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Performance Optimization of Gas Turbine Generator Based on Operating Conditions Using ANN-GA at Saka Indonesia Pangkah Ltd

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***Abstrak*—A Gas Turbine is a rotary engine that extracts energy from a flow combustion gas. The reliability and efficiency of gas turbines is one of the top priorities at Saka Indonesia Pangkah Ltd (SIPL). In order to optimize the operating conditions of a gas turbine, three components are needed. First is the problem formulation which consists of objective functions, problem boundaries or contrains and determination of optimized variables. Second component is a valid model, which represents the characteristics of a gas turbine installed in SIPL. Third component is the optimization technique that is suitable with the optimization problem that will be solved. In this paper, the objective function is maximizing gas turbine efficiency, some operational limitation as constrains by manipulating air to fuel ratio. The model was developed using Artificial Neural Network (ANN) and Genetic Algorithm (GA) was selected as the stochastic optimization technique to solve the problem. The neural network model created directly using the operational data from an actual parameter gas turbine generator. The data needed for ANN-based modeling is around 8150 data sets that will be used to train and validate the ANN model. Variable data sets were divided in two parts, for training purposes is 87.5% and for validation is 12.5%. Weight management for neural networks was carried out using Levenberg-Marquardt algorithm which could give good results with RMSE = 7.3 X 10-3. From the results of the stochastic optimization (GA) simulation, the potential reduction of fuel gas consumption is around 280.8 kg/hr if the air mass flow can be increased from 2.4 kg/s to 2.7 kg/s or efficiency increase up to 10.6%.**

***Keywords*—Fuel Optimization, Gas Turbine Generator, ANN, GA.**

I. INTRODUCTION

GAS turbine (GT) is considered as an internal combustion engine which converts chemical energy from fuel to mechanical energy using the gaseous energy of air as the working fluid. The reliability and efficiency of Gas Turbines is one of the main objectives at Saka Indonesia Pangkah Ltd. Modeling and ANN Simulation in Gas Turbines is a powerful and cost-effective tool for system identification and optimization of gas turbine performance, so that it can be used to predict gas turbine output parameters based on changes in system input with high accuracy, decreased performance, emissions evaluation and engine control systems. Artificial neural networks are inspired by the human brain and are built to simulate the interconnected networks that have the ability to perform pattern recognition, classification and prediction [1]. Many problems deal with researchers can be fixed using neural network models that are principally helpful in some cases such as simulation, fault diagnosis and sensor validation of heat and power plants [2],[3].Relation between input and output seem complicated through modelling therefore considered ANN nonlinear statistical data modelling tools in a simple way. Therefore, the network is trained to learn in a recognition instituted on the input and output [4].

Using data captured during the operation of the Gas Turbine Generator from data logger TT4000 we can generate neural network models, when the operational data are not available, the simulated data can be generated by software engineering. A simulation model can be developed to predict the actual condition of engine performance. In this paper, a proposed ANN-GA simulation model developed to estimate the gas turbine engine performance optimization through a simple GUI.

In this study, optimization means the maximization of the Efficiency (η) value related to fuel usage. The greater the value the less fuel consumption and efficient. Asgari et al. introduced the Artificial Neural Network (ANN) model for simulating single shaft gas turbine operations [5]. Development of ANN-based research for the identification of offline gas turbine systems based on a combination of various training functions, number of neurons and transfer functions using the multi-layer perceptron (MLP) structure is needed to improve the performance of gas turbines. ANN modeling can be applied reliably to identify gas turbine systems and can predict Gas Turbine output parameters based on changes in system input with high accuracy.

II. RESEARCH METHOD

A. ANN Model Based Operational Data

Neural network model of gas turbine can be generated by using different techniques depending on the underlying network structure and associated training algorithm. Therefore, the preferable structure for ANN is the one that can expect dynamic behaviour of the system as precisely as probable based on some basic steps [6].

