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

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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 352 data. The results using of backpropagation neural network method is optimized and accurate enough to10-1 network architecture, namely one input layer with 10 neurons, one hidden layer with 10 neurons and one output layer with one neuron. Parameters used logis activation function and function trainer of training, with a tolerance of error of 0.01; 0.05 learning rate and the maximum epochs much as 1000. The model that is Qprediksi = 0.95 Q simulasi +0.0012. With the correlation coefficient of 0.980. The resulting MSE value is 0.0000177 and value for NSE of 0.597. 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 hydraulic 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 (Bilgin, 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 roughness coefficient is also a fundamental parameter of fluid flow calculations that is still highly demanded in its application (Bilgin & 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 snotuni formally distributed in the three-dimensional shapes due to the presence of the free surface and the secondary current (Azamatulla 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 demonstrated 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 rainfallrun 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.

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

\[ V = \frac{1}{n} R^{2/3} S \] ...........................(1)

Where \( V \) is the average velocity of the cross section, \( N \)is Manning resistance coefficient, \( R \) the hydraulic radius and \( S \) the hydraulic slope. This formula is derived from semi-empirical that has been used hydraulic experts during the 18th century.

Discharge magnitude 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 \((m^3/s)\) orlitersper second \((l/sec)\). Flowis the movement of water in the river channel/channels. Basically discharge measure ments is a measurement of wet cross-sectional area, the flow rate and water level. The general formula is used as Equation (2).

\[ Q = V A \] .................................(2)

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

\[ n = \frac{1}{V} R^{2/3} S \] ...........................(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).

\[ n = n_w + n_f + n'' \] ...........................(4)

Where \( n_w \) is roughness coefficient due to the sidewall, with

\[ n_w = \frac{2g}{b} \left( \frac{u^2}{\sqrt{b}} \right) \] ...........................(5)

Due to friction surfaces (skin friction) or the roughness of granules, the formulation

\[ n_f = \frac{2g}{b} \left( \frac{u^2}{\sqrt{b}} \right) \] ...........................(5)

And the resistance due to form drag (form drag) or roughness shape, with the formulation of with

\[ n'' = \frac{2g}{b} \] ...........................(5)

Equation (3) on a restated as a function of dimension less symbolon open channel roughness coefficient

\[ n_w = f \left( p, R, K, n, S, F, \sigma, g, b \right) \] ...........................(5)

Where \( R \) is the Reynolds number, \( K \) is relative roughness usually expressed as \( k_b \) or \( K_b \) and \( S \) is channels lope, \( F \) is the Froude number and \( \sigma \) is the gradation grain. In the Equation (5) is 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-th hidden unit will calculate the value of the signal (z_j), 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 and e-input node. Mathematically can be described in the back propagation algorithm in Equation(6).

\[ z_{inj} = v_{ij} + \sum_{i=1}^{n} x_i v_{ij} \] ........................(6)

where \( z_{inj} \) is aktivasifunction to calculate the value of the output signal in the hidden node; \( x_i \) is the unit input node; \( v_{ij} \) is the weight that connects the input node ith and jth hidden nodej. And the output signal from the hidden node \( j \) given sigmoid activation function as Equation(7)

\[ z_i = f(z_{inj}) = \frac{1}{1+e^{-z_{inj}}} \] ........................(7)

where \( z_i \) is the signal output of hidden nodej. While each unit of output k(Y_m), as Equation(8)

\[ Y_{-in} = w_0j + \sum_{j=1}^{p} z_j w_{jk} \] ........................(8)

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

\[ Y = f(Y_{-in}) = \frac{1}{1+e^{-Y_{-in}}} \] ........................(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 value between 0-1.

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 Perceptron (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).

\[ R = \frac{\sum xy}{\sqrt{\sum x^2 \sum y^2}} \] ..................................(10)

Where= \( X - \bar{X} \) is the actual discharge, \( \bar{X} \) is the average value of \( X \), \( y = Y - \bar{Y} \). \( Y \) is a discharge or as an imulation result of forecasting, \( \bar{Y} \). is the average value of the \( Y \) value of correlation can be seen in Table 1.

