

Application of Pattern Recognition and Classification Using Artificial Neural Network in Geothermal Operation

Heneka Yoma Priyanga, Dimas Ruliandi

PT. Pertamina Jln. Merdeka Timur No. 1 Jakarta- Indonesia

heneka@utulsa.edu, heneka.priyanga@pertamina.com, dimas.ruliandi@pertamina.com

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ABSTRACT

Pattern Recognition and Classification present a comprehensive introduction to the core concepts involved in automated pattern recognition and classification. There are four best-known approaches for pattern recognition such as template matching, statistical classification, syntactic or structural matching, and neural networks. The main characteristics of neural networks are that they have the ability to learn complex nonlinear input-output relationships, use sequential training procedures, and adapt themselves to the data. Artificial neural networks are computational models that presented systems of interconnected "neurons" that can compute values from inputs by feeding information through the network. An artificial neural network is configured for a specific application, such as pattern recognition or data classification, through a learning process. Like other machine learning methods, neural networks have been used to solve a wide variety of tasks that are hard to explain using conventional rule-based programming. In geothermal operation, such application has been utilized for determining (predicting) a geothermal power plant performance under a broad range of operating conditions. Other than that, the application of artificial neural networks can also be utilized for predicting Bit condition in geothermal drilling, as an accurate determination of drill bit condition can efficiently decrease drilling cost of a geothermal well. An artificial neural network can also be used for estimation of static formation temperatures in geothermal wells, and even for optimization of re-injection in low-temperature geothermal reservoirs.

1. INTRODUCTION

Artificial neural networks (Fig. 1), a biologically inspired computing methodology, have the ability to learn by imitating the learning method used in the human brain, Gharbi & Mansoori (2005). It is an interconnected assembly of simple processing elements, units, or neurons, whose functionality is based on the brain neuron. The processing ability of the network is stored in the inter-unit connection strengths, or weights, obtained by process of adaptation to or learning from, a set of training patterns. Neural networks are well suited to complex problems. They have significant degrees of freedom. Thus, they can capture the non-linearity of the process being studied better than conventional regression methods. ANNs are relatively insensitive to data noise, as they have the ability to determine the underlying relationship between model inputs and outputs, resulting in excellent generalization ability, Gharbi & Mansoori (2005). A neural network model can be subjected to additional training to adapt itself to new situations in which its input-output performance is inadequate.

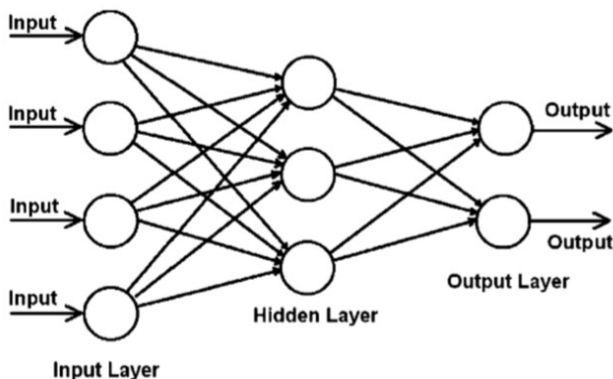


Figure 1: a typical model of Artificial Neural Networks

In computer science and related fields, artificial neural networks are computational models that presented as systems of interconnected "neurons" that can compute values from inputs by feeding information through the network. An artificial neural network is configured for a specific application, such as pattern recognition or data classification, through a learning process. Like other machine learning methods, neural networks have been used to solve a wide variety of tasks that are hard to solve using ordinary rule based programming.

A multilayer perceptron (MLP) or multilayer neural network is an example of artificial neural network (ANN). Multilayer networks solve the classification problem for nonlinear sets by employing hidden layers, whose neurons are not directly connected to the output. The additional hidden layers can be interpreted geometrically as additional hyperplanes, which enhance the separation capacity of the network.

