Optimal Operation of Geothermal Power Plant by Artificial Neural Network

Sitthilith Chanthamaly*, Anucha Promwungkwa, and Kanchit Ngamsanroaj

***Abstract*—Nowadays, technologies have been developed rapidly globally to serve the growth of industries, the economy, and society. At the same time, the power energy industry has applied smart technologies widely to protect against failures in operational processes. Machine learning is one of the key intelligent techniques that can solve potential failures in this industry. This research presents an Artificial Neural Network (ANN) of Machine Learning (ML) for predictive maintenance of production wells that require maintenance at a suitable time at the Fang Geothermal Power Plant in Thailand. The raw data covers a period of 48 months (between 2018 to 2021). The data is gathered from log sheets and historical records, covering 1460 instances. Then, this raw data is calculated in the Thermodynamic and Ratio Power Equation. For the ANN model, the dataset has been separated into two sections for the training set and the testing set, including 664 instances in total. In general, there are two types of ANN models, including Classification Algorithms and Regression Algorithms. This study applies the ANN Classification Algorithms for simulating ANN models. The manual classification technique and the K-mean clustering algorithms are applied for determining the targets of the ANN model. In the simulation of the model, the K-mean clustering algorithms produced the best result, with 99.83% accuracy. The experiment demonstrates that the predictive maintenance could predict accurately, under established criteria, and consistent with the previous maintenance schedules. Therefore, the ANN model will assist operators in assessing and monitoring the system to prevent loss of power generation capacity. This means the model can support the maintenance activities and optimize the operation of the Fang Geothermal Power Plant.**

***Index Terms*—Machine learning, production wells, predictive maintenance, K-mean clustering algorithms.**

I. Introduction

The Fang geothermal power plant is located in the northern part of Thailand, Fang District, Chiang Mai Province. As shown in Fig. 1 [1]. The power plant has been designed as a binary cycle. The geothermal water temperature of the system is between 100-120°C to be able to generate electrical energy, which has a total capacity of 300 kW. The electricity generated will be transmitted through a medium voltage of 22 kV. The structure of the Fang Geothermal Power Plant consists of a Vaporizer & Condenser, Turbine-Generator, Working Fluid, Pump, and the control system. as shown in Fig. 2.

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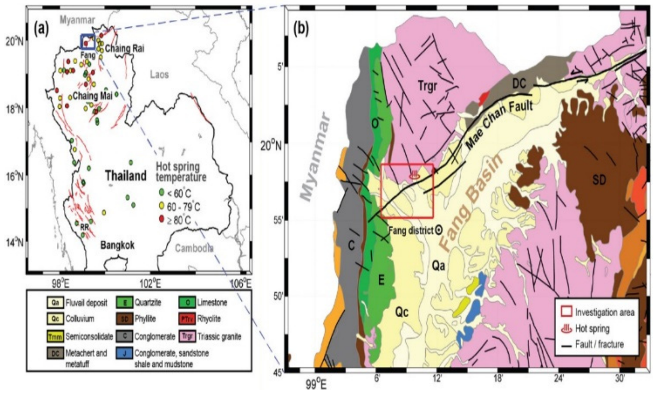

Fig. 1. The project location in Chiang Mai province, Thailand.

Generally, the geothermal power plant system takes in high temperature water from the wells to processing heat into a working fluid in the heat exchanger tank (Vaporizer). Then, the working fluid will vaporize after receiving the heat. After that, the pressure and temperature will increase from vaporization, which will send the steam energy to rotate a turbine of the generator [2].

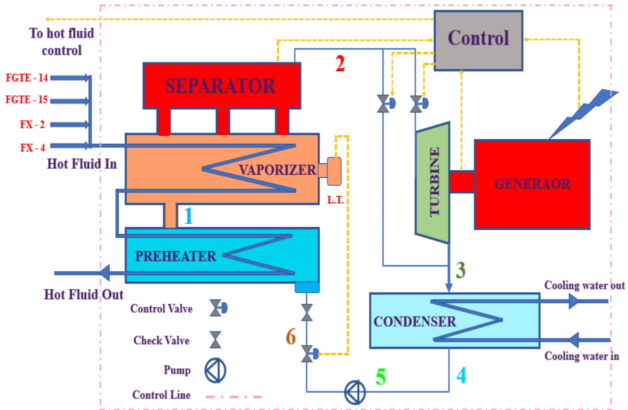

Fig. 2. The binary cycle system at Fang Geothermal Power Plant.

