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Application of artificial intelligence to wastewater treatment: A bibliometric analysis and systematic review of technology, economy, management, and wastewater reuse

Lin Zhao[a,1], Tianjiao Dai[a,1], Zhi Qiao[a,b], Peizhe Sun[a], Jianye Hao[c], Yongkui Yang[a,d,*]

[a] School of Environmental Science and Engineering, Tianjin University, Tianjin 300350, China
[b] Department of Earth and Environment, Boston University, Boston, MA, USA
[c] College of Intelligence and Computing, Tianjin University, Tianjin 300350, China
[d] China-Singapore Joint Center for Sustainable Water Management, Tianjin University, Tianjin 300350, China

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ABSTRACT

Wastewater treatment is an important step for pollutant reduction and the promotion of water environment quality. The complexity of natural conditions, influent shock, and wastewater treatment technology result in uncertainty and variation in the wastewater treatment system. These uncertainties result in fluctuations in effluent water quality and operation costs, as well as the environmental risk of receiving waters. Artificial intelligence has become a powerful tool for minimizing the complexities and complications in wastewater treatment. In this study, we examine the literature from 1995 to 2019 to conduct a large-scale bibliometric analysis of trends in the application of artificial intelligence technology to wastewater treatment. Furthermore, we present a systematic review of four aspects of the application of artificial intelligence to wastewater treatment: technology, economy, management, and wastewater reuse. Finally, we provide perspectives on the potential future directions of new research frontiers in the utilization of artificial intelligence in wastewater treatment plants that simultaneously address pollutant removal, cost reduction, water reuse, and management challenges in complex practical applications.

Contents

Abbreviation: ABM, agent-based model; AFBR, anaerobic fluidized bed reactor; AI, artificial intelligence; ANFIS, adaptive neuro-fuzzy inference system; ANN, artificial neural network; ARIMA, a linear stochastic model; ARMA, autoregressive moving average; ASP, activated sludge process; BN, Bayesian network; BOD_5, 5-day biochemical oxygen demand; BP, back propagation; BRT, boosted regression tree; CNN, convolution neural network; COD, chemical oxygen demand; DM, data mining; DO, dissolved oxygen; ENN, Elman neural network; EPR, evolutionary polynomial regression; ES, expert system; FF, feedforward control; FFNN, feed-forward neural network; FIS, fuzzy inference system; FL, fuzzy logic; FNN, fuzzy neural network; GA, genetic algorithm; GM, grey dynamic modeling; GWO, grey wolf optimizer; HMMs, hidden Markov models; MAPE, mean absolute percentage error; Mard-RCP, moving average residual difference reconstruction contribution plot; MLP, multilayer perceptron; MNLR, multinomial logistic regression; MOOC, Multi-objective optimal control; MOPSO, Multi-objective particle swarm optimization; MPC, model predictive control; MSE, mean square error; MT, model tree; NF, neural-fuzzy; NNE, neural network ensemble; ORELM, outlier robust extreme learning machine technique; PFA, particle filter algorithm; PSO, particle swarm optimization; R^2, determination coefficient; RsFLC, rough set based fuzzy control system; RSM, response surface method; RBF, radial basis function; RL, reinforcement learning; RMSE, root mean square error; RNN, recurrent neural network; SBR, sequential batch reactor; SCFL, supervisory committee fuzzy logic; SDAE, stack denoising auto encoder; SOM, self-organizing map; SVI, sludge volume index; SVM, support vector machine; VAR, vector autoregression; VFA, volatile fatty acid; VMP, volumetric methane production; WNN, wavelet neural network; WWTP, wastewater treatment plant.

* Corresponding author at: School of Environmental Science and Engineering, Tianjin University, No. 92, Weijin Rd., Nankai Dist., Tianjin, 300350, China.
E-mail address: ykyang@tju.edu.cn (Y. Yang).

[1] These authors contributed equally to this work.

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1. Introduction

Artificial intelligence has produced numerous powerful and practical tools for overcoming difficult problems in various fields and solving complex problems in real-world applications. Many researchers have applied AI technology because of its ease of use, high speed operation, and acceptable accuracy without the need to understand physical issues (Rajaee et al., 2019). In medicine, AI technology is used for disease prevention, diagnosis, and treatment (Basile et al., 2019; Gilvary et al., 2019). In the financial sector, AI is a topic gaining increasing attention (Zhang, 2017) and AI is used to predict the flow of financial capital (Yang et al., 2019). It is used in supply chain risk management to weigh risks and develop contingency plans to strengthen against major shifts in the supply chain and potentially prevent significant losses (Baryannis et al., 2019). AI has been used in a variety of engineering disciplines because of its ability to solve practical problems, such as the wastewater treatment (Al Aani et al., 2019; Antwi et al., 2019a; Fan et al., 2018), water environment quality improvement (Ahmed et al., 2019; Rajaee et al., 2019; Wang et al., 2019), river water quality modelling (Elkiran et al., 2019), water resource recycling (Xu et al., 2019), machine fault diagnosis (St-Onge et al., 2019), and aerospace integrated vehicle health management (Ezhilarasu et al., 2019).

The wastewater treatment is the most important step in aqueous pollutant reduction and water environmental quality promotion. The composition of wastewater is very complex, with influent properties and pollutant concentrations and treated effluent varying greatly across wastewater treatment plants (Long et al., 2019). Wastewater treatment is a complex process affected by several chemical, physical and microbiological factors. Also, the stochastic perturbations and influent variability require operators to conduct appropriate operational controls on the system (Loos et al., 2013; Huang et al., 2009). The complexity of natural phenomena, anthropogenic activities, and wastewater treatment process result in many uncertainties in wastewater treatment systems. Moreover, these uncertainties randomly fluctuate given the amount, quality, and removal efficiencies of wastewater (Long et al., 2019). Modern wastewater treatment plants face increasingly stricter emission restrictions, as well as new energy efficiency and resource recycling regulations(Huang et al., 2015; Mamais et al., 2015; Wan et al., 2011). Researchers have tried to apply AI technology to WWTPs to overcome these problems.

The purpose of this review is to further focus on relevant research directions and clarify key scientific issues in the practical application of AI in wastewater treatment. To the best of our knowledge, this is the first attempt toward the application of bibliometric analysis concerning AI for wastewater treatment. Based on the analysis, this paper further provides a systematic overview of the application of AI in four aspects: technology, economy, management, and wastewater reuse. Finally, we put forward specific suggestions for the research direction in the field of AI for wastewater treatment.

2. Bibliometric and review methods

The term “wastewater treatment AND artificial intelligence” was used to search the Science Citation Index for document titles, abstracts, and keywords published from 1995 to 2019. Recently, bibliometrics has been used as an important method for analyzing and predicting research trends (Zhao et al., 2018). The keyword analysis is among the most effective methods in bibliometrics. The co-word analysis was used to identify popular topics. The open source visualization and exploration software Gephi (version 0.8.2) were used to analyze the keywords in the documents obtained. Trends in the application of AI technology to wastewater treatment could be visualized using the resulting co-word network. In addition, based on our bibliometrics analysis, we conducted a detailed literature review on the application of AI in wastewater treatment, including technological performance, economic cost, management, and wastewater reuse, as well as future research trends.

