COMPARISON OF ARTIFICIAL INTELLIGENCE (AI) BASED MODELS FOR SEDIMENT TRANSPORT PREDICTION USING SWOT AND STATISTICAL ANALYSES

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ABSTRACT

The dynamics involved in sediment scour are complicated. Hence, it is a challenging task to create a general empirical optimisation algorithm for reliable sediment load estimation. This study aims to analyse the architectures of assorted artificial intelligence (AI) based model to predict suspended sediment load in fluvial system. An in-depth study on Artificial Neural Network (ANN), Adaptive NeuroFuzzy Inference System (ANFIS), and Support Vector Machine (SVM) was carried out. The goal of this study is to evaluate the performance of AI-based models from various research using statistical as well as Strengths, Weaknesses, Opportunities, and Threats (SWOT) analyses. Three statistical measures of model prediction accuracy including coefficient of correlation (R), root mean square error (RMSE), and mean absolute error (MAE) were used. The results revealed that the SVM and ANFIS models outperformed the other soft computing and conventional models. It is concluded that the SVM and ANFIS models are preferred and may be successfully used to estimate the suspended sediment concentration for the research area.

Keywords: Artificial Intelligence, Sediment Transport, Statistical Analyses, SWOT

1.0 INTRODUCTION

Sediment is usually defined as tiny particulate in the form of fine silt and clay in nature. Sediment can exist as soil-based, mineral substance, decomposing organic substances, and inorganic biogenic matter in the aquatic environment. Sediment transport is the movement of particles along with the flow of water (Pu *et al.*, 2021; Samantaray & Ghose, 2019).

Sediment transport is a complex issue in nature as the sediments travel unpredictable stream wise corresponding to the associated fluid forces. There is no fixed rule or rule of thumb in the sediment transport prediction. Approximate all current sediment transport formulae are based on the premise that sediment transport can be completely represented by stream wise parameters such as velocity or boundary shear stress, while the parameters representing vertical motion of flow such as water depth (pressure) variance over time and space, vertical velocity, as well as seepage are not involved (Vittori *et al.*, 2020; Yang *et al.*, 2009). In the previous research, it was found that the aforementioned parameters could affect the sediment's flow behaviour in terms of mobility and stability. The analysis showed the speed of the flow can provoke upward flow or vice versa, which may cause the erosion. In general, the combination of joint driving forces and resistance forces are the factors to drive sediment transport (Pektas & Dogan, 2015; Yuan *et al.*, 2021).

Since the introduction of AI approaches in hydro-climatology, there has been a significant increase in research effort in the areas of modelling, analysing, forecasting, and prediction of water quantity and quality (Cui *et al.*, 2021; Khozani *et al.*, 2020; Mohammadi *et al.*, 2021; Nourani *et al.*, 2014). There are plenty of models related to the sediment transport prediction, however the study comparing the performance of different models is still limited. Therefore, this study aims to investigate the performance of the AI-based models for sediment transport prediction using statistical and Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis.

2.0 MATERIALS AND METHODS

2.1 Information Collection and Preparation

A comprehensive review study on the application of the AI-based models in sediment transport was conducted to obtain more information on the architecture framework of different AI-based models, as well as their performance. After extracting all the relevant information from the published journal articles, the SWOT and statistical analyses were performed.

For this stage, the systematic review strategy was implemented. The procedure started with framing questions for a review, followed by identifying the relevant work. The main research question for this study is "what are the available AI-based models in sediment transport prediction and their respective performance". Hence, the keywords for information searching were narrowed down to "AI-based models in hydrological application", "sediment transport prediction model", "SWOT analysis in prediction model", etc. After having the keywords, the relevant studies were searched, identified and reviewed. Nevertheless, only the studies matching with certain criteria was selected for further analysis, i.e. it matches with the minimum acceptable level of prediction accuracy, it is specifically for the sediment transport prediction study, etc. The last step in this stage is the findings interpretation using the SWOT and statistical analyses (Huai *et al.,* 2021; Wallwork *et al.,* 2022).