For decades, industries, especially power plants, around the world have developed technologies for preventing damage to their industries. Traditionally, maintenance approaches mostly have applied annual inspection, overhaul planning and monitoring, and waiting until machines damaged. These approaches are unsafe for machines, resulting in a decline in the system's efficiency and an increase of maintenance costs.

Currently, the predictive maintenance (PM) technique has been applied widely by various power plants to indicate the statuses of machines [3]-[5]. The PM method has abilities to detect potential faults during operational processes. The PM method can assist in reducing frequencies of machine failures by using an intervention maintenance approach. Thus, the method helps to support the continuation of operations and

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increase the reliability of a system.

Condition Monitoring (CM) is an important factor in the predictive maintenance approach as CM represents parameters indicating whether failures occur in the machine. These parameters send signals from the sensor to illustrate the actual behavior of the equipment. Then, the signals were recorded as data on computers. The received data can be used in statistical analysis [6]. Which can be applied in machine learning. The machine learning method is a learning process of historical data to predict the future occurrences. This method is called predictive maintenance.

Nowadays, an artificial intelligence method of ML, especially the ANN is considered one of the best techniques for solving problems. In the last decade, an extensive volume of research has applied the ANN to solve complex problems using predictive maintenance technics. S. Das, et al. [7] presented methodologies in conducting the predictive maintenance by using the regression Neural Network Algorithm of machine learning to delineate prognostic health and remaining lifetime of the high-speed milling cutters. Their study showed that the Neural network algorithm yielded the best predicting result for their experiments. S. J. Wu, et la.[8] described the decision support for predictive maintenance based on neural networks. The aims of the research have three components: first, collect the database from the vibration of rolling element bearings; second, using the ANN to estimate the failure time and percent life of roller bearings; and finally, build a cost matrix to optimize the prospective cost per unit time. The integration of condition monitoring, cost analysis, and neural network in predictive maintenance was responded well for optimizing the maintenance activities and minimizing expected costs. M. Bevilacqua, et al. [9] described the optimization and support to decisions making by using preventive maintenance (PM) programs through applying the multi-layer perception-based ANN model. The experiment selected 143 centrifugal pumps. ANN model evaluated and predicted the failure rate occurrence probability of centrifugal pumps. From the result, the ANN model yielded high precisions in prediction of the failure range and proved that the adoption of such maintenance method is viable. Therefore, recently ANNs is a popular technique for modeling and predicting methods. Although the ANN was discovered about 50 years ago. ANN is a mimic of the human brain's biological neural systems. The neuron is an element of the neural network's fundamentals. The neuron is connected in various ways to build a network. By imitating the human brain, and thus an ANN is able to solve complex problems. There are many benefits of the ANN including non-linearity, simplicity, speed, flexibility, and adaptive learning. From many research and wide applications of the ANNs, they showed that ANNs have been used successfully in a number of applied areas such as neurology, engineering, medicine, economics, meteorology, etc [10], [11]. At the same time, ANN is used in the energy area. The development of ANN model in energy systems has been a focus of considerable number of researchers. F. Grimaccia et al. [12] described management of the variable complexity by using the ANN model for decision support to predict the production of a real run-off-river hydroelectric power plant. R. M. Brandão, et al. [13] presented the application of the ANN to fault detection of the electrical generator of the wind turbine. The simulation received data into the model from the temperature, including environment, hydraulics, gear oil, generator, slip ring, bearing, hup control, and nacelle. The experiment of the ANN model is a valid method and has high accuracy in the detection of failures in wind turbines. C. Fu, et al. [14] presented the intelligent-control-maintenance-management system (ICMMS) framework with the ANN model. The objective of the paper is to control maintenance, technical management aspects, and right maintenance at a suitable time within ICMMS by using the ANN for predictive maintenance. The experiment is a diagnosis and predictive maintenance of the electrohydraulic servomechanism with according to three elements - monitoring and forecasting, diagnosis and prognosis, and maintenance decision-making. The ANN model shows satisfactory results for predictive maintenance for the electrohydraulic servomechanism, and thus, it can be applied to other equipment in the hydropower. D. Ruliandi, [15] presented applying the feedforward backpropagation ANN for the prediction of steam consumption unit 4 Kamojang of Geothermal Power Plant (GPP). The dataset for the training of the ANN model received from the turbine generator, cooling tower, steam input parameters, ambient parameters, and condenser parameters. The dataset was divided into 2 sets of training - commissioning data and training major overhaul data. In the testing stage, the ANN model performed moderate results. In the experiment, when an independent measure of steam flow combined with good and sufficient training data, the ANN method can be applied to develop a good performance program and identify the degradation of the plant. C. Yilmaz, and I. Koyuncu, [16] focused on the thermodynamic analysis by using the Multi-Layer Feed-Forward ANN to optimize the Afyon Geothermal Power Plant. The raw data was recorded from the Binary Geothermal Power Plant, which was divided into two datasets - 80x8 training and 20x8 test. The result of the ANN model shows an optimized value of thermodynamics, payback period, and exergy costs. J. L. C. Fannou, et al. [17] studied an application of the ANN model to predict the direct expansion geothermal heat pump. The Levenberg Marquardt (LM) algorithm was used for the training model. The dataset was collected from the discharge pressure, inlet temperature of cooling water, the pressure and temperature inlet/outlet of evaporator. The best result was shown on the LM with 28 neurons on a hidden layer. W. Gang, et al. [18] described creating the predictive control strategy with the ANN model by comparing with the traditional control strategies. The ground source heat pump (GSHP) was selected in this study. The data collection covered 13 weeks for the training model. The dataset was trained by Levenberg Marquardt (LM) algorithm. The ANN model was analyzed in four-years to compare with the conventional operation for each method. The result demonstrated that the new control strategy can make a full application to the advantage of soil and outdoor air. At the same time, it improved energy efficiency. O. Arslan, [19] focused on the improvement of the ANN model to optimize Kalina cycle system-34 in the Simav geothermal field. Three types of back-propagation learning algorithms such as Levenberge Marquardt (LM), Scaled Conjugate Gradient (SCG), and PolaeRibiere Conjugate Gradient (CGP) were used to find an approach and approve the viability of the