3. Application and discussion of AI in wastewater treatment

3.1. Research trends and AI classification used in wastewater treatment

In our bibliometric analysis, we found that with the development of AI technology, the number of published articles applying AI to wastewater treatment research was 19 times greater in 2019 than in 1995, and papers had 36 more citations on average (Fig. 1). Several articles has more than 150 citations discussing about the applications of ANN and NF models on the simulating and predicting of the performance of biological WWTP (Côté et al., 1995; Gernaey et al., 2004; Hamed et al., 2004; Loos et al., 2013). Fig. 2 presents information as a co-word network based on the keywords in the literature that is more systematic and comprehensive; its visual characteristics provide a better intuition of the state of the field. The size of each node is proportional to the number of occurrences of the keyword. The relatedness of the keywords is represented by the thickness of the line between the nodes. Research has mainly focused on the application of AI technology to pollutant removal, the economic and energy efficiency of AI technology in its application to wastewater treatment, the contribution of AI technology to the management of wastewater treatment, and AI research on resource extraction and reuse (Fig. 2). Fig. 3 shows that the ANN and FL models are the most widely used methods in single models, and the NF and ANN-GA models are much more frequently used in hybrid models. Compared to that in 2010–2014, the number of application of the single ANN model increased by 0.93 times in

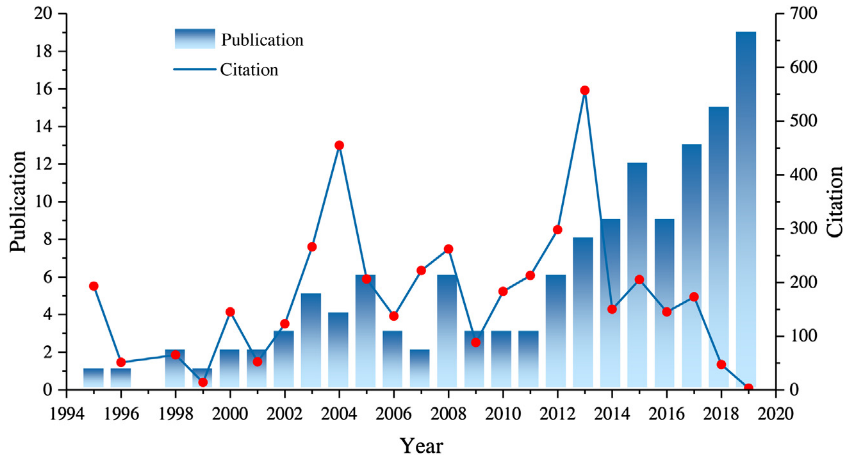

Fig. 1. Publication trends in AI technology applied to wastewater treatment during 1995–2019.

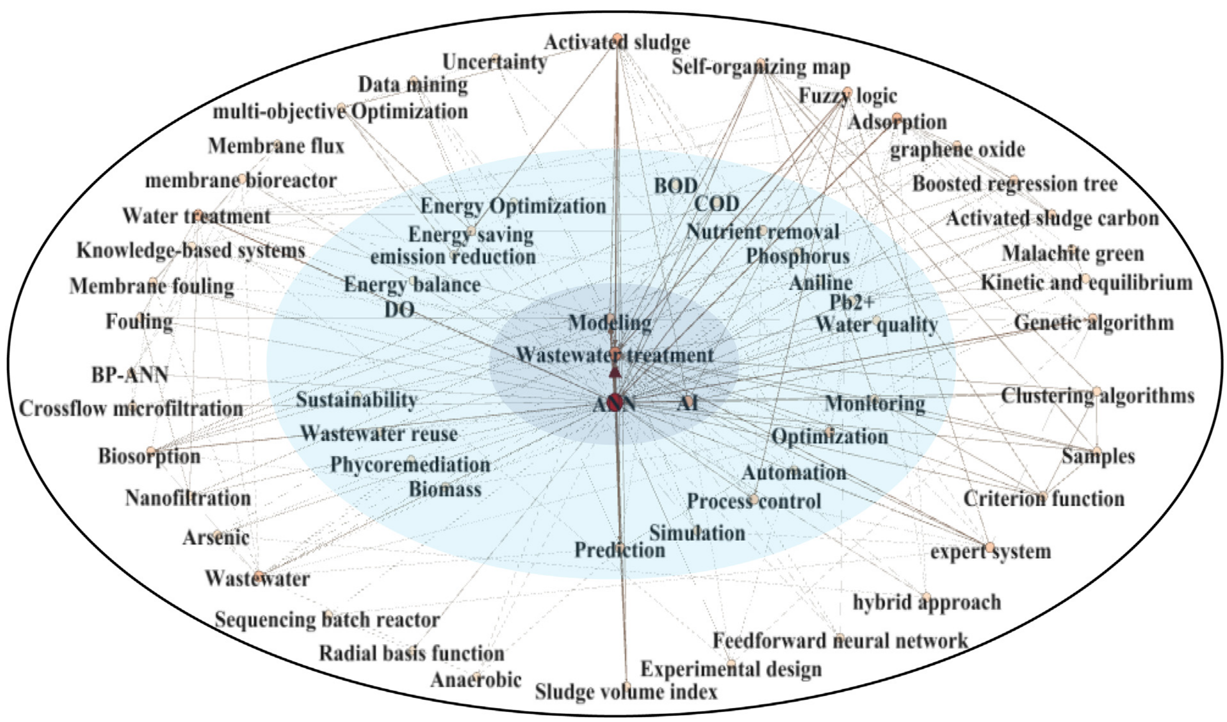

Fig. 2. Co-word network of publications on AI applied to wastewater treatment during 1995–2019.

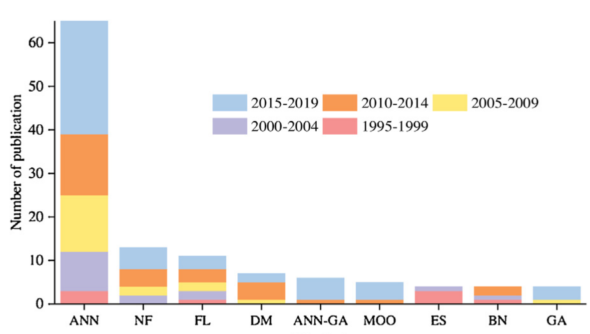

Fig. 3. Frequency and trend of AI techniques applied to wastewater treatment during 1995–2019.

2015–2019. And the number of uses of the hybrid ANN-GA model increased by 4 times in 2015–2019 compared to that in 2010–2014.