An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with an activation function. An ANN can be modeled mathematically as follow:

$$y_i = g_i\left(\sum_{j=1}^n \omega_{ij}x_j + b_i\right) \tag{1}$$

where y_i is the output of the node i , x_j is the j^{th} input to the node, w_{ij} is the interconnection weight between node i and j , and b_i is the bias of the node. The activation function g_i specifies the output of a neuron to a given input. Activation functions commonly used for neurons such as sigmoid function and linear function. Non-linear activation functions are preferred for neurons in the hidden layer. For output neurons, linear and nonlinear activation can be utilized. These activation functions can be expressed as:

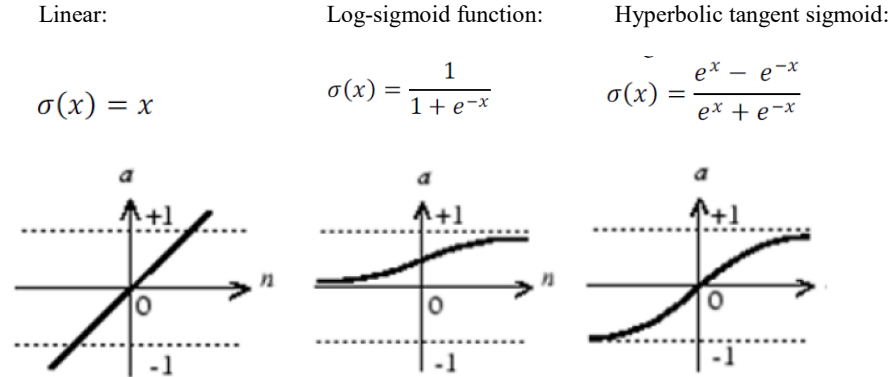


Figure 2: Linier, Log-Sigmoid and Tangent sigmoid activation functions

The performance of an ANN based prediction can be evaluated using various performance measurement methods. This measurement is required to see how good the ANN model could learn from the training data in the training stage, and how good the predicted outputs in the testing stage. The most preferred criterion used to measure ANN performance are correlation coefficient (R), mean squared error (MSE), mean absolute percentage error (MAPE), root mean square error (RMSE), mean absolute error (MAE), or coefficient of determination (R²).

In this paper, the correlation coefficient (R), mean squared error (MSE) and mean absolute percentage error (MAPE) were used to measure the performance of the ANN. The correlation coefficient (R) measure of how well the correlation between outputs and targets. An R value of 1 means a close relationship while 0 means a random relationship. R value is given by

$$R = \frac{cov(a, p)}{\sqrt{cov(a, a) \cdot cov(p, p)}} \tag{2}$$

The mean squared error (MSE) is the average squared difference between outputs and targets. Lower values are better while zero means no error. MSE is calculated from

$$MSE = \frac{1}{N} \sum_{i=1}^N (a_i - p_i)^2 \tag{3}$$

The mean absolute percentage error (MAPE) was used as an error estimating index to evaluate the accuracy/predictive capability of the model. Because this number is a percentage, it can be easier to understand than the other statistics. For example, if the MAPE is 1, on average, the forecast is off by 1%. The equation is:

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{a_i - p_i}{a_i} \right| * 100 \tag{4}$$

where a and p refer to actual and predicted sets respectively, and N is the number of points in the data set.

2. APPLICATION OF ANNS IN GEOTHERMAL POWER PLANT

The ANN model was used for predicting specific steam consumption (SSC) of the plant, using 10 input parameters such as steam input parameters, turbine-generator parameters, condenser parameters, cooling tower parameters, and ambient parameters. The ANN model was trained with 2 different data combination. The first model was trained using commissioning data and after plant major overhaul data (ANN model 1) and the other model was trained only with after plant major overhaul data (ANN model 2). The predictive capability of