ANN model. Its best result was shown in the LM algorithm with 7 neurons in the hidden layer. J. Teeter, et al. [20] described the design of automatic control systems in the plant by the ANN model. The functional link network approach was built to compare with the conventional network approach. The ANN was designed to up-speed the training speed and minimize the complexity in the analysis to estimate future plant outputs and sensitivity information for online neural control adjustment. Similar to the above-mentioned studies, this research aims to build an artificial neural network of machine learning on the ML tool (Rapidminer Program) for improving maintenance activities. This method will be used as a guideline for operators as an alternative maintenance method on suitable times of production wells to optimize the power generation at the Fang Geothermal Power Plant.

The structure of the paper is presented. Following the Introduction in Section I, Section II describes a theory of the determination of parameters with a calculation of mathematic engineering and an Artificial neural network. Section III presents the methodology applied for this research. The result of this research is presented in Section IV, and the last section, which is Section V, is the conclusion of this research.

II. Relevant of Theory

A. Mathematic Engineering

Generally, the thermodynamic analysis such as mass, energy, and exergy will be received from the balance equations [21]. And the thermodynamics of steady-state, steady-flow processes will be able to calculate the value of the heat input, the exergy decrease, the efficiency of energy and exergy, and the rate of irreversibility, respectively. The energy balance and efficiency of thermodynamics equation (1)(2) are used here.

