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PREDICTIVE MODELING OF OZONE DOSING IN DRINKING WATER TREATMENT PLANT USING DEEP LEARNING COMPARATIVE STUDY BETWEEN DEEP NEURAL NETWORKS AND CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT

Ozone is known to be a powerful oxidant and disinfectant in drinking water production processes. The ozone dosing process presents a particularly difficult control problem due to its nonlinear behavior.

Most water treatment plants use ozone dosing by determining the ozone concentration based on operational experience without considering temporal variations in water quantity and quality. In this case, this approach can lead to an overdosing that can increase costs or an underdosing that will influence the quality of the treated water.

Two deep learning models, namely, the DNN model and CNN model, were applied for ozone dosing predictive modeling tasks. Comparing the results obtained in the training and testing processes, we notice that the DNN model with 5 hidden layers outperforms the CNN model. These results seem very encouraging, and the methodologies seem promising.

Keywords: Ozone dosing, Drinking water treatment, Deep learning, Predictive modeling

INTRODUCTION

Drinking water treatment is critical in meeting rising water demand, utilizing both physical and chemical processes to produce high-quality drinking water from surface water sources (Achour and Chabbi, 2014; Harrat and Achour, 2016; Achour and Chabbi, 2017; Achour et al., 2019). The ozonation process, aimed at substituting chlorine for disinfection, removing odor and color, and oxidizing organic matter and micropollutants, plays a crucial role in this process (De Vera et al., 2016; Gomes et al., 2017).

Ozone has become widely adopted in drinking water treatment plants as a primary means of disinfection in recent years (Von Gunten, 2003). The success of ozonation disinfection depends on the amount of ozone used (or ozone exposure) (Wols et al., 2008; Clark et al., 2002). Additionally, ozonation has been found to enhance coagulation, settling, and filtration processes (Muniyasamy et al., 2020). However, overusing ozone in the ozonation process is not cost-effective and can lead to health issues due to high levels of disinfection byproducts (DBP) (da Silva et al., 2014; Sun et al., 2020).

The optimization of ozone dosage is crucial for reliable drinking water treatment. Dosing that is too low can result in inadequate removal of compounds and unreliable disinfection (Oh et al., 2010; Lee et al., 2014). On the other hand, excessive dosing is not only uneconomical but can also cause health problems from high levels of disinfection byproducts (da Silva et al., 2014; Sun et al., 2020). To ensure effective treatment, there are two methods for controlling ozone dosage in the ozonation process (Muniyasamy et al., 2020; Kaiser et al., 2013; Kang et al., 2008, Dan et al., 2021).

The most commonly used method for controlling the ozonation process in drinking water treatment is maintaining a constant ozone dosage. Another approach is keeping a stable dissolved ozone residual level; however, this method is less frequently used. The raw water's quantitative and qualitative variability affects the dissolved ozone residual and can be challenging to predict with precise parameters, making accurate mathematical modeling difficult. (Elovitz et al., 2000; van der Helm et al., 2009;Shin et al., 2016; Audenaert et al., 2010; van der Helm et al., 2007).

In addition, maintaining a constant ozone dosage is a challenge in the ozonation process due to its complex physical and chemical reactions, long time delay, nonlinearity, and multiple sources of perturbations and uncertainties. Keeping a constant dosing strategy under such unpredictable conditions is difficult to achieve (Niu et al., 2021).

Artificial intelligence (AI) has the potential to effectively address complex challenges in water engineering due to its ability to generalize and adapt and its straightforward design.

This results in cost savings and optimized processes in the water and wastewater treatment industries, which have widely adopted machine learning (ML) and deep learning (DL) technologies (Alam et al., 2022; Xie et al., 2022).

Several studies in the water engineering industry have used ML techniques, including artificial neural networks (ANNs), recurrent neural networks (RNNs), random forest (RF), and support vector machine (SVM) (Kim et Ahn., 2022; Ren et al., 2020; Adoabi et al., 2022).

