REAL-TIME MODELLING AND HARDWARE IN THE LOOP SIMULATION OF AN AERO-DERIVATIVE GAS TURBINE ENGINE

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ABSTRACT

Modelling and simulation of gas turbines plays a key role in manufacturing and improving performance of gas turbine engines. In recent years, the importance of ADGTEs in the energy industry has 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 engine dynamics during the full operating range. For this purpose, a real-time modelling and hardware in the loop (HIL) simulation of an aero-derivative gas turbine engine (ADGTE) are developed in this paper. A non-linear autoregressive network with exogenous inputs (NARX) is used to develop this model in MATLAB environment using operational closed-loop data collected from Siemens (SGT-A65) three-spool dry low emission ADGTE. A multiple-input single-output (MISO) NARX models with different configurations are used to represent each of the ADGTE output parameters with the same input parameters. First, data preprocessing and estimation of the order of these

MISO models are performed. Next, a comprehensive computer program code is developed to perform a comparative study and to select the best NARX model configuration, which can represent the system dynamics. Finally, to demonstrate the performance of the MISO NARX model developed in this study, a HIL simulation is performed. In this simulation, the physical ADGTE is replaced with the MISO NARX model, and the physical engine controller is used to control that model. In addition, the neural model is validated with experimental data. The simulation results show that the proposed MISO NARX models followed the targets precisely and can predict the response with high accuracy and reliability. In addition, the proposed model presents high computation speed, which allows for real time applications.

INTRODUCTION

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 manu-

facturers 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 (Ibrahim et al. 2019). GTE modelling methods can be categorized into two main groups including physics based modelling methods (white-box models) and data driven based modelling methods (black-box models). In some cases, the expression of gray-box model may also be used as a combination of the last two methods (Asgari et al. 2014).

Physics based models are based on first principles such as the law of physics, chemistry, etc (Nguyen 2000). This approach has been widely used over many years in order to model gas turbine engines (Bettocchi et al. 1996, Saleh 2017, Petkovic et al. 2019). However, this approach can only be used when there is enough information about the physics of the system. In addition, a white box model has traditionally a high number of non linear equations requiring iterative solutions which occur at the expense of computation time. The computation time challenge is a big problem for real time modelling, especially when the system to model consists of a high number of subsystems as in case of three spool GTEs. Real-time simulation can be used as a powerful tool in developing, testing and tuning control devices of gas turbines.

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 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. 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 feed-forward connections (input/output delays), and those that have feedback or recurrent connections.

There are many works in the literature regarding the usage of static neural networks in modelling and simulation of industrial gas turbine engines. (Fast et al. 2009, 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 & Montazeri-Gh 2018, Asgari et al. 2016, Bahlawan et al. 2017) used NARX neural network to model ADGTE.

Based on the literature survey, in the area of MIMO ANN modelling of gas turbine engines, the research activities used mostly one of the following two methods to generate a nonlinear model for the MIMO engine: Either, by building a neural network model for each output parameter (MISO) with the same structure for each one of them and trained with the same training algorithm (Bahlawan et al. 2017, Asgari et al. 2016), or by building one block neural model to represent the MIMO system (Asgari et al. 2014, Tarik et al. 2017, Salehi & Montazeri-Gh 2018, Ibrahim et al. 2019). However, it is more powerful, as will be shown in this study, to use a different neural network's structure for each output. For this purpose, we proposes to build a MISO NARX neural network model for each output. Moreover, the structure of each neural model is different.

Therefore, this paper presents a novel development approach of a real time black box model for ADGTE based on recurrent neural networks (NARX). Firstly, closed loop experimental data preprocessing was performed as will be explained in the data acquisition and preprocessing subsection. Secondly, generation of multiple MISO ARX models was used to identify the order of the MISO systems to be modelled based on the experimental data. Next, comprehensive computer program was developed to generate multiple MISO NARX neural models for each output parameter from the SGT-A65 ADGTE data with the particularity that each NARX model have its unique configuration based on its function. This program generated 240 NARX models with different structures by changing the neural network parameters (number of neurons, activation function and training algorithm). After that, a comparative performance study using different combinations of MISO NARX neural network architectures for each output parameter was done to select the most appropriate neural network structure in terms of accuracy. Finally, a HIL simulation

bench was assembled to serve as a development and validation platform for real-time model. A real-time machine from Speedgoat was used to run a real time NARX model. This was coupled to a Rockwell Automation rack containing several PLC which were used to run the complete Siemens SGT-A65 ADGTE control system software in its production level native form.

