ARTIFICIAL INTELLIGENCE-BASED PREDICTION MODELS FOR ENVIRONMENTAL ENGINEERING

*Kaan Yetilmezsoy, Bestamin Ozkaya, Mehmet Cakmakci**

Abstract: A literature survey was conducted to appraise the recent applications of artifical intelligence (AI)-based modeling studies in the environmental engineering field. A number of studies on artificial neural networks (ANN), fuzzy logic and adaptive neuro-fuzzy systems (ANFIS) were reviewed and important aspects of these models were highlighted. The results of the extensive literature survey showed that most AI-based prediction models were implemented for the solution of water/wastewater (55.7%) and air pollution (30.8%) related environmental problems compared to solid waste (13.5%) management studies. The present literature review indicated that among the many types of ANNs, the three-layer feed-forward and back-propagation (FFBP) networks were considered as one of the simplest and the most widely used network type. In general, the Levenberg-Marquardt algorithm (LMA) was found as the best-suited training algorithm for several complex and nonlinear real-life problems of environmental engineering. The literature survey showed that for water and wastewater treatment processes, most of AI-based prediction models were introduced to estimate the performance of various biological and chemical treatment processes, and to control effluent pollutant loads and flowrates from a specific system. In air polution related environmental problems, forecasting of ozone (O_3) and nitrogen dioxide (NO_2) levels, daily and/or hourly particulate matter ($PM_{2.5}$ and PM_{10}) emissions, and sulfur dioxide (SO_2) and carbon monoxide (CO) concentrations were found to be widely modeled. For solid waste management applications, reseachers conducted studies to model weight of waste generation, solid waste composition, and total rate of waste generation.

Key words: *Environmental engineering, artificial neural networks, adaptive neuro-fuzzy inference system, black-box modeling*

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1. Introduction

The real-life environmental problems are very complex and highly dependent on several process configurations, different influent characteristics and various operational conditions, such as organic loading rates, influent pH, toxic organic compounds, influent flowrate, hydraulic and sludge retention times, temperature variations, biomass concentration, and doses of applied chemicals, etc. For a sustainable control of environmental related problems, the proposed systems must be continuously monitored and properly controlled due to possible instabilities in circumstance conditions. Therefore, the complicated inter-relationships among a number of system factors in the process may be explicated through a number of attempts in developing representative AI-based prediction models allowing the investigation of the key variables in greater detail [1].

Inspired by the capacities of the human brain, artifical intelligence (AI)-based models integrate the specific attributes of various disciplines, such as mathematics, statistics, physics, computer science, and just recently, environmental engineering applications. The AI-based prediction models have a significant potential for solving complex environmental applications that include large amounts of independent parameters and nonlinear relationships. Because of their predictive capabilities and nonlinear characteristics, several artificial intelligence-based modeling techniques, such as artificial neural networks, fuzzy logic, and adaptive neuro-fuzzy inference systems have recently been conducted in the modeling of various real-life processes in the environmental engineering field [1–3]. Among these AI-based prediction methods, black-box models, such as artificial neural networks (ANN), are very attractive as they do not require prior knowledge regarding the structure and relationships that exist between important variables. When processes are not adequately understood or parameter determination is impractical, there is a distinctive advantage for such black-box modeling. Since their learning abilities make them adaptive to system changes, new forecasting models based on ANN, such as the adaptive neuro-fuzzy inference system (ANFIS), have recently become a popular universal approximator that represents highly nonlinear functions. The ANFIS incorporates a Sugeno-type fuzzy inference system into an adaptive neural network structure consisting of several nodes connected through directional links. As another popular AI-based modeling technique, the fuzzy logic methodology has also been conducted by many researchers as an established and promising method for modeling of various types of environmental problems in recent years [4–10]. Turkdogan-Aydinol and Yetilmezsoy [1] reported that the applicability of the fuzzy logic model is very simple and there is no need to define the complex reactions and their mathematical or biochemical equations. Moreover, due to highly nonlinear structure of the fuzzy logic model, a complex environmental system can be easily modelled [1]. It is also reported that artificial intelligence-based control of real-time process variables may provide several potential advantages, such as protection of the system from possible risks associated with significant fluctuations in influent characteristics, optimization of the process at a reasonable cost, providing a rapid evaluation and estimation of pollutant loads and emissions on energetic basis, and also development of a continuous early-warning strategy without requiring a complex model structure and tedious parameter estimation procedures [1].

Based on the above-mentioned facts, in this study, a literature survey was conducted to evaluate a great deal of flexibility models for their use in real-life applications of environmental engineering field. This study offers an extensive review of recent applications of various AI-based prediction models conducted in the fundamental research areas of environmental engineering, such as water and wastewater treatment processes, air pollution related problems and waste management studies.

2. Modeling Tools

In this section, the basis of the widely used AI-based techniques, such as artificial neural networks, fuzzy logic and adaptive neuro-fuzzy inference systems, are briefly summarized and important mathematical aspects of these methods are highlighted. Moreover, computational issues, advantages and particular theoretical principles are described, and some metholodogical techniques are discussed to make a comparative assessment of the present AI-based prediction models.

2.1 Artificial neural networks (ANN)

To better control a specific environmental process, a robust mathematical tool for predicting the process performance must be developed based on past observations of certain key parameters. Modeling a multivariate system is highly difficult due to the complexity of the environmental processes exhibiting nonlinear behavior that are difficult to describe by linear mathematical models [11]. Although deterministic models (also called white-box models) may provide insight into the mechanism, they require hard work before being applied to a specific environmental process. As an alternative to physical models, artificial neural networks (ANNs) are a valuable forecast tool in environmental sciences. They can be used effectively due to their learning capabilities and their low computational costs [12]. Because of their reliable, robust, and salient characteristics in capturing the nonlinear relationships between variables (multi-input/output) in multivariate systems, numerous applications of ANN-based models have been successfully utilized in the field of environmental engineering in the past decade [13].

The ANN-based models are meant to interact with objects in the real world in the same way that the biological nervous system does. The calibration of ANN-based models is easier than the white-box models as fewer parameters are used in the model development process. For this reason, artificial intelligence techniques using ANN have recently become immensely popular and attractive mathematical tools for both modeling and controlling of several complex environmental processes. When the measured variables begin showing difference in response to ANN, the model can be retrained using the newer data used for cross-checking. These facts and the quality of the results they provide make the ANN-based models more attractive than conventional models [14].

A simple diagram of an ANN model is depicted in Fig. 1. As seen in Fig. 1, each neuron is connected to several of its neighbors, with varying coefficients or weights representing the relative influence of the different neuron inputs to other neurons. The weighted sum of the inputs are transferred to the hidden neurons, where it is transformed using an activation function, such as a tangent sigmoid activation function. In turn, the outputs of the hidden neurons act as inputs to the output neuron where they undergo another transformation. The output of a feed-forward ANN with one hidden layer and one output neural network is given as follows [11]:

$$Y_o = f_o\left[\sum_{j=1}^{HN} WO_j * f_h\left(\sum_{i=1}^{m} WH_{ij} * X_{it} + b_j\right) + b_o\right], \tag{1}$$

where WH_{ij} is the weight of the link between the ith input and the jth hidden neuron, m is the number of input neurons, WO_j is the weight of the link between the jth hidden neuron and the output neuron, f_h is the hidden neuron activation function, f_o is the output neuron activation function, b_j is the bias of the jth hidden neurons, b_o is the bias of the output neuron, and HN is the number of hidden neurons.

