Towards Predictive Maintenance of a Heavy-Duty Gas Turbine: A New Hybrid Intelligent Methodology for Performance Simulation

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ABSTRACT

As the increasing demands of global clean power for the main purpose of lowering environmental pollution, heavy-duty gas turbines are playing an increasingly important role in energy fields because of their low emission, high thermal efficiency, and flexible start-up capacity.

Accurate modeling and simulation of the turbine performance is extremely needed to precisely design a large-watt industrial heavy-duty gas turbine while timely monitoring its performance degradation for fault diagnosis, optimal efficiency and predictive maintenance, which is still very challenging due to the high nonlinearity, system complexity, varying conditions, and strong coupling interaction of high-dimension parameters under the harsh operation environment of the turbine. When ambient conditions change, the major components, such as the compressor, combustor, and turbine often display performance degradation to some degree over operating time so that the performance-based maintenance is needed to maximize the productivity of a gas turbine. Generally, the reliability and effectiveness of performance-based maintenance depends on the real-time efficiency monitoring for timely diagnosis and impending deterioration prognosis for predictive maintenance. In order to improve the reliability and availability of gas turbines at various operating conditions, accurate and efficient simulation of a gas turbine performance provides the fundamental to pursue fault diagnosis and predictive maintenance. This paper presents a new physics informed machine learning methodology to achieve this purpose. The thermodynamic model of a complicated single-shaft gas turbine is first created based on the balances of both flow and power in various subsystems including inlet, compressor, turbine, combustor and exhaust. The characteristic curves of compressor and turbine are utilized to accurately represent the physical mechanism and effectively simulate the high nonlinear behaviors of subsystems. Machine learning based feature extraction are employed to preprocess the multivariate raw data of the turbine. Multilayer artificial neural network models, nonlinear autoregressive with exogenous inputs (NARX) with Bayesian regularization algorithm, are explored to efficiently simulate the start-up transient process of the turbine, thus improve the simulation efficiency and accuracy of the complicated system. Multivariate data collected from a real-world industrial heavy-duty gas turbine is employed to illustrate the effectiveness and feasibility of the proposed methodology.

Key Word: Gas turbine, thermodynamic model, transient performance, Bayesian estimation, neural network

1. INTRODUCTION

With the increasing demand of clean power for the main purpose of lowering environmental pollution globally, the large-watt industrial gas turbine, also known as heavy-duty turbine (HDGT) play an important role in energy fields because of their low emission, high thermal efficiency, high fuel flexibility and flexible start-up capacity. As the quick development of HDGT industry technologies, it is of great significance to explore the mechanism and dynamic characteristics of gas turbines. Accurate modeling and simulation of the gas turbine performance is urgently needed for optimal control, efficiency enhancement and degradation monitoring. However, this is still challenged by high nonlinearity, system complexity, varying conditions, and strong coupling interaction of high-dimension parameters under the harsh operation environment of the HDGT.

The research on dynamic performance and transient behavior of gas turbines began around early 1950s [1]. Most early studies focused on linearized modeling to lower computational efforts and costs. One of the most used simplified models was presented by Rowen [2] through considering the load-frequency and temperature control as well as the turbine's thermodynamic responses as a linear function. Variable inlet guide vane (VIGV) effect was also investigated in the linearized model by Rowen in a separate work [3] . In order to reduce the computational time for sake of real-time applications, techniques based on the model linearization have been often adopted. However, the model only can be linearly approximated for operating status around the design points.

HDGT suffers from transient operation during startup, load change, shutdown, and other environmental disturbances [1]. Models based on nonlinear aerothermal relations have been proposed and applied in analyzing system dynamic characteristics in terms of physics-based and data-driven approaches. The physics-based thermodynamic model [4][5][6] was created based on the balances of both flow and power in various subsystems including inlet, compressor, turbine, combustor, and exhaust. Meanwhile, the characteristic curves of compressor and turbine sections are utilized to represent the physical mechanism. The physics-driven approach is one of the most significant methods in simulating the dynamic characteristics of gas turbines, but its accuracy lies on the precise description of the characteristic curves. It is difficult in obtaining component characteristics, in particular those of the compressor.

