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Application of Artificial Neural Network to Exergy Performance Analysis of Geothermal Power Plant

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ABSTRACT

This paper describes an application of a feedforward backpropagation artificial neural network (ANN), to predict Geothermal Power Plant (GPP) Unit 3 Ulubelu exergy efficiency. Exergy analysis was chosen since it considered as the most practical thermodynamics method for the system's energy evaluation. From the exergy analysis, merging both exergy efficiency and exergy destruction highlights the energy inefficiencies within a system and provides useful information to the managers and decision makers for prioritizing the potentials of improvement. However, the inaccuracy of measuring equipment or instrument is inevitable, especially when the equipment has been in operation for a long time. Thus, the exergy analysis results can be compromised and inaccurate.

The ANN method with backpropagation had been investigated to overcome this problem. The ANN model with 6-4-1 structure has been developed and investigated. The input layer for the ANN model was designed using 6 parameters such as steam inlet pressure, steam inlet temperature, steam flow (inlet), ambient temperature, electricity generation (gross), and condenser pressure as the input, and system's exergy efficiency as the output. The data utilized for the training of the ANN were taken from commissioning period (early operation of the plant), after first year inspection (Turnaround) of the plant, and present data. 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 prediction data and plant real-time data.

It has been found that the ANN model could predict the turbine and overall plant exergy efficiency with good result. However, the exergy efficiency for hot well pump HWP, condenser, and cooling tower (CT) was in poor performance, while the GES's exergy efficiency shows a moderate result. This experiment has shown that the ANN method can be used and developed to predict the exergy efficiency of the geothermal power plant. Nevertheless, several improvements are required for future experiments to achieve a better performance of the ANN. The selection of input parameter, the type of ANN's algorithm used for training, the number of hidden layers used in the model, the number of outputs, or data filtering mechanism are among the required improvements to achieve better prediction results. The ANN provides an effective analyzing and diagnosing tool to understand and simulate the non-linear behavior of the plant and can also be used as a valuable performance assessment tool for plant operators and decision makers.

1. INTRODUCTION

The methods of measuring performance of a geothermal power plant are generally similar as other thermal power plants. Performances can be evaluated through energetic and exergetic performance criteria, which based on the first and second law of thermodynamics respectively. Kaushik (2011) stated that performing exergetic and energetic analysis together can give a complete depiction of system characteristics. Adiprana (2015) performed evaluation and optimization of GPP Unit 1-2-3 Kamojang based on exergy analysis. Acir (2013) and Khoodaruth (2015) performed exergy performance analysis of coal-fired thermal power plant. Both works were involving analysis on each main equipment in the power plant.

Several experiments related to plant performance have been conducted using ANN method to predict plant or equipment performance. Behera (2013) achieved a good result for performance prediction of RPF fired boiler using artificial neural networks approach. The output from the neural networks are temperature, mass flow rate, and pressure of the steam using five input parameters, namely feed water pressure & temperature, conveyor speed, and incinerator exit temperature. They concluded that ANN can efficiently predict the data on steam properties. Hosoz (2007) utilized an artificial neural network to predict the performance of a cooling tower under a broad range of operating conditions. The results show that ANN approach can be applied successfully and can provide high accuracy and reliability for predicting the performance of cooling tower. Prieto (2001) performed feedforward ANNs to predict power plant condenser performance with acceptable error results. Ruliandi (2015) performed experiment of predicting geothermal power plant performance using ANN in terms of specific steam consumption (SSC) with good result. These experiments showed us that ANN method could be used to predict the performance of specific system or equipment.

In this study, the ANN approach has been applied to predict the performance of Ulubelu Unit 3 Geothermal Power Plant in terms of exergy analysis. Exergy analysis can be used to describe overall plant performance since it is calculated directly from input and output parameters of the plant, which are steam input and power generation. However, to better understanding the condition of the plant, it is required that the balance of plant (BOP) efficiency to be calculated as well. The parameters used for the ANN model were taken from the main equipment in a geothermal power plant such as turbine, condenser, cooling tower, pump, and gas extraction system.

2. DESCRIPTION OF ULUBELU UNIT 3 POWER PLANT SYSTEM

Ulubelu Geothermal Field shown in Figure 1 is located in Tanggamus District of Lampung Province, Indonesia. It is located at an elevation of about 800 m above sea level with the ambient temperature of around 20°C - 29°C.

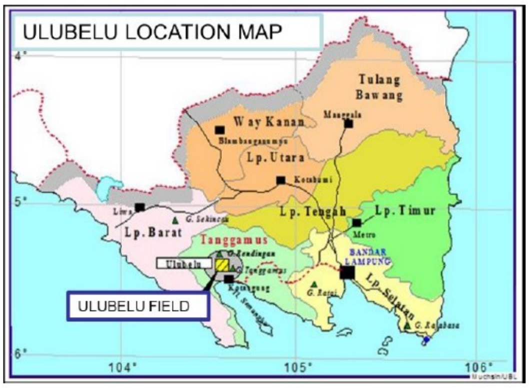


Figure 1: Location map of Ulubelu Geothermal Field.

Its total power generation capacity is 4 x 55 MW which consists of two power plants (Units 1&2) of state electricity company and the other two power plants (Units 3&4) are owned and operated by PT Pertamina Geothermal Energy. The reference power plant discussed in this paper is Ulubelu Unit 3 Geothermal Power Plant (GPP) that commercially operated in 2016. Based on project document of Ulubelu Unit 3&4 (2014), the process flow diagram of Unit 3 GPP is shown in Figure 2.