the model was evaluated in terms of correlation coefficient (R), mean squared error (MSE), and mean absolute percentage error (MAPE) between the ANN model data prediction and plant real time data. The ANN model was tested using normal operation data taken during Feb-April 2015. During the testing stage, even though both ANN models performance yield moderate results, ANN model 2 shows a similar correlation (same positive or negative gradient) with the plant real time data. The difference between ANN model 2 SSC prediction and plant actual real time shows a significant difference. The experiment shows that there is 24 T/h of steam flow or equals to 3.4 to 4 MW (using SSC range 6 – 7 T/MWh) difference between venturi steam flow reading and ANN prediction. Combined with good and sufficient training data, and an independent measurement of steam flow for validation, the neural network approach can be utilized to develop a good performance program that able to identify the degradation of the plant or instruments (in this case is the streamflow instrument, venturi tube). If the data from the instrument reading show noticeable shift from ANN predicted value, then it can be a good sign to perform thorough analysis on the plant to prevent losses.

2.1 ANN Modeling

The ANN model used in this study is implemented under the MATLAB environment. A feedforward structure with backpropagation learning algorithm was used. Ten input parameters as mentioned in Table.1 and the corresponding output SSC were introduced to the networks consist of three layers for training. The activation function in the hidden layer was chosen as the tangent sigmoid function, and for the output layer, linear activation function will be used. Levenberg-Marquardt algorithm will be adopted during the ANN training.

Since the performance of an ANN is depended heavily on the structure of the network, number of hidden layers and neurons are becoming important factor to consider. However, there are no definite methods to determine the optimal number of hidden layers and the optimal number of neurons on each hidden layers, Hosoz et al (2007). Thus, by trial and error with different number of neurons in the hidden layers, it was found that 8 neurons in one hidden layer gave high R and low MSE. Subsection headings should be capitalized on the first letter.

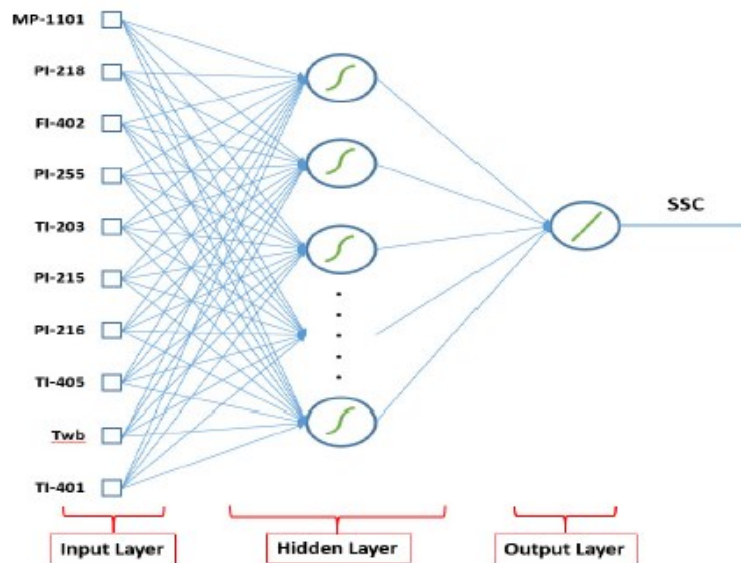


Figure 3: The Structure of the ANN for predicting geothermal power plant SSC

2.2 Selection of Data

A geothermal power plant usually operates as a baseload plant, which means that the power plant will operate continuously and are available 24 hours a day. Besides that, the plant usually operated at maximum its maximum output power. It is easier to analyze baseload like GPP Kamojang unit 4, since it is operated always (unless there is an instruction from grid authority to do so). The data used in this study can be divided into 3 parts, commissioning data, after major overhaul data, and normal operation data. This combination was chosen because we want to get the data when the plant is in its best condition (newly operated plant, or after major maintenance), where the errors due to equipment deterioration or hindrance in plant processes can be minimized. Parts of commissioning data and after major overhaul data will be used randomly for train, validate and testing during training stage of the ANN model. The normal operation data set will be used to verify the SSC prediction of the ANN model against the plant's real instrument reading in the testing stage.

However, not all the data listed above will be used in the training stage. The transient-state data were removed from the available plant data during initial data screening, and the data were filtered according to the procedure described by reference, Smrekar (2009). Some erroneous data that were not reliable and representative according to regular plant operation were also removed from the data set.

