Neural Networks Modelling of Aero-derivative Gas Turbine Engine: A Comparison Study

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Abstract: In this paper, the modelling of aero derivative gas turbine engine with six inputs and five outputs using two types of neural network is presented. Siemens three-spool dry low emission aero derivative gas turbine engine used for power generation (SGT-A65) was used as a case study in this paper. Data sets for training and validation were collected from a high fidelity transient simulation program. These data sets represent the engines operation above its idle status. Different neural network configurations were developed by using of a comprehensive computer code, which changes the neural networks parameters, namely, the number of neurons, the activation function and the training algorithm. Next, a comparative study was done among different neural models to find the most appropriate neural network structure in terms of computation time of neural network training operation and accuracy. The results show that on one hand, the dynamic neural network has a higher capability than the static neural network in representation of the engine dynamics. On the other hand however, it requires a much longer training time.

1 INTRODUCTION

Aero-derivative gas turbine engines (ADGTE) are widely used as a mechanical drive in oil and gas application and power generation. These widespread and increasing applications have sparked a great interest among manufacturers to improve the performance and increase the reliability of the engine, which in turn requires an accurate and real time model to simulate the gas turbine engine dynamics. Siemens SGT-A65 is a three spool ADGTE. The thermodynamic physics based model for this engine configuration is very complicated because of the high number of subsystems and the high number of non linear equations that require to be solved iteratively at the expense of computation time (Hanachi et al., 2015). This makes it challenging if not impossible to use physics based modelling approach in real time model based control applications.

An alternative approach to physics based modelling is data driven based modelling. Neural networks (NNs) is one of the data driven based (black box) modelling approaches which can be used when no or little information is available about the physics of the system. It has the advantage of high computational speed allowing real time applications. The NN model can be used in the development and operational stages of an engine's life to predict the engine's performance, test the performance of the engine control systems and for engine health monitoring.

The main idea behind neural network modelling is to create a simple model of human brain in order to solve complex scientific and industrial problems in many fields. Neural networks can be classified into two main categories, static and dynamic neural networks. Static neural networks are the simplest neural networks, and are characterized by memoryless non linear equations, which means that there are no feedback elements and no delays in the network input. Therefore, the output parameters from the static NN depend only on the current values of the input parameters as shown in Fig. 1a. The multi layer feed forward neural networks (MFFNN) are considered as static neural networks because they have only feed forward transformation of the information from the input layer to the output layer.

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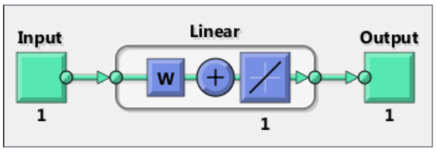
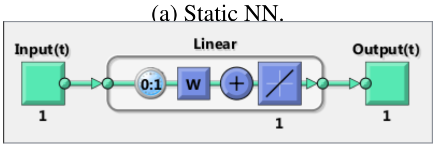
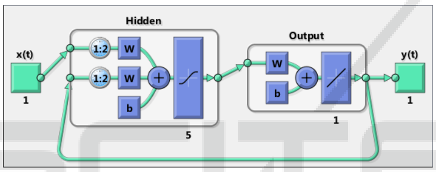
On the other hand, in the case of dynamic neural networks, output parameters from the network depend not only on the current input parameters of the network, but also on the previous input and output parameters of the network. Furthermore, dynamic neural networks can be divided into two categories: those that have only feedforward connections (input/output delays), and those that have feedback as shown in Fig. 1b, or recurrent connections as shown in Fig. 1c.



(a) Static NN.



(b) Dynamic feed forward NN with input delay.



(c) Dynamic with feedback NN.

Figure 1: Neural network types(Beale et al., 2015).