2.2 SWOT Analysis

SWOT analysis is a kind of assessment to examine the performance of the AI-based model in this study. A SWOT analysis is a tool that is widely used to aid in the identification of strategic strategies for an entity or activity. It is recommended for this study because it provides valuable knowledge about the potential feasibility of the method under consideration. SWOT analysis is very useful at the model's front end for assessing environmental factors in performance analyses and gauging the level of expertise, talents, attitudes, abilities, and environmental support in cause analyses (Stolovitch & Keeps, 2006). SWOT analysis contains internal environment and external factor. The internal environment decides a system's strengths and weaknesses, while external factors dictate opportunities and threats. Figure 1 shows the overview of the SWOT analysis.

Strength can be defined as any accessible resource that can be used to boost the efficiency of overall performance (Panigrahi & Mohanty, 2012). Strength can be classified as an internal factor like the structural component of an AI-based model including the

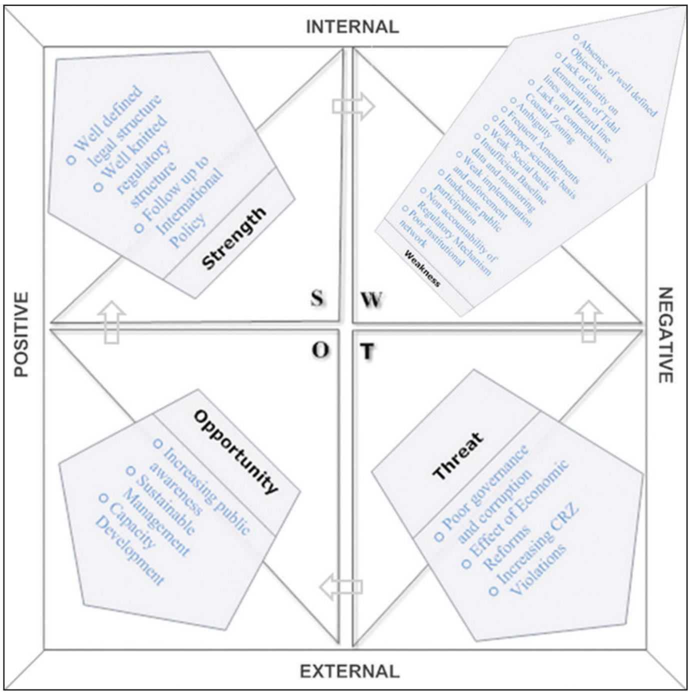

Figure 1: SWOT Analyses Chart (Panigrahi & Mohanty, 2012)

parameters and algorithms. Strength defines the resources and capabilities of system, which can provoke the further development (Panigrahi & Mohanty, 2012). The strength of the AI- based model is also based on the presence of regulatory authorities to ensure that the law is followed throughout the related field.

Weaknesses are defects or deficiencies in any structure that can result in a loss of competitive advantage, productivity, or financial capital (Panigrahi & Mohanty, 2012). Therefore, the approaches aiming for improvement should be proposed to minimise the effect of the weakness. This can be achieved by reviewing more journal articles with critical observation.

The relationship between calculated parameters and algorithm stems from the model's strengths and limitations in the field of sediment transport prediction, which may present opportunities and threats. Opportunities are a confluence of various conditions at a given time that have a favorable outcome (Stolovitch & Keeps, 2006). It is external factors that contribute to the development and brings a good impact to the overall system. Some parties may take benefits at a certain time and situation but cannot be "made" on-demand. Identification of opportunity is worth for the improvement on the model performance.

Threats are described as something that could harm your business, venture, or product (Stolovitch & Keeps, 2006). The threats are detrimental and similar to opportunities because there is no way to prevent or control them from occurring. However, an appropriate analysis could handle and interact with them with ease. Unpredictable threats may affect the performance of the AI-based model and show important effects when anticipation is prepared.

