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An Optimal Upgrading Framework for Water Distribution Systems Operation

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Abstract: Water distribution systems (WDSs) are essential elements for the prosperity and development of societies around the globe. However, over time, the pipeline network starts to age and deteriorate, which results in an increasing rate of breaks and water loss due to leakages. Many countries have started government-funded plans to upgrade and rehabilitate their WDS network components to overcome these challenges. This study proposes an optimization framework that addresses these issues and offers potential benefits. It aims to achieve the optimal upgrading strategies considering network operation (hydraulic) performance and upgrading cost, including investment and non-revenue water costs. The upgrade of the WDS network in the model consists of replacing pipes and controlling the pressure-reducing valve (PRV) settings to reduce leakages. The proposed framework is demonstrated using a small-sized benchmark WDS. The study's outcomes provide the utilities' operators and municipalities' decision-makers with a guiding tool to choose the optimal upgrading strategy for their WDS networks at the lowest cost and optimum operation performance. The methodology involves simulating various leakage scenarios and applying optimization techniques to find the best combination of pipe replacements and PRV settings. This approach ensures a balance between minimizing leakage rates and controlling upgrading costs. The framework achieved a reduction of leakage up to 20% from the original leakage with a 70% probability for the tested benchmark network. The optimization framework can also offer a range of upgrading strategies, with a trade-off between the WDS network leakage reduction and the required cost of the upgrading strategy.

Keywords: optimization; upgrading strategy; water distribution systems; Monte-Carlo simulation

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1. Introduction

Managing the water distribution system is integral to the water services industry. It is necessary to ensure the systems are efficient and able to maintain good quality at the lowest cost possible. Proper system operation is essential to ensure that capital investments in new infrastructure result in sustainable service provision. Without it, the water distribution system will eventually decline to a point where service provision is compromised, leading to more significant water losses, financial losses, and health risks to consumers. Water is a significant issue in developed countries where water is scarce. In developed countries, the non-revenue water (NRW) range is between 45 and 50% [1], and the average NRW in Europe is 25% [2]. The massive scale of water loss has severe implications for network operations, leading to substantial financial costs for utilities. The cost of leaked water includes the value of the lost resource and the increased operational costs associated with compensating for the losses. Extra pumping is often required to maintain adequate pressure throughout the network, which results in higher energy consumption and increased wear and tear to the infrastructure.

Additionally, the environmental impact of wasted water and energy cannot be overlooked, as it contributes to the depletion of natural resources and higher greenhouse gas emissions. To manage these leakages, utility owners apply a combination of reactive and proactive approaches. Reactive measures typically involve responding to visible leaks and bursts, which can be costly and inefficient, as significant water loss may occur before repairs are initiated. Proactive strategies include regular maintenance schedules, pressure management, and advanced technologies like acoustic sensors and smart meters to detect leaks. However, these practices often fall short due to technological limitations, high costs, and the labor-intensive nature of monitoring large and complex networks. As a result, many leaks remain undetected until they become severe, leading to higher repair costs and prolonged water loss.

1.1. Optimization of WDS Design

The management and operation of WDSs have evolved throughout history. The policy of operation for some WDSs in the cities in the past was carried out and based on the operator's experience to fulfill the network's requirements; this led researchers such as [3] to provide an optimal operation policy resulting from the optimization models. Several attempts have been made to optimize WDS design, construction, or operation in the past decades, considering different objectives and variables [4,5]. The optimization objective in these studies was to design WDSs with minimal cost while providing the required water quantities to consumers. The costs considered are the construction costs (pump, pipe, tank) and the operation cost.

Moreover, some studies have considered the state of the flow (transient) in the network and the resilience of the WDS as an objective with the minimization of the cost of the network construction [6]. Ref. [7] developed an optimization model to design a WDS with minimized transient impact on the network, maximized network reliability, and a minimized construction cost. Their presented model offers a trade-off between the construction cost (the pipe size) and the other objectives.

1.2. Optimization of WDS Operation and Economics

Several researchers introduced the economic impact of WDS deficiencies as a variable in the optimization, where the leakage is accounted for as an economic aspect and presented in their model as a cost. Ref. [8] considered two operation strategies regarding the pumping schedule. The first is to pump at night (when the energy tariff is low) and fill the network's tank, and the second is to avoid excessive pumping at low-demand hours (at night) to keep the pressure low in the network. The two strategies were tested considering the leakage in three cases: 10%, 20%, and 40% of the total pumped water. Then, the model is run to test all cases to minimize the cost, considering the cost of the energy only (E) and the cost of the energy with the non-revenue water (E + W). The Ref. [8] optimization model achieved a lower total cost with (E + W) compared to considering the cost of the energy only (E). Moreover, [9] developed a similar optimization model considering the cost of energy (high and low tariff) and leaked water. However, the results of this optimization are sensitive to the variations in energy cost (day/night) and the consideration of leakage.

The operation of the WDS can be improved by applying real-time control (RTC) on the system, as many researchers have demonstrated in their findings. RTC means that the operator has online control of the WDS system elements, such as pumps and valves, to increase or reduce the pressure or flow in the system. The optimization by RTC is realized by the architecture of the control system and operation. Previous research investigated optimizing WDS pumping scheduling using RTC to reduce operational costs [10,11]. Ref. [12] studied the use of RTC control for the pressure control valve in the WDS to achieve more effectiveness and reliability in the pressure-controlling devices.

Economic evaluation was conducted by [13] for leakage control by utilizing PRVs and real-time control (RTC) and considering the cost of repair of the burst pipes. They considered two demand patterns (smooth and peaked) and three leakage levels (low, medium, and high). As for the control cases, it was 1- No Control, 2- Control with PRV, and 3- Control with RTC. For large and small systems, the cost of each case was calculated based on the cost of installing a control system (PRV or RTC), the cost of non-revenue water, the cost of pipe repair, and the cost of operation and maintenance of the system. The authors concluded that in a small system, the effect of the control is minimal; however, in a large system, the use of the control is beneficial even with the high initial installation cost when the water's unit cost is high.