The data-driven approach [7][8] focuses on the large data sets of the complex system for its whole operational range without the need of modelling the system's behavior. In past decades, Artificial neural networks (ANNs) [9][10] have become the effective black-box methods for data processing, modeling, and control of nonlinear systems. They were mainly used to establish the relationships between multiple variables of the system using the monitoring data collected from real-world system operation or the simulated data generated through a physics-based model [9]. For example, Reference [11] represented a zero-dimensional design and off-design modeling of a single-shaft gas turbine using ANN. Reference [12] represented A NARX model to identify dynamics of a heavy-duty IPGT. In this paper, an accurate reduced-order nonlinear model was built using black-box identification techniques. In Reference [13], the behavior of a heavy-duty single-shaft gas turbine using a NARX method was modelled. The main propose was to capture the dynamics of the start-up phase. Numerical results showed that the proposed model can effectively capture the behavior of the gas turbine. The main drawbacks of data-driven methods lie in lack of sufficient historical data and expert knowledge to establish a performance simulation model of a HDGT with acceptable accuracy.

In order to improve the accuracy and efficiency of the performance simulation model for a HDGT at various operating conditions, this paper presents a new hybrid intelligent methodology to adeptly integrate system thermodynamic balance mechanism with multivariate data by seamlessly combing advanced signal processing, machine learning and artificial neural network modeling techniques. The paper is organized as follows. After this introduction, Section two briefly describes major components of a HDGT and its thermodynamic cycle. Section three summarizes the model of a simple cycle and a single shaft HDGT for dynamic studies. Section four presents a simulation model based on the mathematical model created in Section III through MATLAB-SIMULINK. Section five presents a multilayer artificial neural network models to efficiently simulate the start-up transient process of the turbine. Finally, Section six concludes this study.

2. HDGT AND JOULE-BRAYTON CYCLE

Basically, an industrial heavy duty gas turbine (HDGT) for power generation is composed of five major subsystems including inlet, compressor, combustor, turbine, and exhaust. A schematic diagram for a single-shaft HDGT is shown in Figure 1. The air is initially compressed in the compressor. Roughly one third of the compressor discharge air is mixed with the fuel to be burnt in combustor, while the remaining air is mixed with combustor products to become the turbine inlet flow. The flow is then expanded in turbine which converts the energy of the gas into mechanical work, which partially is used to drive the compressor. The remaining part is known as the net power of the gas turbine. Finally, the flow is guided through the exhaust duct to ambient conditions in simple cycle.

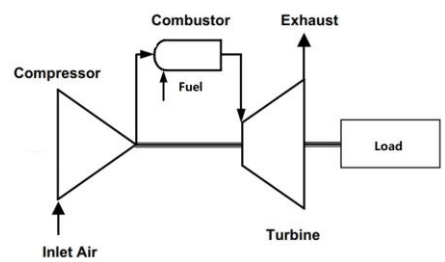


Figure 1. Schematic diagram for a single-shaft HDGT

The thermodynamic process to be simulated is a single shaft gas turbine. The reference thermodynamic cycle that is present is known as the Joule-Brayton cycle. Figure 2 shows a typical standard Joule-Brayton cycle in temperature-entropy diagram. Air has passed through the inlet at point 1 and is compressed by the compressor in an irreversible process to point 2. If we assume that the compression is performed ideally, $s_1 = s_{2s}$, whose subscript s indicates the isentropic process. However, the actual process is non-isentropic, where the gas is heated in the combustor from Point 2 to Point 3. The process is assumed to be isobar at constant pressure so that $p_2 = p_3$. The discharge air is expanded in turbine from Point 3 to Point 4 and the actual process is also non-isentropic. In an open cycle, the exhaust gas is released back into the atmosphere. This implies that $p4 = p1$. Nomenclature of symbols is listed in Table 1.

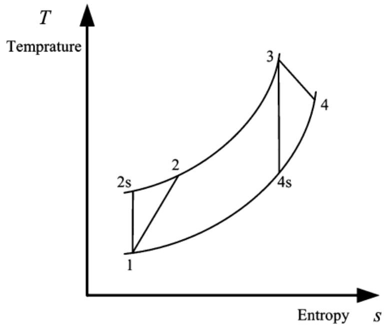


Figure 2. Typical Joule-Brayton cycle in temperature-entropy diagram

Type	*Symbols*	*Description*
Symbols	T	Temperature (K)
	P	Pressure (Pa)
	s	Entropy (kJ/kg)
Subscripts	1	Inlet
	2	Compressor
	3	Combustor
	4	Turbine

