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Artificial intelligence methods in water systems research – a literature review

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We overview selected artificial intelligence methods used in research on water systems, specifically artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS), genetic programming (GP) and support vector machine (SVM) methods. Each method is characterized and the most effective ways of using these methods are discussed. These methods prove widely useful in forecasting changes in selected surface and groundwater quality parameters, forecasting sewage network failures, assessing water treatment options, climate monitoring, drought detection and environmental issues for farmers and producers. Published studies show that artificial intelligence methods should be used in the analysis of water systems, especially since artificial intelligence now appears in search results for over 60,000 environmental articles.

Key words: hydrogeology, machine learning, urban water systems, artificial intelligence, sensors, analysis.

INTRODUCTION

Climate change-related deterioration in the quality of individual environmental factors, population growth and increased waste production have led to the need to create so-called smart cities (Zhang et al., 2019; Sardella et al., 2020; Laino and Iglesias, 2023). Such solutions have many advantages, but their implementation requires the use of modern technical solutions, appropriate policies, the functioning of a rational economy and an educated society to operate appropriate devices (Govindan, 2023).

Almost 80% of the European population lives in cities (Antrop, 2004), and estimates suggest that there may be as much as 35–60% more city dwellers over the next ten years (Melchiorri et al., 2018). The challenge is to ensure the safety and high quality of city services (Bibri et al., 2023).

One solution to the problem seems to be the Internet of Things, aimed at ensuring the delivery of intelligent services, intelligent analytics and reliable communication (Strohbach et al., 2015; Cui et al., 2018). The Internet of Things involves the cooperation of sensors and actuators to collect data and analyze it (Alaa et al., 2017). The impact of artificial intelligence on systems and activities in urban space is constantly growing (Batty, 2018). The increasing amount of data obtained from various types of sensors also increases computational possibilities (Yigitcanlar et al., 2021).

The huge amount of data generated and processed has forced a connection between artificial intelligence methods and Internet of Things solutions. This combination facilitates intelligent and efficient data processing and analysis (Seng et al., 2022). The Internet of Things enhanced by artificial intelligence algorithms can allow for environmental sustainability, climate change monitoring and security.

One of the areas where it is possible to use artificial intelligence connected to the Internet is urban water systems. Changes in water circulation systems in cities are a consequence of urbanization and climate change. Low infiltration of rainwater causes the formation of “urban sewage”, degrading the environment, while extreme weather phenomena pose even greater threats (Ruangpan et al., 2020). Managing water resources in urban space nowadays is a problem set in the context of restoring and maintaining the water cycle (Larsen et al., 2016; Langergraber et al., 2021). The need to provide high-quality water in the quantity required to supply the population requires considerable resources (Oral et al., 2021). Moreover, water resources may be also at risk due to pathogens, nutrients, and heavy metals that migrate into the aquifer, e.g. from landfill leachates (Li et al., 2012; Xiao et al., 2021; Turan et al., 2022).

In this context, particular attention should be paid to the monitoring of the quality (Nielsen, 2006; Quevauviller et al., 2009; Singh et al., 2015) and quantity of groundwater as well as the need for water disinfection and reuse (Hachoumi et al., 2021). An important issue in the protection of water resources is the need to conduct rational waste management (Chrysikou et al., 2007; Bates, 2014; Kong et al., 2016). In order to monitor water quality, limit the negative effects of extreme events such as floods, control the water regime, and ensure water quality in urban water systems, it has become necessary to install sensors and use artificial intelligence for data analysis (Schmitt et al., 2004).

Due to their simplicity and acceptable results, artificial intelligence methods perform much better in terms of efficiency and

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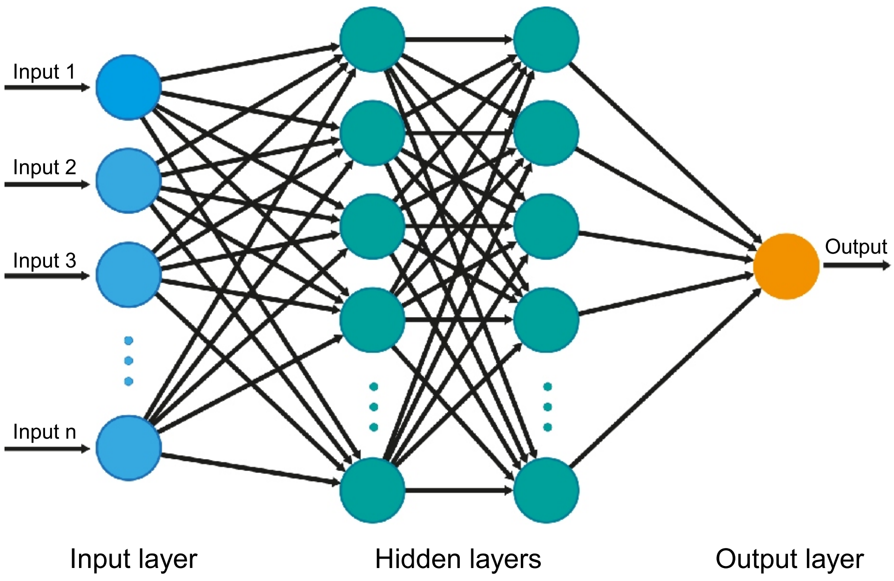

Fig. 1. Architecture of ANNs

forecast accuracy than other conceptual methods. These methods are not without drawbacks, such as the possibility of overtraining or taking into account inappropriate data sets, but they are widely used around the world. Machine learning allows systems to learn directly from data, examples and experience without predefined rules and does not require knowledge of all processes occurring in the environment (Nourani et al., 2008; 2015; Butler et al., 2016).