2.3 Statistical Analysis

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 the analyses purposes and comparison, which are correlation coefficient (R), root mean square error (RMSE), and mean absolute error (MAE). The equations for R, RMSE, and MAE are as shown:

$$R = \frac{n\sum xy - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\sqrt{n\sum y_i^2 - (\sum y_i)^2}} \tag{1}$$

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

$$MAE = \frac{\sum |y_i - x_i|}{n} \tag{3}$$

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

3.0 RESULTS AND DISCUSSION

3.1 Statistical Analyses

Table 1 displayed the statistical performance of the 5 selected models related to sediment transport. The effectiveness of the studied AI-based models is investigated statistically by evaluating and comparing selected statistical parameters, which are R, RMSE and MAE. These statistical parameters were chosen because they are widely utilised to analyse the errors associated in model as goodness of fit between the measured and estimated values. R is a statistical term used to measure the strength in anticipated values that follow the correct trends in the past. In short, it is a measurement of predicted values matching with the observed data from a forecast model. Meanwhile, RMSE can determine the sample variance of errors independently. The model performs better with a smaller RMSE. MAE shows the average of the individual prediction errors. Basically, the greater value of R that is closer to 1 represents better performance of the model. In contrary, a smaller RMSE and MAE indicates a better model performance.

In general, all the models have R value greater than 0.90. SVM-RBF model has highest R value of 0.994 among the others. It is then followed by the ANFIS models with values of 0.9879 (ANFIS-PSO) and 0.9824 (ANFIS-BLM) respectively. In terms of RMSE, it is ranged between 0.0010 to 0.26, where the smallest value is recorded by SVM-RBF model. A similar trend can be observed from the perspective of MAE, where the smallest number of 0.0010 is exhibited by the SVM-RBF model.

3.2 SWOT Analysis

Support vector machine (SVM), adaptive-neuro fuzzy inference system (ANFIS) and artificial neural network (ANN) are the three basic models in sediment transport. Their strength, weakness, opportunity and threat are presented in Table 2.

3.3 Summary

In short, SVM is attractive as it features a optimization parameter to address the issue of computational burden that is typical in ANN and ANFIS modelling. Second, SVM is characterised by a quadratic optimisation method that employs effective ways to avoid the difficulty of having local minima. SVM gives good out-of-sample generalisation when a suitable Gaussian kernel is used. This implies that by selecting proper generalisation evaluation values, SVM is stable even the sample data was bias during the training phase. Meanwhile, ANFIS was proved to adequately manage the inconsistencies and ambiguity of sediment concentration properly. As a conclusion, SVM and ANFIS models has outperformed the ANN model based on the statistical and SWOT analyses.

4.0 CONCLUSION

An assessment of several AI-based models in sediment transport prediction, especially suspended material, was undertaken in this study. AI-based models have yielded promising results in estimating the phenomenon of sediment transport in rivers. According to the statistical analyses and SWOT analyses, SVM and ANFIS performed better than the ANN.

There are some recommendations for future works. Data pre-processing is an important step before estimation model can established after collecting the discharge data. The goal of pre-processing is to eliminate undesired variation. It was noted that the discharge is very important parameter to observe the sediment transport properties. The dynamic behaviour of sediment discharge changes with the flowing velocity, it is advisable to build one more extra model based on discharge parameters. Prediction accuracy will be improved if the categorized data values are closed to another. Furthermore, employment of evolutionary algorithms is better to have good global minima and maxima prediction.

Table 1: Performance Assessment of Different AI Models in Sediment Transport

Models	Sources	R	RMSE	MAE
Adaptive Neuro-Fuzzy Inference System with Backpropagation and Levenberg- Marquardt (ANFIS-BLM)	Bui, *et al.* 2017	0.9824	0.0056	0.0037
Adaptive Neuro-Fuzzy Inference System with Particle Swarm Optimisation (ANFIS-PSO)	Qasem *et al.,* 2017	0.9879	0.2600	0.0570
Artificial Neural Network with Genetic Algorithm and Multi-Objective Optimisation (ANN-GA-MOO)	Yadav *et al.,* 2021	0.9650	0.0090	0.0050
Support Vector Machine with Radial Basis Function (SVM-RBF)	Bababali and Dehghani, 2020	0.9940	0.0010	0.0010
Support Vector Machine with Genetic Algorithm (SVM-GA)	Yadav *et al.,* 2018	0.9813	0.0027	0.0125

