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A SURVEY ON ARTIFICIAL INTELLIGENCE TECHNIQUES FOR VARIOUS WASTEWATER TREATMENT PROCESSES

V. G. Mohan[1], A. F. M. Ali[1], B. L. Vijayan[2] and M. A. Ameedeen*[1]
[1] Faculty of Computing, Universiti Malaysia Pahang, 26600 Pekan, Malaysia.
[2] Faculty of Industrial Sciences and Technology, Universiti Malaysia Pahang, 26300 Gambang, Malaysia.
*corresponding_mohamedariff@ump.edu.my

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Abstract— Pollutant removal percentage is a key parameter for every WWTPs, and it is crucial to predict pollutant removal efficiency. The efficiency of pollutant removal processes can be increased with the help of modeling and its optimization. Statistical models are not practical enough for wastewater treatments due to complicated relationship among input and output parameters. ML models are typically more malleable when modeling non-linear complex datasets with missing data. Many AI techniques are available, and the aim is to investigate the suitable AI technique for designing efficient models for WWTPs. DL and EL are the main techniques reviewed in

Learning, Wastewater Treatment Processes	this work. The EL models showing the most successful performance among other techniques by generally showed their accuracy and efficiency.

I. Introduction

Currently, it is the most defining era for human race is that the time when computing moved from large mainframes to compact computers, and then reached to cloud. Artificial Intelligence (AI) has a major role in these revolutionary changes in technology. AI has been applying extensively in various aspects of engineering as well as technology such as autonomous driving, big data, pattern recognition, intelligent search engine, image understanding, automatic programming, robotics, and human-computer games. To achieve these milestones, AI technology pact with the design of computer systems and programs that are capable of mimic the human features [1, 2].

Generally, the processes in water industries are tough procedures especially in wastewater treatment, and these procedures are facing huge environmental management challenges [3-5]. AI models are generally very efficient when compared with models developed by statistical techniques in the case of modelling complex datasets with missing data and nonlinearities [6, 7]. AI has been considered an unbeatable tool in experimental designs that can generate the optimal variables for modelling and optimizing the wastewater industry [8]. Pollutant removal processes are the ultimate procedure for every wastewater industry [9-11]. These industries always trying to improve the efficiency of pollutant removal processes without increasing the cost [12, 13]. This problem can be easily managed by implementing AI on wastewater treatment processes (WWTPs) for the optimization of pollutant removal processes with the availability of existing data.

Each application of various sectors has been slowly shifting to AI. In parallel, AI techniques also developing rapidly, and it make difficulty to choose suitable techniques to implement predictive models for WWTPs. Therefore, the goal of this review work is to figure out the latest AI techniques suitable to design predictive models for WWTPs. To identify the better one for fulfilling the aim – Deep learning, Regression & Classification Learning and Ensemble Learning are the major techniques reviewing in this article by go through its fundamentals, benefits, and applications. Then go through the comparison and analysis of each technique by show their best results with tables and finally concluded with the best AI technique from this limited knowledge work.

The remaining content of the paper is organized as follows: In Section 2, literature study on Deep Learning and Ensemble Learning as well as its applications. The discussion and the findings of the research questions are discussed in Section 3 and finally, section 4 concludes the study along with future study of the research.

II. Literature Study on AI Techniques for WWTPs

Deep Learning and Ensemble Learning are the two AI techniques reviewed in this review work for AI modelling on WWTPs.

A. Deep Learning

Deep learning (DL) is the core part of AI as well as it is a new concept of machine learning (ML) which has getting more popular. The designs of DL which contain numerous hidden layers called deep networks to learn different type of features with multiple levels of abstraction. DL algorithms pursue to employ the exotic structure in the input sharing to identify better depictions, often at numerous levels, with higher grade learned features defined in terms of lower-level features [14-16].