Machine Learning algorithms are divided into two main groups: supervised and unsupervised learning. The first group uses a training set of examples with correct responses, and the second one identifies similarities between inputs and groups them (Hastie et al., 2009).

Here, we review and compare the application of artificial intelligence methods in urban water systems solutions: specifically, neural networks (ANNs), adaptive neuro-fuzzy inference systems (ANFIS), genetic programming (GP) and support vector machine (SVM) methods. Each of these methods used in urban water systems solutions is characterized. The number of solutions using artificial intelligence methods is constantly growing and is providing huge advantages over traditional methods of environmental management. Selection of material for the preparation of this article was based on a review of current problems related to the functioning of water systems, on the possibility of using software such as Matlab or the Python programming language to create models, and on the timing of publication of relevant articles. The use of so-called deep learning for water systems, however, is not as developed as classic artificial intelligence methods, hence the current study focuses on the methods used.

METHODS

ARTIFICIAL NEURAL NETWORKS (ANNs)

An ANN is a computer program whose task is to model the human brain and its ability to learn tasks at various levels of complexity (Kisi, 2004, 2011). This system is not rule-based like an expert system. An ANN is a mathematical technique that has some similarities to the human brain due to its ability to learn and generalize (Butler et al., 2013). Both biological and artificial neural networks use processing elements, i.e. neurons. Algorithmic functions and learning rules, used to modify the weights in the network in an orderly manner, also play an important role here. Neural networks can be used to approximate features that are unknown, and can cause noisy time series values to emerge from prior values. ANNs consist of processing elements, i.e. neurons, and the connections between them. Network architecture usually distinguishes three separate layers, i.e. input, hidden and output layers. The input layer contains input variables related to the variables analysed. In the hidden and output layers, each neuron passes weighted and biased inputs through the desired transfer (activation) function to produce an output. The general architecture of an ANN is shown in Figure 1.

Due to the fact that ANNs are primarily used for forecasting, they have found many applications in environmental research (Abrahart et al., 2012). Some of these applications concern hydrology and hydrogeology (Dawson and Wilby, 2001; Feng et al., 2008; Nourani et al., 2008; Razavi and Araghinejad, 2009; Taormina et al., 2012; Wu et al., 2014). The possibilities of using ANNs are currently increasing also in industry due to the lower costs of measuring devices, sensors and data availability.

Neural networks in modeling can function as surrogate models that can replace simulation models (Broad et al., 2015). Multi-layer perceptron (MLP) ANNs are the most commonly used types of networks in the field of forecasting (Maier et al., 2010). A MLP represents a typical ANN architecture. After computing the weighted sum of its inputs, each node in the network feeds this sum into a nonlinear activation function so that it can be used to generate an output. These networks can learn complex relationships between inputs and outputs, which can be trained using back-propagation algorithms that adjust the network's weights to minimize the error between predicted and actual outputs (Venkatesan and Anitha, 2006).

Recurrent neural networks (RNNs) are neural networks designed to describe functions and increase performance through feedback connections, that is, passing the results of the hidden layer back to itself (Sameen et al., 2019). They are more functional and technically acceptable than forward networks. Radial basis function (RBF) networks also work with feedback, but

