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RESEARCH ARTICLE

Optimizing water quality in urban distribution networks: Leveraging digital twin technology for real-time demand management

Mohammad Mobadersani[1], Onur Behzat Tokdemir[1], Ali Bedii Candaş[2]

[1] Istanbul Technical University, Faculty of Civil Engineering, Department of Civil Engineering, İstanbul, Türkiye
[2] Middle East Technical University, Faculty of Engineering, Department of Civil Engineering, Ankara, Türkiye

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Abstract

Potable water quality is crucial for society's well-being. Advanced devices and systems and a more specialized examination of quality parameters have improved the water quality in treatment plants. However, the property of the water may change for many reasons, such as pollution injection, water age, and system facility condition, and it may not have the same quality as the water released from the treatment plant. Due to the widespread nature of distribution networks, any contamination in water can quickly be distributed among consumers and cause irreparable damage. As a result, it is essential to preserve water quality until it reaches the final user. Leveraging new technologies and digitalization is the only solution to control and manage these massive and complex infrastructures. Digital twin (DT) is a trend word nowadays that is gaining more popularity. Digital Twin connects the physical infrastructure with the hydraulic model through two-way communication using numerous sensors installed inside the distribution network. Although previous studies have focused on the applicability of digital twin technology on water distribution network, they have failed to consider the potential impact of leveraging digital twin capabilities on water quality management. This article reveals the significance of integrating real-time demand data in hydraulic model to prevent water aging in the system by optimizing water level in tanks and pumps working hours based on network real demand and the role of digital twin for this approach.

1. Introduction

Digital twin (DT) is a trend word nowadays that is gaining more popularity, and most of the industries have implemented it for their work scope, and the construction industry is one of them. Due to the fact that existing infrastructures are aging and start showing imperfections [1], DT in the construction sector, especially infrastructure, has to be used to promote the efficiency of the facilities. Water distribution networks (WDN) are among the most important infrastructures since public health is susceptible to possible diseases in the event of their failure. These networks are spread all over the city, and any contamination can be easily distributed between consumers. Moreover, consumer convenience is highly dependent on a fully operational WDN. Another reason that makes these infrastructures important is that most of the pipes are buried under the ground, and in case of failure, such as a pipe burst, the detection and repair process might be frustrating and time-consuming. With

Correspondence Ali Bedii Candaş ali.candas@alumni.metu.edu.tr

population growth, resource scarcity, and increasing demand for potable water, distribution networks are getting more complex than they were before since these networks have to expand in alignment with the population growth and their required demand rate. All of these reasons make water infrastructure important and hard to manage [2].

Leveraging new technologies such as DT is a solution for controlling and managing these complex infrastructures. Digital Twin connects the physical infrastructure with the hydraulic model through two-way communication using AMI (advanced metering infrastructure) and SCADA (supervisory control and data acquisition) data [3]. Through this connection, the virtual model will be updated continuously with any slight change in the physical counterpart, and the virtual replica could manage the physical network.

The greater part of the literature on DT in WDN is extensive and focuses particularly on enhancing the performance of the networks especially for operation and maintenance stages. A well-equipped digital twins can forecast the performance of water distribution networks by using simulations and historical data. This helps utilities handle important problems like localization and model-based leak detection, which reduces water waste and improves water quality across the network [4]. Conejos Fuertes et al. [5] propose DT model capabilities as follows: optimal design of the network elements, considering network expansion based on its future condition, leak detection, determining optimal daily operation parameters, and early response to warnings to take the best action. Another study done by Curl et al.[6] lists the benefits of DT for WDN as a best operator training tool in a simulation environment, simulating network performance under different conditions and scenarios, and incorporating different alarms. Additionally, Conejos Fuertes et al. [5] explored the idea of a DT for WDN in the Spanish city of Valencia. The digital twin continuously updates the condition of infrastructure components and junction water demand in distribution network using data from Advanced Metering Infrastructure (AMI) and Supervisory Control and Data Acquisition (SCADA). Brahmbhatt et al. [4] proposes conceptual digital twin framework, for real-time simulation of the hydraulic behavior as well as to predict water quality by using typical SCADA system that collects data (pressure, flow rates, and chlorine concentration data).

Although studies have recognized DT for the performance of the distribution network, research has yet to systematically investigate the effect of DT on preserving water quality in WDN. After leaving the treatment center, the water quality may change. For this reason, preserving its quality until it is consumed by the user is as important as efforts made in the treatment center. There are too many factors that can change the water properties during the transition phase when water is still in the distribution network. These factors can be intentional or unintentional. Intentional, such as pollution injection into the system, and unintentional, such as biofilm formation, water age, residual chlorine decay, etc. Water age, or water resident time, refers to the time that water waits in DN until it is consumed by users.