There are many works in the literature regarding the usage of static neural networks in modelling and simulation of industrial gas turbine engines. (Lazzaretto and Toffolo, 2001), (Fast et al., 2009), (Asgari et al., 2013) and (Rahmoune et al., 2015) are considered to be major research activities in this area. These works are based on feed-forward NNs, with a single hidden layer and different numbers of neurons, trained by using a back propagation learning algorithm. More recently, dynamic neural networks have been employed for modelling gas turbine engines. Non linear autoregressive network with exogenous inputs (NARX) is a recurrent dynamic network, with feedback connections enclosing several layers of the network. (Salehi and Montazeri-Gh, 2018), (Asgari et al., 2016) and (Bahlawan et al., 2017) used NARX neural network to model ADGTE.

In this paper, a comparison study between MIMO static feed forward neural network and MIMO NARX dynamic neural networks was performed to model a three spool ADGTE (SGT-A65) above its idle status. A comprehensive computer program was used for both types of NN to change the neural network parameters, namely, the neuron number(from 1 to 20), the activation function (tansig or logisg) as well as different training algorithms (trainlm, trainbr and trainscg). After that, a comparative study was done among different neural models to find the most appropriate neural network structure in terms of training time and accuracy by calculating the overall root mean square error value.

2 AERO-DERIVATIVE GAS TURBINE ENGINE

ADGTE are a popular choice for energy generation as a result of their high reliability, efficiency and flexibility. ADGTE have also been widely used in pumping applications for gas and oil transmission pipelines, offshore platforms and naval propulsion. This kind of gas turbines are derived from high bypass turbofan engines. In this paper, a three spool dry low emission aero derivative gas turbine engine (SGT-A65) was modelled as shown in Fig. 2. This engine consists of two stages low axial low pressure compressor (LPC), eight stages axial intermediate pressure compressor (IPC), six stages axial high pressure compressor (HPC), single stages high and intermediate turbines and five stages low pressure turbine. The low pressure shaft was connected with the power generator. Therefore, it should rotate at fixed revolution (3600 rpm for electricity generation with 60 Hz).

The engine specifications are illustrated in Table 1.

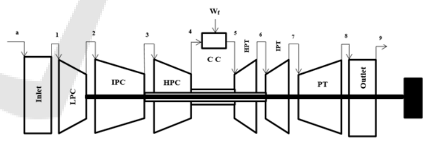


Figure 2: Siemens SGT-A65 aero derivative gas turbine engine.

Table 1: Gas turbine technical data.

Parameter	Value
Exhaust mass flow rate	$171 kg/s$
Output power	$65 MW$
Power turbine speed	$3600 rpm$
Total compression ratio	38 : 1
Exhaust temperature	$437^{o}C$

3 NEURAL NETWORK MODELLING METHOD

3.1 Available Field Data

In this paper, simulated data sets, which were used for training and validation of the neural networks, were provided to us by Siemens high fidelity transient simulation program for the SGT-A65 engine at ISO conditions with a sampling rate of 0.1 sec. Note that, the data was generated from a closed loop set-up with Siemens own controller as the SGT-A65 engine can not be run in open loop. Two sets of six inputs and five outputs data were generated by changing the engine load to cover the entire operating range of the engine:

- Random load change (used for training) consisting of 24170 samples;
- Square load change (used for validation) consisting of 12890 samples;

As can be seen, a large number of training patterns (samples) were used to train the NN. The number of training patterns has an effect on the NN accuracy: a low number of training patterns may increase the NN error due to network over fitting. This means that NN loses its ability to generalize. On the other hand, this large number of training patterns may increase the training computation time.

The SGT-A65 ADGTE input and output parameters that are used, are illustrated in Table 2 and Table 3 respectively.

Table 2: The ADGTE input parameters.

Fuel flow	G_f
LPC bleed off valve	LPBOV
Variable inlet guide vans	VIGV
IPC bleed off valve	NBIP8
IPC variable stator vans	IPVSV
HPC bleed off valve	NBHP3

Table 3: The ADGTE output parameters.

Low-pressure shaft speed	N_L
Intermediate shaft speed e	N_I
High-pressure shaft speed	N_H
Engine shaft power	POWER
Intermediate turbine exit temperature	TGT

Fig. 3 and Fig. 4 show the change of the normalized input and output parameters for the SGT-A65 ADGTE used for training operation. Since the input data to the NN represent the output from the engine controller, the saturations in Fig. 3 are imposed by the controller.

