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Pragmatic analysis of wastewater treatment methods from a statistical perspective

Pournima Pande [a,*] and Ashish Bhagat [b]

[a] Yeshwantrao Chavan College of Engineering, Wanadongari, Nagpur, Maharashtra, India
[b] Jawaharlal Nehru Medical College, Datta Meghe Institute of Medical Sciences, Sawangi (M), Wardha, Maharashtra, India
*Corresponding author. E-mail: pournimapande@yahoo.co.in

PP, 0000-0001-8254-3241

ABSTRACT

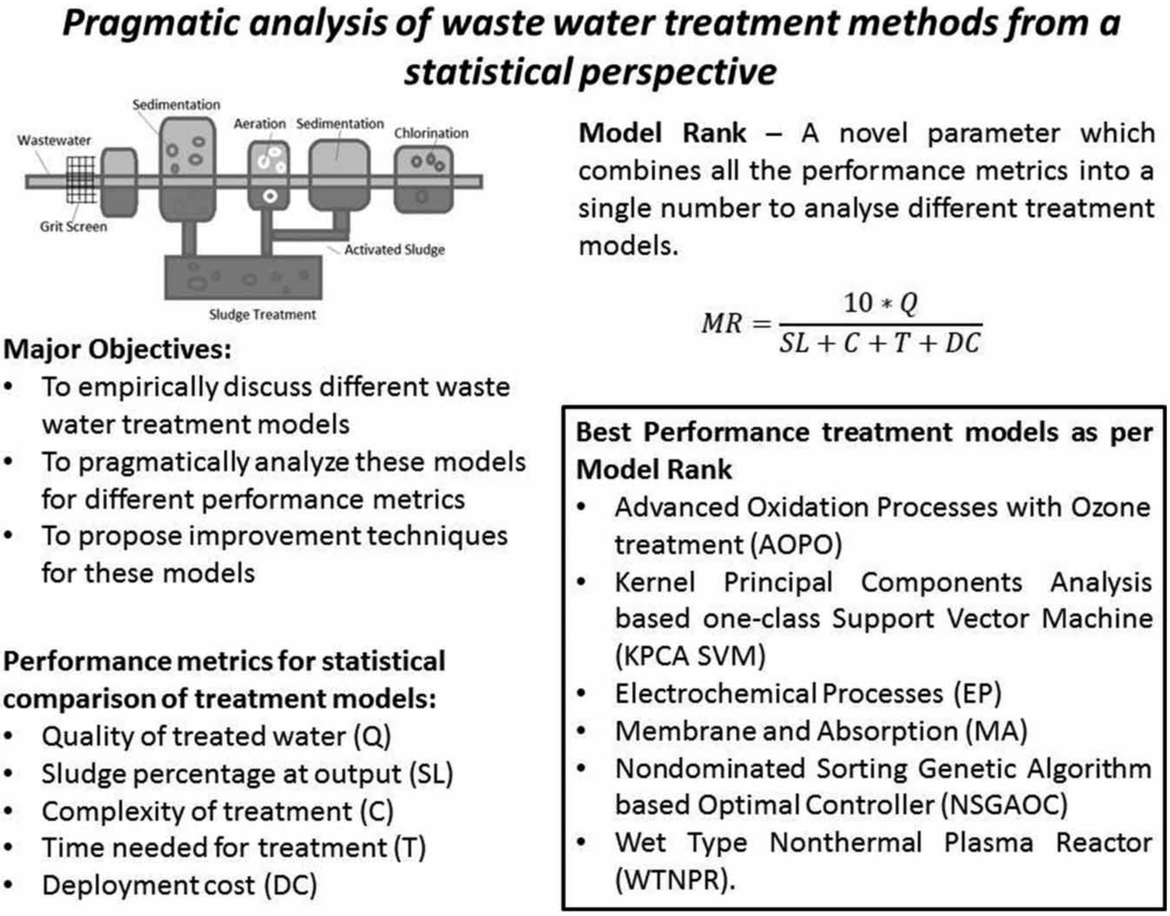
Wastewater treatment is an environmental issue of the utmost importance. Pesticides, industrial waste, chemical fertilizers, and radioactive waste are some of the causes for water pollution. Several models exist for treating contaminated wastewater. In this study an application-specific review of various wastewater treatment models is performed. Extensions to existing treatment models are discussed to improve their performance. The treatment models are compared statistically based on performance metrics such as quality of treated water, sludge percentage at output, complexity of treatment, time needed for treatment, and deployment cost. The treatment models are ranked using a novel parameter called Model Rank, which combines all performance metrics into a single number. According to the results, six models, including Advanced Oxidation Processes with Ozone treatment (AOPO), Kernel Principal Components Analysis based one-class Support Vector Machine (KPCA SVM), and four others, have a rank greater than 3.5. The AOPO model has the highest model rank of 3.85 and performs better than all other models. This study might aid major stakeholders in the waste treatment industry, including researchers, in selecting the appropriate waste water treatment method per their requirements.

Key words: complexity, oxidation, ozone, treatment, wastewater

HIGHLIGHTS

- Application-specific pragmatic review of various wastewater treatment models.
- Assistance in identification of various advantages, limitations, and future research scope in these models.
- Statistical comparison of various performance metrics of different models.
- Using statistical analysis, identifying the best possible method or methods.
- Recommendations of various extensions to models for improving process performance

GRAPHICAL ABSTRACT



1. INTRODUCTION

Water pollution is an immediate and probably one of the most important environmental issues facing humanity. Various factors such as pesticides, industrial wastes, chemical fertilizers, mining activities, radioactive waste, sewage, and wastewater are responsible for water pollution. The design of wastewater management system is thus an environmentally essential field and it involves accurate analysis of various factors such as chemical compositions, biological effects, and wastage analysis. In order to design an effective wastewater treatment model, a wide variety of system components must be integrated. These include but are not limited to grit screens for removing visibly large particles, sedimentation for large sludge removal, aeration for small-sized sludge removal, and chemical treatment for purity improvement. A typical treatment process can be visualized from Figure 1, wherein multiple sedimentation layers are combined with chemical treatment, and other processes in order to obtain usable water (Elnakar & Buchanan 2020).

Different wastewater sources generate different kinds of impurities, which must be treated using impurity-specific processes. These processes also depend upon the application or use of the treated water. For example, chlorination is used for treating water that will be used in swimming pools, while drinking water is treated with disinfectants. Similarly, coagulants are added to drinking water (Elnakar & Buchanan 2020), while multiple anticorrosion agents are used for industrial cleaning water (Comber *et al.* 2019). Thus, a wide variety of inter-process variations are required, which directly depend upon the type of application for which the water is being treated. Machine learning has been utilized in a few approaches to counter the inter-process variations and analyze the effect of treatment on resulting water quality (Mokhtari *et al.* 2020).

