Energy Proceedings
ISSN 2004-2965
Vol 28, 2022

A dual-driven approach for modelling heavy-duty gas turbine based on operational data and intelligent genetic algorithm

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ABSTRACT

In order to build an accurate model of heavy-duty gas turbine, a dual-driven approach is proposed based on operational data and intelligent genetic programming considering rotational speed, inlet/outlet temperature, pressure and generation power. The input-output thermodynamic characteristics of the compressor are obtained by genetic programming and net generation power of gas turbine is expressed by polynomial fitting formula equation, whose coefficients are obtained by least square method. Results show that all the models to calculate temperature ratio, pressure ratio and air mass flow ratio of compressor have a good accuracy, which of temperature ratio can reach 0.01. The accuracy of model to calculate generation power value can reach 0.04. This method for holistic modelling can be applied to other kinds of heavy-duty gas turbine.

Keywords: heavy-duty gas turbine, genetic programming, dual-driven approach, generation power

NONMENCLATURE

Abbreviations	
GP	Genetic programming
LHV	Low Heat Value
IGV	Inlet guide vane
Symbols	
$\dot{n}$	Corrected rotational speed
$\dot{m}$	Corrected mass flow
T	Temperature(K)
G	Mass flow(kg/s)
h	Specific Enthalpy(J/kg)
γ	Specific heat ratio
P	Pressure(kPa)
η	Efficiency
H	Enthalpy(J)
W	Power generation

1. INTRODUCTION

Electricity demand is predicted by International Energy Agency to increase by more than 1000 terawatt-hours in 2021 which is well above pre-pandemic levels. Gas turbine and combined-cycle gas turbine are being adopted in more and more countries [1]. Firing temperatures are getting higher and higher, which can reach 1500℃, 1600℃ and 1700℃ [2,3]. Meanwhile, cooling requirements are increased, and cooling structure is complex [4-5]. Those make many difficulties on building gas turbine model.

Traditional modelling for gas turbine is based on the components' characteristic maps and thermodynamic laws. Compressor and turbine performance maps are usually obtained by stage-stacking method, which requires specific blade profile size, or from commercial software, or from manufactures. In fact, it is hard to obtain specific blade profile size and components' characteristic maps due to manufactures' commercial secret. Therefore, traditional modelling is not suitable when components' characteristic maps are missing.

Some research improved traditional modelling method, where components' maps are obtained by introducing corrected factor or adaptive factor [6-12]. The characteristics of components can be obtained by this method, but only part of the actual operational data is considered for correction, and it is not directly related to the actual operational data.

Data-driven model is a novel method to build gas turbine model, which is based on the field data and reduces dependence on components' size. A. Mehrpanahi [13] took the neural network (NN) method and the derived functions of linear regression (LR), shaft dynamic (SD)-based function, and nonlinear auto-regressive exogenous (NARX) and Hammerstein-Wiener (HW) fitted structures to generate dynamic model based

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on condition monitoring data in the start-up mode. M. Basso [14] built a nonlinear autoregressive with exogenous inputs (NARX) model of PGT10B1 gas turbine. Elias Tsoutsanis [15,16] used a function of corrected mass flow rate mc and corrected rotational speed to express the compressor pressure ratio and the compressor efficiency. A fifth-order polynomial function is used to express the turbine map. The efficiency of turbine is fitted by a trigonometric function. Power turbine map is fitted by a polynomial function of the fourth order and its efficiency is represented by a two term exponential model.

No matter which method, in order to obtain the mathematical expression of components, the form of its function is always needed. However, multi-stage extraction from compressor may cause the form of the function changes. Fig.1 shows typical cooling extraction from different stage in the compressor. When partial cooling air is extracted, the corrected mass flow is changed, which caused the function to need fixing. However, when the cooling extraction occurs in many stages, the function needs to be modified constantly, and the work of obtaining the function form increases. In this research, genetic programming [17,18] is a convenient way to describe the function relationship of input and output parameters. F. Safiyullah [19] used genetic programming to build actual isentropic head model for gas compressors. The deviation between the empirical relations of original equipment manufacturer and actual isentropic head is used to predict the performance degradation.