B. Energy Analysis

When analyzing the rate of kinetic and potential energies constant, the rate of energy balance is expressed by

$$\dot{E}_\iota = \dot{m}_\iota \, (h_i - h_0) \tag{1}$$

where $\dot{m}_\iota$ and h are the mass flow rate and indicating enthalpy.

The energy efficiency of a system is expressed by

$$\eta_1 = \frac{\dot{E}output}{\dot{E}\ input} \tag{2}$$

where, E (output), and E (input) represent total energy output to total energy input, respectively.

C. Ratio Power

The Ratio of power can be expressed by:

$$Ratio = \frac{P_{(per\ day)}}{P_{(max)}} \tag{3}$$

where, P (max) and P (per day) are energy maximum and energy rate per day, respectively.

D. Artificial Neural Network

The artificial neural network is interconnections between the neurons in the different layers of each system. The neural network is arranged in layers. It has associated nodes which include activation functions. The structure of a neural network contains input, hidden, and output layers respectively. For the designed structure of an artificial neural network, the neurons of input layers are interconnected with neurons of hidden layers and a similar pattern is seen across hidden and output layers. The features used dataset define the number of neurons in the input layer and similarly, several classes decide the number of neurons in the output layer. And the random weights are determined as the initial point connecting all the layers. Between the hidden nodes and output have a special function called the activation function [22], [23].

Generally, there are several types of ANN that are commonly used such as Feedforward Neural Network, Radial Basis Function Neural Network, Kohonen Self Organizing Neural Network, Recurrent Neural Network (RNN), Convolutional Neural Network, Modular Neural Network, etc. To understand in detail, the following sample can be used, which is shown in Fig. 3.

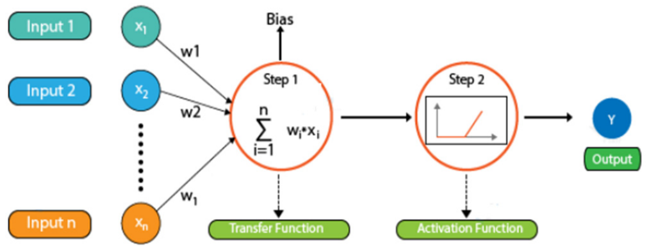

Fig. 3. Structure of the neural network.

The artificial neural network is expressed mathematically as follows [24]:

$$y_i = g_i \left(\sum_{j=1}^{n} w_{ij} x_j + b_i \right) \tag{4}$$

where xj, Yi, wij, bi, and gi are input to the node, the output of the node, interconnection weight between the node, the bias of the node, and the activation function respectively.

The data analysis of the ANN model will be evaluated by the performance measurement methods, which consist of regression and classification performance measurement. For the mean squared error (MSE), mean absolute percentage error (MAPE), root mean square error (RMSE), correlation coefficient (R), and coefficient of determination (R2) were calculated the error in regression type. And the confusion matrix has calculated the error in classification type [25]. The measurement indicates the accuracy of the model for training when compared to the predictive result of the data testing. The confusion matrix was selected to measure the performance of the ANN classification. The performance measure is expressed by the coefficient of determination (confusion matrix)

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

where ACC, TP, TN, FP, and FN are accuracy, true positive, true negative, false positive, and false negative number, respectively.

III. Methodology

A. Data Mining

The data collection demonstrates the behavior and status of the system at Fang Geothermal Power Plants. Generally, conditions indicating the status of the system include a normal stage, alarm stage, changeover of the signal, etc. These conditions are analyzed by the operator and maintenance experts through visual inspections and observations, which is time-consuming and negatively affects the efficiency of power generation. Therefore, this study selects three conditions, Normal, Warning, and Failure to indicate the status of the power generation process. The data used in the experiment has been recorded hourly on the log sheets between 2018 and 2021, consisting of 1460 instances. The raw data covers fifty-nine ranges and seventeen attributes in the log sheet of the power plant's operation, the data from Fang Geothermal Power Plant is complex, with different characteristics, as shown in Fig. 4. Therefore, these data sets are cleaned by ignoring, filtering, and deleting outliers, and removing them before training the model. This is to simplify the data sets and increase the accuracy of the model. The remaining attributes after completing the data preparation process are date and time, energy, and power ratio, which have been applied for training the ANN model. These attributes have been calculated by the Thermodynamic Balance Equation and Power Ratio Equation (1)(2)(3). The final total data set consists of 643 instances, 41 ranges, and three attributes for the ANN model.

