Predictive Model of Parameters Validation for the *Vortexanda* Technique by using Fuzzy Logic and Neural Network

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ABSTRACT

This study used fuzzy and neural network models for validating the non-dimensional parameters of experimental findings from development of vortexanda technique in the urban small hydropower system. Fuzzy and neural network was selected due to the significant contribution in verifying or predicting the parameters especially for the non-linear process. The aim of this study was to establish a validation model to verify the accuracy of non-dimensional parameters in predicting the removal efficiency of the vortexanda technique. The result show both models of Neural Network and ANFIS may become as the satisfactory tools in validating the 4 non-dimensional parameters for predicting the removal efficiency in vortexanda system by achieving only minimal error in validating process. The predictive model will help the decision maker to design the vortexanda system based on the suitable value of non dimensional parameters and removal efficiency estimation. This model could be an easier and interactive approach for the decision maker compared to the conventional method.

Keywords: *Fuzzy, Neural Network, Validation & Non-Dimensional Parameters*

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Introduction

Some researchers delved into neuro and fuzzy models thoroughly, in order to optimize the behavior characteristics of neuro and fuzzy models to achieve accurate and the best performances. They explored the combination development of fuzzy and neural network models which called as 'neuro fuzzy' models, due to the best performance of it's' result for nonlinear, complex and dynamic system. [1] studied the development tools of neural fuzzy models which are based on algorithm's combinations in neural networks, relating to the pattern recognition and regression analysis. However, this combination might be suitable for research aspects which required additional functions or behaviors that can be used in their system such as mathematical, arithmetic and uncertainty systems. For instance, [2] adopted the CoActive Neuro Fuzzy Inference System (CANFIS) and [3] and [4] used Adaptive Neuro Fuzzy Inference System (ANFIS) for simulating and validating their system.

Most researchers compared the fuzzy and neural network models for validating their findings or for choosing the right model in their system. For instance, [5] used both tools to check the consistency of the models to estimate soil moisture rate and the study found that prediction which made by neural network is more accurate than fuzzy logic.

There are many processes of the system which are characterized as dynamics and nonlinear where the relationship could not be solved or validated by the simple regression analysis. In referring to this, Artificial Neural Network and Fuzzy Logic are the reliable tool to be used for adapting the dynamic and nonlinear process in the system. Fuzzy models and neural network are widely used to parameterize the nonlinear functions, multivariable static and dynamic systems. Both of the models could be used to verify or validate the dynamic and nonlinear system based on the training of the input output data from the real observable condition. The real observable data in this study is referring to the experimental data conditions of the *vortexanda* technique as the particle removal system for implementation of urban small hydropower. The technique was developed by [6] as the particle removal technique for developing small hydropower system from the urban water infrastructure.

Therefore, this paper aims to establish a validation model for the purpose of verifying the accuracy of non-dimensional parameters in predicting the removal efficiency of the *vortexanda* technique. Small hydropower system in the urban water infrastructure is feasible to be implemented especially at tropical climate countries if the urban quality of stormwater is improved and quantity of stormwater is sufficient for generating an efficient energy. The establishment of *vortexanda* technique is to solve the problem on quality and quantity of stormwater for the purpose of energy generation as described in [7]. The developed predictive model will help related stakeholders to determine the percentage of removal efficiency in the real system operation.

Methodology

The methods conducted in this study were briefly summarized in the following flowchart as shows in Figure 1. Detail description of each method was explained in the following sections.

