Engineering Creative Design in Robotics and Mechatronics

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Chapter 14
Modelling and Simulation Approaches for Gas Turbine System Optimization

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ABSTRACT

This chapter deals with research activities that have been carried out so far in the field of modelling and simulation of gas turbines for system optimization purposes. It covers major white-box and black-box gas turbine models and their applications to control systems.

1. INTRODUCTION

The rapidly growing knowledge-based industry has been always looking for creative and bright ideas. Mechatronics, as a *multidisciplinary* field of engineering, is one of those innovative phenomena that has contributed many advantages to our industrial society. It represents a unifying paradigm that integrates, permeates, and comprehends fundamental and modern engineering (Habib, 2006). Mechatronics combines a variety of engineering disciplines including mechanics, electronics, computer science, systems design, and control to fulfill the challenges of modern technology and the demand for innovation (Habib, 2008). It has been a powerful solution to many sophisticated problems in complex industrial systems such as Gas Turbines (GT).

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

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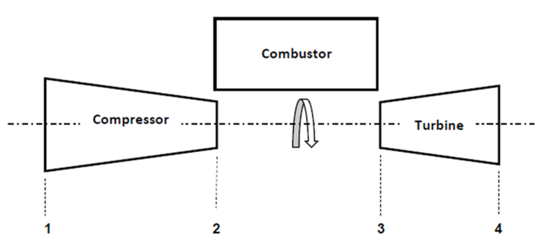
developed rapidly after World War II and became the primary choice for many applications. That was especially because of enhancement in different areas of science such as aerodynamics, cooling systems, and high-temperature materials which significantly improved the engine efficiency. Then, it is not surprising if gas turbines have been increasing in popularity year by year.

Today, gas turbines are one of the major parts of modern industry. They have been playing a key role in aeronautical industry, power generation, and main mechanical drivers for large pumps and compressors. 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.

Figure 1 shows the main components of a single-shaft gas turbine engine; 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.

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 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 generator in a power plant station, a large pump or a large compressor.

Figure 1. A simple schematic of a typical single-shaft gas turbine



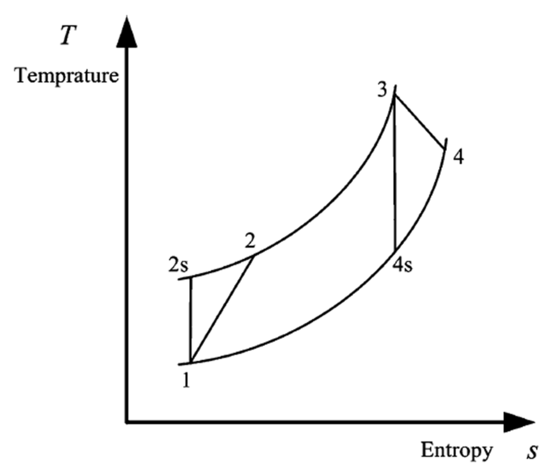
2. GAS TURBINE CYCLE

Gas turbines work based on Brayton cycle. Figure 2 indicates a typical standard 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).

Considering Figure 1 and Figure 2, basic thermodynamic equations for the main parts of a single-shaft gas turbine can be written as follows (Al-Hamdan & Ebadi, 2006). For the compressor:

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

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



$$\gamma_{air} = C_{P_{air}} / C_{v_{air}} \qquad (2)$$

$$\dot{W}_c = \dot{m}_{air} C_{P_{air}} (T_{02} - T_{01}) \qquad (3)$$

in which:

- P_{01} : Compressor inlet stagnation pressure (Pa)
- T_{01} :Compressor inlet temperature (K)
- P_{02} : Compressor outlet stagnation pressure (Pa)
- T_{02} : Compressor outlet temperature (K)
- $C_{P_{air}}$: Specific heat of air in constant pressure (J/kgK)
- $C_{v_{air}}$: Specific heat of air in constant volume (J/kgK)
- γ_{air} : Ratio of specific heats of air
- η_c : Compressor efficiency
- $\dot{W}_c$: Compressor power (W)
- $\dot{m}_{air}$: Mass flow rate of air (kg/s)

Indices 1 and 2 refer to input and output of the compressor. Similar equations can be written for the turbine:

$$T_{04} = T_{03} - T_{03}\eta_t [1 - \left(\frac{P_{04}}{P_{03}}\right)^{\frac{(\gamma_{gas}-1)}{\gamma_{gas}}}] \qquad (4)$$

$$\gamma_{gas} = C_{P_{gas}} / C_{v_{gas}} \qquad (5)$$

$$\dot{W}_t = \dot{m}_{gas} C_{P_{gas}} (T_{03} - T_{04}) \qquad (6)$$

in which:

