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Application Methods artificial neural network(Ann) Back propagation structure for Predicting the value Of bed channel roughnes scoefficient

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Abstract:- Forecasting Manning roughness coefficient act out an important role in hydraulic engineering because it is use full for the design of hydraulic structures, modeling of river hydraulic sand sediment transport. This paper used of back propagation neural network method for predicting the Manning roughness coefficient. Data used in the form of experimental results form the bed configuration in a laboratory and secondary data, *a total of* 352data.The results using of backpropagationneural network method is optimized and accurate enough to7-10-1network architecture, namely one input layer with 10 neurons, one hidden layer with 10 neurons and one output layer with one neuron. Parameters used logsig activation function and function trainer of training, with a tolerance of error of 0.01*;* 0.05learning rate and the maximum epochs much as1000.The model that is $Q_{prediksi}$ = 0,95 Q simulasi +0,0012. *With* the correlation coefficientof0.980.*T*he resulting MSE valueis0.00000177 *and value for* NSE of0.597.The training data as well as the value suit ability the curve of 1:1.

Keywords:- Prediction; Roughness Coefficient;Neural Network Back propagation**.**

I. INTRODUCTION

In engineering hydraulics, Manning roughness coefficient is an important parameter in the design of hydraulic structures, modeling of river hydraulics and sediment transport (Bilgin & Altun, 2008; Greco et al., 2014; Mirauda & Greco, 2014). Roughness coefficient of resistance applied to open channel flow, which is used to calculate the velocity and flow rate (Bilgil, 2003; Bahramifar et al., 2013).

The calculating the roughness coefficient of instead be an easy task because of the complexity of the problem of open channel. As we know that the Manning roughness coefficient roughness coefficient representing the resistance of flow by applying the flow in the channel. There for eroughness coefficientis also a fundamental parameter of fluid flow calculations that is still highly demanded in its application (Bilgil &Altun, 2008).

Resistance of flow in alluvial channels with relatively high accuracy is also a concern for the hydraulic engineer. However, the problem is still unsolved despite numerous investigations over the last few decades (Yang &Tan, 2008). Among the problems are due to changes in channel form the bed configuration, the aspect ratio of the depth and width, the influence of the side wall, and the wall shear stress sisnotuni formally distributed in the three-dimensional shapes due to the presence of the free surface and the secondary current (Azamathulla et al., 2013; Samandar, 2011; Bilgin & Altun, 2008; Yang &Tan, 2008; Guo & Julien, 2005).

Along with the growing world of digital (computer), some of models have been developed to simulate this process. Neither the empirical model (black box model), conceptual model (physical process based), the model continuously (continuous events), lumped models, distribution models and models of single (Setiawan & Rudiyan to, 2004). These models are formed by a set of mathematical equations that reflect the behavior of the hydro logical parameters, so the parameters contained in the equation has a physical meaning (Adidarma, et al., 2004).

The last few years, art official neural networks (ANN) as a form of black box model (black box model), has been successfully used optimally to model non-linear of input-output relationship in a complex hydro logic processes and the potential to become one of the decision-making tool promising in hydrology (Dawson and Wilby, 2001). ANN is a form of artificial intelligence that has the ability to learn from the data and does not require a long time in the making models (Setiawan & Rudiyan to, 2004).

These models uses mathematical equations of linear and non-linear that do not take into account at all physical processes, but the most important in this model is the output produced by the actual approach (Adidarma, et al., 2004). In addition, the ANN was also able to identify the structure and also effective in connecting the input and output of simulation and forecasting models (Setiawan and Rudiyan to, 2004).

The ability of Artificial Neural Networks (ANN) in solving complex problems has been demons trated in various studies, recently, the development of the body in the application of artificial neural net working river engineering like Karunanithi et al. (1994), Fauzy & Trilita (2005), Cigizoglu (2005), Antenatal. (2006), Bilgil& Altun (2008), Samandar (2011), Mary (2011), The control of the water level (Alifia et al., 2012), Azamathulla et al. (2013), and Bahramifar et al. (2013), Model is as irainfallrun off (Doddy & Ardana, 2013), rainfall prediction in Jakarta(Nugroho et al, 2013).

Therefore, this paper will apply the method of ANN. The purpose of this paper is to use the approach of artificial neural network (ANN) for calculating the Manning roughness coefficient using data from laboratory experiments. In the study raised the flow parameter measurements in the laboratory is used for artificial neural network as input parameters. The value of calculating the roughness coefficient is calculated later Maning used to estimate the flow in open channel flow.

II. MATERIALS AND METHODS

2.1 Coefficient of Roughness in Open Channels.

Ina lot of literature it is known that velocity offlowin open channels formulation created by the Robert Manning (1891), as Equation (1)

$$\mathrm{V} = \frac{1}{\mathrm{n}}\mathrm{R}^{2/3}\sqrt{\mathrm{S}} \text{ ....(1)}$$

Where Vis the average velocity of the cross section, Nis Manning resistance co efficient, Ris the hydraulic radius and Sis the hydraulic slope. This formula is derived from semi-empirical that has been used hydraulic experts during the 18th century.