Some improvements in the WDS can be obtained from optimizing the pump operation. Ref. [14] investigated the optimization of variable and fixed speed pumps for the cost of power consumed and the leaked water. The study considered two objective functions: first, to minimize both the power consumption and the leakage reduction, and second, to minimize the power consumption only. Both objective functions were tested using fixed and variable speed pumps to determine the lowest-cost scenario considering the cost of power and non-revenue water. It was concluded that the variable speed outperformed the fixed speed pump regarding the consumed energy and quantity of leaked water. Further optimization of the pump operation could be carried out by introducing the water quality and water storage as investigated by [15], which shows a trade-off between the pump operation and the size of the storage tanks.

1.3. Optimization of WDS Leakage Reduction

Optimization of a WDS can also aim to minimize the deficiencies in the networks. Previous studies investigated the reduction in leakage as an objective to achieve minimal leakage in the WDS. [16] attempted leakage reduction by optimizing the use of controls or pressure-reducing valves, which resulted in reducing the overall leakage in the tested network from 29 L/s to 23.24 L/s. Other authors used the [16] network as a benchmark for their optimization models, which considered the location of the valves and their set points [17–25]. Their optimizations to reduce the leakage in their studies have reduced the overall leakage in the range of 20.78 to 23.09 L/s.

1.4. WDS Optimization Methods

Regarding the method of optimization, [26] attempted to systematically review the optimization of WDS in the past three decades. Numerous studies have utilized evolutionary multi-objective algorithms to design WDNs, including NSGA-II, particle swarm optimization [27], genetically adaptive multi-objective (AMALGAM) [28], and multi-objective genetic algorithms [29], among others. Ref. [30] compared five multi-objective evolutionary algorithms to identify the best Pareto optimal front by eliminating dominated solutions. Non-dominated sorting differential evolution (NSDE) was employed to design optimal WDSs, achieving a Pareto front between cost and resilience. Additionally, a new evolutionary algorithm called GALAXY was developed to optimize WDN design [31]. Various mutation tactics and hybrid forms were introduced to enhance exploitation [32,33]. However, there is no universally accepted standard algorithm for WDN optimization, as improvements in existing algorithms can still yield superior results.

As shown in the reviewed papers, optimizing different variables related to the components of WDSs for planning and operation can help achieve better economic operation performance due to reduced leakage and overall system operation costs. However, the optimization of leakage in WDSs in the case where the location of the leakages is uncertain has not yet been investigated. Locating leakages within the water distribution network is inherently challenging due to several factors. Underground pipes are often difficult to access and pinpointing the exact location of leaks can be complex without visible signs. The heterogeneity of pipe materials, varying infrastructure ages, and noise and interference in urban environments further complicate leak detection. For utility owners, this issue translates into inefficiencies and increased costs as they attempt to locate and repair leaks with limited information. Therefore, this study presents an upgrading framework that addresses the uncertainty in the leakage locations. The framework consists of a pipe classification strategy, a stochastic leakage simulation, and an upgrading optimization model. Monte-Carlo simulation was utilized to test the model against a large number of leakage scenarios in a network to replicate the uncertainty of the leakage locations in a real-life WDS network.

This study aims to develop a framework for upgrading existing networks by minimizing leakages and improving operation performance at the lowest cost. It also aims to present a range of upgrading strategies for the WDS network that allow decision-makers to choose based on their budget and future plans (leakage reduction goal).

2. Material and Method

This section explains the development of the upgrading framework, its relations, elements, and the simulation and optimization models. This section also presents the study methodology used in this research.

2.1. Study Methodology

Figure 1 shows the methodology of this research. First, the water network is integrated into the model, and then the pipes are classified based on their importance. After the pipe classification, leakages are stochastically introduced to the network. The network with leakages is then subjected to the optimization model to reduce leakage and minimize the net improvement cost. During the optimization, the optimization model modifies the network variables (percentage of pipes to be replaced and PRV settings) and communicates with the hydraulic simulation model (that is used to assess the network performance) until optimum results are achieved. To address the uncertainty in leakage locations, the model is run for a large number of stochastic scenarios using Monte-Carlo simulation, where the leakage locations are different each time. The results of all scenarios are collected and analyzed to provide a trade-off of the best upgrading strategy.

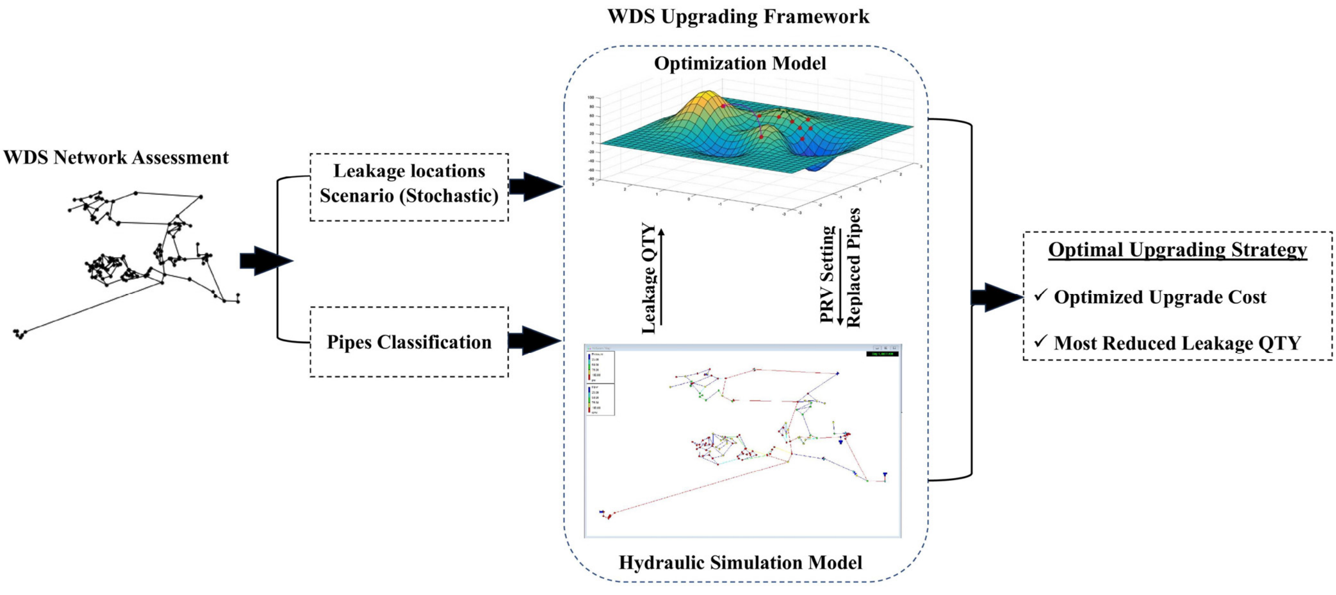

Figure 1. Research methodology.

