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MODERN WATER SUPPLY MANAGEMENT TECHNIQUES AND METHODS: A REVIEW

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ABSTRACT

Water management has become one of the priorities for all countries due to water scarcity and population growth. However, the traditional methods used in this field need much time and high costs to be implemented. Therefore, recent research has focused on developing new alternatives for efficient water management. This review aims to survey the techniques and methods of water distribution management applied in different categories of applications. These are inequity in intermittent water supply (IWS), water demand forecasting (WDF), smart water management using the Internet of Things (IoT), and water leakage monitoring. This review mentions the proposed methods for improving equity in intermittent water supply systems. In addition, it discusses the application of machine learning algorithms to predict future water demand based on water consumption and climate variables. We also cite the application of IoT technology in water management through installing sensors along the network that allow real-time monitoring of WDSs. Finally, we discuss hardware and software methods used to monitor water leakage in WDNs.

Keywords: Water management, inequity, intermittent water supply, internet of things, water demand forecasting, water leakage monitoring.

ABBREVIATION

AFS	Adaptive Fourier Series
AHP	Analytic hierarchy process
ANNs	Artificial Neural Networks
ARIMA	Autoregressive Integrated Moving Average

CC	Correlation Coefficient
CNNs	Conventional Neural Networks
CWS	Continuous Water Supply
DBSCAN	Density Based Spatial Clustering of Applications with Noise
DE	Differential Evolution
DI	Dynamic Inversion
DNNs	Deep Neural Networks
EV	Explained Variance
GA	genetic algorithms
GCNs	Graph Convolutional Neural Networks
GRNN	General Regression Neural Network
IoT	Internet of Things
I-NN	Interrupted Neural Networks
IWS	Intermittent Water Supply
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MARS	Multivariate Adaptive Regression Splines
MCDM	Multicriteria Decision Making
MFCN	Multiscale fully convolutional network
MINLP	Mixed Integer Nonlinear Programming
ML	Machine Learning
MLP	Multilayer Perceptron
MLR	Multiple Linear Regression
MODE	Multi-Objective Differential Evolution
MOEAs	Multiobjective evolutionary algorithms
MOO	Multi-Objective Optimization
MOPSO	Multi-Objective Particle Swarm Optimization
MSRVR	Multiscale Relevance Vector Regression
NLP	Nonlinear Programming
NRW	Non-Revenue Water
Pdv	Peak Percentage Deviation
PID	Proportional integral derivative
PPR	Projection Pursuit Regression
R^2	Nash-Sutcliffe Model Efficiency
RBF	Radial Basis Function
RE	Relative Error
RMSE	Root Mean Square Error

SA	Sequential Addition
SVMs	Support Vector Machines
SVR	Support Vector Regression
WBANN	Wavelet–Bootstrap–Artificial Neural Network
WDF	Water demand forecasting
WDN	Water Distribution Network
WDS	Water Distribution System

INTRODUCTION

The water management of WDSs is a complicated task because of the various problems facing water companies. These problems can be classified into three categories based on the time needed to solve them: short-term, medium-term, and long-term (Bello et al., 2019). Inequity in distribution is a common issue in IWSs in which water is delivered for less than 24 h per day or less than seven days per week (Sarisen et al., 2022). Many techniques and methods have been proposed and applied to improve equity in distribution. The optimization of water distribution design is a method that aims to adjust or build a new water network that obeys the hydraulic constraints and has the lowest cost (Bello et al., 2019). In addition, some studies suggest the sectorization of WDNs, which allows dividing the network into sections called district-metered areas using isolation valves (Bello et al., 2019).

The water demand has significantly increased due to population growth (Habi et al., 2016; Argaz, 2018). However, there is less available water to respond to this demand (De Souza Groppo et al., 2019). This situation made it necessary to develop new strategies and methods that aim to maintain a balance between water demand and supply (Rouissat and Smail, 2022). For this purpose, many researchers have developed WDF models to predict short-term, mid-term, and long-term future water consumption based on time series of water demand and climatic variables (De Souza Groppo et al., 2019). These models are developed using either standard statistical techniques or soft computing methods, and they can be classified into linear and nonlinear methods. (De Souza Groppo et al., 2019).