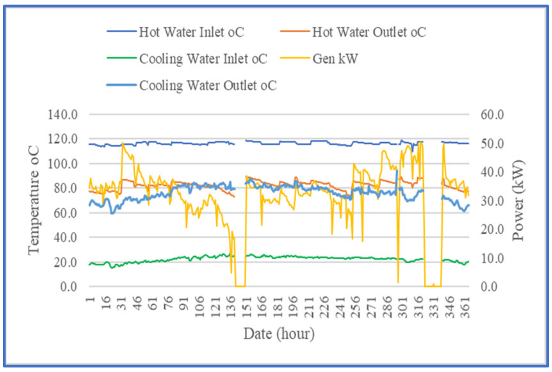

Fig. 4. Graph of raw data of the Fang Geothermal Power Plant.

The data set has been received from the data mining process. The original data has been presented as hourly for 24 hours/day, but for this study, the data has been converted as average daily usages in the period of operation. The total data set consists of 643 instances and 41 ranges. The data set has been divided into training and testing sets for the ANN model. 574 instances and 36 ranges are applied for the training purpose, while 89 instances, and 5 ranges are used for testing the ANN model. The ANN Classification Algorithm of supervised machine learning has been selected as the key simulator to predict and evaluate the performance of the model. The input of the model consists of three attributes: date-time, energy, and power ratio, which is a result of the calculation using the Thermodynamic and Ratio Power Equation. The output of the ANN model has been defined, using two techniques. First, the output of the model is determined manually in three targets: 2 = Normal, 1= Warning, and 0 = Failure. The manual technics for the output of the ANN model are divided into three levels: 2-1-0. The period of operation is divided into 3 equal parts, as shown in Table I.

TABLE I: The First Manual Technique for Output of the ANN Model

Date Time	Energy	Ratio Power	Output
1	6034	1.00	2
2	6006	1.00	2
3	5996	0.99	2
4	5814	0.96	2
5	5780	0.96	2
6	5732	0.95	1
7	5626	0.93	1
8	5623	0.93	1
9	5513	0.91	1
10	5430	0.90	1
11	5394	0.89	0
12	5321	0.88	0
13	5412	0.90	0
14	5419	0.90	0
15	5129	0.90	0

At the same time, the second manual technique is divided into three levels. The last 4 days in the period of operation are set on level 0=Failure, as shown in Table II.

TABLE II: The Second Manual Technique for the Output of the ANN Model

Date Time	Energy	Ratio Power	Output
1	5129	1.00	2
2	4981	0.97	2
3	4800	0.94	2
4	4758	0.93	1
5	4602	0.90	1
6	4530	0.88	1
7	4488	0.88	0
8	4414	0.86	0
9	4262	0.83	0
10	4115	0.80	0

Second, the output of the model is investigated by the K-mean Algorithm of unsupervised machine learning [26]. The K-mean clustering algorithm is used to classify the response classes for the output of the ANN model, as shown in Fig. 5 and Fig. 6 respectively. The scatter port indicates the status of the ANN model output as level 0 = Normal Operation, 1= Warning for Maintenance, and 2 = Require Maintenance.

Many kinds of prediction methods are available, which use statistical data for predicting future values. This study uses the data of the daily log sheets at the Fang Geothermal Power Plant. The objective is to produce the predictive maintenance for the production wells by the Backpropagation neural network (BPNN) Models on the ML Tool (Rapidminer Program) [27]-[30]. The ANN model consists of three layers in the system, including the input layer, hidden layer, and output layer, respectively. Generally, each layer will connect by the synapse to communicate signals and transfer information between the layers. The processing steps of the ANN model are shown in the following flowchart [31]. As shown in Fig. 7.