Artificial intelligence has been applied in the prediction of ozone dose in water treatment with great success in recent years. The use of machine learning algorithms such as artificial neural networks (ANNs), support vector machines (SVMs), and decision tree algorithms has been demonstrated to effectively predict the ozone dose in water treatment processes.

Wang et al. (2014) applied an artificial neural network (RBF) to predict the ozone dose in a water treatment process. The results showed that the ANN model was able to effectively predict the ozone dose with high accuracy. In another study, Dongsheng et al. (2017) used a support vector machine algorithm to predict the ozone dose in water treatment. The results of the study showed that the SVM model was able to achieve high accuracy in the prediction of the ozone dose. Some studies have even utilized hybrid techniques to improve modeling. In a study conducted by Djeddou et al. (2022) at a full-scale drinking water treatment plant in Algeria, various hybrid models were evaluated for predicting ozone dosing. The study revealed that the most effective hybrid ML technique was a combination of a radial basis function neural network (RBFNN) with discrete wavelet transform (DWT), as it outperformed other hybrid models in predicting ozone dosing accurately.

In this study, two deep learning models are presented for predicting ozone dosing in a full-scale drinking water treatment plant located in Oued Al-Athmania, Algeria. The main goal of this application is to evaluate the ability of deep learning models to optimize the ozonation process. The results will serve as a foundation for further model refinement, particularly the evaluation of the innovative approach, the Ozone Dosing Dynamic Strategy (ODDS), which accounts for temporal variations in raw water quality.

MATERIAL AND METHODS

Oued Al-Athmania water treatment plant Presentation

It is located in eastern Algeria and has the capacity to treat 262,000 m^3/day of water from the Sidi Khlifa reservoir dam, which is fed solely by the Beni Haroun dam.

Preozonation is carried out upstream, and then the water goes through coagulation, flocculation, settling, biofiltration, disinfection of nitrified water by ozonation, carbon filtration, and final disinfection with chlorine gas.

Dataset collection

The data used for ozone dosing were obtained from daily operation data, including various measured parameters, namely:

1. pH;
2. Conductivity;
3. Temperature;
4. Turbidity;
5. Dissolved oxygen (DO),
6. Total suspended solids (TSS),
7. Organic matter (OM);
8. Aluminum sulfate (Al_2SO_4) as coagulation;
9. Sulfuric acid (H_2SO_4).

The measurements were taken between 2009 and 2010, covering all seasonal changes in the factors being considered. The input and output data were normalized to a range between 0 and 1, and their statistical parameters are summarized in Table 2.

Table 1: Statistical parameters of inputs and output

		Min.	Max.	Average	S.D.	C.V.
Inputs	Temp.(°C)	5.690	21.364	13.542	4.840	0.357
	pH	7.544	8.413	8.032	0.247	0.030
	Cond.(µs/cm)	962.548	1171.528	1082.391	53.067	0.0490
	Turb. (NTU)	4.460	19.088	10.122	3.371	0.333
	O_2 (mg/l)	2.476	8.296	4.998	1.785	0.357
	TSS (mg/l)	2.924	15.038	8.325	3.099	0.372
	OM (mg/l)	1.124	1.762	1.464	0.178	0.121
	Al_2SO_4 (mg/l)	16.717	44.994	27.721	5.389	0.194
	H_2SO_4 (mg/l)	0.977	10.306	4.794	3.080	0.642
Output	O_3 (mg/l)	1.3	3.45	2.28	0.34	0.15

Deep Neural Networks

Deep neural networks (DNNs) are a type of artificial neural network with multiple hidden layers between the input and output layers. DNNs with more hidden layers can learn and model more complex relationships in input data than shallow neural networks with fewer hidden layers. As a result, DNNs are increasingly being used in a variety of fields, such as image and speech recognition, natural language processing, and predictive modeling (LeCun et al., 2015; Schmidhuber 2015; Goodfellowet al., 2016). DNNs have shown promising results in addressing real-world problems such as classification and regression in predictive modeling. Forward-feeding neural networks, in particular, have been widely used in many applications where data flow sequentially from input to output layers.