- P_{03} : Turbine inlet stagnation pressure (Pa)
- T_{03} : Turbine inlet temperature (K)
- P_{04} : Turbine outlet stagnation pressure (Pa)
- T_{04} : Turbine outlet temperature (K)
- $C_{p_{gas}}$: Specific heat of gas in constant pressure (J/kgK)
- $C_{v_{gas}}$: Specific heat of gas in constant volume (J/kgK)
- γ_{gas} : Ratio of specific heats of gas
- η_t : Turbine efficiency
- $\dot{W}_t$: Turbine power (W)
- $\dot{m}_{gas}$: Mass flow rate of gas (kg/s)

Indices 3 and 4 refer to input and output of the turbine. The following thermodynamic equations can show the relationship between important parameters of the combustion chamber:

$$\frac{1}{F} = \frac{\eta_{cc}(\mathrm{LCV})}{C_{p_{gas}}\left(T_{03} - T_{02}\right)} - 1 \qquad (7)$$

$$P_{03} = P_{02}(1 - \xi_{cc}) \qquad (8)$$

in which:

- η_{cc} : Combustion chamber efficiency
- F : Fuel to air ratio
- $C_{p_{gas}}$: Specific heat of gas in constant pressure
- LCV : Fuel lower calorific value
- ξ_{cc} : Pressure loss in combustion chamber

3. GAS TURBINE MODELLING AND SIMULATION

Manufacturing of the most efficient, reliable and durable gas turbines is a continuous challenge for scientists and therefore, there is a strong potential for further research in this field to get in-depth understanding of the nonlinear behavior of these systems. This potential has been a powerful motivation for researchers and engineers in different disciplines to continue to design, build, develop, and operate new generations of gas turbines and their related control systems based on the latest developments and achievements.

Making models of gas turbines and their related control system has been a useful technical and cost-saving strategy for performance optimization of the equipment before final design process and manufacturing. 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. Models may also be used online on sites for optimization, condition monitoring, sensor validation, fault detection, trouble shooting, etc. Before starting to make a GT model, some basic factors should be considered. GT type, configuration, modelling methods, model construction approaches, modelling objectives as well as control system type and configuration are among the most important criteria at the beginning of the modelling process.

3.1. Gas Turbine Type

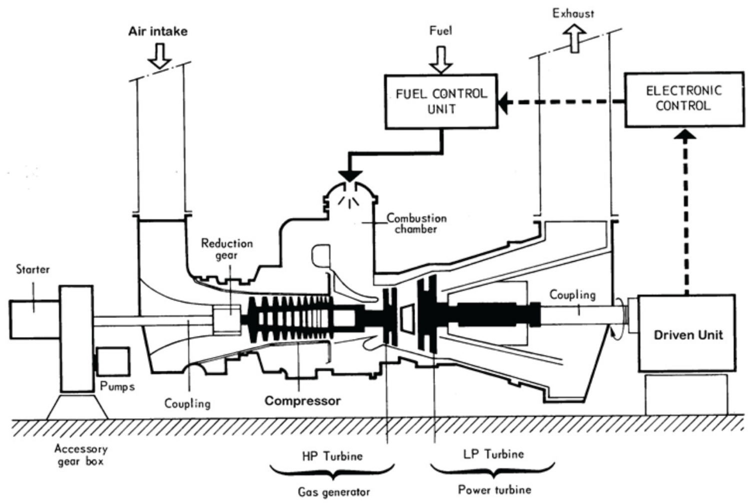
As the first step of modelling, it is necessary to get enough information about the type of gas turbine which is to be modelled. Although there are different types of GT based on their applications in industry, they have the same main common parts including combustion chamber, compressor, and turbine.

Gas turbines are divided into two main categories including aero gas turbines (jet engines) 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 GG is connected to an electro generator, it can be used to produce electrical power. *Industrial Power Plant Gas Turbines (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.

3.2. Gas Turbine Configuration

Configuration of a gas turbine is an 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, intercooling or heat exchange, particular GT configurations are utilized. Gas turbines can be categorized based on the type of their shafts. They may be single-shaft or split-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 3 shows a typical twin-shaft gas turbine engine (MAN Diesel & Turbo Co.).

Figure 3. A typical twin-shaft gas turbine engine (MAN Diesel & Turbo Co.)



3.3. Gas Turbine Modelling Methods

There are different approaches to model a dynamic system such as a gas turbine. Mathematical modelling is considered as a general methodology for system modelling. It uses mathematical language to describe and predict behavior 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. Mathematical models can be classified as "linear and nonlinear," "deterministic and stochastic (probabilistic)", "static and dynamic," or "discrete and continuous" models.

