On-orbit Engine Thrust Prediction Algorithm for Geosynchronous Satellites based on Neural Network

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Abstract. Focused on the problem of complex in-orbit engine thrust prediction algorithm the geosynchronous satellite, a thrust prediction method based on the composition of the propulsion system is proposed in the paper. The method integrates theoretical model and neural network model, and the prediction model is simple and practical. In order to further improve the accuracy of the model, the in-orbit data was used to optimize the modified parameters using the multi-objective genetic algorithm NSGA-II. Finally, the optimized model is applied to different cases. The comparison between the simulation results and flight data shows that the accuracy of the optimized model is significantly improved, and the in-orbit thrust prediction method is correct and effective.

1. Introduction

The geosynchronous satellites generally use bi-propulsion systems, which use nitrogen tetroxide as the oxidant, methyl hydrazine as the fuel. The orbit change is performed by a liquid apogee boost motor and the attitude control during the orbit change is performed by the thrusters.

Before the orbit transfer, it is necessary to predict the engine thrust to determine the final orbital strategy\cite{1}. In addition, due to the deviation between the ground test and the in-flight performance, it is often necessary to re-calibrate the engine thrust through a certain orbit maneuver effect, and then correct the engine thrust of the next orbit transfer according to the calibration result to improve the orbit maneuver effect, and avoid waste of propellant. In general, it is necessary to calculate the performance by constructing complex mathematical models of the propulsion system to obtain the predicted thrust. This way is necessary to establish rigorous mathematical models for the products, especially the pressure regulator and the check valves of the pneumatic system, and the versatility is poor. Once the model needs to be corrected, there will be too many parameters involved, and there will be a large randomness.

Focused on the above problems, this paper proposes a neural network-based on-orbit engine thrust prediction algorithm for geosynchronous satellites. This method establishes the basic models of the pneumatic system based on ground data and avoid complex mathematical formulas according to the working principles. The method is simple and has strong versatility. Meanwhile, flight data can be used to modify the model through the multi-objective optimization method\cite{2-5} to improve the engine thrust prediction accuracy. The calculated output of the optimized model is compared with the experimental data to verify the effectiveness of the algorithm.

2. Calculation model

The unified propulsion system mainly comprises the apogee engine, attitude control thrusters...
branches, the propellant tanks, helium pressurization system including helium tanks, pneumatic regulator, check valves, other pressurant control and isolation assembles. Figure 1 shows a typical satellite unified propulsion system scheme.

The high-pressure gas flows out of the helium tank is depressurized by the pressure regulator. The gas supplied to the propellant tanks at steady flow rate, and then transfer propellants from the tanks through the pipeline, and finally to the engine and the thrusters. During the satellite orbit transfer, the pressure of the helium tank will decrease with the outflow of helium. The output of the pressure regulator and the check valves may vary due to the output characteristics, which will affect the inlet pressure of the engine. Accordingly, the engine thrust changes.

![Figure 1. Schematic diagram of propulsion system](image)

2.1. Helium Tank

The high pressure helium tank can be regarded as a combination of an air chamber and a gas outlet port. The dynamic model can be obtained from the mass flow equation of the helium, the continuous equation and the energy equation. Assuming that the gas is ideal, the dynamics equations of helium tank can be be can be expressed as

\[
\frac{d\rho_g}{dt} = -\frac{Q_g}{V_g} \tag{1}
\]

\[
\frac{dp_g}{dt} = -\frac{\gamma}{\gamma - 1} = \frac{p_g}{\rho_g} \frac{Q_g}{V_g} - \frac{1}{\gamma - 1} q_g S_g \tag{2}
\]

Where, \(V_g\) is the nominal volume of the helium tank, \(Q_g\) is the mass flowrate. \(\rho_g\) is the density of helium, \(t\) is time. \(q_g\) is the heat flux density per unit area of the gas in the helium tank (usually considered as convective heat transfer), \(S_g\) is the contact surface area between the gas and the tube wall in the helium tank, \(\gamma\) is the adiabatic coefficient of helium.

To ensure the in-flight performance of the pneumatic system, multiple pneumatic system tests are
often performed on the ground. Through the pneumatic system test, the output pressure of the check valves can be obtained under different inlet pressures of the pressure regulator. The structure of the pressure regulator and the check valves in the pneumatic system is complicated, and the general mathematical model often has the characteristics of slow calculation and poor versatility. The neural network can effectively solve the above problems.

2.2. Pressure regulator
The neural network model of the pressure regulator is as follows:

\[ p_{\text{reg}} = \text{net}_1(P_g, Q_g) \]  

(3)

Where, \( P_g \), \( Q_g \) are the input vector of the network model. The output vector \( p_{\text{reg}} \) is the pressure regulator output pressure.