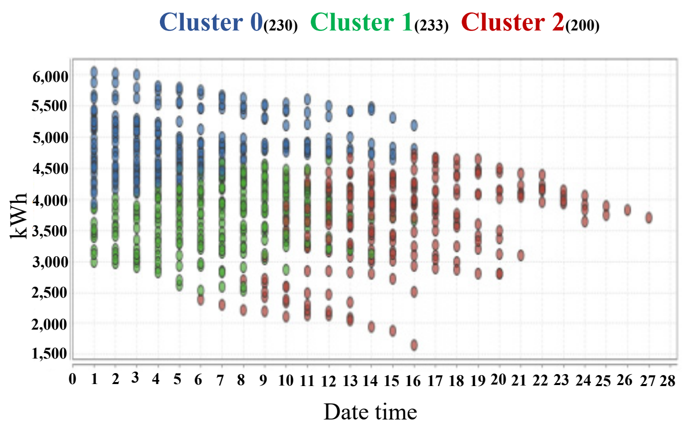

Fig. 5. The K-mean Clusterıng scatter port of date-time with kWh.

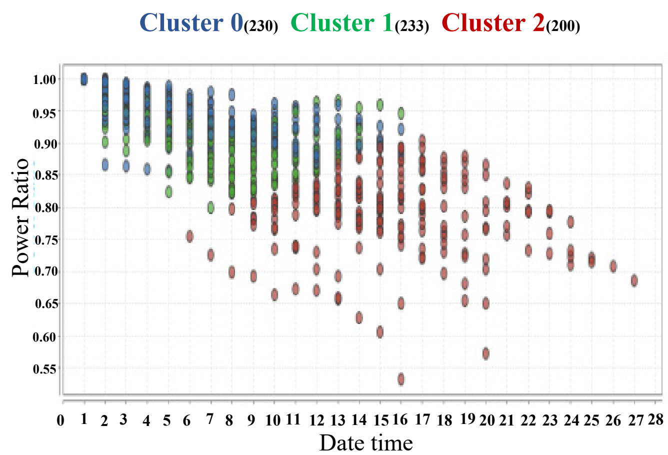

Fig. 6. The K-mean Clustering scatter port of date-time with power ratio.
Development of ANN model.

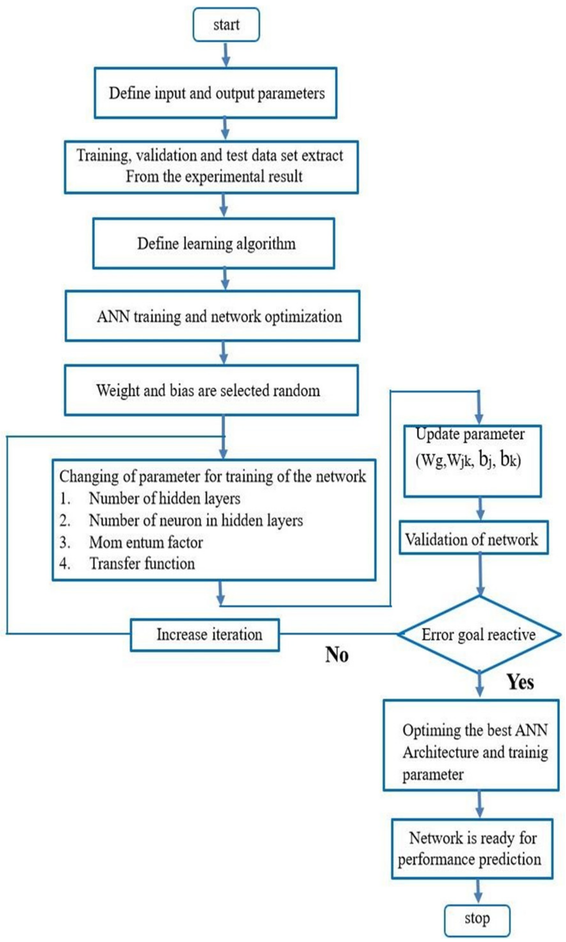

Fig. 7. Flowchart of the ANN model.

