APPLICATION OF RECURRENT NEURAL NETWORK IN ACTUAL SHEAR RATE PREDICTION UNDER WALL SLIP PHENOMENON

Ren Jie Chin[1*], Sai Hin Lai[2], Kok Zee Kwong[3]

Abstract

Wall slip refers to the phenomenon where particles in a suspension move away from the boundary wall, creating a thin liquid-rich layer nearby. This occurrence can significantly affect rheological measurements, notably viscosity, shear stress, and shear rate. Suspensions find widespread use in various industries such as food processing, personal care products, pharmaceuticals, paints, medicine, and agrochemicals. Predicting the actual shear rate traditionally proves challenging, time-consuming, and cost-intensive. Hence, there's a pressing need for a computational model to perform this task with acceptable accuracy. Leveraging the precise input-output mapping capability of recurrent neural network (RNN), it was employed to develop a model for the actual shear rate prediction. Evaluation of these models through statistical analyses reveals that RNN model III outperforms others, boasting the highest coefficient of determination (0.9998), lowest mean squared error (0.000721), root mean squared error (0.001361), most negative Akaike information criterion (-18646.3), Bayesian information criterion (-18635.9), and the smallest percentage error (15%). This developed model provides an alternative means to predict suspension shear rate under experimental constraints.

Received: *9 April, 2025*
Revised: *9 May, 2025*
Accepted: *10 July, 2025*

[1,3]Department of Civil Engineering, Lee Kong Chian Faculty of Engineering and Science, Universiti Tunku Abdul Rahman, 43000 Kajang, Malaysia.

[2]Department of Civil Engineering, Faculty of Engineering, Universiti Malaysia Sarawak, 94300 Kota Samarahan, Sarawak, Malaysia.

****Corresponding author:***
chinrj@utar.edu.my

DOI:
https://doi.org/10.54552/v86i3.242

Keywords:
Actual shear rate; Recurrent neural network; Rheology; Suspension; Wall slip

1.0 INTRODUCTION

Rheology, a branch of physics concerned with the flow of matter, encompasses various intriguing phenomena such as shear-induced migration, pattern formation, and notably, wall slip, which is the primary focus of this study. Wall slip occurs in two-phase or multiphase flow systems where suspended particles migrate away from solid wall boundaries, leaving a thin liquid-rich layer nearby (Agrawal *et al.,* 2023; Ali *et al.,* 2022; Yan *et al.,* 2022). This phenomenon, characterised by a low-viscosity layer, facilitates fluid particle movement along the boundaries. Consequently, rheological measurements such as viscosity, shear rate, and shear stress are significantly influenced (Ahuja & Singh, 2009; Chin *et al.,* 2019a; Chin *et al.,* 2020).

Laboratory experiments have explored factors influencing wall slip. Research indicates that particle size affects wall slip velocity, with larger particles leading to increased slip velocity due to steric hindrance (Deng *et al.,* 2021; Deng *et al.,* 2022). Concentration and temperature also play significant roles, with lower concentrations and higher temperatures correlating with increased wall slip velocities (Akter & Desai, 2018; Barnes, 1995; Chen *et al.,* 2008; Jana *et al.,* 1995).

Determining the actual shear rate for suspensions experiencing wall slip is currently a laborious and costly task, necessitating a mathematical model to accurately predict rheological behavior under such conditions. Given the rise of artificial intelligence (AI), particularly the effectiveness of recurrent neural network (RNN) approaches in diverse fields, employing RNN for shear rate prediction is logical (Deng, 2019; Lai *et al.,* 2022; Loh *et al.,* 2021). This study aims to develop a computational model for predicting actual shear rates in rheological systems affected by wall slip.

2.0 MATERIALS AND METHODS

2.1 Data Collection

Laboratory rheological experiments were undertaken to gather initial data in preparation for the model development. The samples tested involved a mixture of poly(methyl) methacrylate (PMMA) and glycerine. To ensure the reliability of the experimental data, the standard procedures were strictly adhered (Ahuja & Singh, 2009; Chin *et al.,* 2018; Yoshimura & Prud'homme, 1988). Initially, both PMMA particle and glycerine densities were set at 1300 kg/m^3 (Chin *et al.,* 2018; Shaliza *et al.,* 2015). This choice aimed to achieve a neutrally buoyant suspension and prevent density discrepancies that could affect result accuracy (Ahuja and Singh, 2009; Buscall *et al.,* 1993).

