RESUSPENSION VELOCITY PREDICTION OF FINE SEDIMENT USING RADIAL BASIS FUNCTION AND RECURRENT NEURAL NETWORK

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Abstract

Siltation, originating from urbanisation and large-scale development, constitutes a form of water pollution precipitated by the presence of fine sediment, primarily silt and clay. As runoff from sloping terrain carries eroded soil into water bodies, it gives rise to turbid water, detrimentally impacting water quality. Despite numerous research efforts to investigate sedimentation concerns, a comprehensive understanding of siltation problems is still limited. Hence, this study aims to formulate a mathematical model to predict the resuspension velocity of fine sediment in water bodies. Two distinct techniques were employed to construct the predictive model, namely radial basis function (RBF) and recurrent neural network (RNN). The input variables included particle size, flow rate, y-axis movement, d_{max}, and d/d_{max}, while resuspension velocities served as the output. To ensure robust training, the experimental data were partitioned into a ratio of 80:20, with 80% allocated for training and the remainder for testing. The efficacy of the developed AI models was assessed using metrics such as mean absolute error (MAE), root-mean-square error (RMSE), and coefficient of determination (R^2). RBF appears as the model with better performance, with MAE of 0.0003, RMSE of 0.0003 and R^2 of 0.6584.

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1.0 INTRODUCTION

Siltation represents a significant challenge stemming from urbanisation and large-scale development, resulting from the presence of fine sediment, commonly comprised of silt and clay. The runoff of fine sediment from sloped terrain and eroded soil into water bodies substantially impacts water quality, typically with adverse consequences. In Malaysia, several guidelines and regulations exist to manage erosion and sediment, including the Environment Quality Act 1974 by the Department of Environment Malaysia, as well as the Guideline for Erosion and Sediment Control (DID, 2010) and Urban Stormwater Management Manual for Malaysia (MSMA2) (DID, 2012) by the Department of Irrigation and Drainage Malaysia. Retention ponds are mandated in development projects to address erosion control and flood mitigation. However, numerous ponds are encountering low dissolved oxygen levels, primarily due to elevated biological oxygen demand. The persistent issue of siltation within these ponds remains unresolved.

Numerous research endeavours have aimed to mitigate siltation and sediment pollution (Cui *et al.,* 2021; Khozani *et al.,* 2021; Mohammadi *et al.* 2021; Samantaray & Ghose, 2019; Yadav *et al.,* 2021). However, there remains a notable gap in the exploration of fine sediment prediction, particularly within retention structures, owing to the intricate hydrodynamic behavior of fine sediment in water (Deng *et al.,* 2019; Zhang *et al.,* 2020; Zhuang, *et al.,* 2020). Current methods for fine sediment study, particularly particle image velocimetry (PIV) (Kashani *et al.,* 2016a; Kashani *et al.,* 2016b), though effective, are prohibitively costly and impractical for widespread use.

Artificial intelligence, with its capacity for machine learning, offers a viable solution capable of processing vast amounts of complex data, provided sufficient data is supplied to the model. While several studies have explored artificial intelligence in water management, such as water level prediction (Deng, *et al.,* 2021; Deng, *et al.,* 2022), reservoir operation (Chaves *et al.,* 2004), nitrogen level prediction (Chin, *et al.,* 2022) and wall slip researches (Chin *et al.,* 2019; Chin *et al.,* 2020). Therefore, the primary focus of this study is to develop a model to predict the resuspension velocity of fine sediment in water bodies.

2.0 MATERIALS AND METHODS

2.1 Data Collection and Preparation

The dataset utilised in this investigation originates from a prior study (Kashani *et al.,* 2016a), focusing on the hydrodynamic characteristics of fine sediment within retention structures using Particle Image Velocimetry (PIV). It comprises 297 data sets, each featuring six parameters: particle size (μm), flow rate (cm/s), y-axis movement (mm), maximum diameter (d_{max}, mm), the ratio of particle diameter to maximum diameter (d/d_{max}), and the velocity of fine sediment (m/s). The dataset was divided into a training set comprising 80% of the data and a testing set containing the remaining 20%.