AERO DERIVATIVE GAS TURBINE ENGINES

The ADGTEs were created from aero-gas turbine engines, which give them lighter weight, faster response and a smaller footprint compared with their heavy duty GTE counterparts. They are usually offered as packaged units with prefabricated accessory modules for rapid installation. Their modular design also enhances their operability and maintainability. ADGTEs are often seen as a good choice in smaller-scale (up to 200 MW) energy generation. In this paper, Siemens (SGT-A65) three spool ADGTE was modelled. It has a two-stage low pressure, eight-stage intermediate pressure and six-stage high pressure compressor with dry low emission combustion. Furthermore, both high pressure and low pressure turbines consist of a single stage each and the power turbine has five stages used to drive the low pressure compressor and the power generator at fixed speed (3600 rpm used for power generation at 60 Hz). Figure 1 shows a sketch of SGT-A65 aero derivative gas turbine engine with its stations numbers. In addition, the engine specifications are illustrated in Table 1.

Figure 1: Sketch of three spool ADGTE (SGT-A65).

DATA ACQUISITION AND PRE-PROCESSING

The datasets, which are used in this study, consist of four different closed loop time series datasets. Each dataset consists of six input parameters (WF, VIGV, LPBOV, IPVSV, IPBOV, and HPBOV) and seven output parameters (N_L , N_I , N_H , PW, T_{30} , P_{30} , and TGT) representing the engine operation from the Synch-Idle

Table 1: Gas turbine technical data

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

or Synch speed (3600 rpm) with no load regime to Synch speed with full load regime. The starting and shutdown regimes are not represented in this work. Table 2 shows more details about these datasets, where TR is the training dataset and TS is the testing dataset.

Firstly, data preprocessing was performed. The experimental time series datasets $TR1_{exp}$ and $TS1_{exp}$ are used for pre-processing operation for extracting the most valuable information about the system dynamics to use in identification of ANN models. The experimental time series datasets $TS2_{exp}$ and $TS3_{exp}$ are used for model validation to check model generalisation. The experimental datasets $TR1_{exp}$ and $TS1_{exp}$ are cleaned by filtering any measurement noise. A simple second order low pass Butterworth digital filter with cut-off frequency 0.5 Hz was used to remove noise from experimental datasets. After that, cleaned datasets $[TR1_{exp}$ and $TS1_{exp}]$ are re-sampled at a lower frequency $F_s = 10$ Hz instead of high sampling frequency 20 Hz to avoid aliasing effects and to avoid having the poles of the discrete models being very close to the +1 point on the unit circle. In addition, the lower sampling rate reduces the number of data points which reduces the computation time during training operation and reduces data collinearity. The selection of the sampling rate was performed based on the Nyquist sampling criterion, which requires setting the sampling rate at least twice the highest frequency of the system.

Secondly, estimation of the system order by generation of a set of candidate MISO ARX models and determining the best model order in the set. The ARX model structure is one of the simplest parametric structures and it is considered a good starting point for identification process because of its simplicity. The general structure of MISO ARX model is shown in Eqn. (1).

$$A(q^{-1})y(t) = B_1(q^{-1})u_1(t - n_{k_1}) + \dots + B_j(q^{-1})u_j(t - n_{k_j}) \quad (1)$$

$$A(q^{-1}) = 1 + a_1q^{-1} + \dots + a_{n_y}q^{-n_y} \quad (2)$$

Table 2: Time series datasets

Dataset	NO of samples	T_{amb}	P_{amb}	LHV	η_{ih}
$TR1_{exp}$	21983	26	101.32	48360	0.32
$TS1_{exp}$	8117	26	101.32	48360	0.32
$TS2_{exp}$	17186	26	101.32	48360	0.32
$TS3_{exp}$	17231	30	101.32	47826	0.4231

$$B(q^{-1}) = b_1 + b_2 q^{-1} + \dots + b_{n_u} q^{-n_u+1} \quad (3)$$

where $A(q^{-1})$ and $B(q^{-1})$ are coefficient's polynomials to be estimated by using the prediction error method (PEM). MATLAB[®] routine *struc* is used to generate a set of model-order combination of MISO ARX model estimation. The routine *struc* changes n_u and n_y for all inputs and outputs from one to five, as higher-order models result in excessive computational effort and pose the risk of losing particular physical meaning of the model, and uses the input-output delay values n_k from delay estimation step. After that, MATLAB[®] routine *arxstruc* uses the set of model order combination to estimate a set of MISO ARX models based on the $TR1_{exp}$ dataset. The *arxstruc* routine computes loss functions (normalized sum of squared prediction errors) for the set of ARX-models (Ljung 2015). Next, selection of the best ARX model is performed by choosing the ARX model which has the minimum Final Prediction Error (FPE). The FPE evaluates model quality, where the model is tested on another dataset $TS1_{exp}$. Such a procedure is known as cross validation. The most accurate model has the smallest FPE. The FPE equation is defined by the following equation:

