Optimizing pH Prediction in Water Treatment Plant Through A Hybrid PSO-SVM Approach With Empirical Mode Decomposition

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ABSTRACT. The precise prediction of the outlet ph level of water treatment plants (wtps) is a prerequisite for chemical optimization and process efficiency. It also allows treatment process modifications, protects equipment, and ensures water quality.the main objective of this research is to enhance the accuracy of the outlet ph estimates at the bangabandhu water treatment plant (bwtp) in khulna, bangladesh. This study employed particle swarm optimizer (pso)-based support vector machine (svm) techniques to predict the outlet ph of bwtp. Furthermore, a thorough comparison of conventional and hybrid techniques is carried out in the research. The conventional svm model was executed with a variety of raw water variables, such as temperature, ph, and turbidity. For the model, several sets of input features were considered. In the hybrid approach, the empirical mode decomposition (emd) technique was employed as a pre-processing technique in the svm model. The intrinsic mode functions (imfs) and the residue are the input features of the emd-svm model. This configuration enhances the model's ability to capture and utilize both the intrinsic oscillatory modes and residual components for improved performance. In this current study, twenty percent (20%) of the whole data set consisted of test data, while the remaining eighty percent (80%) consisted of training data. The pso

M. Rokonuzzaman et al. (eds.), *Proceedings of the 7th International Conference on Civil Engineering for Sustainable Development (ICCESD 2024)*, Atlantis Highlights in Engineering 34,
https://doi.org/10.2991/978-94-6463-478-5_3

optimizer was used to determine the models' optimal hypermeters, including the kernel function and regularization parameters. In between the conventional models, the optimal r2 was 0.72, whereas the hybrid model gives an r2 value of 0.93. The results highlight that the hybrid model performs better than the conventional approach, proving the usefulness of hybrid models in the bwtp ph level prediction task. It may also be used in a related application to enhance ph prediction in other water treatment plants.

Keywords: Water Treatment Plant, Support Vector Machine (SVM), Empirical Mode Decomposition (EMD), pH

1 Introduction

The outlet pH level forecast of the water treatment plant may have a significant impact on the treatment processes such as coagulation, flocculation, sedimentation, and disinfection. The corrosivity of water is dependent on its pH. Excessively acidic or alkaline water can erode pipelines and equipment, resulting in possible infrastructure damage and maintenance problems. The effectiveness of disinfection techniques (such as chlorination) depends on pH. Maintaining public health through the removal of hazardous bacteria through successful disinfection requires that the outlet water have the proper pH level. Operators can make real-time modifications to treatment procedures to guarantee that treated water regularly fulfils quality criteria by predicting the outlet pH. This optimization can save operating costs and conserve energy and materials.

Several studies have been conducted to forecast water quality parameters such as BOD, COD, pH, TDS, DO, SS, and so on. Most of the research work used machine learning algorithms. The result illustrated that the ML algorithm has the ability to capture the nonlinearity of data. Different ML algorithms, like artificial neural networks, support vector machines, adaptive neurofuzzy interface systems, tree-based models, etc., are very well known in the field of forecasting. The water quality parameters are very nonlinear, and it is very complex to find the intricate pattern of the data. That's why the conventional approach does not always perform effectively. Nowadays, to solve this issue, hybrid machines are becoming very popular. This study focused on the BWTP plant. The BWTP plant is a newly organised plant. There are small sets of historical data present in the plant. It is very challenging to find the complex data pattern using small amounts of water quality data. To solve this issue, this study employed Support a vector machine model. The SVM model is very popular in terms of small-size data.

SVM is an effective machine-learning algorithm widely used in many applications. It is extremely beneficial for forecasting the performance of a water treatment facility (Nourani et al., 2018). The success of SVMs is heavily reliant on the selection of hyperparameters such as kernel type and regularization parameter (Nourani et al., 2018). Optimizing these hyperparameters can significantly improve SVM's predictive ability. There are numerous approaches for determining the best option for finding the hypermeters. The Particle

Swarm Optimization (PSO) was used in this study to find the hypermeters of the SVM model.

