Modelling and simulation of gas turbines

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Abstract: Today, gas turbines (GTs) are one of the major parts of modern industry. They have played a key role in aeronautical industry, power generation, and main mechanical drivers for large pumps and compressors. Modelling and simulation of GTs 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 behavior 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 area. This paper focuses on major research activities which have been carried out so far in the field of modelling and simulation of gas turbines. It covers main white-box and black-box based models and their applications in control systems. This study can be a good reference for current and prospectus researchers who are working or planning to work in this fascinating area of research.

Keywords: Gas turbine; modelling; control; simulation; identification; optimization; dynamics; white-box; black-box.

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1 Introduction

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 (Boyce 2006). Gas turbine is considered as an internal combustion engine which uses the gaseous energy of air to convert chemical energy of fuel to mechanical energy. 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 (Kulikov & Thompson 2004). 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.

This study deals with research activities in the field of modelling and simulation of gas turbines. It covers major white-box and black-box models of gas turbine, and their applications to control systems. The paper is structured as follows:

In section 2, the gas turbine operating principles are briefly described. Classification of gas turbines is presented in section 3. Section 4 demonstrates the necessity and goal of modelling and simulation of gas turbines. Section 5 explains major studies in the field of modelling and simulation of gas turbine for both white-box and black-box approaches. It covers research activities for different kinds of gas turbines including low-power, industrial power plant and aero gas turbines. Related studies on applications of gas turbine models to control system design, for both white-box and black-box models are presented in section 6. Finally, section 7 forms the conclusions of the paper, a short discussion, and suggestions for further research and development activities in the area of modelling and simulation of gas turbines.

2 Operating principles of gas turbines

Figure 1 shows the main components of a typical single-shaft gas turbine engine; including compressor, combustion chamber (combustor), and turbine (Wikimedia Commons 2012). 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.

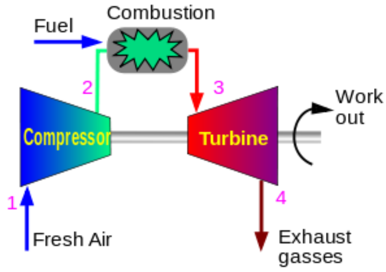

Figure 1 A schematic of a typical single-shaft gas turbine (Wikimedia Commons 2012)

As the figure shows, air enters the compressor at section 1 and is compressed through passing the compressor. The hot and compressed air enters the 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 provides the required energy for rotation of compressor. In aero industry, gas turbine is used as propulsion system to make thrust (using hot exhaust) 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 industrial gas turbines, turbine drives the compressor and the GG mechanical output, which can be an electricity generator in a power plant station, a large pump or a large compressor (Asgari et al. 2011).

Gas turbines work based on Brayton cycle. Figure 2 indicates a typical standard Brayton cycle in temperature-entropy frame (Tavakoli et al. 2009).

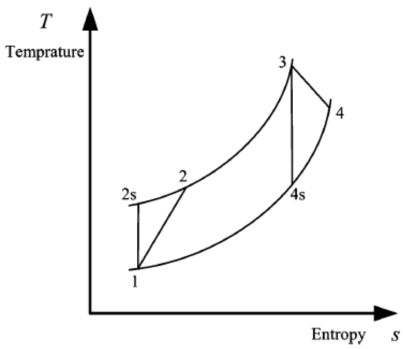

Figure 2 Typical Brayton cycle in temperature-entropy frame (Tavakoli et al. 2009)

As it can be seen from the figure, the actual processes in the compressor (1-2) and turbine (3-4) are irreversible and non-isentropic. Points 2s and 4s show the ideal situation, when these processes are assumed isentropic. Neglecting pressure loss in the air filters and the combustion chamber, processes 2-3 and 4-1 can be considered isobar (Tavakoli et al. 2009).

Gas turbine exhaust gases from a simple-cycle gas turbine (SCGT) can be utilized for steam generation or heating buildings and industrial systems. In these cases, based on the applications, the plant may be called combined cycle power plant (CCPP), advanced combined cycle power plant (ACPP), steam turbine plant (ST), recuperative gas turbine (RGT) or hybrid power plants (HPP). Thanks to the new technology, the efficiency of combined cycle can reach up to 65% (Boyce 2006). Although increasing efficiency of gas turbines is a main goal in design and manufacturing processes, it should not lead to considerable decrease in the availability. According to experience and many analyses, for 1% extra efficiency, 3.3% more capital should be invested (Boyce 2006).