Hamed et al. [11] reported that the tangent sigmoid (*tansig*) activation functions for the input and hidden neurons are needed to introduce nonlinearity into the network in order to make nets more powerful than plain perceptrons. Moreover, the authors reported that a linear activation function, such as *purelin,* could be selected for the output neuron since it is appropriate for continuous valued targets. The mathematical definitions of these functions are given as follows [15]:

$$f(x) = \frac{2}{(1 + e^{-2x})} - 1 \tag{2}$$

$$f(x) = x. \tag{3}$$

Among the many types of ANNs, back-propagation (BP) networks have recently been considered as one of the simplest and most widely used network models [16]. The learning process of a BP network consists of two main iterative steps: forward computing of data stream and backward propagation of error signals. During forward computing, original data is transmitted from the input layer to the output layer through the hidden processing layer, with the neurons of each layer only affecting the neurons of the succeeding layer. One of the main advantages of BP networks over other types of networks is that if the desired output cannot be obtained from the output layer, the error is propagated backwards through the network against the direction of forward computing [16,17]. According to the error signal of BP, the network changes the network connection of all layers to determine the best weight set and realize the correct network output [17]. Therefore, with these two steps performing iteratively, the error between network output and desired output can be minimized using the delta rule [16].

The network training is a process by which the connection weights and biases of the ANN are adapted through a continuous process of simulation by the embedded network's environment. The training function applies the inputs to the new network, calculates the outputs, compares them to the associated targets, and calculates a mean square error. If the error goal is met, or if the maximum number of epochs is reached, the training is stopped and the training function returns the new network and a training record. Otherwise, the training goes through another epoch. During the adaptation phase, the training algorithm receives part of the

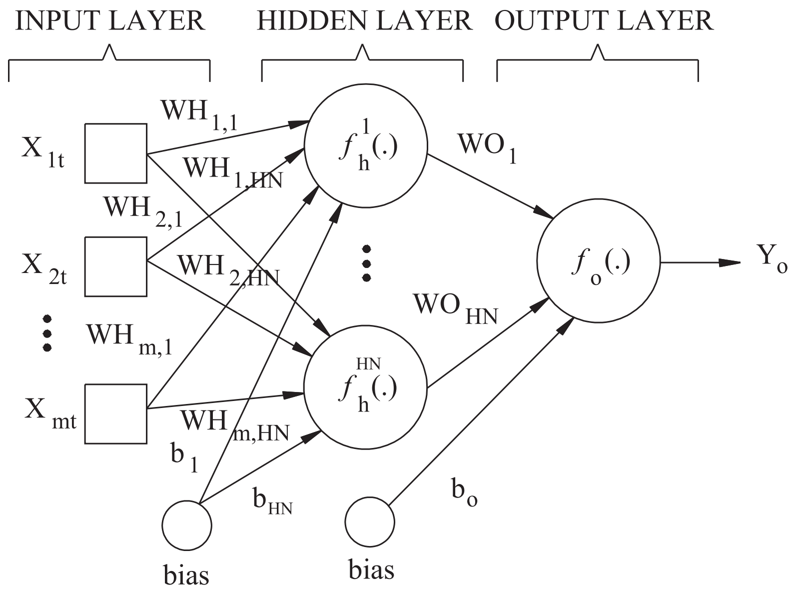

Fig. 1 *Simple schematic of an ANN model (adapted from Hamed [11]).*

data (inputs and outputs) and automatically develops the ANN model. After development, the model could generate the appropriate responses for simulations with varying levels of data input. When the learning is complete, the neural network is used for prediction. The primary goal of training is to minimize an error function by searching for a set of connection strengths and biases that causes the ANN to produce outputs equal or close to the targets. In other words, the training aims at estimating the parameters (WH_{ij}, WO_j, b_j, and b_o) by minimizing an error function, such as the mean square error (MSE), of the output values expressed as follows [11]:

$$MSE = \sum_{t=1}^{N} \frac{(Y_a - Y_o)^2}{N}, \tag{4}$$

where MSE is the mean squared error, N is the number of data points, Y_a is the target output, and Y_o is the network output. In general, ANNs are sensitive to the number of neurons in their hidden layers. Too few neurons may lead to underfitting. Conversely, too many neurons may contribute to overfitting, wherein all training points fit well, although the fitting curve may take wild oscillations between the points. In this case, the error on the training set is driven to a very small value, however, when new data is presented to the network, the error becomes enlarged. Although the network has memorized the training examples, it has not learned to generalize to new situations. This can be prevented either by training with Bayesian regulation, a modification of the Levenberg-Marquardt algorithm (LMA), or by using early stopping with any of the other training routines. In turn, this requires that the user pass a validation set to the training algorithm, in addition to the standard training set [18]. However, in practice, it is difficult to know which training algorithm will perform fastest for a given problem. It will depend on many factors, including the complexity of the problem and the number of data points in the training set [19].

In general, on networks that contain up to a few hundred weights, the LMA will have the fastest convergence. The Quasi-Newton methods are often the next fastest algorithms on networks of moderate size, while the Broyden–Fletcher–Goldfarb–Shanno (BFGS) Quasi–Newton BP algorithm is generally faster than the conjugate gradient algorithms. Of the conjugate gradient algorithms, the Powell-Beale procedure requires the most storage, but usually has the fastest convergence. Meanwhile, the Polak-Ribiére has performance similar to the Powell-Beale, the storage requirements for which (4 vectors) are slightly larger than for the Fletcher-Reeves (3 vectors). The Fletcher-Reeves generally converges in fewer iterations than the Resilient back-propagation algorithm (Rprop). Although more computation is required in each iteration, the Rprop and the scaled conjugate gradient algorithm do not require a line search and have small storage requirements. They are reasonably fast, and are very useful for large problems. The variable learning rate algorithm is usually much slower than the other methods, and has approximately the same storage requirements as Rprop, however, it can still be useful for some problems. The one-step secant algorithm requires less storage and computation per epoch than does the BFGS algorithm, however, it requires slightly more storage and computation per epoch than do the conjugate gradient algorithms. This algorithm can be considered a compromise between the Quasi-Newton algorithms and the conjugate gradient algorithms. In the batch gradient methods, the weights and biases are updated in the direction of the negative gradient of the performance function. The comparative features of the various training algorithms described herein are adapted from the recent work of Yetilmezsoy and Sapci-Zengin [15].

