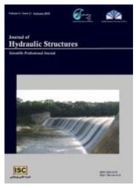
Journal of Hydraulic Structures
J. Hydraul. Struct., 2024;11(3):61-76
DOI: 10.22055/jhs.2025.48258.1328



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Advanced Approaches in Optimizing Water Distribution Networks: A Detailed Analysis on Minimizing Leakage and Enhancing Resilience

Alireza Shahhosseini [1]
Mohsen Najarchi [*,1]
Mohammad Mahdi Najafizadeh [2]
Mohammad Mirhoseini Hezaveh [1]

Abstract

The high costs of constructing water supply networks have shifted design priorities towards minimizing leakage and enhancing reliability. This study applies nonlinear programming (NLP) to optimize a water distribution network (WDN), focusing on leakage reduction and improved performance. By integrating flow-pressure dynamics, the approach incorporates a reliability constraint within Tehran's WDN in Iran. High-risk nodes, identified based on leakage potential using WaterGEMS software, serve as key data points for the NLP model. The findings show that NLP significantly improves pressure distribution across the network, contributing to more stable pressure levels, which is critical for operational efficiency. Furthermore, this method enhances the network's resilience index, effectively reducing the likelihood of leakage and pipe failure. The NLP-optimized network design yields a notable 8.12% reduction in overall pipe costs, indicating both financial and operational advantages of this approach. By addressing these high-risk areas with targeted interventions, the NLP model contributes to a more sustainable network infrastructure that minimizes maintenance needs and extends network lifespan. This comprehensive optimization model thus offers a practical, cost-effective solution for modern water distribution challenges, balancing initial investment with long-term network reliability and leakage control.

Keywords: Nonlinear Programing Optimization, Pressure Management, Water Distribution Network, Water Gems, Lingo.

Received: 29 October 2024; Accepted: 30 December 2024

1. Introduction

WDNs assume a pivotal role in the advancement of urban infrastructure systems, with the primary goal of facilitating the conveyance of water to consumption nodes while concurrently adhering to engineering considerations such as appropriate pressure and velocity. WDNs can be

[*] E-mail: M-najarchi@iau-arak.ac.ir **(Corresponding Author)**
[1] Department of Civil Engineering, Arak Branch, Islamic Azad University, Arak, Iran.
[2] Department of Mechanical Engineering, Arak Branch, Islamic Azad University, Arak, Iran.

configured as either a single reservoir system or a multi-reservoir system, encompassing consumption nodes and interconnected pipes. Frequently, these interconnections form closed loops, thus constituting a closed-loop network. The conveyance of water within a WDN can be achieved through either gravitational forces or a dedicated pumping system. A prototypical WDN is characterized as an intricate system comprising hydraulic control elements interconnected through nodes, facilitating the transportation of water volumes from the source node to the consumer node [1]. The provision of safe and accessible water, essential for drinking, household activities, and recreational pursuits, holds significant implications for public health. Enhanced management of water resources stands to expedite the economic development of nations and contribute to poverty alleviation. As of 2017, approximately 5.3 billion individuals benefitted from access to secure drinking water services, leaving a remaining 2.2 billion people devoid of adequately managed water services. Projections indicate that by the year 2025, nearly half of the global population will reside in regions characterized by water scarcity [2]. Hence, the evaluation of water efficiency becomes imperative, with the enhancement of the water supply network efficiency deemed an unavoidable necessity. Optimization emerges as one of the most effective methods to achieve this objective [3]. Conversely, the considerable challenge posed by water losses attributable to leakages and pipe ruptures constitutes a prominent aspect in the administration of urban Water Distribution Systems (WDSs) [4]. Consequently, mitigating leakage, estimated to range between 35% to 60% in various countries, emerges as a paramount challenge, particularly in aging networks and areas characterized by elevated service pressures [5]. The behavior of WDSs is frequently characterized by nonlinearity due to their composition of numerous elements, including pipes, nodes, reservoirs, pumps, valves, among others [6]. The frequency of leakages and pipe bursts is contingent upon the pressure distribution within the network, thereby rendering pressure a critical variable in WDSs [7]. Implementing Pressure and Discharge Management (PDM) emerges as one of the most efficacious approaches to enhance productivity and reduce leakage within the network [8].
The optimization of water distribution systems represents a complex and intellectually engaging research domain. Early methodologies included deterministic approaches such as dynamic programming (DP) [9-10], hierarchical control methods, linear programming (LP) [11-13], and NLP [14]. These foundational techniques laid the groundwork for the evolution of more sophisticated optimization strategies within the field [15]. Several investigations have demonstrated that the application of optimization techniques, including linear programming (LP), NLP, and heuristic methods, yields enhanced pressure management within WDSs and augments network resiliency. Among diverse objective functions, such as minimizing total leakage or nodal excess pressures, the latter proves to be more efficacious in optimizing WDS productivity [16, 17]. Soltanjalili et al. (2013) devised a methodology for hydraulic analysis of the network, specifically addressing the authentic nodal pressure-demand relationship during failure conditions [18]. Belotti et al. (2012) introduced two overarching categories of solution methodologies for Mixed-Integer Nonlinear Programming (MINLP): single-tree and multi-tree methods [19]. Pecci et al. (2015) implemented and assessed a direct solver for MINLP as well as two distinct reformulation methods tailored for solving sequences of conventional NLPs [20]. Liang et al. (2016) introduced a convex model for the optimal design of WDSs employing the MINLP approach. In this methodology, head loss equations were reformulated into convex inequalities [21].