Table 2: SWOT Analysis for Conventional AI Model in Sediment Transport Studies

AI Models	SWOT Analysis			
	Strength	**Weakness**	**Opportunity**	**Threat**
SVM	• Effectively solve regression analysis (Samantaray, 2019) • Allow the use of non-linear function in the input space through kernel function (Khozani, 2020)	• Heavily dependent on the correct parameters selection (Yadav, 2018; Yadav, 2021) • Adopt trial and error method to select kernel functions and hyperparameters (Nourani, 2014)	• Require proper and multiple combination of input variables to generate strong correlation between input and output data (Khozani, 2020) • Have a good estimation on maximum value while integrating with gene expression programming (Samantaray, 2019) • Show a good ability to predict minimum and middle values while implementing it with radial basis function (Khozani, 2020)	• Consume more time during testing phase due to complicated combined models (Pektas, 2015)
ANFIS	• Employ neural network to tune membership function automatically (Bui, 2017; Qasem, 2017) • Enhance non-linearity between input and output hydrological parameters through the fuzzy logic concept with neural network training algorithms (Cui, 2021)	• Inconsistent during convergence process (Cui, 2021) • Require configurable parameters to achieve trial and error method (Yadav, 2018; Yadav, 2021) • Hard to employ optimisation methods (Cui, 2021) • Require large amount of data to increase prediction accuracy (Qasem, 2017)	• Apply different training algorithms (Yadav, 2018; Yadav, 2021) • Has high tolerance against data sample errors (Bui, 2017)	• Yield a black-box representation through the network training (Qasem, 2017; (Yadav, 2018; Yadav, 2021)
ANN	• Achieve 90% of prediction accuracy (Yang, 2009) • Synthesise machine learning techniques using modelling approach (Qasem, 2017) • Not necessary to have relevant mathematical expression (Nourani, 2014)	• Implement trial-and-error method to alter the weights (Yang, 2009) • Require a vast amount of data during training process (Qasem, 2017)	• Employ antecedent discharge data (Mohammadi, 2021) • Observe the peak value using daily scale (Qasem, 2017)	• Sensitive to the initial weight values (Yang, 2009) • Occasionally stuck by local error minima to reach global minimum (Nourani, 2014)

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REFERENCES

[1] Bababali, H., and Dehghani, R. (2020). Comparison and Evaluation of Support Vector Machine and Gene Programming in River Suspended Sediment Estimation (Case Study: Kashkan River). International Journal of Horticulture, Agriculture and Food Science (IJHAF), 4 (2), 53-61. https://dx.doi.org/10.22161/ijhaf.4.2.5.

[2] Bui, M. D., Kaveh, K., and Rutschmann, P. (2017). Performance Analysis of Different Model Architectures Utilized in an Adaptive Neuro Fuzzy Inference System for Contraction Scour Prediction. IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE), 14(3), 18-32. https://doi.org/10.9790/1684-1403051832.

[3] Cui, X., Yang, F., Wang, X., Ai, B., Luo, Y., and Ma, D. (2021). Deep Learning Model for Seabed Sediment Classification Based on Fuzzy Ranking Feature Optimization. Marine Geology, 432, 106390. https://doi.org/10.1016/j.margeo.2020.106390.

[4] Huai, W., Li, S., Katul, G. G., Liu, M., and Yang, Z. (2021). Flow Dynamics and Sediment Transport in Vegetated Rivers: A Review. Journal of Hydrodynamics, 33, 400-420. https://doi.org/10.1007/s42241-021-0043-7.

[5] Khozani, Z. S., Safari, M. J. S., Mehr, A. D., and Mohtar, W. H. M. W. (2020). An Ensemble Genetic Programming Approach to Develop Incipient Sediment Motion Models in Rectangular Channels. Journal of Hydrology, 584, 124753. https://doi.org/10.1016/j.jhydrol.2020.124753.

[6] Mohammadi, B., Guan, Y., Moazenzadeh, R., and Safari, M. J. S. (2021). Implementation of Hybrid Particle Swarm Optimization-Differential Evolution Algorithms Coupled with Multi-Layer Perceptron for Suspended Sediment Load Estimation. Catena, 198, 105024. https://doi.org/10.1016/j.catena.2020.105024.

