A Physics Informed Machine Learning Approach for Performance Degradation Monitoring of Gas Turbine

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Abstract

The heavy-duty gas turbine is playing an increasingly significant role on power generation due to its lower-emission, higher flexibility and thermo-efficiency. Main subsystems of the gas turbine like compressor, combustor and turbine degrade over the operating time under the harsh environmental conditions, which largely impacts the efficiency and productivity of the system. Therefore, it is critical to develop effective approaches to monitor performance degradation of a heavy-duty gas turbine for system predictive maintenance thus improving the efficiency and productivity of the machine. This paper presents a new physics informed machine learning methodology to predict the degradation of gas turbine by seamlessly integrating thermodynamic heat balancing mechanism, component characteristics, multi-source data and artificial neural network model. The mechanism-based thermodynamic model is established for multiple subsystems considering the balance of flow, mass and energy, and then integrated to a system level for performance simulation of the gas turbine under different conditions. The system model is able to effectively simulate values for those parameters that are not measurable (e.g. GT exhaust flow) or inaccurately measured (e.g. fuel flow). Machine learning based data cleaning approach is employed to preprocess the multivariate raw data of the gas turbine. The difference between design performance data and corrected value obtained from the physics-informed model under ISO conditions is utilized to assess the performance degradation. A Long Short-Term Memory (LSTM) model is established from the fusion of the actual and simulation data to predict the performance degradation of the gas turbine. A comparison study with the classical Nonlinear Autoregressive Network with External Input (NARX) neural network is conducted to demonstrate the advantage of the proposed method.

Key Word: Gas Turbine, Thermodynamic Balance, Performance Degradation Predict, Machine Learning, LSTM

1. Introduction

Nowadays gas turbines are being used extensively in various industries to produce mechanical power and employed to drive various loads such as generators, propeller or pumps. Gas turbines used for power generation are commonly referred to as a heavy-duty industrial gas turbines (HDGT). In the quest to perfect performance and satisfactory operation of HDGT, compressor pressure ratios have increased from about 4:1 to over 40:1 together with high operating temperatures (about 1800K), resulting in thermal efficiencies exceeding 40% (Razakv, 2007). These features such as lower-emission, higher flexibility and thermal efficiency make HDGT a strong competitor to other types of prime movers. However, main subsystems of HDGT like compressor, combustor and turbine degrade over the operating time under the harsh environmental conditions, leading to reduced capacity and thermal efficiency, which largely impacts the efficiency and productivity of the system. Several studies of HDGT suggest that the decrease in output can easily reach 5% after a month's operation (Diakunchak, 1992). Compressor fouling which is the most common form of performance degradation is mainly due to scale deposit formed on the compressor blades by dirt and dust carried in by the air, but periodic compressor washes should alleviate this issue. Therefore, in order to monitor performance degradation of HDGT for system predictive maintenance, it is extremely necessary to develop accurate simulation model and universal time series prediction model, which is still very challenging due to the high nonlinearity, system complexity, varying conditions, and strong cross-coupling of high-dimension parameters under the harsh operation environment of HDGT.

The research on gas turbine performance monitoring has received significant amount of attention in the last three decades. An accurate and fast prediction of the dynamic behavior of gas turbine is very critical for stable operation, predictive maintenance, and fault diagnosis and control design. Analyzing system dynamic characteristics through numeric models has been a popular approach for predicting the transient behavior of gas turbines. Two main models have been widely used for simulating the behavior of a gas turbine. Rowen's model which is the most popular dynamic model proposed in study (Rowen, 1983), is based on thermodynamic balance mechanism. The other model, which is known as IEEE model (deMello, 1994), has deeper sight into internal processes for combined cycle power plants. Camporeale at al. (2002) presented a high-fidelity real-time simulation code based upon an integrated, nonlinear representation of gas turbine components. For the purpose of high fidelity, the actual composition of the working gases and the variation of the specific heats with the temperature, including a stage-by-stage model of the air-cooled expansion, are considered in the mathematical model.