2.3. Check valve
The neural network model of the check valve models are as follows:

\[ Q_{\text{go}} = \text{net}_2(P_{\text{reg}} - P_o) \]  

(4)

\[ Q_{\text{gf}} = \text{net}_3(P_{\text{reg}} - P_f) \]  

(5)

\[ Q_g = Q_{\text{go}} + Q_{\text{gf}} \]  

(6)

The input vector of the network model \( \text{net}_2 \) is the difference between CV1 inlet pressure \( P_{\text{reg}} \) and the oxidant tank pressure \( P_o \), and the output vector is the CV1 output flow \( Q_{\text{go}} \).

The input vector of the network model \( \text{net}_3 \) is the difference between CV2 inlet pressure \( P_{\text{reg}} \) and the fuel tank pressure \( P_f \), and the output vector is the CV2 output flow \( Q_{\text{gf}} \).

Neural network is suitable for system identification and BP model is one of the most widely used neural network models [6-7]. According to the output characteristics of pressure regulator and check valves, a three-layer BP neural network is selected, the transfer function of the hidden layer and the output layer are recommended to select “purelin”. Preliminary training of the network was carried out using ground test data to obtain a preliminary neural network model.

2.4. Tank
As the model shown in figure 2, the tank can be seen as a combination of an air chamber and a gas inlet port, a liquid chamber and a liquid outlet port. The diaphragm between the two chambers is considered to be an ideal geometric isolation surface with equal pressure on both sides. The dynamics equations of helium tank can be expressed as follows.

\[ \frac{dQ_i}{dt} = \frac{1}{V_i} \left( Q_{\text{mi}} - \rho_i dV_i \right) \]  

(7)

\[ \rho_i \frac{dV_i}{dt} = Q_{\text{me}} \]  

(8)
\[
\frac{dp_t}{dt} = \gamma \left( \frac{Q_{m}}{\rho_t} - p_t \frac{dV_t}{dt} \right)
\]

(9)

Where, \( Q_{m} \) is the gas mass flow into the tank, \( Q_{m} \) is the propellant mass flow from the tank. \( V_t, \rho_t \) are the gas volume, pressure and density of the propellant tank, respectively. \( p_t, \rho_t \) are the gas pressure and density of the tank inlet chamber.

2.5. Engine

The engine flow is related to the pressure and temperature at the engine inlet. The relationship can be obtained from the ground test and given in the form of a small deviation equation. The inlet pressure of the engine can be obtained by subtracting the flow resistance of the tank from the pressure of the tank.

\[
P_{eo} = P_o - \Delta P_{lo}
\]

(10)

\[
P_{ef} = P_t - \Delta P_{lf}
\]

(11)

Where, \( P_{eo}, \Delta P_{lo} \) are the engine inlet pressure and flow resistance of oxidizer branch, \( P_{ef}, \Delta P_{lf} \) are the engine inlet pressure and flow resistance of fuel branch.

3. Optimization model

Before the satellite orbit transfer, the theoretical thrust value is given according to the ground test results and the current propulsion system state, and then the subsequent orbit maneuver strategy is formulated. Due to the deviation between the ground test and the in-flight performance, it is often necessary to re-calibrate the engine thrust through a certain orbit maneuver effect to improve the orbit maneuver effect.

The neural network correction model of the pressure regulator is as follows:

\[
p_{reg} = net_1(P_g, Q_g) + a_1
\]

(12)

The neural network correction models of the check valves are as follows:

\[
Q_{go} = net_2(P_{reg} - P_o) \cdot b_1
\]

(13)

\[
Q_{gf} = net_3(P_{reg} - P_t) \cdot b_2
\]

(14)

Where, \( a_1, b_1, b_2 \) are the correction factor.

The flight data available in the existing configuration of the propulsion system is used as a reference value, and the objective function is set as follows:

\[
\min f_1 = \bar{P_o} - p_o
\]

(15)

\[
\min f_2 = \bar{P_t} - p_t
\]

(16)

\( \bar{P_o}, \bar{P_t} \) are the average pressure of the oxidant tank and the fuel tank obtained by simulation, \( p_o, p_t \) are the average pressure of the oxidant tank and fuel tank measured by the pressure sensors PT2 and PT3, respectively.