The integration of IoT technology for real-time monitoring of WDSs has covered a large area of research in the last period. This technology simplifies the management of water networks through a system composed of sensors, communication technologies, controllers, and cloud platforms (Manmeet et al., 2021). In this paper, we cited the application fields of the IoT, which are water leakage management, water quality monitoring, and water consumption control.

According to the literature, water leakage can be divided into three classes: reported, unreported, and background-type leakages (Kazeem et al., 2017). On the other hand, some researchers have classified it from a technical nature perspective to an internally based and externally based system (Kazeem et al., 2017). Water leakage in WDSs has negative impacts on the economy and the environment. The study established in Chile (Maria et al., 2021) estimated the marginal cost of decreasing water leakage as 0.349 €/m3. More than 50% of water production is often wasted in WDSs because of leakage, which can affect the water quality and infrastructure (D Rogers et al., 2014). Therefore, it is too important to detect leakage to minimize its effects on WDNs. To this end, hardware- and software-based methods have been used. Acoustic and nonacoustic detection methods are the two types of hardware approaches (Rui et al., 2015). On the other hand, we have numerical and nonnumerical modeling methods as software-based approaches. (Rui et al., 2015).

After the introduction, we discuss the methods used to improve equity in IWS systems in section 2 of the paper. Section 3 is about the techniques used for WDF. Section 4 analyzes the integration of IoT technology for the real-time monitoring of WDNs. Section 5 surveys the recent research in the field of water leakage monitoring.

INEQUITY IN INTERMITTENT WATER SUPPLY SYSTEMS

It is a well-known fact that IWS provokes inequity in supply that leads to users' complaints. To solve this problem, Chandapillai et al. (2012) analyzed the performance of WDNs under shortage and nondeficit conditions using head-dependent outflow analysis, genetic algorithms, two-loop networks, and Hanoi networks. The authors recommended an additional investment in pipes to achieve a more equitable supply in the network. Similarly, Manohar et al. (2013) combined proportional integral derivative (PID) and dynamic inversion (DI) nonlinear controllers for valve throttling to regulate flows along the network, which led to improved equity in supply. In a similar study, Gottipati et al. (2014) utilized the uniformity coefficient to measure equity in WDN. Their study recommends a staggered supply to ensure equitable supply. For the same purpose, Ilaya-Ayza et al. (2016) proposed a sectorization of a WDN in Bolivia using network clustering and graph theory. The authors based their study on multiple criteria and took the opinion of water company experts. Ilaya-Ayza et al. (2017) applied integer linear programming and multicriteria optimization to reorganize water supply schedules. The authors based their study on many quantitative and qualitative criteria. The proposed method led to a significant reduction in peak flow and equitable pressure along the network. Cambrainha et al. (2018) combined the problem structuring method and multicriteria decision making (MCDM) to create a model capable of balancing water supply-demand strategies in IWS networks. The results show an improvement in equity and pressure along the network. Nyahora et al. (2020) utilized a genetic algorithm to develop a multiobjective optimization (MOO). The objective was to maximize reliability and equity in water supply systems by using multiple cost-effective methods. Subsequently, Gullotta et al. (2021) deployed a sequential addition (SA) algorithm for an optimal location and setting of control valves that lead to ensuring equity in supply. The comparison between the SA algorithm and nondominated sorting genetic algorithm (NSGA-II) reveals the similar performance of the two algorithms with the advantage of the SA algorithm in reducing the computational effort related to the optimization procedure.

