Considerations in Modelling and Control of Gas Turbines – a Review

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***Abstract*—Modelling and control of gas turbines (GTs) have always been a controversial issue because of the complex dynamics of these kinds of equipment. Considerable research activities have been carried out so far in this field in order to disclose the secrets behind the nonlinear behaviour of these systems. Although the results of the research in this area have been satisfactory so far, it seems that there is no end to the efforts for performance optimization of gas turbines. A variety of analytical and experimental models as well as control systems has been built so far for gas turbines. However, the need for optimized models for different objectives and applications has been a strong motivation for researchers to continue to work in this field. This paper is aimed at presenting a general overview of essential basic criteria that need to be considered for making a satisfactory model and control system of a gas turbine. GT type, GT configuration, modelling methods, modelling objectives as well as control system type and configuration are the main preliminary factors for modelling a gas turbine which will be briefly discussed in the paper. Some of the research in this field will be also stated shortly.**

***Index Terms*—Modelling and control, gas turbine, dynamic simulation, mathematical model.**

I. INTRODUCTION

GAS turbine (GT) is considered as an internal combustion engine which converts chemical energy from fuel to mechanical energy using the gaseous energy of air as the working fluid. Although the story of gas turbines has taken a root in history by the invention of *aeolipile (*a rocket style jet engine which span when heated) as the first turbine engine by an Egyptian scientist named Hero [1], it was not until 1930s that the first practical gas turbine was developed by Frank Whittle and his colleagues in Britain for a jet aircraft engine [2]. Gas turbines were developed rapidly after World War II. Enhancement in different areas of science such as aerodynamics, cooling systems, and high-temperature materials significantly improved jet engines efficiency. Therefore, in a short time, GTs became the primary choice for many applications. Since then, gas turbines have been increasing in popularity.

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Today, gas turbines play a key role in different industrial applications. High thermal efficiency and high power output of gas turbine engines have made them very effective and useful in a wide variety of applications in aeronautical industry and power generation. The mechanical power generated by gas turbines can be utilized as main mechanical drivers for large pumps, compressors, generators or impellers. In a jet engine, the output gaseous fluid is used to generate thrust.

Since creation of practical gas turbines, it is a constant challenge for researchers to find optimal solutions to design, manufacture, develop and operate new generations of gas turbines and their related control systems as efficiently, reliably and durably as possible. Making models of gas turbines and their related control system has been a useful technical and cost-saving strategy for optimization of the equipment before final design process and manufacturing. Models may also be used online on sites for optimization, condition monitoring, sensor validation, fault detection, trouble shooting, etc. To make a model, some important basic factors should be considered. GT type, GT configuration, modelling methods, modelling objectives as well as control system type and configuration are among the most important factors at the beginning of the modelling process.

II. GT TYPE

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

GTs 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. 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 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. GGs may also be tied to large pumps or compressors to make turbo-pumps or turbo-compressors respectively.

III. GT CONFIGURATION

Configuration of a gas turbine is an important criterion in GT modelling and control. Although all gas turbines nearly have the same basic structure and thermodynamic cycle, there are considerable distinctions when they are investigated in detail. For instance, in order to enhance gas turbine cycle, system efficiency or output power, different methods such as reheating, intercooling and heat exchange may be utilized in particular GT configurations.

There are basically two main types of gas turbines based on the type of shaft they use; single-shaft and twin-shaft gas turbines. In a single-shaft gas turbine, the power output shaft is directly connected to the same turbine rotor that drives the compressor. In most cases, there is a speed reducer (gear box) between the rotor and the power output shaft. However, a mechanical connection is still available throughout the entire engine. In a twin-shaft gas turbine, there is not any mechanical connection between the Power Turbine (PT) and the gas generator turbine. PT is the component that does the usable work. The gas generator turbine provides the required power for driving the compressor and accessories. With this type of engine, the output speed is controlled by varying the gas generator speed. Also, under particular conditions, the gas generator can run at a reduced rotational speed and still provide maximum rotational speed of power turbine. This greatly extends the life of the gas generator turbine and also improves fuel economy.

