Innovative: International Multi-disciplinary Journal of Applied Technology
(ISSN 2995-486X) VOLUME 04 ISSUE 11, 2026

DEVELOPMENT OF AN ALGORITHM FOR REAL-TIME MATHEMATICAL MODELLING AND CONTROL OF HYDRAULIC PROCESSES IN URBAN WATER TRANSMISSION AND DISTRIBUTION NETWORKS

Akhmadaliev Sardor Sobirjon Ugli
Assistant, Tashkent University of Architecture and Civil Engineering,
Tashkent, Uzbekistan

Abstract:
The article examines variations in hydraulic processes in urban water supply networks and associated facilities. The findings may inform the design and optimisation of water supply systems and contribute to improved operational efficiency. Hydraulic processes occurring in urban water supply networks over the past three years were analysed, and an algorithm was developed based on the results.

Keywords: urban water supply network, hydraulic processes, modelling, hydraulic analysis, flow velocity, water pressure, real-time conditions, adaptability, water losses.

Introduction

Ensuring a continuous supply of high-quality drinking water is a pressing social and engineering challenge worldwide. Population growth and urban expansion are increasing water demand, while climate change and limited water resources are reinforcing the need for efficient use of available water sources. Meanwhile, ageing water supply networks, pipe failures, and shortcomings in operational control are contributing to increased water losses and energy consumption [1]. Under these conditions, improving the operational efficiency of existing water transmission and distribution networks through digital technologies is of considerable importance [2].

Hydraulic conditions in water transmission and distribution networks depend on temporal variations in water demand, pump operating regimes, water levels in storage tanks, and the hydraulic resistance of pipes. If the interactions among these factors are not adequately accounted for, excessive pressure may develop in some parts of the network, while insufficient pressure may occur in others. Excessive pressure increases leakage through existing defects, whereas insufficient pressure limits the delivery of the required quantities of water to consumers [3]. Therefore, it is essential to develop mathematical models that account for varying network operating conditions and to validate them against operational measurements

[4].

Hydraulic modelling and digital monitoring tools enable the analysis of temporal variations in pressure, flow rate, and flow velocity, the identification of problematic network sections, and the assessment of alternative control scenarios [5]. In particular, a model developed using EPANET can be used to investigate interactions between pumps and the network, compare calculated values with field measurements, and select efficient operating regimes [6]. The practical value of such a model depends on how accurately it represents actual operating conditions and how effectively it supports operational decision-making [7].

Calibration of network models has developed from manual adjustment of pipe roughness coefficients to formal optimisation and Bayesian procedures [8]. Joint estimation of nodal demands and pipe roughness from field measurements has also been formulated as a real-time problem [9], and online models that combine EPANET with streaming measurements through data assimilation have been demonstrated for operational networks [10]. In Uzbekistan, EPANET has been applied to the management of water supply systems [11], hydraulic processes have been modelled for the Nurafshon water supply network [12], and the repair of pressure pipelines with polymer composite materials has been examined as a means of reducing failures [13]. However, such models are usually calibrated off-line, and the Hazen–Williams coefficient is kept constant between calibration campaigns, so the model gradually departs from actual operating conditions. The aim of this study is therefore to develop an algorithm that updates the Hazen–Williams coefficient adaptively from real-time measurements and to validate it against field data from an urban water supply network.

Materials and Methods

The water supply network was modelled using the Hazen–Williams equation [14]. The continuity equation was applied at each node to ensure a balance between inflows, outflows, and water demand, accounting for real-time variations in nodal demand, and the resulting system of nonlinear equations was solved by the gradient method implemented in EPANET [15].

$$\sum_{J \in \mathcal{L}(i)} S_{il}\, Q_l\,(t) + \; q_i(t) = 0 \qquad (1)$$

$Q_l(t)$ – time-dependent flow rate in the pipe. $q_i(t)$ – nodal water demand [m^3/s], i – node index, l – pipe index, $S_{il} \; \epsilon \{-1,0,+1\}$ coefficient indicating the flow direction.