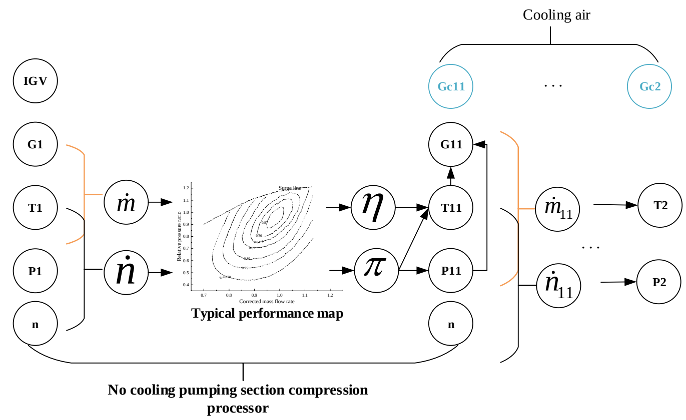


Fig.1 Typical cooling extraction from different stage in the compressor

In this research, GE9FA is taken as research object. Fig.2 shows the logic frame of this research. The field data is obtained from Ban shan Power Plant. Combined with field data, thermodynamic cycle is simplified by taking the compressor and turbine as a whole, respectively. The thermodynamic inputs and outputs of compressor and turbine are the focus. The input-output thermodynamic characteristics of the compressor are obtained by genetic programming. The net generation power of gas turbine is expressed by polynomial fitting formula equation, whose coefficients are obtained by least square method. Lastly, the reliability of the model is verified by independent field data sets.

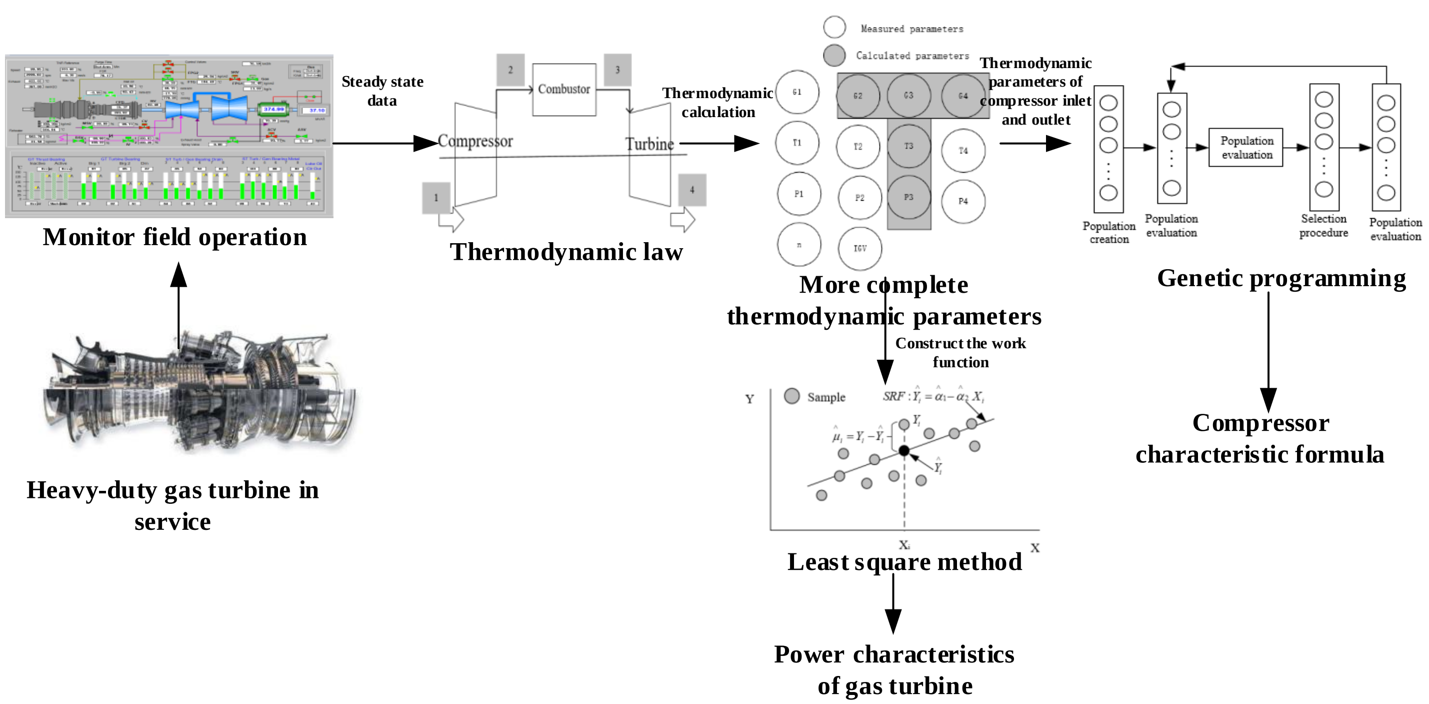
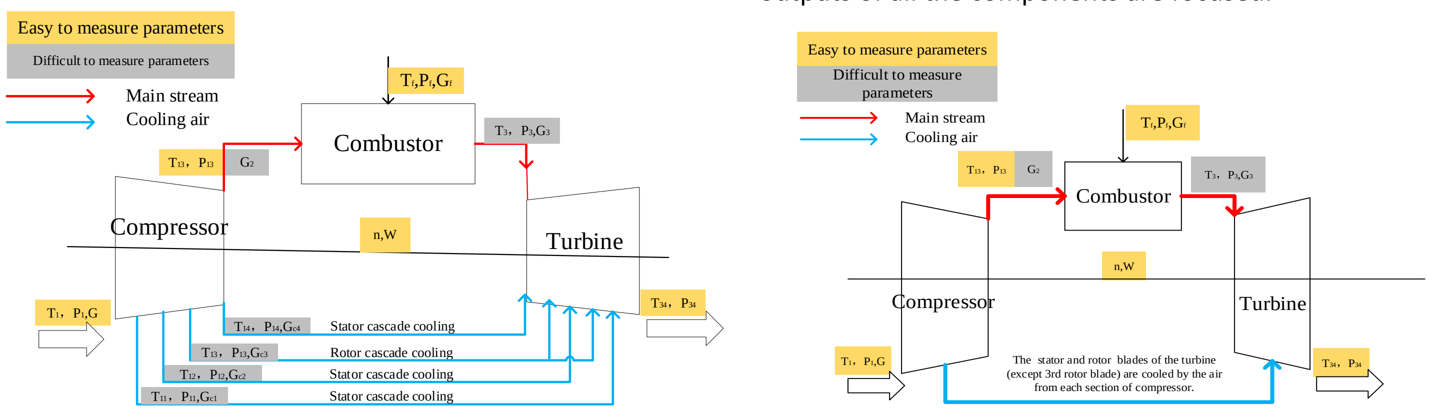