One of the vital steps of neural network model is data acquisition and chosen variables. This step is considered as a first step on modelling and controlling industrial system based on neural network. In which, the neural network model can be created directly using the operational data from an

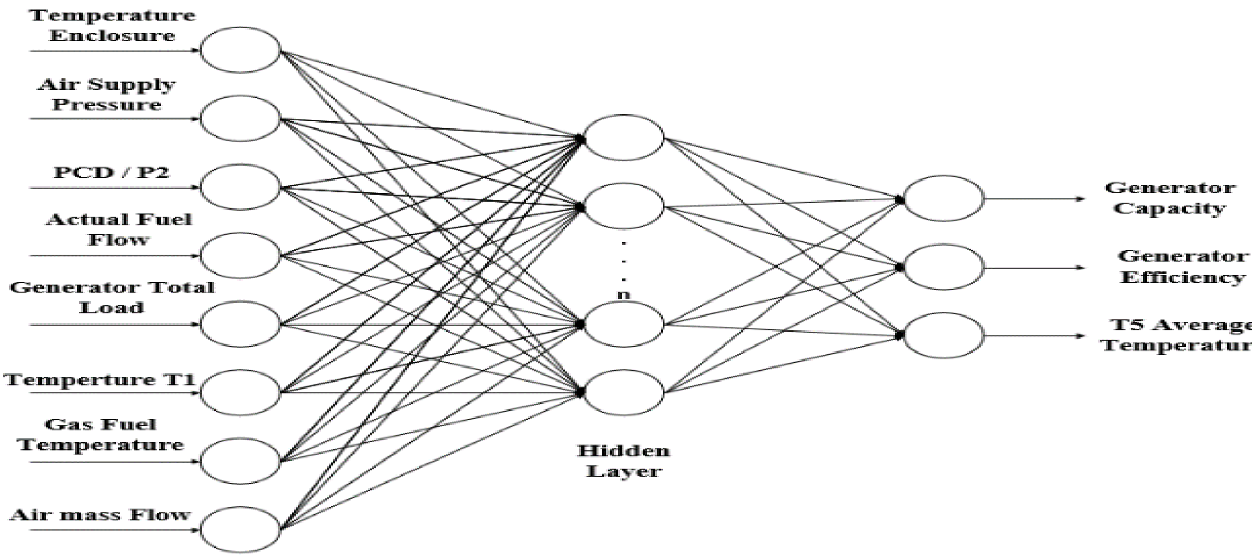

Figure 1. ANN architecture of Gas Turbine.

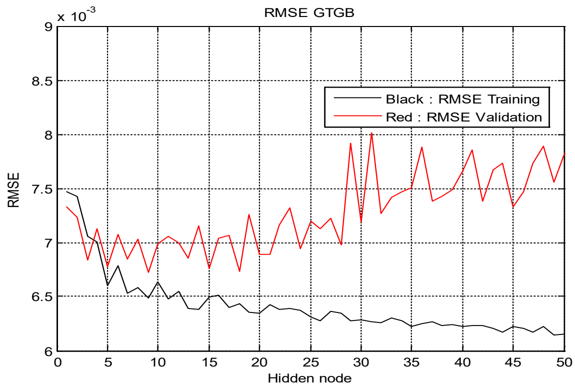

Figure 2. Graph of Root Mean Squared Error (RMSE) GTG.

Table 1.
ANN input and output

Input	Air Supply Pressure (barg) PCD /P2 (barg) Actual Fuel Flow (kg/s) Generator Total Load (kW) Temperature T1 (ºC) Gas Fuel Temperature (ºC) Turbine Air Inlet DP (mbar) Air mass flow (kg/s)
Output	Generator Capacity (Calculated from TT4000) Generator Efficiency (%) T5 Average Temperature (ºC)

actual gas turbine available in a variety of industrial power plants. When an operational data are not available, a simulated data can be generated by software engineering. This data is fed to the network to make a preliminary model for data generation as proposed in this paper. The obtained data should cover the whole operational range of the system, and all passing data during start or stop processes should be removed from the collected data before the modelling process.