2.3 Result

Experimental study was conducted in 2 stage, training stage and testing stage. Data set from commissioning and from after plant major overhaul will be used in the testing stage. Out of 162 data used in the training stage, 70% or 114 data will be used for training purpose,

15% or 24 data for validation, and 15% or 24 data for testing. The data for each purpose was assigned randomly. After training stage was done, the testing data can be fed to the final network to see how good the performance of the ANN when introduced with completely different data set (2015 normal operation data) that used in the training stage.

Performance Criteria	Training	Validation	Testing
R	0.971	0.945	0.9336
MSE	0.000061	0.000277	0.000186
MAPE	0.0899	0.1637	0.1352

Table. 3 ANN model 2 performances during training stage

During the training stage, the 10-8-1 ANN model was fed with the combination of commissioning data and after plant major overhaul data. The results of training, validation, and testing have a good performance and accuracy. Correlation coefficient R above 0.9 shows the strong relationship between predicted values and targets. In addition to the R value, low MSE values also indicate a good SSC prediction. The ANN model's accuracy can be observed from MAPE results, which shows a low percentage of errors.

During this testing stage, 400 data from plant normal operation (steady state) will be used to test the performance of the ANN with the data taken from GPP Kamojang unit 4 real-time operation in 2015. The predicted SSC has a poor overall performance such as mean squared error (MSE) of 0.0324, correlation coefficient (R) of 0.6918, and mean absolute percentage error of 2.3025%. When the testing conducted on the ANN model 2, the result shows a slightly poorer results than the previous experiment. The mean squared error (MSE) becomes 0.1458, correlation coefficient (R) becomes 0.6237, and mean absolute percentage error (MAPE) becomes 5.448%.

Despite the poor performance of both ANN models, we must note that the actual SSC values were calculated from actual plant generation reading from electricity metering MP- 1101 and main steam flow measurement from venturi tube. Since the ANN approach was chosen to predict the SSC from specific reference when the power plant was at its best condition (commissioning and after major maintenance) while the plant will actually degrade over time, some shift towards higher SSC was expected if the predicted SSC was to be compared. In order to evaluate the best ANN model, linear regression analysis. The dotted lines in Fig. 4 represent the best fit straight line. These lines were meant to show and compare the trend correlation between plant real time data and predicted values from both ANN models. The actual data from plant real time show a positive correlation, same with the ANN model 1, while ANN model 2 tends to have a negative correlation. From this perspective, ANN model 1 seems to be a good model.

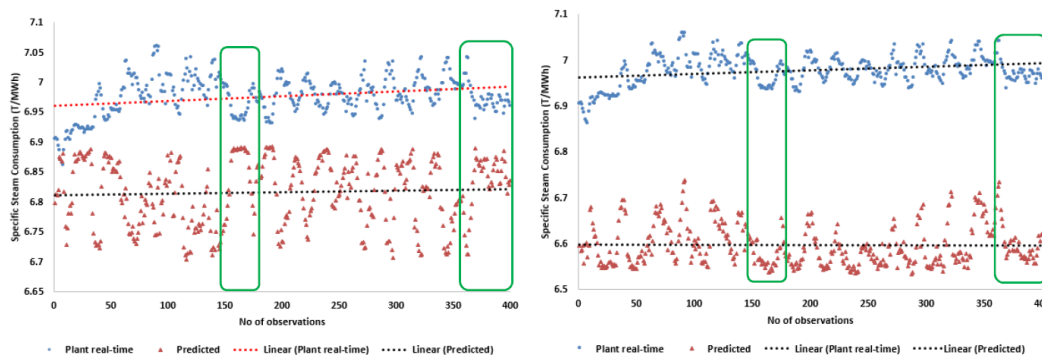


Figure 4: Plant real time data compared with ANN model 1 & 2 prediction

However, ANN model 1 shows different trend behavior than the actual plant reading. When the SSC trend tends to decrease, ANN model 1 SSC prediction was moving to the opposite direction, while ANN model 2 seems to agree with the plant real time SSC trends (marked by green boundary in Fig. 4). Despite the network performances according to MAPE, MSE and R show ANN model 1 has better SSC predictions than ANN model 2, but the SSC prediction values from ANN model 1 has higher SSC fluctuations.