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 behavior, 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 behavior of complex and sensitive systems such as gas turbines, considering nonlinear dynamics is unavoidable.

3.3.2. Deterministic and Stochastic (Probabilistic) Models

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 (Ljung & Glad, 1994). Therefore, in a stochastic model, variable states are described using random probability distributions.

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 (Ljung & Glad, 1994).

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 intervals. A model is called discrete-time when it directly expresses the relationships between the values of the signals at discrete instants of time (Ljung & Glad, 1994). 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.

3.4. Gas Turbine Model Construction Approaches

There are different ways to construct a mathematical model based on the prior information about the system. These approaches can be classified into three main categories including white-box, black-box, and gray-box models.

3.4.1. 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 (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.

3.4.2. Black-Box Models

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.

3.4.3. Gray-Box Models

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 (Norgaard et al., 2000). In this approach, experiments can be combined with mathematical model building to improve model accuracy (Jelali & Kroll, 2004).

3.5. Gas Turbine Control System and Configuration

One of the most important factors in modelling and control of gas turbines is the type and configuration of control system of GT. 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. (Giampaolo, 2009). 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 turbine including "startup 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)* (Boyce, 2002). Control system of gas turbines 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 stable, the controller should be properly related to the process parameters (Boyce, 2002). Figure 4 and Figure 5 show open-loop and closed-loop block diagrams for a typical process respectively.

3.6. 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.

Figure 4. Block diagram of an open-loop system (Daenotes, 2012)

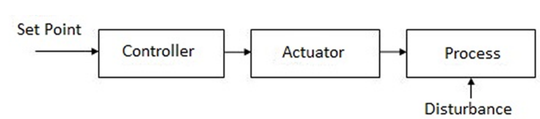
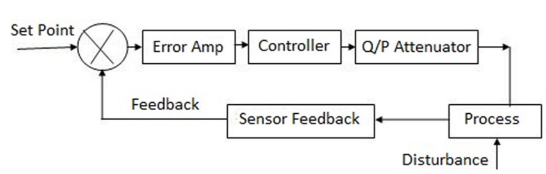


Figure 5. Block diagram of a closed-loop system (Daenotes, 2012)



3.6.1. Condition Monitoring

One of the goals of making a GT model may 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 (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. 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 GT 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.

3.6.2. Fault Detection and Diagnosis

A GT 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.

3.6.3. Sensor Validation

GT 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. If any of the sensors fails to send signal, a GT may not operate correctly and may even face shutdown. 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. 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.

3.6.4. System Identification

One the main objective 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.

3.6.5. Design and Optimization of Control System

Mathematical models may 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). Control as a branch of engineering deals with the behavior 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. 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.

4. WHITE-BOX MODELS OF GAS TURBINES

White-box models of gas turbines can be categorized into power plant gas turbine models 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.

4.1. White-Box Models of Power Plant Gas Turbines

Rowen is a known name in the field of mathematical modelling and simulation of GTs. He presented a simplified mathematical model of a heavy-duty single-shaft power plant gas turbine (Rowen, 1983). He discussed different issues regarding modelling including parallel and isolated operation, gas and liquid fuel systems as well as isochronous and droop governors. The model could be very useful in studies related to power system dynamics. Rowen's model has been a base for many researchers to build up varieties of gas turbine models using different approaches. Rowen, in another effort, presented a simplified model of single-shaft heavy-duty gas turbines in mechanical drive service under different ambient conditions and *Inlet Guide Vanes (IGVs)* positions (Rowen, 1992). He considered the characteristics of control and fuel systems in the new model. Figure 6 shows the block diagram of Rowen's model including fuel and control systems (Rowen, 1983; Tavakoli et al., 2009).

Najjar investigated performance of GTs in single-shaft and twin-shaft operation modes using a model free power gas turbine driving an electric dynamometer (Najjar, 1994). 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 that in single-shaft mode of the free gas turbine engine, power was increased significantly at part load. However, in a twin-shaft mode, torque characteristics at part load were improved remarkably. A model for a twin-shaft combustion turbine was estimated by Hannett et al. (1995). They derived the required data for simulation through the tests for the assessment of governor response to disturbances.

A nonlinear state space model of a 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, GT 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. Figure 7 shows dynamic step response of the simulated model for number of revolutions (Ailer et al., 2001). As it can be seen, the gas turbine is stable at this operational point.