Rheological tests were carried out using a rheometer equipped with a 50 mm diameter parallel plate, with gap heights of 0.75 mm and 1.0 mm. The experiments encompassed six different volumetric concentrations (40%, 45%, 48%, 50%, 52%, and 55%), five temperatures (15°C, 25°C, 35°C, 45°C, and 55°C), and three particle sizes (18 μm, 75.3 μm, and 195.5 μm).

Recurrent neural network (RNN) is a type of deep learning artificial intelligence approach. Its outstanding uniqueness is its ability to handle long sequences of input data. Among the available RNN types, long short term memory (LSTM) was selected to train the model in this research study. LSTM is considered as an advanced RNN because of its ability to solve the vanishing gradient problem in normal RNN through its special structures, known as gates (Gers *et al.,* 2000; Hochreiter & Schmidhuber, 1997; Le *et al.,* 2015).

Similar to the other types of artificial neural networks, RNN consists of three layers which are input layer, hidden layer, and output layer. Among layers, the design of the hidden layers is the most essential as it plays a role as the computational part in a neural network. Mean squared error (MSE) was fixed as the loss function in this research study. A loss function is a measure of how good a prediction model does in terms of being able to predict the expected outcome. MSE is the sum of squared distances between the target variable and predicted values and it is the most commonly used regression loss function (Liu & Sullivan, 2019; Yu *et al.,* 2018). On the other hand, Adaptive Moment Estimation (Adam) optimiser was assigned as the optimisation algorithm. It is an optimisation algorithm that can be used instead of the classical stochastic gradient descent procedure to update network weights iterative based on training data. It is well suited for problems that are large in terms of data and parameters, straightforward to implement and computationally efficient (Liu & Sullivan, 2019; Ruiz *et al.,* 2019).

In addition, the selection of parameters such as learning rate, batch size and activation function is considerably important in designing the architecture of RNN model. Thereby, trial-and-error method was applied to determine the combination that provides the best performance in term of model accuracy. Figure 1 displays the architecture of RNN model.

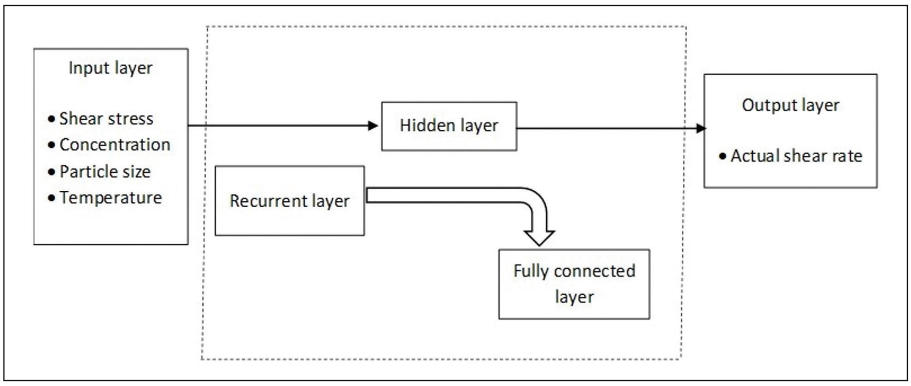

Figure 1: Architecture of RNN

2.3 Statistical Analyses

The effectiveness of all the constructed models was evaluated through a range of statistical analyses, including the coefficient of determination (R^2), mean absolute error (MAE), root mean squared error (RMSE), percentage error (% error), Akaike information criterion (AIC), and Bayesian information criterion (BIC). These analyses aimed to assess the models' suitability in accurately predicting the actual shear rate for suspensions under wall slip conditions (Chin *et al.,* 2019a).

$$R^2 = \left(\frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\sqrt{n\sum y_i^2 - (\sum y_i)^2}}\right)^2 \quad (1)$$

$$\mathrm{MAE} = \frac{\sum |y_i - x_i|}{n} \quad (2)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum (y_i - x_i)^2} \quad (3)$$

$$\text{Percentage error} = \frac{|True\ value - Predicted\ value|}{True\ value} \times 100\% \quad (4)$$

$$\mathrm{AIC} = -2\log L + 2\mathrm{K} \quad (5)$$

$$-2\log L = n(\log 2\pi + 1 + \log \frac{RSS}{n}) \quad (6)$$

$$\mathrm{BIC} = -2\log L + \mathrm{K}\log n \quad (7)$$

where n is the number of data pairs, x is the observed variable, y is the predicted variable, K is the number of model parameters (the number of variables in the model plus the intercept), L is maximised likelihood, and RSS is residual sum of squares.