Reza et al. (2021) built deep neural network (DNN) algorithms to predict water temperature in the Los Angeles River in southern CA, USA. The DNN algorithm outperformed the other models. The DNN model of determination was 26 and 12% higher compared to the two other models.

Le et al. (2019) proposed a DNN model to forecast the flow rate at the Son Tay hydrological station on the Red River, Vietnam. The study revealed that the DNN model achieved remarkable flood forecasting performance, requiring only a small amount of data. These outcomes suggest that the DNN model could serve as the foundation for constructing a real-time flood warning system on the Red River, Vietnam.

According to Agatonovic-Kustrin and Beresford (2000), the architecture of DNNs is inspired by the human brain's information processing capabilities. This property makes DNNs more suitable than other machine learning models, such as support vector machines and decision trees, for processing large datasets and extracting meaningful features.

DNNs are made up of neurons that improve through the learning process. The layers are fully connected, meaning that each neuron in a layer receives input from all neurons in the previous layer and in turn serves as input to all neurons in the subsequent layers (Fig. 1). With the ability to analyze intricate data patterns, DNNs have been utilized in regression analysis, classification, and unsupervised data clustering across various fields.

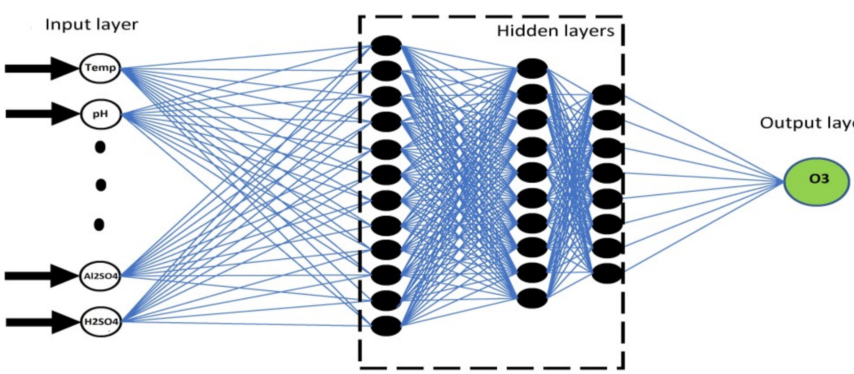

Figure 1: Deep Neural Network

Convolutional Neural Networks

Convolutional neural networks (CNNs) are artificial neural networks that are specifically designed for image and video recognition tasks. It extracts features from the input image using convolutional layers, which are then processed by activation functions, pooling layers, and fully connected layers to make a final prediction (LeCun et al., 2015). The use of convolutional layers, which slide a small filter over the input image, applying transformations to the pixels and building a feature map that summarizes the important information in the input, is a key feature of CNNs. A CNN can learn increasingly complex features and representations of the input data by employing multiple convolutional layers (Baek et al., 2020).

Convolutional neural networks (CNNs) are comparable to deep neural networks (DNNs); however, they are specifically designed to analyze visual imagery. This allows for the incorporation of image-specific features into the neural network architecture, making it well suited for tasks that involve images (O'Shea and Nash 2015).

CNNs can effectively map a large dataset to a final output through a straightforward but precise architecture (Fig. 2). Its weight sharing structure and pooling techniques allow for a reduction in the number of parameters, leading to superior performance compared to DNNs, especially when analyzing visual images. It is worth noting that CNNs are spatially invariant, meaning they do not capture the position and orientation of objects. Thus, if data position is crucial, CNNs may not be a suitable option. In recent times, CNNs have seen widespread use in a range of water and wastewater treatment applications (Lowe et al., 2022).

