# Modelling, Simulation and Control of
# Gas Turbines
# Using Artificial Neural Networks

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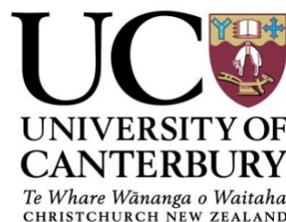


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*This thesis is dedicated to*

*My Dear Parents*

*for their endless love, support and encouragement*

*throughout my entire life.*

# ABSTRACT

This thesis investigates novel methodologies for modelling, simulation and control of gas turbines using ANNs. In the field of modelling and simulation, two different types of gas turbines are modelled and simulated using both Simulink and neural network based models. Simulated and operational data sets are employed to demonstrate the capability of neural networks in capturing complex nonlinear dynamics of gas turbines. For ANN-based modelling, the application of both static (MLP) and dynamic (NARX) networks are explored. Simulink and NARX models are set up to explore both steady-state and transient behaviours.

To develop an offline  ANN-based system identification methodology for a low-power gas turbine, comprehensive computer program code including 18720 different ANN structures is generated and run in MATLAB to create and train different ANN models with feedforward multi-layer perceptron (MLP) structure. The results demonstrate that the ANN-based method can be applied accurately and reliably for the system identification of gas turbines.

In this study, Simulink and NARX models are created and validated using experimental data sets to explore transient behaviour of a heavy-duty industrial power plant gas turbine (IPGT). The results show that both Simulink and NARX models successfully capture dynamics of the system. However, NARX approach can model gas turbine behaviour with a higher accuracy compared to Simulink approach.  Besides, a separate complex model of the start-up operation of the same IPGT is built and verified by using NARX models. The models are set up and verified on the basis of measured time-series data sets. It is observed that NARX models have the potential to simulate start-up operation and to predict dynamic behaviour of gas turbines.

In the area of control system design, a conventional proportional-integral-derivative (PID) controller and neural network based controllers consisting of ANN-based model predictive (MPC) and feedback linearization (NARMA-L2) controllers are designed and employed to control

rotational speed of a gas turbine. The related parameters for all controllers are tuned and set up according to the requirements of the controllers design. It is demonstrated that neural network based controllers (in this case NARMA-L2) can perform even better than conventional controllers. The settling time, rise time and maximum overshoot for the response of NARMA-L2 is less than the corresponding factors for the conventional PID controller. It also follows the input changes more accurately than the PID.

Overall, it is concluded from this thesis that in spite of all the controversial issues regarding using artificial neural networks for industrial applications, they have a high and strong potential to be considered as a reliable alternative to the conventional modelling, simulation and control methodologies. The models developed in this thesis can be used offline for design and manufacturing purposes or online on sites for condition monitoring, fault detection and trouble shooting of gas turbines.

# PUBLICATIONS

During the course of this research, several publications have been made based upon the work presented in this thesis. They are listed here as a reference:

## Book Chapter:

- **Asgari. H.**, Chen. X.Q., and Sainudiin, R. (2013). Modelling and Simulation Approaches for Gas Turbine System Optimization. In M.K. Habib and J.P. Davim (Eds.), Engineering Creative Design in Robotics and Mechatronics. Ch. 14, pp. 240-264, IGI Global.
  DOI: 10.4018/978-1-4666-4225-6.ch014.

## Journal Papers:

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  DOI: 10.1115/1.4026215

- **Asgari, H.**, Chen, X.Q., Menhaj, M.B., and Sainudiin, R. (2013). Artificial Neural Network Based System Identification for a Single-Shaft Gas Turbine. ASME Journal of Engineering for Gas Turbines and Power. 135(9), 092601. 7 pages.
  DOI: 10.1115/1.4024735

- **Asgari, H.**, Chen, X.Q., and Sainudiin, R. (2013). Modelling and Simulation of Gas Turbines. International Journal of Modelling, Identification, and Control (IJMIC). 20(3), 253-270.
  DOI: 10.1504/IJMIC.2013.057137

- **Asgari, H.**, Chen, X.Q., and Sainudiin, R. (2013). Analysis of ANN-Based Modelling Approach for Industrial Applications. International Journal of Innovation, Management, and Technology (IJIMT). 4 (1), 165-169.
  DOI: 10.7763/IJIMT.2013.V4.383

- **Asgari, H.**, Chen, X.Q., Menhaj, M.B., and Sainudiin, R. (2012). ANN-Based System Identification, Modelling and Control of Gas Turbines – A Review. Advanced Materials Research. Vol. 622-623, pp.611-617.
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## Conference Papers:

- **Asgari, H.**, Chen, X.Q., Sainudiin, R., Morini, M., Pinelli, M., Spina, P.R., Venturini, M. (2014). Modelling and Simulation of the Start-Up Operation of a Heavy-Duty Gas Turbine Using NARX Models. Turbo-Expo 2014 (International Congress). Düsseldorf, Germany.

- **Asgari, H.,** Chen, X.Q., and Sainudiin, R. (2012). Analysis of ANN-Based Modelling Approach for Industrial Applications. International Conference on Industrial Applications and Innovations (ICIAI 2012). Hong Kong. 5 pp. (Conference Contribution - Full conference paper)

- **Asgari, H.,** Chen, X.Q., Menhaj, M.B., and Sainudiin, R. (2012). ANN-Based System Identification, Modelling and Control of Gas Turbines – A Review. International Conference on Power and Energy Engineering (ICPEE 2012), Phuket Island, Thailand. 7 pp. (Conference Contribution - Full conference paper)

- **Asgari, H.,** Chen, X.Q., and Sainudiin, R. (2012). Application of Artificial Neural Networks to Rotating Equipment. 3rd Conference on Rotating Equipment in Oil and Power Industries, Tehran, Iran. 10 pp. (Conference Contribution - Paper in published proceedings)

- **Asgari, H.,** Chen, X.Q., and Sainudiin, R. (2011). Considerations in Modelling and Control of Gas Turbines - A Review. 2nd International Conference on Control, Instrumentation, and Automation (ICCIA 2011). Shiraz, Iran. 6 pp. (Conference Contribution - Paper in published proceedings). DOI:10.1109/ICCIAutom.2011.6356635

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# NOMENCLATURE

## ABBREVIATIONS

| | |
|---|---|
| AMPC | approximate model predictive control |
| ANFIS | adaptive network based fuzzy inference system |
| ANN | artificial neural network |
| ARX | autoregressive with exogenous input |
| ASME | American Society of Mechanical Engineers |
| BPNN | backpropagation neural network |
| CCGT | combined cycle gas turbine |
| CCPP | combined cycle power plant |
| CO | carbon monoxide |
| CSGT | control system of gas turbine |
| CT | compressor turbine |
| CUSMUS | cumulative sum (technique) |
| DC | direct current |
| DCS | distributed control system |
| DLE | dry low emission |
| DLN | dry low nitrogen oxide |
| DNN | dynamic neural network |
| FDI | fault detection and isolation |
| FFNN | feedforward neural network |
| GA | genetic algorithm |
| GAST | gas turbine governor model |
| GG | gas generator |
| GPC | generalized predictive control |
| GT | gas turbine |
| HDGT | heavy-duty gas turbine |
| HP | high pressure (gas turbine) |
| IGV | inlet guide vane |
| IPGT | industrial power plant gas turbine |

| | |
|---|---|
| LP | low pressure (gas turbine) |
| MGT | micro gas turbine |
| MIMO | multiple-input and multiple-output |
| MLP | multi-layer perceptron |
| MP | minimum phase |
| MPC | model predictive control |
| MSE | mean square error |
| NARMA | nonlinear autoregressive moving average |
| NARMA-L2 | feedback linearization control |
| NARMAX | nonlinear autoregressive moving average with exogenous inputs |
| NARX | nonlinear autoregressive with exogenous inputs |
| NMP | non minimum phase |
| NMPC | nonlinear model predictive control |
| NN | neural network |
| NO | nitrogen oxide |
| OEM | original equipment manufacturer |
| PD | proportional-derivative (controller) |
| PI | proportional-integral (controller) |
| PID | proportional-integral-derivative (controller) |
| PR | pressure ratio |
| PT | power turbine |
| RBF | radial basis function |
| RBFNN | radial basis function neural network |
| RL | reinforcement learning |
| RMSE | root mean square error |
| RNN | recurrent neural network |
| SIMO | single-input and multiple-output |
| TDL | time delay |
| TIT | turbine inlet temperature |
| TOT | turbine outlet temperature |
| UPFC | unified power flow controller |
| VSV | variable stator vane |

## VARIABLES

| | |
|---|---|
| $C_p$ | specific heat in constant pressure (J/kg K) |
| $C_v$ | specific heat in constant volume (J/kg K) |
| $HR$ | heat rate ( kJ/kWh) |
| $I$ | moment of inertia (kg.m$^2$) |
| $J$ | cost function |
| $LHV$ | lower heating value of fuel (J/kg) |
| $M$ | mass (kg) |
| $\dot{m}$ | mass flow rate (kg/s) |
| $M$ | momentum (N m) |
| $N$ | rotational speed (rpm, or 1/s) |
| $P$ | stagnation pressure (Pa) |
| $Q$ | lower thermal value (J/kg) |
| $Q$ | heat power (W) |
| $R$ | specific gas constant (J/kg K) |
| $S$ | entropy (J/K) |
| $SFC$ | specific fuel consumption (kg/kWh) |
| $T$ | time (s) |
| $T$ | temperature (K) |
| $U$ | externally determined variable (system input) |
| $u'$ | tentative control signal |
| $V$ | volume (m$^3$) |
| $W$ | work (J) |
| $\dot{W}$ | power (W) |
| $Y$ | variable of interest (system output) |

## CONSTANTS

| | |
|---|---|
| $C$ | pressure constant |
| $D$ | delay |
| $F$ | fuel to air mass flow rates ratio |
| $J$ | a natural number |
| $K$ | a natural number |
| $K$ | gain |

| | |
|---|---|
| $N$ | a natural number |
| $N$ | filter coefficient |
| $N_1, N_2, N_3, …, Nu$ | horizons (MPC factors) |
| $PR_C$ | compressor pressure ratio |

## SUBSCRIPTS

| | |
|---|---|
| $00$ | ambient |
| $01$ | compressor inlet |
| $02$ | compressor outlet |
| $03$ | turbine inlet |
| $04$ | turbine outlet |
| $A$ | average value (for compression process in compressor) |
| $C$ | compressor |
| $Cc$ | combustion chamber |
| $D$ | data set |
| $F$ | fuel |
| $G$ | average value (for expansion process in turbine) |
| $Gt$ | gas turbine |
| $In$ | inlet |
| $M$ | measured |
| $Mech$ | mechanical |
| $Med$ | medium |
| $Out$ | outlet |
| $R$ | reference (desired) |
| $T$ | turbine |
| $U$ | system input |
| $Y$ | system output |

## GENERAL SYMBOLS

| | |
|---|---|
| $D$ | derivative (controller) |
| $E$ | error |
| $F$ | function |
| $I$ | integral (controller) |

| | |
|---|---|
| *M* | manoeuvre |
| *N* | number |
| *Nf* | nonlinear function |
| *P* | proportional (controller) |
| *Trainbfg* | BFGS Quasi-Newton training algorithm |
| *Trainbr* | bayesian regularization training algorithm |
| *Traincgb* | conjugate gradient with Powell/Beale restarts training algorithm |
| *Traincgf* | Fletcher-Powell conjugate gradient training algorithm |
| *Traincgp* | Polak-Ribiére conjugate gradient training algorithm |
| *Traingdx* | variable learning rate gradient descent training algorithm |
| *Trainlm* | Levenberg-Marquardt training algorithm |
| *Trainoss* | one step secant training algorithm |
| *Trainrp* | resilient backpropagation training algorithm |
| *Trainscg* | scaled conjugate gradient training algorithm |

## GREEK SYMBOLS

| | |
|---|---|
| $\gamma$ | ratio of specific heats |
| $\eta$ | efficiency |
| $\xi$ | pressure loss coefficient |
| *P* | contribution |

# CHAPTER 1
# INTRODUCTION

Gas turbines (GT) are one of the significant parts of modern industry. They play a key role in aeronautical industry, power generation, and main mechanical drivers for large pumps and compressors. Modelling and simulation of gas turbines has always been a powerful tool for performance optimization of this kind of equipment. Remarkable research activities have been carried out in this field and a variety of analytical and experimental models has been built so far to get in-depth understanding of the nonlinear behaviour and complex dynamics of these systems. However, the need to develop accurate and reliable models of gas turbines for different objectives and applications has been a strong motivation for researchers to continue to work in this fascinating area of research. The study in this field includes white-box and black-box based models and their applications in control systems. Artificial neural networks (ANNs) as a black-box methodology have been regarded as suitable and powerful tools for data processing, modelling, and control of highly nonlinear systems such as gas turbines. Besides, because of the high demand of the

electricity market, the power producers are eager to continuously investigate new methods of optimization for design, manufacturing, control and maintenance of gas turbines.

Gas turbine is as an internal combustion engine which uses the gaseous energy of air to convert chemical energy of fuel to mechanical energy. It is designed to extract as much as possible of the energy from the fuel [1]. The service of gas turbines in industrial equipment and utilities located on power plants and offshore platforms has been increased in the past 50 years. This high demand is because of their low weight, compactness and multiple fuel applications [2]. Although the story of gas turbines has taken a root in history, it was not until 1930s that the first practical GT was developed by Frank Whittle and his colleagues in Britain for a jet aircraft engine [3]. Gas turbines were developed rapidly after World War II and became the primary choice for many applications. That was especially because of enhancement in different areas of science such as aerodynamics, cooling systems, and high-temperature materials which significantly improved the engine efficiency. Then, it is not surprising if gas turbines have been increasing in popularity year by year. They have the ability to provide a reliable and continuous operation. The operation of nearly all available mechanical and electrical equipment and machinery in industrial plants such as petrochemical plants, oil field platforms, gas stations and refineries, depends on the power produced by gas turbines. The wide application of gas turbines throughout the world especially in electrical utilities is due to their reliability, availability, adaptability, fast start capability, low initial cost, and short delivery time [4]. They are easy to silence, independent of cooling water and can operate on a variety of fuels. Gas turbines provide high rates of load growth in summer time and respond fast to load changes [4].

During recent years, considerable research activities have been carried out especially in the field of modelling and simulating of gas turbines. It is just because the need for and use of GTs have become more apparent in the modern industry. Making models of gas turbines and their related control systems has been a useful technical and cost-saving strategy for performance optimization of the equipment before final design process and manufacturing. GT models and simulators can be used for off-design performance prediction, performance deterioration,

evaluation of emissions, turbine creep life usage and the engine control system [5]. Mathematical modelling is considered as a general methodology for system modelling. It uses mathematical language to describe and predict the behaviour of a system.

Great efforts have been made in developing GTs to overcome their related challenging economical and engineering problems [6] and to have a reliable and cost-effective design [7]. One of the best approaches for optimization of design, performance and maintenance of gas turbines is offline modelling and simulation. It helps manufacturers and users in different ways. Manufacturers can evaluate and optimize the performance of a specific model of gas turbine during design and manufacturing processes. Models may also be used online on sites by operators and site engineers for condition monitoring, sensor validation, fault detection, trouble shooting, etc. A variety of analytical and experimental models of GTs has been built so far. However, the need for optimized models for different objectives and applications has been a strong motivation for researchers to continue to work in this area.

This chapter briefly explains the principles of performance of a typical gas turbine. Then a classification of gas turbines is presented. Main considerations in gas turbine modelling including GT types and configurations, modelling methods, control system types and configurations, as well as modelling objectives and approaches are explained in the next steps. Problem definition, research objectives and outline of the thesis form the next sections of this chapter.

## 1.1. GAS TURBINE PERFORMANCE

Gas turbines work based on Brayton cycle. Figure 1.1 shows a typical single-shaft gas turbine and its main components including compressor, combustion chamber (combustor), and turbine. The set of these components is called engine core or gas generator (GG). Compressor and turbine are connected by the central shaft and rotate together.

Figure 1.2 shows standard Brayton cycle in pressure-volume (P-V) and temperature-entropy (T-S) frames respectively [8]. Air enters the compressor at section 1 and is compressed through

passing the compressor. The hot and compressed air enters the combustion chamber (combustor) at section 2. In combustor, fuel is mixed with air and ignited. The hot gases which are the product of combustion are forced into the turbine at section 3 and rotate it. Turbine drives the compressor and the GG mechanical output, which can be an electricity alternator in a power plant station, a large pump or a large compressor. The ideal processes in the compressor (1-2) and turbine (3-4) are isentropic. There is also an isobaric process in the combustor (2-3) and environment (4-1) for the ideal cycle. However, the actual processes in the compressor and turbine are irreversible and non-isentropic. There is also pressure loss during the process in the combustor. Neglecting the pressure loss in the air filters and the combustor, processes 2-3 and 4-1 can be considered isobaric [9].
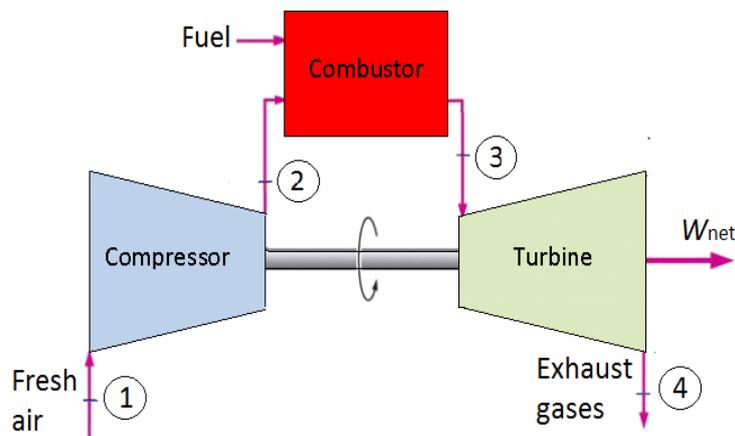


**Figure 1.1:** Schematic of a typical single-shaft gas turbine.
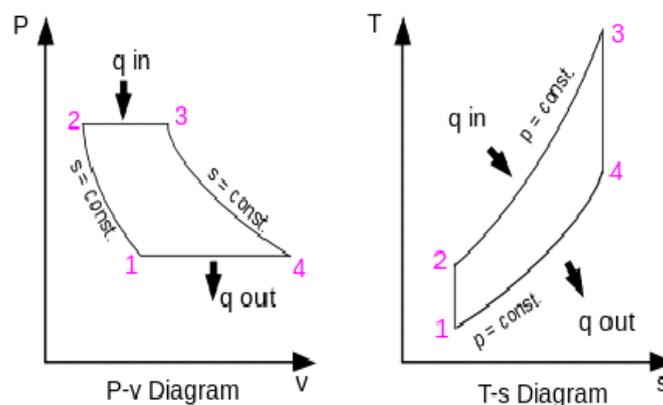


**Figure 1.2:** Typical Brayton cycle in pressure-volume and temperature-entropy frames [8].

## 1.2. GAS TURBINE CLASSIFICATION

Gas turbines can be divided into two main categories including aero gas turbines and stationary gas turbines. In aero industry, gas turbine is used as propulsion system to make thrust and to move an airplane through the air. Thrust is usually generated based on the Newton's third law of action and reaction. There are varieties of aero gas turbines including turbojet, turbofan, and turboprop. In stationary gas turbines, GG may be tied to electro generators, large pumps or compressors to make turbo-generators, turbo-pumps or turbo-compressors respectively. If the main shaft of the gas generator is connected to an electro generator, it can be used to produce electrical power.

In another classification, gas turbines can be divided into the following five groups [2], based on their structure, application, and output power (MW):

- Micro gas turbines (MGT), with 20-350 KW output power.

- Small gas turbines for simple cycle applications, with 0.5-2.5 MW output power and 15-25% efficiency.

- Aero-derivative gas turbines for aerospace industry, with 2.5-50 MW output power and 35-45% efficiency.

- Frame-type heavy-duty gas turbines (HDGT) for large power generation units, with 3-480 MW output power and 30-46% efficiency.

- Industrial-type gas turbines for extensive use in petrochemical plants, with 2.5-15 MW output power and 30-39% efficiency.

In this study, micro and small gas turbines are considered as low-power gas turbines, and industrial types as well as HDGTs that are used in power plants for generating electricity are called industrial power plant gas turbines (IPGT). IPGTs are playing a key role in producing power, especially for the plants which are far away on oil fields and offshore sites where there is no possibility for connecting to the general electricity network.

## 1.3. CONSIDERATIONS IN GAS TURBINE MODELLING

Before making a gas turbine model, some basic factors should be carefully considered. GT type, GT configuration, modelling methods, control system type and configuration, and modelling objectives are among the most important criteria at the beginning of the modelling process [10].

### 1.3.1. Gas Turbine Type

As the first step of modelling, it is necessary to get enough information about the type of gas turbine which is to be modelled. As it was already stated, GT can be an aero or stationary gas turbine. Although there are different types of GT based on their applications in industry, they have the same main common parts including compressor, combustion chamber and turbine. Figure 1.3 shows a typical single-spool aero gas turbine engine [11].
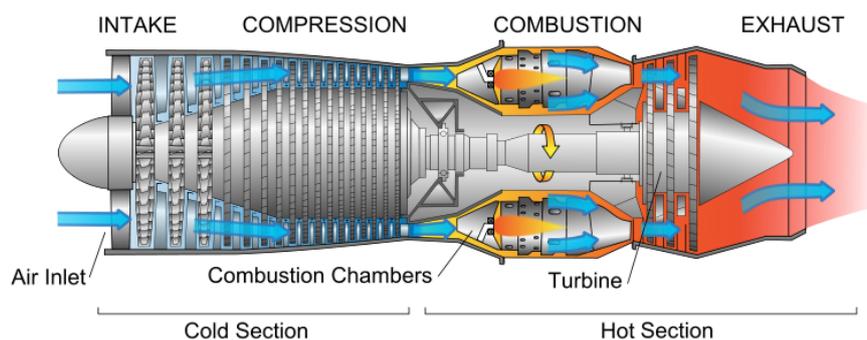


**Figure 1.3:** A typical single-spool turbojet engine [11].

### 1.3.2. Gas Turbine Configuration

Configuration of a gas turbine is another important criterion in GT modelling. Although all gas turbines nearly have the same basic structure and thermodynamic cycle, there are considerable distinctions when they are investigated in details. For instance, to enhance gas turbine cycle, system efficiency or output power, through different methods such as reheating, inter-cooling or heat exchange, particular GT configurations are utilized. Gas turbines can be also categorized based on the type of their shafts. They may be single-shaft or split-shaft (twin-shaft, triple-shaft). In a single-shaft gas turbine, the same turbine rotor which drives the compressor is connected to the power output shaft through a speed reduction. In a split-shaft gas turbine, the gas generator turbine

and the power turbine (PT) are mechanically disconnected. Gas generator turbine, also called compressor turbine (CT) or high pressure (HP) turbine, is the component which provides required power for driving the compressor and accessories. However, power turbine, also called low pressure (LP) turbine, does the usable work. Figure 1.4 shows a typical twin-shaft gas turbine engine [12].
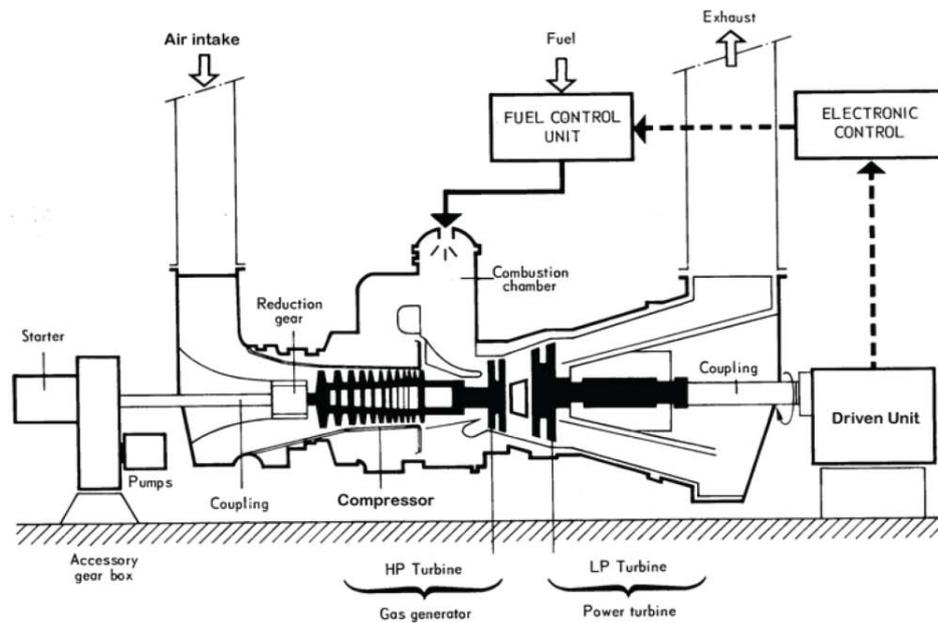


**Figure 1.4:** A typical twin-shaft gas turbine engine [12].

### 1.3.3. Gas Turbine Modelling Methods

Mathematical modelling as a general methodology for system modelling uses mathematical language to describe and predict behaviour of a system. Important advances and development of scientific fields may be tied to the quality of mathematical models and their agreement with the results of experimental measurements. Physics-based modelling is a main branch of mathematical modelling. It implies that the system is governed by the laws of physics, which leads to physically realistic simulation. Physics-based modelling employs equations of mathematical physics, coupled with real-time sensor measurements to set up models suitable for operational usage. Mathematical models can be classified as "linear and nonlinear", "deterministic and stochastic (probabilistic)", "static and dynamic", or "discrete and continuous" models [13].

### 1.3.3.1. Linear and Nonlinear Models

A model is called linear if all objective functions and constraints of the system are represented by linear equations. Otherwise, it is considered as a nonlinear model. Although industrial equipment usually shows nonlinear behaviour, in many cases the model is simplified to be analyzed linearly. There are different methods to linearize a nonlinear system. However, in setting up a model which can accurately predict behaviour of complex and sensitive systems such as gas turbines, considering nonlinear dynamics is unavoidable.

### 1.3.3.2. Deterministic and Stochastic (Probabilistic) Models

From another perspective, a model can be deterministic or stochastic. In a deterministic model, all variable states are determined uniquely by the parameters in the model and by the sets of previous states of these variables. Therefore, a deterministic model expresses itself without uncertainty due to an exact relationship between measurable and derived variables. Conversely, in a stochastic model, quantities are described using stochastic variables or stochastic processes. Therefore, in a stochastic model, variable states are described using random probability distributions [13].

### 1.3.3.3. Static and Dynamic Models

The variables which usually characterize a system change with time. If there are direct, instantaneous links among these variables, the system is called static. If the variables of a system change without direct outside influence so that their values depend on earlier applied signals, then the system is called dynamic [13].

### 1.3.3.4. Discrete and Continuous Models

A mathematical model is called continuous-time when it describes the relationship between continuous time signals. Continuous-time models are shown with a function f (t) that changes over continuous time. A model is called discrete-time when it directly expresses the relationships between the values of the signals at discrete instants of time. Relationship between signal values is

usually expressed by using differential equations. In practical applications, signals are most often obtained in sampled form in discrete time measurements [13].

### 1.3.4. Gas Turbine Control System Type and Configuration

One of the most important factors in modelling and control of gas turbines is type and configuration of their control system. Control system is a vital part of any industrial equipment. Type and configuration of a control system is in a close relationship with the complexity of the system dynamics and the defined tasks during the whole performance period. Lacking a proper control system can lead to serious problems such as compressor surge, overheat, overspeed, etc [14]. The final effect of these problems may be system shutdown and severe damages to the main components of GT.

There are three main functions for the control system of all gas turbines including "start-up and shutdown sequencing control", "steady-state or operational control", and "protection control for protection from overheat, overspeed, overload, vibration, flameout and loss of lubrication". In a power network with several gas turbines, all individual control systems are closely connected with a central distributed control system (DCS) [2]. Control system of gas turbines (CSGT) may be open-loop or closed-loop. In an open-loop control system, the manipulated variable is positioned manually or by using a pre-determined program. However, to control a device in a closed-loop control system, one or more variables of measured data process parameters are used to move the manipulated variable. To keep the closed-loop control system effective and suitable, the controller should be properly related to the process parameters [2]. Figure 1.5 and Figure 1.6 show open-loop and closed-loop control system block diagrams for a typical process respectively.
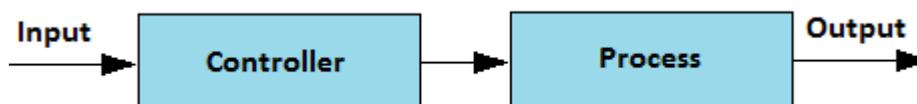


**Figure 1.5:** Block diagram of an open-loop control system.
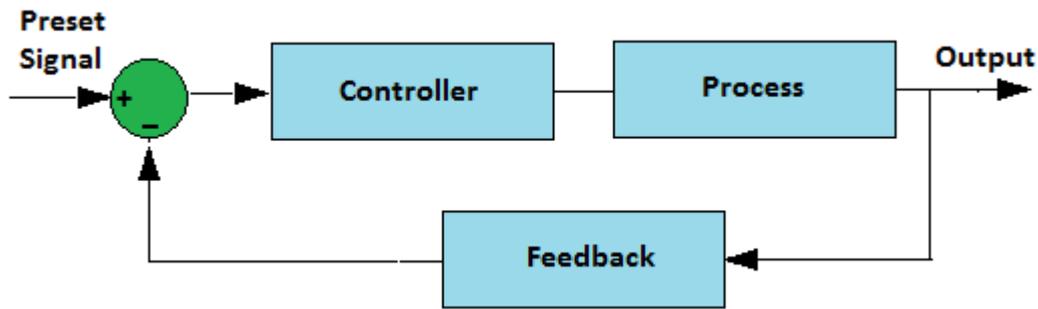
**Figure 1.6:** Block diagram of a closed-loop control system.

### 1.3.5. Gas Turbine Modelling Objectives

There are different goals for making a model of gas turbines such as condition monitoring, fault detection and diagnosis, sensor validation, system identification as well as design and optimization of control system. Thus, a clear statement of the modelling objectives is necessary to make a successful GT model.

#### 1.3.5.1. Condition Monitoring

One of the objectives of making a gas turbine model can be condition monitoring. Condition monitoring is considered as a major part of predictive maintenance. It assesses the operational health of GTs and indicates potential failure warning(s) in advance which help operators to take the proper action predicted in preventative maintenance schedule [15]. Condition monitoring is a very helpful tool in maintenance planning and can be used to avoid unexpected failures. Lost production, overtime, and expediting costs can be effectively prevented by predicting failures before any serious damage occurs in the system. To minimize the maintenance costs for very important and expensive machines such as gas turbines, it is necessary to monitor the operational conditions of vital and sensitive parts of the equipment and to obtain their related data continuously for further analysis. Good condition monitoring reduces the number of wrong decisions, minimizes the demand for spare parts and reduces maintenance costs. A good maintenance system should be capable of monitoring all vital parameters of a gas turbine such as vibration, temperature, pressure,

rotational speed, load, oil level and quality, etc. Besides, it should be able to predict the future state of the system and to prevent unwanted shutdowns as well as fatal breakdowns.

### 1.3.5.2. Fault Detection and Diagnosis

A gas turbine model can be created in order to predict and detect faults in the system. Fault diagnosis acts as an important and effective tool when operators want to shift from preventive maintenance to predictive maintenance in order to reduce the maintenance cost [16]. It concerns with monitoring a system to identify when a fault has occurred as well as to determine the type and location of the fault.

### 1.3.5.3. Sensor Validation

Gas turbine models can be used for sensor validation purposes. Sensors are essential parts of any industrial equipment. Without reliable and accurate sensors, monitoring and control system of the equipment cannot work properly and may even face shutdown. Sensor validation is about detection, isolation and reconstruction of a faulty sensor. It can improve reliability and availability of the system, and reduce maintenance costs. It enhances reliability for the equipment and safety for the personnel. Sensor validation is also an effective tool to prevent unwarranted maintenance or shutdown. It has a considerable effect in increasing equipment's lifetime and assuring reliable performance. It can strengthen automation of the system by providing valid data for diagnostic and monitoring systems.

### 1.3.5.4. System Identification

One the main objectives of gas turbine modelling, is system identification. System identification infers a mathematical description that is a model of a dynamic system from a series of measurements of the system [17]. Despite significant research carried out in this field during the last decades, there is still a need for GT models with higher degree of accuracy and reliability for system identification purposes. This is due to nonlinear and complex nature of GT dynamics.

*1.3.5.5. Design and Optimization of Control System*

Gas turbine models may be created to design or optimize GT control systems. It is obvious that any control system should be able to measure the output of the system using sensing devices, and to take required corrective action if the value of measured data deviates from its desired corresponding value [18]. Control as a branch of engineering deals with the behaviour of dynamical systems. The output performance of the equipment which is under control is measured by sensors. These measurements can be used to give feedback to the input actuators to make corrections toward desired performance. There are increasing demands for accurate dynamic models and controllers, in order to investigate the system response to disturbances and to improve existing control systems. Using new modelling methods can always be investigated as part of optimization process.

### 1.3.6. Gas Turbine Model Construction Approaches

There are many sources regarding modelling and simulation of gas turbines in the literature. Various kinds of models have been built so far from different perspectives and for different purposes. Models of industrial systems can be classified into two main categories including black-box and white-box models.

*1.3.6.1. White-Box Models*

A white-box model is used when there is enough knowledge about the physics of the system. In this case, mathematical equations regarding dynamics of the system are utilized to make a model. This kind of model deals with dynamic equations of the system which are usually coupled and nonlinear [19]. To simplify these equations in order to make a satisfactory model, making some assumptions based on ideal conditions and using different methods for linearization of the system is unavoidable. There are different software such as Simulink-MATLAB and MATHEMATICA which are really helpful in this case.

### 1.3.6.2. Black-Box Models

A black-box model is used when no or little information is available about the physics of the system [19]. In this case, the aim is to disclose the relations between variables of the system using the obtained operational input and output data from performance of the system. Artificial neural network (ANN) is one of the most significant methods in black-box modelling. ANN is a fast-growing method which has been used in different industries during recent years. The main idea for creating ANN which is a subset of artificial intelligence is to provide a simple model of human brain in order to solve complex scientific and industrial problems in a variety of areas.

### 1.3.6.3. Gray-Box Models

In addition to white-box and black-box methods, the phrase gray-box may be also used when an empirical model is improved by utilizing a certain available level of insight about the system [17]. In this case, experiments can be combined with mathematical model building to improve model accuracy [19].

## 1.4. PROBLEM DEFINITION

Literature survey shows that there is a rich source of research activities in the area of modelling, simulation, and control of gas turbines. However, in spite of all the efforts already done in this field, extensive attention still needs to be paid to this area in order to resolve available problems during the processes of design, manufacturing, operation, and maintenance of gas turbines. The following problems can be highlighted in the existing models and control systems of gas turbine:

- Model and control methodologies which are based on white-box approaches rely on thermodynamic and energy balance equations which are coupled and have a high degree of nonlinearity. Therefore, considering assumptions and using linearization methods for simplification and solving these complex dynamics are unavoidable. Consequently, models and control systems that are built on such simplified and/or linearized equations are not accurate enough to capture system dynamics precisely. It, in its turn, leads to

unpredictable problems such as sudden shutdowns especially during operation of the gas turbines which are built based on or using such models. These facts demonstrate the necessity of using techniques and methodologies which are independent of the system dynamics. Besides, the algorithm of proportional-integral-derivative (PID) controllers might be difficult to deal with in highly nonlinear and time-varying processes [20]. ANN has the capability to greatly capture complex dynamics of gas turbines quite independent of the physics of the system. Hence, the necessity of research in this area is obvious.

- Gas turbine components, such as other mechanical equipment, deteriorate gradually and lose their operability and efficiency with time. After couple of years of service in industry, ideal thermodynamic relationships and consequently the corresponding white-box models are subject to major changes and would not be valid anymore. Thus, prediction of behaviour of old gas turbines is very difficult. On the other hand, replacement of old GTs by the new ones requires huge financial sources and in most cases is not economically viable. Fortunately, black-box models are very helpful in this case due to their independence and adaptability to the new conditions. Training and using an up-to-date ANN-based model for condition monitoring on the basis of new data sets of GT parameters, can solve the problem.

- No remarkable attempt can be recognized in the literature to develop a dynamic model of gas turbines (and in particular for the start-up manoeuvre) by means of black-box approaches such NARX models and to validate it against experimental data taken during the normal operation. Building the required models in this specific area can be very effective in understanding and analyzing gas turbine dynamics, and can also provide information about fault diagnostics. A NARX model as a recurrent neural network (RNN) has the capability of capturing dynamics of complicated systems and can be employed for optimization of design and manufacturing of gas turbines. It can also be used to save time and money during the whole operation and maintenance period of GTs.

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- The literature lacks enough sources regarding comparison of physics-based models such as Simulink models with ANN-based models in terms of their deviations from the real systems. It is really interesting and important to know how different methodologies in this field work and what their benefits and limitations are.

- Majority of available gas turbine models have been built based on the steady-state operation of gas turbines. Further research is needed to be carried out in the area of GT transient and start-up procedures.

- There is still a high demand for improving models and control systems which are stable against changes in environmental conditions and system disturbances arising from faults or from load fluctuations in power network of IPGTs.

- Modelling, simulation, and control of gas turbines cover a wide range of research activities. There are different types of gas turbines and a variety of modelling methods and control systems. Even in the field of ANN-based modelling and control, there are varieties of static and dynamic approaches and metrologies which have not been investigated so far. Therefore, new developments in ANN-based structure need to be made for a variety of gas turbines types.

## 1.5. RESEARCH OBJECTIVES AND SCOPE

The main objective of this study is to provide and develop novel approaches and methodologies in modelling, simulation, and control of gas turbines for steady-state and start-up procedures by using ANNs. Steady-state and start-up operations of gas turbines are considered as well as physics-based and ANN-based methodologies are applied. Physics-based and ANN-based models are built and compared on the basis of thermodynamic equations, energy balance relationships, and mathematical analysis. Both simulated and experimental data are employed and MATLAB tools including Simulink and Neural Network Tool-Boxes are used.

Considering the results of the literature survey and the facts already discussed in this chapter, the following research objectives are made:

- Development of a novel ANN-based methodology for offline system identification of gas turbines on the basis of combinations of various training functions, number of neurons and transfer functions by using multi-layer perceptron (MLP) structure. The model can be applied reliably for system identification of gas turbines and can predict output parameters of GTs based on the changes in inputs of the system with a high accuracy.

- Set-up and verification of a nonlinear autoregressive exogenous (NARX) model of start-up operation of an IPGT by using experimental time-series data sets. Comparisons are made between significant outputs of the model and the values of the corresponding measured data. The aim is to show that NARX models are capable of capturing system dynamics during start-up operation.

- Modelling and simulation of the transient behaviour of an IPGT by employing Simulink and NARX approaches. The Simulink model is constructed based on the thermodynamic and energy balance equations in MATLAB environment. The measured time-series data sets are used to model operating characteristics and to make correlations between corrected parameters of the compressor and turbine components. The NARX model is set up on the basis of the same data sets. Comparisons are made between significant outputs of the Simulink and NARX models with the values of the corresponding measured data. The objective is to demonstrate and compare capability of Simulink and NARX models for prediction of the transient behaviour of gas turbines.

- Design of PID and ANN-based controllers for a single-shaft gas turbine. Two different ANN-based control architectures including model predictive control (MPC), and feedback linearization control (NARMA-L2), already implemented in the ANN Tool-Box of MATLAB, are employed. The related control parameters are tuned according to the requirements of the design and comparisons are made among the performances of all controllers.

## 1.6. OUTLINE OF THE THESIS

This study deals with modelling, simulation and control of gas turbines. It provides new approaches and novel solutions in this area. The thesis is structured as follows:

**Chapter 2** presents a comprehensive overview of the literature in the field of modelling, simulation, and control of gas turbines. It covers both white-box and black-box models of GTs. The most relevant scientific sources and research activities for different kinds of GTs including low-power, industrial power plant and aero gas turbines are explored in this chapter.

**Chapter 3** briefly discusses the structure of artificial neural networks and ANN-based model building process including system analysis, data acquisition and preparation, network architecture, as well as network training and validation. It explores different challenges in using ANN-based models for industrial systems and describes advantages and limitations of this approach.

**Chapter 4** introduces a novel ANN-based methodology for offline system identification of a low-power single-shaft gas turbine. The processed data is obtained from a SIMULINK model of a gas turbine in MATLAB environment. A comprehensive computer program code is generated and run in MATLAB for creating and training different ANN models with feedforward MLP structure. The code consists of various training functions, different number of neurons as well as a variety of transfer (activation) functions for hidden and output layers of the network.

**Chapter 5** presents modelling of the transient behaviour of an IPGT using Simulink and NARX models. At the first stage, the Simulink model is constructed based on the thermodynamic and energy balance equations in MATLAB environment. The measured time-series data sets are used to model low-speed operating characteristics and to make correlations between corrected parameters of the compressor and turbine components. The resulting model is tested against measured data sets. At the second stage, a NARX model is set up on the basis of the same time-series data sets and the resulting NARX model is applied to each of the data sets. Comparisons are made between significant outputs of the Simulink and NARX models with the values of the corresponding measured data.

**Chapter 6** gives a model of the start-up operation of a heavy-duty IPGT by using NARX models by using the data taken experimentally during the start-up procedure. The NARX model is set up on the basis of three measured time-series data sets for two different manoeuvres. To verify the resulting models, they are applied to three other available data sets and comparisons are made among significant outputs of the models and the values of the corresponding measured data.

**Chapter 7** elucidates neural network approach for controller design of gas turbines. A conventional PID and neural network based controllers including ANN-based MPC and NARMA-L2 controllers are briefly described, designed and employed to control rotational speed of a single-shaft gas turbine. Finally performances of all controllers are compared and discussed.

**Chapter 8** forms the overall conclusion of this research, discusses possible improvements, and suggests future research and development activities in the area of modelling, simulation, and control of gas turbines.

## 1.7. SUMMARY

This chapter presented the motivations for this research followed by a short discussion about the necessity and goal of modelling and control of gas turbines. Then, a classification of gas turbines was provided and main considerations in gas turbine modelling were presented. The chapter briefly explained the most important criteria and considerations at the beginning of gas turbines modelling process including GT types and configurations, modelling methods, control system types and configurations, as well as modelling objectives and approaches. The chapter also defined the current problems in the area of modelling, simulation and control of gas turbines. Finally, scope and main objectives of this study and the outline of the thesis were briefly presented.

*All the forces in the world are not so*
*powerful as an idea whose time has come.*

Victor Marie Hugo
French poet, novelist, and dramatist, 1802-1885

# CHAPTER 2
# LITERATURE REVIEW

Modelling and simulation of gas turbines plays a key role in manufacturing the most efficient, reliable and durable gas turbines. Besides, GT models can also be used on industrial sites for optimization, condition monitoring, sensor validation, fault detection, trouble shooting, etc. These facts have been strong motivation for scientists to keep carrying out research in this field. There are many sources regarding modelling and control of gas turbines in the literature and a variety of GT models has been built so far from different perspectives and for different purposes. Although some researchers such as Visser et al. [21] tried to introduce a generic model for gas turbines using commercial software, the models presented in the literature are based on varieties of methodologies and approaches.

This chapter presents a comprehensive overview of the most significant studies in the field of modelling, simulation and control of gas turbines based on the classification of GTs [22]. It covers both white-box and black-box models of GTs; each includes models of low-power gas turbines,

industrial power plant gas turbine (IPGT), and aero gas turbines. The concluding remakes from the literature review are presented at the end of the chapter.

## 2.1. WHITE-BOX MODELS OF GAS TURBINES

White-box models of gas turbines can be categorized into low-power gas turbine, industrial power plant gas turbine (IPGT), and aero gas turbine models. In an IPGT, the mechanical power generated by the gas turbine can be used by an alternator to produce electrical power. However, in an aero gas turbine, the outgoing gaseous fluid can be utilized to generate thrust.

### 2.1.1. White-Box Models of Low-Power Gas Turbines

A nonlinear state space model of a low-power single-shaft gas turbine for loop-shaping control purposes was developed by Ailer ( [23],[24],[25]), and Ailer et al. ( [26],[27],[28],[29]). The main idea of these studies was to improve dynamic response of the engine by implementation of a developed nonlinear controller. The model was developed and simulated in Simulink-MATLAB software, based on engineering principles, the gas turbine dynamics and constitutive algebraic equations. Model verification was performed by open-loop simulations against qualitative operation experience and engineering intuition. The researchers considered several assumptions during the modelling process in order to simplify the complicated nonlinear model and to obtain a low-order dynamic model. Although the assumptions made the model appropriate for control purposes, some important aspects of the GT dynamics were neglected during their simplification process.

Abdollahi and Vahedi [30] developed a dynamic model of single-shaft micro turbine generation systems. They tried to present a general model that can be used in different operational ranges. The researchers emphasized on the functionality and accuracy of each of MGT components and the complete model as well. They provided a dynamic model for each component of the micro turbine including gas turbine, DC bridge rectifier, permanent magnet generator as well as power inverter. The models were implemented in Simulink-MATLAB. They showed that the models were suitable

for dynamic analysis of micro turbines under different conditions, and recommended that the model could also be useful to study the effect of micro turbines on load sharing in power distribution network.

Aguiar et al. [31] investigated modelling and simulation of a natural gas based micro turbine using MATLAB. The objective of the research was to present a technical and economical analysis of using MGTs for residential complex based on a daily simulation model and according to the environmental conditions. To evaluate the use of MGT for residential buildings, the researchers considered and analyzed two different configurations, based on the fact that the system was dimensioned to meet the thermal or the electrical demand. The results of the analysis could be useful for the investors who are interested to predict the cost of investment, operation and maintenance of these turbines for power generation.

Ofualagba [32] presented modelling of a single-shaft MGT generation system suitable for power management in distributed generation applications. Detailed mathematical modelling of the control systems was investigated and simulation of the developed MGT system was carried out by using Simulink /MATLAB. The developed model had the capability of matching with the power requirements of the load, within MGT's rating.

An approximate expression for part-load performance of a micro turbine combined heat and power system heat recovery unit was identified by Rachtan and Malinowski [33]. They stated that the expression could greatly facilitate mathematical modelling, design, and operation of cogeneration plants based on MGTs and help in prediction of available thermal power. Malinowski and Lewandowska [34] explored an analytical model of a MGT for part-load operation. They calculated exergy destruction or loss for each MGT component. In thermodynamics, exergy is the theoretical desired output of a system during a process as it interacts to equilibrium [35]. They employed universal formulas with adjustable coefficients to overcome the problems caused by lack of information about the compressor and turbine performance maps; which are usually not

disclosed by the manufacturers. The model was validated against and showed good agreement with the experimental and manufacturer's data.

Hosseinalipour et al. [36] developed static and linear dynamic models of a MGT. They employed thermodynamic equations and maps of the MGT components to build the static model. Static and dynamic equations and a linearization methodology were used to set up the linear dynamic model. The models were validated and a comparison was made between the results of the static model and the results of the dynamic model for the steady-state condition.

### 2.1.2. White-Box Models of Industrial Power Plant Gas Turbines (IPGTs)

Rowen [37] presented a simplified mathematical model of a heavy-duty single-shaft gas turbine. The objective of his study was to investigate power system stability, to develop dispatching strategy, and to provide contingency planning for the system upsets [37]. Rowen tried to make a simplified model that could cover the full spectrum of gas turbines and appropriate turbine-generator characteristics. He discussed different issues regarding modelling including parallel and isolated operations, gas and liquid fuel systems as well as isochronous and droop governors. The resulting model was very useful in studies related to power system dynamics. Although Rowen's model has been a base for many researchers to build up varieties of gas turbine models using different approaches, it is limited to simple cycles and single-shaft gas turbines. He stated that engineering considerations and careful evaluation of the intended purpose are essential prior to use of the model [37]. Rowen [38] in another effort, investigated a simplified mathematical model for the same gas turbine with characteristics and features that affect the application of this kind of gas turbine to mechanical drive services with variable speed. The new features that were not included in his previous study [37] included calculation of exhaust flow, accommodation of variable ambient temperature and modulating inlet guide vanes (IGVs). He intended to present a simple, but highly-flexible and fairly-accurate model. The characteristics of both fuel and control systems were incorporated in the model. Rowen's studies made it possible to simulate any heavy-duty single-shaft gas turbine.

Najjar [39] investigated performance of GTs in single-shaft and twin-shaft operation modes using a model of a free power gas turbine driving an electric dynamometer. GT operational data and their related curves for important parameters such as thermal efficiency, specific fuel consumption and net output power were considered in order to estimate GT performance. The results showed when the free power turbine engine was run in the single-shaft mode (especially with a low speed ratio), power was increased significantly (about 75% in the low-power region) at part loads. However, running the free power turbine engine in the two-shaft mode showed better torque characteristics at part load, which is really important for transport applications and traction systems [39].

Bettocchi et al. [40], and Binachi et al. [41] respectively explored dynamic models of single-shaft and multi-shaft gas turbines for power generation. An investigation for using of exhaust gases of an open-cycle twin-shaft gas turbine was performed by Mostafavi et al. [42]. They carried out a thermodynamic analysis and concluded that at low temperature ratios, pre-cooling could increase the efficiency and specific network of the cycle. Besides, depending on the cycle pressure ratio and the degree of pre-cooling, the pre-cooled cycle could operate at a higher compressor pressure ratio and temperature ratio without increasing the maximum cycle temperature.

A model for a twin-shaft gas turbine was estimated by Hannett et al. [43]. They conducted a field testing program to obtain the required data for simulation of the model and assessment of the GT governor response to disturbances. During the process of model derivation, the model structure consisting of pertinent variables and parameters was determined. The researchers considered steady-state characteristics of the GT carefully in order to capture dynamic responses of important variables including rapid load changes and load rejections. To adjust the model parameters, an intelligent trial and error process was employed until reasonable matches are obtained between tests and simulations. This methodology was the only practical procedure for the model derivation because of the nonlinearity of the process and its controls. The researchers had to provide the required performance data for each GT component including the compressor, combustor, and

turbines. Regardless of the complicated process of the model derivation, the resulting model could be useful for studies of system dynamics.

A dynamic model for a twin-shaft gas turbine was developed by Ricketts [44] based on a generic methodology and by using design and performance data. Because of the significant contribution of the effects of heat soak in the GT components, to the dynamic characteristic of the gas turbine, they were included in the model. The model complexity was sufficient to predict transient performance and to facilitate designing an appropriate adaptive controller.

Crosa et al. [45] explored a nonlinear physical model to predict the off-design and steady-state dynamic behaviour of a heavy-duty single-shaft gas turbine using Simulink-MATLAB. They used dynamic equations of mass, momentum, and energy balances to model the system. The air bleed cooling effect, the mass storage among the stages, and the air bleed transformations from the compressor down to the turbine were took into account for the model building process. Performance of the resulting model was quite satisfactory for prediction of thermodynamic variables.

Nagpal et al. [46] presented their field experiences in testing and model validation of turbine dynamic models and the associated governors for IPGTs when they were in service. Based on the field measurements, they showed that gas turbine governor model (GAST) which is a widely used model to represent the dynamics of GT governor systems, has two main deficiencies. Firstly, the model could not predict GT operation accurately at high levels of loads. Secondly, the accurate adjustment of the model parameters, according to the oscillations around the final setting frequency, may not be attained.

Kaikko et al. [47] presented a steady-state nonlinear model of a twin-shaft industrial gas turbine and its application to online condition monitoring and diagnostic system. They utilized condition parameters to evaluate the engine condition and the impact of performance deviations on the costs. Using the condition parameters, the performance was predicted at the reference operating conditions for the engine with the current health status. Evaluation of the GT performance

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parameters in reference, actual, expected and corrected states enabled the researchers to properly identify the deviations and their root causes. They also concluded that the applied computational method in their study could be adapted to other modelling, condition monitoring and diagnosis of gas turbines. The methodology employed by the researchers had some advantages compared with the commonly applied component matching procedures. Their recommended method facilitated the selection of the modelling parameters as well as application of the models for providing and controlling of the results.

Al-Hamdan et al. [48] discussed modelling and simulation of a single-shaft gas turbine engine for power generation based on the dynamic structure and performance of its individual components. They used basic thermodynamic equations of a single-shaft gas turbine to model the system. The researchers developed a computer program for the engine simulation which could be used as a useful tool to investigate GT performance at off-design conditions and to design an appropriate efficient control system for specific applications. Figure 2.1 shows variations of temperatures in different sections of the modelled GT versus net power output. $T_{02}$, $T_{03}$, and $T_{04}$ are output temperatures of compressor, combustor and turbine respectively [48].
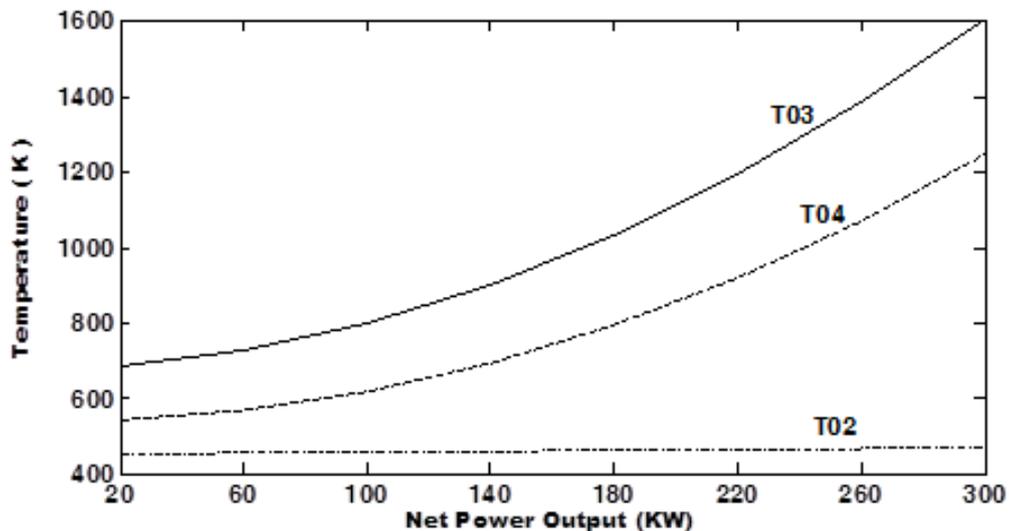


**Figure 2.1:** Variations of temperatures versus net power output [48].

A simplified desktop performance model of a typical heavy-duty single-shaft gas turbine in power generation systems was developed by Zhu and Frey [49]. They built a model which could be accurate and robust to variations under different operational conditions. The researchers investigated a methodology for assessment and rapid analysis of the system alternations. The methodology could be implemented in a desktop computing environment. They applied sensitivity analysis to assess the model for a variety of fuels in terms of composition, moisture and carbon contents. The model could also be used to evaluate $CO_2$ emissions.

Camporeale et al. [50] investigated an aero-thermal model for two different power plant gas turbines with a relatively high level of accuracy. They presented a novel methodology for developing a high-fidelity real-time code in Simulink-MATLAB using an object-oriented approach for gas turbine simulation. The technique was based on a nonlinear representation of gas turbine components. The researchers composed and solved a set of ordinary differential equations and nonlinear algebraic equations to present the mathematical model of the gas turbines. The flexibility of the code allowed it to be easily adapted to any configuration of power plants. Figure 2.2 shows how the real-time simulation software interacted with hardware control devices of the GTs [50].
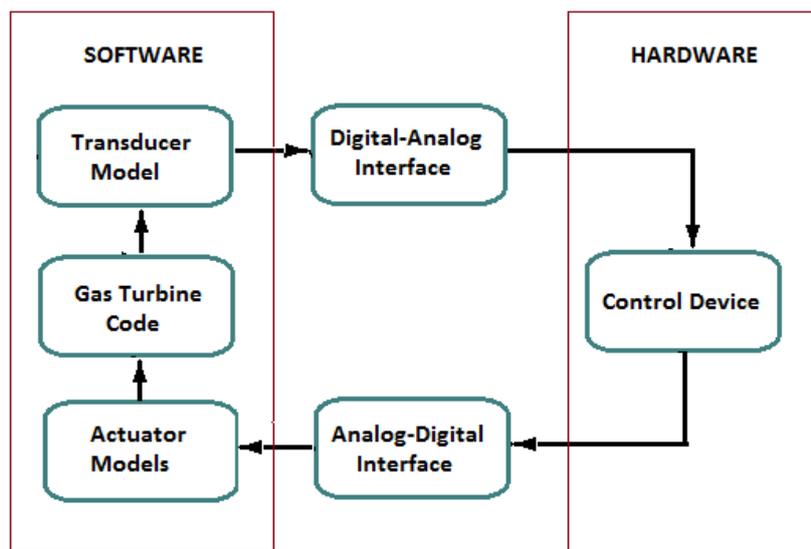


**Figure 2.2:** The diagram for how real-time simulation software interacted with hardware control devices [50].

A gas turbine fully-featured simulator was developed and implemented by Klang and Lindholm [51]. They discussed the simulator set-up both technically and economically and chose a robust hardware solution based on the basic requirements. The simulator could be useful for testing the GT control system, trying out new concepts and training operators.

