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Prediction Of BOD And COD For Sewage Treatment Plant Using Artificial Neural Network Approach

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ABSTRACT
In this study, the knowledge base of a genuine wastewater treatment plant was acquired using a Neuro Vector Machine modelling approach, which was subsequently applied as a process model. The study shows that ANNs integrated with Support Vector Machine (SVM) are capable of accurately capturing the characteristics of plant functioning. The trained ANN plant model is included into a computer model. Utilizing plant scale data collected from a nearby wastewater treatment plant, the designed program is put into use and evaluated. For plant operators and decision-makers, it serves as a useful performance assessment tool. When employing COD as an input in the crude supply stream, the proposed model accurately predicted the effluent stream's biological oxygen demand (BOD), chemical oxygen demand (COD), and total suspended solids (TSS). One may argue that combining three crude supply inputs—BOD, COD, and TSS—rather than just one produced better model predictions than using just one crude supply input. The proposed approach for the Vitthalwadi STP data is done and presented via a graphical user interface and attained an Accuracy of about 95.6%.

Key Words: *Artificial neural networks; Wastewater plant; Modeling; Wastewater treatment; BOD; COD; TSS.*

1. INTRODUCTION

With an increasing population over the past few decades, increasing industrial and agricultural wastewater, and climate change, there are challenges to adequately process the wastewater. Sewage treatment is a process of removing chemical and biological contaminants such as wastewater and household. It mainly involves three processes namely physical, chemical, and biological. These treatments help us to remove contaminants from wastewater. In 2010, only 20% of the wastewater produced globally is treated with sewage treatment plants, which has been increased now up to a range of about 75%. Globally, 2 million tons of domestic sewage, industrial waste, and agricultural waste are released into waterways every day. This leads to a global death of about 1.8% people due to water-borne diseases every year. Therefore, there is a need to treat sewage in treatment plants to improve the quality of wastewater and cause no harm and pollution to the environment. Sewage treatment is also being referred to as solid and liquid wastewater treatment. Municipal wastewater mainly consists of water with small concentrations of dissolved organic and inorganic solids and suspended matter. The solid substances present in the wastewater are soap, lignin, protein, synthetic detergents etc. Even it contains some decomposition products produced from various synthetic and natural organic chemical industries. Wastewater also included inorganic substances produced from domestic and industrial sources. Also contains potentially toxic elements such as zinc, chromium, cadmium, copper, lead, mercury, etc. These toxic concentrations can affect humans and limit their agricultural use. To a lesser extent, pathogenic viruses, protozoa, bacteria, and worms may present in wastewater.

To maintain stable performance in a sewage treatment plant, it is desirable to know in advance the effective water characteristics of the sewage treatment plant. Characteristics such as COD, BOD, pH, conductivity, total nitrogen (TN), total phosphate (TP), total suspended solids (TSS), suspended solids (SS) flow rate, biological loading are important parameters to be identified. The process of the sewage treatment plant has an important relationship between these parameters. The prediction of effluent characteristics is very important for the optimization of the sewage treatment plant process. The previous study of many researchers suggests that the challenge in modelling sewage treatment plant performance is the complex dynamic nonlinear behavior of sewage treatment systems due to the interdependencies seen in the operational parameters of the sewage treatment plant process. Traditional modelling methods like mathematical models, least squares regression and partial differential equations may be able to show general trends but often struggle predicting the outcome of

specific events, making these models of less value for capital planning the modelling of sewage treatment plants is an area of interest for sewage treatment industry for its prediction and forecasting abilities. It is a cost-effective method to identify potential future capacity issues and could prove a powerful tool for long-term capital planning. The experience of researchers shows that controlling the activated sludge process is still difficult for many plants modelling method which has gained significant popularity since the 1990s is the artificial neural networks (ANN) approach. ANNs can find highly complex nonlinear relationships. This, in combination with the results not physically being measured, is a major barrier for the water treatment industry to adopt implementation of models within sewage treatment plant control. Since the 1990s the Artificial Neural Network (ANN) modelling approach has gained popularity for prediction and forecasting due to its ability to capture complex nonlinear relationships. The application of ANNs in the field of water treatment has been somewhat limited to date but the technique could prove to be a powerful tool in creating accurate models for predicting the performance of water treatment plants. In this research, the characteristics of influent and effluent stream of Vitthalwadi STP of Pune Municipal Corporation is found for 143 days specifically from months May 2023 to October 2024. These months are selected because, the maximum inflow of crude waste for this plant occurs during this interval. This is concluded from the previous 10 years data. The data of this particular interval is taken, that is properties namely COD, BOD, TSS and pH values of influent and effluent water. By this the efficiency of the plant is came to know. Later to optimize the treatment process, a model is created using ANN technique and it is then integrated with Support Vector Machine (SVM) to improve the accuracy. The error value is found and is greatly used to predict the efficiency of the plant in giving respective properties of treated and non-treated waste water. The efficiency of the plant, model techniques introduced, optimizing methods etc are clearly discussed in this article.

2. METHODOLOGY AND MODEL DEVELOPMENT

The Vitthalwadi STP is one of the most important STP when compared to other stp's in the Pune Municipal Corporation. The total capacity of this treatment plant is 32 MLD. Like other treatment plants it is designed and built to withstand heavy suspended and dissolved solids in wastewater. The average dry weather flow is 16 MLD and the peak flow is 29 MLD. Fig 1 shows the location of VSTP zone and plant, and Fig 2 displays the semantic treatment process of the plant. That grid and floating the breeze of crude sewage or removed by grit collector and grit elevators. Mechanical drive scrappers or used to scrap settled solids into the PST hoopers. The hydro valves that open in the consolidation sludge tank remove these settled solids. To lower the volume of mixed liquor, aerobic bacteria are activated by aeration and mixing with activated sludge. With the aid of mechanically powered aerators, the primary treated effluent is combined with the activated sludge recovered from the secondary settlement tank and uniformly dispersed in channels for aeration. The secondary settlement tanks are used to help mixed liquor that has settled out of the aeration tank. The secondary processed effluent is pre-chlorinated in the post-treatment and raised by screw pumps for even distribution to sand filters. The resulting stream flows into the wet well and is known as final effluent (FE). The Vitthalwadi STP's data sources were thoroughly examined. The decision was made to link the inputs of the crude solid (CS) stream to the outputs of the secondary treatment effluent (STE) stream. This is so that more complete data could be made accessible for the STE stream, whose outputs were essentially identical to those of the FE stream.