Based on the above-mentioned facts, it can be noted that the performance of the various algorithms can be affected by the accuracy required of the approximation, which is dependent on the mean square error, versus that of several representative algorithms. When the problem formulation has a combinatorial nature, the definition of each process parameter results in a complex interaction of variables used in the calculations. A number of benchmark comparisons of the various training algorithms are needed in order to choose the best-suited algorithm for obtaining a good performance on the laborious interactive and nonlinear problems. In general, the LMA will have the fastest convergence on combinatorial function approximation (or nonlinear regression) problems [18].

Since ANN-based models contain no preconceptions regarding what the model shape will be, they are ideal for cases with low system knowledge. They are useful for functional prediction and system modeling where the physical processes are not understood or are highly complex. Consequently, it is believed that ANN-based techniques, which have recently been applied to various environmental problems, may provide a good alternative to statistical and theoretical techniques, as well as to iterative problems, because of their speed and capability of learning, robustness, nonlinear characteristics, non-parametric regression capabilities, generalization properties, and ease of working with regards to high-dimensional data.

2.2 Fuzzy logic methodology

The fuzzy logic system based on linguistic expressions includes uncertainty rather than numerical probabilistic, statistical, or perturbation approaches. Fuzzy set theory [20] was introduced to provide a definition for uncertainties caused by imprecision and vagueness present in real-world applications [21,22]. Rihani et al. [23] reported that fuzzy logic has recently become a useful tool for modeling highly complex systems whose behaviors are not well understood. Considering the complex qualitative relationships among the variables in an environmental system, the fuzzy logic methodology has the advantage of the relatively simple mathematical calculations in linguistic terms instead of complicated equations used in the conventional methods. Since a fuzzy logic-based model does not need to handle tedious empirical formulations and complex mathematical expressions, this technique provides a transparent and a systematic analysis for the interpretation of dynamic behavior of an environmental-based problem by a set of logical connectives [3].

Jantzen [24] reported that a general fuzzy system has basically four components: fuzzification, fuzzy rule base, fuzzy output engine, and defuzzification. In fuzzification step, numerical inputs and output variables are converted into linguistic terms or some specific adjectives (such as low, high, big, small, etc.), and the corresponding degrees of the one or more several membership functions are determined [25]. Since multiple measured crisp inputs first have to be mapped into the specific fuzzy membership functions, Sozen et al. [26] reported that the fuzzification process requires good understanding of all the variables.

Fuzzy rule base contains some rules that include all possible fuzzy relations between inputs and outputs. In fuzzy set theory, there are no mathematical equations and model parameters, and therefore, all the uncertainties, non-linear relationships, and model complications are included in the descriptive fuzzy inference procedure in the form of IF–THEN statements [27]. The fuzzy inference engine takes into account all the predefined fuzzy rules in the fuzzy rule base and learns how to transform a set of inputs to corresponding outputs [27]. In this step, two kinds of inference operators, minimization (min) and product (prod), are basically performed in collection of all the relations among inputs and outputs fuzzy sets in the fuzzy rule base [3,2,28]. Since decision is based on all of the rules in the fuzzy inference system, the rules must be combined in order to make the decision. Aggregation is the process by which the fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set. The input of the aggregation process is the list of fuzzy sets that represent the outputs of each rule. The output of the aggregation process is a fuzzy set. There are a number of different aggregation methods available, such as: maximum (*max*), sum of the each rule's output set (*sum*), and the probabilistic OR (*probor*) method. The nature of the information retrieval dictates that the determination of the ranking should be done based on all of the rules. In general, the sum aggregation method appears to be a much better fit [29]. Altunkaynak et al. [25] reported that fuzzy inference part, the second phase of the fuzzy logic controller, includes many fuzzy conditional statements derived from the knowledge of an expert and/or available literature. In this phase, fuzzy rule base stores the knowledge and rules expressed in the IF–THEN format for deriving the outputs [28]. Moreover, the data base contains descriptions of the input and output variables, and the decision making logic evaluates the control rules [30]. Since the objective of fuzzy logic is to explain the relationships between input and output variables (or actions and conclusions) and then estimates the parameters of the model, therefore, some implications are needed to be defined in the form of IF–THEN (IF premise THEN consequent) logical statements, called rules [23,31]. Instead of a definition for the developed fuzzy set categories, such as moderately low, low, moderate, moderately high, high, etc., the membership functions can be defined as A, B, C, D, E, etc., to simplify processing of the rules [3].

In the defuzzification step, linguistic results obtained from the fuzzy inference are translated into a crisp numerical output (real value) by using the rule base provided [28,30]. In the literature, several defuzzification methods, such as centre of gravity (COG or centroid), bisector of area, mean of maxima, leftmost maximum, rightmost maximum, have been reported [24]. It is appearent from several fuzzy logic-based studies [1,3,25,27,29,32] that the centroid method is the most widely used defuzzification technique, since it satisfies the underlying properties of the system and exhibits the best performance. It is determined as follows [1,3,26,27]:

$$(y_i)_d = \frac{\sum\limits_{i=1}^{n} \mu\left(y_i\right) y_i}{\sum\limits_{i=1}^{n} \mu\left(y_i\right)}, \tag{5}$$

where $(y_i)_d$ is the defuzzified output, y_i is the output value (or the centroidal distance from the origin) in the ith subset, and $\mu(y_i)$ is the membership value of the output value in the ith subset. For the continuous case, the summations in Eq. (5) are replaced by integrals, as given by Sadiq et al. [32]. On the basis of above-mentioned fuzzy steps, a detailed schematic of a sample MISO (multiple inputs and single output) fuzzy system is depicted in Fig. 2.

The situations of uncertainties in fuzzy-logic are defined via giving appropriate membership functions to the elements of the set that represent the situation. The value of the variation between 0 and 1 (the highest level) for each element is called membership degree and its value in subset is called membership function [33]. In fuzzy models, the shape of membership functions of fuzzy sets can be triangular, trapezoidal, bell-shaped, sigmoidal, or another appropriate form, depending on the nature of the system being studied [31,34]. Among them, triangular and trapezoidal shaped membership functions are predominant in current applications of the fuzzy set theory, due to their simplicity in both design and implementation based on little information [3,23]. A schematic overview of the trapezoidal-based membership function is given in Fig. 2. The trapezoidal curve is the membership function of a vector, x, and depends on four scalar parameters, a, b, c, d, as follows [1,3,25,26,35]:

$$\mu\left(x\right) = \mu\left(x; a, b, c, d\right) = \left\{ \begin{array}{c} 0,\ x \le a \\ \frac{x-a}{b-a},\ a \le x \le b \\ 1,\ b \le x \le c \\ \frac{d-x}{d-c},\ c \le x \le d \\ 0,\ d \le x \end{array} \right\}. \tag{6}$$

In the applications of the fuzzy system in both control and forecasting, there are two types of fuzzy inference systems, namely, Mamdani-type [36] and Takagi-