3.0 RESULTS AND DISCUSSION

3.1 RNN Models Evaluation

A total of 9000 datasets were gathered from rheological tests. Among these, 7200 datasets (equivalent to 80% of the total) were allocated for training the RNN model, while the remaining 1800 datasets were set aside for testing purposes. Previous studies suggest that the typical range for training data percentage lies between 60% to 80% (Akter & Desai, 2018; Alimissis *et al.,* 2018; Zhang *et al.,* 2018). In this instance, the upper limit was chosen to facilitate the models in capturing the most comprehensive input-output patterns.While designing the architecture of RNN, the choice of the parameters such as batch size, learning rate and activation function in recurrent layer play an important role to achieve a presentable output. Under such a circumstance, a series of RNN models which differ in term of the above-mentioned parameters were developed. However, only the selected models (as shown in Table 1) were discussed in this section. The statistical performance of each RNN model was presented in Table 2.

From Table 2, the developed RNN models were evaluated using R^2, MAE, RMSE, AIC and BIC. Among the examined models, the highest recorded R^2 value is 0.9998. Such a value which is approximate to 1 which reflects that there is a very strong relationship between the predicted value and actual value. On the other hand, it is noticed that the MAE and RMSE values show a decreasing from model I to model III and then the trend was turned over after model III, meaning that the performance of the model III is the best in term of MAE and RMSE among the investigated RNN models. AIC is defined as analysis to determine the relative quality of a statistical model for a given set of data. In other words, it is a measure of the goodness of fit of an estimated statistical model. Meanwhile, BIC is a type of model selection among a class of parametric models with different numbers of parameters. According to the general rule, the model with a more negative AIC and BIC values is more favourable as the estimated values are considerably well-suited to the developed model. The model that meets the criterion is model III. Both of its AIC and BIC values is the most negative, showing that the predicted value fit the best in model III.

Table 1: Parameters combination corresponding to each RNN model

Models	Epoch	Batch Size	Learning Rate	Activation Function in Recurrent Layer
I	256	20	0.000010	ReLu
II	256	20	0.000010	Sigmoid
III	256	20	0.000010	Tanh
IV	256	40	0.000010	Tanh
V	256	20	0.000100	Tanh
VI	256	20	0.000001	Tanh

Table 2: Statistical performance of each RNN model

Models	R^2	MAE	RMSE	AIC	BIC
I	0.8972	0.026321	0.039757	-6497.5	-6486.5
II	0.9737	0.011739	0.016056	-9761.6	-9750.6
III	0.9998	0.000721	0.001361	-18646.3	-18635.3
IV	0.9873	0.008391	0.011412	-10990.7	-10979.7
V	0.9613	0.017883	0.022510	-8545.3	-8534.3
VI	0.8532	0.029563	0.040982	-6388.3	-6377.3

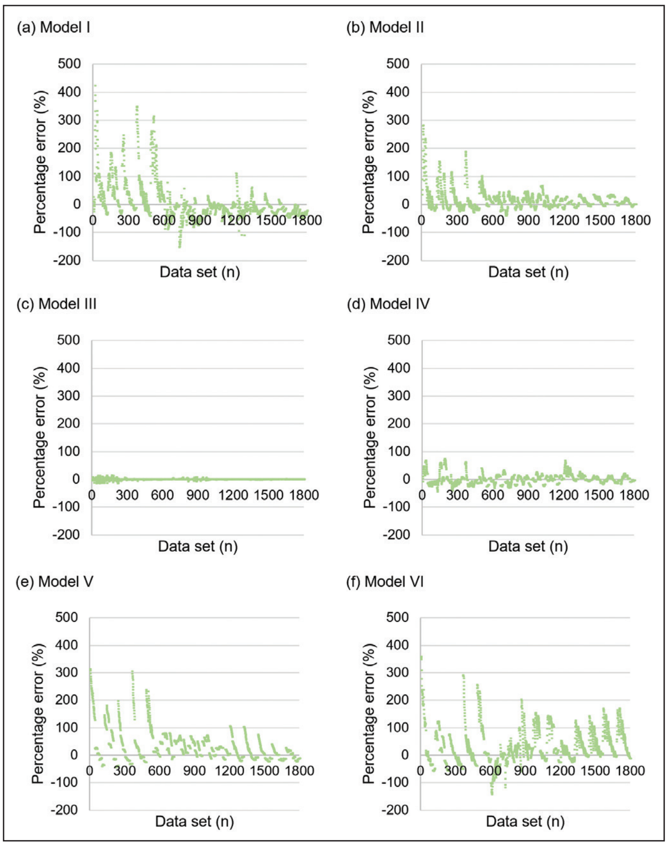

Figure 2: Percentage error of the respective dataset corresponding to each RNN model