Dischargeormagnitude of the flow of the river/canal is flowing through the volume flow through ariver cross section/channel per unit time (Chow, 1959; Soewar no, 1995). Usually expressed in units of cubic meters per second (m3 / s) orlitersper second (l /sec). Flowis the movement of water in the river channel/channels. Basically discharge measure mentis a measurement of wet cross-sectional area, the flow rate and water level. The general formula is used as Equation (2).

$$\mathrm{Q} = \mathrm{V.A} \text{ ....(2)}$$

Today, Manning equation is more often used as a formulation in hydraulic engineering and expressed respective lyin Equation (3).

$$\mathrm{n} = \frac{1}{\mathrm{V}}\mathrm{R}^{2/3}\sqrt{\mathrm{S}} \text{ ....(3)}$$

Formulation development at Manning formula also applied to the linear separation method. This linear separation method has been widely recognized by experts as a hydraulic principles and approaches on the sum of components resistance. Resistance to the flow in the channel digolongan into 2 (two) types, the first friction surface (skin friction) that is generated by the boundary surface resistance and depending on the depth of the flow relative to the size of the elements on the surface roughness limit, both opposition form (form resistance) or form drag namely roughness related to the geometry of the surface roughness of granules and barrier forms associated with the basic configuration that govern vortex and secondary circulation. This principle has been developed in a natural resistance component with rigid base and a natural resistance component with a flexible base (Meyer-Peter & Muller, 1948; Einstein and Barbarossa, 1952; England, 1966; Smith & McLean, 1977; Griffiths, 1989; Yang & Tan 2008).

Manning equation formulation in linear separation method as Equation (4).

$$n = n_w + n' + n'' \text{ ....(4)}$$

Where$n_w$isroughness coefficientdue tothe sidewall, with$n_w = \frac{R^{1/6}}{\sqrt{g}}\left(\frac{u_{*w}}{U}\right)andu_{*w} = \sqrt{\tau_w/\rho}$. $n'$is the resistance due to friction surfaces(skin friction) or the roughness of granules, the formulan$\frac{n'}{R^{1/6}}\sqrt{g} = \frac{\sqrt{\tau_0{}'/\rho}}{U} = \frac{u_*{}'}{U}andn''$ is the resistance that is due to form drag(form drag) orroughnessshape, with the formulation ofn with $\frac{n''}{R^{1/6}}\sqrt{g} = \frac{u_*{}''}{U}$. Equation (3) on a restated as a function of dimension lesssymbolonan open channel roughness coefficient($\frac{n''}{n'}$)as in Equation(5).

$$\frac{n''}{n'} = f\left(R_e, K_r, \eta, S, F_r, \sigma, \frac{b}{h}\right) \text{ ....(5)}$$

Where $R_e$is the Reynolds number, $K_r$is relative roughness usually expressed ask_s/R where$k_s$isequivalentwallsurface roughness, ηis across-sectional geometries, S is channels lope, $F_r$is the Froude number and σ is the gradation grain. In the Equation (5) are further tested from the description of the mechanism and limit the flow channel by Yen (2002&1992). Symbol function in Equation (5) is not linear and

complex. For the sake of simplification made in the conventional approach. As noted, the problem of flow in open channels may be completed with an error limit of ± 10% (Bilgil, 1998).
These indications show the new and accurate methods are still needed. The existence of the methods that have high accuracy will reduce error rates. At the ends of the artificial neural network approach to the efficiency of the pre-assessment approach to predict the roughness coefficient through the use of Artificial Neural Network (ANN).

2.2 Artificial Neural Network (ANN).

Neural Network (NN) is a learning method that is inspired by the biological network learning system that occurs on the network of nerve cells (neurons) are connected with one another. NN structure used is Back propagation (BP) which is a systematic method for training multiplayer. This method has a powerful mathematical basis, objective and this algorithm to get the form of equation and the coefficient in the formula by minimizing the number of error squared error by the model developed in the training set (Bilgil & Altun, 2008).

2.3 Algorithm a *Back propagation* (BP)

Back propagation algorithm on neural network (BPPN) is a systematic approach to training (calibration) on multi layer percept on neural networks or multilayer (multilayer perceptrons). Layer (layer) The first consists of a set of inputs and the final layer is the output (target). Among the input layer and output layer there is a layer in the middle, which is also known as hidden layers (hidden layers), could be one, two, three and so on. In practice, the number of hidden layers is at most three layers. Input layer mere present asking input variables, hidden layer represents non linearity(non-linearity) of the network system while the output layer contains variable output, the last layer output from the hidden layer directly used as the output of the neural network.
BP training process requires three stages of data input for training feed forward, back propagation to the value of the error (the error) as well as the adjustment of the weight values of each node of each layer on ANN. Beginning with feed forward value input, each input to the unit-i(x_i) receiving an input signal which will then be transmitted to the hidden layerz_1, ..., z_p. Furthermore, the j-the hidden unit will calculate the value of the signal (zj), which will be tram smitted to the output layer, using the activation function (f)
In simple terms of BPNN described as follows, an input pattern in corporate into the network system to produce output, which is the compared with the actual output pattern. If there is no difference between the output of the system and the actual network, then the learning is not necessary. In other words, a weight that indicates the contribution of input node to hidden nodes, as well as from hidden node to output, in which case the difference (error) between the output of the system with the actual network, then the weights repaired one backwards, from the output passes the rough hidden node andr e-input node. Mathematically can be described in the back propagation algorithm in Equation(6).