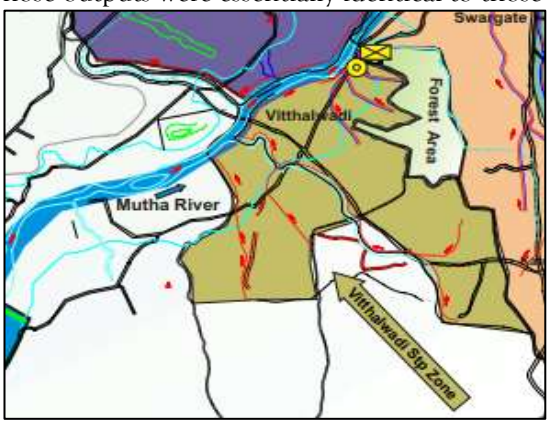

Fig. 1. Location of Vitthalwadi STP zone

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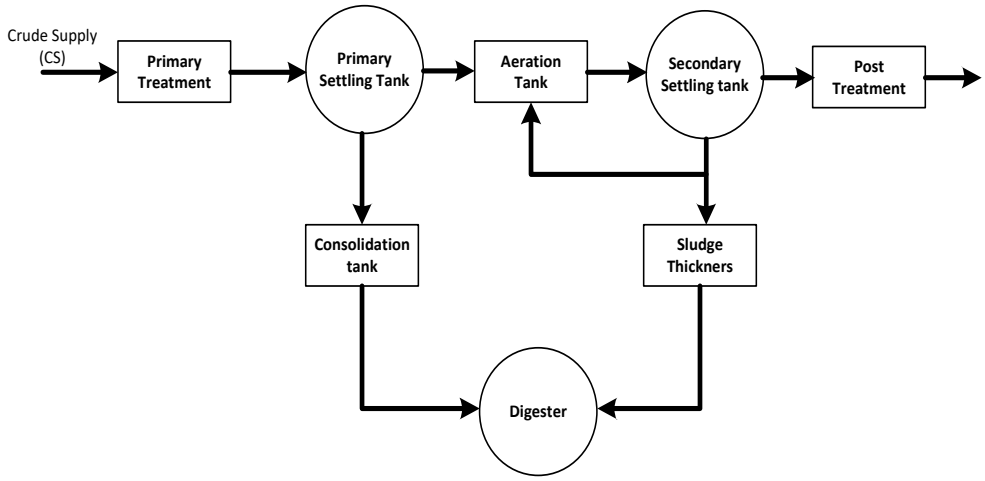

Fig. 2. Schematic Diagram of Vitthalwadi STP

As a result, data on the BOD, COD, and TSS in the CS stream and STE stream were gathered over the course of 143 days. This time frame met the criteria since it accounts for maximum fluctuations in the variables under study. Nearly every day, measurements were made in the plant. For BOD in the crude supply, COD in the supply, TSS in the supply, BOD in the STE stream, COD in the stream, and TSS in the STE stream, respectively, the conventions BOD-CS, COD-CS, TSS-CS, BOD-STE, COD-STE, and TSS-STE are valid. Because they can be used as indicators of how well a wastewater treatment plant is performing, the BOD, COD, and TSS were chosen. The efficiency of the collected data is analyzed properly and based on the data collected, Fig 3 is plotted for clear observation. Which shows the clear efficiency of Vitthalwadi STP in treating the water water.

