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ARTIFICIAL NEURAL NETWORK-BASED MODEL OF AJAOKUTA STEEL THERMAL POWER PLANT

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ABSTRACT

This paper develops the identification of thermal power plant using artificial neural network (ANN) technique taking Ajaokuta steel power plant as a case study. The thermal power plant, built in 1987, has a full capacity of 60MW at a frequency of 50Hz. Data was collected from the Ajaokuta steel power plant for the input/output parameters of the main components for the identification process. This include governor valve position, superheated steam flow rate to the turbine, turbine blades torque as well as the frequency of the generated electrical power. Firstly, identification models for the governor, turbine and generator were separately developed. To simplify the process, each model is treated as a single input single output (SISO) system. Then, the thermal power plant was modelled as a whole taking frequency as the input and generated electrical power as the output. The obtained data is used to train a feedforward neural network with one hidden layer in Matlab environment. An exhaustive search routine was developed to control the choice of the architecture (training function and number of layers of neurons) for the feedforward ANN models during the identification process. This optimizes the developed ANN model for every component of the power plant. A correlation analysis on the inputs/output dependencies reveals 95% confidence. To validate the developed ANN models, dynamic linear models were estimated using ARMAX method. Similarly, the order of each ARMAX model was chosen to minimize the mean square error. Compared to the ARMAX models, the accuracy of the proposed ANN models outweigh that of their numerical counterparts by 6.32, 0, 99.82, and 3.09 percent for the governor, turbine, generator and the complete plant respectively. Thus, the identified ANN models provide better representation of the thermal power plant.

Keywords: Model Identification; Artificial neural network (ANN); Thermal power plant; Turbine; Generator; Governor

1.0 INTRODUCTION

Different types of power plant systems are available for the generation of electricity. The plants can be classified as either conventional such as thermal, hydro, nuclear, gas, diesel etc. or non-conventional such as wind, solar, geo-thermal, and biogas. The capacity of non-conventional power generating plants is generally lower than that of their conventional counterparts.
In addition, for non-conventional power plants, power generation is normally distributed over a wide area. This is unlike the conventional generating plants which are centralized. Large scale power systems are normally composed of control areas or regions representing coherent groups of generators.
In practice, for interconnected power system, the generation normally comprises of a mixture of thermal, hydro, nuclear and gas power generation. However, owing to their high efficiency, nuclear plants are usually kept at base load close to their maximum output without deploying the automatic generation control (AGC) system. On the other

hand, gas power plants are ideal for meeting the varying load demand; as such they are commonly deployed to meet peak demands only. Thus, thermal or hydro power plants are the natural choice for AGC (Srinivasa, 2012).

Traditionally, the techniques adopted in modelling thermal power plants (see Figure 1) during AGC analysis were mainly mathematical (based on the fundamental principles guiding the system dynamics). Such models may not always capture the system dynamics correctly (Wojciech and Michal, 2012) as their effectiveness relies on the validity of the assumptions made over time and the effect of wear and tear on system components. As a result, this paper modelled the thermal power plant using the Artificial Neural Network (ANN). The ANN is an intelligent modelling technique that has proven to produce more robust models as compared to the traditional mathematical approaches (Karna and Ahmad, 2016). Figure 2 shows a typical multi-layer ANN structure with interconnection weights. Artificial neural network is a data-driven model. It has been considered as a suitable alternative to the parametric models (white-box models) during the last few decades (Hamid et al., 2013). ANN is a group of interconnected artificial units (neurons) with linear or nonlinear transfer functions. Neurons are arranged in different layers including input layer, hidden layer(s) and output layer. The number of neurons and layers in an ANN model depends on the degree of complexity of the system dynamics.