Fig.2. The logic frame of this research

2. METHODOLOGY

2.1 *Heavy-duty gas turbine description*

The GE9FA gas turbine unit in the Ban shan combined gas and steam cycle power plant is taken as research object. The Fig.3(a) shows the specific cooling process and air flow process of the unit, whose cooling process is complex. The axial compressor has 18 stages from 0 to 17. The cooling air is abstracted from the stage 9, 13, 16 and 18 to the stage 3, 2 and 1 of turbine. Due to the lack of cooling thermodynamic parameters, it is difficult to build the detailed and accurate model of gas turbine. Therefore, the overall gas turbine model is built by simplifying the cooling process. Fig.3(b) shows the simplified thermodynamic process. The inputs and outputs of all the components are focused.



(a) (b)

Fig.3. The structure of the GE9FA gas turbine

2.2 *Field data processing*

The operational field data is from May 2020 to October 2021. According to the characteristics of combined gas and steam cycle, the steady state is defined that the variance of TOT in fifteen minutes is less than 0.5.

$$\frac{1}{15}\sum_{i=1}^{15}(T_{4i}-\mu)^2<0.5 \qquad (1)$$

In which, T_{4i} is the turbine outlet temperature at i number, μ is the expectation of 15 numbers.

2.3 Mathematical model of gas turbine

Some assumptions are necessary in the modelling process.

(1) The air or the flue gas is considered as ideal gas, whose thermodynamic properties are calculated by Dalton's law of partial pressure based on polynomial fitting formula [20]. The composition of air is assumed to keep the constant.

(2) The combustion efficiency is 0.995 and pressure loss in the combustor is 0.35.

(3) When the load is over 200MW, the turbine is considered to be operate in the stagnation zone [21].

(4) The sum of air or flue gas leakage is 8.9kg/s [22].