Particle Swarm Optimization also known as PSO, is a very popular optimizer used to solve different complex problems. PSO is a very effective optimization technique in the case of forecasting the water treatment plant's water quality parameters estimation (Information Science and Engineering (ICISE), 2009 1st International Conference on : Date, 26-28 Dec. 2009., 2009) such as turbidity (García Nieto et al., 2014), dissolved oxygen (Li et al., 2017) etc. This optimization process is very well known in terms of other forecasting criteria such as rainfall (Wang et al., 2013a), water level (Kandananond, 2012) , water quality (Achite et al., 2022), water quality monitoring (Ladjal et al., 2020) and so on. PSO was motivated by the flocking behavior of birds and has been effectively applied to a variety of optimization challenges.

The signal decomposition method works incredibly well for identifying intricate data patterns. (Ren et al., 2016). The historical time series outlet pH data of BWTP was decomposed using the empirical mode decomposition (EMD) approach. Empirical Mode Decomposition is a signal processing approach well-known for its signal decomposition methodology and frequently employed in a variety of complicated applications. The IMFs and residues help identify the underlying pattern and trend of the actual data (Santhosh et al., 2019). EMD gives a wide range of understandings of the signal by breaking it into IMFs and residuals. (Meng et al., 2019). In this study, EMD was utilized as a preprocessing approach to select the input feature. This is called a hybrid approach. This study used two different input selection approaches: hybrid and conventional, to estimate the outlet pH level of BWTP. For developing a water quality parameter estimation model, researchers have used water quality parameters as an input feature. This traditional approach has some limitations; it does not always give a positive correlation. Sometimes it makes a higher percentage of errors by using these parameters as an input feature. It is also time-consuming and costly to collect comprehensive water quality data. Sometimes the data consists of impurities and needs to be preprocessed. By considering these limitations, this study used the signal decomposition approach, which requires only one historical output of pH data. It saves time and money to make a forecast model and gives better performance than the conventional approach.

The primary objective of this study is to evaluate the BWTP plant's forecast performance. It is focused on outlet pH forecasting employing the SVM algorithm. It investigates the effectiveness of preprocessing techniques using EMD. It also compares the hybrid and conventional ML approaches to forecasting outlet pH.

2 Methodology

2.1 Study Area and Data Collection

Khulna city is situated in the southwestern part of Bangladesh, near the Rupsha River, and

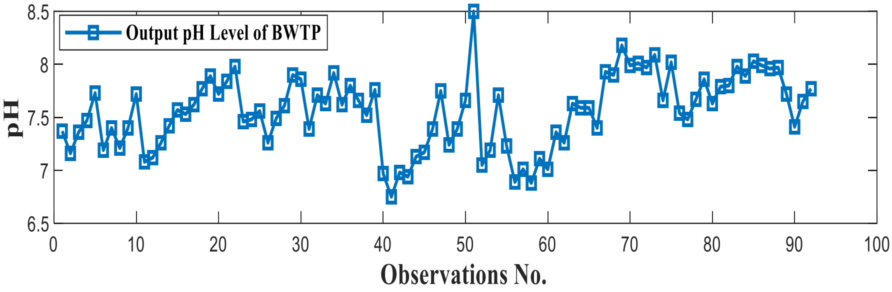

Fig. 1. Time Series Plot of Outlet pH

is the third largest city in Bangladesh. Khulna is situated with GPS coordinates of approximately 22° 49' 12.0000" N for latitude and 89° 33' 0.0108" E for longitude. The city corporation area is 45.65 square kilometers with 718735 people, according to the report for 2022. In Khulna, many of the areas are affected by groundwater salinity problems. However, there are no major potable water sources in the city corporation area. Rainfall and groundwater are the main sources of water, which is not sufficient compared to the demand. Khulna WASA (Water Supply and Sewerage Authority), an organization from Khulna City Corporation, was established in 2008 to manage water supply and sewerage services in Khulna city. It is committed to providing services to all people or customers to supply the necessary amount of portable water and solutions for sewerage. It provides services to an area of 45.60 square kilometers. Around 1.10 million people get services from it. KWASA supplies water through a pipe line in its area, and the present water supply of KWASA is 110 MLD. KWASA contributes to public health, environmental sustainability, and the overall quality of life in the region.