2.2. WDS Upgrading Framework

The framework is built employing Python code using the assigned libraries for each model that provide the required functions for the framework. The models in the framework are the hydraulic simulation and the optimization model, as shown in Figure 1. The pipes in the network are classified based on their importance (represented by their size, length, age, and flow), and the top 10% of the pipes will be considered for replacement in the optimization. This study is focused on the uncertainty of the leakage's locations in networks; therefore, the leakage locations are selected stochastically, and then the optimization model will provide the best cost to invest in a network upgrade along with optimal PRV settings. After the pipe classification, leakages will be introduced to the network stochastically to simulate a network overall leakage with percentages ranging from 10% to 55%, representing the actual leakage in a real network. The optimization algorithm modifies the PRV settings and selects the percentage of pipes that will be replaced to find the best upgrading strategies that satisfy the optimization objectives (minimum leakage and minimum upgrading cost). The model will provide the best solution for the leakage scenario with stochastic leakage locations; thus, the model will be run around 1000 times to have sufficient scenarios to analyze the results using Monte-Carlo simulation and provide the network owners/operators with a trade-off between leakage reduction and the cost of the upgrade.

2.2.1. Hydraulic Simulation Model

This study uses the WNTR (Water Network Tool for Resilience) library in Python. WNTR is a versatile and comprehensive framework designed for water distribution system analysis and resilience assessment. As a tailored tool for researchers, WNTR's modular design enables the seamless integration of hydraulic solvers, demand, and water quality models, facilitating customized simulations. It allows for smooth integration with optimization processes and supports probabilistic analyses, enhancing its capability to handle uncertainty in leakage locations and other variables. Additionally, WNTR provides easy-to-use tools for introducing leakage, replacing pipes, and measuring performance metrics. Overall, WNTR aims to provide a comprehensive tool for analyzing and improving water network resilience, including various simulation tools and metrics for thorough network analysis [34].

2.2.2. Optimization Model

The Pymoo library in Python is used to build the optimization model. Pymoo serves as an asset in multi-objective optimization, with its versatile tools for solving complex optimization problems. The Non-Dominated Sorting Genetic Algorithm (NSGA-II) follows the general outline of a genetic algorithm with a modified mating and survival selection. In the NSGA-II, individuals are first selected front-wise. By doing so, there will be a situation where a front needs to be split because not all individuals are allowed to survive. In this splitting front, solutions are selected based on crowding distance. The crowding distance is the Manhattan Distance in the objective space. However, the extreme points are desired to be kept every generation and, therefore, are assigned a crowding distance of infinity. Furthermore, to increase some selection pressure, the NSGA-II uses a binary tournament mating selection. Each individual is first compared by rank and then crowding distance. Within Pymoo, the NSGA-II excels in handling problems with multiple conflicting objectives, providing a Pareto-based approach to identify solutions that represent the optimal trade-offs among competing goals. This algorithm is known for its efficiency and scalability. As an integral component of Pymoo, the NSGA-II enables researchers across diverse domains to tackle intricate decision-making problems, offering a reliable means to explore and navigate the landscape of multi-objective optimization [35].

The method used in Pareto analysis often termed a brute-force dominance check involves systematically comparing each solution in a dataset with every other solution to determine dominance relationships based on multiple objectives [36]. While straightforward, this method can become computationally expensive as the dataset size increases. To reduce computation time in large-scale multi-objective optimization problems, more efficient algorithms like the fast non-dominated sorting algorithm (NSGA-II) or the strength Pareto evolutionary algorithm (SPEA2) are commonly used. This method identifies and extracts Pareto front solutions from a dataset containing multiple objective function values. The code iterates through all pairs of solutions, checking for dominance relationships based on the Pareto principle, which is the essence of multi-objective Pareto analysis.

The objective functions of the optimization are (a) minimizing the leakage in the network and (b) minimizing the upgrade cost (replacement of pipes). The optimization variables are (a) the number of pipes to be replaced (the limits are between 0 and 10% of total pipes) and (b) the settings of existing PRVs in the network (the setting of PRVs to be between 15 and 45 m). The constraint in the model is that the pressure in the network shall not be less than zero (to avoid negative pressure). The optimization decision variables and constraint are summarized in Table 1, and the optimization algorithm structure is illustrated in Figure 2.

Table 1. Optimization Decision Variables and Constraint.

Decision Variable Type	# of Decision Variable	Range
PRV Setting	8	15 to 45 m
Replaced Pipes %	1	0 to 10%
Total	9	
Constraint	**Range**	
Minimum Pressure	>0	

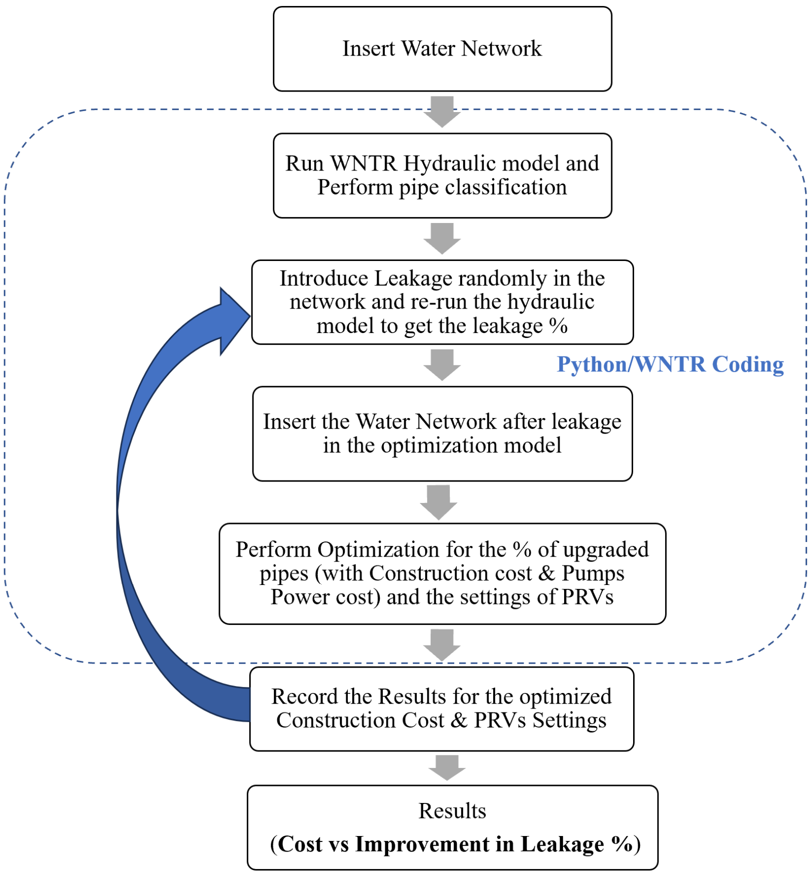

Figure 2. Optimization algorithm structure.

