

MODELING AND EFFICIENCY OPTIMIZATION OF COMBINED GAS AND STEAM POWER PLANT USING MULTI-LAYER PERCEPTRON

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ABSTRACT

This paper is a research that deals with modeling and efficiency optimization of a Combined Gas and Steam Turbine (COGAS) using Multilayer Perceptron. Two different models are developed and compared by using both thermodynamics and a black-box based approach. They are implemented using the MATLAB tools including Simulink and Neural Network toolbox respectively. The power plant was modeled thermodynamically and implemented in MATLAB environment. A Simulink model was also constructed based on thermodynamic equations, implemented in MATLAB to generate the data used for training, validation and optimization of the power plant. The Multilayer Perceptron (MLP) model was set up by using the data sets generated from the simulink model and employed for the COGAS efficiency optimization. The results showed that both Simulink and MLP models are reliable and capable of satisfactory prediction of the optimized efficiency of the power plant above 60% with efficient training, parametric variation and iterative configuration of the MLP network.

Key words: Multi-layer Perceptron, Optimization, Efficiency, COGAS.

1. INTRODUCTION

Combined gas and steam (COGAS) power plant is a system that utilizes the properties of two different power plants for power generation. The gas turbine (GT) exhaust temperature can be as high as 550°C. Interestingly, the steam turbines (ST) require high temperature source for steam generation. It thus makes sense to take advantage of the very desirable characteristics of the gas-turbine cycle high-temperature exhaust gases as the energy source for the steam power cycle (1); (2). Combining thermal cycles with different working fluid is quite interesting because their advantages characteristically complement each other. 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 (3). Along with its

wide and successful application in land-based power plants, the COGAS concept is being extended to provide an alternative form of power plant for ships (4). Optimization of industrial systems, such as the COGAS plant, is one of several conventional methodologies for improving the thermal efficiency as well as component design optimization, manufacturing, trouble shooting and maintenance. COGAS models can be categorized into two main groups which are the white-box and black-box models. Each of these approaches has its own characteristics, benefits, and limitations. White-box models are used when there is enough information about the physics of the system. They make use of dynamic equations of the system which are usually coupled and nonlinear (5). Artificial neural networks (ANN) as a black box model are used when there is little knowledge about the physics of

the system. In this case, there is no need to struggle with the complicated dynamic equations of the system (3); (5); (6). To develop a reliable black-box model, various multi-layer perceptron (MLP) based architectures have to be trained based on the values of different parameters of the system. Black-box methodology is employed to show the relationships between variables of the system using the measured operational data or data generated by means of a simulation tool (5); (6).

Considering the role and importance of optimization in turbo machineries and its direct effect on COGAS performance characteristics, it therefore makes engineering sense for researchers to continue to work in this fascinating area to fill the existing knowledge and information gaps (7). Artificial neural network (ANN) has been employed in recent years as a powerful tool for modeling, simulation and optimization of complex industrial systems with linear and nonlinear dynamics like the COGAS plant. In this work, a SIMULINK model of a COGAS plant based on previous research by Rowen is briefly presented (8); (9); (10). This is used in MATLAB environment to generate the data set that is employed in MLP neural network architecture for training, validation and optimization. This work will deal with novel methodology for optimization of a COGAS plant thermal efficiency using ANN-based MLP architecture.

2.0 METHODOLOGY

The modeling and optimization of the COGAS plant is implemented utilizing the approach stated below: modeling the COGAS plant using thermodynamic analysis, SUMULINK modeling of the COGAS plant implemented in MATLAB environment to generate operational data for the training and optimization of the COGAS plant using ANN-based MLP architecture.