IV. MODELLING METHODS

There are different approaches to model a dynamic system such as gas turbine. Mathematical modelling is considered as a general methodology for system modelling. It uses mathematical language to describe and predict the behaviour of a system. Mathematical models may be classified as follows:

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

2) Deterministic and Stochastic (probabilistic) Models: In a deterministic model, all variable states are determined uniquely by 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 [3]. Therefore, in a stochastic model, variable states are described using random probability distributions.

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 [3].

4) Discrete and Continuous Models: A mathematical model is called continuous-time when it describes the relationship between continuous time signals, usually by using differential equations. 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, usually by using difference equations [3]. In practical applications, signals are most often obtained in sampled form in discrete time measurements.

From another perspective, Mathematical models can be classified into two main categories including white-box and black-box models based on the prior available information of the system.

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. 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.

Significant progress has occurred in gas turbine modelling using white-box methods. Some highlights in this area are briefly summarized below. A simplified mathematical model of a heavy-duty gas turbine suitable for use in dynamic power system studies and in dynamic analysis of connected equipment was presented by Rowen [4]. He also presented a simplified mathematical model of single shaft gas turbines in mechanical drive service [5]. Nagpal et al. reported their field experiences in testing and modelling of gas turbines and their associated governors [6]. A nonlinear model of gas turbine for loop-shaping control purposes was developed by Ailer et al. [7]. Evans et al. studied the linear multivariable modelling of an aircraft gas turbine [8]. Centeno et al. reviewed the gas turbine dynamic models for power system stability studies [9]. Arkov. Kulikov and Breikin discussed a life cycle support system for dynamic modelling of gas turbines [10]. Experiments were carried out by Henrion et al. to derive linearized models of aircraft turbofan engine dynamics from standard engine simulators used in industry [11]. Abdollahi and Vahedi presented a dynamic model of micro-turbine generation systems using SIMULINK/MATLAB [12]. Visser et al. described generic approach for gas turbine adaptive modelling [13]. Al-Hamdan and Ebaid discussed modelling and simulation of a gas turbine engine for power generation [14]. Zhu et al. presented a simplified performance model of gas turbine combined cycle systems. They focused on a methodology for assessment of gas turbine-based power generation systems that can be implemented in a desktop computing environment in order to facilitate rapid analysis of system alternatives [15]. B. Tavakoli et al. recommended an educational guide to extract the parameters of heavy-duty gas turbines in dynamic studies based on operational data [16].

2) *Black-Box Models:* A black-box model is used when no or a little information is available about the physics of the system. 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.

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. Fig. 1 shows a simple structure of a typical ANN with four inputs, one output and five neurons.

ANN, as a data-driven model, has been considered a suitable alternative to white-box models during the last few decades. ANN-based models can be created directly from 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 behaviour of the system as accurately as possible.

Selecting the right parameters of GTs as inputs and outputs of the 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.

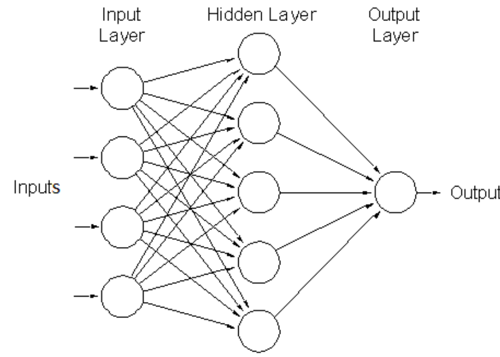

Fig. 1. A simple structure of a typical Artificial Neural Network (ANN) with input, hidden and output layers

Significant progress has been made in modelling of gas turbines using ANNs. As examples of such research, one can refer to investigation by Lazzaretto and Toffolo [17]. They studied a gas turbine design and off-design model in which the difficulties due to the lack of knowledge about stage-by-stage performance were overcome by constructing artificial neural networks. The estimation of a NARMAX (nonlinear auto-regressive moving average with exogeneous Input) model of an aircraft gas turbine was presented by Chiras, Evans and Reesa [18]. They also applied an orthogonal estimation algorithm to estimate a NARMAX model for an aircraft gas turbine [19]. In another effort, they modelled fuel flow to shaft speed relationship of an aero gas turbine engine using feedforward neural network [20]. The performance of the estimated model was validated against a range of small and large signal engine tests. Chiras, Evans and Rees recommended a Global Nonlinear Modelling of gas turbine dynamics using NARMAX Structure [21]. Nonlinear modelling of micro-turbines using NARX (nonlinear autoregressive exogenous) structure was investigated by Jurado [22].