$$FPE = \frac{1 + \frac{d}{N}}{1 - \frac{d}{N}} V \quad (4)$$

where d is the total number of estimated parameters and N is the length of the data record. V is the loss function (quadratic fit) for the structure in question. Table 3 summarizes the results from order estimation process for all MISO ARX models for all output parameters of the engine and uses these results in the non-linear NN identification process. This will be illustrated in the next subsection.

ENGINE REAL TIME MODEL

In this paper, MISO NARX recurrent dynamic neural network is employed to simulate the SGT-A65 ADGTE. The fol-

Table 3: System order and delay estimation results

Output parameter	n_y	n_u	n_k
N_H	4	[4 4 4 4 4]	[1 0 2 0 0 0]
N_I	4	[4 4 4 4 4]	[1 1 3 0 0 0]
N_L	4	[4 4 4 4 4]	[0 2 1 1 0 0]
PW	4	[2 2 4 4 4]	[1 0 3 0 0 0]
TGT	4	[1 4 4 1 1 4]	[1 0 0 0 0 0]
T_{30}	4	[3 1 4 2 1 1]	[6 2 4 3 0 0]
P_{30}	4	[1 2 2 1 1 4]	[0 0 2 1 0 0]

lowing equation relates NARX model output parameters to its input parameters,

$$y_i(t) = f(y_i(t-1), y_i(t-2), \dots, y_i(t-n_y), u_j(t-1), u_j(t-2), \dots, u_j(t-n_u)) \quad (5)$$

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.

Another important parameter in the NARX configuration is the training architecture. The NARX network training can be implemented via two architectures: (i) series-Parallel architecture (S&Pr), where the network is trained in open loop mode then transformed to closed loop mode for validation operation, (ii) parallel architecture (Pr), where the network is trained and validated in closed loop mode. In this paper, to get the optimal NARX model structure which can represent the ADGTE dynamics, we perform an extensive comparative performance study using different combinations of NARX neural network architectures, training algorithms and activation functions while using different numbers of neurons. As a result, a comprehensive computer program was developed in the MATLAB environment (Ibrahim et al. 2019). This program generates 240 NARX models with different structures by performing the following:

1. Changing of the number of neurons from 1 to 20.
2. Usage of two activation functions *logsig* and *tansig*.
3. Usage of three training algorithms *trainlm*, *trainscg* and *trainbr*.
4. Training the network with series-parallel architecture and parallel architecture.

The network training parameters are defined as: (i) the mean square error (mse) performance function which is minimized until it reaches a sufficiently low cut-off value of (0.01), (ii) the maximum number of training epochs (1000) which represents the number of times that all 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. The $TR1_{exp}$ dataset is partitioned into 80% used for training the network and 20% used for cross validation. After finishing the network training operation, the $TS1_{exp}$ dataset is used for testing the network and evaluating its generalization performance. ($RMSE$) was used for the evaluation of the network performance in the training and testing operation. It was calculated for the whole set of data of each output parameter from the NN, and defined according to Eqn. (6),

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N \left(\frac{y_m - y}{y_{max}} \right)^2} \quad (6)$$

where, y_m is the actual output and y is the predicted output. 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 testing process and training time. Next, the best NN was selected based on the minimum value of ($RMSE$) during testing operation. Table 4 summarizes the best MISO NARX models for each output parameters of the engine.

HIL SIMULATOR ARCHITECTURE

HIL simulation is a technique for performing system testing in a comprehensive, cost-effective and repeatable way. This technique is most often used in the development of systems which cannot be tested easily, thoroughly and repeatedly in their operational environment. In the HIL simulation, interactions between physical and simulated components are rendered in real time. There are few works in the literature regarding the usage of HIL simulation of industrial gas turbine engines (Montazeri-Gh et al. 2016, Salehi & Montazeri-Gh 2019).