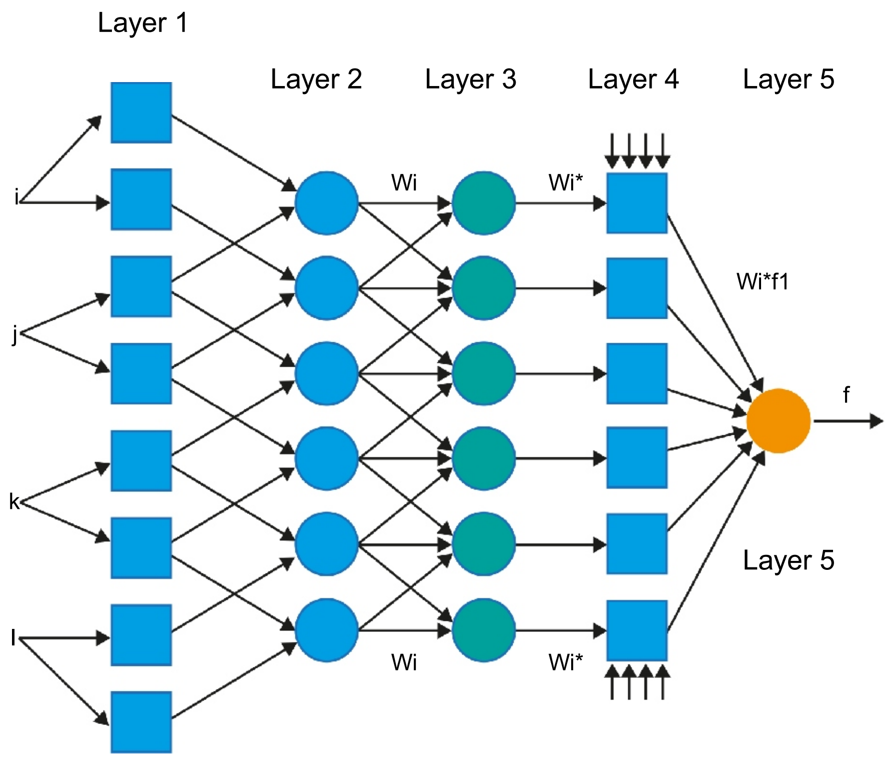

Fig. 2. ANFIS general architecture

they only have one hidden layer. These networks are characterized by high approximation accuracy and high convergence speed. An RBF uses a Gaussian transfer function and standard Euclidean distance to measure the distance of the input vector from a centre vector (Song and Li, 2011). A special type of ANN comprises self-organizing map networks (SOM), which consist of one input layer and one output layer called the "Kohonen" layer (Boniecki et al., 2004). The input layer is connected to the output layer for this architecture. These networks map the high-dimensional input space to a low-dimensional space.

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEMS

An adaptive neuro-fuzzy inference system is a combination of an adaptive neural network and fuzzy logic principles (FIS). Jang (1993) introduced the architecture together with a learning procedure for this method to simulate nonlinear functions, determine nonlinear components, and predict cluttered time series (Fazilat et al., 2012; Safa et al., 2016). The FIS works as input-output mapping that has a learning capability to approximate nonlinear functions. There are two approaches to a FIS: Mamdani and Sugeno. The first one uses fuzzy membership functions, while the second approach uses linear or constant fuzzy logics.

An ANFIS is a five-layer feed-forward network to create a hybrid model capable of practical fit and efficient performance where all nodes are adaptive in the first and fourth layers. Non-adaptive nodes exist in the other layers. The nodes in the second layer are fixed nodes whose functions are multiplied by input signals to generate an output signal. There are fixed nodes with a function in the third layer to calculate the ratio of each node's strength to the sum. There are four fixed nodes in the fifth layer with a node function to calculate the total output. An ANFIS uses a unique algorithm known as a hybrid-learning algorithm which breaks down into gradient descent method and least-squares method to update the parameters (Wang et al., 2009). A general ANFIS architecture is shown in Figure 2.

GENETIC PROGRAMMING

A Genetic Algorithm is a population-based optimization algorithm that resembles natural evolution theories inspired by Darwinian concepts. A Genetic Algorithm uses reproduction, selection, crossover, and mutation to discover better solutions to a given problem that has a random starting set of solutions. Genetic programming is a generalization of the genetic algorithm. The Genetic Algorithm operates in a straightforward way inspired by the mutation-selection process. A Genetic Program (GP) considers an initial population of randomly generated equations. There are random variables, numbers and functions in the algorithm scheme (Li et al., 2023). Solutions are represented in binary code as strings of 0 or 1. Evolution happens across generations. In each generation, the fitness of each individual in the population is evaluated. The algorithm terminates when a maximum number of generations have been produced. The root mean squared error between forecasted and observed data is used as the fitness function. A GP generates an initial population of random computer programs composed of primitive functions and problem terminals. Then it iteratively performs generations by executing each program in the population, determining its usefulness, creating a new generation, and copying the selected program to the population. Ultimately, the algorithm selects the best solution (Shiri et al., 2013). A general flowchart of the algorithm is shown in Figure 3.

SUPPORT VECTOR MACHINE (SVM)

An SVM is a statistical machine learning theory that was created by Alexey Chervonenkis and Vladimir Vapnik in 1963 (Ebrahimi and Rajaee, 2017). The Support Vector Machine al-

