the modest increase in total edge cuts appears acceptable because it was accompanied by substantial improvements in balance, modularity, pressure uniformity, and path consistency.

The water-quality component represents another important contribution of the study. The proposed framework simultaneously minimized expected contamination detection time and expected contaminated-water volume while maximizing detection likelihood. This differs from sectorization strategies that emphasize mainly hydraulic or topological performance. Sensor placement in WDNs is itself a difficult combinatorial problem because only a limited number of locations can typically be instrumented, while contamination may originate from numerous possible points. Previous studies have demonstrated the value of graph-based learning for improving monitoring coverage. Peng et al. applied graph neural network clustering to pressure sensor placement and reported that graph-based clustering can produce better-balanced monitoring zones and more effective sensor distribution than conventional approaches (Peng et al., 2022). Sun et al. proposed adaptive attributed graph clustering for sensor placement with reduced dependence on fully calibrated hydraulic models, illustrating the potential of graph-based methods when complete model information is unavailable (X. Sun et al., 2025). Likewise, Qi et al. employed unsupervised graph-based deep clustering for monitoring-point placement in drainage systems, supporting the broader applicability of learned graph representations to infrastructure monitoring (Qi et al., 2025). The present findings build on these studies by coupling monitoring objectives directly with network sectorization rather than treating sensor placement and partitioning as fully independent design stages.

The graph similarity and community partitioning analysis further supported the validity of the detected DMA structure. Adjusted Mutual Information (AMI) values indicated meaningful agreement between community assignments and the underlying structural characteristics of the network, with stronger performance around intermediate community levels and an average AMI approaching 0.38 for the refined classifications. Although these values do not imply perfect equivalence between partitions, they indicate that the resulting communities preserve substantive structural information. This is important because an optimized partition should not merely satisfy numerical objectives while losing correspondence with the original network topology. Research on pipeline-network configuration in different urban environments has demonstrated that graph communities can capture meaningful variations in infrastructure organization, vulnerability, and spatial development (Deng et al., 2025). The current AMI results therefore provide additional evidence that the proposed partitions reflect actual network structure rather than artificial divisions generated only by the optimization process.

The strong performance of the proposed framework can also be interpreted in terms of the adaptive search characteristics introduced by reinforcement learning. Conventional metaheuristic algorithms use predefined behavioral mechanisms that may not optimally adjust to the changing structure of a multi-objective search space. SNS, for example, uses imitation, conversation, disputation, and innovation mechanisms to balance exploitation and exploration (Talatahari et al., 2021). By combining these mechanisms with PPO, the present study introduces an adaptive decision layer capable of modifying the search trajectory in response to accumulated rewards. This interpretation aligns with recent work demonstrating that reinforcement learning can enhance multi-objective SNS algorithms in complex engineering design problems (Peng et al., 2025). It is also theoretically consistent with context-based multi-task reinforcement learning, where agents improve decision making by learning representations that capture relevant environmental and task conditions (Sodhani et al., 2021). Thus, the performance gains observed here are plausibly attributable to the capacity of RL to learn which search behaviors are most beneficial under different sectorization states.

The results also correspond with developments in other complex network optimization domains. Deep reinforcement learning has recently been applied directly to social-network graph partitioning, demonstrating that adaptive agents can learn effective partition decisions in high-dimensional graph environments (Cao et al., 2025). Likewise, reinforcement learning has been successfully used in multi-regional smart-grid optimization, where multiple interacting objectives, regional constraints, and dynamic operating conditions must be coordinated simultaneously (Q. Sun et al., 2025). Although water networks differ physically from electrical and social networks, these studies support the more general proposition that RL is particularly useful when decision problems involve sequential adaptation, competing system-level objectives, and large combinatorial search spaces. The current findings extend that proposition to WDN sectorization and monitoring.