Water age is one of the factors that can change the quality of water [7-9]. As shown in Table 1, a study done by the U.S. Environmental Protection Agency [10] has categorized water quality problems associated with increased water age into three groups as; chemical, biological and physical issues. Moreover, it has been proven that water age affects the residual chlorine volume. Chlorine is the most common disinfectant for drinking water as it is cheap, effective, widely available, and easy to apply [11]. It can react with occurring organic and inorganic matter in treated water [11, 12]. To keep the treated water free of microbiological contamination as it moves through the network of pipes, an appropriate residual concentration of chlorine is usually maintained throughout the distribution system [13]. Research done by Wang et al. [14] indicated that the residual chlorine declined with the increase of water age. According to U.S. Environmental Protection Agency

Table 1. Water quality problems associated with water age (From U.S. Environmental Protection Agency [10])

Chemical issues	Biological issues	Physical issues
Disinfection by product formation	Disinfection by product Biodegradation	Temperature increases
Disinfectant decay	Nitrification	Sediment Deposition
Corrosion control effectiveness	Microbial regrowth/recovery/shielding	Color
Taste and odor	Taste and odor	

[10], two main factors which greatly affects the water quality are; reaction within the bulk water itself, and the interaction between the pipe wall and the water. To solve the first issue, the only required volume of water have to exist in the tanks to prevent any interaction between large volume of water.

This consideration is crucial, particularly within distribution networks where tanks are often of significant scale. Any surplus water within the tanks not only compromises water quality but also leads to considerable wastage. Moreover, to prevent the interaction between pipe wall and water, water has to wait minimum possible duration inside the pipes and be consumed by users. As a result, in order to minimize the impact of these factors, water stagnation in both tanks and pipeline has to be minimized.

In order to reduce the water age, water has to be consumed as soon as it is injected into the network. To reach this paradigm, tank filling rates and pump working schedules have to be in alignment with real-time demand data from the network. These pumping schedules have to be set in such a way that water waits the minimum time in the system. The main problem is that, DNs are not limited to a single tank or reservoir. These networks usually consist of different zones, each of which is supported by different tanks and reservoirs and the consumption rates in these zones are neither constant nor similar.

With population growth, demand values for zones are changing. Residential zones of a city are usually more congested than industrial regions. Also, the functionality of zones has a tremendous impact on consumption rates. Research shows that there is a correlation between house surroundings and water demand [15]. Moreover, household size largely affects indoor water consumption rates [16-18]. Also, the peak consumption hour in zones is quite different. The main cause of these differences, is the type of buildings located in the zones. Buildings can be categorized into different types, such as residential buildings, factories, restaurants, schools, commercial offices, hospitals, hotels and hostels, cinemas, etc.

One way of calculating the exact consumption of a building is by using its billing information. Authorized consumption can be domestic, industrial, or commercial [19] and it can be billed or unbilled by a managing entity [20]. By using the billing data of the houses and implementing machine learning algorithms such as linear regression, the real consumption amount of the city can be predicted. These algorithms are able to predict future demand for the network based on attributes such as season, number of houses connected to the junction, population of the household in the covered area, historical data gathered from bills, consumption hour, building type and its functionality, etc. Tinker et al. [21] use regression analysis to show the relation between housing characteristics and climate on water consumption.

One significant benefit of a distribution network's digital twin is its ability to simulate demands, registered consumption, and the actual behavior of the network. This simulation is based on data recorded by in-situ sensors about water levels, pressures, and flow calibration. This allows for the replication of all control operations within the network [6]. For instance, AMI is a new technology that collects real-time data on the infrastructure and sends it to the data center [22, 23]. AMI data can be used to estimate demand for real-time hydraulic modeling to enhance the liability of the network.

Although there is a growing body of literature that recognizes the importance of digital twin for infrastructures such as water distribution networks, previous studies have failed to consider the broader implications of DT over water quality. This includes its capability of involving real-time demand data from a DN in a hydraulic model. The aim of this research is to investigate the impact of leveraging real-time data on water age and residual chlorine amount, which is another water quality parameter. The research also aims to find the best hydraulic modeling step to involve digital twin technology. The present study utilizes two distinct scenarios with a difference in their demand data allocation for a hydraulic model of a city. Results obtained from water age comparison of the network for both scenarios indicate the importance of synchronizing the distribution network with real-time demand data. Based on the findings, leveraging digital twin technology, especially in controlling water height in the tanks and pump working schedule, is crucial for improving network efficiency and preserving water quality.

2. Methodology

This study aims to explore the effects of utilizing real-time demand data on key water quality parameters, including water age and residual chlorine levels. For this reason, two distinct scenarios have generated that are only different in their demand values for comparison of the water age and chlorine tracking throughout the network. Oshnavieh city with a population of 45,000 is located in the West Azerbaijan province of Iran. The city is geographically divided into two sections: north and south. The hydraulic model for the north section, accommodating 21,000 residents, was developed using WaterGEMS [24] projecting a 30-year operational span. As depicted in Fig 1, the network is partitioned into three distinct zones. Through demographic analysis, accounting for growth rates and employing geometric methods, the population for the final year was estimated at 28,000.

Demand values of the distribution network is calculated based on networks; climatic region, domestic and public green area, per capita consumption, public consumption, unbilled consumption, and population mentioned in design criteria of urban and rural water supply and distribution systems [25]. For the first scenario, Total demand of the network is calculated based on Table 2 and using Equation 1.

$$[(\mathrm{T} \times \mathrm{C}_1) + \mathrm{U}] \times \mathrm{Population} \qquad (1)$$

$$[(166 \times 1.9) + 25] \times 28000 = 9531200\ \mathrm{L/day} = 110\ \mathrm{L/sec}$$

The total calculated demand value must be distributed among 498 junctions within the network. In this study, demand allocation at each junction follows a methodology based on junction covered area. This approach utilizes Thiessen polygons, as illustrated in Fig 2. The rationale behind employing Thiessen polygons lies in the fact that each polygon encompasses a junction, and all consumers situated within that polygon are closer to that specific junction than any other junction.