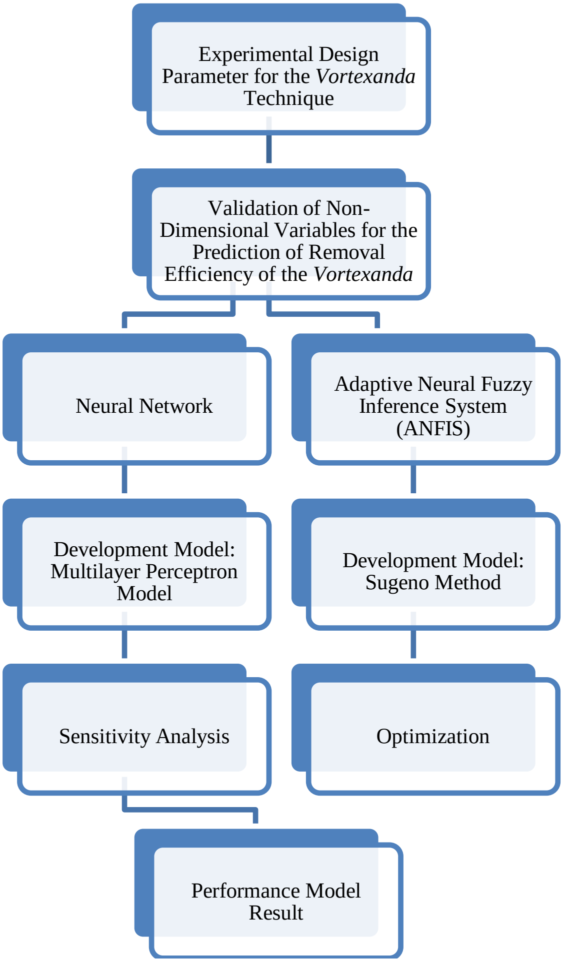

Figure 1: Research Flowchart

Experimental Design Parameter

In order to determine the removal efficiency for these combination effects, the detail analysis of the selection on significant design parameters has to be conducted. The list of parameters from Table1 is started from the storage container components until the coanda effect screen component. There are 10 parameters out of 14 parameters have been selected as the significant design parameters in the experimental work.

Table 1: Selection of dependency of design parameters for components on experimental work.

Component	Parameter	Symbol	Unit	Dimension
Storage tank	Change of concentration	**ΔC**	mg/L=kg/m^3	M/L^3
	Particle Size	$\mathbf{P_s}$	µm	L
	Initial concentration,C_0	**Co**	mg/L=kg/m^3	M/L^3
	Concentration of particle settlement	**Cs**	mg/L=kg/m^3	M/L3
Vortex /Hydrocyclone	water and particle Density	ρ_w ; ρ_p	mg/L=kg/m^3	M/L3
	Inlet Velocity$_v$	$\mathbf{V_i}$	m/s	L/T
	Tangential velocity	$\mathbf{V_t}$	m/s	L/T
	Centrifugal acceleration	**a**	m/s^2	L/T^2
	Volumetric flowrate(used the Qoutflow from orifice)	$\mathbf{Q_v}$	m^3/s	L^3/T
	0.798cP for temp 30 degree (cP=0.01P=1mPa.s) OR 10^{-6}m^2/s	**µ**	m^2/s	
	$mv_\Phi{}^2/r$	$\mathbf{F_c}$	kgm/s^2	ML/T^2
Coanda Effect Screen	Degree of Accelerator Plate	**Degree**		Dimensionless
	gravity acceleration	**g**	m/s^2	L/T^2
	Width of slot	$\mathbf{W_{slot}}$	m	L
	Outflow rate	**Qc**	m^3/s	L^3/T

Dimensional analysis is conducted to reduce amount of the experiment time and also to come out with the basic design parameter which influence the removal efficiency of these combination techniques. Other than that, dimensional analysis also helps to maintain the dynamic similarity with the real condition at the field site. Equation 1 shows the 10 parameters which has been selected based on the dependency from the list of important parameter. Equation 2 shows the basic design parameters from the dimensional analysis.

$$\Delta C = P_s \,;\, C_{o\,;}\, Q \,;\, V_{i\,;}\, \mu \,;\, \rho \,;\, d;\, g;\, W_{slot\,;}\, S_D \tag{1}$$

$\Delta C = Change\ of\ concentration$
P_s = *Particle Size*
C_o = *initial concentration*
$Q = Q_{inflow}$ *to the vortex section*
V_i = *inlet velocity*
μ = *viscosity of water*
ρ = *Density of water*
D = hydraulic diameter= inlet diameter of hydrocyclone
G = gravity at accelerator plate of coanda
W_{slot} = *Width of slot*
S_D = *Slope degree*

$$\frac{\Delta C}{C_0} = \mathrm{f}\left[\frac{g^{1/5}P_s}{Q^{2/5}} ;\ \mathrm{Re};\ \frac{g^{1/5}W_{slot}}{Q^{2/5}} ;\ \mathrm{S_D}\right] \tag{2}$$