Development of a dynamic model of a single-shaft gas turbine for a combined cycle power plant (CCPP) was explored by Mantzaris and Vournas [52]. They used Simulink-MATLAB to investigate stability of the turbine and its control system against overheat as well as changes in frequency and load. The results showed that the existence of speed, frequency and air control loops were necessary for the plant stability against disturbances. To make the model response faster, the researchers ignored some blocks with small time constants in the model for reducing the order of the model and simplifying the calculations. To allow stable and reliable operation of the plant, it was also suggested that the airflow gate opening limits be expanded during the full-load operation.

Yee et al. ( [53],[54]) carried out a comparative analysis and overview of different existing models of power plant gas turbines. They identified, presented and discussed various kinds of GT models in terms of their application, accuracy and complexity. It was concluded from the research that despite their complexity, physical models are the most accurate ones and suitable for detailed study of the gas turbine dynamics. However, it was stated that physical models are not appropriate for use in large power system studies. It was also indicated that for a more detailed analysis of power systems and their governors' behaviour, the frequency-dependent model was the best choice. It was particularly useful in the case of weak systems with large frequency variations. The study also demonstrated that the frequency and ambient temperature could significantly affect gas turbine operation under certain operating conditions. Unfortunately, the study did not cover black-box models of gas turbines [53]. A similar study was carried out by Shalan et al. [55] for the gas turbines in CCPPs. They performed a complementary and comparative analysis of different gas turbine models response in terms of their applications and accuracy. In another effort, Liang et al. [56] carried out a study on performance simulative models of gas turbines. The objective was to improve accuracy of nonlinear simulation models of GTs. They explored the influence of variations

of oil to gas ratio, specific heat, and power turbine outlet pressure on the engine in order to establish a nonlinear dynamic simulative model of twin-shaft gas turbines. The simulation results showed that the proposed simulative model was more accurate to reflect the engine dynamics compared to the previous ones. Hosseini et al. [57] employed a systematic methodology to build a multiple model structure of a prototype IPGT under normal operation. According to the methodology, linear and nonlinear modes were decomposed and treated separately. They concluded that the algorithm could be employed for identification of single-shaft IPGTs.

A zero-dimensional simulation model for design and off-design performance of a twin-shaft gas turbine was developed by Lazzaretto and Toffolo [58]. The aim of the study was to correctly mange the operation of power plant gas turbines and their reactions to the variations of load and ambient temperature. The researchers determined the values of thermodynamic quantities and the overall performances of the gas turbine plant. To predict nitrogen oxide ($NO_X$) and carbon monoxide ($CO$) pollution, available semi-empirical correlations for pollutant emissions were adapted by tuning their coefficients on the experimental data. The researchers concluded that the applied methodology can be employed to manage the economical and environmental aspects of the plant operation.

Razali [59] developed an analytical model of a gas turbine to simulate the actual trend of the GT performance and to predict its degradation. The actual composition of the working gases and variation of the specific heat with temperature are taken into account for simulating the model. The values of three output parameters from the resulting model including GT exhaust temperature, GG exit temperature, and the actual load, were compared with the corresponding actual outputs, and the deviations were measured as indicators of the GT degradation.

A modified methodology was presented by Khosravi-el-hossani and Dorosti [60] to determine the exhaust energy in the new edition of ASME PTC 22 which is about flow rate of flue gas. The method was based on exhaust gas constituent analysis and combustion calculations. It was shown that the method could enhance the precision of ASME PTC 22 by more than one percent. The gas turbine performance test was also improved based on the obtained operational data. They stated

that the proposed methodology could be an appropriate alternative for gas turbine standard performance test and could be employed to evaluate gas turbine performance without measurement of input fuel components, which could reduce the cost of measuring and data gathering.

The parameters of a single-shaft HDGT were estimated using its operational data based on Rowen's model [37] by Tavakoli et al. [61]. They applied simple physical laws and thermodynamic assumptions in order to derive the GT parameters using operational data. They suggested that the study could be useful for educational purposes especially for the students and trainers who were interested in gas turbine dynamics. Figure 2.3 shows the block diagram of Rowen's model including fuel and control systems, employed by the researchers ( [37], [61]).
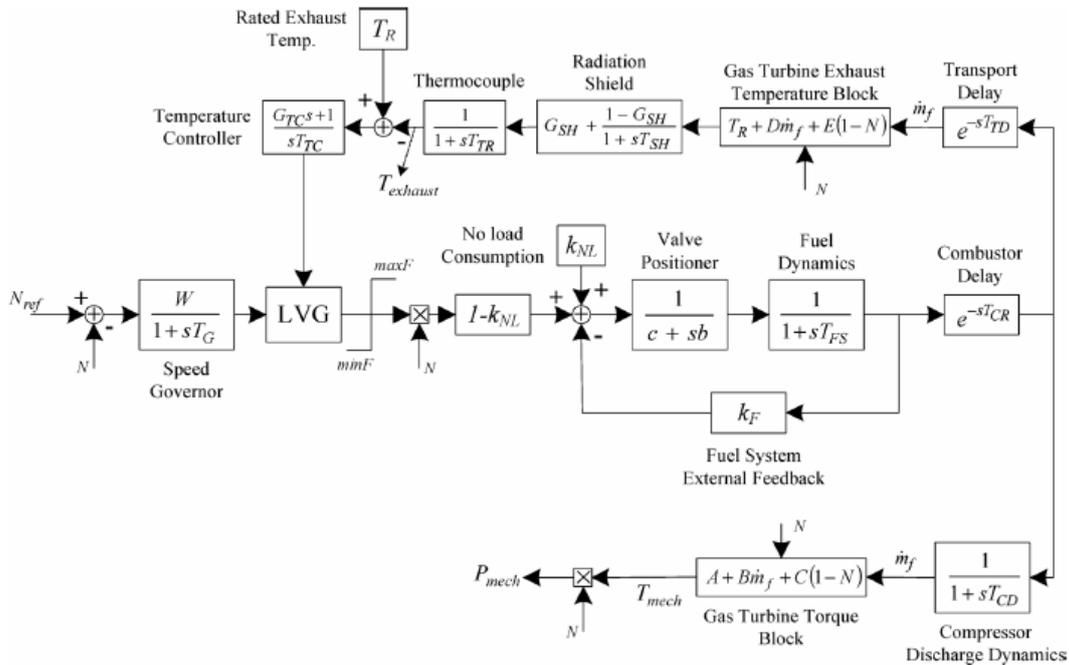


**Figure 2.3:** Rowen's model for heavy-duty gas turbines dynamics ( [37], [61]).

Simple models of the systems for a power plant simulator were developed by Roldan-Villasana et al. [62] based on the mass, momentum and energy principles. The modelled systems were classified into seven main groups including water, steam, turbine, electric generator, auxiliaries, gas turbine and minimized auxiliaries. They concluded that the simulator could be very useful for training of operators.

Yadav et al. [63] applied graph networks approach to analyze and model a single-shaft open-cycle gas turbine. They used graph theory and algorithms to identify pressure and temperature drops, work transfer rates, rate of heat and other system properties. Because of the similarities in the results from this approach with the results from conventional methods, it was suggested that the new technique could be used for optimization of GT process parameters.

In a couple of different efforts, Ibrahim and Rahman ( [64],[65]), and Rahman et al. ( [66],[67]) developed computational models of a power plant gas turbine in MATLAB environment. They investigated the effect of operational conditions (compressor ratio, air to fuel ratio, turbine inlet and exhust temperatures, efficiency of compressor and turbine) on the power plant performance (compressor work, heat rate, thermal efficiency, specific fuel consumption). It was observed that the output power and thermal efficiency decreased linearly with increase of both air to fuel ratio and ambient temperature. They also concluded that the peak power, efficiency and specific fuel consumption occurred at higher compressor ratio with low ambient temperature.

Weber [68] investigated modelling of a modern power plant gas turbine engine performance at partload. At the first step, thermodynamic characteristics at full-load for the engine was employed in commercial software including MATLAB, and Python, and then part load performance thermodynamic characteristics were derived by using a computer programming code that was entirely flexible while remaining computationally efficient.

Shalan et al. [69], in another effort, employed a simple methodology to estimate parameters of a Rowen's model ( [37],[38]) for heavy-duty single-shaft gas turbines. The parameters of the model were derived using the performance and operational data. A variety of simulated tests was performed in Simulink-MATLAB environment and the results were compared with and verified against the results of previous studies. The researchers stated that the proposed methodology could be applied to any size of gas turbines.

Liu and Su [70] developed a nonlinear model of an IPGT for faults diagnosis purposes. The gas turbine was a part of a combined cycle generation unit. The objective of the research was to build a

health monitoring based thermodynamic model to explain quantitatively the degradation phenomenon in the gas path components of gas turbines. By using the component level nonlinear model, errors caused by linearization could be avoided. The dynamic model could evaluate steady-state behaviour of the gas turbine for off-design performance. The results showed that faults could be detected and isolated by using a model-based gas path analysis.

The effect of ambient temperature on performance of three-shaft gas turbines, under different control strategies, was investigated by Gao and Huang [71]. They showed that ambient temperature greatly affected the gas turbines performance. They demonstrated that GT specific power and thermal efficiency, particularly when the gas turbine worked in off-design conditions, decreased as the ambient temperature increased. They also concluded that the effect of variations of ambient temperature on three-shaft gas turbines was different under different work conditions, and suitable relevant factors should be considered for choosing the appropriate control strategy.

Memon et al. [35] investigated a model of simple and regenerative cycle gas turbine power plants. The objective of the research was to optimize the cycles for maximization of "net power output, energy and exergy efficiencies" and minimization of "$CO_2$ emissions and costs of the cycles". To estimate the response variables with a high degree of accuracy, the model equations were developed through regression analysis. The results showed that the regenerative cycle had smaller exergy destruction rate and thus more efficiency for a given operating condition compared with the corresponding values in the simple cycle.

To investigate the potential possibilities for improvement of part-load efficiency of gas turbines operating under variable speed, dynamic gas turbine model for both single-shaft and twin-shaft engines were explored by Thirunavukarasu [72]. For this purpose, the mathematical models of the individual GT components were developed on the basis of thermodynamic laws, and the resulting model was validated for the design, off-design and transient cases by using available data from the literature. Besides, to explore the dynamic potential interaction between the GT operation and the electrical and thermal systems, the engine model was integrated with power

generation, distribution , and thermal systems. Moreover, a variable speed parametric study is performed by using the developed gas turbine model. The results showed that the efficiency increased as load decreased, and that the improvement of efficiency for single-shaft engines was larger compared to twin-shaft engines.

Shaw et al. [73] presented a gas turbine based model of a CCPP by using actual existing data. They explored effects of variations of ambient temperature and used operational data to validate the model. The results showed that changes in ambient temperature heavily affected the performance (particularly the output power) of the GT part of the GT cycle, but its effects on the performance of the steam cycle was almost negligible. They concluded that CCPP operation is more stable than a stand-alone GT in hot weather in summer.

Wiese et al. [74] developed a physics-based dynamic model of a gas turbine and validated it against transient test data. It was concluded that the overall system dynamics could be captured well and the dynamic model could be used in a model-based gas turbine controller.

Al-Sood et al. [75] explored an irreversible gas turbine Brayton cycle by developing a general mathematical model. The cycle incorporated compressor, gas turbine, intercooler, reheater, and regenerator. They proposed a general mathematical formula which showed the effect of each of the operating parameters on each of the performance parameters. They stated that the formula could be applicable under any operational conditions of the cycle regardless of values of the other parameters.

### 2.1.3. White-Box Models of Aero Gas Turbines

Kim et al. [76] developed a model for a single-shaft turbojet engine using Simulink-MATLAB. The transient behaviour and changes of different engine parameters was predicted by the model-based on variations of the fuel flow rate. The researchers considered different flight conditions in their simulation such as fuel cut-off. Comparison of the simulation output with another dynamic code for gas turbines and showed satisfactory results.

Evans et al. [77] examined a linear identification of fuel flow rate to shaft speed dynamics of a twin-shaft gas turbine which was a typical military Rolls Royce Spey engine. They studied direct estimation of s-domain models in frequency domain and showed that high-quality models of gas turbines could be achieved using frequency-domain techniques. They discussed that the technique might be used to model industrial systems, wherever a physical interpretation of the model is needed. In another effort, Evans et al. [78] presented the linear multi-variable model of a twin-shaft aero gas turbine typical Rolls Royce Spey military turbofan using a frequency-domain identification technique. The technique was employed to estimate s-domain multi-variable models directly from test data. The researchers examined the dynamic relationship between fuel flow rate and rotational speed in the form of single-input and multiple-output (SIMO). The main advantage of the model was its capability to be directly compared with the linearized thermodynamic models. The research showed that a second-order model could present the most suitable model and the best estimation of the engine. The researchers suggested that the techniques investigated in their study could be used to verify the linearized thermodynamic models of gas turbines. Figure 2.4 shows the Rolls Royce Spey engine modelled by Evans et al. [78].
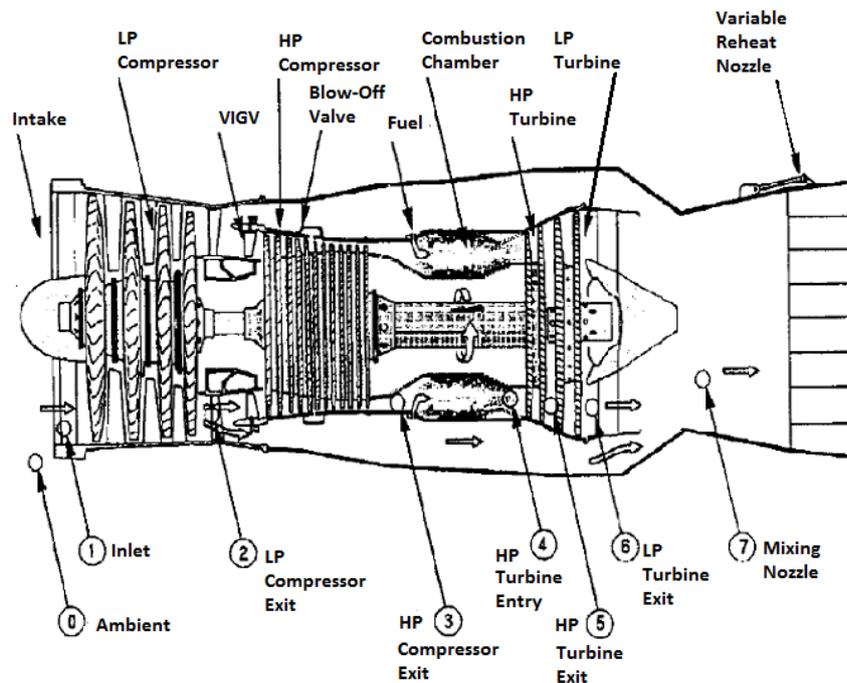


**Figure 2.4:** A typical Rolls Royce Spey Engine [78].

Arkov et al. [79] employed four different system identification approaches to model a typical aircraft gas turbine using the data obtained from a twin-shaft Rolls Royce Spey engine. The motivation behind their research was to minimize the cost and to improve the efficiency of gas turbine dynamical testing techniques. The four employed techniques by the researchers included "multi-sine and frequency-domain techniques for both linear and nonlinear models", "ambient noise excitation", "extended least-squares algorithms for finding time-varying linear models" and "multi-objective genetic programming for the selection of nonlinear model structures" [79]. A description of each technique and the relative merits of the approaches were also discussed in the study. In another effort, Arkov et al. [80] discussed a life cycle support for dynamic modelling of aero engine gas turbines. They investigated different mathematical models and their applications at life cycle stages of the engine controllers. They developed a unified information technology and a unified information space for creating and using GT mathematical models at the life cycle stages. Standard methodologies for system modelling and appropriate software were employed for implementation of this new concept, and consequently performance enhancement of the control system.

Riegler et al. [81] explored modelling of compressor behaviour in gas turbine performance calculations by using a methodology for extrapolating the compressor maps. The research covered the extreme part-load regime of compressor operation. Using corrected torque instead of efficiency in the maps could facilitate calculation of gas turbine behaviour for the operating conditions. The researchers stated that the methodology employed in this study could also be used for typical turbomachinery relationships in turbines.

Behbahani et al. [82] employed Simulink-MATLAB to develop a nonlinear dynamic model of a two-shaft turbine engine for diagnostics and prognostics purposes. The model has the capability to successfully be adapted to various turbine engines. They also designed a controller to control the rotor speed. A survey of prognostic techniques for turbine engines was also carried out in the research.

A novel dimensionless modelling approach for prediction of performance of aero gas turbine engine parameters was proposed by Pourfarzaneh et al. [83]. They set up a systematic series of experiments on the engine to obtain functional parameters of the GT components. The results showed a very good agreement between theoretical and experimental values. A new flexible analytical methodology for linearization of an aero gas turbine engine model was investigated and developed by Chung et al. [84]. Abbasfard [85] explored a modified linear multiple model for a single-shaft aero gas turbine engine by using a novel symbolic computation-based methodology for linearization of the system. The simulation results showed that the proposed method had the capability of resolving fault detection and isolation (FDI) problems of the engine.

Lu et al. [86] proposed a model of an aero gas turbine engine for sensor fault diagnostics purposes. The architecture of the model was composed of two nonlinear engine models including real-time adaptive performance and on-board baseline models. They also presented a novel approach to sensor fault threshold based on the model errors and noise level. The researchers concluded that the proposed approach was easy to design and tune with long-term engine health degradation. In another effort, Lu et al. [87] employed a model-based approach for health parameters estimation of an aero gas turbine engine, and stated that the suggested methodology was efficient.

## 2.2. BLACK-BOX MODELS OF GAS TURBINES

The following summarizes the most important studies carried out so far by using black-box models of gas turbines. As in white-box models, black-box models can be categorized into low-power, industrial power plant, and aero gas turbine models.

### 2.2.1. Black-Box Models of Low-Power Gas Turbines

A NARX model was employed by Jurado [88] to model a power plant MGT and its related distribution system dynamics. However, the nonlinear terms in the model were restricted to the second order. The modelling objective was to investigate the impacts of this kind of gas turbine on

the transient and long term stability of the future distribution systems. The resulting model was capable of modelling both low and high amplitude dynamics of MGTs. The quality of the model was examined by cross validation. The model was tested under different operational conditions and electrical disturbances. The results showed that NARX methodology could be applied successfully to model MGT dynamics in non-isolated mode [88].

Application of ANN and adaptive network based fuzzy inference system (ANFIS) to MGTs was presented by Bartolini et al. [89]. They used ANN and ANFIS to explore unavailable experimental data in order to complete the MGT performance diagrams. They also analyzed and predicted emissions of pollutants in the exhausts and investigated the effects of changes of ambient conditions (temperature, pressure, humidity) and load on MGT's output power. The results indicated that ANN could effectively assess both MGT performance and emissions. It was also shown that ambient temperature variations had more effect on the output power than humidity and pressure. Besides, MGTs were less influenced by ambient conditions than load.

Nikpey et al. [90] developed an ANN-based model for monitoring of combined heat and power MGTs by using the data collected from a modified MGT on a test rig. A systematic four-step sensitivity analysis was performed to investigate the relevance of the input and output parameters as well as influence of input parameters on the prediction accuracy of each output. The results demonstrated that the compressor inlet measurements had very significant impacts on improvement of the prediction accuracy of the model, and could also act as representatives of ambient measurements, so that ambient measurements could be excluded from the inputs. The results of sensitivity analysis also showed that compressor inlet temperature, compressor inlet pressure, and power were the most significant input parameters. The final result indicated that the ANN model could predict the normal performance of the MGT with high reliability and accuracy.

### 2.2.2. Black-Box Models of Industrial Power Plant Gas Turbines (IPGTs)

Lazzaretto and Toffolo [91] investigated a zero-dimensional design and off-design modelling of a single-shaft gas turbine using ANN. They used analytical method and feedforward neural network

(FFNN) as two different approaches to predict GT performance. Appropriate scaling techniques were employed to construct new maps for the gas turbine using available generalized maps of the compressor and turbine. The new maps were validated using the experimental data obtained from real plants. Off-design performance of the gas turbine was obtained using modifications of the compressor map according to variable inlet guide vane closure. A commercial simulator was employed to solve the set of equations of the developed analytical model. Different sets of independent variables that could be selected according to the available data, allowed a high flexibility in the choice of the adjustment criteria. However, the effects of internal parameter variations on GT performance were not considered in the analytical approach. The results from the simulator were used for training the FFNN. The resulting ANN model showed excellent prediction accuracy with just about one percent error. The researchers emphasized the reliability of the ANN model in making accurate correlations between important thermodynamic parameters of complex thermal systems.

Ogaji et al. [92] applied ANN for multi-sensor fault diagnosis of a stationary twin-shaft gas turbine using Neural Network Tool-Box in MATLAB. The GT performance was thermodynamically similar to the Rolls Royce Avon engine. The required data for training the networks were derived from a nonlinear aero-thermodynamic model of the engine's behaviour. The researchers presented three different ANN architectures. The first ANN was used to partition engine measurements into faults and no-faults categories. The second network was employed to classify the faults into either a sensor or a component fault. The third ANN was applied to isolate any single or dual faulty sensors and then to quantify the magnitude of each fault, via the difference between the network's inputs and outputs. The results indicated that ANN could be used as a high-speed powerful tool for real-time control problems [92].

Arriagada et al. [93] applied ANN for fault diagnosis of a single-shaft industrial gas turbine. They obtained data sets from ten faulty and one healthy engine conditions. The data sets were employed to train a feedforward MLP neural network. The trained network was able to make a diagnosis about the gas turbine's condition. The results showed that ANN could identify the faults

and generate warnings at early stages with high reliability. Figure 2.5 shows a schematic drawing of the ANN and the interpretation of the outputs [93]. As it can be seen from the figure, the inputs correspond to the 14 measured parameters in the real engines, as well as the ones controlled by the operators and the control system. The parameters include ambient temperature, IGV angle, mass flow rate, fuel flow rate, load, pressure, temperature, etc. The desired outputs from the ANN are unique combinations of 28 binary numbers arranged in a graphical display. The training process of the ANN stopped when it showed the best performance based on a selected number of hidden neurons and weights. The ANN could be named 14-H-28 according to its structure [93].
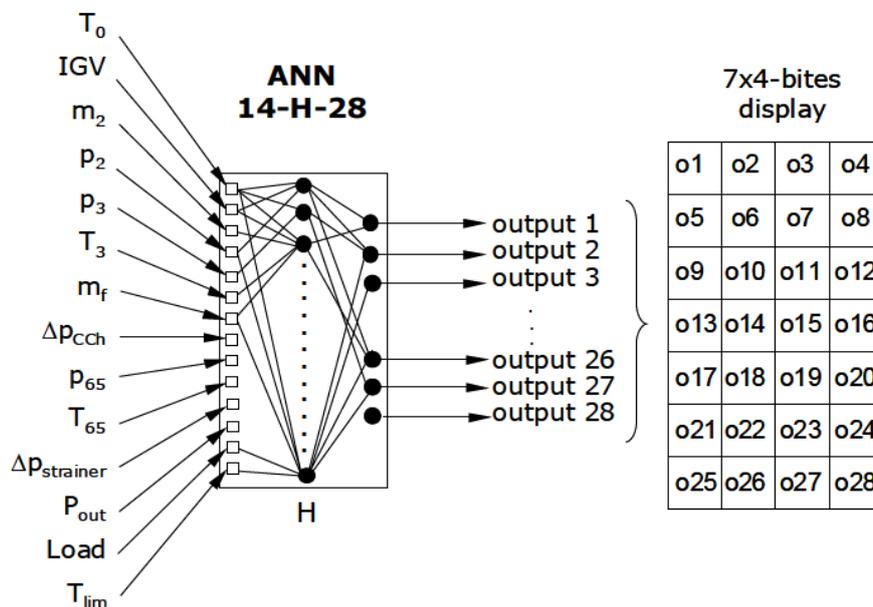


**Figure 2.5:** A schematic drawing of the ANN model and the interpretation of the outputs in a graphical display [93].

Basso et al. [94] applied a NARX model to identify dynamics of a small heavy-duty IPGT. Their objective was to make an accurate reduced-order nonlinear model using black-box identification techniques. They considered two operational modes for the gas turbine; when it was isolated from power network as a stand-alone unit and when it was connected to the power grid. The parameter estimation of the NARX model was performed iteratively using Gram-Schmidt procedure. Both forward and step-wise regressions were investigated and many indices were evaluated and

compared to perform subset selection in the functional basis set and to determine the structure of the nonlinear model. A variety of input signals were chosen for system identification and validation purposes.

Kaiadi [95] developed an ANN-based modelling of a heat and power plant for monitoring and performance analysis purposes by employing commercial software for training cross validation and testing processes. The model-building process was divided into two sub-modules. Two different ANN models were developed separately and then linked to each other. To make the data set as reliable as possible, data pre-processing was carried out before the training stage.

Bettocchi et al. [96] investigated an artificial neural network model of a single-shaft gas turbine as an alternative to physical models. They tried to explore the most appropriate neural network (NN) model in terms of computational time, accuracy and robustness. The researchers considered a network with 15 inputs and 6 outputs. The required data sets for training of the network were obtained from a cycle program, previously calibrated on the gas turbine engine. The obtained data covered the whole operational range of the gas turbine and the researchers considered different health states. They concluded that a feedforward MLP with a single hidden layer (including 60 neurons) trained with at least 2000 training patterns was the most appropriate network. They observed that ANN could be very useful for the real-time simulation of GTs especially when there was not enough information about the system dynamics. In a similar study, Bettocchi et al. [97] developed a multiple-input and multiple-output (MIMO) neural network approach for diagnosis of single-shaft gas turbine engines. In another research, Spina and Venturini [98] used field data sets and applied ANN to train operational data through different patterns in order to model and simulate a single-shaft gas turbine and its diagnostic system with a low computational and time effort.

Simani and Patton [99] used a model-based approach to detect and isolate faults on a single-shaft industrial gas turbine prototype. They suggested exploiting an identified linear model in order to avoid nonlinear complexity of the system. For this purpose, black-box modelling and output estimation approaches were applied due to their particular advantages in terms of algorithmic

simplicity and performance achievements. The suggested fault diagnosis strategy was especially useful when robust solutions were required for minimizing the effects of modelling errors and noise, while maximizing fault sensitivity. To verify the robustness of the obtained solution, the proposed FDI approach was applied to the simulated data from the GT in the presence of measurement and modelling errors. Yoru et al. [100] examined application of ANN method to exergetic analysis of gas turbines which supplied both heat and power in a cogeneration system of a factory. They compared the results of the ANN method with exergy values from the exergetic analysis and showed that much closer exergetic results could be attained by using the ANN method.

Fast et al. [101] applied simulation data and ANN technique to examine condition-based maintenance of gas turbines. In another effort, Fast et al. [102] used real data obtained from an industrial single-shaft gas turbine working under full load to develop a simple ANN model of the system with very high prediction accuracy. A combination of ANN method and cumulative sum (CUSMUS) technique was utilized by Fast et al. [103] for condition monitoring and detection of anomalies in GT performance. Application of ANN to diagnosis and condition monitoring of a combined heat and power plant was discussed by Fast et al. [104]. Fast applied different ANN approaches for gas turbine condition monitoring, sensor validation and diagnosis [105]. To minimize the need for calibration of sensors and to decrease the percentage of shutdowns due to sensor failure, an ANN-based methodology was developed for sensor validation in gas turbines by Palmé et al. [106]. Nozari et al. [107] employed MLP models for an IPGT, based on a nonlinear dynamic system identification approach to detect and isolate the gas turbine faults. The proposed method for fault detection and isolation was tested and validated on a single-shaft IPGT. Besides, to show the benefits of the method, a comparative study with other related works in the literature was carried out. In another study, Nozari et al. [108] explored fault detection and isolation on the IPGT by using MLPs and linear neuro-fuzzy method.

### 2.2.3. Black-Box Models of Aero Gas Turbines

A nonlinear autoregressive moving average with exogenous inputs (NARMAX) model of an aircraft gas turbine was estimated by Chiras et al. [109]. They employed nonparametric analysis in time and frequency domains to determine the order and nature of nonlinearity of the system. The researchers combined time-domain NARMAX modelling, time and frequency domain analysis, identification techniques and periodic test signals to improve GT nonlinear modelling. In another investigation, Chiras et al. [110] applied a forward-regression orthogonal estimation algorithm to make a NARMAX model for a twin-shaft Rolls Royce Spey aircraft gas turbine. A nonlinear relationship between dynamics of the shaft rotational speed and the fuel flow rate was also explored and discussed in the study. To validate the model performance, the researchers examined static and dynamic behaviour of the engine for small and large signal test. The results were satisfactory and could be matched with the results from another previously estimated model. In another effort, Chiras et al. [111] used FFNN to model the relationship between fuel flow rate and shaft rotational speed dynamics for a Spey gas turbine engine. They showed the necessity of using a nonlinear model for modelling high-amplitude dynamics of gas turbine engines. Chiras et al. [112] also recommended a global nonlinear model of gas turbine dynamics using NARMAX Structures. They investigated both linear and nonlinear models of a twin-shaft Rolls Royce Spey gas turbine. Their suggestion for a global nonlinear model was based on the fact that linear models vary with operational points. They discussed a simple method for identification of a NARX model. The performance of this model was satisfactory for both small and high amplitude tests. However, due to inherent problems with discrete-time estimation and great variability of the model parameters, the physical interpretability of the model was lost.

Ruano et al. [113] presented nonlinear identification of shaft-speed dynamics for a Rolls Royce Spey aircraft gas turbine under normal operation. They used two different approaches including NARX models and neural network models. The researchers realized that among the three different structures of NN including radial basis function (RBF), MLP and B-spline, the latter delivered the

best results. They employed genetic programming tool for NARMAX and B-spline models to determine the model structure.

Two different configurations of backpropagation neural networks (BPNN) were developed by Torella et al. [114] to study and simulate the effects of gas turbine air system on an aero engine performance. For the first configuration, to improving the accuracy of the model, different network structures in terms of training methods and number of hidden layers were investigated for on-design simulation of a large turbofan engine. For the second configuration, the researchers derived a computer code to set up BPNNs for simulation of the air system operation; working with or without faults. The applied methodology was very useful when diagnostics and troubleshooting of the air system were investigated. The researchers discussed the problems, the most suitable solutions and the obtained results. They emphasized that the BPNN training did not cover multiple faults as well as the influence of sensor noise and fault on the air system fault identification.

Breikin et al. [115] employed a genetic algorithm (GA) approach for dynamic modelling of aero gas turbine engines for condition monitoring purpose during the engine cruise operation. They applied real engine data to the algorithm to estimate parameters of the linear reduced-order model. They compared the results of the approach with traditional modelling techniques used in industry and realized that GA affords flexibility in the choice of performance metrics.

Badihi et al. [116] applied artificial neural networks to estimate the fuel flow injection function to the combustor chamber of a jet engine. They used Simulink-MATLAB to make a mathematical model and to generate required data for training a feedforward MLP neural network. They showed that the resulting ANN model had the capability to accurately predict performance parameters of the engine. Mohammadi et al. [117] used MLP neural networks with dynamic processing units for detection of faults in a twin-shaft aero gas turbine engines. They verified the capability of the trained network by conducting varieties of simulations. Neural networks were employed by Loboda et al. [118] for fault identification of an aero gas turbine. Both MLP and radial basis networks were used and compared in terms of accuracy and computation time. The

results showed that the RBF was a little more accurate than MLP, but it needed much more computation time. Tayarani-Bathaie et al. [119] investigated using a set of SISO dynamic neural network (DNN) based models for fault detection of an aircraft engine. They carried out various simulations to demonstrate the performance of the proposed fault detection scheme. Kulyk et al. [120] proposed a methodology for obtaining test and training data sets and formulating input parameters of a static neural network for diagnosing aero gas turbine engines and recognising individual and multiple defects in the air-gas path units. They considered the operation of the engine in a wide range of modes.

## 2.3. APPLICATIONS OF GAS TURBINE MODELS TO CONTROL SYSTEM DESIGN

Modelling and simulation of gas turbines play a significant role in control areas. Different control strategies and a variety of controllers can be employed and tested on gas turbine models before implementation on real systems. This section explains the main research activities in this field and shows how gas turbine models can improve GT control systems and prevent huge costs associated with the implementation of controllers on real systems. Applications of gas turbine modelling to control systems can also be categorized into white-box and black-box approaches.

### 2.3.1. White-Box Approach in Control System Design

Ricketts [44] showed that the dynamic model developed for a twin-shaft gas turbine by using a generic methodology and performance data sets, could represent an ideal application to adaptive control schemes. Ailer [121] and Ailer et al. ( [122],[123],[124],[125]) carried out different research to design and develop control systems for a low-power industrial gas turbine based on the results they already achieved in nonlinear modelling of the GT. They used nonlinear modelling methodology on the base of thermo-dynamical equations to model the system. They linearized the model to be able to design different kinds of controllers. Agüero et al. [126] applied modifications in a heavy-duty power plant gas turbine control system. One of the modifications limited speed deviations to the governor, which in its turn, limited power deviation over dispatch set point.

Another modification could prevent non-desired unloading of the turbine. The researchers investigated turbine dynamic behaviour before and after the modifications were made.

Centeno et al. [127] reviewed typical gas turbine dynamic models for power system stability studies. They discussed main control loops including temperature and acceleration control loops, their applications and implementations. They also explained different issues which should be considered for modelling of temperature and acceleration control loops. The performance of the control loops were simulated against changes in gas turbine load. Figure 2.6 shows the block diagram of the basic temperature control loop for the GT model [127].
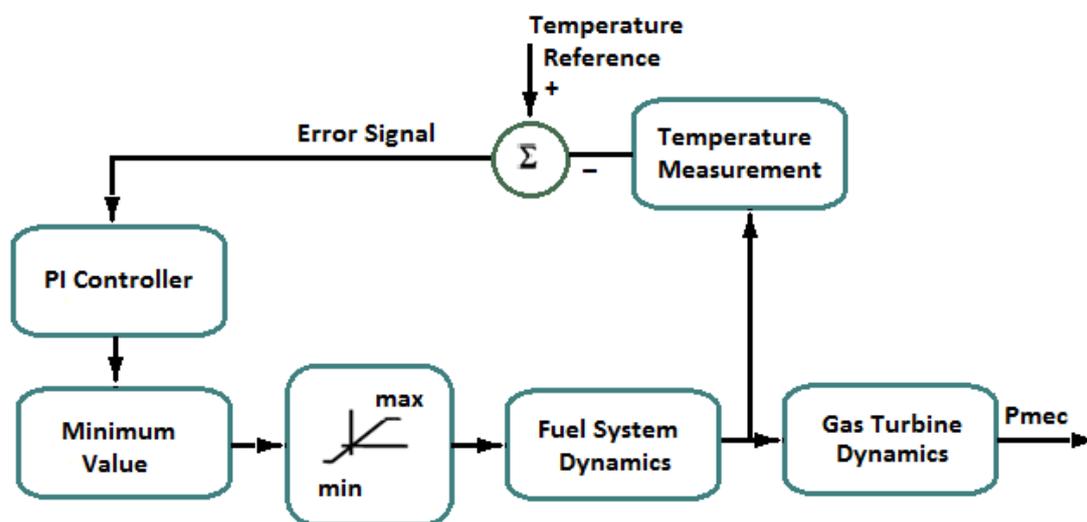


**Figure 2.6:** Block diagram of the basic temperature control loop for a gas turbine model [127].

Ashikaga et al. [128] carried out a study to apply nonlinear control to gas turbines. They reported two applications of nonlinear control. The first one was the starting control using the fuzzy control, and the other was the application of the optimizing method to variable stator vane (VSV) control. The objective was to increase thermal efficiency and to decrease nitrogen oxide emission. However, the algorithms for solving optimization problems were complicated, time-consuming and too large to be installed easily in computers. Zaiet et al. [129] proposed modelling and nonlinear control of a gas turbine based on the previous studies in the literature. They stated that their methodology could provide more flexibility in design of strategies, controlling the speed and surge simultaneously, and accelerating the compressor without stalling problems.

Lichtsinder and levy [130] developed a simple and fast linear model for real-time transient performance of a jet engine control. They formulated control system specifications to specify the maximal variance of the fuel flow command during transient manoeuvre. They define and employed a novel generalized function definition and discussed the application of this technique for the development of the model. The resulting model showed a high accuracy for variance of the fuel flow rate. Comparison of the simulation results to the conventional models showed that the new model can successfully be used for large input variances.

Pongraz et al. [131] used an input-output linearization method to design an adaptive reference tracking controller for a low-power gas turbine model. They discussed a third-order nonlinear state space model for a real low-power single-shaft gas turbine based on dynamic equations of the system. In their model, fuel mass flow rate and rotational speed were considered as input and output respectively. A linear adaptive controller with load torque estimation was also designed for the linearized model. According to the results of simulation, the required performance criteria were fulfilled by the controlled plant. The sufficient robustness of the system against the model parameter uncertainties and environmental disturbances were also investigated and approved.

Tong and Yu [132] presented a dynamic model of a micro turbine and its nonlinear PID controller. Their research objective was to improve the stability of the micro turbine system. The simulation results demonstrated that although the nonlinear PID controller has better adaptability and robustness than the classical the PID, micro turbine system could not operate smoothly at all operating modes. Therefore, they suggested that for getting better performance, it was necessary to use both the auto-disturbance rejection control and the nonlinear robust coordinated control methodologies.

Najimi and Ramezani [133] designed a robust controller for an identified model of a power plant gas turbine. The applied model was built on the basis of Rowen's model [38] and by using real data for tuning the GT parameters. The controller design objectives were to adjust the GT rotational speed and exhaust gas temperature simultaneously by controlling fuel signals and

compressor IGV position. Simulation results showed that the proposed controller for the nonlinear model of the system fairly fulfilled the predefined objectives as it could maintain turbine speed and exhaust gas temperature within the desired interval, under load disturbances and nonlinear uncertainties. Compared to MPC and PID controllers, the robust controller decreased maximum amplitude of the speed deviations remarkably.

Kolmanovsky et al. [134] developed a robust control system for aero gas turbines. The purpose of the study was to preserve stability and tracking performance of the engine under uncertainties such as surge margins, and large inlet distortions. To develop verifiable stable control architectures for gas turbine engines, Pakmehr et al. [135] investigated a nonlinear physics-based dynamic model of a twin-shaft aero engine. A stable gain scheduled controller was presented and a stability proof was explored for the closed-loop control system. Besides, a gain scheduled model reference adaptive control for MIMO nonlinear plants with constraints on the control inputs was studied.

There have also been remarkable academic researches, trying to develop theoretical background of MPCs. An overview of industrial MPC technology was presented by Qin et al. ( [136],[137]). Richalet ( [138],[139]) discussed industrial applications of MPC. A pedagogical overview of some of the most important developments in MPC theory, and their implications for the future of MPC theory and practice, was discussed by Nikolaou [140]. Rawlings provided a review of MPCs for tutorial purposes [141].

### 2.3.2. Black-Box Approach in Control System Design

The neural network controllers typically suffer performance degradation when dealing with unstable inverse models. Besides, the stability and robustness of the neural network approaches are difficult to be analyzed. However, the neural network controllers are widely known for their excellent reference tracking capability and their flexibility for implementation on various systems. Although PID controllers are still being widely used in control loops in the majority of industrial plants, their algorithm might be difficult to deal with in highly nonlinear and time-varying processes [20]. For these reasons, the learning-based control methodology such as neural network

has been widely used in various industrial applications. There is a strong motivation for development of a large number of schemes for ANN-based controllers due to their successful industrial applications [142]. ANN-based models for control systems can be trained using the data generated from a previously simulated model of the plant, or can be obtained directly from special open loop experiments performed on the plant [143]. It has been demonstrated that the input-output data sets of the system parameters obtained from a plant which is controlled by a linear controller can be reliably used for ANN training process [144].

Remarkable efforts have been done during recent decades to use neural networks based controllers (Neurocontrol) for industrial systems. A survey in Science Direct and IEEE databases shows that the number of papers in the field of neurocontrol has been increased significantly from 1990 to 2008 [145]. Agarwal [142] presented a systematic classification of various neurocontrols and showed that the neurocontrol studies are essentially different despite all their similarities. Hunt et al. [146] and Balakrishnan and Weil [147] also carried out a literature survey in this area in 1992 and 1996 respectively. Rowen and Housen [148] investigated GT airflow control for optimum heat recovery and its advantages at gas turbine part-load conditions. They discussed performance and control flexibility of both single-shaft and twin-shaft gas turbines in industrial heat recovery applications and demonstrated the adaptability of GTs in meeting unique industrial process requirements. Hagan et al. ( [149],[150]) presented an overview of neural networks and their applications to control systems. Their research covered different issues such as MLP neural network for function approximation, the backpropagation algorithm for training MLPs, several techniques for improving generalization as well as three different control architectures including model reference adaptive control, model predictive control, and feedback linearization control.

Investigation for the practical use of ANN to control complex and nonlinear systems was carried out by Nabney and Cressy [151]. They utilized multiple ANN controllers to maintain the level of thrust for aero gas turbines and to control system variables for a twin-shaft aircraft gas turbine engine in desirable and safe operational regions. The main idea behind the research was to minimize fuel consumption and to increase the engine life. They aimed to improve the performance

of control system by using the capability of ANN in nonlinear mapping instead of using varieties of linear controllers. They used MLP architecture with a single hidden layer to train the networks. The researchers applied a reference model as an input to the ANN controller. The results showed that performance of the applied ANN controller was better than conventional ones. However, they could not track the reference models as closely as they expected.

Another effort was carried out by Dodd and Martin [152], more or less with the same objectives. They proposed an ANN-based adaptive technique to model and control an aero gas turbine engine and to maintain thrust at a desired level while minimizing fuel consumption in the engine. They suggested a technique which consequently could lead to maximizing thrust for a specified fuel, lowering the critical temperature of the turbine blades and increasing the engine life. In their research, a FFNN with sigmoid activation function was utilized to model the system. The simplicity and differentiability of the neural network helped the researchers to calculate necessary changes to controllable parameters of the engine and consequently to maintain the level of the thrust in a targeted point. Figure 2.7 shows the block diagram of the ANN model. The inputs correspond to fuel rate, final nozzle area and inlet guide vane angle. The only output is thrust [152].
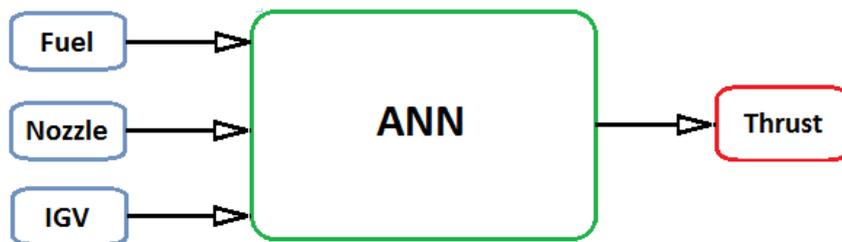


**Figure 2.7:** Block diagram of an ANN-based aero gas turbine model for system optimization consists of minimizing fuel while maintaining thrust [152].

Psaltis et al. [153] employed a multi-layer neural network processor and used different learning architectures to train the neural controller for a given plant. Lietzau and Kreiner ( [154],[155]) explored the principles and possible applications of model-based control concepts for jet engines. They investigated modelling methods for real-time simulation and online model adaptation. To improve the transient stability performance of a power system, Dash et al. [156] presented a radial

basis function neural network (RBFNN) controller with both single and multi neuron architecture for the unified power flow controller (UPFC). They observed that RBF controller with multi-neuron structure performed better and showed a superior damping performance compared with the existing PI controllers. They also demonstrated that RBF model is very useful for the purpose of real-time implementation.

Development of an intelligent optimal control system with learning generalization capabilities was explored by Becerikli et al. [157]. They used a DNN as a control trajectory priming system to overcome the non-dynamic nature of popular ANN architectures. The trained DNN helped to generate the initial control policy close to the optimal result. Litt et al. [158] explored an adaptive, multi-variable controller for deterioration compensation of the thrust due to aging in an aero engine gas turbine. They used the relationship between the level of engine degradation and the overshoot in engine temperature ratio, which was the cause of the thrust response variation, to adapt the controller. A mathematical model of a combined cycle gas turbine (CCGT), as part of a large-scale national power generation network, was developed by Lalor and O'Malley [159]. The objective was to study the response of CCGT to the frequency disturbance and to investigate the effects of increasing proportions of CCGT generation on the entire network when the model was integrated into a larger model.

Junghui and Tien-Chih [20] presented a new control approach by employing a PID controller and a linearized neural network model. Their research objective was to make a balance between nonlinear and conventional linear control designs in order to improve the control performance for the nonlinear systems. Although the proposed method provided a useful physical interpretation of the system dynamics, and it was effective in reducing the variance of the system output caused by disturbances, there were several drawbacks such as convergence problems that could have a serious impact on the controller design.

Some of the researchers tried to develop ANN-based MPC for control of processes. Sahin et al. [160] proposed a neural network approach for a nonlinear model predictive control (NMPC). They

showed that the MPC can be effectively employed to control nonlinear industrial processes without linearization requirement. Ławryńczuk ( [161],[162]) discussed details of NMPC algorithms for MIMO processes modelled by means of neural networks of a feedforward structure. Jadlovská et al. [163] presented classical and NARX approaches to design generalized predictive control (GPC) algorithm for a nonlinear system. They concluded that the intelligent neural GPC controller performance which used linearization techniques showed tremendous advantages over the conventional nonlinear predictive controller. Suarez et al. [143] developed a new predictive control scheme based on neural networks to linearize nonlinear dynamical systems. Cipriano [164] discussed implementation of fuzzy predictive control for power plants using nonlinear models based on fuzzy expert systems, and using fuzzy logic to characterize the objective function and the constraints. A NMPC for frequency and temperature control of a heavy-duty IPGT was developed by Kim et al. [165]. They showed that the proposed control system has superior performance to PID control in terms of responses to disturbances in electrical loads.

Ghorbani et al. ( [166],[167]) and Mu & Rees [168] explored applications of ANN-based MPC to gas turbines. Mu and Rees [168] investigated nonlinear modelling and control of a Rolls Royce Spey aircraft gas turbine. They used NARMAX and neural networks to indentify the engine dynamics under different operational conditions. The researches applied an approximate model predictive control (AMPC) to control shaft rotational speed. The results proved that the performance of AMPC as a global nonlinear controller was much better than gain-scheduling PID controllers. AMPC showed optimal performance for both small and large random step changes as well as against disturbances and model mismatch. In another effort, Mu et al. [169] examined two different approaches to design a global nonlinear controller for an aircraft gas turbine. They compared and discussed the properties of AMPC and NMPC. The results showed that both controllers provided good performance for the whole operational range. However, AMPC showed better performance against disturbances and uncertainties. Besides, AMPC could be gained analytically, required less computational time and avoided local minima.

A combination of RNN and reinforcement learning (RL) was employed by Schaefer et al. [170] to control a gas turbine for stable operation on high load. High system identification quality of RNN could facilitate the network training by using limited available data sets. Sisworahardjo et al. [171] presented a neural network controller for power plant MGTs. They applied both PI and ANN controllers to control voltage, speed, temperature and power. They concluded that ANN-based controller had a better performance in terms of error measures.

Yamagami et al. [172] developed an optimal control system for the gas turbines of CCPPs as a result of development of the control systems for the entire power plant including steam turbines, waste heat recovery boilers, and auxiliary machines. Implementation of a MPC on a heavy-duty power plant gas turbine was investigated by Ghorbani et al. ( [166],[167]). They built a model of the system based on a mathematical procedure and autoregressive with exogenous input (ARX) identification method. The research objective was to design a controller that could adjust rotational speed of the shaft and exhaust gas temperature by the fuel flow rate and the position of IGV. The MPC controller showed superior performance to both PID controller and SpeedTronic control system.

Using PID and ANN controllers for a heavy-duty gas turbine plant was investigated by Balamurugan et al. [173]. Their work was based on the GT mathematical model already developed by Rowen [37]. They applied Ziegler-Nichols method to tune PID controller parameters. Besides, they trained an ANN controller using backpropagation method to control the speed of the gas turbine. The simulation results showed that the ANN controller performed better than the PID controller. Figure 2.8 shows a comparison of gas turbine plant response with PID and ANN controllers [173].

Bazazzadeh et al. [174] developed a mathematical model of a controller for an aero gas turbine by using fuzzy logic and MLP-based neural network methods in Simulink-MATLAB environment. The neural networks were employed as an effective method to define the optimum fuzzy fuel functions. The resulting controller could successfully achieve the desired performance and stability.
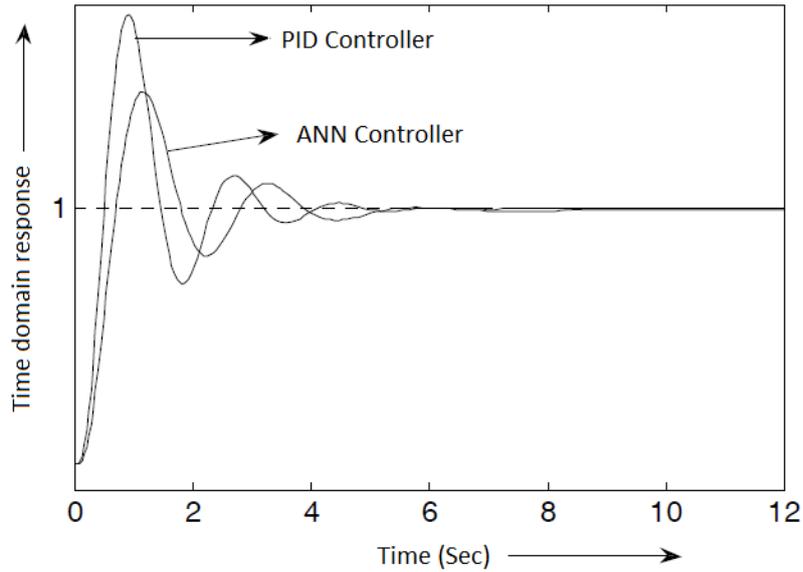
**Figure 2.8:** A comparison of gas turbine plant response with PID and ANN controllers [173].

## 2.4. FINAL STATEMENTS ON THE LITERATURE

As it can be seen from the literature, the outcome of the research in the field of modelling, simulation, and control of gas turbines has been very effective in GT performance evaluation and optimization before final design and manufacturing processes. However, there is still a great need for further system optimization. To approach an optimal model as closely as possible, researchers need to unfold the unknowns of complicated nonlinear dynamic behaviour of these systems in order to minimize undesirable events such as unpredictable shutdowns, overheating and overspeed during the GT operation. Therefore, as it was discussed in Chapter 1, further research and development activities need to be carried out in this field.

Since it is desirable to design gas turbines with high performance, high reliability and cost effectiveness, an extensive effort still needs to be devoted towards understanding their complex natural dynamics and coupled parameters. For instance, system disturbances arising from faults or from load fluctuations in power network of power plant gas turbines may drive GTs to instability. Exploring reaction of gas turbines to the system disturbances and changes in environmental conditions is still a challenging issue. Therefore, there is an increasing demand for accurate dynamic models, to investigate the system response to disturbances and to improve existing control

systems. The investigated models and control systems which were built on the base of simplified and/or linerallized equations are not accurate enough to capture system dynamics precisely. Therefore, a precise analysis needs to be carried out regarding the problems that linearization may cause for modelling and control of gas turbines ( [175],[176]). Application of ANN as a fast and reliable method to stabilize the system against disturbances can be investigated further. In this case, dynamic behaviour of the system can be predicted and controlled using novel control methods in the presence of a number of uncertainties, such as environmental conditions and load changes.

In the area of black-box models, there are many different types of ANN architectures in terms of network topology, data flow, input types and activation functions, such as recurrent, RBF and Hopfield networks. The ANN models can also be trained with varieties of algorithms such as backpropagation Levenberg-Marquardt algorithm, non-gradient based training methods and genetic algorithm. As it can be seen from the literature, each of the research activities in the field of modelling of gas turbines investigated the issue from a specific perspective and has its own limitation(s). For instance, Chiras et al. ( [109],[110],[111],[112]), Ruano et al. [113], and Torella et al. [114] concentrated on ANN-based modelling of aero gas turbines. They employed a variety of ANN-based techniques and approaches such as MLP, NARMAX, NARX, RBF, BPNN and B-spline, to explore nonlinear dynamics of aero gas turbines. While some researchers such as Jurado [88], and Bartolini et al. [89] investigated micro gas turbines using ANN techniques, other researchers explored ANN-based IPGTs. The major contributions in this area include the studies carried out by Lazzaretto and Toffolo [91], Jurado [88],  Bartolini et al. [89], Basso et al. [94], Bettocchi et al. ( [96],[97],[177],[178]), Yoru et al. [100], Simani and Patton [99], Palmé et al. [106], Fast et al. ( [101],[102],[103]), Fast and Palmé [104], Fast [105], Spina and Venturini [98], Ogaji et al. [92], and Arriagada et al. [93]. The results of these studies have indicated that ANN can be very useful for the real-time simulation of gas turbines, specifically when there is not enough information about the system dynamics. It has also been shown that ANN could be used as a high-speed powerful tool for real-time control problems [92]. ANN has the capability to identify system faults and to generate warnings at early stages with high reliability [93].

Ogaji et al. [92], Arriagada et al. [93], Fast et al. ( [101],[102],[103]), Palmé et al. [106], Fast et al. [104], and Fast [105], explored applications of ANN for fault diagnosis, condition monitoring and/or sensor validation purposes. Fast et al. [103] just considered a full-load situation for ANN-based system identification and modelling of single-shaft gas turbines. In some GT models, the nonlinear terms in the model were restricted to the second order [88]. Besides, most of the ANN-based models of gas turbines were built on the basis of a specific training function (*trainlm*) and transfer functions ('tansig' or 'logsig' type in the hidden layer, and 'purelin' type in the output layer). Besides, some research activities just concentrated on dynamic behaviour of individual main components of gas turbines such as compressors and combustors. For instance, one can refer to neural network techniques employed by Ghorbani et al. ( [179],[180]), Palmé et al [181], Mozafari et al. [182], and Sethi et al. [183].

As it can be seen from the literature, none of the past ANN research activities on gas turbines conduct an extensive performance comparative study using combinations of different network architectures, training algorithms and different number of neurons. A comprehensive and comparative study in this field can be very useful in system identification and modelling of gas turbine engines. Approximating an ANN model with high generalization capabilities and robustness for IPGTs can be extensively investigated using simulated data or operational data of real GTs and based on the flexibility that ANN provides for modelling of different types of systems. For this purpose, different ANN architectures can be explored for gas turbines in order to attain such a model which can predict dynamic behaviour of the system as accurately as possible and can also be employed as a powerful tool in condition monitoring, trouble shooting and maintenance of gas turbines. Besides, majority of both white-box and black-box models in the literature have been built based on the steady-state operation of gas turbines, when GTs have already passed the start-up procedure and run in a stable mode. Unfortunately, the literature lacks enough investigation about modelling and simulation of GT transient behaviour and start-up operation, especially for IPGTs. Among the limited number of studies covering this topic, one can refer to the works by Agrawal and Yunis [184], Balakrishnan and Santhakumar [185], Peretto and Spina [186], Henricks [187],

Beyene and Fredlund [188], Kim et al. ( [189],[190],[191]), Shin et al. [192], Davison and Birk [193], Huang and Zheng [194], Xunkai and Yinghong [195], Sanaye and Rezazadeh [196], Kocer [197], Corbett et al. [198], Alobaid et al. [199], Zhang [200], Rezvani et al. [201], Daneshvar et al. [202], Rahnama et al. [203], Refan et al. [204] and Sarkar et al. [205]. There are also some white-box and black-box methodologies regarding simulation of transient behaviour of individual main components of gas turbines such as compressors which can be effectively applied to gas turbines. For instance, one can refer to neural network techniques employed by Venturini ( [206],[207]), to explore transient behaviour of compressors. Similar efforts were carried out by Venturini [208], and Morini et al. ( [209],[210]) by using white-box methods. Therefore, because of the importance and sensitivity of these procedures in GT service life, further research is needed to be carried out in this area.