$$z_{in_j} = v_{0j} + \sum_{i=1}^{n} x_i v_{ij} \qquad (6)$$

where z_{in_j} is aktifivasifunctionto calculate thevalue ofthe outputsignalin thehidden nodej; $x_i$isthe valueinthe inputnode ; v_{ij} = is theweight valuethat connects theinputnode iwith ahiddennotej. ; $v_{0j}$is avaluebiaswhichconnects thebiasnode1with thehidden nodej.nisthe number of inputnodesin the inputlayer.
And the output signal from the hidden node j given sigmoid activation function as Equation(7)

$$z_i = f(z_{in_j}) = \frac{1}{1+e^{-z_{in_j}}} \qquad (7)$$

where$z_i$isthe signaloutputofhidden nodej. While each unit of output k(Y_{in}),as Equation(8)

$$Y\_in = w_{0j} + \sum_{j=1}^{p} z_j w_{jk} \qquad (8)$$

And the activation function to calculate the value of the output signal, as Equation(9)

$$Y = f(Y\_in) = \frac{1}{1+e^{-Y\_in}} \qquad (9)$$

During the training process progresses, each unit of output compares the target value. for a given input pattern for calculating the value of the parameters that would improve(update) the weight of the value of each unit in each layer(Hertz et al., 1991). Nodes in the output layer have a valuebetween0-1.

2.4 Artificial Neural Network (ANN) in Determining a Bed Roughness Coefficient.

In this paper, the calculation of roughness coefficient in open channels is performed using Multilayered Perception (MLP) artificial neural network. In the literature more likely to use the MLP learning algorithms to back propagation algorithm Rumelhart et al. (1986). In this algorithm optimization of weights during the learning process that can use the latest formulation weight given as the output function (level of movement) of the brain (neurons).

2.5 Performance Model.

Performance models used to measure the accuracy of the model. In this paper, the performance of the model is used to determine the degree of correspondence between the actual data with the results of forecasting used measure of correlation coefficient, with the formula in Equation (10).

$$R = \frac{\sum xy}{\sqrt{\sum x \sum y}} \quad \text{..................................(10)}$$

Where= $X - \bar{X}$,X isthe actualdischarge,$\bar{X}$is the averagevalue ofX, $y = Y - \bar{Y}$, Y is a discharge or as imulation result of forecasting, $\bar{Y}$, is the average value of the Y value of correlation can be seen in Table.1

Table1. Correlation Coefficient Values

Correlation Coefficient(R^2)	Iimplication
1	perfect positive
0,6 <R^2 □ 1	Good positive direct
0 <R^2 □ 0,6	Direct weakly positive
0	There is norrelationship
-0,6 □R^2< 0	Weak negative direct
-1 □R^2< -0,6	Negativestraightgood
-1	negative perfect

Source: Soewarno, 1995.

The media n square error (mean square error, MSE). MSE is a measure of the accuracy of the model by squaring the error for each point of data in a data set and the no btain the average or median value of the sum of the squares. The formulation of MSE as Equation(11)

$$MSE = \frac{\sum_{i=1}^{N}(y_i - \hat{y_i})^2}{N} = \frac{\sum_{i=1}^{N} e_i^2}{N} \quad \text{..............................(11)}$$

Where $y_i$isthe actual valueof data, ($\hat{y_i}$) is the value o f the results of forecasting, Nis the number of data observations, and$e_i$is per-point error data. Then used a common procedure error calculating per-point data, which for the time series followed formulation is: data = pattern + errors for easy, error(error) is written with an e, the data with the data pattern of X and X. In addition, the sub script i (i =1,2,3, ..., n) are included to show the data point to-i, so writtene$e_i = X_i - \bar{X}$. If youjustwant to know the magnitude of the error regardless of the direction it is called absolute error or$e_i = |X_i - \bar{X}|$

Another criterion is the accuracy of the model or Nash Sutcliffe Model Efficiency Coefficient (NSE). Nash gives a good indication for matching of 1:1between simulations and observations. Formulation of Nash as Equation(12).

$$NSE = 1 - \left[\frac{(Q_{obs} - Q_{sim})^2}{(Q_{obs} - \bar{Q}_{obs})^2}\right] \quad \text{....................................(12)}$$

WhereQ_{obs} areobservational data, $\bar{Q}_{obs}$ is the averageobservational dataandQ_{sim} is the value ofthe simulation results. NSE value criteria can be seen in Table(2).