In recent years, numerous studies show that these dynamic models allow for simulating and predicting gas turbines behavior by making approximations around transient behaviors. Kurosaki et al. (2018) proposed an efficient numerical integration method for a volume dynamics model in gas turbine transient simulations. The proposed model was applied to transient simulations of a compressor rig test model composed of a compressor, a nozzle with variable geometry and a volume placed between them. Tsoutsanis and Meskin (2019) presented a dynamic performance model of a gas turbine. The model is developed in Simulink and validated with an engine simulation commercial software. Although significant progress has been made in the simulation of physics-driven models, the fact is that the accuracy of model lies on the precise description of the characteristic curves and it is difficult to obtain component characteristics, in particular those of the compressor. Meanwhile, it is widely known that the time of operational monitoring based on physics-driven model rise with the complexity of the model. In this context, the data-driven approach (Liu & Karimi, 2020, Asgari & Chen, 2018) focuses on actual multivariate data to simulate the behavior of real and complex systems. These models (Kumar et al. 2023) offer fast predictions that is essential for field deployment. Bahlawan et al. (2018) proposed a NARX method to capture the start-up dynamics phase. Numerical results showed that the proposed data-driven models could capture the behavior of the gas turbine with effect. However, the data-driven model is based on statistics and machine learning technology, and the ability of machine learning technology to handle multivariate raw data, which is usually accompanied by noise and the problem of over-fitting & generalization, presents additional challenges when modeling gas turbine.

This paper presents a new physics informed machine learning methodology to predict the degradation of HDGT by seamlessly integrating thermodynamic heat balancing mechanism, component characteristics, multi-source data and artificial neural network model. The mechanism-based thermodynamic model is established for multiple subsystems considering the balance of flow, mass and energy, and then integrated to a system level for performance simulation of HDGT under different conditions. The measurements from a real-time, on-line performance monitoring of gas turbines over a period of one year and machine learning based data cleaning approach is employed to preprocess the multivariate raw data. The thermodynamic model is utilized to calculate expected and corrected performance and compare it with measurements and design performance. The deviation between design performance data and corrected value under ISO conditions is utilized to assess the performance degradation. In this paper, we use the corrected relative efficiency ($\eta_{corrected}/\eta_{design}$) of the compressor and turbine to assess the degradation of the compressor and turbine, respectively. The trend of effective efficiency η_e of the unit reflects the degradation of overall unit. A Long Short-Term Memory (LSTM) model is established to predict three evaluating indicators (overall effective efficiency η_e, compressor efficiency η_c, turbine efficiency η_t). A comparison study with the classical Nonlinear Autoregressive Network with External Input (NARX) neural network is conducted to demonstrate the advantage of the proposed method.

The paper is organized as follows. After this introduction, Section 2 briefly describes thermodynamics of gas turbine cycles and summarizes mechanism-based thermodynamic model of a simple cycle and a single shaft HDGT. Section 3 presents the performance calculation using the model proposed by Section 2 to evaluate the expected and corrected performance. Section 4 briefly introduces the LSTM and showcases the developed model for predicting performance degradation indicators. Section 5 presents the results of practical application examples with a comparison study with NARX model. Finally, Section 6 concludes this study.

2. Thermodynamic Model

A gas turbine must have at least the following components: compressor, combustor and turbine. Basically, a single-shaft gas turbine consists of a compressor, combustor and a turbine as shown in Fig. 1. The gas turbine can also include other components, such as secondary air systems, for cooling and protection of turbine components.

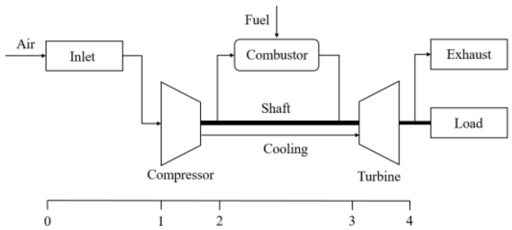

Figure 1. Schematic layout of a single-shaft gas turbine

Next, we will introduce the mathematical models of each module separately. Nomenclature of subscripts numbers is shown in Fig. 1.

2.1. Inlet System

The inlet system belongs to the auxiliary system of a gas turbine, and its function is to transport air and filter impurities. Assuming that it is an adiabatic process with the pressure loss but without energy loss.

$$T_1 = T_0 \tag{1}$$

$$P_1 = \sigma P_0 \tag{2}$$

where σ is the inlet pressure loss coefficient.

2.2. Compressor Module

The characteristic of the compressor is normally represented by using non-dimensional groups. It is very useful to carry out off-design performance calculations of the gas turbine. The definitions of these groups are given as follows:

1. Corrected mass air flow $G_1\sqrt{T_1}/p_1$
2. Corrected rotational speed $n/\sqrt{T_1}$
3. Pressure ratio $\pi_C = p_2/p_1$
4. Isentropic efficiency η_C

A typical compressor characteristic curves is shown in Fig. 4 and expressed as follows:

$$\pi_C = f_1\left(G_1\sqrt{T_1}/p_1, n/\sqrt{T_1}\right) \tag{3}$$

$$\eta_C = f_2\left(G_1\sqrt{T_1}/p_1, n/\sqrt{T_1}\right) \tag{4}$$

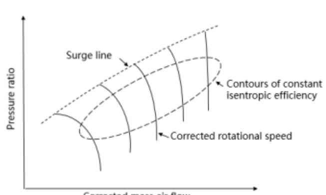

Figure 4. Compressor characteristic curves

From Figure 4, it can be seen that as the speed increases, the constant rotational speed line becomes vertical. Figure 4 also shows the surge line. Due to an unstable phenomenon known as surge, any operation on the left side of the surge line is impossible.