V. CONTROL SYSTEM TYPE AND CONFIGURATION

One of the most important factors in modelling and control of gas turbines is the type and configuration of control system of the GT which is to be modelled. 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 dynamics of the system and the defined tasks during the whole performance period. Lacking a proper control system for gas turbines can lead to serious problems such as compressor surge, over heat temperature for the turbine, over speed for the power turbine, etc [23]. 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 start up and shut down sequencing control, steady-state or operational control, and protection control for protection from over heat, over speed, over load, 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) [24].

Gas turbine control systems can 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, a closed-loop control system receives one or more measured data process variables and uses them to move the manipulated variable in order to control a device. It is very important that controller is properly related to the process parameters to ensure closed-loop stability while still providing effective control [24].

Significant research has been carried out in the field of control system for gas turbines. Rowen presented a simplified mathematical model for control of load frequency and temperature in gas turbines [4], [5]. Exploring the practical use of ANN for controlling complex nonlinear systems was done by Nabney and Cressy [25]. They used ANN to maintain system variables in safe operating regions as well as to govern the engine thrust in a gas turbine engine typical of those used to power commercial aircrafts. Dodd and Martin proposed a technique for controlling aero gas turbines in order to maintain thrust while minimising fuel consumption in engine [26]. They used ANN to model the engine. An adaptive reference tracking control of a low-power gas turbine model based on input-output linearization was presented by Pongrácz et al. [27]. Modelling and nonlinear control of a low-power gas turbine was investigated by Ailer [28]. Ashikaga et al. investigated using a nonlinear control for gas turbines [29]. Mu and Rees used a novel model predictive control strategy called approximate model predictive control (AMPC) to control a shaft speed of a gas turbine engine [30]. They and Liu designed an advanced controller for aircraft gas turbine engines using NARMAX and neural network [31]. Ghorbani et al. implemented a model predictive control (MPC) strategy to a heavy-duty gas turbine power plant [32]. Balamurugan et al. used fuzzy logic ANN controller for a heavy gas turbine plant [33]. They trained a multilayer neural network using backpropagation method to control the speed of the gas turbine.

VI. MODELLING OBJECTIVES

There may be 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 a pre-request for a successful GT model.

A. 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 provide early warning of potential failure so that preventative maintenance action may be taken [34]. 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 operating 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 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.

As an example of using GT model for condition monitoring, one can refer to the research by T.V. Breikin et al. [35]. He investigated a model-based condition monitoring of aero gas turbine engines. He applied Genetic algorithms for the dynamic modelling of aero engines by estimating parameters of the linear reduced-order model.

B. Fault Detection and Diagnosis

A GT model may be created in order to predict and detect faults in the system. Fault diagnosis plays an important role in the efforts for gas turbine operators to shift from preventive maintenance to predictive maintenance, and consequently to reduce the maintenance cost [36]. It concerns with monitoring a system in order to identify when a fault has occurred as well as to determine the type and location of the fault.

As an example of a medium-size industrial gas turbine model for fault diagnosis, one can refer to the research carried out by Arriagada et al. [37]. The researchers used ANN to make a diagnosis about the gas turbine's condition. They obtained the required data set which included only parameters that were actually measured in the real engines. The results of the research showed that an ANN-based fault diagnosis model was capable of fault isolation and identification with high reliability. Besides, it could identify many fault types before they were fully developed. Fig. 2 shows a schematic drawing of their ANN and the interpretation of the outputs in a graphical display [37]. As it can be seen from the model 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. They include ambient temperature, inlet guide vanes angle, mass flow rate, fuel flow rate, load, pressure and temperature in different sections of the turbine, etc. As it can be seen from Fig. 2, the ANN desired outputs are unique combinations of 28 binary numbers which are arranged in a graphical display. The training process of the ANN stopped when it showed the best performance based on the selected number of hidden neurons and weights for the network. The ANN can be named 14-H-28 according to its structure [37].