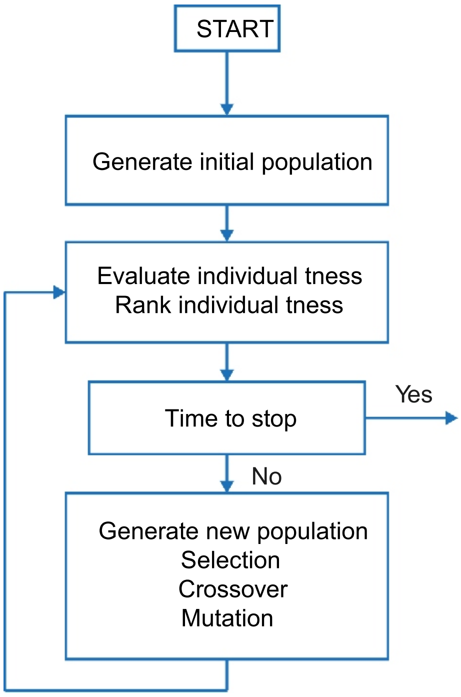

Fig. 3. The general flowchart of GA

gorithm is intended for regression and classification problems. The input vectors supporting the model structure are selected through a model training process (Ebrahimi and Rajaee, 2017). An SVM constructs hyper-planes in an infinite dimensional space which separates n-dimensional space into various classes, making it easy to place a different point in the appropriate category. The mapping schemes are designed to ensure that dot products may be computed easily. There are two types of SVM: a linear type SVM algorithm is useful in cases where the data set can be divided into two classes separated by a single straight line and a non-linear type SVM, which is useful in cases where the data set cannot be divided into classes using a straight line.

The quality of classification is determined by the hyperplane of the SVM algorithm. It is the best possible decision boundary, among various possible decision boundaries, that accurately classifies classes in n-dimensional space. A hyperplane is preferred where the distance between two data points is maximum. In terms of an SVM, support vectors are also distinguished, i.e. the closest data indicators influencing the position of the hyperplane (Bansal et al., 2020). Note that this method works best where there is a clear separation between classes in high-dimensional spaces. It is important that the number of sample values is greater than the number of spaces (Vapnik, 1998). The overall architecture of the SVM is shown in Figure 4.

APPLICATIONS OF SELECTED METHODS

ARTIFICIAL NEURAL NETWORK

The use of artificial neural networks may be a promising alternative to classical statistical methods. The water supply network in the north of France was described by Jafar et al. (2010).The database was built by collecting available data on historical failures, pipe characteristics, hydraulic pressure, soil type, and pipe locations. The database includes 4,862 water supply networks, in which 424 failures were recorded during the observation period. Based on the initial database analysis, six ANN models were established. They are classified according to input indicators: three material layers (plastic, cement and metallic), two layers of the number of failures (low, high) and the global model. The model was subjected to two calibrations. Data from 1991–1999 were used for calibration, and data from 2001–2004 were used to validate the ANN model. The average squared error (ASE) system was used to calculate both training and test patterns. The performance of ANN models is assessed by comparing target and predicted values. The highest ability to predict ANN failures was obtained for the "High-Fail" model and the lowest for the AMC model, which may be due to the smaller database. The study indicates that ANNs can be effectively used to develop investment strategies for the maintenance and renovation of urban water networks.

The effectiveness of ANNs in assessing the efficiency of municipal wastewater treatment was described by Ghosh et al. (2021), who discussed the water quality parameters of biochemical oxygen demand (BOD) and chemical oxygen demand (COD). Four important predictor variables such as inlet concen-

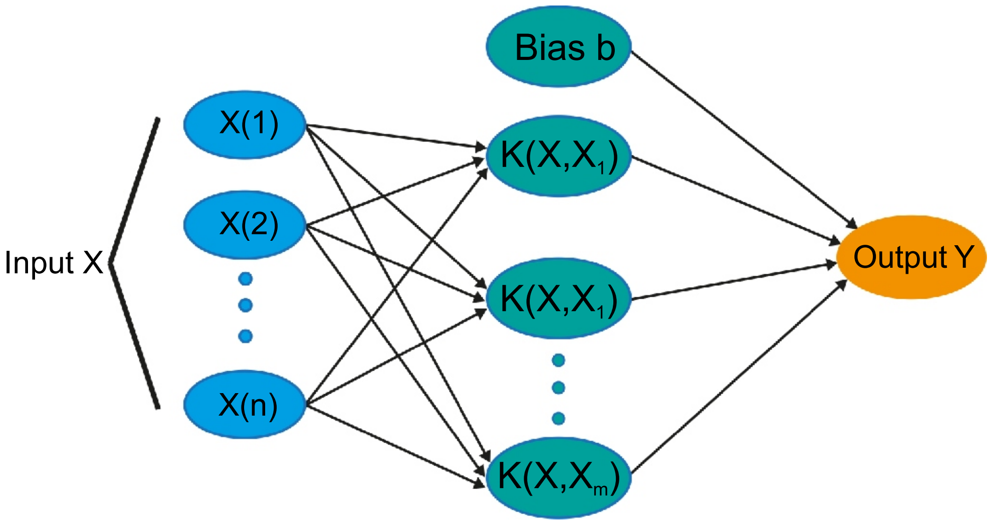

Fig. 4. The general architecture of an SVM

tration, plant density, hydraulic retention time and pH value were analysed from secondary sources of laboratory experiments that were conducted around the world. For BOD, after removing redundant data, the set contains 85 inputs. For COD, with the same improvements, the dataset contains 84 inputs. In total, data came from 12 experiments covering BOD and COD remediation variables in wastewater. The model proved effective despite data from different wastewater media, plant densities, pH and retention times in different climate zones. The predictive model will enable urban policymakers, urban planners, and water managers to predict the wastewater remediation potential of any urban water body in order to make informed wastewater decisions.