Design optimization of water distribution networks

Due to population growth, there is a dire need to either optimize the water distribution design or expand its capacity to satisfy the water demand. In this context, Vasan et al. (2010) developed a methodology based on the DENET computer model combined with EPANET to optimize the design of the WDN. For the same goal, Dong et al. (2012) applied and compared the performance of differential evolution (DE) and genetic algorithms (GA) considering the solution quality and efficiency. The results revealed that the DE algorithm performs better than the GA algorithm. In the same research area, Bragalli et al. (2012) employed a mixed integer nonlinear programming (MINLP) search and nonconvex continuous NLP (nonlinear programming) relaxation, which conducts an accurate hydraulic operation of the WDN. Neelakantan et al. (2014) analyzed the expansion of an existing WDN in India using a differential evolution-based optimization module and hydraulic simulation. In a similar study, Ilaya-Ayza et al. (2016) proposed a greedy algorithm to set a schedule for pipe modification stages. This approach prepared the network for a transition from IWS to CWS. Monsef et al. (2019) applied and compared multiobjective differential evolution (MODE), multiobjective particle swarm optimization (MOPSO) algorithms, and NSGA-II. The comparison reveals that the MODE was faster than the two other algorithms in achieving the optimal design of the WDS.

Gradual transition from intermittent to continuous water supply

Waterworks in some countries opt for IWS due to water scarcity. However, the WDS is designed to work under CWS. For this reason**,** Ilaya-Ayza et al. (2018) analyzed a gradual transition process for a sectorized WDN from IWS to CWS. The authors considered qualitative and quantitative criteria in selecting sectors to increase the network capacity by stages. Furthermore, the authors used the analytic hierarchy process (AHP) methodology to include the opinions of water company experts. The results described the transition process, which passes through three stages from IWS to CWS. Subsequently, El Achi et al. (2020) studied the gradual transition from IWS to CWS using a theoretical hybrid hydraulic model, which was applied to a district composed of seven zones in Amman (Jordan). The approach permits improving service during the transition process. For the same purpose, Sánchez et al. (2022) employed flow/pressure control that guarantees water availability and ensures adequate service pressure during peak demand hours. In addition, the method simplifies the decision-making for the water-operating agency.

WATER DEMAND FORECASTING

Many machine-learning algorithms were used and compared for short-, medium-, and long-term WDF to visualize their performance in the prediction process. Alvisi et al. (2007) described a short-term WDF model to replicate the recurring patterns remarked at different levels (daily, weekly, and annual) by including the persistent effects. The authors found that the model forecasts the future hourly water demands accurately. Msiza et al. (2007) compared the performance of both artificial neural networks (ANNs) and support vector machines (SVMs) in short- and long-term WDF. The results indicated that ANNs give more accurate predictions than SVMs. In a similar study, Manuel Herrera et al. (2010) defined and compared many algorithms to predict hourly and weekly water demand in southeastern Spain. SVMs performed better than multivariate adaptive spline, projection pursuit regression, and random forests. In construction, ANNs had less accuracy in the forecasting process. Subsequently, Behboudian et al. (2014) analyzed the application of ANNs for long-term WDF. In addition, they compared the results of multilayer perceptron (MLP) and those of the linear regression model to evaluate the forecasting accuracy. The results show that the MLP can decrease uncertainties and improve the accuracy of long-term prediction. Yun et al. (2014) recommended a multiscale relevance vector regression model (MSRVR) to predict daily urban water demand. The results visualize the high performance of MSRVR in forecasting and following the chaotic pattern of daily urban water. In another work, Tiwari et al. (2015) developed a methodology based on a hybrid-wavelet-bootstrap-artificial neural network (WBANN) to predict weekly and monthly urban water demand. The authors also compared the performance of the WBANN with those of ANNs, bootstrap-based ANN (BANN), and wavelet-based ANN (WANN) models in cases of restricted data availability. The results visualize the efficiency of the WBANN and BANN in forecasting medium-term urban water demand. Landicho et al. (2019) deployed the AHP to determine the weights of the identified WDF model. The authors found that the SVMs were the best model for predicting midterm and long-term water forecasting. On the other hand, the autoregressive integrated moving average (ARIMA) was the most preferred model to predict short-term demand.