Bangabandhu water treatment plant, located in Pathorghata, Khulna, is the plant that is under the KWASA. It provides potable water to the city. The Bangabandhu Water Treatment Plant collects the raw water from the Madhumati River. After processing the water, quality water is served to users. The plant measures several water quality parameters, such as pH, turbidity, temperature, TDS, TS, salinity, chloride, etc. Several parameters are tested before the process, and to ensure the water quality, several water quality parameters are measured by the supplied water.

The present study examined a dataset that included weekly data for three water quality measures. The dataset encompassed several variables, such as pH, temperature, and turbidity. All data was collected on the same day, from September 16, 2021, to June 15, 2023. The data contained some errors, like the fact that there were no recordings on several days when the plant was experiencing technical issues. The data set was pre-processed by averaging and cleaning the data to correct for missing values. The time-series plot of the fluctuation of pH is illustrated in Fig.1.

2.2 Input Feature Selection:

Input Feature Selection of the Conventional SVM Model. The input features for the SVM model were chosen by assessing the correlation matrix of water quality parameters. Table 1 presents the correlation matrix of the input and output variables. The correlation matrix shows that temperature and turbidity are negatively correlated with the outlet pH. The inlet pH is positively correlated with the outlet pH level. Both the negative and positive correlated parameter combinations were considered for the analysis. Several input features were tested in this study to develop the model. The selected input features for both the conventional SVM and EMD-SVM models are shown in Table 2.

Table 1: Correlation Between Input and Output Variables

	Temperature	Turbidity	pH(inlet)	pH(outlet)
Temperature	1.00			
Turbidity	0.35	1.00		
pH(inlet)	-0.02	-0.29	1.00	
pH(outlet)	-0.38	-0.38	0.72	1.00

Input Feature Selection of the EMD-SVM Model. Empirical Mode Decomposition (EMD). Empirical Mode Decomposition (EMD) is a signal decomposition technique. It partions the actual complex signals into different subcomponents known as Intrinsic Mode Functions (IMFs) and also calculates the residual between the actual and newly generated signals (Huang et al., 2014). This method is very effective for complex data analysis where the signal is composed of highly nonlinear oscillations and transients. There are several data decomposition techniques, like EEMD, wavelet analysis, spectrum analysis (SSA), principal component analysis (PAC), etc. EMD starts with the preparation of a one dimensional signal. The fundamental concept of EMD is to divide the time series signal (pH level) into IMFs. IMFs represent a different frequency signal (Chen et al., 2014).

The EMD approach consists of several stages. It starts with the historical pH data. EMD then finds the maximum and minimum points in the signal, creates upper and lower envelopes using cubic spline curves, and computes a mean curve by averaging these envelopes. By subtracting the mean curve from the original pH signal, the first IMF (IMF1) is obtained. The first IMF produces the highest-frequency