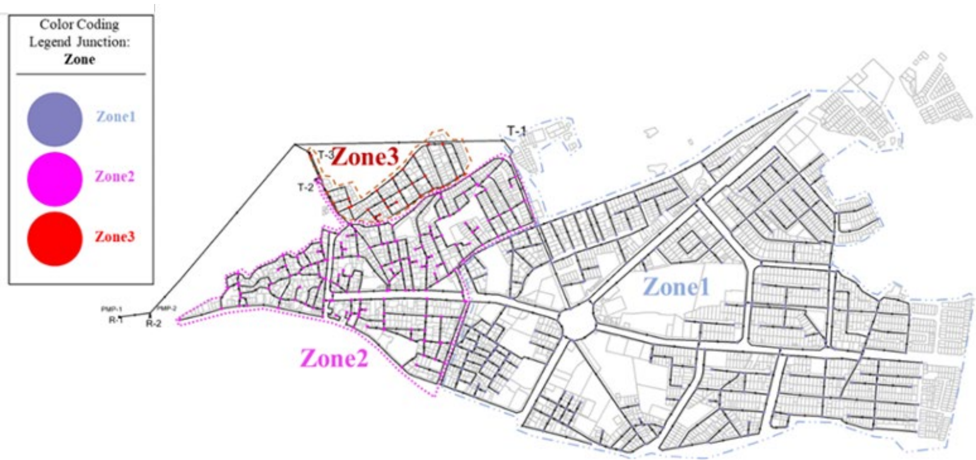

Fig. 1. Oshnavieh city partitioning

Table 2. Demand allocation parameters

Parameter	Definition	Suggested value	Unit	Source (Code 117-3)
C_1	Maximum daily consumption coefficient	1.9	Unitless (Coefficient)	Table:1-8
D	Domestic consumption per capita	Based on population: 130	L/person/day	Table:1-6
IC	Industerial and commercial consumption	12% D=15.6	L/person/day	Clause 1-4-2-3-4
DG	Domestic green area consumption per capita	5 (based on network's climatic region)	L/person/day	Table:1-7
PC	Public consumption per capita	12% D=15.6	L/person/day	Clause 1-4-2-3-3
T	Total per capita consumption	D+IC+DG+PC=130+15.6+5+15.6= 166	L/person/day	Clause 1-5-2-3-6
U	Unbilled consumption	15% T=15%166=25	L/person/day	Clause 1-4-2-3-5

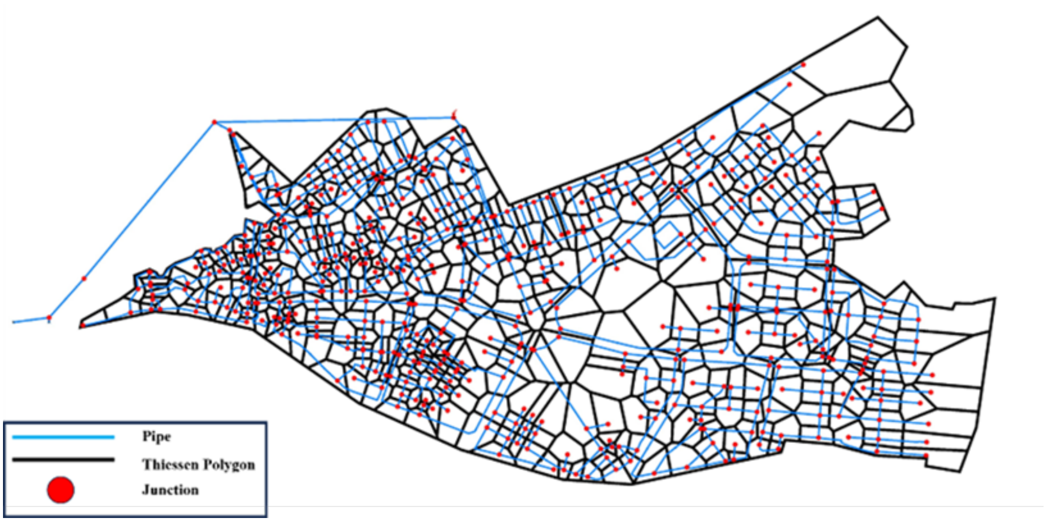

Fig. 2. Thiessen polygon formation for demand allocation

Consequently, this method ensures a balanced distribution of demands among junctions, promoting a more uniform allocation.