Anomaly detection in the time series of water demand

According to the literature, WDF models are developed using time series of water demand. However, these data generally include anomalies and may affect the prediction process. In this context, Herrera et al. (2011) deployed ANNs to cope with negative data in time series information. After that, they developed a methodology based on ARIMA models for short-term WDF. In addition, the authors opted for hybrid models to interpolate linear and nonlinear parts of the time series modeled by ARIMA. The results implied that the model performs well in the prediction process. For the same objective, Brentan et al. (2017) proposed a Fourier time series process to cope with anomalies in time series. After that, they implemented support vector regression (SVR) to estimate short-term water demand. The model allows for determining the optimal size of the training data for the offline model. Yan et al. (2022) proposed unsupervised anomaly detection in hourly water demand data through an asymmetric encoder-decoder. They also compared the suggested methodology with the Z score, isolation forest, local outlier factor, and seasonal hybrid ESD. The findings clarified that the proposed method outperforms the other alternatives in detecting anomalies in water demand data.

Water demand forecasting using climate variables and water demand data

Some researchers have considered climate variables in addition to water consumption to forecast future water demand. Bakker et al. (2014) developed an adaptive heuristic model, a transfer/noise model, and a multiple linear regression (MLR) model for short-term WDF. The study has analyzed the prediction of water demand with and without consideration of weather as an input. The main findings were a reduction in both the largest and the average error prediction. In addition, it gives a detailed comparison between the models' performances in the forecasting process. In the same field of study, Al-Zahrani et al. (2015) combined ANNs and time series and then compared the results without combination (using only time series). The results prove that the temperature was the main factor in training the model. The authors also found that the combination of ANNs and time series outperforms the results without the combination.

Table 1: The methods used for water demand forecasting according to the mentioned references

Author	Employed variables	city/country	measures of accuracy	Forecast horizon	methods employed
Alvisi et al. (2007)	water demand	Castelfranco Emilia, Italy	EV, RMSE, MAPE	hourly, daily	Pattern-based Water Demand Forecasting (Patt_WDF) model
Msiza et al. (2007),	water demand	Gauteng Province, South Africa	The practicality of the water demand figures	daily	SVMs, Artificial Neural Networks (ANNs): MLP, RBF
Manuel Herrera et al. (2010)	water demand, temperature, wind velocity, millimeters of rain and atmospheric pressure	a city in southeastern Spain	RMSE, MAE	hourly	ANNs, PPR, Random forests, MARS, SVR and Weighted pattern-based model
Herrera et al. (2011)	water demand	a village of southeast Spain	RMSE, MAE	hourly	ARIMA, ANNs: I-NN

Yun et al. (2014)	water demand	Chongqing, China	RMSE, MAPE, CC	daily	MSRVR
Bakker et al. (2014)	water demand, temperature	Netherlands	MAPE, RE, R^2	daily	MLR, Adaptive Heuristic model, a Transfer/-noise model
Behboudian et al. (2014)	water demand, temperature	Neyshabur, Iran	RMSE, MAE, MAPE	monthly	ANN
Al-Zahrani et al. (2015)	water demand, humidity, temperature, rainfall intensity, rainfall occurrence and wind speed	Al-Khobar city, Saudi Arabia	MAPE, R^2	daily	Time series models, ANNs: GRNN
Tiwari et al. (2015)	water demand, temperature, total precipitation	Calgary, Canada	Pdv, RMSE, MAE	weekly, monthly	WBANN
Brentan et al. (2017)	water demand	Franca, Brazil	RMSE, MAPE, R^2	hourly	SVR, AFS