<table>
<thead>
<tr>
<th>Correlation Coefficient(( R^2 ))</th>
<th>Implication</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>perfect positive</td>
</tr>
<tr>
<td>0.6 &lt; ( R^2 ) ≤ 1</td>
<td>Good positive direct</td>
</tr>
<tr>
<td>0 &lt; ( R^2 ) ≤ 0.6</td>
<td>Direct weakly positive</td>
</tr>
<tr>
<td>0</td>
<td>There is no relationship</td>
</tr>
<tr>
<td>-0.6 &lt; ( R^2 ) &lt; 0</td>
<td>Weak negative direct</td>
</tr>
<tr>
<td>-1 &lt; ( R^2 ) &lt; -0.6</td>
<td>Negative straight good</td>
</tr>
<tr>
<td>-1</td>
<td>negative perfect</td>
</tr>
</tbody>
</table>


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 contain the average or median value of the sum of the squares. The formulation of MSE as Equation (11)

\[ MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y})^2 \] ..................................(11)

Where \( y_i \) is the actual value of data, \( \bar{y} \) is the value of the results of forecasting, \( N \) is the number of data observations, and \( e \) 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 + error for easy, error(error) is written with an equation, the data with the data pattern of \( X \) and \( X \). In addition, the subscript \( i \) (i = 1, 2, 3, ..., n) are included to show the data point-to-i, so written \( e_i = X_i - \bar{X} \). If you just want to know the magnitude of the error regardless of the direction it is called absolute error \( |e_i| = |X_i - \bar{X}| \).

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

\[ NSE = 1 - \frac{\sum_{i=1}^{N} (Q_{obs} - Q_{sim})^2}{\sum_{i=1}^{N} (Q_{obs} - \bar{Q}_{obs})^2} \] ..................................(12)

Where \( Q_{obs} \) are observational data, \( \bar{Q}_{obs} \) is the average observational data, \( Q_{sim} \) is the value of the simulation results. NSE value criteria can be seen in Table 2.

<table>
<thead>
<tr>
<th>Nash Sutcliffe Model Efficiency Coefficient (NSE) Value</th>
<th>Interpretasi</th>
</tr>
</thead>
<tbody>
<tr>
<td>NSE &gt; 0.75</td>
<td>Good</td>
</tr>
<tr>
<td>0.36 &lt; NSE ≤ 0.75</td>
<td>Satisfy</td>
</tr>
<tr>
<td>NSE ≤ 0.36</td>
<td>Not satisfactory</td>
</tr>
</tbody>
</table>

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:
2. Data from experiments Guyle and White (1966).
4. The result of the experiment from Wibowo (2015)
Table 3. Results of Research Data

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope (S)</td>
<td>0.0015-0.0101</td>
<td>0.006-0.0100</td>
<td>0.007-0.013</td>
<td>0.00001-0.00305</td>
</tr>
<tr>
<td>Discharge (Q) (m³/s)</td>
<td>0.028 – 0.643</td>
<td>0.003-0.008</td>
<td>0.003-0.006</td>
<td>0.024-0.410</td>
</tr>
<tr>
<td>Ratio (b/h)</td>
<td>2.247-42.105</td>
<td>3.587-9.524</td>
<td>0.667-1.000</td>
<td>3.288-19.335</td>
</tr>
<tr>
<td>Velocity (V) m/s</td>
<td>0.212-1.898</td>
<td>0.132-0.411</td>
<td>0.214-0.429</td>
<td>0.105-1.318</td>
</tr>
<tr>
<td>Reynolds Numbers (Re)</td>
<td>2.157-98.753</td>
<td>14.446-50.29</td>
<td>0.003-29.211</td>
<td>4.35-11.42</td>
</tr>
<tr>
<td>Froude Numbers (Fr)</td>
<td>0.089-1.714</td>
<td>0.152-0.324</td>
<td>0.194-0.353</td>
<td>0.073-1.049</td>
</tr>
<tr>
<td>Fricative (τ)</td>
<td>0.0015-1.734</td>
<td>0.291-0.842</td>
<td>0.727-1.982</td>
<td>0.021-4.685</td>
</tr>
<tr>
<td>Roughness coefficient (n)</td>
<td>0.010-0.040</td>
<td>0.011-0.026</td>
<td>0.012-0.042</td>
<td>0.015-0.028</td>
</tr>
<tr>
<td>Sample</td>
<td>269</td>
<td>40</td>
<td>16</td>
<td>64</td>
</tr>
</tbody>
</table>

2.7 Mapping 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).

\[
n' = \frac{1}{n} \log \left( \frac{R_e}{d_s} \right) + S + F_r \sigma b + \tau
\]

Where \( R_e \) is Reynolds number = \( \frac{u d_s}{v} \), \( v \) 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 Froude number \( \frac{V}{\sqrt{gh}} \), \( V \) = average speed of the flow \( \frac{Q}{A} \), \( Q \) is the flow rate, \( \sigma \) is the gradation grain, with \( \sigma = \frac{d_{50} + d_{16}}{2} \), \( b \) is the channel width (m), \( \tau \) is the shear stress = \( \rho gh S \), \( S \) 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 \( X_6 \) and shear stress \( X_7 \).