For the Reynolds number value, it is referred to the fluid Reynolds for the experimental work. To maintain the dynamic similarity, Reynolds number is scaled down to 1/10 for being experiment in the small scale. Specific derivation of equation from [8] on $\mathrm{V}^2 = \frac{4\mathrm{da}}{3\mathrm{C_D}}\frac{\rho_\mathrm{p} - \rho_\mathrm{f}}{\rho_\mathrm{f}}$ using Kaska equation [8] has come out with the equation of $C_d = \frac{24}{Re} + \frac{4}{\sqrt{Re}} + \frac{4}{9}$. Therefore, from this derivation the Reynolds number can be derived to the formula as $Re_p = \mathrm{Re}\,[1 + \frac{\sqrt{Re}}{6} + \frac{Re}{54}]$. The Reynolds number experiment has been scaled down for maintaining the dynamic similarity. Therefore, the $\mathrm{Re_{ap}} = 1/10\mathrm{Re_{real/simulation.}}$

Validation of Non-Dimensional Variables using Neural Network and Adaptive Neural Fuzzy Inference System (ANFIS)

In this study, Artificial Neural Network and Adaptive Neural Fuzzy Inference System (ANFIS) were used as the validation process for checking the accuracy of non-dimensional parameters in predicting the removal efficiency of the *vortexanda* technique. Removal efficiency result of the *vortexanda* technique has been used as the dependence variable which needs to check its accuracy based on the 4 variables predictors. The 4 variables predictor is the non-dimensional parameters as depicted in Table 2 which had undergone dimensional analysis. The range value is referred to the range of each π(pi) that had been tested in the experimental conditions.

Table 1: Range of Pi dimensionless parameter

	Π	**Range**
Pi Parameter	$\mathbf{\Pi 1 = \frac{g^{1/5} P_s}{Q^{2/5}}}$	0.00125~ 0.005
	Π2 = Re	6357 ~ 19070
	$\mathbf{\Pi 3 = \frac{g^{1/5} W_{slot}}{Q^{2/5}}}$	2.898 ~ 3.610
	$\mathbf{\Pi 4 = S_d}$	15^0 , 30^0 & 45^0

Artificial Neural Network (ANN)

The development of model by using ANN, multilayer perceptron procedure was used to predict removal efficiency of the system in *vortexanda* technique. Multilayer perceptron is capable to predict and validate dependent variables based on values of independent predictor variables. The dependent variables is classified as the nominal measurement with numeric type while the independent variables is classified as the categorical factors which represented the Pi 1 = $\frac{g^{1/5} P_s}{Q^{2/5}}$, Pi2= Re , Pi 3 = $\frac{g^{1/5} W_{slot}}{Q^{2/5}}$ and Pi 4 = S_d . Details of the network information for the model development of *vortexanda* technique are explained in Table 3.

Table 1: Network Information for Model Development of Vortexanda technique

Network Information			**Explanation/Details**
Input Layer	Factors	Pi1, Pi2, Pi3 and Pi4	Predictors or Factors
Hidden Layer	Number of Units	12	Representation of 3 categories of important values which contains unobservable nodes or units
	Number of Hidden Layers	2	Work as the function of predictors
	Number of unit in hidden layer 1	3	
	Number of unit in hidden layer 2	2	
	Activation Function	Sigmoid	Activation function connects the weighted sums of units in a layer to the values of units in the attaining layer. $\gamma(c) = 1/(1+e^{-c})$ It takes real valued arguments and transforms them to the range (0,1)
Output Layer	Dependent Variables	Removal Efficiency (RE)	Response based on the predictions made by the predictors or factors. The output unit is produced accordingly from the function of the hidden units in part of the network type and user control specification
	Number of Units	1	
	Rescaling method for Scale Dependents	Standardized	Subtract the mean and divide by the standard deviation, (x-mean)/s
	Activation Function	Sigmoid	$\gamma(c) = 1/(1+e^{-c})$ It takes real valued arguments
	rror Function	Sum of Squares	The error function that the network tries to minimize during training. All the sum of squares and error values are computed for the rescaled values of the dependent variable.