Discussion about details of the entire research directory in this thesis is not possible. Although aero gas turbines and stationary gas turbines have the same basic structures, they have many differences in details. Because of high demand of electricity market for optimization of power plant gas turbines and the need for extensive research in modelling and control of these types of gas turbines, special attention needs to be paid to this area.

## 2.5. SUMMARY

This chapter presented a comprehensive overview of the literature in the field of modelling, simulation, and control of gas turbines. It discussed most relevant scientific sources and significant research activities in this area for different kinds of gas turbines. Main white-box and black-box models and their applications to control systems were investigated for low-power, aero and power plant gas turbines. It was shown that despite significant studies in this area, further research needs to be carried out to resolve unpredictable challenges that arise in the manufacturing processes or in the operation of industrial plants. These challenges may be found in a variety of areas such as design, commissioning, condition monitoring, fault diagnosis, trouble shooting, maintenance, sensor validation, control, etc.

*All things are artificial,*
*for nature is the Art of God.*

Sir Thomas Browne
English Author, 1605-1682

# CHAPTER 3
# ANN-BASED SYSTEM INDENTIFICATION FOR INDUSTRIAL SYSTEMS

Since artificial neural network was presented for the first time by Bernard Widrow from Stanford University in 1950's, it has been a constant challenge for researchers to find optimal ANN-based solutions to design, manufacture, develop and operate new generations of industrial systems as efficiently, reliably and durably as possible. Getting enough information about the system which is to be modelled is the first step of system identification and modelling process. Besides, a clear statement of the modelling objectives is necessary for making an efficient model. Industrial systems may be modelled for condition monitoring, fault detection and diagnosis, sensor validation, system identification or design and optimization of control systems [211].

A variety of analytical and experimental methods have been suggested so far for industrial system modelling. One of the novel approaches for system identification and modelling of gas turbines is employing ANN-based techniques. ANN has the power to solve many complex

problems. It can be used for function fitting, approximation, pattern recognition, clustering, image matching, classification, feature extraction, noise reduction, extrapolation (based on historical data), dynamic modelling and prediction.

This chapter briefly presents artificial neural networks and their main elements and structures. At the next step, ANN-based model building process including system analysis, data acquisition and preparation, network architecture, as well as network training and validation is explained. Different challenges in using ANN-based methodologies for industrial systems and their applications, advantages and limitations are also discussed in this chapter.

## 3.1. ARTIFICIAL NEURAL NETWORK (ANN)

The main idea behind the creation of artificial neural network was to resemble the human brain in order to solve complicated problems in a variety of scientific areas such as engineering, psychology, linguistics, philosophy, economics, neuroscience, etc. ANN is defined as a computing system which is made up of a group of simple, highly interconnected processing elements (neurons) with linear or nonlinear transfer functions. These elements process information by their dynamic state response to external inputs [212]. 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. ANN learns the relation between inputs and outputs of the system through an iterative process called training. Each input into the neuron has its own associated weight. Weights are adjustable numbers which are determined during the training process. Selecting the right parameters as inputs and outputs of ANN is very important for making an accurate and reliable model. The availability of data for the selected parameters, system knowledge for identification of interconnections between different parameters and the objectives for making a model are basic factors in choosing appropriate inputs and outputs. Accuracy of the selected output parameters can be examined by sensitivity analysis. Figure 3.1 shows a simple structure of a typical ANN with four inputs, two outputs and three neurons in one hidden layer.
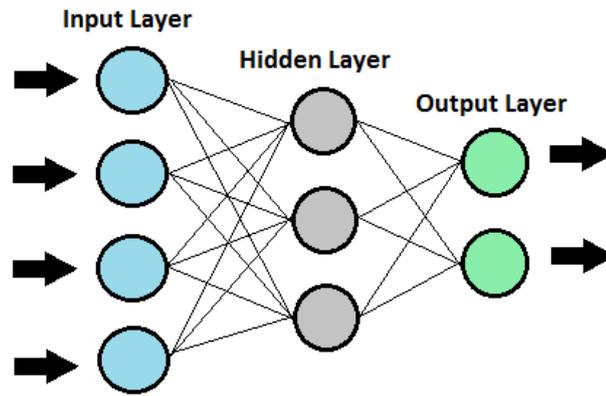
**Figure 3.1:** A simple structure of an ANN with input, hidden and output layers.

## 3.2. THE MODEL OF ARTIFICIAL NEURON

Artificial neuron is the basic and fundamental element of all artificial neural network structures. Figure 3.2 shows a simple single-input neuron with its input, output, and components including the sum and function blocks [213]. $p$, $w$, $b$, $f$, and $a$, are scalar input, scalar weight, bias, transfer (activation) function, and scalar output respectively. The neuron output is calculated by Equation 3.1. The parameters $w$ and $b$ can be adjusted by learning rules so that the relationship between the input and output meet the expected goal [149]. Bias is a weight which is not connected to other nodes, and its input is always set to one. The purpose of bias is to offset the origin of the transfer function for more rapid convergence. Thus, bias allows a node to have an output even if the input is zero.
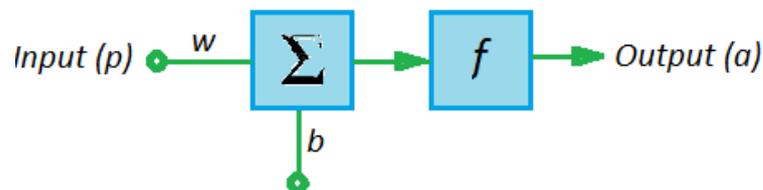


**Figure 3.2:** Single-input neuron structure.

$$a = f(w * p + b) \tag{3.1}$$

A neuron usually has more than one input. Figure 3.3 and Figure 3.4 show multiple-input neuron structures with one and multiple neurons in the hidden layer respectively [149]. $R$ and $S$ indicate the number of elements in input vector, and the number of neurons in the layer. In this case, the input $P$, the weight $w$, and the output $a$, would be vectors, and Equation 3.1 would have a matrix nature as it is shown in Figure 3.3 and Figure 3.4. A Neural network may have several layers operating in parallel. Each layer has its own inputs, outputs, and components.
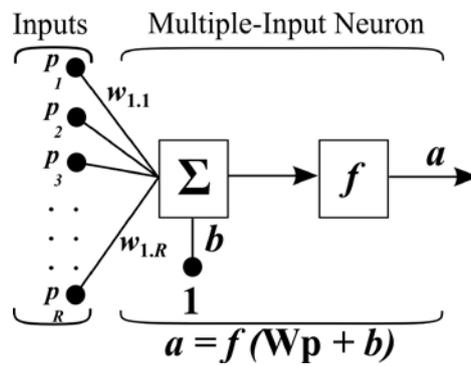


**Figure 3.3:** Multiple-input neuron structure [149].
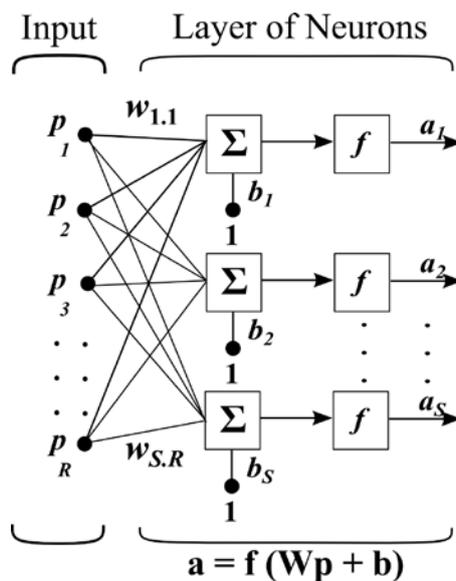


**Figure 3.4:** Matrix form of multiple-input neuron structure [149].

## 3.3. ANN-BASED MODEL BUILDING PROCEDURE

ANN, as a data-driven model, has been considered as a suitable alternative to white-box models during the last few decades. ANN models for gas turbines can be created using different approaches due to the varieties of network structures, training algorithms, type of the activation functions, number of neurons, number of hidden layers, values of weights and biases as well as data structures. However, the best structure for ANN is the one that can predict dynamic behaviour of the system as accurately as possible. The following presents the main steps for setting up an ANN-based model.

### 3.3.1. System Analysis

Before training of any ANN model, it is normally needed to do an extensive system study including system configuration and history record, technical characteristics, operational conditions, monitoring system, available parameters, sensors situation and reliability, accessibility of the system data, availability of performance curves, etc. This step is necessary to establish a suitable input and output structure for the ANN model. It is also necessary to find out the method that is more compatible with the research expectations.

### 3.3.2 Data Acquisition and Preparation

Data acquisition is the first step and a vital part of ANN-based modelling and control of an industrial system. ANN-based models can be created directly using the operational data from an actual GT available in a variety of industrial power plants. The data can be obtained offline, if the system is run in idle mode. However, in this case, the effect of load changes may not be investigated.

When operational data are not available, simulated data from original equipment manufacturers (OEMs) performance or generated by engineering and/or commercial software such as Simulink-MATLAB may be used. In the latter case, system information is fed to the software to make a preliminary model for data generation and to set up the black-box model. The obtained data should cover the whole operational range of the system. All transient data during start or stop processes

should be removed from the collected data before the modelling process. The required data for modelling of IPGTs can be collected from the gas turbines available in a variety of industrial power plants all over the world.

Format of the data structures affects network training. Input vectors could occur concurrently or sequentially in time. For current vectors, inputs occur at the same time or in no particular time sequence. In this case, order is not important and a number of networks could run in parallel. One input vector could be presented to each of the networks. For concurrent vectors, inputs occur sequentially in time and the order in which the vectors appear is important. ANN Tool-Box in MATLAB can employed to model the system and to design the appropriate control system after the stage of data acquisition is completed.

### 3.3.3. Network Architecture

ANN can be classified into static (feedforward) and dynamic (feedback) categories. In static networks, there is no feedback element or delay, and output can be calculated directly from the input through feedforward connections. In dynamic networks, the output depends both on the current input to the network and on the current or previous inputs, outputs, or states of the network. Figure 3.5 shows a feedforward neural network (FFNN) with three layers [214]. Figure 3.6 shows a NARX network with two layers [214].

#### 3.3.3.1. Feedforward Neural Network

As Figure 3.5 shows, neurons in a FFNN model are grouped in layers which are connected to the direction of the passing signal (from left to right in this case). There are no lateral connections within each layer and also no feedback connections within the network. The best-known ANN of this type is MLP [214]. There is at least one hidden layer in a FFNN. MLP is the one of the most common used ANN in scientific applications. It can be used for function fitting, pattern recognition, and nonlinear classification. Among the different ANN structures, MLP is the first choice for modelling and simulation of nonlinear behaviour of industrial systems such as gas turbines [215].
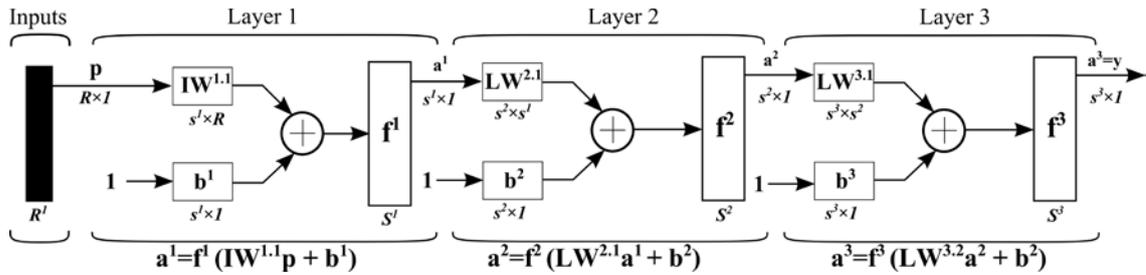
**Figure 3.5:** Three-layer feedforward neural network [214].
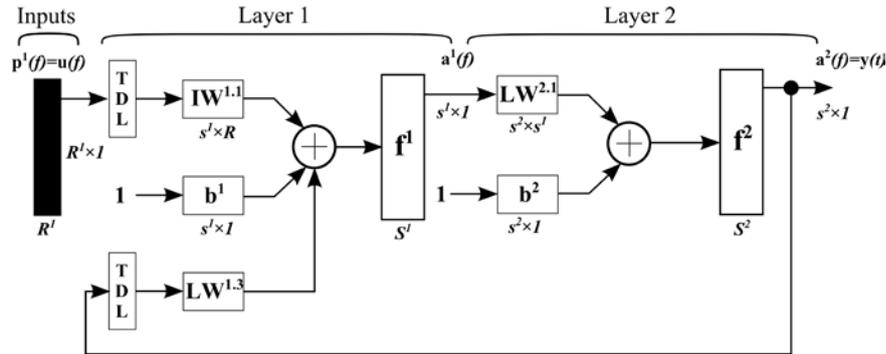


**Figure 3.6:** NARX network with a two-layer feedforward network [214].

### 3.3.3.2. Feedback (Recurrent) Neural Network

Feedback neural network, also called dynamic or recurrent neural network, is a type of ANN structure that allows modelling of time-domain behaviours of a dynamic system. The outputs of a dynamic system depend not only on present inputs, but also on the history of the system states and inputs. A current neural network structure is needed to model such behaviours. One of the most commonly used feedback neural networks is nonlinear autoregressive network with exogenous inputs (NARX). It is a recurrent network with feedback connections enclosing several layers of the network. NARX network has many applications. It can be used for modelling of nonlinear dynamic systems such as IPGTs. As a predictor, it can predict the next value of the input signal. It can also be employed for nonlinear filtering purposes to make the target output as a noise-free version of the input signal. As Figure 3.6 shows, NARX model can be implemented by using a FFNN to approximate the function $f$ [214]. In this figure, a two-layer feedforward network is used for the approximation. The dependent output signal $y(t)$ is regressed on previous values of the output

signal and previous values of an independent (exogenous) input signal. *TDL* indicates time delay [214].

### 3.3.4. Network Training and validation

Training or learning paradigms for an ANN can be mainly classified as supervised and unsupervised. In supervised learning, inputs and targets (desired outputs) are known and the ANN model is trained in a way that maps inputs to the outputs. Supervised learning is employed for regression and classification purposes. However, in an unsupervised learning, targets are unknown and the underlying relationship within the data sets has to be disclosed by the ANN using the data clustering method. Unsupervised learning is used for filtering and clustering of data.

There are two different styles of training in ANNs; incremental training and batch training. In incremental training, weights and biases of the network are updated each time an input is presented to the network. In batch training, the weights and biases are only updated after all inputs are presented. Batch training methods are generally more efficient in MATLAB environment, and they are emphasized in the Neural Network Tool-Box software. However, there are some applications where incremental training can be useful, so that paradigm is implemented as well [214].

The training process of ANN involves the variation of one or more parameters. For example, it is needed to change the number of neurons in the hidden layer in order to attain the best converging network. The number of neurons indicates the complexity that can be approximated by the neural network. It is desirable to use the simplest possible network structure with the least number of input parameters. The developed model can be utilized to validate new process measurements. A true neural network training procedure is usually based on an iterative approximation in which the parameters are successively updated in numerous steps. Such a step can be based on a single data item, on a set of them, or on all available data points. In each step, the desired outcome is compared with the actual one and, using the knowledge of the architecture, all parameters are changed slightly such that the error for the presented data points decreases [214].

Before training is started, the collected data are divided into three subsets including training, validation and test data sets. The first subset is the training set, which is used for computing the gradient and updating the network weights and biases. The second subset is the validation set which is used to verify the model that has been created. The error on the validation set is monitored during the training process. The validation error decreases during the initial phase of training, as does the training set error. The network weights and biases are saved at the minimum of the validation set error. And finally, the test set is used after training and validation for a final test. Testing the neural network with similar data as that used in the training set is one of the few methods used to verify that the network has adequately learned the input domain. In most instances, such testing techniques prove adequate for the acceptance of a neural network system.

The validation data set is used to stop training early if further training on the primary data will hurt generalization to the validation data. Test vector performance can be used to measure how well the network generalizes beyond primary and validation data. When the training is complete, the network performance can be checked to see if any changes need to be made to the training process, the network architecture or the data sets. The first thing to do is to check the training *record;tr*. This structure contains all of the information concerning the training of the network. For example, *tr.trainInd*, *tr.valInd* and *tr.testInd* contain the indices of the data points that were used in the training, validation and test sets respectively. The *tr* structure also keeps track of several variables during the course of training such as the value of the performance function, the magnitude of the gradient, etc.

### 3.3.4.1. Number of Hidden Layers and Neurons

Choosing the right number of hidden layers and available neurons in each layer is very vital in training a neural network. It has been already shown that any muti-dimentional nonlinear mapping of any continuous function can be carried out by a two-layer MLP with suitable chosen number of neurons in its hidden layer [216]. Therefore, the main task in modelling industrial systems using MLP is to determine the right number of neurons in the hidden layer for approaching an optimal

ANN. Although increasing the number of neurons sometimes is necessary to catch nonlinear dynamics of the system, it does not mean that it can always and necessarily improve the model accuracy and generalizability.

### 3.3.4.2. Training Algorithms

Different training algorithms can be used for training ANNs. The available training algorithms in the NN Tool-Box software, which use gradient or Jacobian-based methods, are as follows [214]:

- *Trainlm:* Levenberg-Marquardt

- *trainbr:* Bayesian Regularization

- *trainbfg:* BFGS Quasi-Newton

- *trainrp:* Resilient Backpropagation

- *trainscg:* Scaled Conjugate Gradient

- *traincgb:* Conjugate Gradient with Powell/Beale Restarts

- *traincgf:* Fletcher-Powell Conjugate Gradient

- *traincgp:* Polak-Ribiére Conjugate Gradient

- *trainoss:* One Step Secant

- *traingdx:* Variable Learning Rate Gradient Descent

### 3.3.4.3. Transfer Functions

Transfer (activation) functions transform activation level of a unit (neuron) into an output signal [217]. There is various transfer functions included in the Neural Network Tool-Box software. Karlik et al. [217] and Debes et al. [218] discussed various transfer functions and their applications to neural networks. The two common transfer functions that are employed for MLP are *Log-Sigmoid* and *Tan-Sigmoid*. These functions are differentiable and can cope with nonlinearity of the industrial systems. Figure 3.7 shows different transfer functions that can be used for training neural networks.

$a = hardlim(n)$
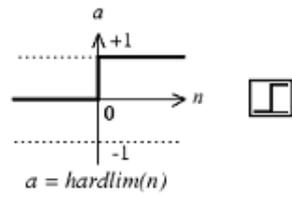
*Hard-Limit Transfer Function*

$a = hardlims(n)$
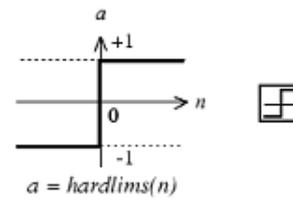
*Symmetric Hard-Limit Transfer Function*
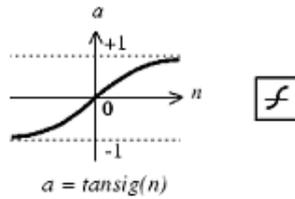
$a = tansig(n)$

*Tan-Sigmoid Transfer Function*
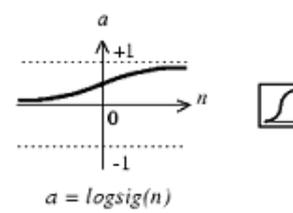
$a = logsig(n)$

*Log-Sigmoid Transfer Function*
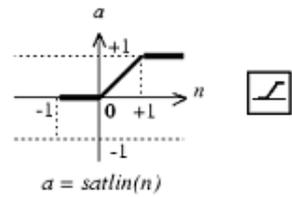
$a = satlin(n)$

*Satlin Transfer Function*
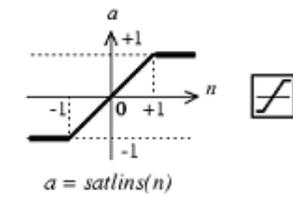
$a = satlins(n)$

*Satlins Transfer Function*

$a = purelin(n)$
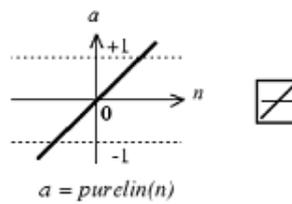
*Linear Transfer Function*

$a = poslin(n)$
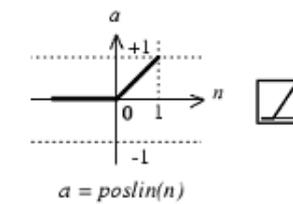
*Positive Linear Transfer Function*

$a = tribas(n)$
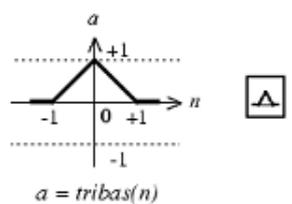
*Triangular Basis Function*

$a = radbas(n)$

*Radial Basis Function*

$a = softmax(n)$
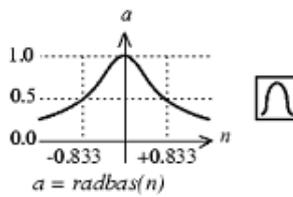
$a = softmax(n)$
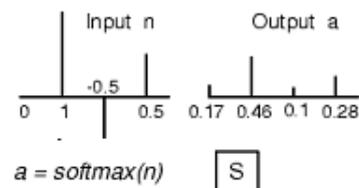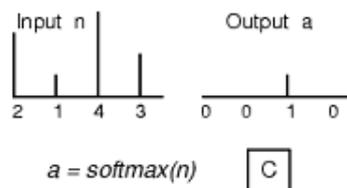
**Figure 3.7:** Neural network transfer functions.

### 3.3.4.4. Weight Values

Before training an ANN, the initial values of weights and biases have to be determined. Initialization of the weights and biases can be done automatically by the ANN Tool-Box software or it can be adjusted manually through writing and running codes in MATLAB.

### 3.3.4.5. Error Criteria

The objective in training a neural network is to minimise the error as much as possible. Minimization of error simply means improving performance of the training and getting a more accurate model. Different definitions and types of error may be considered during training a neural network. For instance, absolute error is defined as the difference between the measured (actual) output and the desired output (target). However, it is common to use mean square error (*MSE*) or root mean square error (*RMSE*) when training MLPs. *MSE* and *RMSE* are defined according to the Equation 3.2 and Equation 3.3 respectively, where $y_m$ is the measured data, $y$ is the prediction of the model and $n_d$ is the number of data sets. Minimization of the error can be achieved by changing weights and/or training algorithms.

$$MSE = \frac{1}{n_{\text{d}}} \sum_{i=1}^{n_{\text{d}}} \left( \frac{y_{mi} - y_i}{y_{mi}} \right)^2 \tag{3.2}$$

$$RMSE = \sqrt{\frac{1}{n_{\text{d}}} \sum_{i=1}^{n_{\text{d}}} \left( \frac{y_{mi} - y_i}{y_{mi}} \right)^2} \tag{3.3}$$

### 3.3.4.6. Training Stop Criteria and Overfitting

When training a neural network, a stop criterion is determined to avoid what is called overtraining or overfitting. ANN has the potential tendency to overfit during training process. Overfitting can occur during training process when the ANN gets too specialized to fit the training data extremely well, but at the expense of reasonably fitting the validation data. Overfitting is reflected by the steady increase in the validation error accompanied by a concomitant steady decrease in the training error. Poor performance due to overfitting is one of the most common

problems in training ANNs. It can be overcome by using the cross-validation method, decreasing the number of neurons in hidden layer(s), or adding a penalty term to the objective function for large weights. By using the cross-validation method, the network performance is measured during training process and if any incentive is given, the training is stopped before maximum number of epochs is reached. Epoch is a neural network term for iteration in a training process. The number of epochs shows the number of times that all patterns are presented to the neural network. More epochs means more training time. In each epoch of an ANN, all the weight values of the neurons are updated.

## 3.4. ANN APPLICATIONS TO INDUSTRIAL SYSTEMS

Artificial neural network as a fashionable area of research has a wide range of potential applications that spans science, art, engineering, etc [219]. It has many advantages over conventional modelling approaches ( [220],[221]). These advantages are due to the special structure and algorithm of the network. ANN methodology can be a suitable alternative to classical statistical modelling techniques when obtained data sets indicate nonlinearities in the system ( [222],[223]). It has a demonstrated capability to solve combinatorial optimization problems in industrial plants [224].

ANN is a powerful tool in system identification and modelling due to its excellent ability to approximate uncertain nonlinearity to a high degree of accuracy. It can perform implicit nonlinear modelling and filtering of the system data [224] and detect coupled nonlinear relations between independent and dependent variables without any need for dynamic equations ( [225],[226]). ANN offers a cost-effective and reliable approach to condition monitoring. The collected data related to the condition of the system can be classified and trained by using artificial neural networks in order to generalize a methodology for data analysis at any time of the measurement. ANN can be applied to examine condition-based maintenance [101] to detect anomalies [103] and to isolate faults [99] in the performance of industrial systems. Using ANN for sensor validation leads to more cost-

effective maintenance. ANN-based methodology can be developed to minimize the need for calibration of sensors and to decrease the percentage of shutdowns due to sensor failure [106].

ANN has been considered as an acceptable solution to many outstanding problems in modelling and control of nonlinear systems. Real data obtained from an industrial system can be used to develop a simple ANN model of the system with very high prediction accuracy [102]. In control design process, a neural network may directly implement the controller (direct design). In this case, a neural network will be trained as a controller based on some specified criteria. It is also possible to design a conventional controller for an available ANN model (indirect design). In this case, the controller is not itself a neural network. In many cases, the obtained data from the systems located on industrial factories and plants may include noisy data. Besides, some sorts of data may be inaccurate or incomplete due to faulty sensors. These tend to happen when the system is old and/or maintenance is poor. ANN has the capability to work considerably well even when the data sets are noisy or incomplete. It can learn from incomplete and noisy data [227].

ANN requires less formal statistical training to be developed [228]. Training ANN is simple and does not need professional statistical knowledge. If the data sets and appropriate software are available, then even newcomers to the field can handle the training process. However, experience and statistical background can still be very useful and effective during the whole performance. ANN can be developed using different training algorithms [228]. It also has the capability of dealing with stochastic variations of the scheduled operating point with increasing data and can be used for online processing and classification [224].

In addition to applications of ANN to industrial systems, it has many general advantages such as simple processing elements, fast processing time, easy training process and high computational speed. Capturing any kind of relation and association, exploring regularities within a set of patterns and having the capability to be used for very large number and diversity of data and variables, are other characteristics of ANN. It provides a high degree of adaptive interconnections between elements and can be used where the relations between different parameters of the system are

difficult to uncover with conventional approaches. ANN is not restricted by variety of assumptions such as linearity, normality and variable independence, as many conventional techniques are. It even has the ability to generalize the situations for which it has not been previously trained. Generally, it is believed that the ability of ANN to model different kinds of industrial systems in a variety of applications can decrease the required time on model development and thus leads to a better performance compared with conventional techniques [17].

## 3.5. ANN LIMITATIONS

As any modelling technique, artificial neural network has its own limitations on the basis of the particular application and methodology under consideration ( [220],[221]). The basic challenges to be resolved include training time, upgrading of trained neural nets, selection of the training vector and integration of technologies in the problem domain [224]. Despite all investigations carried out so far, ANN as a black-box technique is still restricted to clearly identify the importance of every single input parameter during the training process [228]. There is little intuitive information about what actually happens inside the network during learning process and one can hardly intuitively interpret the internal workings of an ANN. There are many issues in terms of methodology which need to be resolved [228].

There are remarkable difficulties for using ANN models on industrial sites. Compared with other conventional models, ANN models may be more difficult to use on operational fields. Special software and hardware is required to implement the model. The correct Interpretation of the output is not also easy. To implement an ANN model, sometimes many computational resources such as mainframes, minicomputers, and processors are needed. For more complicated systems, more resources are required [228].

To train, validate and test an ANN, usually large amount of data sets are required. There is no fixed number of data sets for an optimal training process. It may differ case by case for different industrial systems. However, the amount of the obtained data should be large enough to disclose underlying structure of the system as accurately as possible and to provide sufficient understanding

of the system dynamics. The data sets may be on-site operational data or simulated data by a previously confirmed model. Data acquisition especially on operational sites may be a difficult and time-consuming process. New data sets cannot be fed directly to the trained ANN to improve its performance and it is needed to be trained again against all of the available data sets. Manipulating time-series data in ANN is also a complicated issue. A unique ANN model is trained to solve just a specific problem. It means getting good results from an ANN model for a specific problem, does not guarantee to solve other problems. ANN relies on empirical development. It is a nearly new technique and still needs to be developed based on the practical implementations and experiments gained by researchers.

## 3.6. SUMMARY

There are different approaches and methodologies in system identification and modelling of industrial systems. Artificial neural network is increasingly considered as a suitable alternative to white-box models over the last few decades. The nature and strength of the interrelations of system variables as well as the nature of applications are vital criteria for training a neural network with sufficiently rich empirical data.

This chapter briefly introduced artificial neural networks and their types and structures. It also provided details of an ANN-based model building procedure including system analysis, data acquisition and preparation, network architecture, as well as network training and validation. Applications and limitations of ANN approach for system identification and modelling were also discussed in this chapter. It is important to notice that approximation and error are inseparable parts of any system identification method and ANN is not an exception. Many issues need to be considered when a comparison is made between ANN and any of the conventional modelling techniques.

Johann Wolfgang von Goethe

German writer and politician, 1749-1832

# CHAPTER 4
# MODELLING AND SIMULATION OF A SINGLE-SHAFT GAS TURBINE

Gas Turbines have been used widely in industrial plants all over the world. They are the main source of power generation in places such as offshore plants and oil fields which are far away from urban areas. The key role of GTs in the developing industry has motivated researchers to explore new methodologies in order to be able to predict dynamic behaviour of these complex systems as accurately as possible. A variety of analytical and experimental techniques has been developed so far to approach an optimal model of gas turbines. Fortunately, black-box system identification techniques and specifically ANN-based approaches can effectively assist researchers who work in this field. As it was already stated in Chapter 2, the study in this area can be categorized into IPGT, aero and low-power gas turbine models ( [229],[230]). Artificial neural network is one of the techniques that has been played a significant role in system identification and modelling of industrial systems. This is due to its capability to capture dynamics of the systems without any

prior knowledge about their complicated dynamical equations. Because of sophisticated and nonlinear dynamic behaviour of GTs, significant attention still needs to be paid to the dynamics of these systems to unfold unknowns behind undesirable events during gas turbine operation. As it can be seen from the literature, each research activity in the field of modelling of gas turbines investigated the issue from a specific perspective and has its own limitation(s). According to the methodology used in this study, various backpropagation training functions, different number of neurons and a variety of transfer functions were employed to train the network in order to explore an accurate ANN model using MLP structure. To increase the level of generalization for the model, the data sets were partitioned randomly for training, validation and test purposes.

In this chapter, firstly a SIMULINK model of a low-power gas turbine based on a previous research [28] is presented. Then, an ANN-based system identification process is developed. The process includes generating the required data sets from the Simulink model, writing the computer program code and training the network. Finally, the results are presented, and concluding remarks are discussed [231].

## 4.1. GAS TURBINE SIMULINK MODEL

The data for this study was generated using a re-simulated nonlinear dynamic model of a low-power single-shaft gas turbine. The model has been already developed and verified for loop-shaping control purposes by Ailer et al. [28]. The main idea of their study was to improve dynamic response of the engine by implementation of a developed nonlinear controller. The model was developed and simulated in Simulink-MATLAB, based on engineering principles, gas turbine dynamics, constitutive algebraic equations, and by using operational data. Model verification was performed by open-loop simulations against qualitative operation experience and engineering intuition [28]. Figure 4.1 shows a schematic of the main components of a single-shaft gas turbine engine; including compressor, combustion chamber (combustor), and turbine.
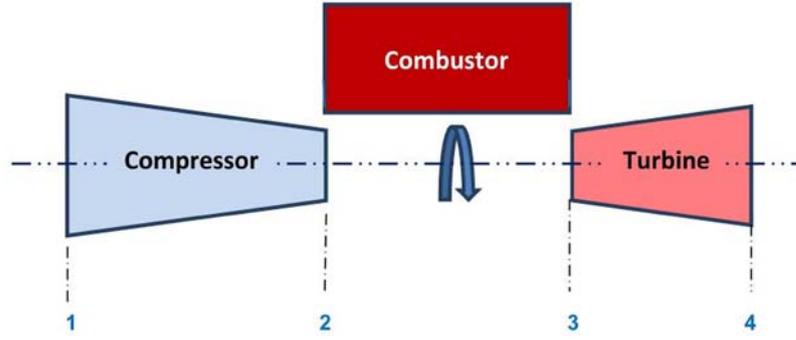
**Figure 4.1:** A schematic of a typical single-shaft gas turbine.

In this study, the SIMULINK model was built using the same principles and equations. Equations 4.1, 4.2 and 4.3 indicate the main equations of the gas turbine employed in the Simulink model [28]. Definition of each of the parameters in these equations is provided in Table 4.1. A simplified feature of the Simulink model is shown in Figure 4.2. In this figure, $N$ and $T_{04}$ are shown as the outputs of the system. $\dot{m}_f$, $M_{load}$, $T_{01}$ and $P_{01}$ are considered as inputs of the model. The other GT parameters can also be considered as outputs of the system. Figures 4.3 to 4.8 show subsystems of the Simulink model in MATLAB environment.

$$\frac{dm_{cc}}{dt} = \dot{m}_c + \dot{m}_f - \dot{m}_t \tag{4.1}$$

$$\frac{dP_{03}}{dt} = \frac{P_{03}}{m_{cc}}(\dot{m}_c + \dot{m}_f - \dot{m}_t) + \frac{P_{03}}{T_{03}\,C_{vmed}\,m_{cc}}(\dot{m}_c C_{p_{air}} T_{02} - \dot{m}_t C_{p_{gas}} T_{03} + q_f \eta_{cc} \dot{m}_f -$$

$$C_{vmed} T_{03}(\dot{m}_c + \dot{m}_f - \dot{m}_t)) \tag{4.2}$$

$$\frac{dN}{dt} = \frac{1}{4\pi^2 In}\left(\dot{m}_t C_{p_{gas}}(T_{03} - T_{04})\eta_{mech} - \dot{m}_c C_{p_{air}}(T_{02} - T_{01}) - 2\pi \frac{3}{50} N M_{load}\right) \tag{4.3}$$

**Table 4.1:** Definition of parameters in equations 4.1, 4.2 and 4.3.

| Parameter | Symbol | Unit |
|-----------|--------|------|
| rotational speed (number of revolutions) | $N$ | $1/s$ |
| temperature at section 1 | $T_{01}$ | $K$ |
| temperature at section 2 | $T_{02}$ | $K$ |
| temperature at section 3 | $T_{03}$ | $K$ |
| temperature at section 4 | $T_{04}$ | $K$ |
| pressure at section 1 | $P_{01}$ | $Pa$ |
| pressure at section 2 | $P_{02}$ | $Pa$ |
| pressure at section 3 | $P_{03}$ | $Pa$ |
| pressure at section 4 | $P_{04}$ | $Pa$ |
| air mass flow rate in compressor | $\dot{m}_c$ | $kg/s$ |
| gas mass flow rate in turbine | $\dot{m}_t$ | $kg/s$ |
| fuel mass flow rate | $\dot{m}_f$ | $kg/s$ |
| gas mass in combustion chamber | $m_{cc}$ | $kg$ |
| time | $t$ | $s$ |
| specific heat of air in constant pressure | $C_{P_{air}}$ | $J/kg\ K$ |
| specific heat of gas in constant pressure | $C_{P_{gas}}$ | $J/kg\ K$ |
| medium Specific heat in constant volume | $C_{v_{med}}$ | $J/kg\ K$ |
| lower thermal value of fuel | $q_f$ | $J/kg$ |
| combustion chamber efficiency | $\eta_{comb}$ | — |
| mechanical efficiency | $\eta_{mech}$ | — |
| moment of Inertia | $I$ | $kg\ m^2$ |
| moment of load | $M_{load}$ | $N\ m$ |
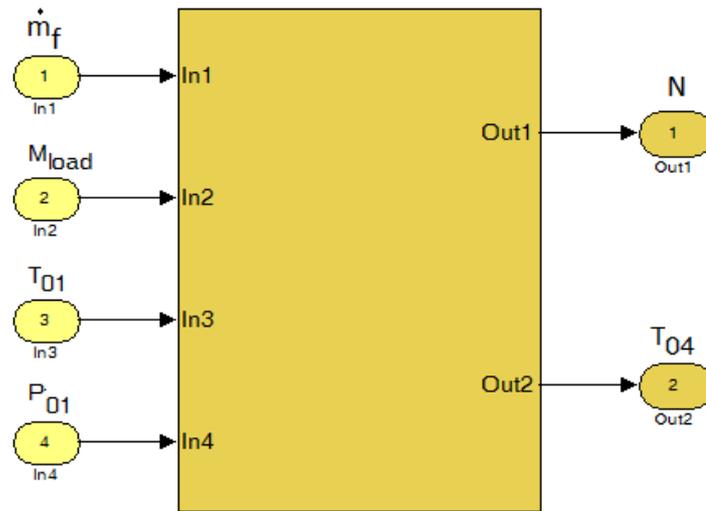
**Figure 4.2:** Simplified simulink model of the gas turbine.
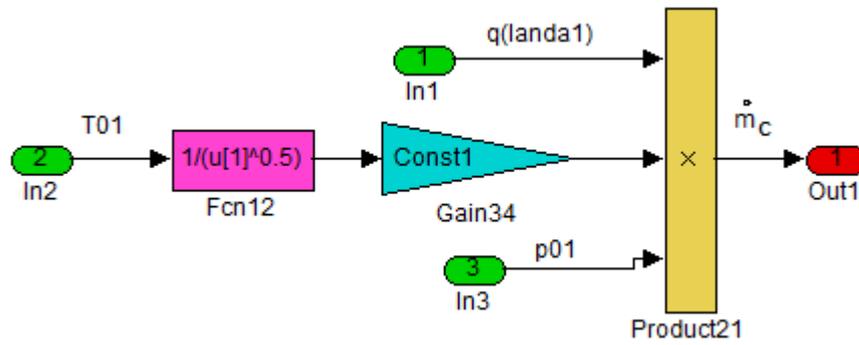


**Figure 4.3:** Subsystem number 1 of the GT Simulink model for creating mass flow rate in the compressor.
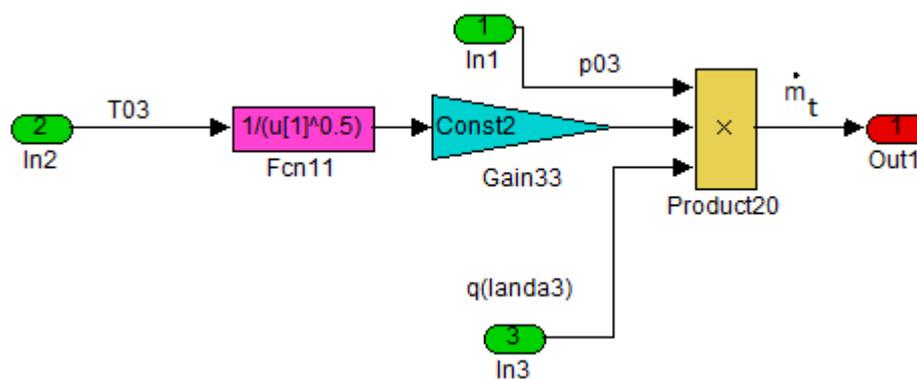


**Figure 4.4:** Subsystem number 2 of the GT Simulink model for creating mass flow rate in the turbine.

**Figure 4.5:** Subsystem number 3 of the GT Simulink model for creating $T_{03}$ and $P_{03}$.
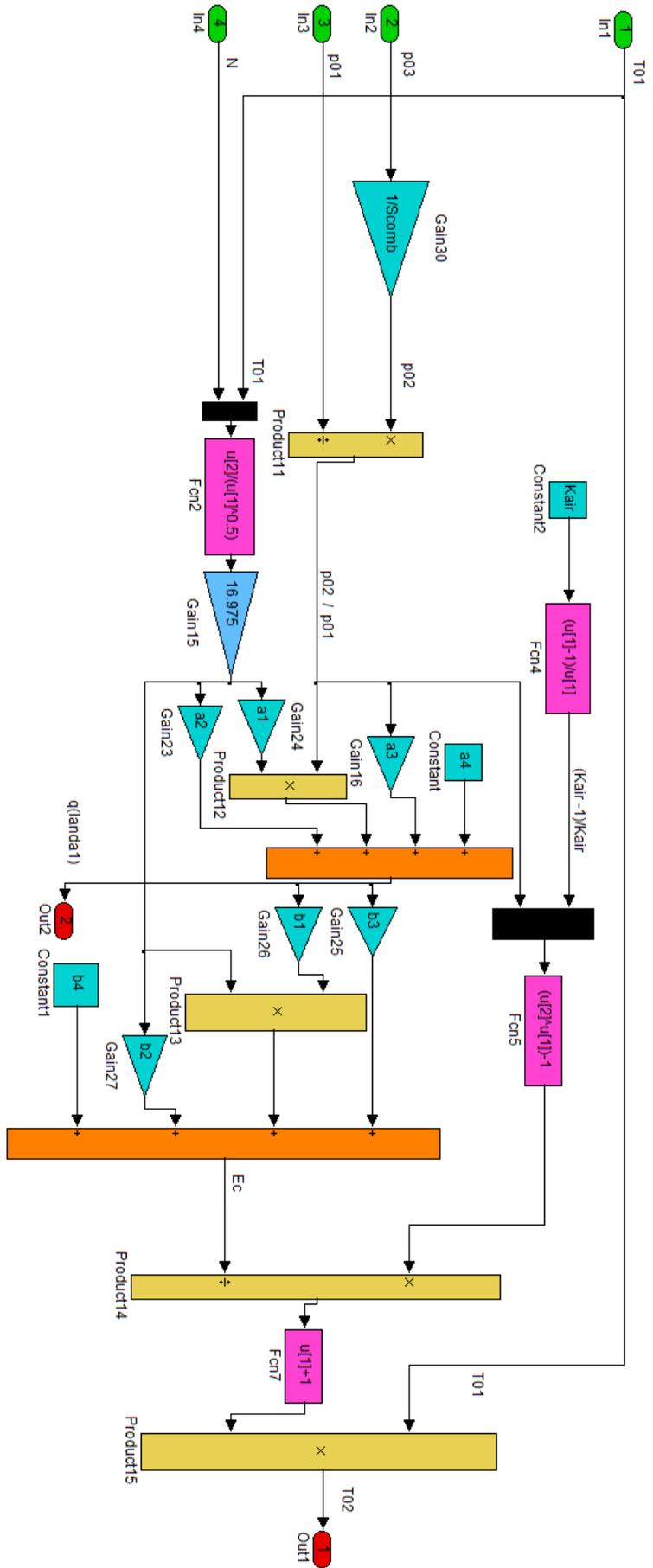
**Figure 4.6:** Subsystem number 4 of the GT Simulink model for creating $T_{02}$.
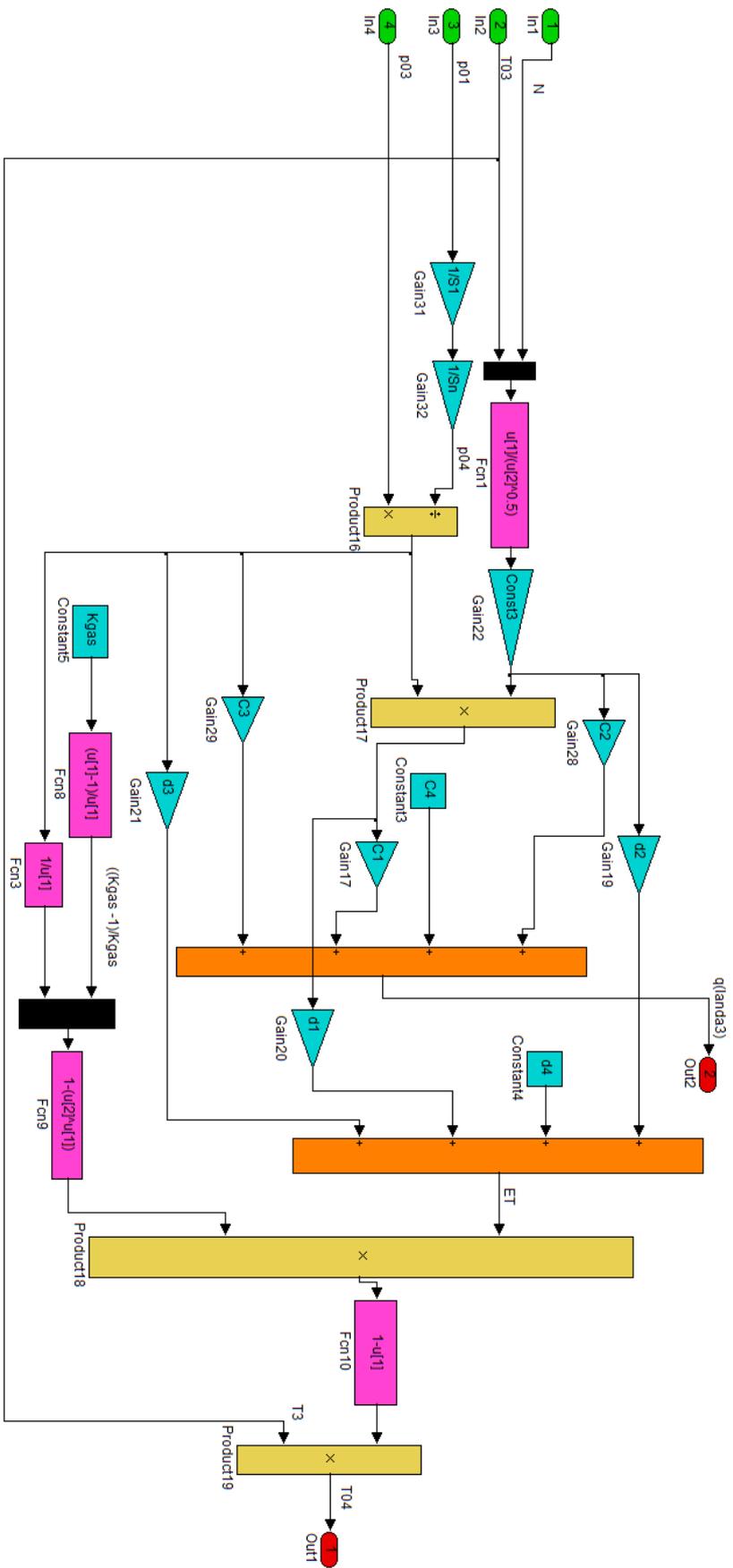
**Figure 4.7**: Subsystem number 5 of the GT Simulink model for creating $T_{04}$.
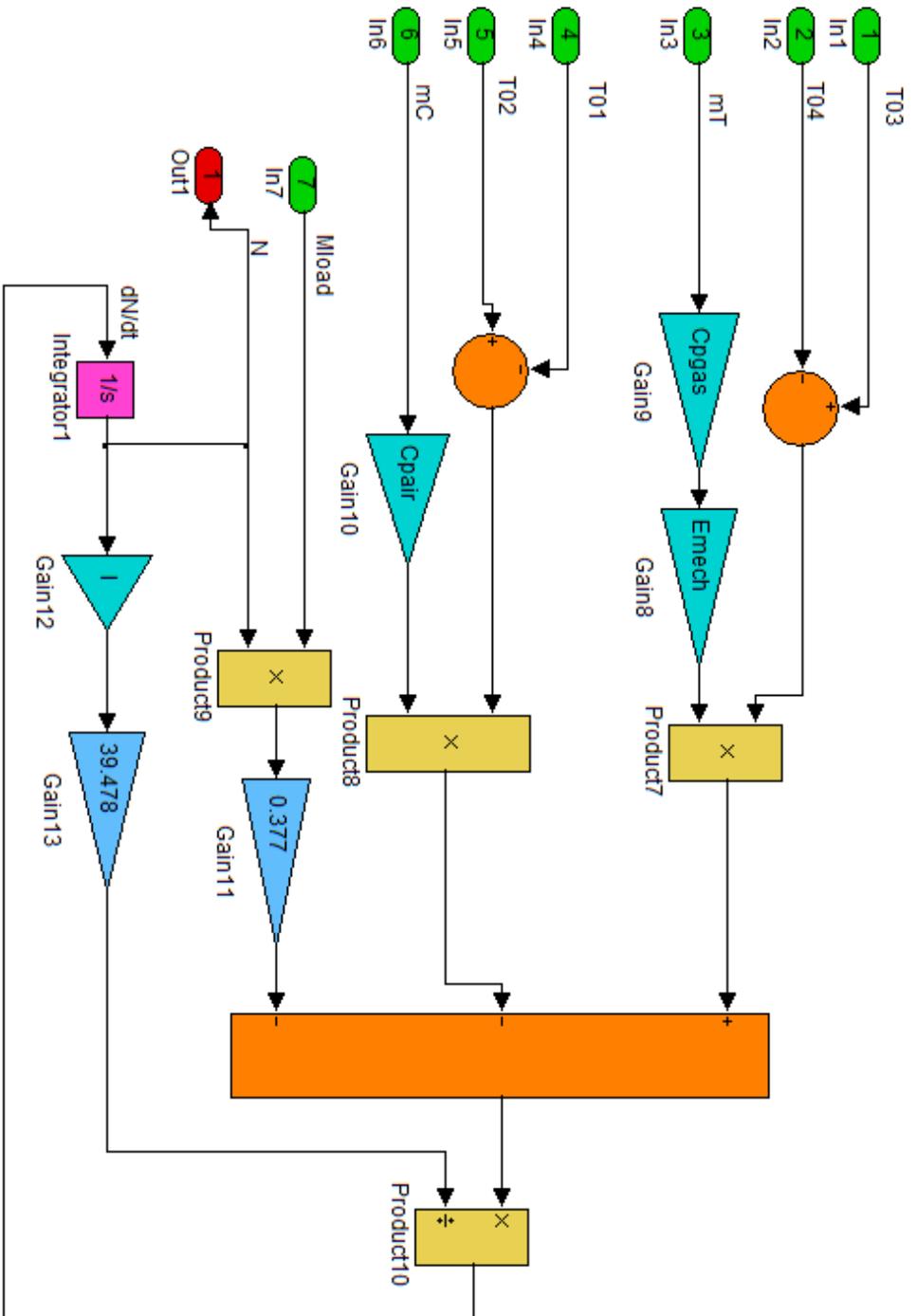
**Figure 4.8:** Subsystem number 6 of the GT Simulink model for creating rotational speed equation.

## 4.2. ANN-BASED SYSTEM IDENTIFICATION

During recent decades, artificial neural network based models have been considered as suitable alternatives to white-box models. In this section, ANN-based system identification for the gas turbine is carried out through data generation and training processes.

### 4.2.1. Data Generation

The required data for the ANN-based modelling were generated for the whole operational range of the engine using the Simulink model already developed in this chapter. About 3000 such data sets were employed for training an accurate ANN-based model for the purpose of system identification. In this work, four variables including fuel rate, compressor inlet temperature and pressure, and moment of load were considered as inputs. The outputs of the model consist of seventeen different GT parameters. Table 4.2 and Table 4.3 show the inputs and outputs (targets) of the model. Indices 1, 2, 3 and 4 refer to the corresponding sections in Figure 4.1. It is necessary to say that the generated data sets are not of time-series type and do not show a continuous dynamics of the system. They are used to train a MLP neural network to predict the output parameters of the system based on the values of input parameters.

### 4.2.2. Training Process

It has been already shown in the literature that any muti-dimentional nonlinear mapping of any continuous function can be carried out by a two-layer MLP with suitable chosen number of neurons in its hidden layer [216]. Therefore, a MLP model with two layers was employed for system identification of the gas turbine in this study. Figure 4.9 shows a schematic of the ANN structure of the gas turbine. As it can be seen from this figure, the inputs and desired outputs correspond to the four and seventeen GT parameters respectively. The ANN can be named 4-H-17 according to its structure with one hidden layer.

**Table 4.2:** Gas turbine input parameters for the ANN-based model.

| Parameter | Symbol | Unit | Operational Range |
|---|---|---|---|
| fuel mass flow rate | $\dot{m}_f$ | $kg/s$ | [0.00367; 0.027] |
| compressor inlet temperature | $T_{01}$ | $K$ | [243.15; 308.15] |
| compressor inlet pressure | $P_{01}$ | $kPa$ | [60; 110] |
| moment of load | $M_{load}$ | $Nm$ | [0; 363] |

**Table 4.3:** Gas turbine output parameters for the ANN-based model.

| Parameter | Symbol | Unit |
|---|---|---|
| rotational speed (number of revolutions) | $N$ | $1/s$ |
| temperature at section 1 | $T_{01}$ | $K$ |
| temperature at section 2 | $T_{02}$ | $K$ |
| temperature at section 3 | $T_{03}$ | $K$ |
| temperature at section 4 | $T_{04}$ | $K$ |
| pressure at section 2 | $P_{02}$ | $kPa$ |
| pressure at section 3 | $P_{03}$ | $kPa$ |
| pressure at section 4 | $P_{04}$ | $kPa$ |
| Air mass flow rate | $\dot{m}_{air}$ | $kg/s$ |
| compressor efficiency | $\eta_c$ | __ |
| turbine efficiency | $\eta_t$ | __ |
| compressor power | $\dot{W}_c$ | $kW$ |
| turbine power | $\dot{W}_t$ | $kW$ |
| net gas turbine power | $\dot{W}_{net}$ | $kW$ |
| gas turbine efficiency | $\eta_{gt}$ | __ |
| specific fuel consumption | $SFC$ | $kg/kWh$ |
| mass ratio (flow rate) of fuel to air | $F$ | __ |
| pressure ratio in compressor | $PR_c$ | __ |

**ANN**
**4-H-17**



$\dot{m}_f$

$T_{01}$

$P_{01}$

$M_{load}$

N

$T_{02}$

$T_{03}$

$T_{04}$

$P_{02}$

$P_{03}$

$P_{04}$

$\dot{m}_{air}$

$\eta_c$

$\eta_t$

$\dot{W}_c$

$\dot{W}_t$

$\dot{W}_{net}$

$\eta_{gt}$

SFC

F

$PR_c$

H
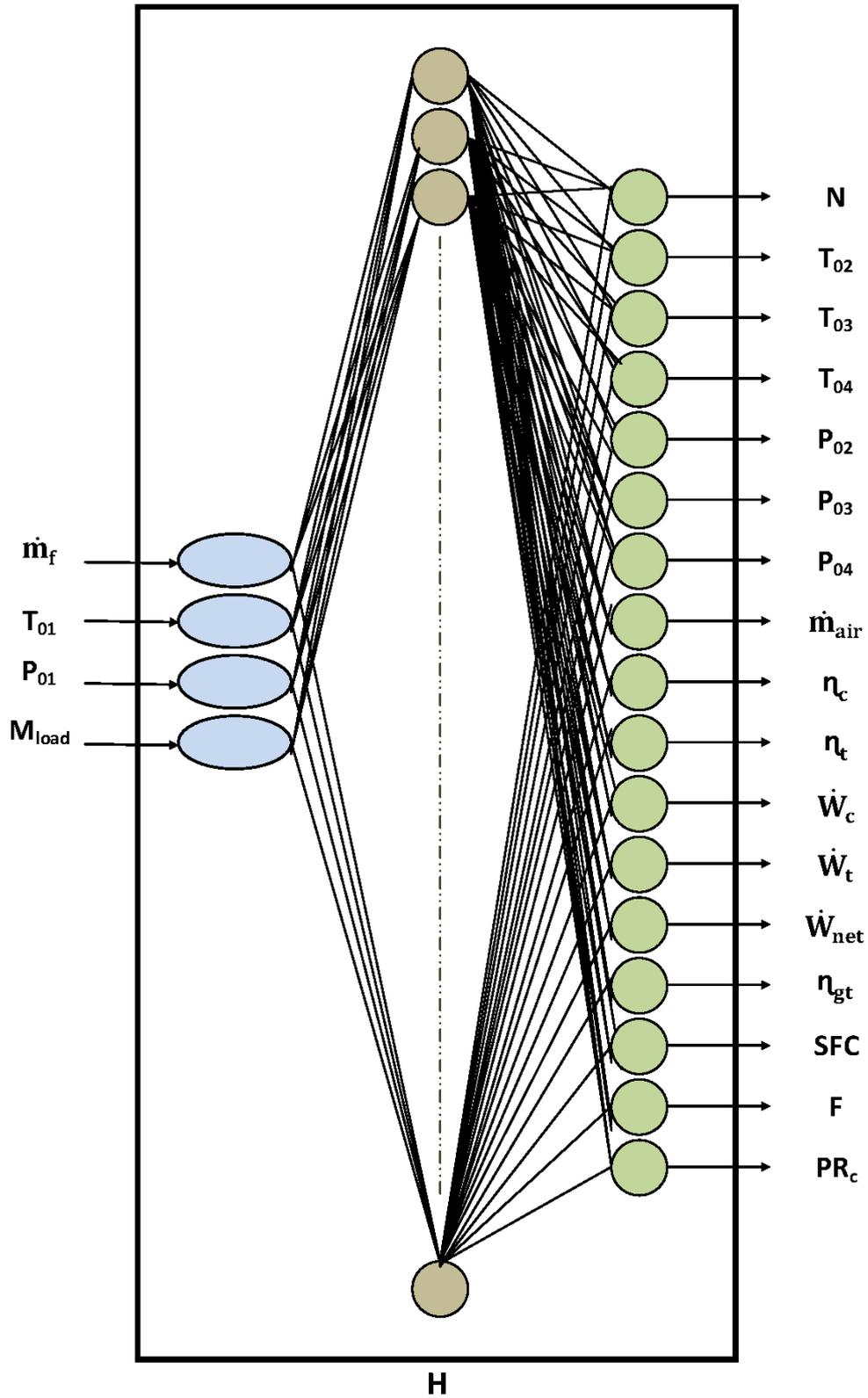
**Figure 4.9:** A schematic of the ANN structure for the gas turbine engine.