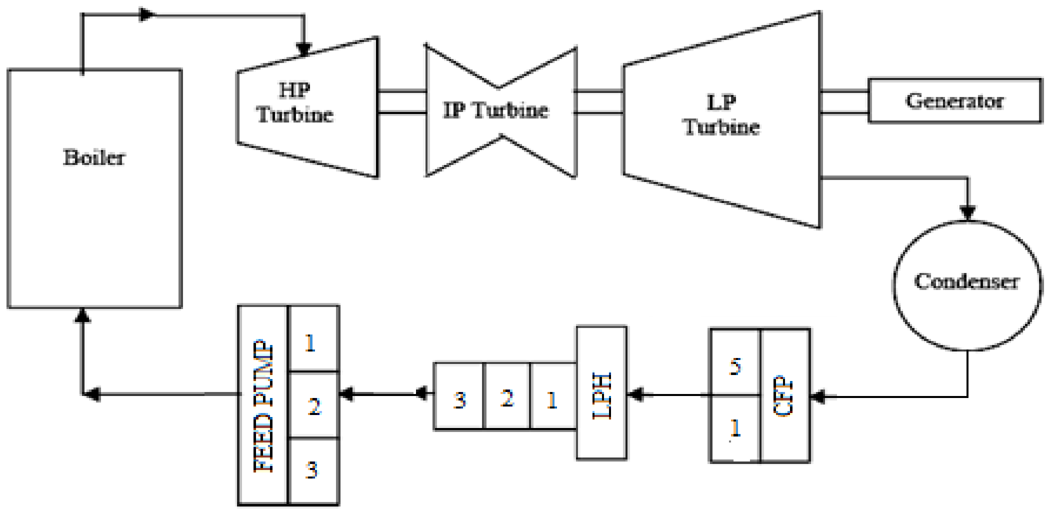

Figure 1: Schematic Diagram of a Thermal Power Plant (Gupta and Tewari, 2011)

The ANN can be used effectively in system identification and also in controlling linear and nonlinear systems. Many neural network structures are suggested to map the input/output system dynamics such as feed-forward, recurrent and partially recurrent method (Arif and Mazin, 2008).

While previous works on identification of thermal power plants are mostly focused on modelling either boiler versus turbine or turbine versus generator, this work will develop ANN models for the governor, turbine and generator units. Finally, a mathematical model based on Autoregressive Moving Average Exogenous (ARMAX) technique will be used to validate the obtained ANN models.

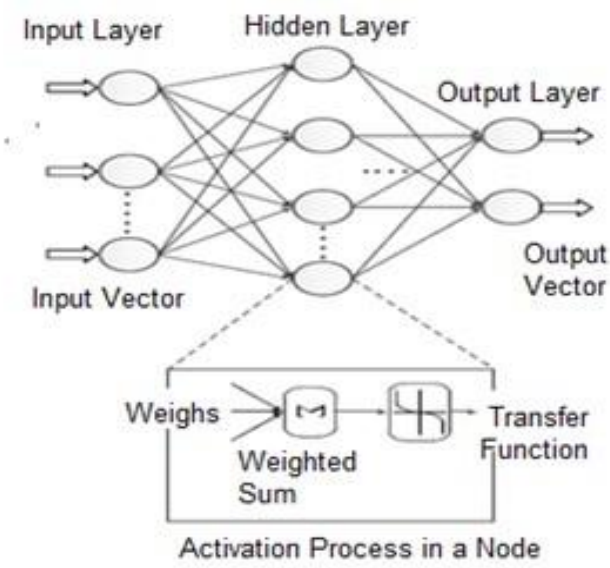

Figure 2: A Typical ANN Structure (Hamid et al., 2013)

Chan and Cherng (2012) modelled turbine cycles using a neuro-fuzzy (ANFIS) based approach to predict turbine-generator output for nuclear power plant. The results showed that the ANFIS based turbine cycle model was capable of accurately estimating turbine-generator output as it provides more reliable results than the PEPSE® based turbine cycle models.

Hamid et al. (2013) applied artificial neural network for system identification of a single-shaft gas turbine. ANN of two layers, feedforward multilayer was used to train the data. Validation was done by comparing mean square error performance of the simulated model for every training function adopted and result showed that the modelled output tracks the actual output with a regression of 0.9997.

Orosun and Adamu (2014) developed a neural network based model for an industrial oil fired boiler of a thermal power plant. It is a two layer feedforward NN with tansigmoid for the activation function and purelin for the input/output layer. The back propagation algorithm used was trainlm. Validation test shows that the modelled and actual outputs agreed with a correlation of 0.97.

Furthermore, Mehdi and Alireza (2014) applied perceptron neural network in predictive maintenance of thermal power plant equipments (lubricating system, hydraulic system, cooling system, fuel system and electric system). This is because predictive maintenance is depended on failure prediction of equipment. Results show that the model has prediction ability of 0.1877 mean squared error. Predicting failure time of equipment according to environmental conditions eases maintenance planning in terms of number of visits and required services as well as timely procurement of parts and storage costs.