ANN used in this research is Multi Layer Perceptron (MLP) with Finite Impulse Response (FIR) input structure and trained with Levenberg-Marquardt training algorithm. The training algorithm used in this research is the Levenberg-Marquardt for neural network training algorithm. Although this training algorithm is more complex than the back-propagation algorithm, this algorithm is able to produce better results. derivation for Levenberg-Marquardt algorithm can be seen in the journal written by Norgaard which discusses the application of artificial neural networks in modeling and controlling dynamic systems [7]. The ANN architecture of Gas Turbine used is shown in Figure 1.

ANN model was developed using operational data from the plant. Training data for this ANN was collected during two years of operation in 2018-2020. Survey and data collection are needed to determine the problem, model and determine what variables are available and can be used in solving this optimization problem. From the data collection obtained several variables that are available and can be used in modeling using ANN. The data needed for ANN based modeling is around 8150 data sets which will be used to train and validate the ANN model. The variable data set was divided in two parts, for training purposes is 87.5% and for validation is 12.5%.

The proposed neural network model for gas turbine consists of three main stages as follows:

1) Stage 1(training)

Stage 1(training): This stage includes the calculation of neural network weights that determined by randomly initializing connection weights. The selection of input data and chosen output variables are presented in this stage. One hidden layer was chosen and the network was optimized regarding the number of neurons in this layer [8].

2) Stage 2(validating):

Stage 2(validating):This stage includes measuring the network's performance during training according to a certain conditions (RMSE reached 6.6 x 10^{-3}). In case if it does not have any notable progress, the training process stops [9].

3) Stage 3(testing):

Stage 3(testing):In this stage, the test set provided to the network to ensure that a correct generalization capability has been obtained. In the proposed model, a new data set that was different from data, which used in the training process, is

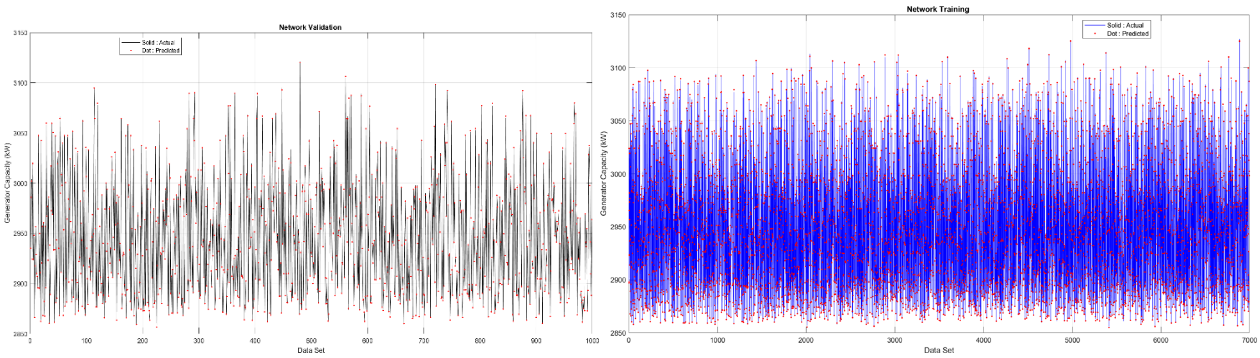

Figure 3. Data Training and Validation NN Generator Capacity.