SMART WATER MANAGEMENT USING THE INTERNET OF THINGS TECHNOLOGY

WDS management using traditional methods requires much time and effort. Consequently, the integration of the IoT in this field has been studied to simplify the management process. Robles et al. (2014) developed a water management model to decouple decision support systems, implement subsystems and monitor business processes by integrating IoT technologies. The authors found that the proposed model simplified the management of specific vendor equipment in a water management domain. The research established by Verma et al. (2015) discussed the use of IoT technology in the water management field. The authors focused on achieving a large sensing distance through ground-level reservoirs and overhead tanks. In addition, the model enables real-time analysis and visualization of water data**.** Sammaneh et al. (2019) combined IoT technology with big data analysis to develop a model for smart water management. The method consisted of gathering and examining data from users before storing them in cloud computing. The model simplifies controlling water consumption and conserving this resource. For the same aim, Abdul Aziz et al. (2022) combined IoT technology and a geographical information system (GIS) to create a model composed of four layers. The findings clarify the model efficiency in terms of continuous water consumption analysis and delivering real-time water parameter information. Alghamdi et al. (2022) introduced a methodology for leakage detection based on the long-range wide-area network (LoRaWAN) to overcome the costly application of IoT technology over a large area. The findings visualize the efficiency of the suggested method in leakage detection and water monitoring in housing complexes. Ali et al. (2022) established a methodology based on IoT technology for real-time monitoring of WDNs. The proposed method allows administrators and users to control water quality, detect leakage, and measure water consumption. Nie et al. (2020) utilized the supervisory controller and data acquisition (SCADA) to manage WDSs. This methodology simplifies the control of water consumption and ensures the sustainability of WDNs. Pasika et al. (2020) suggested a system to monitor the water quality and the water level in the tank. This system was composed of sensors capable of generating data from the network and a microcontroller unit responsible for transmitting the data to an IoT application called ThinkSpeak. Slaný et al. (2020) developed an IoT model for smart metering and water leakage management using the minimum night flow method. The model allows for detecting leakage with an accuracy of 95%. In addition, its average relative error in the metering process was less than 3%. Ali et al. (2022) employed the internet of things (IoT) for water leakage detection, water quality monitoring, and water meters. The process passed through several parts to permit real-time monitoring of WDNs.

WATER LEAKAGE MONITORING

Water leakage in WDSs is a common problem worldwide because it causes water and energy wastage. Thus, it is necessary to develop methods to reduce the impacts of this problem. To this end, Weifeng Li et al. (2011) developed a methodology that employed noise loggers to detect and control water leakage in the network. Furthermore, the authors deployed the geographic information system to optimize the tool responsible for leak detection. The proposed system detected 14.2% of the total nonobvious leakage cases in the core area of Beijing, which proves the system's reliability. Jensen et al. (2018) developed a methodology using reduced networks to detect and potentially isolate leakage in a WDS with multiple inlets. The numerical findings show the high performance of the suggested model in leak detection. Rathore et al. (2022) implemented a methodology to identify leakage in a WDS with multiple inlets using a self-adaptive reduced-order model that can assess the pressure in the network. The proposed method allows localizing leakage for many nodes. Latchoomun et al. (2020) deployed the Harmonistic oscillator tank (HOT) to decrease leakage and energy consumption in WDSs considering high and low levels of leakage. They also compared the HOT to two other scenarios (direct pumping and pumping through a variable-speed drive in a loop). The results imply that the HOT outperforms the mentioned methods. Feng et al. (2021) proposed a methodology based on a virtual district metering area (V-DMA) to identify water leakage areas in WDNs. The authors deployed a visual AHP to detect high leakage areas in the V-DMA. The suggested method simplifies the in situ identification of water leakage. Hu Xuan et al. (2021) used density-based spatial clustering of applications with noise (DBSCAN) to section a large water network. They also deployed multiscale fully convolutional networks (MFCNs) to identify the leakage area. The results visualized that the proposed approach aims to detect leakage accurately and decrease water losses. Kızılöz et al. (2022)