From Eq. (5) the compressor discharge temperature is calculated by:

$$T_2 = T_2\left[1 + \frac{1}{\eta_C}\left(\pi_C^{\frac{k_a - 1}{k_a}} - 1\right)\right] \tag{5}$$

The compressor specific work input is given by:

$$W_C = G_1 \cdot c_{pa} \cdot (T_2 - T_1) \tag{6}$$

where k_a and c_{pa} are the compressor ratio of specific heats and the specific heat of air at constant pressure, respectively.

2.3. Combustor Module

The purpose of burning fuel in a combustor is to increase the temperature of the gas and to generate heat inputs which control the power output of a gas turbine. Heavy-duty industrial gas turbines are generally not limited by weight and size and may be necessarily allowed to burn more forms of fuels, including liquid and gaseous fuels. These features of industrial combustors include:

1. Volume of combustor is relatively larger.
2. Enabling lower quality fuels to be burnt in the combustor.
3. Lower pressure losses in the combustor.

Applying the laws of conservation of mass and conservation of energy result in respectively.

$$V_B \frac{d\rho}{dt} = G_2 + G_f - G_3 \tag{7}$$

$$V_B \frac{d\rho u}{dt} = G_2 h_2 + G_f H_u \eta_B - G_3 h_3 \tag{8}$$

where V_B is the volume of combustor, G_f is the fuel flow rate, H_u is the lower heating value of the fuel and η_B is the combustion chamber efficiency. The station numbers 2 and 3 refer to the inlet and discharge of the combustor, respectively.

From the gas state equation,

$$\rho = \frac{P}{R_g T} \tag{9}$$

Taking the derivative with t on both sides of the gas state equation, yields

$$\frac{d\rho}{dt} = \frac{1}{R_g} d\left(\frac{P}{T}\right) = \frac{1}{R_g T}\frac{dP}{dt} - \frac{P}{R_g T^2}\frac{dT}{dt} \tag{10}$$

By combining Eqs. (7) and (10), the dynamics of the combustor outlet pressure is described as follows

$$\frac{dP_3}{dt} = \frac{R_g T_3 (G_2 + G_f - G_3)}{V_B} + \frac{P_3}{T_3}\frac{dT_3}{dt} \tag{11}$$

By combining Eq. (8) and Eq. (10), the combustor discharge temperature is obtained by

$$\frac{dT_3}{dt} = \frac{R_g T_3 \left[k_g (G_2 h_2 + G_f H_u \eta_B - G_3 h_3) - h_3 (G_2 + G_f - G_3) \right]}{P_3 V_B c_{pg}} \tag{12}$$

where k_g is the ratio of specific heats of the gas, and c_{pg} is the specific heat of the gas at a constant pressure.

2.4. Turbine Module

As with compressors, it is convenient to represent the performance of turbine according to non-dimensional parameters such as flow rate and rotation rate. Unlike the compressor, there is no question of turbine surging. It can be assumed that the gas flow in turbine is quasi-steady. As such, Ferrier Gale formula is used to estimate the characteristic of a turbine. The isentropic efficiency of the turbine is defined as:

$$\eta_T = \left[1 - 0.4 \cdot \left(1 - \frac{n}{n_0} \right)^2 \right] \cdot \left(2q - q^2 \right) \tag{13}$$

where

$$q = \frac{n \cdot G_{30}}{n_0 \cdot G_3} \tag{14}$$

where n_0 and G_{30} are the rotational speed and mass air flow rate at the designed condition, respectively. The turbine discharge temperature is given by

$$T_4 = T_3 \left[1 - \left(1 - \frac{1}{\pi_T^{\frac{k_g - 1}{k_g}}} \right) \eta_T \right] \tag{15}$$

The power produced by the expanding gas is given by

$$W_T = G_3 \cdot c_{pg} (T_3 - T_4) \tag{16}$$

2.5. Turbine Blade Cooling

Turbine blade cooling is designed to maintain the blade metal temperature at a safe value, thereby achieving cooling and protection of the turbine. Normally the compressed air is used as the cooling medium extracted from the compressor discharge and bled into the turbine. For the equivalently cooled flow has been modeled, the model can be represented using two distinguishable phases as follows: (1) mixing between main flows and the cooling air of the turbine inlet, and (2) mixing between the new main flows and the cooling air at the exit of turbine. The equivalent enthalpy value at the inlet is given by:

$$h_{e3} = \frac{G_3 h_3 + G_{ein} h_c}{G_3 + G_{ein}} \tag{17}$$

where G_{ein} is the cooling air flow rate at inlet and h_c is the enthalpy of cooling air. The ratio of fuel to air of the gas entering the mixer is obtained from the relation:

$$f_{e3} = \frac{G_3 \times \left(\dfrac{f_3}{1 + f_3} \right)}{G_3 \times \left(\dfrac{1}{1 + f_3} \right) + G_{ein}} \tag{18}$$