The inclusion of machine-learning and graph-derived information also reflects a broader movement toward data-driven infrastructure design. Bahrami Chegeni et al. demonstrated that graph-theory-based features can support machine-learning models for the optimal design of WDNs, illustrating that structural descriptors contain significant predictive information regarding high-quality engineering configurations (Bahrami Chegeni et al., 2025). Similarly, genetic and evolutionary approaches to community detection have shown that identifying optimal communities can be formulated as an optimization process rather than a fixed clustering task (Ma & Fan, 2020). Together with the findings of the present study, this evidence suggests that future WDN optimization is likely to increasingly combine graph theory, machine learning, metaheuristics, and physical simulation rather than relying on any one methodology in isolation.

From a sustainability and management perspective, the results are particularly relevant because water utilities must allocate limited resources while maintaining service continuity and public-health protection. Sustainable water-supply assessment requires consideration of technical, environmental, and operational dimensions simultaneously (Mondal et al., 2023), while supply-side water-management research highlights the persistent difficulties associated with infrastructure constraints, optimization capacity, and efficient resource allocation (Jojozi et al., 2025). The present framework addresses these challenges by providing a multi-criteria decision-support approach in which hydraulic robustness, topological organization, and contamination monitoring can be evaluated within a common optimization process. The demonstrated improvements in the Thi-Qar network therefore suggest that RL-enhanced community-based sectorization may be especially valuable in networks where financial constraints make comprehensive physical upgrading difficult and where available monitoring resources must be deployed selectively.

The present study has several limitations that should be considered when interpreting the findings. First, the framework was evaluated on a single case-study network in Thi-Qar, and network-specific characteristics such as topology, demand distribution, source configuration, and existing infrastructure may influence algorithmic performance. Second, only selected hydraulic, topological, and water-quality criteria were incorporated, whereas other potentially important considerations, including lifecycle cost, pipe failure probabilities, valve reliability, energy tariffs, chlorine decay, stochastic contamination behavior, and emergency firefighting demand, were not explicitly modeled. Third, the analysis was based on modeled network conditions rather than a continuous real-time operational implementation, and consequently the effects of sensor failure, telemetry delay, uncertain demand, inaccurate hydraulic parameters, and incomplete field data were not examined. Finally, although the RL framework achieved substantial improvements, its computational requirements, sensitivity to hyperparameter selection, convergence behavior, and robustness across alternative initializations require more systematic investigation before generalized conclusions can be drawn.

Future research should validate the proposed framework across networks of different sizes, layouts, source configurations, and levels of hydraulic complexity, including megacity-scale systems and networks with intermittent supply. Further studies should explicitly introduce uncertainty in demand, pipe roughness, contamination occurrence, equipment availability, and future network expansion and should compare deterministic and stochastic formulations of the optimization problem. Dynamic DMA management also deserves particular attention, whereby automated valves could permit district boundaries to change in response to demand peaks, contamination events, pipe failures, or emergency conditions. Future models could additionally integrate detailed water-quality processes, including chlorine residual, water age, and contaminant transport, as well as economic objectives such as sensor cost, valve installation cost, pump energy consumption, maintenance expenditure, and lifecycle investment. Comparative benchmarking against alternative reinforcement-learning algorithms, evolutionary methods, graph neural networks, and conventional multi-objective metaheuristics would clarify the specific contribution of PPO and SNS. Finally, field implementation and digital-twin integration would provide an important next step for assessing whether the benefits observed under simulation can be reproduced under real operational constraints.

For practice, water utilities can use the proposed framework as a decision-support tool for prioritizing DMA formation, boundary control, sensor placement, and network rehabilitation in situations where simultaneous improvement of monitoring and hydraulic performance is required. Rather than selecting DMA boundaries solely on the basis of geographic convenience or minimum installation cost, practitioners should evaluate district balance, modularity, path structure, pressure distribution, resilience, and water-quality detection performance together. Utilities should also implement the method incrementally, beginning with pilot districts in which hydraulic models and monitoring data are sufficiently reliable, and subsequently recalibrate the optimization framework using observed operational data. Particular attention should be given to districts with large pressure variability, weak structural cohesion, long internal travel paths, or limited contamination-detection capability, because these areas are likely to benefit most from adaptive redesign. Integration with supervisory control, smart meters, pressure sensors, and automated valves could ultimately support progressively more responsive and data-driven management of urban water distribution systems.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

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