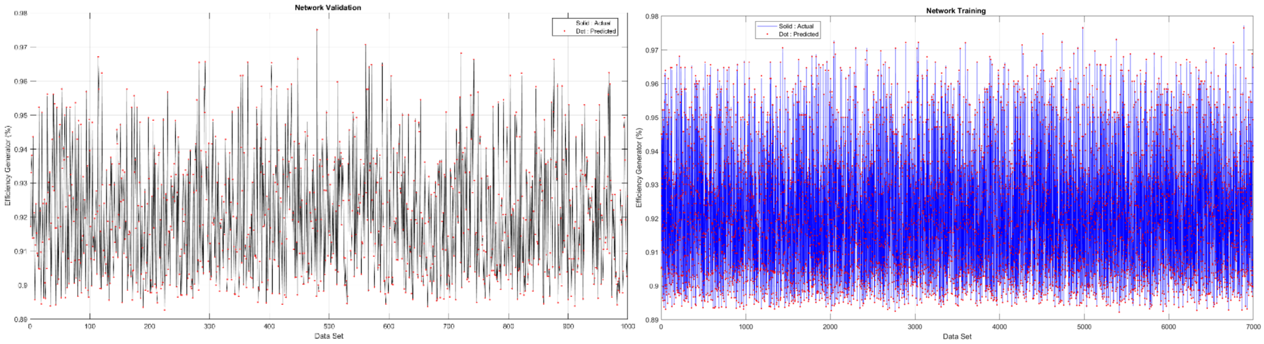

Figure 4. Data Training and Validation NN Generator Percent Efficiency.

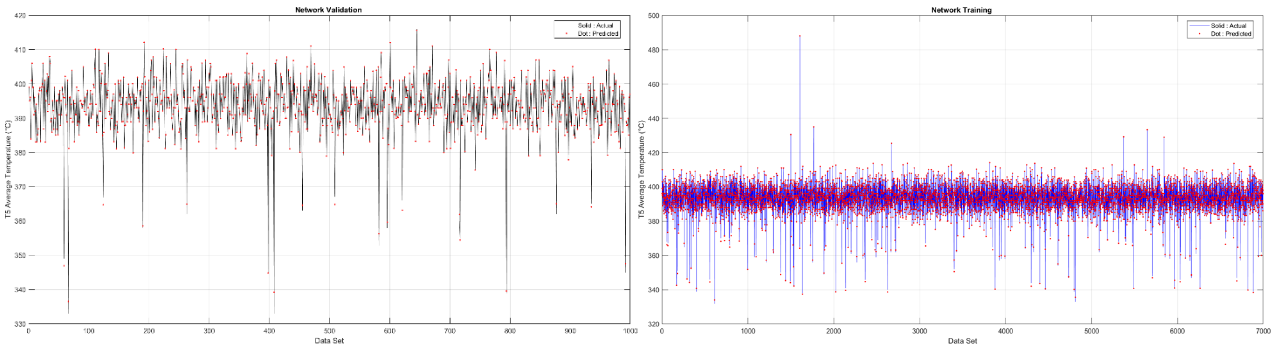

Figure 5. Data Training and Validation NN T5 Average Temperature.

provided. The validation of the Gas Turbine Generator (GTG) model is done by providing the input that has not been trained to ANN and recording the Root Mean Squared Error (RMSE). The basis for determining the best ANN model is the number of hidden nodes (HN) that produce the lowest RMSE training and validation values. Figure 2 shows the lowest RMSE during training and validation is at HN 9 reached 6.6 x 10^{-3}.

$$RMSE = \sqrt{\frac{\sum_{i-1}^{n}(y_i - \hat{y}_i)^2}{N}}$$

where
N: total number of data
y_i: represents observed values
$\hat{y}_i$: represents predicted values

B. Generator Efficiency Using Genetic Algorithms

The optimization used is the Genetic Algorithm. Genetic Algorithm is an adaptive method commonly used to solve for an optimization system. Genetic Algorithm (GA) in this research is designed to produce the best optimum value. The most difficult part of designing GA is the determination of the objective function and the fitness function, because a slight error in the objective function and the fitness function can produce a GA that is less good at doing optimization. The objective function of GA Optimization used in this research is to increase the efficiency of the Generator and predict T5 average temperature, so when the power generator predictions can reach the maximum capacity T5 average temperature is still below the T5 high setpoint.