The equivalent temperature at the inlet is obtained as a function of the inlet enthalpy and the ratio of fuel to air:

$$T_{e3} = f\left(h_{e3}, f_{e3} \right) \tag{19}$$

The parameter calculation method at the outlet is similar to that at the inlet, and the equivalent enthalpy, the ratio of fuel to air and the equivalent temperature at the exit of turbine is given by Eqs. (20)-(22) respectively.

$$h_{e4} = \frac{G_{ein} h_{ein} + G_{eout} h_c}{G_3 + G_{ein} + G_{eout}} \tag{20}$$

$$f_{e4} = \frac{G_3 \times \left(\dfrac{f_3}{1 + f_3} \right)}{G_3 \times \left(\dfrac{1}{1 + f_3} \right) + G_{ein} + G_{eout}} \tag{21}$$

$$T_{e4} = f\left(h_{e4}, f_{e4} \right) \tag{22}$$

where G_{eout} is the cooling air flow rate at outlet. Based on the mathematical model of turbine blade cooling module, Figure 5 shows the Simulink representation of the cooled blocks.

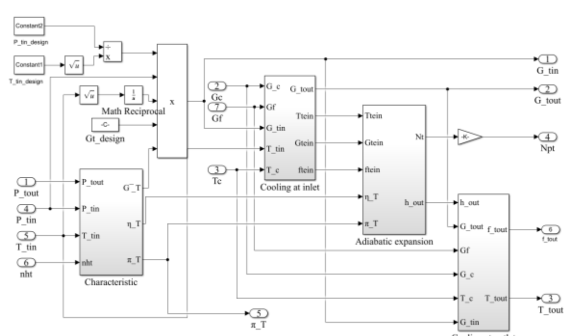

Figure 5. Simulink scheme of cooled blocks at turbine

2.6. Rotating Shaft Dynamic

As shown in Figure 1, the shaft connects the compressor, the turbine and the load. Depending on the moment of inertia I, the angular acceleration produced by unbalanced torque among the turbine-generated torque M_T, the reverse torque from the compressor M_C and the loading M_L, is given by:

$$I\frac{d\omega}{dt}=M_T-M_C-M_L \tag{23}$$

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

$$\frac{dn}{dt}=\frac{900}{I\pi^2 n}(W_T-W_C-W_L) \tag{24}$$

where W_T, W_C and W_L represent the mechanical power of the turbine, compressor and electrical load, respectively.

2.7. Thermophysical Property Calculation

To simplify the explanation of gas turbine behavior during off-design operation, we make the following assumptions:

1. The medium of gas turbine is ideal gas and the internal gas flow is approximately one-dimensional steady flow.
2. The influence of metal thermal inertia can be ignored.

However, when the medium of gas flows in a gas turbine, its composition and temperature varies. It will cause significant deviation if the temperature changes are ignored. Therefore, the effect of temperature on the specific heat is considered in this study.

Isentropic adiabatic process, according to the definition of specific entropy:

$$ds=\frac{\delta Q}{T}=C_p\frac{dT}{T}-R\frac{dp}{p} \tag{25}$$

When changing from state 1 to state 2 in the isentropic process:

$$s_2-s_1=\int_{T_1}^{T_2}C_p\frac{dT}{T}-R\ln\frac{p_2}{p_1}=0 \tag{26}$$

$$\int_{T_1}^{T_2}C_p\frac{dT}{T}=R\ln\frac{p_2}{p_1} \tag{27}$$

Defined Φ as a function related to temperature:

$$\int_{T_1}^{T_2}C_p\frac{dT}{T}=\Phi(T_2)-\Phi(T_1) \tag{28}$$

By combining Eq. (27) and Eq. (28), we can obtain Eq. (29):

$$\Phi(T_2)-\Phi(T_1)=R\ln\frac{p_2}{p_1}=R\ln\pi \tag{29}$$

For the convenience of calculation, natural logarithm is changed to the ordinary logarithm as follows:

$$\Phi(T_2)-\Phi(T_1)=\frac{R}{\lg e}\lg\pi \tag{30}$$

The entropy function is defined by:

$$\Psi=\frac{\lg e}{R}\Phi \tag{31}$$

By combining Eq. (30) and Eq. (31), the calculation equation Eq. (32) to evaluate the entropy of the isentropic adiabatic process is obtained by:

$$\Psi_2\text{-}\Psi_1=\lg\pi \tag{32}$$

The composition of gas varies according to the ratio of fuel to air f, thus thermophysical property calculation should take it into consideration. The ratio of fuel to air on a mass basis for complete combustion is called as the stoichiometric fuel-air ratio f_{st}.

