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Performance optimization of combined gas and steam power plant using artificial neural network

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ABSTRACT

The ever increasing demands for higher thermal efficiency from power plants have resulted to wide range of research in this regard. This work is one of such researches that deal with the performance optimization of a Combined Gas and Steam Turbines (COGAS) plant using Artificial Neural Network (ANN). A mathematical model of the COGAS plant was developed based on thermodynamic analyses and energy balance equations. This was used to develop a program and run in MATLAB environment to generate data for the ANN training. A comprehensive ANN program code was developed and implemented in MATLAB environment to create, configure, train and optimize the COGAS plant. Various ANN-based models of a two layered MLP structure with different configurations were trained and investigated. Results show that the Multilayer Percentron (MLP) structure with two layers consisting of 10 neurons in the hidden layer, trainlm as its training function with tansig as its transfer functions for the hidden and output layers give an optimal model. It was observed that trainlm has a superior performance characteristic in terms of minimum MSE, compared with other training functions. The resulting model could predict the optimized performance output of the system with high degree of accuracy with a minimum MSE at 816 epochs. This point gives the lowest MSE performances value of 1.0056e-11 and regression plot between 0.99999 and 1. By simulating the target values and analyzing same, the results show the lowest and highest thermal efficiency to be 0.69951 and 0.76413. The uniqueness of this research is essentially in its methodology and will remain invaluable in future works that will focus towards improving the thermal efficiency of power plants.

Key words: artificial neural network, optimization, thermal efficiency, COGAS.

1. INTRODUCTION

A gas turbine (GT) is an internal combustion engine that uses the gaseous energy of air to convert chemical energy of fuel into mechanical energy. The steam turbine is a device that extracts thermal energy from pressurized steam and uses it to produce mechanical work. Thermodynamically, when two thermal cycles are combined in a single power plant the efficiency that can be achieved is higher than that of one cycle alone and energy is conserved (Sayed and Khaled, 2013; Ghaeth Fandi et al. 2018).

Combination of cycles with different working media is quite interesting because their advantages can complement one another. Normally, when two cycles are combined, the cycle operating at the higher temperature level is called the "topping cycle". The waste heat it produces is then used in a second process that operates at a lower temperature level and is therefore called the "bottoming cycle" (Mohanty, 2014). It thus makes engineering sense to take advantage of the very desirable characteristics of the gas-turbine cycle at high temperatures and to use the high-temperature exhaust gases as the energy source for the steam power cycle (Ogbonnaya and Ugwu, 2012).

The combination most widely accepted for commercial power generation and marine propulsion application is that of a gas topping cycle with a steam bottoming cycle (Tiwari et al, 2012). Along with its wide and successful application in land-based power plants, the combined gas and steam turbines (COGAS) concept is being extended to provide an alternative form of power plant for ships (Jefferson et al, 2014). COGAS should not be confused with combined steam and gas power plants, which employ oil-fired boilers for steam turbine propulsion during normal cruising and the gas turbines is supplemented for high speed and faster response/reaction times Flexibility provided by these systems satisfies utility power- generations (Famous O Igbinovia et al. 2018), industrial-cogeneration and ship propulsion applications where the efficiency of these systems can exceed 60% (Marek and Wojciech, 2011). Presently, the world most efficient power plant is a 66.22 percent combine cycle power plant built by general electric in partnership with Electricite de France (EDF).

Modeling and simulation of combined cycles has always been a powerful tool for their performance optimization. However, the need to develop accurate and reliable models of COGAS for different objectives and applications has been a strong motivation for researchers to continue to work in this fascinating area (Asgari et al, 2013).

Artificial neural network (ANN) introduced in 1943 by McCulloch and Pitts has shown a high and strong potential to be considered as a reliable alternative to the conventional modeling approaches, simulation, optimization and control methodologies due to their independence and adaptability to new conditions (Asgari et al, 2014). This work will deal with novel methodology for performance optimization of a COGAS plant using ANN-based architecture.