Genetic algorithm is used as an optimizer in this research. The genetic algorithm is known as the initiation process which consists of the selection, crossover, and mutation processes [10]. For this research, there are variations of chromosomes in one generation [11]. The maximum generation used in this research is 200, which means the total population will be 20,000. The chromosomes are processed using three operators, namely: selection, crossover, and mutation. In this research, elitism is also implemented in this optimization. Elitism is a mechanism that guarantees top-fit chromosomes in a population are always taken to the next generation. For this research, the optimizer used elitism by 5%, crossover probability (Pc) by 0.7, and mutation

Before Optimization	Air Supply Pressure	PCD (P2)	Actual Fuel Flow	Generator Total kW	T1 Temperature	Gas Fuel Temp	Turbine Air Inlet DP	Air mass flow	Generator Capacity	Generator Efficiency	T5 Average Temperature	AFR
MIN	6.67	6.68	0.0775	283	14.9	35.2	11.3	0.670934	2856	0.8925	332	6.51041
MAX	7.39	7.53	0.242222	1673	33.2	62.1	12.9	2.447537	3127	0.9771875	488	19.08412
After Optimization	**Air Supply Pressure**	**PCD (P2)**	**Actual Fuel Flow**	**Generator Total kW**	**T1 Temperature**	**Gas Fuel Temp**	**Turbine Air Inlet DP**	**Air mass flow**	**Generator Capacity**	**Generator Efficiency**	**T5 Average Temperature**	**AFR**
A wide range of operating data	6.8	6	0.4	1341	16.6	30.2	10.5	1.9	3.20E+03	1	440.4008	4.6885
Constraint Variable Output T5 range 680 - 740	7.1	7.4	0.1	2377.2	31	27.1	12.5	2.7	3.20E+03	1	695.015	24.7279
Constraint Variable Output Eff: 0.9 - 1, Generator Total KW: 2000 - 2800 KW and AFR: 14-20	6.9	7	0.2	2567.3	20	54.9	11.3	2.2	3193.3	0.9916	409.9	19.8

Figure 7. Optimum value after optimization.

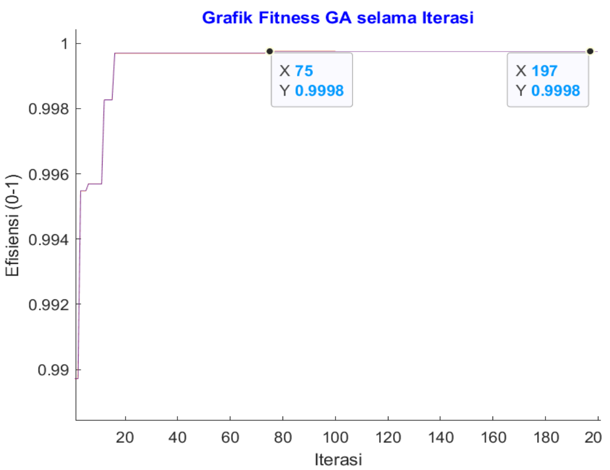

Figure 6. Genetic Algorithm fitness graph.

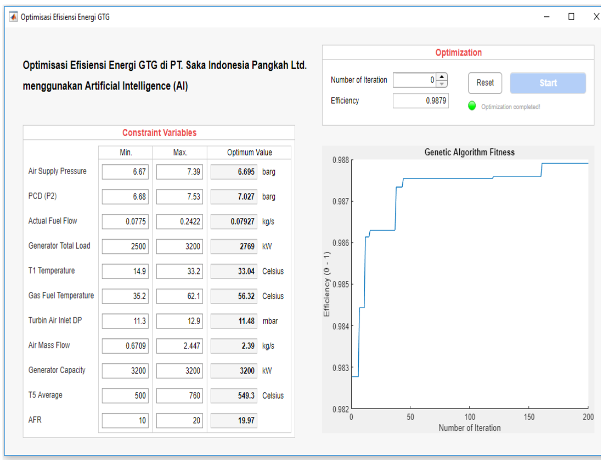

Figure 8. The GUI of ANN-GA.

probability (Pm) by 0.001. According to the optimization parameter described, 200 chromosomes for each generation were produced using GA as overall heat transfer coefficient. Initial chromosomes (genotype) in the first generation were chosen randomly. Each scenario corresponding to a chromosome was simulated in the GTG simulation model. The GTG simulation estimates the optimum value under the constraint input variables.