Table 2 Criteria Value Efficiency Model Nash Sutcliffe Coefficient (NSE).

***Nash Sutcliffe Model Efficiency Coefficient* (NSE) Value**	**Interpretasi**
NSE > 0,75	Good
0,36 <NSE ≤ 0,75	Ssatisfy
NSE ≤ 0,36	Not satisfactory

Source : Motovilov et al., 1999

2.6 Data from Experiment

This paper aims to analyze the performance of artificial neural network back propagation method in predicting the bottom friction coefficient. Writer wanted to know how the performance of artificial neural networks back propagation method to recognize patterns of data parameters that's lope, depth, grain and flow. The data used for learning and then to evaluate the use of ANN obtained experiment. The data will be used by the laboratory results of several researchers and the results of its own research, the data include:

1. DataexperimentalWangandWhite(1993).
2. Data fromexperimentsGuyetal. (1966).
3. Research data fromSisingih(2000).
4. The result ofthe experimentfrom Wibowo(2015)

Table3. Results of Research Data

Parameter	Guyetal. (1966).	Wibowo(2015)	Sisingih(2000)	Wang White(1993).
Slope(S)	0,00015-0,0101	0,006-0,0100	0,007-0,013	0,00001-0,00305
Discharge (Q) (m^3/s)	0,028 – 0,643	0,003-0,008	0,003-0,006	0,024-0,410
Ratio (b/h)	2,247-42,105	3,587-9,524	0,667-1,000	3,288-19,335
Velocity(V) m/s	0,212-1,898	0,132-0,411	0,214-0,429	0,105-1,318
Reynolds Numbers (Re)	2,157-98,753	14,446-50,29	0,003-29,211	4,35-11,42
Froude Numbers (Fr)	0,089-1,714	0,152-0,324	0,194-0,353	0,073-1,049
Fricative (τ)	0,0015-1,734	0,291-0,842	0,727-1,982	0,021-4,685
Roughness coefficient (n)	0,010-0,040	0,011-0,026	0,012-0,042	0,015-0,028
Sample	269	40	16	64

2.7Mapping Neural Network in the Roughness Coefficient.

In a study of open channel flow roughness coefficient and the relationship between flow parameters will be given to the function as Equation (5).

$$\frac{n''}{n'} = f\ (R_e, \frac{ds}{h}, S, F_r, \sigma, \frac{b}{h}, \tau_*)$$

Where R_e is Reynolds number = $(u_* d_s / \nu)$, ν is the kinematic viscosity, $d_s$is granular particles (mm), h is the average depth, S is the slope of the elongated base channel, F_r is Frounde number $\left(V_r/\sqrt{gh}\right)$, V_r = average speed of the flow (Q/A), Q is the flow rate, σ is the gradation grain, with$\sigma = \frac{1}{2}\left(\frac{d_{84}}{d_{50}} + \frac{d_{50}}{d_{16}}\right)$ b is the channel width (m), τ is the shear stress = ρghS, S slope hydraulic, g is the acceleration of gravity and R is radius hydraulic. With the data in Table (3.1) as a measurement parameter input (input) and output (output) is written in pairs on a set of data created. This data set is used to calculate the roughness coefficients using Manning formula. For learning in artificial neural network, the parameters on the right side of the symbol Equation (2.5) is given as input and roughness coefficient as a target parameter. In the learning process half of the data set used for artificial neural network learning, the time remaining is used to evaluate the implementation of the artificial neural network learning.

Input data consists of relative roughness(X_1), Reynolds number(X_2), Slope(X_3),the Froude number(X_4), gradation grain (X_5), the depth-width ratio(X_6)andshear stress(X_7).

2.8Network Architecture in Neural Network

In the analysis of roughness coefficient prediction of basic channels, network architecture used is many layered network architecture (multilayer) as in Figure(1).

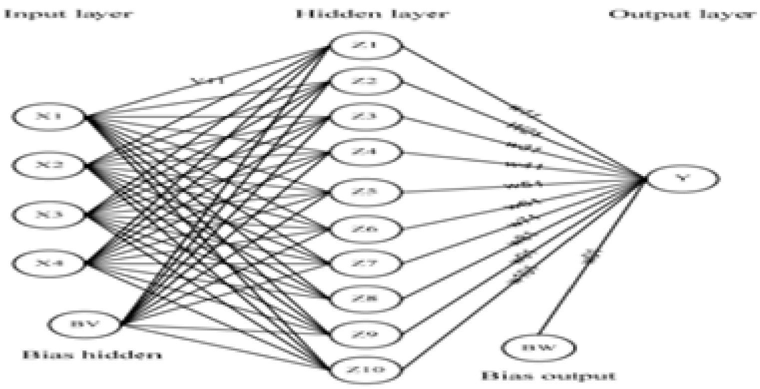

Figure1.Network Architecture with Back propagation

Specification: X is input nodes in the input layer; Z is hidden node (hidden layer); Y is the output node in the output layer; $V_{1,1},\ldots,V_n$ isthe weightofthe inputlayerto thehidden; $W_{1,1},\ldots,W_n$ is the weight of the hidden layer to the output ; $b_v$isbiasfromthe inputlayerto thehiddenlayer; $b_w$isbiasof thehiddenlayertothe output layer.