The energy balance across a network element was formulated using Bernoulli equation, with the piezometric heads expressed as follows.

$$H_i(t) - \; H_j(t) = h_{l,ij}\;(Q_{ij}(t)) + h_{mahalliy,ij}(t) + H_{nasos,ij}(t) \qquad (2)$$

The Hazen–Williams equation was used for hydraulic modelling of water transmission networks because it enables rapid computation, facilitates model calibration, and is compatible with EPANET [16]. Its differences from the Darcy–Weisbach and Chézy–Manning formulas in modelling water supply systems were taken into account [17], as was an improved form of the equation proposed for pressurised flow [18].

$$h_l^{HW}(Q) = 10{,}67\,\frac{L}{C^{1.852} D^{4.871}} * Q^{1{,}852} \qquad (3)$$

The head added to the network by the pump was expressed as a polynomial function of flow rate to simplify the representation of the manufacturer's characteristic curves. This formulation allows the pump head to be incorporated directly into the energy balance in Eq. (2) and enables the use of Newton's method. Identifying the time-dependent coefficients $a_k\;(t)$ from real-time measurements accounts for factors such as pump rotational speed, valve settings,

and wear. Consequently, the pump model adapts to operating conditions, improving the accuracy of network simulations.

$$h_{nasos}(a,t) = Q_0(t) + a_1(t)\,Q + a_2(t)\,Q^2 \quad (4)$$

Head loss per unit length $j_l(t) = \frac{1000\,h_{f,l}}{L_l} = \frac{10670}{C_l^{1.852} D_l^{4.871}}\,|Q_l(t)|^{1.852}$ (5)

$j_l(t)$ head loss per unit length m/km L_l – m

Hence, the head loss in the pipe section is expressed as $h_{f,l}(t) = \frac{j_l(t)\,L_l}{1000}$ (6)

$h_{f,l}(t)$ – head loss per unit length in these pipe sections, m/km, i.e., the head loss per kilometre of pipe.

The actual resistance coefficient for each pipe section was determined from field measurements [19].

$$C_l(t) = \left[\frac{10.67 L_l \left|Q_l^{\text{o'lchov}}(t)\right|^{1.852}}{D_l^{4.871} h_{f,l}^{\text{o'lchov}}(t)}\right]^{1/1.852} \quad (7)$$

```python
def hisobla_C(L, D, Q, h_f):
    """
    L   – quvur uzunligi, m
    D   – quvurning ichki diametri, m
    Q   – suv sarfi, m³/s
    h_f – ishqalanishga tegishli napor yo‘qolishi, m
    """
    if L <= 0 or D <= 0 or h_f <= 0:
        raise ValueError("L, D va h_f musbat bo‘lishi kerak.")
    if Q == 0:
        raise ValueError("Q = 0 bo‘lganda C ni aniqlab bo‘lmaydi.")

    return (
        10.67 * L * abs(Q)**1.852
        / (D**4.871 * h_f)
    )**(1 / 1.852)
```

```python
# Shartli misol — tajriba natijasi emas
L = 100.0              # m
D = 100.0 / 1000       # 100 mm → m
Q = 10.0 / 1000        # 10 l/s → m³/s

H_i = 35.0             # boshlang‘ich pyezometrik napor, m
H_j = 32.2             # oxirgi pyezometrik napor, m
H_nasos = 0.0          # nasos qo‘shadigan napor, m
h_mahalliy = 0.2       # mahalliy napor yo‘qolishi, m

# Oqim i tugundan j tugunga yo‘nalgan
h_f = H_i - H_j + H_nasos - h_mahalliy

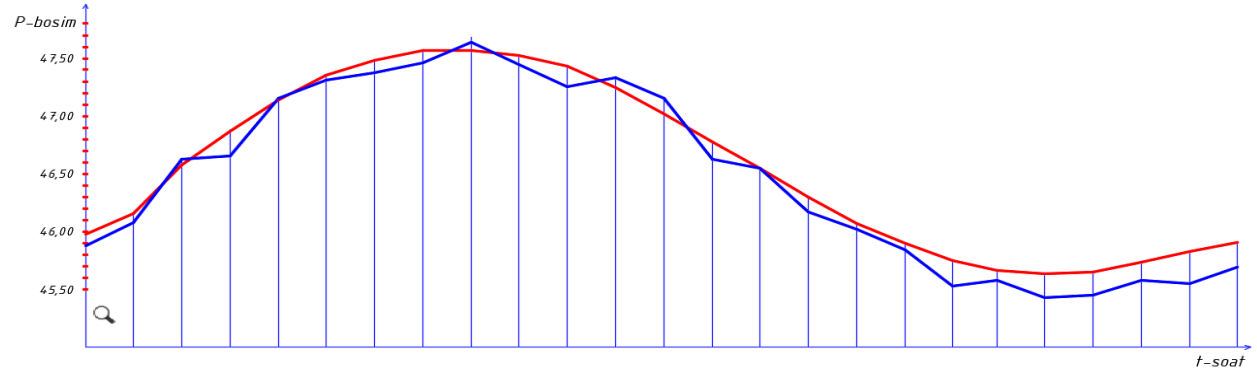
C = hisobla_C(L, D, Q, h_f)

print(f"Ishqalanish napor yo‘qolishi: {h_f:.2f} m")
print(f"O‘lchovga mos C koeffitsienti: {C:.1f}")
```