Table 1. Nomenclature of symbols of Joule-Brayton cycle

3. THERMODYNAMIC MODELING OF HDGT

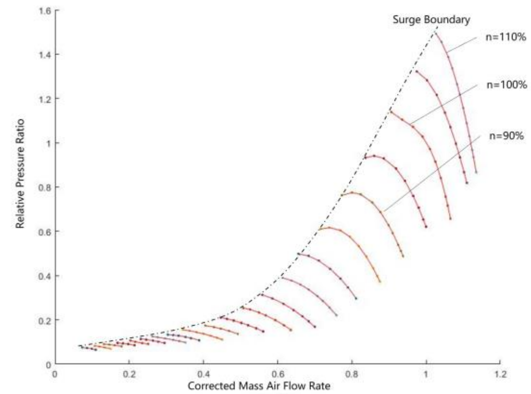
The thermodynamic model of a complicated single-shaft gas turbine is created based on the balances of both flow and power in various subsystems including inlet, compressor, combustor, turbine, and exhaust.

A. Compressor Module

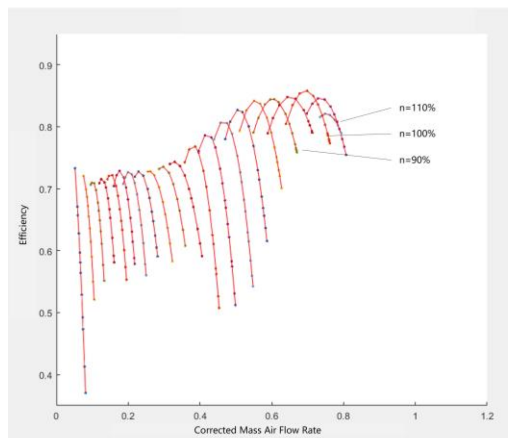
The characteristic curves of the compressor are utilized to accurately represent the physical mechanism and effectively simulate the high nonlinear behaviors of subsystems. The curves provide both the corrected mass air flow rate $G_{in,C}\sqrt{T_{in,C}}/p_{in,C}$ and the isentropic efficiency η_C as a function of the pressure ratio $\pi_C = p_{out,C}/p_{in,C}$, corrected rotational speed $n/\sqrt{T_{in,C}}$, and variable inlet guide vane (VIGV), expressed as follows:

$$\begin{cases} \dfrac{G_{in,C}\sqrt{T_{in,C}}}{p_{in,C}} = f_1\left(\pi_C, n/\sqrt{T_{in,C}}, VIGV\right) \\ \eta_C = f_2\left(\pi_C, n/\sqrt{T_{in,C}}, VIGV\right) \end{cases} \tag{1}$$

where VIGV is to regulate the air mass flow drawn into the compressor. In a simple cycle operation, the VIGV control is only active during the start-up of a gas turbine. In this section, the VIGV are assumed to be fully open. Since the actual data are discrete, the *Polyfit* function in MATLAB is employed to fit the characteristic curves of the compressor from the experimental data obtained from Camporeale and Fortunato [5], as shown in Figure 3.



a)



b)

Figure 3. Characteristic curves of compressor: a) Relative pressure ratio and b) Efficiency

The air temperature at the compressor exit is given by

$$T_{out,C} = T_{in,C}\left[1 + \frac{1}{\eta_C}\left(\pi_C^{\frac{k_a - 1}{k_a}} - 1\right)\right] \tag{2}$$

where the compressor ratio of specific heats k_a vary with the temperature is evaluated at the arithmetic average temperature between the inlet and the outlet. The compressor mechanical power is given by

$$P_C = G_{in,C} \cdot c_{pa} \cdot (T_{out,C} - T_{in,C}) \tag{3}$$

where c_{pa} is the specific heat of air at constant pressure.

B. Combustor Module

Regarding the single-shaft gas turbine, the compressor and turbine subsystems are considered as volume-less components during the transient stage. A plenum is placed in the combustor in order to take into account the unsteady mass balance within the compressor pipe, compressor exhaust and combustor. Applying the law of conservation of mass results in

$$\frac{V_p}{mRT_{out}} \times \frac{dp_{out}}{dt} = G_{in} - G_{out} \tag{4}$$

where V_p is the volume of the plenum module, m is the polytropic coefficient, and R is the gas constant.

