Chapter

Introductory Chapter: Gas and Wind Turbines and Their Models

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1. Introduction

Turbomachines, in particular, a gas turbine (GT) and a wind turbine that are considered in the present book, are indispensable for power generation, transportation, and many other industries.

In the last decades, a GT industry has exposed a considerable growth [1]. A gas turbine combines high power and efficiency with relatively low weight and compactness. A turboshaft engine presents a principal driver for electricity production. It is also widely used in offshore oil platforms, petrochemical plants, refineries, gas stations, and so on. Many marine and other kinds of transport are equipped by gas turbine engines as well. Depending on a particular application and the range of produced power, the types of GTs embrace heavy-duty, aircraft-derivative, industrial, vehicular, small, and micro gas turbines [1]. Another large area of GT application is air transport. Different aircraft gas turbine engines, which can generally be divided into turbofans, turboprops, and turboshafts, have revolutionized the aviation industry [2] and so far have no alternatives.

Following a general development of the industry of gas turbines, the use of their mathematical models becomes more intensive. Modeling and simulation of GTs have been an effective way of design and manufacture. For example, the use of engine models enables to evaluate and optimize the engine performance before the engine fabrication. In addition to the design of the gas turbine engine itself, engine modeling and simulation are widely used in the development of control and monitoring systems [2–4].

To have high power and efficiency performances, a gas turbine must operate near its functional and structural limits at different steady-state and dynamic modes. For doing so, an engine control system should be accurate enough. In the beginning of the gas turbine technology development, much experimentation was done to design this system. However, since the engine and its control system are more and more complex and expensive, physical experimenting to tailor, test, and validate the system is expensive and therefore limited. For this reason, mathematical modeling and simulation of GTs have been increasingly useful and effective methodology of the control system development. As a result of investigations, better understanding of engine dynamic behavior was gained, and more complex and exact engine dynamic models were developed. These models allow accurate predicting and analyzing engine dynamics. They also help a lot with decreasing fuel consumption and the development and optimization of multiple engine control laws.

The abovementioned complexity and expensiveness of GTs and high demands to engine reliability and safety at low maintenance costs make it unavoidable to use advanced monitoring systems. Through diagnostic processing of engine measured parameters, these systems allow us to gain the knowledge about the health conditions of main engine components and subsystems. Ideally, it is possible to have the necessary information about the influence of engine faults on the measured parameters by physical embedding the faults in real engines. However, it is a too risky and expensive way, and the assessment of engine technical state is usually based on different mathematical models. Since the diagnostic quality strongly depends on the accuracy of the models used, the issue of the diagnostic models development is important [4]. Although, many diagnostic GT models have been proposed and constructed so far, the existing demand for optimized models for different objectives and engine applications motivates the investigators to continue their efforts to further enhance gas turbine modeling.

Let us now come back to wind turbines. They present the principal source of renewable energy. Although wind turbines now generate only about 1% of the total energy, their development rate is by far higher than the rates of traditional energy sources, and the total power production is already about two times greater than the production of solar plants [5]. Being a megastructure, a wind turbine must meet strict requirements of reliability and safety. On the other hand, massive electricity production should be cost-effective. Due to these contradictory demands, as with gas turbines, the turbine itself and its control and monitoring systems need thorough optimization. To this end, a wide use of accurate mathematical modeling and simulation is a very effective strategy. For specific purposes, many different wind turbine models, e.g., aerodynamic, mechanical, economical, and environmental, have been proposed so far. For the needs of control and diagnostics, the general-purpose model that describes both aerodynamic and electric parts of the power plant is mainly used.

2. Gas turbine modeling

As with the models of other technical systems, the gas turbine models fall into two general categories: physics-based models and data-driven models. The physics-based models rely on the theory of gas turbines and therefore perform accurate simulation of various steady-state and transient modes. Being more complex than the data-driven models, physics-based models have however extended capabilities and offer the knowledge that can hardly be obtained from real data, for example, the information about the influence of the faults on engine performances. The data-driven models (aka black box models) do not require the information about internal structure and operation of the simulated engine. To build these models, optimization methods or, in the case of neural networks, machine learning techniques are employed using available real information as input data. These models are widespread because of their simplicity. The variety of such models is described in detail in the book [3].

2.1 Thermodynamic model and its derivations

Among physics-based gas turbine models, a nonlinear component-based model also called a thermodynamic model is primarily used for development of control and diagnostic systems. The model relies on the gas turbine theory [6]. The model involves aerothermal relations to compute gas path variables, and engine components such as compressors, combustion chamber, and turbines are given by their performance maps. The most of diagnostic methods are applied to engine at steady states. In this case, model output variables $\vec{Y}$ are computed employing operational conditions $\vec{U}$ and health parameters $\vec{\Theta}$ as input data. In this way, the static model structure is given by

$$\vec{Y} = F\left(\vec{U}, \vec{\Theta}\right). \tag{1}$$

The health parameters can shift a little the components' maps that allow considering a varying technical state of the engine. Mathematically, expression (1) is a result of solving a system of nonlinear algebraic equations that reflect the balance of mass, heat, and mechanical energy. For the engines of complex structure, the number of equations reaches 15–20.