### 4.2.3. Code Generation

To obtain an accurate network structure and to assure good generalization characteristic of the gas turbine model, a comprehensive computer code was generated and run in MATLAB for a two-layer MLP network consisting of various backpropagation training functions, transfer functions and different number of neurons. The thirteen different training functions, applied in the code, included *trainbfg, trainb, traincgb, traincgf, traincgp, traingd, traingda, traingdm, traingdx, trainlm, trainoss, trainrp,* and *trainscg*. The six transfer functions employed in the code consisted of *tansig, logsig, purelin, hardlim, satlin,* and *poslin*. The number of neurons tried in the program varied from 1 to 40.

Figure 4.10 shows the flow diagram of the computer code for ANN-based system identification of the gas turbine. As it can be seen from Figure 4.10, after feeding and normalizing the data sets, they are randomly partitioned into training (70%), validation (15%) and test (15%) categories. At the next step, the structure of the network (MLP) is specified. After determination of number of neurons in the hidden layer, training function as well as transfer functions for the hidden and output layers, training process of the network is started and repeated two more times for the same adjusted factors, so that the best performance among the three trials, is specified and recorded in a matrix. The process is repeated in four main loops of the code for different number of neurons (1 to 40), different types of backpropagation training functions, as well as combinations of different transfer functions for the hidden and output layers. The results of all performances are recorded into a matrix and are sorted on the basis of their performance errors (*MSE*). According to the code, for each training process, the best performance is calculated as an average of the best test performance and one-epoch-ahead of the best validation performance, which is called average performance in this chapter. In this study, one 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. Finally, the accurate ANN model is recognized from the sorted results and tested again for verification.
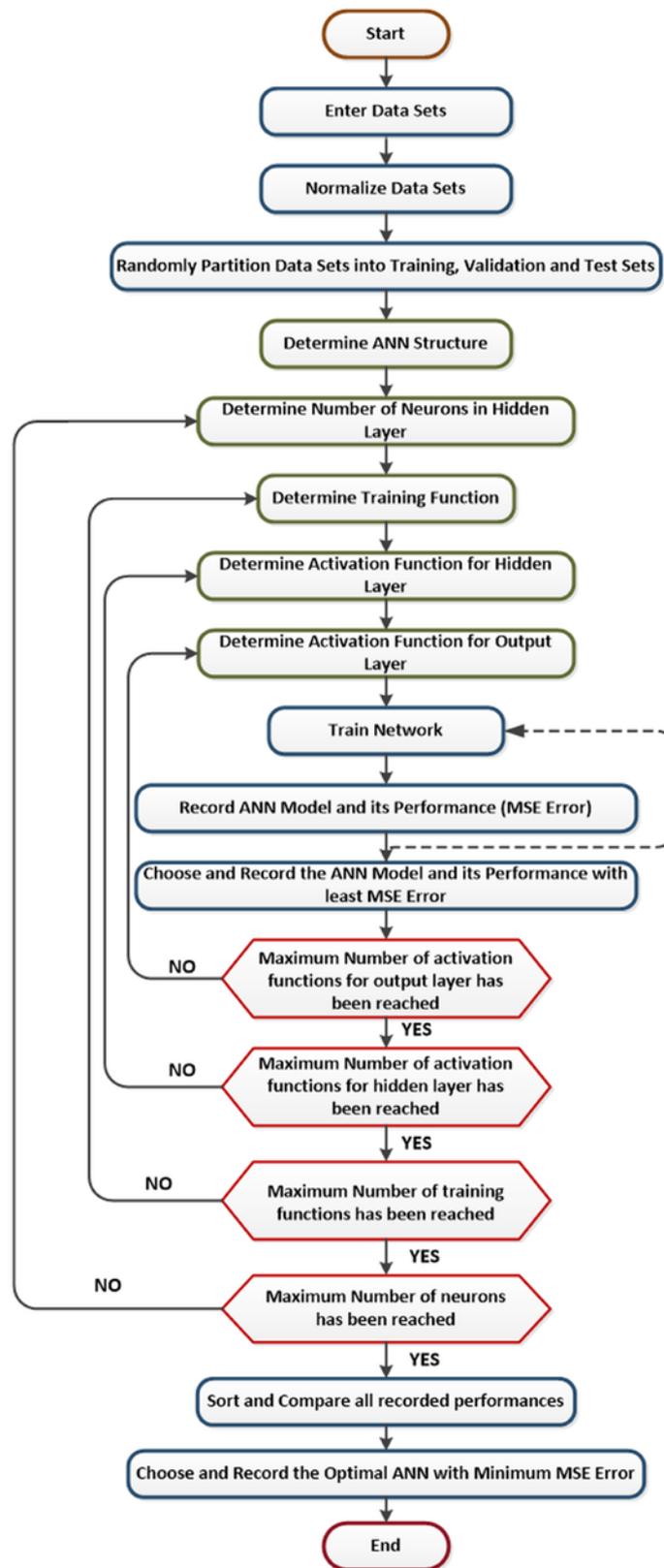
**Figure 4.10:** Flow diagram of the generated computer code for A NN-based system identification of the GT.

## 4.3. MODEL SELECTION PROCESS

In order to find the best model for the gas turbine engine, the generated code was run in MATLAB and 18720 (40*13*6*6) different ANN structures were trained using randomly partitioned data sets for training, validation and test purposes. The results of the trainings were recorded and the performances were evaluated and compared in terms of their mean squared errors (*MSE*). Finally, the most accurate MLP with minimum *MSE* was selected and tested again to assure good generalization characteristics of the model. The results from the model for different parameters of the gas turbine (predicted values) were compared with the values of the generated data from the Simulink model. Table 4.4 indicates the best performances in terms of different training functions. As it can be seen, a two-layer MLP with 20 neurons in the hidden layer, using *trainlm* as its training function, and *tansig* and *logsig* as its transfer functions for the hidden and output layers, showed the best performance. It can also be seen that *trainlm* has a superior performance in terms of minimum *MSE*, compared with each of the other training functions.

Figure 4.11 shows details of the best resulting network based on the average performance of all the trained structures. Performance of the ANN for training, validation, and test has been also shown in this figure. As it can be seen, the iteration in which the validation performance error reached the minimum is 24. The mean square error of the performance at this point is quite low. The training continued for 10 more iterations before the training stopped.

Figure 4.12 shows the regression plot that indicates the relationship between outputs of the network and outputs of the system (targets). The R value is an indication of the relationship between the outputs and the targets. As Figure 4.12 shows, R values for all the graphs are very close to 1. Therefore, the result for each of training, validation, and test data sets indicates a very good fit. Figures 4.13 through 4.28 compare output GT parameters of the Simulink and ANN-based models. For clarity of the figures, just outputs of 200 data sets out of 3000 are shown. As Figures 4.13 through 4.28 show the outputs of the ANN model followed the targets precisely. It shows that

the resulting neural network based model can predict the reaction of the system to changes in input parameters with high accuracy and is capable of system identification with high reliability.

**Table 4.4:** Best performance for different training functions.

| Training Function | Number of Neurons | Transfer Function in Hidden Layer | Transfer Function in Output Layer | *MSE* for Best Average Performance |
|---|---|---|---|---|
| *trainlm* | 20 | *tansig* | *logsid* | 2.49E-06 |
| *traincpg* | 20 | *purelin* | *hardlim* | 1.11E-05 |
| *traincgf* | 20 | *logsig* | *logsig* | 1.15E-05 |
| *traincgb* | 18 | *logsig* | *satlin* | 1.16E-05 |
| *trainscg* | 20 | *tansig* | *satlin* | 1.36E-05 |
| *trainbfg* | 19 | *purelin* | *satlin* | 1.50E-05 |
| *trainoss* | 20 | *tansig* | *logsig* | 6.68E-05 |
| *trainrp* | 16 | *tansig* | *satlin* | 0.000189 |
| *traingdx* | 15 | *tansig* | *satlin* | 0.000251 |
| *traingda* | 10 | *satlin* | *satlin* | 0.000688 |
| *trainb* | 4 | *hardlim* | *hardlim* | 0.063675 |
| *traingdm* | 2 | *tansig* | *logsig* | 0.087112 |
| *traingd* | 2 | *logsig* | *hardlim* | 0.090159 |
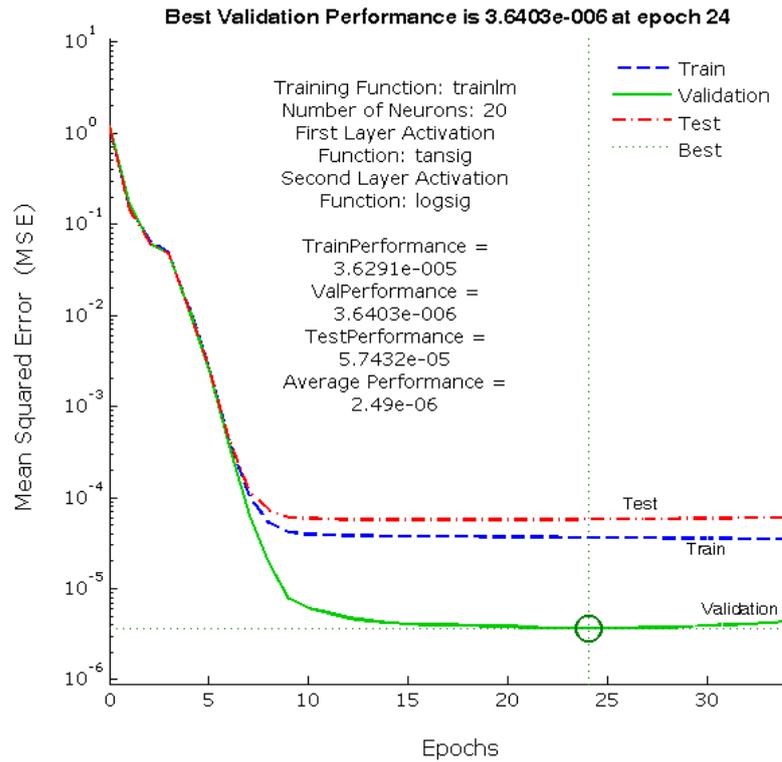
**Figure 4.11:** Performance of the resulting MLP model.
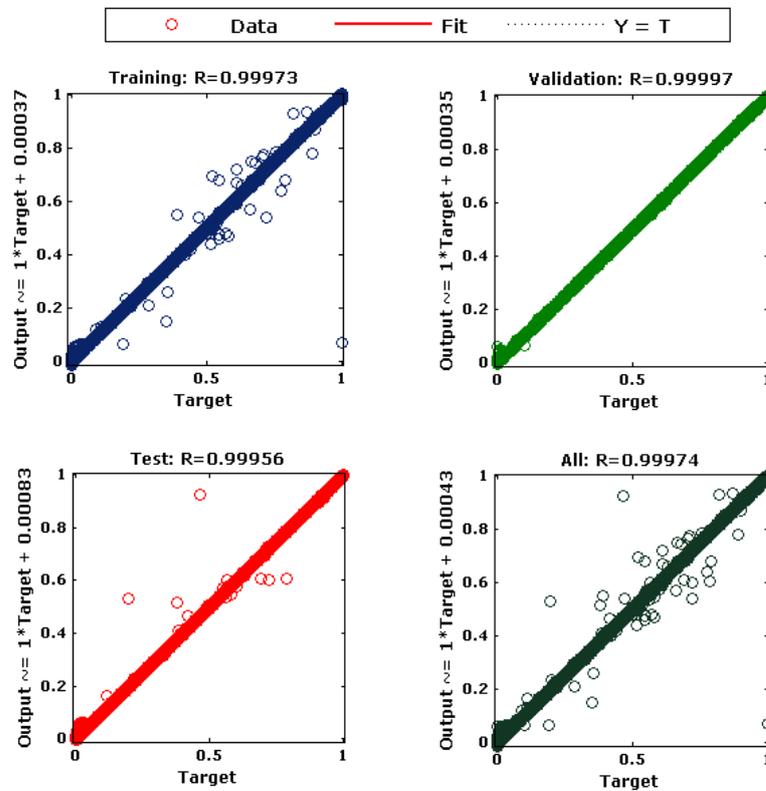


**Figure 4.12:** Regression of the resulting MLP model.
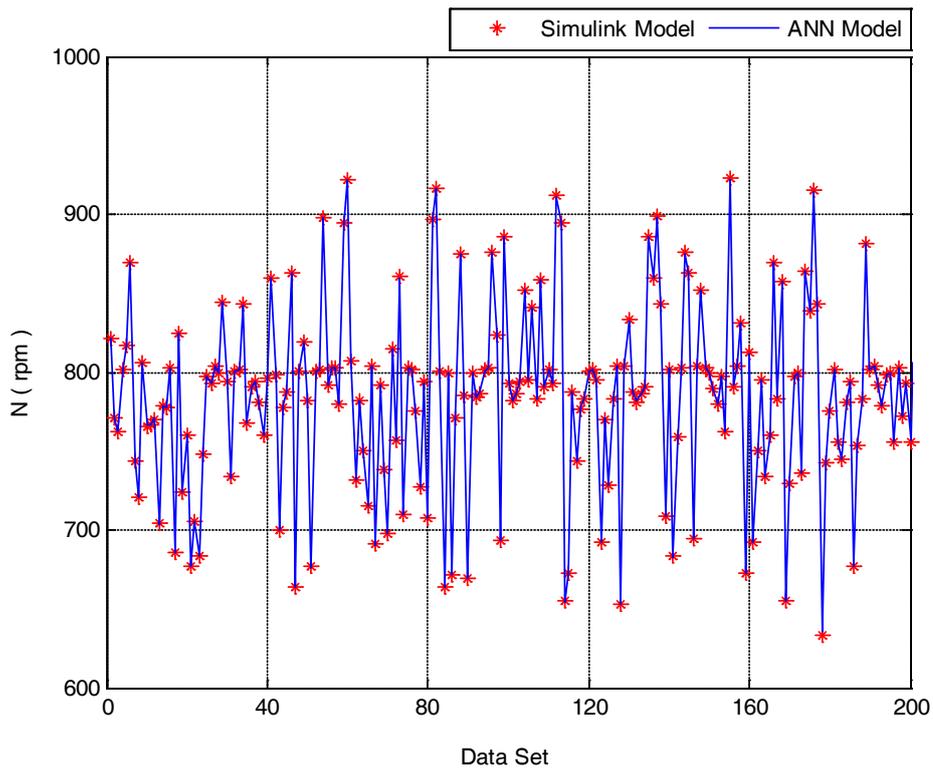
**Figure 4.13:** Comparison between outputs of the Simulink and ANN models for the rotational speed.
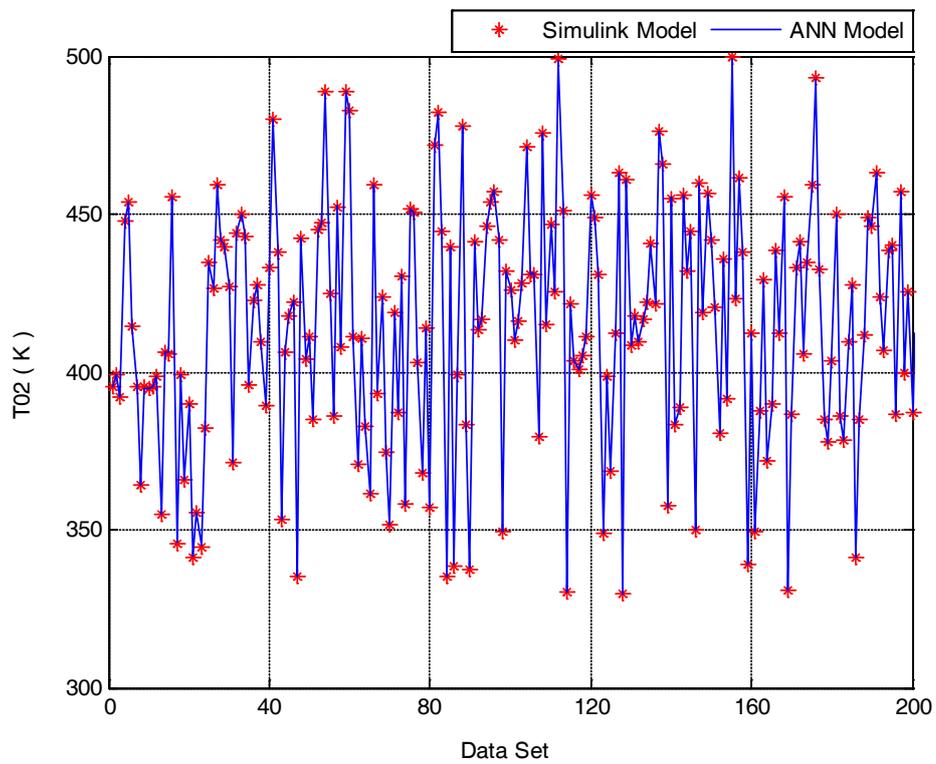


**Figure 4.14:** Comparison between outputs of the Simulink and ANN models for the compressor outlet temperature.

90
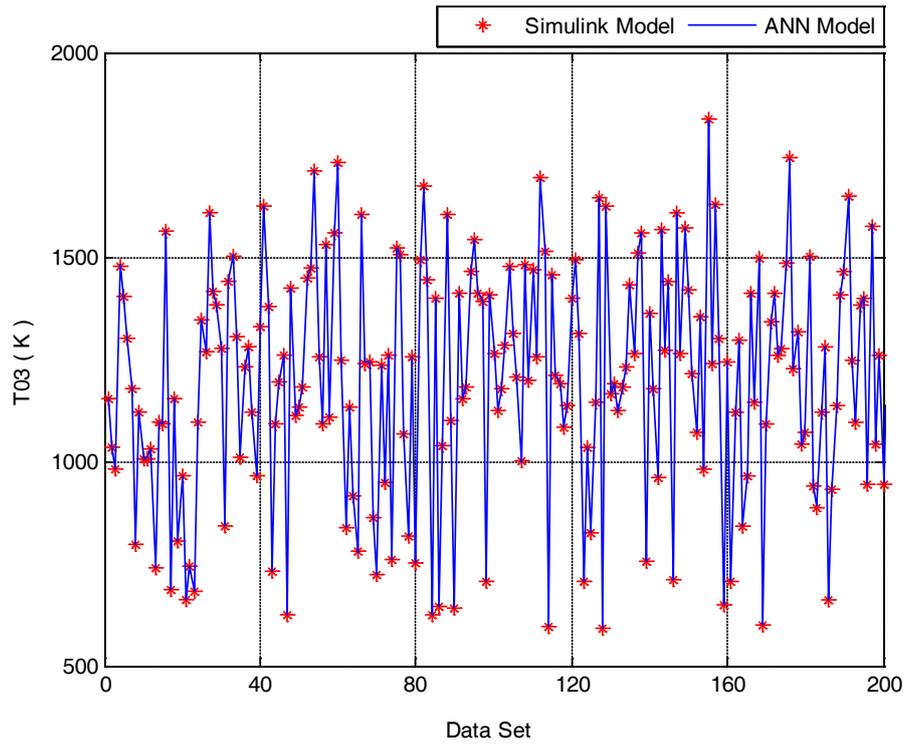
**Figure 4.15:** Comparison between outputs of the Simulink and ANN models for the turbine inlet temperature.
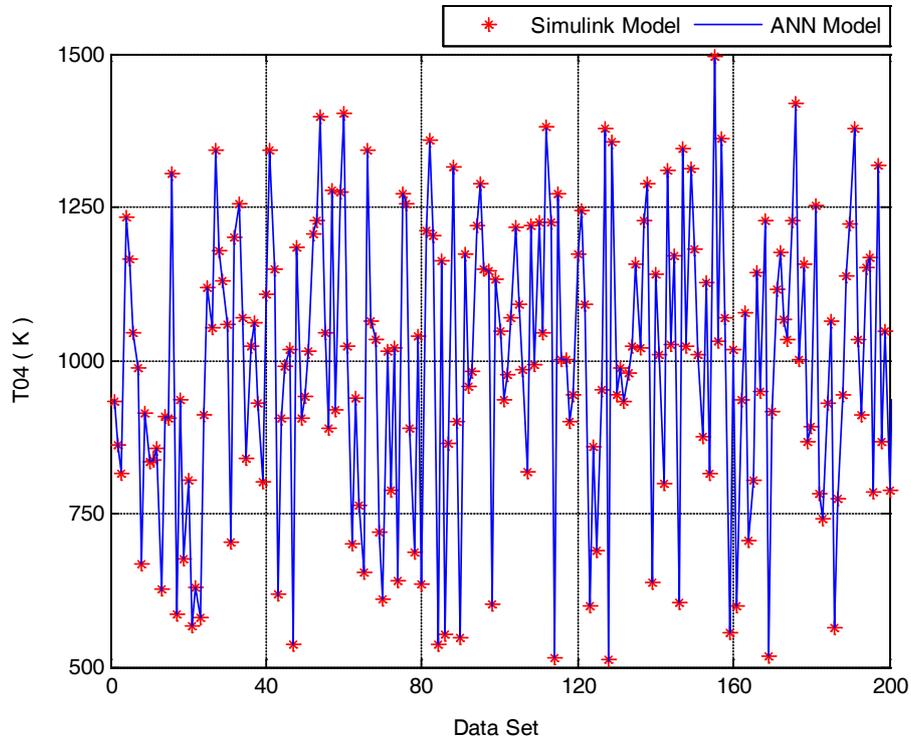


**Figure 4.16:** Comparison between outputs of the Simulink and ANN models for the turbine outlet temperature.

91
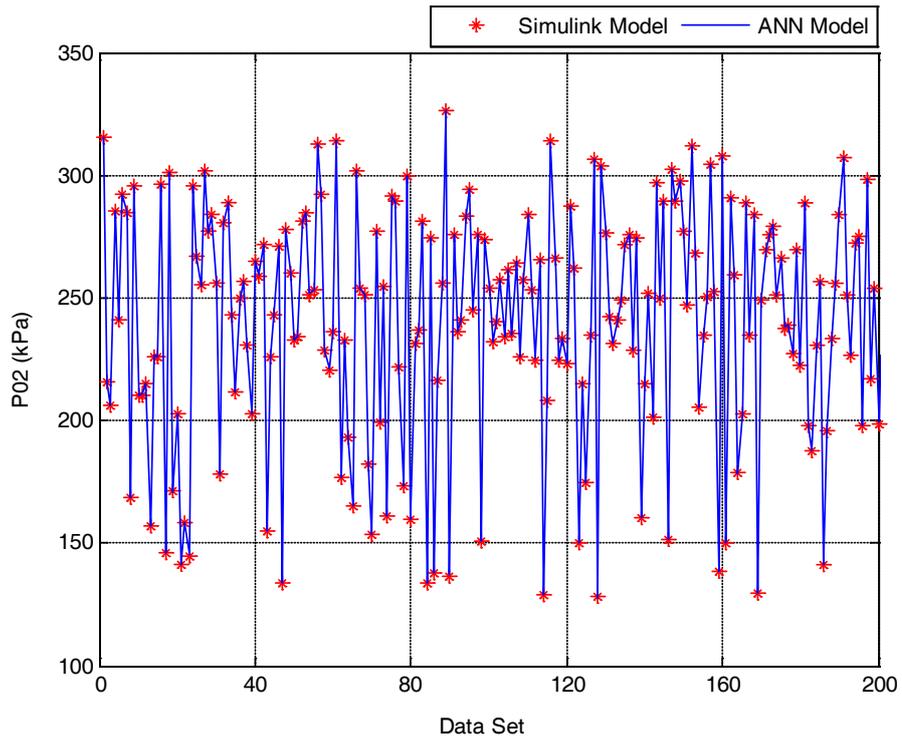
**Figure 4.17:** Comparison between outputs of the Simulink and ANN models for the compressor outlet pressure.
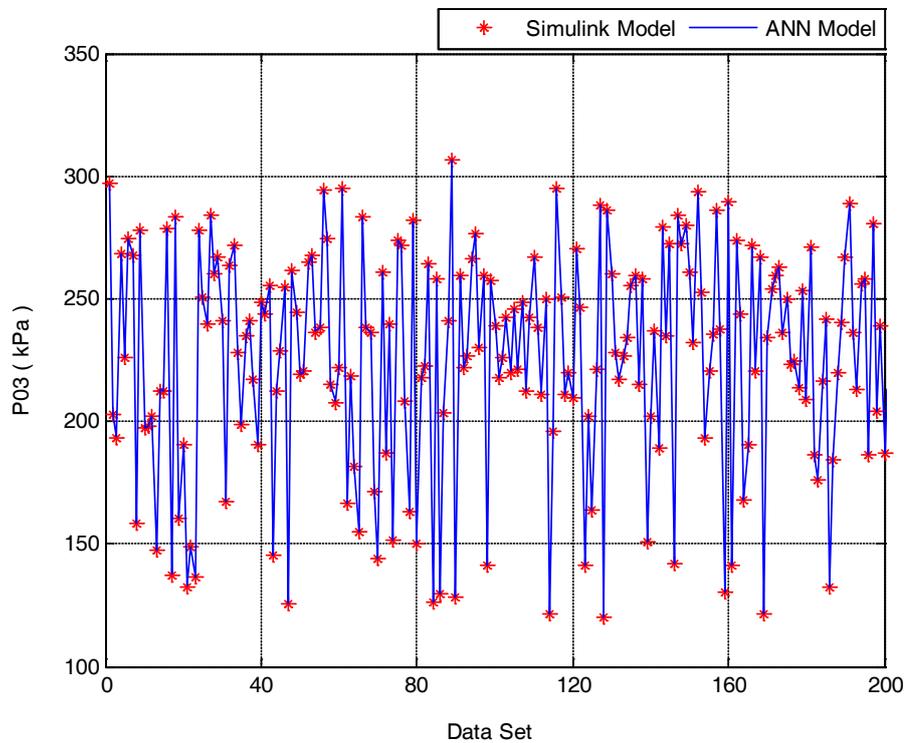


**Figure 4.18:** Comparison between outputs of the Simulink and ANN models for the turbine inlet pressure.
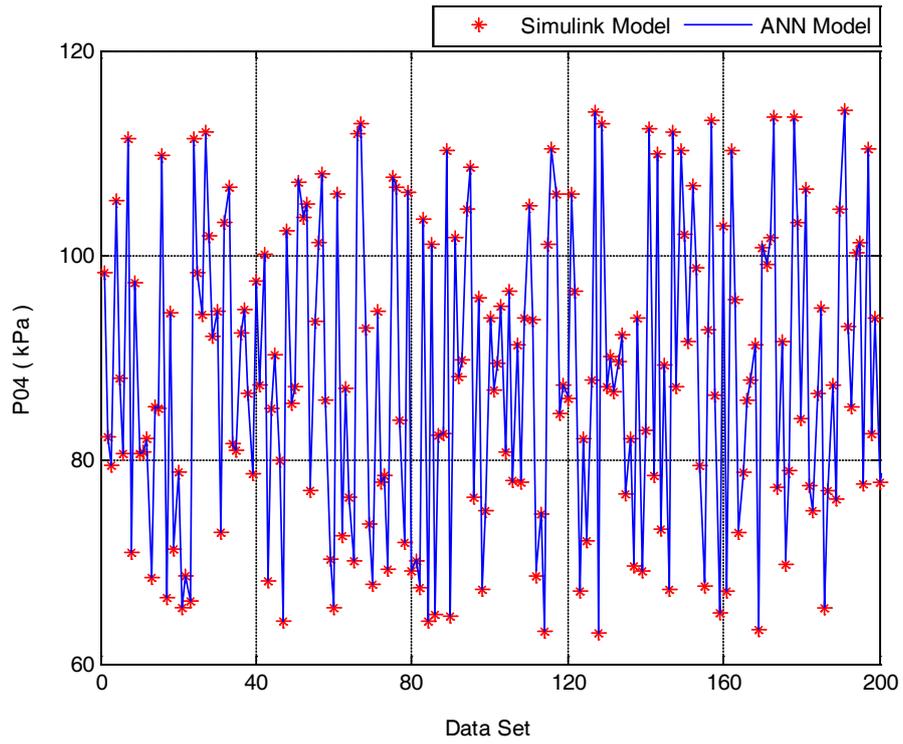
**Figure 4.19:** Comparison between outputs of the Simulink and ANN models for the turbine outlet pressure.
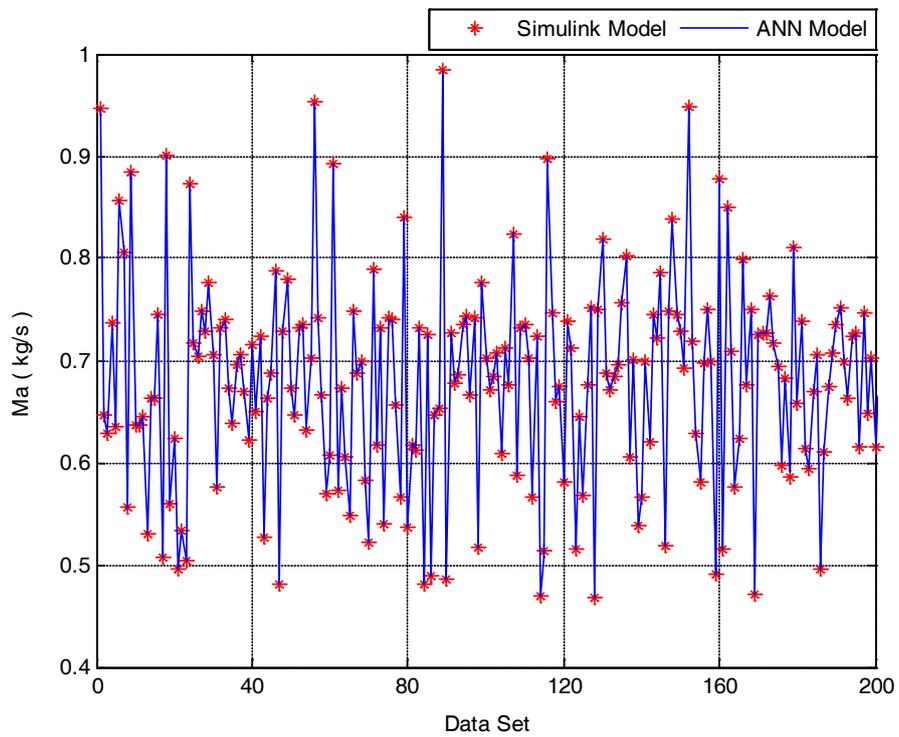


**Figure 4.20:** Comparison between outputs of the Simulink and ANN models for the air mass flow rate.
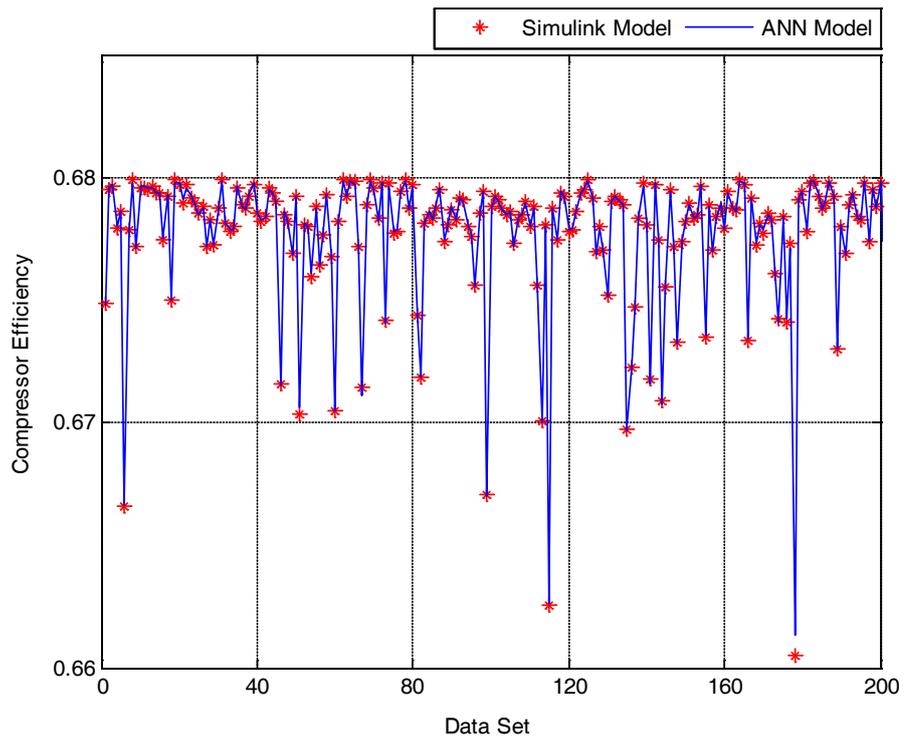
**Figure 4.21:** Comparison between outputs of the Simulink and ANN models for the compressor efficiency.
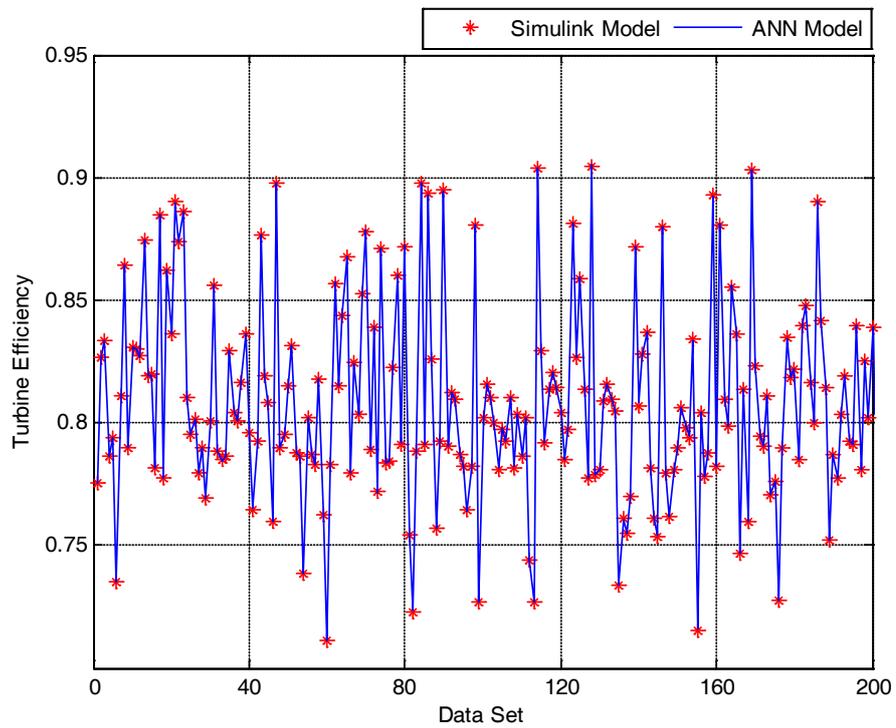


**Figure 4.22:** Comparison between outputs of the Simulink and ANN models for the turbine efficiency.

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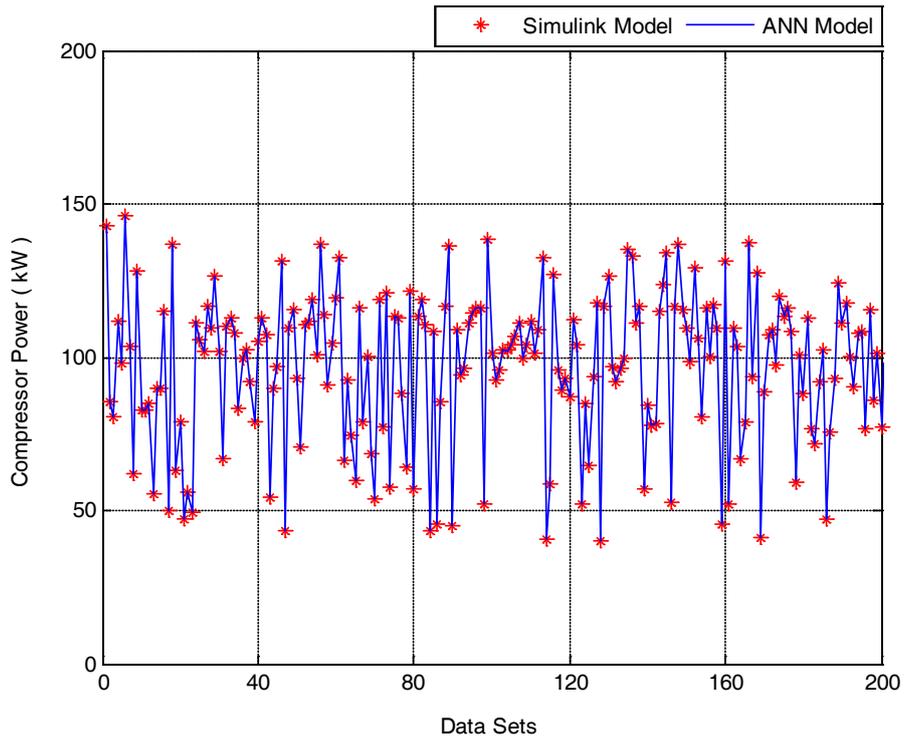
**Figure 4.23:** Comparison between outputs of the Simulink and ANN models for the compressor power.
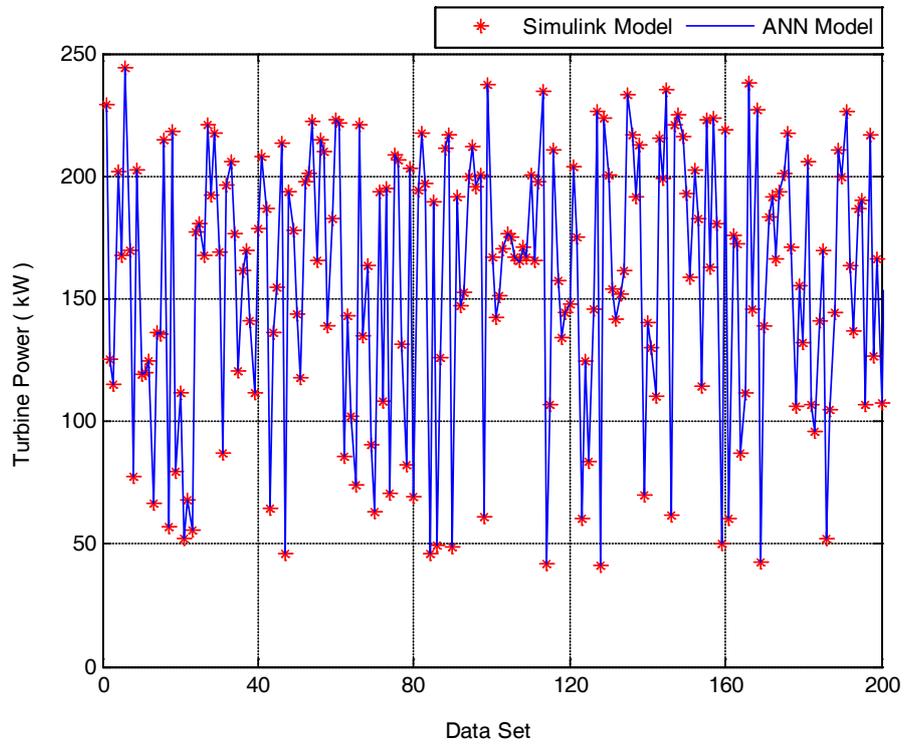


**Figure 4.24:** Comparison between outputs of the Simulink and ANN models for the turbine power.
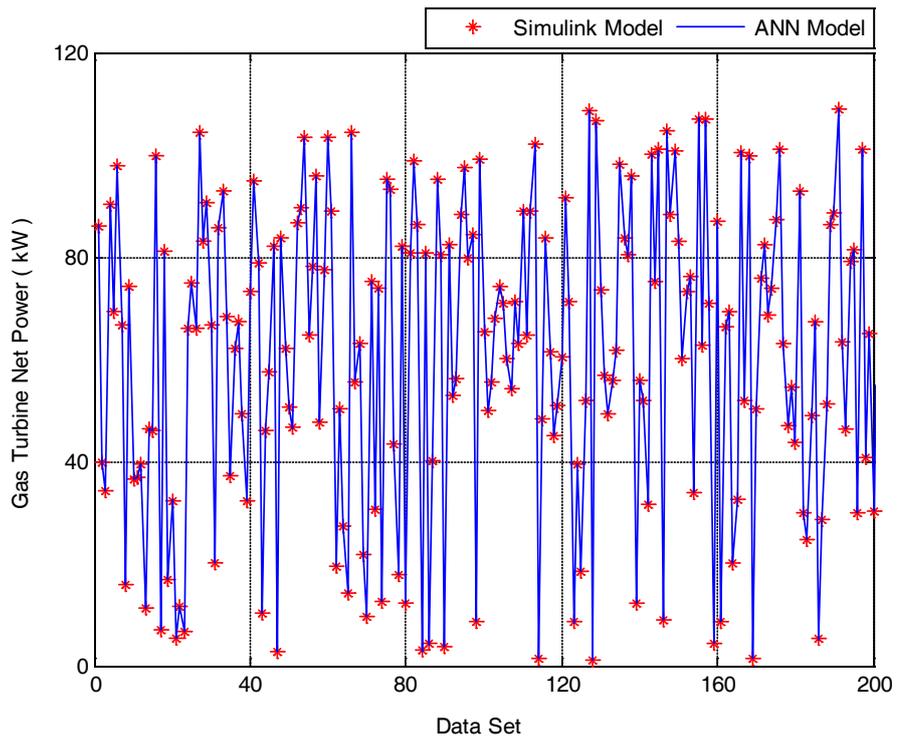
**Figure 4.25:** Comparison between outputs of the Simulink and ANN models for the gas turbine net power.
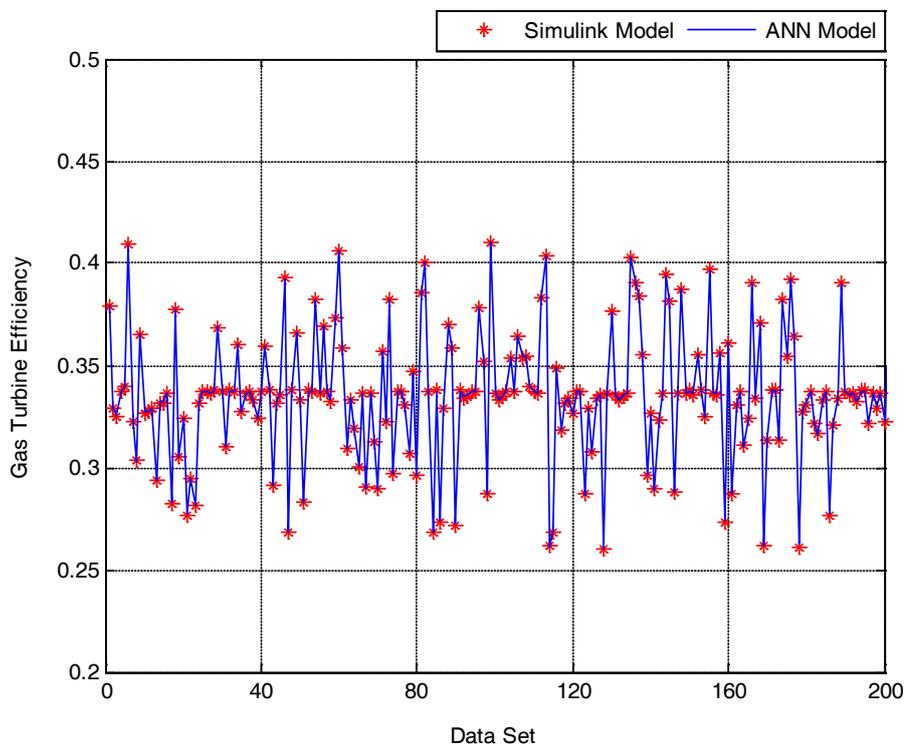


**Figure 4.26:** Comparison between outputs of the Simulink and ANN models for the gas turbine efficiency.

96
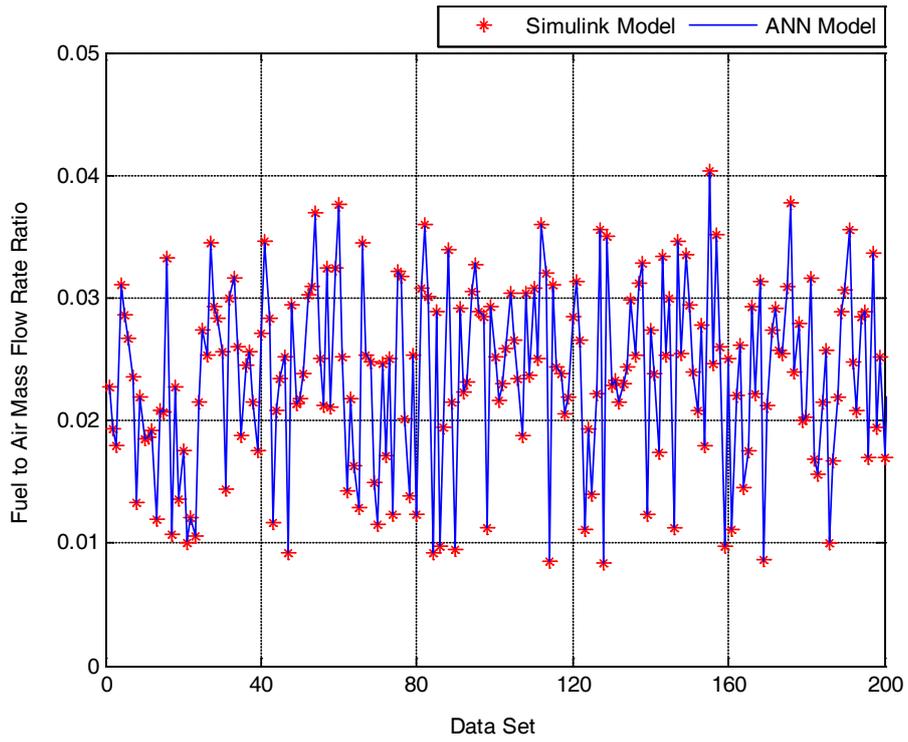
**Figure 4.27:** Comparison between outputs of the Simulink and ANN models for the fuel to air mass flow rate ratio.
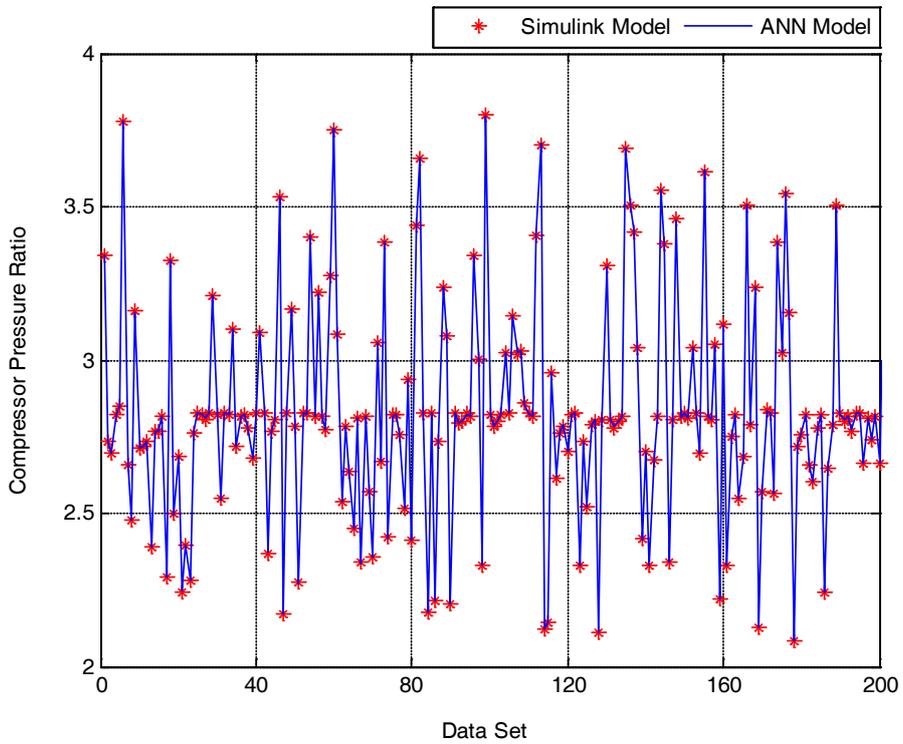


**Figure 4.28:** Comparison between outputs of the Simulink and ANN models for the compressor pressure ratio.

## 4.4. SUMMARY

Artificial neural network has been used as a robust and reliable technique for system identification and modelling of complex systems with nonlinear dynamics such as gas turbines. It can provide outstanding solutions to the problems that cannot be solved by conventional mathematical methods. ANN-based techniques can be applied to the systems through a variety of approaches that include different structures and training methods.

In this chapter, firstly a Simulink model of a low-power gas turbine was developed based on thermodynamic and energy balance equations. In the next step, a new ANN-based methodology was applied to offline system identification of the gas turbine. A comprehensive computer program code was generated and run in MATLAB environment using the obtained data from the Simulink model. Code generation was on the basis of combinations of various training functions, and number of neurons and type of transfer functions. The methodology provided a comprehensive view of the performance of over 18720 ANN models for system identification of the single-shaft gas turbine.

The resulting model showed that the ANN-based method can be applied reliably for system identification of gas turbines. It can precisely predict output parameters of the GT based on the changes in the inputs of the system. The methodology of this study can also be used to predict performance of similar gas turbine systems with high accuracy when training from real data obtained from this type of gas turbine. This is particularly useful when real data is only available over a limited operational range. It was also observed that *trainlm* has a superior performance in terms of minimum *MSE*, compared with each of the other training functions.

# CHAPTER 5
# MODELLING AND SIMULATION OF THE TRANSIENT BEHAVIOUR OF AN IPGT

Modelling and simulation of industrial systems, such as gas turbines is a significant methodology for system optimization. A gas turbine model can be employed to clarify details of design strategies, manufacturing procedures, operating manoeuvres and even maintenance guidelines. Using black-box approach, as a branch of artificial intelligence, has opened a new horizon to the area of modelling and simulation of industrial systems. Black-box methodology is used to disclose the relationships between variables of the system using the measured operational data or data generated by means of a simulation tool. Artificial neural network (ANN), as a data-driven model, is one of the most significant methods in black-box modelling.

Because of the importance of transient behaviour of gas turbines during start-up and its direct effect on GT performance and life time, extensive research is still necessary to fill the existing information gaps. According to the literature, no model has been developed so far to simulate gas

turbine transient behaviour during start-up and near full-speed operation by using Simulink and NARX models. One of the few examples of such simulation models is documented by Asgari et al. [232], where a NARX model was set up and optimized for the simulation of the start-up operation of an IPGT. Moreover, another challenging issue in this study is the use of field data for model development and testing. Therefore, the set-up and application of these models can help in understanding and analyzing the transient behaviour of gas turbines.

In this chapter, two separate simulation models using both white-box and black-box methods are built, to simulate very low-power operating region for an IPGT. The modelling and simulation is carried out on the basis of the experimental time-series data sets obtained from an IPGT located in Italy [233]. The specifications of the gas turbine are described in section 5.1. The subject of section 5.2 is data acquisition and preparation. Sections 5.3 and 5.4 present the physics-based modelling approach in Simulink and the set-up of a black-box model by using NARX modelling approach respectively. The comparison of all the significant measured and predicted variables and a summary of the study are presented in sections 5.5 and 5.6 respectively.

## 5.1. GAS TURBINE SPECIFICATIONS

The gas turbine modelled in this research is the General Electric PG 9351FA, which is a heavy-duty single-shaft gas turbine used for power generation. The main specifications of this IPGT are summarized in Table 5.1.

**Table 5.1:** Gas turbine specifications.

| GT type | Number of shafts | Rotational speed (rpm) | Pressure ratio | TIT (°C) | TOT (°C) | Air flow rate (kg/s) | Power (kW) | HR (kJ/kWh) | Efficiency ( % ) |
|---------|------------------|------------------------|----------------|----------|----------|----------------------|------------|-------------|------------------|
| GE 9351FA | 1 | 3000 | 15.8 | 1327 | 599 | 648 | 259500 | 9643 | 37.3 |

## 5.2. DATA ACQUISITION AND PREPERATION

The data sets used for model set-up and verification were taken experimentally during several start-up manoeuvres. The data sets cover the range 420-3000 rpm. Power is also very low (less than 24 MW), compared to the nominal power approximately equal to 260 MW. Therefore, these data are representative of the operating conditions during start-up and also account for all the conditions related to this type of transient operation (e.g. bleed valve opening, IGV control, etc.). In general, the data sets during start-up can be categorized as:

- Cold start-up: the gas turbine was shut down some day before start-up.

- Warm start-up: the gas turbine was shut down some hours before start-up.

- Hot start-up: the gas turbine was shut down just few hours or less before start-up.

The data sets used in this study refer to cold start-up. Moreover, each of the data sets may fall into different combinations of the following conditions:

- If the starter is on or off: 1 or 0

- If the gas turbine is connected to the grid or not: 1 or 0

- If customer trip happens or not: 1 or 0

- If the flame is on or off: 1 or 0

In this research, the operating conditions sketched below are considered:

- The starter is off: 0

- The gas turbine is connected/disconnected to/from the grid: 1 or 0

- Customer Trip doesn't happen: 0

- The flame is on: 1

For instance, the manoeuvre [0 1 0 1] refers to the situation, when the starter is off, the gas turbine is connected to the grid, customer trip does not happen, and the flame is on.

In this study, the measured time-series data sets [0 1 0 1] and [0 0 0 1] are called M1 and M2 and are used for Simulink model tuning. The two other data sets including [0 1 0 1 a] and [0 1 0 1 b] which were used for verification of the models, are specified as M3 and M4. Table 5.2 shows

more details of these data and the operational range for the input parameters. The time step for the data acquisition is one second. Figure 5.1 shows the variations of load for other manoeuvres. With respect to M2 and M4, the changes of the load of M3 are smaller. As Table 5.2 indicates, manoeuvre M4 is the longest manoeuvre. Load for M1 is very low and nearly constant.