A dynamic model for a twin-shaft gas turbine was developed by Ricketts based on a generic methodology (Ricketts, 1997). The model could also be used for 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 in-

Figure 6. Rowen's model for a heavy-duty gas turbines (Rowen, 1983; Tavakoli, et al., 2009)

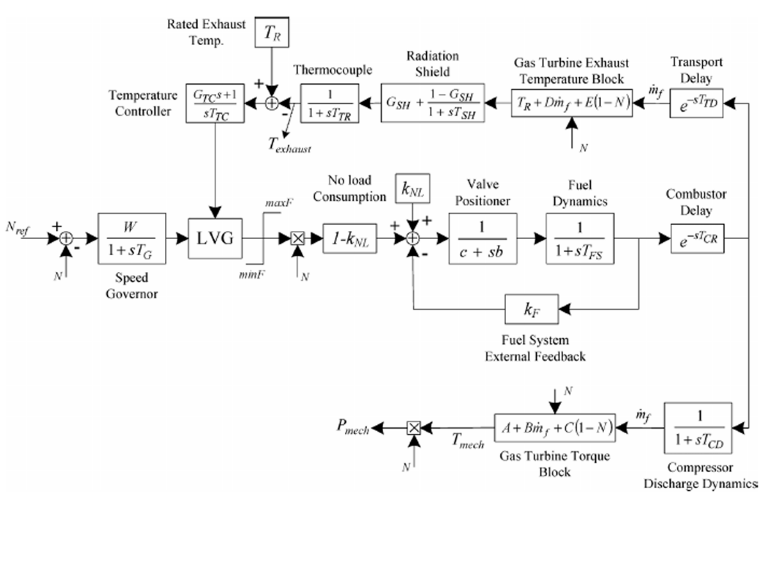
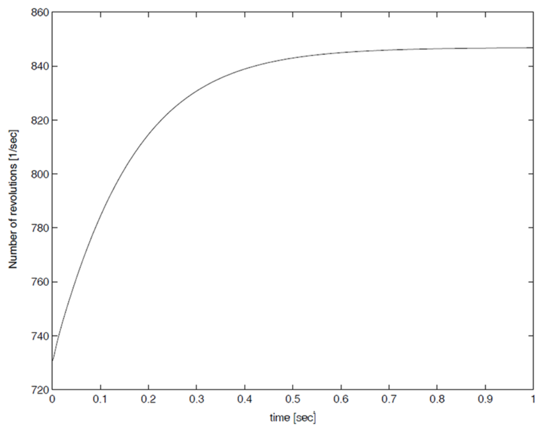


Figure 7. Dynamic step response of the system (1/sec.) (Ailer, et al., 2001)

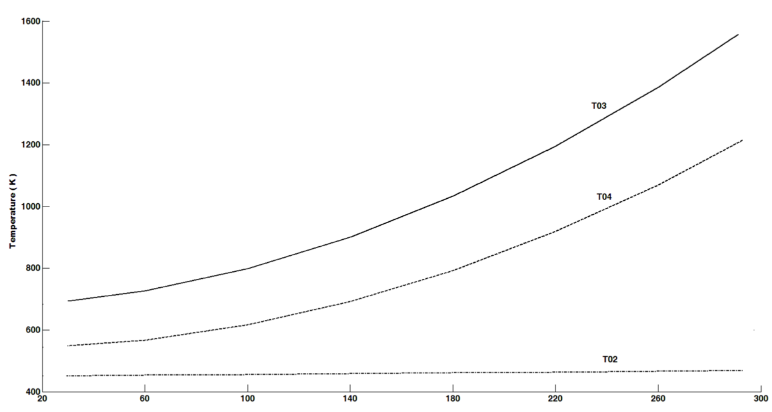


crease the efficiency and specific network of the cycle. Besides, the pre-cooled cycle could operate at a higher compressor pressure ratio and temperature ratio without increasing the maximum cycle temperature. Nagpal et al. presented their field experiences in testing and model validation of turbine dynamic models and their associated governors for Industrial power plant gas turbines (Nagpal et al., 2000). 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.

Al-Hamdan and Ebaid 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 (Al-Hamdan & Ebadi, 2006). They used basic thermodynamic equations of a single-shaft gas turbine to model the system. They 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 8 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.

Kaikko et al. presented a steady-state nonlinear model of a twin-shaft industrial gas turbine and its application to online condition monitoring (Kaikko et al., 2002). They evaluated the GT performance parameters in references, actual, expected and corrected states. They concluded that the applied computational method in their

Figure 8. Variations of various temperatures (K) versus net power output (KW) (Al-Hamdan & Ebadi, 2006)