$$(1+f)y=(f+\frac{f}{f_{st}})y_{st}+(1-\frac{f}{f_{st}})y_a \tag{33}$$

where y_a is the specific thermal property of air, and y and y_{st} represent the specific thermal properties of gas with fuel-air ratio f and f_{st}, respectively. Defined θ as follows:

$$\theta=(y_{st}-y_a)\frac{1+f_{st}}{f_{st}} \tag{34}$$

Eq. (33) can be described with θ as follows:

$$y=y_a+\frac{f}{1+f}\theta \tag{35}$$

In conclusion, the correction function Eq. (36) can be used to calculate the specific heat capacity c_p, enthalpy h and entropy φ according to fuel-air ratio f.

$$\begin{cases} c_p=c_{pa}+\dfrac{f}{1+f}\theta_{c_p} \\ h=h_a+\dfrac{f}{1+f}\theta_h \\ \Psi=\Psi_a+\dfrac{f}{1+f}\theta_\Psi \end{cases} \tag{36}$$

In the above calculation, it is assumed that the working medium is dry air, but the actual air sucked in is wet, and the influence of air humidity on the thermal process must be considered. Relative humidity (RH) refers to the ratio of the mass of water vapor in a humid air to the mass of water vapor in saturated air at the same temperature and pressure. Air moisture content d_{air} (i.e., the ratio of water vapor mass to dry air mass in the air) is calculated by:

$$d_{air} = 0.622 \frac{RH \cdot p_s}{p - RH \cdot p_s} \tag{37}$$

Now Eq. (35) can be described with d_{air} and f:

$$y' = \frac{(1+f)y + d_{air} y_w}{1 + f + d_{air}} \tag{38}$$

For the convenience of calculation, refer to the method of fitting thermal properties and corresponding θ functions using temperature polynomial approximation:

$$\begin{cases} c_p, \theta_{c_p} = \sum_{i=0}^{n} a_i \tau_i, \theta_{c_p} \\ h, \theta_h = 10^{-3} \sum_{i=1}^{n} i a_i \tau^{i-1} \\ \Psi, \theta_\Psi = 10^{-3} \sum_{i=1}^{n} \frac{i}{i-1} a_i \tau^{i-1} + \Psi_0 \end{cases} \tag{39}$$

where temperature independent variable $\tau = T \times 10^{-3}$ and T is gas temperature. Encode the calculation function Eq. (39) into an S function and embed S function into the Simulink model.

2.8. Model Integrations for Simulation

The component model was developed in Matlab-Simulink which is a complete object-oriented tool used for modeling and simulation of integrated and complex systems. Figure 6 shows the integrated system performance model introduced above for the subsystems including compressor, combustor, turbine, rotating shaft, and secondary air system and control unit. For clarity, the simulation model of each subsystem consists of many blocks:

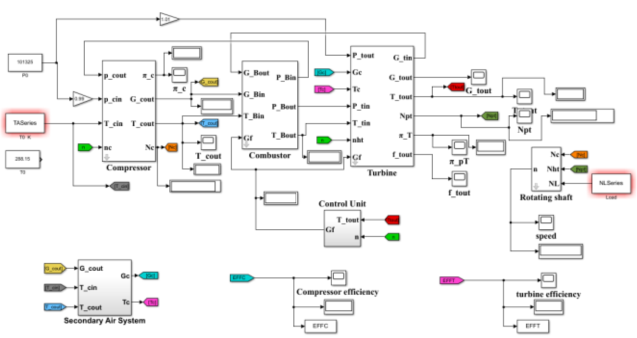

Figure 6. Simulink scheme of thermophysical model

3. Performance Deterioration Assessment

Due to the complexity of actual operating conditions, gas turbines cannot operate for prolonged periods at their design conditions. A change in ambient conditions and power demand from design conditions results in the gas turbine (GT) performance deviating from its design point, also called off-design condition. In order to eliminate the impact of ambient conditions and dependency on operating point during the deterioration prediction, the corrected parameters are calculated by adjusting actual operating to rated conditions. For the purpose of performance monitoring the deterioration prediction of gas turbine is presented in this study, with an integrated procedure as shown in Fig. 7. The model at the actual mode for the calculated performance deterioration is consistent throughout the whole operation. The indicators that characterize performance degradation include three efficiency values of the entire machine, compressor and turbine.