**Table 5.2:** Time-series data sets for different manoeuvres.

| Manoeuvre | Type of Data Set | Number of Data | Operational range of the inputs | | | |
|---|---|---|---|---|---|---|
| | | | $T_{01}$ $(K)$ | $P_{01}$ $(Pa)$ | $\dot{m}_f$ $(kg/s)$ | $\dot{W}_{load}$ $(MW)$ |
| M1 | [0 0 0 1] | 1336 | [296.48; 301.50] | [99570; 99909] | [3.74; 4.60] | $\simeq 0.3$ |
| M2 | [0 1 0 1] | 1165 | [297.04; 303.15] | [99570; 99670] | [3.99; 4.50] | [3.30; 18.70] |
| M3 | [0 1 0 1 a] | 1506 | [290.37; 295.37] | [101940; 102040] | [4.42; 4.80] | [4.42; 4.76] |
| M4 | [0 1 0 1 b] | 3296 | [299.26; 302.59] | [100950; 101070] | [4.27; 6.90] | [18.20; 23.70] |
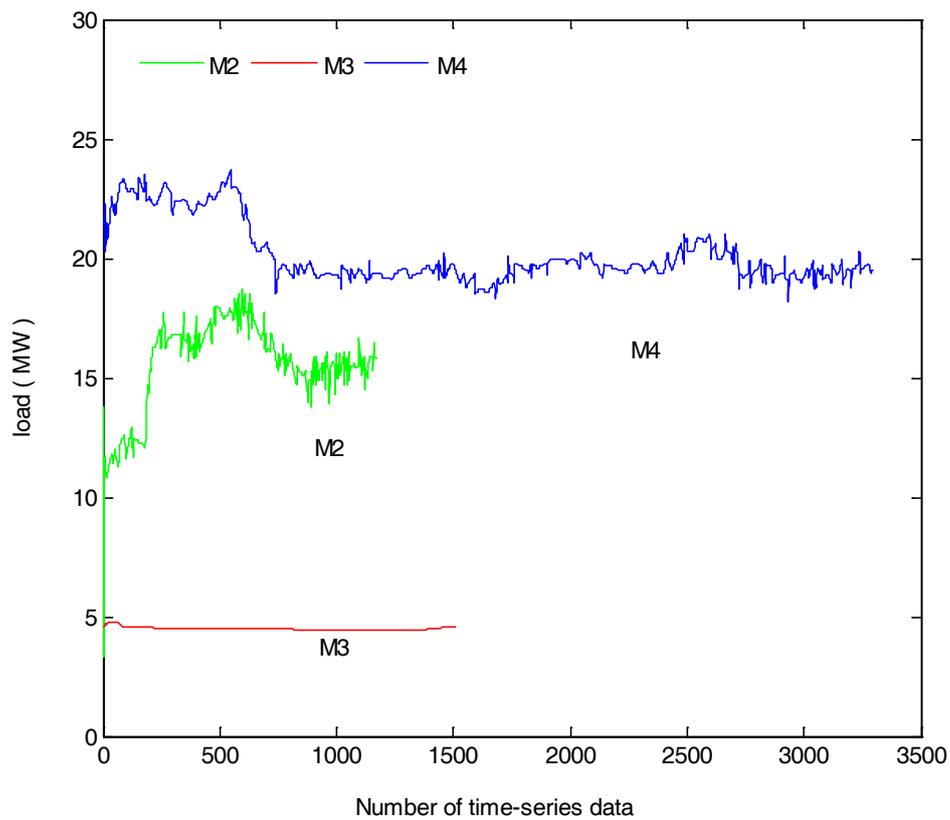


**Figure 5.1:** Variations of load for different manoeuvres.

## 5.3. PHYSICS-BASED MODEL OF IPGT BY USING SIMULINK- MATLAB

The Simulink model of the gas turbine was built by using the operational time-series data sets and by employing the thermodynamic equations for its components. The data sets were used to approximate the correlations between corrected parameters in the compressor and turbine. The approximations were obtained by using the Curve Fitting Tool in MATLAB. The set-up of the Simulink model consisted of modelling the four main components including compressor, combustion chamber, turbine and rotational parts dynamics. Each component was considered as a single block, stacking dynamic behaviour of all the individual stages into a single block with only the inlet and exit conditions of the component. The main thermodynamic equations used in the physics-based model are reported below. The modelling assumptions and the parameter values will be also discussed in the following.

- **Compressor**

$$T_{02} = T_{01} + \frac{T_{01}}{\eta_c}\left[\left(\frac{P_{02}}{P_{01}}\right)^{\frac{(\gamma_{air}-1)}{\gamma_{air}}} - 1\right] \tag{5.1}$$

$$\gamma_{air} = {C_{P_{air}}}\big/{C_{v_{air}}} \tag{5.2}$$

$$\dot{W}_c = \dot{m}_{air}C_{P_{air}}(T_{02} - T_{01}) \tag{5.3}$$

- **Turbine**

$$T_{04} = T_{03} - T_{03}\eta_t\left[1 - \left(\frac{P_{04}}{P_{03}}\right)^{\frac{(\gamma_{gas}-1)}{\gamma_{gas}}}\right] \tag{5.4}$$

$$\gamma_{gas} = {C_{P_{gas}}}\big/{C_{v_{gas}}} \tag{5.5}$$

$$\dot{W}_t = \dot{m}_{gas}(C_{P_{gas\_03}}T_{03} - C_{P_{gas\_04}}T_{04}) \tag{5.6}$$

- **Combustor**

$$\frac{1}{F} = \dot{m}_a / \dot{m}_f = \frac{\eta_{cc} * LHV}{\left(C_{p_{gas\_03}} T_{03} - C_{p_{air\_02}} T_{02}\right)} - 1 \tag{5.7}$$

$$P_{03} = P_{02}(1 - \xi_{cc}) \tag{5.8}$$

- **Equilibrium (balance) equation**

$$\left(\dot{W}_t - \dot{W}_c - \dot{W}_{load}\right) = (2\pi/60)^2 \, I \, N \, (dN/dt) \tag{5.9}$$

### 5.3.1. Measured Parameters

The parameters which were measured directly from the IPGT include: rotational speed ($N$), alternator power ($\dot{W}_{load}$), ambient pressure ($P_{00}$), ambient temperature ($T_{00}$), compressor inlet stagnation pressure ($P_{01}$), compressor inlet temperature ($T_{01}$), compressor outlet stagnation pressure ($P_{02}$), compressor outlet temperature ($T_{02}$), turbine outlet temperature ($T_{04}$), and fuel flow rate ($\dot{m}_f$).

### 5.3.2. Calculated or Estimated Parameters

To formulate the correlation between corrected parameters of the compressor and turbine components of the GT, to be used in the Simulink models, calculation or estimation of some unmeasured parameters was unavoidable. These parameters can be extracted by employing thermodynamic relationships or general experimental results about gas turbines.

#### 5,3.2.1. Turbine Inlet Stagnation Pressure

As the Equation 5.8 shows, in practical applications, $P_{03}$ can be approximated by considering a linear decrease with respect to $P_{02}$. The loss pressure in combustion chamber ($\xi_{cc}$) is about 3%.

#### 5,3.2.2. Turbine Outlet Stagnation Pressure

As a practical routine, turbine outlet stagnation pressure is estimated according to the Equation 5.10. The coefficient $C$ was assumed a constant value and is approximated as: $C \simeq 0.03$ bar.

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$$P_{04} \simeq P_{00} + C \tag{5.10}$$

### 5,3.2.3. Specific Heat of Air and Gas at Constant Pressure

Specific heat of air and gas at constant pressure was calculated based on the fact that it is a function of average temperatures during the compression and expansion processes in the compressor and turbine. After determination of $C_p$, specific heat of air and gas at constant volume was calculated using the following equations:

$$\gamma = C_p/C_v \tag{5.11}$$

$$R = C_p - C_v \tag{5.12}$$

$C_p$ is calculated using the Equations 5.13 to 5.16. *Ta* and *Tg* respectively refer to the average temperatures during the compression and expansion processes in the compressor and turbine [48].

If $T_a < 800\ K$:

$$C_{P_{air}} = 1018.9 - 0.13784 * T_a + 1.9843E - 04 * T_a{}^2 + 4.2399E - 07 * T_a{}^3 -$$
$$3.7632E - 10 * T_a{}^4 \tag{5.13}$$

$$C_{p_{gas}} = C_{P_{air}} + \left(\frac{F}{1+F}\right) * (-359.494 + 4.5164 * T_g + 2.8116E - 03 * T_g{}^2 - 2.1709E -$$
$$05 * T_g{}^3 + 2.8689E - 08 * T_g{}^4 - 1.2263E - 11 * T_g{}^5) \tag{5.14}$$

*If* $T_a > 800\ K$ :

$$C_{P_{air}} = 798.65 + 0.5339 * T_a - 2.2882E - 04 * T_a{}^2 + 3.7421E - 08 * T_a{}^3 \tag{5.15}$$

$$C_{p_{gas}} = C_{P_{air}} + \left(\frac{F}{1+F}\right) * (1088.8 - 0.1416 * T_g + 1.916E - 03 * T_g{}^2 - 1.2401E - 06 *$$
$$T_g{}^3 + 3.0669E - 10 * T_g{}^4 - 2.6117E - 14 * T_g{}^5) \tag{5.16}$$

### 5,3,2,4. Turbine Inlet Temperature and Mass Flow Rate of Air

When $\dot{W}_{load}$ is approximately constant (i.e. acceleration is zero), Equation 5.9 can be written as:

$$\dot{W}_t = \dot{W}_c + \dot{W}_{load} \qquad\qquad (5.17)$$

Then, by replacing $\dot{W}_c$ from the Equation 5.3, $\dot{W}_t$ can be determined and the Equation 5.6 can be written as follows:

$$T_{03} = \frac{C_{P\,gas\_04}}{C_{P\,gas\_03}} T_{04} + \frac{\dot{W}_t}{\dot{m}_{gas} C_{P\,gas\_03}} \qquad\qquad (5.18)$$

in which:

$$\dot{m}_{gas} = \dot{m}_f + \dot{m}_a \qquad\qquad (5.19)$$

Besides, the Equation 5.7 can be written as:

$$T_{03} = \frac{C_{P\,air\_02}}{C_{P\,gas\_03}} T_{02} + \frac{\eta_{cc} * LHV}{C_{P\,gas\_03} * (1 + \dot{m}_a / \dot{m}_f)} \qquad\qquad (5.20)$$

Finally, the Equation systems of 5.18 and 5.20 can be solved for $T_{03}$ and $\dot{m}_a$. For this purpose, a computer code was written and run in MATLAB, and these parameters were calculated for the available data sets.

### 5,3,2,5. Efficiency and Corrected Parameters of the Compressor and Turbine

The code already written for calculation of $T_{03}$ and $\dot{m}_a$ was developed to calculate efficiency and corrected parameters for both the compressor and the turbine. Compressor efficiency ($\eta_c$) and turbine efficiency ($\eta_T$) were calculated using the following equations:

$$\eta_c = T_{01} * \left[ \left( \left( \frac{P_{02}}{P_{01}} \right)^{\frac{(\gamma_{air} - 1)}{\gamma_{air}}} \right) - 1 \right] / (T_{02} - T_{01}) \qquad\qquad (5.21)$$

$$\eta_T = (T_{03} - T_{04})/\left[T_{03} * \left(1 - \left(\frac{P_{04}}{P_{03}}\right)^{\frac{(\gamma_{gas}-1)}{\gamma_{gas}}}\right)\right] \qquad (5.22)$$

### 5.3.3. Model Architecture

Figure 5.2 shows the block diagram of the gas turbine system. It includes four inputs and four outputs. The inputs are compressor inlet temperature ($T_{01}$), compressor inlet stagnation pressure ($P_{01}$), fuel flow rate ($\dot{m}_f$), and network load ($\dot{W}_{load}$). The outputs consist of rotational speed ($N$), compressor pressure ratio ($PR_C$), Compressor outlet temperature ($T_{02}$), and turbine outlet temperature ($T_{04}$). Figure 5.2 outlines model inputs and outputs, while Figure 5.3 shows the block diagram of the Simulink model in MATLAB environment, to highlight the information flow. Figures 5.4 to 5.7 show subsystems of the Simulink model in MATLAB environment.
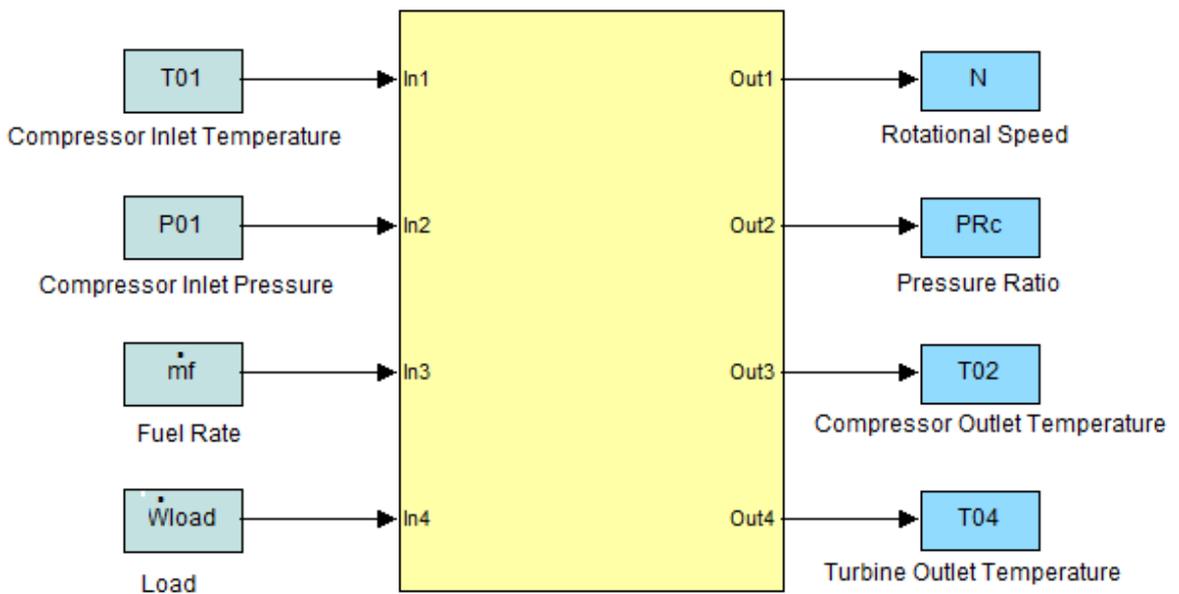


**Figure 5.2:** Block diagram of the Simulink model of the IPGT.
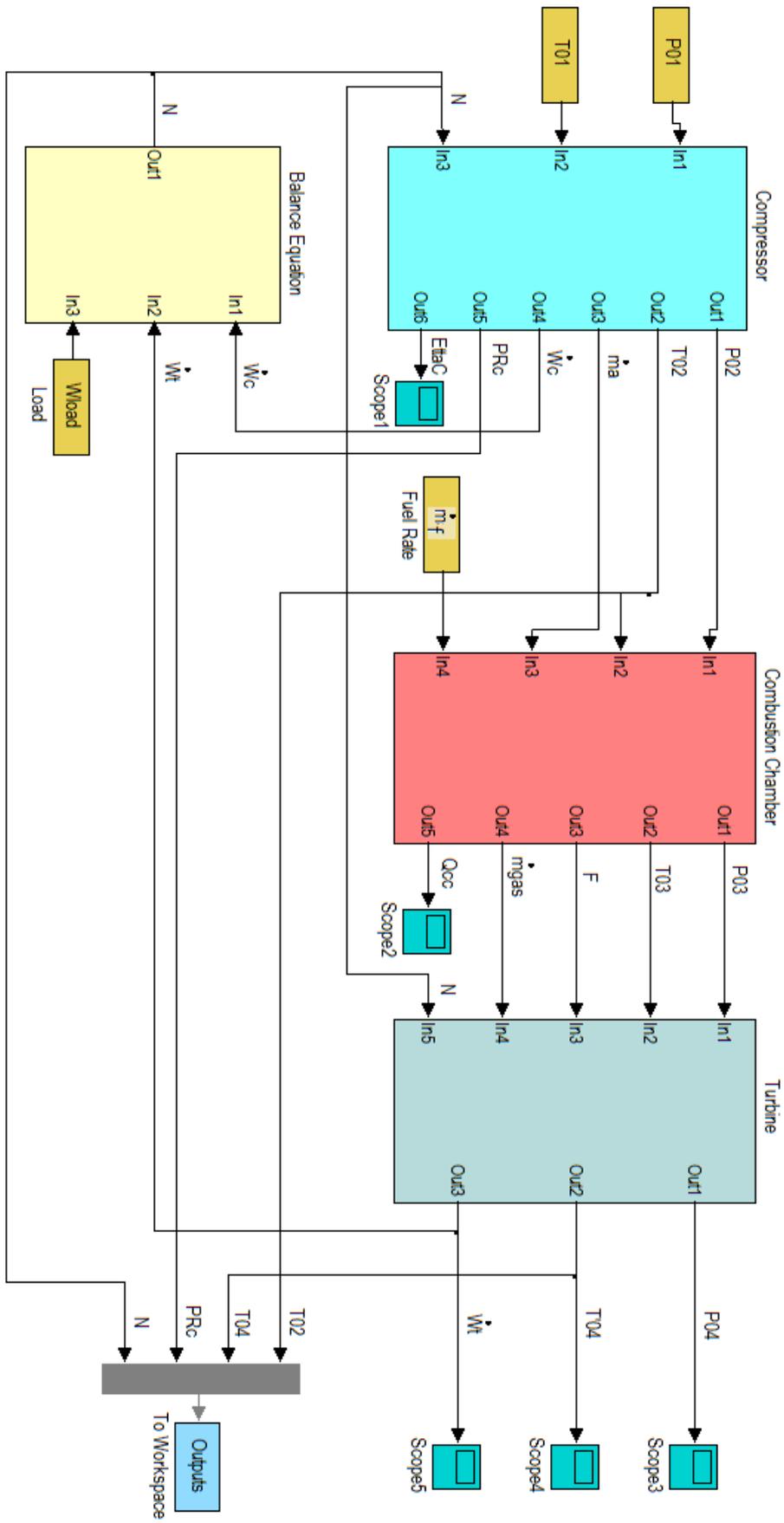
**Figure 5.3:** Simulink model of the IPGT.
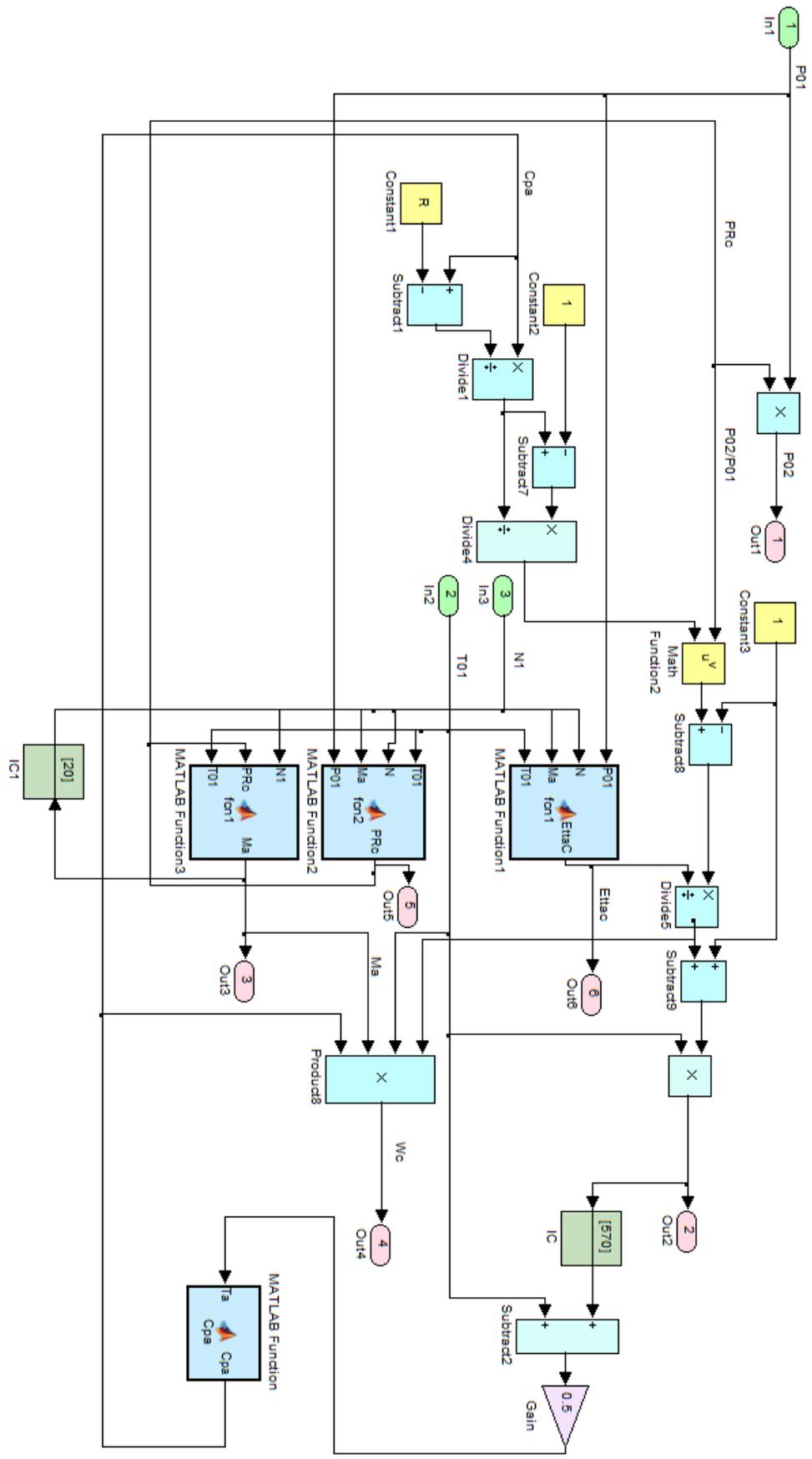
**Figure 5.4:** Subsystem number 1 of the IPGT Simulink model for creating the compressor model.
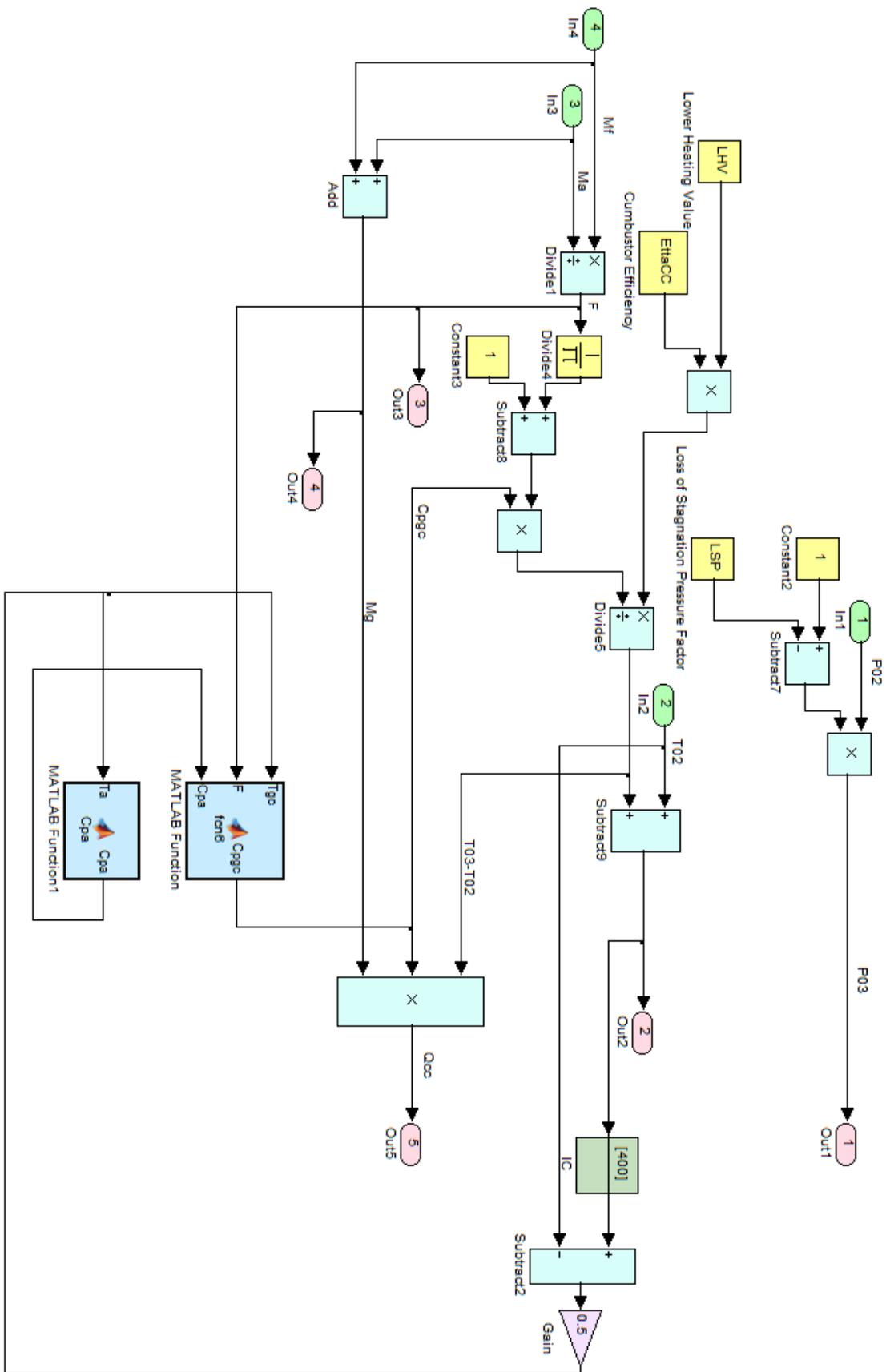
**Figure 5.5:** Subsystem number 2 of the IPGT Simulink model for creating the combustion chamber model.
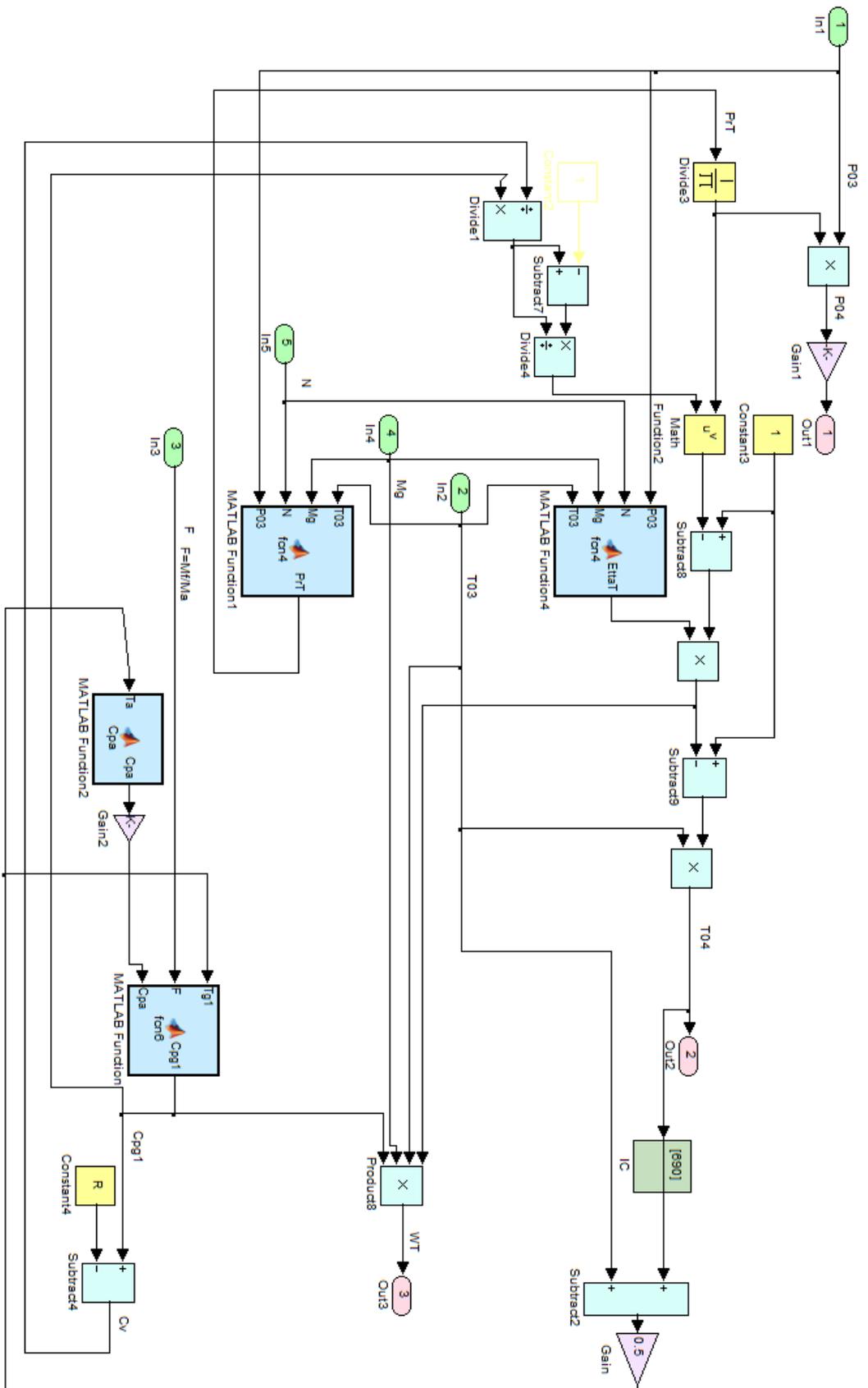
**Figure 5. 6:** Subsystem number 3 of the IPGT Simulink model for creating the turbine model.
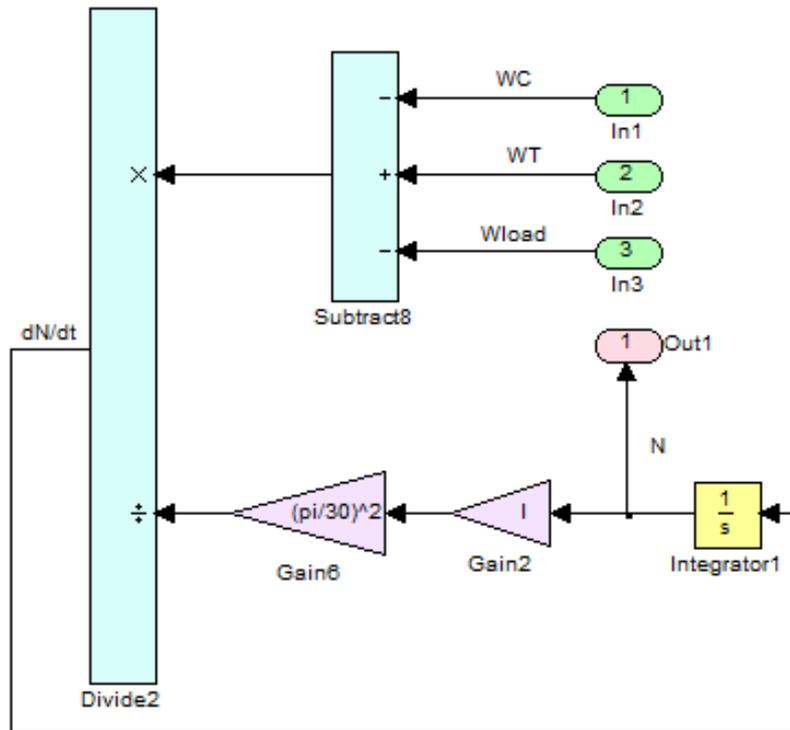
**Figure 5.7:** Subsystem number 4 of the IPGT Simulink model for modelling the balance equation.

### 5.3.4. Discussion on Physics-Based Modelling Approach

As outlined in the previous equations in this chapter, only one equation is used to account for system dynamics, i.e. torque balance, since this is usually recognized as the most influencing factor on transient behaviour. Instead, all the other equations represent steady-state correlations among the different thermodynamic quantities, calculated by using the performance maps obtained by fitting the experimental data used for model tuning, through the Curve Fitting Tool in MATLAB. This is a key step for tuning the model, which allows reproducing actual gas turbine behaviour, in the considered operating region. Fitting the experimental data also allows to smooth measurement uncertainty, which affects the measured data sets, which, in this study, were taken by using standard gas turbine sensors. Another innovative aspect of the developed model is the iterative procedure adopted for estimating turbine inlet temperature and inlet mass flow rate, as discussed in section 5.3.2.4. This procedure assures that, at any time point, the energy balance is satisfied and it is in agreement with the instant measured values. Finally, it has to be stressed that this dynamic model has been developed and will be validated in the next sections by using field data.

## 5.4. NARX MODEL of IPGT

The nonlinear autoregressive network with exogenous inputs (NARX) is a recurrent dynamic network, commonly used in time-series modelling. NARX includes feedback connections enclosing several layers of the network. The defining equation of the NARX model is as follows [214]:

$$y(t) = f(y(t-1), y(t-2), ..., y(t-n_y), u(t-1), u(t-2), ..., u(t-n_u)) \qquad (5.23)$$

in which, *y* is the variable of interest, and u is the externally determined variable. The next value of the dependent output signal $y(t)$ is regressed on previous values of the output signal and previous values of an independent (exogenous) input signal. NARX models can be implemented by using a FFNN to approximate the function $f$ [214]. NARX networks have many applications. For instance, they can be used for nonlinear filtering of noisy input signals or prediction of the next value of the input signal. However, the most significant application of NARX network is to model nonlinear dynamic systems [214].

In this study, the Neural Network Tool-Box in MATLAB was employed to tune the NARX models by using measured time-series data sets. A NARX model was trained separately for M1 to predict outputs for [0 0 0 1] start-up condition. For the whole time-series data sets related to M2, M3 and M4 manoeuvres, another NARX model was trained and the final NARX models were obtained after trial-and-error efforts for getting reliable and accurate models in terms of accuracy of the trends and *RMSE* for output parameters. The resulting model was tested against each of the M2, M3 and M4 manoeuvres separately. Inputs and outputs of the NARX models are the same corresponding parameters as in the Simulink model. Figure 5.8 and Figure 5.9 show the block diagram and the closed-loop structure of the NARX model in MATLAB environment. As it can be seen from Figure 5.9, the best result for both NARX models is related to networks with one hidden layer with 9 neurons, using Levenberg-Marquardt backpropagation (*trainlm*) as the training function, and a tapped delay line with delays from 1 to 2 at the input. This means that the NARX model makes use of the regressed outputs *y(t-1)* and *y(t-2)* at time points *(t-1)* and *(t-2)*.
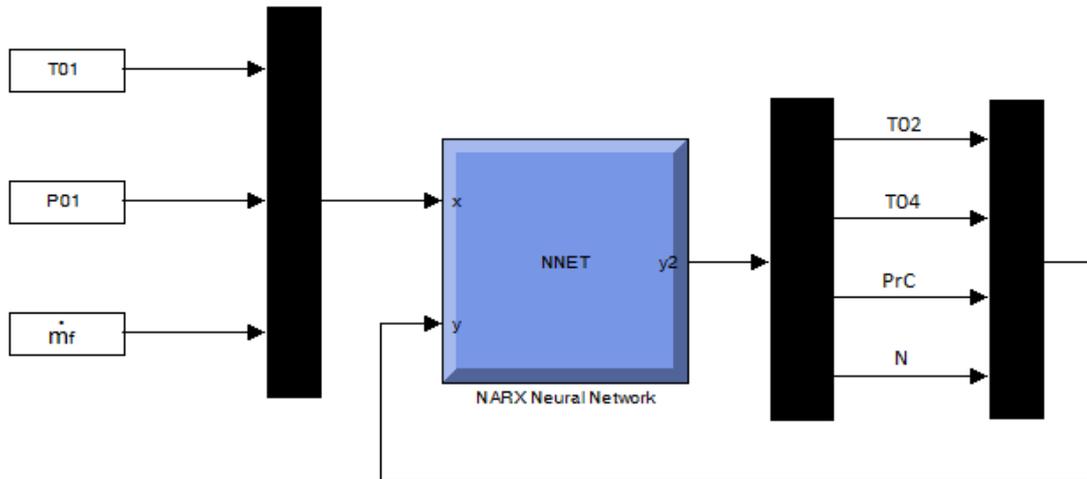
**Figure 5.8:** Block diagram of complete NARX model of the IPGT.
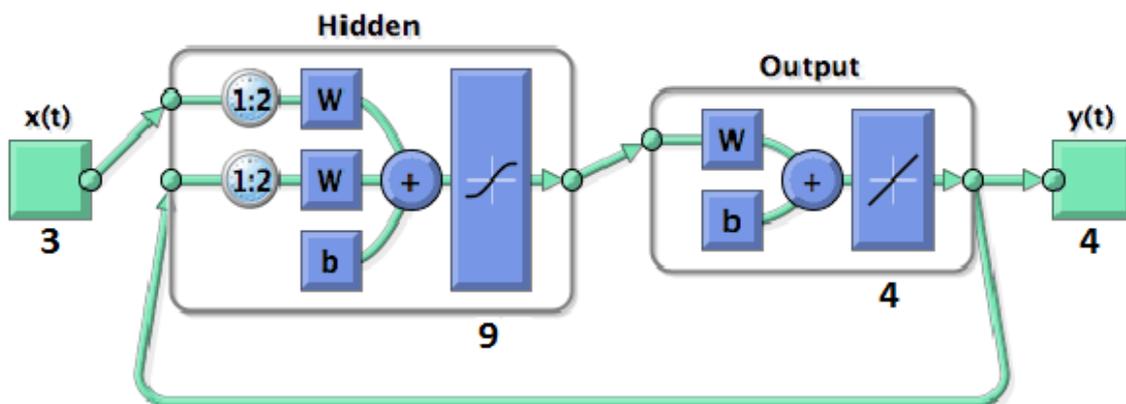


**Figure 5.9:** NARX model of the IPGT.

Figure 5.10 shows the details of the final trained network. Performance of the NARX for training, validation, and test is also shown in the figure. As it can be seen, thirteen iterations were required so that the validation performance error reached the minimum. The *MSE* of the performance at this point was quite low (less than 0.014). The training continued for 6 more iteration before the training stopped. Values of the measured data and the predictions of NARX models were compared on the basis of *RMSE* already defined according to Equation 3.3 in Chapter 3.
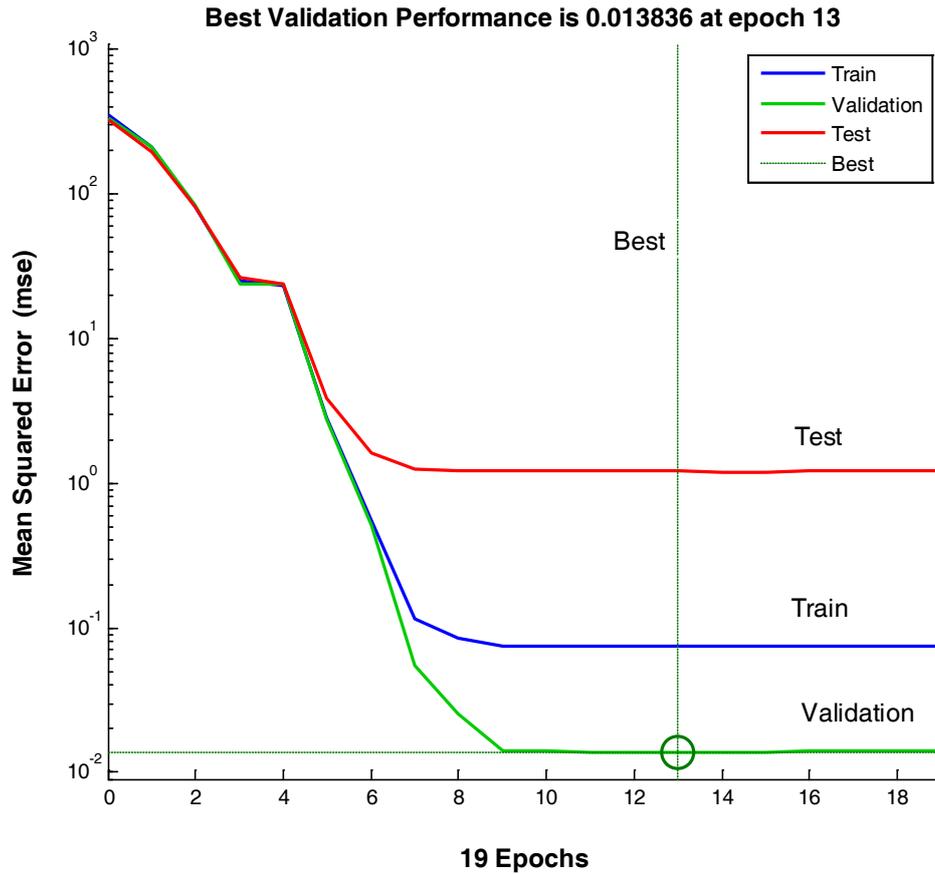
**Figure 5.10:** Performance of the trained NARX model.

## 5.5. COMPARISON of PHYSICS-BASED and NARX MODELS

The trend over time of the prediction of the two simulation models (physics-based model developed in Simulink and NARX model) for the four outputs (rotational speed, pressure ratio, compressor outlet temperature, turbine outlet temperature) is compared to the trend over time of measured data. The comparison is made both for the "training" curves M1 and M2 (Figures 5.11 through 5.14 and 5.15 through 5.18, respectively) and for the curves M3 and M4 used to assess the generalization capability of the simulation models (curve M3 in Figures 5.19 through 5.22 and curve M4 in Figures 5.23 through 5.26). Figure 5.27 summarizes the results in terms of *RMSE* for all the manoeuvres, to allow a synoptic view. *RMSE* already defined according to Equation 3.3 in Chapter 3. It should be noted that, during the simulation phase, the NARX model is fed with the

regressed outputs at time points *y(t-1)* and *y(t-2)* estimated by the NARX model itself at antecedent time steps.

As it can be seen, M1 is reproduced very accurately by both models. The maximum *RMSE* of Simulink and NARX models are 2.2 % and 0.96% (both for $T_{04}$) respectively. M2 is also reproduced with a satisfactory prediction. The maximum values of *RMSE* of Simulink and NARX models for this manoeuvre are 4.3% and 2.1% (both for $PR_C$). M3 is also simulated with acceptable accuracy. The maximum *RMSE* of Simulink and NARX models are 3.9% and 2.8% (both for $PR_C$) respectively. The results for M4 are also satisfactory enough for prediction of GT dynamics. The maximum errors of Simulink and NARX models for this manoeuvre are 4% and 1.7%, both for $PR_C$.

It can be noticed that despite higher errors at the beginning of simulation until the stabilization of the response, the *RMSE* were satisfactory in the Simulink model. The *RMSE* of rotational speed, pressure ratio, compressor outlet temperature, and turbine outlet temperature for all manoeuvres were equal to or less than 0.8%, 4%, 1.6%, and 3.1% respectively. The maximum error of the Simulink and NARX models were respectively 4.3% and 2.8%.

Overall, the results show that both Simulink and NARX models can simulate and predict dynamic behaviour of the gas turbine with acceptable accuracy. However, in this study, the NARX model showed more accuracy compared to the Simulink model. It can be also noticed that despite higher errors at the beginning of simulation until the stabilization of the response, the *RMSE* seemed satisfactory in the Simulink model in all cases for all the outputs.
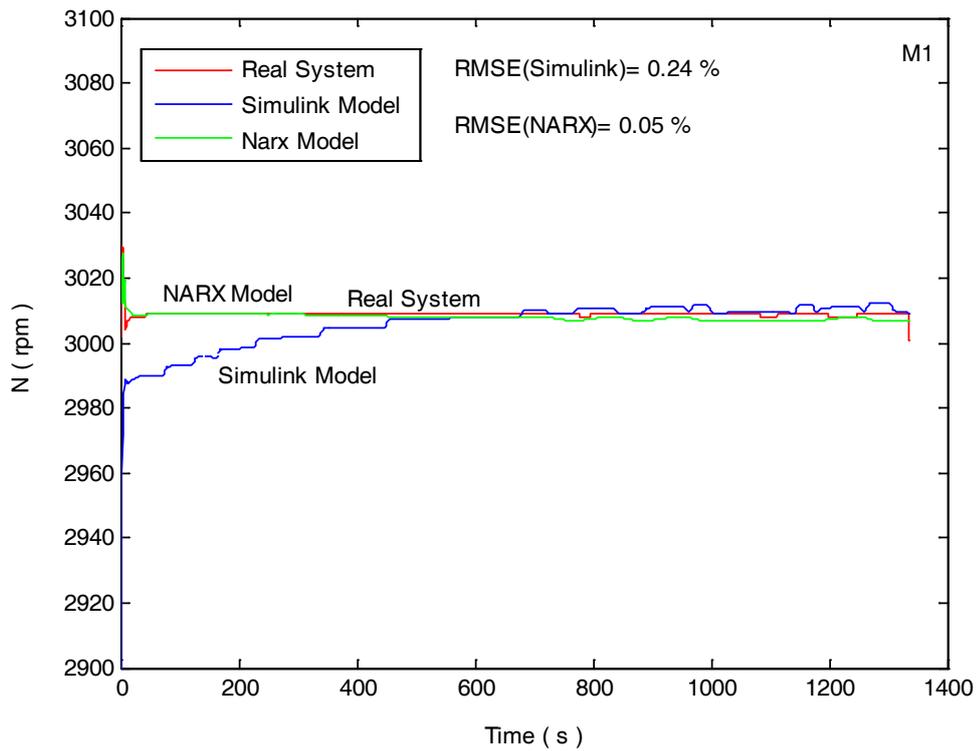
**Figure 5.11:** Variations of rotational speed for the manoeuvre M1 for the real system, Simulink model, and NARX model.
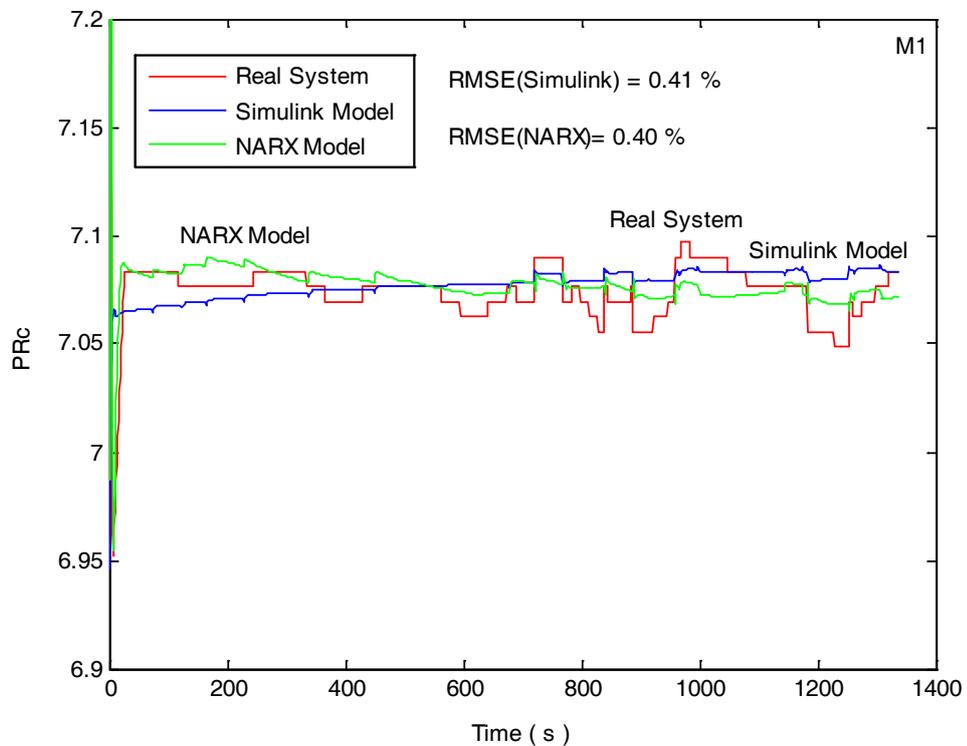


**Figure 5.12:** Variations of compressor pressure ratio for the manoeuvre M1 for the real system, Simulink model, and NARX model.
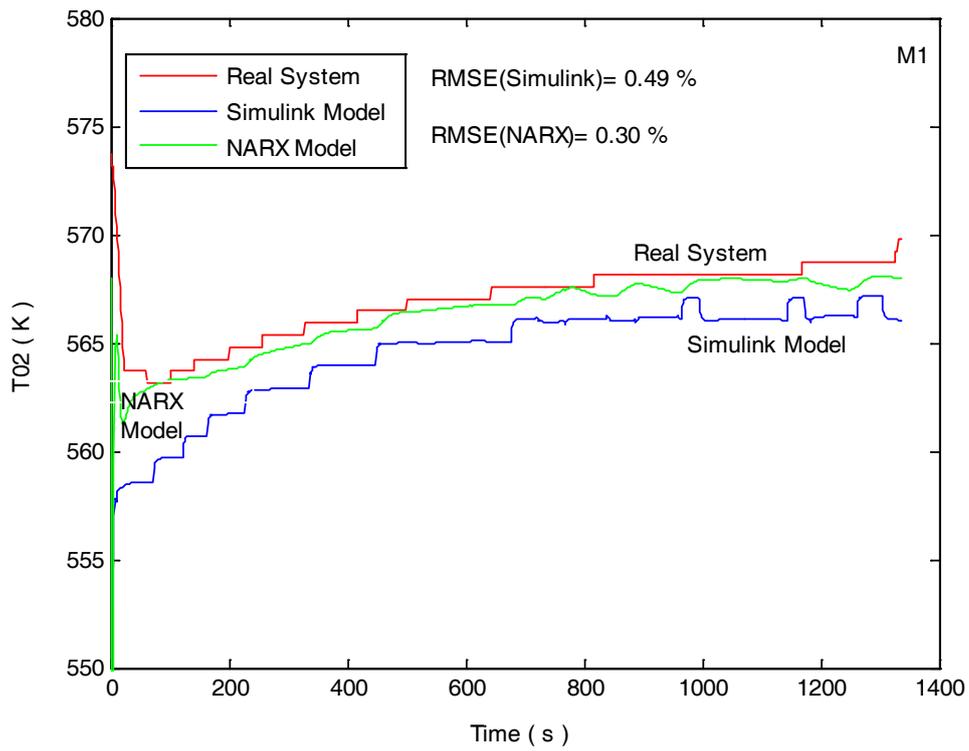
**Figure 5.13:** Variations of compress outlet temperature for the manoeuvre M1 for the real system, Simulink model, and NARX model.
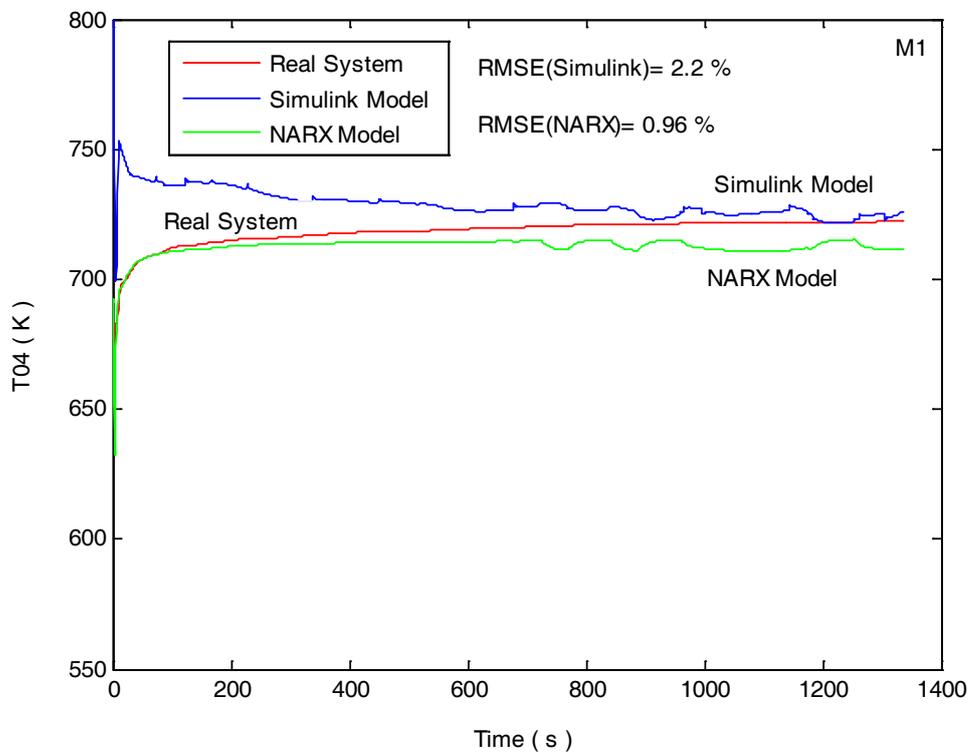


**Figure 5.14:** Variations of turbine outlet temperature for the manoeuvre M1 for the real system, Simulink model, and NARX model.