2. METHODOLOGY

The performance optimization of the units that make up the entire system of this COGAS plant with technical parameters shown below in Fig 2.1, are implemented utilizing the approach stated below: modeling the COGAS plant, writing a program to implement the modeling in MATLAB and to use the obtained operational data from a COGAS plant for the performance optimization of the COGAS plant using ANN architecture. The technical details of the COGAS system used for this research are shown in Appendix A.

2.1. Analytical Model of the COGAS System

For the purpose of this research, fig. 2.1 shows the schematic diagram of the COGAS plant used for the modeling.

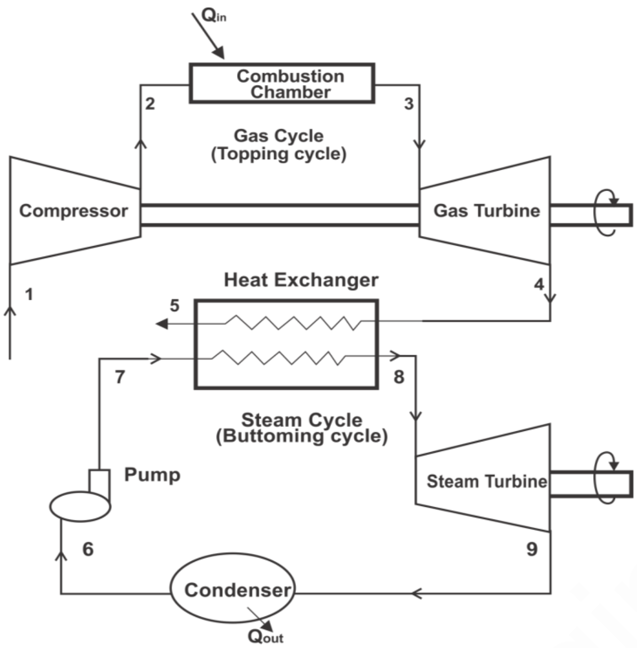


Figure 2.1 Schematic diagram of a COGAS plant
Source: Ogbonnaya, 2004

The modeling was carried out in segment for mathematical convenience and simplification starting with the gas turbine modeling, steam turbine modeling and the combined cycle.

2.1.1. Modeling the COGAS plant

In the GT cycle (topping cycle) as shown in fig. 2.1, the air is compressed isentropically in the compressor from state 1 to 2 where its temperature rises from T_1 to T_2. According to Ogbonnaya and Ugwu (2012), the work done in the compressor is given by:

$$W_{gC} = m_a C_{p_a}(T_2 - T_1) \qquad (2.1)$$

$$= m_a C_p T_1 (\tfrac{T_2}{T_1} - 1) \qquad (2.2)$$

But the pressure ratio is given by the expression below;

$$\tfrac{T_2}{T_1} = P_r^{\left(\frac{\gamma-1}{\gamma}\right)} \qquad (2.3)$$

Considering the pressure ratio of the turbine, equation (2.1) becomes

$$W_{gc} = m_a C_p T_1 \left(P_r^{\left(\frac{\gamma-1}{\gamma}\right)} - 1\right) \qquad (2.4)$$

The expression for the work done, W_{gt} by the turbine is:

$$W_{gt} = m_a C_p (T_3 - T_4) \qquad (2.5)$$

According to Rai et al (2013) and Cengal and Boles (2010), the efficiency of the gas turbine is:

$$\eta_{gas.tur} = \frac{m_a C_p\left(T_3 - \left(\frac{T_3}{P_r^{\left(\frac{\gamma-1}{\gamma}\right)}}\right)\right) - m_a C_p T_1\left(P_r^{\left(\frac{\gamma-1}{\gamma}\right)} - 1\right)}{m_a C_p\left(T_3 - T_1 P_r^{\left(\frac{\gamma-1}{\gamma}\right)}\right)} \tag{2.6}$$

$$\eta_{gas.tur} = \frac{\left[\left(T_3 - \left(\frac{T_3}{P_r^{\left(\frac{\gamma-1}{\gamma}\right)}}\right)\right) - T_1\left(P_r^{\left(\frac{\gamma-1}{\gamma}\right)} - 1\right)\right]}{\left(T_3 - T_1 P_r^{\left(\frac{\gamma-1}{\gamma}\right)}\right)} \tag{2.7}$$