2.3.1 Axial compressor

The characteristics of axial compressor can usually be expressed by four parameters, which are $\pi_c, \dot n_1, \dot m_1$ and η_c. When the IGV is considered, it is necessary to add IGV to the characteristics.

$$\eta_c = f(\dot m_1, \dot n_1, IGV) \qquad (2)$$

$$\pi_c = f(\dot m_1, \dot n_1, IGV) \qquad (3)$$

2.3.2 Combustion chamber

The mass and energy balance is considered in the combustion chamber.

$$G_3 = G_2 + G_f \qquad (4)$$

$$h_3 \bullet G_3 = G_f \bullet LHV \bullet \eta_b + h_2 \bullet G_2 + h_f \bullet G_f \qquad (5)$$

2.3.3 Axial turbine

The assumption is made that the flow is chocked at the nozzle of the turbine. The input thermodynamic characteristics are described by Eq(6).

$$\frac{\dot m_3\sqrt{T_3R_3}}{P_3\sqrt{\gamma_3}} = \frac{\dot m_{30}\sqrt{T_{30}R_{30}}}{P_{30}\sqrt{\gamma_{30}}} \qquad (6)$$

2.3.4 Mathematical model of electrical power

The net generation power is the work made by the turbine minus the work consumed by the compressor. Whether compressor consumption or turbine output, they can usually be expressed as the difference in enthalpy between inlet and outlet of working medium. However, due to the cooling air abstracted from compressor to turbine, the power is not the enthalpy difference of the inlet and outlet multiplied by the flow rate. Therefore, the generation power is assumed as the function of enthalpy of inlet and outlet of compressor and turbine.

$$W=\alpha_1 H_1+\alpha_2 H_2+\alpha_3 H_3+\alpha_4 H_4 \tag{7}$$

The unknown values of empirical coefficients are estimated by the least squares method. The criterion of estimation has a following form.

$$\sum_{i=1}^{n}\frac{(W_i^{\mathrm{model}}-W_i^{means})^2}{\mathrm{n}}\rightarrow \min \tag{8}$$

2.3 *Genetic programming for the characteristics of compressor*

Genetic programming [17] is a method for optimizing both the structure and parameters of an input-output map. The mapping can be represented by the recursive function tree, in Fig.4. There are four components, which are data set, actuation, sensors and constants, and functions. Control law is the mapping of inputs and outputs, which is the target. Actuation is the dependent variable. Sensors are variables. Functions are mathematical symbols and common functional forms, which are +, -, x, /, sin, cos, log, exp and tanh in this research.

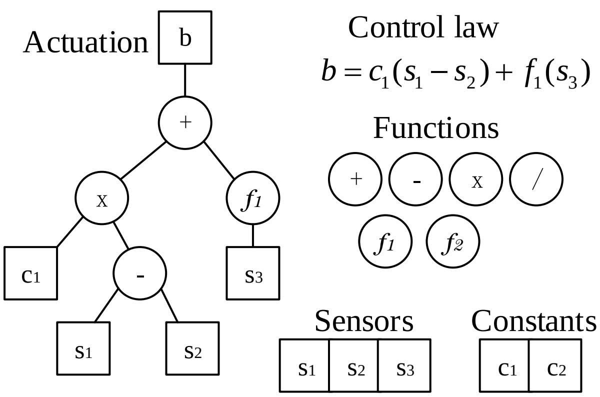


Fig.4 The recursive function tree

Fig.5 shows the process of obtaining compressor input-output characteristics by GP. Firstly, it is necessary to make clear the independent and dependent variables, which is used to determine sensors. According to field data and thermodynamic calculation, the compressor outlet mass flow corresponding to the steady state can be obtained. Therefore, the outlet mass flow can be described by the m1, n1 and IGV. Meanwhile, the temperature and pressure ratio of inlet and outlet can also be described by m1, n1 and IGV. Meanwhile, fitness function is required to build. The value of fitness J is set. When fitness meets the requirements or generation reaches the maximum set value, the program is stopped.