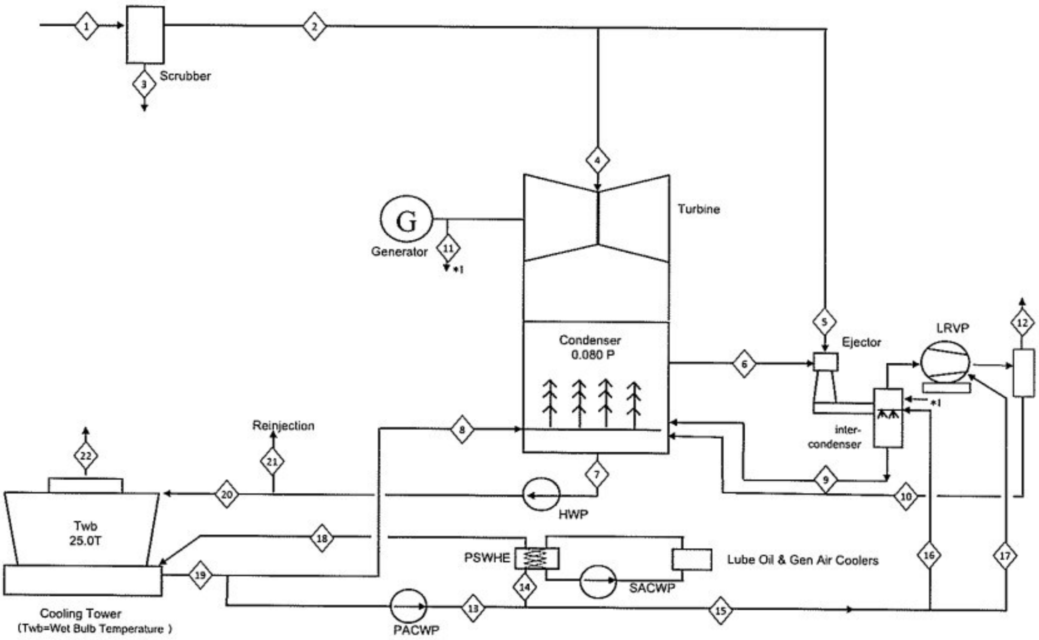


Figure 2: Simplified process flow diagram of Ulubelu Unit 3 GPP.

To generate a total of 55 MW of electric power, Unit 3 GPP requires more than 300 tons/hour of steam supply. Steam from the steam field is delivered to the steam scrubbing system through 40” main pipeline. The steam scrubber separates water droplet which includes the impurities from the steam and drains out the condensate with impurities to the outside of the steam system. The steam from the steam scrubber will be delivered to the turbine and ejectors of the Gas Extraction System (GES). The steam will flow and rotate the shaft of the turbine coupled with the generator at an inlet pressure around 7 bar and expands as exhaust steam to an outlet pressure around 0,08 bar. At the condenser, the exhaust steam and the non-condensable gas (NCG) from the outlet of the turbine are condensed and cooled respectively by contacting with the main cooling water from the cooling tower. The mixture of steam condensate, main cooling water, and drain from GES is delivered to the cooling tower and the reinjection line by two hot well pumps (HWP). NCG of 1,5 wt% is included in the steam at the rated operating condition. GES will extract the NCG which accumulates as the exhaust steam condenses in the condenser. The extracted NCG is sent to the cooling tower and then disperse by the cooling tower fan.

3. EXERGY ANALYSIS

Moran and Saphiro (2016) stated that an opportunity exists for doing work whenever two systems at different states are brought into communication. In principle, work can be developed as the systems are allowed to come into equilibrium. When one of the two systems is a suitably idealized system called an exergy reference environment or simply, an environment, and the other is some system of interest, exergy is the maximum theoretical work obtainable as they interact to equilibrium.

For the system operating at steady state with no heat transfer with its surroundings, the steady-state form of the exergy rate balance for control volume can be expressed as

$$0 = \sum_i \dot{E}_{fi} - \dot{W}_{cv} - \sum_o \dot{E}_{fo} - \dot{E}_d \tag{1}$$

where

$$\dot{E}_{fi} = \dot{m}_i e_{fi} \tag{2}$$

$$\dot{E}_{fo} = \dot{m}_o e_{fo} \tag{3}$$

The term $\dot{m}_i e_{fi}$ is the time rate of exergy transfer accompanying mass flow and flow work at inlet i. Similarly, $\dot{m}_o e_{fo}$ is the time rate of exergy transfer accompanying mass flow and flow work at outlet o. The rate of exergy transfer accompanying the power $\dot{W}_{cv}$ is the power itself. The term $\dot{E}_d$ is the time rate of exergy destruction due to irreversibility within the control volume. The flow exergies e_{fi} and e_{fo} are evaluated using

$$e_f = h - h_0 - T_0(s - s_0) \tag{4}$$

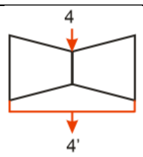
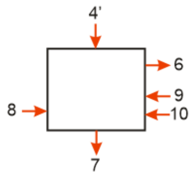
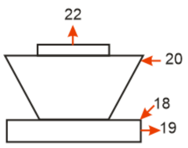
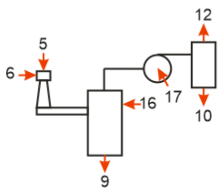
and for ideal gas using

$$e_f = c_p\left(T - T_0 - T_0 \ln\frac{T}{T_0}\right) + RT_0 \ln\frac{P}{P_0} \tag{5}$$

where h, s, T, P, c_p, and R are enthalpy, entropy, temperature, pressure, ideal gas specific heat, and gas constant, respectively. The term h_0 and s_0 represent the respective values of these properties when evaluated at the dead state (T_0 and P_0).

At the dead state, the value of exergy is zero because there is no possibility of a spontaneous change within the system or the environment, nor can there be an interaction between them. In this paper, the dead state condition is evaluated at 25°C and 0,92 bar. Finally, the equations to calculate the exergetic efficiency of the main equipment at Ulubelu Unit 3 GPP are shown in Table 1.