According to Ogbonnaya and Ugwu (2012), the net work done by the ST as shown in fig. 2.1 is given by the expression:

$$W_{net.steam} = W_{st} - w_P \tag{2.8}$$

Equation (2.8) can be written as;

$$W_{net.steam} = m_s(h_8 - h_9) - m_s(h_7 - h_6) \tag{2.9}$$

Therefore, the ST cycle efficiency will be given by;

$$\eta_{st} = \frac{m_s[(h_8 - h_9) - (h_7 - h_6)]}{m_s(h_8 - h_7)} \tag{2.10}$$

From Cengel and Boles (2010), the net efficiency of the combined cycle can be obtained from the expression:

$$\eta_{combined} = \frac{(W_{net.gas} + W_{net.steam})}{Q_{sg}} \tag{2.11}$$

$$\eta_{combined} = \left[\frac{\left[m_a C_p\left(T_3 - \left(\frac{T_3}{P_r^{\left(\frac{\gamma-1}{\gamma}\right)}}\right)\right) - T_1\left(P_r^{\left(\frac{\gamma-1}{\gamma}\right)} - 1\right)\right] + m_s[(h_8 - h_9) - (h_7 - h_6)]}{m_a C_p\left(T_3 - T_1 P_r^{\left(\frac{\gamma-1}{\gamma}\right)}\right)}\right] \tag{2.12}$$