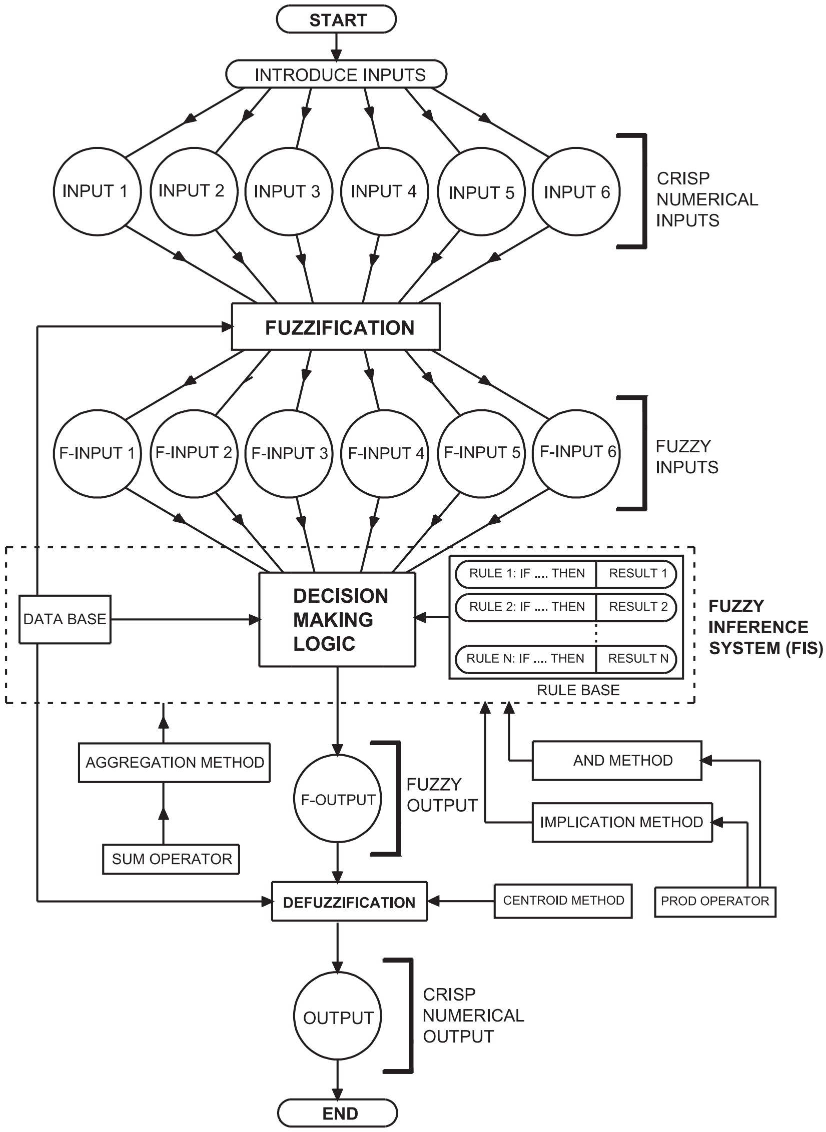

Fig. 2 *A detailed schematic of a sample MISO fuzzy system (adapted from Yetilmezsoy et al. [3]).*

Sugeno-type [37] fuzzy systems [23,38,39]. Sadrzadeh et al. [39] reported that each IF–THEN rule produces a fuzzy set for the output variable in the Mamdani approach, and hence defuzzification step is indispensable to obtain crisp values of the output variable. Because of allowing a simplified representation and interpretation of the fuzzy rules, Mamdani's fuzzy inference method is the most commonly applied fuzzy methodology [1,3,27,31,35,40].

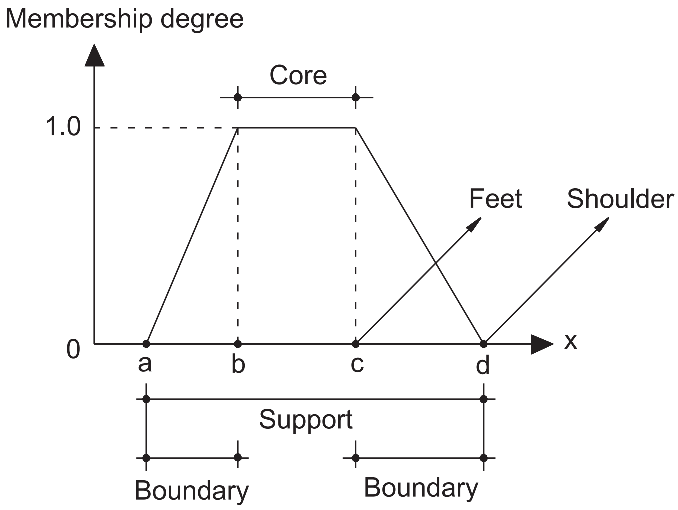

Fig. 3 *A schematic overview of the trapezoidal-based membership function.*

2.3 Adaptive neuro-fuzzy inference systems (ANFIS)

The ANN-based methods have been successfully used in various disciplines for modeling, however, the lack of interpretation is one of the major drawbacks of their utilization. Wieland et al. [12] reported that one of the major shortcomings of ANNs is that they do not reveal causal relationships between major system components and thus are unable to improve the explicit knowledge of the user. Another problem is due to the fact that reasoning is only done from the inputs to the outputs. In cases where the opposite is requested (i.e., deriving inputs leading to a given output), neural networks can hardly be used. There are also some basic aspects of fuzzy inference system that are in need of better understanding [41]. In order to overcome the problematic combinations of ANNs and fuzzy systems, a new system combining ANN and the fuzzy system, called the adaptive network-based fuzzy inference system, was proposed by Jang [41]. However, even before Jang [41] published his paper, Lin and Lee [42] and Wang and Mendel [43] had already published their respective works on adaptive neuro-fuzzy inference systems. Jang and Sun [44] expressed that adaptive neuro-fuzzy inference systems and the adaptive network-based fuzzy inference systems have the same aim. Therefore, they used adaptive neuro-fuzzy inference systems (ANFIS) to stand for adaptive network-based fuzzy inference systems.

Operation of the ANFIS looks like FFBP network. Consequent parameters are calculated forward while premise parameters are calculated backward [45]. The ANFIS is composed of two parts, antecedent and conclusion, which are connected to each other by fuzzy rules based on the network form. There are two learning methods in neural section of the system: Hybrid learning method and BP learning method. In fuzzy section, only zero or first order Sugeno inference system or Tsukamoto inference system can be used, and output variables are obtained by applying fuzzy rules to fuzzy sets of input variables [37,41,45,46]:

$$\text{Rule 1: } If\ x\ is\ A_1\ and\ y\ is\ B_1,\ then\ f_1 = p_1 x + q_1 y + r_1 \tag{7}$$

$$\text{Rule 2: } If\ x\ is\ A_2\ and\ y\ is\ B_2,\ then\ f_2 = p_2 x + q_2 y + r_2, \tag{8}$$

where p_1, p_2, q_1 and q_2, are linear parameters, and A_1, A_2, B_1 and B_2 nonlinear parameters. The first-order Sugeno FIS (type-3 fuzzy reasoning) is depicted in Fig. 4a, and the corresponding equivalent ANFIS architecture (type-3 ANFIS) is illustrated in Fig. 4b. The corresponding equivalent ANFIS architecture consists of five layers, namely, a fuzzy layer, a product layer, a normalized layer, a defuzzy layer and a total output layer.