2.1 Thermodynamic Model of the COGAS

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

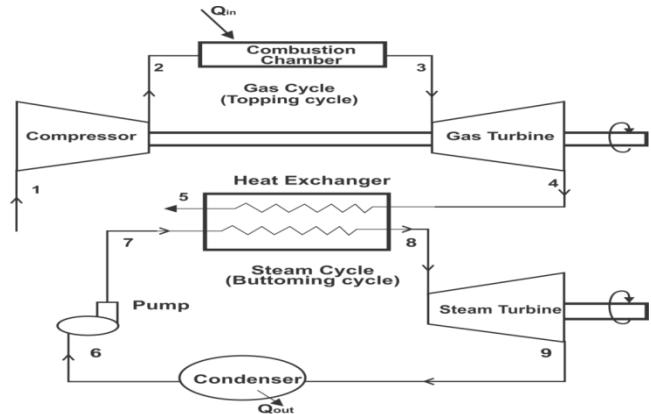


Fig. 2.1 Schematic diagram of a COGAS plant
 Source: Ogbonnaya, 2004

The modeling will be carried out in stages for Mathematical convenience and clarity.

2.1.1 Modeling the GT Section

In the GT cycle (topping cycle) as shown in fig. 2.1, the air is compressed from state 1 to 2 in the compressor where its temperature rises from T_1 to T_2 . According to (1); (11), the work done in the compressor is given by:

$$W_{gc} = m_a C_{p_a} (T_2 - T_1) \quad (2.1)$$

$$= m_a C_p T_1 \left(\frac{T_2}{T_1} - 1 \right) \quad (2.2)$$

But the pressure ratio is given by the expression below;

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

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

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

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

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

According to (12), the efficiency of the gas turbine is:

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

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

According to (1); (10); (12), the net work done by the ST as shown in fig. 2.1 is given by the expression:

$$W_{net.steam} = W_{st} - w_p \quad (2.8)$$

Equation (2.8) can be written as;

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

Therefore, the ST cycle efficiency will be given by;

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

From (12), the net efficiency of the combined cycle can be obtained from the expression:

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

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

The Simulink Model

Fig. 2.2 shows a dynamic model of a COGAS plant for a single shaft system. This model consists of several blocks describing various parameters to be trained and validated in order to optimize the performance of the system. There are blocks related with speed/load, temperature control, fuel control, air control and other blocks for gas turbine, waste heat recovery boiler/steam turbine, rotor shaft, and temperature transducer making up a complete COGAS plant.

The speed/load block (governor) for determining the fuel supply V_d when compared with a reference load and rotor speed deviation (13). The temperature control block (overheat control) is for controlling the exhaust temperature (T_4) of the gas turbine. The measured temperature is obtained with the help of various transducers and compared with a reference temperature. Then the output of the temperature control is combined with speed/load control to determine the fuel demand that is, using low selected values.

The performance of the fuel control block is according to the minimum value provided by the speed/load control and temperature control. This determines the fuel flow M_f . Air control block in the model is used to adjusting the air flow rate in the gas turbine (GT). This help in obtaining the required exhaust temperature in order to maintain the temperature below a referenced temperature using suitable offset. All the parameters of the COGAS used in the model are given in Table 2.1.