In this study, a review of machine learning approaches is performed, which will allow researchers to evaluate various nuances, advantages, limitations, and future improvements in these models. A parametric analysis of the reviewed models is carried out, in terms of quality of treated water, sludge percentage at output (SL), complexity of treatment, time needed for treatment, and deployment cost (DC). Upon referring this analysis, researchers

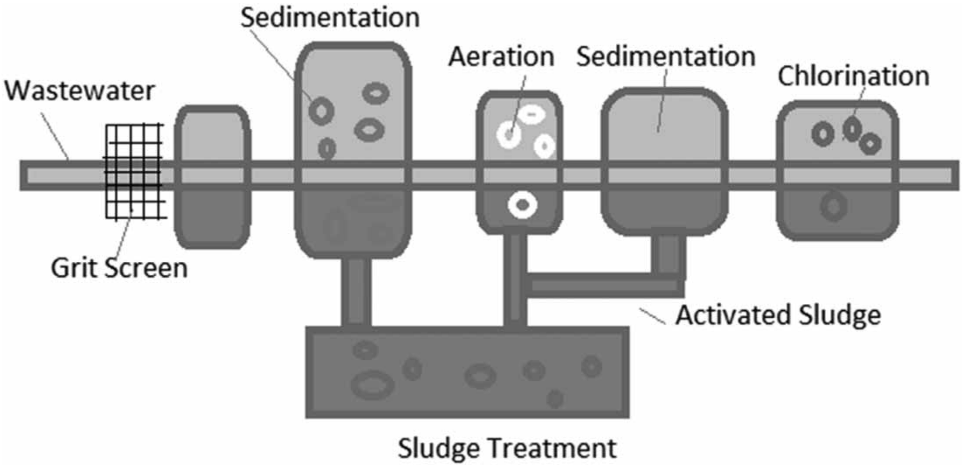


Figure 1 | A typical wastewater treatment model.

would be able to identify the most optimum models for application-specific water treatment. This is done because there is such a large range of performance, it can be challenging for users to choose the strategy that will work best for the deployment they are responsible for.

In this study, an application-specific and pragmatic review of various wastewater treatment models is performed. A statistical comparison of these models in terms of various performance metrics such as the quality of treated water, the percentage of sludge at output, the complexity of treatment, the amount of time required for treatment, and DC is carried out. Recommendations for extending the reviewed models are proposed in order to improve their overall performance. These additions can be tested in labs for the purpose of developing a wastewater treatment that is both quick and effective. This study also recommends a variety of machine learning techniques for streamlining the purification processes, which can contribute to an improvement in overall efficiency. The main objectives of the study are to empirically review various wastewater treatment models, propose improvement techniques for these models, and pragmatically analyze these models in terms of performance metrics.

The review is going to help readers identify various advantages, nuances, limitations, and future research scope in each of the models, and it will do so by providing them with information. Researchers are able to determine the most effective methods for their use cases by making use of this statistical analysis, and they are also able to combine the reviewed methods in order to design an effective hybrid method for the treatment of wastewater if this proves to be necessary.

2. LITERATURE REVIEW

Various system models are available for the treatment of wastewater, and each of them is applicable for different usage scenarios. For instance, the work in Zhou *et al.* (2020) discusses a topology-controlled hydration model that uses hydrogels for treating wastewater. In order to make the process more effective, solar irradiation is used for improving filtering capabilities of hydrogels, leading to formation of interpenetrating polymer networks (IPNGs). IPNG has the capability of activating over 50% contained water, thereby taking it to the intermediate filtering stage. The model has been tested on different levels of IPNG variants, and IPNG5 was observed to be the most effective in treating water. It results in higher purity than its counterparts with better sludge treatment but has a higher cost and greater treatment complexity than its counterparts.

The treatment complexity can be reduced via the use of effluent treatment as suggested in Mehralian *et al.* (2020), wherein authors have demonstrated that the use of sequencing batch reactors (SBRs) for agriculture targeted water treatment has better efficiency than sedimentation and aeration processes. The model has lower complexity, and better water quality, but higher cost due to use of different SBRs. It is currently applied for agricultural applications but can be extended to other types of water treatments via chemical modifications. Such modifications are proposed in Cheriyamundath & Vavilala (2021), wherein authors have proposed the use of nanomaterials including metal-based nano adsorbents (MBNAs), carbon nanotube (CN), nano membranes (NMs), and nano photocatalysts (NPs) for improving water quality. They are used to remove various oil contaminants, microbes, dyes, mycotoxins, etc. These materials, however, have some side-effects on local flora and fauna, which must be countered using effective safety measures.

Textile-based water treatment also makes use of similar models (Deng *et al.* 2020). Apart from nanomaterials authors have proposed the use of photodegradation (PD), advanced oxidation processes with ozone treatment (AOPO), electrochemical processes (EPs), coagulation–flocculation (CF), membrane and absorption (MA), and sonication (SC) for improving water quality. Authors recommend that a combination of these processes can further improve water quality; thus engineers must focus on analyzing the effects of combining these models on the resulting quality of water. Environmental effects of these processes are discussed in Choudri *et al.* (2020), wherein authors have proposed that the treatment of water from pharmaceuticals, personal care products, heavy metals, nanoparticles, etc. can cause genotoxicity, cytotoxicity, ecotoxicity, etc. This can accelerate the process of antibiotic-resistant bacteria formation, parasites and virus formation, thus, management of biosolids and sludge must be carried out carefully. Furthermore, the resulting water must be used for quality-specific scenarios.

Health implications of this usage are discussed in Kesari *et al.* (2021), wherein authors have estimated that fresh water has values of lower nitrogen, ammonia, phosphorus, potassium, calcium, and magnesium, when compared with municipal water, but it has higher sodium content, which makes it useful for drinking purposes. Variations of these levels can cause disastrous effects on human and plant health, which can be observed from Figure 2, wherein diseases such as cholera, anemia, ecotoxic yield, etc. are directly linked with the quality of water. In order to avoid these issues, a novel high-quality wastewater treatment model is proposed in Kesari *et al.* (2021), which uses multistage filtering model (MSFM). These include multiple screens, grit chambers, aeration tanks, gravity-based thickening tanks, centrifuge dewatering tanks, ultrasonication, etc.