In the combustion process, the compressed air is mixed with the fuel to be burnt in the combustor. The high-temperature combustion mixture then leaves the combustion system and enters the turbine where the energy of hot gases is converted into work. Modeling the performance of a combustor is focused on the variation of temperature and pressure at the combustion chamber outlet. Taking the derivative with t on both sides of the gas state equation, $\rho=P/R_gT$, yields

$$\frac{d\rho}{dt} = \frac{1}{R_g T}\frac{dP}{dt} + \frac{P}{R_g}(-\frac{1}{T^2})\frac{dT}{dt} = \frac{1}{R_g T}(\frac{dP}{dt} - \frac{P}{T}\frac{dT}{dt}) \tag{5}$$

By combining Eqs. (4) and (5), the dynamics of the combustor outlet pressure is described as follows

$$\frac{dp_{out,B}}{dt} = \frac{R_g T_{out,B}(G_{in,B} + G_f - G_{out,B})}{V} + \frac{p_{out,B}}{T_{out,B}}\frac{dT_{out,B}}{dt} \tag{6}$$

where $G_{in,B}$, G_f and G_{out} are the mass flow of the air at the combustor inlet, the fuel, and the gas at the combustor outlet, respectively; $P_{out,B}$ and $T_{out,B}$ are the temperature and pressure of the combustion chamber outlet, respectively. Applying the energy conservation yields

$$Q = G_{in,B}h_{in,B} + G_f H_u \eta_B - G_{out,B}h_{out,B} = \frac{1}{k_g}\frac{d(Mh)}{dt} \tag{7}$$

where $h_{in,B}$ and $h_{out,B}$ are the enthalpy values of the combustor inlet and outlet gas, respectively; H_u is the lower heating value of the fuel; η_B is the combustion efficiency; k_g is the ratio of specific heats of the gas, and M is the gas quality. The combustor outlet temperature is obtained by

$$\frac{dT_{out,B}}{dt} = \frac{R_g T_{out,B}\left[k_g Q - h_{out,B}(G_{in,B} + G_f - G_{out,B})\right]}{PVc_{pg,B}} \tag{8}$$

C. Turbine Module

Similar to the compressor module, the characteristic curves of the turbine subsystem provide the corrected mass air flow rate $\frac{G_T\sqrt{T_{in,T}}}{p_{in,T}}$ and the isentropic efficiency η_T as a function of pressure ratio $\pi_T = p_{in,T}/p_{out,T}$ and corrected rotational speed $n/\sqrt{T_{in,T}}$, given by

$$\begin{cases} \frac{G_{in,T}\sqrt{T_{in,T}}}{p_{in,T}} = f_1\left(\pi_T, n/\sqrt{T_{in,T}}\right) \\ \eta_T = f_2\left(\pi_T, n/\sqrt{T_{in,T}}\right) \end{cases} \tag{9}$$

Assuming that the turbine module behavior is quasi-steady, Ferrier Gale formula is used to estimate the turbine characteristic curves by assuming a quasi-steady flow as follows

$$\eta_T = \left[1 - 0.4\cdot\left(1 - \frac{n}{n_0}\right)^2\right]\cdot\left(2q - q^2\right) \tag{10}$$

where $q = \frac{n \cdot G_{T0}}{n_0 \cdot G_T}$, n_0 and G_{T0} are the rotational speed and mass air flow rate at the designed condition, respectively.

The gas temperature at the end of expansion is given by

$$T_{out,T} = T_{in,T}\left[1 - \left(1 - \frac{1}{\pi_T^{\frac{k_g - 1}{k_g}}}\right)\eta_T\right] \tag{11}$$

where the ratio of specific heats of the gas k_g is evaluated at the temperature, which is the arithmetic average between the inlet and the outlet. The power produced by the expanding gas is given by

$$P_T = G_{in,T} \cdot c_{pg}(T_{in,T} - T_{out,T}) \tag{12}$$

where c_{pg} is the specific heat of the gas at a constant pressure.

D. Rotating Shaft

As shown in Figure 1, the rotating shaft connects the compressor, turbine and, eventually, applied load. The angular acceleration produced by unbalanced torque among the turbine-generated torque M_T, the reverse torque from the compressor M_C and the generator M_G, and the friction torque M_f, is given by the angular momentum equilibrium, depending on moment of inertia I as follows:

$$I\frac{d\omega}{dt} = M_T - M_C - M_G - M_f \tag{13}$$

Taking the angular acceleration $\omega=\pi n/30$ and $P=M\omega$, the rotational motion of the shaft can be expressed by the following equation:

$$\frac{dn}{dt} = \frac{900}{I\pi^2 n}(P_T - P_C - P_G - P_f) \tag{14}$$

where P_T, P_C, P_G, and P_f represent the internal mechanical power of the turbine, compressor, electrical load, and a sum of power losses including rotor friction along with the other connected devices.