Neural networks have also been used in research on detecting land cover changes and predicting urban development (Al-Dousari et al., 2023). They examined the effectiveness of random forest (RF) classification based on machine learning in monitoring land cover classes for 2016 and 2021 for the Kuwait metropolitan region. In the first part, spatial-temporal Land Use Land Cover (LULC) maps were developed based on remote sensing data. Then, historical (2016) and current (2021) LULC data, future (2026) LULC patterns and urban development changes were assessed using the multilayer perceptron neural network Markov chain model. The accuracy assessment of the spatial development maps obtained reached levels of 93.6% and 95.3%. The value of the kappa coefficient was 0.86 (for 2016) and 0.93 (for 2021). The results showed an 11% increase in built-up area. The overall forecast accuracy was 83.6%. Development was expected to increase by 15% between 2021 and 2026. The results of the research conducted by Al-Dousari et al. (2023) show that MLPNN techniques combined with remote sensing and geographic information systems can be used to determine land cover and predict urban growth while achieving high accuracy and precision.

Selim et al. (2023) described a predictive model for dissolved oxygen in a city lake. They used typical water quality parameters: temperature, pH, conductivity and oxidation-reduction potential (ORP) for Hatirjheel Lake in Dhaka. Data was collected using three standard real-time sensors such as an optical sensor for dissolved oxygen, an inductive conductivity sensor for salinity, conductivity and temperature data and a pH sensor for pH. The correlation study showed a positive linear correlation for pH, temperature, salinity and conductivity, and the model was corroborated by an R-score of 0.687 and root-mean-square error of 0.834. An ANN method was developed using the Levenberg-Marquardt algorithm. The performance of the models was verified, and the R2 accuracy was 0.963 for MLR and 0.93 for ANN. The ANN model performed better than the regression model. This suggests that AI is more efficient relative to the linear model. However, the network model validation process resulted in a lower value of R2 = 0.80, highlighting the importance of further validation and refinement to improve model performance.

Another example of the use of artificial intelligence is monitoring water quality in rivers in China (Chen et al., 2023). This study proposed a multi-source remote sensing water quality inversion method, solving the problem of scale inconsistency of multi-source remote sensing data. The concentrations of chlorophyll a (Chla), nitrogen (NH3-N) and turbidites (TUB) in the Nanfei River were used as experimental indicators. A novel self-optimizing machine learning monitoring method was proposed that could automatically find optimal model parameters based on a small number of samples and reduced training time. To increase the correlation between water quality parameters and remote sensing data, a feature improvement method was used. Then, to solve the problem of the quantity and quality of data coming from multiple sources, a spatial mapping method was used to obtain consistency of water quality information. The results showed that for unmanned aerial vehicle (UAV) images, the R2 of Chla, TUB and ammonium NH3-N can achieve accuracies of 0.917, 0.877, and 0.846, respectively. Using satellite imagery, R2 for Chla, TUB, and NH3-N can achieve accuracies of 0.827, 0.679, and 0.779, respectively. The main result was that the method used provides a new way of monitoring the air and ground space of urban inland rivers.

These results indicate that ANN models have wider applications than traditional regression models. An important issue in obtaining the best possible model performance results is the adjustment of the transfer function, learning algorithm and network architecture.

ANFIS

The evolutionary algorithm (EA) is a new technique to improve the performance of artificial intelligence models such as ANFIS and ANN. Azad et al. (2019) investigated the applicability of ANFIS with particle swarm optimization (PSO) and ant colony optimization for adjacent domains (ACOR) to estimate water quality parameters in three stations along the Zayandehrood River in Iran. This study also compared the ANFIS-PSO and ANFIS-ACOR methods with the classic ANFIS method, which uses least squares and gradient descent as training algorithms. Water quality parameters in this study included electrical conductivity (EC), total dissolved solids (TDS), sodium adsorption rate (SAR), carbonate hardness (CH), and total hardness (TH). The analysis of the results obtained results showed that SAR and CH were the two parameters whose estimation was the most accurate. The ANFIS-PSO model is a better model than the ANFIS-ACOR. EA models could improve the performance of ANFIS at all three stations for different water quality parameters.

Air temperature information can provide farmers and food producers with knowledge on climate monitoring, drought detection and environmental issues. The use of ANFIS for such monitoring was described by Karthika and Deka (2015). The study used meteorological data and air pollution (SO_2) data observed at Bhadra station for air temperature forecasts using a new hybrid method (wavelet-ANFIS). Data from the finely distributed wavelet subseries were used as input to ANFIS. The hybrid wavelet-ANFIS method (Gauss affiliation), the hybrid wavelet-ANFIS method (Gbell affiliation) and the ANFIS method were compared. The hybrid wavelet-ANFIS method (Gaussian affiliation) shows a coefficient of determination (R2) of 0.95 and RMSE of 0.74, which is better than the other two methods. The study shows that the hybrid model (Wavelet-ANFIS) has a greater potential to predict air temperature than the ANFIS model.