Figure 2 illustrates the detail of architecture model for validating the non-dimensional parameters of *vortexanda* in anticipating its removal efficiency. This architecture is called as a feedforward architecture because the connections in the network flow forward from the input layer to the output layer without any feedback loops. This architecture model was run for the three classification type of data that is called as training, testing and validation phase. Testing and validation phases are important to examine the accuracy of this model in predicting the removal efficiency of this *vorteaxanda* technique. The brown and blue line in the Figure 1 indicates different synaptic weights which can be updated after each of training phase to ensure the accuracy of the prediction. Synaptic weight displayed the coefficient estimates that showed the relationship between the units in a given layer to the units in the following layer. It was based on the training sample eventhough the active dataset was separated into training, testing or validation data. The synaptic weight was estimated base on the scaled conjugate gradient to optimize the algorithm with the training phase of data.

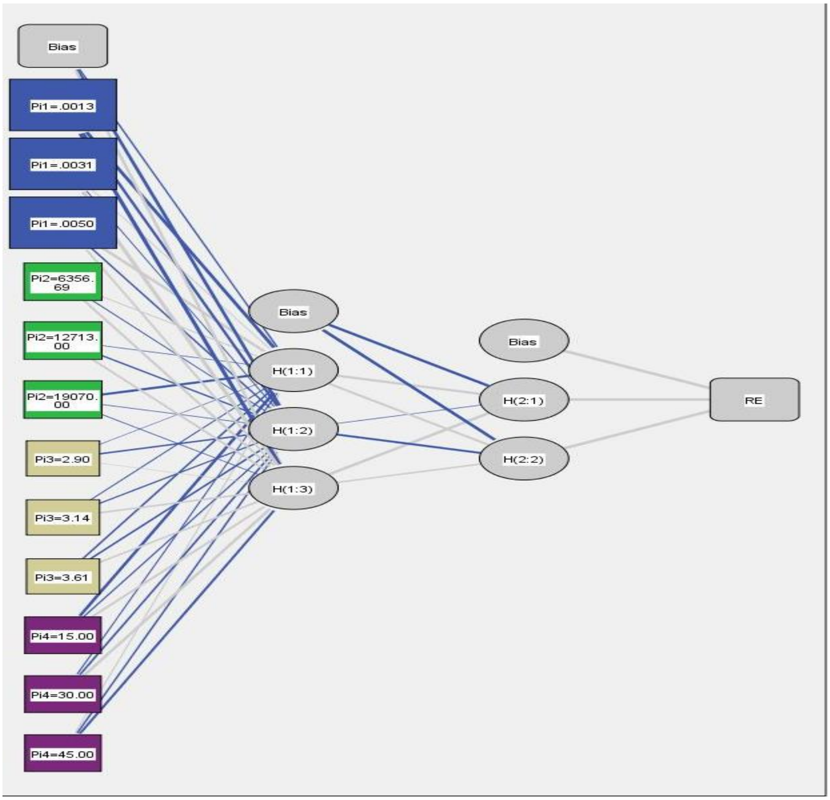

Figure 2: Feedforward architecture with 2 hidden layer for neural network validation model development on the *vortexanda* technique

Sensitivity Analysis

Sensitivity analysis was the computation in showing the importance of each non-dimensional parameters in influencing the removal efficiency result. The detail important analysis is depicted in Figure 3. In this sensitivity analysis, it was based on the combined training and testing samples.

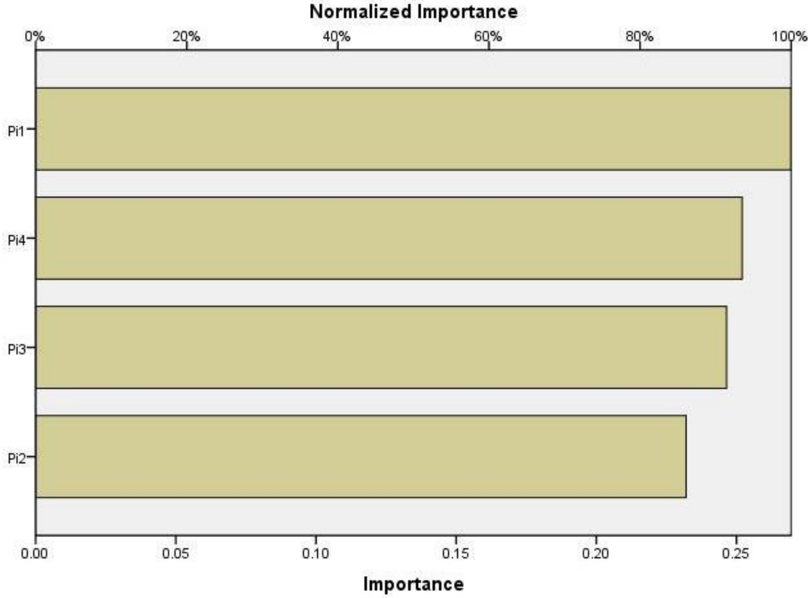

Figure 3: Importance of the Independent Parameters to Predict the Removal Efficiency