According to the design criteria of urban and rural water supply and distribution systems (Code117-3) [25], it is recommended that, under normal circumstances, the useful volume of tanks should fall within the range of 50% to 80% of the maximum expected daily consumption by the project's completion. In this study, where the maximum expected daily consumption is 110 liters per second, adhering to this guideline an assuming 80% of the maximum expected daily consumption, a total required tank capacity volume is 9500 cubic meters. This network comprises three tanks distributed across each zone, with the total required capacity divided among them based on their respective covered area ratios. Tank capacities are designated as follows: T-1: 6500, T-2: 2500, and T-3: 500 cubic meters. All tanks are situated in the northeast section of the city and operate independently without interconnection. These tanks are supported by two wells and two submerged BRTS 435/3 pumps, facilitating a supply of 110 liters per second and a head of 90 meters (The altitude within the system ranges from 1426 to 1543 meters).

Consumption patterns vary throughout the day. With certain hours experiencing peak levels of demand, it is imperative for tanks to accommodate these fluctuations and effectively address the heightened demand. To address this issue, the network applies a maximum hourly demand coefficient, as illustrated in Fig 3, to ensure that system can respond to these spikes in demand effectively.

To effectively manage pump operation hours and scheduling, specific control parameters are established for each tank within the system. Each tank is characterized by three critical levels: the minimum level, designated for sedimentation purposes; the initial level, triggering pump activation when water falls equal to or below this threshold; and the maximum level, prompting pump deactivation when water reaches this height. Across all tanks, these levels are set at 0.5, 1.5, and 3.8 meters, respectively. Pump operation hours can be tailored based on these defined parameters. In order to identify the most optimal pump schedules that prevent either overflows or depletion of tanks, various control strategies are evaluated. Ultimately, the most effective control strategy entails both pumps initiating operation when the water level in Tank 1 reaches or falls below 3.5 meters, and ceasing operation once the water level reaches 3.8 meters. Furthermore, efforts have been made to regulate water levels in Tanks 2 and 3 through adjustments to the control settings of Pump 2. Consequently, Pump 2 is activated when the water level in Tanks 2 and 3 drops to or below 1.5 meters.

As introduced earlier in this section, distribution networks are typically designed to operate over a span of 20 to 30 years. However, during the initial years of operation, the demand values are lower due to the smaller population size. Consequently, in the second scenario, the total demand is computed using Equation 1 for a population of 21,500 individuals. Based on this calculation required demand for second scenario is 84 L/sec. It's important to note that all other aspects and parameters of the two scenarios, including tank capacities, tank condition controls, and hourly demand coefficients, remain consistent.

At last, to assess the impact of scenarios on residual chlorine values throughout the network, chlorine tracking must be conducted. The recommended amount of free chlorine remaining after half an hour of contact in normal conditions should be at least 0.5–0.8 milligrams per liter at any point in the network and at least 0.2 milligrams per liter at the point of water consumption [26]. With this in mind, repetitive modeling of chlorine injection has been performed, testing different chlorine values to determine the sufficient injection amount. Finally, 1 milligram per liter of chlorine was found to be the optimum value to be injected from the inlet pipe of the tanks.

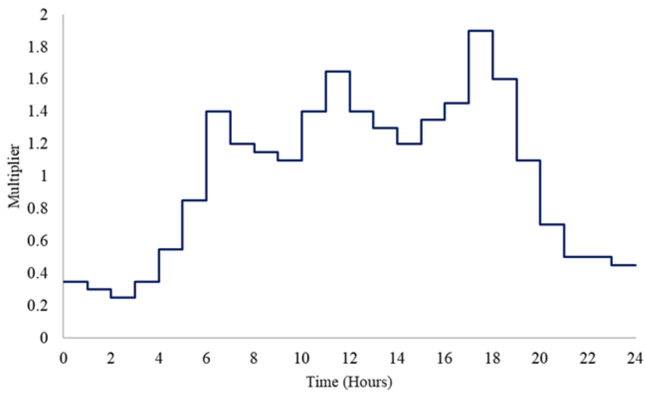

Fig. 3. Hourly demand coefficients

Demand value for second scenario:

$[(166 \times 1.9) + 25] \times 21500 = 7318600$ L/day

$= 84$ L/sec

3. Results

For better understanding the impact of using real-time demand data on water quality parameters, Water age and residual chlorine values of junctions have calculated for all three zones and results are shown in Fig 4 and Table 3. As it is shown in Fig 4, all zones start with a steep positive slope that means water age is increasing with a very fast rate. The reason is that water consumption rate of the network is lower than tanks filling rates and water continues accumulation for near 55 hours in the tank. Afterward tanks controller conditions start to work when water height reaches the numbers mentioned in methodology section. As a result, water age starts to fluctuate between ranges that are shown in Table 3. According to a survey involving over 800 water supply networks in the USA, the average water age is 1.3 days, while the maximum is three days [27, 28] that indicates the similarity of our results to an actual network condition.

4. Discussion

According to the average water age comparison in the result section, all 3 zones have faced at least a 7-hour drop between the two scenarios. Results indicate that water ages are higher in the second scenario. Based on results obtained from the comparison of both scenarios, there are two major factors that affect the water age in distribution networks. First is the total demand value of the junctions that can directly affect water age caused by stagnation in pipes. With higher demands, the network has to respond and start emptying pipes faster than usual, which reduces stagnation in pipes. The second factor is the tank capacity itself and water level inside it. Before being injected into the network, water has to wait inside the tank. Tank filling rate is based on certain control conditions set in the design phase of the network. Based on these controls, pumps start or stop working when water reaches a certain level in the tank. This process has a great effect on the water age inside the tanks with higher capacities.