Singh and Kekatos (2019) formulated the intricate task of optimal water flow scheduling as a mixed-integer non-convex problem. This formulation integrates essential flow and pressure constraints pertinent to fixed-speed pumps, tanks, reservoirs, and pipes. The adapted problem structure allowed for its solvability as a mixed-integer second-order cone program, ensuring the derivation of WDS-feasible solutions under specific conditions [22]. Jimenez-Cabas et al. (2018) introduced a methodology for leak localization in WDSs utilizing flow readings [23]. Awwalu et al. (2023) asserted the critical importance of ensuring effective water supply in response to the challenges posed by a growing population and increasing water scarcity. They proposed a multi-objective optimization model, encompassing various constraints, decision variables, and objectives related to cost and reliability. Leveraging mixed-integer Linear Programming (LP), the model aimed to optimize the allocation of water resources, minimize costs, and enhance the reliability of water distribution systems [24]. In a separate study, Biscos et al. (2003) delineated an operational optimization methodology for potable water distribution networks. Primary objectives included the maximization of low-cost power usage and the maintenance of target chlorine levels at delivery points [25]. Over time, with the aging of infrastructure and the potential impact of natural disasters such as earthquakes, the likelihood of pipe breakage increases [26]. The assessment of water distribution system performance has been conducted based on three criteria: reliability, flexibility, and vulnerability [27]. In order to effectively respond to perceived or actual shocks, the system necessitates absorptive, adaptive, and restorative capacities of flexibility [28]. Butler et al. (2016) specifically defined resilience in WDSs as the degree to which the system minimizes the magnitude of service failure over its design life when subjected to exceptional conditions [29]. Failure modes within WDSs can be broadly classified into structural failure and functional failure [30]. The system's response to pipe failure serves as an indicator of its resilience to the loss of structural connectivity [31]. An investigation revealed that the depth of pipe establishment, corrosion, obsolescence of pipes, and the use of improper pipe types were identified as the most significant causes of failures in the Ahvaz WDS during the period of 2006-2008 [32]. Morani et al. [33] investigated optimizing water distribution networks by integrating pumps as turbines (PATs) and pressure-reducing valves (PRVs) to enhance energy production and reduce water waste. Using a new mixed-integer nonlinear model, their approach demonstrated significant improvements in water and energy savings compared to existing methods, highlighting the feasibility of recoverable energy utilization. Mohammadi et al. [34] evaluated replacing pressure-reducing valves (PRVs) with pumps as turbines (PATs) in water distribution networks using genetic algorithms and WaterGEMS modeling. Results showed a 33% reduction in leakage, a 0.41 increase in Nodal Pressure Reliability Index (NPRI), and a 58% decrease in average network pressure, demonstrating PATs' effectiveness in pressure control and energy recovery.

This study proposes a novel and comprehensive approach to optimizing urban water distribution networks by leveraging NLP integrated with hydraulic simulation tools and advanced performance indices. Unlike conventional optimization methods, this research uniquely incorporates reliability and failure indices as key constraints, addressing the dual challenges of leakage mitigation and network resiliency enhancement. By utilizing WaterGEMS software for hydraulic simulation and integrating its outputs into the NLP optimization framework, the methodology ensures a more precise identification of high-risk nodes and a targeted intervention strategy. This innovative approach not only optimizes pressure distribution but also introduces a systematic framework that balances operational efficiency, long-term sustainability, and resilience under varying demand and network conditions. The research thus pioneers a new standard in urban water network management, offering a versatile and effective solution to address both current and future challenges in water supply systems.

2. Materials and Methods

2.1. Case Study

Tehran, the capital of Iran, qualifies as a megacity with a population of approximately 8.9 million, situated at coordinates 35.69˚N and 51.42˚E. It holds paramount significance politically, socially, and economically, standing as the most important and populous city in Iran. Consequently, the effective management of its extensive water network, comprising multiple reservoirs, and an intricate network of pipes, pumps, valves, etc., is imperative for ensuring proper urban operation and mitigating potential social and political challenges. Due to the absence of comprehensive data for the entire network, a specific segment of its WDS was chosen for simulation within the Water GEMS simulation model. The proposed NLP model was then applied to this selected segment. Ultimately, the results obtained from these models were compared to derive optimized conditions for the designated part of the network (See Fig. 1).