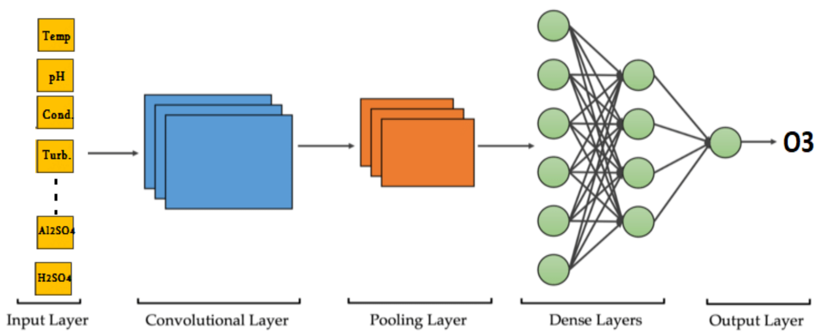

Figure 2: Convolutional Neural Network

Performance Evaluation

The training and testing processes of both the DNN and CNN models were assessed using statistical parameters such as the root mean square error (RMSE), mean absolute error (MAE), correlation coefficient (R), and Nash-Sutcliffe efficiency coefficient (NSE). These parameters were expressed as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(\mathrm{OD}_i^{measured} - \mathrm{OD}_i^{predicted}\right)^2}{N-1}} \tag{1}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\mathrm{OD}_i^{measured} - \mathrm{OD}_i^{predicted}\right| \tag{2}$$

$$NSE = 1 - \frac{\sum_{i=1}^{N}\left(\mathrm{OD}_i^{measured} - \mathrm{OD}_i^{predicted}\right)^2}{\sum_{i=1}^{N}\left(\mathrm{OD}_i^{measured} - \overline{\mathrm{OD}_i^{measured}}\right)^2} \tag{3}$$

$$R = \frac{\sum_{i=1}^{N}\left(\mathrm{OD}_i^{measured} - \overline{\mathrm{OD}_i^{measured}}\right)\left(\mathrm{OD}_i^{predicted} - \overline{\mathrm{OD}_i^{predicted}}\right)}{\sqrt{\sum_{i=1}^{N}\left(\mathrm{OD}_i^{measured} - \overline{\mathrm{OD}_i^{measured}}\right)^2 \sum_{i=1}^{N}\left(\mathrm{OD}_i^{predicted} - \overline{\mathrm{OD}_i^{predicted}}\right)^2}} \tag{4}$$

where OD is the ozone dose (mg/l) and $\overline{\mathrm{OD}}$ is the mean ozone dose (mg/l).

RESULTS AND DISCUSSION

The feasibility of the proposed models in predicting ozone dosing was evaluated by training two different deep learning structures, a DNN and a CNN, on a training set. The prediction performance of these two models on new samples stored as a test set was reported. Both the DNN and CNN models were fed with a list of nine inputs.

The number of hidden layers for the two networks was determined through a trial and error process using a manually specified subset of the search space. This process started with the simplest architecture, a one-layer network, and took computation time per step into consideration.

The DNN model comprised 5 hidden dense layers, as a further increase in the number of layers did not result in a significant decrease in loss while also negatively impacting processing time, according to testing. The CNN model consisted of 4 convolutional layers, with a similar outcome where higher layers did not significantly improve loss. The training and testing were carried out on a computer equipped with an ASUS AMD Rayzen TM 5 R5-3550H CPU at 3.7 GHz and 16 GB of RAM.

The models were constructed using the Keras library in Python, which provides an interface for deep learning. MSE was selected as the loss function due to its high sensitivity to large errors compared to the mean absolute error. The Adam optimizer was utilized to optimize the CNN model, while the DNN model was optimized using the RMSprop method. Both models were trained on the same dataset of 182 samples, with the datasets being randomly divided into training and testing sets in a 70:30 ratio. The hyperparameter values that were selected are presented in Table 2.

Table 2: Developed Models Description

	CNN model	DNN model
Input shape	(n, 9, 1)	(n, 9)
Number of layers	Total of 7	Total of 7
Batch size	8	32
Number of epochs	500	500
Loss function	MSE	MSE
Optimizer	Adam	RMSprop
Learning rate	10^{-3}	10^{-3}
Number of parameters	70,209	15,265

According to the results of the experiment with the training dataset, the prediction of ozone dosing resulted in an estimated root-mean-squared-error of 0.0382 and 0.0426 for the CNN and DNN models, respectively. The mean absolute error was 0.091 for the CNN model and 0.0299 for the DNN model. The performance parameters of the CNN model showed R = 0.9936 and NSE = 0.9861, whereas the DNN model had a slightly better correlation coefficient estimated as R = 0.9967 and NSE = 0.9845, which is close to the CNN model. Both models, the CNN and DNN, performed well in the training process, as shown in Table 3.