Table 2: The equations to calculate the exergetic efficiency of Ulubelu Unit 3 GPP.

Equipment	Schematic	Exergy Rate Balance	Exergetic Efficiency	Equation
Turbine		$0 = \dot{E}_{fi} - \dot{E}_{fo} - \dot{W}_{gross} - \dot{E}_d$ $\dot{E}_{fi} = \dot{E}_4$ $\dot{E}_{fo} = \dot{E}_{4'}$	$\eta_{II,turbine} = 1 - \frac{\dot{E}_d}{\dot{E}_{fi} - \dot{E}_{fo}}$	(6)
Condenser		$0 = \dot{E}_{fi} - \dot{E}_{fo} - \dot{E}_d$ $\dot{E}_{fi} = \dot{E}_{4'} + \dot{E}_8 + \dot{E}_9 + \dot{E}_{10}$ $\dot{E}_{fo} = \dot{E}_6 + \dot{E}_7$	$\eta_{II,condenser} = 1 - \frac{\dot{E}_d}{\dot{E}_{fi}}$	(7)
Hot Well Pump		$0 = \dot{E}_{fi} - \dot{E}_{fo} + \dot{W}_{HWP} - \dot{E}_d$ $\dot{E}_{fi} = \dot{E}_7$ $\dot{E}_{fo} = \dot{E}_{7'}$	$\eta_{II,HWP} = 1 - \frac{\dot{E}_d}{\dot{W}_{HWP}}$	(8)
Cooling Tower		$0 = \dot{E}_{fi} - \dot{E}_{fo} + \dot{W}_{fan} - \dot{E}_d$ $\dot{E}_{fi} = \dot{E}_{18} + \dot{E}_{20} + \dot{E}_{i,air}$ $\dot{E}_{fo} = \dot{E}_{19} + \dot{E}_{22} + \dot{E}_{o,air}$	$\eta_{II,coolingtower} = \frac{\dot{E}_{fo}}{\dot{E}_{fi}}$	(9)
Gas Extraction System		$0 = \dot{E}_{fi} - \dot{E}_{fo} + \dot{W}_{LRVP} - \dot{E}_d$ $\dot{E}_{fi} = \dot{E}_5 + \dot{E}_6 + \dot{E}_{16} + \dot{E}_{17}$ $\dot{E}_{fo} = \dot{E}_9 + \dot{E}_{10} + \dot{E}_{12}$	$\eta_{II,GES} = \frac{\dot{E}_{fo}}{\dot{E}_{fi}}$	(10)

For the exergetic efficiency or the second law efficiency of the overall power plant $\eta_{II,GPP}$ can be evaluated by using

$$\eta_{II,GPP} = \frac{\dot{W}_{net}}{\dot{E}_1} \tag{11}$$

where $\dot{W}_{net}$ and $\dot{E}_1$ represent the respective values of the net electric power of the GPP and the time rate of exergy of the steam supply to the GPP at state 1.

4. ARTIFICIAL NEURAL NETWORK MODEL DEVELOPMENT

Artificial neural networks (ANN) are computational models that presented as systems of interconnected "neurons" that can compute values from inputs by feeding information through the network. The concept of ANN is pretty similar with the work of a human brain. There are collection of connected nodes (neurons) where each connection (like synapses in a human brain) can transmit a signal from one neuron to another. By mimicking this concept, an ANN can be developed to process a signal (input) to produce some specific output. Figure 3 shows the neurons (biological) and corresponding input-output in ANN.

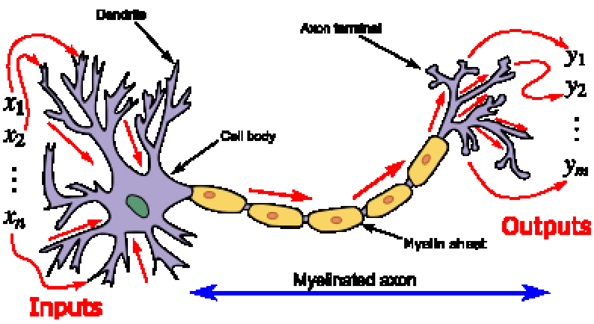


Figure 3: The neurons (biological) and corresponding input-output in an artificial neural network (https://en.wikipedia.org/wiki/Artificial_neural_network)

There are many application of an ANN 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. An ANN can be modeled mathematically as follow:

$$y_i = g_i(\sum_{j=1}^{n} \omega_{ij} x_j + b_i) \tag{12}$$

where y_i is the output of the node i, x_j is the j^{th} input to the node, ω_{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.

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 (R^2).

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

$$R = \frac{cov(a,p)}{\sqrt{cov(a,a) \cdot cov(p,p)}} \tag{13}$$

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

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(a_i - p_i)^2 \tag{14}$$

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

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{(a_i - p_i)}{a_i}\right| * 100 \tag{15}$$

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

4.1 ANN Modelling

The ANN model in this work was developed using MATLAB. A feedforward structure with backpropagation learning algorithm was used. Six input parameters were chosen as the input layer as shown in Table 2. These parameters were selected from exergetic efficiency calculation parameters. One must note that not all parameters used in exergetic efficiency were necessarily used as the input for the ANN. The main parameters such as steam input (pressure, flow, temperature) were selected since these parameters represent the input "fuel" to the system (plant). The generator gross output was selected as this parameter represent the output of the system. Dry bulb temperature and condenser vacuum pressure were selected since the environment condition and cooling system performance can be represented by the vacuum pressure of the condenser.

Table 2: Input parameters for the ANN model.