2.9Training Process

The training process was conducted on the data as input parameters of network nodes ;
Toleransi error = 0,01; Learning Rate (α) = 0,5; number of iterations = 1000 times

III. RESULTS AND DISCUSSIONS.

3.1 Experiment Results

Determination parameters of the neural network is done by searching for the best value of the hidden neurons are used. Furthermore, to facilitate the calculation of the iteration process and running experiment data, then use the software MATLAB. Here are the results of the experiments have been conducted to determine the number of neurons in the hidden layer Table(4).

Table 4. Comparison of Results of Experiments on Bed Relative Value Roughness Coefficient (n '/ n')

Running	Arsitektur Jaringan	Function Activation	MSE	Correlation Coefficient
1	7-10-1	logsig	0,0102	0,908
2	7-9-1	logsig	0,0188	0,928
3	7-8-1	logsig	0,0292	0,920
4	7-7-1	logsig	0,0295	0,911
5	7-6-1	logsig	0,0566	0,909
6	7-5-1	logsig	0,0202	0,915
7	7-4-1	logsig	0,0360	0,916

Based on several the experiments that have been done, the architecture of artificial neural networks for the prediction of roughness coefficientter optimal basic channel sare7-10-1architecture. This architecture consists of one input layer with10neurons, onehiddenlayerwith10neuronsandoneoutput layer with one neuron. The resulting MSE value is 0.0102andthe correlation coefficient 0.908. Pictures of the jar in gent architecture can be seen in the Figure (2) and (3).

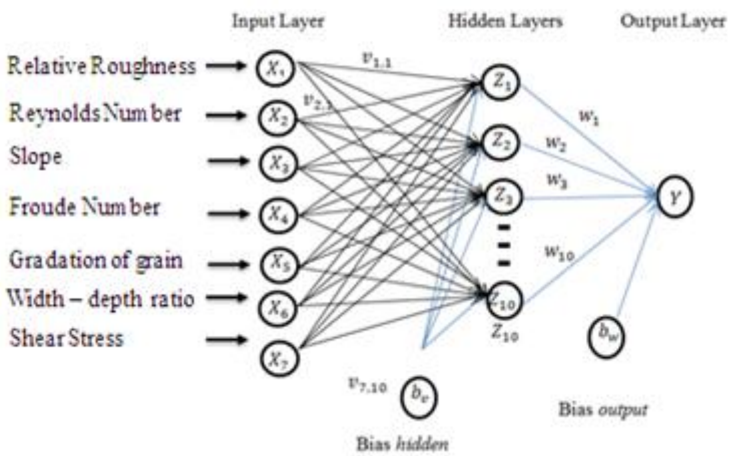

Figure 2.Architecture Data Network with Back propagation

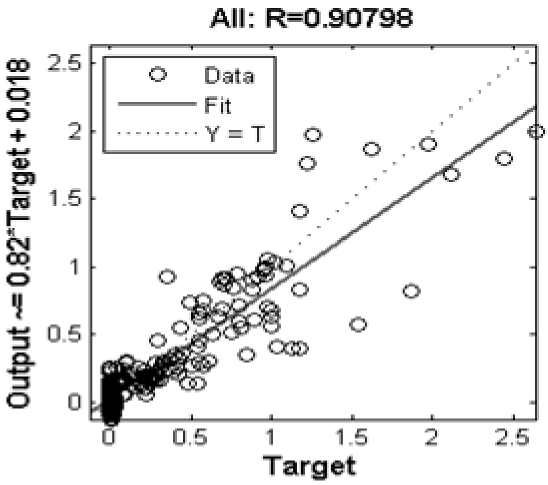

Figure 3. Neural Network Training with Matlab

3.2 Development of Model

The next process is to develop a model that is based on the data Equation (2.5). by using multiple linear regression method. Results of the model development using basic rough ness relative (n "/n ') in de pthandr elativegraincan be seen in Equation (13) and(14).

$$\frac{n''}{n'} = 0{,}378 + 64{,}621R_e - 0{,}537\frac{ds}{h} - 0{,}00242\,S - 0{,}005F_r - 0{,}065\sigma + 0{,}008\frac{b}{h} + 0{,}152\,\tau_* \quad ..(13)$$

where the correlation coefficient(R^2) of 0,602.MeanSquareError(MSE) of 4,565andValueEfficiencyModelNashSutcliffeCoefficient (NSE) of 0,597.

$$\frac{n''}{n'} = 0{,}167 + 64{,}876R_e - 0{,}549\frac{ds}{h} - 0{,}00013\,S - 0{,}0037F_r - 0{,}0284\sigma + 0{,}0034\frac{b}{h} + 0{,}136\,\tau_* \quad ...(14.)$$

The correlation coefficient(R^2) of 0.634, Mean Square Error(MSE) of 4.805andValueEfficiencyModelNashSutcliffeCoefficient (NSE) of 0.625.