Figure 1. Algorithm **for** implementing Eq. (7) in Python.

Results

Accuracy of the hydraulic model under real-time operating conditions was assessed by comparing measured and simulated values over a 24-hour period.



Soat	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Tadqiqot (H)	45,97	46,28	46,59	46,88	47,14	47,34	47,49	47,58	47,59	47,53	47,42	47,24	47,03	46,79	46,55	46,30	46,08	45,90	45,75	45,67	45,63	45,65	45,72	45,83
Sonli yechim	45,88	46,18	46,63	46,65	47,15	47,06	47,39	47,47	47,64	47,45	47,26	47,33	47,15	46,63	46,55	46,17	46,02	45,85	45,52	45,57	45,42	45,45	45,58	45,51

Figure 2. Pressure variations at network nodes.

The results show close agreement between the measured pressure heads, H_meas, and those calculated using the numerical model, H_sim. The observed and simulated values exhibit similar overall trends and temporal variations, supporting the model's ability to represent actual hydraulic behaviour. Minor discrepancies observed at certain nodes during specific periods may be attributed to transient pressure fluctuations and variations in consumer demand. Overall, the

close agreement between simulated and measured values indicates that the proposed approach provides a basis for real-time pressure prediction and control in the water supply. Under actual operating conditions, discrepancies between calculated values and field measurements arise from factors such as changes in the number of consumers, temporal pressure fluctuations, and uncertainty in the hydraulic gradient. These factors reduce the accuracy of hydraulic analyses and hinder effective water distribution management. A new approach was developed to address this problem. The proposed algorithm introduces an adaptive coefficient that is updated using real-time measurements. This coefficient converts the Hazen–Williams equation into an adaptive formulation, allowing simulated flow rates and pressure heads to be adjusted to better match measured values.

The new coefficient is expressed in the following general form:

$$k(t) = f\big(P(t), V(t), Q(t)\big) \quad (8)$$

The algorithm processes real-time measurements supplied to the EPANET model and dynamically updates the Hazen–Williams coefficient (C) [20]. The procedure begins with the input of the initial operating parameters.

Field measurements often contain random fluctuations in flow rate or pressure. To reduce these fluctuations, a moving average filter is applied to the most recent (n) measurements. The resulting smoothed values are then passed to the subsequent stages of the algorithm [21].

$$X_f(t) = \frac{1}{n}\sum_{i=0}^{n-1} X\,(t - i * dt\,) \quad (3.14)$$

A low-pass filter allows slowly varying, smooth signal components to pass while attenuating or eliminating high-frequency fluctuations and noise.

$$Y(t) = \ a * X(t) + (1 - a) * Y\,(t - 1) \quad (8)$$

In water supply networks, signals typically represent time-varying measurements of pressure, flow velocity, or flow rate used by the algorithm. These signals may contain high-frequency noise, including second-scale fluctuations caused by sensor errors, electrical interference, and pump pulsations, as well as slowly varying components.

Low-frequency variations include daily fluctuations in consumer demand. For example, pressure may decrease substantially during the morning (07:00–09:00) and evening (18:00–21:00) peak demand periods, while remaining relatively stable during the daytime. These variations occur at a low frequency associated with the daily demand cycle and represent meaningful changes in system behaviour rather than measurement noise.

Changes in the volume of water stored in a water tower or reservoir also contribute to low-frequency pressure variations. Gradual rises and falls in water levels within these facilities produce slowly varying pressure signals in the network. Extended operating periods and automatic shutdowns several times a day may also cause slow pressure fluctuations. In addition, gradual changes in the hydraulic gradient associated with reduced water demand in a particular area may lead to a progressive increase in pressure.