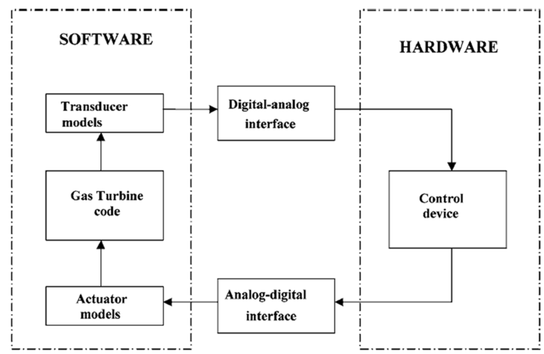


study could be adapted to other modelling, condition monitoring and diagnosis of gas turbines. Abdollahi and Vahedi developed a dynamic model of single-shaft micro turbine generation systems (Abdollahi & Vahedi, 2004). They provided a dynamic model for each component of the micro turbine including gas 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. A gas turbine fully-featured simulator was developed and implemented by Klang and Lindholm (Klang & Lindholm, 2005). They discussed 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.

An aero-thermal model of gas turbines was presented by Camporeale et al. (2006). They modelled and simulated two different power plant gas turbines in SIMULINK environment of MATLAB. They also applied an object-oriented approach to develop a modular real time simulation code for gas turbines. The flexibility of the code allowed it to be adapted to any configuration of power plants. Figure 9 shows the diagram for the real-time simulation software interacted to hardware control devices (Camporeale et al., 2006).

Aguiar et al. investigated modelling and simulation of a natural gas based micro turbine using MATLAB (Aguiar et al., 2007). 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. 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. A simplified desktop performance model of a typical single-shaft heavy-duty 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.

Figure 9. The diagram for real-time simulation software interacted to hardware control devices (Camporeale, et al., 2006)



Development of single-shaft dynamic model for a combined-cycle plant was explored by Mantzaris and Vournas using SIMULINK/MATLAB (Mantzaris & Vournas, n.d.). They investigated stability of the turbine and its control system against overheat as well as changes in frequency and load. Yee et al. carried out a comparative analysis and overview of different existing models of power plant gas turbines (Yee & Milanovic, 2008). They identified, presented and discussed various kinds of GT models in terms of their application, accuracy and complexity. However, the study did not cover the black-box models of gas turbines.

A methodology was applied by Khosravy-el-Hossani et al. to determine the exhaust energy in the new edition of ASME PTC 22 which is about flow rate of flue gas (Khosravy-El-Hossani & Dorosti, 2009). They showed that this method could enhance the precision of ASME PTC 22 by more than one percent. The gas turbine performance test was improved based on the obtained operational data. A methodology was also suggested for calculation of GT performance estimation without measurement of input fuel components. 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. The study can be useful for educational purposes especially for the students and trainers who are interested in gas turbine dynamic studies.

Simple models of the systems for a power plant simulator were developed by Roldan-Villasana et al. based on the mass, momentum and energy principles (Roland-Villasana et al., 2010). 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. applied graph networks approach to analyze and model a single-shaft open-cycle gas turbine (Yadav et al., 2010). 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. Shalan et al. employed a simple methodology to estimate parameters of a Rowen's model for heavy-duty single-shaft gas turbines (Shalan, 2011). Variety of simulated tests was performed using SIMULINK/MATLAB and the results were compared with and verified against the involved scientific articles in the literature.

4.2. White-Box Models of Aero Gas Turbines

Evans, Rees, and Hill 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 (Evans et al., 1998). 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.

Arkov et al. 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 (Arkov et al., 2000). 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". A description of each technique and the relative merits of the approaches were also discussed in the study. Kim et al. developed a model for a single-spool turbojet engine using SIMULINK/MATLAB (Kim et al., 2000). The transient behavior and changes of different engine parameters could be 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.

Evans et al. 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 (Evans et al., 2001). 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 10 shows the Rolls Royce Spey engine modelled by Evans et al. (2001).

Arkov et al. discussed a life cycle support for dynamic modelling of aero engine gas turbines (Arkov et al., 2002). 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.

5. BLACK-BOX (ANN-BASED) MODELS OF GAS TURBINES

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 11 shows a

Figure 10. A typical Rolls Royce Spey engine (Evans, et al., 2001)