The AI technologies involved in wastewater treatment research are classified in Fig. 4; they can be divided into single and combined methods. ANNs are a major AI approach, and modeled on biological neurons (López et al., 2017; Zhang and Pan, 2014). When given an appropriate training algorithm and a right amount of data, ANNs can solve multivariate nonlinear problems (Wang and Deng, 2016). ANNs are also frequently adopted in the experimental designs to remove contaminants during the water/wastewater treatment (Fan et al., 2018). ANNs use highly simplified models composed of many processing elements—artificial neurons—connected by links of variable weight to form black box representations of systems. Each neuron receives input signals from other neurons, processes them, and sends out the output, which in turn is passed on as input to subsequent neurons(Chakraborty et al., 2019). The ANN learns from training data and captures the relationships between data points, which can be used for simulation, prediction, and optimization. ANNs are a type of information processing system that resembles the human brain (Zhang et al., 2019)—they vary from

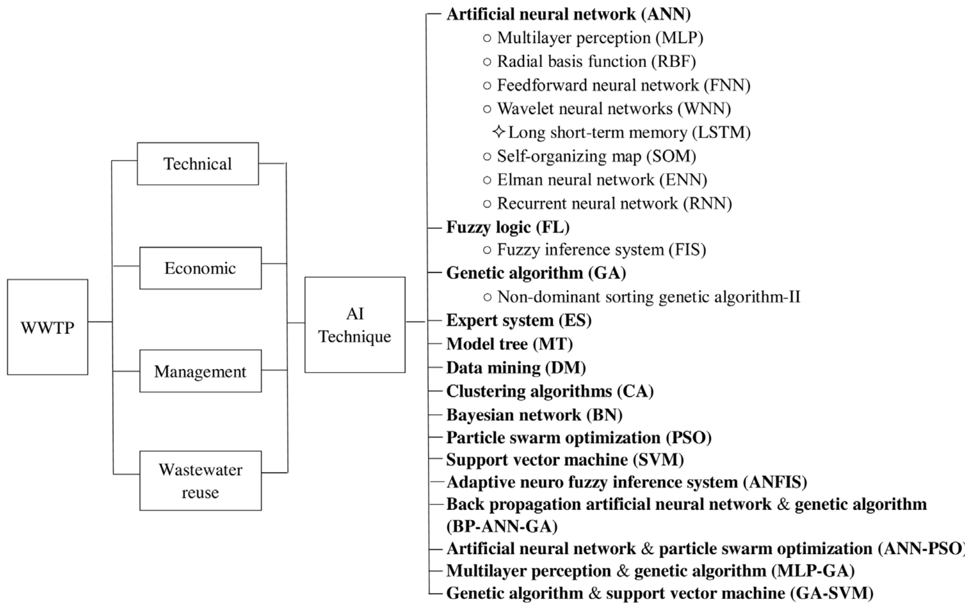

Fig. 4. Classification tree of AI technology used in wastewater treatment.

those with only one or two layers of single direction logic to complex multi-input networks with many directional feedback loops and layers. Several ANNs, such as RBF, MLP, FNN, WNN, SOM, ENN, RNN, and deep learning network, can be used to establish models and simulate wastewater treatment process.

In addition to ANN, FL, GA, and ES are typical single AI technologies. The FL was developed in modeling complex and imprecise systems, which is composed of four components: FIS, fuzzification, defuzzification, and fuzzy rules (Bagheri et al., 2019; Zadeh, 1983). The most widely used is FIS, which consists of four parts: fuzzifier, inference engine, knowledge base, and defuzzifier (Chanapathi and Thatikonda, 2019). GA, an evolutionary algorithm, uses Darwin's theory to model the natural evolutionary process to achieve the minimum or maximum objective function (Al Aani et al., 2019; Chau and wing, 2006). The main principles of applying genetic operators to chromosomal populations are selection, crossover, and variation. In GA, a solution set is represented by a population of strings of individual decision variables that include multiple questions (Adeloye and Dau, 2019). ES, based on the expertise and experience of multiple experts in a particular field, can simulate the decision-making process to solve complex problems (Wagner, 2017).

AI technology also includes some atypical methods, such as MT, DM, clustering algorithm, BN, PSO, and SVM. The MT model can be used to solve continuous class problems by splitting the input into subdomains and applying a linear multivariate regression model to subdomains. It can also obtain a structural representation of the dataset by using a piecewise linear model to approximate a nonlinear relationship (Rahimikhoob, 2014; Sattar et al., 2019). In DM, problems are solved by dividing them into several subproblems (subdomains) and combining the result of these subproblems. Clustering is an unsupervised method of grouping data using a given measure of similarity (Bagheri et al., 2019). The clustering algorithm, a quantitative multivariate statistical analysis, organizes the unclassified feature vectors into clusters according to the principle of aggregation. BN, a Bayesian belief network, is directed acyclic graphs model that includes nodes and directed edges of connected nodes (Graham et al., 2019). Each node stands for a random variable and the conditional probability distribution of association of nodes (Li et al., 2013). The PSO, an evolutionary meta-heuristic algorithm, solves optimization problems by starting from a random solution and looking for the optimal solution through iteration (Qiao et al., 2019). SVM is a generalized linear classifier that solves the binary classification problem based on the optimal separation principle of classes (Sousa et al., 2014). SVMs and related algorithms have developed rapidly for application to the pattern recognition (Lu et al., 2019).

The ANFIS (hybrid of neural & fuzzy methods) has been used with the objective of further improving the performance of ANNs (Mohandes et al., 2011; Potter and Negnevitsky, 2006; Yang et al., 2011). ANFIS uses a hybrid of backpropagation and least-squares algorithms to adjust the premise and conclusion parameters, and can automatically generate "If/Then" rules. ANN-GAs use a GA to iteratively optimize the parameters in the neural network and increase its problem solving power.

3.2. Applications of AI to the technical performance of wastewater treatment

Table 1 summarizes the application of different AI technologies to the removal of pollutants from wastewater.

Most AI techniques were modeled using experimental data to simulate, predict, confirm, and optimize contaminant removal in wastewater treatment processes. Experimental data set were either divided into three parts (training, validation, and testing) or two parts (training and testing). The training set was used to develop the model, the validation data set was used to optimize the model, and the testing data set was used to test the model in the prediction stage. Model performance is the result of the test involving the comparison of the experimental data with the predicted data. As shown in Table 1, the model performance indicates an almost perfect match between the experimental data and the prediction results, based on R^2, RMSE, performance efficiency, accuracy, and integral of the squared error.

3.2.1. Conventional pollutant removal

(1) COD: There are many models for simulating, predicting, and optimizing COD removal in biochemical and physicochemical treatment process of WWTP. Moral et al. studied the ASP at the Iskenderun Wastewater Treatment Plant, also using an ANN model, predicting the effluent COD with a determination coefficient (R^2) of 0.632 (Moral et al., 2008). An ANFIS was developed

Table 1
Application of AI technologies to pollutant removal during wastewater treatment.