3.2 MIMO Static Neural Model

For this MIMO model, a feed forward multilayer neural network was used to simulate the SGT-A65 ADGTE. This type of NN consists of an input layer with a number of nodes equal to the number of inputs, one or more hidden layers with a certain number of neurons, and an output layer with a number of neurons equal to the number of NN outputs. The first parameter to be fixed is the number of hidden layers the static NN needs to have. Cybenco (Cybenko, 1989) proved that NN with one hidden layer of hyperbolic tangent or sigmoid activation function and one output layer of linear activation function could simulate any non linear system. Therefore, in this study, one hidden layer feed forward neural network was used. To get an optimized neural network structure which can represent the ADGTE dynamics, a comprehensive computer program was generated and run in Matlab environment. This program generates different neural models by changing the following parameters:

- Change of the number of neurons from 1 to 20.
- Usage of two activation functions logsig and tansig.
- Usage of three training algorithms: Levenberg-Marquardt training algorithm (trainlm), Scaled conjugate gradient training algorithm (trainscg) and Bayesian regularization training algorithm (trainbr).

At each computation cycle, training of the NN was performed by using random load change data sets. The stop network training parameters used are: (i) the mean square error performance function which is minimized until it reaches its minimum value (0.01), (ii) the maximum number of training epochs (1000) which represents the number of times that all the the training patterns are presented to the NN and (iii) the maximum number of validation increase (100) which represents the number of successive epochs in which the performance function fails to decrease. Training operation was repeated three times for the same neural network with the same input data set to increase the accuracy of the network. A preliminary analysis which was carried out to evaluate the influence of the number of training repetition showed that the use of training repetition higher than three requires a great computational effort, while it only allows a small improvement of NN performance. Note that the training operation was done in a computer with

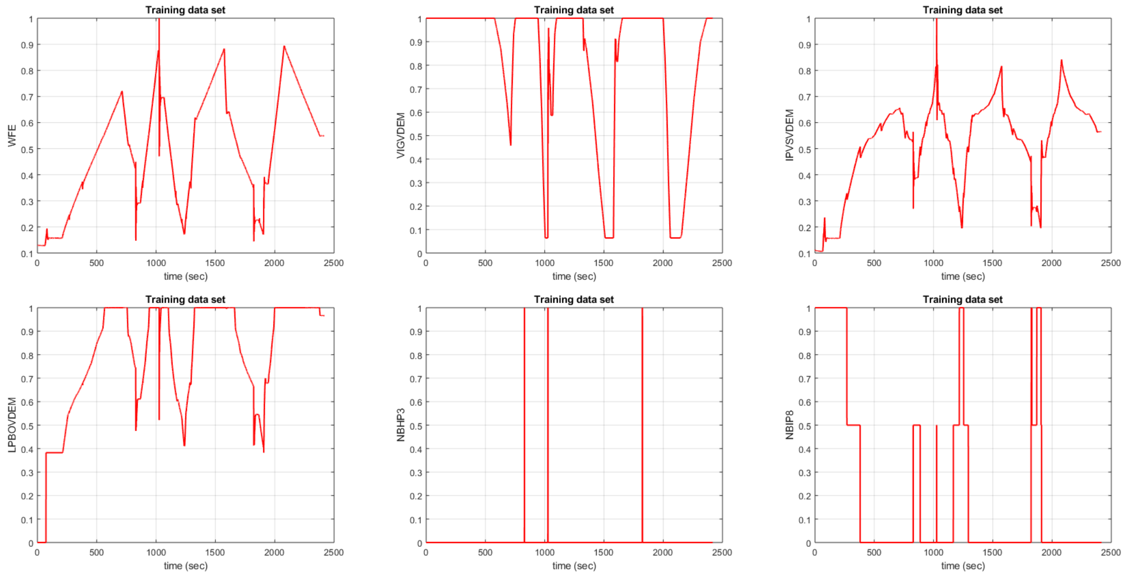


Figure 3: Normalized input parameters for model training.