Applications of DL for WWTP

The one of the important applications of DL is Convolutional Neural Network (CNN), which become the top architecture for most image characterization, phrase classification, passage recognition, image recognition, face recognition, detection tasks, etc. [17]. Fukushima [18] has first introduced the concept of CNN in 1998 which consists of neurons and each neuron has a liable weight as well as bias. These neurons are allocated in three layers – an input layer, an output layer, and multiple hidden layers. In that, hidden layers comprise – a convolutional layer (CL), a pooling layer (PL), a fully connected layer (FCL) and different normalization layers. The peculiarity of CL is that it can merge two sets of information by applying convolution operation. Then, PL is used for reducing the dimensionality by associating the output of neuron cluster at one layer with the single neuron. Then, the primary purpose of FCL is for classifying the input into several classes according to the training datasets and FCL connects every neuron in one layer to every neuron in another layer. Due to these specialties, CNN method has shown better efficiency in terms of automatic feature extraction and deep feature representation in late years [19]. Some research studies regarding the applications of DL in WWTPs have been discussed in the Table 1.

The techniques developed from CNN has been used in many areas such as medical field, image classification, computer vision, etc. From the best knowledge, few studies are done on wastewater treatment by using CNN. Anyhow CNN models require a vast number of data samples for the model to perform in better way. Although, there should be a drawback is that when the traditional dataset is added into the data, then the data become heavily imbalanced and need more studies on it [20]. However, CNN should be a future scope and can use as best techniques in industrial level applications especially in wastewater treatment.

Table 1: Few applications of DL for WWTP

Applications	Contribution	References
AI prediction model for WWTP through the combination of CNN and Recurrent Neural Network	This combination of model has been used to automatically extract the local features from WWTP dataset.	[19]
A DL with multiple regression model for WWTP by using Regression CNN (RegCNN)	CNN has been used accurately and rapidly for predicting output water quality indicators.	[21]
Dissolved oxygen (DO) AI prediction model for aquaculture systems based up on deep belief network (DBN)	The model shows better prediction accuracy and stability.	[22]
Classification of microbeads in urban wastewater	The study shown that CNN has achieved a classification performance of 89% accuracy with actual data.	[23]
AI classification model on sewage sludge and rapeseed straw	Results have been shown that CNNs are an essential tool, and these models provide a simplified as well as cost-effective approach to the approximate evaluation.	[24]

An adaptive mode CNN modelling to industrial process	The results showed that the proposed method achieved the highest prediction accuracy.	[25]

B. Ensemble Learning

Newly, tree-based ensemble AI models have been progressively used to predict efficiency of WWTPs. Ensemble Learning (EL) models are based on the speculative concept that using a class of models composed of multiple weak learners can enhance the eventual output of the collective model, which is specified as a strong learner. Random Forest (RF) is one of the commonly used tree-based ensemble models where the decision tree models are used as weak learners [26].

RF is an updated version of bagged trees and the features used for the building of the tree have been selected randomly [27, 28]. This technique is one of the excellent ensemble methods that can boost the performance. RF do not overfit and offer chances for detailing and visualization of input, such as variable selection and it is quick and robust to noise. Moreover, RFs have been the best performing general-purpose regression techniques available to show a dynamic performance on most of the experimental problems. RF algorithms are a kind of EL and the reason is that, the values of a random vector sampled independently on the values of each tree were mapped with the same distribution [29]. Thus, RF having many decision trees which displays the mean of the decisions contributed by each tree. They can work fast, commonly show a substantial development over single tree algorithms such as classification and regression trees (CART), and achieve common error frequencies that cross check properly to usual statistical techniques [30, 31].

A general class of supervised AI techniques [32, 33] which are occupied on the logic of a decision tree (DT) [34] called DT learning and this technique is mainly used to find classifiers or regressors. The main aim of classification is for assigning a discrete value, or assigning a discrete class, and to attribute tuples. Then, regression goes with assigning a real-valued number that should be within some range of accuracy. Some attributes of the data have focused by each node in the DT, and this can determine what kind of class or value the data is most likely to have, and the attribute's value has finally given [35, 36]. RF algorithms can train several DTs of the training data on random subsets rather than dealing with just a single DT. Then, each tree providing its own prediction to the ensemble's end prediction, while the time of regression or classification on new data. Then look through the classification only, final prediction should be the class with most votes [30, 37].