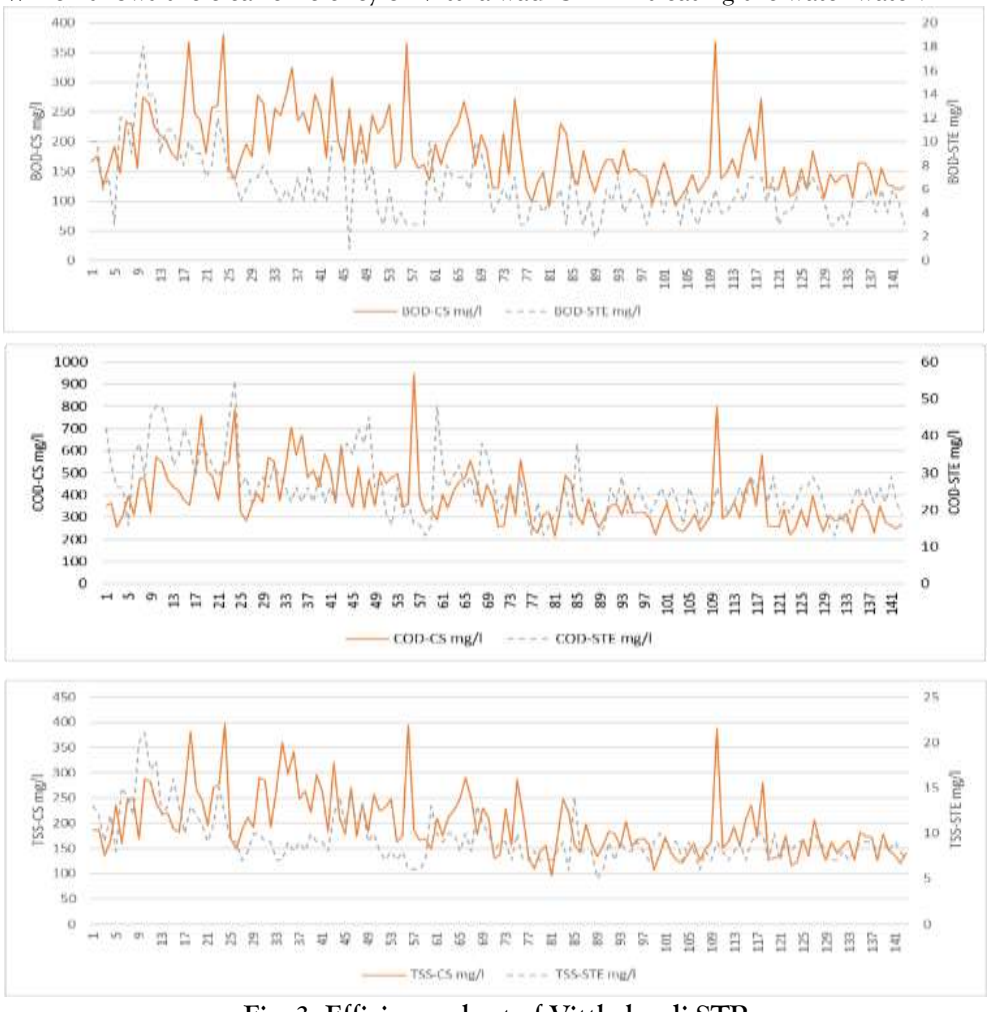

Fig. 3. Efficiency chart of Vitthalwadi STP

2.1. Data preparation, preprocessing, and statistical analysis

On the unprocessed experimental data, data refinement was done by eliminating any outliers, or unexpected points. These outliers exist for a variety of causes, including transcription or transposition problems brought on by poor data input. Human or experimental mistake are two more causes. To identify trends in the data set, various statistical modifications can be carried out. These are known as smoothing techniques, and they aim to lessen or get rid of the data's short-term volatility. Because it can capture changes in the time series' direction better than an unadjusted series, a smoothed series is preferred to an unsmoothed one. Data smoothing also minimizes the unfavorable impact of potential noise in the process data. For some time series, the traditional moving average method was produced by averaging many historical data points and dividing the available data points into longer time units using the formula below:

$$\bar{y}_t = \frac{y_t + y_{t-1} + \cdots + y_{t-n-1}}{n} \quad (1)$$

where n is the number of time periods in the average, t is the current time period, and y is the variable being measured. Most of the time, researchers utilize moving averages of three, four, or five points (n = 3, 4, or 5). It should be underlined that the series is more smoothly behaved the greater the n. The four-degree moving average was applied in this study to smooth out the raw data. As a result, the ANN model was applied to predictions using smoothed data series. Data scaling is the last step in the data preparation process. This is how neural networks prepare their data on a regular basis. Here, achieving a nearly uniform statistical distribution of the values for each net input and output is the key goal. The values should also be adjusted to meet the input neurons' range. The data sets are often standardized to have zero mean and one standard deviation or scaled such that they always fall within a predetermined range. The data set's mean and standard deviation are normalized to achieve this.

2.2. Machine learning algorithms

Machine Learning (ML) algorithms for wastewater treatment such as Support Vector Machine and Artificial Neural Networks is applied to optimize wastewater treatment processes by predicting critical treatment parameters and improving operational efficiency.

2.2.1. Support vector machine

Support vector machine is a supervised machine learning algorithm effective for classification and regression tasks. It is highly useful in the context of wastewater treatment due to its robustness in handling high-dimensional data and its ability to identify the optimal hyperplane that maximizes the margin between different classes or continuous outputs.

In this study, SVM is applied to predict treatment outcomes such as pH, Total Suspended Solids (TSS), Chemical Oxygen Demand (COD), and Biological Oxygen Demand (BOD), based on various treatment parameters like inlet flow rates, treatment duration, and aeration levels. The Implementation details are as follows,

- Feature Selection: Important features such as inflow pH, temperature, flow rate, and aeration are selected as inputs to the SVM model, as these significantly impact wastewater treatment outcomes.
- Parameter Tuning: The penalty parameter (C) and kernel function (linear, polynomial, or radial basis function) are tuned to optimize performance, striking a balance between low error and model complexity.
- Cross-Validation: Cross-validation is employed to validate the generalizability of the model, ensuring its ability to predict treatment outcomes under various conditions.

The SVM algorithm seeks to find an optimal hyperplane that maximizes the margin between different classes (or regression values) in the data. Using the same optimization principles, SVM is formulated as:

$$f(\mathrm{x}) = \mathrm{w}^T \phi(x) + b \quad (2)$$

where x is the two-dimensional residual vector to be classified, w is the optimal *p*-dimensional column vector to be solved, b is the optimal threshold, and $\phi(x)$ represents a *p*-dimensional mapping of the sample x from input space to feature space.

The classifier classifies the data x by:

$$y = \mathrm{sign}\,(\mathrm{w}^T \phi(\mathrm{x}) + b) \quad (3)$$

Here, **w** and b are solutions to the optimization problem:

$$\min_{\mathbf{w},b,\xi} \frac{1}{2} \| \mathbf{w} \|^2 + C \sum_{i=1}^{n} \xi_i \quad (4)$$

$$\text{Subject to } y_i(\mathbf{w}^T \phi(\mathbf{x}_i) + b) \geq 1 - \xi_i, \xi_i \geq 0, i = 1,2,\dots,n \quad (5)$$

where C is a positive scalar called the penalty coefficient, y_i is the label for sample x_1, and ξ_i is the slack variable for sample x_i.

Transforming this optimization problem to the dual space, the problem is formulated as follows

$$\max_{\alpha} \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(\mathbf{x}_i, \mathbf{x}_j) \quad (6)$$

$$\text{Subject to } \sum_{i=1}^{n} \alpha_i y_i = 0, 0 \leq \alpha_i \leq C, i = 1,2,\dots,n \quad (7)$$

where α is the Lagrangian multiplier vector, $K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i)^T \phi(\mathbf{x}_j)$ is the kernel function, and H is a square matrix with elements $H_{ij} = y_i y_j K(\mathbf{x}_i, \mathbf{x}_j)$.

In the dual space, the decision function is:

$$f(\mathbf{x}) = \sum_{i=1}^{n} \alpha_i y_i K(\mathbf{x}_i, \mathbf{x}) + b \quad (8)$$

where α_i are the elements of the optimal vector solution for the dual problem. The instances with non-zero Lagrangian multipliers are support vectors, which constitute the decision function for SVM along with their labels and the threshold b.

In wastewater treatment, this classifier can separate different treatment efficiency levels or predict continuous values of parameters like COD or BOD**.**

2.2.2. Neural Network Modeling: background and methodology

In order to help cognitive scientists comprehend the complexity of the nerve system, neural networks were first developed in the 1940s. They underwent steady development and were used in many branches of science. The ANNs are essentially mathematical constructs that draw inspiration from the way that the human brain learns. To address a variety of issues in the areas of system identification, forecasting, pattern recognition, classification, process control, and many others, they are built and used as alternative mathematical tools. (Huang and Mujumdar, 1993; Baker and Richards, 2002). The development of ANN's underlying learning and optimization algorithms as well as the consolidation of its theoretical foundation were both influenced by the interest in ANN as a tool for mathematical modeling. The modeling and simulation of chemical processes is one of these interesting research fields. The use of mechanistic models, which rely on basic material and energy balances as well as actual correlations, is fraught with mathematical challenges and frequently results in imprecise results. In these circumstances, neuron-based modeling is a reliable replacement. This is as a result of the positive aspects associated with their use.