The development of control algorithms and some diagnostic methods (see, e.g., [7]) relies on dynamic simulation. Within the thermodynamic model, the simulation at transients can be expressed by

$$\vec{Y} = F\left(\vec{U}(t), \vec{\Theta}, t\right). \tag{2}$$

In contrast to the static simulation according to Eq. (1), the operating conditions $\vec{U}$ are now time functions. Time t is also separately added to the arguments to take into consideration inertia factors, namely, inertia moments of engine rotors, mass and energy accumulation in gas capacities, and warming-up of massive metal elements. Expression (2) is determined by the solution of differential equations that reflect combined operation of the engine components under dynamic conditions. The dynamic model is usually developed on the basis of the static model and uses approximately 70% of its software. In this way, these models constitute a common program complex of the thermodynamic model.

As the thermodynamic model is complex and relatively slow, a number of simplified data-driven models are determined on its basis.

To quantify fault influence in gas turbine diagnostics, a healthy engine performance (baseline model $\vec{Y}_0 = F(\vec{U})$) is required. As mentioned in [8], a simple second-order polynomial function provides accurate approximation of an engine baseline. For one gas path variable Y and three operating conditions u_i, this function looks like

$$Y_0(\vec{U}) = a_0 + a_1u_1 + a_2u_2 + a_3u_3 + a_4u_1u_2 + a_5u_1u_3 + a_6u_2u_3 + a_7u_1^2 + a_8u_2^2 + a_9u_3^2 \tag{3}$$

Unknown coefficients a_j for all the variables $\vec{Y}$ are determined by the least squares method using the data generated by the static nonlinear model as input information. Real data collected under test bed or field conditions can also be used.

Another simplified model obtained in the basis of the thermodynamic model is a linear static model presented by

$$\delta\vec{Y} = H\delta\vec{\Theta} \tag{4}$$

For a fixed operating mode ($\vec{U}$-const), this model relates small relative changes $\delta\vec{Y}$ and $\delta\vec{\Theta}$ of the gas path variables and operating conditions, respectively. The necessary influence coefficients of a matrix H are computed according an expression

$$H_{ij} = \frac{\delta Y_i}{\delta \Theta_j} = \frac{Y_i\left(\vec{\Theta}_j\right) - Y_i\left(\vec{\Theta}_0\right)}{Y_i\left(\vec{\Theta}_0\right)} \Bigg/ \frac{\Theta_j - \Theta_{0j}}{\Theta_{0j}}. \tag{5}$$

The required values $Y_i\left(\vec{\Theta}_0\right)$ and $Y_i\left(\vec{\Theta}_j\right)$are calculated by the nonlinear static model which runs one time for a healthy engine state and then one time for each variation $\delta\Theta_j$ introduced by turn in health parameters.

One more model based on the thermodynamic model is called a linear dynamic state space model and is presented by the two following equations:

$$\begin{aligned}\dot{\vec{X}}(t) &= A\overrightarrow{\Delta X}(t) + B\overrightarrow{\Delta U}(t)\\ \overrightarrow{\Delta Y} &= C\overrightarrow{\Delta X}(t) + D\overrightarrow{\Delta U}(t)\end{aligned} \tag{6}$$

where $\vec{X}$ stands for a vector of state space variables and Δ denotes a difference between dynamic and static values of variables. Unknown matrices A, B, C, and D are computed through the static nonlinear model in the same way as the matrix H.

2.2 Thermodynamic model improvements

The development and diagnostic use of thermodynamic models began in the 1970s inspired by the works of Saravanamuttoo (for instance, [9]). Since then, many enhancements have been introduced in this model.

Stamatis et al. [10] proposed an adaptive simulation by an identified thermodynamic model, and then they used such simulation in gas turbine diagnostics [11].

Paper [12] introduces ellipsoid functions that more accurately describe components performance maps in a thermodynamic model. As a result, better model identification at steady states and transients is gained.

In the well-known universal software GasTurb [13] developed since the 1990s, there are special tools that help to verify and correct the compressor and turbine maps.

A more radical way to enhance compressor description is described in [14]. It is proposed to replace a compressor map by a stage-based compressor model. It is shown that the thermodynamic model after such a modification allows to identify faulty stages and recognize compressor fouling, tip wear, and erosion, thus making the diagnosis more profound.

Volponi et al. [15] propose to compliment a traditional thermodynamic model by a neural network-based data-driven model that compensates systematic measurement errors. The authors show that the new hybrid model considerably enhances simulation accuracy.