A HIL simulation bench was assembled to serve as a development and validation platform for real-time model validation. A real-time machine from Speedgoat (with Intel Quad-Core i7 3770K @ 3.5 GHz CPU, 4096 MB of RAM) was used to run

a real time MISO NARX models. These models are then automatically translated in C-Code through Matlab Real-Time Workshop (RTW) and compiled to generate an executable code for the chosen real-time platform (Speedgoat) on which the program will be downloaded. This was coupled to a Rockwell Automation rack containing several PLCs which were used to run the complete Siemens SGT-A65 ADGTE control system software in its production level native form. Because the full (non simplified) version of the control system software was used, it required up to 4 PLCs to work together; the ECS, PCS, SIS and finally SEM. The SEM was already available and was required in this study because it provided all the hundreds of different signals (for all sub-system sensors, actuators and operator inputs) and in the right sequence in order to satisfy all the control sequences of the ECS/PCS/SIS in all engine operating modes like starting, managing power generation and stopping. Figure 2 shows the HIL setup used for testing the NARX model performance, with all of the components numbered.

Figure 2: HIL system architecture.

List of components:

1. RSLogix 5000 integrated development environment from Rockwell Automation
2. Matlab from Mathworks with Speedgoat library from Speedgoat
3. 8 port gigabit network switch
4. 1756-ENBT 10/100 Mbps Ethernet Bridge from Rockwell Automation, fitted in a 1756 Backplane from Rockwell Automation
5. Real-Time target machine; "Performance" model from Speedgoat with an Intel i7 processor
6. 1756-EN2TR EtherNet/IP communication module from

Table 4: The best MISO NARX models configuration

Output parameter	NO of neurons	activation function	training algorithm	S & PR / Pr	Training RMSE	Testing RMSE
N_H	2	trainbr	S & PR	logsig	0	0.0022
N_I	3	trainscg	S & PR	logsig	0.0002	0.0018
N_L	2	trainlm	Pr	logsig	0.0006	0.0007
PW	15	trainscg	S & PR	logsig	0.0004	0.0107
TGT	11	trainscg	S & PR	logsig	0.0002	0.0119
T_{30}	15	trainlm	S & PR	logsig	0.0002	0.0076
P_{30}	5	trainscg	S & PR	logsig	0.0041	0.005

Rockwell Automation

7. IO755 EtherNet/IP Scanner I/O module from Speedgoat
8. 1756-L73 ControlLogix Controller from Rockwell Automation executing the Engine Control System (ECS) code
9. 1756-L73 ControlLogix Controller from Rockwell Automation executing the Plant Control System (PCS) code
10. 1756-L73 ControlLogix Controller from Rockwell Automation executing the Safety Instrumented System (SIS) code
11. 1756-L73 ControlLogix Controller from Rockwell Automation executing the Simple Engine Model (SEM) code

In addition, the communication protocol between the controller rack and the Speedgoat real-time machine was Ethernet/IP. The 1756-EN2TR (item 6) card acted as master and the IO755 (item 7) card acted as slave (its firmware allows either master or slave applications).

RESULTS AND DISCUSSION

In this section, validation of the generated real time MISO NARX models for all engine output parameters is performed by using the testing datasets ($TS1_{exp}$). Note that for space reasons only figures from N_H , PW and N_L prediction are presented. Firstly, Figure 3 to Figure 5 show that the MISO NARX models capture the fast change in low pressure spool speed parameter, high pressure spool speed, and power demand. A summary of results is shown in Table 5. One can observe that the NARX model demonstrates a significantly good performance in identification of the gas turbine engine dynamics.

To show the advantages of using the proposed MISO NARX models with different structures in the prediction of engine performance instead of using an individual MIMO NARX model, which was proposed in author's previous work (Ibrahim et al.

Figure 3: $TS1_{exp}$ testing results-NH. **Figure 4: $TS1_{exp}$ testing results-PW.**

Table 5: Regression performance [$RMSE$] of ADGTE MISO NARX models.

Data set	N_H	N_I	N_L	PW	TGT	T_{30}	P_{30}
$TS1_{exp}$	0.0022	0.0018	0.0007	0.0107	0.0119	0.0076	0.005

Figure 5: $TS1_{exp}$ testing results-NL.

2019), a comparison between N_H , N_I , N_L , PW , and TGT estimated by MISO NARX model and that estimated by the MIMO NARX model is performed. Figure 6 through Figure 8 show that, the MISO NARX model can provide higher accuracy and higher robustness in real time than the MIMO NARX neural model approach. A summary of results is shown in Table 6. One can observe that the MISO NARX model demonstrates a significantly better performance in identification of the gas turbine engine dynamics than the MIMO NARX model, as it results in an improvement in accuracy of nearly 58%, compared with the MIMO NARX model.