2.8 Network 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).
Specification: X is input nodes in the input layer; Z is hidden node (hidden layer); Y is the output node in the output layer; \( V_{1,1}, \ldots, V_{1,n} \) isthe weightofthe inputlayerto thehidden; \( W_{1,1}, \ldots, W_{n} \) is the weight of the hidden layer to the output ; \( b_v \) is biasfromthe inputlayerto thehiddenlayer; \( b_w \) is biasof thehiddenlayerto the output layer.

2.9 Training Process
The training process was conducted on the data as input parameters of network nodes; Toleransi error = 0.01; Learning Rate (\( \alpha \)) = 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>
<thead>
<tr>
<th>Running</th>
<th>Arsitektur</th>
<th>Function Activation</th>
<th>MSE</th>
<th>Correlation Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7-10-1</td>
<td>logsig</td>
<td>0.0102</td>
<td>0.908</td>
</tr>
<tr>
<td>2</td>
<td>7-9-1</td>
<td>logsig</td>
<td>0.0188</td>
<td>0.928</td>
</tr>
<tr>
<td>3</td>
<td>7-8-1</td>
<td>logsig</td>
<td>0.0292</td>
<td>0.920</td>
</tr>
<tr>
<td>4</td>
<td>7-7-1</td>
<td>logsig</td>
<td>0.0295</td>
<td>0.911</td>
</tr>
<tr>
<td>5</td>
<td>7-6-1</td>
<td>logsig</td>
<td>0.0566</td>
<td>0.909</td>
</tr>
<tr>
<td>6</td>
<td>7-5-1</td>
<td>logsig</td>
<td>0.0202</td>
<td>0.915</td>
</tr>
<tr>
<td>7</td>
<td>7-4-1</td>
<td>logsig</td>
<td>0.0360</td>
<td>0.916</td>
</tr>
</tbody>
</table>

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, one hidden layer with10neurons and one output layer with one neuron. The resulting MSE value is 0.0102 and the 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
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 roughness relative \( n''/n' \) in depth and relative grain can be seen in Equation (13) and (14).

\[
\frac{n''}{n'} = 0.378 + 64.621R_e - 0.537 \frac{d_s}{h} - 0.00242S - 0.005F_r - 0.065\sigma + 0.008 \frac{b}{h} + 0.152 \tau, \quad \ldots (13)
\]

where the correlation coefficient \( R^2 \) of 0.602. Mean Square Error (MSE) of 4.565 and Value Efficiency Model Nash Sutcliffe Coefficient (NSE) of 0.597.

\[
\frac{n''}{n'} = 0.167 + 64.876R_e - 0.549 \frac{d_s}{h} - 0.00013S - 0.0037F_r - 0.0284\sigma + 0.0034 \frac{b}{h} + 0.136 \tau, \quad \ldots (14)
\]

The correlation coefficient \( R^2 \) of 0.634, Mean Square Error (MSE) of 4.805 and Value Efficiency Model Nash Sutcliffe Coefficient (NSE) of 0.625.

The formulation of the theoretical linear separation \( n''/n' \) can be seen as Equation (15).

\[
\frac{n''}{n'} = 0.1167n + 0.0182 \ldots \ldots \ldots \ldots \ldots (15)
\]

By giving the value of the correlation efficient \( R^2 \) 0.020 Mean Square Error (MSE) of 0.000254 and Value Efficiency Model Nash Sutcliffe Coefficient (NSE) of 0.02.