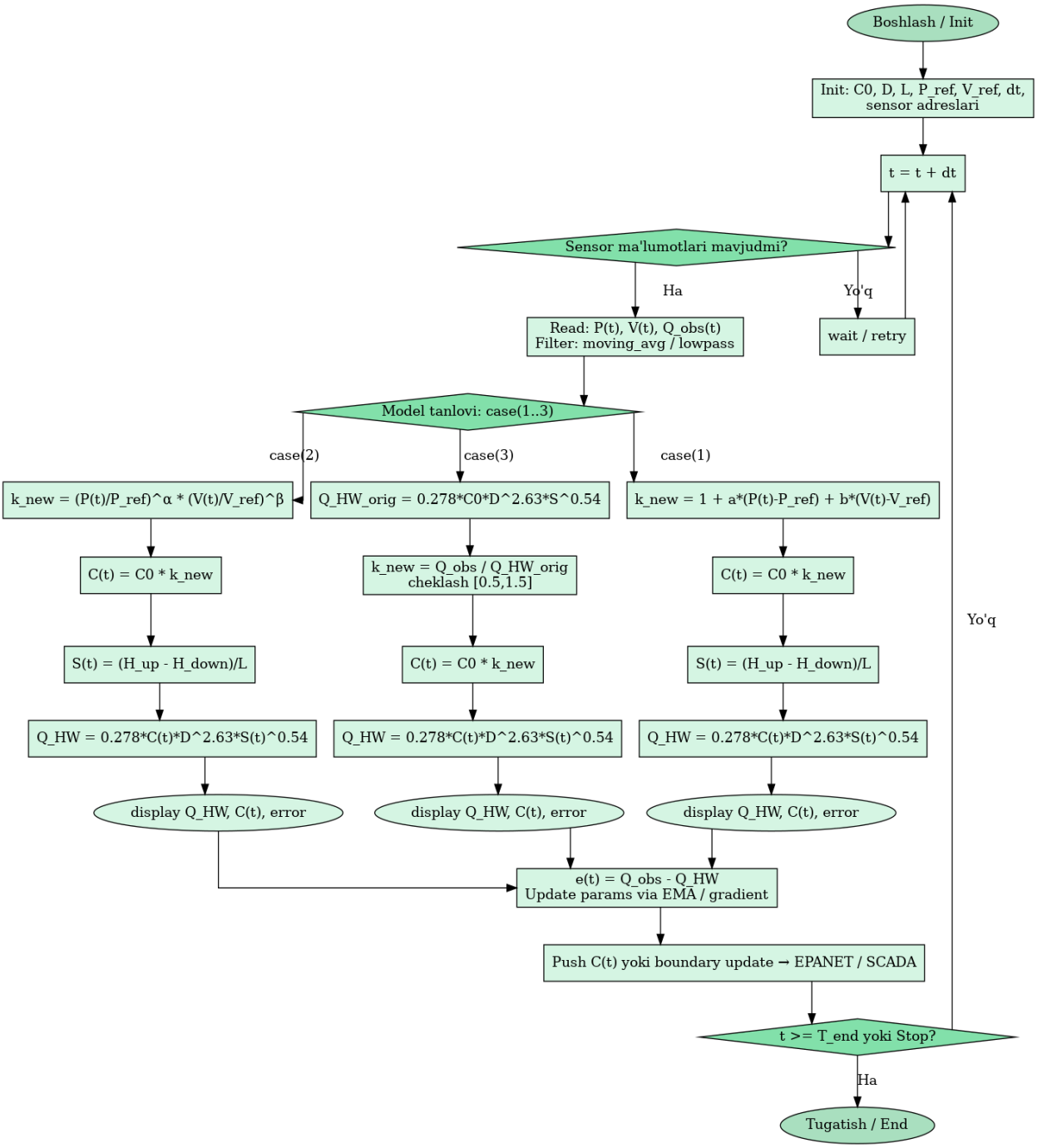


Figure 3. Algorithm for adaptive identification of the Hazen–Williams coefficient.

In the proposed algorithm, measured pressure, flow velocity, and flow rate data are processed and filtered. The adaptive coefficient (k(t)) is then updated using the filtered data to adapt the Hazen–Williams equation to actual operating conditions. Three variants of the algorithm were examined and their results compared: linear correction, a relative-indicator approach, and a measured-flow-based approach. In practical application, the third variant achieved the highest accuracy because it uses measured flow rates directly for adaptation.