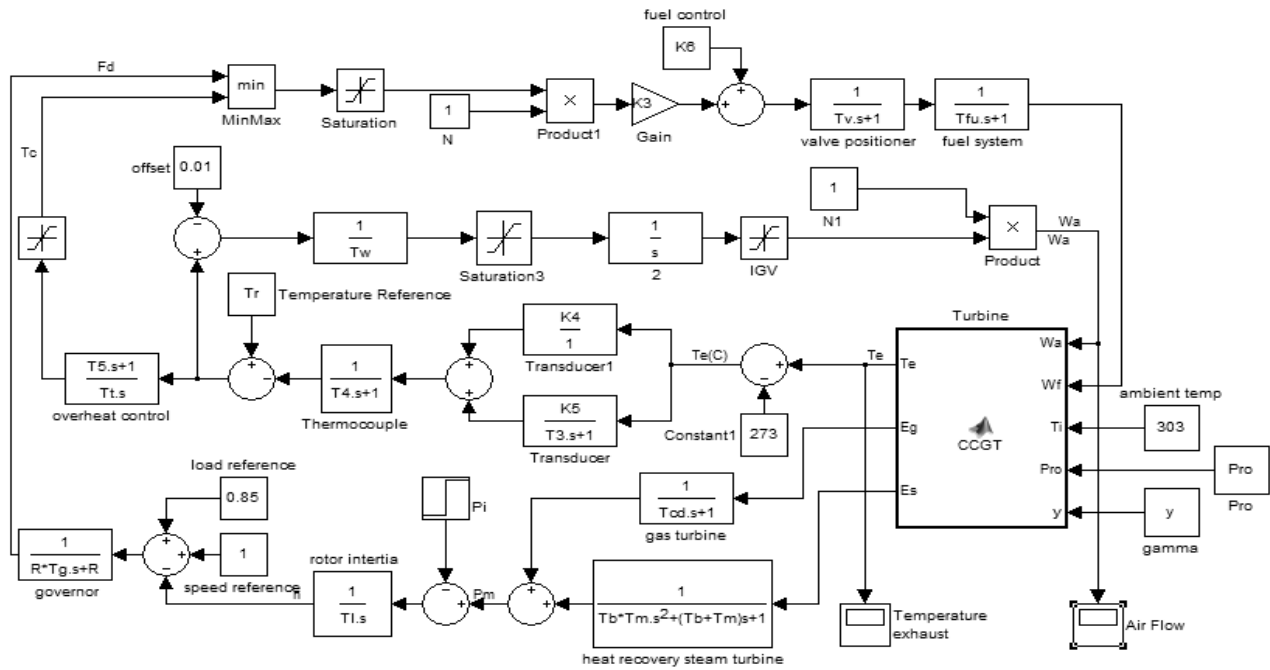


Fig. 2.2 Simulink Model of Combined Gas and Steam Power Plant
Source: Rai et al. 2013

2.2 Designing and Programming the MLP Model

MLP is one of the most useful neural networks in function approximation and prediction. 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. 2.3, where the first layer is sigmoid and the second layer is a purlin, can be trained to approximate any function arbitrarily well (14). These functions are differentiable and can cope with nonlinearity of industrial systems.

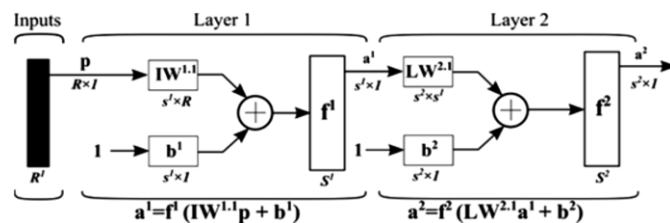


Fig. 2.3 MLP network with two layers

Source: Beale et al, 2011

2.2.1 Data collection

The data required for the MLP modeling were obtained from the SUMULINK model of the COGAS plant programmed and implemented in MATLAB environment to generate the required inputs data set for the MLP training, validation and COGAS optimization.

2.2.2 Creating, configuration and Training 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 (15). In this context, the MLP neural network is used with two hidden layers.

During the training process, the weights are adjusted in order to make the actual outputs (predicted) close to the target output of the network

(16); (17). In this work, the generated data of the COGAS plant are used for the training.

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.

2.2.3 Programming and MLP code generation

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 using the mean square error (MSE). Table 2.1 and Fig. 2.3 show the COGAS input parameter and flow chart to develop the MLP model and optimization respectively.

A comprehensive computer code was generated and run in MATLAB for a two-layered MLP network consisting of different configurations to obtain a maximally trained and optimized MLP structure that will ensure good generalization characteristic of the COGAS model. Fig. 2.3 provides a detailed and lucid description of MLP code generation for COGAS optimization process.

The results of all the performances of the network are recorded and sorted on the basis of their measure-MSE performance. In this study, three thousand epochs was considered for the entire training process of the MLP network. This is to ensure that the training would reach a dominating local minimum before stopping, from which the optimal MLP model was identified from the sorted results.