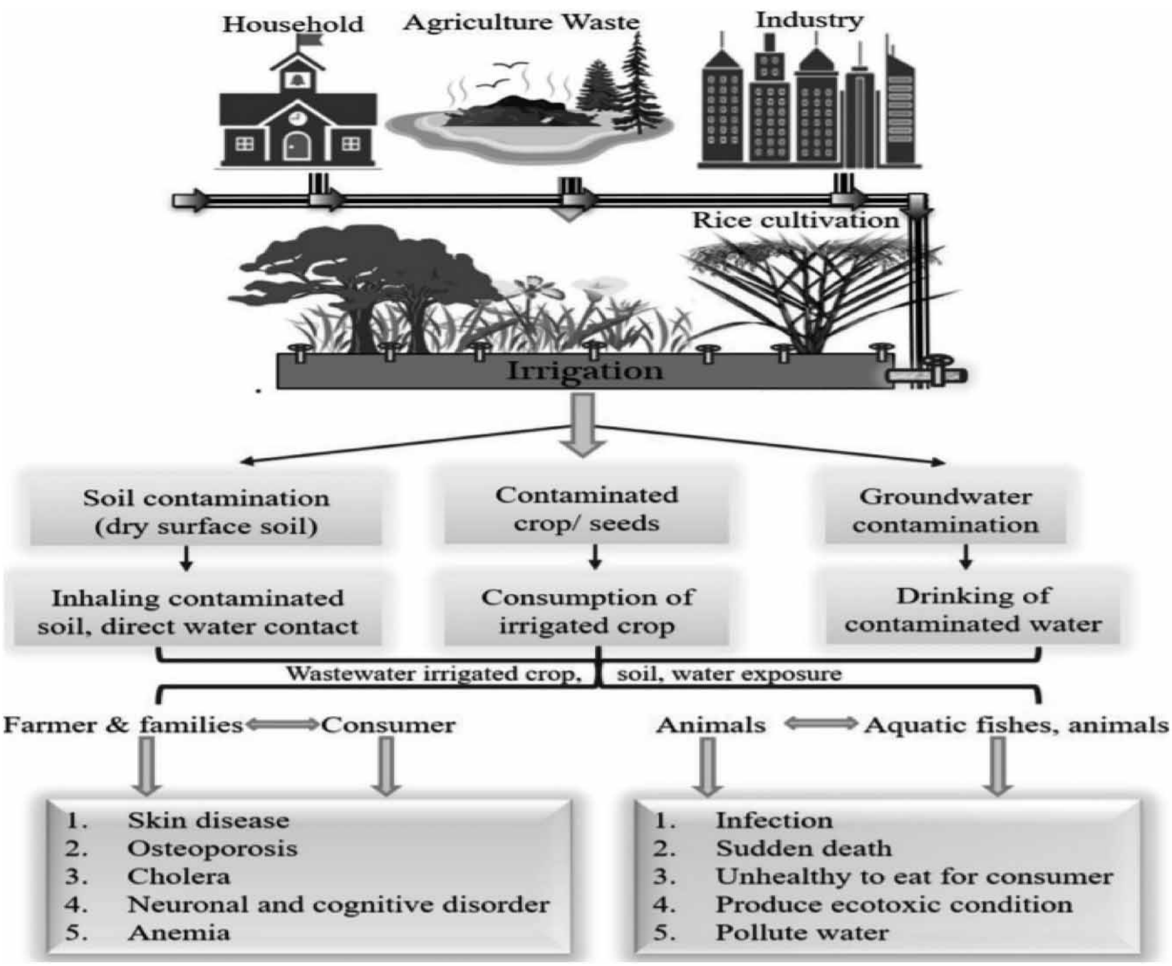


Figure 2 | Impact of improper wastewater treatment on flora and fauna health (Kesari *et al.* 2021).

Due to use of these stages, the MFSM technique is capable of improving water quality for drinking purposes, but has greater complexity, and requires higher cost than other models. This model is currently operated manually, which reduces its processing speed.

A self-organizing sliding mode-based controlling process improves the processing speed as discussed in Han *et al.* (2019). Here, authors have combined fuzzy neural networks with sliding mode-based control, for automatic quality checking and reducing structural complexity of treated water. This process generates a model for fixed and adaptive structural analysis of water, which makes it useful for a wide variety of applications. After examination of the internal working of this model, it is observed that the self-organizing fuzzy neural network (SOFNN) model improves quality of resulting water, but is highly complex, and requires a larger DC when compared with application-specific models.

A highly efficient wastewater treatment model is described in Tung *et al.* (2018), where authors have used a synthetic version of 'superparamagnetic iron oxide @ carbon' (SPIC) for reducing carbon shell, and arsenic particles. The SPIC method is highly expensive, and thus is used for treatment of highly corrupted water, in rare cases. But the model has low complexity, high efficiency of treatment, and requires very low delay for processing the water, and thus can be used for epidemic like global situations. The cost of this model is also affected due to the use of oxidization processes and security concerns, which can be reduced via the models proposed in dos Santos Silva *et al.* (2019) and Adepu & Mathur (2021), where authors have used Kalman filters for oxygen intake optimization, and distributed attack detection for securing wastewater management sites. Addition of these models, however, would further increase the complexity of deployment.

The model's reliability performance can be improved via use of sensor failure detection as proposed in Thiyagarajan *et al.* (2018), which would intimate plant operator(s) about any faulty water quality observations. This would assist in reduction of redundant operations for fixing water treatment equipment. The work in Malisa *et al.* (2019) discusses various recycling methods and proposes an urban wastewater recycling (UWWR) model for treatment, which assists in 50% better water reuse. Similar methods are proposed in Cheng *et al.* (2019a), wherein authors have deployed nonlinear data-based techniques for monitoring influent water conditions. The model uses Kernel Principal Components Analysis-based one-class Support Vector Machine (KPCA SVM) for anomaly detection during water treatment and can be used for securing large-scale treatment plants with minimum error, and high throughput.

Microwave heating (MWH) can be used for improving the quality of sewage sludge as proposed in Karlsson *et al.* (2019), wherein authors have used 2.45 GHz ranged waves for penetrating certain depths of wastewater. Due to this, porous sewage sludge along with other heavy metal and invisible impurities are removed from water. This process is depicted in Figure 3, where it is observed that the proposed model reduces sludge settlement delay from 6 months to almost less than 1 day, thereby improving the overall speed of operation.

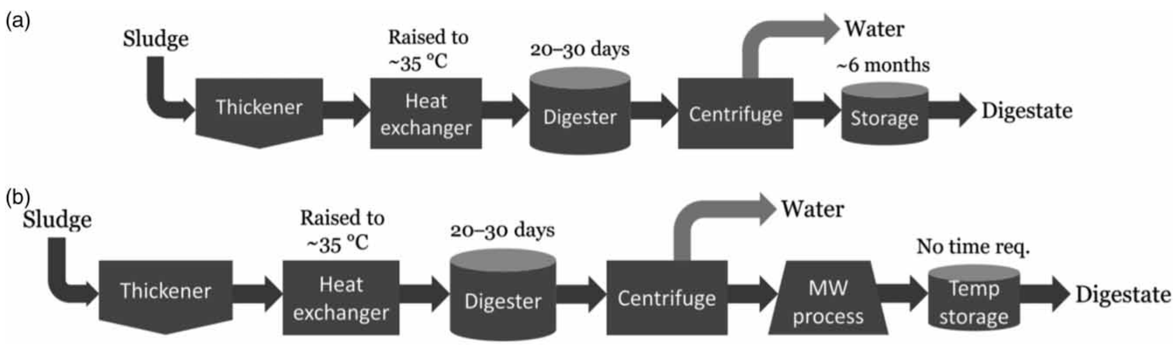


Figure 3 | (a) Non-microwave process and (b) microwave-based water treatment process.