Another experiment conducted in this stage was sorting each ANN input parameter from the smallest value to the largest value. The data plot was analyzed to see the behavior and relation between plant actual real time data with predicted data from two different models. The trend lines from Fig. 4-6 show a clear sign that ANN model 2 has a similar correlation (same positive or negative gradient) with the plant real time data. When the trend was sorted based on steam parameters (steam temperatures and pressures as in Fig. 5), the trend correlation became clearer. From this experiment, the difference of SSC between plant real time and ANN model 2 was found to be 0.38 T/MWh on average or 24 T/h of steam flow or equals to 3.4 to 4 MW (using SSC range 6 – 7 T/MWh) of electricity.

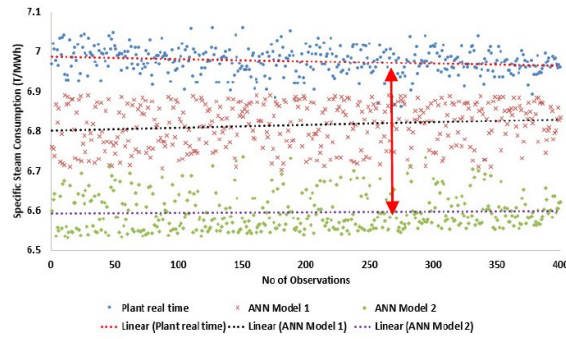


Fig. 13 Sorting data by power generation (smallest power generation to largest power generation)

Figure 4: Sorting data by power generation (smallest power generation to largest power generation)

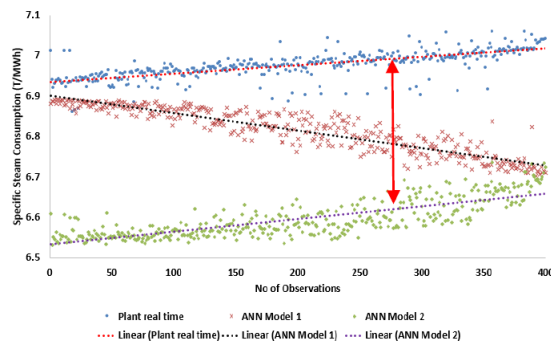


Fig. 14 Sorting data by pressure (the trendlines are a bit similar when sorting with temperature).

Figure 5: sorting data by pressure, (the trend lines are a bit similar when sorting with temperature)

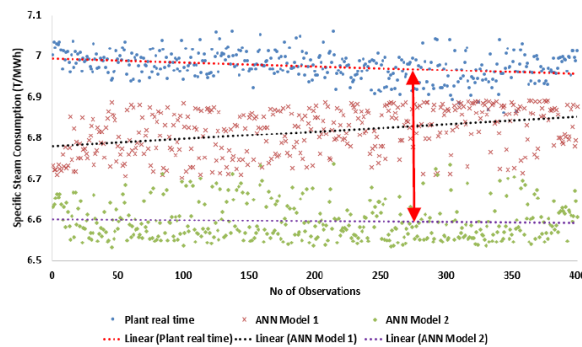


Fig. 15 Sorting data by cooling water flow

Figure 6: sorting data by cooling water flow

3. APPLICATION OF ANNS IN GEOTHERMAL DRILLING OPERATION

In this study two application of artificial neural networks have been used. First application was artificial neural networks for clustering, drilling parameters as input data and the output of this application is an estimation of bit grading based on the clustering result. The drill bit grade estimation is necessary because from the field the data that available is bit-grading data before we put new drill bit into the well and after we pull out the bit out of the well. The output data from the first networks were used to train the second networks. The second application is using artificial neural networks as data fitting tools, with the same drilling parameter as the input and the target for these

networks is bit grading estimation from the first networks. The trained Artificial Neural Networks is able to predict bit grade using drilling parameters as input.