Item	No.	Simulation or Prediction Objective	Treatment Process	AI Model	Training data sets/%	Validation data sets/%	Testing data sets/%	Model Performance	Reference
	1	COD	Aeration, nitrification & denitrification	ANN	75	–	25	0.632[a]	(Moral et al., 2008)
	2	COD	Anoxic oxic biological	ANFIS	70	18	12	0.982[a]	(Wan et al., 2011)
	3	COD	Anaerobic digestion	ANN-GA ANN	70	30	–	196.1[b] 447.7[b]	(Huang et al., 2016)
	4	COD	Fenton oxidation	MLP-ANN	61	17	22	0.975[a]	(Sabour and Amiri, 2017)
	5	COD	Aeration diffusion	SCFL	80	–	20	0.950[a]	(Nadiri et al., 2018)
	6	COD	Aeration diffusion	ARMA-VAR BP-ANN GA-BP-ANN	95	–	5	113.56[b] 303.51[b] 232.6[b]	(Man et al., 2019)
	7	COD	Activated sludge	GM-GA				0.85[a]	(Chen et al., 2010)
Conventional pollutant	8	BOD_5	Aeration diffusion	ANN	70	–	30	0.810[a]	(Hamed et al., 2004)
	9	BOD_5	Aeration diffusion	SCFL FL	81	–	20	0.960[a] 0.820[a]	(Nadiri et al., 2018)
	10	BOD_5	Biological	NNE	–	–	–	20 %[c]	(Nourani et al., 2018)
	11	BOD_5	Activated sludge bioreactor	ARIMA-ORELM	–	–	–	0.990[a]	(Lotfi et al., 2019)
	12	NH_4^+, NO_3-	Contact aeration	BP-ANN	–	–	–	90 %[d]	(Chen et al., 2003a,2003b)
	13	PO_4^{3-}	Sequencing batch reactor	ABM	–	–	–	0.580[b]	(Bucci et al., 2012)
	14	NO_3-	Biochemical	MOPSO	–	–	–	0.034[e]	(Han et al., 2018a, 2018b)
	15	TN	Biological	NNE	–	–	–	5 %[c]	(Nourani et al., 2018)
	16	PO_4^{3-}	Anaerobic and aerobic	Q-learning	–	–	–	–	(Pang et al., 2019)
	17	Total inorganic nitrogen	Arobic activated sludge	HMMs-MNLR	–	–	–	84 %[d]	(Suchetana et al., 2019)
	18	NH_4^+, TN	Anammox & Partial nitritation	FFBP-ANN	70	15	15	0.997[a]	(Antwi et al., 2019a, 2019b)
	19	TN TP	Sequencing batch reactor	BN	–	–	–	93.1 %[d] 95.2 %[d]	(Li et al., 2013)
	20	PO_4^{3-}	Adsorption	BP-ANN-GA	68	22	11	0.990[a]	(Zhang and Pan, 2014)
	21	Cu^{2+}	Membrane	RBF-ANN	–	–	–	0.997[a]	(Messikh et al., 2015)
	22	Cd^{2+}	Adsorption	ANFIS	–	–	–	0.921[a]	(Fawzy et al., 2016)
	23	As^{3+} As^{5+}	Phytoremediation	ANN	60	20	20	1.000[a] 1.000[a]	(Podder and Majumder, 2016)
	24	As^{3+}	Adsorption	BP-ANN	59	–	42	0.980[a]	(Mandal et al., 2015)
	25	Pb^{2+}	Adsorption	BP-ANN	70	15	15	0.970[a]	(Reynel-Avila et al., 2015)
	26	Pb^{2+}	Adsorption	MLP-ANN RSM	–	–	–	0.990[a] 0.956[a]	(Peiman et al., 2019)
	27	Mn^{2+}	Extraction	BP-ANN-PSO	76	12	12	0.981[a]	(Khajeh and Barkhordar, 2013)
	28	Cr^{6+}	Adsorption	BP-ANN-GA	77	–	23	0.995[a]	(Mohan et al., 2015)
Typical pollutant	29	Naphthalene	Photodegradation	ANN	60	20	20	0.943[a]	(Jing et al., 2014)
	30	Methylene blue	Photocatalytic	RBF-ANN	–	–	–	–	(Ranjbar-mohammadi et al., 2019)

Table 1 (*Continued*)

Item	No.	Simulation or Prediction Objective	Treatment Process	AI Model	Training data sets/%	Validation data sets/%	Testing data sets/%	Model Performance	Reference
	31	Methylene blue	Adsorption	MLP-ANN	70	15	15	0.988^a	(Asfaram et al., 2017)
				RBF-ANN				0.999^a	
	32	Tris-styrene	Adsorption	BP-ANN-GA	45	–	19	0.986^a	(Ghaedi et al., 2016)
				MLR	–	–	–	0.751^a	
	33	Trichlorophenol	Adsorption	MLP-ANN	–	–	–	0.999^a	(Dlamini et al., 2014)
	34	Methylene blue	Adsorption	BP-ANN	70	15	15	1.000^a	(Asfaram et al., 2016)
		Malachite green						0.999^a	
	35	Malachite green	Adsorption	BP-ANN-GA	75	–	25	0.966^a	(Ghaedi et al., 2015)
	36	Bisphenol A	Adsorption	ANN	60	20	60	0.997^a	(Vakili et al., 2019)
				RSM				0.995^a	
		Carbamazepine		ANN				0.997^a	
				RSM				0.984^a	
		Ketoprofen		ANN				0.998^a	
				RSM				0.998^a	
		Tonalide		ANN				0.993^a	
				RSM				0.994^a	
	37	Boron	Electrocoagulation	ANN	80	–	20	0.973^a	(da Silva Ribeiro et al., 2019)
	38	Microbead	Physico-chemical	CNN	75	–	25	89 $\%^d$	(Yurtsever and Yurtsever, 2019)
	39	Zn^{2+}, Cu^{2+}, Pb^{2+}, Cd^{2+}, Ni^{2+}, As^{3+}	Adsorption	ANN	9	–	1	0.948^a	(Zhu et al., 2019)
				Random forest				0.973^a	
	40	COD	Sequencing batch reactor	MLP-ANN	70 70	15	15	0.990^a	(Bagheri et al., 2015)
				RBF-ANN		–	30	0.990^a	
		NH_4^+		MLP-ANN	70	15	15	0.990^a	
				RBF-ANN	70	–	30	0.990^a	
		TP		MLP-ANN	70	15	15	0.990^a	
				RBF-ANN	70	–	30	0.940^a	
Mixed pollutant	41	COD	Anaerobic oxic biological	SDAE	81	–	19	5.94^b	(Shi and Xu, 2018)
		NH_4^+						1.27^b	
		TN						1.26^b	
	42	COD	Sequencing batch reactor	BP-ANN	52	24	24	0.955^a	(Kundu et al., 2013)
		NH_4^+						0.958^a	
	43	Methylene blue	Adsorption	BP-ANN	69	15	15	0.990^a	(Mazaheri et al., 2017)
				BRT				0.992^a	
		Cd^{2+}		BP-ANN				0.989^a	
				BRT				0.991^a	
	44	Pb^{2+}	Adsorption	MLP-ANN	63	19	19	1.000^a	(Dil et al., 2017)
		Malachite green						1.000^a	

a: Determination coefficient (R^2); b: Root mean square error (RMSE); c: Performance efficiency; d: Accuracy; e: Integral of the squared error.

to predict the COD removal at a full-scale paper mill wastewater treatment plant using anoxic or oxic processes with a minimum MAPE of 1.0 % and an R^2 value of 0.982 (Wan et al., 2011). A GA-ANN and non-dominant sorting GA-II were proposed for multi-objective optimization of an anaerobic digestion operation. Compared with the ANN model, the GA-ANN model had a lower MSE, a higher root mean square normalization error, a higher average absolute percentage error, and a higher correlation coefficient (Huang et al., 2016). Sabour and Amiri used RSM and BP-ANN modeling methods to study the performance of Fenton process; BP-ANN showed superior performance—with a higher R^2 value of 0.97–0.98, an RMSE of 1.45–1.86, and average error of 2–4 %—compared to RSM (Sabour and Amiri, 2017). In general, the ANN models are widely employed single ones for understanding biochemical treatment processes, and simulation with the combined models (GA-ANN and ANFIS) gave better results. A hybrid artificial intelligence model based on ARMA and VAR was applied to predict the COD load of urban sewage treatment plants. Its prediction accuracy was higher than those of BP-ANN and GA-BP-ANN, up to nearly 99 % (Man et al., 2019). A hybrid model combining GM and GAs was used to accurately predict the COD concentration in treated wastewater in the industrial wastewater treatment plants. This model was evaluated by comparing with results from the ANN and Monte Carlo analysis, and gave good prediction performance (R^2 0.85, RMSE 57.9, MAPE 20.2 %)(Chen et al., 2010).