The process of estimation of fitness values is repeated until the 200th chromosome. Then a new population is generated following the GA procedure of selection, crossover and mutation. In each generation, the fitness value of each chromosome in the GA was calculated and evaluated. By using elitism 5%, it means the 5% best chromosomes were copied to the new population, while the rest were copied using a classical method. Such individuals may be lost if they are not selected to reproduce or if they are destroyed via crossover or mutation.

The 95% of the chromosomes were processed in single-point crossover, with crossover probability (Pc) of 0.7, where the two mating chromosomes are cut once at corresponding points and the sections after the cuts are exchanged. A cross-site or crossover point was selected in random along the length of the mated strings and bits next to the exchanged cross-sites. After crossover, each individual has a small chance of mutation (Pm = 0.001). Pc and Pm values were chosen based on Goldberg's study (1989) [12],[13].Thus, this process is repeated until the 200th chromosome and the given generations are simulated or if the maximum fitness has been reached. The best fitness value was used to choose the chromosome corresponding to the gas turbine efficiency.

III. RESULT AND DISCUSSION

In order to find the best model for the gas turbine engine, the generated code was run in MATLAB and the data needed for ANN based modeling is around 8150 data sets which will be used to train and validate the ANN model. After training, ANN needs to be validated using data that has never been used during ANN training. For training the total is 7000 data (87.5%) while the remaining 1000 data (12.5%) for validation. The results of the trainings were recorded and the performances were evaluated and compared in terms of their root mean squared errors (*RMSE*). Finally, the most accurate

MLP with minimum *RMSE* was selected and tested again to assure good generalization characteristics of the model. Figure 2 indicates the best performances in terms of different training functions.The list of input and output parameters for this ANN is shown in Table 1.

A. Modeling and Validation of Artificial Neural Networks

The proposed neural network model of gas turbine is shown in Figure 1 with input layer, one hidden layer and output layer based on thermodynamic process.

Figure 3 through figure 5 shows the resulting neural network based model can predict the reaction of the system to changes in input parameters with high accuracy and is capable of system identification with high reliability. Figure 3 through figure 5 it shows the results of these predictions obtained graphs of training data results and data validation for Generator Capacity, Generator Percent Efficiency and T5 Average Temperature (^{o} C). Data Training and Validation NN Generator Percent Efficiency can see Figure 4.

B. Optimazation of Gas Turbine Generator Using Algorithms

ANN modeling results that have been carried out through the training process and validation are optimized using genetic algorithms. Genetic algorithm optimization is performed to obtain the value of the variables in the Turbine Gas Generator operation to produce the highest efficiency value, so that the best input variable is obtained.

The Graph of genetic algorithm optimization can be seen in the figure 6. Figure 7 can be seen some values of input parameters that improving the efficiency of the Generator can be achieved by increased the PCD values and to reduce the fuel consumption through increased air mass flow. From the data presented before optimization shows the Generator load at 870 kW requires gas fuel flow in 0.12889 kg/s (464 kg/h), After optimization with a simulation of Generator load at 2377 kW requires a gas fuel flow in 0.1 kg / s (360 kg / h) then there is a potential savings that can be obtained around 104 kg/h. This economic benefit will be obtained if air mass flow can be increased from 1.58 kg/s to 2.7 kg /s or efficiency increase up to 10.6%.

Figure 8 shows the GUI of ANN-GA monitoring model. This simple GUI based on a thermodynamic model to calculate the engine performance and this can be used for offline estimation of expected performance of the Gas Turbine parameter with varying conditions.

IV. CONCLUSSION

Based on the results and analysis of data from the study that has been done, the conclusions obtained are as follows:(a)The simulation results of Gas Turbine Generator modeling already represent real conditions in the field; (b)The application of Artificial Intelligence-based controls on a gas turbine generator system is able to produce a picture of the input output of a GTG system;(c)The application of GAO to the gas turbine generator system when implemented will be able to save operating costs up to 280.8 kg / h

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