Recently, Karna and Ahmad (2016) adopted neural network to model coal fired thermal power plant of 210MW capacity with reduced number of input. Neural network was used to train the collected data, while fuzzy curve method was used to identify the input parameters that affect the output most. Evaluation and validation of the model are performed by predicting the boiler-turbine parameters using different set of actual plant data. This plant is different from the proposed power plant as it is fired with coal, while the proposed plant is fired with fuel.

2. MATERIALS AND METHOD

In this section, the method used in realizing the artificial neural network based model for the Ajaokuta steel thermal power plant is discussed. The following sub-sections describe the data acquisition and pre-processing procedure, ANN model development and evaluation.

2.1. Data Acquisition and Processing

The data chosen in this work was based on the operational knowledge of the power plant with respect to frequency-load association. As such, the map for the input – output parameters that were collected during visitations to the thermal power plant is shown in Figure 3.

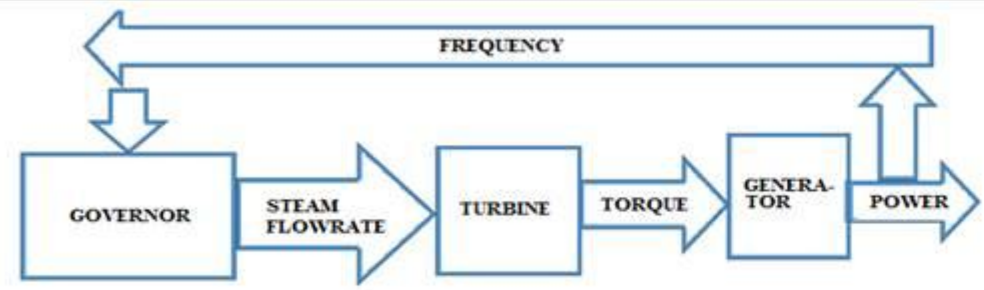

Figure 3: Input/output Dependencies for the Governor, Turbine and Generator Interconnections

From Figure 3, the input that corresponds to the governor is the frequency of the generated power while the output corresponds to the position of the valve through which the superheated steam gets to the turbine. Also, the input that corresponds to the turbine unit is the flow rate of the superheated steam at the valve or regulator, while the output corresponds to the turbine torque. The input of the generator is the turbine resultant torque, while the output corresponds to the generated power. For the complete plant, the input to the plant corresponds to the same frequency while the output corresponds to the generated output power (Kumar and Dixit, 2014). These data were manually recorded and kept and were taken at an interval of every two hours.

Two years data was collected from 2008 to 2009 for the purpose of this work which amounts to a dataset with almost 3000 entries. The collected data was pre-processed through normalization and treatment of the outliers.

This was done to mitigate the challenges posed by data outliers to proper learning by the neural network. Normalization, however, helped to filter out the various units of parameters into common scale (Lopes and Ribeiro, 2013). Data outliers were treated by replacing them with their averages.

The proportion of missing data constitutes less than 3% of the overall collected data. Thus, such missing data were realized through data treatment. In this work, collected data was pre-processed by: (i) treating the outliers (through averaging), and (ii) normalization of all variables to within 0 and 1. Outliers and missing data or recording disturbances were removed and replaced with their averages. It is important to note that, for the 3000 entries in the collected dataset, 97.9% data are available from the industry, only the remaining 2.1% were realised through data treatment. Normalization was done by dividing every data variable with its maximum value. Table 1 shows a cross-section of the collected data as well as some pre-processing done to the governor's dataset.

Table 1: Cross-Section of the Collected Data before and After Pre-processing – Raw Data (Processed Data)

S/N	Normalized Frequency (Hz)	Normalized Valve Position (CM)	Normalized Flowrate (Tone/cm^3)	Normalized Power (MW)	Normalized Torque (Nm)
45	50.4 (0.972)	76 (0.844)	102(0.000102)	25(0.5)	51(0.00833)
46	50.3(0.9707)	76 (0.844)	101(0.000101)	25(0.5)	51.4(0.0083)
47	50.5 (0.974)	73 (0.817)	181(0.000181)	25(0.5)	50.9(0.0084)
48	50.6 (0.976)	75 (0.833)	190 (0.00019)	25(0.5)	51.5(0.0083)
49	49.4 (0.953)	75 (0.833)	193(0.00019)	46(0.92)	51.7(0.0151)