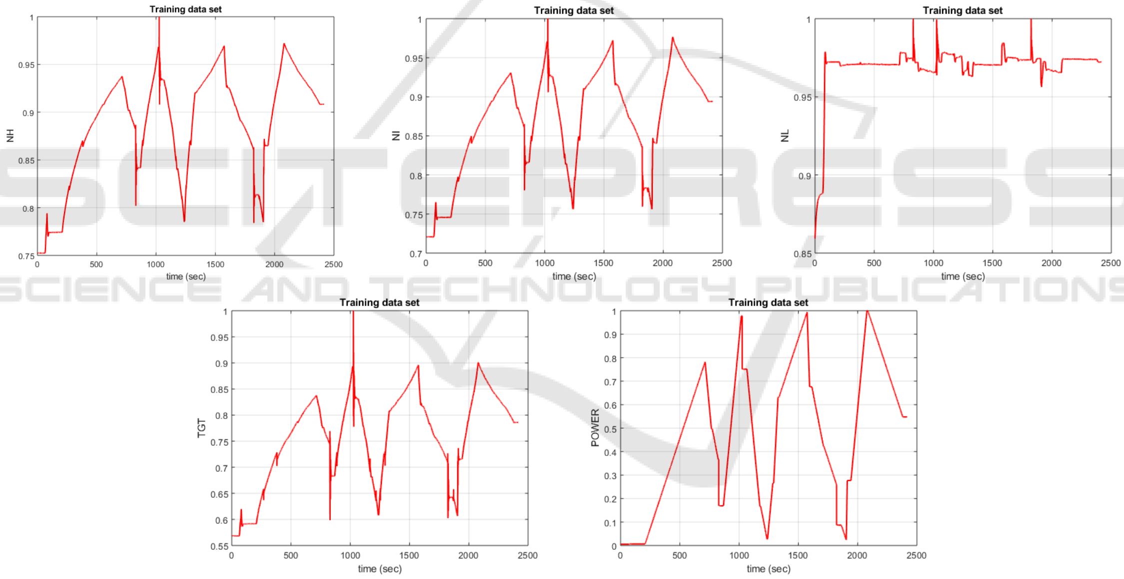


Figure 4: Normalized output parameters for model training.

64 GB RAM and processor intel(R)Xeon(R) CPU E3-1225 v6 @ 303GHz.

After that, validation of the trained network was performed with another data set (Square load change data set). The results of each computation cycle were recorded in a matrix form which includes the network structure, the root mean square error (*RMSE*) for training process, RMSE for validation process and training time. RMSE was used for the comparison of the NNs. It was calculated for the whole set of data of each output parameter from the NN, and defined according to Eqn. (1),

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\frac{y_m - y}{y_m})^2} \quad (1)$$

where, n is the number of data samples, y_m is the actual output and y is the predicted output. An overall RMSE of NN was also calculated as the sum of RMSE of each output parameter.

To select the most appropriate static neural model structure, the output data from the developed computer program was divided into two groups as follows:

First Group. Static NNs with tansig activation function, different numbers of neurons and different training algorithms.

Second Group. Static NNs with logsig activation function, different numbers of neurons and different training algorithms.

Next, the best NN from each group was selected based on the minimum value of overall RMSE during validation operation and minimum value of training time. Fig. 5 shows the results analysis for first group with respect to the overall value of the RMSE. Fig. 6 shows the results analysis for first group with respect to the time consumed in the training phase.The results of the second group are not shown for space reasons. It can be noticed that the overall RMSE decreases and the training time increases as number of neurons in hidden layer increases. In particular, when NN was trained by usage of trainlm or trainbr algorithms, overall RMSE is smaller than overall RMSE of NN trained by trainscg algorithm. On the other hand, NNs trained by trainscg algorithm had the smallest training time. However, the fast reduction in training time by using (*trainscg*) was due to the fact that the maximum number of validation increase was reached. Table 4 summarizes the best result from each group. As can be seen from Table 4 the best static MIMO neural model configuration which can represent SGT-A65 ADGTE should have eighteen neurons in the hidden layer, using *tansig* as activation function and using Levenberg-Marquardt (*trainlm*) as training algorithm. In addition, the difference in the training time between the best NN model in the first and second group is small, which can be neglected in comparison to network accuracy.