No	Parameter	Tag ID	Unit
1	Dry bulb temperature	UBL0CYQ01FP002WS	ºC
2	Steam inlet temperature	UBL3LBB31CT001XQ01	ºC
3	Steam inlet pressure	UBL3LBB21FP001	bar
4	Steam flow (inlet)	UBL3LBB31CF001	m^3/h
5	Generator output (gross)	UBL3CRU01GH005XQ03	MW
6	Condenser vacuum pressure	UBL3MAG01CP002XQ01	bar

As for the output layer, since the network was expected to return a value of exergetic efficiency, then a single node was implemented. Each exergetic efficiency result values calculated by using equations from Table 1 will be used as the output layer, thus there were six ANN models in total (overall plant, cooling tower, HWP, turbine, GES, and condenser ANN). After defining the input and output layer, the next thing to do is defining how many hidden layer node that should be used in the ANN. The empirical equation according to Chen (2013) can be used to determine the number of neurons (node) in hidden layer:

$$\sum_{i=0}^{n} C_M^i > k \tag{16}$$

where k is the number of samples, M is the number of neurons in the hidden layer, n is the number of neurons in the input layer. If $i > M$, specify $C_M^i = 0$

$$M = \sqrt{n+m} + c \tag{17}$$

where m is the number of neurons in the output layer, c is a constant between [0, 10].

$$M = log_2 n \tag{18}$$

$$M = \sqrt{nm} \tag{19}$$

$$M = \sqrt{0.43nm + 0.12m^2 + 2.54n + 0.77m + 0.86} \tag{20}$$

Thus, since the neurons in input layer ($n = 6$) and neurons in output layer ($m = 1$) then the hidden layer neurons (node) can be calculated using formula M = 4.

In this paper, Levenberg-Marquardt algorithm was adopted for the ANN training. The activation function (transfer function) used for the hidden layer is a hyperbolic tangent sigmoid and linear transfer function for the output layer. The transfer function can be expressed as:

1. Hyperbolic tangent sigmoid:

$$\sigma(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{21}$$

2. Linear:

$$\sigma(x) = x \tag{22}$$

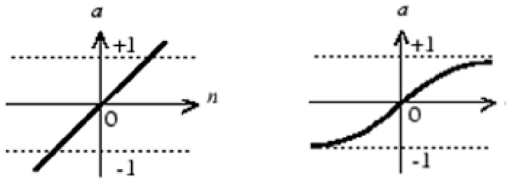


Figure 4: Linear and tan-sigmoid.

The ANN model was developed and implemented in the MATLAB. The structure of the network can be seen from Figure 5

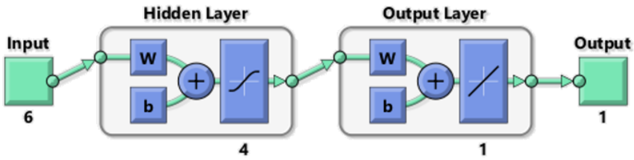


Figure 5: Structure of the ANN Model.

4.2 Selection of Training Phase and Testing Phase Data

The data used in this study were taken from real time operation data. The data set can be divided into two parts, the present data for testing phase and best/ideal condition data (after commissioning or after plant overhaul) for training purpose. The best/ideal condition data was taken from after the plant in operation (after commissioning) and combined with the data after plant undergo first year inspection. This data were chosen to be used as training dataset for the ANN since the accuracy or performance of equipment/measurement tools in the plant was considered still in good condition, thus equipment deterioration or hindrance in plant processes can be considered insignificant. The details of each data set are:

1) Training data :
   This data set will be used for training purpose. The data was taken on July - Sept, 2016 during and after commissioning of Ulubelu Unit 3 and on August – October 2017 after the plant undergo first year inspection (overhaul). The time-series data collected at an hourly interval.

2) Testing data :
   This data set will be used for testing purpose only (after the ANN has been trained using the training dataset). The data was taken on May - July 2019 during normal operation. The time-series data collected at an hourly interval.

However, not all the data collected above will be used. 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 Prieto (2001). Some erroneous data that were not reliable and representative according to regular plant operation were also removed from the data set. The final dataset statistics are as follow

Table 3: Statistics of the data used in training and testing stage.

Parameters	Training (N_{TR} = 154)				Test (N_{TS} = 298)			
	Max	Min	Avg	Std Dev	Max	Min	Avg	Std Dev
Dry bulb temperature	26,975	18,975	21,941	1,250	27,150	19,550	23,001	1,642
Steam inlet temperature	168,861	164,017	165,481	1,325	167,336	164,303	165,708	0,503
Steam inlet pressure	6,839	6,046	6,337	0,253	6,548	6,056	6,335	0,086
Steam flow (inlet)	321,686	244,254	308,728	9,326	347,670	230,537	325,644	14,747
Generator output (gross)	49,028	33,990	47,663	1,634	52,858	33,426	49,586	2,348
Condenser vacuum pressure	0,077	0,063	0,070	0,003	0,089	0,059	0,079	0,005

5. RESULTS AND DISCUSSION

Experimental study was conducted at two stages, exergy and ANN analysis. There are 2 datasets used as mentioned previously. The exergy efficiency was calculated for every data in both dataset and was compared to the prediction result from the ANN. During the 2nd stage (ANN analysis), dataset 1 was used for the training phase of the ANN model. Out of 154 data used in the training phase, 70% or 108 data will be used for training purpose, 15% or 23 data for validation, and 15% or 23 data for testing. The data for each purpose was assigned randomly. After training phase was done, the testing phase can be performed. The dataset 2 can be fed to the final network to see how good the performance of the ANN when introduced with completely different dataset that used in the training stage.

5.1 Exergy Analysis Results and Discussion

The temperature, pressure, and mass flow rate of fluid for calculating exergy efficiencies are taken from the Distributed Control System (DCS) of Ulubelu Unit 3 GPP. The data was taken from three different occasions: after commissioning dated on 8 July – 8 September 2016 (1st data), after First Year Inspection (FYI) dated on 28 August – 28 October 2017 (2nd data), and the present operating conditions dated on 1 May – 1 July 2019 (3rd data). Table 4 shows the average value of exergy efficiencies of the main equipment as well as of the overall Ulubelu Unit 3 GPP for all three data.