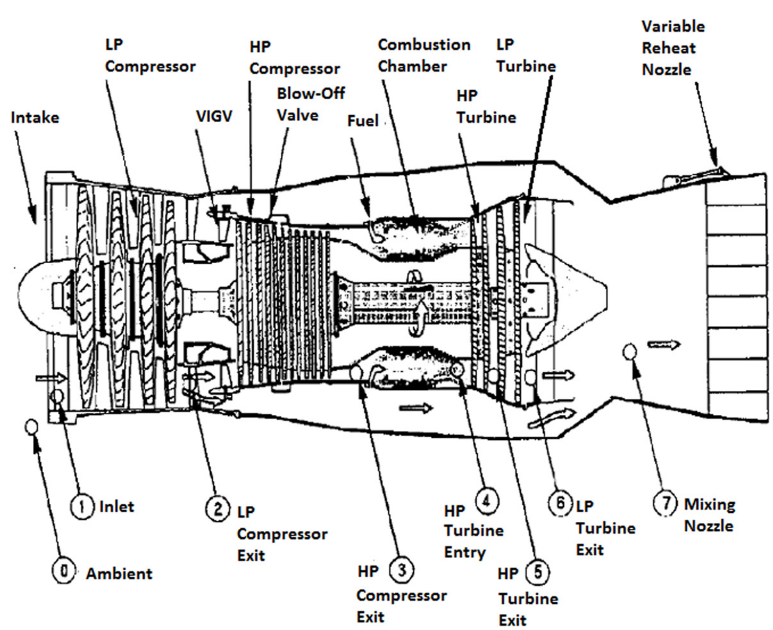
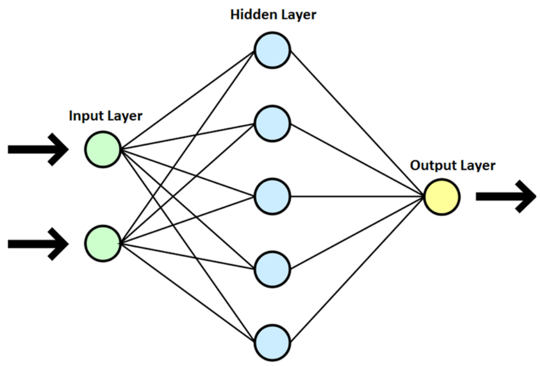


Figure 11. A simple structure of a typical artificial neural network (ANN) with input, hidden, and output layers (Wikimedia Commons, 2012)



simple structure of a typical ANN with two inputs, one output and five neurons in the hidden layer (Wikimedia Commons, 2012).

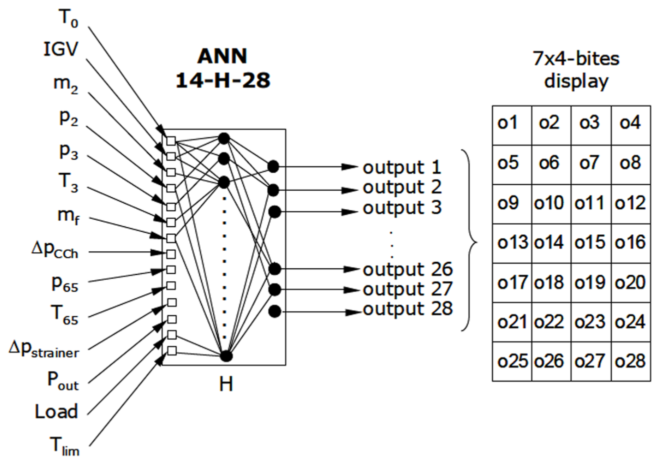
ANN, as a data-driven model, has been considered as a suitable alternative to white-box models during the last few decades. ANN-based models can be created directly using the operational data from an actual GT or simulated data from *Original Equipment Manufacturers (OEMs)* performance. Simulated data 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 based on the flexibility that ANNs provide. This flexibility is based on the number of neurons, number of hidden layers, values of the weights and biases, type of the activation function, structure of the network, training styles and algorithms as well as data structure. 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 (ANN-based) models can be categorized into power plant and aero gas turbine models.

5.1. Black-Box (ANN-Based) Models of Power Plant Gas Turbines

A single-shaft gas turbine design and off-design model was presented by Lazzaretto and Toffolo (2001). They used analytical method and feedforward neural network as two different approaches to model the system. Appropriate scaling techniques were employed to construct new maps for the gas turbine using the available generalized GT maps. The new maps were validated using the obtained experimental data. Ogaji et al. applied three different architectures of ANN for multi-sensor fault diagnosis of a stationary twin-shaft gas turbine using neural network toolbox in MATLAB (Ogaji et al., 2002). The results indicated that ANN could be used as a high-speed powerful tool for real-time control problems. Arriagata et al. applied ANN for fault diagnosis of a single-shaft industrial gas turbine (Arrigada et al., 2003). 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 12 shows a schematic drawing of the ANN and the interpretation of the outputs in a graphical display (Arrigada et al., 2003).

Figure 12. 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 as it is shown in Figure 7, 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. applied a *Nonlinear Autoregressive with Exogenous Inputs (NARX)* model to identify dynamics of a small heavy-duty power plant gas turbine (Basso et al., 2004). The 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. They showed that in order to reduce the complexity and improve the simulating capability of the model, the ingredients should be chosen carefully.