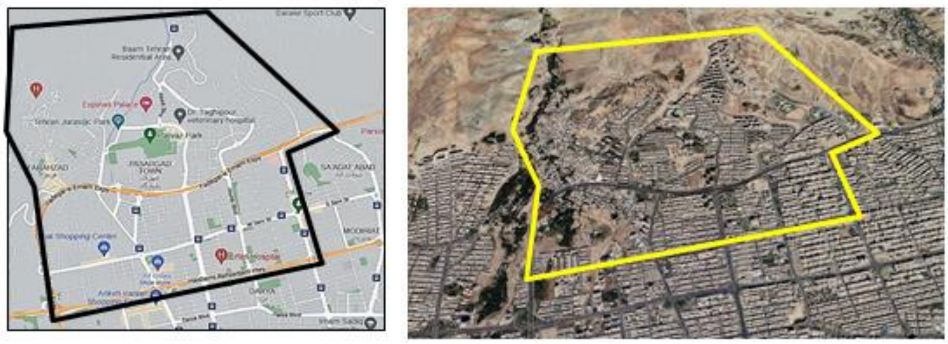

Figure 1. Location of the selected part of Tehran WDS

The study area exhibits high population density, with approximately 11,800 residents per square kilometer. The selected WDS, situated in the northwest of Tehran, spans an area of approximately 546 hectares, catering to a population of around 180,000 people. This WDS operates on a gravity-based water supply system sourced from four reservoirs, encompassing 1,124 pipes and connecting to 988 nodes (referring to Fig. 2). The average base water demand for the area is 495.3 liters per second. Behzadian et al. (2008) introduced a methodology for estimating the roughness coefficients of pipes. This approach, based on the primary characteristics of pipes and considerations related to water quality, facilitates the estimation of roughness coefficients, specifically the Hazen-Williams C-factor, for the pipes within the network [35].

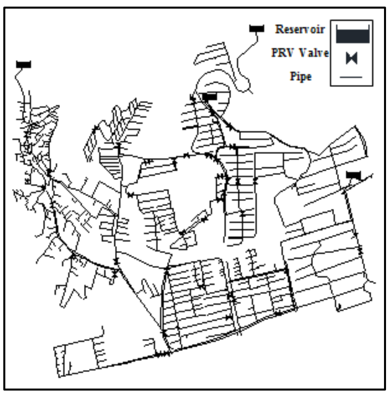

Figure 2. Simulation of the selected WDS (Water GEMS model)

2.2. Simulation Model

WaterGEMS stands out as a robust software tool designed for hydraulic simulation in WDSs. One of its noteworthy features is the capacity for Pressure Dependent Demand (PDD) analysis, wherein demand varies as a function of pressure. PDD can be characterized in two primary manners: a pressure-demand relationship utilizing a power function, and a pressure-demand piecewise linear curve. A conventional power function for such analysis is represented as follows [36]:

$$Q_i = K_i P_i^{0.5} \tag{1}$$

Where Ki is leakage coefficient of node i, P_i is the pressure of node i and Q_i is leakage rate of node i. Leakage coefficient, K, has been considered as decision variable for optimization process [39].

Various scenarios, encompassing hourly, daily, and extended period simulation (EPS) scenarios, are taken into account to model diverse demand conditions within the network. Hourly and daily scenarios are constructed by applying incremental coefficients to base demands for hourly and daily simulations, respectively. In this study, aligned with the water consumption pattern in the study area, the incremental coefficient is set at 1.3 for both of these scenarios. The EPS scenario is formulated by multiplying incremental and decreasing coefficients for different hours of the day. These coefficients are derived from the consumption pattern provided by the local WDS management organization.

2.3. Optimization Model

The Lingo software is employed to formulate an NLP optimization model for the chosen WDS. The research process, encompassing problem definition, data collection, methodology, evaluation criteria, and output (problem objective), is succinctly summarized in Table 1.

Table 1. Problem Methodology

Project definition	Objective 1: Investigation of hydraulic effects of pressure distribution on leakage in WDS	Recognize sensitive and critical points
	Objective 2: reduction of WDS failure risk	Improving network resiliency through optimization of pressure distribution
Input data	Topographic and WDS characteristic maps	GIS environment
	Tables of water consumption by network subscribers	Tables prepared by Tehran Regional Water Organization
Methodology	Simulation of the selected WDS	WDS modelling (WaterGEMS v8i)
	Creating the Optimization Model	NLP modelling (Lingo 17)
Evaluation criteria	Classification	Return periods of 5, 10, 25, 50 and 100 years
	Assessment	Compare with allowed pressures
		Compare the pressures and the total cost with the simulation model
Output	For Objective 1:	Checking the adequacy of pressures and finding critical points
	For Objective 2:	Computing the resiliency index for the selected WDS

2.4. Problem Theories

The pressure within a pipe is defined as the average pressure between the two pipe joints. The reduction of nodal pressures plays a crucial role in minimizing total leakage within a WDS. The objective function of the proposed model, aimed at minimization, is articulated as follows in Eq. 2:

$$Z=B\sum_{j=1}^{h}\sum_{i=1}^{k} C_i L_i P_{ij}^{\eta} \qquad i\in I=\{1,\cdots,k\}, j\in J=\{1,\cdots,h\} \tag{2}$$