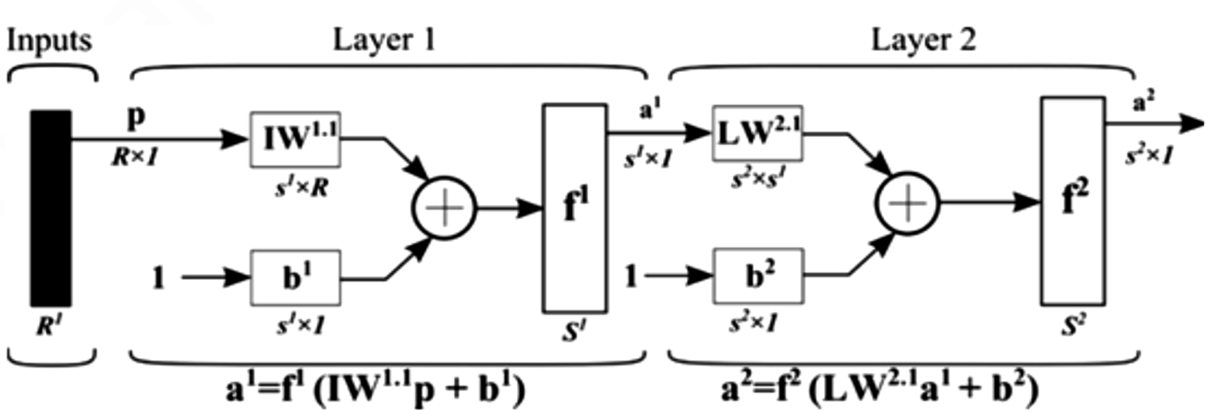


Figure 2.2 MLP network with two layers

Source: Beale et al, 2011

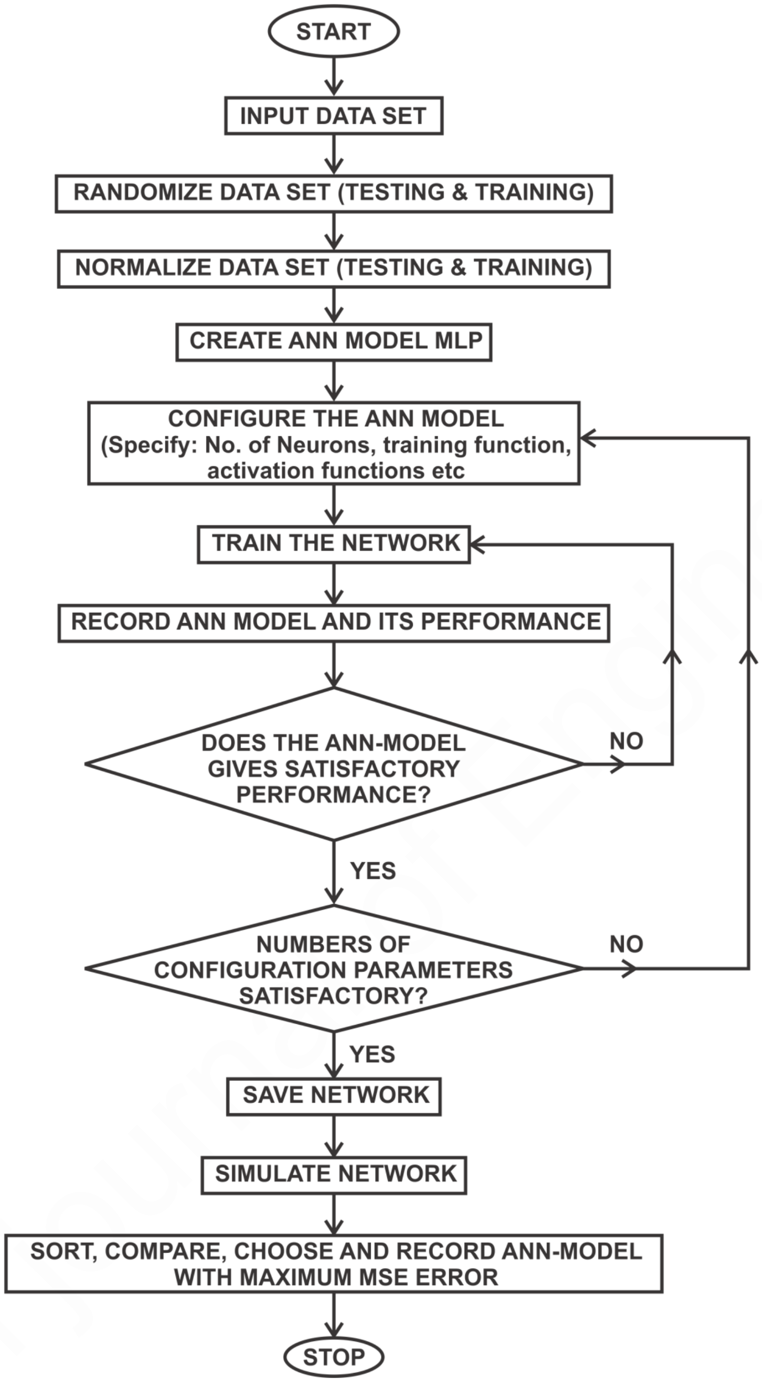


Figure 2.3 Flow Chart of Generated Computer Code for MLP of the COGAS Plant

2.2. Designing and Programming the ANN Models Using MLP

MLP is one of the most useful neural networks in function approximation. The development of the back-propagation learning algorithm for determining weights in MLP has made these networks the most versatile neural network (Assi and Jama, 2010). Many design parameters can be determined by trial and error when working with MLP. A network of two layers that is used in this work and shown in fig. 2.2, where the first layer is sigmoid and the second layer is linear, can be trained to approximate any function arbitrarily well (Beale et al, 2011). These functions are differentiable and can cope with nonlinearity of industrial systems.

2.2.1. Data collection

The data required for the ANN-based modeling were obtained from a combined gas and steam turbine developed for ship propulsion and programmed in MATLAB to generate the required inputs data set for the ANN training.

2.2.2. Creating, configuration and initialization of the network

This stage involves specifying the neural network to be used, the number of hidden layers, neuron in each layer, transfer function in each layer, training function, weight/bias learning function and performance function (Kaiadi, 2006). In this context, the MLP neural network is used with two hidden layers.

2.2.3. Training the network

During the training process, the weights are adjusted in order to make the actual outputs (predicted) close to the target output of the network (Nikpey et al, 2013). In this work, the operational data of the COGAS plant are used for the training. As stated earlier, the back-propagation training algorithm is used in updating the weight and bias of the MLP network. MATLAB provides in-built transfer functions like the: Log-sigmoid, tan-sigmoid and purelin transfer as used in this work.