Steps for the Optimization Model:

1. Pipe importance (PI) classification is performed on the network pipes to rank the pipes from a leakage point of view. This pipe classification reflects the criticality of the pipe in affecting leakage quantities in the network. The pipe ranking is based on pipe age, diameter, and length, as derived from [37], and the used equation is as follows:

$$PI = \frac{Ap/Aavg}{Dp/Davg} \tag{1}$$

where:

$$Aavg = \frac{\sum Ap\ \times\ Lp}{\sum Lp} \cdot Davg = \frac{\sum Dp\ \times\ Lp}{\sum Lp}$$

Ap: pipe age, *Dp*: Pipe diameter, *Lp*: pipe length.

After the PI value is established for each pipe, the flow for each pipe is calculated using the hydraulic simulation, and the pipes with the same PI value are arranged by their flow (high flow is ranked higher). The ranking is then saved in a separate table to be called in the model. Since the model is trying to address the uncertainty over which pipe is leaking, the pipe leakage rate is assumed to be unknown and thus not considered in the pipe classification.

2. Leakage is then introduced stochastically in the network so that the overall leakage in the network will be between 20 and 40%. This range was set to match the average system leakage for deteriorated infrastructures. Equation (1) also defines the probability that a pipe leaks (based on the pipe's age, diameter, and length). Therefore, the leaking pipes differ in each model run since leakage is introduced to pipes probabilistically following the pipe leakage probability.

3. After introducing leakage, the network is integrated into the optimization code. The optimization process has two objectives: (1) minimize the leakage in the network and (b) minimize the upgrade cost (replacement of pipes). In the first objective function to minimize leakage, the optimization algorithm adjusts parameters such as PRV settings and the percentage of pipes to be replaced. The hydraulic model then simulates network behavior based on these variables, with the output revealing the minimum achievable leakage for the network.

In the second objective function, the optimization framework aims to minimize the net cost of investment associated with leakage reduction efforts. The net investment cost is the pipe replacement cost minus the saved energy cost for one year in operation. This objective entails considering cost components, including the expense of pipe replacements and savings derived from reduced pump energy consumption. The cost of pipe replacements is calculated based on the percentage or number of pipes replaced, with the cost per linear meter applied. The cost of pipe replacements, which includes the cost of pipes and all construction works, is set at USD 50 per linear meter [38] for pipes with a diameter of 200 mm, consistent with the top 10% of pipes in the benchmark network. Energy costs related to pump operation are factored in as savings, with the net cost of investment computed as the difference between pipe replacement costs and the accrued energy savings cost. Specifically, the cut in pump energy cost is considered a saving, with the cost estimated for one year of operation using a fixed unit price of USD 0.0853 per KW-h.

By integrating these objectives into a unified optimization framework, the methodology ensures a balanced approach to water network management. The structured sequence of operations facilitates stakeholders' informed decision-making, from variable adjustment to simulation and cost analysis.

2.3. Demonstration

A small-sized benchmark WDS network, presented in Figure 3, which was adopted originally from [39], is used to demonstrate the proposed upgrading framework for Water Distribution Systems Operation. The chosen benchmark WDS (hereafter BWDS) comprises 126 nodes, one consistent head source, 168 pipes, eight PRVs, two tanks, and two pumps with one demand pattern. The system was simulated for a total extended period duration of 24 h. This network was utilized in this study to test the framework and to analyze its performance as a pilot to present an indication of the applicability for all other networks with similar elements.

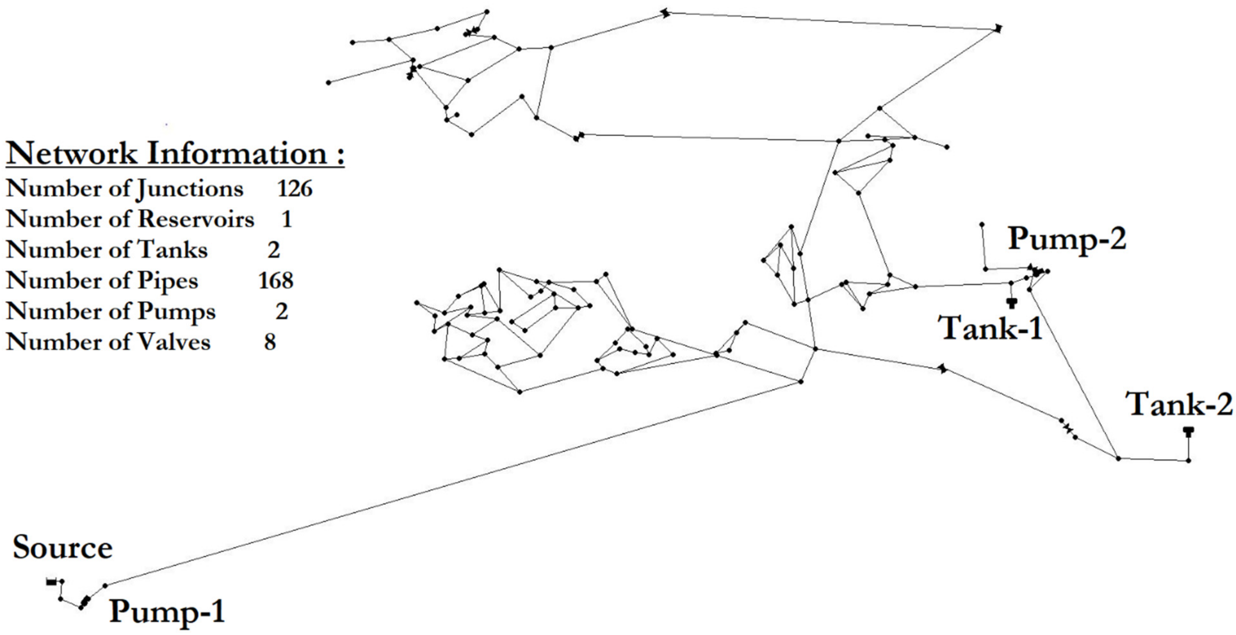

Figure 3. BWDS network layout.