Where P_{ij} is defined as:

$$P_{ij}=\Phi(EL_i, Q_{ij}, EL_{mj}) \qquad m\in M=\{1,\cdots,n\} \tag{3}$$

The values of leakage coefficients are considered as decision variable. Constraints of the problem are:

$$\sum_{m=1}^{n} V_{mj+1}=\sum_{m=1}^{n} V_{mj}+\sum_{m=1}^{n} I_{mj}-QT_j \tag{4}$$

$$P_{min}<P_{ij}<P_{max} \tag{5}$$

$$\sum_{m=1}^{n}\sum_{j=1}^{h} I_{mj}<I_{day} \tag{6}$$

$$FI_{ij}=Q_{ij}(P_{min}-P_{ij}) \tag{7}$$

$$FI_j=\frac{\sum_{i=1}^{k} FI_{ij}}{\sum_{i=1}^{k} Q_{ij}P_{min}} \tag{8}$$

$$0\leq FI_{ij}<FI_{max} \tag{9}$$

$$RI_j=\frac{\sum_{i=1}^{k} FI_{ij}}{\frac{\sum_{i=1}^{k} FI_{ij}}{FI_j}-\sum_{i=1}^{n} Q_{mj}EL_m} \tag{10}$$

$$RI_j>RI_{min} \tag{11}$$

Where B is penalty factor of value 10000, i is node number of network, h is the hours number of selected performance period, n is the number of the reservoirs, j is time counter, C is constant value of pressure-leakage relationship in node, L is the pipe length (m), EL is node elevation (m), Q is demand discharge (m^3/s), η is power of pressure-discharge relationship of value 1.18, P is pressure (pa), V is water volume in the reservoir (m/s), Q_T is total demand discharge (m^3/s), Q is output discharge of the reservoir (m^3/s), P_{min} and P_{max} are the minimum and maximum pressure in each node (pa), I is input discharge into the reservoir (m^3/s), I_{day} is daily maximum required water volume (m^3), RI is resiliency index of WDN, RI_{min} is the minimum value of resiliency index, FI is failure index and FI_{max} is the maximum allowable failure index. Failure and resiliency indices are utilized to accomplish minimum level performance of WDN system under desired conditions. Pressure lower than the minimum will lead to system failure. Introduced by ASCE (1998), resiliency is described the required time to recover from a failure situation to normal one [38].

The objective function (Eq. 2) will be subject to multiplication by a penalty coefficient in case its constraints are not fulfilled. The penalty coefficient is assigned a substantial value in the order of 10^4 to discourage non-reasonable or non-optimal solutions. Nodal pressure is determined as a function of the node elevation, water demand, and water level in each storage tank (Eq. 3), and these values are obtained from the simulation model. The daily input water to the tanks and the bounds on nodal pressures serve as constraints for the proposed algorithm. Solving MINLP problems poses significant challenges, and various methods have been employed to address them. In WDSs, the inherent non-convex nature of the problem implies that all methods converge to local minimum points under appropriate assumptions. The quality of the solution is contingent upon the initial point selected. Consequently, it is crucial to acknowledge, as highlighted by Pecci et al. [20] , that comparing different approaches should consider this characteristic. If a solution is obtained through multiple random initial guesses and yields an average zone pressure close to the best-known solution, it can be deemed acceptable. In this study, potential leakage points, identified as nodes with pressures exceeding the maximum allowable, are determined using the simulation model. Subsequently, an NLP optimization model has been constructed utilizing Lingo software. The optimization model incorporates pipe materials and diameters as variables, aiming to achieve an optimized situation concerning pressure distribution and network reliability. Network reliability is quantified through the resiliency index, which is a function of the system hydraulic failure index (Eq. 8). The failure index, in turn, is expressed as a function of nodal pressures and demands, as outlined in Eqs. 5 and 6.

2.5. Statistical evaluation criteria

Multivariate techniques encompass methods for classifying and conducting diagnostic analysis, which involve the segregation of diverse groups of objects or observations and the allocation of new objects to pre-established categories. Diagnostic analysis involves combining variables x1, x2, ..., xn to generate a novel variable, denoted as y. This new variable, referred to as the recognition function, is formulated to ensure that the value assigned to each participant effectively delineates individuals into distinct categories. The primary goal is to create a robust framework for categorizing and identifying patterns within multivariate datasets. To express the concept described above mathematically, let's consider $x_1, x_2, \ldots, x_n$ as descriptive variables and y as a dependent variable of a multilevel qualitative type. The objective of diagnostic analysis is to find a linear function represented as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n \tag{12}$$

In this equation, y is the dependent variable, and $\beta_0, \beta_1, \ldots, \beta_n$ are coefficients corresponding to each descriptive variable $x_1, x_2, \ldots, x_n$. The goal of diagnostic analysis is to determine the optimal values for the coefficients β to create a linear function that effectively captures the relationship between the descriptive variables and the multilevel qualitative dependent variable y. This function is designed to assist in categorizing and differentiating observations based on the provided descriptive variables.