Although the delay in water treatment reduces drastically, but it increases the cost of treatment due to the requirement of high-speed and high-efficiency microwave equipment. This model finds its application in a wide variety of scenarios that demand high purity of water. Efficiency of such processes can be improved via the addition of influent load forecasting in wastewater, and then scheduling treatment activities accordingly.

The work in Heo *et al.* (2021) proposes such a model, wherein authors have discussed use of multimodal and ensemble deep learning (MEDL) for prediction of wastewater output from systems, which assists in scheduling treatment activities. Due to this scheduling, delay needed for treatment reduces drastically, and availability of usable water is improved. Such deep learning models are also useful for scheduling treatment activities, and automating them.

A multiple objective predictive control (MOPC) method that uses an adaptive fuzzy neural network (AFNN) for estimation of coagulants, and other chemicals are proposed in Han *et al.* (2020). Here, authors are able to achieve better water quality than manual processes, but the model showcases large computational delay, and high complexity of deployment. This complexity is reduced via the use of Transfer Multiple Objective Optimization Algorithm (TMOOA), which assists in reducing complexity, and delay of treatment via coarse grained control of internal process timings. A similar model is proposed in Han *et al.* (2021a), wherein authors have used intelligent optimal control system with flexible objective function (IOCS-FOF), and Multiple Objective Optimization Algorithm for Flexible Objective (MOAFO) for scheduling treatment activities. It is observed that the IOCS-FOF model has better water quality than MOAFO, but the former has higher complexity, and requires larger delays for control. The IOCS-FOF model, however, is useful for yielding drinking water, and thus is used in a wide variety of treatment plants.

The efficiency of models can be improved if instead of process-based methods for prediction of treatment steps, data-based prediction is used. An example of this improvement is discussed in Han *et al.* (2018), wherein authors have used prediction models for controlling dissolved oxygen (DO) levels via a self-organizing fuzzy neural network (SOFNN). This network is trained using adaptive second-order Levenberg-Marquardt, which assists in reducing computational complexity via reduction of redundant training and validation steps. Due to use of SOFNN as observed from Figure 4, this model is capable of highly efficient water quality output, with moderate level of complexity, and moderate DC.

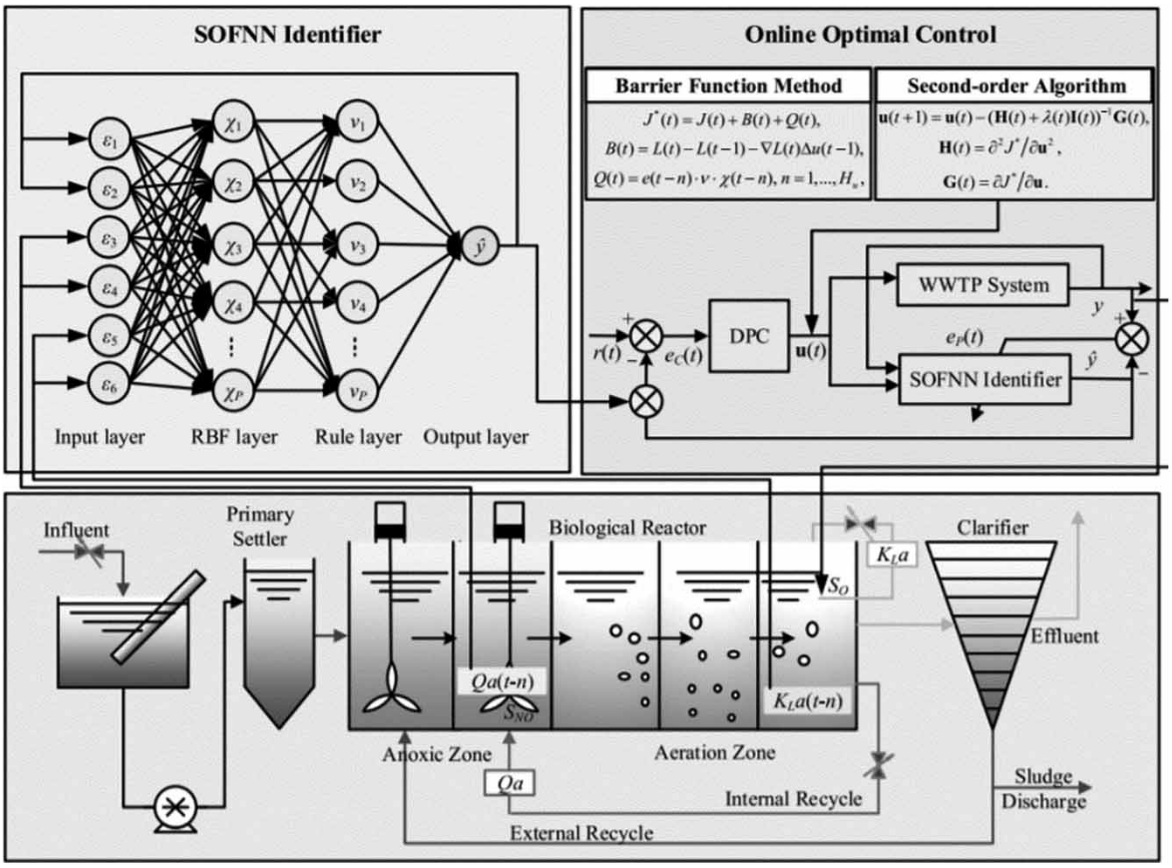


Figure 4 | Use of SOFNN for scheduling treatment activities (Han *et al.* 2018).

The SOFNN model's utility can be further extended via use of Integrated Magnetics Current Doubling Rectifier (IMCDR), which uses electrosynthesis to remove unwanted particles from wastewater. The IMCDR model has lower cost than most other methods, but has chances of contamination due to use of metal electrodes for cleaning. This model is highly useful for treating water intended to be used in agriculture, industrial cleaning, and other applications that are non-intrusive to human and animal bodies.

Performance of treatment scheduling can be further improved via use of deep neural network (DNN)-based models, such as long-short-term-memory (LSTM) and deep reinforcement learning (DRL) proposed in Pisa *et al.* (2019) and Seo *et al.* (2021), wherein control of activated sludge reactors, thickeners, anaerobic digestors, etc. is done via deep learning-based prediction. The LSTM and DRL models have better scheduling capabilities than artificial neural networks (ANNs), due to storage and analysis of a larger number of events. These models, however, require more memory, and have higher complexity than ANN, thereby are being used only under high-performance computing environments.