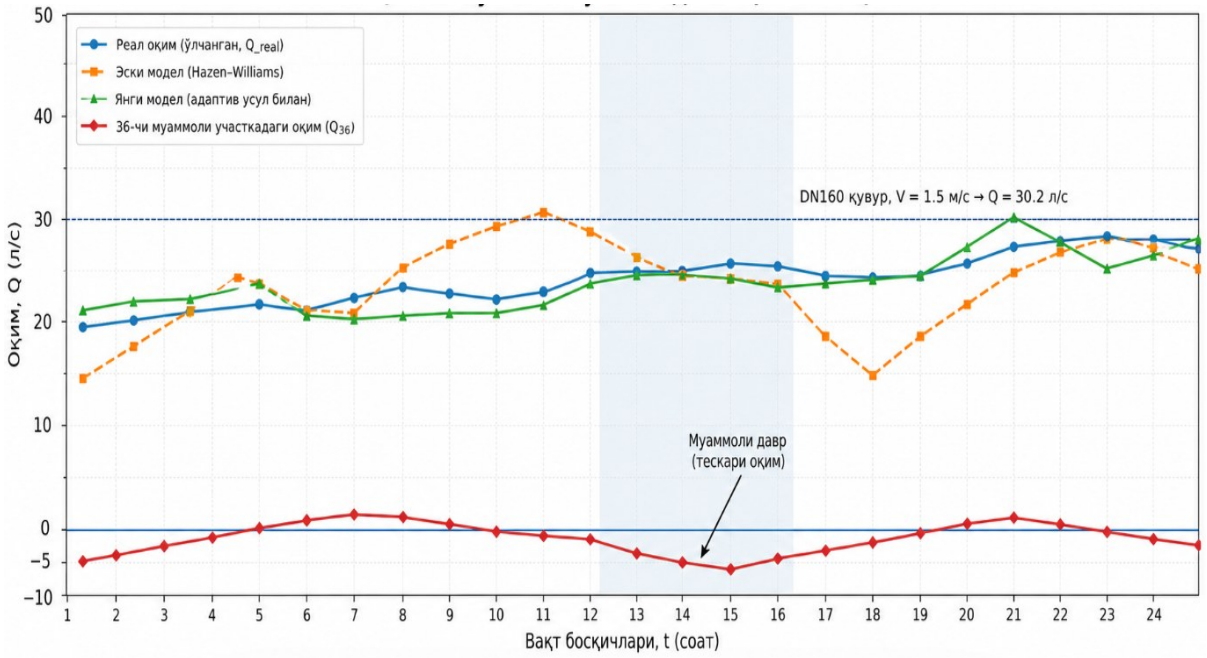


Figure 4. Comparison of measured and modelled flow rates in an urban water supply network.

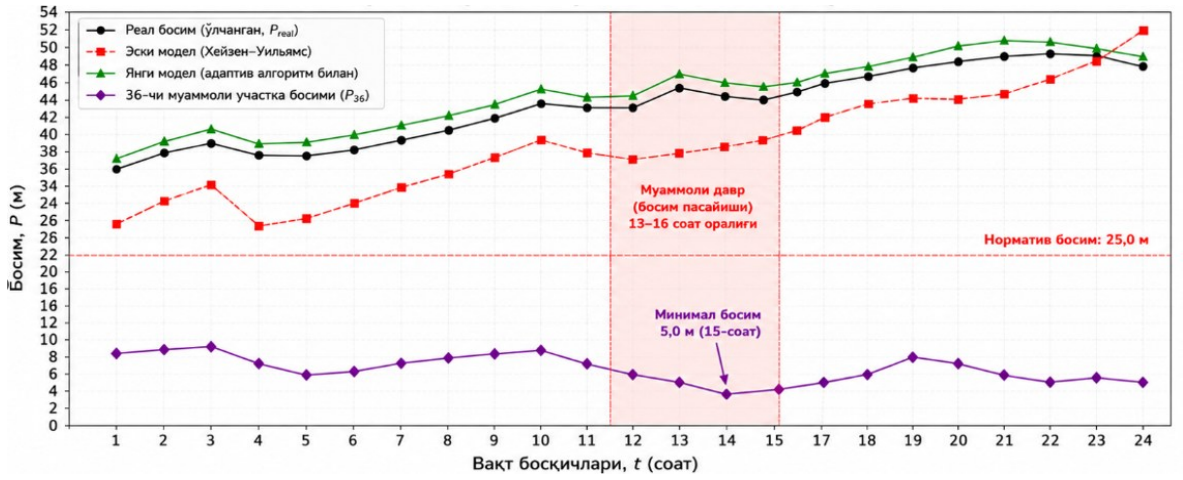


Figure 5. Comparison of measured and simulated pressures in the water supply network.