The formulation of the the oreticallinearseparation(n "/n ') can be seena sEquation(15)

$$\frac{n''}{n'} = 0{,}1167\,n + 0{,}0182 \quad ....(15)$$

By giving the value of the correlation efficient(R^2) 0,020 Mean Square Error(MSE) of 0.000254andValueEfficiencyModelNashSutcliffeCoefficient (NSE) of 0.02.

The formulation on the basis of Manning rough ness(n) can be seen as Equation(16)

$$n = 0{,}0287 + 0{,}104R_e - 0{,}013\frac{ds}{h} - 1{,}0187\,S + 0{,}002F_r - 0{,}0017\sigma + 0{,}0001\frac{b}{h} - 0{,}0015\,\tau_* \quad ...(16)$$

Generate the correlation coefficient (R^2) of 0.411, Mean Square Error (MSE) of 0.000757andValue Efficiency Model Nash Sutcliffe Coefficient (NSE) of 0,955.By using the default batch algorithm a back propagation, iteratingthecalibrationstage (training) until the model is designed to stop, the model usedepoch1000 times with a time of 2 (two) seconds for each model. Calibration is a process oradjustingthe values of the parameters of model to achiev eabestmatchbetweenobservationsand variables predictive variables. Match betweenthe actual data(observations) withforecasting resultsbased onthe results ofthe calibrationis indicated bythe correlation coefficient. The values ofthe weightsof thenetworkANNachievedfromthe calibrationresultswill be usedin theverification phase(testing). the accuracy offorecasting results, performancecriteriarepresentedbythe model