The complexity of models must be reduced for improving their scalability. The work in Liu *et al.* (2021) proposes such a low-complexity LSTM-based model, which utilizes particle swarm optimization (PSO) with attention mechanism (AM) for prediction of chemical oxygen demand (COD) during treatment. The combined model is observed to have lower complexity, and better speed of operation than LSTM, but it requires larger storage and has higher DC due to combination of multiple processing models.

Image processing can also be used for estimation of water quality, and then recommend treatment steps depending upon the estimation. Work in Khan *et al.* (2018) proposes an image processing model that estimates sludge volume index (SVI) in estimating locations of sludge in amplified wastewater images. Image processing models are highly useful for non-intrusive analysis, and can be combined with deep learning models such as the ones proposed in Cheng *et al.* (2020). Here, authors have compared LSTM, gated recurrent unit (GRU), bi-directional LSTM (BiLSTM), and a combination of these models for improving wastewater treatment efficiency. These models utilize various treatment parameters including hardness, coagulation effects, application of use, etc. and derive an automatic plan for achieving high accuracy of treatment. These models are useful for small-scale to medium-scale applications (scale indicates quantity of water processed per unit time), and can be extended to large-scale processing units via modeling of adaptive multiple output softening sensors. This is possible because these sensors are capable of reducing delay needed for softening via parallel processing of water lines.

Design of sensors is discussed in Wu *et al.* (2019), wherein multiple output partial least square (MOPLS) method is used for modelling. The MOPLS method is capable of achieving higher speeds than linear models, but requires costlier equipments, which limits its applicability to large-scale water treatment plants. Similar models are proposed in Liu *et al.* (2020a) and Cheng *et al.* (2019b), wherein authors have discussed the use of Dynamic Bayesian Networks Based on Fuzzy PLS (DBNFPLS) and optimized forest model with SVM (OFSVM) for fault diagnosis during wastewater treatment. Both these models are equally capable of high-quality water output but require higher delays than the MOPLS model, which restricts them to very large-scale treatment plants.

Fuzzy logic and bioinspired approaches are very useful when planning impurity detection systems, because impurity levels are also represented in fuzzy ranges. The work in Lamas & Giacaglia (2021) and Han *et al.* (2021b) proposes fuzzy logic small wastewater treatment plant (FLSWTP), and dynamic multiple objective particle swarm optimization (DMOPSO) models for small to moderate scaled water treatment plants. These models have better impurity removal capabilities when compared with Multiple Objective Genetic Algorithm (MOGA), virtual reference feedback tuning control strategy (VRFT-CS), adaptive multiple objective differential evolution control strategy (AMODCS), and Nondominated Sorting Genetic Algorithm-based Optimal Controller (NSGAOC) models, thereby improving their applicability to real-time treatment environments. These models are useful for scheduling any kind of treatment process, and can be applied to wet-type nonthermal plasma reactor (WTNPR) defined in Kuroki *et al.* (2020), which is used for nitrogen, arsenic, and sulphur removal. The experimental setup for this model is visualized in Figure 5, wherein different analysis engines, and sampling models are depicted. These engines are connected to a wet-type plasma reactor, which assists in analysis of different gas types in contaminated water samples. The model is observed to have high efficiency, moderate level of complexity and cost, but has low scalability because it requires different gas chambers for different types of impurities. Efficiency of this model might be improved if deep learning methods for scheduling and material saving are applied to it.

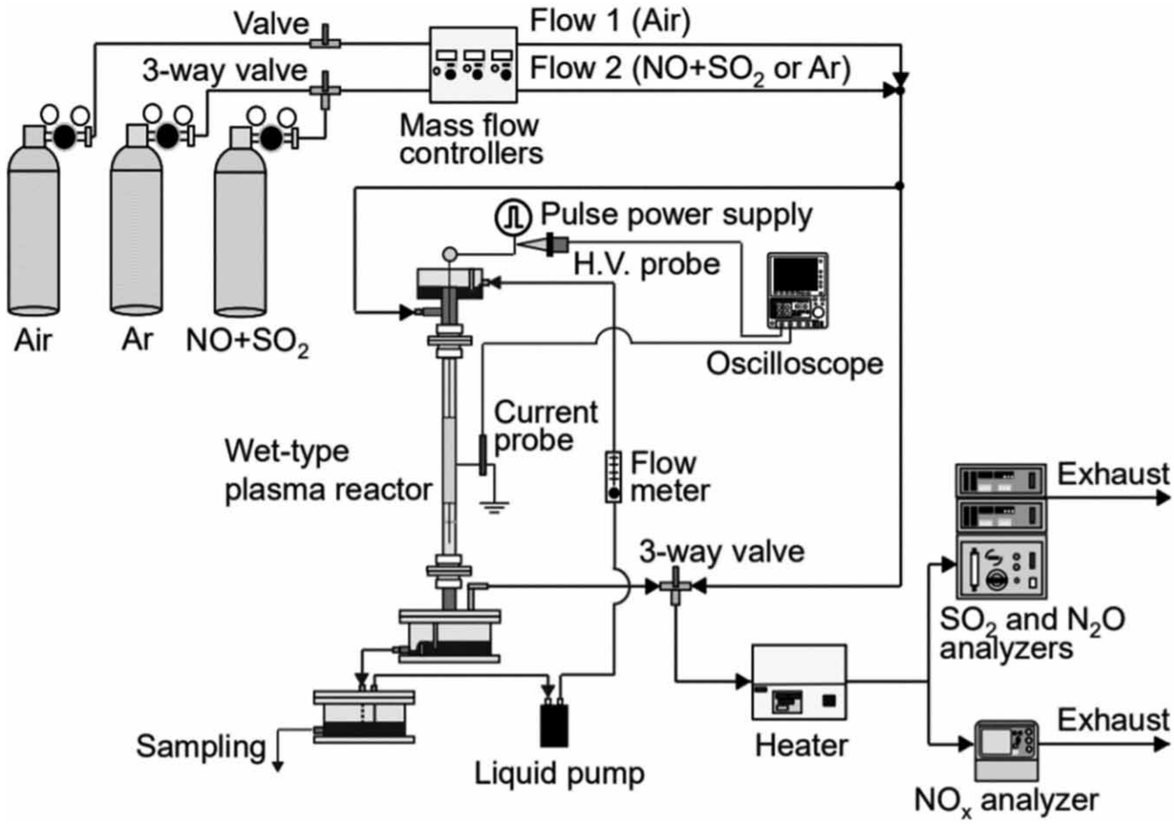


Figure 5 | Treatment of nitrogen, arsenic, and sulphur using different treatment engines (Kuroki *et al.* 2020).