The above described enhancements contribute to a whole thermodynamic model or its static part. Nevertheless, simulation of transients has specific issues to address, and fast and accurate dynamic models are in demand [16]. Following this demand, paper [17] describes the model of turbine clearance dynamics intended to complement a traditional physics-based dynamic model. Such an extension of the traditional model does not practically change computation time but allows to consider a dynamic turbine performance and significantly enhance the accuracy of engine dynamic simulation.

The present book meets the mentioned demand for improved dynamic models addressing two related problems. The first problem presents the extension of dynamic model operation on engine starting (see Chapter 2). It is proposed to simulate the starting by a linear dynamic model supplemented with a simplified static model. The second problem presents accurate simulation of gas capacities in a nonlinear dynamic physics-based model (Chapter 3). A lot of different variations of capacity models are considered and compared, and the recommendations of application are given.

2.3 Estimation of unmeasured variables

In addition to traditional diagnostic functions, estimation of important unmeasured engine variables can be included into a gas turbine monitoring system.

Examples of such estimation include engine power [18] or thrust [19], compressor and turbine efficiencies [20, 21], and compressor air mass flow [21]. These variables help with monitoring of the mission of gas turbines, their integrity, and overall efficiency. They allow a more profound diagnosis of engine components as well.

The issue of unmeasured variable estimation is challenging because it must allow for an engine technical state. A reasonable solution for an offline monitoring is using a thermodynamic model. However, this model has intrinsic inaccuracy, is critical to computer resources, and is not always available. A Kalman filter-based dynamic model affords a faster estimation [19], but it has additional linearization and approximation errors, and its development still needs a thermodynamic model.

For online monitoring, a good choice is using simple thermodynamic relations that allow computing some important unmeasured variables, for example, component efficiencies [20] and airflows [21], through measured quantities. Nevertheless, this choice is available only for few variables.

In contrast, paper [22] offers a universal data-driven method to estimate any necessary unmeasured gas path variable. Additionally, to draw diagnostic information for online monitoring, it is proposed to extend traditional computing the measured quantity deviations on the unmeasured variables.

Chapter 4 of the present book presents new models of unmeasured variables to monitor engine lifetime. To evaluate the lifetime, the temperatures of gas and air around a critical element, turbine blade, should be known. Various variations of data-driven and physics-based models for these unmeasured variables are formed. By model comparison, the optimal ones are chosen and recommended for real applications.

3. Gas turbine control

The type and configuration of a GT control system is an important factor. They are closely related with the complexity of engine dynamics and control tasks. An improper control system can cause severe damages to engine health. Control programs depend on engine operation modes such as start-up, dynamic operation, steady-state operation, and shutdown. In addition to a specific program for each mode, the control system has various protection programs to avoid overspeed, overheat, flameout, and so on.

Gas turbine control systems are usually of a closed-loop type. The system elaborates a correction to a control variable (e.g., fuel consumption) on the basis of a discrepancy between actual and necessary values of a controlled variable (e.g., rotor speed). To be effective, the closed-loop controller should "know" accurate relations between engine parameters. A conventional approach to controller development relies on generalized engine performances and average operating conditions. However, engine operating and health conditions vary along time.

As advanced gas turbines have several control variables, more flexible control laws can be developed to take into consideration actual engine operating conditions and technical state. Modem digital controllers are capable to realize such complex control and, as a result, minimize fuel consumption, extend engine life, and reduce maintenance costs.

4. Wind turbines

As with gas turbines, wind turbines are an important energy source. However, in contrast to the formers, they have the lowest greenhouse gas emissions and water consumption. Large turbines constitute wind farms to generate electricity for domestic consumption and for the electrical grid. Typically, they have a three-blade horizontal axis construction. The power limit of such a wind turbine is 16/27 times the kinetic energy of the passing air. The power losses include friction of rotor blades, mechanical losses in bearings and gearbox, and losses in a generator and converter. In commercial turbines, these losses can be lessen up to 20–25%. A general trend to increase efficiency and reduce maintenance costs is increasing power and size of a turbine unit. The large wind turbine has a capacity of 9.5 MW, overall height of 220 m, and diameter of 164 m [23].

The efficiency can decrease because of the dust and insects in the air and possible ice accretion resulting in the altered aerodynamic profiles and efficiency losses of 1.2% per year. To monitor turbine performance and structure, accelerometers and strain sensors are usually installed in the nacelle. To assess the dynamics of turbine blades, digital image correlation and stereophotogrammetry are currently applied [24].

As with gas turbines, the design of such large structures as wind turbines needs mathematical modeling. In particular, for developing more accurate control and diagnostic systems, the general-purpose model that describes both aerodynamic and electric parts of the wind power plant is on demand. Chapter 5 of the present book introduces such a model.

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