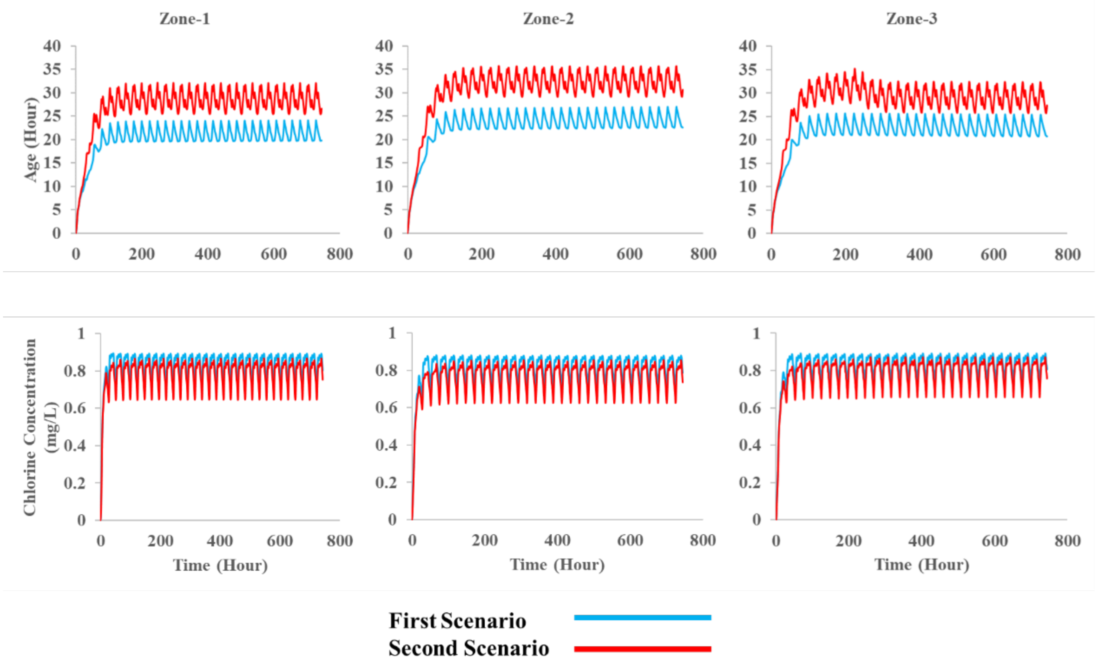

Fig. 4. Water age and residual chlorine values

Table 3. Water age and chlorine fluctuation ranges and averages

	Zone-1			Zone-2			Zone-3		
Water-Age (Hour)	Min-Range	Max-Range	Average	Min-Range	Max-Range	Average	Min-Range	Max-Range	Average
First Scenario	19	24	20	22	26	23	21	26	22
Second Scenario	25	32	27	29	36	31	26	33	28
Residual-Chlorine (mg/l)	Min-Range	Max-Range	Average	Min-Range	Max-Range	Average	Min-Range	Max-Range	Average
First Scenario	0.71	0.9	0.82	0.69	0.88	0.81	0.72	0.89	0.82
Second Scenario	0.64	0.87	0.78	0.61	0.86	0.76	0.64	0.87	0.78

To find the factor with the highest impact on water age, the retention time of each tank is compared to its corresponding zone. The results of these studies are shown in Fig 5. The graph of the average water age of each zone is overlapping the age graph of its corresponding tank, and there is a slight difference between them. To be more precise, as shown in Table 4: Average water age comparison between zones and tanks, the average water age of each tank is calculated for both scenarios. This minor difference shows the significant role of tank filling rates on retention time.

Residual chlorine is another factor that has been analyzed in the results section to understand its correlation with real-time demand data. According to the data from the hydraulic model, the total difference between the average residual chlorine of two scenarios for zone 1, zone 2, and zone 3 is 4.7%, 5.1%, and 4.2%, respectively. It is concluded from the numbers that there is no significant correlation between real-time demand data and residual chlorine amounts, and further investigation has to be taken. By correctly managing the tank filling percentage and planning the pumping system's working hours, water age can be reduced to the lowest possible level. To reach this paradigm, the network has to operate in a way to support only the required amount of water at the time. Otherwise, excessive water will accumulate in the tank and increase the network's water age. Demand data is an essential input for the design of the distribution network and vital for operating management. As a result, collecting real-time demand data is essential for quality monitoring. To keep water levels low in the tanks and prevent water stagnation as much as possible, model needs to have the real-time consumption amount of the network.

According to the literature there are lots of factors that have to be considered while determining the consumption rates of the water distribution networks. Variables such as the number of residents, type of household, household size, and appliance usage have been recognized as factors contributing to the diversity in household water consumption [29]. Water loss due to the leakage is approximately 30% of total water for urban usage [30], hence it has to be considered precisely in demand values. Another research by Ibrahim A et al. [31] indicates that seasonal fluctuations significantly influence per capita water usage. To achieve this, the structure of these systems needs to evolve towards intelligence by integrating more sophisticated elements such as advanced sensors, communication technologies, and real-time monitoring capabilities into devices and components.