E. Control Module

Nowadays control systems are being widely employed in every process industry. A control system in the power generation is able to quickly react and handle process anomaly thus avoiding accidents. The control system in this study involves the rotational speed, turbine exhaust temperature, acceleration, and fuel limits. The fuel demand signal relies on the minimum values of rotational speed, temperature and acceleration control.

In many literatures, various kinds of control logic have been proposed such as PID (Proportional Integral Derivative) control, state space control, etc. The PID-controller provides relatively simple controllers to tune up the system. Among them, the P (proportional) and I (integral) parts are mostly used. In this study, PI controllers were used to control the design and off-design conditions. The mathematical formulation of the PI controller is given by

$$u(t) = K\left(\frac{1}{T_i}\int e(t)dt + e(t)\right) \tag{15}$$

4. MODEL INTEGRATIONS FOR HDGT SIMULATION

The component models are developed in the modeling and simulating environment of Matlab-Simulink which is a complete object-oriented tool for modeling and simulation of integrated and complex systems for use. The Simulink environment provides an easy means to embedding the equations by means of a graphical user interface [7].

The main purpose of this section is to integrate the simulation models of subsystems proposed in the previous section to simulate the dynamic behavior of a gas turbine under various scenarios such as environmental temperature variation, loading change and shutdown except for the startup process. Furthermore, the integrated model can verify that the designed controllers are able to quickly handle process responses. Figure 4 shows the integrated system performance model for a HDGT. For sake of clarity, the HDGT model is displayed as an ensemble of subsystems composed of many blocks: compressor, combustor, turbine, rotating shaft and control unit. The control variable is the fuel flow rate. Figure 5 shows the block diagram for the control unit. The fuel demand signal is determined by the minimum values of rotational speed, temperature and acceleration control, and the fuel flow rate is determined by solving thermodynamic balance of the system given the speed or temperature at each time-step.