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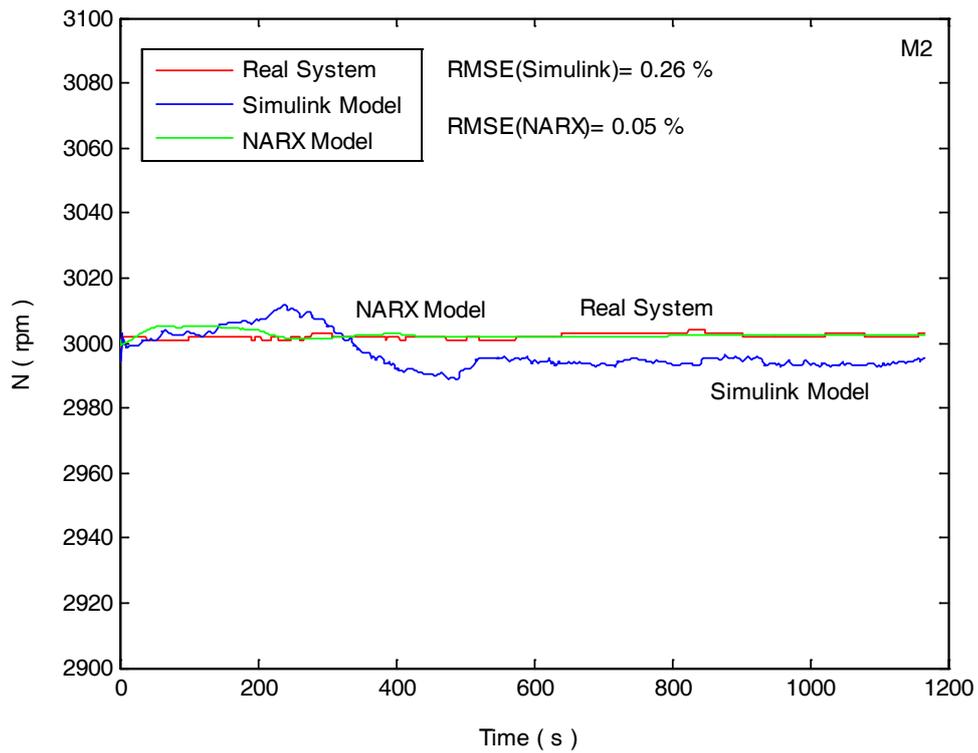
**Figure 5.15:** Variations of rotational speed for the manoeuvre M2 for the real system, Simulink model, and NARX model.
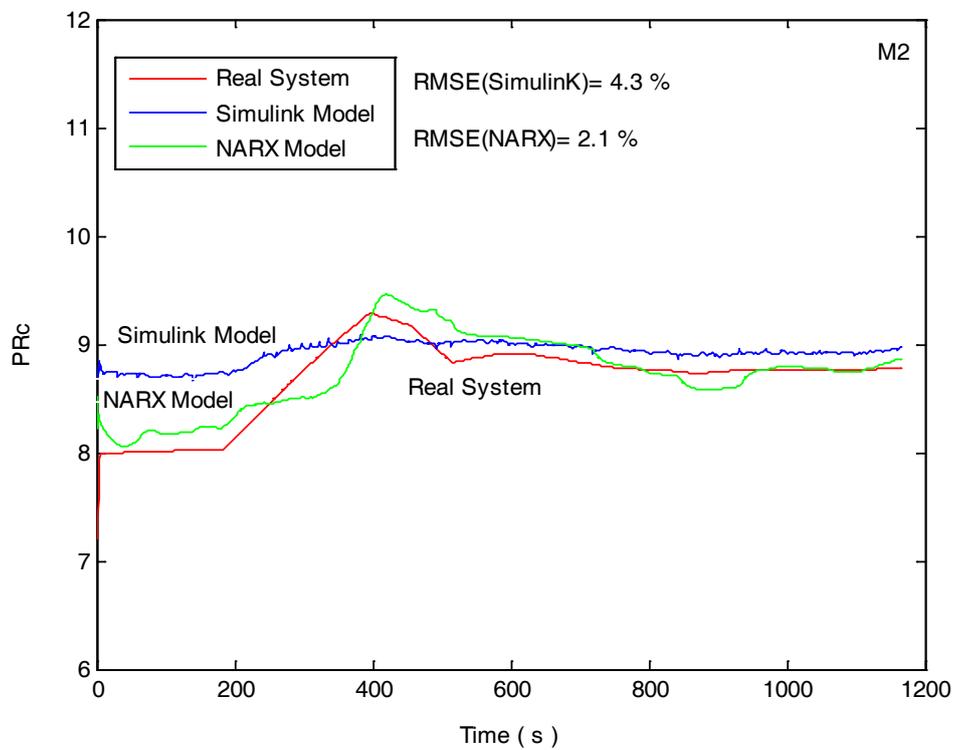


**Figure 5.16:** Variations of compressor pressure ratio for the manoeuvre M2 for the real system, Simulink model, and NARX model.
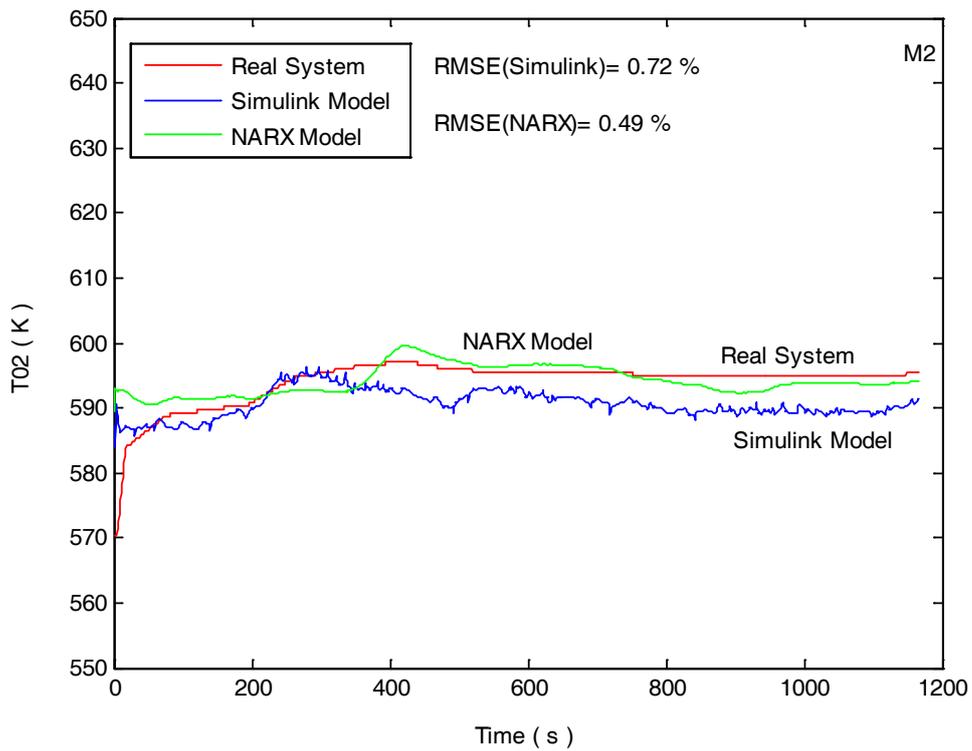
**Figure 5.17:** Variations of compress outlet temperature for the manoeuvre M2 for the real system, Simulink model, and NARX model.
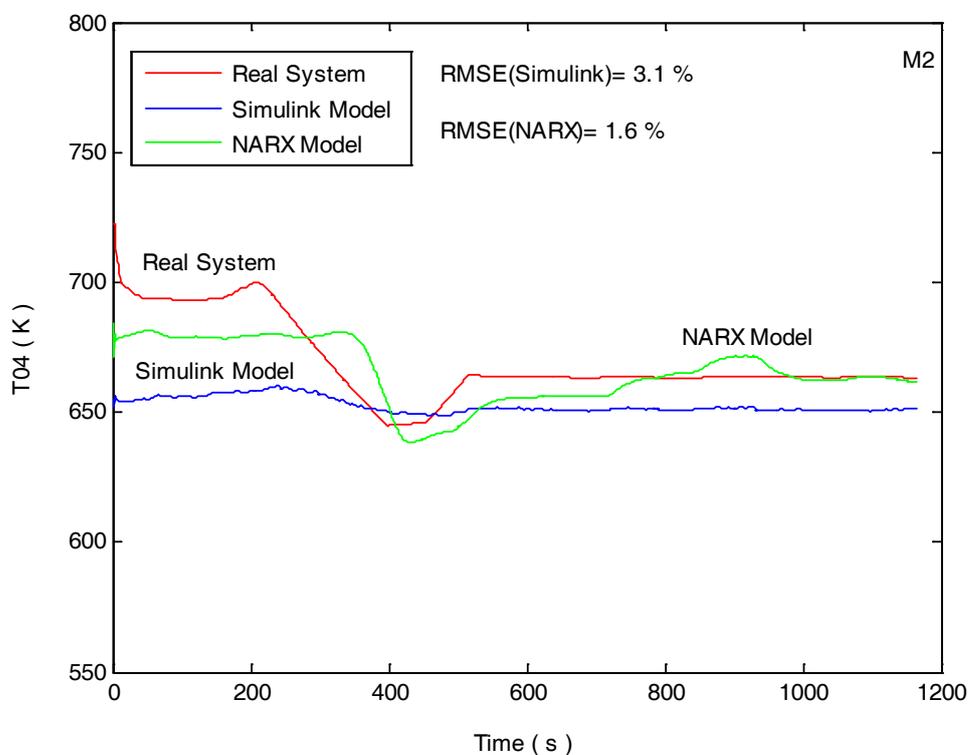


**Figure 5.18:** Variations of turbine outlet temperature for the manoeuvre M2 for the real system, Simulink model, and NARX model.
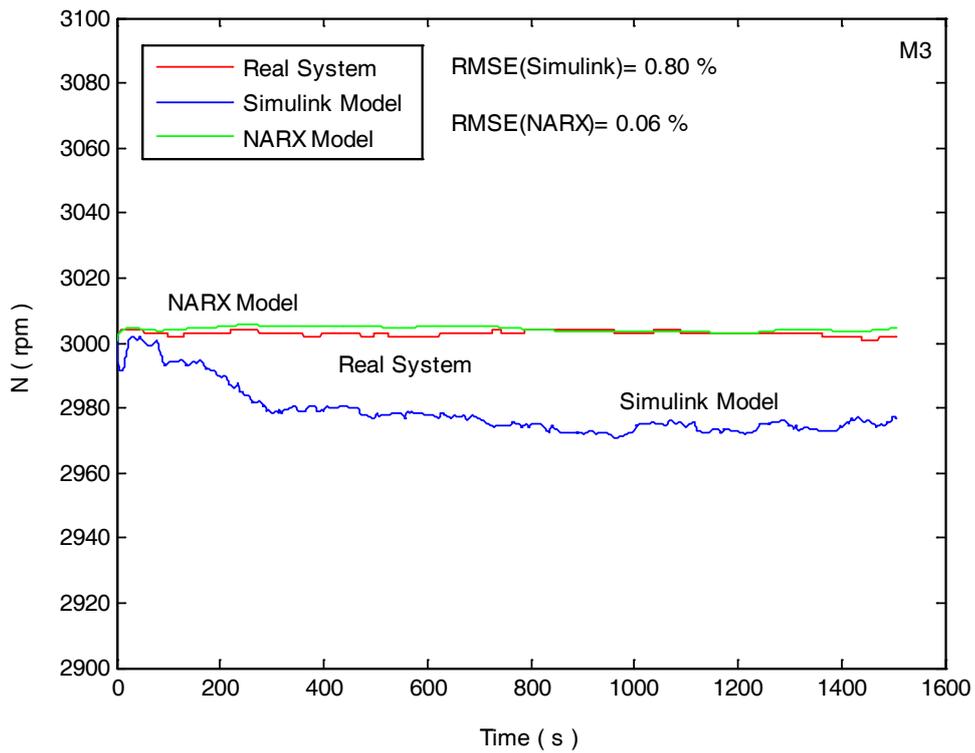
**Figure 5.19:** Variations of rotational speed for the manoeuvre M3 for the real system, Simulink model, and NARX model.
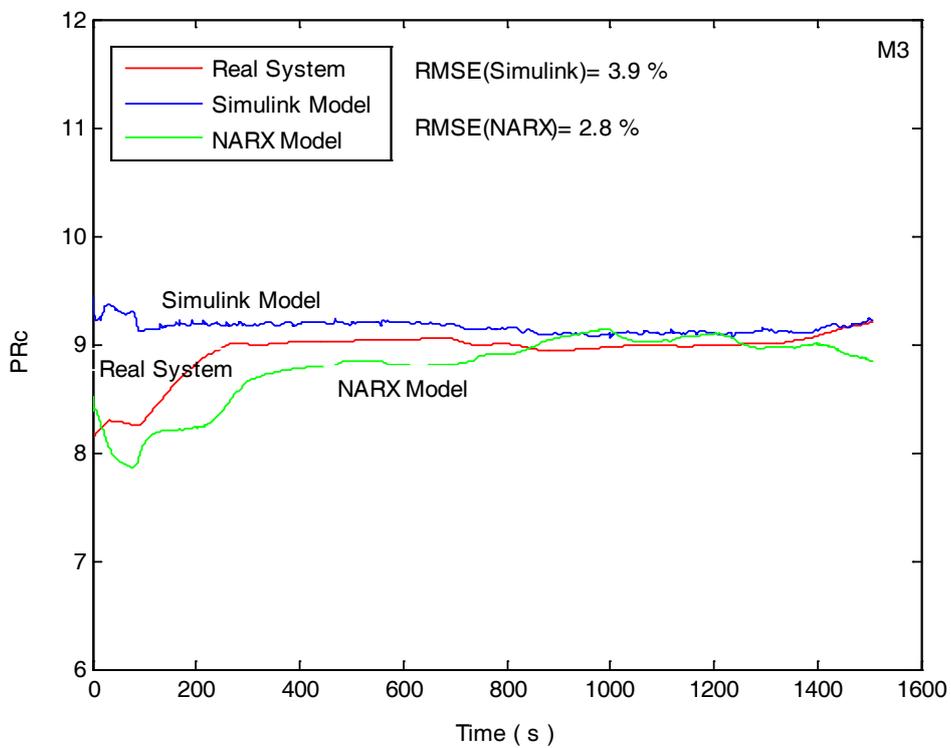


**Figure 5.20:** Variations of compressor pressure ratio for the manoeuvre M3 for the real system, Simulink model, and NARX model.
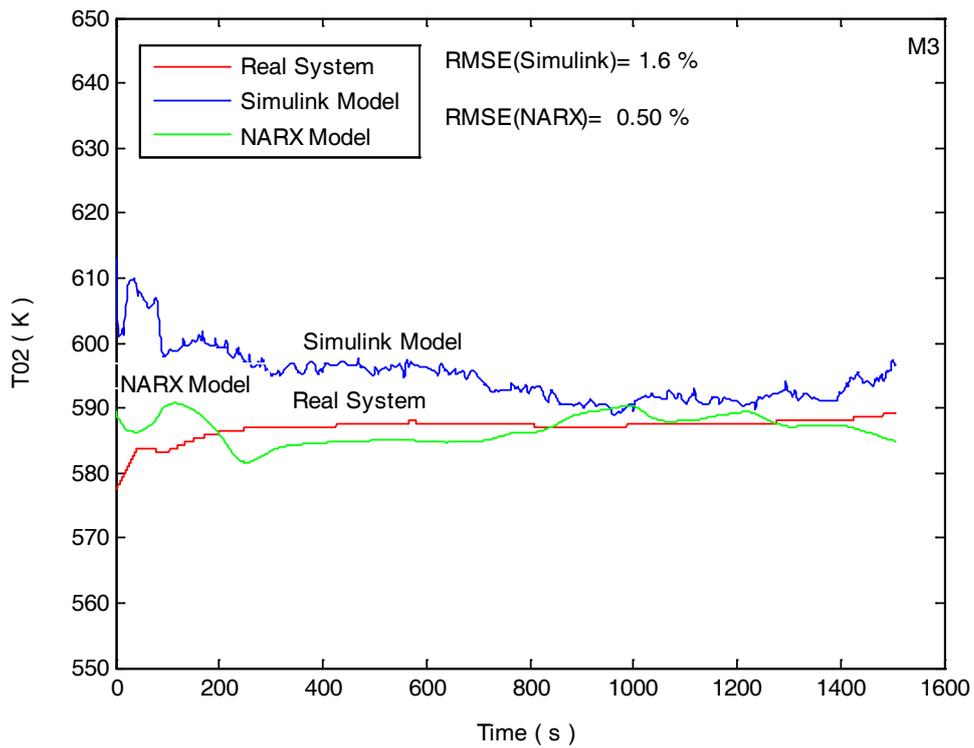
**Figure 5.21:** Variations of compress outlet temperature for the manoeuvre M3 for the real system, Simulink model, and NARX model.
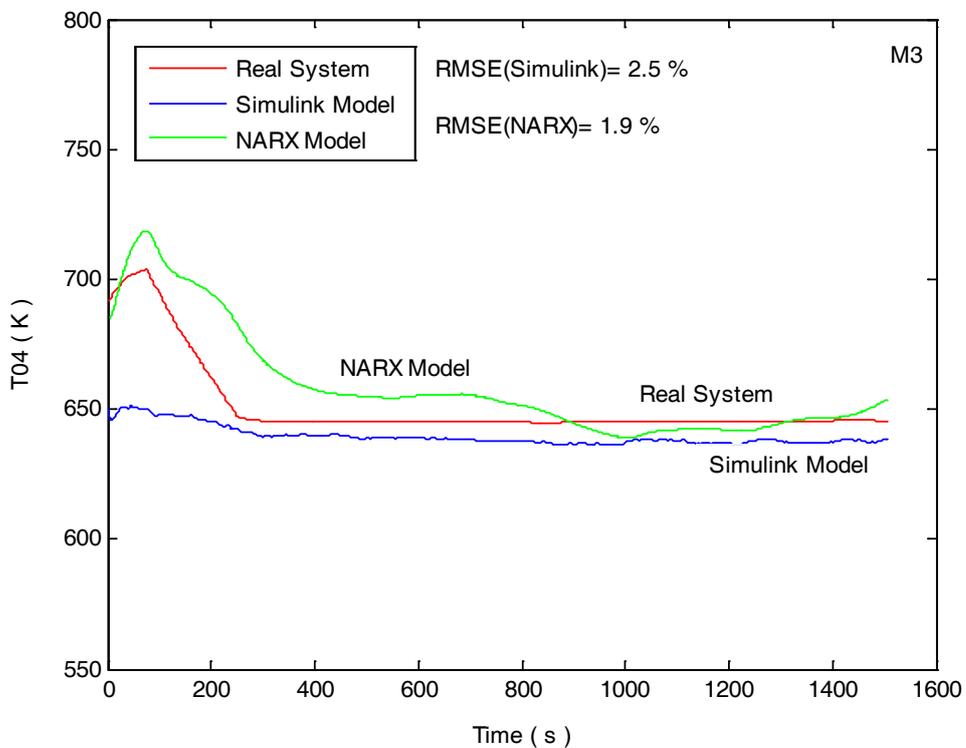


**Figure 5.22:** Variations of turbine outlet temperature for the manoeuvre M3 for the real system, Simulink model, and NARX model.
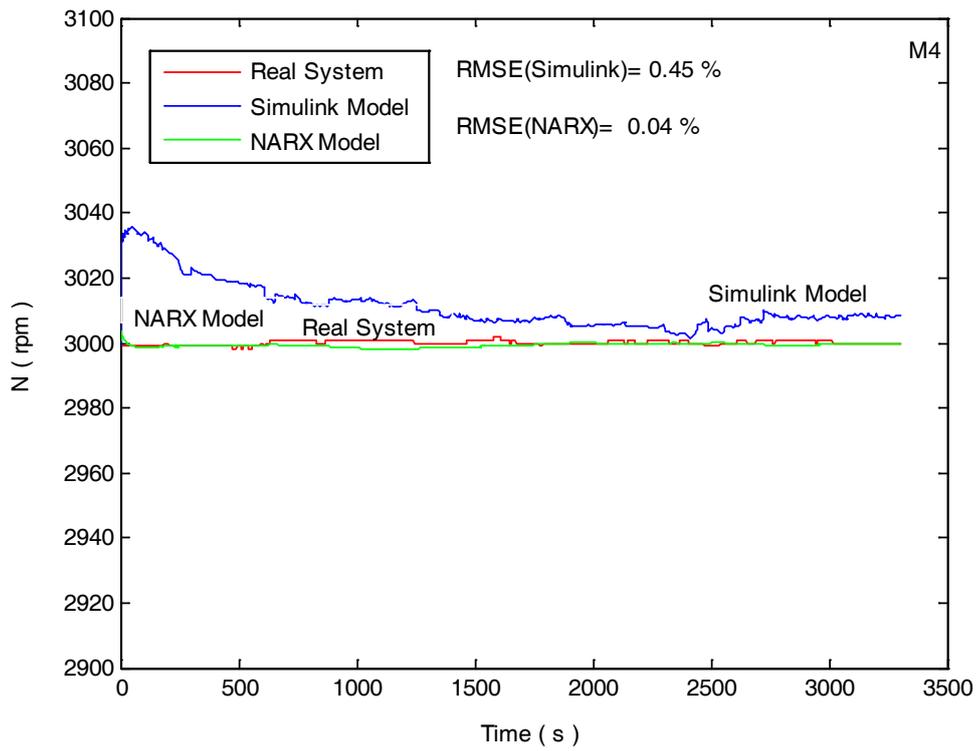
**Figure 5.23:** Variations of rotational speed for the manoeuvre M4 for the real system, Simulink model, and NARX model.
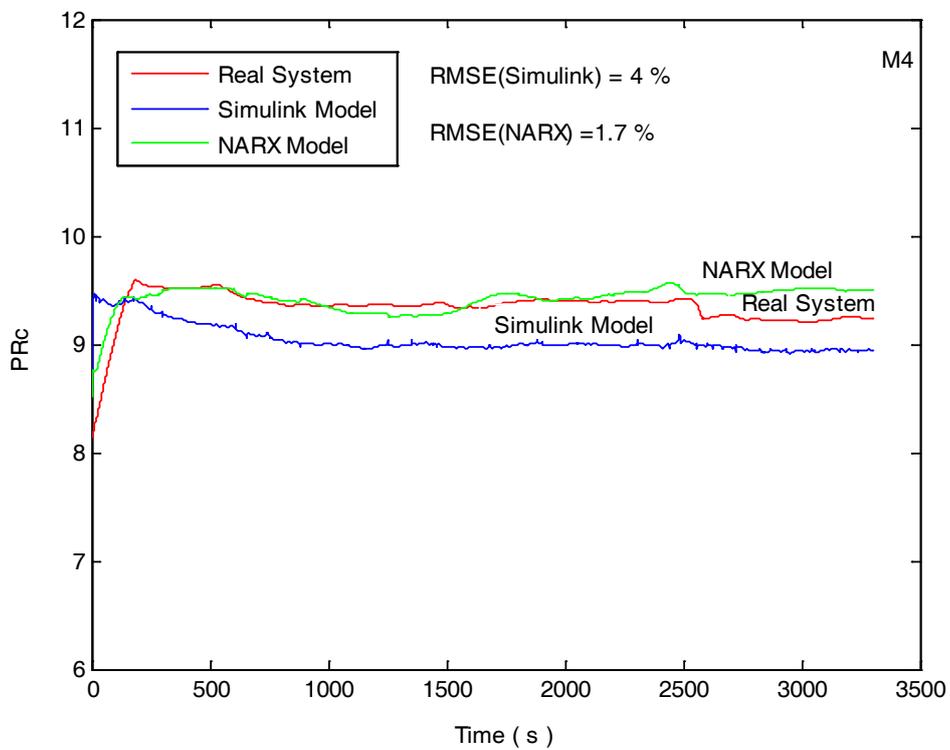


**Figure 5.24:** Variations of compressor pressure ratio for the manoeuvre M4 for the real system, Simulink model, and NARX model.
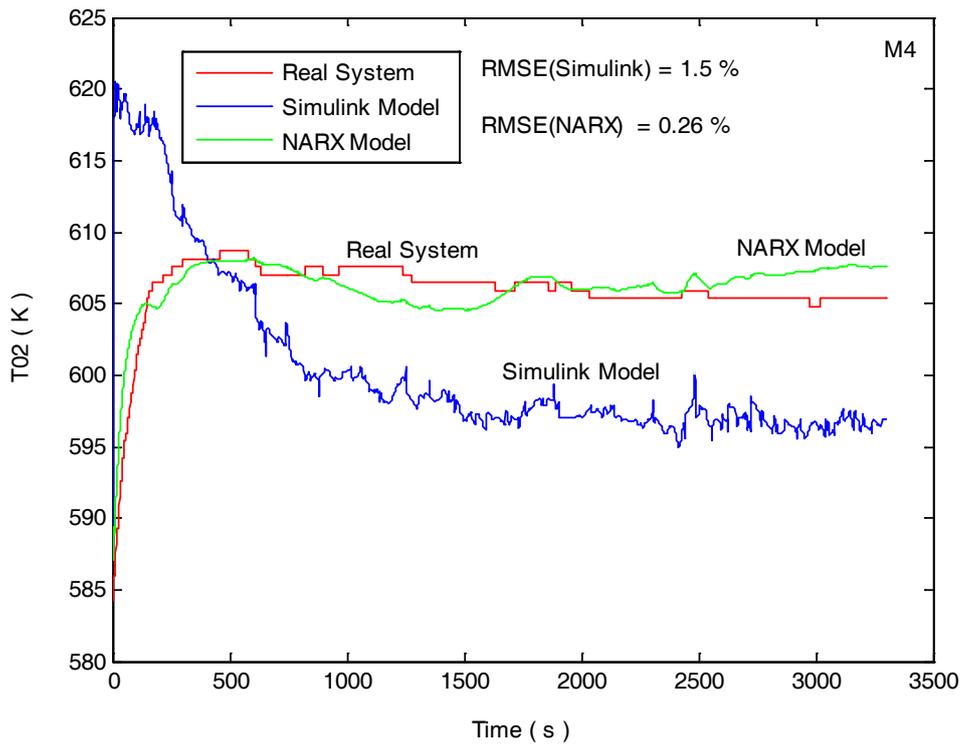
**Figure 5.25:** Variations of compress outlet temperature for the manoeuvre M4 for the real system, Simulink model, and NARX model.
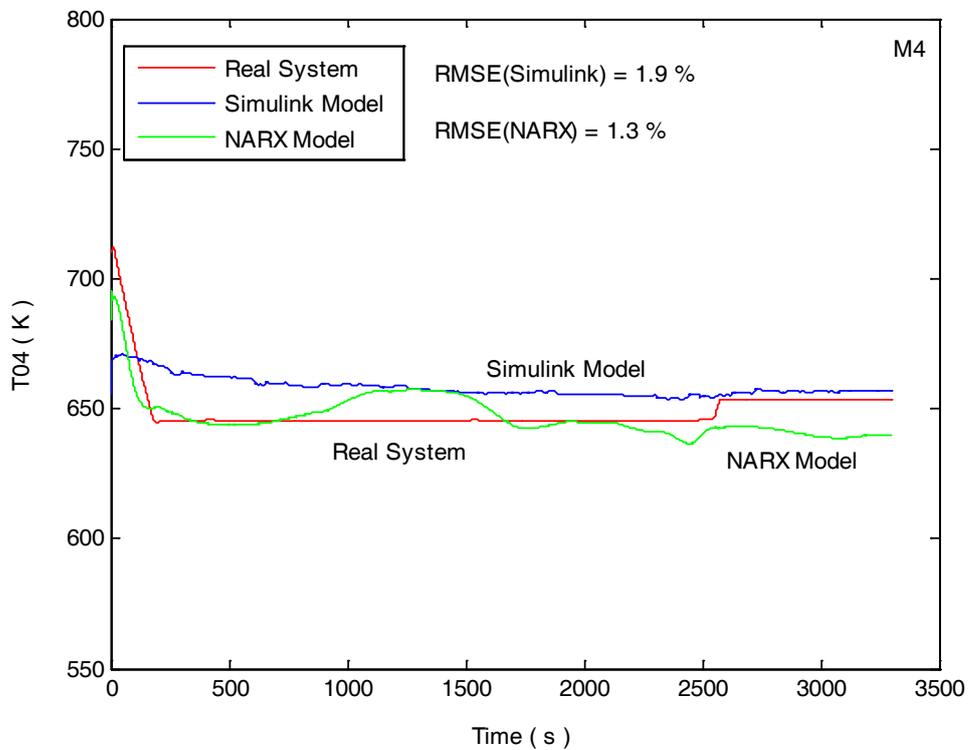


**Figure 5.26:** Variations of turbine outlet temperature for the manoeuvre M4 for the real system, Simulink model, and NARX model.
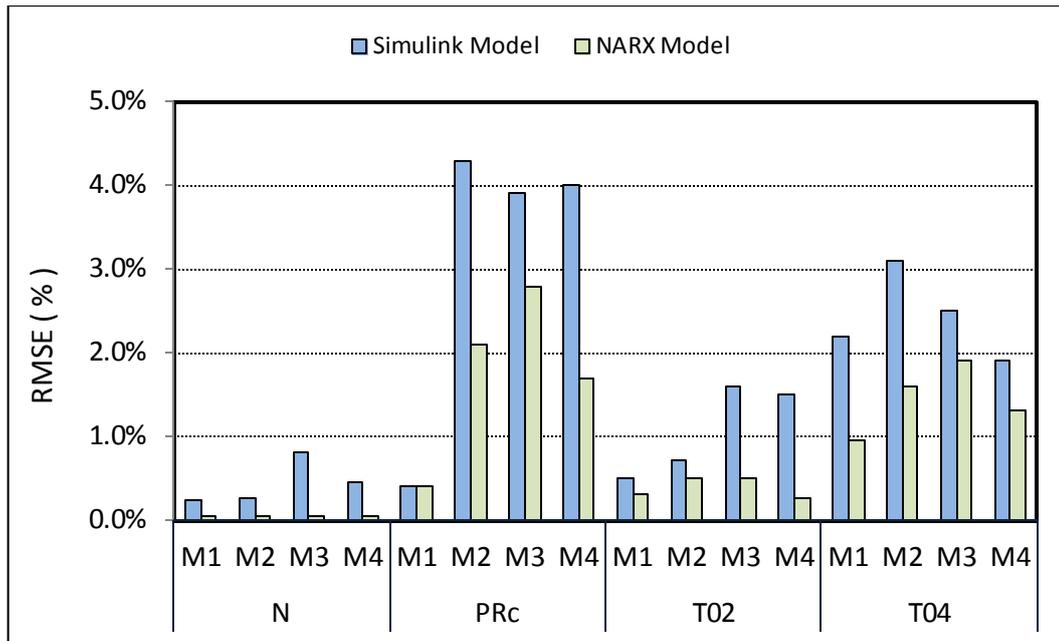
**Figure 5.27:** *RMSE* (%) of the Simulink and NARX models for main selected outputs of all the manoeuvres.

## 5.6. SUMMARY

In this chapter, Simulink and NARX models of a heavy-duty single-shaft power plant gas turbine were set up for simulating two different transient manoeuvres in the very low-power operating region. The main objective of the research was to explore and predict transient behaviour of IPGTs. Thermodynamic and energy balance equations were employed to model the gas turbine in Simulink-MATLAB environment. Correlations between corrected parameters of the gas turbine components (compressor and turbine) were investigated by using measured data sets and by using Curve Fitting Tool in MATLAB. The same time-series data sets were employed to build NARX model for the IPGT. To verify the models, the resulting Simulink and NARX models were tested against two other time-series data sets. For this purpose, four important outputs from the IPGT models and their corresponding values from the measured data sets were compared and the related results were captured and figured. These outputs were rotational speed, compressor pressure ratio, compressor outlet temperature, and turbine outlet temperature. The results showed that both Simulink and NARX models successfully captured dynamics of the system. They provided satisfactory prediction of the dynamic behaviour of the gas turbine for the studied manoeuvres.

The simplicity of the thermodynamic model developed above is one of strong points of this research. In fact, accurate modelling would have required the knowledge of bleed flows and IGV control. Since the information about bleed flows is usually unknown (they are confidential manufacturer's data) and IGV control logic is not always known (in this case, it was not available, since this information is confidential manufacturer's data as well), this lack of information was overcome by implicitly accounting for these effects (which mainly affect the inlet mass flow rate) by means of two innovative procedures:

- The performance maps, which relate the corrected parameters, were obtained directly from measured data (only from the "training" data sets M1 and M2, not from the "verification" data sets M3 and M4) by using the Curve Fitting Tool available in MATLAB. The fine tuning of these correlations represented a key and challenging phase of the thermodynamic model set-up.

- The inlet mass flow rate and the turbine inlet temperature were estimated at each time step by means of an iterative procedure on Equations 5.18 through 5.20. A specific MATLAB routine was written and dedicated to this calculation.

The choice of developing a neural network model to cover this range of operation goes in the same direction, i.e. developing a simple model to reproduce a very complicated and usually difficult-to-model unsteady behaviour. The results from this research indicated that NARX approach modelled gas turbine behaviour with higher accuracy compared to Simulink approach. It was shown that ANN can be considered as a reliable and powerful tool in identification of systems dynamics. Moreover, the NARX approach to transient analysis may have the potential to provide some diagnostic information for the whole gas turbine.

# CHAPTER 6

# MODELLING AND SIMULATION OF THE START-UP OPERATION OF AN IPGT BY USING NARX MODELS

Accurate modelling would require the knowledge of bleed flows and inlet guide vanes control. However, the operational modes with modern DLN (dry low nitrogen oxide) and DLE (dry low emission) systems as well as involving fuel splits and bleed action are very complex. Since such pieces of information are usually unknown or they are confidential manufacturer's data, the adoption of a black-box approach allows the implicit incorporation of all these phenomena in a simple simulation model. For this reason, NARX models of start-up procedure for a heavy-duty IPGT are constructed in this study. The modelling and simulation are carried out on the basis of the experimental time-series data sets.

This chapter represents one of the few attempts to develop a dynamic model of the IPGT (and in particular for the start-up manoeuvre) by means of NARX models and validate it against

experimental data taken during normal operation by means of standard measurement sensors and acquisition system. Building the required models in this specific area can be very effective in understanding and analyzing gas turbine dynamics, and can also provide information about fault diagnostics.

The gas turbine modelled in this chapter is the same IPGT already described in Table 5.1of Chapter 5. It is a heavy-duty single-shaft gas turbine for power generation (General Electric PG 9351FA). GT start-up procedure is described in the next section. Then, the main steps for data acquisition and preparation, NARX modelling, and the results of the comparison of NARX prediction to experimental measurements are discussed. This chapter ends up with the summary and concluding remarks.

## 6.1. GAS TURBINE START-UP

Start-up period is the operating period before the gas turbine reaches stable combustion conditions. To start to work, gas turbines need an external source, such as an electrical motor or a diesel engine. GTs use a starter until the engine speed reaches a specific percentage of the design speed. Then, engine can sustain itself without the power of starter.

Gas turbine start-up procedure can be divided into four phases including dry cranking, purging, light-off and acceleration to idle ( [234],[235]). In dry cranking phase, the engine shaft is rotated by the starting system without any fuel feeding. In purging phase, residual fuel from previous operation or failed start attempts is purged out of the fuel system. In this phase, the rotating speed is kept constant at a value which ensures a proper mass flow rate through the combustion chamber, the turbine and the heat recovery steam generator. During light-off, fuel is fed to the combustor, and igniters are energized. This causes ignition to start locally within the combustor, followed by light-around of all the burners. Finally, in acceleration to idle phase, the fuel mass flow rate is further increased and the rotational speed increases towards idle value.

## 6.2. DATA ACQUISITION AND PREPARATION

The data sets for this study were taken experimentally during several start-up manoeuvres and cover the whole operational range of the IPGT during start-up. These data are representative of the operating conditions during start-up and, therefore, they account for all the conditions related to this type of transient manoeuvre (e.g. bleed valve opening, IGV control, etc.).

The required data for this research were chosen among the whole available data sets for the IPGT that were already categorized and discussed in section 5.2 of Chapter 5. The following two manoeuvres from cold start-up were considered for making the models:

- The starter is on: 1

- The gas turbine is connected to the grid or not: 1 or 0

- Customer trip doesn't happen: 0

- The flame is on: 1

The manoeuvres can be classified as [1 1 0 1] or [1 0 0 1]. For instance, [1 1 0 1] refers to the situation when the starter is on, the gas turbine is connected to the grid, customer trip does not happen, and the flame is on.

The measured time-series data sets which are used for training the NARX models are called TR1, TR2 and TR3. They cover the whole operational range of the gas turbine during the start-up procedure. The time step for data acquisition is one second.

A combination of TR1, TR2 and TR3 was considered for training in such a manner that the resulting model can be confidently generalized for the GT start-up simulation. The data sets TE1, TE2 and TE3 are employed for test and verification of the resulting model. Table 6.1 shows more details about these data and the operational range for the input parameters.

It can be seen that the values of compressor inlet temperature and pressure of the training data sets are different, since they were taken in different seasons (August, October, and December). This choice was made on purpose, with the aim to improve the generalization capability of the NARX models. Moreover, the range of variation of $T_{01}$ for TE1, TE2 and TE3 is included in the range of

variation of $T_{01}$ of the training data sets. Figure 6.1 shows the trends over time of fuel mass flow rate. It can be seen that the trends of all manoeuvres are similar, but the rate of change of the rotational speed to reach the full-speed/no-load condition is different for each manoeuvre. In particular, TE1 is very close to TR3, while the trend of the fuel flow for TE2 and TE3 lies in the middle between TR1 and TR3.

**Table 6.1:** Experimental time series data sets.

| Data sets | Number of data | Operational range of the inputs | | |
|:---:|:---:|:---:|:---:|:---:|
| | | $T_{01}$ (K) | $p_{01}$ (kPa) | $M_f$ (kg/s) |
| TR1 | 450 | [289.8; 292.6] | [101.6; 101.9] | [0.73; 4.90] |
| TR2 | 362 | [281.5; 295.9] | [102.3; 102.6] | [0.98; 5.10] |
| TR3 | 510 | [305.4; 308.7] | [101.6; 102.0] | [0.28; 4.80] |
| TE1 | 538 | [295.9; 299.3] | [100.6; 101.0] | [0.37; 4.80] |
| TE2 | 408 | [299.8; 300.9] | [100.6; 101.0] | [0.49; 4.80] |
| TE3 | 397 | [298.7; 299.8] | [100.6; 100.9] | [0.52; 4.80] |
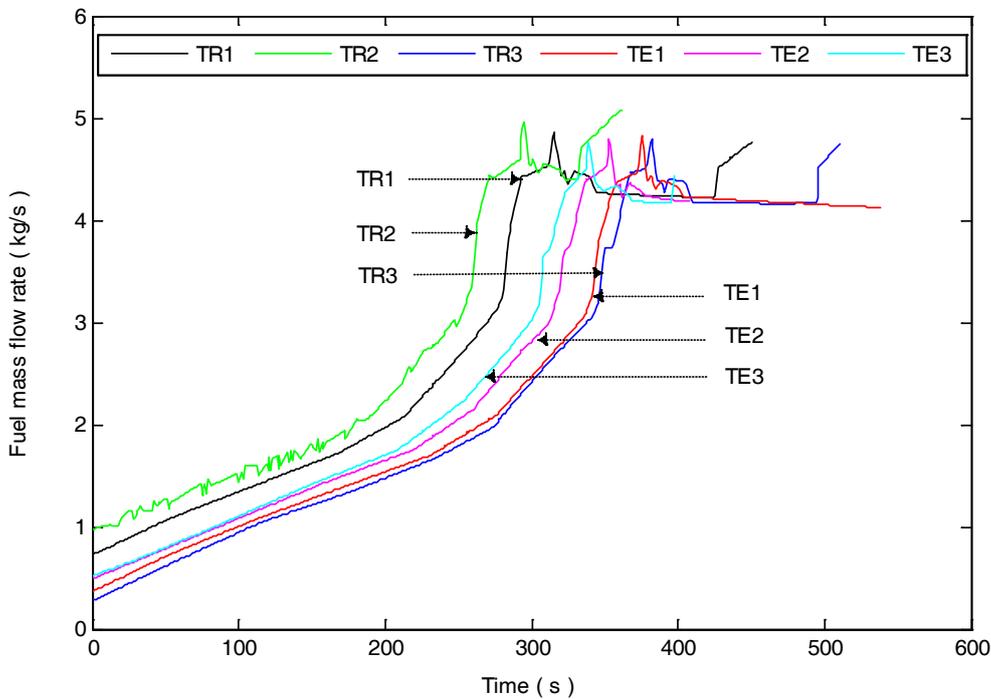


**Figure 6.1:** Trend over time of fuel mass flow rate.

## 6.3. GAS TURBINE START-UP MODELLING BY USING NARX MODELS

As already stated in Chapter 5, NARX has a recurrent dynamic nature and is commonly used in time-series modelling. NARX includes feedback connections enclosing several layers of the network. Recall that the defining equation of the NARX model can be written as follows [214]:

$$y(t) = f(u(t-1), u(t-2), \dots, u(t-n_u), y(t-1), y(t-2), \dots, y(t-n_y)) \qquad (6.1)$$

where $y$ is the output variable and u is the externally determined variable. The next value of the dependent output signal $y(t)$ is regressed on previous values of the output signal and previous values of an independent (exogenous) input signal.

As it can be noticed from Equation 6.1, the NARX models developed in this paper use as inputs only the variables at antecedent time steps. In fact, the exogenous input variable at the current time step $u(t)$ is not an input. This characteristic is remarkable since this modelling approach allows the set-up of a software tool which, for instance, may also be used for real-time control optimization and gas turbine sensor diagnostics to be run in parallel with the considered gas turbine.

In this study, the Neural Network Tool-Box in MATLAB was employed to build NARX models for a combination of the measured time-series data sets of TR1, TR2 and TR3 in such a manner that the resulting model will cover the whole operational range of the gas turbine start-up operation. The resulting models were obtained after carrying out a thorough sensitivity analysis on NARX parameters (i.e. number of neurons in the hidden layer, number of feedback connections, NARX architecture, and number of delayed time points), in order to get the best possible model in terms of accuracy of the trends and *RMSE* for the output parameters. At the same time, the structure of the models was kept as simple as possible by considering the minimum required number of neurons and delayed time points. The models were tested against TE1, TE2 and TE3 manoeuvres separately.

Figure 6.2 and Figure 6.3 show the closed-loop structure of the NARX models and the block diagram of the complete NARX model used for GT simulation, respectively. As Figure 6.3 shows, the model includes three inputs and four outputs. The inputs are compressor inlet temperature $T_{01}$, compressor inlet stagnation pressure $P_{01}$, and fuel mass flow rate $M_f$. These quantities were

selected, since they are always available, even in poorly instrumented GTs. The outputs are compressor outlet temperature $T_{02}$, turbine outlet temperature $T_{04}$, compressor pressure ratio $PR_C$ and rotational speed $N$. Figure 6.3 also shows that the complete NARX model has a MISO structure, as also made for instance in [97].
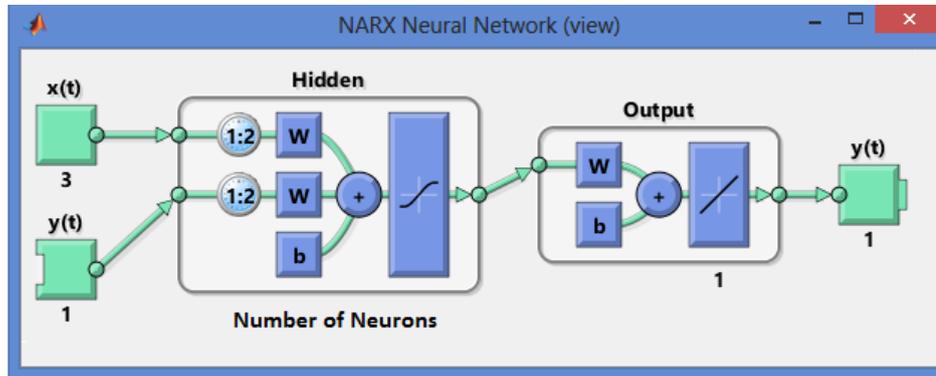


**Figure 6.2:** Closed-loop structure of a single NARX model.
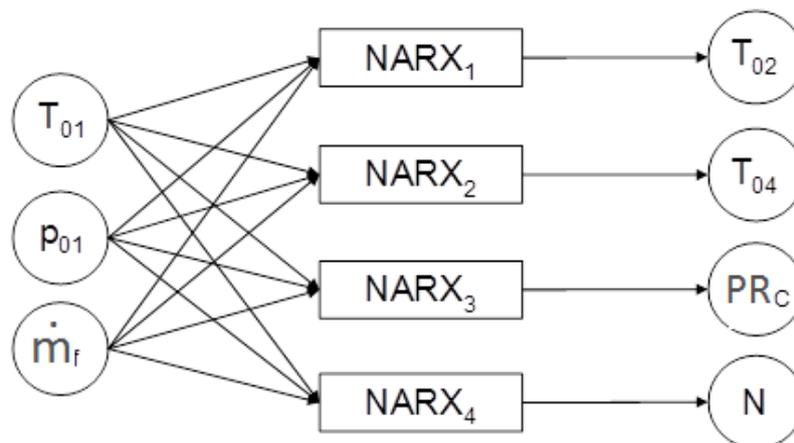


**Figure 6.3:** Block diagram of the complete NARX model for IPGT simulation.

The NARX model for each output parameter was trained separately with different number of neurons in order to get the most accurate prediction. Each model was trained by using Levenberg-Marquardt backpropagation (*trainlm*) as the training function, one hidden layer and a tapped delay line with delays from 1 to 2 seconds at the input. In fact, the NARX model with regressed outputs *y(t-1)* and *y(t-2)* at time points *(t-1)* and *(t-2)* proved to be most accurate solution, by using a lean structure. With regard to the optimal number of neurons in the hidden layer, the best results for the

outputs $T_{02}$, $T_{04}$, $PR_C$ and $N$ were obtained by using twelve neurons in the hidden layer. Values of the measured data and the predictions of NARX models were compared on the basis of *RMSE* already defined according to Equation 3.3 in Chapter 3.

### 6.3.1. NARX Model TRAINING

Figures 6.4 through 6.7 show the variations of the four output parameters during the gas turbine start-up process of the manoeuvres TR1, TR2, and TR3 for the real system (measured data sets) and the trained NARX models.

It should be noted that the training data sets TR1, TR2 and TR3 are supplied as a sequence to the NARX models, as required for the training phase. The simulation results in Figures 6.4 through 6.7 were obtained by simulating these manoeuvres one by one. It can be observed that the most significant deviations between measured and simulated values occur during the initial phase of the data sets. This means that the NARX models require a time frame of approximately one minute to stabilize and correctly reproduce the gas turbine behaviour (this delay is very clear in Figure 6.12, Figure 6.16 and Figure 6.20 for $T_{04}$).

In general, Figures 6.4 through 6.7 highlight that the NARX models can also follow the physical behaviour when the trend remains almost stationary. Moreover, the NARX models tend to smooth the rapid variations, as shown in Figure 6.7 for $T_{04}$.

Figure 6.8 reports the results of the training phase in terms of *RMSE*. To account for the initial delay of the NARX models to work correctly, the values corresponding to the first ten seconds of each data set are not used for *RMSE* calculation.

The *RMSE* values slightly depend on the considered training curve, with the exception of $N$ for TR3 (*RMSE* equal to 12.0%). The *RMSE* values for $T_{02}$, $T_{04}$, $PR_C$ and $N$ vary in the range 0.7%-4.1%, 0.8%-2.6%, 4.6%-5.6% and 3.0%-12.0%, respectively. Given that the NARX models are trained with merely three input measurements from experimental data and can generally reproduce the physical behaviour, the *RMSE* values were considered acceptable and the training phase was considered satisfactory.
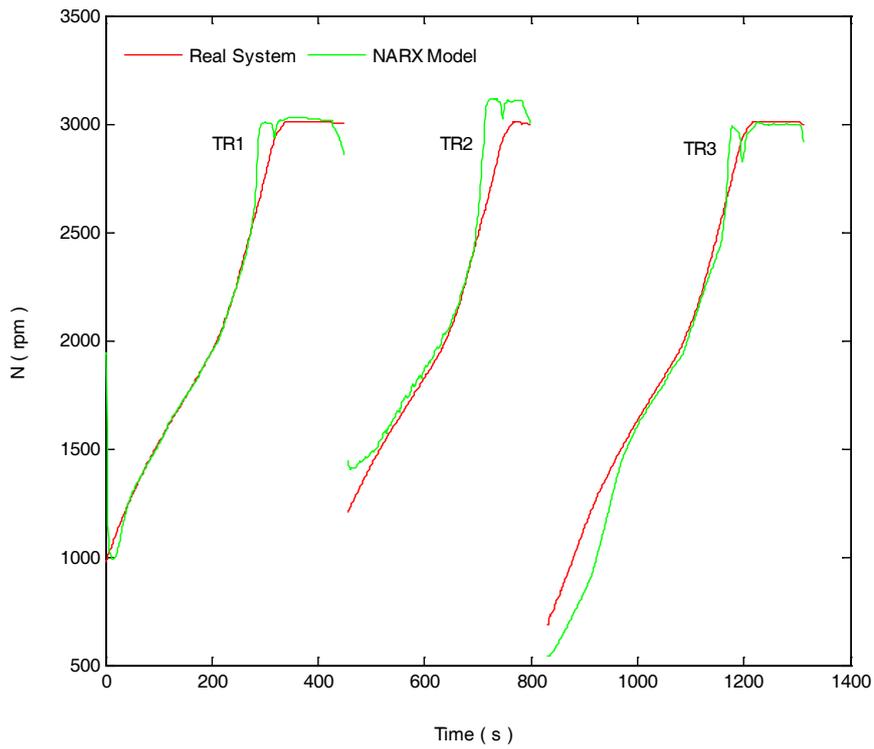
**Figure 6.4:** Variations of rotational speed N for the training manoeuvres TR1, TR2 and TR3.
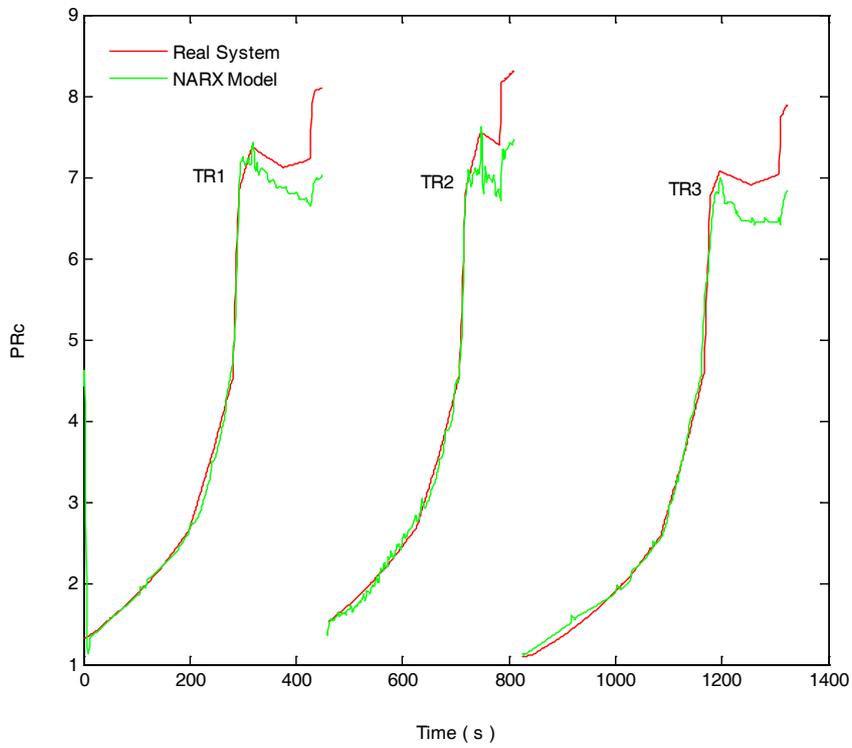


**Figure 6.5:** Variations of compressor pressure ratio PRc for the training manoeuvres TR1, TR2 and TR3.

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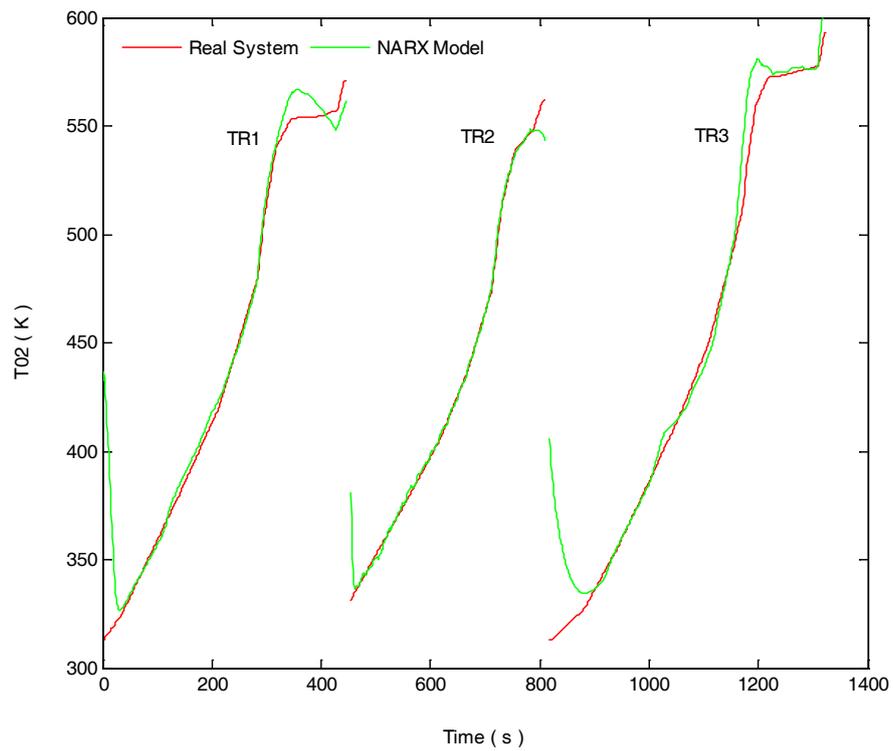
**Figure 6.6:** Variations of compress outlet temperature T02 for the training manoeuvres TR1, TR2 and TR3.
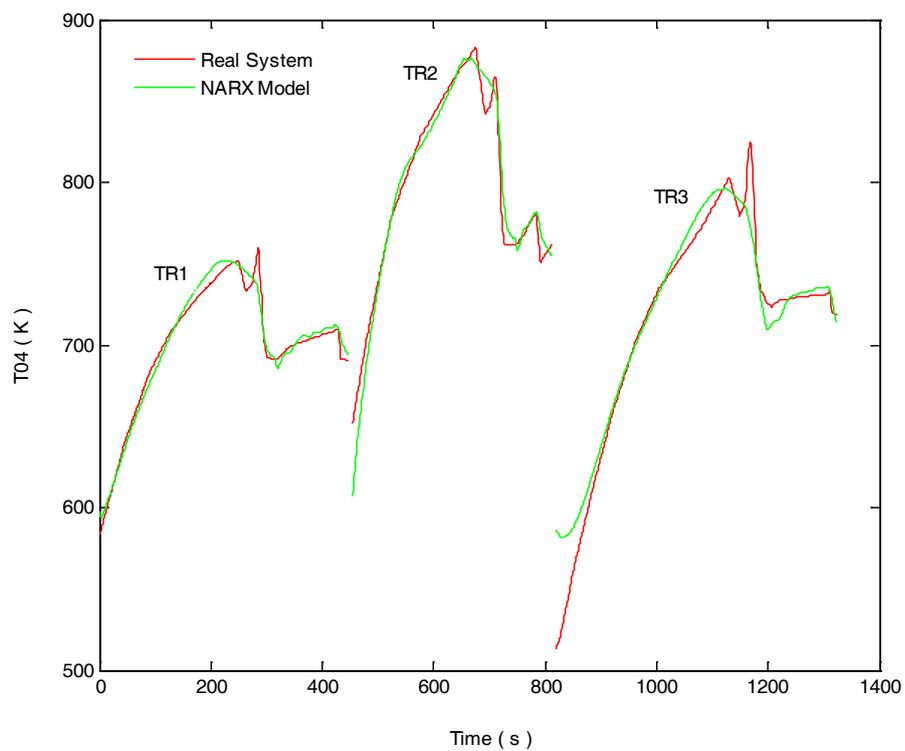


**Figure 6.7:** Variations of turbine outlet temperature T04 for the training manoeuvres TR1, TR2 and TR3.
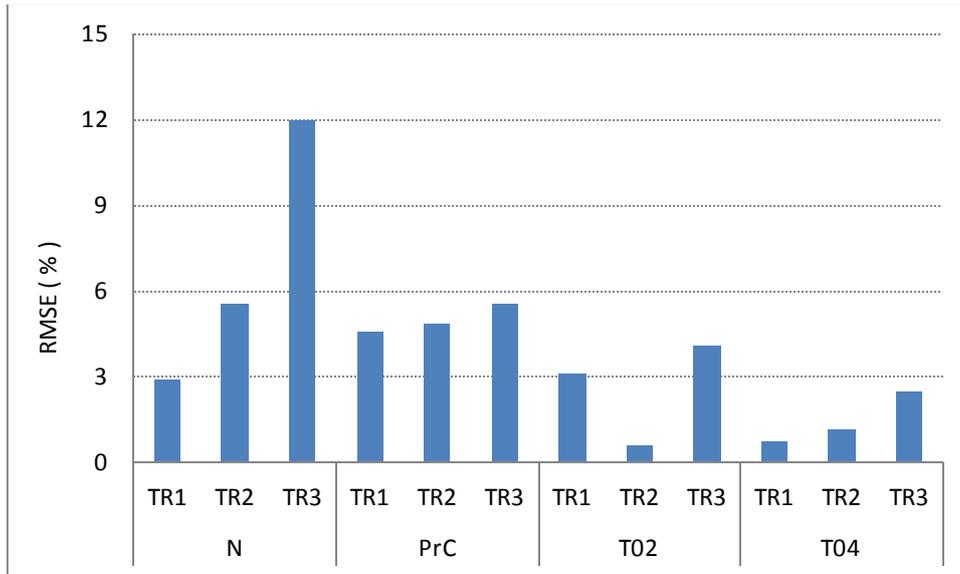
**Figure 6.8:** *RMSE* of the NARX models for the training manoeuvres TR1, TR2 and TR3.

### 6.3.2. NARX Model Validation

For validation, the NARX models were tested against three other available experimental time-series data sets which are indexed as TE1, TE2 and TE3. Figures 6.9 through 6.20 show the results for TE1, TE2, and TE3, respectively. It should be noted that, during the simulation phase, the NARX models are fed with the regressed outputs at time points $y(t-1)$ and $y(t-2)$ estimated by the NARX model itself at antecedent time steps.

It can be seen that, in all cases, the trends of the real system and the NARX models are very similar. This means that the NARX models can follow the changes in GT parameters, even though they are subject to significant changes. In fact, as an example, the rotational speed is varied from 500 rpm to 3000 rpm in approximately six minutes and consequently the compressor pressure ratio increases from about 1 to about 7.

At the same time, the NARX models can also reproduce less significant changes, as, for instance, can be observed in the trends of turbine outlet temperature $T_{04}$. Finally, the stable operation can also be reproduced very satisfactorily, as it can be clearly seen during the last minutes of each transient manoeuvre (in particular, in Figures 6.9-6.12). As it can be seen, there are just two cases with a noticeable deviation of the measured and predicted trends, i.e. the compressor

pressure ration *PRc* for TE2 and TE3 (see Figure 6.14 and Figure 6.18). In any case, as shown below, the overall deviation can still be acceptable. Therefore, it can be concluded that the NARX models reproduced the three testing transients TE1, TE2 and TE3 with a good accuracy. Figure 6.21 summarizes the results in terms of *RMSE* for the testing manoeuvres. Also in this case, to account for the initial delay of the NARX model to work correctly, the values corresponding to the first ten seconds of each data set are not used for *RMSE* calculation.

A different behaviour can be observed for compressor and turbine outlet temperatures, compared to pressure ratio and rotational speed. In fact, *RMSE* values for temperatures are always lower than approximately 3.5%. Otherwise, though the overall trend is reproduced almost correctly, the *RMSE* maximum values of *PRc* and *N* are almost twice (7.4% for *PRc* and 7.1% for *N*). As observed for the training data sets, the *RMSE* values slightly depend on the considered training curve.

In conclusion, the results show that the NARX models have the potential to simulate and predict gas turbine dynamic behaviour. However, Figure 6.12 and Figure 6.21 highlight that general guidelines about the order of magnitude of the errors are difficult to draw, since they may change as a function of the considered manoeuvre and measurable quantity. Moreover, unfortunately, they cannot usually be optimized contemporarily. The results reported here represent a good compromise on the NARX model prediction capability of the four selected output variables.