used the age parameter with other inputs to create a model that determined the performances of WDNs. The authors deployed machine learning approaches to estimate the values of ILI and then to improve its prediction performance. The study implies that the suggested model presents a reliable solution for evaluating network performance in the case of limited data. Mubvaruri et al. (2022) analyzed nonrevenue water (NRW) in Zimbabwe by employing water balances, the international water association, and holistic flow balance between source and DMAs. The authors recommended replacing faulty water meters, restoring pumping and gravity transmission mains, and installing flow controllers to avoid tank overflows. Vanijjirattikhan et al. (2022) deployed SVMs, conventional neural networks (CNNs), and deep neural networks (DNNs) to detect leakage in WDSs. The authors collected leakage sound data from water companies to train these models. The results show that DNNs outperform CNNs and SVMs. Novice operators, therefore, used this algorithm to pinpoint the leakage. The model gave similar results to the experts, with an accuracy of over 90%.

Water leakage monitoring using control valves

Pressure-reducing valves (PRVs) are widely used to control pressure and minimize leakage in WDSs. In this context, Samir et al. (2017) proposed using fixed pressure-reducing valves (PRVs) to model leakage in the WDS of Alexandria city in Egypt. The authors suggested modeling leakage as a function of pipe length and pressure. A simulation of the DMAs of the city was implemented using WaterCAD to create leakage scenarios. The model enables a leakage reduction of 37% for the best scenario. Shushu et al. (2021) analyzed the NRW in an unplanned WDN. The authors proposed diminishing pressure using PRVs. They also suggested dividing the DMA into zones to simplify its management. The results show that the proposed method reduced leakage by 46%, which proves its performance compared to other methods used for NRW. In similar research, Babel et al. (2021) found that conserving water can be assured by reducing the service pressure. On the other hand, pressure augmentation leads to preserving energy. The authors also mentioned that PRVs decrease both leakage and energy consumption. Hanaei et al. (2022) established research to minimize water leakage through pressure regulation in the network. To efficiently place the PRVs, the authors employed a genetic algorithm (GA). Furthermore, they suggested using pumps as turbines (PATs) to generate electricity. The results imply that PRVs and PATs enable decreasing water leakage. On the other hand, the PATs produced 153 MW of electricity per year. Price et al. (2022) proposed an algorithm for optimal positioning and setpoints of PRVs in WDNs. The main contribution of that method was to fill the gap in terms of a realistic conception of water leakage reduction. The findings visualize the performance of the suggested approach in detecting critical nodes and assuring required service pressure with admissible setpoint values.

Water leakage monitoring and energy consumption

Water leakage monitoring leads to conserving the energy used to pump water. In this context, Gao et al. (2014) applied the optimal pump schedule to create a model that monitors leakage and reduces the energy consumption of a multisource WDN. The authors also deployed the NSGA-II for the optimization process. The proposed model aims to decrease energy consumption and water leakage. For the same purpose, Ávila et al. (2022) applied discretized hourly analysis throughout the year to a WDN in Ecuador. The results show that the proposed methodology decreases water leakage by 120000 m3 a year and, as a result, reduces energy consumption by 34490 kWh.

CONCLUSION

This paper discusses the approaches, methods, and techniques applied to improve the conditions of WDNs. Many recent studies focused on discussing the problem of inequity in IWSs. The gradual transition to CWS, sectorization, and optimization of IWS design were recommended to improve equity in distribution through mathematical approaches, machine learning algorithms, and decision-making methods. Second, this paper enumerates the machine learning algorithms used to predict future water demand based on only the time series of water consumption as a variable or with consideration of climate variables to improve forecasting accuracy. Third, the integration of IoT technology in water management is highlighted in a section of this survey. The IoT enables the real-time monitoring of WDNs using sensors placed along the network. Finally, we recap the hardware and software methods used to detect, monitor, and minimize leakage in WDNs.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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