3. Results

The framework will produce optimized results from each objective, minimum net cost of investment, and reduced leakage. The results are presented in a Pareto front to show the optimum result from the two objectives. As a result of the reduction in leakage, the saved cost of non-revenue water (NRW) after the leakage reduction is estimated for each scenario with its respective investment cost category. Moreover, the framework variables were analyzed for their behavior and impact on the model results.

3.1. Framework Outputs

The framework solutions are a Pareto front set with the best solutions for each scenario. The total solutions for all 1000 scenarios are almost 40,000 solutions. Each solution has the net cost of investment and its respective leakage improvement.

3.1.1. Analysis of Investment Cost and Leakage Improvement

The pipe replacement cost is gradually set up from 1% to 10% of the high-priority pipes in the network. The model tries to replace 1% of pipes at a time, and if there is any improvement, it will be considered an acceptable solution, and it could be multiple solutions if there is an improvement in other pipe replacement options in the same scenario. The order of pipe replacement is on a cumulative basis, and each replacement percentage has its respective cost. The zero cost is an improvement scenario achieved by only changing the PRV settings with no pipe replacement. The model investigates the effectiveness of pipe replacement for the reduction of leakage in the network; thus, the model selects the percentage of pipes to be replaced and then assesses the hydraulic model leakage reduction, if any. In Figure 4, from the 1000 scenarios, each optimum result of the pipe replacement and leakage reduction improvement as a percentage of the original leakage is shown. Figure 4 shows that the higher the investment in pipe replacement is, the greater is the leakage reduction.

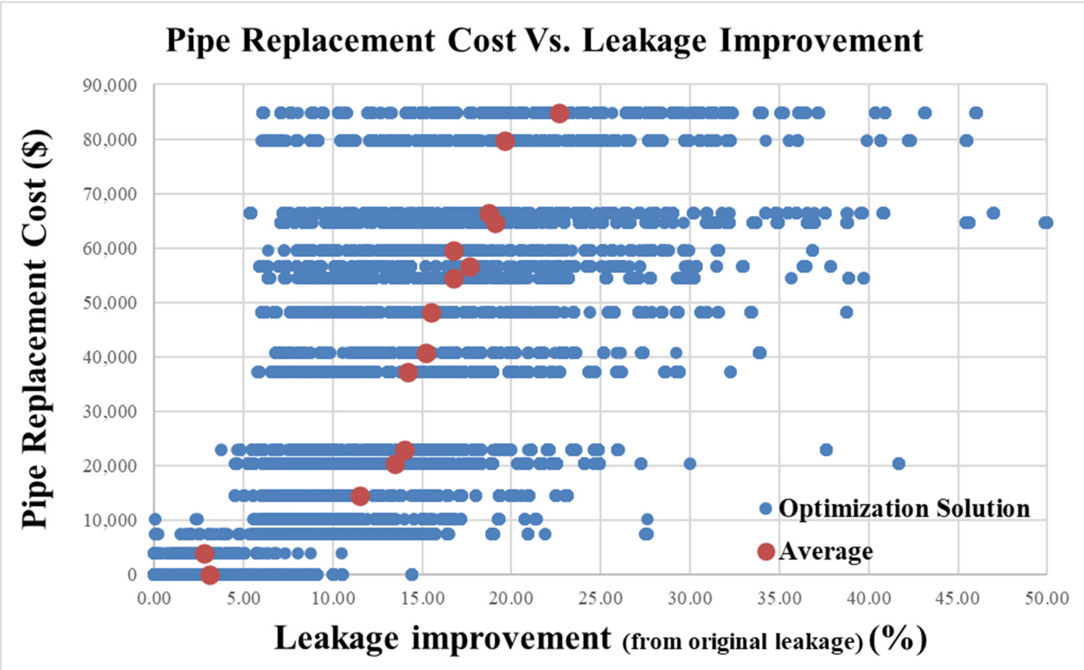

Figure 4. Relationship between the investment in pipe replacement cost and leakage improvement.

3.1.2. Non-Revenue Water (NRW) Assessment

There are other cost savings expected from leakage improvement besides the energy savings, such as the cost of non-revenue water. The non-revenue water cost can be derived from the framework results as the leakage quantities saved after the optimization. Figure 5 shows the relationship between the expected NRW cost savings and the investment in pipe replacement.

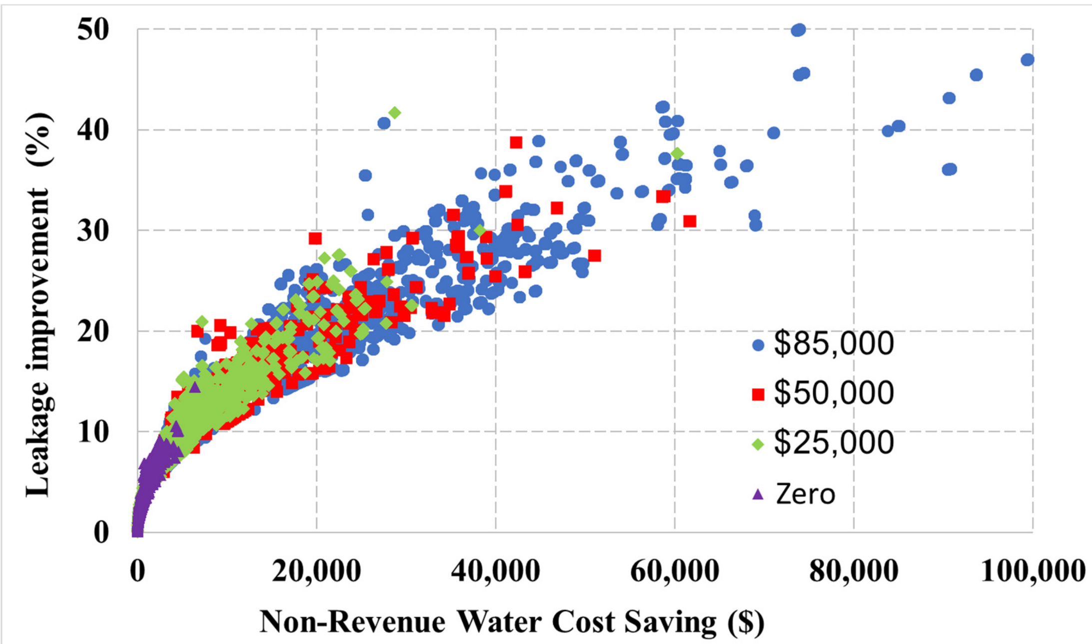

Figure 5. Expect non-revenue water cost savings for each investment category.