2.2.4. Programming the neural network model

In this paper MATLAB (R2016a) is used to write script files for developing MLP ANN models and performance functions for calculating the model performance error statistic using MSE. Table 2.1 and Fig. 2.3 show the COGAS input parameter and flow chart respectively to develop the ANN model.

2.2.5. ANN code generation

To obtain a maximally trained and optimized ANN structure to ensure good generalization characteristic of the COGAS model, a comprehensive computer code was generated and run in MATLAB for a two-layer MLP network consisting of different back-propagation training functions, transfer functions and a number of neurons. The number of neurons applied in the program ranges from 5 to 40.

As shown in Fig. 2.3, after inputting and normalizing the data sets, they are randomly partitioned by default in MATLAB into training-70%, validation-15% and testing-15%. The next step involves specifying structure of the neural network-MLP and the configuration of the network by assigning the number of neurons, training function and transfer functions for the hidden and output layers. At this point the network is ready for the training process to commence and this is repeated two more times for the same adjusted factors, so that the best performance among the trials is identified, chosen and recorded. The process is repeated in two main loops of the code for different numbers of neurons (5 to 40), various back-propagation training functions, and a combination of different transfer functions for the hidden and output layers.

The results of all the performances of the network are recorded and sorted on the basis of their performance measure-MSE. According to the code, all the weight values of the neurons are updated in each epoch. In this study, one thousand epochs was considered for the entire training process of the MLP network. This is to ensure that the training would not be stopped before reaching a dominating local minimum, from which the optimal ANN model was identified from the sorted results.

Table 2.1 COGAS Input Parameters for the ANN-based models

Parameters	Symbol	Unit	Operational Range
GT compressor inlet temperature	T_1	K	$[273.15; 328.15]$
GT compressor inlet pressure	P_1	bar	$[1.01325; 21.0325]$
GT pressure ratio	P_r	-	$[11.5; 20.8]$
GT inlet temperature to the turbine	T_3	K	$[1650; 1850]$
GT air mass flow rate	m_a	Kg/sec	$[67.9268; 77.9268]$
GT fuel mass flow rate	m_g	Kg/sec	$[0.00367; 0.2661]$
ST steam mass flow rate	m_s	Kg/sec	$[0.79; 60.75]$
ST enthalpy before entering the pump	h_6	KJ/kg	$[174.0; 194.0]$
ST enthalpy after the pump	h_7	kJ/kg	$[182.06; 202.0]$
ST enthalpy after the boiler	h_8	kJ/kg	$[3398.0; 3599.0]$
ST enthalpy after the turbine	h_9	kJ/kg	$[2102.8; 2302.8]$
ST inlet temperature	T_5	K	$[500.0; 550.0]$
ST boiler pressure	P_5	Bar	$[80.0; 100.0]$
Specific heat capacity of air	C_p	kJ/kgk	$[1.005; 1.010]$

Ratio of specific heat	γ	-	$[1.33; 1.44]$
ST Condenser pressure	P_6	Bar	[0.08;0.10]

3. RESULTS PRESENTATION AND ANALYSIS

To obtain an optimized network structure and to ensure a good optimization of the COGAS model, a comprehensive training of a two-layered MLP network in MATLAB environment was carried out. Different ANN structures were trained using partitioned data sets for training, validation and testing purposes. In this work, three thousand epochs was considered for the whole training process of the ANN, to be sure that the training would not be stopped before reaching a dominating local minimum.

The results of the trainings were recorded and the performance was evaluated and compared in terms of their mean square error (MSE). Optimal ANN with minimum MSE was selected and tested again to ensure good generalization characteristics of the optimized COGAS model. The results from the model for different parameters of the ANN were compared are presented in Table 3.1.