As shown in Fig. 4b, each node in the ANFIS architecture is characterized by a node function with fixed or adjustable parameters. Model parameters values are determined through the learning or training phase of a neural network, while model performance is evaluated by the sufficiently fitted training and testing data. Moreover, model performance evaluates error values, such as root mean square error (RMSE), which are, in turn, minimized by back-propagation and the hybrid learning algorithms allowed by ANFIS. As shown through the ANFIS architecture, nodes found in the same layer have similar functions. The following sections discuss the relationship between the output and input of each layer in the ANFIS.

As seen in Fig. 4b, Layer 1 is *the fuzzy layer*, in which x and y are the input of nodes A_1, A_2, B_1 and B_2, respectively. A_1, A_2, B_1 and B_2 are the linguistic labels used in the fuzzy theory for dividing the membership functions. Parameters in this layer are referred to as premise parameters. Every node i in Layer 1 is an adaptive node with a specific function. Nodes in Layer 1 implement fuzzy membership functions, mapping input variables to corresponding fuzzy membership values. The membership relationship between the output and input functions of this layer can be expressed as [47]:

$$Q_{1,i} = \mu_{A_i}(x)\text{, for i = 1, 2 or,} \tag{9}$$

$$Q_{1,i} = \mu_{B_i}(y)\text{, for i = 1, 2,} \tag{10}$$

where x or y is the input to node i, and A_i or B_i is the linguistic label (such as small, large, etc.) associated with this node function, $Q_{1,i}$ denotes the output functions, and $\mu_{Ai}(x)$ or $\mu_{Bi}(y)$ usually denotes the bell-shaped membership functions with a maximum equal to 1 and a minimum equal to 0, such as [41]:

$$\mu_{A_i}(x) = \frac{1}{1 + \left[\left(\frac{x-c_i}{a_i}\right)^2\right] b_i} \tag{11}$$

or

$$\mu_{A_i}(x) = \exp\left[-\left(\frac{x-c_i}{a_i}\right)^2\right], \tag{12}$$

where (a_i, b_i and c_i) is the parameter set. As the values of these parameters change, the bell-shaped functions vary accordingly, thus exhibiting various forms of membership functions on linguistic label, $A_{i.}$ In fact, any continuous and piecewise differentiable functions, such as commonly used trapezoidal and triangular-shaped membership functions, are also be used as node functions in this layer [41].

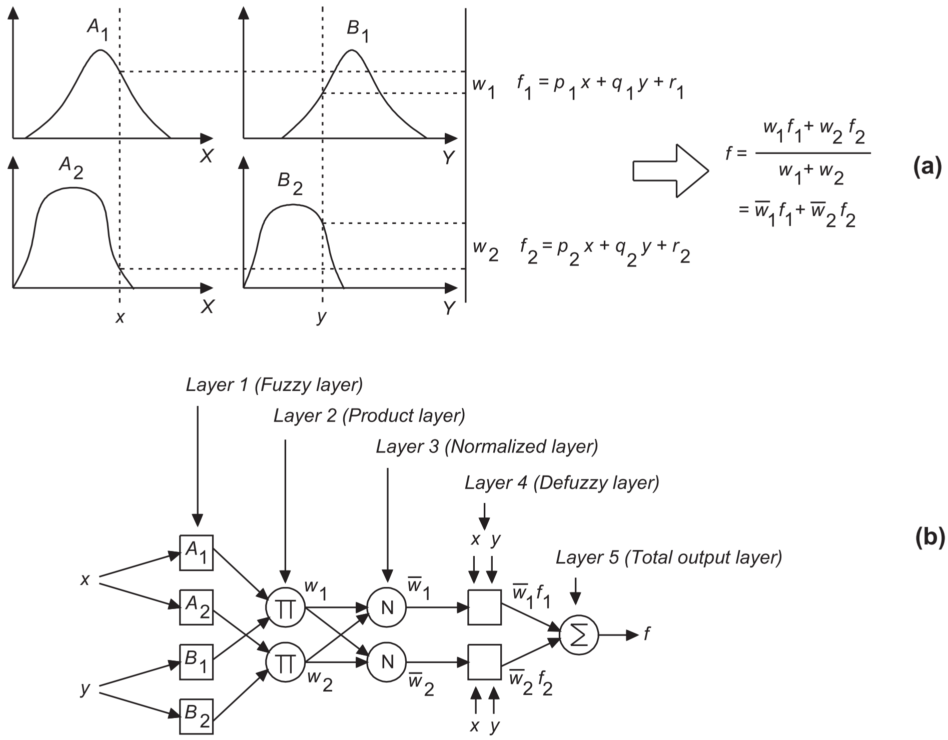

Fig. 4 *(a) The first-order Sugeno FIS (type-3 fuzzy reasoning) and (b) equivalent ANFIS architecture (type-3 ANFIS) (adapted from Jang [41]).*

Layer 2 is *the product layer* that consists of two fixed circle nodes labeled π, which multiply the incoming signals and provide the outputs of the product. The output w_1 and w_2 are the weight functions of the next layer. The output of this layer is the product of the input signal, which is defined as follows [41,47]:

$$Q_{2,i} = w_i = \mu_{A_i}(x)\,\mu_{B_i}(y)\,, \text{ for i = 1, 2,} \tag{13}$$

where $Q_{2,i}$ denotes the output of Layer 2. Each node output represents the firing strength of a rule [41].

The third layer is *the normalized layer* whose nodes are labeled N. The ith node calculates the ratio of the ith rules firing strength to the sum of all rule's firing strengths. Its function is to normalize the weight function in the following process [41,47]:

$$Q_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, \text{ for i = 1, 2,} \tag{14}$$

where $Q_{3,i}$ denotes the output of Layer 3. The outputs of this layer are called *normalized firing strengths.*

The fourth layer is *the defuzzy layer* whose nodes are adaptive. Every node i in this layer is an adaptive node with a specific function. The output equation is

$\overline{w_i}\,(p_i x + q_i y + r_i)$, where p_i, q_i and r_i denote the linear parameters or so-called *consequent parameters* of the node. The defuzzy relationship between the input and output of this layer can be defined as follows [41,47]:

$$Q_{4,i} = \overline{w_i} f_i = \overline{w_i}\,(p_i x + q_i y + r_i)\,, \tag{15}$$

where $Q_{4,i}$ denotes the output of Layer 4.

The fifth layer is *the total output layer* whose node is labeled Σ. The output of this layer is the total of the input signals, which represents the vehicle shift decision result. The results can be written as [41,47]:

$$Q_{5,i} = overall\ output = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, \tag{16}$$

where $Q_{5,i}$ denotes the output of Layer 5.