Percentage error is another important indicator to evaluate the performance of a mathematical model. The smaller the percentage error, the better the performance of the computational model. In other words, a low percentage error describes a more accurate prediction. Figure 2 shows the percentage error with respect to each dataset corresponding to each RNN model while Figure 3 exhibits the maximum percentage error of each RNN model. In sum, most of the models display a wide range of percentage error with a maximum percentage error approximates to 75% or even higher, indicating that the predicted value from the models has a huge difference with the actual value. However, the only and one model which does not follow such trend is model III. It shows an outstanding performance in terms of percentage error where the percentage error of all its predicted dataset fall within the range of ±15%, meaning that the model can achieve at least 85% of accuracy. At the same time, its maximum percentage error is recorded at 15%, showing that the degree of difference between the observed and predicted value is considerably low.

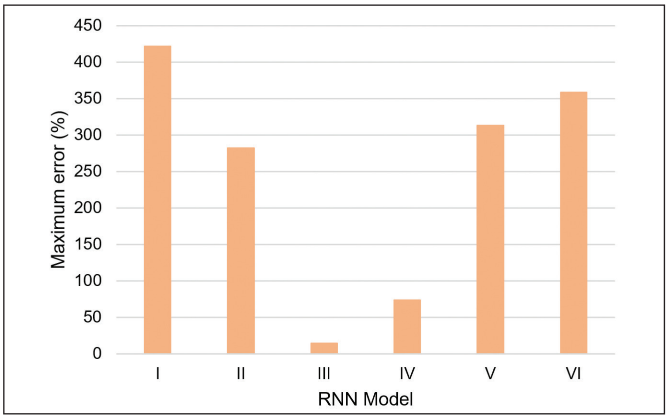

Figure 3: Maximum percentage error for each RNN model

Therefore, with such outstanding performance as discussed above, the highest R^2 value of 0.9998, lowest MAE value of 0.000721 and RMSE value of 0.001361, most negative AIC value of -18646.3 and BIC value of -18635.3 and smallest maximum percentage error of 15%, model III has become the prior choice among the examined RNN models.

3.2 Models Comparison

In a previous study, a multilayer perceptron neural network (MLP-NN) (Chin *et al.,* 2019b) model and radial basis function network (RBFN) (Chin *et al.,* 2023) were developed to predict actual shear rates. However, there is still considerable room for improvement to achieve a higher level of prediction accuracy.

In this section, the best-performing RNN model was compared with the MLP-NN model (Chin *et al.,* 2019b) and RBFN (Chin *et al.,* 2023) using a series of statistical analyses, including coefficient of determination, mean absolute error, root mean squared error, Akaike information criterion, Bayesian information criterion, and percentage error.

As depicted in Table 3, a significant improvement is evident across all evaluated aspects when comparing the MLP-NN and RBFN models to the RNN model. Firstly, in terms of MAE and RMSE errors, the RNN model exhibits the lowest values, followed by the RBFN model and then the MLP-NN model, indicating that the RNN model can generate more accurate outputs. Similarly, a comparable trend is observable from the perspective of AIC and BIC. The most negative values are observed in the RNN model, suggesting that the predicted output fits better in the RNN model compared to the MLP-NN and RBFN models.

Lastly, in terms of percentage error, which is a crucial indicator in AI prediction model development, the error, as shown in Figure 4, has improved from the previously developed MLP-NN model (75%) and RBFN model (53%) to RNN model (15%). In other words, the maximum percentage error has been significantly reduced, with the RNN model achieving a substantial improvement of around 40%.