In contrast, during the testing phase, the prediction of ozone dosing (OD) by the DNN model has an estimated RMSE of 0.1699 and MAE of 0.1, whereas the CNN model has an RMSE of 0.3341 and MAE of 0.1982. The performance of the DNN model remains good with R = 0.8784 and NSE = 0.7554, whereas the performance of the CNN model significantly decreases with R = 0.5443 and NSE = 0.2428.

Table 3: Performance parameters of the CNN and DNN models

	Train				Test			
	RMSE	MAE	R	NSE	RMSE	MAE	R	NSE
CNN model	0.0382	0.0291	0.9936	0.9861	0.3341	0.1982	0.5443	0.2428
DNN model	0.0426	0.0299	0.9967	0.9845	0.1699	0.1000	0.8784	0.7554

The results indicate that the DNN model has better generalization abilities and outperforms the CNN model significantly when tested on new data that were not present in the training phase. In terms of complexity, the CNN model has a significantly higher number of parameters (70,209) compared to the DNN model (15,265).

Figs. 3, 4, 5 and 6 present the scatter plot of the observed ozone dosing compared to the predicted values by both the DNN and CNN models, as well as the response of the DNN model in predicting ozone dosing.

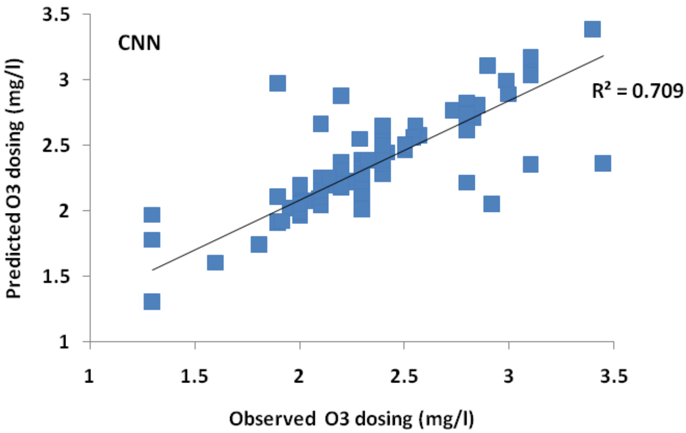

Figure 3: Observed ozone dosing vs predicted ozone dosing using the CNN model.

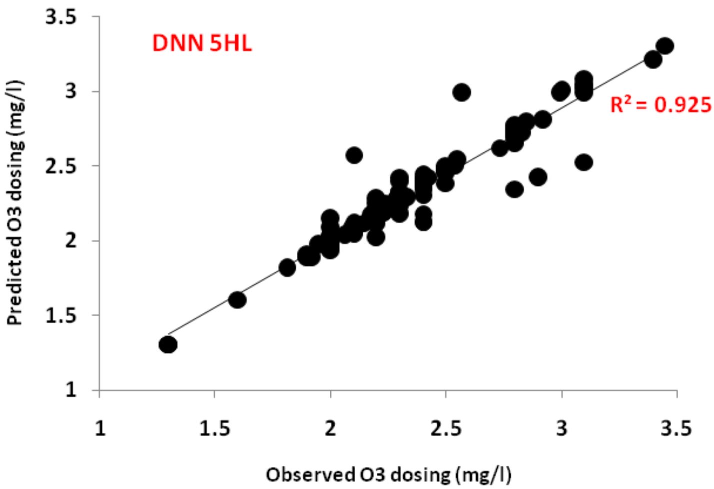

Figure 4: Observed ozone dosing vs predicted ozone dosing using the DNN model.