2.2. ANN and ARMAX Model Development

The training was done using neural network training environment in Matlab. The data is partitioned into three sets, 75% for the training, 15% for testing and 15% for validation check (Hamid et al 2013). Figure 4 shows a flow chart of an algorithm that was developed to give the optimal training function and number of neurons that give least MSE for the governor, turbine, generator and the complete plant models. The code when executed, it begins to search for the optimal number of neurons from 1 to 50 and optimal training function among trainlm, trainscg, trainrp, trainbr, trainbfg, traincgf, trancgp, traingda, traingdm and traindx that gives the minimum MSE for the governor, turbine, generator and the complete plant models. The training function versus neuron count that gave the least MSE value for the governor, turbine, generator and the complete power plant are (trainbr, 46), (trainscg, 44), (trainbr, 50) and (traingda, 32) respectively. A two layer feedforward NN with purelin for the input/output layer was adopted during the NN architecture design. Figure 5 shows a typical NN structure developed for governor model.

In the same manner, Figure 6 shows a flow chart of an algorithm that was developed for the realization of ARMAX models. The code when executed, it chooses optimal number of polynomial order from 2 to 9 that gives the least MSE for the governor, turbine, generator and the complete plant model. Validation was done by comparing the MSE of the ANN based models to that of the ARMAX based models. To investigate the possible presence of seasonal peculiarity in the data used in the development of the ANN and ARMAX based models, the second part of the dataset collected for the following year was used to repeat the entire modelling of the governor, turbine, generator and the whole plant. Least MSE values for the ANN and ARMAX based models from the second set of data were compared to that from the first set data.

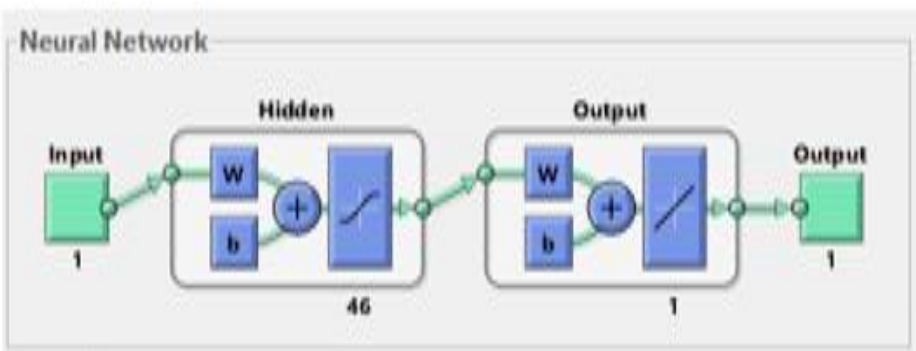

Figure 5: Structure of the Governor's ANN model (Schematic generated with Matlab ANN Tool)