The feedforward networks (FFNNs), feedback networks (FBNNs), recurrent networks (RNNs), and self-organized networks are some topological categories for ANNs. They can also be divided into further categories based on application, connection type, and teaching techniques. The FFNN seen in Fig. 4 is the network type that is most frequently applied in the modeling and prediction fields. One input layer, one output layer, and at least one hidden layer makes up the network in this design. The process by which the FFNN derives its output from its input, layer by layer, throughout the network is referred to as "feedforward." In this instance, cycles are not formed by the connections made by network neurons. No matter how complicated the network is, the neuron is a basic component that serves as its foundation. It uses predetermined activation functions to calculate an output by performing a weighted sum of its inputs. To incorporate nonlinearity into the network, activation functions for the hidden units are required. The most popular options for activation functions are the sigmoidal functions, including logistic and tanh, and the gaussian function. The number of neurons and their interconnection patterns determine the nervous system architecture. A set of input–output pairs are supplied into the network, which is then trained to replicate the outputs. The weights of the neurons are changed during training in order to reduce the quadratic error between observed data and computed outputs.

ANNs are particularly effective for modelling complex, non-linear relationships, making them suitable for predicting key parameters in wastewater treatment. ANNs can learn patterns from historical treatment data and be used to optimize operational parameters to enhance treatment efficiency. The ANN model for wastewater treatment consists of an input layer, hidden layers, and an output layer. The input layer includes key treatment parameters like inflow characteristics (pH, COD, TSS), treatment duration, and aeration levels.

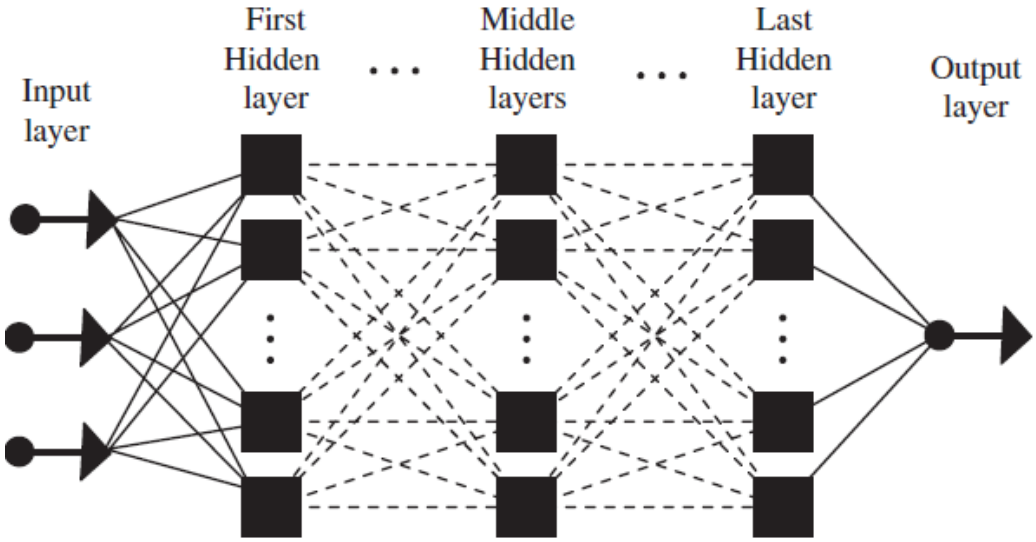

Fig. 4. Multi-layer ANN structure schematic.

The hidden layers process these inputs and learn complex relationships through weight adjustment during training. The output layer provides predictions for crucial outcomes such as treated water pH, COD, BOD, and TSS. The phases include Training, Validation, and Testing which are provided in detail as follows,

- Training Phase: The model is trained using historical data from the wastewater treatment plant, where weights are adjusted using backpropagation to minimize prediction errors.
- Validation Phase: A separate validation dataset is used to tune the model and prevent overfitting, ensuring it generalizes well to unseen data.
- Testing Phase: The trained model is evaluated on a test dataset to determine its predictive accuracy for various treatment scenarios.

The ANN follows standard feed-forward mechanisms, with inputs passing through the network:

$$\boldsymbol{a^{(l)} = f\left(W^{(l)} a^{(l-1)} + b^{(l)}\right)} \quad (9)$$

where $a^{(l)}$ is the activation of the l-th layer, $W^{(l)}$ are the weights, $b^{(l)}$ are the biases, and f is the activation function. In the backpropagation phase, the error is propagated back through the network to update the weights:

$$\Delta W^{(l)} = \eta \delta^{l} a^{(l-1)^{T}} \quad (10)$$

where η is the learning rate and $\delta^{(l)}$ is the error term for the l-th layer.

As previously said, input-target training data are typically pretreated in order to enhance the numerical situation for the optimization issue and for improved training process behavior. As a result, the data are typically split into three subsets: training, validation, and testing. By minimizing a suitable error function, the training subset data are used to implement network learning and fit the network weights. The training method typically employed for this purpose is backpropagation. In a feedforward network, it describes a technique for calculating the gradient of the case-wise error function with regard to the weights. After that, the networks' performance is compared by separately analyzing the error function using the validation subset data. The generalization of the network is next evaluated using the testing subset data (i.e., how well the network predicts targets for inputs outside the training set); this process is sometimes referred to as holdout validation).

Underfitting or overfitting can occur in improperly trained neural networks. The first one covers the situation where a network is not sufficiently sophisticated to properly detect the signal in a challenging data set. On the other hand, the latter circumstance arises when a network becomes overly complicated and may accommodate both the signal and the noise. Even with noise-free data, this situation must be avoided as it could result in predictions that are well outside the bounds of the training set. Numerous methods have been described to prevent underfitting and overfitting, including model selection, jittering, early stopping, weight decay, Bayesian learning, and network combining.

A key component of the overall design of NNs is choosing the network structure. To minimize computer processing, provide good performance, and prevent overfitting, the structure must be tuned. Numerous variables

affect how many concealed units are best, among other things. The complexity of the sought-after function to be modeled, the size of the training set, the amount of noise in the targets, the type of activation functions employed, and the training procedure all interact to affect the sizes of the hidden layers. Without training multiple networks and calculating the generalization error of each, the optimal number of hidden units cannot be determined. High training error and high generalization error due to underfitting may arise if there are few hidden units. However, using a large number of hidden units might reduce training error at the expense of network generalization, which worsens overfitting. By applying ANN, this study aims to predict and optimize wastewater treatment parameters, improving efficiency and ensuring compliance with regulatory standards.