Table 2.1: COGAS Input Parameters for the MLP-based Optimization

Parameters	Sym	Unit	Operational Range
GT compressor inlet temperature	T_1	K	[268; 271.5]
GT compressor inlet pressure	P_1	Bar	[1.01325; 8.0325]
GT pressure ratio	P_r	-	[11.5; 15.5]
GT inlet temperature to the turbine	T_3	K	[1750; 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	[50.79; 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	-	[1.35; 1.44]
ST Condenser pressure	P_6	Bar	[0.07; 0.10]

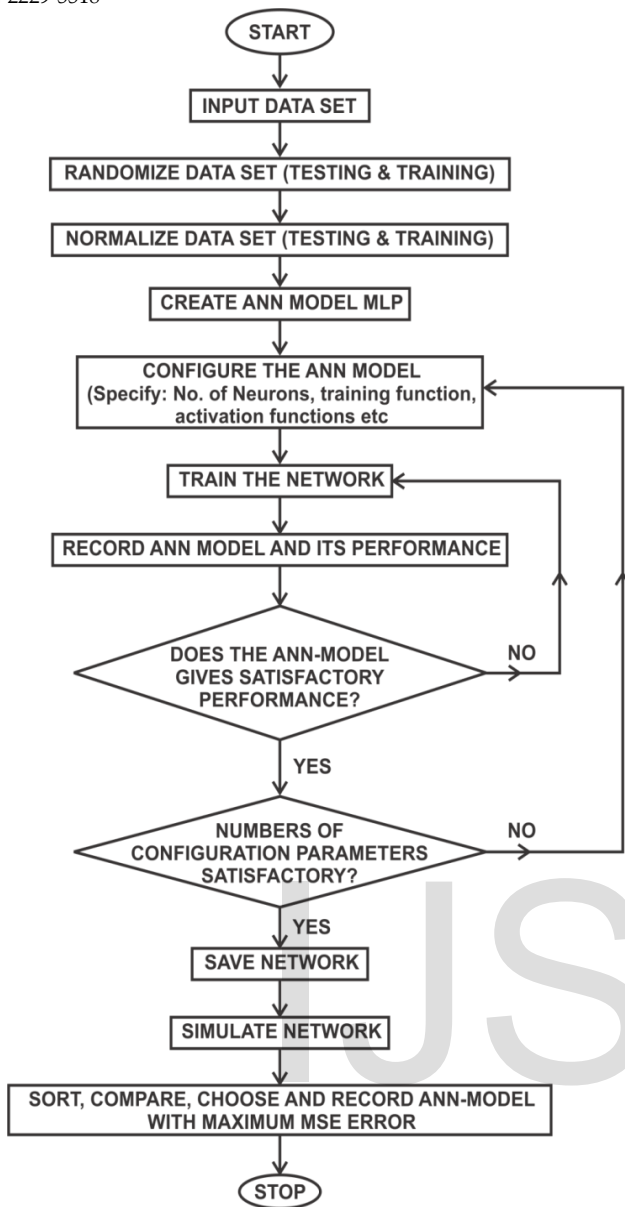


Fig.2.3: Flow Chart of Generated MLP Code for COGAS Plant Optimization

3.0 Results Presentation and Discussion

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 MLP structures were trained using partitioned data sets for training, testing and validation purposes. In this work, three thousand epochs was considered for the whole training process of the MLP-based architectures, 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 MLP 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 MPL were compared and are presented in Table 3.1

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
Traindg	16-5-1	Logsig	Tansig	321	4.6278e-10
Traingm	16-10-1	Logsig	Tansig	285	4.0652e-10
Trainlm	16-10-1	Tansig	Purlin	206	3.2923e-10
Trainbr	16-20-1	Tansig	logsig	816	2.0056e-11
Traingd	16-20-1	Pursig	Logsig	370	2.1941e-10
Trainlm	16-30-1	Logsig	Purlin	459	1.7856e-10
Trainlm	16-40-1	Losig	Purlin	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: lagsigs for hidden and purlin for the output layers, with 30 neurons showed the best performance.

Fig 3.1 show the screen capture for the MLP model of the COGAS with 16 input parameters, hidden layer with 30 neurons, output layer with one neuron and one output which represent the optimized COGAS thermal efficiency.

graphs are between 0.99999 and 1. This result for each of training, validation and testing data sets indicates a very good fit.