Although ANN and fuzzy logic models are the basic areas of artificial intelligence concept, the ANFIS combines these two methods and uses the advantages of both methods. Since the ANFIS is an adaptive network which permits the usage of ANN topology together with fuzzy logic, it includes the characteristics of both methods and also eliminates some disadvantages of their lonely-used case. Therefore, this technique is capable of handling complex and nonlinear problems. Even if the targets are not given, the ANFIS may reach the optimum result rapidly. In addition, there is no vagueness in ANFIS as opposed to ANNs [45,48]. Moreover, the learning duration of ANFIS is very short compared to ANN-based models. It implies that ANFIS may reach to the target faster than ANN. Therefore, when a more sophisticated system with a high-dimensional data is implemented, the use of ANFIS instead of ANN would be more appropriate to overcome faster the complexity of the problem [45].

In the ANFIS structure, the implication of the errors is different from that of the ANN case. In order to find the optimal result, the epoch size is not limited. In training high-dimensional data, the ANFIS can give results with the minimum total error compared to ANN and fuzzy logic methods. Moreover, fuzzy logic method seems to be the worst in contrast to others at a first look, since the rule size is limited and the number of membership functions of fuzzy sets were chosen according to the intuitions of the expert. However, if different types of membership functions and their combinations had been tested and more membership variables and more rules had been used to enhance the prediction performance of the proposed diagnosis system, better results would have been available [1,45].

3. Modeling Applications in Environmental Engineering

In this section, recent applications of AI-based prediction models in the field of environmental engineering are examined in terms of solid waste management, water/wastewater treatment and air pollution related problems, and the important findings obtained in these studies are summarized.

3.1 Waste management

Municipal solid waste management systems require accurate prediction of waste generation for proper planning and design. However, predicting the amount of generated waste is difficult because of various fluctuating parameters. In a study, the hybrid of wavelet transform-adaptive neuro-fuzzy inference system and wavelet transform-artificial neural network was used to predict the weekly generation of waste [49]. In another study, Zade and Noori [50] proposed an appropriate model for predicting the weight of waste generation in Mashhad with a feed-forward artificial neural network. In a recent study, Jahandideh et al. [51] used two predictor models, the ANN and multiple linear regression, to predict the total rate of medical waste generation and classify them as sharp, infectious, or general. Srivastava and Nema [52] used the fuzzy system to forecast the solid waste composition of Delhi, India between 2007 and 2024. Similar studies on waste management have been carried out in recent years [53–55].

3.2 Water and wastewater treatment

Yabunaka et al. [56] conducted studies on a novel application of a BP-ANN model for the prediction of algal bloom in Lake Kasumigaura, Japan. They concluded that the ANN model achieved a reasonable effectiveness with respect to learning the relationship between the set of selected water quality parameters and algal bloom. Karul et al. [57] used a three-layer Levenberg-Marquardt feed-forward learning algorithm to model the eutrophication process in three water bodies in Keban Dam Reservoir, Mogan, and Eymir Lakes of Turkey. Despite the very complex and extraordinary nature of Keban Dam Reservoir, they observed a relatively good correlation coefficient between the measured and predicted values. For Mogan and Eymir Lakes, predictions between the measured and ANN outputs proved to be satisfactory, with a maximum correlation coefficient of approximately 0.95. They emphasized that the ANN-based models were able to model nonlinear behavior in eutrophication process reasonably well. In addition, the models could successfully estimate some extreme values from validation and test data sets that were not used in training the ANN. Hamed et al. [11] developed two ANN-based models to predict the performance of a wastewater treatment plant (WWTP) in the Greater Cairo district, Egypt, with an average flow rate of 1 million m^3/day. They obtained daily records of biochemical oxygen demand (BOD) and suspended solids (SS) concentrations from the plant laboratory through various stages of the treatment process over 10 months. The authors concluded that the ANN-based models proved to be an efficient and robust tool in predicting WWTP performance. In another study, Onkal-Engin et al. [58] used an ANN trained with a BP algorithm to determine the relationship between sewage sample odors and related BOD values. They reported that the proposed ANN model could successfully classify the sewage samples collected from different locations of a WWTP.

Another ANN-based modeling study was undertaken by Yetilmezsoy and Sapci-Zengin [15] to predict chemical oxygen demand removal efficiency (CODRE) of up-flow anaerobic sludge blanket (UASB) reactors treating diluted real cotton textile wastewater. In the study, a three-layer ANN model (9:12:1) with tangent sigmoid transfer function (*tansig*) at a hidden layer with 12 neurons and a linear transfer function (*purelin*) at output layer was proposed to forecast CODRE values. Results showed that the ANN model predicted precise and effective CODRE values with a saticfactory correlation coefficient of approximately 0.83 for nine different process parameters. Moreover, Yetilmezsoy and Demirel [13] developed a three-layer ANN model (5:11:1) for modeling Pb(II) adsorption from aqueous solution by Antep pistachio (*Pistacia Vera* L.) shells. After BP training combined with principal component analysis (PCA), the proposed ANN model was able to predict adsorption efficiency, and the linear regression between the network outputs and the corresponding targets were proven satisfactory with a correlation coefficient of approximately 0.94 for the five model variables used in the study. In another study, Karaca and Ozkaya [59] developed an ANN-based model, namely Neural Networks-Leachate Production (NN-LEAP), for controlling daily leachate flowrate in a municipal solid waste (MSW) landfill site. They predicted daily leachate flow rates in the MSW landfill area, with a correlation coefficient of approximately 0.95 and a mean squared error (MSE) of 0.00168. The authors concluded that the proposed ANN model could provide an effective prediction of daily leachate discharges and showed reliable and fast outputs in controlling and management of the flow rate levels in the MSW landfill area. Al-Mutari et al. [60] utilized ANN-based models to investigate the relationships between the effluent biological activity of a contact stabilization process (Hawalli WWTP, Kuwait) and microfauna community distribution by using BP and general regression algorithms. In the study, the microfauna distribution data of a contact stabilization process were used in an ANN system to model and predict the biological activity of the effluent. The authors optimized the architecture of the back-propagation neural network (BPNN) model in four steps. In the optimization study, six different ANN architectures were trained to find the optimum architecture for the BPNN model. The study concluded that the genetic adaptive general regression neural network (GRNN) model could be used as a powerful and simple tool for the modeling process.