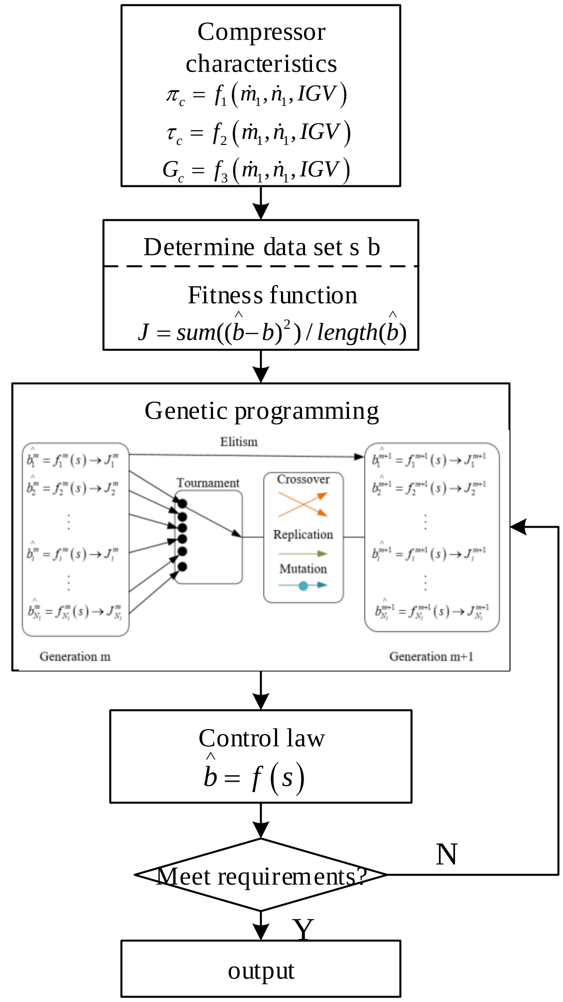


Fig.5 The process of obtaining compressor input-output characteristics by GP

3 RESULT AND DISCUSSION

3.1 Operational data

The steady state point accounts over 120000. Taking the generation power as an example, the processing of other field measured parameters is similar to the generation power. Fig.6(a) shows the generation power at steady state from May 2020 to October 2021. In order to facilitate calculation, the field data is taken through the interval 10, as shown in Fig.6(b). Compare the data before and after interval fetching, and the field data trend remains unchanged. 12000 groups of field data sets are selected as the research object. The first 10000 groups of field data sets are used as training sets, and the last 2000 groups are verification sets or test sets.

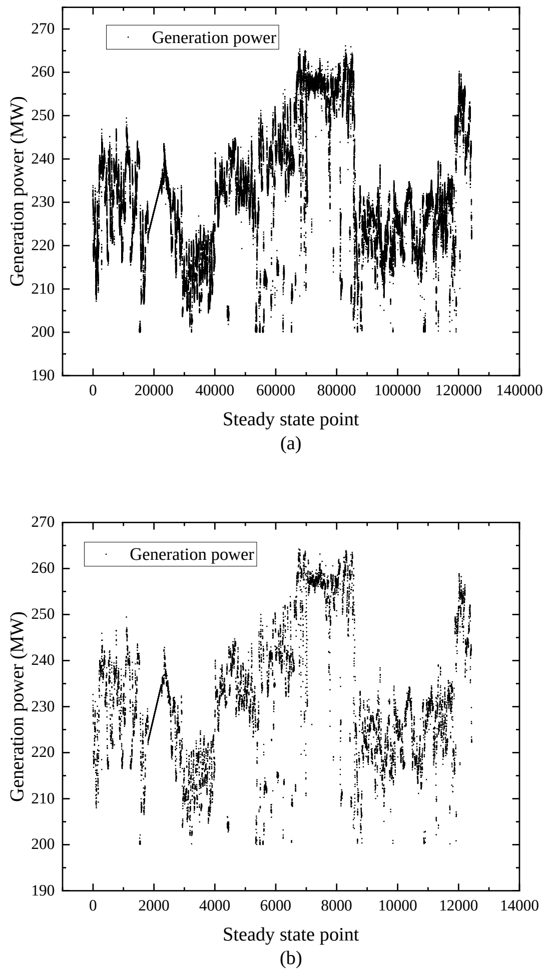


Fig.6 The generation power at steady state from May 2020 to October 2021

3.2 Model validation

According to the known design point parameters, inlet and outlet thermodynamic parameters of combustor can be calculated, which are used to compare with the designed point, as shown in Table 1. T_3 is a dominant parameter to judge the rationality of thermodynamic calculation. The relative error between T_3 from model and from designed point is 1.36%. Meanwhile, the air flow at the inlet of combustion chamber is estimated. All the relative errors are within 1.5%. Therefore, thermodynamic model is reasonable and reliable.

Table 1 Comparison between value calculated by model and designed point

Parameters	Value from model	Designed point
T_1(K)	288	288
P_1(KPa)	99	99
G_1(kg/s)	645	645
T_3(K)	1714	1691
T_4(K)	888	888