It has to be considered that the comparison to experimental data was mainly intended to evaluate the agreement of the trends, rather than the numerical values. According to the modelling hypotheses made in this study, the structure of the NARX models was kept as simple as possible, so that only three usually available variables were supplied as inputs. Moreover, the differences in the numerical values can also be attributed to the accuracy of the gas turbine experimental measurement system.
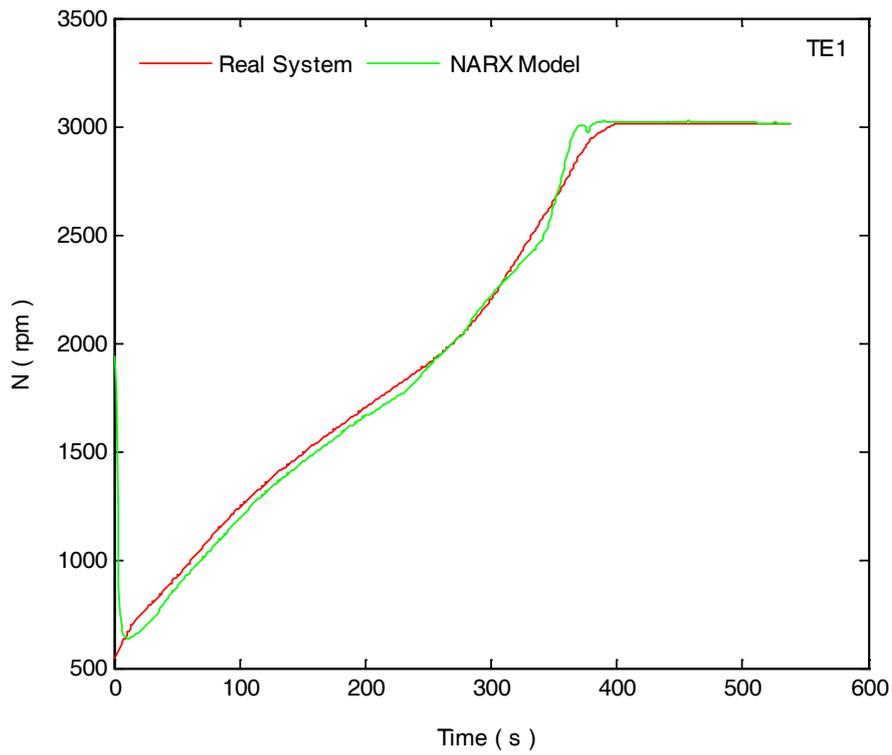
**Figure 6.9:** Variations of rotational speed N for the testing manoeuvre TE1.
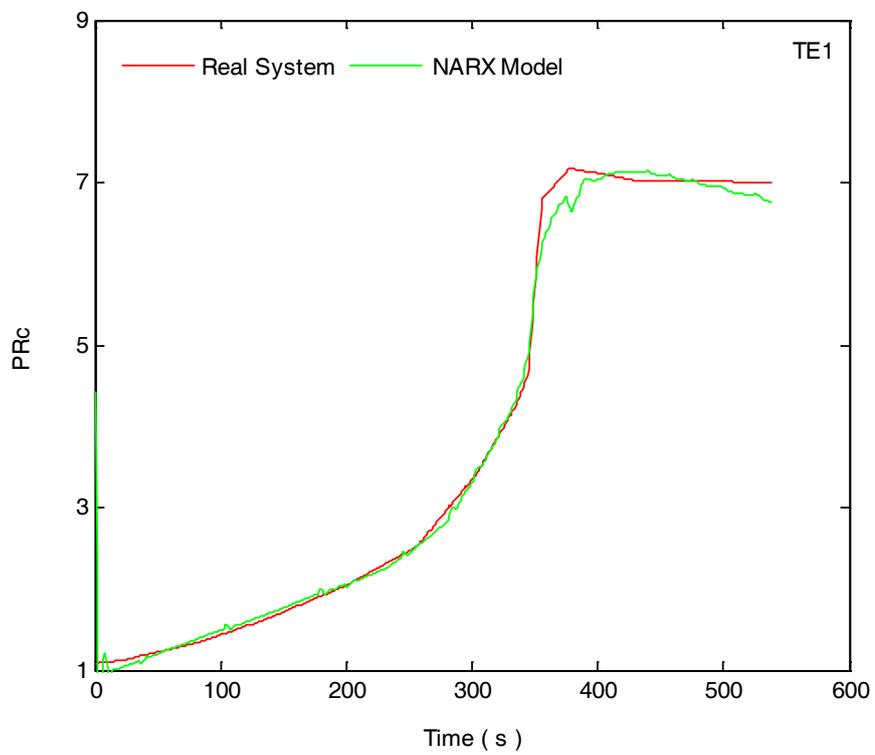


**Figure 6.10:** Variations of compressor pressure ratio PRC for the testing manoeuvre TE1.

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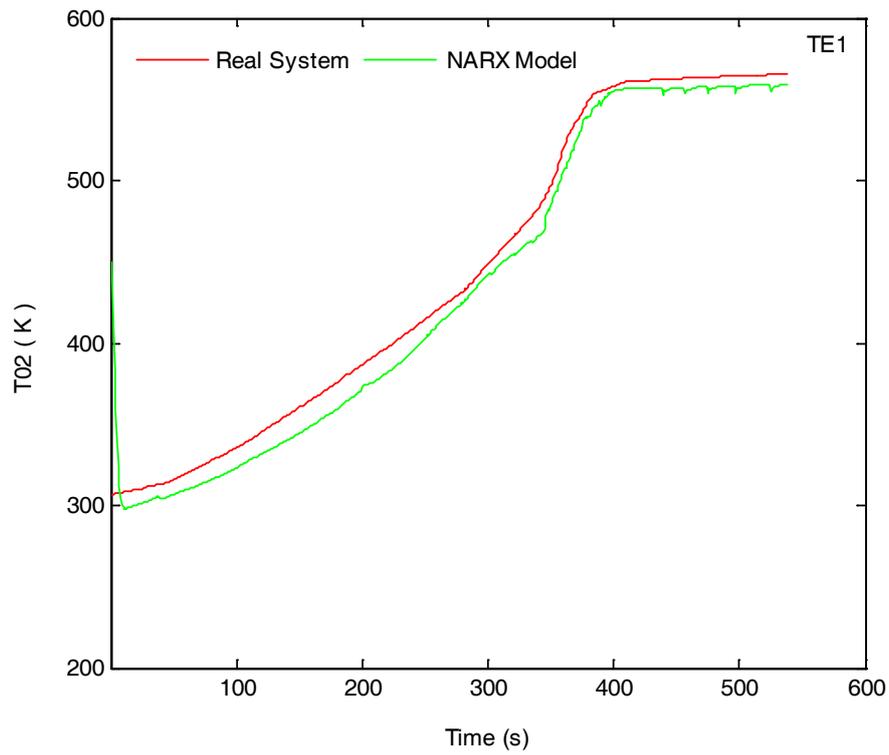
**Figure 6.11:** Variations of compressor outlet temperature T02 for the testing manoeuvre TE1.
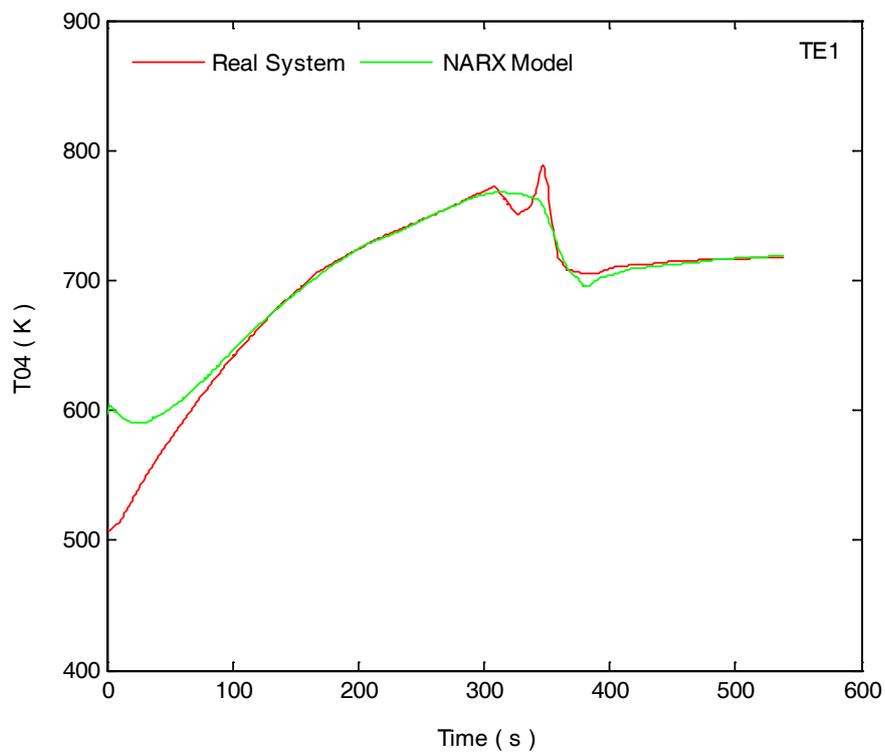


**Figure 6.12:** Variations of turbine outlet temperature T04 for the testing manoeuvre TE1.
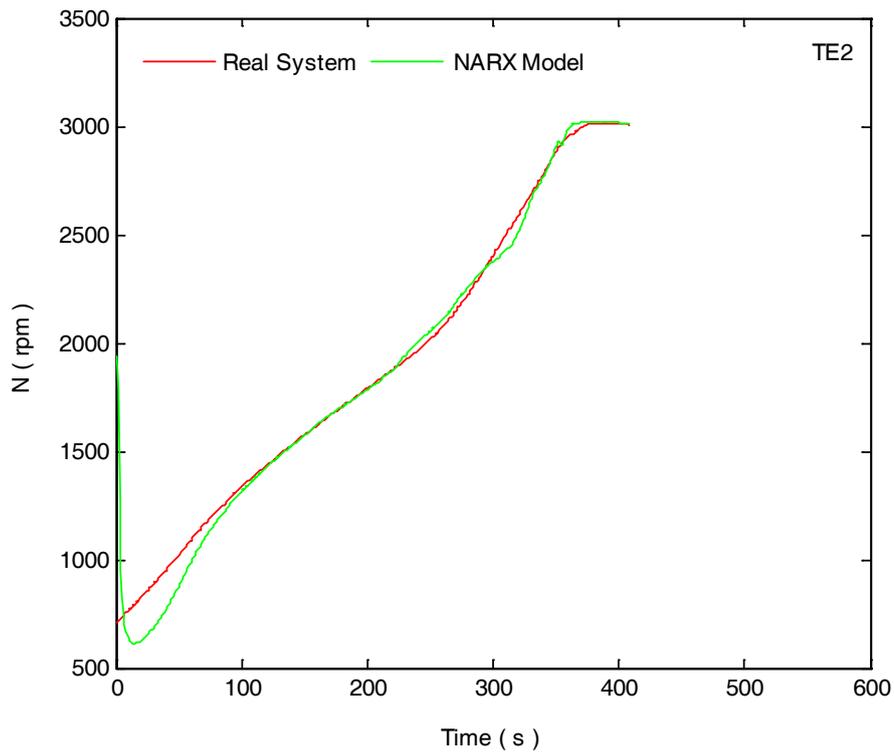
**Figure 6.13:** Variations of rotational speed N for the testing manoeuvre TE2.
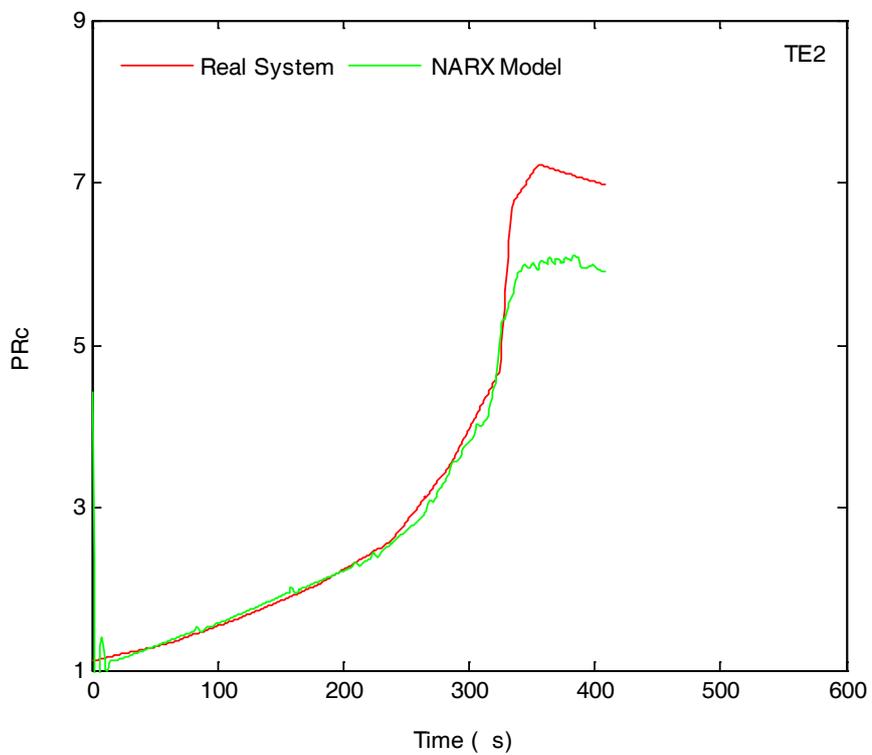


**Figure 6.14:** Variations of compressor pressure ratio PRC for the testing manoeuvre TE2.
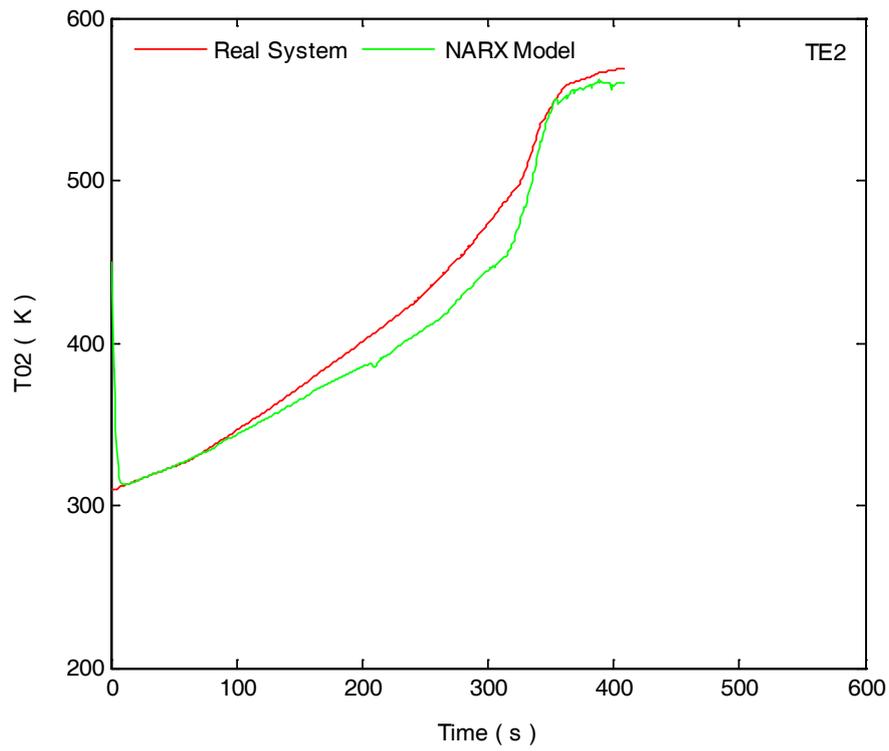
**Figure 6.15:** Variations of compressor outlet temperature T02 for the testing manoeuvre TE2.
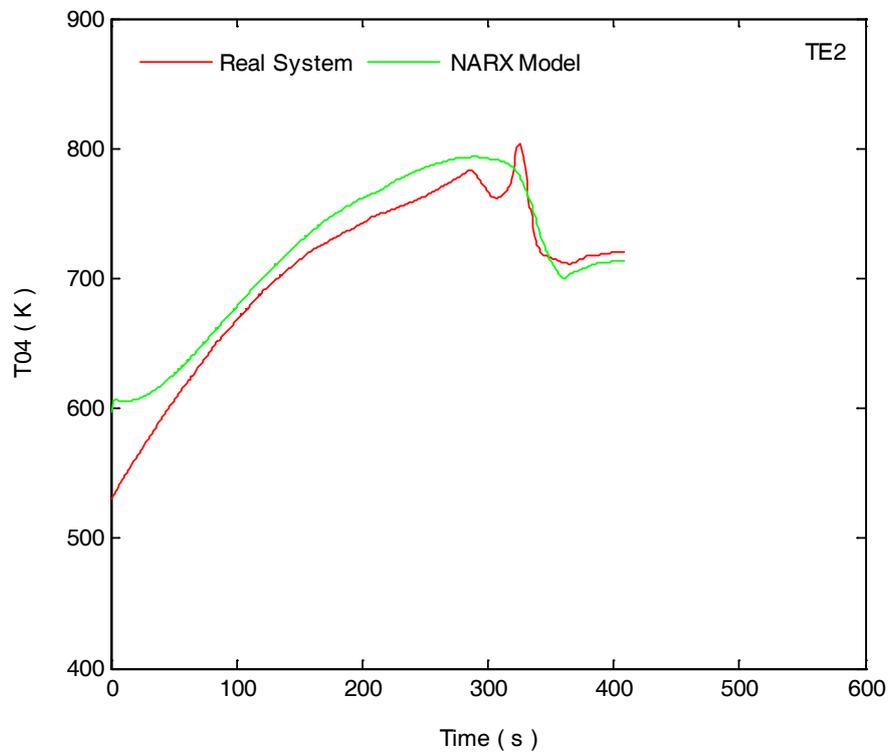


**Figure 6.16:** Variations of turbine outlet temperature T04 for the testing manoeuvre TE2.
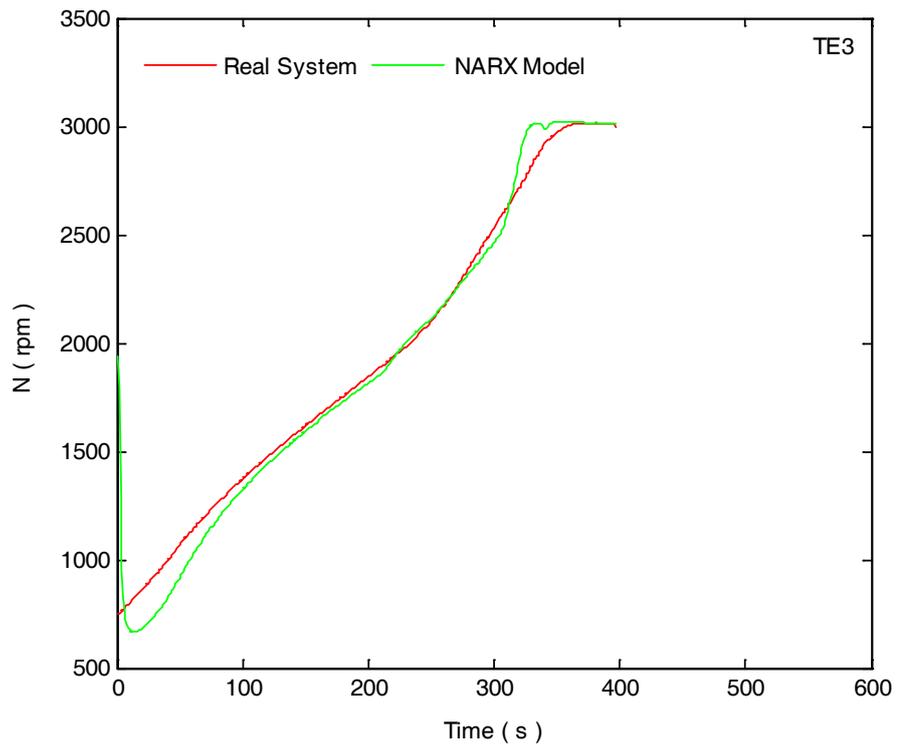
**Figure 6.17:** Variations of rotational speed N for the testing manoeuvre TE3.
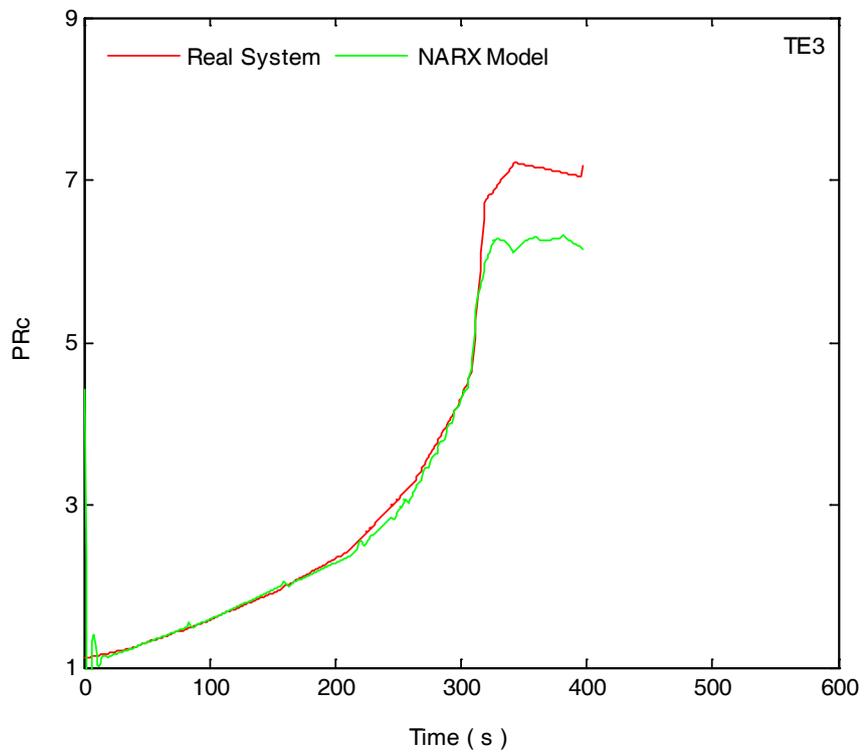


**Figure 6.18:** Variations of compressor pressure ratio PRC for the testing manoeuvre TE3.
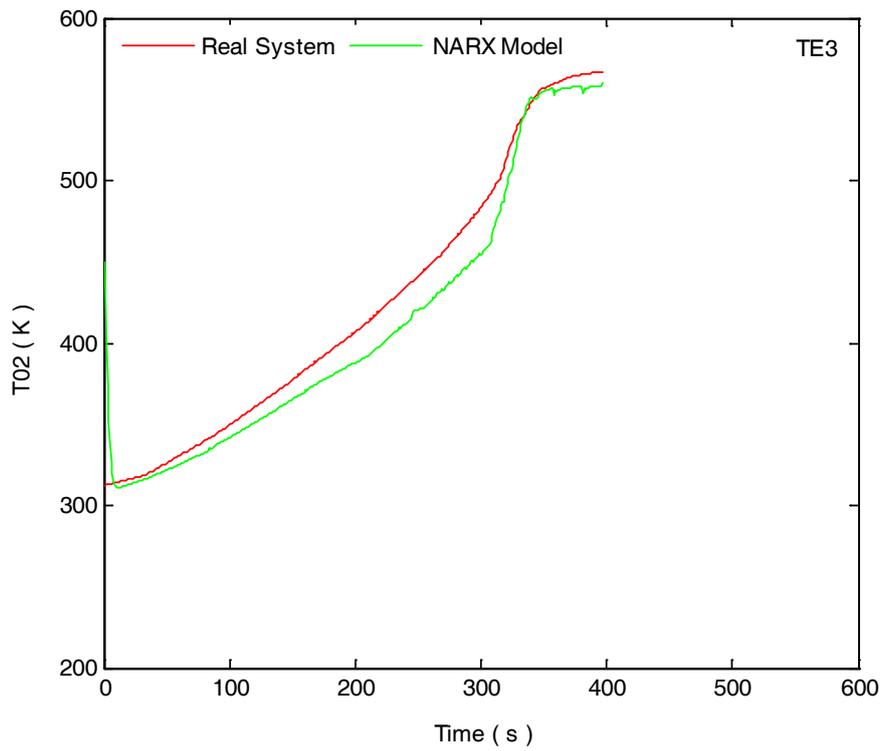
**Figure 6.19:** Variations of compressor outlet temperature T02 for the testing manoeuvre TE3.
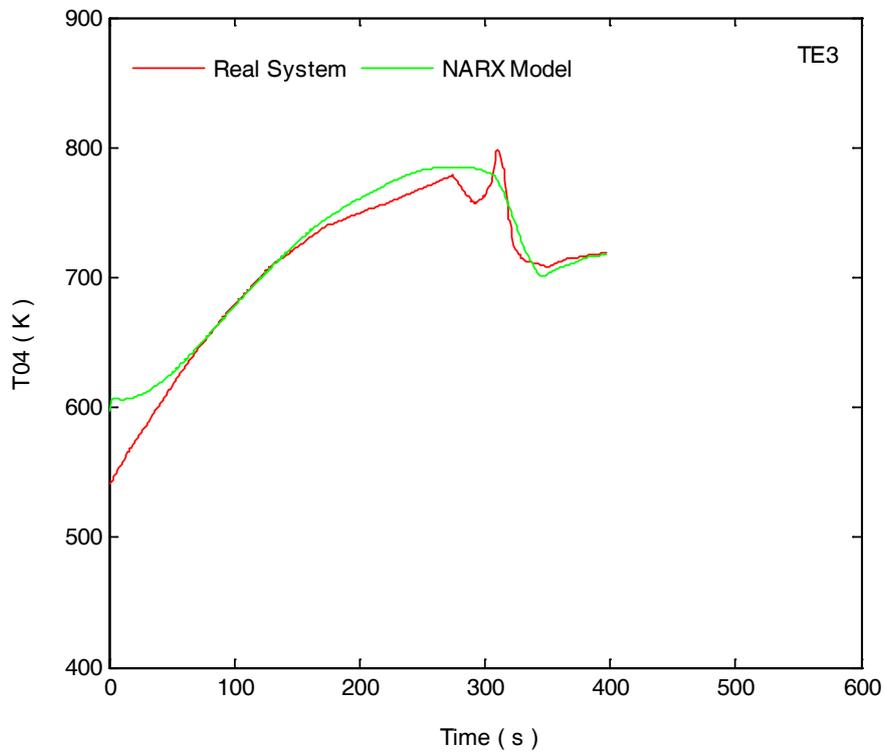


**Figure 6.20:** Variations of turbine outlet temperature T04 for the testing manoeuvre TE3.
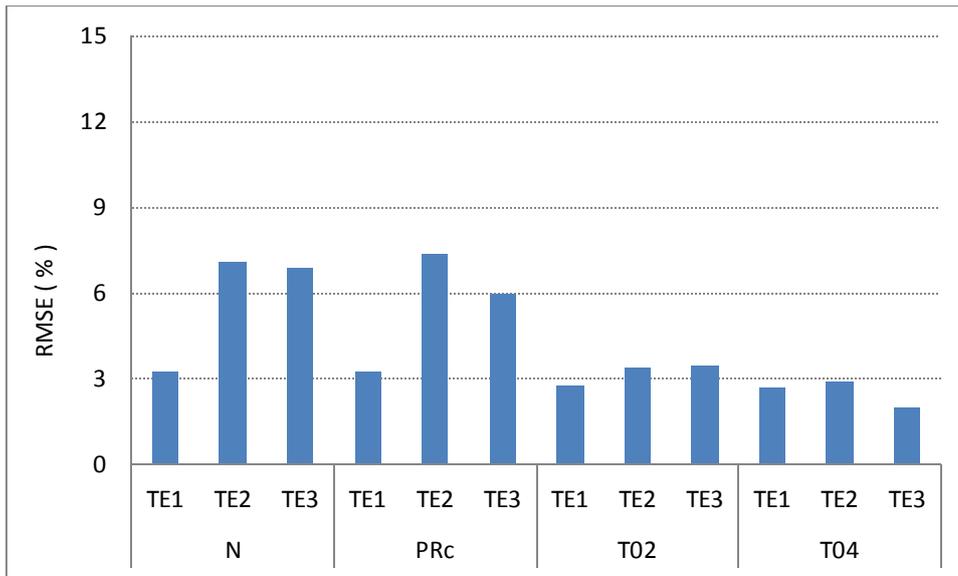
**Figure 6.21:** *RMSE* of the NARX models for the testing manoeuvres TE1, TE2 and TE3.

## 6.4. SUMMARY

In this chapter, the dynamic behaviour of a heavy-duty single-shaft gas turbine during the start-up phase is investigated. For this reason, NARX models of the IPGT were constructed by using three measured time-series data sets. The resulting NARX models were tested against three other available experimental data sets for verification of the models.

For this purpose, four important outputs from the models and their corresponding values from the measured data sets were compared (compressor and turbine outlet temperature, compressor pressure ratio and rotational speed, as a function of compressor inlet temperature and pressure and fuel mass flow rate). According to the results, the NARX models actually have the capability of capturing and predicting GT dynamics during start-up. In most cases, the deviation between measured and simulated values is acceptable (e.g. lower than approximately 3.5% for compressor and turbine outlet temperatures), but it can also increase to non negligible values for compressor pressure ratio and rotational speed (maximum deviations equal to 7.4% and 7.1%, respectively). In general, the physical behaviour is well grasped by the NARX models and the influence of the considered data set is negligible.

One of the strong points of this research is the simplicity of the developed NARX models. It is clear that accurate modelling (e.g. through a physics-based approach) does need much information about the bleed flows and IGV control which are usually unknown as they are confidential manufacturer's data or simply unavailable. For this reason and in order to overcome this lack of information, NARX models were employed as a black-box tool to model the gas turbine for the whole range of start-up operation. The resulting NARX models can reproduce a very complicated and usually difficult-to-model unsteady behaviour and can capture system dynamics with acceptable accuracy. It was shown that neural networks can be considered a reliable alternative to conventional methods in system identification and modelling.

The results of this modelling approach, which uses as inputs only the variables at antecedent time steps (i.e. no information about the current time step is required), allow the set-up of a powerful and easy-to-build simulation tool which may be used for real-time control and sensor diagnostics of gas turbines.

*True creativity often starts where language ends.*

Arthur Koestler
Hungarian-British author and journalist, 1905-1983

# CHAPTER 7
# DESIGN OF NEURAL NETWORK BASED CONTROLLERS FOR GAS TURBINES

Modelling of control systems before their implementation in real plants is an efficient and cost-saving strategy in industrial applications. The need for controllers with high quality standards to reliably manipulate operations in complex industrial systems has been increasing dramatically. These controllers should have the capability of dealing with restrictions on control strategies and internal variables [143]. This necessity has led to development of different kinds of controllers which can be successfully applied to industrial plants. However, because of the nonlinear nature of industrial systems and deviation of control systems from the design objectives, there are still high demands for controllers and control approaches which can incorporate system nonlinearity. Artificial neural networks have a high capability in modelling and control of dynamic systems such as gas turbines.

In this chapter, the structures of a conventional PID controller and ANN-based controllers including MPC and feedback linearization control (NARMA-L2) are briefly described and their related parameters will be set up according to the requirements of the controller design for a single-shaft gas turbine. Finally a comparison is made among the performances of these controllers.

## 7.1. GAS TURBINE CONTROL SYSTEM

The gas turbine system which is used for controller design purposes in this chapter, is a nonlinear dynamic model of a low-power single-shaft gas turbine which was developed and verified for loop-shaping control purposes [28] and was already discussed and simulated in Chapter 4. It is employed for designing of PID and ANN-based controllers in this chapter. Figure 7.1 shows the closed-loop diagram of the control system for the gas turbine engine system. It includes the plant which is the gas turbine system, the controller, random reference and indicator blocks. Fuel mass flow rate and rotational speed are input and output of the plant respectively. The controller could be any of the controller structures including MPC, NARMA-L2, or PID, as will be discussed later in this chapter. They are already implemented in MATLAB software and their parameters need to be tuned according to the control requirements.
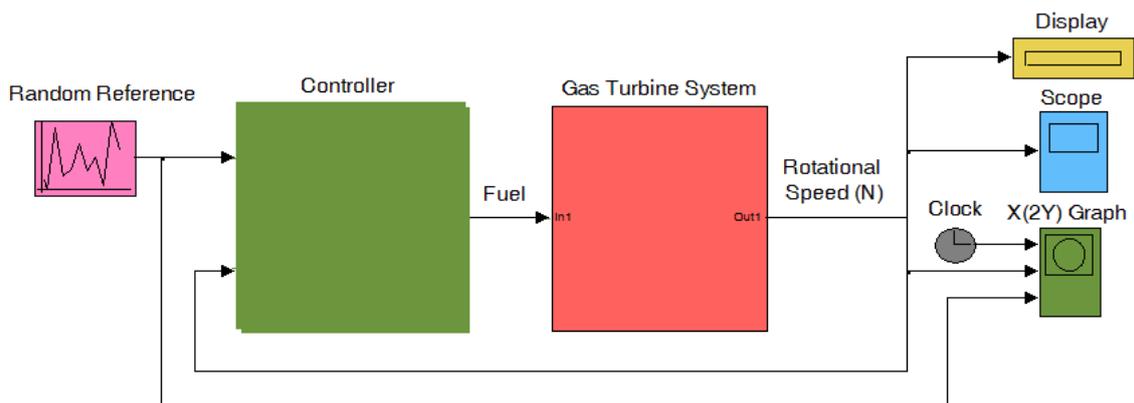


**Figure 7.1:** The closed-loop diagram of the control system for the gas turbine engine system.

Figure 7.2 shows the random reference block diagram with the adjusted values. The aim is to maintain the rotational speed at a constant value of 700 rpm (set point) when the input of the control system changes with the random reference (step function). The random reference is

adjusted between 695 and 705 rpm with a sample time of 0.2 second. It produces random step functions based on the adjusted parameters.
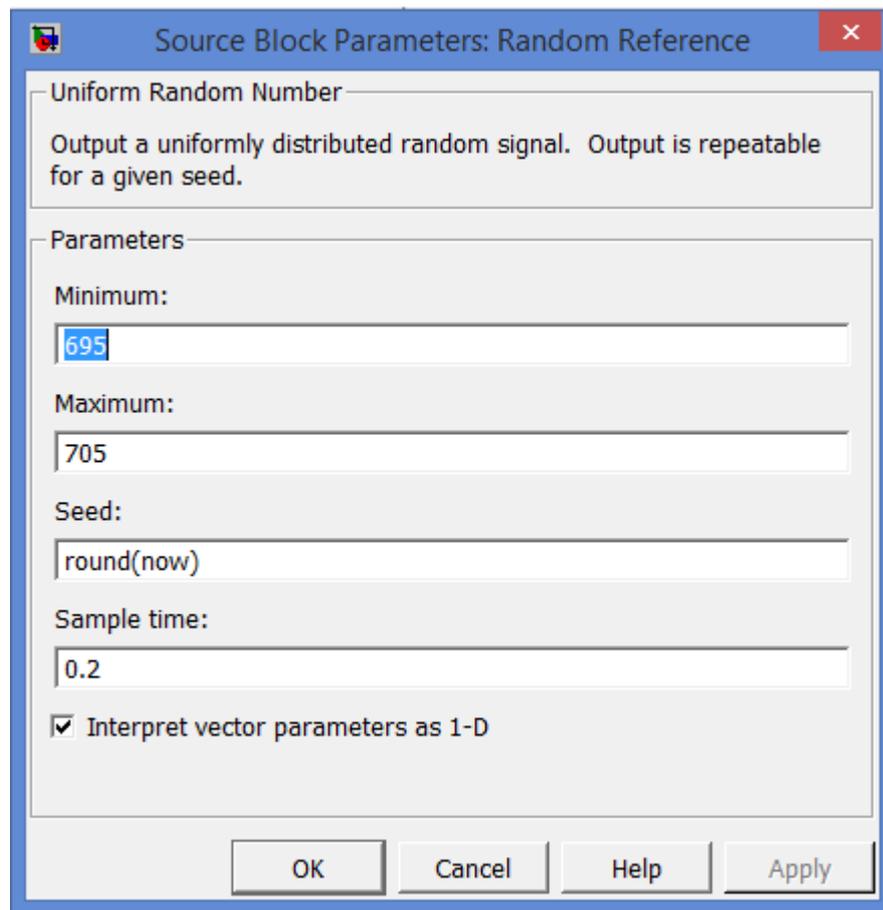


**Figure 7.2:** Random reference block diagram.

The objective of the controller design in this study is to achieve to a satisfactory response (to the reference input) for each of the controllers with the following conditions:

- *Rise time < 0.5 sec.*

- *Settling time < 2 sec.*

- *Maximum overshoot < 15%*

- *Steady-state error < 5%*

Figure 7.3 shows a typical response to a standard test signal (input) which is usually a step function (random reference) with its characteristics including rise time ($T_r$), settling time($T_s$), peak

time ($T_p$), maximum overshoot ($M_p$), and steady-state error ($e_{ss}$). The following provides a short definition of these terms:

- *Rise time:* The time required for the response signal to rise from 10% to 90% of the final value (its set-point value).

- *Settling time:* The time elapsed for the response signal to get and remain within an error band ($\pm 5\%$) of the final value.

- *Peak time:* The time elapsed for the response signal to reach its first maximum value.

- *Maximum overshoot:* The maximum peak value of the response curve measured from the desired response of the system.

- *Steady-state error:* The error that remains after transient conditions disappear in a control system.
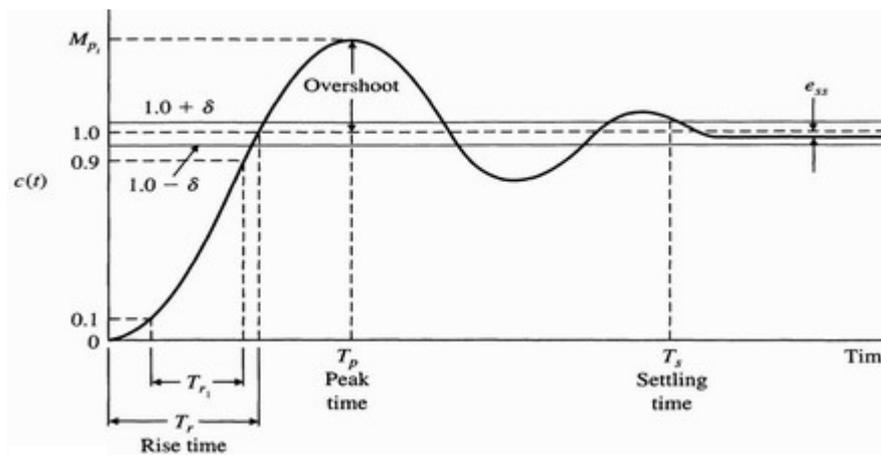


**Figure 7.3:** A typical response to a standard test signal with its characteristics.

## 7.2. MODEL PREDICTIVE CONTROL

Model Predictive Control pioneered by Richalet et al. [138] and Cutler et al. [236], has been widely used in a variety of process plants all around the world. The most important benefits of MPC which has made it successful for industrial applications include capability of handling structural changes, non-minimal phase and unstable processes as well as multi-variable control problems [237]. Besides, MPC have plenty of time for online computations and can take account of actuator limitations. It is an easy to tune method and can operate closer to constraints.

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Figure 7.4 shows a basic structure of MPC [237]. As it can be seen from this figure, the model predicts output of the system based on the future inputs, past inputs, and past outputs. Output is compared to a reference value and the difference (error) goes to the optimizer which determines the future inputs for the model. Optimization process occurs on the base of system constraint(s) and a pre-defined cost function.
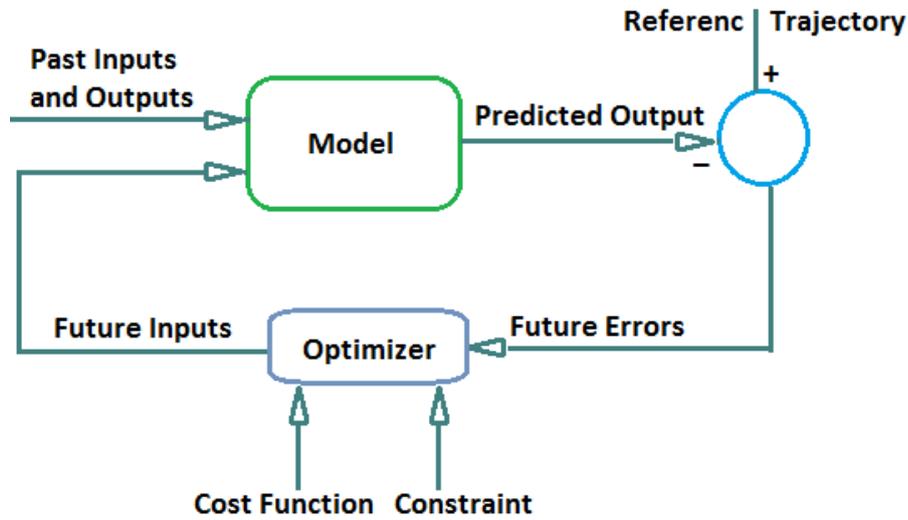


**Figure 7.4:** A basic MPC structure [237].

In an ANN-based MPC, a neural network represents the forward nonlinear dynamics of the plant. It is used to predict future plant performance. The function of controller is to calculate the control input that optimizes plant performance over a specified future time horizon.

The receding horizon technique presented by Soloway et al. [238] is the basis of MPC methodology. According to this methodology, the predictions of the plant response over a specified time horizon, made by the NN model, are employed by a numerical optimization program to determine the control signal that minimizes the following performance criterion over the specified horizon [214]. Equation 7.1 shows the mathematical description of the MPC process.

$$J = \sum_{j=N_1}^{N_2} (y_r(t+j) - y_m(t+j))^2 + \rho \sum_{j=1}^{N_u} (u'(t+j-1) - u'(t+j-2))^2 \qquad (7.1)$$

where $N_1, N_2$ and $N_u$ represents the horizons over which the tracking error and the control increments are evaluated. $u'$, $y_r$, and $y_m$ are the tentative control signal, the desired response, and the network model response. The $\rho$ value determines the contribution that the sum of the squares of the control increments has on the performance index. This process is also illustrated in Figure 7.5 [214]. As this figure shows, the controller, which has been already implemented in Simulink, consists of the NN plant model and the optimization block [214]. The optimization block determines the values of $u'$ that minimize $J$, and then the optimal u is input to the plant [214].
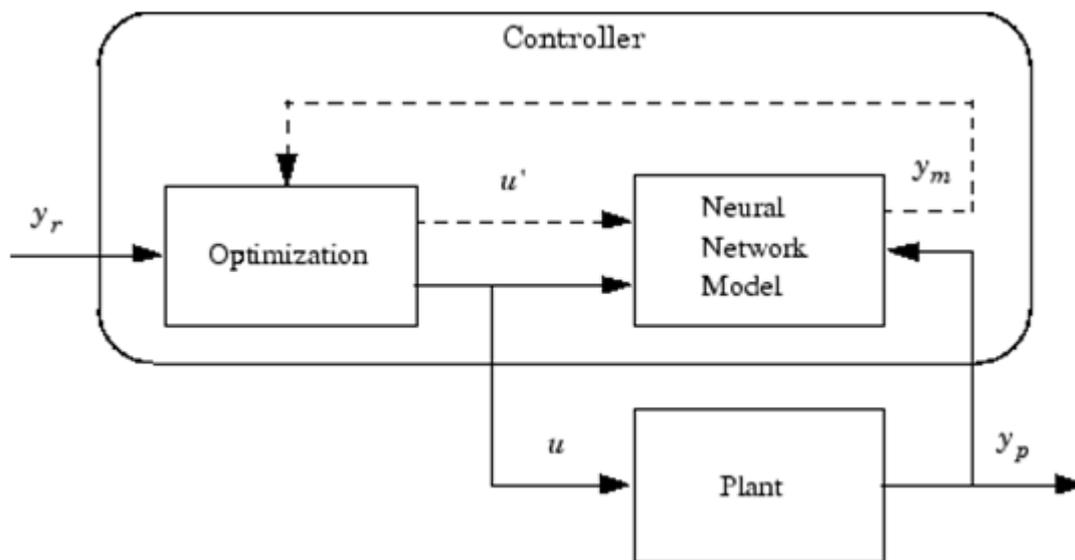


**Figure 7.5:** Neural network based model predictive controller [214].

### 7.2.1. Design of ANN-Based MPC

The first step in MPC design process is to determine the neural network plant model (system identification). Then, the plant model is used by the controller to predict future performance [214]. NN is trained using the NN training signal which is the prediction error between the plant output and the neural network output. Previous plant outputs and previous inputs are employed by the NN plant model to predict future values of the plant output. Figure 7.6 shows the training process flowchart of the NN plant model. This network has been implemented in Neural Network Tool-Box

software of MATLAB and can be trained offline using different training algorithms for the operational data sets obtained from the plant [214].
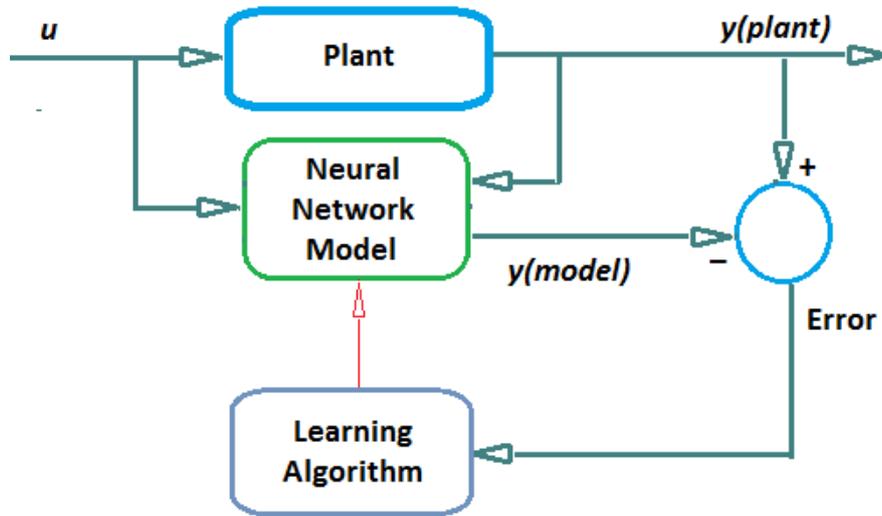


**Figure 7.6:** Training process in an ANN-based MPC [214].

The closed-loop diagram of the control system for the gas turbine engine system with the MPC is similar to Figure 7.1 when the controller block is replaced by the NN predictive controller block shown in Figure 7.7. This block already implemented in Simulink /MATLAB. Design of ANN-based MPC in MATLAB environment includes different steps which will be explained in the following sections.
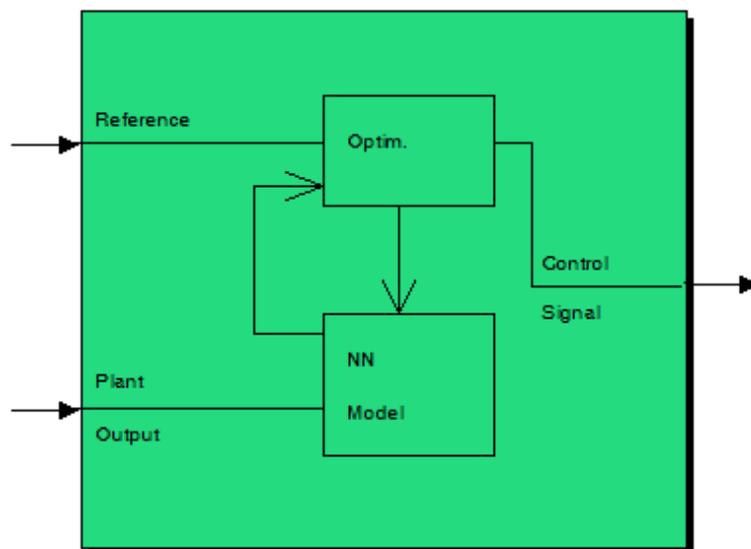


**Figure 7.7:** ANN-Based model predictive control block [214].

Before the controller is designed, system identification process should be completed and the neural network plant model must be developed. The optimization algorithm employs these predictions to determine the control inputs that optimize future performance. Figure 7.8 shows the block diagram of plant identification for CSGT system with all the adjusted parameters for generating data, and training the neural network model of the system.
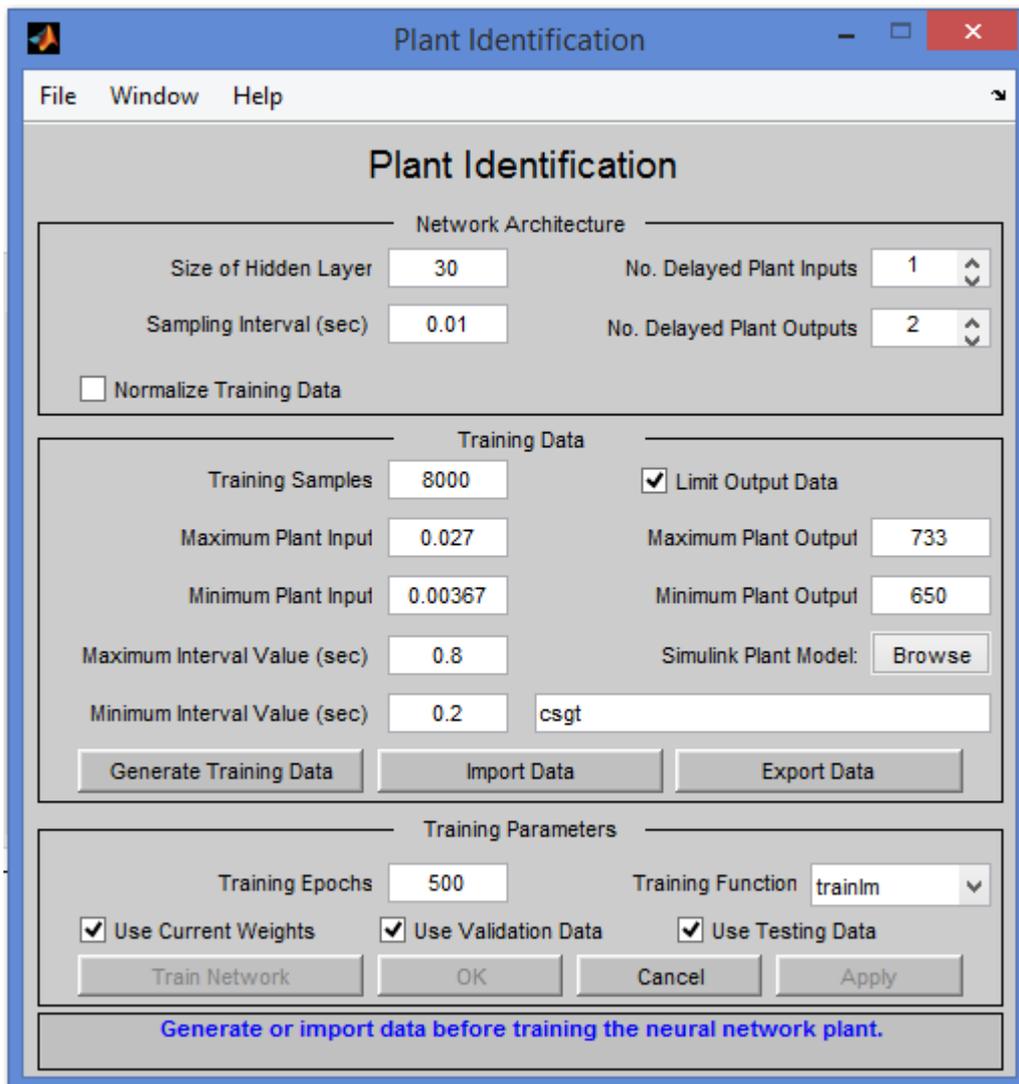


**Figure 7.8:** Gas turbine system identification block diagram for MPC.

As it can be seen from Figure 7.8, minimum and maximum values for the plant input (mass fuel rate) are 0.00367 and 0.027 kg/s. For the plant output (rotational speed), minimum and maximum values are 650 and 733 rpm respectively. Before the neural network training stage, 8000 data sets

for the GT input and output was generated by considering the minimum and maximum interval values as 0.2 and 0.8 seconds respectively. These data were generated using the "Generate Training Data" option. The integrated program can generate training data by applying a series of random step inputs to the Simulink plant model. The size of hidden layer and the number of delayed plant inputs and outputs were adjusted at 30 and 2 seconds respectively. The sampling interval was fixed at 0.02 second. The training proceeds according to the selected training function (*trainlm*). After the training is complete, the response of the resulting plant model is displayed, as it is shown in Figure 7.9. Separate plots for validation data is shown in Figure 7.10. As it can be seen from Figure 7.9 and Figure 7.10, the results of training for neural network model of the GT are satisfactory.
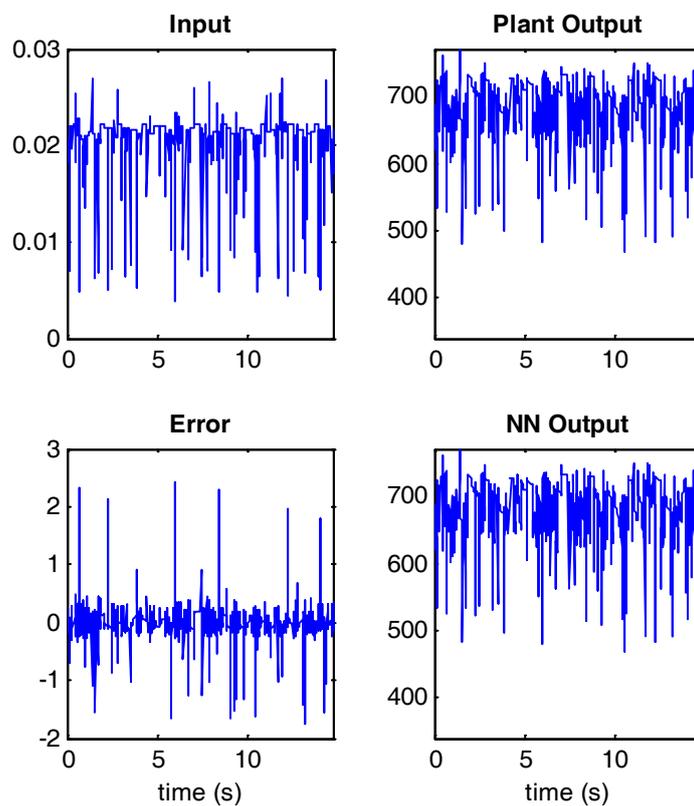


**Figure 7.9:** Training data for neural network predictive control.
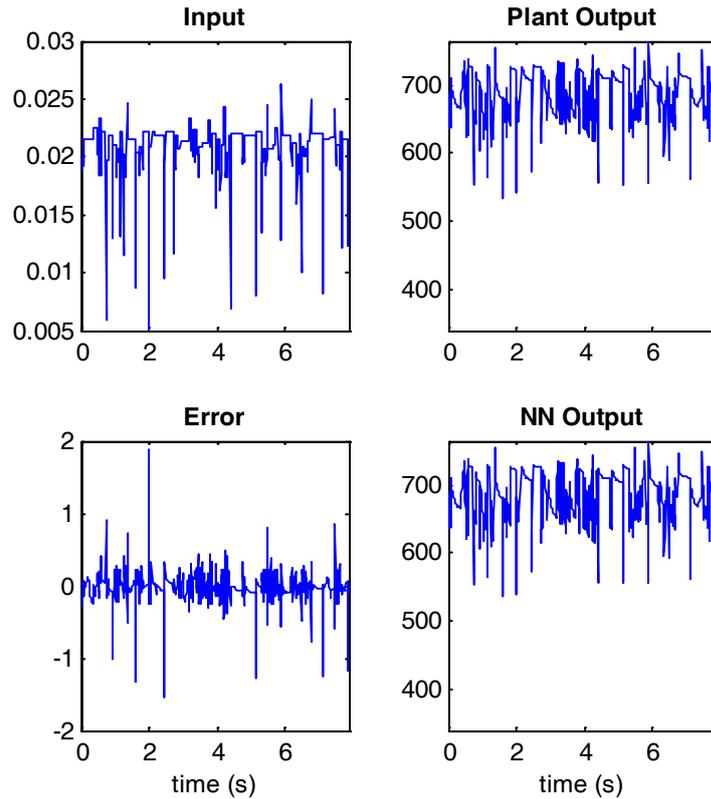
**Figure 7.10:** Validation data for neural network predictive control.