In a recent study, Ozkaya et al. [61] presented an ANN model for predicting the methane fraction in landfill gas originating from field-scale landfill bioreactors constructed at the Odayeri Sanitary Landfill, Istanbul, Turkey. The authors reported that the proposed ANN model performed remarkably ($R = 0.96$) by predicting the methane fraction from the MSW and an understanding of the simultaneous effects on multiple factors. In another study, Ozkaya et al. [62] used a popular ANN-BP algorithm for modeling the performance of a biological Fe^{2+} oxidizing fluidized bed reactor (FBR) and control of Fe^{3+} recycle during heap bioleaching. The study concluded that the proposed ANN approach provided an excellent match between the measured and the predicted concentrations. More recently, Sahinkaya [63] conducted studies on ANN modeling of zinc recovering in sulfidogenic completely stirred tank reactor (CSTR) for five input variables (feed pH, feed SO_4^{2-}, feed Zn, feed chemical oxygen demand (COD), and operating time) and four output variables (effluent SO_4^{2-}, effluent COD, effluent acetate, and effluent Zn). Results indicated that the developed ANN model showed a satisfactory match between the measured and the predicted concentrations of sulfate ($R = 0.998$), COD ($R = 0.993$), acetate ($R = 0.976$), and zinc ($R = 0.827$) in the CSTR effluent. Apart from the above-mentioned studies, several other successful ANN modeling studies [64–69] have recently been conducted, specifically in various parts of the field of wastewater engineering.

In addition to ANN modeling studies, several ANFIS-based models have recently been proposed to evaluate and optimize various wastewater treatment processes. For a real-scale anaerobic WWTP operating under unsteady state conditions, Perendeci et al. [70] proposed a conceptual ANFIS-based using available on-line and off-line operational input variables to estimate the effluent COD. The study concluded that the developed ANFIS model with phase vector and history extension successfully represented the behavior of the considered treatment system. In another study, Civelekoglu et al. [71] employed ANFIS-based models for the prediction of carbon and nitrogen removal in the aerobic biological treatment stage of a full-scale WWTP treating process wastewaters from the sugar production industry. In the study, a total of six independent ANFIS models were developed with or without PCA using the correlations among the influent and effluent data from the plant. With the use of PCA, results showed that the ANFIS modeling approach could be an effective advanced technique for performance prediction and control of treatment processes. Moreover, Cakmakci [6] used an ANFIS-based technique for modeling anaerobic digestion system of primary sludge of the Kayseri WWTP, Turkey. In the study, effluent volatile solid (VS) and methane yield were predicted by the ANFIS model using the routinely measured parameters in the anaerobic digester. The study concluded that due to highly nonlinear structure of the ANFIS model, a highly complex system, such as anaerobic digestion process, could be easily modeled. Furthermore, there have been other computational studies in the literature reporting the implementation of neuro-fuzzy-based models on water and wastewater treatment processes [39,72–74].

ANFIS-based models have recently been used for water treatment process. Chun et al. [75] used an ANFIS-based model to optimize coagulant dosage used for turbidity removal in a water treatment plant. They obtained a better performance than in their previous works using ANN. Similar to Chun et al. [75], ANN and ANFIS models were used by Wu and Lo [76] to model polyaluminum chloride (PAC) dosing of the surface water of Northern Taiwan. They obtained results similar to those of Chun et al. [75], indicating that the self-predicting model of ANFIS is better than the ANN model for PAC dosage predictions.

Filter head loss was estimated by Cakmakci et al. [77] using this ANFIS model. In their study, rule base sets were generated with subtractive clustering and grid partition. They determined that using a grid partition for modeling was superior to that of subtractive clustering. The RMSE values of training, testing, and checking at the optimum rule base set were of the same order of magnitude. The correlation coefficients were greater than 0.99 in both tap and deionized water. Therefore, filter iron removal rate was also modeled by Cakmakci et al. [78]. They obtained best results for tap and deionized water with grid partition and subtractive clustering. Model results were evaluated by index of agreement (IA). The IA values for tap water was 0.996 and 0.971. The IA of the output values expressed as follows [78]:

$$\mathrm{IA} = 1 - \frac{\sum_{i=1}^{N} (O_i - P_i)^2}{\sum_{i=1}^{N} (|O_i - O_m| + |P_i - O_m|)^2}, \tag{17}$$

where O_i is observed and P_i is predicted value, O_m and P_m represents the average value of observed and predicted values, and RMSE represents the differences between observed and predicted data. IA varies between 0 and 1.0, representing perfect agreement between observed and predicted values.

Autoregressive integrated moving average (ARIMA) and Takagi-Sugeno (TS) fuzzy methods were used by Altunkaynak et al. [25] for predicting future monthly water consumption values from three antecedent water consumption amounts, considered as independent variables. The TS fuzzy predicted results better than the ARIMA. Firat et al. [79] compared two types of FIS for predicting municipal water consumption time series. Their results demonstrated that the ANFIS model is superior to Mamdani fuzzy inference systems (MFIS). An ANFIS-based model was used by Firat and Gungor [80] to estimate the flow of River Great Menderes, located in western Turkey. As a result, they discovered that ANFIS could be successfully applied for river flow estimation, providing high accuracy and reliability. Finally, a principal component analysis-adaptive neuro-fuzzy inference systems (PC-ANFISs) method was used by Goodarzi et al. [81] for the analysis of ternary mixtures of Al(III), Co(II) and Ni(II) over the range of 0.05–0.90, 0.05–4.05, and 0.05–0.95 g/mL, respectively. As a result, the method accurately and simultaneously determined the content of metal ions in several synthetic mixtures.

It has become apparent from the literature that artificial intelligence-based prediction models, such as ANN and neuro-fuzzy techniques, can be successfully implemented as complementary technologies in actual applications of water and wastewater treatment processes. The applicability of these models is very simple, posing no need to identify nonlinear relationships between multiple variables and define the complex biochemical reactions in the water and wastewater media.

3.3 Air pollution

Air pollution has become one of the most critical environmental issues in the last decade in many parts of the world. As a result of population growth, rapid industrialization, high density of vehicle traffic, domestic heating, electricity production, antropogenic activities, and natural sources, the quality of life has deteriorated in many urban regions due to high level of various toxic air pollutants [18,82]. In particular, increasing concentrations of these pollutants in limited areas constitute severe acute and chronic health problems such as respiratory illnesses, cardiovascular diseases, bronchospasm, pulmonary edema, pneumonitis, acute bronchitis diseases, and lung cancer [83–86]. In recent years, it has become more important to struggle with this specific environmental problem due to its detrimental effects on public health.

In order to curb the increasing deterioration of ambient air quality, urgent risk assessment and proper risk management tools are needed to ensure a robust and resilient control of high pollution levels. However, in practice, monitoring all process parameters for various operating conditions is difficult due to the complex and nonlinear nature of air pollution-based problems. For this purpose, mathematical models have become essential tools in both design and operation when working with high dimensional data. To undertake these tasks, proper air pollution models are needed to develop warning and control strategies, as well as to investigate future emission scenarios [87]. Akkoyunlu et al. [18] reported that better control of air pollution may be achieved by the use of robust and reliable computational approaches, such as artificial intelligence-based models, to predict certain key parameters, as well as to capture the existing nonlinear relationships between multi-input and -output variables in a complex system.