Bettocchi et al. investigated artificial neural network model of a single-shaft gas turbine as an alternative to physical models (Bettocchi et al., 2004). 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. developed a *Multiple-Input, Multiple Outputs (MIMO)* neural network approach for diagnosis of single-shaft gas turbine engines (Bettocchi et al., 2005). A 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 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. Simani et al. carried out a study to detect and isolate faults on a single-shaft industrial gas turbine prototype (Simani & Patton, 2008). 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.

Magnus Fast et al. applied simulation data and ANN technique to examine condition-based maintenance of gas turbines (Fast et al., 2008). In another effort, Fast et al. 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 (Fast et al., 2009a). A combination of ANN method and *Cumulative Sum (CUSMUS)* technique was utilized by Fast et al. for condition monitoring and detection of anomalies in GT performance (Fast et al., 2009b). To minimize the need for calibration of sensors and to decrease the percentage of shutdowns due to sensor failure, an ANN-based methodology was also developed for sensor validation in gas turbines by Fast et al. (Fast et al., 2009c). Application of ANN to diagnosis and condition monitoring of a combined heat and power plant was also discussed by Fast et al. (Fast & Palme, 2010). Fast applied different ANN approaches for gas turbine condition monitoring, sensor validation and diagnosis (Fast, 2010).

Yoru et al. examined application of ANN method to exergetic analysis of gas turbines which supplied both heat and power in a cogeneration system of a factory (Yoru et al., 2009). 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. Application of ANN and *Adaptive Network-Based Fuzzy Inference System (ANFIS)* to MGTs was investigated by Bartolini et al. (2011). They investigated the effects of changes of ambient conditions (temperature, pressure, humidity) and load on MGT's output power. The results indicated 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. Black-Box (ANN-Based) 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 (Chiras et al., 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). 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. carried out a research regarding nonlinear identification of shaft-speed dynamics for a Rolls Royce Spey aircraft gas turbine (Ruanoa et al., 2003). 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. Different configurations of *Back Propagation Neural Networks (BPNN)* were used by Torella, Gamma and Palmesano to study and simulate the effects of gas turbine air system on engine performance (Torella et al., 2003).

6. APPLICATIONS OF GT MODELS IN CONTROL SYSTEM DESIGN

Modelling and simulation of gas turbines can play a significant role in control areas. Research activities regarding applications of modelling in control systems can also be categorized into white-box and black-box (ANN-based) approaches.

6.1. White-Box Approach

A dynamic model for a twin-shaft gas turbine which was developed by Ricketts based on a generic methodology, were used for designing an appropriate adaptive controller (Ricketts, 1997). Pongrácz et al. used an input-output linearization method to design an adaptive reference tracking controller for a low-power gas turbine model (Pongracz et al., 2000). 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.

Ashikaga et al. carried out a study to apply nonlinear control to gas turbines (Ashigaga et al., 2003). They reported two applications of nonlinear control. The first one was the GT starting control using the fuzzy control, and the other was the application of the optimizing method to *Variable Stator Vane (VSV)* control. The aim 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. Agüero et al. applied modifications in a heavy-duty power plant gas turbine control system (Aguero et al., 2002). 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 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. Centeno et al. reviewed typical gas turbine dynamic models for power system stability studies (Centeno et al., 2002). 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 13 shows the block diagram of the basic temperature control loop for the GT model (Centeno et al., 2002).

6.2. Black-Box (ANN-Based) Approach

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 controllers was better than conventional ones; but they could not track the reference models as closely as they expected.

Another effort was carried out by Dodd and Martin, more or less with the same goals (Dodd & Martin, 1997). They proposed an ANN-based adaptive technique to model and control an aero gas turbine engine and to maintain thrust at 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 14 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 14. Block diagram of an ANN-based aero gas turbine model for system optimization consists of minimizing fuel while maintaining thrust (Dodd & Martin, 1997)

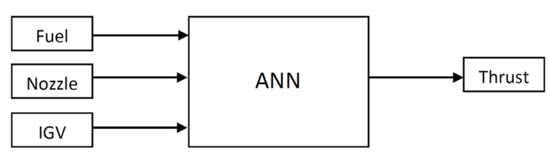
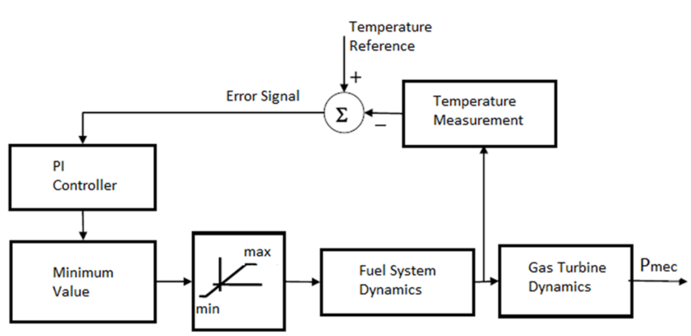