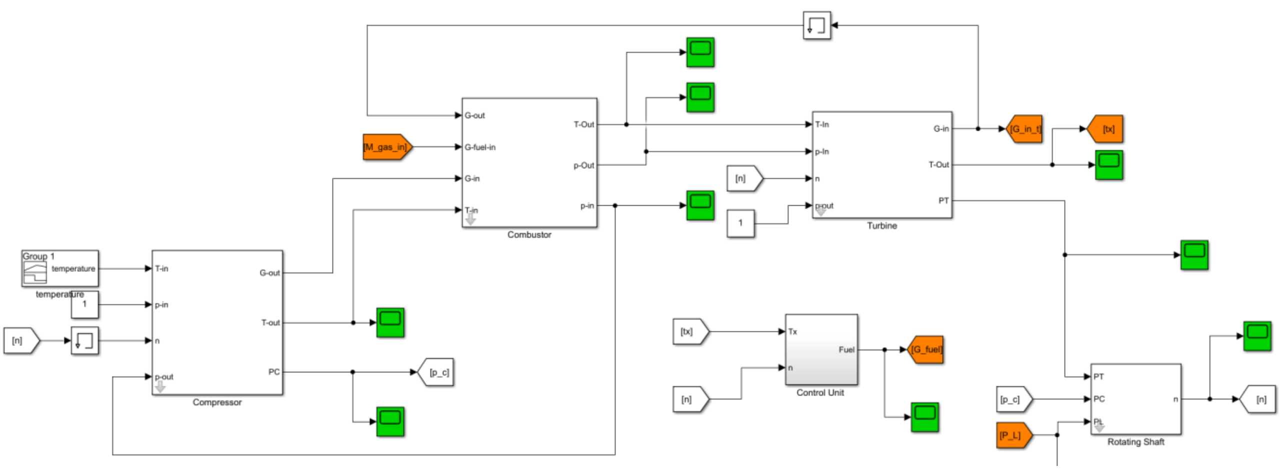


Figure 4. Simulink scheme of the HDGT

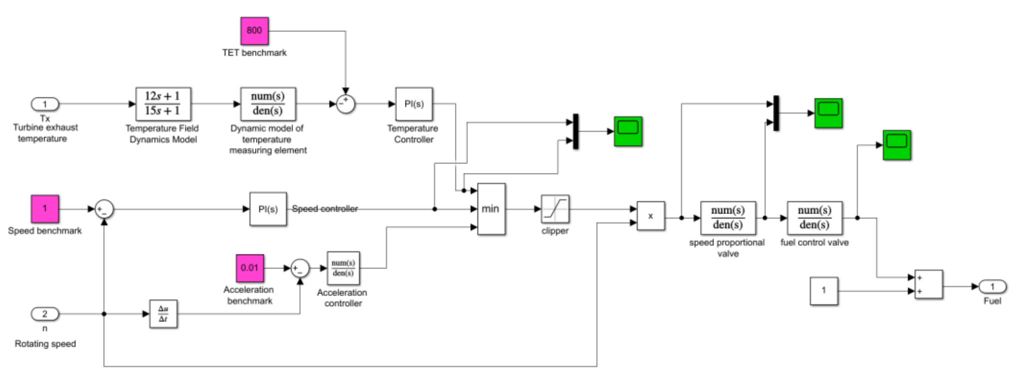


Figure 5. Block diagram for the control unit

The loading variation testing form half to full loading is simulated to verify that the simulation model is able to effectively capture the dynamics behavior. Figure 6(a) shows the time series plot of the power demand P_G in a nondimensional form, which is obtained by dividing the power demand by its rated work point value. The time unit for the x axis is the second(s). The power demand varies from 0.5 to 1 at the 100th second, then decreases to 0.2 at the 200th second. Figure 6(b) shows the controlled variable i,e, the rotational shaft speed n. The curve clearly shows the dynamic behavior in the two different procedures of load dropping and load rising. The curve representing the control variable is drawn in Figure 6(c). The fuel mass flow rate G_f is normalized to its design point value. For example, when the load power drops at the 200th second, the rotation speed n does not change rapidly, while the amount of fuel injected into combustor is still invariant. As such, the rotor speed suddenly rises since the total power P does not change and load power demand P_G drops. The fuel flow rate is adjusted by the control system to reduce accordingly, so that the speed decreases and eventually stabilizes at the rated value. Upon the load rising, the rotation speed and the fuel flow rate keep changing in the opposite direction of the above.

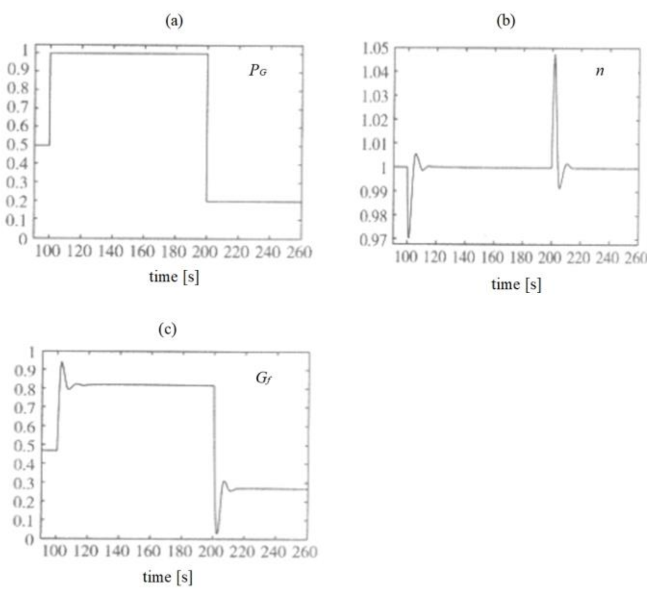


Figure 6. Dimensionless results; (a) applied load; (b) controlled variables; (c) control variables;

5. START-UP MODELING BY USING NARX MODELS

As above mentioned, the simulation model can accurately capture the dynamic behavior of a gas turbine under various conditions except for the start-up process. HDGTs require an external source called starter to start up. The start-up process of gas turbine units refers to starting from static state (turning) to reaching a certain speed. Generally, heavy-duty gas turbine unit starts by using the generator for AC synchronous motor, A static frequency conversion device (SFC) is usually used as a starter to add alternating current of the adjustable frequency to the generator stator. It is very difficult to simulate the starter as the SFC module requires modeling the electrical flow. Moreover, the start-up process is a typical transient process, which largely influences the reliability and availability of a HDGT. Accurate modeling the starting process of a turbine would prolong its service life while reducing its operation and maintenance costs. Accordingly, this section presents a black-box method to capture the start-up process of HDGT. Part A introduces the start-up process of a gas turbine. Part B solves an Autoregression Problem with External Input with a NARX Neural Network.