The GT performance deterioration (Deviation) can be quantified by calculating parameters such as heat balance and performance correction utilizing actual data. Figure 8 shows the process of performance analysis and calculation. In Fig.8, *Heat balance* point for performance analysis is the validated measurement for the actual operating conditions (or respectively calculated value from the on-line heat balance). Then the performance model discussed in the previous section produces the *Expected* value under current conditions (ambient, load, and cooling system). In general, the difference between the *Heat Balance* and *Expected* data is the current degradation, the performance loss against the new and clean gas turbine under actual operating conditions. In order to eliminate the impacts from the ambient condition change, current degradation is transferred to rated condition (ISO condition in this paper) by model calculation. The *Rated* data are treated as the benchmark used as the simulation base. These data can be used as the original design data at the ISO condition. The *Corrected* data are used as the *Heat balance* data transposed back to the ISO condition. In this paper, we use the corrected relative efficiency ($\eta_{corrected}/\eta_{design}$) of the compressor and the turbine to assess their degradation. The trend of the unit effective efficiency η_e reflects the overall degradation of the unit.

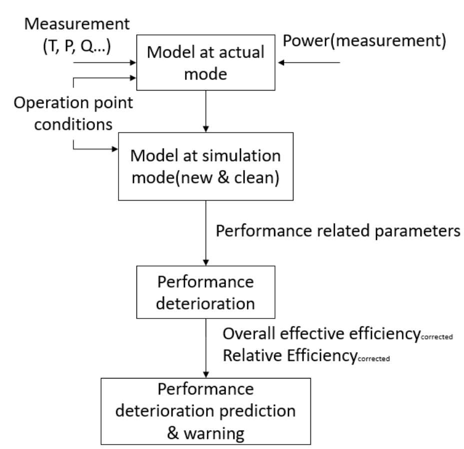

Figure 7. Integrated procedure for calculating rates

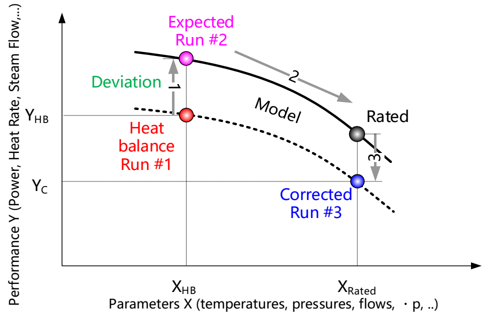

Figure 8. Physics-based performance calculation

4. Performance Deterioration Prediction

It is critical to develop effective approaches to monitor performance degradation of a heavy-duty gas turbine for system predictive maintenance. A Long Short-Term Memory (LSTM) is established from performance degradation indicators discussed in the previous section to predict the performance degradation of the gas turbine. Specifically, we begin this section by introducing the fundamental LSTM model briefly. Then, we provide more detailed explanation of the algorithm's theoretical foundation and design decision that underlies the proposed framework.

4.1. LSTM

LSTM stems from the RNN (Recurrent neural network) model. RNN is a prototypical artificial neural network that identifies temporal patterns in time series data with high accuracy and efficiency. The LSTM network, which incorporates memory units to facilitate learning of long-range temporal dependencies, to forget previously the hidden states and to update them given new information, was proposed by Hochreiter & Schmidhuber (Hochreiter & Schmidhuber, 1997) to resolve the problem of gradient vanishing and explosion upon training RNN model with the back-propagation through time (BPTT) (Werbos, 1990). As shown in Figure 9, the LSTM incorporates three control gates of input, output and forget G as well as a memory cell. Given a sequence of inputs (x_1, … , x_t), the LSTM model computes the hidden control sequence (h_1, … , h_{t-1}, h_t) and the cell memory sequence (c_1, … , c_{t-1}, c_t). This process can be described by the following set of equations:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (40)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (41)$$

$$C_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (42)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (43)$$

$$h_t = o_t \odot \tanh(C_t) \quad (44)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot C_t \quad (45)$$

where i_t, f_t, and o_t represents the gates of input, forget and output respectively, W denotes the weight matrix and b denotes bias. Additionally, σ and tanh denote the sigmoid and tanh functions respectively.