Drinking water sources may be contaminated with various substances depending on geological conditions and agricultural, industrial and other human activities (RadFard et al., 2019). The quality of drinking groundwater in villages of Bardascan and determination of the water quality index were assessed. Water samples were taken from 30 villages and eighteen parameters were determined, including: calcium hardness, total hardness, turbidity, pH, temperature, total dissolved substances, electrical conductivity, alkalinity, magnesium, calcium, potassium, sodium, sulfates, bicarbonates, fluorides, nitrates, nitrites and chlorides. The groundwater quality index was estimated using the ANFIS method. Spatial locations were described using GPS. The results of this study showed that water hardness, electrical conductivity, sodium, and sulfate in 66, 13, 45 and 12.5% of surveyed villages, respectively, were higher than Iranian drinking water standards. Based on drinking water quality, 3.3, 60, 23.3 and 13.3% of villages were rated as excellent, good, poor and very poor, respectively. The research showed that regular monitoring is necessary to ensure consumers have safe drinking water at optimal levels, consistent with WHO and national limits, especially in villages with poor and very poor water quality status.

Suparta et al. (2020) demonstrated that floods limit the development of cities and may also pose a threat to life and property. Monthly rainfall in southern Tangerang, Indonesia, was predicted with an average test success rate of ~80%. This technique used 6 years of historical rainfall data to predict future rainfall, with the mapping function in the 1950s for training and testing purposes being 4:2, giving the best forecast results. In this ANFIS technique, a time series containing no numbers or being empty (no data) will have a disadvantage in terms of ANFIS capabilities. Characteristics of the data that are highly variable or very extreme will also yield low predictive scores. Since 10 years of historical, year-long rainfall data are not available, it was concluded that future studies should predict rainfall amounts using other parameters that are closely correlated, such as surface temperature, relative humidity and wind speed. Further analysis will also include categories of rainfall that have the potential to trigger flash floods, including urban floods affecting areas where there is rapid housing development or the conversion of marginal areas to residential areas.

In another study, MLR, ANN, ANFIS techniques were developed to predict dissolved oxygen concentration in the lower reaches of the Agra River (Abba et al., 2017). For this purpose, monthly input data were used which included dissolved oxygen, pH, biological oxygen demand and water temperature at three different locations, namely upstream, middle, and downstream. Performance was assessed using the coefficient of determination and RMSE. The dissolved oxygen result showed that both ANN and ANFIS can be used for modelling in Agra city and also indicates that an ANN model is better than ANFIS and shows significant advantage over MLR.

As ANFIS allows the approximation of any real continuous function on a compact set with any degree of accuracy, which makes functional mapping possible that uses the advantages of both ANN and FIS, it can be concluded that it gives better results than only ANN. In publications assessed, only one comparison was made in which ANN was more favourable.

GENETIC PROGRAMMING

Genetic programming is a methodology based on evolutionary algorithms that is best suited for modeling nonlinear dynamic systems. In the first article discussed, in single- and multi-site studies, an algorithm was trained to capture the dynamics of urban rainfall runoff using a series of reservoirs, with each reservoir being a storage unit in the catchment corresponding to different depths below the surface (Chadalawada et al., 2016). The hydrometeorological data used in the study are for the Kent Ridge National University Singapore catchment - a small urban catchment (8.5 ha) that receives an average annual rainfall of 2500 mm. Conceptual Hydrogeological Modeling in Genetic Programming is an R-based GP optimization program designed to identify systems in the field of hydrology. Elements of the conceptual model (reservoir model) were incorporated into the GP structure to determine rainwater runoff in cities. The study showed that the dual-basin model provided a better representation of this urban watershed in terms of performance and complexity when tested with real data.

Rebuilding sewage infrastructure is cheaper than repairing it after a failure. To counteract the occurrence of network failures, a predictive model can be built. This task was undertaken by Hoseingholi and Moeini (2023). For this purpose, genetic programming was used in the Isfahan region, using data from 2014–2017, and the results obtained were compared with the results of the corresponding artificial neural network. Three different approaches were proposed. In the first approach, called GA-CLU-T, the number of pipe failures was predicted from all the data. in the second, called GA-CLU-Y, models were created and trained based on data from 2014, and the resulting model was used to predict the number of pipe failures in future years. Finally, a third model called GA-CLU-R was proposed to determine the number of pipe failures in other regions. Here, two different models were proposed for each GP approach. The result shows that the best RMSE (R2) values for the first, second and third approaches for the test dataset were 0.00316 (0.966), 0.00074 (0.996) and 0.00075 (0.997), respectively. The results show that the accuracy of the results of GP models is better than that of the corresponding ANN models. Comparison of the results obtained showed that the methods proposed are practical in that the sewage operator can use them to plan maintenance and assess the repair time of the sewage network, to thus reduce operation and maintenance costs.