Discussion

The close agreement between measured and simulated pressures and flow rates supports treating model parameters as time-varying quantities rather than values fixed after a single calibration. Unlike off-line calibration, in which the Hazen–Williams coefficient is adjusted periodically, the proposed algorithm updates it continuously, which is consistent with the data-assimilation approaches discussed in the Introduction. Changes in the coefficient over time can reflect physical processes in the pipes, such as internal corrosion and deposit formation associated with residual chlorine [22], so tracking the adaptive coefficient may also serve as an indirect indicator of pipe condition. The approach can further be combined with water quality models, for example models of sodium hypochlorite dispersion in transmission pipelines [23]. The main limitations are the dependence of the adaptive coefficient on the number and placement of measurement points and the risk that the coefficient absorbs errors in demand allocation rather than true changes in pipe roughness.

Conclusion

An algorithm for analysing and controlling hydraulic processes in urban water transmission and distribution networks was developed and validated under urban water supply network conditions. Comparisons between calculated results and field measurements demonstrated the algorithm's ability to assess hydraulic conditions within the network. Operating regimes selected using the algorithm reduced uneven pressure distribution in problematic sections and improved the alignment of water flows with consumer demand.

The developed algorithm enables the prediction and analysis of variations in pressure, flow velocity, and flow rate in each network section under different operating regimes. This supports the identification of sections susceptible to insufficient or excessive pressure, the selection of optimal pump operating regimes, and informed operational decision-making.

The findings demonstrate the potential of the algorithm to improve the operation of urban water supply networks. Integration with a monitoring system could enable regular assessment of network conditions, support measures to reduce water losses, and promote efficient use of water and energy resources. Furthermore, updating the adaptive coefficient using operational measurements allows the model to account for changing hydraulic conditions and improve agreement between simulated and observed values. This provides a basis for identifying deviations from expected network behaviour and assessing corrective actions. Future research should evaluate the algorithm across networks with different configurations and demand patterns, assess its robustness to measurement uncertainty, and examine its suitability for integration with automated control systems.

References

[1] R. Puust, Z. Kapelan, D. A. Savic, and T. Koppel, "A review of methods for leakage management in pipe networks," Urban Water Journal, vol. 7, no. 1, pp. 25–45, 2010, doi: 10.1080/15730621003610878.

[2] S. S. Akhmadaliev, "Application of geographic information systems in the design of urban engineering systems," Architecture, Construction and Design, vol. 19, no. 1, pp. 333–335, 2024.

[3] G. Germanopoulos, "A technical note on the inclusion of pressure dependent demand and leakage terms in water supply network models," Civil Engineering Systems, vol. 2, no. 3, pp. 171–179, 1985, doi: 10.1080/02630258508970401.

[4] T. M. Walski, "Technique for calibrating network models," Journal of Water Resources Planning and Management, vol. 109, no. 4, pp. 360–372, 1983, doi: 10.1061/(ASCE)0733-9496(1983)109:4(360).

[5] A. B. Abdurakhmonov and S. S. Akhmadaliev, "Features of interactive analysis and synthesis of flow distribution in engineering networks," in Architecture, Heritage and Modernity, 2022, pp. 568–570.

[6] L. A. Rossman, H. Woo, M. Tryby, F. Shang, R. Janke, and T. Haxton, EPANET 2.2 User Manual, EPA/600/R-20/133. Cincinnati, OH, USA: U.S. Environmental Protection Agency, 2020.

[7] D. A. Savic, Z. S. Kapelan, and P. M. R. Jonkergouw, "Quo vadis water distribution model calibration?," Urban Water Journal, vol. 6, no. 1, pp. 3–22, 2009, doi: 10.1080/15730620802613380.

[8] Z. S. Kapelan, D. A. Savic, and G. A. Walters, "Calibration of water distribution hydraulic models using a Bayesian-type procedure," Journal of Hydraulic Engineering, vol. 133, no. 8, pp. 927–936, 2007, doi: 10.1061/(ASCE)0733-9429(2007)133:8(927).