In scenarios where the dependent variable possesses k levels, the objective is to assign new observations $x_1, x_2, \ldots, x_n$ to one of the k groups based on y. The purpose of diagnostic analysis is to categorize items (such as people, customers, objects, etc.) into two or more groups based on a set of characteristics that describe each item (e.g., gender, age, income, weight). Generally, we allocate an item to predefined groups based on our observations, ensuring that each item belongs to only one group. Periods where it is impossible to assign items to groups should be excluded from the analysis to prevent erroneous results. These instances can be identified after establishing the diagnostic equations for group membership.

One of the primary applications of this technique is the classification of subjects into designated groups. Common statistical criteria for selection include Wilks Lambda, Pillai's Trace, Mahalanobis square distance, and the F-group ratio. Wilks Lambda is a widely used statistical criterion in this analysis. In the presented case, water consumption data for each node in liters per second (Lit/s) was randomly divided into three groups. Using SPSS software, diagnostic analysis was conducted on the data, resulting in a correct grouping rate of 61.2%.

It is worth noting that in the studied WDN, no PRVs were considered. The primary reason for not including PRVs is that the optimization approach employed in this research focuses on improving nodal pressures and reducing leakage through adjustments to pipe materials and diameters. By optimizing these parameters, the need for additional pressure management devices, such as PRVs, is minimized. Furthermore, the selected network segment operates under gravity-based pressure control, which inherently reduces the necessity for PRVs.

3. Results and discussion

For statistical assessment, the water consumption data for each node in liters per second (Lit/s) were initially randomly divided into three groups. Subsequently, using SPSS software, diagnostic analysis was executed on the data. The results of this test indicated that 61.2% of the data groupings were correct, as depicted in Table 2. To improve the accuracy of grouping, corrections were made for some data that were initially placed in the wrong group based on Wilks Lambda. Following the corrections, a second diagnostic analysis test was performed, resulting in an increased grouping accuracy of 95.1%, as illustrated in Table 3. Ultimately, the data were categorized into three groups, and the discharge range for each group is presented in Table 4.

Table 2. Data Classification Results

Classification Results [a,c]

		Zone	Predicted Group Membership			Total
			1	2	3	
Original	Count	1	227	20	3	250
		2	35	34	16	85
		3	92	42	67	201
	%	1	90.8	8.0	1.2	100.0
		2	41.2	40.0	18.8	100.0
		3	45.8	20.9	33.3	100.0
Cross-validated b	Count	1	227	20	3	250
		2	35	34	16	85
		3	92	42	67	201
	%	1	90.8	8.0	1.2	100.0
		2	41.2	40.0	18.8	100.0
		3	45.8	20.9	33.3	100.0

a. 61.2% of original grouped cases correctly classified.

b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

c. 61.2% of cross-validated grouped cases correctly classified.

Table 3. Re-diagnostic analysis on data grouping after Wilks Lambda correction

Classification Results [a,c]						
		zone	Predicted Group Membership			Total
			1	2	3	
Original	Count	1	339	0	0	339
		2	15	128	0	143
		3	0	11	43	54
	%	1	100.0	0	0	100.0
		2	10.5	89.5	0	100.0
		3	0	20.4	79.6	100.0
Cross-validated b	Count	1	339	0	0	339
		2	15	128	0	143
		3	0	12	42	54
	%	1	100.0	0	0	100.0
		2	10.5	89.5	0	100.0
		3	0	22.2	77.8	100.0

a. 95.1% of original grouped cases correctly classified.

b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

c. 95.0% of cross-validated grouped cases correctly classified.

Table 4. Flow range in each group in Lit/s

Zone	Q min	Q max
Zone 1	*0.001*	*0.290509*
Zone 2	*0.291005*	*1.084105*
Zone 3	*1.170139*	*15.32253*

In Figure 3, the network pressure values are compared between the different scenarios of the simulation model. It can be seen that the EPS scenario plays the most important role and is the dominant scenario. Thus, its results should be compared with the results of the NLP method in which the pipe diameters and the pipe materials are defined as variables. The maximum and minimum amounts of nodal pressures in EPS scenario are 67.8 and 10.8 meters, respectively. The allowed pressure according to the regional standards for water network design, varies between 15 and 60 meters.