Table 4: The average exergetic efficiencies of Ulubelu Unit 3 GPP.

Equipment	**Exergetic Efficiency [%]**		
	1st data	**2nd data**	**3rd data**
	8 Jul - 8 Sep 2016	**28 Aug - 28 Oct 2017**	**1 May - 1 Jul 2019**
Turbine	86,8	86,8	86,9
Condenser	47,6	56,4	55,4
HWP	77,4	85,1	89,6
Cooling Tower	41,5	46,8	47,3
GES	25,8	23,2	23,9
Overall Plant	67,3	68,0	66,3

From the values shown in Table 4, the change in exergetic efficiency from time to time can be occurred due to many factors such as the differences in operating conditions, ambient conditions, quality of the steam supply, the measuring instrument conditions, and the equipment conditions itself. Some of noticeable changing:

a. In the condenser, the value of exergetic efficiency is greatly influenced by how low or vacuum the pressure inside the condenser affected by the main cooling water when condensing and cooling the exhaust steam from the turbine.
b. In the hot well pump, besides the equipment conditions itself, the value of exergetic efficiency is greatly affected by the changes in enthalpy of the water it flows.
c. In the cooling tower, the value of exergetic efficiency is greatly affected by the changes in temperature and humidity of the water and the cooling air from its surroundings.

5.1 ANN Performance

During the testing phase, 298 data from plant normal operation were used to test the performance of the ANN. There are 6 ANN models, one for every exergy efficiency calculated in the Table 1 (including overall plant efficiency). The performance results for each model were evaluated in terms of correlation coefficient (R), mean absolute percentage error (MAPE), and mean squared error (MSE). The linear regression analysis (the dotted straight lines in Figure 6-11) was also implemented since the data used in this experiment was taken from plant real time data, then the linear regression is the easiest method to check how the actual data and predicted data from ANN related to each other, since we can visualize the shifting of exergy efficiency that can occur due to equipment condition degradation or instrumentation accuracy degradation.

Exergy efficiency of overall plant was calculated and compared with the prediction result of ANN model. The mean squared error (MSE) was 0.5223, correlation coefficient (R) was 0.8529, and mean absolute percentage error (MAPE) was 0.871 %. The results show that the performance of ANN prediction of the overall plant exergy efficiency was good. From linear regression analysis, the ANN model prediction was slightly under the operation data. This could mean that from ANN prediction, the overall plant efficiency should be lower than the real time condition as shown in Figure 6.

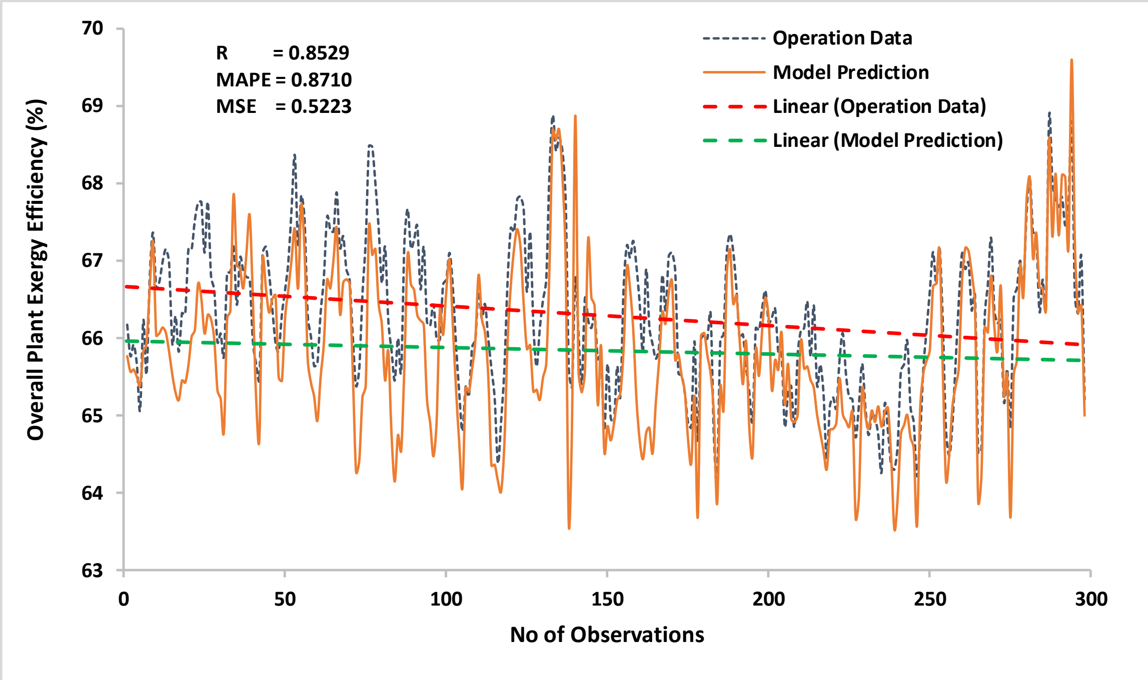


Figure 6: Result of ANN model from testing phase for overall plant's exergy efficiency.

Exergy efficiency of hot well pumps (HWP) was calculated and compared with the prediction result of ANN model. The mean squared error (MSE) was 22.3, correlation coefficient (R) was 0.2378, and mean absolute percentage error (MAPE) was 4.45%. The results show that the performance of ANN prediction of HWP exergy efficiency was poor. However, from linear regression analysis, the ANN model prediction shows similar result with overall plant efficiency as shown in Figure 7.