3.1 Artificial Neural Networks Modeling

The MATLAB environment was used to implement The Artificial Neural Networks to determine the condition of the bit based on selected the drilling parameter. The Artificial Neural Networks structure is feed-forward backpropagation. The number of hidden layer is three, the input layer, hidden layer, and output layer. In each layer has a number of neuron or element. The number of neurons in the input layer is 5 and 1 in the output layer. There is no consistent method to define the number of neurons in the hidden layer, trial and error commonly used to get the best performance of the Artificial Neural Networks. In this study, eight neurons of hidden layer gave the best performance of the networks. Figure 7 shows the structure of the Networks.

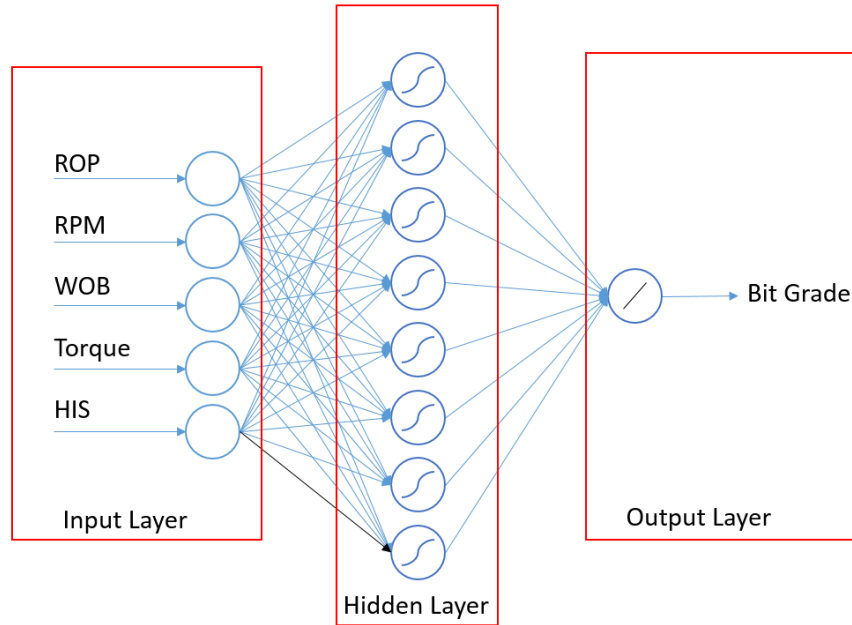


Figure 7: The Structure of the ANN for predicting drill bit grade

3.2 Data Selections

Data selections is important part in implementation an artificial neural networks. The drilling parameter that as used in this application is from Ulubelu Geothermal Field, well number UBL-B6. Due to the lack of the formation hardness information, the data that can be used from this well is only from section 12 ¼ inch. In this section, the lithology has relatively homogeneous hardness. The data taken from this well is from 900m to 1700m measured depth with total 516 data sets from 5 different bits. One sets consist of five different drilling parameters and condition of the bit when the bit put into the well and pull out of the well. The detail of the drilling bit data is shown in table 1.

The problem is the bit grade is needed in every set of data. Neural Networks can be used to clustering purposes, by grouping the random data into groups of data with similarity. This Neural Networks is a self-organizing map consists of a competitive layer that can classify a dataset of vectors with any number dimension into as many classes as the layer has neuron. In this case, 3 by 3 matrix, which classify the drilling parameter set into nine groups.

The output of this clustering process is estimation of drill bit grade for each data set of drilling parameter. This output data together with sets of drilling parameter is used to train Artificial Neural Networks for fitting purpose. The data, inputs and related outputs, than randomly divided to three groups, the training group, the validation group and the testing group

3.3 Result

The MATLAB environment was used to implement The Artificial Neural Networks to determine the condition of the bit based on selected the drilling parameter. The Artificial Neural Networks structure is feed-forward backpropagation. The number of hidden layer is three, the input layer, hidden layer, and output layer. In each layer has a number of neuron or element. The number of neurons in the input layer is 5 and 1 in the output layer. There is no consistent method to define the number of neurons in the hidden layer, trial and error commonly used to get the best performance of the Artificial Neural Networks. In this study, eight neurons of hidden layer gave the best performance of the networks.