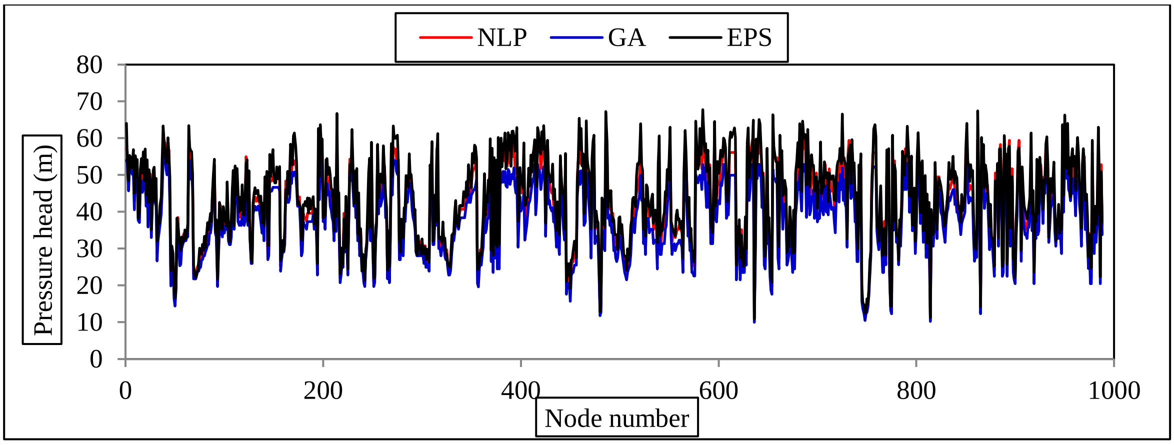

Figure 3. Comparison of nodal pressures for different scenarios in simulation model.

Fig. 4 provides a comparison of nodal pressures, sorted in ascending order, between the EPS scenario and the NLP model. The comparison reveals that the NLP model has not only decreased the maximum nodal pressures by approximately 17.2%, thus reducing the risk of pipe breaks, but also enhanced network performance by increasing the minimum nodal pressures from 5 meters to 11 meters. Table 5 presents detailed information regarding pipes, including maximum pressure values and total costs, for both the simulation and optimization models. The table highlights that, in comparison to the simulation model, the NLP approach has reduced the number of pipe sizes from 15 to 7 sizes and lowered the total cost of pipes by approximately 12.85%. This demonstrates the effectiveness of the NLP model in optimizing the system while minimizing costs and improving network performance.

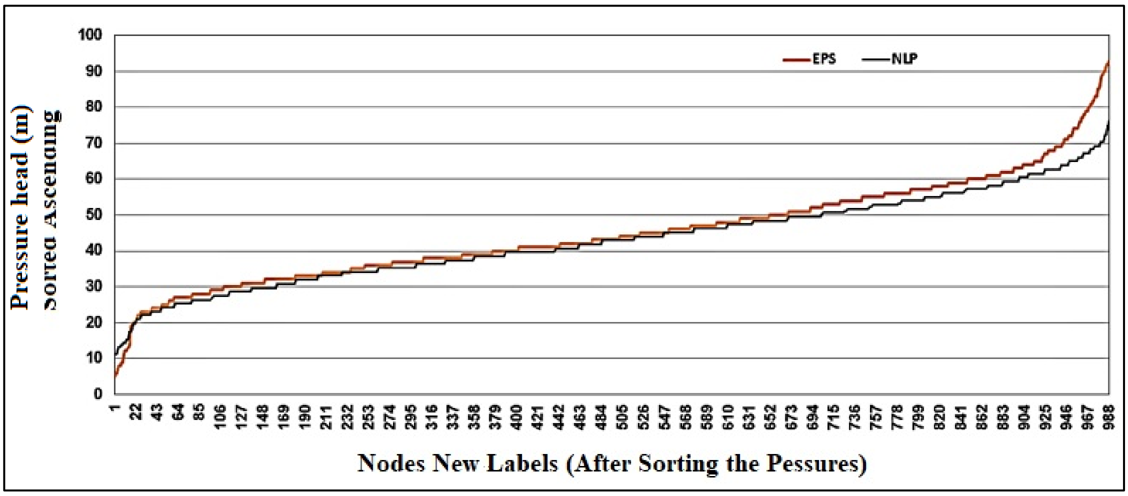

Figure 4. Comparison of nodal pressures (sorted ascending) in EPS scenario (simulation model) and NLP optimization model

Table 5. Comparison of the network characteristics in simulation and optimization models

Characteristics	Simulation Model	Optimization Model (NLP)
Pipe Materials	Ductile Iron (DI) Polyethylene (PE) Steel PVC	DI PE
Pipe Diameters (mm)	100, 141, 150, 176, 200, 250, 300, 350, 400, 500, 600, 700, 800, 900	150, 200, 300, 400, 500, 700
Maximum Pressure (m)	93	77
Minimum Pressure (m)	5	11
Total Pipe Cost (10^9 IRR*)	541.74	472.10
Benefit changes (%)	----	+12.85

*IRR= Iranian Rials

Fig. 5 presents a comparative analysis of nodal pressures, without sorting, within the EPS scenario as implemented in the simulation model and the NLP optimization model. The results indicate a discernible reduction in the maximum and an augmentation in the minimum nodal pressures achieved through the application of the NLP methodology. Furthermore, the graphical representation elucidates the mitigation of pressure fluctuations within the network facilitated by the NLP optimization model. In Fig. 6, the network pressure distribution for various scenarios is depicted within the simulation model. Each distinct color corresponds to a specific pressure range, as delineated below:

- Yellow denotes pressures below 18 m,
- Cyan represents pressures ranging from 18 to 30 m,
- Blue signifies pressures between 30 and 50 m,
- Magenta denotes pressures spanning 50 to 60 m,
- Pale red indicates pressures within the range of 60 to 70 m,
- Dark red represents pressures surpassing 70 m.