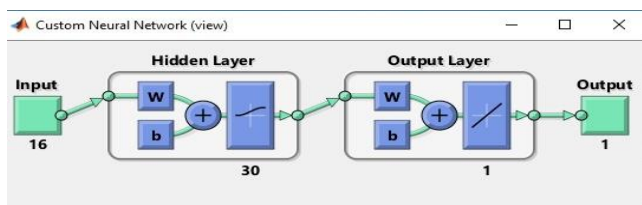


Fig. 3.1 MLP Model of the COGAS Plant

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 the graph, the epoch in which the validation performance error reached the minimum is 459. This point gives the lowest MSE performances value of $1.7856e-10$.

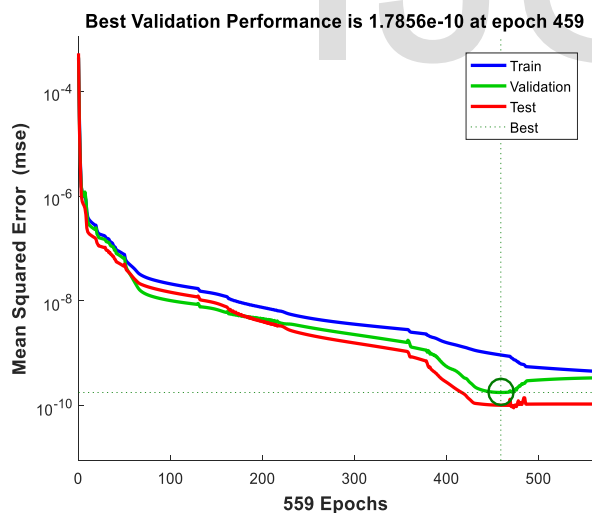


Fig. 3.2 Performance Curve of Optimal MLP Network

The related regression plot for this MLP structure after training is shown in fig. 3.3. This gives an indication of the relationship between outputs of the network and the outputs of the system (targets). As shown by the figure, the R values for all the

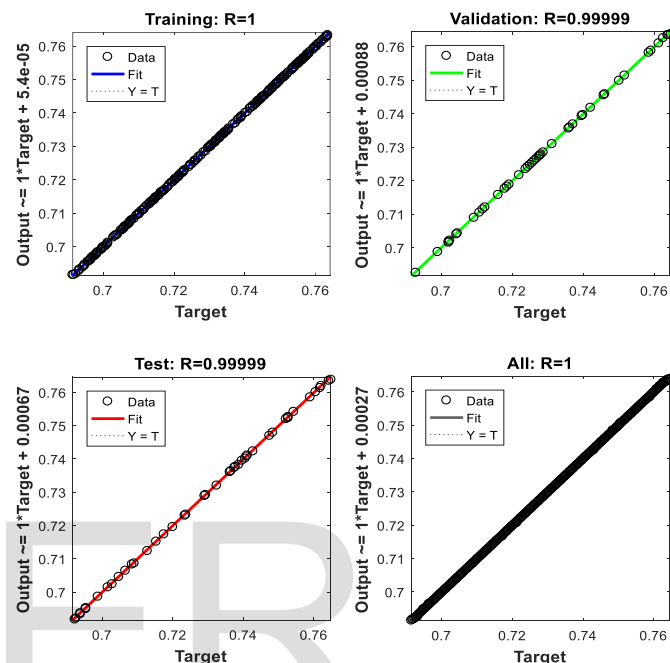


Fig. 3.3 Regression of the Optimal MLP Network

4.1 Conclusion

In this research work, thermodynamics analysis and SIMULINK were employed to model the COGAS plant. A comprehensive computer program code was developed and run in MATLAB environment. The data generated from the SIMULNK model of the COGAS plant in MATLAB environment were employed in a two-layered MLP structure for optimization purposes. A method which involves data validation has evolved in this wok.

The results obtained based on this research work, showed that the epoch in which the validation performance error reaches the minimum is 459 and

the regression value ranges between 0.99999 and 1. Similarly, the network simulation yielded an overall thermal efficiency above 60%. The results are evident to conclude that a proper MLP 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 MLP to produce results with a high degree of accuracy and reliability.

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