In the past decade, it has become apparent that ANN-based prediction models have been effectively conducted on a substantial number of research activities in the field of air pollution engineering. In these investigations, several authors have developed different types of ANN models, and the results have been compared with the forecasts obtained using multiple regression models. For instance, Yetilmezsoy [88] proposed an ANN model and a new empirical model to determine optimum body diameter (OBD) of air cyclones for 505 different artificial scenarios given in a wide range of five operating variables, namely, gas flow rate, particle density, temperature, and two design parameters, namely, K_a and K_b, selected in the cyclone design. The study concluded that maximum diameter deviations from the well-known Kalen and Zenz's model were recorded as 1.3 cm and 0.0022 cm for the empirical model and ANN outputs, respectively. Although both approaches produced promising results, the ANN model exhibited speed and practicality, as well as a more robust and superior performance in the prediction of OBD values. In another study [19], an ANN-based approach and nonlinear regression analysis were performed for the determination of single droplet collection efficiency (SDCE) of countercurrent spray towers. The authors reported that predicted results obtained from the nonlinear regression analysis and the ANN model were in agreement with the theoretical data, and that all predictions proved to be satisfactory with a correlation coefficient of approximately 0.921 and 0.99, respectively. The study concluded that the development of a new mathematical model and the creation of an ANN-based model for the prediction of SDCE of countercurrent spray towers eliminated complex interactions of variables and difficult iterative calculations typically performed in the theoretical approach.

Agirre-Basurko et al. [14] developed two multilayer perceptron (MLP)-based models and one multiple linear regression-based model to forecast ozone (O_3) and nitrogen dioxide (NO_2) levels in Bilbao, Spain. In their study, traffic variables were used as predictor variables in the developed models. Results indicated the MLP-based models showed remarkably better performance than the multiple linear regression model in predicting pollutant concentrations. There have also been other studies [12,89–93] on the prediction of tropospheric and surface O_3 concentrations reporting the advantages and adaptability properties of artificial intelligence-based models. Moreover, the use of ANN allows the prediction of daily and/or hourly particulate matter ($PM_{2.5}$ and PM_{10}) emissions [94–97] in many urban and residential areas. ANN-based models have also been used in the prediction of urban and ground-level SO_2 concentrations, demonstrating successful results when considering the complex and nonlinear structure of the atmosphere [18,98,99]. In a recent study, Nunnari et al. [100] modeled SO_2 concentration at a point by intercomparing several stochastic techniques, such as ANN, fuzzy logic, and generalized additive techniques. Because the ANN models worked better in the prediction of critical episodes, they recommended the ANN approach for the implementation of a warning system for air quality control.

More recently, several adaptive neuro-fuzzy techniques emerging from the fusion of ANN and FIS have successfully found application in various areas of air pollution control. For instance, Yildirim and Bayramoglu [82] used an adaptive neuro-fuzzy logic method to estimate the impact of meteorological factors on SO_2 and total suspended particular matter (TSP) pollution levels over the city of Zonguldak, Turkey. The study concluded that the proposed ANFIS model satisfactorily forecast the trends in SO_2 and TSP concentration levels, with performance levels between 75–90% and 69–80%, respectively. An artificial intelligence-based modeling approach was also conducted in a recent study by Noori et al. [101] to predict daily carbon monoxide (CO) concentration in the atmosphere of Tehran, Iran, by means of developed ANN and ANFIS models. In the study, forward selection (FS) and gamma test (GT) methods were implemented for selecting input variables and developing hybrid models with ANN and ANFIS. The authors concluded that FS-ANN and FS-ANFIS models were the best models, considering R^2, mean absolute error, and developed discrepancy ratio statistics, for predicting pollution episodes. In another study, Carnevale et al. [102] applied neuro-fuzzy and ANN systems to control ozone and PM_{10} concentrations in northern Italy. The study concluded that the selected source-receptor models were proven effective for the evaluation of both the impact of emission reduction strategies on pollution indices and the costs of such emission reductions.

Although the dispersion and transport of mechanisms of atmospheric pollutants under several meteorological conditions are very complicated, a number of attempts in developing prediction models can help to develop a continuous strategy for air pollution control [18]. If properly designed and evaluated, the artificial intelligence-based air pollution models could play a considerable role in planning strategies for a proper management of air quality and provide a rational basis for the control of air pollution [82]. Consequently, based on the literature review, it can be concluded that artificial intelligence-based models have provided better results compared to conventional linear/nonlinear regression methods due to their ability to precisely discriminate the arbitrary nonlinear functional relationship between input and output data sets. Apart from the above-mentioned studies described separately herein, several other successful attempts to model various complex real-life processes using AI-based techniques can also be found in the recent literature [103–110].

4. Conclusions

In this study, recent applications of the widely used AI-based prediction models, such as ANN, fuzzy logic and ANFIS, are specifically investigated for the real-life problems of the environmental engineering field. This study includes a series of straightforward, yet complex, problems, such as waste management, water and wastewater treatment, and air pollution, that illustrate how AI-based prediction models can be used in solving environmental engineering problems, and provides the necessary tools to get started using these elegant and efficient new techniques. These techniques serve as a modern paradigm for computing complex natural processes with the power and basic principles of the prediction modeling, together with simulated biological and environmental data sets and real applications in the field.

Although the AI-based prediction models can provide enormous capability and flexibility on forecasting of various environmental variables, the present survey concluded that verification and validation of the proposed models using various descriptive statistics have been addressed only in a very small number of studies in the literature. Measuring the goodness of the estimate is an important part of model development, and it can be achieved by visual and numerical methods. It is noted that visual methods make it possible to get an intuitive hold of the model performance, however, numerical methods provide a more robust ground for comparing and enhancing the models in a scientific way. Therefore, besides coefficient of determination (R^2), we suggest that various statistical performance indicators, such as mean-absolute error (MAE), root mean-square error (RMSE), systematic and unsystematic RMSE (RMSE_S and RMSE_U, respectively), mean-squared error (MSE), index of agreement (IA), mean bias error (MBE), the factor of two (FA2), fractional variance (FV), proportion of systematic error (PSE), Fisher's F-test, p-values, t-statistics, standard error of estimate, coefficient of variation (CV), Durbin–Watson statistic, adjusted determination coefficient (R_a^2), intercept and slope of the adjusted line between observed and predicted values, Mallow's Cp statistic, chi-square (χ^2) test, and suitable parametric or non-parametric tests, etc. must also be used as helpful tools to describe model's prediction performance and the error, and to express the significance of the proposed model.

From the viewpoint of environmental engineering, most AI-based prediction models are conducted for the solution of water/wastewater and air pollution related environmental problems compared to waste management applications. Considering the predictive capability and non-linear characteristic of the AI-based approach, additional modeling studies are needed for various complex problems in the field of waste management, particularly in developing countries. Moreover, results indicated that most of the studies had used only one type of modeling technique. Since the applicability of AI-based models is simple and there is no need to define the complex reactions and their mathematical or biochemical equations, it is suggested that different AI-based models must be conducted simultaneously to find the most appropriate model structure for the solution of a specific environmental problem.

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