3. Results and discussion

3.1. Statistical analysis

The correlation matrix (CM) is used to investigate the extent to which a linear model may capture the relationship between the variables in a multivariable statistical investigation. A table of every conceivable correlation coefficient between a group of variables is called the CM. Each component of this matrix represents a correlation coefficient, which assesses how linearly related two variables are to one another (column variable versus row variable). The most often used indicator of correlation or association is the correlation coefficient, sometimes known as the Pearson product moment correlation coefficient. The Z-scores for the two variables, Z_X and Z_Y, added together and divided by the total number of scores is how the correlation coefficient is defined.

$$\boldsymbol{R} = \frac{\sum \boldsymbol{Z_x Z_y}}{\boldsymbol{N}} \tag{11}$$

The Pearson product moment correlation coefficient can be calculated using the following method if the Z-scores equation is inserted into it:

$$\boldsymbol{R} = \frac{\sum (\boldsymbol{X}-\boldsymbol{\mu_x})(\boldsymbol{Y}-\boldsymbol{\mu_y})}{\boldsymbol{N}_{\boldsymbol{\sigma_x \sigma_y}}} \tag{12}$$

where N is the number of accessible subjects, μ_x and μ_Y are the means of the X and Y scores, respectively; $\boldsymbol{\sigma_x}$and $\boldsymbol{\sigma_y}$ are the variances of the X and Y scores. The goal of computing the CM is to use linear relationships to predict one variable from another. It does not provide any hint of any nonlinear relationships. However, this matrix provides a preliminary indication of the variables in the data set that are likely to be correlated.

3.2. Modeling results

The design process for neural networks that was previously discussed is used to model the STP. For this investigation, the MATLAB software's neural networks toolbox is used. For the plant modeling, two ANN input topologies are taken into account. In the first method, the effluent variables are predicted using each of the influent variables (TSS, COD, or BOD). The second method involves predicting the corresponding output variables in the effluent stream using multiple input variables. For the first technique, the input–output data are organized into two vectors (one input and one output), and for the second approach, four vectors (three inputs and one output). By figuring out the minimum and maximum of each vector variable and scaling the data with regard to these restrictions, the data vectors are pre-processed to fall inside the range. The MATLAB function premnmx is used to do this. The effectiveness of network training will be improved by doing this. Each vector in the data set was split into three groups: training, validation, and testing, in that order (4:2:1). After conducting a number of early experiments to compare the training speed and reaction times of various network topologies, each network structure is chosen. In order to keep the network construction as straightforward as possible, all single input networks have three levels (an input layer, a hidden layer, and an output layer), while multi-input networks use four layers (two hidden layers). Results for one hidden layer in the case of many inputs were subpar. The number of outputs determines how many neurons can be found in the output layer. On the other hand, the first two layers' number of neurons are chosen after testing how well the networks function in various configurations. It is noted that the smallest number of neurons in the hidden layer to get a final answer was 40. But in the event of multiple inputs, the two hidden layers each have 20 and 10 neurons. 80 neurons were needed in the buried layer for the prediction of TSS using the BOD as an input. The chosen structures guarantee adequate training speed and quick simulation times for a particular network performance. The sorts of neurons that make up the network layers, or their constituents, were assumed to be tan-sigmoidal and linear. This is a

typical option for neural networks that approximate functions.

The optimization algorithm used for all network training runs was the Levenberg–Marquardt. The MATLAB routine *trainlm* with memory reduction was used for the optimization. Based on previous experience, it was found that this algorithm attains fast learning speed and high performance relative to other optimization algorithms. The mean square errors (MSE) between the actual plant output and the network predictions serve as the basis for the performance function that is used for training. The training process was triggered based on the chosen network structure to reach a performance target of 1103 for a maximum of 1000 training epochs. 0.01 was chosen as the learning rate. After multiple trial-and-error runs, the value of this option was discovered. It was discovered that this value guarantees steady, rapid learning. In this study, the time needed to train the networks ranged from 2 to 5 minutes for single input networks and from 10 to 20 minutes for the three multi-input networks. The multi-input networks' complex structural design is to blame for this. To ensure network generalization and avoid over- or under-fitting, the early network training termination strategy was adopted. Figs. 5–8 display the experimental influent and effluent BOD, COD, pH & TSS for the respective days. In influent sample, the peak BOD crossed 300mg, COD crossed 600mg, pH value rages from 2.7 to 17.7 and finally TSS reached around300mg and above in certain period.

Based on the Figs. 9–12 shows the simulated influent and effluent BOD, COD, pH & TSS values for the Vitthalwadi STP. The variation between the experimental and the simulated values are similar in many points. The possibility of the error is not so high, this can be easily obderved through the charts. It has been observed using Figs. 13-15, that utilizing COD as an input in the CS stream produced more accurate forecasts of the BOD and COD than the forecast that is predicted by using TSS as an input in the CS stream. When employing BOD as an input in the CS stream, poor predictions of the outputs were produced. The values of MSE and R (a measure of goodness-of-fit) in figures 13-15 is very less when compared to the other methods as described in Table 1 and Fig 16. When COD/CS is utilized as a feed input for the ANN predictions of the outputs, it can be shown that MSE values are the lowest and R values are close to 1.0.