Adaptive Neural Fuzzy Inference System (ANFIS)

Adaptive Neural Fuzzy Inference System (ANFIS) is recognized as the nonlinear methodology which combines the learning capability of neural network with the ability in determining of the Fuzzy Inference System. In every layer of the ANFIS structure represents every step of Fuzzy Logic and the network is trained by using the concept of neural network. In this study, ANFIS was used as the 2nd method to evaluate the accuracy of non-dimensional parameters in predicting the removal efficiency of the *vortexanda* technique.

Development Model

Sugeno method in development of ANFIS model is suitable for *vortexanda* technique because it can react with the multiple independent variables and operate in a nonlinear dynamic system. Moreover, sugeno method is also well-suited with the mathematical analysis and works well with optimization and adaptive techniques. Figure 4 depicts the ANFIS toolbox function which constructed the Fuzzy Inference System whose membership function parameters were altered using either a backpropagation algorithm alone or in combination with a least squares type of method. This alteration allowed the fuzzy systems to learn from the data which they were modeling. A network type was almost similar to the neural network which inputs were loaded through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs. All of these network types finally were used to interpret the input/output map. In order to determine the accuracy of the model development, two sets of data classification also run by using ANFIS model which represented the training and checking phase. Model validation by using checking data was the process which the input vectors from the input/output data were sets on which the FIS was not trained and verified using the trained FIS model. This purpose was to observe the predictions of FIS model by using the corresponding data set output values.

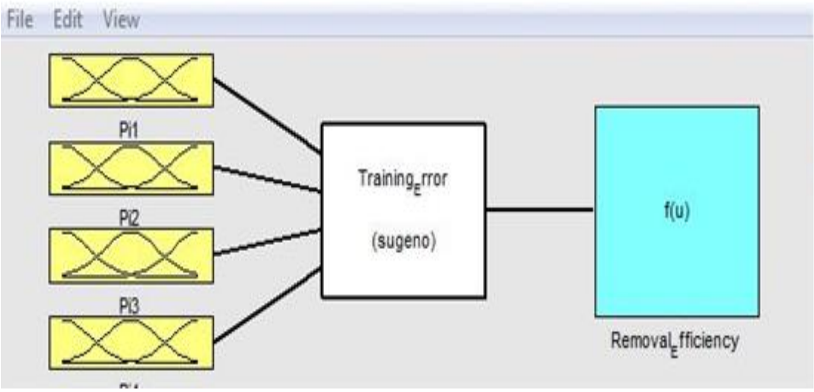

Figure 4: ANFIS Toolbox Function in constructing the Fuzzy Inference System

The entire implication process of the model development which shows in Figure 5 is the rule viewer. It helps to check the active rules or how the membership function shapes influence the final output. The rule viewer displays a roadmap of the whole fuzzy inference process and each rule can be viewed by clicking the rule in status line.