3 Classification of gas turbines

Based on the structure, application, and the output power (MW), gas turbines can be classified into five main groups (Boyce 2006) including:

- Micro gas turbines (MGTs), 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 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 for compressor type train, 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 heavy-duty gas turbines that are used in power plants for generating electricity are called industrial power plant gas turbines (IPGT). Figure 3 shows a typical single-spool aero gas turbine engine (Wikimedia Commons 2012).

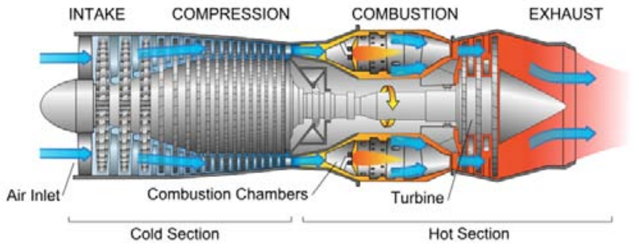

Figure 3 A typical single-spool turbojet engine (Wikimedia Commons 2012)

4 Modelling and simulation of gas turbines

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. Great efforts have been made in developing GTs to overcome their related challenging scientific and engineering problems. One of the best approaches for optimization of design, performance and maintenance of gas turbines is off-line 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. Before making a gas turbine model, some basic factors should be carefully considered. Modelling objectives, GT type, GT configuration, and modelling methods, are among the most important criteria at the beginning of the modelling process.

There are different goals for making a gas turbine model. A GT can be modelled for condition monitoring, fault detection and diagnosis, sensor validation, system identification, design optimization and improvement of control systems. Thus, a clear statement of the modelling objectives is necessary to make a successful GT model.

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 (Clifton 2006). 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.

A gas turbine model may 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 (Lee et al. 2010). 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.

GT models can also be used for sensor validation purposes. Sensor validation is about detection, isolation and reconstruction of a faulty sensor. Some sensors may fail to report correct data due to different reasons or may become unavailable during maintenance operation. Sensor validation 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.

One the main objectives of gas turbine modelling, is system identification. System identification infers a mathematical description (a model) of a dynamic system from a series of measurements of the system (Norgaard et al. 2000). Despite all 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 because of the nonlinear and complex nature of GT dynamics.

Gas tribune models may also be created to design or optimize GT control system. 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 (Burns 2001). In spite of the significant research in this field, there are still 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 such as power-oriented graphs (POG) technique (Grossi et al. 2012) should always be investigated as part of optimization process.

5 Gas turbine model construction approaches

There are different approaches to model a dynamic system such as gas turbine. 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 can be classified into two main categories including black-box and white-box models. The following summarizes the most important studies in this field.

5.1 White-box models of gas turbines

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 (Jelali & Kroll 2004). 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.

According to the classification of gas turbines in section 3, white-box models of gas turbines can be categorized into low-power, industrial power plant, and aero gas turbine models. In a power plant gas turbine, the mechanical power generated by gas turbine will be used by a generator to produce electrical power. However, in an aero gas turbine, the outgoing gaseous fluid can be utilized to generate thrust.

5.1.1 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 et al. (2001). The main idea 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 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 simplification process.

Abdollahi and Vahedi (2004) 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. The researchers 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. (2007) investigated modelling and simulation of a natural gas based micro turbine using MATLAB. The main objective of the research was to present a technical and economical analysis of using *micro gas turbines (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 attend the thermal or the electrical demand side. In the first case, it was necessary to buy electricity from the grid to completely attend the electricity demand. However, in the second case, there would have an excess of thermal energy. The results of the analysis could also be useful for the investors who are interested to predict the cost of investment, operation and maintenance of these turbines for power generation.