Design of energy and material saving management using deep networks (EMSMDNs), and cooperative fuzzy neural network (CoFNN) is proposed in Wang *et al.* (2020) and Han *et al.* (2021c) for reducing redundancies for material use, energy use, component use, etc. during wastewater treatment. Due to this optimization, the proposed model is capable of reducing cost of wastewater deployment systems by 10–15%, which makes them highly useful for a wide variety of system deployments. These models are further expanded to cyber physical systems (CPSs) (Elsahwi *et al.* 2018), which assist in providing a user-friendly approach toward wastage reduction and monitoring via cloud infrastructures.

Electrochemical methods (EMs) (Saetta *et al.* 2019) are also useful for cyanide removal from wastewater with higher efficiency than chemical or sedimentation processes. While, data-driven iterative adaptive critic (DDIAC) strategy (Wang *et al.* 2021), stacking ensemble learning (SEL) (Liu *et al.* 2020b), chemical treatment of anaerobic reactor (CTAR) (Zeb *et al.* 2020), and discharged plasma-based reactor (DPBR) design (Xiang *et al.* 2019) are proposed by authors, these models are highly application-specific, and do not scale well due to their inherent internal compositions. Thus, water output from these models is used for non-drinking purposes only. Inspired by these approaches the work in Harrou *et al.* (2021) and Chistiakova *et al.* (2020) propose designs of data-driven soft sensors (DDSSs), and feedback and feedforward aeration control (FFAC) models. These models have a general purpose, and utilize chemical composition for reducing impurities, thereby assisting in better quality of water, which can be used for human and animal use. Even after several treatment steps, many concerns are raised by the authors, which include, preservation of genetic data, flora and fauna privacy issues, etc. A survey of these issues can be observed in Jacobs *et al.* (2021), wherein authors have aggregated these issues, and suggested recommendations for countering them. Based on these recommendations, work in Iratni & Chang (2019) suggests different control techniques including proportional integral control (PI), PI differential control (PID), feedback-based control, etc. These strategies will assist in mitigating genetic issues by analyzing and preserving water samples which pose privacy threats to the governments, and other monitoring agencies.

Based on this review it is observed that wastewater treatment is a very diverse field, and a large number of methods are available for it. All these models vary in terms of algorithmic performance, thus next section compares them w.r.t. various parameters which include quality of treated water, SL, complexity of treatment, time needed for treatment, and DC. Upon referring this comparison, researchers would be able to identify optimum methods for their water treatment requirements.

3. STATISTICAL ANALYSIS

Based on the detailed discussion, it can be observed that the reviewed models have vast differences in terms of performance, type of application, scalability, etc. Thus, in this section these models are compared with respect to quality of treated water (Q), SL, complexity of treatment (C), time needed for treatment (T), and DC. All these parameters are converted into fuzzy ranges of low (L), medium (M), high (H), and very high (VH) depending upon components used in each internal process. These observations are tabulated in Table 1.

Based on this evaluation, it can be observed that MBNA (Cheriyamundath & Vavilala 2021), CN (Cheriyamundath & Vavilala 2021), NP (Cheriyamundath & Vavilala 2021), SOFNN (Han *et al.* 2019), SPIC (Tung *et al.* 2018), MWH (Karlsson *et al.* 2019), LSTM PSO (Liu *et al.* 2021), BiLSTM (Cheng *et al.* 2020), CTAR (Zeb *et al.* 2020), and DDSS (Harrou *et al.* 2021) methods have highest water treatment quality, and thus can be used for large-scale wastewater plants. Similarly, sludge levels for MBNA (Cheriyamundath & Vavilala 2021), SOFNN (Han *et al.* 2019), SPIC (Tung *et al.* 2018), MWH (Karlsson *et al.* 2019), SBR (Mehralian *et al.* 2020), and IOCS-FOF (Han *et al.* 2021a) are observed to be lowest, which makes them suitable for drinking water-based treatment applications. From these models the MBNA model is observed to be most effective in terms of quality and sludge levels. While in terms of computational complexity PD (Deng *et al.* 2020), AOPO (Deng *et al.* 2020), SVI (Khan *et al.* 2018), IMCDR (Elsahwi *et al.* 2019), FLSWTP (Lamas & Giacaglia 2021), and MA (Deng *et al.* 2020) are the most effective, MEDL (Heo *et al.* 2021), FLSWTP (Lamas & Giacaglia 2021), MBNA (Cheriyamundath & Vavilala 2021), SPIC (Tung *et al.* 2018), MWH (Karlsson *et al.* 2019), and NP (Cheriyamundath & Vavilala 2021) have the lowest treatment delay. This is because the later models utilize chemical reactions in order to speed-up the treatment process. In terms of deployment costs, TMOOA (Han *et al.* 2020), IMCDR (Elsahwi *et al.* 2019), EP (Deng *et al.* 2020), MOPC (Han *et al.* 2020), PD (Deng *et al.* 2020), AOPO (Deng *et al.* 2020), SC (Deng *et al.* 2020), and EM (Saetta *et al.* 2019) outperform other models; thus, are widely used for low-cost wastewater treatment. Based on this comparison, researchers can select the best model for their application, but it is difficult to identify a model with optimum quality, sludge level, complexity, delay, and cost, thus, a novel model rank (MR) is estimated for these models using Equation (1),

$$MR = \frac{10 \times Q}{SL + C + T + DC} \tag{1}$$

This metric is evaluated for each model by converting the fuzzy ranges into numerical entities. Results of this evaluation are tabulated in Table 2, which will assist in identification of the most optimum models for treatment of wastewater.

Higher value models are more effective than lower values models, and thus must be used for real-time wastewater treatment purposes. From this evaluation and from Figure 6, it can be observed that AOPO (Deng *et al.* 2020), KPCA SVM (Cheng *et al.* 2019a), EP (Deng *et al.* 2020), MA (Deng *et al.* 2020), NSGAOC (Han *et al.* 2021b), WTNPR (Kuroki *et al.* 2020), MWH (Karlsson *et al.* 2019), EMSMDN (Wang *et al.* 2020), and CoFNN (Han *et al.* 2021c) have better overall performance than other models, and must be used for efficient deployment of wastewater treatment plants.