### 7.2.1.2. Adjustment of Controller Parameters for ANN-Based MPC

After the system identification process is completed, the model predictive controller is designed. Figure 7.11 shows neural network predictive control block diagram with its adjusted parameters. In this figure, the controller horizons $N_2$ and $N_u$ have been tuned at 7 and 2 respectively. $N_1$ is fixed at the value 1 by default. The weighting factor $\rho$ and the search parameter $\alpha$ have been adjusted at 0.05 and 0.01 respectively. The task of parameter $\alpha$ is to control the optimization by specifying how much reduction in performance is required for a successful optimization step. The number of iterations of the optimization algorithm at each sample time has been tuned at 2 seconds. Besides, different linear minimization routines can be used by the optimization algorithm. *csrchbac* is the best selected minimization routine for this design.
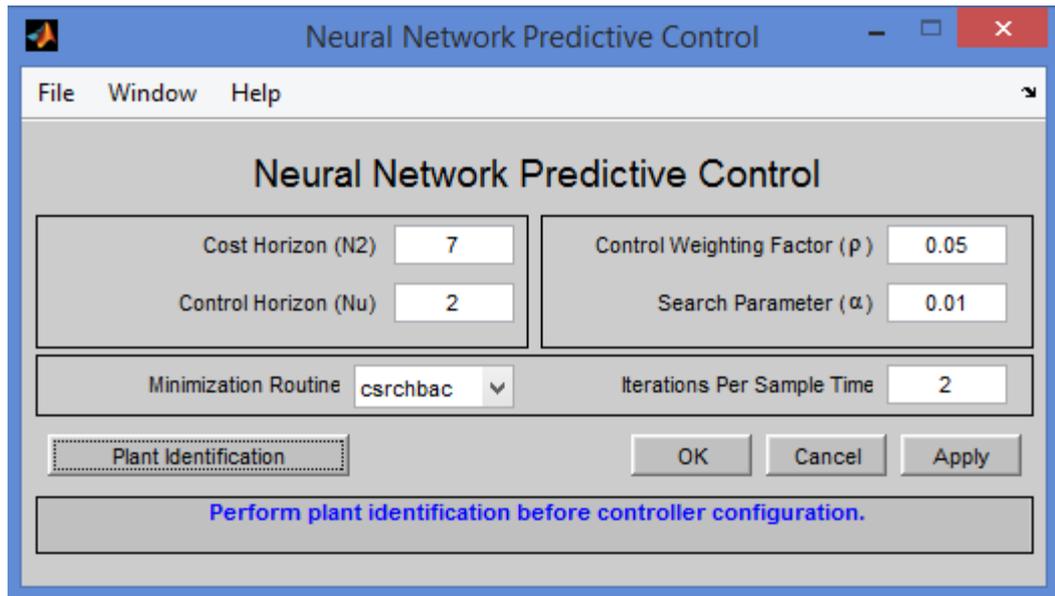
**Figure 7.11:** Neural network predictive control block diagram.

## 7.2.2. Simulation of ANN-Based MPC

Simulation is the last stage of ANN-based control design after adjustment of the controller parameters. Now the closed-loop control system shown in Figure 7.1can be run to simulate the whole system. The result of simulation is shown in Figure 7.12.
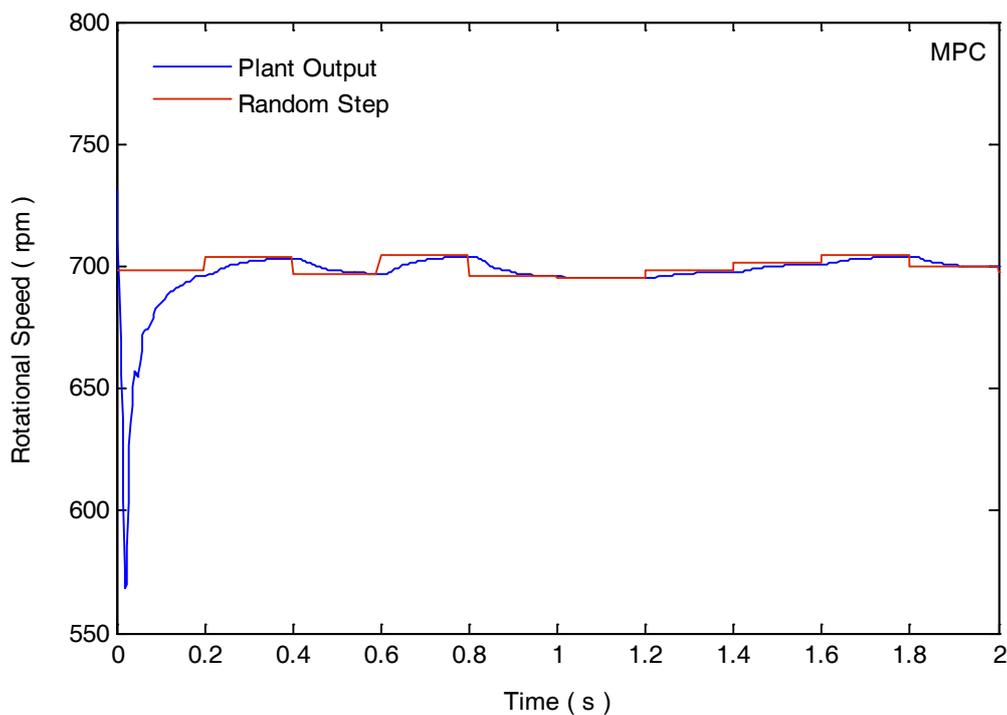


**Figure 7.12:** Response of gas turbine system with MPC to random step inputs.

## 7.3. FEEDBACK LINEARIZATION CONTROL (NARMA-L2)

The nonlinear autoregressive moving average (NARMA) model is a standard model that is employed to represent general discrete-time nonlinear systems. The NARMA model represents input-output behaviour of finite-dimensional nonlinear discrete-time dynamical systems in a neighbourhood of the equilibrium state [239]. However, it is not suggested for adaptive control purposes using neural networks because of its nonlinear dependence on the control input [239]. Equation 7.2 indicates the mathematical description of the NARMA.

$$y(k + d) = Nf[y(k), y(k - 1), \ldots y(k - n + 1), \ u(k), u(k - 1), \ldots u(k - n + 1)] \quad (7.2)$$

where $u(k)$ is the system input, and y(k) is the system output. A neural network is needed to be trained to approximate the nonlinear function $Nf$ for the system identification stage. Because the NARMA model described by equation 7.2 is slow, an approximate model is used to represent the system. This model which is called NARMA-L2 can be described mathematically according to Equation 7.3, where $d \geq 2$.

$$y(k + d) = Nf[y(k), y(k - 1), \ldots y(k - n + 1), \ u(k), u(k - 1), \ldots u(k - n + 1)] +$$
$$g[y(k), \ldots y(k - n + 1), \ u(k), \ldots u(k - n + 1)].u(k + 1) \quad (7.3)$$

The corresponding controller for NARMA-L2 model is mathematically defined according to Equation 7.4, which is realizable for $d \geq 2$. Figure 7.13 shows a block diagram of NARMA-L2 controller with approximation functions $f$ and $g$, and the time delays $TDL$, all implemented in the NARMA-L2 control block. Controller is a multi-layer neural network that has been successfully applied in the identification and control of dynamic systems [214]. The main idea behind the NARMA-L2 is transforming nonlinear system dynamics into linear dynamics. It is a rearrangement of the NN plant model which is trained offline.

$$u(k + 1) = \frac{y_r(k + d) - f[y(k), \ldots y(k - n + 1), u(k), \ldots u(k - n + 1)]}{g[y(k), \ldots y(k - n + 1), u(k), \ldots u(k - n + 1)]} \quad (7.4)$$
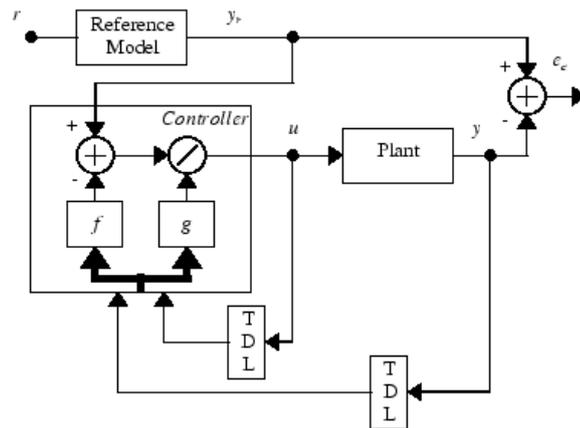
**Figure 7.13:** A block diagram of NARMA-L2 controller [214].

### 7.3.1. Design of NARMA-L2

NARMA-L2 controller block has been already implemented in Simulink-MATLAB. There are two main steps in using NARMA-L2 including system identification and control design. In system identification stage, a neural network model of the plant is developed. This stage that includes the block diagram representation of the system identification and the training process is similar to system identification of MPC that was already described in this chapter. The closed-loop diagram of the control system for the gas turbine engine system with the NARMA-L2 controller is also similar to Figure 7.1, when the controller block in this figure is replaced by NARMA-L2 controller block which is shown in Figure 7.14.
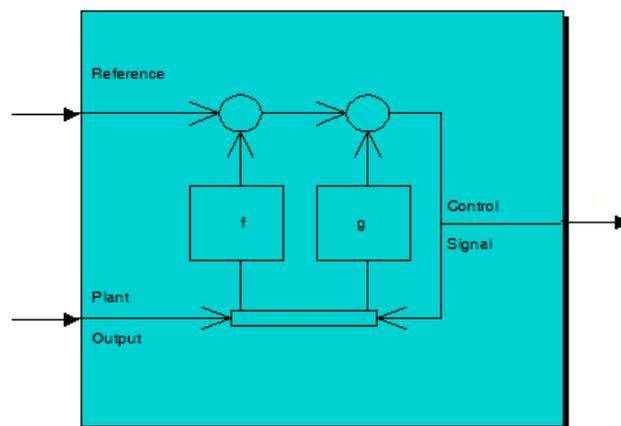


**Figure 7.14:** NARMA-L2 control block [214].

Figure 7.15 shows the block diagram of plant identification for the gas turbine control system (CSGT) which uses the NARMA controller with all the adjusted parameters for generating data, and training the neural network model of the system.
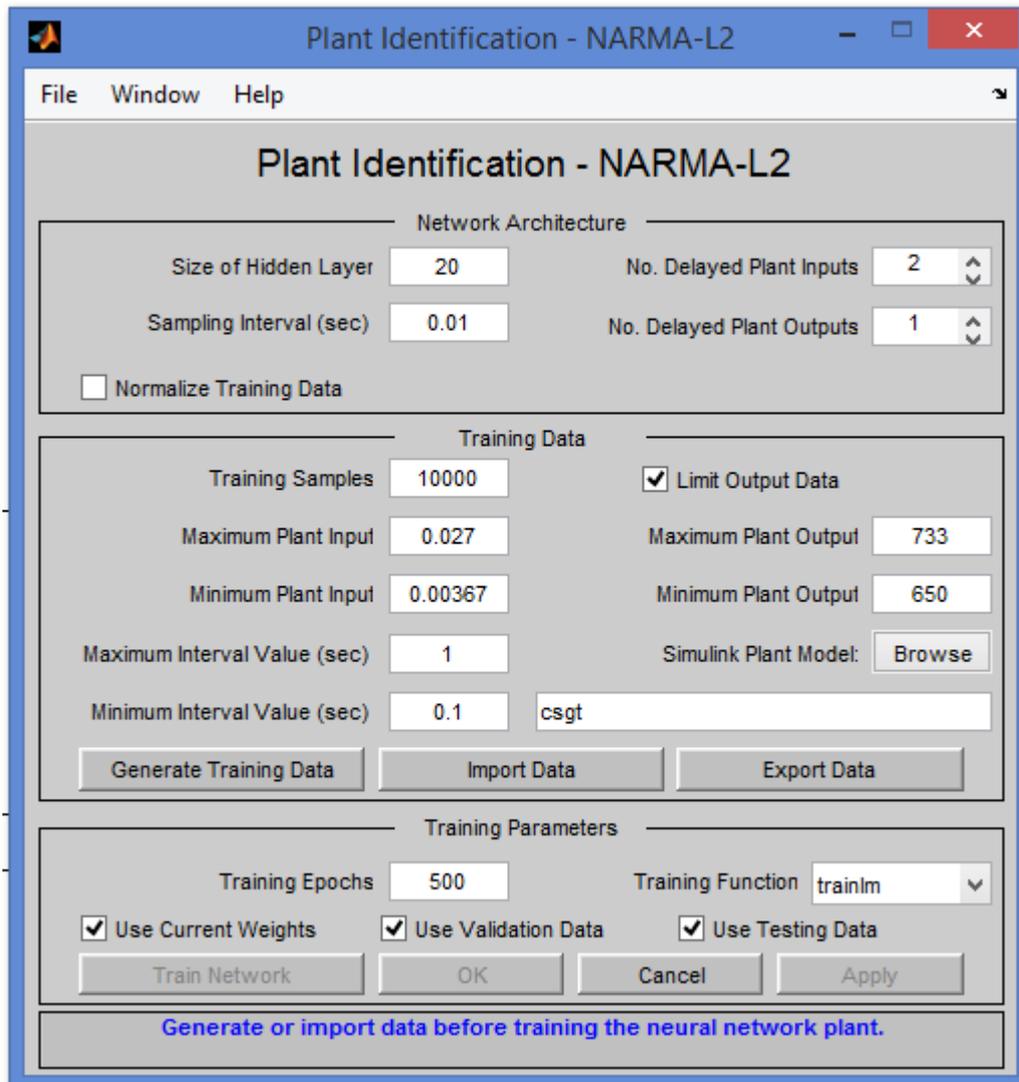


**Figure 7.15:** Gas turbine system identification block diagram for NARMA-L2.

As it can be seen from this figure, minimum and maximum values for the plant input (fuel mass flow rate) are 0.00367 and 0.027 kg/s. For the plant output (rotational speed), minimum and maximum values are 650 and 733 rpm respectively. Before the neural network training stage was performed, 10000 data sets for the GT input and output was generated by considering the minimum and maximum interval values as 0.1 and 1 seconds. These data were generated using the option

*Generate Training Data.* The integrated program can generate training data by applying a series of random step inputs to the Simulink model of the plant. The size of the hidden layer and the number of delayed plant inputs and outputs were adjusted at 20, 2, and 1 respectively. The sampling interval was fixed on 0.01 second. The training proceeded according to the selected training function (*trainlm*). After the training was completed, the response of the resulting plant model was displayed, as in Figure 7.17. Separate plots for validation data is shown in Figure 7.18. As it can be seen from Figure 7.17 and Figure 7.18, the results of training for neural network model of the GT are satisfactory.

### 7.3.2. Simulation of NARMA-L2

Simulation is the last stage of NARMA controller design. At this stage, the closed-loop control system can be run to simulate the whole system. The result of simulation is shown in Figure 7.16. The result shows that NARMA-L2 controller can accurately follows the value and trend of changes in the system input. Besides, the reaction of the controller to the changes is very fast.
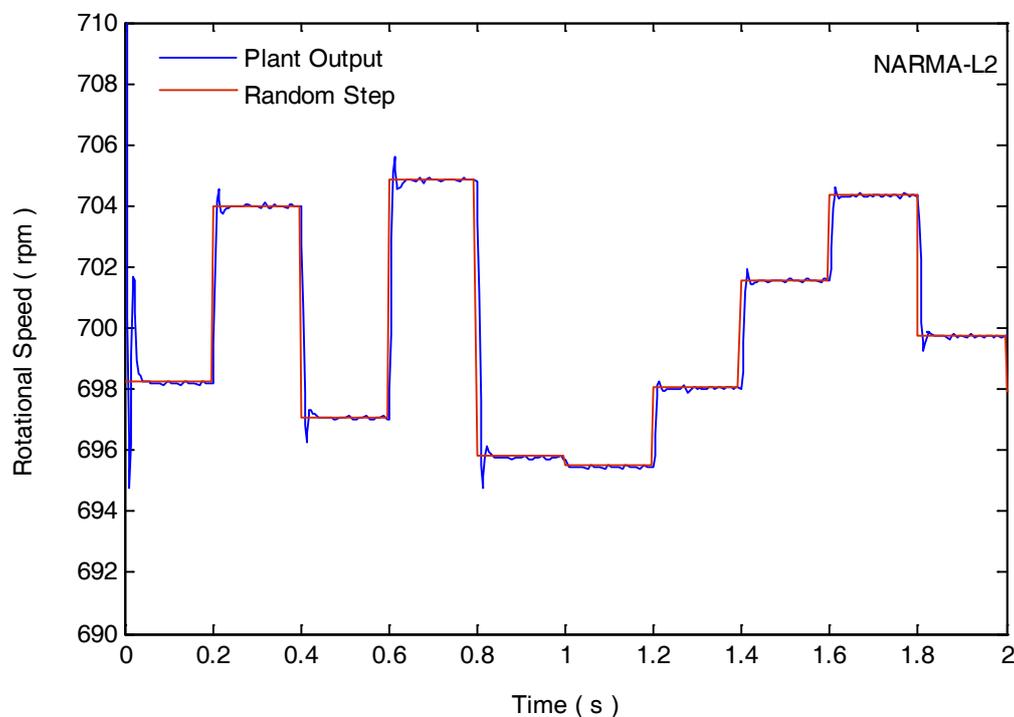


**Figure 7.16:** Response of gas turbine system with NARMA-L2 controller to random step inputs.
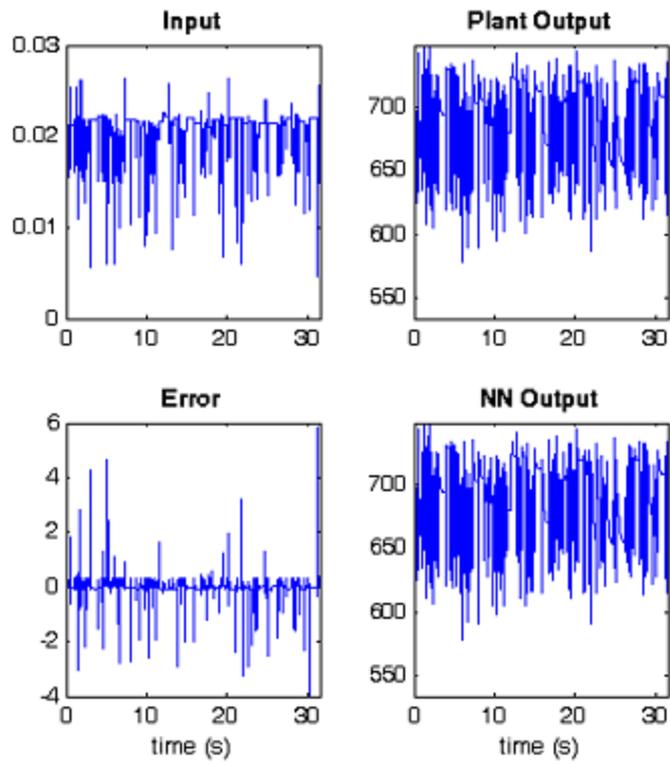
**Figure 7.17:** Training data for NARMA-L2 controller.
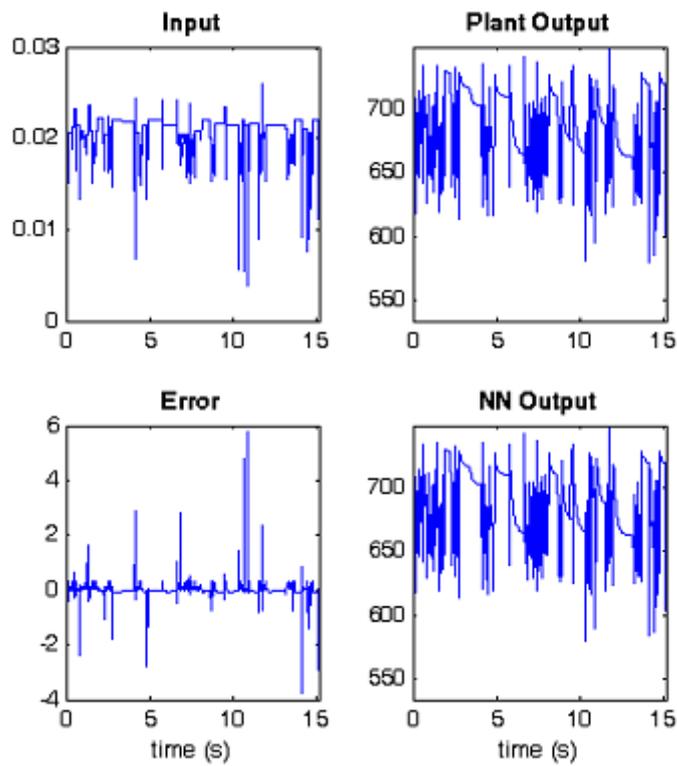


**Figure 7.18:** Validation data for NARMA-L2 controller.

## 7.4. PID CONTROL

A proportional-integral-derivative (PID) controller was firstly introduced to industry in 1939 and has remained the most widely used controller in industrial control systems until today [240]. PID is a generic feedback control system that acts on the basis of difference between values of a measured process variable and a desired set point. The controller objective is to minimize this difference, which is called error, by adjusting the process control inputs. The PID controller includes the proportional ($P$), the integral ($I$) and the derivative ($D$) values that can be interpreted in terms of time. $P$, $I$, and $D$ respectively depend on the present error, accumulation of past errors, and prediction of future errors [240]. By tuning these three parameters, the controller can provide the required control action designed for a specific process. Based on the application, It is also usual to use just PI, PD, P or I controllers. The popularity of PID controllers is specifically because of their flexibility for giving the designer a larger number of design options on the basis of the system dynamics. The PID algorithm is described by Equation 7.5.

$$u(t) = K\left(e(t) + \frac{1}{T_i}\int_0^t e(\tau)\,d(\tau) + T_d\frac{de(t)}{d(t)}\right) \tag{7.5}$$

where $y$ is the measured process variable, $r$ is the reference variable, $u$ is the control signal and $e$ is the control error. The controller parameters are proportional gain $K$, integral time $T_i$, and derivative time $T_d$. The control signal is thus a sum of three terms including $P$, $I$ and $D$. The reference variable is often called the set point [241]. Figure 7.19 shows the block diagram of a PID controller operating in an in-series path with the plant, as it is used in this study [242].
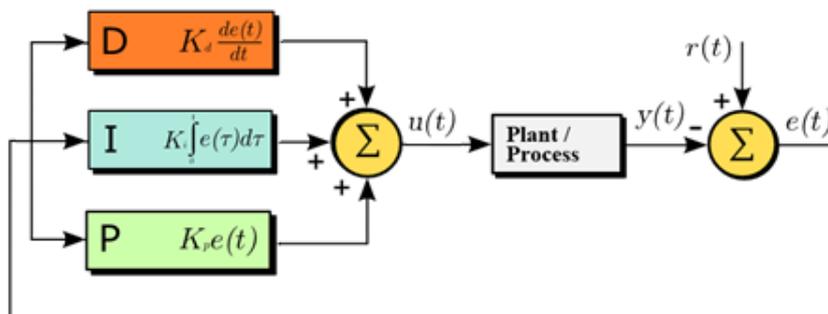


**Figure 7.19:** Block diagram of a PID controller in an in-series path with the plant [242].

### 7.4.1. Design of PID Controller

   PID controller block has been implemented in the Simulink-MATLAB and its gains are tuneable either manually or automatically according to the PID tuning algorithm in MATLAB. The closed-loop diagram of the control system for the gas turbine engine system with the PID controller is also similar to Figure 7.1, when the controller block is replaced by PID controller block which is shown in Figure 7.20.
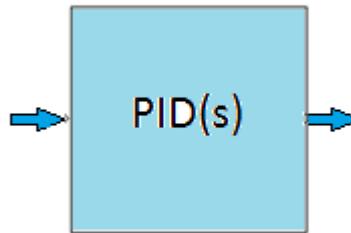


**Figure 7.20:** PID control block in MATLAB [214].

   The objective of tuning the PID gains is to achieve a good balance between performance and robustness, while keeping the closed-loop stability. Therefore, the tuning is performed in a way that the closed-loop system tracks reference changes, suppresses disturbances as rapidly as possible, and its output remains bounded for bounded input. Besides, the loop design should have enough gain margin and phase margin to allow for modelling errors or variations in system dynamics. According to the algorithm, at the first stage of the tuning, an initial controller is designed by choosing a bandwidth to achieve the balance between performance and robustness based upon the open-loop frequency response of the linearized model. When the response time, bandwidth, or phase margin is interactively changed using the PID tuner interface, the new PID gains are computed by the algorithm. This process continues until the desirable PID controller is achieved [214]. According to the algorithm, Equation 7.5 can be rewritten as follows:

$$u = P + I\ \frac{1}{s} + D\ \frac{N}{1+N\frac{1}{s}} \tag{7.6}$$

where P, I and D are proportional, integral and derivative gaing respectively. N is filter

coefficient. Table 7.1 shows the values of the tuned PID gains. Figure 7.21 shows the PID control algorithm block with the tuned PID gains for the gas turbine engine system.

**Table 7.1:** Tuned PID gains for the gas turbine engine.

| PID element | Tuned gain value |
|---|---|
| P | 1.085496262366938e-04 |
| I | 0.008414700379816 |
| D | 1.023227413576635e-07 |
| N | 2.173913000000000e+02 |
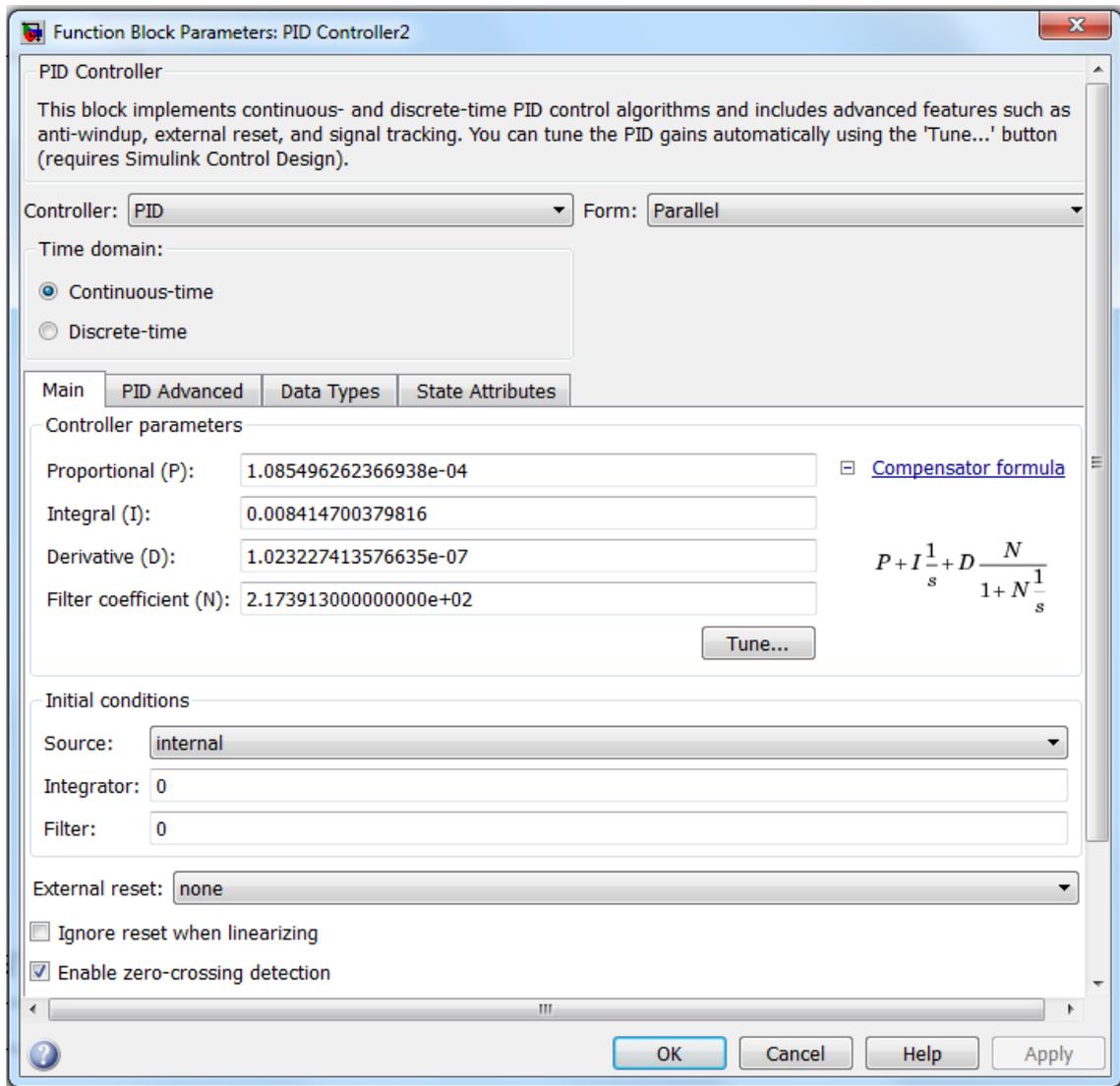


**Figure 7.21:** PID control algorithm block for tuning PID gains.

### 7.4.2. Simulation of PID Controller

After the completion of PID controller design, the closed-loop control system can be run to simulate the whole system. The result of simulation is shown in Figure 7.22. As it can be seen from this figure, the response of the controller to the changes of the system input is fast, and after about 0.2 second, it is stabilized and followed the value and trend of the changes.
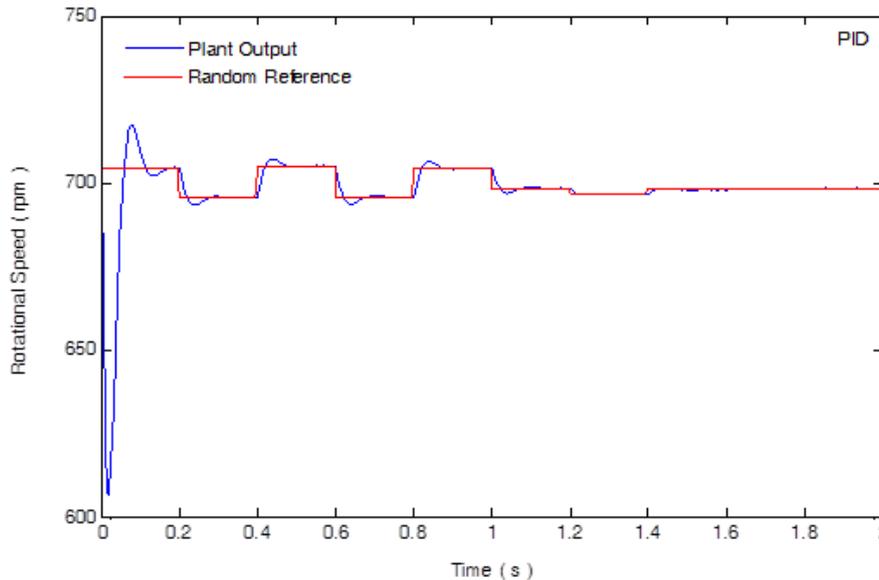


**Figure 7.22:** Response of gas turbine system with PID controller to random step inputs.

## 7.5. COMPARISON OF CONTROLLERS PERFORMANCE

To compare the results of performances for all three designed controllers, they were run in a common Simulink environment with the same input for their control systems. Figure 7.23 shows the resulting Simulink model including the designed ANN-based model predictive controller (MPC), feedback linearization controller (NARMA-L2), and conventional PID controller. Specifications of the random reference (step function) and the gas turbine system for all controllers are the same as already discussed in this chapter. The simulation was run for two seconds which was enough time for capturing the complete dynamics of all three controllers. Figure 7.24 shows the performances of the controllers. Figure 7.25 and Figure 7.26 show the same performances from closer perspectives to the set point of rotational speed (700 rpm) and the initial response respectively.

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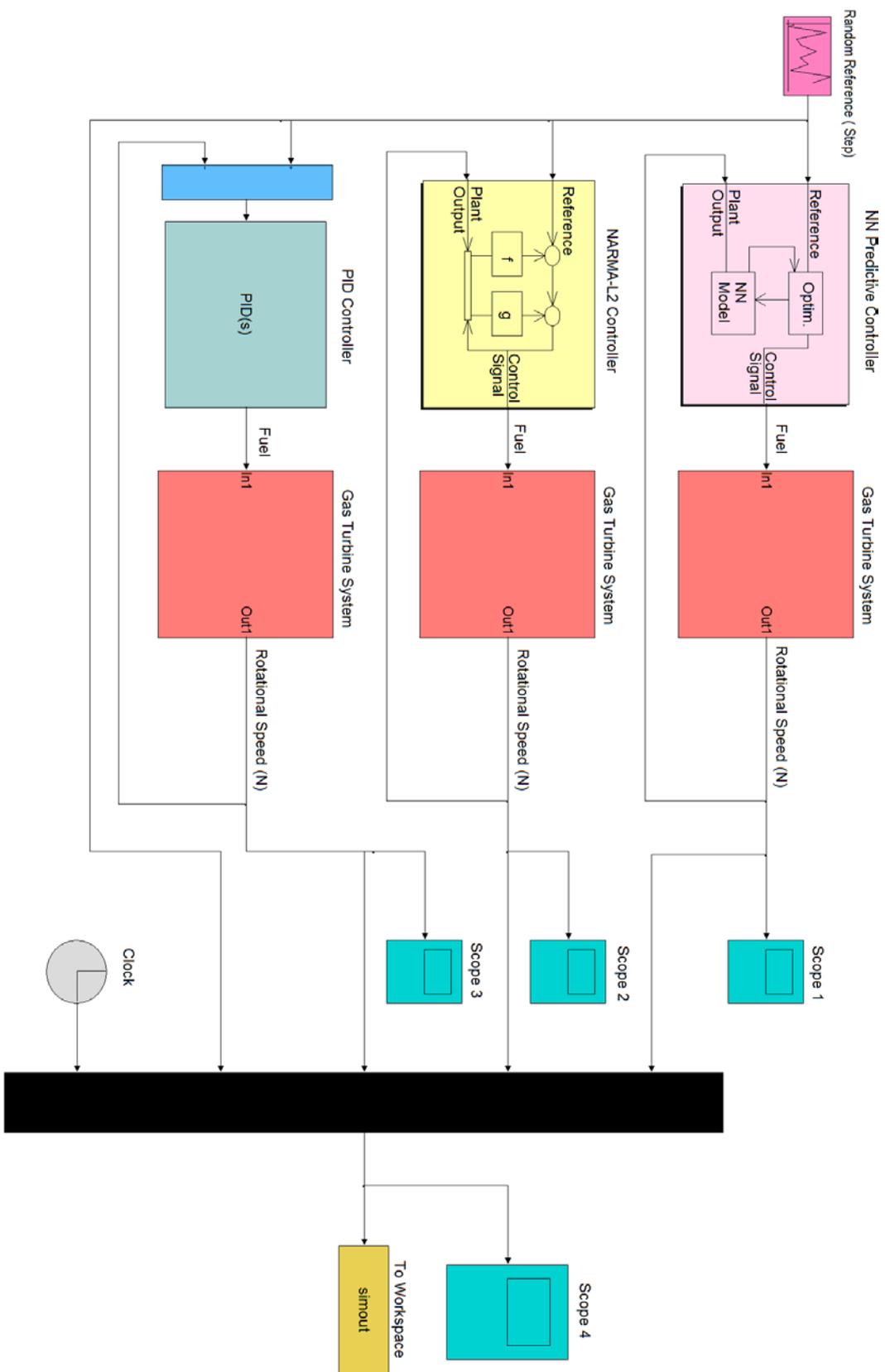
**Figure 7.23:** Simulink model of the ANN-based MPC , NARMA-L2 and PID controllers for a single-shaft gas turbine.
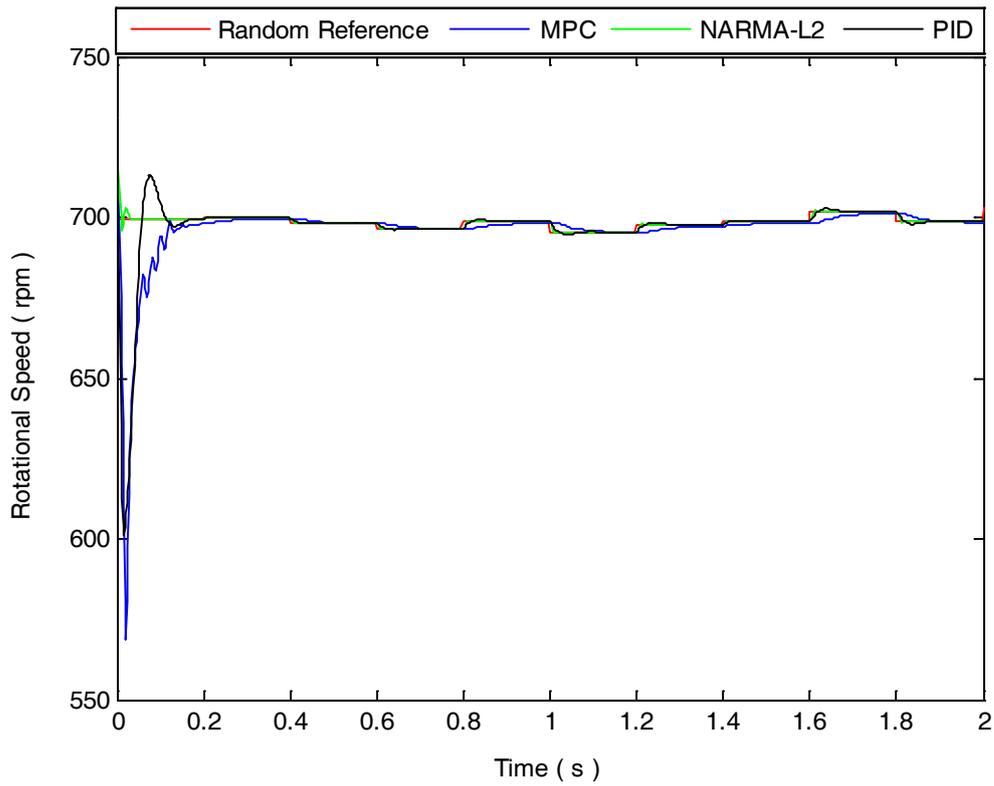
**Figure 7.24:** Performances of three different controllers for a single-shaft gas turbine.
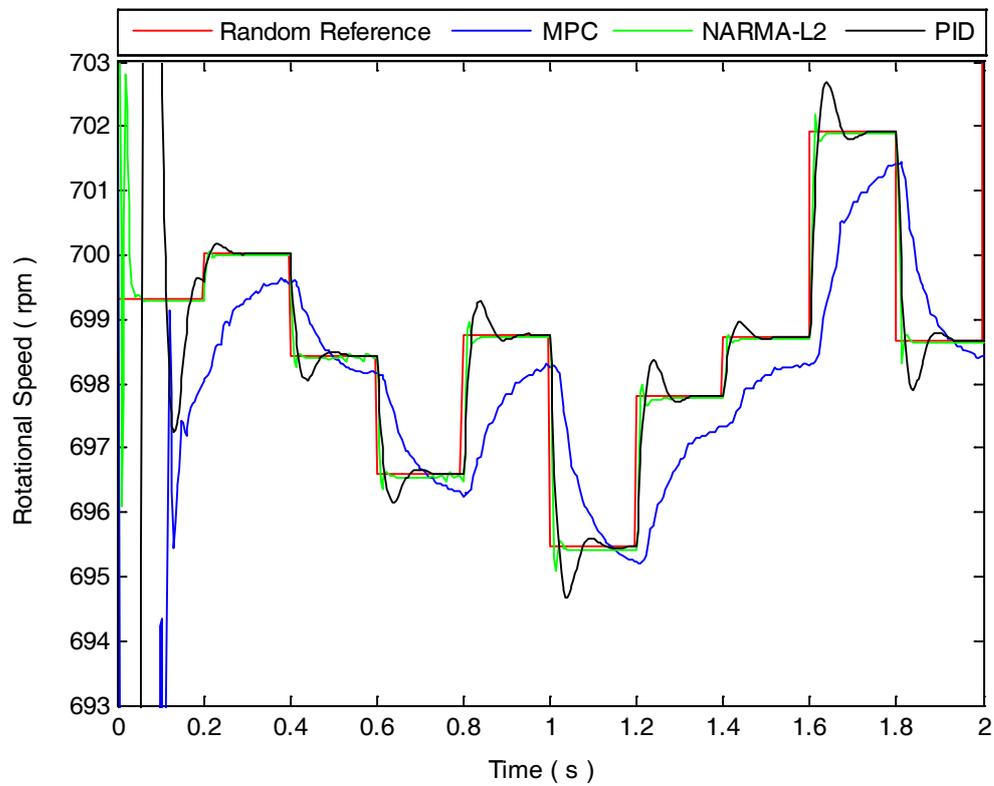


**Figure 7.25:** A close-up perspective of the performances of three different GT controllers.
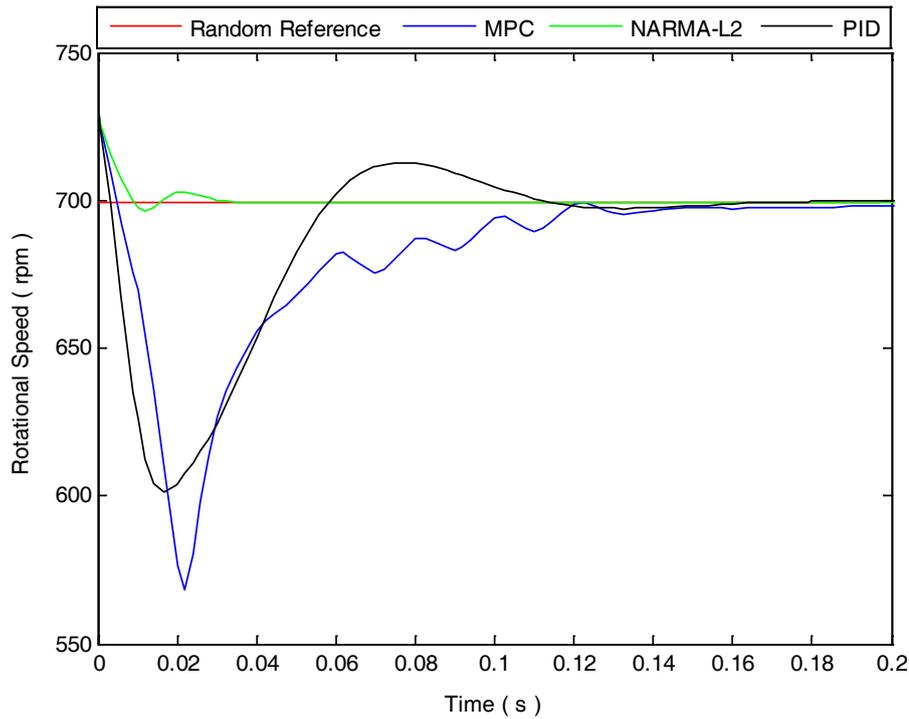
**Figure 7.26:** A close-up perspective of the initial responses of three different GT controllers.

As it can be seen from Figure 7.24, Figure 7.25 and Figure 7.26, all three controllers satisfied the controller design objectives. However, NARMA-L2 controller has a superior performance compared to MPC and PID. It follows the value and trend of the changes faster and more accurately. The settling time, rise time, maximum overshoot and maximum steady-state error for the response of NARMA-L2 is considerably less than the corresponding values for the other controllers.

As it can be seen from Figure 7.26, the step response of the gas turbine system with each of the controllers starts with an *undershoot*. This is because the gas turbine is a non minimum phase (NMP) system. This is explained in next section of this chapter.

## 7.6. NON-MINIMUM PHASE SYSTEMS

From a controller point of view, all systems can be divided into three main groups based on their phase response and locations of the poles and zeros of their transfer functions in the complex plane, also called *S* plane. This classification consists of minimum phase (MP), pass, and non minimum

phase (NMP) systems. When all poles and zeros of the transfer function of a system are located in the left half of the complex plane, it is called a minimum phase system. In this case, the poles and zeros have negative real parts. In a pass system, the transfer function has a pole-zero pattern which is anti-symmetric about the imaginary axis. A non minimum phase system is the one that its transfer function has one or more poles or zeros in the right half of the complex plane. Figure 7.27 and Figure 7.28 show the step response of a typical type of NMP and MP systems respectively [243]. As it can be seen from Figure 7.27, a NMP system behaves faulty at the start of the response with an *undershoot*. The output becomes first negative before changing direction and converging to its positive steady-state value. This kind of behaviour, which makes the response slow, could arise due to time delay in the system. Some of the system identification techniques do not take into account time delay and approximate the system as non minimum phase. NMP systems may face internal stability issues which can be fixed using appropriate controllers.
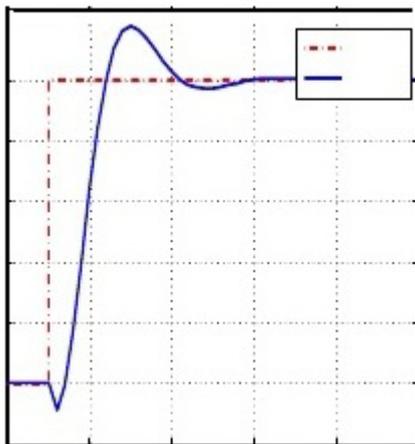


**Figure 7.27:** Step response of a non minimum phase system [243].
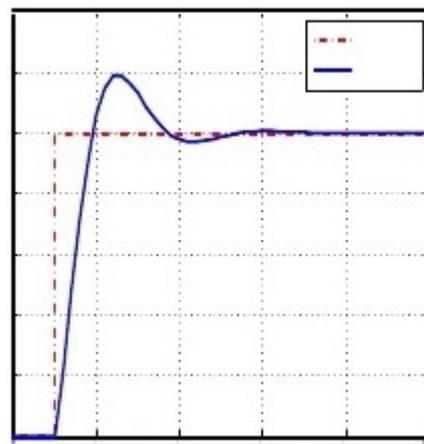
**Figure 7.28:** Step response of a minimum phase system [243].

NMP phenomenon has been already observed in gas turbine systems [244]. The *undershoot* observed in Figure 7.26 is because of the fact that the gas turbine system in this study is a NMP system. However, as it can be seen from the figures, the controllers could quickly and successfully correct this behaviour and bring the system to a stable situation. The reaction of NARMA-L2 as an ANN-based controller to the faulty behaviour is quicker than the PID controller. NARMA-L2

shows again a superior performance compared with other controllers in this case. It's settling time, rise time and maximum overshoot is less than the conventional PID controller. The previous experience and research results demonstrate that if the response is well-controlled by designing a suitable controller, then NMP phenomenon does not make a problem for operation of gas turbines [244].

## 7.7. SUMMARY

This chapter presented three different controller structures for a low-power single-shaft gas turbine already discussed in Chapter 4. These controllers consist of ANN-based model predictive controller, ANN-based feedback linearization controller (NARMA-L2), and conventional PID controller. These controllers were briefly described and their parameters were adjusted and tuned in Simulink-MATLAB environment according to the requirement of the gas turbine system and the control objective. Finally, performances of the controllers were explored and compared. The results showed that NARMA-L2 has a superior performance to other investigated controllers in this study. The settling time, rise time and maximum overshoot for the response of NARMA-L2 is less than the corresponding factors for the conventional PID controller. Although the ANN-based MPC controller performance was weaker than the other ones, it can be improved considerably by online training on sites.

*Whether our efforts are, or not, favoured by life, let us be able to say,*
*when we come near the great goal, " I have done what I could".*


Louis Pasteur
French Chemist and Microbiologist, 1822-1895


# CHAPTER 8
# CONCLUSION AND FUTURE WORK


## 8.1. CONCLUSION AND RESEARCH CONTRIBUTION

This thesis investigated novel methodologies for modelling, simulation and control of gas turbines using artificial neural networks. New approaches presented in this area could help to pave the way for the design and manufacturing of more efficient, reliable and durable GTs. The models developed in this thesis could also be used online on sites for optimization, condition monitoring, sensor validation, fault detection and trouble shooting of gas turbines.

In the field of modelling and simulation, two different types of gas turbines were modelled and simulated using both Simulink and neural network based models. Simulated and operational data sets were employed to demonstrate the capability of neural networks in capturing complex nonlinear dynamics of gas turbines, especially when enough information about physics of the system is not available. For ANN-based modelling, the application of both static (MLP) and

dynamic (NARX) networks were explored. Simulink and NARX models were set up to explore both steady-state and transient behaviour of gas turbines.

In the area of control system design, both conventional (PID) and ANN-based (MPC and NARMA-L2) controllers are employed and it was proved that in some cases, neural network based controllers could perform even better than conventional controllers.

Overall, it was concluded from this thesis that in spite of some controversial issues regarding using artificial neural networks for industrial applications, ANNs have a high and strong potential to be considered as a reliable alternative to conventional modelling, simulation and control methodologies.

This thesis has made the following contributions to the area of modelling, simulation and control of gas turbines:

- This research presented a comprehensive overview of the literature in the field of modelling, simulation, and control of gas turbines [Chapter 2]. It covered both white-box and black-box models. The most relevant research activities for different kinds of GTs including low-power, industrial power plant and aero gas turbines were explored and discussed in term of methodologies, strengths and weaknesses. It was shown that despite remarkable studies in this area, further research still needs to be carried out to resolve unpredictable challenges that arise in manufacturing processes or in the operation of industrial plants. These challenges may be found in a variety of areas including design, commissioning, condition monitoring, fault diagnosis, trouble shooting, maintenance, sensor validation and control.

- This study discussed the structure of artificial neural network and its training process. It explored different challenges that arise when using ANN-based models for industrial systems and described advantages and limitations of this approach [Chapter 3]. It was shown that ANN can be used to model, simulate, and control a wide class of industrial

systems with nonlinear and complex dynamics in a variety of applications. The practical use of ANN to control complex and nonlinear systems was also investigated. It was explored that ANN requires less formal statistical training to be developed using different training algorithms. It provides high degree of adaptive interconnections between elements and can be used where the relations between different parameters of the system are difficult to uncover with conventional approaches. It was shown that despite all the limitations, using ANN can still lead to remarkable enhancements in the process of industrial system modelling and control.

- This research developed a novel artificial neural network based methodology for offline system identification of a low-power gas turbine [Chapter 4]. The processed data was obtained from a Simulink model of the gas turbine in MATLAB environment. A comprehensive computer program code was generated and run in MATLAB for creating and training different ANN models with feedforward MLP structure. The code consisted of various training functions, different number of neurons as well as a variety of transfer (activation) functions for hidden and output layers of the networks. In order to find the best model for the gas turbine engine in terms of minimum error and accurate performance, 18720 different ANN structures were trained using randomly partitioned data sets for training, validation and test purposes. The results of the trainings were recorded and the performances were evaluated and compared. The resulting ANN structure was tested again to assure good generalization characteristics of the model. The results from the selected model for seventeen output parameters of the gas turbine (predicted values) were compared with the values of the generated data from the Simulink model. It was demonstrated that the ANN-based method can be applied reliably for the system identification of gas turbines. It could precisely predict output parameters of the GT based on changes in the inputs of the system. It was also observed that Levenberg-Marquardt training algorithm (*trainlm*) had a superior performance compared to each of

the other training functions. The methodology of this study can be used to predict performance of similar gas turbine systems with high accuracy.

- This study explored transient behaviour of a heavy-duty IPGT in the low-power operating region using Simulink-MATLAB and NARX models [Chapter 5]. Thermodynamic and energy balance equations were employed to model the gas turbine. Correlations between corrected parameters of the compressor and turbine components were investigated by using measured time-series data sets and employing Fitting Tool in MATLAB. The same data was used to build NARX models for the IPGT. To verify the models, the resulting Simulink and NARX models were tested against two other data sets. For this purpose, four important outputs from the IPGT models and their corresponding values from the measured data sets were compared and the related results were captured and figured. These outputs were rotational speed, compressor pressure ratio, compressor outlet temperature, and turbine outlet temperature. The simplicity of the thermodynamic model is one of the strong points of the research. The lack of information about bleed flows and IGV control was overcome by implicitly accounting for these effects (which mainly affect the inlet mass flow rate) by means of two innovative procedures:

1) The performance maps, which relate the corrected parameters, were obtained directly from measured data by using the Curve Fitting Tool of MATLAB. The fine tuning of these correlations represented a key and challenging phase of the thermodynamic model set-up.

2) The inlet mass flow rate and the turbine inlet temperature were estimated at each time step by means of an iterative procedure.

The choice of developing a neural network model to cover this range of operation goes in the same direction, i.e. developing a simple model to reproduce a very complicated and usually difficult-to-model unsteady behaviour. The results showed that both Simulink and NARX models captured dynamics of the system and provided satisfactory prediction of

the gas turbine behaviour. However, NARX approach modelled gas turbine behaviour with higher accuracy compared to Simulink approach.

- This research developed a complex model of the start-up operation of an IPGT by using NARX models [Chapter 6]. The model was set up on the basis of three measured time-series data sets taken experimentally during the normal start-up operation by means of standard measurement sensors and acquisition system. The structure of the NARX model was kept as simple as possible, i.e. only three usually available variables are supplied as inputs. To verify the resulting model, it was tested against three other available data sets. It was observed that in all cases the trends of the real system and the NARX model are very similar. This means that the NARX models could follow the changes in the gas turbine parameters, even though they are subject to significant changes. At the same time, the NARX models could also reproduce less significant changes. The stable operation can also be reproduced very satisfactorily. The results showed that NARX model has the potential to simulate and predict gas turbine dynamic behaviour.

This study investigated the design and application of a conventional PID and two neural network based controllers (MPC and NARMA-L2) for a gas turbine engine [Chapter 7]. Fuel mass flow rate and rotational speed were considered as input and output of the plant (gas turbine system) for control purpose respectively.  The objective of the controllers design was to maintain the rotational speed at a constant value when the input of the control system changes with the random reference. After the system identification processes were completed and the neural network plant models were developed, the related parameters for all controllers were tuned and set up according to the requirements of the controller design for the gas turbine. To compare the performance results for all three controllers, they were run in a common Simulink environment with the same input for their control systems. Results showed that NARMA-L2 has a superior performance compared with MPC and PID, in terms of both reaction speed and settling time, and that It follows the value and

trend of the changes more accurately compared to other controllers. The settling time, rise time and maximum overshoot for the response of NARMA-L2 is less than the corresponding factors for the conventional PID controller. It also follows the input changes more accurately than the PID.

## 8.2. FUTURE WORK

Modelling, simulation, and control of gas turbines cover a very wide range of research activities. There are different types of gas turbines and varieties of approaches and methodologies for modelling and control purposes. Even using artificial neural network approach includes many methods and structures. However, by considering the scope and results of this thesis, the future efforts and upcoming research outputs in this area can be highlighted as follow:

In the field of modelling and simulation, further research can be carried out in the following directions:

- The same methodology can be employed by using Simulink and NARX models to investigate dynamic behaviour of twin-shaft gas turbines in both steady-state and transient conditions. Especially in the field of transient behaviour, the number of research activities in the literature is very limited and there is a big gap which needs to be filled up.

- For ANN-based modelling approach, a variety of architectures can be used and compared. There are different static and dynamic neural networks that can be applied for simulation of gas turbines.

- The investigation of NARX model capability as a multi-step ahead predictor, with the final aim to optimize design, operation and maintenance of gas turbines can be carried out further.

- Based on the available information about the physics of the system, it is possible to combine physical laws with data driven (ANN) modelling to form a kind of grey-box

modelling. In this case, an empirical model can be improved by employing certain available level of insight about the system.

In the field of control, further studies can be conducted in design and development of the following controllers:

- The same methodology can be employed to investigate using ANN-based controllers for twin-shaft gas turbines in both steady-state and transient conditions.

- Both conventional and ANN-based controllers can be designed and applied to control ANN-based models of gas turbines for single-shaft and twin-shaft gas turbines.

- Self-tuneable and flexible controllers can be employed in gas turbines with different configurations. Adaptation to the platform changes should be considered during the design and development process.

- Robust and re-configurable control systems with the capability of switching between different control strategies based on mission conditions can be designed and implemented in gas turbines. Compensation capability of such control systems for environmental changes, most failures and different missions is very important. They should guarantee performance of gas turbines under severe operational conditions.

- Neural model reference controllers and neural adaptive controllers with superior control behaviour and high adaptability can be employed. The controllers should contribute towards high-performance, cost-effectiveness and high-reliability. The gas turbine model can be used to predict the effect of controller changes on plant output, which consequently allows the updating of controller parameters. The objective should be to maximize system robustness, output power and efficiency.

- Implementation of neural networks to gas turbines is a very important issue which needs significant efforts and attention in addition to enough facilities and finance.

By highlighting the above mentioned facts, remarkable enhancements can still be achieved in the process of modelling, simulation and control of gas turbines. The methodologies can be improved and developed so that they could be applicable to a wide range of operational conditions for a variety of gas turbines. They could also be capable of identification of gas turbines parameters and prediction of their complex dynamic behaviour as accurately as possible. The upcoming research outputs in this area can effectively help to design, manufacture, operate and maintain gas turbines in desirable conditions. The future efforts will bring advancements in technology and can lead to manufacturing gas turbines with minimum energy consumption and therefore maximum efficiency.

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