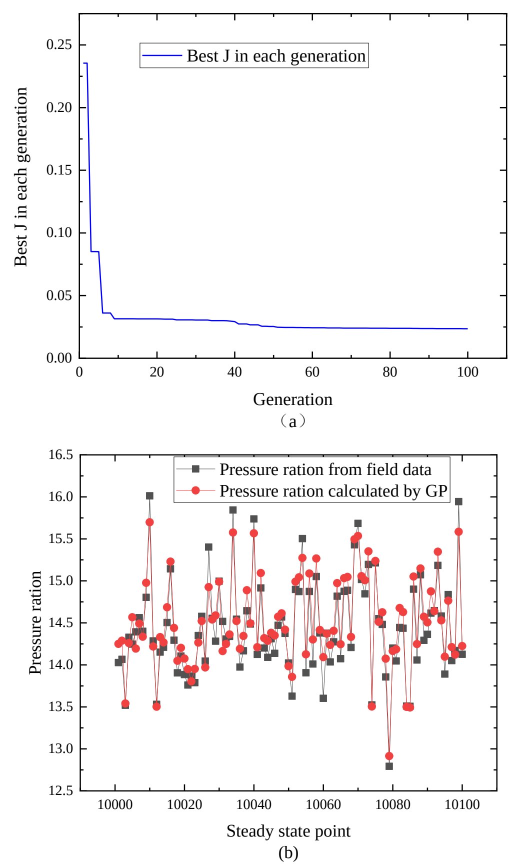
3.3 Input-output characteristics of axial compressor

The function of pressure ratio is obtained by GP,

Π c=(((exp(S1) .* (cos(In(exp((-1.839)))) + cos(cos(tanh(In(S1)))))) .* ((2.696 + (/(cos((exp(S2) + ((-0.8836) .* 3.036))),(/(sin(((/(S2,9.421)) + sin(exp(In(exp(In(S0)))))),1.528))))) - cos(((/(In((/((-1.815),S1))),((-6.814) + exp(tanh(In(S1)))))) - (-5.015))))) + (In(sin(((/(S2,9.421)) + sin(exp(In(exp(In(S0)))))))) .* In((/((cos(cos(exp(exp(sin(exp(sin((S1 + In(S1))))))))) + cos(cos(exp(exp(sin((S1 + (exp(S2) + ((-0.8836) .* 3.036))))))))),((-2.235) .* ((cos(exp((/(tanh((In(S1) - (-5.015))),1.528)))) .* (-0.3086)) + (exp(9.506) + exp(((-0.8836) .* 3.036)))))))))).

Where S0 is IGV, S1 is corrected mass flow, S2 is corrected rotational speed.

Fig.7 shows the result of pressure ration by GP. Fig.7(a) shows the best fitness in each generation. After generation 70, the best fitness almost keeps the constant, which is converged. Fig.7(b) shows the pressure ration comparison between field data and that from GP. Fig.7(c) and Fig.7(d) shows the relative error distribution between field data and that from GP in the training set and test set, whose are in high coincidence. In the whole data set, the accuracy of pressure ration function can be considered to be within 0.04.



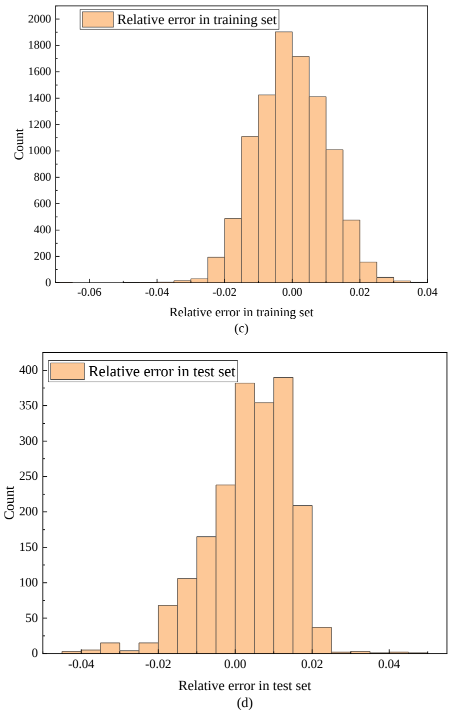


Fig.7 The result of pressure ration by GP

The function of temperature ratio of inlet and outlet compressor is obtained,

Π_t =exp(((/(((/((/((tanh(ln(S1)) .* 6.883),((cos((-2.692)) .* (/(S0,(-6.595)))) .* (/(S0,(-6.595)))))),cos((-5.304)))) .* (-3.392)),ln(5.274))) + (/(sin(S2),cos((/((/((/(sin(((/(((-1.315) .* tanh(sin((/(S0,(-6.595)))))),(cos((-2.692)) - (/(0.165,((cos((-2.692)) .* cos((-2.692))) .* (/(S0,(-6.595))))))))) + 2.289)),((/(sin((((-2.315) + S0) - (/(S0,7.009)))),(cos((-2.692)) - ln(S1)))) + 2.289))),((/(sin((sin((((-2.315) + S0) - (/(S0,7.009)))) - (/(((/(((-5.73) .* 6.883),(((-9.783) .* (0.6062 - (-2.799))) .* (cos((-0.1671)) .* ((-9.247) .* (-9.562)))))),ln(S1))))),(tanh((-9.975)) - sin(S2)))) + 2.289))),((cos((-2.692)) .* (/(S0,(-6.595)))) - ((/(S0,7.009)) - (/(((-0.6787) - exp(cos(sin((7.893 - (/(S0,7.009))))))),exp((tanh((S2 + cos((/(((-6.364) .* S2),ln(4.02)))))) + tanh((sin((/(S0,(-6.595)))) - 6.778)))))))))))))))