IV. Result

This study uses the ANN Classification Algorithm of supervised machine learning. For the input of the ANN model, it applies three attributes: date and time, energy, and power ratio. The output of the ANN model is defined in three levels of response classes. Two techniques such as the Manually Classified Technique and the K-mean Clustering Technique are applied to classify the response classes output of the ANN model. The manual classification is determined by the three response class outputs: 2 = Normal, 1 = Warning, and 0 = Failure. The accuracy of the ANN model is 73.34%, as shown in Table III.

TABLE III: The ANN Classification Training Model (Manual Technique)

	True cluster 0	True cluster 1	True cluster 2	Class precision
Pred. cluster 0	184	28	1	86.38%
Pred. cluster 1	34	163	69	61.28%
Pred. cluster 2	0	21	74	77.89%
Class recall	84.40%	76.89%	51.39%	

Accuracy: 73.34%

The determination of response class outputs by the k-mean Algorithm is indicated as 0 = Normal, 1 = Warning, and 2 = Failure. The accuracy of the ANN model using the k-mean Algorithm is 99.83% as shown in Table IV.

TABLE IV: The ANN Classification Training Model (K-mean Technique)

	True cluster 0	True cluster 1	True cluster 2	Class precision
Pred. cluster 0	200	1	0	99.50%
Pred. cluster 1	0	209	0	100%
Pred. cluster 2	0	0	164	100%
Class recall	100%	99.52%	100%	

Accuracy: 99.83%

The experiment results of the two techniques for classifying the response class outputs are compared by using the Confusion Matrix. The accuracy result is shown in Table V.

TABLE V: The Result of ANN Classification Model

ANN model	**Output Classify by**	**Result Accuracy (%)**	
		Training	**Testing**
Classification	**Manually**	**73.34**	**76.4**
	K-mean	**99.83**	**100**

According to Table I, the performance of the ANN model can be concluded as follows: the best result of classifying the response classes by the k-mean Clustering Algorithm for the ANN model can predict with a high accuracy rate of 99.83%. The calculation in the Confusion Matrix for data testing has a similar high accuracy rate of 100%. Based on the observation, the prediction of the ANN model will respond to the class output levels of the maintenance schedule, when power generation changes or ratio power decrease in the period of operation. The result demonstrates that the prediction is correct in following with the established criteria (Normal = 0, Warning = 1, and Failure = 2). Thus, it can be stated that the simulation has a precise prediction. The ANN Classification Algorithm has shown similar high accuracy when compared with previous maintenance activities. The response classes output of the ANN model in Class 0 and Class 1 indicate the normal status of power generation. At the same time, the response class output in Class 2 represents an abnormal status of the power generation and requires maintenance. Therefore, maintenance activities can be undertaken based on the results of the response classes in the ANN model. It is seen that the prediction result is consistent with the established target. This means the method has abilities to optimize maintenance activities at the Fang Geothermal Power Plant.

V. Conclusion

This research studies an Artificial Neural Network (ANN) of machine learning as an alternative for predictive maintenance of production wells that require maintenance at a suitable time at the Fang Geothermal Power Plant. The raw data from the Fang Geothermal Power Plant's system between 2018 to 2021 is applied to predict the remaining useful life of the production wells by using the Classification Algorithm of the ANN model. The prediction of the ANN model is validated to identify its accuracy. The experiment reveals that the outputs from the k-mean clustering in classification algorithms of the ANN model have the highest accuracy when compared to the manual classification outputs. The accuracy of the ANN classification algorithms is calculated in the confusion matrix through testing steps to find an error rate. In the simulation of the ANN model, the prediction has good performance and high accuracy. The prediction results follow the established criteria and are under the previous maintenance schedules. This model will be able to assist operators to decide on maintenance interventions. In addition, the model can be used as guidelines for planning maintenance activities to optimize operation the system in the Fang Geothermal Power Plant.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Sitthiltih Chanthamaly conducted the research, analyzed the data, and wrote the paper. Anucha Promwungkwa and Kanchit Ngamsanroaj provided advice for conducting the research, analyzing the data, and reviewed the paper. All authors had accepted and approved the final version

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