(2) BOD_5: ANN, SCFL, FL and NNE were used for simulating, predicting, and optimizing BOD_5 removal in biochemical wastewater treatment process. ANN model was effective for predicting BOD_5 removal in aeration diffusion wastewater treatment plants, with R^2 values of 0.63–0.81 (Hamed et al., 2004). Nadiri et al. found that the SCFL model, with a higher R^2 value of 0.960 and lower MAPE of 4 %, was better than individual FL when predicting the BOD effluent of the Tabriz Wastewater Treatment Plant (Nadiri et al., 2018). A classical MLR and three different AI-based nonlinear models—FFNN, ANFIS, and SVM—were applied to predict the performance of removal of BOD_{eff} in wastewater treatment process. In predicting BOD_{eff}, at the verification phase, the ensemble models increased the performance efficiency of AI modeling by 14 %, 20 %, and 24 % through simple averaging ensemble, weighted averaging ensemble, and NNE respectively (Nourani et al., 2018). The combined model of ARIMA and ORELM was applied to predict wastewater effluent such as BOD_5, COD, total dissolved solids and total suspended solids, and R^2 of effluent BOD model was 0.99 to achieve the best performance (Lotfi et al., 2019).

(3) Nutrients: There are many models for simulating, predicting, and optimizing nutrient removal in biochemical and physicochemical wastewater treatment process. An ANN model was used to predict the nitrogen content of treated wastewater using the contact aeration process. The prediction accuracy of the model may reach 90 % (J. C. Chen et al., 2003a,2003b). An ABM was developed for enhanced biological phosphorus removal. The calibrated maximum acetate uptake rate for polyphosphate-accumulating organisms with traditional population-level modeling is 38 % lower than that of the ABM with parameter randomization (Bucci et al., 2012). Han et al. proposed an improved MOOC strategy, based on the improved multi-objective PSO algorithm to obtain the optimal set value for nitrate in wastewater treatment. The integral of the squared error of MOOC was 0.0344 and the integral absolute error was 0.1012 (Han et al., 2018b). A novel optimization method was developed using an improved Q-learning algorithm to reach the excellent and stable effluent quality through an optimal control strategy of anaerobic and aerobic processes in a biological phosphorus removal system (Pang et al., 2019). To predict the performance of biofilm systems that treat domestic wastewater, an SDAE deep learning network was built based on a traditional anaerobic/aerobic process. HMMs and MNLR were developed to predict total inorganic nitrogen in treated wastewater with the accuracy of the mixed model of 84 % (Suchetana et al., 2019). BNs were used to predict wastewater SBRs to determine the effluent quality of wastewater treatment systems. When comparing the predicted results with monitoring data, the TN_{out} and TP_{out} accuracy rates were 93.1 % and 95.2 %, respectively (Li et al., 2013). The ANN and GA were combined to simulate the potential of nanocomposite absorbents to remove phosphate from water, with an R^2 value of 0.99 (Zhang and Pan, 2014). In a word, ANN combined with GA model was used in nutrient removal in biochemical treatment processes. Single models—ABMs, ANNs, SDAEs, and BNs—gave higher errors and lower accuracy. Two novel feedforward BP-ANN models were developed to simulate the removal of $NH_4^{\ +}$ and TN in wastewater during the Anammox and Partial nitritation process with R^2 values of 0.989–0.997 and index of agreement of 0.993–0.998 (Antwi et al., 2019b).

3.2.2. Typical pollutant removal

(1) Heavy metals: The RBF-ANN model was applied in the emulsion liquid membrane process to predict copper removal efficiency. Compared with other neural networks, RBF-ANN can be trained more quickly. The predicted values well fit with the experimental data, with an R^2 value of 0.997 (Messikh et al., 2015). The adsorption efficiency of Cd^{2+} ions from aqueous solution to *Typha domingensis*, based on the ANFIS, showed that the adsorption of Cd^{2+} ions was mainly affected by pH (Fawzy et al., 2016). ANNs were used to predict the algae remediation efficiency of As^{3+} and As^{5+} from wastewater. As^{3+} and As^{5+} had the maximum phycoremediation of 85 % and 88 %, respectively. The experimental and model simulation data have R^2 values of 0.9998 (for As^{3+} and As^{5+}), and that the established ANN model could determine the elimination process of As^{3+} and As^{5+} under various conditions (Mandal et al., 2015; Podder and Majumder, 2016). MLP-ANN has higher prediction accuracy (R^2 0.990) than that of RSM when simulating the effect of thiosemicarbazide modified chitosan on Pb^{2+} removal (Peiman et al., 2019).

(2) Organic pollutants: ANN could accurately predict the degradation of photoinduced polycyclic aromatic hydrocarbon in seawater (Jing et al., 2014). MLP-ANN and RBF-ANN methods could simulate and optimize the removal efficiency of methylene blue and malachite green from water, with the MLP-ANN model outputting better predictions than the other (Asfaram et al., 2017; Ranjbar-mohammadi et al., 2019). MLR and ANN-GA were used to simulate the adsorption behavior of the triamide on single-walled and multi-walled carbon nanotubes, showing that the ANN model found a more accurate adsorption efficiency than the MLR model. The ANN-GA had an R^2 value of 0.986 and an MSE of 0.0005. The MLR had an R^2 value of 0.751 and an MSE of 0.011 (Ghaedi et al., 2016). ANN could also well optimize the removal of micropollutants (bisphenol A, carbamazepine, ketoprofen and tonalide) in water using the chitosan/zeolite fixed-bed column (Vakili et al., 2019). Based on RSM and ANN, the effects of $K_2S_2O_8$ and H_2O_2 was investigated on the solar degradation of 2-nitrophenol in water. And ANN has better prediction than that of RSM model with higher R^2 value of 0.9877 (Tou et al., 2018). To determine the emerging contaminant of microplastic in water, CNN was used to classify the microbeads in wastewater based on the microscopic image with a classification performance of 89 % (Yurtsever and Yurtsever, 2019).

3.2.3. Mixed pollutants

A SBR was simulated based on an MLP-ANN and RBF-ANN, with COD, total phosphate (TP), and NH_4^+-N removal efficiencies of 86 %, 79 % and 93 %, respectively (Bagheri et al., 2015). For all MLP-ANN and RBF-ANN models, R^2 values varied from 0.90 to 0.99 and the RMSE approached zero. The simulation results showed that the MLP-ANN had a higher R^2 and lower RMSE value than the RBF-ANN model. The SDAE deep learning network predictions, with RMSE of

5.94 (COD), 1.27 (NH_4-N) and 1.26 (TN), was the best compared to five other tested models (a BP-ANN, a support vector regression, an extreme learning machine, a gradient enhancement decision tree, and a stacking auto-encoder) (Shi and Xu, 2018). BP-ANN models were trained and tested reasonably well to predict COD and NH_4-N removal during the SBR with 3.3 % experimental error and an R^2 value of 0.95 (Kundu et al., 2013). Both the BRT and BP-ANN model could predict and simulate the adsorption of methylene blue and Cd^{2+} on walnut carbon successfully, with $R^2 > 0.98$ (Mazaheri et al., 2017). Both the BP-ANN-GA and MLP-ANN models could simulate and optimize the removal of Pb^{2+} and malachite green from aqueous solution, with removal rates of at least 98.7 % and R^2 values of greater than 0.999 (R^2 = 0.99970 and 0.99994, respectively, for removal of Pb^{2+} and malachite green) (Dil et al., 2017). The random forest was found to have good accuracy and prediction performance (R^2 0.973) for modeling the adsorption of six heavy metals (Zn^{2+}, Cu^{2+}, Pb^{2+}, Cd^{2+}, Ni^{2+}, As^{3+}) in biochar (Zhu et al., 2019). In general, the removal of heavy metals from wastewater mainly comprises of physical and chemical treatment processes; ANN and its combinations are widely used models of these processes, with R^2 values close to 1.