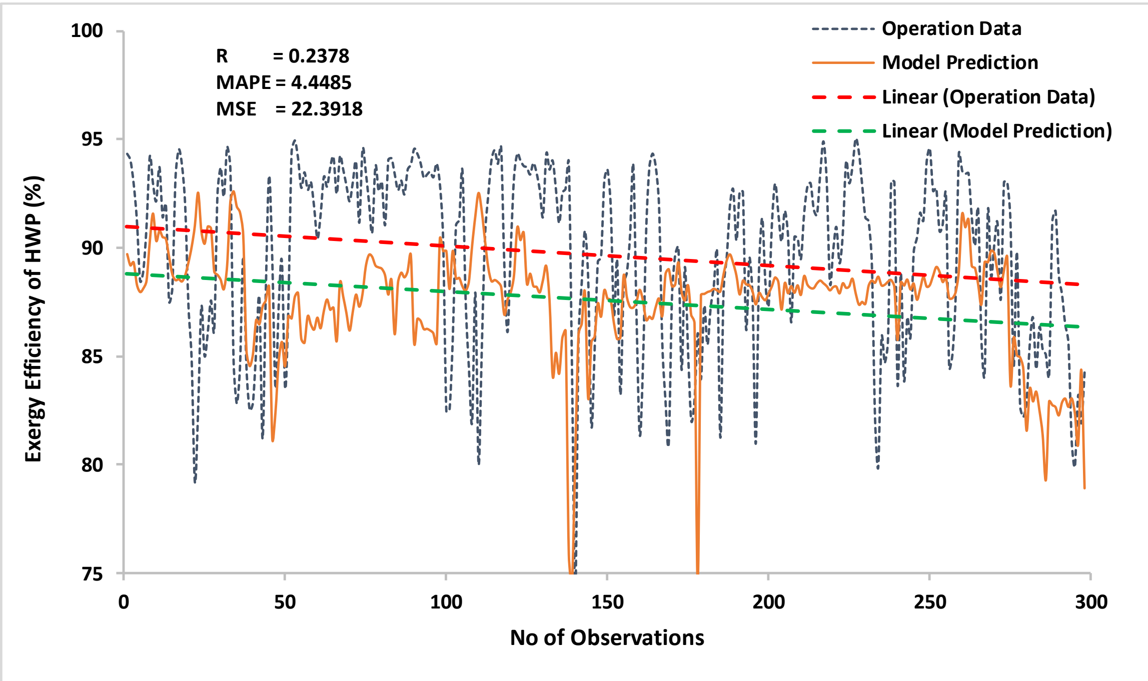


Figure 7: Result of ANN model from testing phase for HWP's exergy efficiency.

Exergy efficiency of cooling tower (CT) was calculated and compared with the prediction result of ANN model. The mean squared error (MSE) was 460.8453, correlation coefficient (R) was 0.3999, and mean absolute percentage error (MAPE) was 39.577%. The results show that the performance of ANN prediction of CT's exergy efficiency was poorer than the HWP's. From linear regression analysis, the ANN model prediction shows different slope compared to overall plant efficiency and HWP's. Furthermore, the regression analysis shows that the prediction result from ANN has better efficiency, as shown in Figure 8.

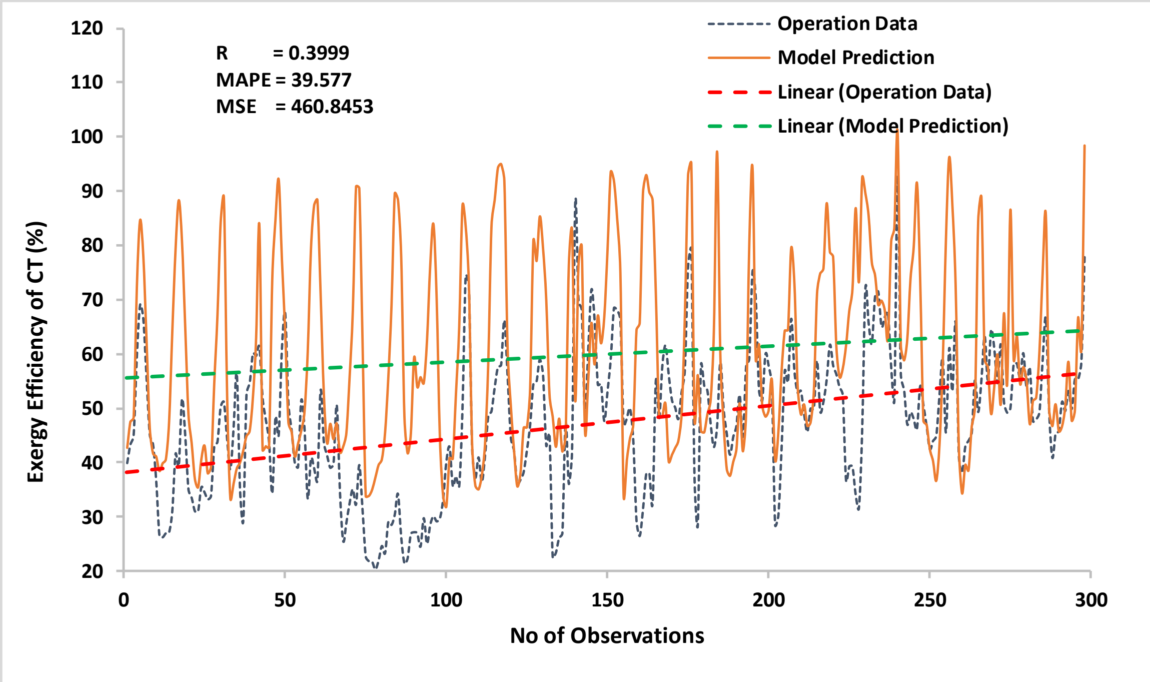


Figure 8: Result of ANN model from testing phase for CT's exergy efficiency.