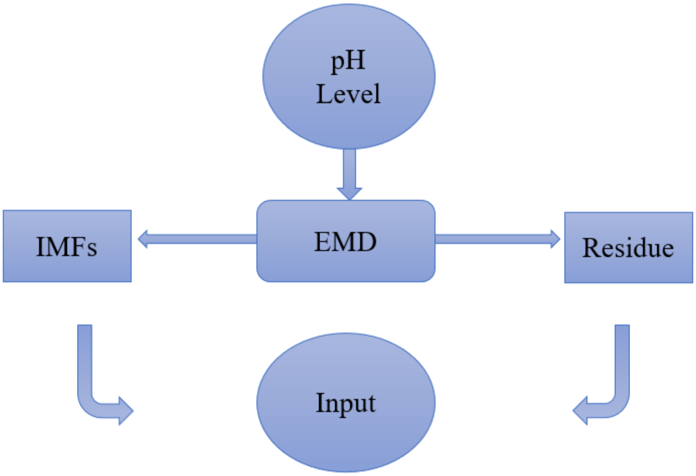

Fig. 2. Input Selection Process for EMD-SVM

changes shown in Fig. 3. This process is repeated until the stopping requirements are met. In this study,the five IMFs are presented in Fig. 3. In the SVM model, these IMFs and the residue were set as the input features of the EMD-SVM model (Fig. 2). Since these IMFs are generated from the original signal, the SVM model easily captures the nonlinearity of the data.

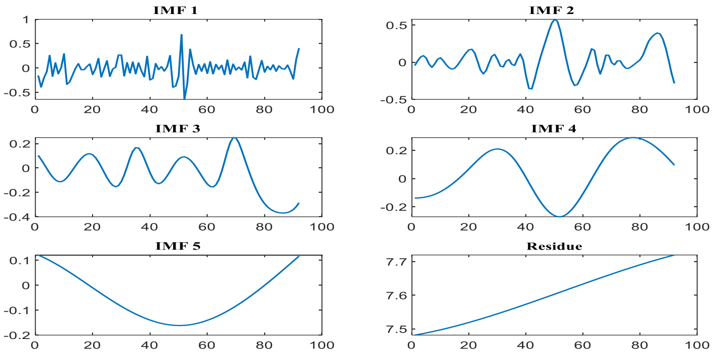

Fig. 3. Decomposition of Outlet pH Level

2.3 Support Vector Machine (SVM)

For regression and classification issues, Support Vector Machines (SVMs) are powerful supervised Machine Learning (ML) methods (Kazem et al., 2016). The SVM model incorporates a hyperplane, which is a straight line that splits data points into two groups, in a two-dimensional feature space. It forms a hyperplane in higher dimensions. Finding the hyperplane with the largest margin, or the separation between the hyperplane and the nearest data points for each class, is the aim of a support vector machine (SVM). This is known as the "maximum-margin hyperplane" in general. Support vectors are used to locate the hyperplane since they are the nearest data points to it. The margin needs to be computed using these data points.

Even so, SVMs can still effectively classify data by using a kernel function to translate the data onto a higher-dimensional space when the data cannot be divided into discrete portions in the feature space. Common Kernel functions include the radial basis function (RBF) kernel, the polynomial Kernel, the gaussian Kernel, and the linear Kernel. The C parameter regulates the trade-off between raising the margin and lowering the classification error. A small C may lead to some classification errors, even though it promotes a larger margin. Less misclassifications, but a smaller margin, could result in a large C. The SVM regression model is defined by the equation that follows:

$$y = f(x) = w\varphi(x_i) + b$$

where the weight and bisector factors are w and v, respectively, and the multidimensional feature space is represented by $\varphi(xi)$. Estimating w and b is feasible by minimising the error (Belaid & Mellit, 2016).

In SVM, the kernel function allows the algorithm to implicitly transform the input data into a higher-dimensional space so that a hyperplane may separate the classes more effectively. The choice of Kernel function can significantly affect how well the SVM model performs. The optimal option depends on the specifics of the work at hand. Various kernel functions capture different kinds of data relationships. In this work, the optimal kernel function was determined using the PSO optimizer.

Particle Swarm Optimization (PSO) algorithm. Particle Swarm Optimization (PSO) is an optimization algorithm developed by Kennedy and Eberhart in 1995 (Wang et al., 2013b). It is inspired by natural collective behaviors such as bird flocking, bee swarming, and fish schooling. (Du et al., 2017). This algorithm solves complex optimization problems by leveraging the inherent principles of cooperation and self-organization found in these animal groups.