Achieving this goal relies heavily on the utilization of smart home technologies, predominantly built upon the Internet of Things (IoT) [32].

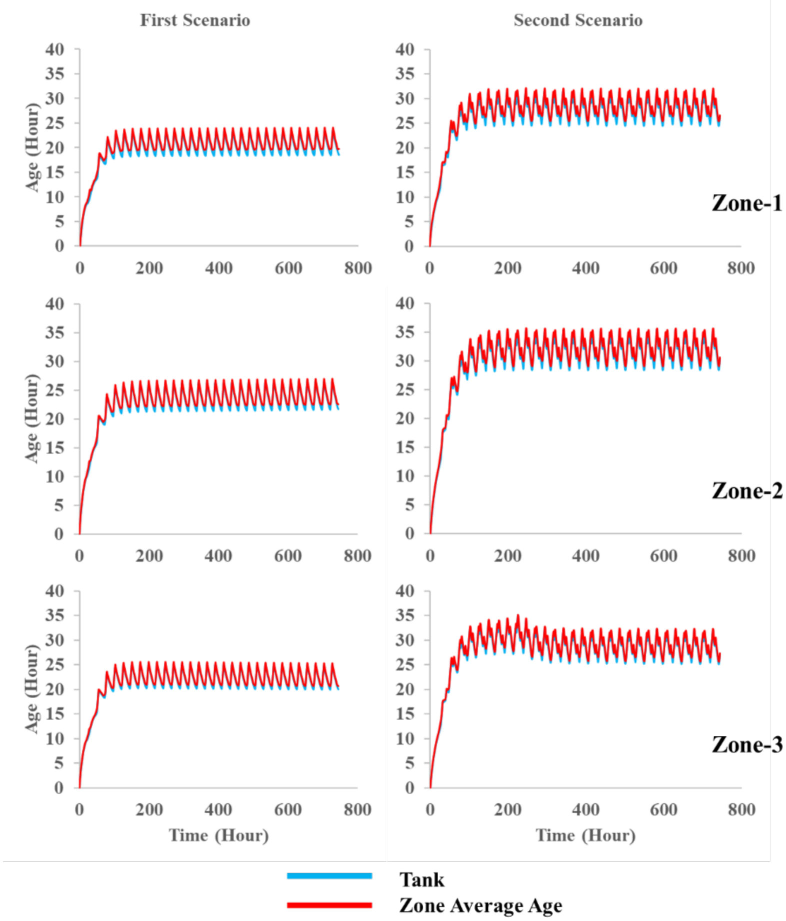

Fig. 5. Age comprison graph between zones and tanks

Table 4. Average water age comparison between zones and tanks

Average-Water-Age (Hour)	Tank-1	Zone-1	Tank-2	Zone-2	Tank-3	Zone-3
First Scenario	19	20	22	23	21	22
Second Scenario	26	27	30	31	28	28

This is essential because of their adaptability, efficiency, and ease of integration into smart grids, enabling effective management and balancing of resources across interconnected buildings within a shared grid network [33]. The Internet of Things (IoT) entails a group of interconnected objects identifiable across a digital network, remotely managed to enhance efficiency, precision, and economic advantages for end-users. IoT seamlessly integrates the physical and digital realms through sensors that observe the environment, gather data, and generate responses in line with the dynamics of the associated system [23]. Panjwani et al. [34] suggested an Internet of Things (IoT) framework designed to monitor individual users' water consumption. This system incorporates ultrasonic sensors for level monitoring and flow sensors to measure consumption. Afifi et al. [35] conducted trials on an Internet of Things (IoT) system tailored for detecting leaks and bursts in intermittent water distribution networks (WDN), using an adaptive version of Kalman filter algorithms [36]. AMI is another new technology that collects real-time data on the infrastructure and sends it to the data center

[22, 23]. AMI data can be used to estimate demand for real-time hydraulic modeling to enhance the liability of the network. With this real-time demand data from the network, the water height in the tanks can be controlled using SCADA systems. These systems can remotely control and monitor distribution network components such as pumps, tanks, and reservoirs [37]. To apply the mentioned technologies and methods in the model, each house block should be connected to its respective zone, as shown in Fig 6. The purpose of this connection is determining the accurate consumption and demand data and the required water level of tank in each zone.

As it is mentioned digital twin capabilities in WDN are not limited to demand allocation. Real-world water distribution systems are subject to dynamic changes in demand, flow rates, pressure variations and other factors. Hydraulic models may not fully capture these dynamics, leading to differences in water height between the model and reality. As a result, twin technology has to be used for system calibration. Rao et al. [38] suggests an IoT framework which measures water level in tank using ultrasonic sensor. In another research by Raha et al. [39] the goal was to create an affordable and durable Internet of Things (IoT) system for monitoring water levels in a tank. The system triggers a warning buzzer and LED indicator when the water level falls below 5%. Leveraging these techniques are useful for controlling. In summary, through the strategic adoption of advanced technologies like IoT and real-time monitoring systems, DT can modernize water distribution networks, effectively minimizing water age and optimizing resource allocation. By embracing these innovations, it is possible to pave the path towards a more sustainable and resilient water infrastructure, ensuring the efficient management of this vital resource for the benefit of present and future generations.