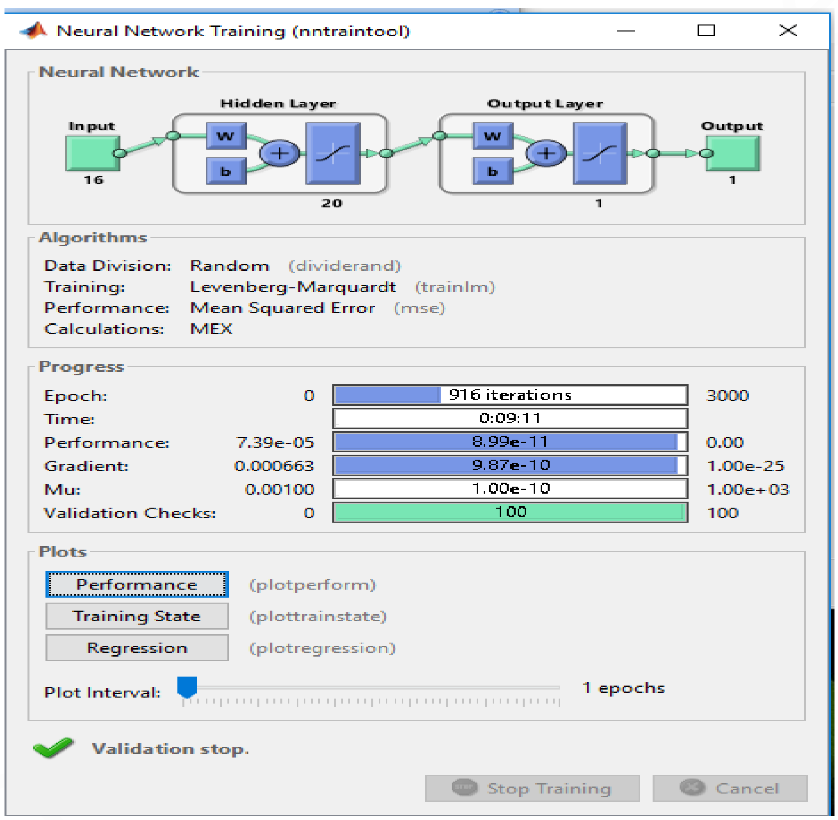


Figure 3.1 Screen capture for MLP training with 20 neurons

Table 3.1 Best Performance for Different MLP Configurations

Training function	Structure of MLP network	Transfer function in hidden layer	Transfer function in output layer	Best validation performance epoch	Best validation performance (MSE)
Trainlm	16-5-1	Tansig	Logsig	628	6.1187e-09
Trainlm	16-5-1	Tansig	Tansig	321	4.6278e-10
Traingdm	16-5-1	Tansig	Tansig	285	4.0652e-10
Trainbr	16-10-1	Tansig	Purlin	206	3.2923e-10
Trainlm	16-20-1	Tansig	Tansig	816	1.0056e-11
Trainlm	16-20-1	Tansig	Logsig	370	2.1941e-10

Traingd	16-30-1	Tansig	Tansig	459	1.7856e-10
Trainlm	16-40-1	Logsig	Purelin	nil	Nil

Table 3.1 indicates the best performance in terms of different MLP structures and training functions. It is observed that a two-layered MLP structure using training function: trainlm, transfer functions: tagsigs for hidden and output layers, with 20 neurons showed the best performance (the least MSE).

Fig 3.1 show the screen capture for the ANN training with 16 input parameters of the COGAS, hidden layer with 20 neurons, output layer with one neuron and one output which represent the COGAS thermal efficiency. Fig 3.1 also shows various parametric configuration of the MLP network. From the screen it can be seen that the training and validation stopped at an epoch of 916 iterations having reached the best performance validation epoch of 826.

Detail of the most optimal trained network based on performance of all the trained structures is shown in fig. 3.2. Performance of the MPL for training, validation and testing are indicated by the curves. From fig. 3.2, the epoch in which the validation performance error reached the minimum is 816. This point gives the lowest MSE performances value of 1.0056e-11. The training continued for another 82 more iteration (epoch) before the training stopped.