Table 3: Comparison of the best-performed model corresponding to each AI technique

Model	MLP-NN (Chin *et al.* 2019b)	RBFN (Chin *et al.*, 2023)	RNN
R^2	0.9967	0.9998	0.9998
MAE	1.146804	0.001058	0.000721
RMSE	1.652898	0.001447	0.001361
AIC	-7657.3	-18426.5	-18646.3
BIC	-7646.4	-18415.5	-18635.9
Max. % Error	75	53	15

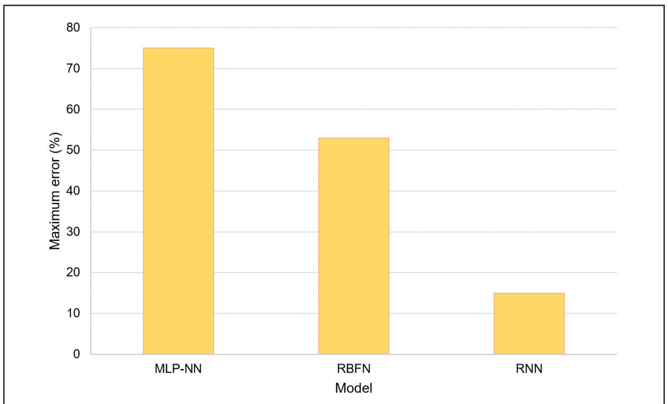

Figure 4: Maximum percentage error with respect to each model

4.0 CONCLUSION

The primary objective of this research study is to assess the suitability of RNN approaches in constructing mathematical computational models capable of accurately predicting real-life outputs. When designing the architecture of the RNN model, selecting parameters such as batch size, learning rate, and activation function is a crucial step. Hence, a trial-and-error method was employed to determine the most suitable parameters for the RNN models, aiming to achieve improved prediction accuracy.

In this study, numerous RNN models were constructed, and their performance was evaluated through various statistical analyses. Among the examined RNN models, model III demonstrated outstanding performance. It attained an R^2-value of 0.9998, mean absolute error of 0.000721, root mean squared error of 0.001361, Akaike information criterion of -18646.3, Bayesian information criterion of -18635.9, and maximum percentage error of 15%. Comparing the developed RNN model with the MLP-NN and RBFN models from previous literature, a significant improvement in model performance is evident, particularly in the RNN model, where the maximum percentage error has reduced to 15%, representing an almost fivefold enhancement. These findings highlight the potential for enhancing AI prediction models by implementing more advanced approaches, leveraging their unique features to improve overall performance.

There are some recommendations for future work. Since the RNN has successfully improved the prediction accuracy, it shows that an advanced machine learning model performs better than the conventional model (MLP-NN and RBFN). So, it should seek the possibility of integrating the RNN with different optimisation algorithms to form a hybrid model for prediction accuracy improvement purposes. In addition, a wider range of datasets can be collected, by using different particle sizes and temperatures. ■

ACKNOWLEDGMENT

This research was supported by the Ministry of Higher Education (MoHE) Malaysia through the Fundamental Research Grant Scheme project (FRGS/1/2023/WAB02/UTAR/02/1) and was partly supported by Malaysia Toray Science Foundation (4417/0005).

AUTHORS' CONTRIBUTIONS

- **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.

REFERENCES

[1] Agrawal, S., Das, P. K., & Dhar, P. (2023). Microfluidic soluto-hydrodynamics using interactive patterned wall-slip and oscillatory thermo-capillarity. *Microfluidics and Nanofluidics, 27,* 18. https://doi.org/10.1007/s10404-023-02627-6.

[2] Ahuja, A., & Singh, A. (2009). Slip velocity of concentrated suspensions in Couette flow. *Journal of Rheology, 53,* 1461-1485. https://doi.org/10.1122/1.3213090.

[3] Akter, T., & Desai, S. (2018). Developing a predictive model for nanoimprint lithography using neural networks. *Materials and Design, 160,* 836-848. https://doi.org/10.1016/j.matdes.2018.10.005.

[4] Ali, A., Sarkar, S., Das, S., & Jana, R. N. (2022). A report on entropy generation and Arrhenius kinetics in magneto-bioconvective flow of Cross nanofluid over a cylinder with wall slip. *International Journal of Ambient Energy,* 1-16. https://doi.org/10.1080/01430750.2022.2031292.

[5] Alimissis, A., Philippopoulos, K., Tzanis, C. G., & Deligiorgi, D. (2018). Spatial estimation of urban air pollution with the use of artificial neural network models. *Atmospheric Environment, 191,* 205-213. https://doi.org/10.1016/j.atmosenv.2018.07.058.