3.3. Applications of AI to the economic performance of wastewater treatment

Table 2 summarizes the application of different AI technologies to cost and energy reduction during wastewater treatment.

3.3.1. Energy consumption

Han et al. proposed an improved MOOC strategy and developed an adaptive kernel function model that could describe the complex dynamic processes of water quality and energy consumption. Compared with the adaptive multi-objective differential evolution algorithm and PI controller strategy, this MOOC reduced energy consumption values by 1.6 %, 1.2 %, and 2.2 % under dry, rainy, and stormy weather conditions, respectively (Han et al., 2018b). A DM method was used to optimize the ASP by controlling DO in the wastewater to be treated. If energy savings were prioritized over effluent quality, airflow could be reduced by 15 % (Kusiak and Wei, 2012). Asadi et al. applied a model developed by DM to the optimization of the aeration process; due to aeration oxygen reduction, energy consumption was reduced by 31.4 % while maintaining the same (higher than standard) effluent quality (Asadi et al., 2017). The pump system is an important component in energy consumption during the wastewater treatment. The ANN was used to model the pump energy consumption and fluid flow rate to reduce the energy consumption with a model error of < 3 % (Zhang et al., 2012). Statistical learning and deep RL were combined in an innovative predictive control to reduce the electricity consumption, with 16.7 % decrease compared to the normal operating condition (Filipe et al., 2019). The data-driven neural networks developed to improve the performance of the sewage pumping system could maintain pumping performance while conserving energy, with average energy savings of about 10 %; the highest energy saving scenario represented a 25 % decrease in energy use (Zhang et al., 2016). FL control was applied to reduce the energy consumption of WWTP, demonstrating that aeration fuzzy control could achieve energy savings of greater than 10 % while still maintaining a good level of removal (Fiter et al., 2005). The fuzzy neural was used to demonstrate the performance of ANFIS controllers in achieving economic objectives in a series of computer simulations. As a powerful and efficient DO control tool, this model could save nearly 33 % of the operating cost (Huang et al., 2009). A two-level hierarchical control strategy including MPC and FF was developed to achieve operating cost goals considering the wastewater quality

Table 2
Application of AI technologies to cost and energy reduction during wastewater treatment.

No.	Description	Treatment process	AI model	Performance		Reference
				Model	Cost & Energy reduction	
1	Energy	Activated sludge	MOOC	1.0 %[a]	1.6 %	(Han et al., 2018b)
2	Energy	Activated sludge	DM	–	15 %	(Kusiak and Wei, 2012)
3	Energy	Aerobic biological	DM	–	31 %	(Asadi et al., 2017)
4	Energy	Typical treatment	ANN	0.93[b]	10 %	(Zhang et al., 2016)
5	Energy	Wastewater collecting and grid	ANN	3 %[c]	–	(Zhang et al., 2012)
6	Energy	Aerobic biological	RL	2.43 %[c]	16.7 %	(Filipe et al., 2019)
7	Energy	Continuously stirred tank reactor	FL	–	10 %	(Fiter et al., 2005)
8	Energy	Aerobic biological	ANFIS	0.99[b]	33 %	(Huang et al., 2009)
9	Energy Total cost	Activated sludge	MPC-FF	0.066[d]	6 % 0.8 %	(Santín et al., 2015)
10	Operational cost	Activated sludge	RL	–	6 %	(Hernández-Del-Olmo et al., 2012)
11	Operational cost	Aerated submerged biofilm	NF	–	38 %	(Chen and Chang, 2007)
12	Operational cost	Sequencing batch reactor	RsFLC	–	1.2 %	(Chen et al., 2003a,2003b)
13	Operational cost	Aerobic biological	NSGA-II	–	4.1 %	(Sweetapple et al., 2014)
14	Total cost	Oxic reactor	ES	–	40 %	(Bozkurt et al., 2016)

a: Accuracy; b: Determination coefficient (R^2); c: Mean absolute percentage error; d: Integral of the absolute error.

and energy consumption. This strategy reduced overall costs by 0.8 % and aeration energy by about 6 % (Santín et al., 2015).

3.3.2. Other costs

A model-free RL was used to minimize operating costs and maintain water quality at acceptable levels, thereby improving the performance of wastewater treatment plants (Hernández-Del-Olmo et al., 2012). Model-based operating costs are reduced by 6 % compared to Benchmark Simulation A BP-ANN was built to predict the adsorption of As^{3+} on cerium hydrochloride with reducing the cost of adsorbent materials (Mandal et al., 2015). A fuzzy system was combined with a BP-ANN to simulate aeration during aerated submerged biofilm wastewater treatment. To address the issue of variable inflow rates and organic load requirements, the AI system controlled the airflow rate of wastewater treatment process. The system could save approximately 38 % of the operation costs using the fuzzy control (Chen and Chang, 2007). A rough set-based hybrid NF control system, including an ANN, GA, and FL was developed to improve the accuracy of the control system. This efficiently hybrid control achieved the real-time control objectives for dealing with uncertainties in wastewater treatment process. The average operational cost of the RsFLC was 1.2 % less than that of fuzzy logic control system (W. C. Chen et al., 2003a,2003b). The non-dominant sorting genetic algorithm-II was used to study the efficiency of an economical method for reducing the emissions of greenhouse gas during wastewater treatment. The maximum emission reduction was 18.5 %, which could reduce the corresponding operating costs by 4.1 % (Sweetapple et al., 2014). An expert-based mathematical programming framework was established to propose a multi-criteria retrofitting measure. It selected and optimized the oxic-anammox reactor as the treatment process due to the high biogas production and low energy consumption (Bozkurt et al., 2016). In general, construction and operational costs—including energy and reagents—were optimized using DM, GA, ANN, NF, FL, and ES models and may reduce costs by up to 30 %.

3.4. Applications of AI to the management performance of wastewater treatment

Table 3 summarizes the application of different AI technologies for operation management during wastewater treatment.