Fig. 6 illustrates that both the maximum and minimum pressures within the EPS scenario surpass the permissible range. Additionally, the analysis indicates an increased count of critical points within the network when compared to both the hourly and daily scenarios. Fig. 7 depicts the pressure distribution within the NLP optimization model of the network. The characteristics of the pressure distribution align with those delineated in Fig. 6.

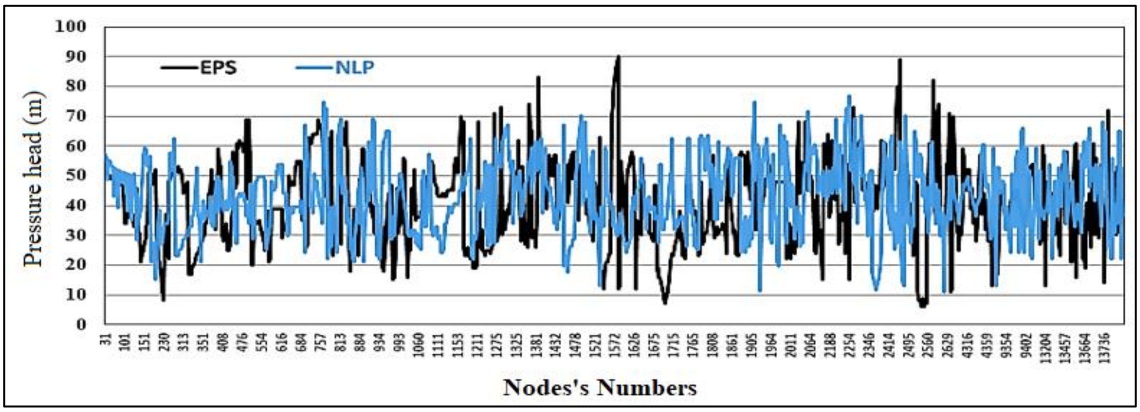

Figure 5. Comparison of nodal pressures (not sorted) in EPS scenario (simulation model) and NLP optimization model

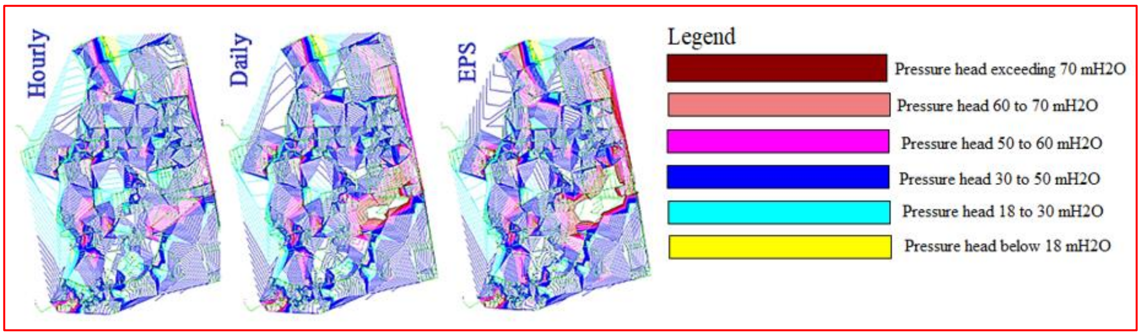

Figure 6. Pressure distribution in the network for different scenarios in simulation model.

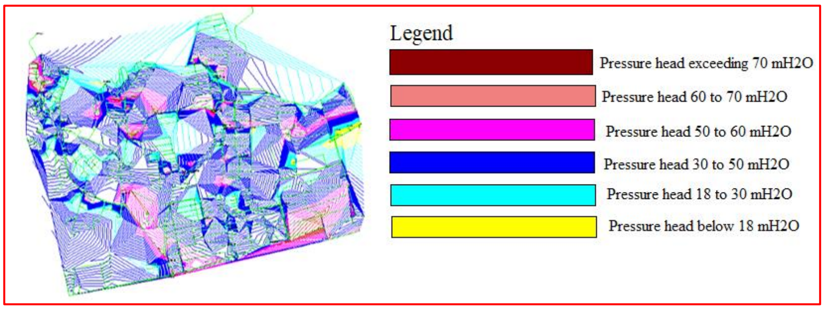

Figure 7. Pressure distribution in NLP optimization model

In the hourly, daily, and extended period simulation (EPS) scenarios, the resiliency indices for the model under consideration exhibit average values of 0.071, 0.070, and 0.074, respectively. In contrast, the resiliency index for the NLP model is recorded at 0.069. Flexibility, as defined by ASCE in 1998 [36], denotes the temporal requirement for a water system to restore normal functioning subsequent to a failure event. Accordingly, a lower flexibility index indicates a heightened capacity of the network to swiftly revert to normalcy, thereby enhancing the overall stability of the water supply network. Consequently, the employment of the NLP yields superior network resiliency, contributing to a reduction in the likelihood of failures. The specific values of the WDS resiliency index can be found in Table 6.