5.1.2 White-box models of industrial power plant gas turbines (IPGTs)

Rowen is a known name in the field of modelling and simulation of gas turbines. He presented a simplified mathematical model of a heavy-duty single-shaft gas turbine (Rowen 1983). The objective of the study was to investigate power system stability, to develop dispatching strategy, and to provide contingency planning for the system upsets (Rowen 1983). Rowen tried to make a simplified model that could cover the full spectrum of generator-drive gas turbines and appropriate turbine-generator characteristics (Rowen 1983). 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 cycle and single-shaft gas turbines with generator drive. Engineering considerations and careful evaluation of the intended purpose are essential prior to use of the model (Rowen 1983). Rowen, 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 turbines to mechanical drive services with variable speed (Rowen 1992). The new features that were not included in his previous study (Rowen 1983) 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 the 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.

Shalan et al. (2011) employed a simple methodology to estimate parameters of a Rowen's model for heavy-duty single-shaft gas turbines. The parameters of the model were derived using the performance and operational data. Variety of simulated tests was performed in SIMULINK/MATLAB environment and the results were compared with and verified against the results of involved scientific articles in the literature. The applied methodology can be applied for any size of gas turbines.

The parameters of a single-shaft heavy-duty gas turbine were estimated using its operational data based on Rowen's model by Tavakoli et al. (2009). They applied simple physical laws and thermodynamic assumptions in order to derive the GT parameters using operational data. The study can be useful for educational purposes especially for the students and trainers who are interested in gas turbine dynamic studies. Figure 4 shows the block diagram of Rowen's model for heavy-duty gas turbines, including fuel and control systems (Rowen 1983 & Tavakoli et al. 2009).

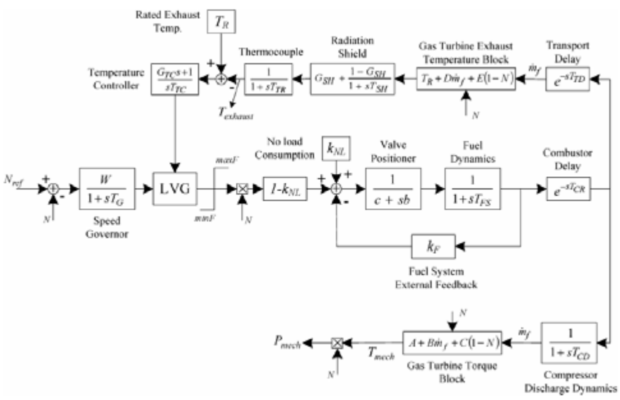

Figure 4 Rowen's model for heavy-duty gas turbines for dynamic studies (Rowen 1983 & Tavakoli et al. 2009)

Najjar (1994) investigated performance of GTs in single-shaft and twin-shaft operation modes using a model 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 (Najjar 1994).

A model for a twin-shaft gas turbine was estimated by Hannett et al. (1995). 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 digital 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 (Hannett et al. 1995).

A dynamic model for a twin-shaft gas turbine was developed by Ricketts (1997) 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.

An investigation for using of exhaust gases of an open-cycle twin-shaft gas turbine was performed by Mostafavi et al. (1998). 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 precooling, the pre-cooled cycle could operate at a higher compressor pressure ratio and temperature ratio without increasing the maximum cycle temperature (Mostafavi et al. 1998).

Nagpal et al. (2000) presented their field experiences in testing and model validation of turbine dynamic models and their associated governors for industrial power plant gas turbines when they were in service. Based on the field measurements, they showed that GAST model 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. (2002) 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 is predicted at the reference operating conditions for the engine with the current health status. Evaluation of the GT performance parameters in references, 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.

A gas turbine fully-featured simulator was developed and implemented by Klang and Lindholm (2005). They discussed the simulator setup both technically and economically as well as 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.

Al-Hamdan and Ebaid (2006) 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 5 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 (Al-Hamdan & Ebaid 2006).

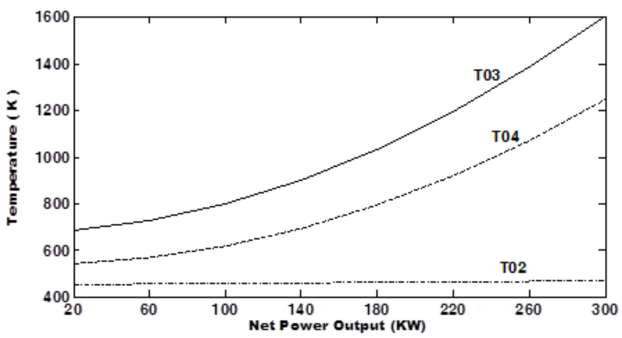

Figure 5 Variations of different temperatures (K) versus net power output (KW) (Al-Hamdan & Ebaid 2006)

A simplified desktop performance model of a typical heavy-duty single-shaft gas turbine in power generation systems was developed by Zhu et al. (2007). 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.