A. What is start-up phrase

The start-up period ranges from the firing till the steady-state combustor conditions. GTs utilizes an external source called starter, such as an electrical motor, until the GT speed reaches a prescribed percentage of the design speed. GT start-up procedure can be divided into four stages, including dry cranking, purging, light-off, and acceleration to idle [13]. During dry cranking, the engine shaft is rotated by the starter system without any fuel feeding. In the purging phase, residual combustible gas and fuel in the gas path is removed. The rotating speed is kept at a constant value with a proper mass flow rate through the combustor and the turbine in this phase. Then, during the light-off phase, the fuel is supplied to the combustor and igniters are triggered. Finally, in the process of acceleration to idling phase, the fuel mass flow rate further increases meanwhile the rotational speed increases toward the idling value.

B. NARX Methodology

NARX (nonlinear autoregressive with exogenous input) is one of most widely used artificial neural network (ANN) modeling methods. As a recurrent neural network (RNN), the NARX model can capture the dynamics of complex systems such as GTs [14]. NARX model is defined by

$$y(t) = f\left[y(t-1),..., y(t-n_y), u(t-1),..., u(t-n_u) \right] \quad (16)$$

where y is the output variable and u is an exogenous input variable. The output signal $y(t)$ is dependent on previous values of the output signal and previous values of an independent (exogenous) input signal x. The NARX model is mainly employed for modeling nonlinear dynamic systems [13]. In addition, it can be used to predict the next value of the input signals. Training of a NARX model in this study consists of following steps: selection of the training datasets, definition of training algorithm, and a sensitivity analysis on the number of neurons.

Training Datasets. The training datasets from Ref. [18] cover the entire operating range of the GT during the start-up procedure. As shown in Table 2, the model includes four inputs and four outputs. Moreover, this paper considers VIGV at the conditions of transient operation.

Type	*Symbols*	*Description*
Inputs	$T_{in,C}$	Compressor Inlet Temperature
	$P_{in,C}$	Compressor Inlet Pressure
	G_f	Fuel Mass Flow Rate
	VIGV	Variable Inlet Guide Vane
Outputs	$T_{out,C}$	Compressor Outlet Temperature
	$T_{out,T}$	Turbine Outlet Temperature
	π_C	Compressor Pressure Ratio
	n	Rotational Speed

Table 2. Four inputs and four outputs in NARX model

The four measured time series datasets are used for NARX model training and testing. More details concerning the operating range for the two input parameters of the training datasets are shown in Table 3. The data sampling frequency is 5s. The training datasets should be chosen in such a strategy that the NARX model is well generalized enough for various scenarios. The NARX model is first set up following Ref. [9], including both the fastest and slowest variations of the training ratio. In this example, the training datasets not only cover the entire operating range of the GT, but also include the maximum and minimum values of all the inputs and outputs. The two measured time series datasets, called 1-TR and 2-TR in Table 3, are used for NARX model training. The datasets 3-TE and 4-TE in Table 3 are used to validate and test the trained models, in order to judge the accuracy of the model prediction.

NO.	**1-TR**	**2-TR**	**3-TE**	**4-TE**
date	07.20	1.10	12.20	08.25
pressure	100.117	103.637	102.202	100.258
temperature	305	276	289	302

Table 3. NARX model training samples and environmental parameters

Training Algorithm. The training of all NARX models is an open loop structure, as shown in Figure 6. The NARX models are trained by using the Bayesian regularization algorithm, which is well generalized with a slower training speed in comparison to other training methods like maximum likelihood method.

Nonlinear Autoregressive Network with External Input. Once the training, testing and validating datasets are defined, the number of neurons needs to be determined for the NARX model. The optimal number of neurons in the hidden layer is assumed to be 12 in this section, according to Ref. [15], where the performance of NARX models with 6, 12, and 18 neurons was extensively compared. Each NARX model is trained by using the Bayesian regularization algorithm, one hidden layer and tapped delay lines with two delays (1:2) both for inputs *x(t)* and output *y(t)*. This means that the previous time-steps are (t-1) and (t-2), according to the analysis performed in Ref. [14].