Table 6. Resiliency index for simulation and optimization model

Hour	Simulation Model Scenario			Optimization Model
	Hourly	Daily	EPS	NLP
1	0.051	0.042	0.054	0.041
2	0.039	0.039	0.061	0.039
3	0.045	0.039	0.061	0.044
4	0.046	0.048	0.056	0.045
5	0.045	0.047	0.038	0.038
6	0.058	0.054	0.053	0.055
7	0.056	0.054	0.049	0.053
8	0.081	0.077	0.081	0.080
9	0.080	0.082	0.083	0.081
10	0.084	0.076	0.088	0.086
11	0.085	0.083	0.098	0.082
12	0.086	0.081	0.088	0.082
13	0.088	0.083	0.085	0.084
14	0.085	0.088	0.088	0.086
15	0.085	0.088	0.089	0.086
16	0.086	0.091	0.089	0.080
17	0.083	0.092	0.082	0.084
18	0.084	0.086	0.087	0.081
19	0.080	0.084	0.086	0.079
20	0.083	0.084	0.086	0.082
21	0.087	0.081	0.085	0.080
22	0.062	0.066	0.064	0.062
23	0.065	0.063	0.067	0.064
24	0.054	0.052	0.059	0.056
Average	0.071	0.070	0.074	0.069

In order to strengthen and improve the hydraulic efficiency of the selected WDS in this area, several methods are proposed, as following:

- In the event of a new incident within the network, it is recommended to substitute the damaged pipe with the segment derived from the optimization model specific to that pipe. Subsequent to this replacement, a re-simulation of the network using WaterGEMS software should be conducted to systematically investigate the impact of this alteration on the network status. This method facilitates the anticipation of potential future failure points within the network, thereby enhancing predictive maintenance strategies.
- An additional strategy involves assessing the impact of modifying the configuration of pressure relief valves within the network to decrease the number of critical points. This approach, coupled with the replacement of damaged pipes with optimized sections, warrants simultaneous modeling of both considerations within WaterGEMS software. Such concurrent modeling endeavors yield practical outcomes that offer enhanced utility for WDS administrators in devising effective network management strategies.
- An alternative approach is to advocate for the implementation of a diverse array of tools designed to measure network hydraulic parameters. This proactive measure aims to ensure that network simulation is grounded in precise and accurate data. The persuasive effort directed towards network administrators underscores the importance of employing a comprehensive suite of measurement tools, thereby enhancing the reliability and accuracy of the data upon which network simulations are based.
- Establishing a dedicated network simulation team, which leverages the data acquired through the aforementioned measurement tools, holds the potential to significantly enhance the accuracy of predicting critical points within the network. This collaborative initiative ensures that professionals with specialized expertise can systematically analyze and interpret the data, leading to more precise identification and prediction of critical points in the network.

4. Conclusion

This study proposes a novel framework integrating NLP with hydraulic simulation tools, uniquely incorporating reliability and failure indices as constraints. By addressing both leakage reduction and network resiliency enhancement comprehensively, the approach sets a benchmark for cost-efficient and sustainable urban WDN management, advancing the state of the art in this critical area. Within this research, nodal pressures in a specified segment of the Tehran's WDS were calculated through both a simulation model and an optimization model employing NLP. The simulation model encompassed diverse scenarios, while the optimization model introduced an objective function featuring variables such as pipe materials and diameters. A comparative analysis of the outcomes from these two models was conducted to ascertain optimized nodal pressures, aiming to mitigate pipe bursts and network leakage. This paper specifically contrasts the application of NLP in a segment of the Tehran's WDS with the simulation model implemented through WaterGEMS. The overarching findings derived from this comparative study are:

- The employment of NLP with an objective function incorporating variables such as pipe materials and diameters yields superior results, contributing to a more advantageous and efficient network.
- NLP effectively decreases the maximum nodal pressures from 93m to 77m and from 5m to 11m, respectively, thereby mitigating the risk of leakage.
- NLP enhances network performance by increasing the minimum nodal pressures from

5m to 11m.
- The total cost of pipes incurred throughe NLP method is 12.85% lower than that of the simulation model.
- NLP optimization of the WDS involves changes in both material and size of pipes. In the selected WDS, the number of pipe sizes is reduced from 15 to 7, and the number of pipe materials from Ductile Iron (DI), Polyethylene (PE), Steel, and Polyvinyl Chloride (PVC) to Ductile Iron and Polyethylene.
- NLP yields an improved value for WDS resiliency index, serving as a valuable tool for system reliability assessment and network efficiency. A more reliable network, as indicated by the resiliency index, corresponds to a reduction in leakage.

Acknowledgement

The authors would like to thank he Ministry Energy of Iran, the Islamic Azad University, Arak Branch, and the Tehran Regional Water Organization, for providing the research data.

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