5. Conclusion

The purpose of this study is to demonstrate the importance of using real-time demand data to preserve water quality in distribution networks. To achieve this, two distinct hydraulic scenarios were generated, and water age and residual chlorine, which are water quality parameters, were analyzed in both scenarios. The first scenario reflects the network condition in its last operating year, and the model was designed based on system demand data according to the design criteria of urban and rural water supply and distribution systems (Code117-3). The second scenario uses the same hydraulic model; however, this time demand data was based on the current population and needs of the network. A water age comparison of these scenarios indicates that hydraulic model adjustments based on system true demand data can significantly prevent water aging.

Fig. 6. House block connection to junction

This result leads the study to another comparison, this time between stagnation time inside the tanks and the average water age of the water inside the pipelines. The aim of this comparison is to find the root cause of water aging. Based on the findings, water aging caused by stagnation in tanks is more severe than the effect of water stagnation time in pipelines. Moreover, a chlorine comparison of two scenarios shows that the residual chlorine values of the two scenarios are nearly the same, and no correlation between water age and chlorine values has been found.

Although the current study is based on a small network and population, the purpose of this study was to highlight the significance of utilizing real-time demand data for maintaining water quality in distribution networks. By comparing two distinct hydraulic scenarios, research aimed to demonstrate how adjustments based on true demand data can mitigate water aging and preserve water quality. These findings underscore the potential of digital twin (DT) technology in revolutionizing water quality management. The comparison between scenarios revealed that hydraulic model adjustments informed by real-time demand data significantly prevented water aging. This suggests that leveraging DT for accurate demand estimation and synchronizing tank operations accordingly could be instrumental in preventing water quality.

One of the limitations of this study is the uniform demand distribution between zones, which prevents this research from assessing the severity of water age in zones with different demands, consumer numbers, and total pipe length. The reason for this limitation is the lack of billing data and population congestion information. In terms of future work, it would be interesting to repeat the experiments described here using the capabilities of digital twins in real-time demand data collection on a bigger network with higher required demands and tank capacities to develop a deeper understanding of the digital twin impact on preserving water quality.

Declaration

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Author Contributions

M. Mobadersani: Writing-Original draft preparation, Data curation. O. B. Tokdemir: Reviewing and Editing, Supervision. A. B. Candaş: Reviewing and Editing, Supervision.

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Not applicable.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Ethics Committee Permission

Not applicable.

Conflict of Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

[1] Ishiwatari Y, Mishima I, Utsuno N, Fujita M (2013) Diagnosis of the ageing of water pipe systems by water quality and structure of iron corrosion in supplied water. Water Science and Technology: Water Supply 13(1): 178-183.

[2] Sarni W, White C, Webb R, Cross K, Glotzbach R (2019) Industry leaders chart the transformation journey. International Water Association (IWA) and Xylem White Paper.

[3] Shafiee ME, Barker Z, Rasekh A (2018) Enhancing water system models by integrating big data. Sustainable Cities and Society 37: 485-491.

[4] Brahmbhatt P, Maheshwari A, Gudi RD (2023) Digital twin assisted decision support system for quality regulation and leak localization task in

large-scale water distribution networks. Digital Chemical Engineering 9: 100127.

[5] Conejos Fuertes P, Martínez Alzamora F, Hervás Carot M, Alonso Campos JC (2020) Building and exploiting a Digital Twin for the management of drinking water distribution networks. Urban Water Journal 17(8): 704-713.

[6] Curl JM, Nading T, Hegger K, Barhoumi A, Smoczynski M (2019) Digital twins: The next generation of water treatment technology. Journal of the American Water Works Association 111(12): 44-50.

[7] AWWA EPA, UUSEPA (2002) Effects on Water Age on Distribution System Water Quality. Washington DC.

[8] Rossman LA, Clark RM, Grayman WM (1994) Modeling chlorine residuals in drinking-water distribution systems. Journal of Environmental Engineering 120(4): 803-820.

[9] Wu C, Wu Y, Gao J, Zhao Z (2005) Research on water detention times in water supply network. Journal of Harbin Institute of Technology 12(1): 188-193.

[10] EPA U (2002) Effects on Water Age on Distribution System Water Quality. Washington DC.

[11] Karadirek IE, Kara S, Muhammetoglu A, Muhammetoglu H, Soyupak S (2016) Management of chlorine dosing rates in urban water distribution networks using online continuous monitoring and modeling. Urban Water Journal 13(4): 345-359.

[12] Mays WL (200) Water Distribution Systems Handbook. The McGraw-Hill Companies, Inc., New York.

[13] Abokifa AA, Maheshwari A, Gudi RD, Biswas P (2019) Influence of dead-end sections of drinking water distribution networks on optimization of booster chlorination systems. Journal of Water Resources Planning and Management 145(12): 04019053.

[14] Wang F, Li W, Li Y, Zhang J, Chen J, Zhang W, Wu X (2018) Molecular analysis of bacterial community in the tap water with different water ages of a drinking water distribution system. Frontiers of Environmental Science & Engineering 12: 1-10.