[6] Barnes, H. A. (1995). A review of the slip (wall depletion) of polymer solutions, emulsions and particle suspensions in viscometers: its cause, character and cure. *Journal of Non-Newtonian Fluid Mechanics, 56,* 221-251. https://doi.org/10.1016/0377-0257(94)01282-M.

[7] Buscall, R., McGowan, J., & Morton-Jones, A. J. (1993). The rheology of concentrated dispersions of weakly attracting colloidal particles with and without wall slip. *Journal of Rheology, 37,* 621-641. https://doi.org/10.1122/1.550387.

[8] Chen, L., Duan, Y., Zhao, G., & Liu, M. (2008). Effects of temperature, solid particle size and concentration on wall slip behaviour of coal-water slurry in pipelines. *Journal of Chemical Industry and Engineering (China), 59*(9), 2206-2213.

[9] Chin, R. J., Lai, S. H., Shaliza, I., & Wan Zurina, W. J. (2018). Factors affect wall slip: Particle size, concentration and temperature. *Applied Rheology, 28,* 15775-1-9. https://doi.org/10.3933/applrheol-28-15775.

[10] Chin, R. J., Lai, S. H., Shaliza, I., Wan Zurina, W. J., & Elshafie, A. (2019a). Rheological wall slip velocity prediction model based on artificial neural network. *Journal of Experimental and Theoretical Artificial Intelligence, 31*(4), 659-676. https://doi.org/10.1080/0952813X.2019.1592235.

[11] Chin, R. J., Lai, S. H., Shaliza, I., Wan Zurina, W. J., & Ahmed Elshafie, A. H. (2019b). New approach to mimic rheological actual shear rate under wall slip condition. *Engineering with Computers, 35,* 1409-1418. https://doi.org/10.1007/s00366-018-0670-y.

[12] Chin, R. J., Lai, S. H., Shaliza, I., Wan Zurina, W. J., & Elshafie, A. (2020). ANFIS-based model for predicting actual shear rate associated with wall slip phenomenon. *Soft Computing, 24,* 9639-9649. https://doi.org/10.1007/s00500-019-04475-5.

[13] Chin, R. J., Lai, S. H., Lee, F. W., & Kwong, K. Z. (2023). Actual shear rate prediction associated with wall slip phenomenon using radial basis function network. *The Journal of The Institution of Engineers Malaysia, 84*(1), 16-21. https://doi.org/10.54552/v84i1.206.

[14] Deng, B., Chin, R. J., Tang, Y., Jiang, C., & Lai, S. H. (2019). New approach to predict the motion characteristics of single bubbles in still water. *Applied Sciences, 9*(19), 3981. https://doi.org/10.3390/app9193981.

[15] Deng, B., Lai, S. H., Jiang, C., Kumar, P., El-Shafie, A., & Chin, R. J. (2021). Advanced water level prediction for a large-scale river–lake system using hybrid soft computing approach: a case study in Dongting Lake, China. *Earth Science Informatics, 14,* 1987-2001. https://doi.org/10.1007/s12145-021-00665-8

[16] Deng, B., Liu, P., Chin, R. J., Kumar, P., Jiang, C., Xiang, Y., . . . Luo, H. (2022). Hybrid metaheuristic machine learning approach for water level prediction: A case study in Dongting Lake. *Frontiers in Earth Science, 10*. https://doi.org/10.3389/feart.2022.928052

[17] Gers, F. A., Schmidhuber, J., & Cummins, F. (2000). Learning to forget: Continual prediction with LSTM. *Neural Computation, 12*(10), 2451-2471. https://doi.org/10.1162/089976600300015015

[18] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation, 9*(8), 1735-1780. https://doi.org/10.1162/neco.1997.9.8.1735.

[19] Jana, S. C., Kapoor, B., & Acrivos, A. (1995). Apparent wall slip velocity coefficients in concentrated suspensions of noncolloidal particles. *Journal of Rheology, 39*(6), 1123-1132. https://doi.org/10.1122/1.550631.

[20] Lai, S. H., Bu, C. H., Chin, R. J., Goh, X. T., & Teo, F. Y. (2022). New approach to predict fecal coliform removal for stormwater biofilters application. *IIUM Engineering Journal, 23*(2), 45-58. https://doi.org/10.31436/iiumej.v23i2.2173.