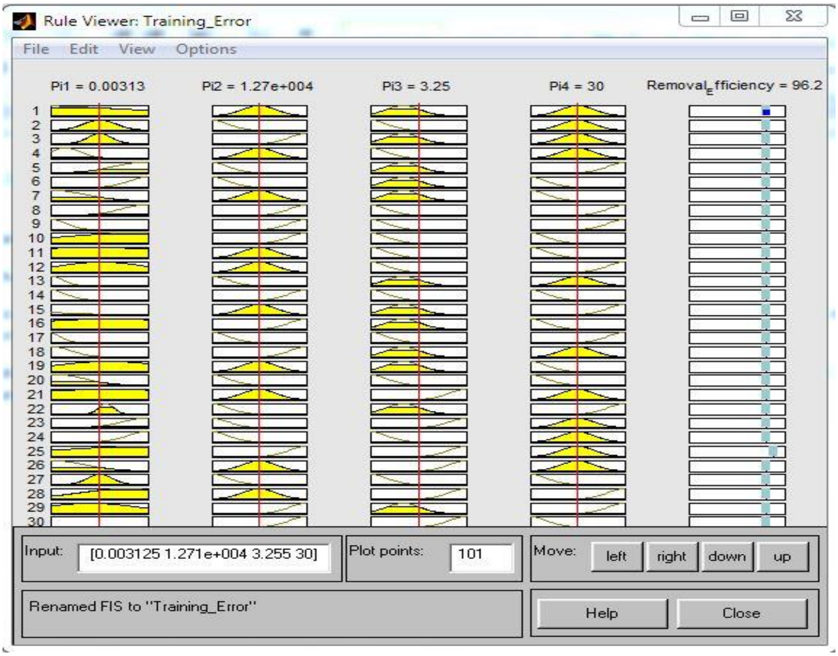

Figure 5: Rule viewer of ANFIS in validating the removal efficiency of *vortexanda* technique

The independent variables connected with the membership functions changes through the learning process as shows in Figure 6. Computation of these variables (or their adjustment) was facilitated by a gradient vector. This gradient vector prepared a measure of the well method in fuzzy inference system which was modeling the input/output data for a given set of parameters. Several optimizations were applied when the gradient vector was obtained in order to alter the variables in reducing some error measure. This measurement error was also referred as discrepancy ratio which was usually defined by the sum of squared difference between actual and desired outputs. In this model, combination of least squares estimations with back propagation was used for the function of membership variables estimation.

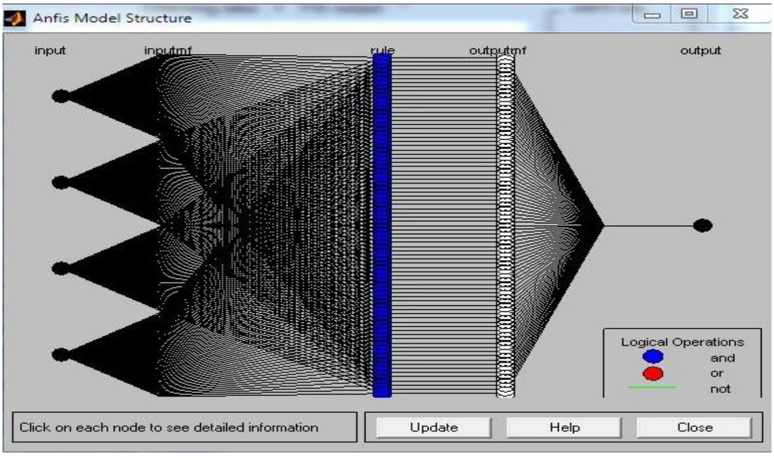

Figure 6: Details of the ANFIS model Structure by using AND method

Performance of Model Result

Artificial neural network and Adaptive neural inference system (ANFIS) had been used for validating non-dimensional variables in predicting the removal efficiency of *vortexanda* system. These tools were choosing based on its function to predict the developed *vortexanda* system in this study. Moreover, the variables factors / predictors in *vortexanda* system are involving the nonlinear and complex systems. Therefore, tools like neural network and ANFIS are suitable for validating the non-dimensional independent variables through the model performance structure.

The development models will be useful for decision maker to predict the removal efficiency of vortexanda based on the basic variables which was proposed in this study. The advantage of this tools is because it could work on conditions where the relationship among of the variables may be quite dynamic or nonlinear [1, 2] and [9]. The developed models could provide an analytical alternative to conventional techniques which are often limited by stringent assumption of normality, linearity and variable independence. These make the models useful as the decision tool on the *vortexanda* design.

Performance of Model Result by using Neural Network Model

Performance of model summary on the developed neural network is tabulated in Table 4 which represents the training, testing and holdout/validation sets. The purpose of training and testing data sets is to set up the architectural model and holdout data sets to validate the model. There is no actual data of removal efficiency in output data of validation sets. Validation set only comprised of 4 variables input data which the purpose is to validate the architecture of the neural network model in predicting the removal efficiency of *vortexanda* technique. The accuracy of prediction was determined by using sum of squares errors and relative error. Relative error is referred to the percentage of incorrect prediction when the computation was undergone of the each phase.