Development of single-shaft dynamic model for a combined-cycle plant was explored by Mantzaris and Vournas (2007) using SIMULINK/MATLAB. They investigated 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 was expanded during full load operation.

Camporeale et al. (2006) 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 MATLAB-SIMULINK using an object-oriented approach for gas turbine simulation. The technique was based on a lumped, 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 allows it to be easily adapted to any configuration of power plants. Figure 6 shows the diagram for the real-time simulation software interacted to hardware control devices of the gas turbines (Camporeale et al. 2006).

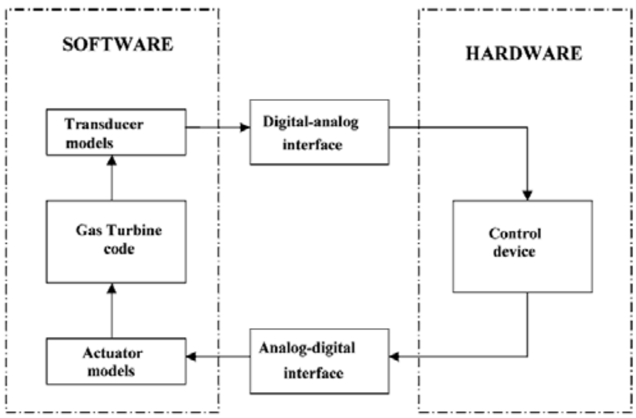

Figure 6 The diagram for real-time simulation software interacted to hardware control devices (Camporeale et al. 2006)

Yee et al. (2008) 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 mentioned that physical models are not appropriate for the use in large power system studies. It was also indicated that for a more detailed analysis of power systems and their governors' behavior, 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 (Yee et al. 2008).

A zero-dimensional simulation model for design and off-design performance of a twin-shaft gas turbine was developed by Lazzaretto and Toffolo (2008). The objective 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 and carbon monoxide 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 energetic, economic and environmental aspects of plant operation (Lazzaretto and Toffolo 2008).

A modified methodology was presented by Khosravy-el-Hossani and Dorosti (2009) 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. The suggested methodology can be an appropriate alternative for gas turbine standard performance test and can be employed to evaluate gas turbine performance without measurement of input fuel components, which can reduce the measuring cost and data gathering.

Simple models of the systems for a power plant simulator were developed by Roldan-Villasana et al. (2010) 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. (2010) 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.

5.1.3 White-box models of aero gas turbines

Evans, Rees and Hill (1998) 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. Evans et al. (2001) presented the linear multivariable model of a twin-shaft aero gas turbine (a typical Rolls Royce Spey military turbofan) using a frequency-domain identification technique. The technique was employed to estimate s-domain multivariable models directly from test data. The researchers examined the dynamic relationship between fuel flow rate and rotational speeds in the form of *single-input, multi-output (SIMO).* The main advantage of the model was its capability to be directly compared with the linearized thermodynamic models of the GT. The output of the research showed that a second-order model could present the most suitable model and the best estimation of the engine. The techniques investigated in the research can be used to verify the linearized thermodynamic models of gas turbines. Figure 7 shows the Rolls Royce Spey engine modelled by Evans et al. (2001).

