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A New Hybrid Modeling Method for Performance Digital Mock-Up of Hypersonic Vehicle

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Abstract: For the characteristics that a hypersonic vehicle has a large span of flight height and flight Mach number, and complicated flight environment, the model of which is highly nonlinear, unstable and multivariablecoupled, where using a single modelling approach is often difficult to achieve high modeling accuracy, hybrid modeling method is proposed to design its performance digital mock-up. The performance digital mock-up hybrid model are designed by using fuzzy set theory, neural networks and system identification method based on combination of the three fuzzy neural network identification method and technology. The simulation results show that high modeling accuracy of this modeling method is generally conventional neural network or fuzzy identification incomparable.

Keywords: hypersonic vehicle, hybrid modeling, fuzzy neural network, performance digital mock-up, system identification

1 Introduction

Hypersonic aircraft generally refers to five times faster than the speed of sound flying aircraft [1]. Its highly nonlinear multivariable coupling model and there, but due to changes in altitude and flight Mach number range, flying the external environment is very complex, making hypersonic aircraft is very sensitive to changes in shape, aerodynamic parameters and atmospheric conditions [2]. At present, the control method is widely used to approximate linearization of nonlinear [3] problem, is suitable to model the lower order of aircraft, but for the order of the model is relatively high, the aerodynamic parameters of hypersonic vehicle, may no longer apply [4].

Hypersonic vehicle concept performance digital mock-up technology with the development of CAD, virtual prototyping technology, software technology and computer-related technologies and proposed structural relationship virtual prototype aircraft built with precise geometric attributes defined based on the use of CAE pre-processing and modeling tools to create product features quality analysis model, at each stage of product development capabilities with a variety of CAE tools for real-time product quality, coordinated and comprehensive analysis of the simulation, using visualization tools applicable to the quality of the product's features characteristics described, implemented in close connection with the whole process of product development with the user, resulting in deeper and more substantive than the traditional exchange of CAD technology [5].

The development of hypersonic vehicle involves many subjects mechanical, hydraulic, electrical, power, fuel, control and other professional disciplines, the need for a large number of the transfer and exchange of information, this is a complex and lengthy process; at the same time, because of the rapid development of market economy, the increasingly shortened product lifecycle, also requires enterprises to make a quick response to vary from minute to minute market information. Therefore, methods of passing a new data become the urgent request, environment at that time so, led to the emergence of digital design technology in computer aided geometric modeling technology based on [6].

The original performance digital mock-up only have the basic elements of the relationship and assembly constraints, and its function in the coordination geometry of the space between the main components, only a simple interference analysis, motion simulation, this initial prototype is called the geometric figures prototype[7]. The biggest drawback to this simple geometric

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coordinate-based digital prototype that does not have the ability to perform complex motion analysis system. Thus, there is an urgent need to extend the functionality of the prototype geometry. Thus, the performance of the proposed prototype concept became inevitable. With the development of the concept of performance prototype CAD technology, virtual prototyping technology, software technology and computer-related technologies proposed.

Prototype hypersonic aircraft performance modeling methods are currently modeling interface-based, high level architecture (HLA)-based methods, methods based on the Unified Modeling Language and digital prototype ontology-based modeling methods for complex systems, the use of foregoing any single modeling methods are often ineffective[8]. To this end, this paper presents a hybrid modeling approach to design performance prototype integrated modeling approach. Simultaneously using two or more of the same modeling methods for complex systems modeling tasks. We use two or more single modeling methods complement each other, mutual support and coordination to achieve the same goal of a system modeling system modeling method called hybrid modeling approach[9]. This modeling approach is not produced by the superposition effect, but better, higher quality and efficiency of the system modeling.

In the mixed modeling method, the field of complex system has appeared in many hybrid modeling method is effective and technology. Such analysis, the combination of aircraft control system used by the mechanism analysis and system identification method of statistical method and technology, fuzzy identification method and technology theory and system identification method combining fuzzy set with uncertain complex system uses; set theory, neural network and system identification method is the combination of the three identification method of fuzzy neural network and based on Performance Analysis of performance digital mock-up hybrid modeling problem of the application of fuzzy[10].

2 Hypersonic vehicle model

Winged-cone is the concept of hypersonic aircraft for the NASA program, is a standard model of hypersonic flight research. The longitudinal model general follows[11,12]:

$$\dot{V} = \frac{T\cos a - D}{m} - g\sin y \tag{1}$$

$$\dot{\gamma} = \frac{L + T\sin a}{mV} - \frac{g\cos y}{V} \tag{2}$$

$$\dot{q} = M_y / I_y \tag{3}$$

$$\dot{a} = q - \dot{\gamma} \tag{4}$$

$$\dot{h} = V\sin\gamma \tag{5}$$

Where

$$L = \frac{1}{2}\rho V^2 s C_L, D = \frac{1}{2}\rho V^2 s C_D$$

$$M_\gamma = \frac{1}{2}\rho V^2 s\,\bar{c}(C_M(a) + C_M(\delta) + C_M q)$$

$$C_L = 0.6203a$$

$$C_D = 0.6450a^2 + 0.0043378a + 0.003772$$

$$C_M(a) = -0.035a^2 + 0.036617a + 5.3261\times 10^{-6}$$

$$C_M(\mathrm{q}) = [\bar{c}/(2V)]q(-6.796a^2 + 0.3015a - 0.2289)$$

$$C_M(\xi_e) = 0.0292(\xi_e - a)$$

Parameter values and their uncertainty range is [13]:

$$m = 136820(1 + \Delta m)kg$$

$$I_y = 9.49(1 + \Delta I)\times 10^6 kg.m^2$$

$$S = 334.73(1 + \Delta S)m^2$$

$$\bar{c} = 24.38(\Delta\,\bar{c})m$$

$$\rho = 1.25(I + \Delta\rho)\times 10^{-2} kg/m^3$$

Where

$$|\Delta m| \le 0.03, |\Delta I| \le 0.02, |\Delta S| \le 0.03$$

$$|\Delta\bar{c}| \le 0.002, \left|\sum\rho\right| \le 0.03$$

Wherein the engine throttle setting value β_{com} , and $\xi_e$is the deflection angle of the elevator control amount; h is the flight speed V and the output of the flying height. Comprehensive integrated hypersonic vehicle to validate the model shown in Figure 1.