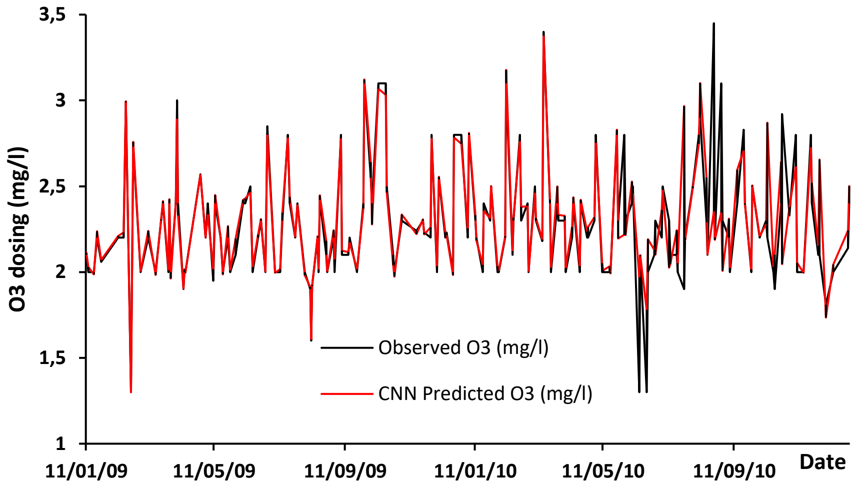

Figure 5: Response of the DNN model for the prediction of ozone dosing (all data).

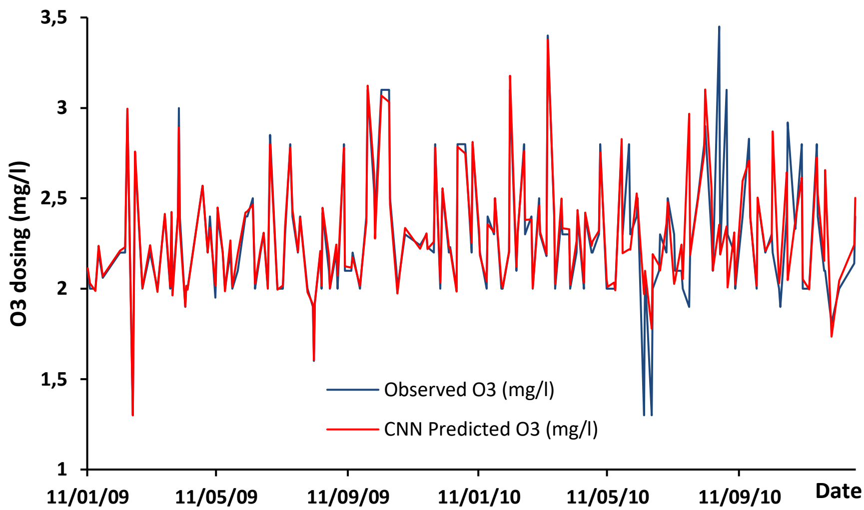

Figure 6: Response of the CNN model for the prediction of ozone dosing (all data).

CONCLUSION

Deep learning (DL) models are applied to predict ozone dosing in a full-scale drinking water treatment plant. A comparison was made between a deep neural network (DNN) and a convolutional neural network (CNN) in terms of their prediction performance and simplicity. The results indicated that both models were capable of accurately predicting ozone dosing during the training phase, with the DNN model being faster and producing fewer errors (root mean square error and mean absolute error).

In terms of prediction accuracy, the testing results show that the DNN model outperforms the CNN model. Because of its larger number of parameters, the CNN requires more data for training and has a longer computation time. To obtain accurate predictions, it is critical to choose appropriate hyperparameters, architecture, and input parameters; however, this may result in longer computation time and larger training data requirements for the CNN model.

These findings spur us to continue exploring ways to enhance prediction accuracy and optimize the use of DNNs, as well as to examine hybrid approaches that incorporate the best features of both deep learning models. Additionally, there are several aspects of the models developed in this study that warrant further study, such as determining the impact of various inputs on generalization and efficiency.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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