Exergy efficiency of gas extraction system (GES) was calculated and compared with the prediction result of ANN model. The mean squared error (MSE) was 1.8243, correlation coefficient (R) was 0.5749, and mean absolute percentage error (MAPE) was 4.3532%. The results show that the performance of ANN prediction of GES's exergy efficiency was moderate. From linear regression analysis, the ANN model prediction shows a similar slope compared to the GES's. However, the regression analysis shows that the prediction result from ANN has lower efficiency, as shown in Figure 9.

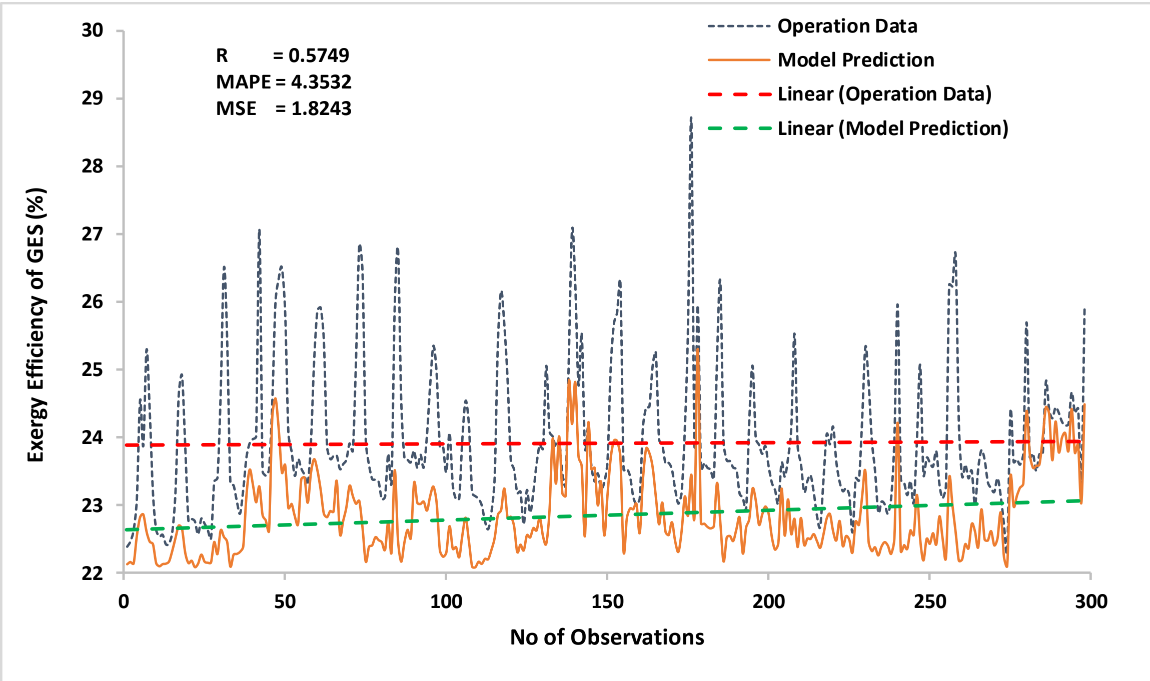


Figure 9: Result of ANN model from testing phase for GES's exergy efficiency.

Exergy efficiency of condenser was calculated and compared with the prediction result of ANN model. The mean squared error (MSE) was 141.7401, correlation coefficient (R) was 0.3255, and mean absolute percentage error (MAPE) was 14.2812%. The results show that the performance of ANN prediction of condenser's exergy efficiency was poor. The regression analysis shows that the prediction result from ANN has lower efficiency, as shown in Figure 10.

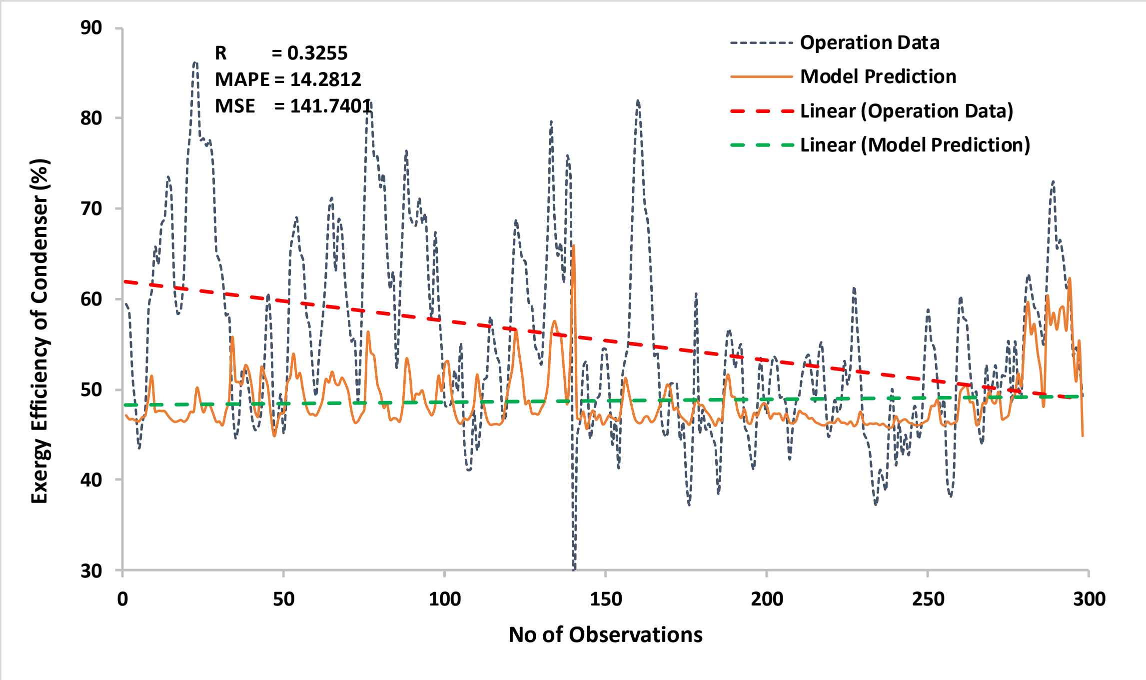


Figure 10: Result of ANN model from testing phase for condenser's exergy efficiency.