The formulation on the basis of Manning roughness \( n \) can be seen as Equation (16).

\[
n = 0.0287 + 0.104R_e - 0.013 \frac{d_s}{h} - 1.0187S + 0.002F_r - 0.0017\sigma + 0.0001 \frac{b}{h} - 0.0015 \tau, \quad \ldots (16)
\]

Generate the correlation coefficient \( R^2 \) of 0.411, Mean Square Error (MSE) of 0.000757 and Value Efficiency Model Nash Sutcliffe Coefficient (NSE) of 0.955. By using the default batch algorithm a back propagation, iterating the calibration stage (training) until the model is designed to stop, the model used epoch 1000 times with a time of 2 (two) seconds for each model. Calibration is a process of adjusting the values of the parameters of the model to achieve the best match between observations and variables predictive variables. Match between the actual data (observations) with forecasting results based on the results of the calibration is indicated by the correlation coefficient. The values of the weights of the network ANN achieved from the calibration results will be used in the verification phase (testing). The accuracy of the forecasting results, performance criteria are represented by the model.
Application Methods artificial neural network (Ann) Back propagation structure for Predicting the value

Figure 4. Simulation Results between data Flume and Simulation Discharge
Simulation models according Refsgaard (2000) is an effort to validate at the use of the model to gain knowledge or in sight to far reality and to brain forecasts that can be used by water 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) and produce a model in Equation (17).

\[ Q_{\text{flume}} = 0.436 Q^n_{0.8834} \]

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

\[
\frac{n'}{n} = 0.378 + 64.621R_e - 0.537 \frac{d_{50}}{h} - 0.00242S - 0.005F_r - 0.065\sigma + 0.008 \frac{b}{h} + 0.152 \tau_a \]

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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

\[
\frac{n'}{n} = 0.378 + 64.621R_e - 0.537 \frac{d_{50}}{h} - 0.00242S - 0.005F_r - 0.065\sigma + 0.008 \frac{b}{h} + 0.152 \tau_a \]

<table>
<thead>
<tr>
<th>Model Development</th>
<th>Correlation Coefficient ((R^2))</th>
<th>MSE</th>
<th>NSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN method</td>
<td>0.980</td>
<td>1.7E-06</td>
<td>0.844</td>
</tr>
<tr>
<td>Linear separation method</td>
<td>0.859</td>
<td>4.324</td>
<td>0.774</td>
</tr>
<tr>
<td>Analysis of the relative dimensions of grain</td>
<td>0.378</td>
<td>4.817</td>
<td>0.287</td>
</tr>
<tr>
<td>Analysis of the relative depth dimension</td>
<td>0.377</td>
<td>4.817</td>
<td>0.388</td>
</tr>
</tbody>
</table>

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

\[
\frac{n'}{n} = 0.378 + 64.621R_e - 0.537 \frac{d_{50}}{h} - 0.00242S - 0.005F_r - 0.065\sigma + 0.008 \frac{b}{h} + 0.152 \tau_a \]
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 to 4.565% (<5%). Error below 5% indicates that the error between the actual model and simulation is below to lernece. 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 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 theoreticallinear separation method ($n'/n'$) can be seenas Equation(19).

\[
\frac{n'}{n} = 0.1167 n + 0.0182 \quad \text{..................(19)}
\]

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 lernece and very Good. Value Efficiency Model Nash Sutcliffe Coefficient (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)

\[
n = 0.0287 + 0.104 R_e - 0.013 \frac{dx}{h} - 1.0187 S + 0.002 F_r - 0.0017 \sigma + 0.0001 \frac{h}{h} - 0.0015 \tau \quad \text{..................(20)}
\]

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 lernece and very Good. Value Efficiency Model Nash Sutcliffe Coefficient (NSE) of 0.955 (NSE > 0.75) which shows that the interpretation under condition of the actual model and the simulation under condition correlate 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 variables of 0.980 (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 lernece 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 $Q_{\text{flume}} = 0.436 Q_{\text{simula}}$ 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 lernece 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) of 0.774 (NSE > 0.75) which shows that the interpretation of the actual model and the simulation under condition correlate 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 causaing 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 propagation best regression model based input with architecture 7-10-1 of 7 units of input the input layer -10 hidden units in the hidden layer -1 unit of output the output layer is more accurately used forecasting of the characteristics of the actual

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with the value of the correlation between variables at 0.980 with model obtained the $Q_{\text{prediks}} = 0.95 Q_{\text{simulas}} + 0.0012$. NSE value of 0.844 and MSE of 0.0000177.

4. Modelling a separation can be used to estimate the flow rate to the conditions for the basic shape of channels.

5. Linear separation model can be used to estimate the flow rate by the basic conditions of the channel shape to the shape of the channel $Q_{\text{flume}} = 0.436 Q_{\text{simulas}}^0.8834$ with ($R^2 = 0.859$).

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REFERENCES


Application Methods artificial neural network (Ann) Back propagation structure for Predicting the value