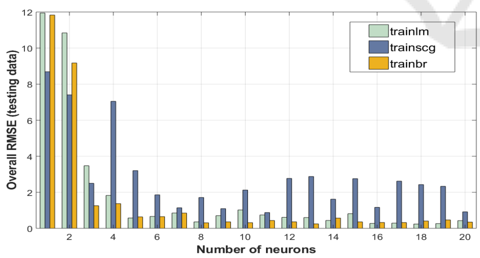


Figure 5: Influence of number of neurons with tansig activation function and different training algorithms.

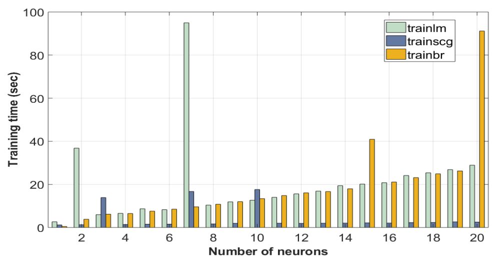


Figure 6: Influence of number of neurons with tansig activation function and different training algorithms on the training time.

3.3 MIMO Dynamic Neural Model

There are many types of dynamic neural networks in the literature (Norgaard et al., 2000). In this paper, MIMO NARX recurrent dynamic neural network is employed to simulate the SGT-A65 ADGTE, which has feedback connections enclosing several layers of the network. The following equation relates NARX model output parameters to its input parameters,

$$\begin{aligned} y_i(t) = f(&y_i(t-1), y_i(t-2), \cdots, y_i(t-n_y) \\ &, u_j(t-1), u_j(t-2), \cdots, u_j(t-n_u)) \end{aligned} \tag{2}$$

where, n_y and n_u are the number of regressed outputs and regressed inputs respectively. These two parameters represent the most important parameters in the NARX network configuration, and can be evaluated by using system order estimation. In this study , we used $n_y = 2$ and $n_u = 2$ based on the literature (Asgari et al., 2016; Bahlawan et al., 2017).

Another important parameter in the NARX configuration is the training architecture. The NARX network training can be implemented via two architectures:

Series-parallel Architecture (S&Pr) the network is trained in open loop mode then transformed to closed loop mode for validation operation.

Parallel Architecture (Pr) the network is trained and validated in closed loop mode.

To get the optimal NARX model structure which can represent the ADGTE dynamics, a comprehensive computer program was generated and run in Matlab environment. This program generates different NARX models by changing the neural network parameters as shown in the static neural network for fair comparison purposes. These parameters are as follows:

- Change of the number of neurons from 1 to 20.
- Usage of two activation functions logsig and tansig.
- Usage of three training algorithms trainlm, trainscg and trainbr.
- Train the network as series-parallel architecture and parallel architecture.

The stop network training parameters are the same as the ones for the MIMO static neural network, also the training operation was performed on the same computer as for MIMO static network. At each computation cycle, training of the NARX network was performed by using random load change data set. After that, validation for the trained network was performed

Table 4: The best result from each group of MIMO static neural model.

No of neurons	activation function	training algorithm	Testing RMSE	training time
18	tansig	trainlm	0.2388	25.404 sec
14	logsig	trainlm	0.2475	17.844 sec

with another data set (Square load change data set). The results of each computation cycle were recorded in a matrix form which includes the network structure, RMSE for each output parameters in training and validation phases, the overall root mean square error RMSE for validation phase and training time. The output data from the developed computer program was divided into four groups as follows:

First Group: series-parallel NARX with tansig activation function, different numbers of neurons and different training algorithms [Fig. 7 and Fig. 8].

Second Group: series-parallel NARX with logsig activation function, different numbers of neurons and different training algorithms.

Third Group: parallel NARX with tansig activation function, different numbers of neurons and different training algorithms.

Fourth Group: parallel NARX with logsig activation function, different numbers of neurons and different training algorithms.