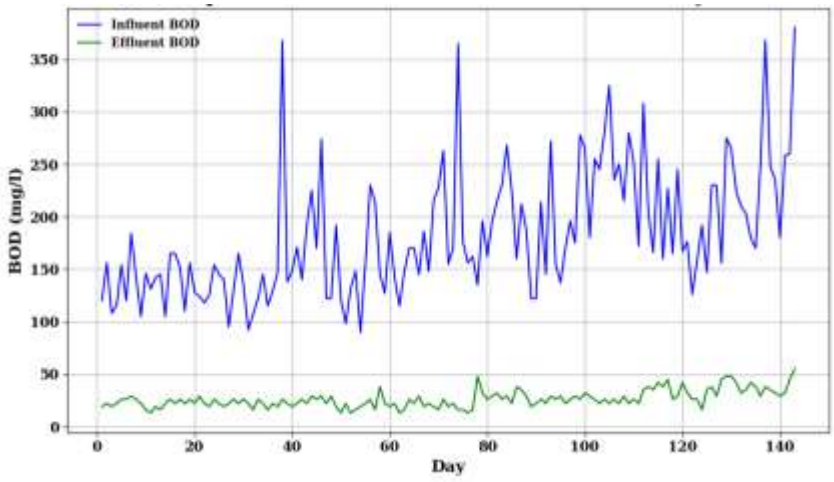

Fig. 5 Experimental influent and effluent BOD over days

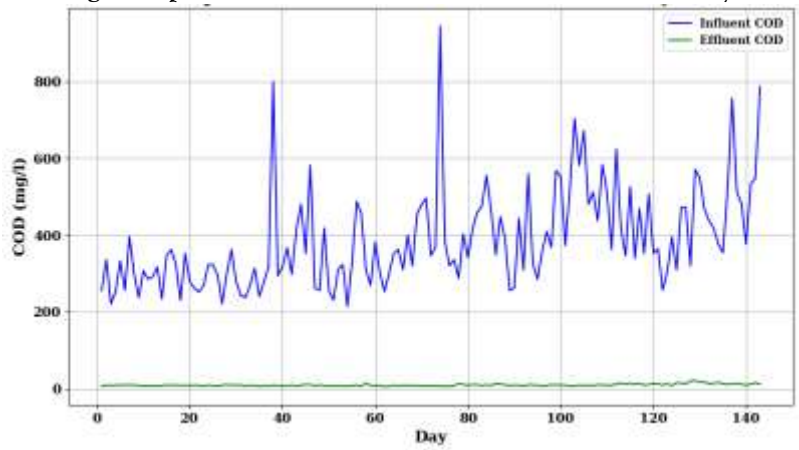

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Fig. 6 Experimental influent and effluent COD over days