Applications of RF in Wastewater Industry

The literature study of EL in this paper has discussed in the following Table 2. As per the few studies regarding EL showing that it's a new area for industrial WWTPs. Anyhow this AI technique is showing better efficiency, robustness and reliable for predicting the parameters which comes in small scale level of WWTPs performances. More research on EL can be assured that this should be one of the best techniques can use in WWTPs predictions as well as its data analysis.

Table 2: Some applications of EL for WWTPs

Applications	Contribution	References
Proposed a model for predicting ammonium concentrations at WWTP inlets.	An ensemble approach based on existing studies to develop model prediction bound creating new opportunities for modelling on Predictive Control for WWTPs.	[38]
A proposed method to identify an ensemble of behavioural model datasets for WWTP analysis.	Results showed that the proposed methodology is a new footstep as well as helpful to verify predictions by Monte Carlo analysis.	[39]
Proposed an ensemble classification method for fault diagnosis in WWTP.	Found that the performance of G-mean value and accuracy of minority class in a case study of WWTPs have been improved.	[40]
Proposed a soft sensing model for effluent quality prediction by using EL.	Ensemble models are adequate for the proposed methodology.	[41]
Implementation of a multi-grained cascade forest (gcForest) ensemble method for effluent quality prediction of WWTPs.	As a comparison with some conventional modelling methods, gcForest model shows prediction excellence for effluent suspended solid (SS) and effluent COD.	[42]

Proposed a selective ensemble extreme learning machine modelling to enhance the effluent efficiency predictions of WWTPs.	The proposed method has shown better performance than the traditional effluent quality measurements.	[43]
Proposed a novel methodology for predicting the effluent quality parameters for an industrial WWTP.	Results have been showed that the ensemble models provide the good performance for predicting.	[44]
An ensemble approach for WWTP performance analysis using three different AI based non-linear models.	Neural network ensemble (NNE) model can consider as a best ensemble method for the proposed approach.	[45]
An ensemble method for predicting biochemical oxygen demand (BOD) in river water has developed	Bagging with K-star algorithm is the ensemble method used for the prediction as the base classifier was applied to the dataset.	[46]
A novel ensemble process monitoring method was proposed based on genetic algorithm (GA) for selected distinction of principle components.	Studies showed that an actual WWTP show the excellent performance of the proposed method compared with several Principal Component Analysis (PCA)-based methods as well as strong generalization ability of the ensemble method.	[47]

III. Discussion and Findings

DL models require a huge number of samples for the model to perform smoothly. The drawback of DL is that while the traditional dataset is added into the data cause heavily imbalanced. DL should be a future scope and can use as best technique in WWTPs. EL is a new area for industrial WWTPs, and this technique is showing better efficiency, robustness and reliability which comes in small scale level of WWTPs performances. More research is required for EL to make one of the best techniques in water treatment industries.

IV. Conclusions

AI model predictions are inherently statistical in nature that enable machines to improve at tasks by using ML techniques. The ML algorithms include parsing data, learn from it, and then decide or predict with all uncertainties. Furthermore, predictions are ideally intercalating the data points corresponding to previously seen data. Anyhow, AI models that estimates unknown dependency between a system's inputs as well as its outputs from the existing data. Also, if dependency is discovered, it can be used to predict the future system's outputs from the known input values. There are many studies on AI modelling in the wastewater industry. The key parameter prediction in wastewater treatment plants is a very important procedure and can reduce the number of experiments, energy, cost, and resources. Anyhow, a few AI techniques have been reviewed which are trendy for the modelling on WWTPs. From the limited study concluded that ensembled AI techniques can be the next stage for AI implementation on wastewater sector which shown good results in sample datasets which having complex features.

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