Performance Evaluation. The mean-square error (MSE) is employed to compare the measured data (*ym*) to NARX model predictions (*ys*), as defined by:

$$MSE = \frac{1}{n}\sqrt{\sum_{i=1}^{n}\left(\frac{y_{mi}-y_{si}}{y_{mi}}\right)^2} \tag{17}$$

where n is the amount of data points in each dataset.

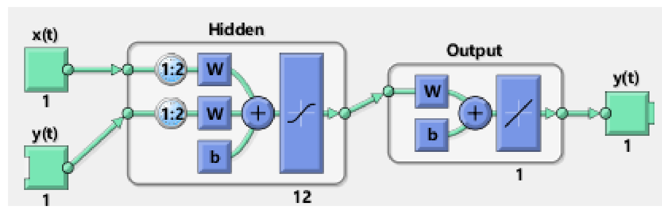


Figure 6. Open-loop structure of a NARX model

In this study, the Neural Network Toolbox in MATLAB is employed to build NARX models. The results in terms of MSE are shown in Figure 7. The smaller the MSE, the higher the quality of the built NARX model. It is clearly observed that model training is satisfactory for all outputs and all the types of start-up maneuvers. In fact, all R values shown in Fig. 8 are higher than 0.98. This indicates that the proposed NARX model provide a promising tool to simulate all start-up scenarios.

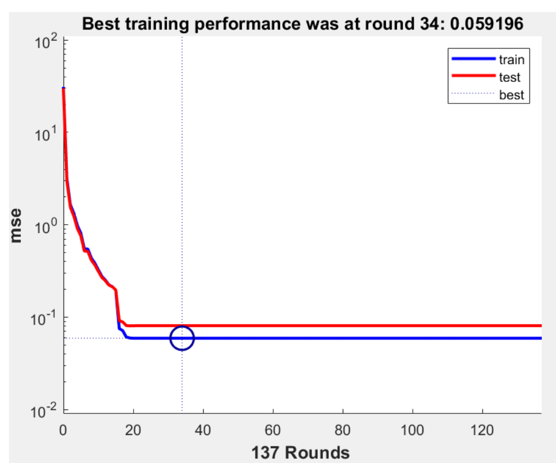


Figure 7. MSE evaluation indicators of a NARX model

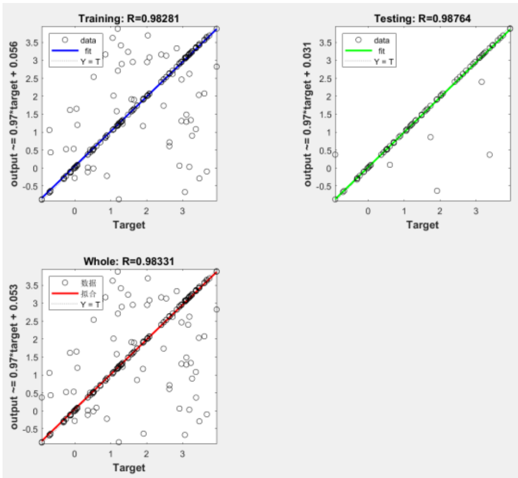


Figure 8. R evaluation indicators of a NARX mode

6. CONCLUSIONS

This paper presents a hybrid physics-based and data-driven intelligent methodology, so called physics-informed neural network (PINNs) model, to simulate the all-scenario performance of a heavy-duty gas turbine (HDGT). The steady-state off-design behavior of the large HDGT system is first simulated by adeptly integrating the thermodynamic balance models of five major subsystems namely, inlet, compressor, turbine, combustor, and exhauster. The performance model effectively represents the nonlinear mathematical characteristics of the system allowing for reproducing the behavior of the gas turbine under working conditions varying from half to full-load. Moreover, the designed controllers are able to handle fast process responses in the complicated gas turbine.

Furthermore, multilayer artificial neural network models, so-called NARX, are explored to efficiently simulate the start-up transient process of the turbine, thus improving the simulation efficiency and accuracy of the complicated system. Bayesian regularization algorithm is developed to estimate the model parameters. Multivariate data collected from a real-world industrial heavy-duty gas turbine is employed to illustrate the effectiveness and feasibility of the proposed methodology.

In future research, the proposed new modeling method will be explored for fault diagnosis and performance-based predictive maintenance of a HDGT through timely efficiency degradation monitoring and anomaly alarming, thus improving the reliability and productivity of the turbomachine through the PINNs-based smart maintenance.

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