2.2 Model Development

In this study, MATLAB was used for the model development. The radial basis function (RBF) network comprises three fixed layers: an input layer, a hidden layer utilising radial basis functions, and an output layer, as shown in Figure 1. The input layer receives the training data, while the hidden layer employs a radial basis Gaussian function as its activation function. The output layer utilises a linear function to produce output. Training the radial basis function network model is straightforward and offers relatively fast training speeds compared to other types of neural networks. The dataset is organised and classified into matrix form for training within the RBF network model. Training the radial basis function network model is user-friendly and exhibits relatively rapid training speeds in comparison to other neural networks. The dataset is structured and organised into a matrix format for training within the RBF network model. The only adjustable training parameter in the RBF network model developed in MATLAB is the spread constant. Consequently, the training process involves various values for the spread constant, starting from 0.1 to 1.0, with incrementing in intervals of 0.1. The detail of the model development is shown in Table 1.

On the other hand, the architecture of the Recurrent Neural Network (RNN) model varies in terms of the number of layers and nodes, depending on the input values of both parameters. Information input into the RNN model is processed through a loop within the layers, where the output of each layer serves as the input for the subsequent layer, thus allowing for the refinement of results, as shown in Figure 2. Consequently, training the RNN model requires a longer duration due to this iterative process. MATLAB offers the Layer Recurrent Network, which enables users to customise the training function, learning function, and performance function of the network model. The user interface facilitates easy adjustment of the desired number of layers and neurons to meet specific requirements. The RNN model employed the TRAINLM training function, LEARNGDM learning function, and MSE performance function.

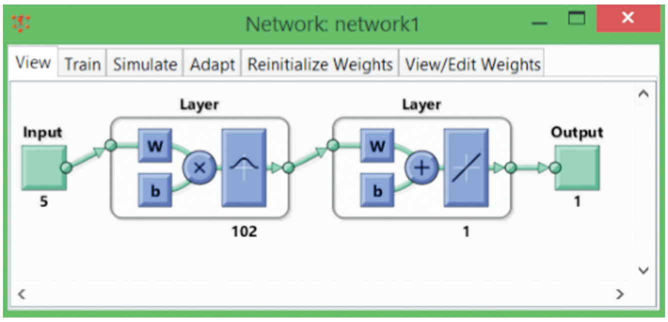

Figure 1: Architecture of RBF model

Table 1: Detail of the developed RBF models

Models	Spread Constant
Model I	0.1
Model II	0.2
Model III	0.3
Model IV	0.4
Model V	0.5
Model VI	0.6
Model VII	0.7
Model VIII	0.8
Model IX	0.9
Model X	1.0

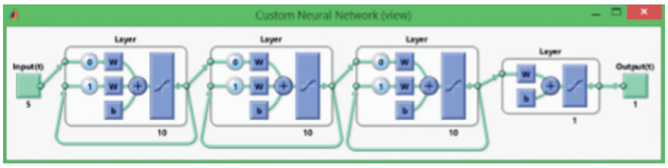

Figure 2: Architecture of the RNN model

Table 2: Detail of the developed RNN models

Models	No. of Neuron			
	Layer 1	Layer 2	Layer 3	Layer 4
Model I	20	10	1	-
Model II	20	20	1	-
Model III	20	30	1	-
Model IV	30	10	1	-
Model V	30	20	1	-
Model VI	30	30	1	-
Model VII	10	10	10	1
Model VIII	20	20	20	1
Model IX	30	30	30	1

The adjustable training parameters include epoch, training time, goal, minimum gradient, and maximum number of failures. However, after several training attempts, altering these parameters does not significantly impact the outcomes. Consequently, these parameters are kept constant for subsequent training sessions, with values set as follows: (i) epoch number: 1000, (ii) training time: infinity, (iii) goal: 0, (iv) minimum gradient: 1x10-7, and (v) maximum number of failures: 6. The RNN model was trained with varying numbers of layers and neurons as shown in Table 2.