Table 4: Model summary of the developed neural network architecture in computation of vortexanda efficiency

	Model Summary	
Training	Sum of Squares Error	0.078
	Relative Error	0.037
	Stopping Rule Used	Maximum number of epochs (100 exceeded)
	Training Time	00:00:00.090
Testing	Sum of Squares Error	0.057
	Relative Error	0.034
Holdout	Relative Error	0.156

Results in Figure 7 illustrates a significant prediction model which was successfully established based on 4 independent variables by estimating the removal efficiency of *vortexanda*. The correlation coefficient, R2 is 0.9552 accordingly to the good agreement between predicted and experimental data of removal efficiency. This is referred to the architecture of designed neural network which achieved very little amount of relative error and sum of squares error for all training, testing and validation sets. Early stopping procedure was utilized in order to avoid the over fitting and to enhance robustness of the architecture model. Calibrated model was validated using the testing data set for each of training step. This procedure helped to avoid the over fitting of data and reduced the error especially in validation data set.

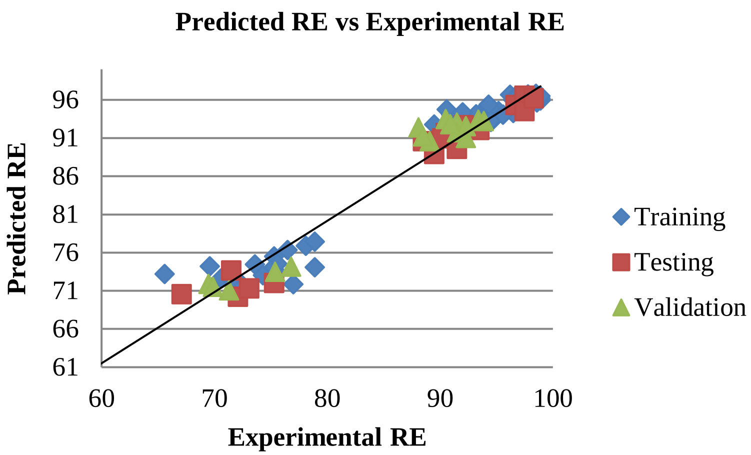

Figure 7: Scatter Plot of the Prediction Removal Efficiency for Training, Testing and Validation Sets by using Neural Network

Some arguments are raised due to the small quantity of datasets which were applied in this type of neural network algorithm; but the result had showed great agreement of prediction in between predicted and experimental values. The great prediction indicated that the algorithm for the neural network architecture in this study should be satisfied to be applied in the small data sets. This is because of the weightage value in the neural reduced the overtraining problem and type of architecture which used in the analysis. There are numerous studies that mentioned the limitations and dubious result of neural network to be applied in the small datasets. However, there is also some algorithms which use in the neural network can be suited with the small data sets case For instance, [10] proved that posterior probability neural network (PPNN) could deal with the small data sets in many fields. The area of neural network to be implied in the small data sets in different fields also had been investigated by [11] and [12].

Performance of Model Result by using ANFIS Model

Development of the ANFIS structure is depends on the structure which has minimal error during the training of datasets, Therefore, some trial of ANFIS structure has been modeled by examining the root mean square error (RMSE) before and after training of data sets in training and validation phases. Overtraining and less accurate prediction are avoidable to ensure the model can be functioned as the good model in future. The result of only suitable structure is discussed in detail for this part.

The developed structure for computing the removal efficiency from vortexanda system is trained by using hybrid learning algorithm. Data errors may affect the accuracy of the ANFIS model in two different ways. First, data of chosen variables which used to build and train the model may contain errors. Second, the developed model may use input data containing errors to the model even the training data are free of errors. Therefore, the quality of data based on the experimental results could be examined by using this ANFIS model.

Comparison of checking data with the trained dataset system is represented in Figure 8 which showed by the ANFIS Editor. The checking data was utilized for examining the ability of fuzzy inference system to generalize at each epoch. It was important for learning part which the input number was large or the data itself was noisy. A fuzzy inference system was required to detect a given input/output data due to developed model structure which has been constructed might have a tendency to overfit the trained data. This is normally happening for the large number of training epochs. If overfitting occur, the fuzzy inference system may not respond to other independent data sets, especially if they are corrupted by noise. Therefore, validation or checking data was useful for these situations which it helped to cross-validate the fuzzy inference model. Performance of the model to responds with the data was checked through this cross-validation phase.