Figure 13. Block diagram of the basic temperature control loop for a gas turbine model (Centeno, et al., 2002)



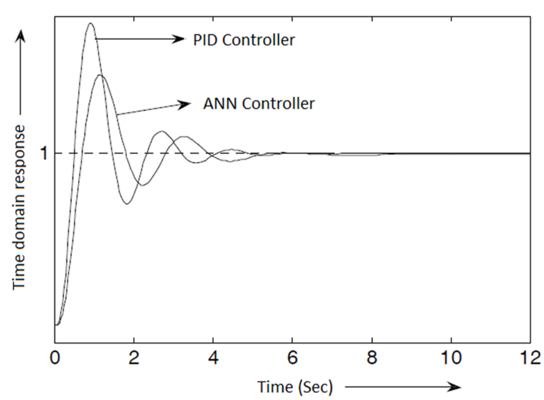
Mu and Rees investigated nonlinear modelling and control of a Rolls Royce Spey aircraft gas turbine (Mu & Rees, 2004). They used NARMAX and neural networks to indentify the engine dynamics under different operational conditions. An *Approximate Model Predictive Control (AMPC)* was applied in order to 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, in another effort, examined two different approaches to design a global nonlinear controller for an aircraft gas turbine (Mu et al., 2004). 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.

Spina and Venturini 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 (Spina & Venturini, 2007). Implementation of a *Model Predictive Control (MPC)* to a heavy-duty power plant gas turbine was investigated by Ghorbani et al. (Ghorbani et al., 2008). They modeled the system based on a mathematical procedure and *Autoregressive with Exogenous Input (ARX)* identification method. The goal was to design a controller which 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. 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 GT. The simulation results showed that ANN controller performed better than the PID controller. Figure 15 shows a comparison of gas turbine plant response with PID and ANN controllers (Balamurugan et al., 2008).

7. CONCLUSION

Modelling and simulation of gas turbines plays a key role in manufacturing the most efficient, reliable and durable gas turbines. This fact has been a strong potential and motivation for scientists to keep carrying out significant research in this field. The outcome of the research, so far, has been very effective to evaluate and optimize performance of gas turbines before final design and manufacturing processes. Besides, GT models can also be used on industrial sites for optimization, condition monitoring, sensor validation, fault detection, trouble shooting, etc. There are different approaches and methodologies in modelling and control of gas turbines. Choosing the right method

Figure 15. A comparison of gas turbine plant response with PID and ANN controllers (Balamurugan, et al., 2008)



and creating the right model based on the required application depends on different factors such as GT type, GT configuration, modelling methods, model construction approaches and modelling objectives. By highlighting these factors, remarkable enhancements can be achieved in the process of modelling and control of gas turbines.

In this chapter, a brief overview of significant research activities in the area of modelling and simulation of gas turbines were briefly reviewed and discussed. Main white-box and black-box models and their applications in control systems were investigated for both aero and power plant gas turbines. Despite all the efforts carried out so far in the field of modelling, simulation and control of gas turbines using mathematical and experimental methods, there is still a great need for further system optimization. To approach an optimized 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 the following areas:

1. 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.
2. System disturbances arising from faults or from load fluctuations in power network of power plant gas turbines could drive GTs to instability. Exploring reaction of gas turbines to the system disturbances and environmental condition changes 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 system. 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.
3. Approximating an ANN model with high generalization capabilities and robustness for industrial power plant gas turbines can be extensively investigated using operational data of real GTs and based on the flexibility that ANN provides for modelling of different types of systems. 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. For this purpose, different ANN architectures can be explored for gas turbines using operational data in order to attain or customize the optimal model. The obtained optimal model should predict dynamic behavior of the system as accurately as possible. It can be used as a powerful tool in condition monitoring, trouble shooting and even maintenance of gas turbines.
4. A neural adaptive controller with superior control behavior and high adaptability needs to be designed for GT models. The controller should contribute towards high-performance, cost-effectiveness and high-reliability. The GT model can be used to predict the effect of controller changes on plant output, which consequently allows the updating of controller parameters. The goal is to maximize system robustness, output power and efficiency.

The upcoming efforts can lead to optimal models and control algorithms with minimal supervision and energy consumption. A methodology can be developed to identify system parameters and to predict dynamic behavior of the system as accurately as possible. This methodology can be applicable to a wide range of operational conditions. The future will bring advancements in technology that enables the development of optimized reliable gas turbines.

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