[15] Shandas V, Parandvash GH (2010) Integrating urban form and demographics in water-demand management: An empirical case study of Portland, Oregon. Environment and Planning B: Planning and Design 37(1): 112-128.

[16] DeOreo WB, Mayer PW, Dziegielewski B, Kiefer J (2016) Residential End Uses of Water, Version 2. Water Research Foundation.

[17] Ghavidelfar S, Shamseldin AY, Melville BW (2017) A multi-scale analysis of single-unit housing water demand through integration of water consumption, land use and demographic data. Water Resources Management 31(7): 2173-2186.

[18] Wentz EA, Wills AJ, Kim WK, Myint SW, Gober P, Balling Jr RC (2014) Factors influencing water consumption in multifamily housing in Tempe, Arizona. The Professional Geographer 66(3): 501-510.

[19] Ramos HM, Kuriqi A, Besharat M, Creaco E, Tasca E, Coronado-Hernández OE, Pienika R, Iglesias-Rey P (2023) Smart water grids and digital twin for the management of system efficiency in water distribution networks. Water 15(6): 1129.

[20] Abansi CL, Hall RA, Siason IM (2018) Water demand management and improving access to water. Water Policy in the Philippines: Issues, Initiatives, and Prospects 233-259.

[21] Tinker A, Bame S, Burt R, Speed M (2005) Impact of "non-behavioral fixed effects" on water use: Weather and economic construction differences on residential water use in Austin, Texas. Electronic Green Journal 1(22).

[22] Nguyen KA, Stewart RA, Zhang H, Sahin O, Siriwardene N (2018) Re-engineering traditional urban water management practices with smart metering and informatics. Environmental Modelling & Software 101: 256-267.

[23] Shafiee ME, Rasekh A, Sela L, Preis A (2020) Streaming smart meter data integration to enable dynamic demand assignment for real-time hydraulic simulation. Journal of Water Resources Planning and Management 146(6): 06020008.

[24] Bentley WaterGems CONNECT Edition v. 10.02 (Hydraulics Modeling Software. https://www.bentley.com/software/openflows-watergems/). 2022, Bentley.

[25] Ministry of Energy. Islamic Republic of Iran (2013) Iranian Standards for the Design of Urban and Rural Water Transmission and Distribution Systems (revision and completion of publication 117-3).

[26] Iran IOSAIRO (2010) Drinking Water Physical and Chemical Specification. Institute of Standards and Industrial Research of Iran: Islamic Republic of Iran.

[27] AWWA A (1992) Water Industry Database: Utility Profiles. Denver, Colo.

[28] Chondronasios A, Gonelas K, Kanakoudis V, Patelis M, Korkana P (2017) Optimizing DMAs' formation in a water pipe network: the water aging and the operating pressure factors. Journal of Hydroinformatics 19(6): 890-899.

[29] Rathnayaka K, Maheepala S, Nawarathna B, George B, Malano H, Arora M, Roberts P (2014) Factors affecting the variability of household water use in Melbourne, Australia. Resources, Conservation and Recycling 92: 85-94.

[30] Guo G, Yu X, Liu S, Xu X, Ma Z, Wang X, Huang Y, Smith K (2020) Novel leakage detection and localization method based on line spectrum pair and cubic interpolation search. Water Resources Management 34: 3895-3911.

[31] Ibrahim AS, Memon FA, Butler D (2021) Seasonal variation of rainy and dry season per capita water consumption in Freetown city sierra Leone. Water 13(4): 499.

[32] Ali AS, Abdelmoez MN, Heshmat M, Ibrahim K (2022) A solution for water management and leakage detection problems using IoTs based approach. Internet of Things 18: 100504.

[33] Kamara-Esteban O, Sorrosal G, Pijoan A, Castillo-Calzadilla T, Iriarte-Lopez X, Macarulla-Arenaza AM, Martin C, Alonso-Vicario A, Borges CE (2016) Bridging the gap between real and simulated environments: A hybrid agent-based smart home simulator architecture for complex systems. In: 2016 Intl IEEE Conferences on Ubiquitous Intelligence & Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People, and Smart World Congress: 220-227.

[34] Panjwani A, Chand S, More A, Panjwani R (2020) Water usage control and management based on IoT. International Journal of Scientific Research in Computer Science, Engineering and Information Technology 6(3):730-736.

[35] Afifi M, Abdelkader MF, Ghoneim A (2018) An IoT system for continuous monitoring and burst detection in intermittent water distribution networks. In: 2018 International Conference on Innovative Trends in Computer Engineering 240-247).

[36] Ye G, Fenner RA (2011) Kalman filtering of hydraulic measurements for burst detection in water distribution systems. Journal of Pipeline Systems Engineering and Practice 2(1): 14-22.

[37] Berglund EZ, Shafiee ME, Xing L, Wen J (2023) Digital twins for water distribution systems. Journal of Water Resources Planning and Management 149(3): 02523001.

[38] Rao KR, Srinija S, Bindu KH, Kumar DS (2018) IOT based water level and quality monitoring system in overhead tanks. International Journal of Engineering & Technology 7(2): 379-383.

[39] Raha MH, Ahmed S, Paul D (2019) Aqua: water level audit and alimentation for smart city. In: 2019 International Conference on contemporary Computing and Informatics 54-58.