The outputs from the model are the net investment cost and the leakage improvement for each situation. The relationship between the net investment cost (pipe replacement—saved energy cost (per year)) and the leakage improvement % (from the original leakage) was investigated, which further shows that the higher the investment is, the more leakage improvement is achieved.

3.1.3. Analysis of Energy Saving Cost

The benchmark WDS used in this framework has two pumps and the pumps' main function is to fill the tanks in the network. The pump operation time is determined by the filling time of the tanks. When leakage is introduced in the network, the filling time is increased, which results in more operation time for the pumps, requiring additional power. The model tries to reduce the leakage in the network while minimizing the net cost. Therefore, the model changes its variables (PRV settings and number of pipes replaced) to achieve the best cost, including the best energy-saving cost. To understand the framework's behavior in energy savings, the best-performing solutions for all 1000 scenarios are collected and plotted against each scenario's original leakage (before optimization). Figure 6 shows each scenario's best-performing energy cost-saving solution against the original leakage percentage. The best-performing solutions selection strategy was based on the best performing on the single objective of the energy-saving cost. The figure shows that the higher the original leakage is, the more savings in energy costs are expected. For example, for scenarios with 10% to 20% leakages, most of the best performance for energy savings is approximately USD 21,000, from 20% to 30% is USD 31,000, and from 30% and more, most savings are USD 38,000. However, the relationship presented in Figure 6 does not show a consistent pattern when using all the solutions instead of only the best performer.

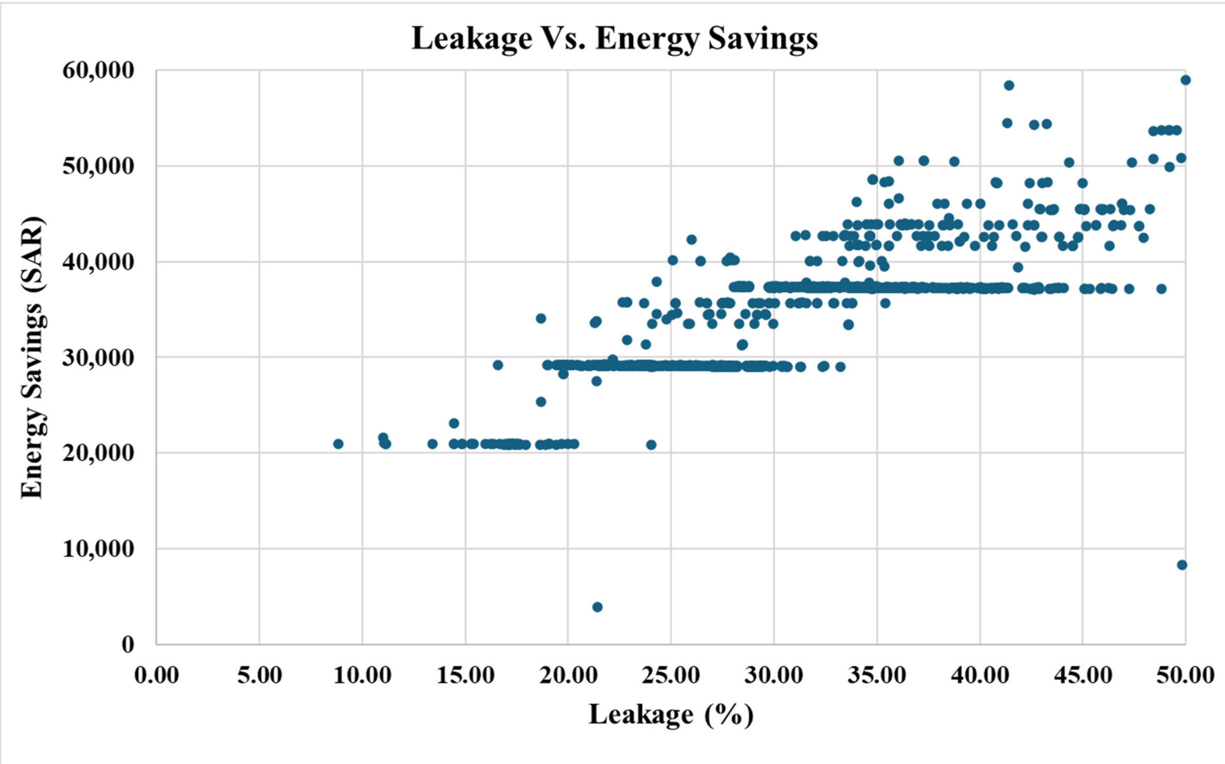

Figure 6. A relationship between the original leakage percentage and the saved energy cost for each scenario.

3.1.4. The Impact PRV Setting

There are eight PRVs in the benchmark network, and their settings are part of the variables in the optimization model. The change in the PRV settings is set within the range of 15 to 45 m, and this range was determined to keep the network pressure within the standard acceptable range. In the model, there is a constraint preventing any negative pressure in the network, and changing PRV settings is the primary variable that controls this constraint. With each scenario, the location of the leakage and quantities changes, and with that, the PRV settings must change to fulfill the constraint requirements and achieve the optimization objectives of leakage reduction. The impact of changing the setting of the PRV on leakage reduction was noticeable for the solutions that include no pipe replacement, and leakage reduction is only achieved by changing the settings of PRVs. The impact of changing the settings of the PRVs in the solution with a pipe replacement is still to be captured in a pattern, which could be investigated in future work. Moreover, some scenarios were investigated individually to establish a relation between PRV settings and energy savings, and it was found that there is a positive impact of the settings changes, but no clear trend could be established.

The integration of PRV settings with a pipe replacement offers confidence to each solution that the hydraulic operation is carried out with optimum efficiency through the reduction in leakages or the saved pump energy. Moreover, the changes in the PRV settings are facilitated to fulfill the constraint of preventing negative pressure in the network.