2.3 Evaluation Metrics

On the other hand, the model evaluation is an essential step to test the accuracy or reliability of a model in performing the prediction. In this study, three statistical indicators were chosen for analysis purposes and comparison, which are mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2) (Lai *et al.*, 2022; Loh *et al.*, 2021). The equation for MAE, RMSE and R^2 are as shown:

$$\mathrm{MAE} = \frac{\sum |y_i - x_i|}{n} \quad (1)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum (y_i - x_i)^2} \quad (2)$$

$$R^2 = \left[\frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\,\sqrt{n\sum y_i^2 - (\sum y_i)^2}}\right]^2 \quad (3)$$

where n is the number of data pairs, x is the observed variable, and y is the predicted variable.

3.0 RESULTS AND DISCUSSION

3.1 Model Evaluation for RBF

Table 3 shows the statistical analyses of the developed RBF models. To rank the model with better performance, lower MAE and RMSE values are preferable, indicating a lower error of the model. Meanwhile, for the comparison in terms of R^2, a higher value should be selected, showing that the predicted value fits closer to the actual value.

In general, the MAE value ranges between 0.0003 and 0.00059. The lowest MAE value was recorded at 0.0003, by Models I and II. Meanwhile, from the perspective of RMSE, both Model I and Model II have shown a similar value, which is 0.0003. The RMSE value is the lowest if compared with the other developed RBF models.

On the other hand, R^2 value approaching 1 represents a better proportion of the variance in the predicted variable in a regression model. A higher R^2 value is always favourable. Hence, for this study, the highest R^2 value is 0.6584, recorded by Model II.

In summary, based on the statistical metrics, such as MAE, RMSE and R^2, Model II appears as the best-performed model as it has the lowest MAE and RMSE values, showing at 0.0005 and 0.0006 respectively, and the highest R^2 value of 0.6584.

Table 3: Statistical analyses of the developed RBF Models

Models	MAE	RMSE	R^2
Model I	0.0003	0.0003	0.6345
Model II	0.0003	0.0003	0.6584
Model III	0.0012	0.0013	0.0881
Model IV	0.0006	0.0007	0.4452
Model V	0.0015	0.0019	0.0117
Model VI	0.0011	0.0016	0.0083
Model VII	0.0019	0.0028	0.0005
Model VIII	0.0028	0.0044	0.0090
Model IX	0.0041	0.0070	0.0201
Model X	0.0059	0.0109	0.0239

Table 4: Statistical analyses of the developed RBF Models

Models	MAE	RMSE	R^2
Model I	0.0004	0.0009	0.3148
Model II	0.0006	0.0008	0.2446
Model III	0.0007	0.0014	0.1384
Model IV	0.0007	0.0010	0.1929
Model V	0.0005	0.0006	0.3558
Model VI	0.0006	0.0009	0.2143
Model VII	0.0005	0.0009	0.2873
Model VIII	0.0003	0.0003	0.4381
Model IX	0.0004	0.0004	0.3611

Table 5: Comparison between the outperformed RBF and RNN models

Models	MAE	RMSE	R^2
RBF Model II	0.0003	0.0003	0.6584
RNN Model VIII	0.0003	0.0003	0.4381

3.2 Model Evaluation for RNN

Table 4 presents the statistical analyses of the developed RNN models, in terms of MAE, RMSE, and R^2. Across the models, MAE values range from 0.0003 to 0.0007, showing the difference in terms of MAE among the models is relatively small. Meanwhile, referring to the RMSE, the highest value is 0.0014 while the lowest value is 0.0003, recorded by Model III and Model VIII, respectively. On the other hand, in terms of R^2, the value varies from 0.1384 to 0.4381. The lowest value is shown by Model III, indicating the predicted value of Model III has a relatively high deviation from the actual value.

In a nutshell, considering MAE, RMSE, and R^2, Model VIII emerges as the best-performing model with the lowest MAE and RMSE values of 0.0003 and 0.0003 respectively, along with the highest R^2 value of 0.4381.