3.4.1. Evaluation, prediction, and diagnosis

(1) Biological process: Biological wastewater treatment process often encounter difficulties because the experience gained from the operation of one WWTP is not easily applied to another. ANFIS and ANN were developed to evaluate aerobic biological wastewater treatment process. This study showed that aeration performance induced by ANFIS was better than that by ANN. The R^2 value of the ANFIS model was 0.99 and the R^2 value of the ANN was 0.95 (Huang et al., 2009). Sattar et al. evaluated and predicted the aeration efficiency of stepped helium in three flow regimes based on adaptive learning networks (EPR and MT), which performed better than existing regression-based equations. In addition, the EPR was superior to the MT in that it provided one equation for each regime, whereas the MT provided several (Sattar et al., 2019). The NF model was used to predict the performance of high-speed anaerobic processes—an AFBR, anaerobic filter, and upflow anaerobic sludge blanket reactor—to different disturbances. Experiments showed that neural fuzzy modeling simulates system performance well. Applied to AFBR, the RMSEs of the VMP rate, influent TOC, and VFA were 0.146, 6.67, and 6.55, and the R^2 were 0.99, 0.83, and 0.72. Applied to the anaerobic filter, the RMSEs of VMP, TOC, and VFA were 0.154, 39.92, and 50.62, and the R^2 were 0.93, 0.97, and 0.88. Applied to upflow anaerobic sludge blanket, the RMSEs of VMP, TOC, and VFA were 0.40, 9.37, and 7.24, and the R^2 were 0.88, 0.84, and 0.81 (Tay and Zhang, 2000). A Kohonen self-organizing feature map neural network was established to create a model that evaluated the performance of a wastewater treatment plant (Çinar, 2005). BNs were used to diagnose the interference of anaerobic wastewater treatment systems. At the mixed-liquor volatile suspended solid concentrations up to 25,000 mg L^{-1}, the COD removal and methane production rate increased to 98 % and 25 $L \cdot d^{-1}$, respectively (Sahely and Bagley, 2002). The sudden organic overload caused by accidents or cleaning operations in treatment plants were the main disturbances of wastewater treatment process. A fuzzy ES was developed to diagnose the state of a pilot wastewater treatment plant, analyzing its operating trends and providing reliable information and good advice for operators (Carrasco et al., 2002). Carrasco et al. diagnosed the acidification status of anaerobic wastewater treatment plants with FL (Carrasco et al., 2004). To monitor the SVI, ANN models (MLP-ANN and RBF-ANN) were developed to predict sludge bulking in wastewater treatment plants. The prediction result of the MLP-ANN was found to be more accurate than that of RBF-ANN; moreover, the MLP-ANN had the highest R^2 value (0.99) and the lowest RMSE value (4 mL/g) for denormalized data (Bagheri et al., 2015). An advanced the structure of self-organizing recurrent radial basis function neural network using an information-oriented algorithm and a modified LM algorithm was established to improve the prediction accuracy of SVI in the biological wastewater treatment. In this research, the detection accuracy of the fault variable was 1.0 % and the proposed intelligent detection method was effective (Han et al., 2018a). In order to detect the incipient fault diagnosis during the wastewater treatment, a new fault diagnosis framework based on the Mard-RCP with Granger causal was established and applied in Benchmark Simulation Model 1 and a full scale WWTP. This model could accurately diagnose incipient sensor fault, sludge bulking and influent shock (Cheng et al., 2019). ANN, gene expression programming and least squares SVM were used to simulate and optimize membrane bioreactor performance by calculating membrane fouling resistance. Among, the least squares SVM has the best optimization effect (MSE 0.0002, R^2 0.99) (Hamedi et al., 2019). An improved PFA based on variable frequency mutation strategy was used to diagnose process faults in activated sludge wastewater treatment process. The algorithm gave well estimation accuracy and fault diagnose in the activated sludge process (Yu et al., 2019). The hybrid model of ANFIS and GFO was built to model and predict the influent flow rate from short-term to long-term. And this hybrid model showed better prediction accuracy and higher efficiency than those of ANFIS (Dehghani et al., 2019).

(2) Physical processes: The AI was also used to control membrane fouling during filtration in water and wastewater treatment. The flux decline was simulated in crossflow microfiltration through a FFNN model that provided accurate predictions, with an R^2 value of 0.99 (Aydiner et al., 2005). MLP-ANN and ANN were well used to represent the evolution of overall hydraulic resistance in a cross-flow microfiltration and membrane bioreactor for wastewater treatment, respectively (Dornier et al., 1995; Schmitt and Do, 2017). ANNs were used to predict pollution in large-scale membrane bioreactors, determining that (in addition to traditional ANN models) SVMs, RNNs, ENNs, WNNs, and SOMs also had strong membrane pollution prediction capabilities (Bagheri et al., 2019). The accuracy of the WNN prediction was higher than that of BP-ANN model. RBF-ANN could quantify the interfacial energy of membrane fouling in membrane bioreactors by establishing the non-linear relationship between the energy and five key factors (Chen et al., 2019). Feedforward BP-ANN, ANFIS, RBF-ANN and SVM technical models were used to predict the flow rate of influent in WWTP which greatly affects the treatment performance. Model performance results with five year data showed that SVM and feed-

Table 3
Application of AI models for operation management during wastewater treatment.

No.	Operation Management objective	Treatment Process	AI Model	Training data sets/%	Validation data sets/%	Testing data sets/%	Performance	Reference
1	Aeration efficiency	Aerobic biological	ANFIS ANN	78	–	22	0.99[a] 0.95[a]	(Huang et al., 2009)
2	Aeration efficiency	Aeration or reaeration	EPR MT	75	–	25	0.88[a] 0.93[a]	(Sattar et al., 2019)
3	Anaerobic system	Anaerobic fluidized bed Anaerobic filter Upflow anaerobic sludge	NF	–	–	–	0.82[a] 0.92[a] 0.84[a]	(Tay and Zhang, 2000)
4	Pump system	Typical treatment process	DM	80	–	20	0.93[a]	(Zhang et al., 2016)
5	Sludge bulking	Sequencing batch reactor	MLP-ANN RBF-ANN	70	–	30	0.99[a] 0.96[a]	(Bagheri et al., 2015)
6	Sludge bulking	Activated sludge	Information-oriented algorithm	57	–	43	1.0 %[b]	(Han et al., 2018a)
7	Sludge bulking	Activated sludge	Mard-RCP	60	–	40	–	(Cheng et al., 2019)
8	Activated sludge process fault	Activated sludge	PFA	–	–	–	0.25[c]	(Yu et al., 2019)
9	Permeate flux	Microfiltration	FFNN	67	–	33	0.99[a]	(Aydiner et al., 2005)
10	Membrane fouling	Cross-flow microfiltration	MLP-ANN	63	–	37	–	(Dornier et al., 1995)
11	Permeate flux	Membrane bioreactor	RBF-ANN RBF-ANN-GA MLP-ANN MLP-ANN-GA	67		33	0.99[a] 0.99[a] 0.99[a] 0.99[a]	(Schmitt and Do, 2017)
12	Membrane fouling	Membrane bioreactor	ANN/SVM/RNN/ENN/WNN/SOM	–	–	–	–	(Bagheri et al., 2019)
13	Membrane fouling	Membrane bioreactor	RBF-ANN	50	28	22	2.23 %[d]	(Chen et al., 2019)
14	Membrane fouling	Membrane bioreactor	Least squares SVM	80	–	20	0.99 [a]	(Hamedi et al., 2019)
15	Daily flow rate	Activated sludge	SVM BP-ANN ANFIS RBF-ANN	70	–	30	1435.4[c] 1445.9[c] 1515.6[c] 1501[c]	(Najafzadeh and Zeinolabedini, 2019)
16	Influent flow rate	Wastewater treatment	ANFIS-GWO ANFIS	70	–	30	0.98[a] 0.97[a]	(Dehghani et al., 2019)
17	Monitoring control	Oxidation–reduction & neutralization	SOM	–	–	–	–	(Garća and González, 2004)
18	Sensor control	Anaerobic Aerobic	NF BP-ANN NF BP-ANN	80	10	10	0.96[a] 0.90[a] 0.98[a] 0.95[a]	(Huang et al., 2010)
19	Automated control	Activated sludge	RL	–	–	–	–	(Hernández-Del-Olmo et al., 2012)
20	Automated control	Biological reactor	Hybrid AI	–	–	–	–	(Wen and Vassiliadis, 2002)
21	Systematic control	Activated sludge	MOOC	–	–	–	–	(Dai et al., 2016)

a: Determination coefficient (R^2); b: Accuracy; c: Root mean square error (RMSE); d: Relative error.

forward BP-ANN have more accurate prediction of flow rate than those of ANFIS and RBF-ANN (Najafzadeh and Zeinolabedini, 2019).