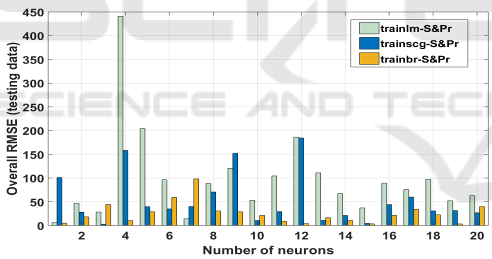


Figure 7: Influence of number of neurons with tansig activation function and different training algorithms.

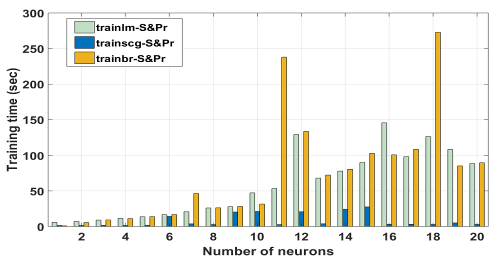


Figure 8: Influence of number of neurons with tansig activation function and different training algorithms.

Note that, only figures from the first group will be shown for space reasons. As can be seen, NARX network with logsig activation function trained in parallel architecture with trainscg or trainbr algorithms gave the best results with respect to the overall RMSE values. However, this improvement in network accuracy came at the expense of increasing the training time. On the other hand, the fast training time was due to the stop of network training as the value of maximum number of validation increase was reached. Note also that the training time increases as the number of neurons in the hidden layer increases. Moreover, in a comparison of different structures of the NARX NN, the results showed that the logsig activation function was superior to the tansig activation function.

Table 5 summarizes the best result from each group. As can be seen, the best MIMO NARX model configuration which can represent SGT-A65 ADGTE should be a fourteen neurons in the hidden layer, using *logsig* as activation function and using Bayesian regularization (*trainbr*) as training algorithm in the parallel architecture. This selected network took much more time for training but made a good prediction for all of the engine parameters, especially the low pressure spool speed (RMSE for low pressure spool speed was 0.0009). On the other hand, NARX network with eighteen neurons, tansig activation function, and trained in parallel architecture with trainbr algorithm gave a lower training time than the selected network. However, the RMSE for the low pressure spool speed (0.0059) is higher than the one in the selected network.

4 COMPARISON RESULTS

In this section, a comparison between the best MIMO static neural model and the best MIMO NARX dynamic neural model was performed. Both MIMO static neural model and MIMO NARX dynamic neural model were tested against the square data set. The results are presented in Fig. 9 to Fig. 12 and summary of these results was shown in Table 6. In a comparison of MIMO static NN with MIMO NARX dynamic NN, the following results are obtained:

- The MIMO static NN and MIMO NARX dynamic NN could represent the ADGTE with acceptable accuracy.
- Eventhough the MIMO static NN has slightly better performance (in term of overall RMSE) than the MIMO NARX dynamic NN, the MIMO NARX dynamic NN captures better the fast

Table 5: The best result from each group of MIMO NARX model.

No of neurons	activation function	training algorithm	S & PR / Pr	Testing RMSE	Training time
3	tansig	trainscg	S & PR	2.8760	1.7020 sec
18	logsig	trainscg	S & PR	1.1524	12.5930 sec
18	tansig	trainbr	Pr	0.3268	299.9670 sec
14	logsig	trainbr	Pr	0.3225	1333.9 sec

change in low pressure spool speed parameter, high pressure spool speed, intermediate pressure spool speed and intermediate turbine exit temperature.

- The training time in the MIMO NARX dynamic NN is higher than that in the MIMO static NN. The increase in training time of the NARX network may be due to the feedback connections and the higher number of parameters which should be evaluated during training phase.

- The generalization capability of the MIMO NARX dynamic NN is higher than that in the MIMO static NN.

- The MIMO static NN gave satisfactory results, because a sufficient and adequate training data set was used.

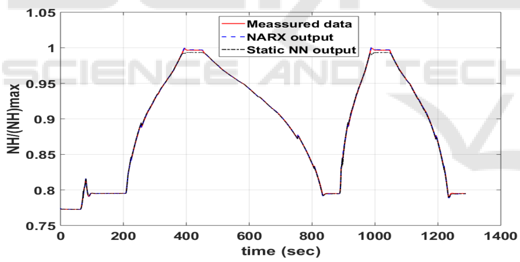


Figure 9: Variation of *NH* for the testing data.