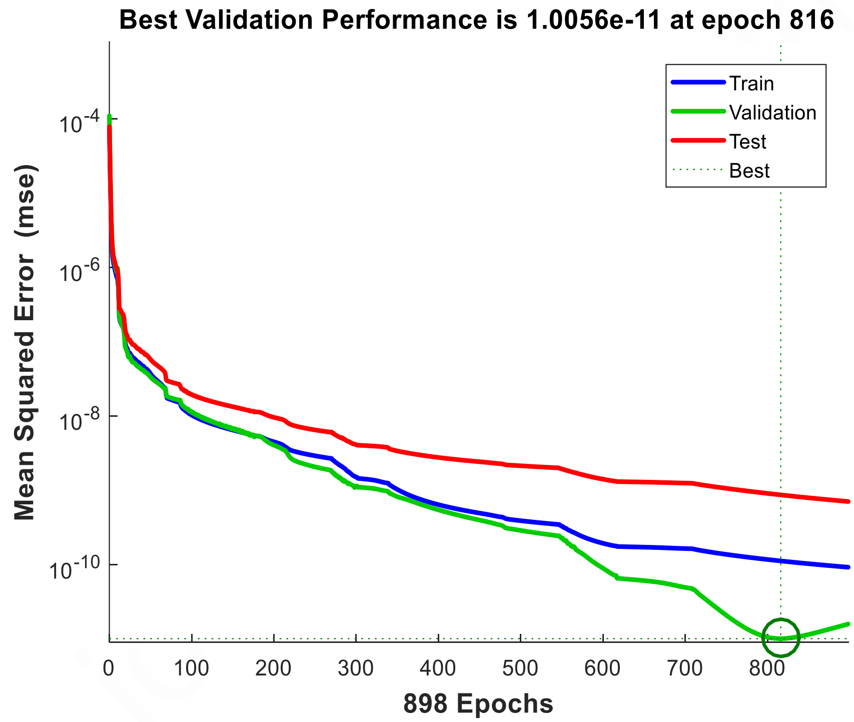


Figure 3.2 Performance Curve of Optimal MLP Network

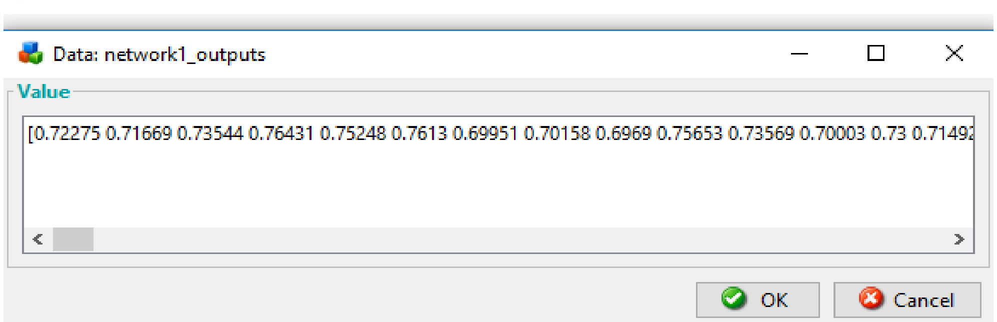


Figure 3.3 Screen Capture of Simulated Result of the MLP Network

The values of the optimized outputs of the target set obtained from simulating the MLP network is shown in fig. 3.3. The results of the simulation give the lowest predicted thermal efficiency of 0.69951 and a highest thermal efficiency of 0.76413. More graphs of the ANN performance obtained from training the MLP network of different architecture of different characteristic curves are shown in Appendix B.

4. CONCLUSION

In this research work, thermodynamics and energy balance equations were employed to model the COGAS plant. A comprehensive computer program code was generated and run in MATLAB environment using the COGAS data obtained for ship propulsion. A method which involves data validation has evolved in this wok. The data generated from the modeled COGAS plant in MATLAB environment was employed in ANN with two-layered MLP structure for optimization purpose.

The results obtained based on this research work showed that the epoch in which the validation performance error reaches the minimum is 628. Also, the network simulation yielded an overall thermal efficiency between 69.9% and 76.4%. The results are evident to conclude that a proper ANN configuration and iteration enhance the improvement of the training performance and optimization characteristics of the COGAS system. It also identified the fact that modeling, simulation and analysis can be handled using ANN to produce results with a high degree of accuracy and reliability.