Fig.8 shows the result of temperature ration by GP. Fig.8(a) shows the best fitness in each generation. After generation 60, the best fitness almost keeps the constant, which is converged. Fig.8(b) shows the pressure ration comparison between field data and that from GP. Fig.8(c) and Fig.8(d) shows the relative error distribution between field data and that from GP in the training set and test set, whose are in high coincidence. In the whole data set, the accuracy of pressure ration function can be considered to be within 0.01.

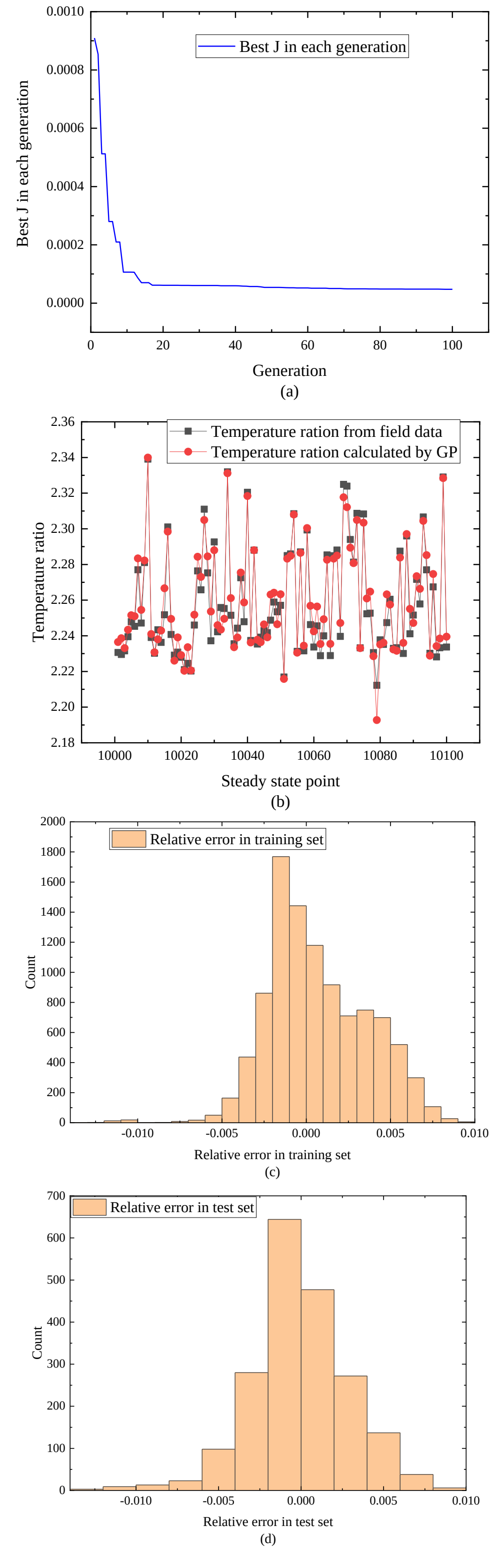


Fig.8 The result of temperature ratio by GP

The function of air mass flow ratio of inlet and outlet compressor is obtained,

Π_G =sin(cos(exp((((/((/((/((/(6.932,7.783)), cos(sin((4.18 .* ((9.365 .* (/((-7.053),S0))) .* ((-0.8205) + 3.75)))))),cos(sin(sin(((9.365 .* (/(S1,(-2.034)))) .* (-7.676))))))),(-9.474))) .* sin(((/((/((/(((((/((-3.623),(/(S1,(-2.034))))) + (tanh((-2.533)) + (-6.339))) - sin((/((-7.053),S0)))) + sin(((9.365 .* (/((-7.053),S0))) .* (-