The first step of the PSO optimizer is initialization. It defines the problem and creates a population of probable solutions called particles. Each particle presents a solution, which consists of a position and velocity vector. The velocity and position are initiated randomly. After that, it evaluates the fitness based on the current position. There is a fitness function that measures the effectiveness of the current solution. It updates the position based on the objective, and it changes the convergence of the solution. This process will repeat until the solution is optimal. The basic working process is shown in Fig. 4.

It has been used effectively in machine learning. The machine learning model has influential hypermeters that have a great impact on the result. It is very time-consuming and uncertain to find the optimal hypermeters. In the support vector machine algorithm, the kernel function, regularization parameters, gamma, etc. influence the model outcomes. To find these hypermeters, the PSO optimization technique was used in this study.

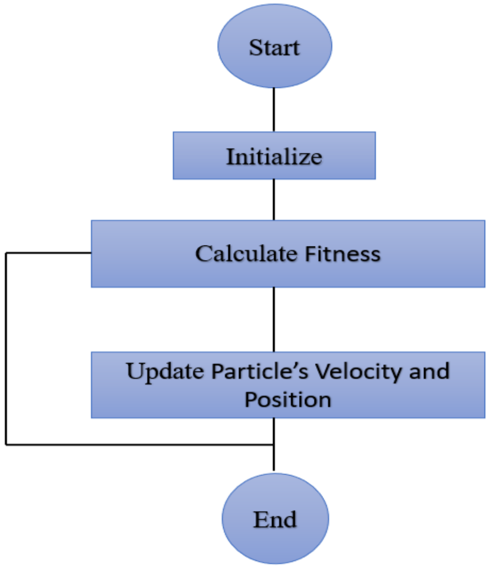

Fig. 4. The basic working process of the PSO optimizer

3 Performance evaluation

To evaluate the model performance, four performance matrixes were used: MSE (Mean Squared Error), RMSE (Root Mean Square Error), MAE (Mean absolute Error), and R2 (Coefficient. of Determination).

The average squared difference between predicted and actual values is calculated using MSE. MSE is calculated as the mean of squared differences using the formula:

$$MSE=(\frac{1}{n}) \sum(y_i - \bar{y})^2$$

Where n presents the number of data points, y_i is the i^{th} actual value, ȳ is the mean of the actual values.

RMSE presents the root mean squared error and measures the average difference between predicted and actual values.

$$\text{RMSE}=\sqrt{(\frac{1}{n}) \sum(y_i - \bar{y})2}$$

MAE means the mean absolute error, which measures the average absolute difference between the actual and forecast values. The following equation measures the MAE:

$$\text{MAE}= (\frac{1}{n}) \sum(y_i - \bar{y})$$

The coefficient of determination (R2) calculates the fitness of a model. It measures the accuracy of the model. The range of the R2 value is between 0 and 1. The higher R2 value means the mode fits well. The R2 value is very reliable for evaluating model performance. The following equation is used to measure the R2 value.

$$R^2 = 1- (\frac{\sum(y_i-\bar{y})^2}{\sum(y_i-\hat{y})^2})$$

Where y_i presents the i^{th} actual value, ȳ is the mean of the actual values, ŷ is the predicted value.