Recommendations

Based on the findings from the ANN training and simulation results, recommendations are as follows:

1. ANN should be employed to maximize the optimization characteristics of COGAS systems.
2. ANN methodology should be used to predict the thermal efficiency and performance of similar COGAS systems.
3. Reasonable attention and consideration should be given to the thermodynamic properties of COGAS systems.
4. Iterative approach should be adopted in parametric configuration of ANN-based architecture for result oriented optimization of COGAS systems.

APPENDIX A

Technical Details of the COGAS Used In This Work

Gas turbine:

Manufacturer	General Electric
Model	GE9351FA
Fuel	Natural Gas
Number of shaft	1
Frequency	$50H_Z$
Pressure ratio	15.8
Compressor inlet temperature	$273.15K$
Turbine inlet temperature	$1950K$
Exhaust temperature	$872K$
Power	$259.5MW$
Thermal Efficiency	37.3%
Heat rate	$9643\, KJ/Kwh$
Air flow rate	$802\, kg/s$

Steam turbine

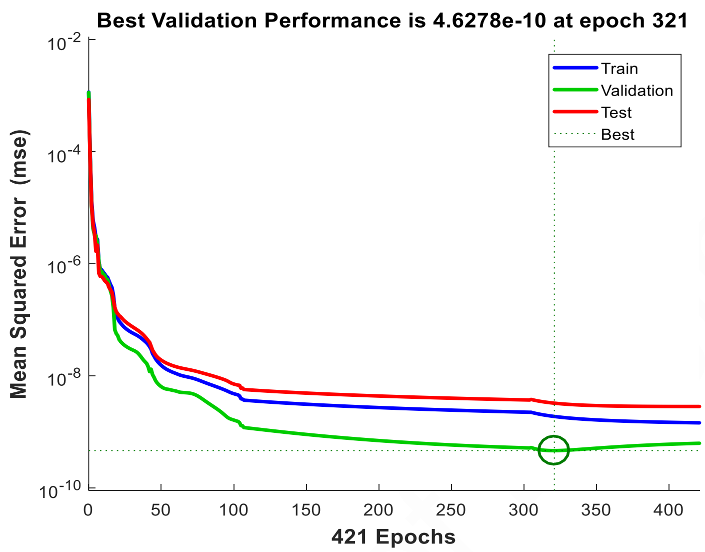
Manufacturer	Babcock
Model	D2248B
Steam flow rate	$70.74\, kg/s$
Power	$120MW$
Thermal efficiency	42%
Inlet pressure	$80bar$
Condenser pressure	$0.08bar$
Inlet temperature	500^0C

Calculated parameters

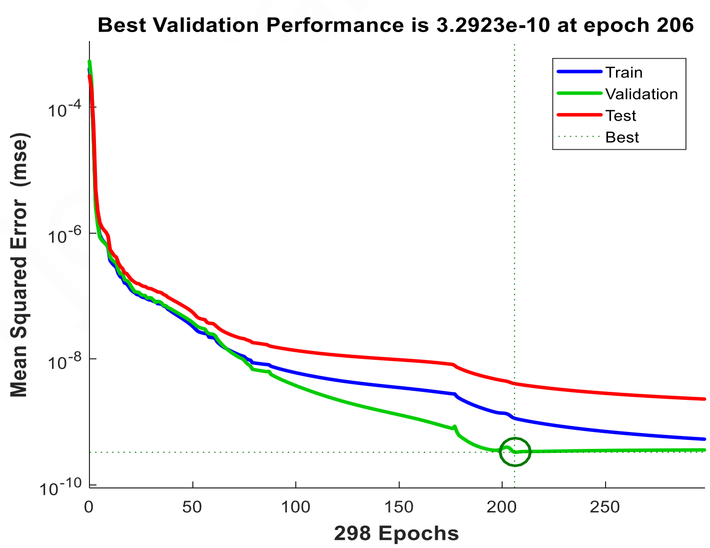
Steam enthalpy at state 6,h_6	$174\,Kj/kg$
Steam enthalpy at state 7,h_7	$182.06\,Kj/kg$
Steam enthalpy at state 8,h_8	$3398\,Kj/kg$
Steam enthalpy at state 9,h_9	$2102.8\,Kj/kg$

APPENDIX B

Performance of optimal MLP network with 5 neuron



Performance of optimal MLP network with 10 neuron



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