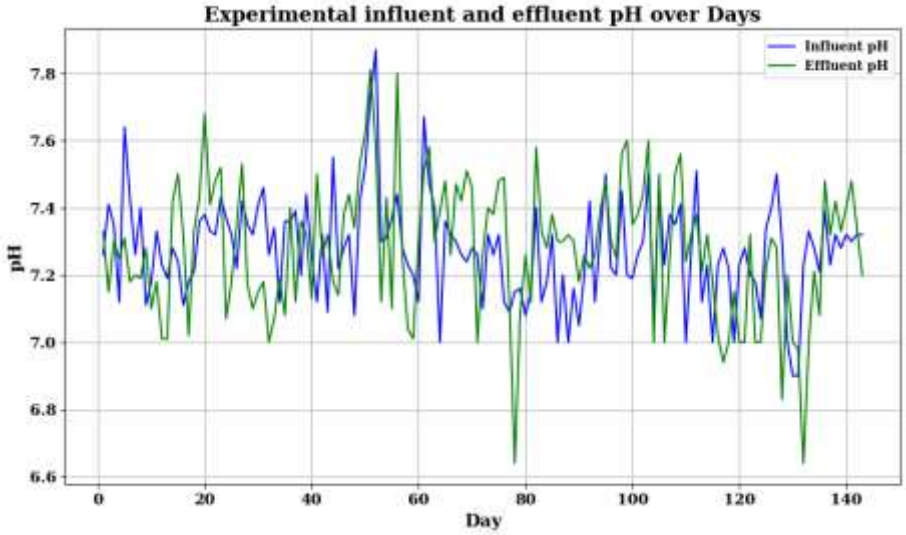

Fig. 7 Experimental influent and effluent pH over days

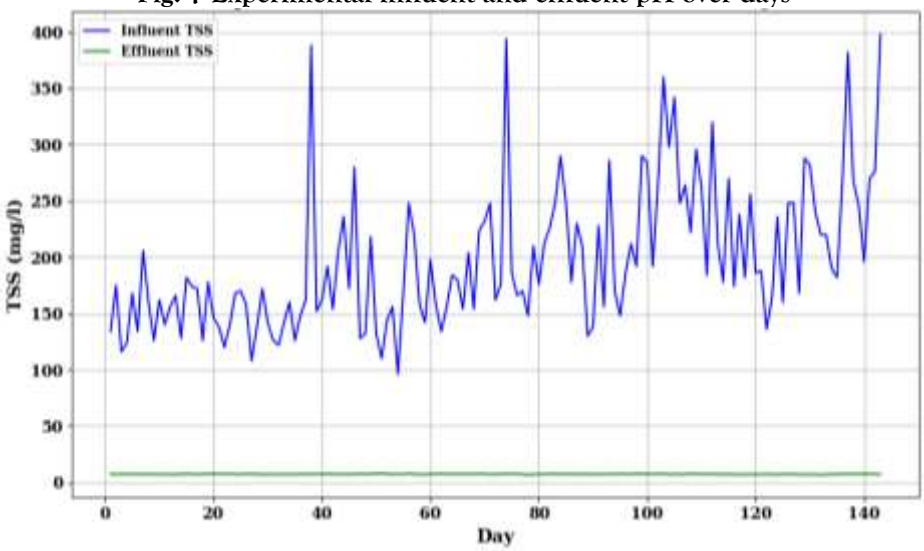

Fig. 8 Experimental influent and effluent TSS over days

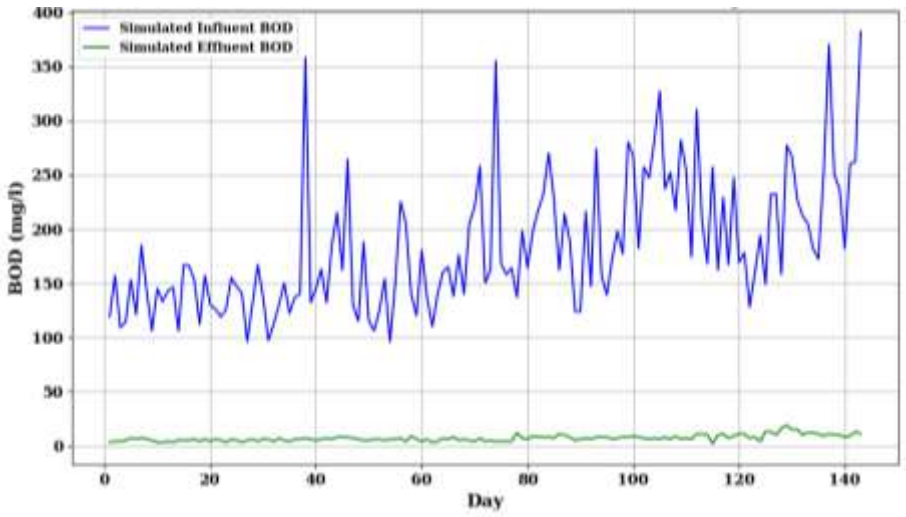

Fig. 9 Simulated influent and effluent BOD over days

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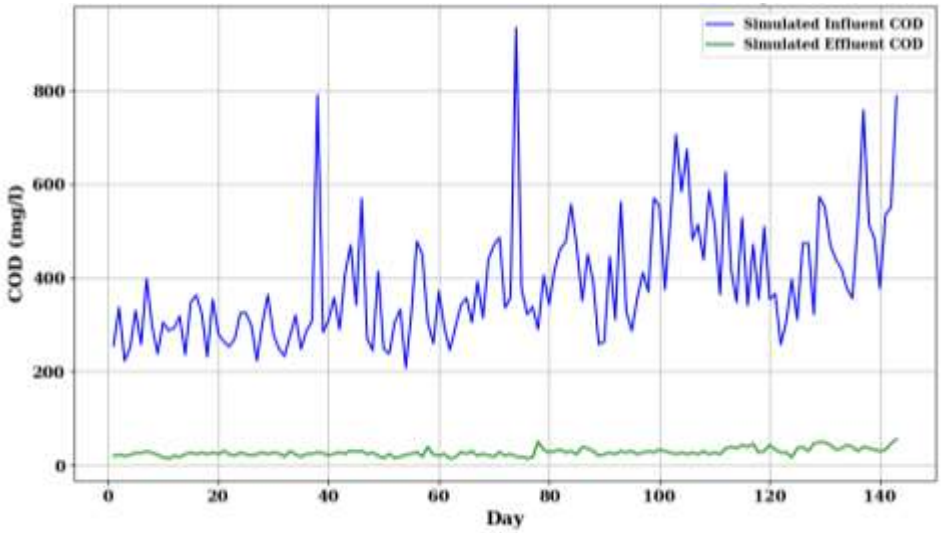