3.1.5. Use of Framework

To categorize the results, the solutions are cumulated for all scenarios, and a Monte-Carlo analysis is conducted to estimate the probability of achieving a leakage improvement target for each scale of pipe replacement investment. Figure 7 is drawn from the combined solutions with their investment cost category against the probability of achieving leakage improvement targets after the Monte-Carlo simulation. Figure 7 shows the trade-off between the investment in pipe replacement and the improvement in leakage reduction with the probability of each desired leakage improvement against the cost. Figure 8 represents the cumulative optimum solutions after categorizing each solution cost (investment) with the respective leakage improvement.

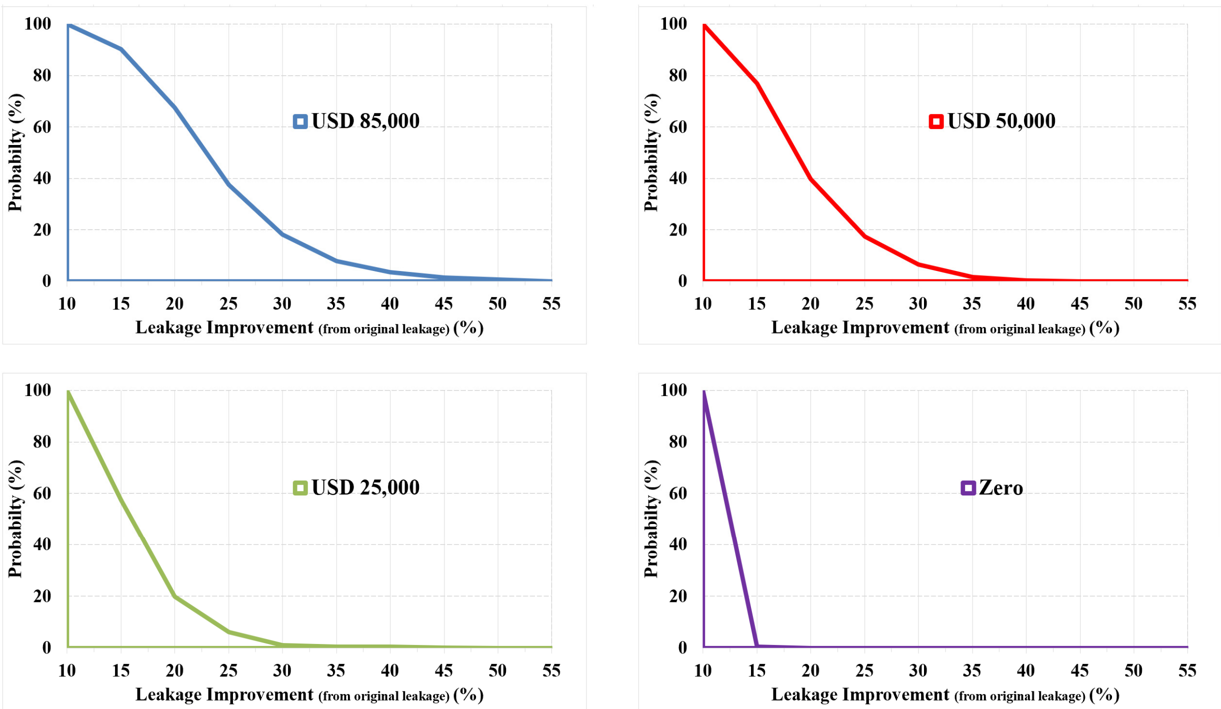

Figure 7. Probability of leakage improvement for each investment category.

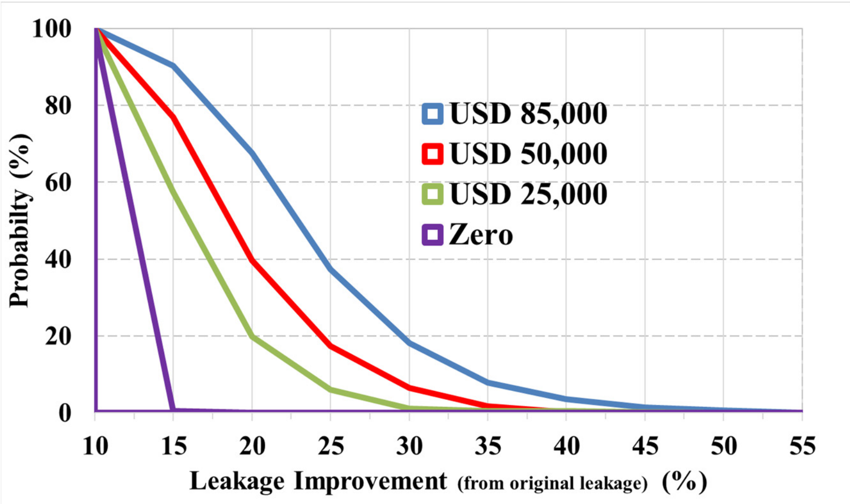

Figure 8. Combined results of investment in pipe replacement relation with leakage improvement probability.

The following example illustrates the utility of the framework. In the case of the benchmark network under study, which had a 40% leakage, the facility owner/operator proposed to reduce the leakage by 20% (from 40% to 32%). From Figure 8, to achieve the 20% leakage improvement, each investment in pipe replacement has its respective probability generated from the large number of stochastic scenarios shown in Table 2. From the model, in 70% of the scenarios, investing USD 85,000 in pipe replacement of the higher importance pipes achieved a 20% reduction in leakage despite the percentage of the original leakage.

Table 2. Probability of leakage improvement by 20%.

Investment ($)	85,000	50,000	25,000	Zero
Probability (%)	70%	40%	20%	0%

The WDS operator/owner can determine the water unit price based on their economic situation. Adding another perspective on the NRW cost savings and the model results, the expected reward from NRW savings can be calculated based on the probability of achieving the leakage improvement for an investment choice. The expected reward is calculated using Equation (2).

$$\text{Expected Reward from NRW} = \text{Probability} \times \text{Cost of Saved Water} \quad (2)$$

where:

Cost of Saved Water = Water QTY per year x Leakage % × Targeted leakage reduction % × Cost of water

Probability = the probability of the leakage improvement for the investment choice.