3.4.2. Control and automation

The basic biological behavioral mechanism of ASP was not well understood, and the lack of reliable automation instruments has caused many problems in its application. AI approaches maximized the knowledge extracted from data and operator experience, and applied this knowledge to help operators improve the management and control of wastewater treatment plants, allowing operators to better understand and improve the performance of wastewater treatment facilities. And the decision support systems could be used to solve the problems of complexity and dynamicity including the control and automation in WWTPs (Mannina et al., 2019). A SOM-based plant supervision technology was developed to visualize the status and monitoring of wastewater treatment process (Garća and González, 2004). A hybrid system was proposed using FL and neural network theory to implement adaptive software sensors for wastewater treatment plants. The simulation effect of their NF model with the R^2 value of 0.96-0.98 was better than that of a BP-ANN (Huang et al., 2010; Huang et al., 2009). A hybrid AI-based automatic control system was proposed to apply in G2 (a real-time ES developed by the Gensym Corp) and ESs, to control the operation of wastewater treatment process in real time. The range of the BOD controlled by the ES was 20.1–21.3 mg/l and that by the AI hybrid system was 20.6–21.5 mg/l. These results showed that hybrid AI technology provided another method for operating complex wastewater treatment processing that improved processing equipment efficiency while reducing energy consumed during operation (Wen and Vassiliadis, 2002). Multi-objective optimization was used to solve the prospects of multiple conflicts, such as effluent quality, operating cost, and operational stability; the study indicated that multi-objective optimization resulted in better control performance in wastewater treatment process compared to conventional methods (Dai et al., 2016). The behavior of the economic model predictive controller using FNN and FIS models differed from a reduced phenomenological model controller in that it could capture the process more accurately.

Integrated distributed ESs were developed to supervise the control system of an entire WWTP and overcome the main problems of traditional control strategies and systems based on individual knowledge. The ES consists of three modules for detecting faults, identifying plant operation problems, and transition process states that arise due to problems associated with the other two modules. The results of the study indicated that the developed distributed ES kept the effluent characteristics within acceptable limits while operating the plant at the lowest possible cost (Gernaey et al., 2004; Rodriguez-Roda et al., 2002). Although the expert system could already supervise the wastewater treatment plant 24 h a day, the knowledge of the expert system must be obtained in advance from plant operators or from previous data. Hernández-del-Olmo et al. (2012) proposed the automation of the entire WWTP, an ABM based on learning capabilities. This approach was adaptable, without excessive reliance on the operations and decisions of plant operators or engineers; the model was generated from the interaction with the environment (Hernández-Del-Olmo et al., 2012).

3.5. Applications of AI to the wastewater reuse

Many researchers are working on sustainable water/wastewater management in WWTPs (Jia et al., 2019; López-Morales and Rodríguez-Tapia, 2019; Man et al., 2019). AI technology could achieve the recovery of clean water, energy, and various materials during wastewater treatment. Wastewater reuse could improve the quality of the environment and generate economic benefits while increasing water savings (Bozkurt et al., 2016). An established neural network model was used to evaluate the wastewater reuse potential generated by contact aeration for groundwater recharge (J. C. Chen et al., 2003a,2003b). In order to enhance the cost effectiveness of wastewater reuse, the rainfall index was considered as a useful input in the model, and decisions differed with weather conditions. Akhoundi and Nazif prioritized wastewater reuse applications and treatment technologies with evidence-based reasoning methods (Akhoundi and Nazif, 2018). Wastewater reuse was mainly directed to agricultural irrigation, artificial recharging of groundwater, and industrial applications. The evidence-based reasoning method provided a coordinated and comprehensive approach to assessing the sustainability of wastewater reuse.

4. Conclusions and prospects

This study analyzed four aspects of the application of AI technology to wastewater treatment: technology, economics, management, and wastewater reuse by bibliometric analysis and systematic review. The ANN and FL models are the most widely used methods in single models, and the NF and ANN-GA are much more frequently used in hybrid models. We analyzed the technical support of AI for wastewater in terms of predicting and optimizing the removal of conventional pollutants, typical heavy metals, organic pollutants, and mixed pollutants. In the study of conventional pollutants (COD, BOD, TN, NH_4, NO_3-, TP, and $PO_4{}^{3-}$) removal, models such as ANN, FL, ANFIS, ABM and ANN-GA were mainly used, and their accuracy (R^2) ranged between 0.63-0.99. The prediction accuracy of ANN, ANN-GA, and ANN-PSO for heavy metal (Cu^{2+}, Cd^{2+}, As^{3+}, Mn^{2+}, and Cr^{6+}) removal in wastewater were as high as 0.948-1.000. The removal of organic pollutants and mixed pollutants was mainly studied by ANN and had high R^2 of about 0.99. The application of AI technology could also reduce operational costs by up to 30 % by reducing the consumption of energy, chemicals, and labor using DM, ANN, RL, ANFIS, NF, FL, and ES models. By controlling aeration, AI technology can reduce energy consumption by an average of 15 %. AI technology mainly uses models such as ANN, ANN-GA, DM, MT, SVM, NF and ANFIS in management of wastewater treatment to help simulate, predict, evaluate, and diagnose wastewater treatment operations. In the biological wastewater treatment process, AI technology assisted in improving aeration efficiency, pump efficiency, and addressing sludge expansion problems (R^2 0.82-0.99). ANN and ANN-GA were used to control membrane fouling in physical treatment of water and wastewater treatment (R^2 0.99). AI technologies (ANN, ANFIS, NF, RL, and MOOC) improved processing efficiency and reduced costs by controlling the daily flow, influent flow, monitoring systems, and automation of WWTP (R^2 0.90-0.99). AI technology could support the sustainable development of wastewater treatment through water reuse, and increased water saving while improving environmental quality and generating economic benefits. ANNs, FLs, DMs, and GAs were the most widely used single models for wastewater treatment, though combined methods—such as NF and ANN-GA—could provide higher accuracy and lower error.

The five following points are worthy of special attention for future research:

(1) Further hybridization of single AI models is required to manifest greater potential for generating optimal operation, higher pollutant removal, and lower operational cost, especially under complex operational circumstances.
(2) The prediction ability of AI technologies should be strengthened by variation of important parameters of wastewater treatment process, in order to provide operators with the opportunity

to capably manage parameter shocks and ensure wastewater discharge water quality standards.

(3) The smaller size and narrow range of the experiment-based data limited the practical application of AI models; we recommend that future studies provide a larger amount of field or online data to support AI models to become more user-friendly, and perform faster and more accurately in practical applications of wastewater treatment.

(4) A model should be developed that combines systemic and comprehensive aspects of wastewater treatment, including interactions between technology, economics, management, and wastewater reuse. Such a model should help adequately address pollutant removal, cost reduction, water reuse, and management challenges simultaneously.

Declaration of Competing Interest

The authors declare no competing interests.

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