3.3 Summary

From the statistical analyses, RBF Model II and RNN Model VIII outperform the other RBF and RNN models. With a further comparison between the two selected models, according to Table 5, it is noticed that the RBF Model II has shown a better performance than the RNN Model VIII. In terms of MAE and RMSE, both models exhibit the same value, recorded at 0.0003, which is a relatively small value. Meanwhile, from the perspective of R^2 as shown in Figures 3 and 4, RBF Model II displays a higher value, recorded at 0.6584.

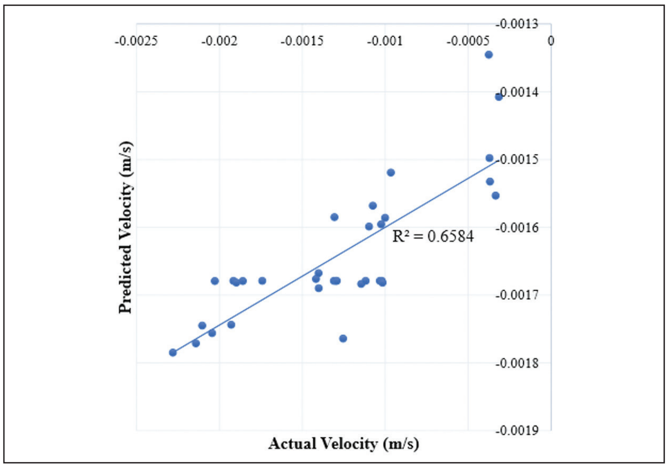

Figure 3: Scatter plot of predicted resuspension velocity versus actual resuspension velocity for RBF Model II

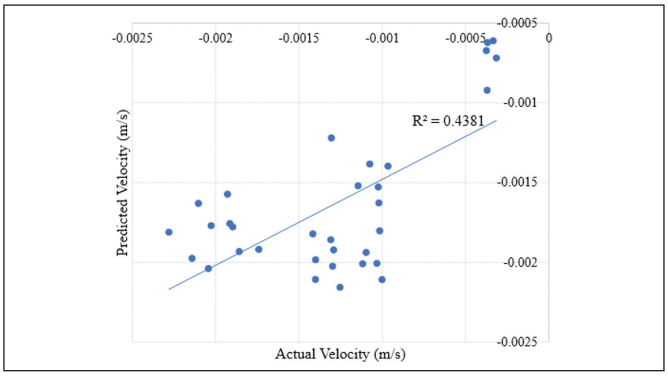

Figure 4: Scatter plot of predicted resuspension velocity versus actual resuspension velocity for RNN Model VIII

4.0 CONCLUSION

Two different mathematical models were utilised for the training and testing processes to predict the resuspension velocity of fine sediment. Each model employed a distinct approach to handling the data. The efficiency of the RBF model surpassed that of the RNN model. The RBF network exhibited faster training times and offered a more straightforward operational procedure compared to the RNN. In terms of result analysis, the RBF network model achieved R^2 values closer to 1 (with a value of 0.6584) in the resuspension velocity prediction task, outperforming the RNN model, with a value of 0.4381. Meanwhile, the MAE and RMSE values of the best-performed model for both RBF and RNN techniques are the same.

This study is limited to the application of RBF and RNN models. The model accuracy may be further improved. So, there are some recommendations for future work. First of all, a wider range of datasets could be collected to improve the prediction accuracy of the developed AI models. In addition, rather than having conventional machine learning models, hybrid or metaheuristic AI approaches (such as artificial neural network-particle swarm optimisation (ANN-PSO) model, genetic algorithm based support vector machine (GA-SVM) model, etc.) can be implemented to predict the resuspension velocity of fine sediment in water bodies. ■

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- **Ren Jie Chin**: Conceptualisation, study design, data collection, formal analysis and Writing—original draft preparation.
- **Sai Hin Lai**: Conceptualisation, and Supervision.
- **Kok Zee Kwong**: Literature review, and Writing—Review and Editing.

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