4 Results and Discussion

In this study, conventional and hybrid input generation techniques were tested in the SVM model for forecasting outlet pH. To build the model, several regularization parameters were set for checking the model's performance. The code sets the seed for the random number generator. It ensures that, when the code runs several times, the generated random number remains the same as in both training and testing. The data set was divided into two phases. The first 80% of the data from the whole set was set as training data, and the remaining data was set as the test data. The same things are fixed for both the conventional and hybrid approaches. The three base models were chosen using the traditional approach. The M-1 model used all of the parameters, including temperature, inlet pH, and turbidity, which shows MSE, RMSE, MAE, and R2 values of 0.04, 0.2, 0.16, and 0.72, respectively. The M-2 model, which consists of turbidity and pH as input, gives

MSE, RMSE, MAE, and R2 of 0.07, 0.26, 0.22, and 0.24, respectively. The M-3 model used the inlet pH as the input; it gives MSE, RMSE, MAE and R2 values of 0.06, 0.24, 0.19, and 0.28, respectively. In the hybrid approach, the IMFs and residue were set as the input features of the EMD-SVM model, and it shows MSE, RMSE, MAE, and R2 values of 0.0009, 0.03, 0.02, and 0.93, respectively. The forecast outcomes with respect to the four performance criteria are shown in Table-3.

Table 2: Selected Input Features

Feature Model	Input
M-1	Temperature, Turbidity, pH (Inlet)
M-2	Turbidity, pH (Inlet)
M-3	pH (Inlet)
M-4	IMFs and Residue

The study employs Support Vector Machine (SVM) model with various kernel functions to address the potential non-linearity in the data. This also includes radial basis functions (RBF), gaussian, polynomial, and linear functions. This study also focuses on optimizing SVM hyperparameters, which include regularization parameter (C) and kernel function selection through Particle Swarm Optimization (PSO).
In the M-1 and M-4 models, the linear kernel was the best-fit kernel. The Gaussian kernel function, on the other hand, was found optimal for Models M-2 and M-3, emphasizing its effectiveness in capturing complicated patterns within the data (Table-3). The PSO finds the optimal C of 1 for M-1, M-2, and 10 for M-3.

Table 3: Performance of Selected Models

Model	Feature Model	MSE	RMSE	MAE	R2	Kernal Function
	M-1	0.04	0.2	0.16	0.72	Linear
SVM	M-2	0.07	0.26	0.22	0.24	Gaussian
	M-3	0.06	0.24	0.19	0.28	Gaussian
EMD-SVM	M-4	0.0009	0.03	0.02	0.93	Linear

The forecast results demonstrate that the EMD-SVM technique outperforms the conventional SVM model in terms of pH level prediction. When employing the EMD-SVM technique, the error performance measures show noticeably less error, indicating a higher degree of prediction accuracy in comparison to the conventional SVM model. All of the performance matrices for the models that were chosen are displayed in Table-3. The M-1 model provides the best results among the conventional SVM feature models.

Compared to the M-1 model, the EMD-SVM model produces forecast results that are more accurate. It reduces the MSE, RMSE, and MAE by 97.75%, 85%, and 87.5%, respectively, and increases R2 by 29.16% compared to the M-1 model. The forecast results are shown in Fig. 5, with a scatter plot in Fig. 6.