[9] D. Kang and K. Lansey, "Demand and roughness estimation in water distribution systems," Journal of Water Resources Planning and Management, vol. 137, no. 1, pp. 20–30, 2011,

doi: 10.1061/(ASCE)WR.1943-5452.0000086.
[10] I. Okeya, Z. Kapelan, C. Hutton, and D. Naga, “Online modelling of water distribution system using data assimilation,” Procedia Engineering, vol. 70, pp. 1261–1270, 2014, doi: 10.1016/j.proeng.2014.02.139.
[11] D. E. Makhmudova and S. S. Akhmadaliev, “Using EPANET software to manage water supply systems in Uzbekistan,” Architecture, Construction and Design, vol. 19, no. 2, pp. 263–267, 2024.
[12] D. E. Makhmudova, B. B. Ulugbekov, L. V. Kotova, Sh. T. Rustamov, and S. S. Akhmadaliev, “Modelling hydraulic processes in the water supply networks of Nurafshon,” Universum: Technical Sciences, vol. 10, no. 139, pt. 3, 2025.
[13] S. S. Akhmadaliev, Sh. T. Rustamov, and U. R. Kidirbaev, “The methods of repairing pipelines working under pressure using polymer composite materials,” in Proc. Int. Sci. Tech. Conf. “Climate Change and Water Resources Hydrology”, Nov. 2023, pp. 445–449.
[14] D. E. Makhmudova and S. S. Akhmadaliev, “Application of the Hazen–Williams equation in modelling hydraulic processes in water supply systems,” Architecture, Construction and Design, vol. 19, no. 2, pp. 259–262, 2024.
[15] E. Todini and S. Pilati, “A gradient algorithm for the analysis of pipe networks,” in Computer Applications in Water Supply, Vol. 1: Systems Analysis and Simulation, B. Coulbeck and C.-H. Orr, Eds. Letchworth, U.K.: Research Studies Press, 1988, pp. 1–20.
[16] L. S. Abdulameer, N. Dzhumagulova, H. Algretawee, L. Zhuravleva, and M. H. Alshammari, “Comparison between Hazen-Williams and Darcy-Weisbach equations to calculate head loss through conveyancing treated wastewater in Kerbala city, Iraq,” Eastern-European Journal of Enterprise Technologies, 2022, doi: 10.15587/1729-4061.2022.251385.
[17] Sh. N. Imamnazarov and S. S. Akhmadaliev, “Differences between the Hazen–Williams, Darcy–Weisbach, and Chézy–Manning formulas in modelling water supply systems,” Architecture, Construction and Design, vol. 19, no. 4, pp. 1051–1054, 2024.
[18] M. S. Darweesh, W. A. Salah, T. M. Awwad, E. M. Ragab, and A. A. Ahmed, “An improved form of Hazen-Williams equation for pressurized flow,” Engineering, Technology & Applied Science Research, vol. 14, no. 3, pp. 14640–14644, 2024, doi: 10.48084/etasr.7511.
[19] M. Akhmadalieva, Z. Akhmadaliev, and I. Ganieva, “Adaptive identification algorithm for the Hazen–Williams coefficient (EPANET integration),” Science and Innovation, vol. 4, no. 10, 2025.
[20] S. S. Akhmadaliev and Z. S. Akhmadaliev, “Using EPANET software to manage water supply systems,” in Proc. Republican Sci. Pract. Conf. “The Role of Intellectual Youth in the Advancement of Science and Technology”, Apr. 2024, pp. 667–670.
[21] D. E. Makhmudova and S. S. Akhmadaliev, “Developing a modeling algorithm for hydraulic processes and water quality in water supply systems,” in Proc. Int. Conf. Economics, Finance, Banking and Management, Paris, France, Nov. 2025, pp. 127–133.
[22] F. García-Ávila et al., “Effect of residual chlorine on copper pipes in drinking water systems,” Journal of Engineering Science and Technology Review, vol. 12, no. 2, pp. 119–126, 2019, doi: 10.25103/jestr.122.17.
[23] S. S. Akhmadaliev, “Modeling the hydraulic dispersion of sodium hypochlorite (NaClO) in the pipelines of the Chigirik water supply facility,” Science and Innovation, vol. 4, no. 9, 2025.