Meanwhile, taking into account the maximum deviation of the pneumatic system between in-flight performance and ground test, we can set the constraint function as follows:

\[-0.3 \leq a_i \leq 0.3; 0.5 \leq b_i \leq 2; 0.5 \leq h_i \leq 2\]

(17)

In this paper, the genetic algorithm is used to optimize the model. The specific calculation process is as follows:
1) Try to select the correction factor $a_1$, $b_1$, $c_1$, and if not, $a_1$ take 0, $b_1$, $c_1$ take 1;

2) Calculate the current engine flow rate through the small deviation equation by the tank pressure and temperature data of the propulsion system before the orbit transfer;

3) Calculate the tank pressure ($P_s$, $P_f$) by the current engine flow rate;

4) Calculate the flow rate of check valves ($Q_{go}$, $Q_{gf}$) by the tank pressure and the pressure regulator pressure;

5) Calculate the pressure output of the pressure regulator ($p_{reg}$) and the helium tank ($p_h$) according to the check valve flowrate;

6) Cycle steps 2) to 5) until the end of the orbit transfer;

7) Subtract the on-orbit average tank pressure of the orbit transfer process from the pipeline flow resistance, obtain the inlet pressure of the engine, and substitute the engine equation to obtain the average predicted thrust of the orbit transfer;

8) Taking $a_1$, $b_1$, $c_1$ as the parameters to be optimized, loop steps 1) to 7) to obtain the fitness function, and solve the optimization model through the multi-objective genetic algorithm NSGA-II, when obtaining a feasible solution that meets the accuracy requirements, the calculation is terminated. Output the optimal solution to the model optimization problem.

9) Substitute the optimal solution into step 1), and calculate the predicted current thrust of the orbit transfer by step 2) to step 6).

4. Examples and results analysis

Related parameters settings:

The helium tank volume is 150L and the initial pressure is 23MPa; the nominal volume of the propellant tank is 1412L, the initial pressure of the oxidant tank is 1.505MPa, and the initial pressure of the fuel tank is 1.523MPa. The initial mass of the MON-1 is 1518.808 kg, and the initial mass of the MMH is 916.357 kg. The ignition time is 3208s. During ignition, the on-orbit average pressure of oxidant tank $p_o$ is 1.443 MPa and the on-orbit average pressure of fuel tank $p_f$ is 1.441 MPa.

The modified parameters $a_1$, $b_1$, $c_1$ are optimized by the NSGA-II algorithm. After the algorithm is finished, the pareto optimal solutions are obtained. A set of optimal correction parameters ($a_1$ = 0.0177, $b_1$ = 0.9719, $b_2$ = 0.9719) are selected in the pareto points, while $f_1 = 4.7306$ Pa, $f_2 = 1.4642$ Pa.

Figure 3 and Figure 4 show the pressure variation curves of the oxidant tank and the fuel tank during the ignition process. It can be seen that by optimizing the calculation, the simulation curve is almost coincident with the in-flight performance curve.

![Figure 3. Pressure variation curves of the oxidant tank during the ignition process.](image1)

![Figure 4. Pressure variation curves of the fuel tank during the ignition process.](image2)

In order to further verify the effectiveness of the optimization model, the optimization model is used to predict the engine thrust under different working conditions. The results are given in Table 1.
$\bar{F}_c$ is the calibration thrust thrust that is maintained after the satellite orbit transfer; $\bar{F}_p$ is the prediction thrust value of the maintained model based on the parameters before orbit transfer, $T$ is ignition time.

It can be seen that the average pressure of optimized model calculation results are basically the same as average pressure of the test results. The difference between calibration thrust and prediction thrust are small, the relative error is within 0.2%, which can meet the requirements for on-orbit use. The results show that the optimization model is correct and effective.

Table 1. Optimization results under different cases.

| $T$ / s  | $\bar{P}_o$ / MPa | $\bar{P}_f$ / MPa | $\bar{F}_c$ / N | $\bar{P}_o$ / MPa | $\bar{P}_f$ / MPa | $\bar{F}_p$ / N |
|----------|-------------------|-------------------|----------------|-------------------|-------------------|----------------|
| 1        | 1.433             | 1.441             | 503.376        | 1.443             | 1.441             | 503.250        |
| 2        | 1.463             | 1.461             | 508.931        | 1.463             | 1.460             | 508.508        |
| 3        | 1.470             | 1.472             | 511.711        | 1.473             | 1.471             | 511.271        |
| 4        | 1.425             | 1.423             | 498.694        | 1.427             | 1.427             | 499.137        |

5. Conclusion

In this paper, a neural network-based thrust prediction method is proposed for the engine thrust prediction during geostationary satellites. Combined with on-orbit data, the calculation model is studied. The results show that:

1) Combined with ground test data, the prediction model is simpler, more practical and more versatile by selecting a suitable neural network structure to replace the complex valve model.

2) Focused on the difference between the ground test and the in-flight performance of the propulsion system, the multi-objective genetic algorithm NSGA-II is used to optimize the key parameters. The model performance is similar to the in-flight performance, and the model correction method is effective.

3) The optimized model is verified by different cases. The engine thrust prediction error is kept within 0.2%, which satisfies the requirements for on-orbit use. The on-orbit thrust prediction method is correct and effective.

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