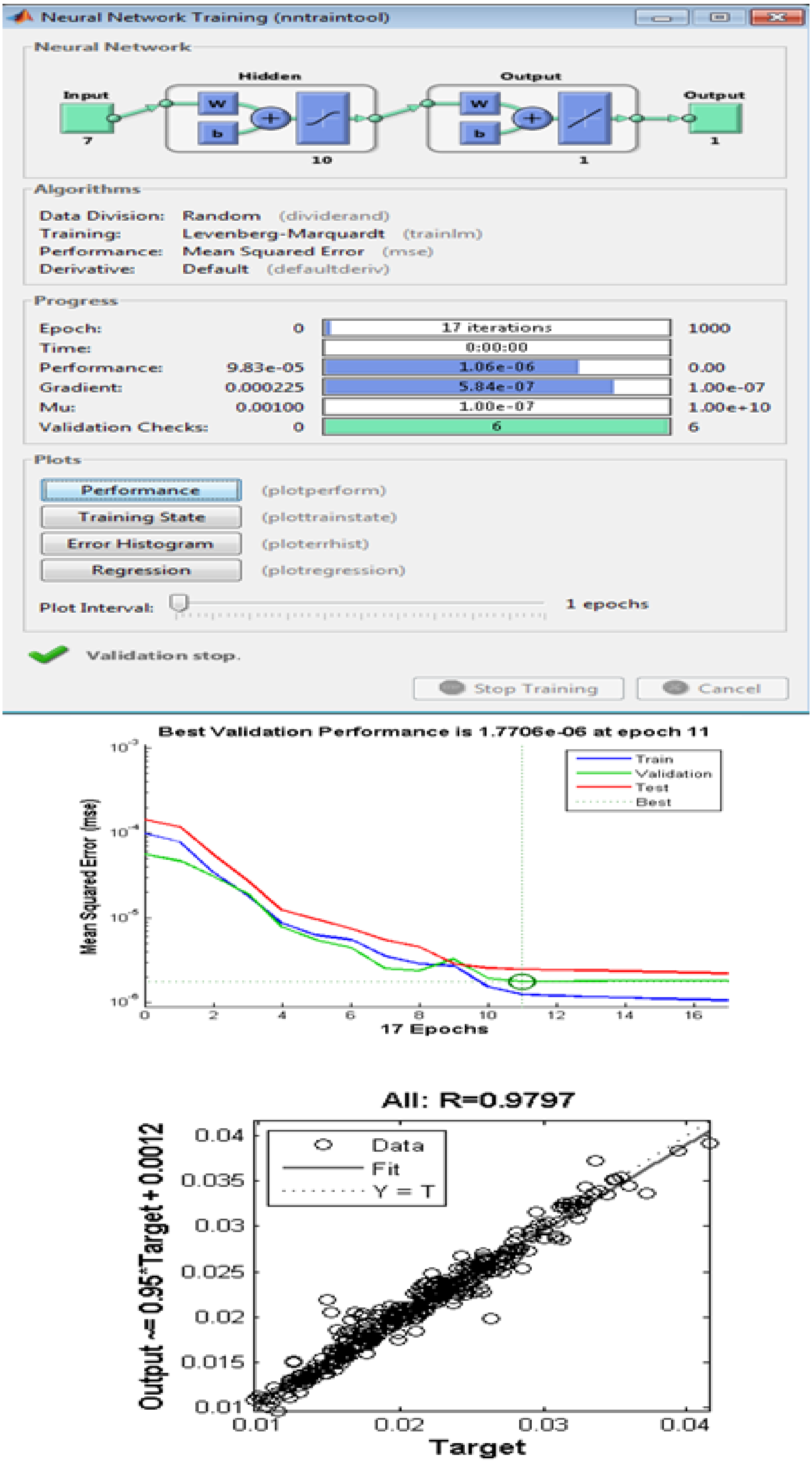

Figure 4.Simulation Results between data Flume and Simulation Discharge

Simulation models according Refsgaard (2000) is an effort to valid at the use of the model to gain knowledge or in sigh to far reality and too btain forecasts that can be used by waterre source managers. Simulation stage is the final process after the process of calibration and verification carried out. In this stage, the overall roughness coefficient data is used as input data to calculate the flow rate. By using the method of linear separation then compared with the results of the discharge flume as in Figure(5) andproducea modelin Equation(17).

$$Q_{flume} = 0{,}436\ Q^{0{,}8834}{}_{Separation\ \ linear} \quad \text{.............(17)}$$

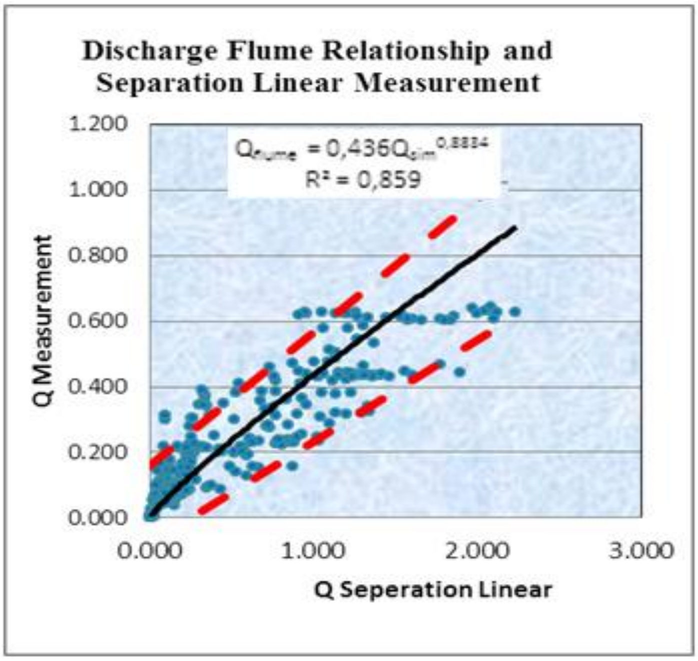

Figure 5 The Relationship between the Discharge data and Flume Simulation

The results of simulations of discharge and discharge flume, asin Table (5).

Table 5 Correlation between Discharge Simulation Results and debilitated Flume.

Model Development	Correlation Coefficient (R^2)	MSE	NSE
ANN method	0,980	1,7 E-06	0,844
Linear separation method	0,859	4,324	0,774
Analysis of the relative dimensions of grain	0,378	4,817	0,287
Analysis of the relative depth dimension	0,377	4,817	0,388

Source of data: the results of calculations.

3.3 Discussion.

•The Pre Data Analysis.

Data roughness coefficient of line arseparation results (n) cannot be used directly but through the calculation of flow rate. In connection with the separation of each line a roughness coefficient values should be described in advance to obtain the value n 'and n"as well as due to the influence of the side wall shear. The influence of the shape of the base konfiguasri very important, so the need for separation of the regime and form the basis of the conditions that occurred.

•Input Data Model Analysis on Bed Roughness Coefficient Value

Input data consists of the relative roughness(X_1), Reynolds number(X_2), Slope(X_3), the Froude number(X_4), gradation of grain (X_5), the depth-width ratio(X_6) and shear stress(X_7) on the modeling coefficient s roughness obtained the following results

$$\frac{n''}{n'} = 0{,}378 + 64{,}621R_e - 0{,}537\frac{ds}{h} - 0{,}00242\ S - 0{,}005F_r - 0{,}065\sigma + 0{,}008\frac{b}{h} + 0{,}152\ \tau_* \quad \text{...........(18)}$$

With a correlation coefficient (R^2) of 0.602(0.6 <R^2 <1) which shows the relationship between input variables (independent variables) have a positive direct relationship Good. This means that data is correlated. Mean Square Error (MSE) amounted to4.565% (<5%). Error below 5% indicates that the error between the actual model and simulation is below to lerance. ValueEfficiencyModelNashSutcliffeCoefficient (NSE) of 0,597(0,36 <NSE ≤0,75) which shows that the interpretation between actual and simulated models in satisfactory condition, or can be correlated with Good. Similarly, also by using the relative depth. Thus, the data input can be used on the production model of the channel bottom friction coefficient.