High levels of soil impermeability as well as increased urbanization contribute to the occurrence of floods around the world. To mitigate the negative effects of floods, low impact development (LID) techniques may be used. These aim to preserve the hydrology of urban catchments closer to pre-development conditions through the use of distributed stormwater control systems. Lopes et al. (2021) explored the use of hydrological simulation models integrated with optimization techniques as an alternative, to aid in LID scenario planning. This study tested the feasibility of using an adaptation of the NSGA-II genetic algorithm together with the SWMM hydrological model to aid in the optimal design of an LID scenario aimed at reducing stormwater runoff and total costs in different return periods. The study analyzed a combination of permeable pavements, green roofs and bioretention cells, and the model was optimized for rainfall with return periods of 10, 25 and 50 years. The results showed that the model was able to find multiple optimal solutions with different levels of runoff reduction at different costs. However, the research revealed some limitations related to practical applications and possible oversizing of adjacent LID layers.

The GP is considered an algorithm that gives worse results in water level forecasts (Rajaee et al., 2019), though it turned out to be more effective than ANN in solving problems related to sewage infrastructure.

SUPPORT VECTOR MACHINE

A analysis for the northern Colombian city of Riohacha used physics-based modeling using 2D models (Cardenas-Mercado et al., 2023). The study aimed to identify social and economic variables and flood magnitude under extreme hazard conditions. To obtain twenty social hydrological variables, a survey analysis was conducted using the Kruskal-Wallis test and multiple correspondence analysis. Determination of the optimal combination of parameters and calibration of the TELEMAC-2D hydrodynamic model was based on the iterative use of SVM. The curve number (CN) and the Manning friction coefficient were used as calibration parameters. The optimization process included introducing SVM dummies for the socio-hydrological variables CN and the Manning friction coefficient, testing as many as 20,000 parameter combinations, and the evaluation included mean absolute error (MAE), mean error (ME), relative absolute error (RAE), mean squared error and inertia root mean square error (IRMSE). In standard simulations, RMSE values of 0.48 m, MAE of 0.37 m, and an IRMSE of 1.37 m, were obtained. In contrast to the previous indicators, the ME indicator slightly increased from 0.15 m to 0.17 m after taking into account the socio-hydrological variables. The authors suggest that the results achieved may provide further scope for optimization, especially through the implementation of digital terrain models, which would allow obtaining a more realistic representation of the complexity of urban structures. Additionally, potential improvements may include expanding research related to the integration of social and hydrometeorological variables to more accurately analyse flood risk and identify more precise tools for predicting crisis situations.

The concept of green development is an innovative approach that assumes simultaneous progress in the field of environmental protection and socio-economic development. As part of one study, based on the grey water footprint theory and using physical and statistical models, the main goal was to conduct a comprehensive analysis, assessment and forecasting of the spatio-temporal dynamics of the evolution of the relationship between the water environment and the social economy in the Yangtze River area (Deng et al., 2021). The concept of grey water footprint in this context is defined as the amount of freshwater necessary to absorb pollutants, taking into account natural background concentrations and applicable water quality standards in a given area. The results of the study revealed interesting trends: firstly, in the period from 2003 to 2017, the grey water footprint carrying capacity indicators, such as KCOD, KNH3-N and KTP have been systematically decreasing, which indicates an observed decrease in the degree of coordination of connections, especially noticeable from east to west; secondly, the degree of coordination of connections showed a decreasing spatial trend, while increasing temporally in the years 2003-2017; thirdly, sustainable development (Plan IV) turned out to be the optimal scenario, bringing about an improvement in the overall degree of coordination. It is worth adding that, in addition to describing the results, the study also contained political suggestions which added to its practical value. The results may influence the achievement of sustainable water management. Their implications go beyond theoretical aspects, offering concrete guidelines for making political decisions and actions aimed at improving the state of the environment and the quality of life of local communities.

In a further study, an innovative support vector machine (SVM) model used a complex polynomial kernel function to forecast monthly water demand in the Canadian city of Kelowna (Shabani et al., 2017). The focus was mainly on precisely examining the effectiveness of phase space reconstruction before determining the optimal combination of input variables for the prediction models. The results obtained clearly show that the optimal delay time of the input variables significantly increases the efficiency of SVM models. As part of the analysis, the AMI technique was used, to precisely determine the optimal delay time for explanatory variables, such as water demand, temper-