Fig. 10 Simulated influent and effluent COD over days

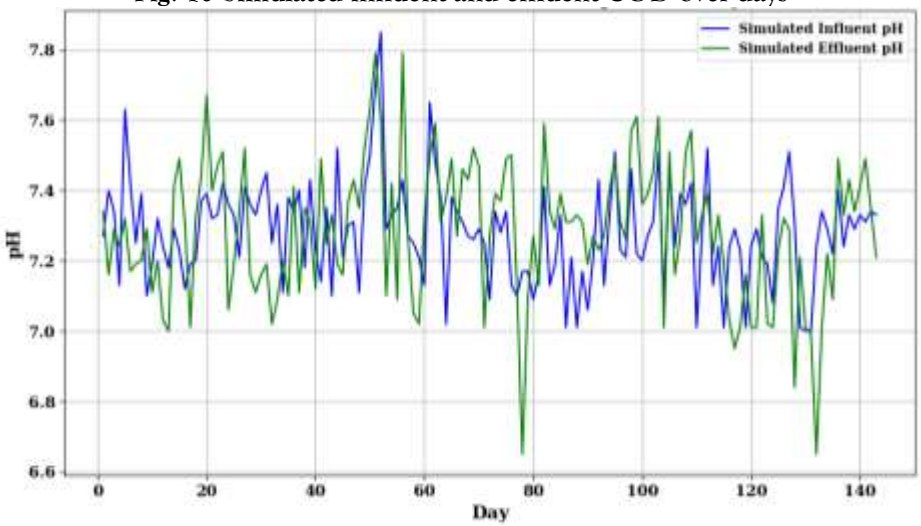

Fig. 11 Simulated influent and effluent pH over days

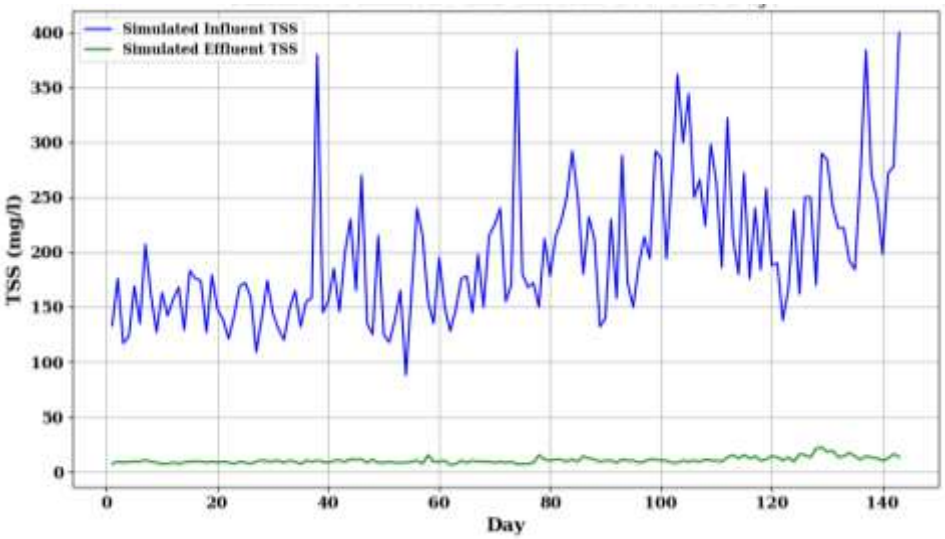

Fig. 12 Simulated influent and effluent TSS over days

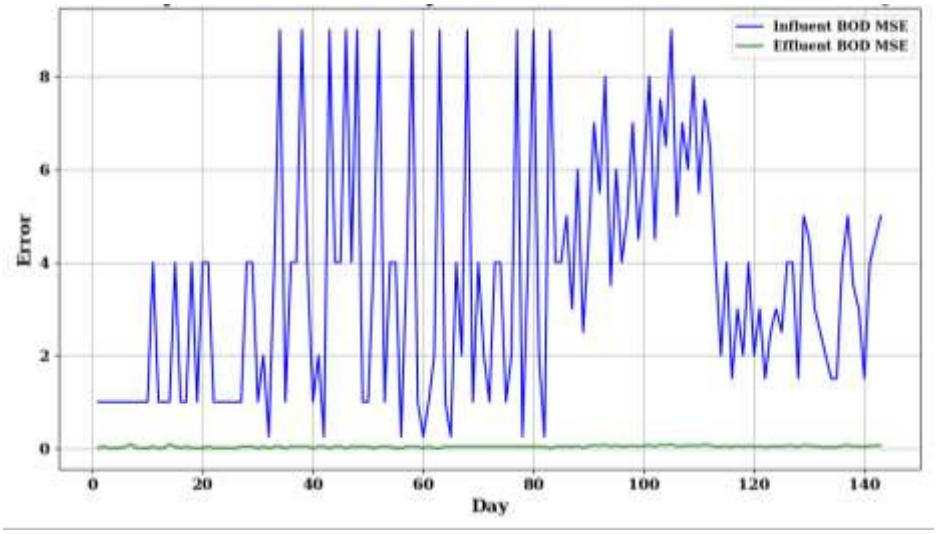

Fig. 13. Mean square error between Exp. & Sim. for BOD over days

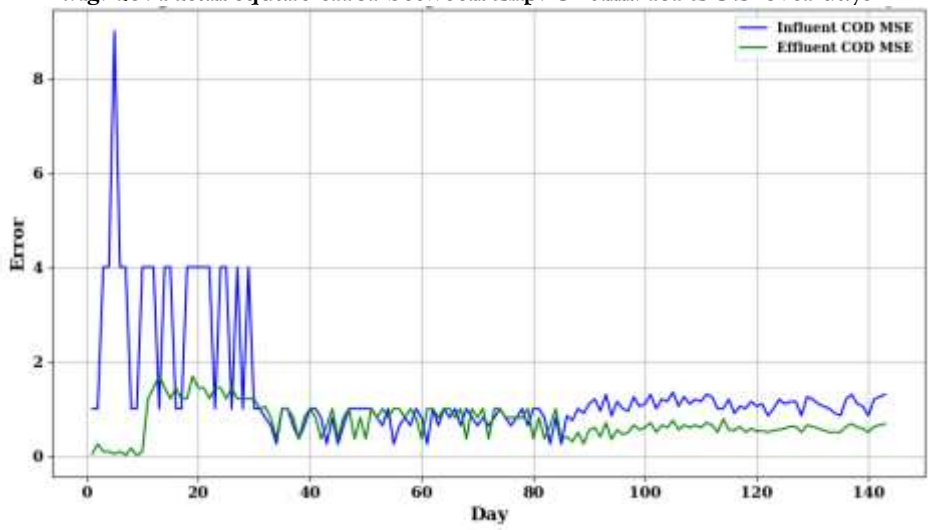

Fig. 14. Mean square error between Exp. & Sim. for COD over days

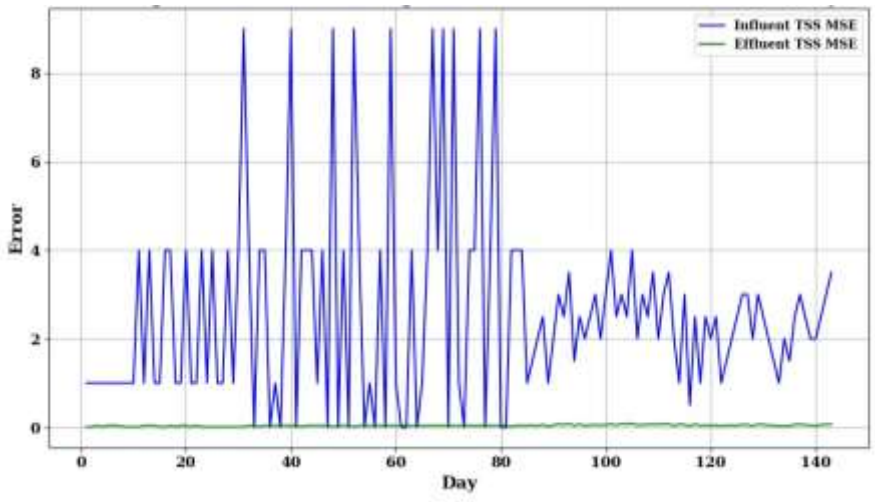

Fig. 15. Mean square error between Exp. & Sim. for TSS over days

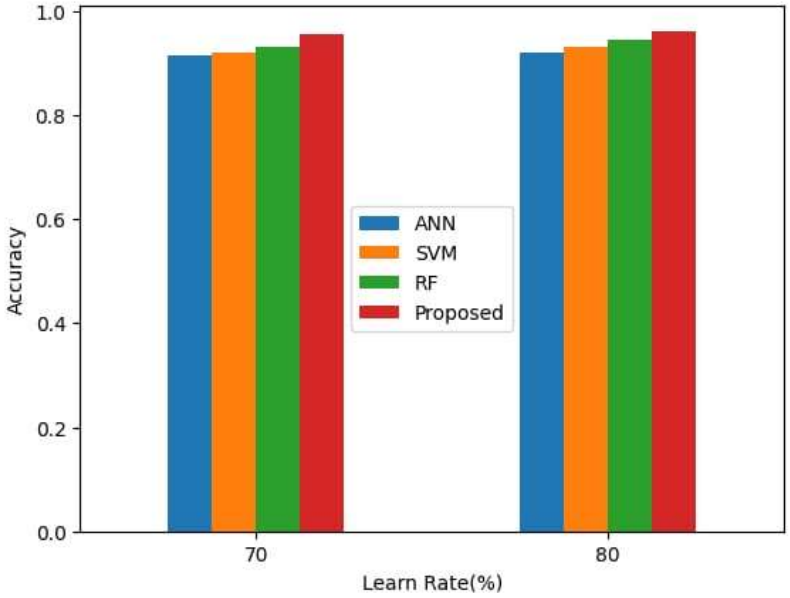

Fig. 16. Comparison of different approaches in terms of Accuracy

Table 1: Evaluation of performance in terms of Accuracy

Model	Split ratio (70% training, 30% testing)	Split ratio (80% training, 20% testing)
ANN	91.589	92.058
SVM	92.058	93.151
RF	93.0281	94.448
Proposed	94.828	95.621

CONCLUSIONS

Modeling a STP is challenging because of the plant's high nonlinearity, the non-uniformity and variability of the crude supply, and the biological treatment's inherent complexity. This issue was resolved, and the interdependency of the input–output variables was found, using a Neuro Support Machine modeling approach. Without employing mechanistic bio-modeling, which is extremely complex and unreliable, plant input–output data were used to forecast plant behavior. The single input and multi-input network topologies utilized in this study's modeling yielded equivalent forecasts of the plant performance requirements. When the COD was utilized as a network input, the first strategy produced better predictions. The second strategy, on the other hand, produces accurate results for every predicted variable. The efficiency, generalization, and simplicity of the ANN and SVM modeling technique make it an appealing option for modeling complicated systems, such as wastewater treatment processes.

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