[7] Nourani, V., Baghanam, A. H., Adamowski, J., and Kisi, O. (2014). Applications of Hybrid Wavelet–Artificial Intelligence Models in Hydrology: A Review. Journal of Hydrology, 514, 358-377. https://doi.org/10.1016/j.jhydrol.2014.03.057.

[8] Panigrahi, J. K., and Mohanty, P. K. (2012). Effectiveness of the Indian Coastal Regulation Zones Provisions for Coastal Zone Management and Its Evaluation Using SWOT Analysis. Ocean & Coastal Management, 65, 34-50. https://doi.org/10.1016/j.ocecoaman.2012.04.023.

[9] Pektas, A. O., and Dogan, E. (2015). Prediction of Bed Load via Suspended Sediment Load Using Soft Computing Methods. Geofizika, 32(1), 27-46. https://doi.org/10.15233/gfz.2015.32.2.

[10] Pu, J. H., Wallwork, J. I., Khan, Md. A., Pandey, M., Pourshahbaz, H., Satyanaga, A., Hanmaiahgari, P. R., and Gough, T. (2021). Flood Suspended Sediment Transport: Combined Modelling from Dilute to Hyper-Concentrated Flow. Water, 13(3), 379. https://doi.org/10.3390/w13030379.

[11] Qasem, S. N., Ebtehaj, I., and Riahi Madavar, H. (2017). Optimizing ANFIS for Sediment Transport in Open Channels using Different Evolutionary Algorithms. Journal of Applied Research in Water and Wastewater, 4(1), 290-298. https://doi.org/10.22126/arww.2017.773.

[12] Samantaray, S., and Ghose, D. K. (2019). Sediment Assessment for A Watershed in Arid Region via Neural Networks. Sadhana, 44(10), 1-11. https://doi.org/10.1007/s12046-019-1199-5.

[13] Stolovitch, H. D., and Keeps, E. J. (2006). Handbook of Human Performance Technology: Principles, Practices, and Potential. John Wiley & Sons Hoboken, New Jersey, United States.

[14] Vittori, G., Blondeaux, P., Mazzuoli, M., Simeonov, J., and Calantoni, J. (2020). Sediment Transport Under Oscillatory Flows. International Journal of Multiphase Flow, 133, 103454. https://doi.org/10.1016/j.ijmultiphaseflow.2020.103454.

[15] Wallwork, J. T., Pu, J. H., Kundu, S., Hanmaiahgari, P. R., Pandey, M., Satyanaga, A., Khan, Md. A., and Wood, A. (2022). Fluids, 7(1), 23. https://doi.org/10.3390/fluids7010023.

[16] Yadav, A., Chatterjee, S., and Equeenuddin, S. M. (2018). Suspended Sediment Yield Estimation Using Genetic Algorithm-Based Artificial Intelligence Models: Case Study of Mahanadi River, India. Hydrological Sciences Journal, 63(8), 1162-1182. https://doi.org/10.1080/02626667.2018.1483581.

[17] Yadav, A., Chatterjee, S., and Equeenuddin, S. M. (2021). Suspended Sediment Yield Modeling in Mahanadi River, India by Multi-Objective Optimization Hybridizing Artificial Intelligence Algorithms. International Journal of Sediment Research, 36(1), 76-91. https://doi.org/10.1016/j.ijsrc.2020.03.018.

[18] Yang, C. T., Marsooli, R., and Aalami, M. T. (2009). Evaluation of Total Load Sediment Transport Formulas Using ANN. International Journal of Sediment Research, 24(3), 274-286. https://doi.org/10.1016/S1001-6279(10)60003-0.

[19] Yuan, S., Tang, H., Li, K., Xu, L., Xiao, Y., Gualtieri, C., Rennie, C., and Melville, B. (2021). Hydrodynamics, Sediment Transport and Morphological Features at the Confluence Between the Yangtze River and the Poyang Lake. Water Resources Research, 57(3), e2020WR028284. https://doi.org/10.1029/2020WR028284.

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