7.676)))),cos(sin(((9.365 .* (/((-7.053),S0))) .* (-7.676)))))),cos(sin((4.18 .* ((9.365 .* (/((-7.053),S0))) .* ((-0.8205) + 3.75))))))),(-9.474))) - ((9.365 .* cos(S2)) .* (-7.676))))) - cos((tanh((/((/((/(((tanh((9.365 .* ((-0.8205) + 3.75))) - sin((9.365 .* cos(2.529)))) + sin(((9.365 .* (my_div((-7.053),S0))) .* (-7.676)))),cos(sin(((9.365 .* cos(S2)) .* (-7.676)))))),cos(sin(((9.365 .* cos(S2)) .* sin((9.365 .* (my_div((-7.053),S0))))))))),(-9.474)))) .* sin((cos(S1) - ((9.365 .* cos(S2)) .* (-7.676)))))))))

The result is similar with the pressure ratio and temperature ratio. Fig.9(a) and Fig.9(b) shows the relative error distribution between field data and that from GP in the training set and test set, whose are in high coincidence. In the whole data set, the accuracy of pressure ration function can be considered to be within 0.025.

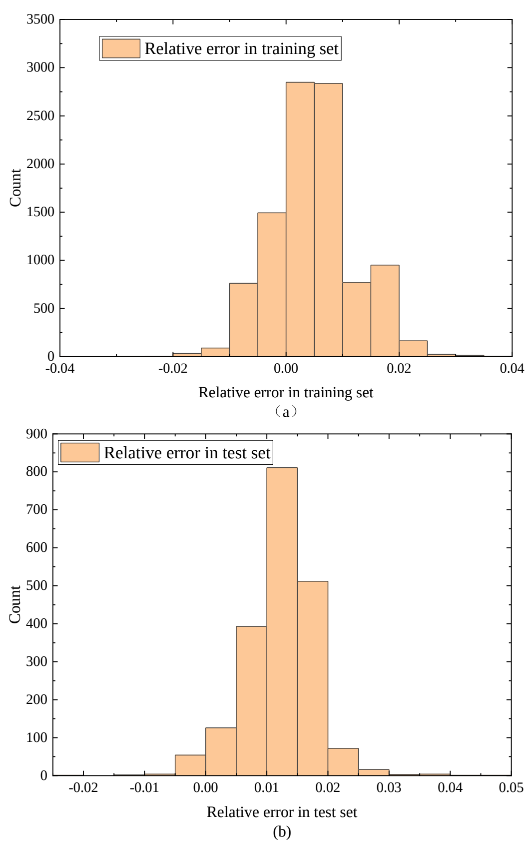


Fig.9 The relative error distribution in the training set and test set

3.3 Generation power of gas turbine

According to the least squares method, the coefficients of net generation power are obtained in Table 2. Fig.10 shows the result in the training set and verification set. The relative in the verification can be considered to be within 0.04.

Table 2 The coefficients of net generation power

Coefficient	α_1	α_2	α_3	α_4
Value	-6.258 e-05	7.971 e-07	-2.481 e-08	6.078 e-06

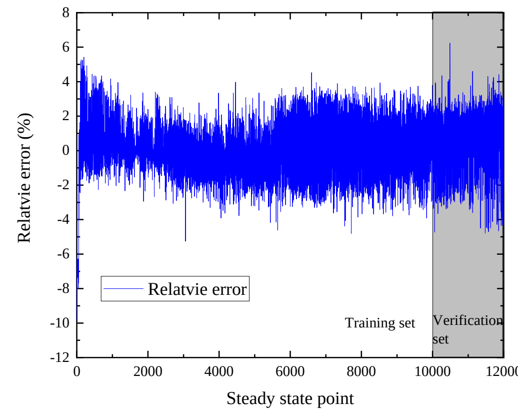


Fig.10 The result in the training set and verification set

4 CONSLUSIONS

1) When heavy-duty gas turbine is complex and components' characteristics are lack, the simplified model can be constructed based on field data and thermodynamic laws, which can be used to monitor the operation performance.
2) Input-output characteristics of compressor can be obtained by genetic programing. The function of temperature ratio, pressure ratio and air mass flow ratio are in good agreement with the actual law. The function of temperature ratio has the best agreement with the actual law, whose accuracy can reach 0.01.
3) The net generation power can be expressed by the inlet and outlet enthalpy of compressor and turbine, whose accuracy can be within 0.04.

ACKNOWLEDGEMENT

The research is supported by National Science and Technology Major Project (J2019-I-0009-0009), National Natural Science Foundation of China under Grant No. 52176013, Shanghai Rising-Star Program under Grant No. 20QA1404700, National Science and Technology Major Project (J2019-I-0012-0012).

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