4. RESULTS AND DISCUSSION

As a result of the evaluation that was conducted as part of the review, it has been determined that the water treatment processes of MBNA, CN, NP, SOFNN, SPIC, MWH, LSTM PSO, BiLSTM, CTAR, and DDSS have the highest quality, and as a consequence, they are appropriate for use in large-scale wastewater plants. This conclusion was reached due to these processes having been shown to be suitable for use. In a similar vein, it has been claimed that the levels of sludge that are observed for MBNA, SOFNN, SPIC, MWH, SBR, and IOCS-FOF are the lowest, which qualifies them for usage in treatment applications that include the treatment of drinking water. It has been found that, among these models, the MBNA model is the most effective in terms of both the quality and the levels of sludge. This conclusion was reached after it was investigated. MEDL, FLSWTP, MBNA, SPIC, MWH, and NP have the shortest treatment delay, but PD, AOPO, SVI, IMCDR, FLSWTP, and MA are the

Table 1 | Empirical analysis of different wastewater treatment models

Method	Q	SL	C	T	DC
IPNG (Zhou *et al.* 2020)	H	M	H	H	VH
SBR (Mehralian *et al.* 2020)	M	L	H	M	H
MBNA (Cheriyamundath & Vavilala 2021)	VH	L	VH	L	VH
CN (Cheriyamundath & Vavilala 2021)	VH	M	H	M	VH
NM (Cheriyamundath & Vavilala 2021)	H	M	H	M	H
NP (Cheriyamundath & Vavilala 2021)	VH	M	VH	L	H
PD (Deng *et al.* 2020)	M	H	L	H	M
AOPO (Deng *et al.* 2020)	M	H	L	H	M
EP (Deng *et al.* 2020)	L	H	M	VH	L
CF (Deng *et al.* 2020)	L	H	M	VH	M
MA (Deng *et al.* 2020)	H	M	L	H	L
SC (Deng *et al.* 2020)	M	H	M	H	M
MSFM (Kesari *et al.* 2021)	H	M	M	H	VH
SOFNN (Han *et al.* 2019)	VH	L	H	VH	VH
SPIC (Tung *et al.* 2018)	VH	L	VH	L	VH
KPCA SVM (Cheng *et al.* 2019a)	M	H	M	M	H
MWH (Karlsson *et al.* 2019)	VH	L	VH	L	H
MEDL (Heo *et al.* 2021)	M	H	H	L	H
MOPC (Han *et al.* 2020)	H	M	H	H	M
TMOOA (Han *et al.* 2020)	H	M	H	M	L
IOCS-FOF (Han *et al.* 2021a)	H	L	H	H	H
MOAFO (Han *et al.* 2021a)	M	M	H	M	M
SOFNN (Han *et al.* 2018)	H	M	VH	VH	VH
IMCDR (Elsahwi *et al.* 2019)	M	M	L	M	L
LSTM (Pisa *et al.* 2019)	H	M	VH	H	VH
DRL (Seo *et al.* 2021)	H	L	H	VH	VH
LSTM PSO (Liu *et al.* 2021)	VH	M	H	M	VH
SVI (Khan *et al.* 2018)	M	H	L	M	H
LSTM (Cheng *et al.* 2020)	H	H	VH	H	VH
GRU (Cheng *et al.* 2020)	H	M	H	H	H
BiLSTM (Cheng *et al.* 2020)	VH	M	H	VH	VH
MOPLS (Wu *et al.* 2019)	M	H	H	H	VH
DBNFPLS (Liu *et al.* 2020a)	H	M	VH	H	H
OFSVM (Cheng *et al.* 2019b)	H	M	VH	H	VH
FLSWTP (Lamas & Giacaglia 2021)	M	M	L	L	H
DMOPSO (Han *et al.* 2021b)	H	M	H	H	H
MOGA (Han *et al.* 2021b)	M	M	H	VH	H
VRFT-CS (Han *et al.* 2021b)	L	H	VH	H	M
AMODCS (Han *et al.* 2021b)	M	H	VH	M	M
NSGAOC (Han *et al.* 2021b)	M	M	VH	VH	VG
WTNPR (Kuroki *et al.* 2020)	H	M	M	M	VH
EMSMDN (Wang *et al.* 2020)	H	L	VH	H	VH
CoFNN (Han *et al.* 2021c)	H	M	VH	VH	M
EM (Saetta *et al.* 2019)	H	H	M	H	M
DDIAC (Wang *et al.* 2021)	M	H	VH	H	VH
SEL (Liu *et al.* 2020b)	H	M	H	VH	VH
CTAR (Zeb *et al.* 2020)	VH	M	H	M	H
DPBR (Xiang *et al.* 2019)	H	L	VH	M	VH
DDSS (Harrou *et al.* 2021)	VH	H	M	H	VH
FFAC (Chistiakova *et al.* 2020)	H	M	VH	H	H

Table 2 | MR for each method

Method	MR
IPNG (Zhou *et al.* 2020)	2.86
SBR (Mehralian *et al.* 2020)	2.67
MBNA (Cheriyamundath & Vavilala 2021)	2.67
CN (Cheriyamundath & Vavilala 2021)	2.50
NM (Cheriyamundath & Vavilala 2021)	2.50
NP (Cheriyamundath & Vavilala 2021)	2.14
PD (Deng *et al.* 2020)	2.73
AOPO (Deng *et al.* 2020)	3.85
EP (Deng *et al.* 2020)	3.57
CF (Deng *et al.* 2020)	2.31
MA (Deng *et al.* 2020)	3.57
SC (Deng *et al.* 2020)	2.86
MSFM (Kesari *et al.* 2021)	2.31
SOFNN (Han *et al.* 2019)	2.14
SPIC (Tung *et al.* 2018)	1.88
KPCA SVM (Cheng *et al.* 2019a)	3.64
MWH (Karlsson *et al.* 2019)	3.33
MEDL (Heo *et al.* 2021)	3.00
MOPC (Han *et al.* 2020)	1.43
TMOOA (Han *et al.* 2020)	2.86
IOCS-FOF (Han *et al.* 2021a)	2.31
MOAFO (Han *et al.* 2021a)	2.31
SOFNN (Han *et al.* 2018)	2.14
IMCDR (Elsahwi *et al.* 2019)	2.86
LSTM (Pisa *et al.* 2019)	1.25
DRL (Seo *et al.* 2021)	2.31
LSTM PSO (Liu *et al.* 2021)	2.00
SVI (Khan *et al.* 2018)	1.33
LSTM (Cheng *et al.* 2020)	2.50
GRU (Cheng *et al.* 2020)	1.67
BiLSTM (Cheng *et al.* 2020)	1.76
MOPLS (Wu *et al.* 2019)	2.50
DBNFPLS (Liu *et al.* 2020a)	3.13
OFSVM (Cheng *et al.* 2019b)	2.67
FLSWTP (Lamas & Giacaglia 2021)	1.67
DMOPSO (Han *et al.* 2021b)	2.22
MOGA (Han *et al.* 2021b)	2.50
VRFT-CS (Han *et al.* 2021b)	2.35
AMODCS (Han *et al.* 2021b)	2.35
NSGAOC (Han *et al.* 2021b)	3.57
WTNPR (Kuroki *et al.* 2020)	3.57
EMSMDN (Wang *et al.* 2020)	3.33
CoFNN (Han *et al.* 2021c)	3.33
EM (Saetta *et al.* 2019)	2.86
DDIAC (Wang *et al.* 2021)	2.67
SEL (Liu *et al.* 2020b)	3.13
CTAR (Zeb *et al.* 2020)	2.50
DPBR (Xiang *et al.* 2019)	2.94
DDSS (Harrou *et al.* 2021)	2.35
FFAC (Chistiakova *et al.* 2020)	2.22