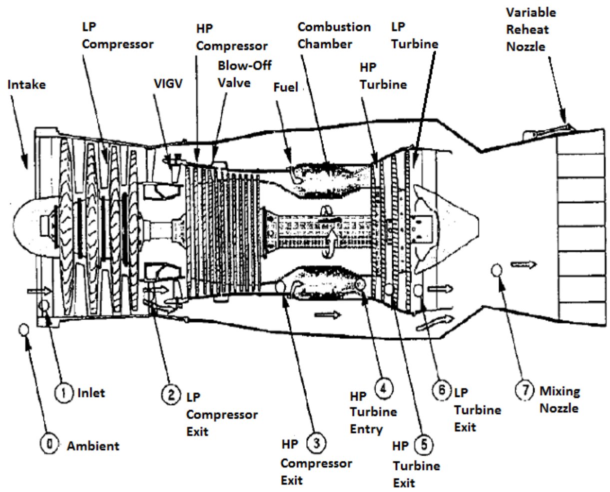

Figure 7 A typical Rolls Royce Spey Engine (Evans et al. 2001)

Arkov et al. (2000) employed four different system identification approaches to model a typical aircraft gas turbine using the obtained data 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” (Arkov et al. 2000). A description of each technique and the relative merits of the approaches were also discussed in the study. Arkov et al. (2002) 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 engine controllers and 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.

Kim et al. (2000) developed a model for a single-spool turbojet engine using SIMULINK/MATLAB. The transient behavior 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. The simulation output was compared with another dynamic code for gas turbines and showed satisfactory results.

5.2 Black-box models of gas turbines

A black-box model is used when no or little information is available about the physics of the system (Jelali & Kroll 2004). 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. One of the novel approaches for optimization of gas turbines is employing ANN-based identification and modelling technique. A neural network model is a group of interconnected artificial units (neurons) with linear or nonlinear transfer functions. Neurons are arranged in different layers including input layer, hidden layer(s) and output layer. The number of neurons and layers in an ANN model depends on the degree of complexity of the system dynamics. ANNs learn 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 training the network. Figure 8 shows a simple structure of a typical ANN with five inputs, two outputs and three neurons in the hidden layer (Kunzle 2003).

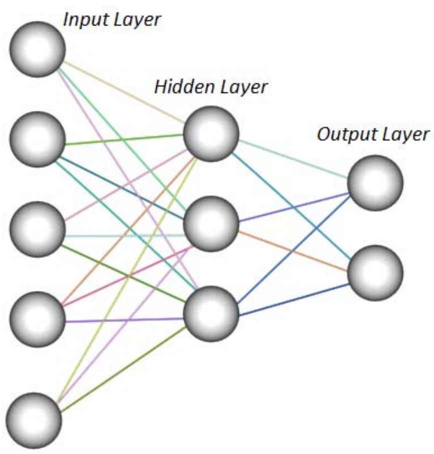

Figure 8 A simple structure of a typical artificial neural network (ANN) with input, hidden and output layers (Kunzle 2003)

ANN, as a data-driven model, has been considered as a suitable alternative to white-box models during the last few decades. ANN-based models can be created directly using the operational data from an actual GT or simulated data from *original equipment manufacturers (OEMs)* performance. Simulated data may be used when operational data are not available. The obtained data should cover the whole operational range of the system. All transient data during start or stop process should be removed from the collected data before the modelling process. ANN models for gas turbines can be created using different approaches and the flexibility that ANNs provide. This flexibility is based on the varieties of structures of the network, training styles and algorithms, types of the activation function, number of neurons, number of hidden layers, values of the weights and biases as well as data structures. However, the best structure is the one which can predict dynamic behavior of the system as accurately as possible. Selecting the right parameters of GTs as inputs and outputs of a neural network 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.

There are a considerable number of research sources regarding black-box system modelling and simulation of gas turbines in the literature. The following summarizes the most important studies which have been carried out so far in this area. As in white-box models, black-box models can be categorized into low-power, industrial power plant, and aero gas turbine models.

5.2.1 Black-box models of low-power gas turbines

A *nonlinear autoregressive with exogenous inputs (NARX)* model was applied to model a power plant micro gas turbine and the related distribution system dynamics (Jurado 2005). 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 turbines 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 technique. The model was tested under different operational conditions and electrical disturbances. The results showed that NARX models can be successfully applied to the black-box modelling of MGT dynamics in non-isolated mode (Jurado 2005).

Application of ANN and *adaptive network-based fuzzy inference system (ANFIS)* to MGTs was presented by Bartolini et al. (2011). 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. Besides, they investigated the effects of changes of ambient conditions (temperature, pressure, humidity) and load on MGT's output power. The results indicated that ANN can 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.