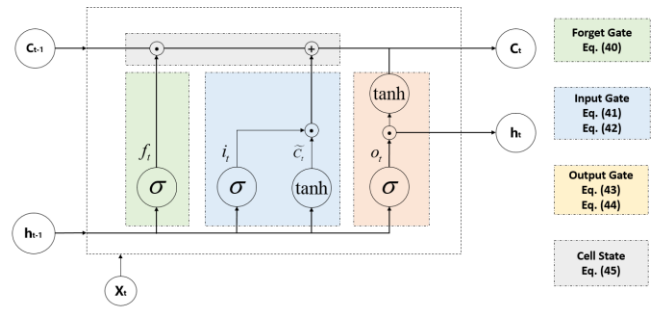

Figure 9. Diagram of a basic LSTM

4.2. Deterioration Prediction Model

Conventionally, a time series prediction model is designed to take a value to be predicted as an input. Figure 10 shows a schematic diagram of the LSTM model. The model mainly includes an input layer, an LSTM layer, and an output layer. This section is based on the Python deep learning framework *Pytorch* to construct a LSTM model, which includes a LSTM layer and a fully connected layer. Probability in Dropout layer is 0.2. The training hyperparameters mainly include the batch size (=6) of model update samples, the number of hidden units (=800), and the initial learning rate r_0 (=0.001). The mean square error (MSE) is employed in the loss function to obtain the corresponding error value. Adam is utilized as the optimization function, which is a first-order optimization algorithm that replaces the traditional random gradient descent process. It can iteratively update the weights of the neural network based on training data, where the MSE value continuously decreases, achieving the training of the autoregressive prediction model. The autoregressive sliding window is selected for one-step prediction of deterioration indicators. For example, the first ten data for training, the 11th data for prediction labels, the 2nd to 11th data for prediction of the 12th data, and so on, which continuously slides backwards for model training. The top 70% and 30% of datasets are used to trained and validate the models respectively, in order to judge the accuracy of the model prediction.

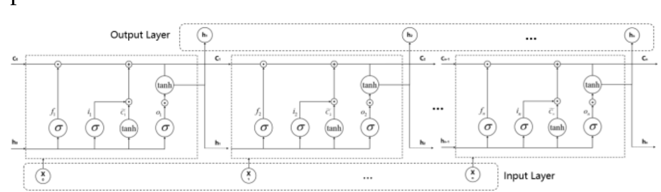

Figure 10. LSTM neural network model structure

This article evaluates the prediction model using mean square error (MSE), which is employed to compare the measured data (y_i) to model predictions ($y_i^{'}$), as defined by:

$$MSE = \frac{\sum_{i}^{n}\left(y_i - y_i^{'}\right)^2}{n} \quad (46)$$

where n is the amount of data points in each dataset. The smaller the MSE, the smaller the difference between the predicted and true values.

5. EXPERIMENTAL RESULT

5.1. Data

The sensor measurements from the real-time, on-line performance monitoring of gas turbines over a period of two months from September 1, 2009 to April 27, 2010 in the interval of 10min are used in this example to demonstrate the effectiveness of the proposed methodology. The parameters related to performance are shown in Table 2.

5.2. Data Analysis

According to the corrected value calculation introduced in Section 3, the thermodynamic SIMULINK model is utilized to calculate corrected performance. The deviation between design performance data and corrected value under ISO conditions is utilized to assess the performance degradation. The calculated corrected relative efficiency ($\eta_{corrected}/\eta_{design}$) of the compressor and turbine is utilized to assess the degradation of the compressor and turbine, respectively. The trend of effective efficiency η_e of the unit reflects the degradation of the overall unit. The calculation results are shown in Table 3.

5.3. Model Prediction

The total number of complete datasets is 63325 after data preprocessing. The input datasets are divided into 70% training and 30% testing sets. The division is based on chronological order rather than randomization. The LSTM model is established to predict three evaluation indicators η_e, η_c and η_t. As an example, Figure 11 shows the comparison of the raw data and prediction results for the overall effective efficiency η_e of partial time series. In LSTM model, 50 time steps in future are predicted, which is shown as forecasted values Fig. 11. The multi-step prediction method constructs a model based on its previous values, once the number of prediction steps exceeds a certain threshold, the predicted values will gradually dominate over the measured values, leading to a deteriorating performance.

5.4. Comparison Study

The widely used NARX (nonlinear autoregressive with exogenous input) model is employed as another RNN model in this example for comparison purpose. The NARX model is defined as

$$y(t) = f\left[y(t-1),\ldots,y(t-n_y),u(t-1),\ldots,u(t-n_u)\right] \quad (47)$$

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 to model nonlinear dynamic systems. In addition, it can be used to predict the next value of the input signals. We use the NARX model described in Liu & Jiang (2022) to predict the GT performance degradation results. The number of neurons in the hidden layer is set to be 12 in this section. Each NARX model is trained with 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). Figure 12 shows the prediction results for overall effective efficiency η_e of partial time series based on NARX Model.