The Artificial Neural Network has been successfully generated to predict the bit grading for a geothermal drilling operation. The input parameters for the network are displayed in the following table. The input parameters were taken from UBL-B6, Ulubelu field, Bit Size:

12 ¼ inches, depth 1036-1700 m. This section has same formation characteristic so that the lithology hardness can be neglected. The networks input parameters are displayed in the following table. The Output of the Artificial Neural Networks is drill bit grade (condition), which is divided into three classifications: 0 – new bit or unworn bit, 1 – fair condition bit, and 3 – a completely worn out or unusable bit.

In the training process, the input and output data was divided into three sets; a training set, a validation set, and a testing set. Each of the input and output data contains of 507 data sets divided based on 80/10/10 rule to 405, 51, 51 data sets. A number of training processes have been conducted to achieve the best performance of the networks. Three hidden layer feed-forward network with hidden sigmoid neurons and linear output neuron can fit multi-dimensional mapping problems arbitrary well, given consistent data and enough neurons in its hidden layer. The number of neurons at the three hidden layers are 8. The Networks was trained with Lavenberg-Marquardt back-propagation algorithm.

Networks performance measured using three parameters, correlation coefficient, mean square error and comparing the output with the target. These three parameters can be seen as explained below.

Table 3.

Artificial Neural Networks Performance.

Stage	Samples	MSE	R
Training	412	0.0338	0.957
Validation	52	0.0514	0.935
Testing	52	0.0351	0.970
Total	507	0.0401	0.962

Correlation coefficient has been calculated for each single training stages. Correlation coefficient above 0.9 showed the input and predicted output has a strong relationship. In addition to the R value, MSE also calculated to describe network performance for each single training stages. On average, MSE of the result is 4%, the low value of MSE indicated a good prediction of Bit Grading.

In order to verify the performance of the networks prediction, figure 8-10 show the comparison between of bit grade target and network prediction for each drilling bit, which is showing a satisfactory result.

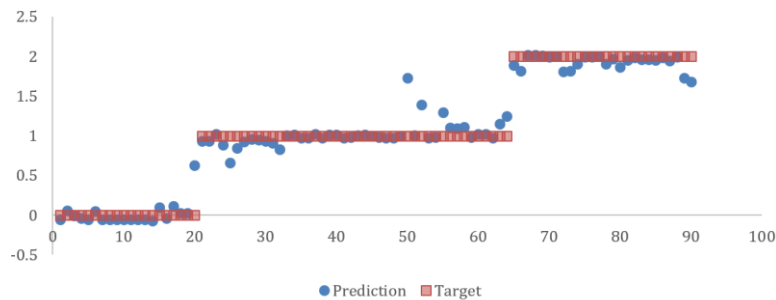


Figure 8: Bit Grade Prediction vs. Target. Well: UBL-B6, section 12 ¼”, Bit No. 1