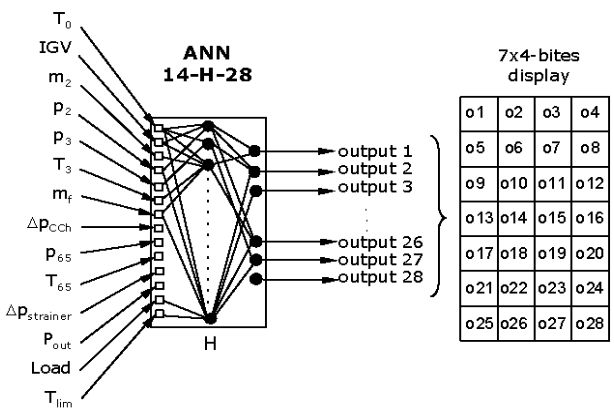

Fig. 2. Schematic drawing of the ANN and the interpretation of the outputs in a graphical display [37]

C. 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 optimally and may even face shutdown.

Sensor validation is detecting, isolating and reconstructing a faulty sensor. Some sensors may fail to report correct data due to different reasons or may even become unavailable because of failure or maintenance activities. Sensor validation can improve reliability and availability of the system, and reduce maintenance costs. It enhances reliability and safety for the equipment and personnel respectively. 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 of the equipment. It can strengthen automation of the system by providing valid data for diagnostic and monitoring systems.

As an example of making a model for sensor validation, one can refer to the research by Palmé et al. They presented a "sensor validation-based" model for GTs to develop a method for evaluating sensor accuracy in order to minimize the need for calibration and to avoid shutdowns due to sensor faults [38]. The proposed method was based on training ANNs as classifiers to recognize sensor drifts. The method was evaluated on one single-shaft and one twin-shaft gas turbine. According to the results, the proposed method is capable of early detection of sensor drifts for both types of machines.

D. System Identification

One the main objectives of modelling of gas turbines are system identification. System identification infers a mathematical description, a model of a dynamic system from a series of measurements of the system [39]. Although significant research has been done so far in the field of modelling of gas turbines using mathematical and experimental methods, there are still unpredictable events during operation of GTs because of the complexity and nonlinear behaviour of these systems. Therefore, there is a strong motivation for many researchers to continue to work in this field. They want to apply new methodologies in order to make a reliable prototype model for GTs. Such a model can predict the behaviour of the system as accurately as possible.

As examples of GT modelling for system identification, one can refer to research carried out by Evans, Rees and Hill [40]. They considered a twin-shaft gas turbine and investigated the identification of the fuel flow to the shaft speed dynamics in order to validate thermodynamic engine models. They examined the direct estimation of s-domain models in the frequency domain. Arkov et al. applied a variety of system identification techniques to the derivation of models of aircraft gas turbine dynamics [41]. They used four system identification approaches including ambient noise data, multisine testing and frequency-domain identification, multi-objective genetic programming (to select model structure) and time-varying models (estimated using extended least squares with optimal smoothing). Ruano et al. investigated identification results for the shaft-speed dynamics of an aircraft gas turbine, under normal operation [42].

E. 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, and to take required corrective action if the value of measured data deviates from its desired corresponding value. This in turn necessitates a sensing device [43]. Control as a branch of engineering deals with the behaviour of dynamical systems. The output performance of the equipment which is under control is measured by sensors. These measurements can be used to give feedback to the input actuators to make corrections toward desired performance. In spite of the active 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 improve existing control systems for GTs. As examples of GT modelling for control, one can refer to the research carried out by Mu and Rees [30]. They investigated a novel model predictive control strategy called approximate model predictive control (AMPC) to control a shaft speed of a gas turbine engine.

VII. Conclusion

There are different approaches and methodologies in modelling and control of gas turbines. Choosing the right method and creating the right model based on the required application depends on different factors. In this paper, a brief overview of basic consideration for making a satisfactory model of gas turbines was discussed. A short description of each of these factors including GT type, GT configuration, modelling methods, modelling objectives as well as control system type and configuration was provided. Samples of significant research related to each of the areas were presented. By highlighting the mentioned factors, remarkable enhancements can be achieved in the process of modelling and control of gas turbines.

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