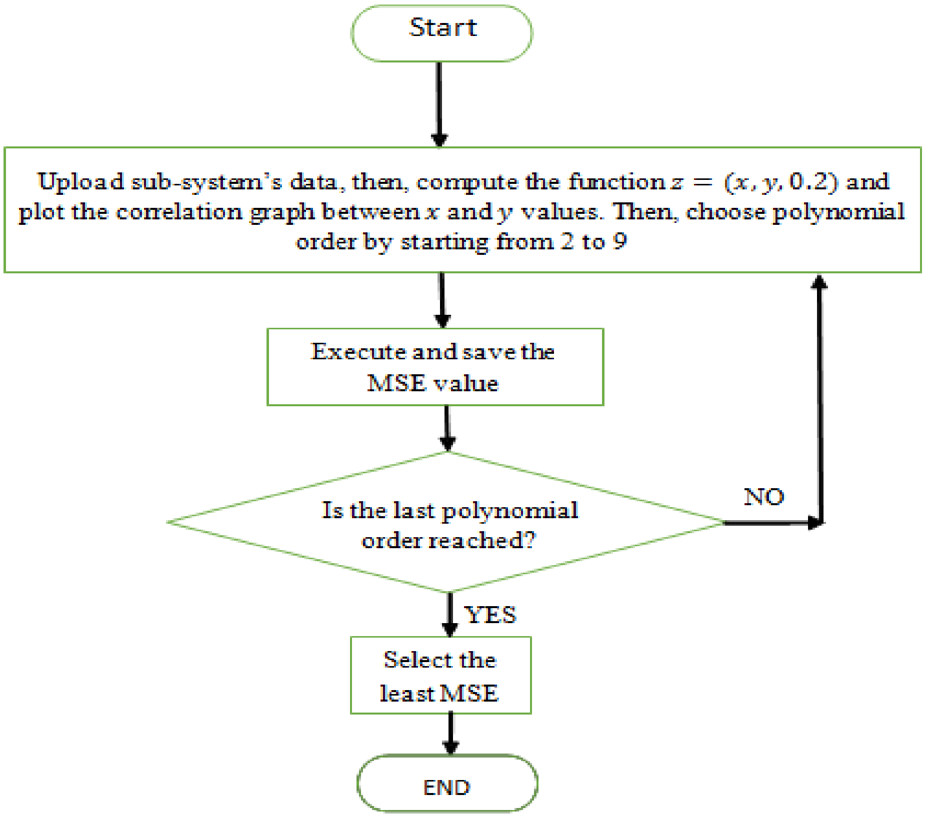

Figure 6: Flow Chart for the ARMAX Model Development

3. RESULTS AND DISCUSSION

3.1. Results

This section presents the results for the proposed model identification of the thermal power plant using the artificial neural network (ANN). It also presents model and dataset validation results.

Validation and test lines meet at the second epoch according to Figure 7. This point is indicated with the dotted reference line (labelled Best in the Legend). The train line indicates the output plot when the network suffers generalization during training. At this moment, the training stops even if no any training criterion has been met. The same explanation goes for Figures 8, 9, and 10. 4.2. Analysis and Discussion of Results

Table 2 shows the degree of agreement (mean squared error) between the two outputs. Also from the same table, comparison between MSE values of NN and ARMAX based models for validation purpose are shown.

Table 2: Mean Square Error (MSE) values for the ANN and ARMAX Models over the First and Second Set of Dataset

System Unit	MSE for ANN		MSE for ARMAX	
	(First Dataset)	(Second Dataset)	(First Dataset)	(Second Dataset)
Governor	0.0024	0.0023	0.002562	0.002469
Turbine	3.4938	2.7182	4.795	4.95
Generator	2.2997	1.3240	0.01261	0.01313
Complete Power Plant	0.0157	0.0156	0.0162	0.01471

Moreover, Table 2 reveals the strong agreement between the MSE values obtained from the first and second datasets for the ANN based models for the Governor, Turbine, Generator, and the complete plant. This result suggests absence of seasonal peculiarities associated with the dataset used to develop the ANN models. Table 3 compares the ANN and ARMAX models and summarizes the percentage enhancements by the ANN model over the individual units as well as in the complete plant model.

Table 3: Summary of MSE Values for ANN and ARMAX Based Models

System Unit	Mean Square Error (MSE)		Percentage Enhancement (%)
	ANN Based Model	ARMAX Based Model	
Governor	0.0024	0.002562	6.32
Turbine	3.4938	4.795	27.14
Generator	2.2997	0.01261	99.82
Complete Plant	0.0157	0.0162	3.09

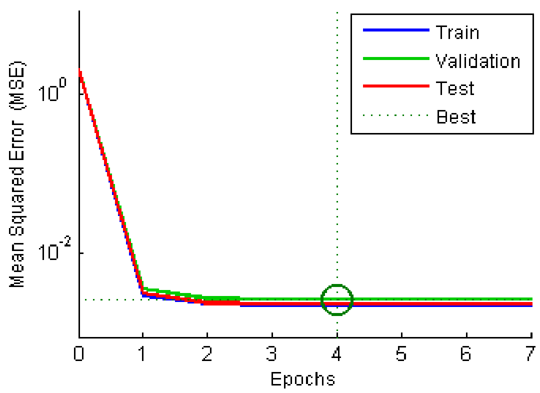

Figure 7: Plot of Governor's Validation Performance

(Best validation performance is 0.0026497 at 4th epoch)

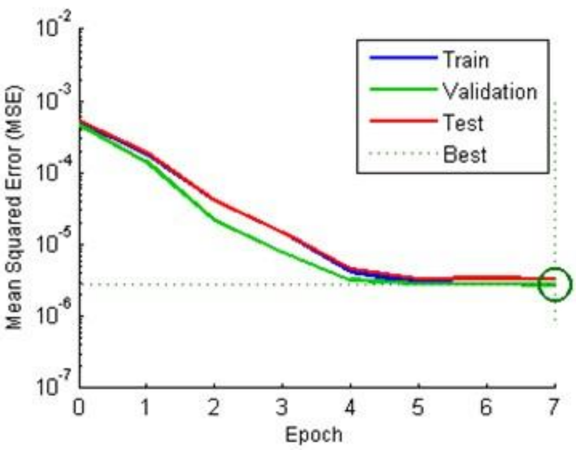

Figure 8: Plot of Turbine's Validation Performance

Figures 7 through 10 demonstrate, graphically, the close agreements between the developed ANN models test results and measured (validation) data obtained from the power plant.