Table 2. Performance parameters.

Name	Description
AFPAP	Air Inlet Pressure
CTIM	Compressor Inlet Temp
CTD	Compressor Exhaust Temp
CSGV	Inlet Guidance Vane Angle
AFQ	Compressor Airflow
DWATT	Active Power Output
DPF	Generator Power Factor
FQG	Fuel Flow
FTG	Fuel Temperature
TNH	Turbo Speed
TTXM	Exhaust Temp
AFPEP	Exhaust Pressure Drop

Table 3. Calculation results.

No.	η_c	η_t	η_e
1	0.980853	1.007787	0.358025
2	0.980391	1.007877	0.357936
3	0.979327	1.0079	0.35814
4	0.977788	1.008501	0.358213
5	0.97888	1.008244	0.358065
6	0.980684	1.004558	0.356793
7	0.981135	1.005707	0.357567
8	0.980024	1.005231	0.355421
9	0.97736	1.00402	0.352567
10	0.970023	1.003782	0.351589
… …			
63325	0.977831	0.998599	0.347

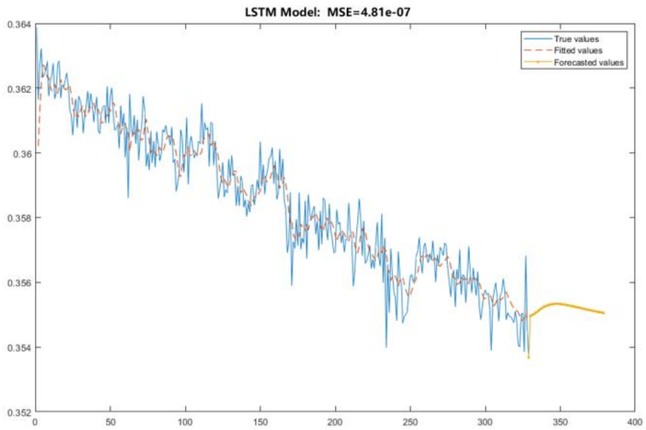

Figure 11. LSTM prediction result of partial time series

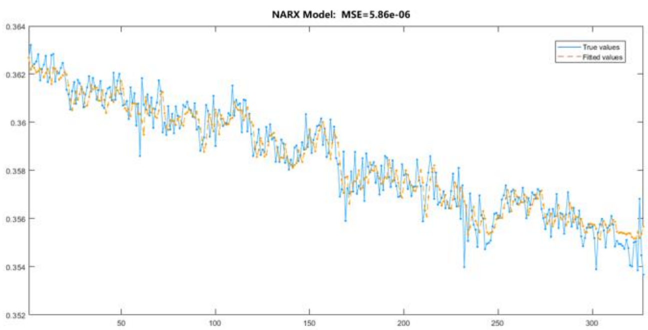

Figure 12. NARX prediction result of partial time series

5.5. Result Analysis

Based on the model mentioned earlier, traditional LSTM models and NARX models are constructed to predict the performance degradation in a single step. The results show that the MSE obtained by traditional LSTM is $4.81e^{-7}$, while the MSE obtained by NARX is $5.86e^{-6}$. Compared to NARX, the MSE predicted by the traditional LSTM indicates the better curve fitting effect.

6. CONCLUSION

In this work, a new physics informed machine learning methodology to predict the degradation of gas turbine by seamlessly integrating thermodynamic heat balance mechanism, component characteristics, multi-source data and artificial neural network model. The followings findings are obtained:

1. The mechanism-based thermodynamic model is established for multiple subsystems considering the balance of flow, mass and energy, and then integrated to a system level for performance simulation of the gas turbine under different conditions.
2. In order to eliminate the impact of ambient conditions and dependency on operating point during the deterioration prediction, the corrected parameters are calculated by adjusting from actual operating conditions to rated conditions. An integrated procedure is proposed. The indicators which characterize performance degradation are also determined.
3. A long short-term memory (LSTM) is established from the fusion of the actual and simulation data to predict the performance degradation of the gas turbine. A comparison study with the classical Nonlinear Autoregressive Network with External Input (NARX) neural network is conducted to demonstrate the advantage of the proposed method.

Currently, the thermodynamic physical model's outcomes serve as inputs for machine learning such as LSTM and NARX prediction models. In future research, physics integrated machine learning model will be developed for perform degradation.

NOMENCLATURE

c_p	specific heat capacity
k	ratio of specific heats
f	fuel-air ratio
h	enthalpy
s	entropy
I	moment of Inertia
M	torque
n	rotating speed
dt	time step
T	temperature
P	pressure
G	mass flow
V	voltage
W	work
π	Pressure ratio or expansion ratio
η	efficiency

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