5.2.2 Black-box models of industrial power plant gas turbines (IPGTs)

Lazzaretto and Toffolo (2001) 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 as two different approaches to predict GT performance. Appropriate scaling techniques were employed to construct new maps for the gas turbine using the available generalized maps of the compressor and turbine. The new maps were validated using the obtained experimental data 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 parameters variations on GT performance were not considered in the analytical approach. The results from the simulator were used for training the feed-forward neural network. 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. (2002) applied ANN for multi-sensor fault diagnosis of a stationary twin-shaft gas turbine using neural network toolbox 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 non-linear aero-thermodynamic model of the engine's behavior. 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 (Ogaji et al. 2002).

Arriagata et al. (2003) applied ANN for fault diagnosis of a single-shaft industrial gas turbine. They obtained a comprehensive data set from ten faulty and one healthy engine conditions. The data were trained using feedforward *multi-layer perceptron (MLP)* structure. The trained network was able to make a diagnosis about the gas turbine's condition when a new data set was presented to it. The results proved that ANN could identify the faults and generate warnings at early stages with high reliability. Figure 9 shows a schematic drawing of the ANN and the interpretation of the outputs in a graphical display (Arrigada et al. 2003).

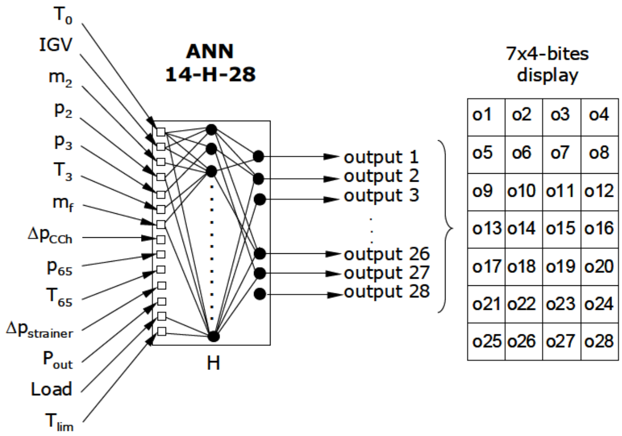

Figure 9 A schematic drawing of the ANN model and the interpretation of the outputs in a graphical display (Arrigada et al. 2003)

As it can be seen from the ANN architecture, 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, inlet guide vanes angle, mass flow rate, fuel flow rate, load, pressure, temperature, etc. As the Figure 9 shows, 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 for the network. The ANN can be named 14-H-28 according to its structure (Arrigada et al. 2003).

Basso et al. (2004) applied a NARX model to identify dynamics of a small heavy-duty power plant gas turbine. 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 NARX model was performed iteratively using Gram-Schmidt procedure. Both forward and step-wise regressions were investigated and many indexes 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 from narrow to broadband) were chosen for system identifcation and validation purposes (Basso et al. 2004).

Bettocchi et al. (2004) 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 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, is the most appropriate network. They observed that ANN can be very useful for the real time simulation of GTs especially when there were not enough information about the system dynamics. In another effort, Bettocchi et al. (2007) developed a *multiple-input, multiple outputs (MIMO)* neural network approach for diagnosis of single-shaft gas turbine engines. They considered an ANN structure with 15 inputs and 6 outputs. The researchers observed that the most suitable model is a feedforward MLP with a single hidden layer (including 60 neurons) and continuous sigmoidal activation function, trained with at least 1000 training patterns. They also suggested when data sets were affected by measurement uncertainty, 4000 training patterns corrupted with random errors contained in the range of measurement uncertainty, could be used (Bettocchi et al. 2007). In a similar effort, Spina and Venturini (2007) 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 (2008) 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, because of their particular advantages in terms of algorithmic simplicity and performance achievement. The suggested *fault diagnosis (FDI)* 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 (Simani and Patton 2008).

Yoru et al. (2009) 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 the exergy values from exergy analysis and showed that much closer exergetic results could be attained by using ANN method.

Magnus Fast et al. (2008) applied simulation data and ANN technique to examine condition-based maintenance of gas turbines. In another effort, Fast et al. (2009a) 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. (2009b) for condition monitoring and detection of anomalies in GT performance. 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 Fast et al. (2009c). Application of ANN to diagnosis and condition monitoring of a combined heat and power plant was discussed by Fast and Palme (2010). Fast (2010) applied different ANN approaches for gas turbine condition monitoring, sensor validation and diagnosis.