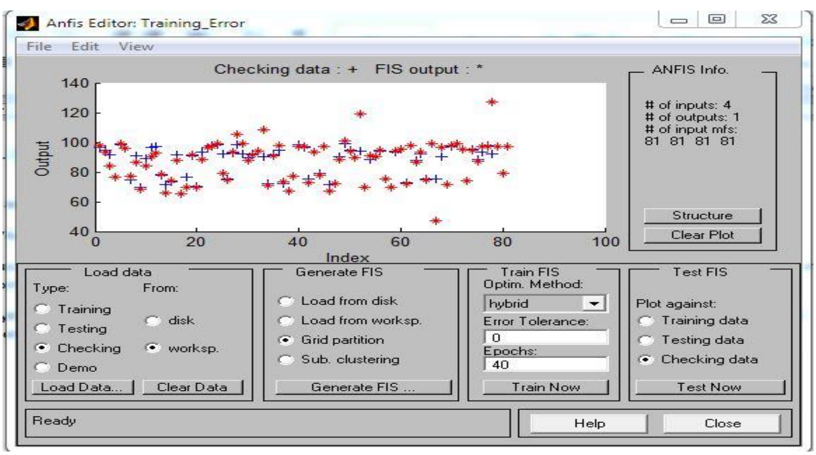

Figure 8: ANFIS Editor of the Testing the Fuzzy Inference System with the Checked Data Set

Figure 9 shows the scatter plot of the predicted and experimental of removal efficiency after undergone 1000 epochs of hybrid learning using the ANFIS function and 40 epochs of hybrid checking. The figure shows a great agreement between predicted and experimental of removal efficiency values which meant that the 4 independent variables data was well function to predict the removal efficiency in the *vorteaxanda* system. The coefficient of determination R2 for the both training and checking data sets is around 0.9675 which indicated an accurate prediction was achieved by utilizing the influence factors of non-dimensional variables in *vorteaxanda* system.

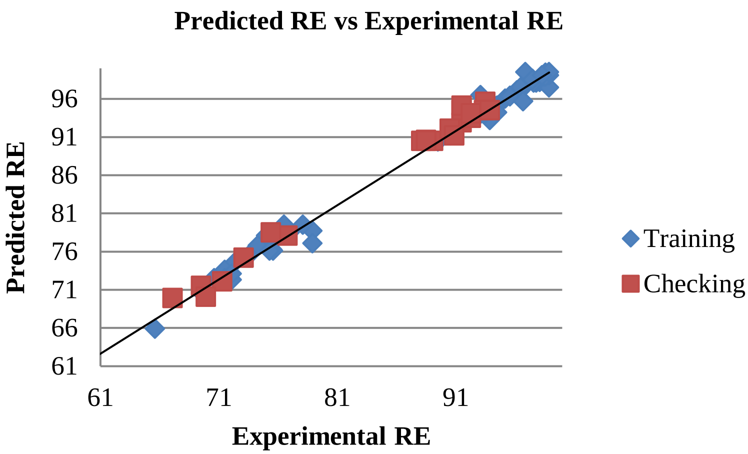

Figure 9: Scatter Plot of the Prediction Removal Efficiency of Training and Checking data sets by using ANFIS

Conclusion

This paper presents an Artificial Neural Network and ANFIS techniques for the prediction of removal efficiency of *vortexanda* technique based on 4 non-dimensional parameters. The predicted results for both techniques are found to be close to the experimental values. Both models of Neural Network and ANFIS shows the satisfactory perfomance in validating the parameters for predicting the removal efficiency in *vortexanda* system by achieving only minimal error in validating process. These models are flexible nonlinear models which allows for the analysis, validation and interpretation of the results. It will be more easier and interactive approach for the decision maker that want to design the *vortexanda* system compared to the conventional methods of numerical validation such as nonlinear regression. Therefore, in future studies, the real site implementation of the small urban hydropower system from the stormwater's source could be more easier to be conduct through the predictive model of the *vortexanda* system.

Acknowledgement

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