•Separation of Linear Model Analysis on the Bed Roughness Coefficient Value.

The model obtained in the the oreticallinearseparation method(n "/n ') can be seenas Equation(19).

$$\frac{n''}{n'} = 0{,}1167\, n + 0{,}0182 \quad ....(19)$$

By giving the value of the correlation coefficient(R^2) 0,020(0 <R^2 <0.6) which shows the relationship between input variables (independent variables) have a direct relationship weakly positive. This means that data is correlated poorly. Mean Square Error (MSE) of 0,000254(<5%). Error below 5% indicates that the error between the actual model and simulation is below to lerance and very Good. ValueEfficiencyModelNashSutcliffeCoefficient (NSE) of 0,02(NSE <0.36) which shows that the interpretation of the actual model and simulation in less than satisfactory condition or less correlated is good.

• Analysis on the Model Manning the Bed Roughness Coefficient Value

The model formulation Manning invitation dimensional analysis*(n)* can be seen as Equation(20)

$$n = 0{,}0287 + 0{,}104R_e - 0{,}013\frac{ds}{h} - 1{,}0187\, S + 0{,}002F_r - 0{,}0017\sigma + 0{,}0001\frac{b}{h} - 0{,}0015\,\tau_* \quad ....(20)$$

By giving the value of the correlation coefficient (R^2) 0.411(0 <R^2<0.6) which shows the relationship between input variables (independent variables) have a direct relationship weakly positive. This means that data is correlated poorly. Mean Square Error (MSE) of 0,000757(<5%). Error below 5% indicates that the error between the actual model and simulation is below to lerance and very good. Value Efficiency Model Nash Sutcliffe Coefficient (NSE) of 0,955(NSE>0.75) which shows that the interpretation of the actual model and the simulation under condition scorrelate well.

•Analysis on Manning on Flow Model.

Based on the Table(4.2) obtained results for the model artificial neural network(ANN) have satisfactory results, whether of the correlation between the variablesof0,980(0,6 <R^2<1) which shows the relationship between input variables (independent variables) have a relationship strong positive immediately. This means that the data correlates very well. Mean Square Error (MSE) of 0,00000177(<5%).

Error below 5% indicates that the error between the actual model and simulation is below to lerance and shown very good relationship. For the best fore casting method is the method that produces the smallest error. Value Efficiency Model Nash Sutcliffe Coefficient (NSE) of 0.597(0.36 <NSE ≤0.75) which shows that the interpretation between actual and simulated models in satisfactory condition, or can be correlated with either. Similarly, also by using the relative depth.

Similarly, the flow separation method that shows the results of the correlation between variables in the model$Q_{flume} = 0{,}436\, Q_{simulasi}^{0{,}8834}$ with R^2=0,859 (0,6 <R^2< 1) which shows the relationship between input variables (independent variables) has a direct relationship strong positive. This means that the data correlates very well. Mean Square Error (MSE) of 0,00000177(<5%). Error below 5% indicates that the error between the actual model and simulation is below to lerance and devoted relationship very well. For the best fore casting method is the method that produces the smallest error. Value efficiency model Nash Sutcliffe coefficient (NSE) of0,774(NSE >0,75) which shows that the interpretation of the actual model and the simulation under condition scorrelate well.

Whereas the method of analysis dimensions that are less good result.

IV. CONCLUSION

Based on the analysis and discussion it can be concluded as follows:

1. Utilization of ANN to the practical application of basic channels for ecastin groughness coefficient generally reliable.
2. The best results from the model ANN depends on the quality of the data, including in this case the length of the data so that the model ANN is able to perform pattern recognition in put and output relationship.
3. ANN Back propagationbestregression modelbasedinputwitharchitecture7- 10 -of 1 (7 units of inputto theinputlayer-10hidden unitsin the hidden layer-1 unitof outputin the output layer) is moreaccuratelyused inforecastingkoefsienbasicroughnessandprovedmore capablefollowthe characteristicsofthe actual

datawiththe value ofthe correlationbetween variablesat0.980 with modelobtainedthe$Q_{prediksi} = 0{,}95\ Q_{simulasi} + 0{,}0012$,NSEvaluesof 0.844andMSE of0.00000177.

4. Modellinearseparationcan beused to estimate theflow rateto the conditionsforthe basic shapeof channels.

5. Linearseparation modelcanbe usedto estimatethe flow rate bythe basicconditions oftheirshapeto the shape ofthe channel$Q_{flume} = 0{,}436\ Q_{simulasi}^{0{,}8834}$ with (R^2=0.859).

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