5.2.3 Black-box models of aero gas turbines

A *nonlinear auto-regressive moving average with exogeneous inputs (NARMAX)* model of an aircraft gas turbine was estimated by Chiras, Evans and Reesa (2001a). 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, they applied a forward-regression orthogonal estimation algorithm to make a NARMAX model for a twin-shaft Rolls Royce Spey aircraft gas turbine (Chiras et al. 2001b). A nonlinear relationship between dynamics of shaft rotational speed and the fuel flow rate was also explored and discussed. To validate the model performance, the researchers examined static and dynamic behavior 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, they used feedforward neural network to model the relationship between the fuel flow and shaft rotational speed dynamics for a Spey gas turbine engine (Chiras et al. 2002a). They validated performance of the nonlinear model against small and large signal engine tests. They also showed the necessity of using a nonlinear model for modelling high-amplitude dynamics of gas turbine engines. They also recommended a global nonlinear model of gas turbine dynamics using NARMAX Structures (Chiras et al. 2002b). The researchers 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. (2003) 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 (NN) models. The researchers realized that among the three different structures of NN including *radial basis function (RBS)*, 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 *back propagation neural networks (BPNN)* were developed by Torella, Gamma and Palmesano (2003) 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 experience, 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.

6 Applications of gas turbine models to design of control systems

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

6.1 White-box approach

Ricketts (1997) 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.

Agüero et al. (2002) 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. According to the last modification, operators were allowed to adjust set points of dispatched power, grid frequency and required spinning reserve regulated by the dispatch center. The researchers investigated the turbine dynamic behavior before and after the modifications were made.

Ashikaga et al. (2003) 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 NO_x emission. However, the algorithms for solving optimization problems were complicated, time-consuming and too large to be installed easily in computers.

Centeno et al. (2002) 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 10 shows the block diagram of the basic temperature control loop for the GT model (Centeno et al. 2002).

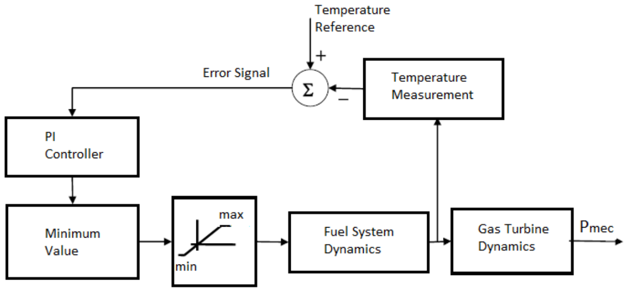

Figure 10 Block diagram of the basic temperature control loop for a gas turbine model (Centeno et al. 2002)

Pongrácz et al. (2008) 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.

6.2 Black-box approach

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. That is why the learning based control methodology such as neural network has been widely used in various industrial applications.

Investigation for the practical use of artificial neural networks to control complex and nonlinear systems was carried out by Nabney and Cressy (1996). 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 (1997), 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 feedforward neural network with sigmoidal 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 11 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 (Dodd & Martin 1997).

Figure 11 Block diagram of an ANN-based aero gas turbine model for system optimization consists of minimizing fuel while maintaining thrust (Dodd & Martin 1997)

Mu and Rees (2004) 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 ones. AMPC showed optimal performance for both small and large random step changes as well as against disturbances and model mismatch. Mu, Rees and Liu (2004), in another effort, examined two different approaches to design a global nonlinear controller for an aircraft gas turbine. They compared and discussed the properties of AMPC and *nonlinear model predictive control (NMPC)*. The results showed that the 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 the local minimum.

Implementation of a *model predictive control (MPC)* on a heavy-duty power plant gas turbine was investigated by Ghorbani et al. (2008). They modeled 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. (2008). Their work was based on the GT mathematical model already developed by Rowen (1983). They applied *Ziegler Nichols's (ZN)* 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 ANN controller performed better than the PID controller. Figure 12 shows a comparison of gas turbine plant response with PID and ANN controllers (Balamurugan et al. 2008).