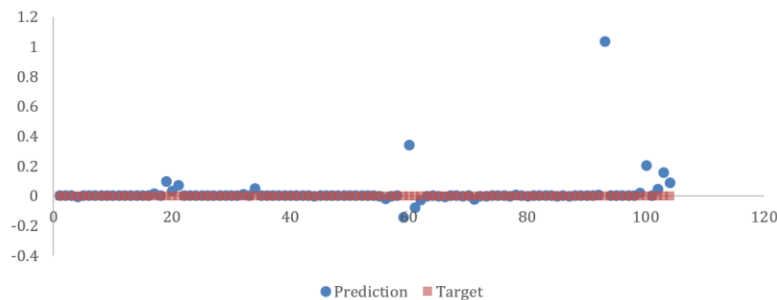
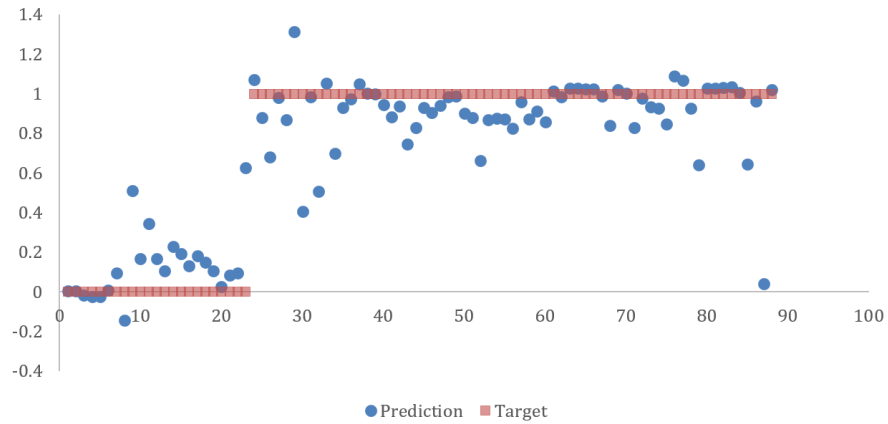
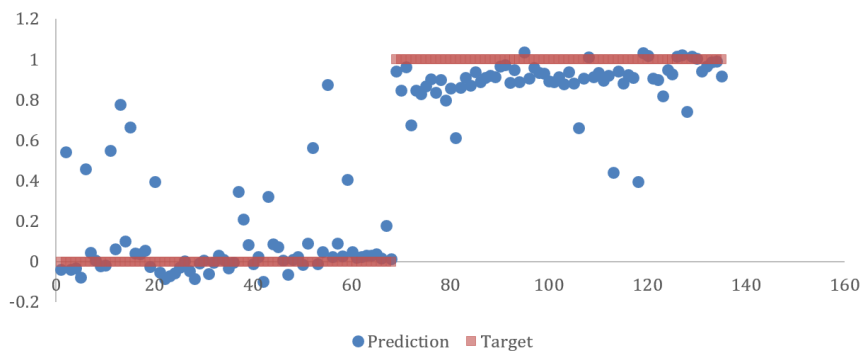


Figure 8: Bit Grade Prediction vs. Target. Well: UBL-B6, section 12 ¼”, Bit No. 2



Bit Grade Prediction vs. Target. Well: UBL-B6, section 12 1/4”, Bit No. 3



Bit Grade Prediction vs. Target. Well: UBL-B6, section 12 1/4”, Bit No. 4

4. CONCLUSIONS

The applicability and capability of neural network approach for predicting geothermal power plant SSC & drill bit grade has been investigated. For predicting geothermal power plant SCC, a 10-8-1 network architecture (input-hidden-output) was found to give high correlation coefficient and low mean squared error during the training stage. The training stage conducted using 3 different dataset, commissioning dataset, after plant major overhaul dataset, and normal operation dataset. Since the plant setting between normal operation and after plant major overhaul was different with commissioning, it was found that the ANN model that trained with commissioning data included (ANN model 1) shows different SSC trend behaviour compared to the one that trained without commissioning data included (ANN model 2). Even though in terms of performance parameters (MSE, R, and MAPE) the ANN model 2 yield moderate result, but the SSC trendlines show agreeable result between plant real time data and predicted SSC in terms of trend correlation.

On the other hand, for predicting the bit grade in geothermal drilling, a total of 507 data set of five different drilling parameter including the rate of penetration, weight on bit, torque, rotation per minute and hydraulic horsepower per square inch of the bit has been used to train and generate feed forward back propagation artificial neural networks. Although, lithology parameter was neglected because the data that has been used assumed to have the same lithology, the result is acceptable.

Combined with good and sufficient training data, and independent measurement for validation, the neural network approach can be utilized to develop a good performance program that able to predicting geothermal power plant SCC and predicting the degradation of drill bit condition.

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