[21] Le, Q. V., Jaitly, N., & Hinton, G. E. (2015). A simple way to initialize recurrent networks of rectified linear units. *arXiv:1504.00941.* https://doi.org/10.48550/arXiv.1504.00941.

[22] Liu, Z., & Sullivan, C. J. (2019). Prediction of weather induced background radiation fluctuation with recurrent neural networks. *Radiation Physics and Chemistry, 155,* 275-280. https://doi.org/10.1016/j.radphyschem.2018.03.005.

[23] Loh, W. S., Chin, R. J., Ling, L., Lai, S. H., & Soo, E. Z. (2021). Application of machine learning model for the prediction of settling velocity of fine sediments. *Mathematics, 9*(23), 3141. https://doi.org/10.3390/math9233141.

[24] Ruiz, L. G., Capel, M. I., & C.Pegalajar, M. (2019). Parallel memetic algorithm for training recurrent neural networks for the energy efficiency problem. *Applied Soft Computing, 76,* 356-368. https://doi.org/10.1016/j.asoc.2018.12.028.

[25] Shaliza, I., Wong, S. D., Baker, I. F., Zamzam, Z., Sato, M., & Kato, Y. (2015). Influence of geometry and slurry properties on fine particles suspension at high loadings in a stirred vessel. *Chemical Engineering Research and Design, 94,* 324-336. https://doi.org/10.1016/j.cherd.2014.08.008.

[26] Yan, Z., Yin, S., Chen, X., & Wang, L. (2022). Rheological properties and wall-slip behavior of cemented tailing-waste rock backfill (CTWB) paste. *Construction and Building Materials, 324,* 126723. https://doi.org/10.1016/j.conbuildmat.2022.126723.

[27] Yoshimura, A., & Prud'homme, R. (1988). Wall slip corrections for Couette and parallel disk viscometers. *Journal of Rheology, 32,* 53-67. https://doi.org/10.1122/1.549963.

[28] Zhang, Y., Chen, H., Yang, B., Fu, S., & Jie Yu, Z. W. (2018). Prediction of phosphate concentrate grade based on artificial neural network modeling. *Results in Physics, 11,* 625-628. https://doi.org/10.1016/j.rinp.2018.10.011.

PROFILES

REN JIE CHIN received his BEng. and Ph.D. degrees in Environmental Engineering from University of Malaya, Malaysia, in 2015 and 2019, respectively. He is currently an Assistant Professor in the Department of Civil Engineering, Lee Kong Chian Faculty of Engineering and Science, Universiti Tunku Abdul Rahman, Malaysia. He is a registered Professional Technologist (Malaysia Board of Technologists). He has been the leader or been part of the team for about several national and international research projects. His research direction focused on flood, drought, and water resources management in the context of climate change, which involved computational simulation, development of decision support system, artificial intelligent, and optimisation models. He has published a total number of 48 research papers in reputed ISI journals and conference proceedings.
Email address: chinrj@utar.edu.my

SAI HIN LAI is a Professor at the Department of Civil Engineering, Faculty of Engineering, University Malaysia Sarawak. He is a registered Professional Engineer (PEng, Malaysia), Chartered Engineer (CEng, UK), Fellow of Asean Academy of Engineering & Technology (FAAET), and Institution of Engineering and Technology (FIET). He has been the leader or been part of the team for about 50 national and international research projects. His researches are focused on flood, drought, and water resources management in the context of climate change, which involved computational simulation, development of decision support systems, artificial intelligence models & latest optimisation techniques. He has published more than 100 research articles in reputed SCI journals, and delivered about 20 keynote / invited speeches in the past 5 years.
Email address: shlai@unimas.my

KOK ZEE KWONG received his BEng. (Civil and Construction Engineering) from Curtin University of Technology, Malaysia. He received his Ph.D. (Civil Engineering) from Universiti Malaysia Sabah. He is currently an Assistant Professor in the Department of Civil Engineering, Lee Kong Chian Faculty of Engineering and Science, Universiti Tunku Abdul Rahman, Malaysia. He is a registered Professional Engineer (PEng, Malaysia). He has been the leader or been part of the team for about several national and international research projects. His research direction focused on structural engineering (NDT structural assessment and health monitoring as well as piezoelectric smart material). He has published a total number of 21 research papers in reputed ISI journals and conference proceedings.
Email address: kwongkz@utar.edu.my