The complexity of the developed ANN model and all ANNs in general depends on the architecture and the training of the network. For the two layer feed-forward neural network, there are 2 layers to which the remaining $n-1$ neurons can be distributed besides the output neuron. The worst case (regarding complexity) would be that the nodes are equally distributed, which results in $\left(\frac{n-1}{2}\right)^2 \in O(n^2)$, that is, vector product of the number of nodes in layer i with number of nodes in layer $i-1$..

The main caveat of neural networks is the training time and existing theoretical results show that successfully learning with ANNs is computationally hard in the worst case (Roi et al., 2014). However, in this work, the training of the identification model was done offline; thus, the cost and training time are not critical since realtime application is not required.

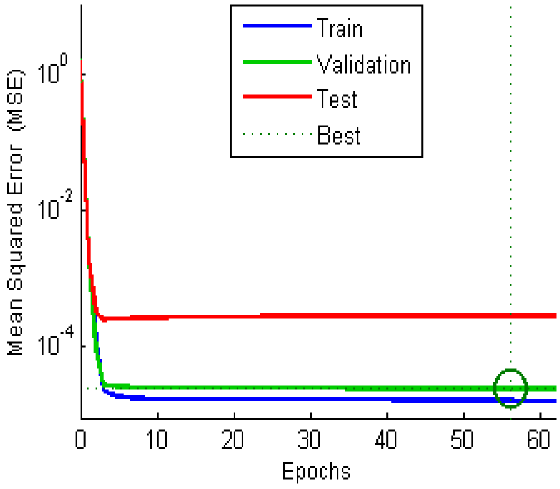

Figure 9: Plot of Generator's Validation Performance (Best Validation Performance is 2.3886e-05 at epoch 56)

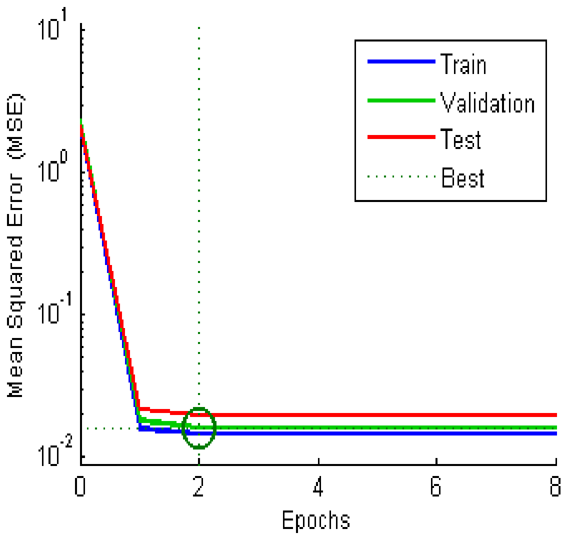

Figure 10: Plot of Complete Plant's Validation Performance (Best Validation Performance is 0.016256 at epoch 2)

4.0 CONCLUSION

Thermal power plant was modelled using artificial neural network (ANN) model identification technique by discretely modelling the plant units that interconnect to generate electrical power. These units include the governor, turbine and the generator. A model for the complete plant is also developed. The accuracy of the developed ANN-based models have shown improvements over the ARMAX models by 6.32% for the governor, 0.00002714% for the turbine, 99.82% for the generator and 3.09% for the complete plant. It was found that the developed ANN model can effectively serve as a black-box model for the thermal power plant and its sub-units – escaping the burden of resorting to complex mathematical modelling. Furthermore, the ANN model, which is derived from data, is more robust and adaptive to disturbance as a result of ageing of components due to wear and tear or other environmental impacts. Using the identified model of the thermal power plant to design and simulate controllers to improve frequency and power stability will be the focus of future research.

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