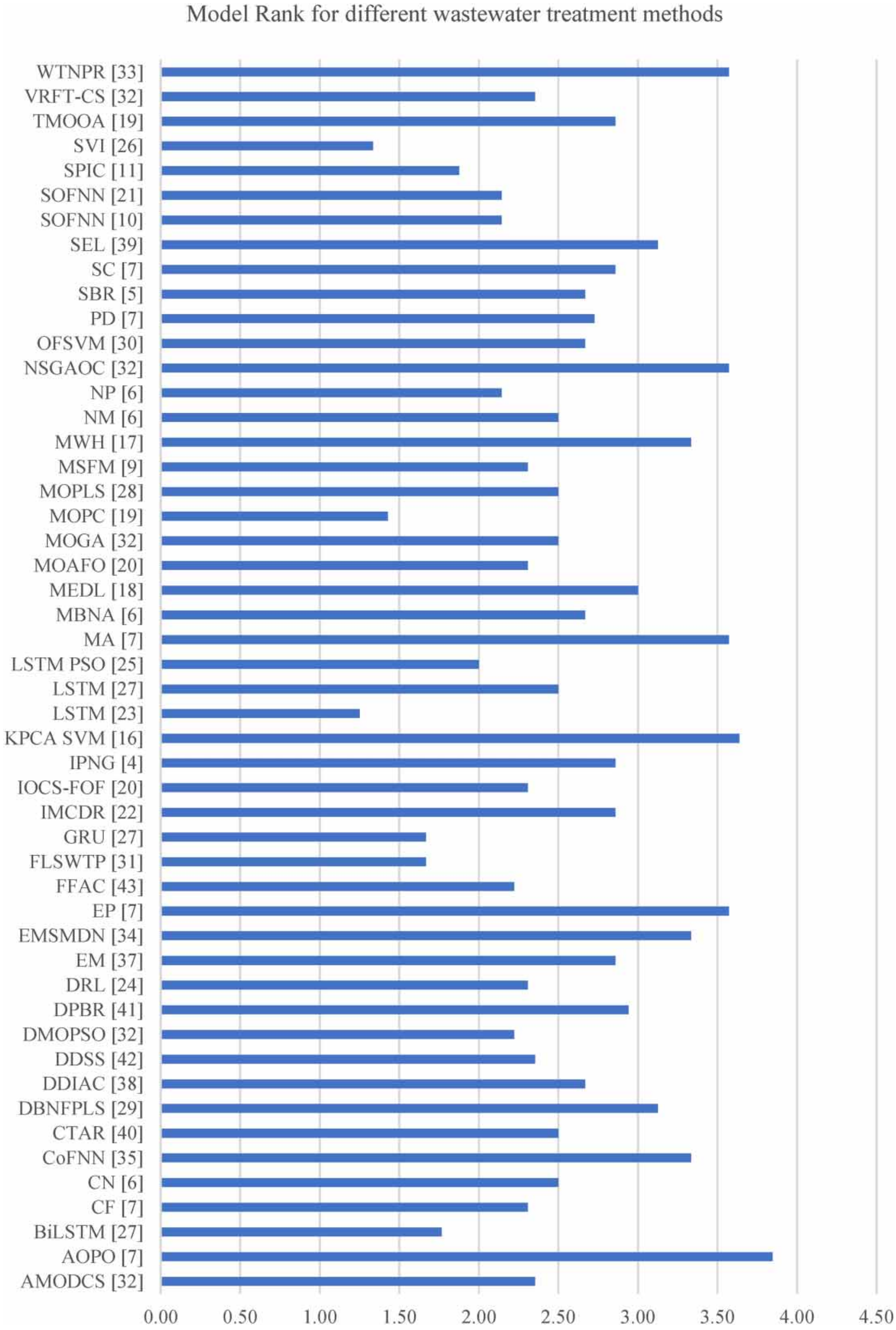


Figure 6 | Pragmatic analysis of reviewed models.

most effective in terms of computational complexity. This is because the algorithms in question are more effective than their counterparts. This is owing to the fact that later iterations use chemical techniques in order to speed-up the treatment process. Because of their superior performance in comparison to other models in terms of deployment costs, TMOOA, IMCDR, EP, MOPC, PD, AOPO, SC, and EM are often used for low-cost wastewater treatment. It is essential that models with higher values be used for the goal of real-time wastewater treatment. This is due to the fact that models with higher values have a better success rate than models with lower values. It was also shown that AOPO, KPCA SVM, EP, MA, NSGAOC, WTNPR, MWH, and EMSMDN have a better overall performance than other models, and it is imperative that these models be used for the efficient deployment of wastewater treatment plants.

To summarize, various wastewater treatment methods are compared based on their performance metrics. MR is calculated for each method and higher value of the MR denotes higher effectiveness of the model. Although an extensive review of treatment methods was carried out, it might be argued that an in-person investigation of all the treatment methods could perhaps make the results of this study more usable for industry stakeholders. Due to the heavy potential cost and manpower requirement for such an investigation, however, the authors had to decide not to go along with it. Another limitation of the study is that particular performance metric might be more important than others in specific applications. In such scenarios the formula for MR will have to be modified in order to compare the models.

5. CONCLUSION

From this study, it can be observed that a wide variety of computational models are available for wastewater treatment, and each of them vary in terms of different performance measures. Upon detailed analysis of these models, it was also observed that very few methods are used for core-treatment of water, and a vast majority of proposed models optimize these core-treatment methods using deep learning. Deep learning models assist in scheduling tasks for water treatment, which assists in reducing redundancies, and improving quality of resulting water purity level. This also reduces running cost, and complexity of deployment, which is highly recommended for any wastewater treatment model. Thus, MBNA (Cheriyamundath & Vavilala 2021), CN (Cheriyamundath & Vavilala 2021), NP (Cheriyamundath & Vavilala 2021), SOFNN (Han *et al.* 2019), SPIC (Tung *et al.* 2018), MWH (Karlsson *et al.* 2019), and LSTM PSO (Liu *et al.* 2021), have better water quality, than its counterparts, and thus must be used for real-time processing purposes. In terms of overall efficiency, AOPO (Deng *et al.* 2020), KPCA SVM (Cheng *et al.* 2019a), EP (Deng *et al.* 2020), MA (Deng *et al.* 2020), NSGAOC (Han *et al.* 2021b), and WTNPR (Kuroki *et al.* 2020), outperform all other techniques, and must be used for designing an effective wastewater treatment plant. In future, researchers can fuse these models, and estimate their performance for drinking, and non-drinking types of water. Furthermore, ensemble deep learning models must be used to improve scheduling efficiency of the treatment plant, thereby reducing wastage, and saving running costs for small, medium and large-scale wastewater treatment scenarios.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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