In addition, gas turbine engines operate at different operation condition. Therefore, it is necessary to test the MISO NARX models performance in different operation condition from the condition in which the model was built. Figure 9 through Figure 11 show the results for both the MISO NARX models and MIMO NARX model test using the dataset $TS3_{exp}$. A summary of results is shown in Table 6. One can observe that, both approaches can capture engine dynamics. However, there is a decrease in accuracy when testing the models at different operation condition from that used during model training operation. In addition, the accuracy decrease by using MIMO NARX model is higher than that of the MISO NARX model. So that, the MISO

NARX model approach has a higher generalization and robustness than the MIMO NARX approach. In addition, this improvement in model performance is due to the fact that the MISO NARX model is less complex than the MIMO NARX, which in turn reduces the chances of overfitting.

Figure 6: The comparison between the performance of MISO NARX model and MIMO NARX model using $TS2_{exp}$ - N_H .

CONCLUSION

This paper presents a novel methodology for the development of data driven based model of ADGTE, in order to simulate the dynamic performance of the ADGTE during the full operating range in real time. A MISO NARX neural models was introduced to predict the ADGTE output parameters in real time. First, Data collection and preparation was performed, which includes collection of closed loop data from operational testing of the SGT-A65 ADGTE. After that, data cleaning and re-sampling was performed to generate eight datasets for system identification. Finally, HIL test bed has been prepared for the verifica-

Table 6: The comparison between the performance of MISO NARX model and MIMO NARX model.

Data set	NN model	N_H	N_I	N_L	PW	TGT
$TS2_{exp}$	MIMO	0.0169	0.0117	0.0665	0.1054	0.2976
	MISO	0.0022	0.01	0.0008	0.0082	0.2925
$TS3_{exp}$	MIMO	0.0193	0.0188	0.0273	0.0563	0.3708
	MISO	0.0053	0.0176	0.0024	0.0668	0.3467

Figure 7: The comparison between the performance of MISO NARX model and MIMO NARX model using $TS2_{exp} - PW$.

Figure 8: The comparison between the performance of MISO NARX model and MIMO NARX model using $TS2_{exp} - N_L$.

tion of the generated MISO NARX real time model of a three-shaft ADGTE. As shown in the results, the MISO NARX models can represent the ADGTE during the full operating range with a good accuracy even with different input scenarios. Also, another important gain was the very low execution time (40.5 μ s as compared to more than 10 ms using the same real time machine) which can support many real time applications like model based controller design, sensor fault verification and engine health monitoring. In addition, decreasing the complexity of the neural model reduces the chances of overfitting. However, the single MISO NARX neural model may not be able to provide accurate prediction when it operates outside the field in which it was trained. Therefore, the future work will be the usage multiple of expert neural models to represent each output parameter at different operation conditions to improve the generalization of the neural model.

Figure 9: The comparison between the performance of MISO NARX model and MIMO NARX model using $TS3_{exp} - N_H$.

Figure 10: The comparison between the performance of MISO NARX model and MIMO NARX model using $TS3_{exp} - PW$.

Figure 11: The comparison between the performance of MISO NARX model and MIMO NARX model using $TS3_{exp} - N_L$.

NOMENCLATURE

ADGTE Aero-derivative gas turbine engine.
 ARX Autoregressive with exogenous inputs.
 ECS Engine control software.
 HIL Hardware-in-the-loop.
 HPC High pressure compressor.

HPBOV Number of opened HPC bleed off valves .

IPC Intermediate pressure compressor.

IPVSV Variable stator vanes position % .

IPBOV Number of opened IPC bleed off valves.

LHV Fuel heating value.

LPC Low pressure compressor.

LPBOV Low pressure bleed-off valves position %.

N_L The LPC speed.

N_I The IPC speed.

N_H The HPC speed.

P_{amb} Ambient pressure.

P_{30} The HPC exit pressure.

PCS Plant control software.

PLC Programmable Logic Controllers.

PW The engine shaft power.

RMSE Root mean square error.

SEM simplified engine model.

SIL software- in-the-loop.

SIS Safety Instrumented System.

T_{amb} Ambient temperature.

T_{30} The HPC exit temperature .

T_{GT} The intermediate turbine exit temperature.

trainbr Bayesian regularization training algorithm.

trainlm Levenberg-Marquardt training algorithm.

trainscg Scaled conjugate gradient training algorithm.

VIGV Variable inlet guide vanes position %.

WF Fuel flow rate (kg/s).

η_{th} Thermal efficiency.

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