Exergy efficiency of turbine was calculated and compared with the prediction result of ANN model. The mean squared error (MSE) was 0.0001, correlation coefficient (R) was 0.9887, and mean absolute percentage error (MAPE) was 0.0058%. The results show that the performance of ANN prediction of turbine's exergy efficiency was the best among the other results. From linear regression analysis, the ANN model prediction shows a similar slope compared to the overall plant and HWP's efficiency. The regression analysis shows that the prediction result from ANN has lower efficiency, as shown in Figure 11.

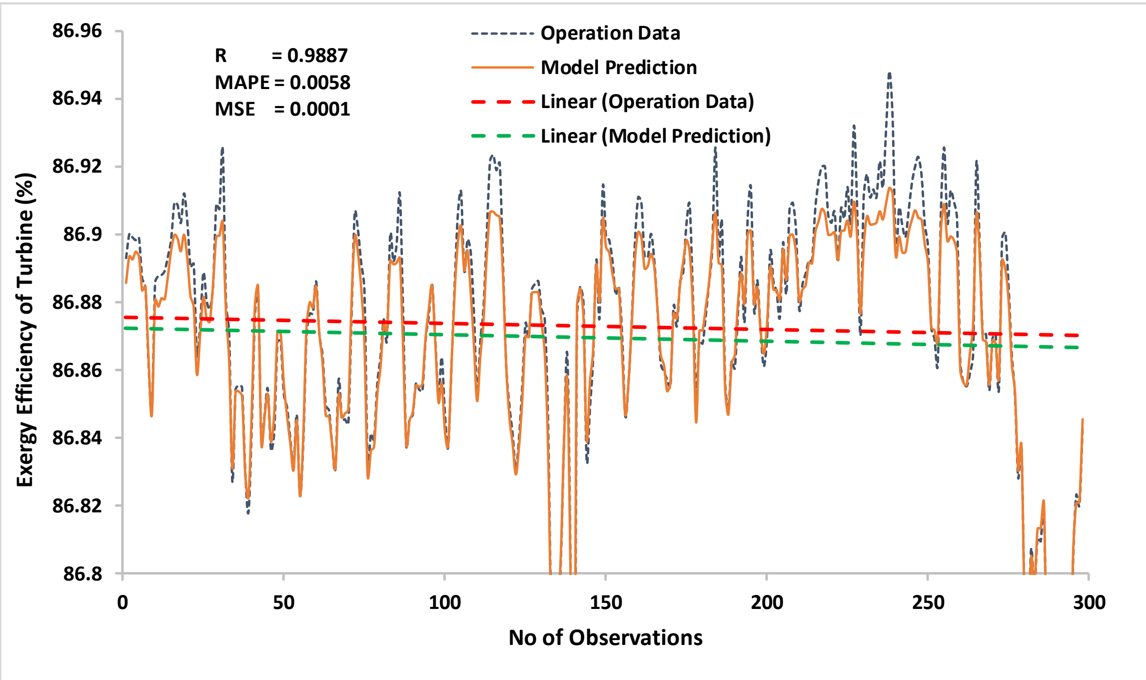


Figure 11: Result of ANN model from testing phase for Turbine's exergy efficiency.

The performance results of ANN models during testing stage to predict exergy efficiency of Ulubelu Unit 3 Geothermal Power Plant is shown in Table 5. The best ANN performance was the turbine's model, followed by the overall plant.

Table 5: ANN model performances during testing stage.

Performance Criteria	Plant Overall	HWP	CT	GES	Turbine	Condenser
R	0.8529	0.2378	0.3999	0.5749	0.9887	0.3255
MSE	0.5223	22.3918	460.8453	1.8243	0.0001	141.7401
MAPE	0.0087	0.0445	0.3958	0.0435	0.0001	0.1428

6. CONCLUSIONS

In this paper, a novel approach to predicting exergy efficiency for geothermal power plant has been investigated. For this purpose, a 6-4-1 network architecture (input-hidden-output) was developed. The dataset used for the ANN's training and testing was taken from Ulubelu Unit 3 geothermal power plant real-time data. From the testing phase, it was found that the ANN model can predict turbine and overall plant exergy efficiency with good result. However, the exergy efficiency for HWP, condenser, and CT were found to be in poor performance, while the GES's exergy efficiency shows a moderate result.

From the exergy analysis perspective, the exergetic efficiency of overall plant from 2016 to 2019 has not changed drastically, which is around 66-68% even though there was a noticeable change in the value of exergetic efficiency in some equipment. This might be affected by the operating conditions, ambient conditions, quality of steam supply, or the conditions of measuring instrument and the equipment itself. From the ANN experiment, it can be shown that ANN method can be developed and used to predict the exergy efficiency of the geothermal power plant. Nevertheless, several improvements are required for future experiments to achieve a better performance of the ANN. The selection of input parameter, the type of ANN's algorithm used for training, the number of hidden layers used in the model, the number of outputs, or filtering of the data used are among the required improvements to achieve better prediction results.

By utilizing ANN method, exhaustive data collection and thermodynamic calculation were not required anymore. The necessity to check and make sure that the input data reading from every instrument used for thermodynamic calculation to achieve exergy efficiency can be greatly reduced since we only need several input parameters to predict the exergy efficiency of the system. The ANN provides an effective analyzing and diagnosing tool to understand and simulate the non-linear behavior of the plant and can be used as a valuable performance assessment tool for plant operators and decision makers.

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