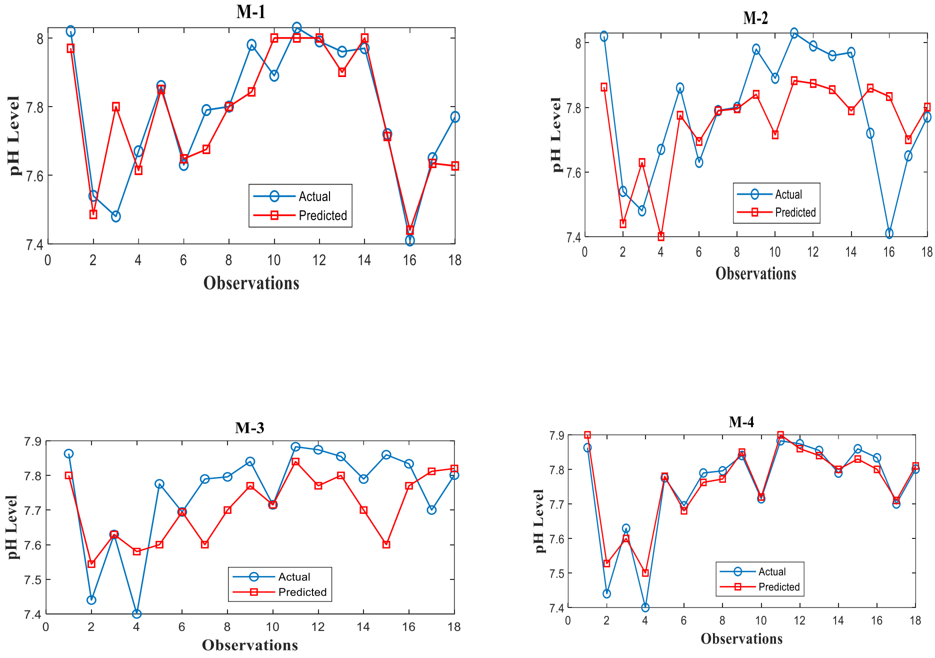

Fig. 5. Forecast Results of the M-1, M-2, M-3, and M-4 Models

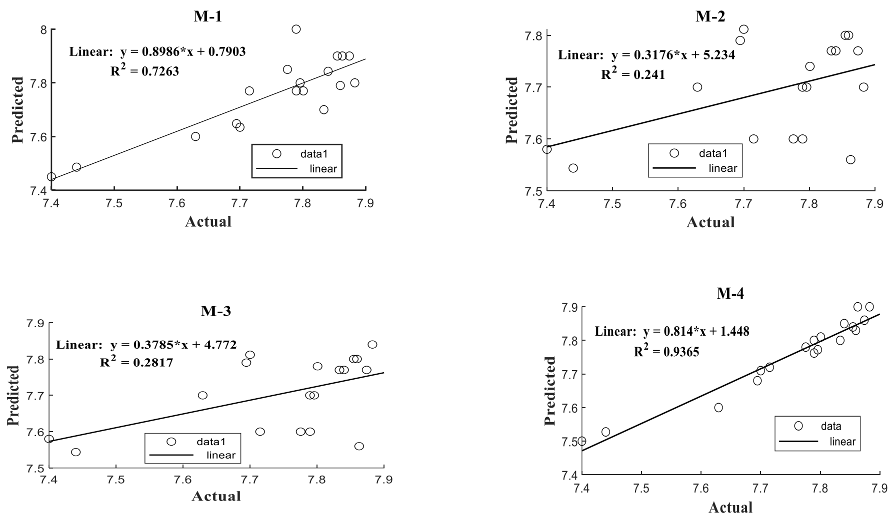

Fig. 6. Scatter Plot of the M-1, M-2, M-3, and M-4 Models

The model outcomes suggest that the preprocessing technique (EMD) has the ability to significantly improve the overall accuracy of pH predictions at the Bangabandhu Water Treatment Plant. The observed outcomes highlight the benefits of using EMD as a preprocessing technique and show that it can improve the accuracy and reliability of pH forecasts made in the plant's water treatment operations.

The study has some limitations, such as using limited water quality parameters as model inputs and limited SVM model hyperparameter sets, which may have influenced the results. There may be several signal decomposition techniques; this study used only EMD as a preprocessing tool. Despite those limitations, the study's findings should motivate other research that could use various machine learning models and different signal decomposition methods.

5 Conclusion

The accuracy of the hybrid model was investigated to forecast the outlet pH level by employing historical data. The results of the SVM model outlined that the EMD preprocessing procedure is a compelling method for outlet pH estimation compared with the conventional methodology. The hybrid model enhanced the R2 value by 29.16% and reduced the errors of MSE, RMSE, and MAE by 97.75%, 85%, and 87.5%, respectively. The results additionally recommend that this sign decay procedure might apply to one more plant for estimating different water quality parameters. Overall, the study successfully illustrated the importance of a hybrid approach in forecasting the pH level of the BWTP plant.

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