Table 1

Details of the reviewed papers

No	Authors (year)	Used models	Main topic	Input variables
1	Jafar et al. (2010)	ANN	model of the failure rate and estimation of the optimal replacement time for the individual pipes in an urban water distribution system	ID of pipe, material, diameter, length, thickness, age at which the pipe failure occurred, soil type assigned, location, pressure variation, number of failures
2	Karthika and Deka (2015)	ANFIS	air temperature prediction	rainfall, wind speed, humidity, sunshine hour, SO_2
3	Chadalewada et al. (2016)	GP	urban rainfall-runoff process modeling	rainfall intensity, discharge at the catchment outlet, evapotranspiration
4	Abba et al. (2017)	ANN, ANFIS	prediction of the dissolved oxygen concentration in a river	dissolve oxygen, pH, biological oxygen demand, water temperature
5	Shabani et al. (2017)	SVM	prediction of the monthly water demand	water demand, temperature, precipitation
6	Azad et al. (2019)	ANFIS	estimation of water quality	EC, total dissolved solids, SAR, carbonate hardness, total hardness, pH, concentrations of sodium, chlorine, carbonate, bicarbonate, sulfate, magnesium and calcium
7	RadFard et al. (2019)	ANFIS	estimation of water quality	calcium hardness, total hardness, turbidity, pH, temperature, total dissolved solids, electrical conductivity, alkalinity, concnetration of magnesium, calcium, potassium, sodium, sulphate, bicarbonate, fluoride, nitrate, nitrite and chloride
8	Suparta and Samah (2020)	ANFIS	rainfall prediction	average monthly rainfall values
9	Deng et al. (2021)	SVM	estimation of water quality in river	dissolved oxygen, permanganate index, ammonia nitrogen value
10	Ghosh et al. (2021)	ANN	urban wastewater remediation efficiency modeling	inlet concentration, plant density, hydraulic retention time, biochemical and chemical oxygen demand and pH
11	Lopes et al. (2021)	GA	runoff reduction levels modeling	technical parameters of storm water system, precipitation
12	Al-Dousari et al. (2023)	ANN	land use cover change model	Google Earth maps, terrain model data
13	Cardenas-Mercado et al. (2023)	SVM	physics-based flood model creation	initial condition of wetlands and water depth, base flow, altimetric information incorporated with the digital terrain model, precipitation
14	Chen et al. (2023)	ANN	water quality prediction	UAV multispectral data and measured water quality data
15	Hoseingholi and Moeini (2023)	GA	pipe failure prediction	pipe diameters, pipe slopes, distance between two manholes (pipe length), pipe cover depth and pipe age
16	Selim et al. (2023)	ANN	predictive models for dissolved oxygen in creating an urban lake	temperature, pH, conductivity and oxidation reduction potential

ature and rainfall. Particular attention was paid to the optimal delay time of these variables, both individually and in the context of a model that takes into account all the delays noted until the optimal value is obtained. Importantly, the results obtained clearly indicate that a model using additional information as independent time series can significantly outperform models focused solely on the individual optimal delay time for individual variables. It should be emphasized that support vector machines have shown high sensitivity to the reconstruction of the phase space of input variables, which highlights the importance of appropriate design of input data for demand forecasting models. The study provided a new perspective on the importance of the optimal delay time, precisely determined using the average mutual information. The results suggest the need to implement advanced combination strategies in the input data of forecasting models to achieve more effective and precise results.

SVM is a very good machine learning method that can be used to solve not only classification problems, but also prediction problems. Good performance of this method is related to the selection of kernel functions and parameter values, which can be selected randomly or using optimization methods.

A summary of the articles described is shown in Table 1.

CONCLUSIONS

Artificial intelligence methods have been used in water system research. The research results as described confirm the wide use of artificial intelligence methods in forecasting changes in selected surface and groundwater quality parameters, forecasting sewage network failures, assessing water treatment options, climate monitoring, drought detection and environmental issues for farmers and producers.

The analysis encompassed four methods: ANN, ANFIS, GP and SVM. As our re-view covered non-comparable topics, it is difficult to indicate one method that would be the most effective for all the applications described. However, our analysis show that these methods provide more effective results than traditional (linear) statistical methods. When using artificial intelligence methods in research on water systems, attention should be paid to the quality of the input data so that the model developed is as accurate as possible. Each use of artificial intelligence methods should be supported by verification of the results obtained. The artificial intelligence methods described work best in modeling changes in water quality or groundwater level modeling, and it is for these issues that deep learning methods will be described in a subsequent paper.

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LIST OF ABBREVIATIONS

ACOR – ant colony optimization for adjacent domains
ANN – artificial neural network
ANNs – artificial neural networks
ANFIS – adaptive neuro-fuzzy inference system
ASE – average square error
BOD – biochemical oxygen demand
CH – carbonate hardness
Chla – chlorophyll a
CN – curve number
COD – chemical oxygen demand
EA – evolutionary algorithm
EC – electrolytic conductivity
FIS – fuzzy logic principles
GA – genetic algorithm
GP – genetic programming
LID – low impact development
LULC – Land Use Land Cover
MLP – multilayer perceptron
ORP – oxidation-reduction potential
PSO – particle swarm optimization
RBF – radial basis function
RF – random forest
RNNs – recurrent neural networks
SAR – sodium adsorption rate
SOM – self-organizing map networks
SVM – support vector machine
TDS – total dissolved solids
TH – total hardness
TUB – turbidity
UAV – unmanned aerial vehicle