As an example, in the case of the studied benchmark network with 30% leakage and 20% targeted leakage reduction from the original leakage, the saved NRW cost in one year of operation is:

Cost of Saved Water = 5149 m^3/day × 365 days × 30% × 20% × 0.8$/$m^3$ = 90,210$

Therefore, for USD 85,000 investment, 30% leakage and 20% targeted leakage reduction from the original leakage (from Figure 7):

Expected Reward from NRW = 0.7 × USD 90,210 = USD 63,147

Additionally, the cost savings in energy could be included in the expected reward. The energy savings cost at 30% leakages is around USD 29,000 per year (from Figure 6); thus, the overall savings = 90,210 + 29,000 = USD 119,210.

Therefore: **Overall Expected Reward =** 0.7 × USD 119,210 = USD 83,446

4. Discussion

The framework presented in the study offers a solution to address the complex challenge of reducing leakage in water distribution systems. By generating a Pareto front set comprising the best solutions from many scenarios, totaling nearly 40,000 solutions, the framework provides a comprehensive approach to optimizing investments in pipe replacement for leakage reduction. Each solution not only entails the cost of investment in pipe replacement, but also quantifies the corresponding improvement in leakage.

A Monte-Carlo analysis is employed to distill the extensive dataset into actionable insights, yielding the probability of leakage improvement for varying levels of pipe replacement investment. This probabilistic approach enables stakeholders to make informed decisions tailored to their specific goals and constraints. The resulting Figure 7 encapsulates the trade-off between investment in pipe replacement and the probability of achieving a desired reduction in leakage, thereby facilitating decision-making by visualizing cumulative optimal solutions.

Moreover, the utility of this framework extends beyond mere leakage reduction, encompassing cost savings from mitigated non-revenue water (NRW) losses. By quantifying the NRW cost savings derived from optimized pipe replacement, Figure 5 elucidates the financial benefits accrued alongside leakage improvement. Notably, the framework's outputs provide a holistic view, highlighting various investment strategies' cost-effectiveness.

Furthermore, categorizing data points by related pipe replacement cost adds another layer of insight, enabling stakeholders to discern cost-performance trade-offs more intuitively. Thus, by integrating technical optimization with economic analysis, this framework offers a systematic approach to address the multifaceted challenges of leakage reduction in water distribution systems, empowering stakeholders to make informed decisions for sustainable water management.

Study Implications

This research holds significant theoretical implications for water distribution system management, particularly in scenarios where leakage locations are unknown, requiring innovative approaches to uncertainty quantification. By utilizing Monte-Carlo simulation techniques to gauge uncertainty and incorporating a process for pipe replacement within the optimization framework, the study contributes to theoretical advancements in uncertainty analysis and infrastructure upgrading strategies. The integration of Monte-Carlo simulations enables the exploration of a wide range of possible leakage scenarios, allowing for informed decision-making under uncertainty. At the same time, the systematic approach to prioritizing pipes for replacement based on pipe hydraulic properties adds further depth to the optimization process. Additionally, the gradual adjustment of pipe replacement costs and iterative assessment of leakage reduction demonstrates the dynamic nature of optimization strategies. This approach enhances the theoretical understanding of how uncertainty affects optimization outcomes and underscores the importance of probabilistic modeling in addressing real-world complexities.

Moreover, this research offers practical implications for water utilities and infrastructure managers seeking to optimize water distribution systems. Through its integrated optimization framework addressing leakage reduction and cost minimization objectives, the study provides a valuable tool for decision-makers to enhance system efficiency and sustainability. By incorporating Monte-Carlo simulation to assess uncertainty surrounding leakage locations, the research enables utilities to make informed decisions under unpredictable conditions. This facilitates more reliable planning and resource allocation strategies, leading to improved system performance and reduced non-revenue water losses. Furthermore, the comprehensive cost assessments empower stakeholders to conduct thorough cost-benefit analyses, aiding in prioritizing investment strategies based on financial feasibility. Overall, the practical implications of this research extend to implementing more effective and resilient water infrastructure management practices, ultimately ensuring communities' reliable access to clean water.

Finally, this study presents significant managerial implications for water utility managers and infrastructure stakeholders tasked with optimizing water distribution systems. The integrated optimization framework outlined in this study offers managers a valuable tool for guiding decision-making processes toward achieving simultaneous leakage reduction and cost minimization objectives. By adopting this framework, managers can strategically allocate resources and prioritize investments to optimize system performance while minimizing operational costs. Moreover, the framework enables managers to conduct thorough financial analyses, facilitating informed budget allocation and investment prioritization. Overall, the managerial implications of this research highlight the potential for improved operational efficiency, cost-effectiveness, and resilience in WDS management practices.

5. Conclusions

This study developed an optimization framework aimed at enhancing the operation and upgrading of water distribution systems (WDSs) by effectively minimizing leakages and associated costs. By employing Monte-Carlo simulations to address the uncertainties inherent in leakage locations, the framework provides utility operators with system upgrade strategies. The framework demonstrates its effectiveness in reducing leakage rates and optimizing upgrade costs. The dual approach of identifying critical pipes for replacement and adjusting pressure-reducing valves (PRVs) resulted in a reduction in leakages from 20% to 5% of the original leakage with its respective probabilities and corresponding cost savings. These results underscore the framework's ability to enhance system efficiency while maintaining cost-effectiveness. The framework presented in this study can offer the facility operators a trade-off between the upgrade cost and desired leakage reduction while the location of the actual leakages in the network is unknown. The methodology proposed in this research offers a flexible systematic approach that can be applicable across different WDS configurations. The WDS element can be integrated into the framework as required. For example, in future work, integrating the setting of WDS pumps in the framework would provide an interesting optimization aspect that could offer further improvements. Ultimately, this systematic approach empowers utilities and operators to implement cost-effective strategies for leakage reduction while simultaneously optimizing resource allocation, thereby enhancing the efficiency and sustainability of water distribution systems operation and asset management.

Limitations and Future Work

For future research, exploring additional variables within the optimization process would be prudent. For instance, including hydraulic pump settings and adjusting replaced pipe sizes could provide further insights into system optimization. Additionally, integrating the cost implications of installing new PRVs into the model could enhance its effectiveness. While the network utilized in this study represents a small-sized network, there is potential to extend the framework to encompass larger networks with diverse pipe and valve configurations. Therefore, future work could include applying this framework to real-world, large-scale networks to assess its applicability and effectiveness across different WDS contexts.

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