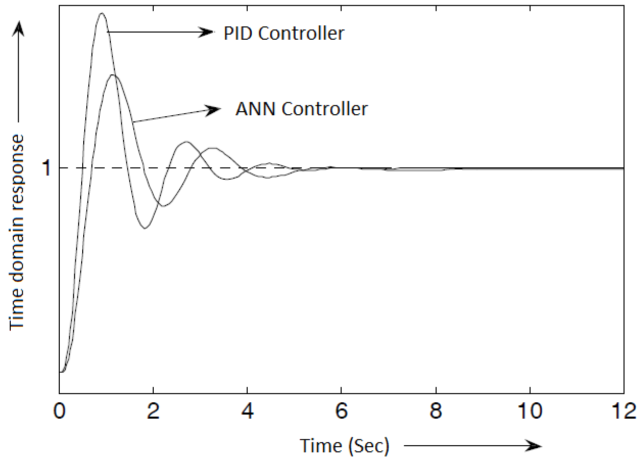

Figure 12 A comparison of gas turbine plant response with PID and ANN controllers (Balamurugan et al. 2008)

7 Conclusion and discussion

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. In this study, operating principles, classification as well as objectives and different approaches for modelling and simulation of gas turbines was briefly presented. The study also covered and discussed significant research activities in the area of modelling and simulation 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.

As it can be seen from the literature, the outcome of the research in the field of modelling and simulation of gas turbines has been very effective in their performance evaluation and optimization before final design and manufacturing processes. However, despite all the mentioned efforts in this study, 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 behavior of these systems in order to minimize undesirable events such as unpredictable shutdowns, overheating and overspeed during operation. Further research and development activities can 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. Application of ANN as a fast and reliable method to stabilize the system against disturbances can be investigated further. In this case, dynamic behavior of the system can be predicted and controlled 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 are also trained with varieties of algorithms such backpropagation, delta rules method, BSGS algorithm, Gauss-Newton method, Levenberg-Marquardt algorithm or non-gradient based training methods such as the Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). As this study showed, 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. (2001 a, 2001 b, 2002 a, 2002 b), Ruano et al. (2003), and Torella et al. (2003) concentrated on ANN-based modelling of aero gas turbines. Jurado (2005), and Bartolini et al. (2011), investigated micro gas turbines using ANN technique. Ogaji et al. (2002), Arriagada et al. (2003), Fast et al. (2009 a, 2009 b, 2009 c, 2009 d), Fast and Palme (2010), and Fast (2010), explored applications of ANN for fault diagnosis, condition monitoring and/or sensor validation purposes. Fast et al. (2009 b) just considered the 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 (Jurado, 2005). 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).

As it can be seen, no of the past ANN researches 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 industrial power plant gas turbines 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 or customize the optimal model. The resulting model should predict dynamic behavior of the system as accurately as possible. It can also be used as a powerful tool in condition monitoring, trouble shooting and even maintenance of gas turbines.

It should be also noticed that further study is still necessary to be carried out in the field of application of gas turbine models to control systems. For instance, an uncoupled multi-model emulator can be used to design controllers for nonlinear systems such as gas turbines (Bahri et al. 2012). Using neural network-based adaptive sliding mode controllers (Goléa et al. 2012) or adaptive fast finite-time multiple-surface sliding controllers (Khoo et al. 2012) can be investigated as new methodologies in this area. Further studies can also be conducted in design and development of the following controllers:

- Self-tuneable and fexible controllers that can be employed in a short time in gas turbines with different configurations. Adaptation to the platform changes such as payload and sensors should be considered during the design and development process.

- Robust controllers that can guarantee performance of gas turbines under severe operational conditions.

- Re-configurable control systems with the capability of switching between different control strategies based on mission conditions. Compensation capability of such control systems for environment changes, most failures and different missions is very important.

- Neural adaptive controller with superior control behavior and high adaptability. The controller 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.

By highlighting the mentioned factors, remarkable enhancements can be achieved in the process of modelling, simulation and control of gas turbines. The upcoming efforts can lead to optimal models and control algorithms with minimal supervision and energy consumption. The methodologies can be developed to identify system parameters and to predict dynamic behavior of the system as accurately as possible. These methodologies can be applicable to a wide range of operational conditions. The future will bring advancements in technology that enables the development of optimized and reliable gas turbines.

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