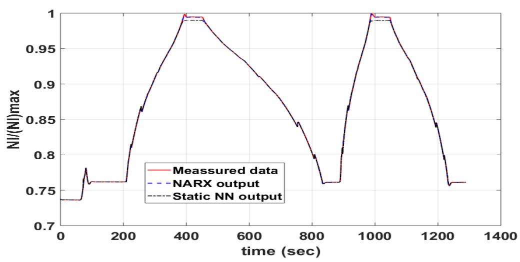


Figure 10: Variation of *NI* for the testing data.

Dynamic networks are generally more powerful than static networks. Therefore, the dynamic neural networks can be used in multi step ahead prediction applications. However, it takes much more training time.

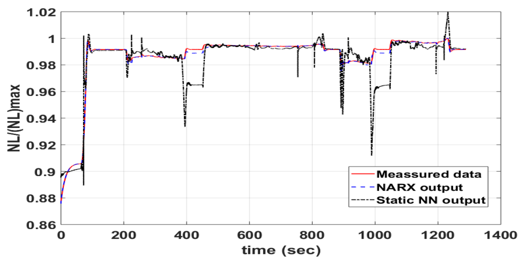


Figure 11: Variation of *NL* for the testing data.

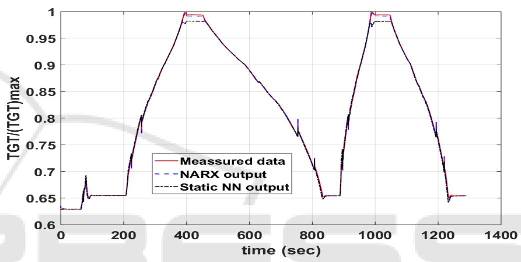


Figure 12: Variation of TGT for the testing data.

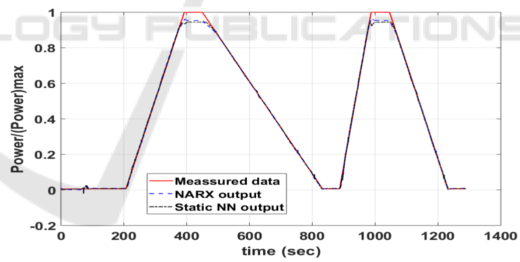


Figure 13: Variation of power for the testing data.

5 CONCLUSIONS

In this paper, data driven modelling and identification of Siemens SGT-A65 ADGTE is done using two types of neural networks; static feed forward NN and NARX dynamic NN. First, two sets of simulated data from a high fidelity transient simulation program were collected for training and validation process of the networks. Second, selection of the best appropriate neural model structure in both the static and dynamic networks was performed by using a comprehensive computer program, which changes the NN parameters and performs training and validation of the produced

Table 6: Static and dynamic neural model comparison results.

Output parameter	Static NN RMSE	NARX model RMSE
N_L	0.01120	0.00098
N_I	0.00190	0.00039
N_H	0.00150	0.00047
POWER	0.21890	0.31890
TGT	0.00530	0.00170
Overall RMSE	0.23880	0.32250
Training time	25.404 sec	1333.9 sec

networks. The output data from this program were recorded in a matrix form. After that, analysis of these recorded data was performed by dividing the data into different groups and selection of the best model structure from each group based on the minimum value of RMSE. Finally, comparison results between static NN and dynamic NN showed a good capability of the dynamic neural networks over the static neural networks in representation of the dynamic response of ADGTE. However, the training time of the dynamic NN was higher than that in the static NN.

Since, there is no general methodology or rule to define the neural network parameters, the way to select the best network configuration is traditionally obtained by trial-and-error. This paper may work as a guideline for researchers in selection of the best feed forward and NARX neural network configuration which can represent ADGTE during its full range above its idle status.

In general, the developed NN models for the ADGTE can be an effective tool for real time simulation of gas turbines and model based control applications.

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