3 Hypersonic aircraft performance digital mock-up hybrid modeling method

3.1 System identification method

System identification method using a mechanism analysis, expert experience with hybrid modeling approach combining system identification. Modeling, the first or the expertise to determine the structure of the model class and model, and then use the system identification method to identify the dimensions of the model, the order parameter and the amount of time delay through the mechanism analysis[14]. This modeling approach and analysis of a single mechanism or system identification method compared to produce significant results as follows: to improve the modeling accuracy. reduce the amount of information needed to make mathematical modeling $(1 - \rho) \times 100\%$,where

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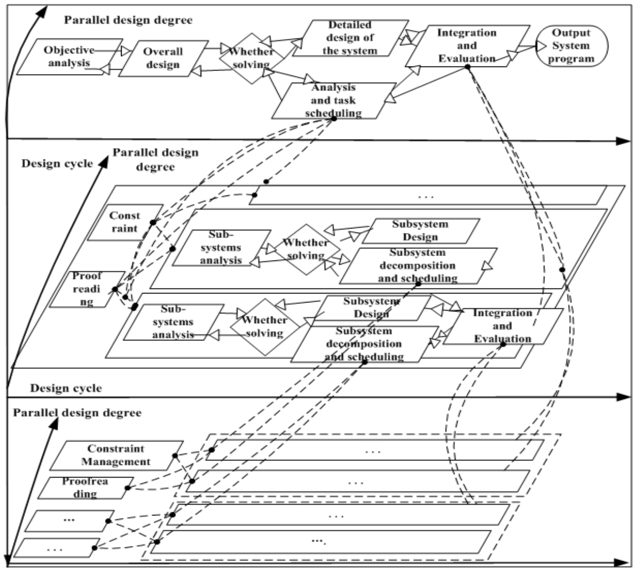

Fig. 1: Performance digital mock-up integrated verification model

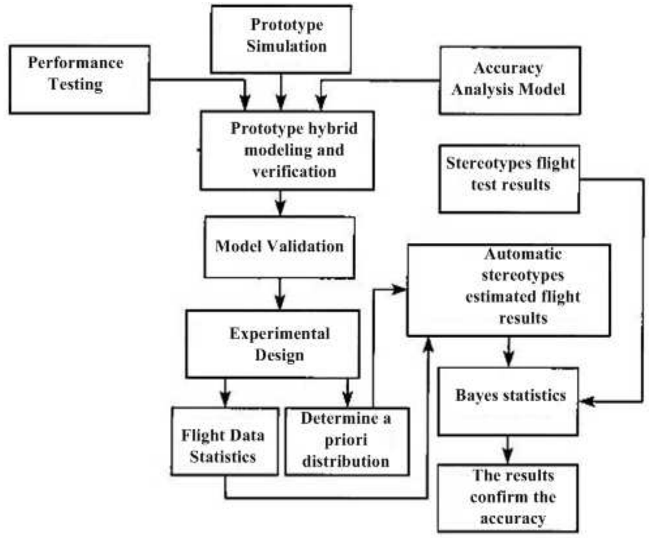

Fig. 2: Determine the performance of the performance digital mock-up integrated precision-guided flowchart

$\rho = \sum_{i=0}^{n} \rho_i, \rho_i$ is used to obtain the corresponding according to identification test instead of parameter α_i unknown truth value ρ_i estimation,$\rho_i = \rho\,(a = a_i)$:ρ is the mechanism analysis method considering the distribution characteristics of vector system is part of the α. significantly improve the modeling efficiency K_a,it is given by:

$$K_a = \frac{m_c}{m} = \frac{[\sum_{i=0}^{n} \rho_i \sqrt{\alpha_i(1-\alpha_i)}]^2}{(A/\sum_{i=0}^{n} \rho_i)(1-A/\sum_{i=0}^{n} \rho_i)} \tag{6}$$

Where, $m_c$is the use of a single system when identification method, the total number of iterations to achieve model identification; m is the use of a statistical analysis method, the total number of iterations to achieve the model; A is the index system effectiveness; α_i is a system of vector α in determining the index value under the conditions of validity.

Obviously, the K_a value is greater, modeling and analysis of efficiency of a statistical method is higher.Performance is usually based on the prototype system identification test statistical method, namely model shooting, hybrid modeling physical test and a combination of integrated system identification method for determining shown in Figure 2,Performance analysis of the accuracy of the model obtained from the prototype mechanism analysis, testing and research of target fire control system accuracy tests are real test, its purpose is to determine the accuracy or error guided by statistical method, to obtain samples of the actual point of impact value $(y_i, z_i)(i = 1, 2, \ldots, n)$; according to mathematical statistics the method can be obtained digital features guided error estimates $(\hat{y}, \hat{z})$, so we have

$$\hat{y} = \overline{y} = \frac{1}{n}\sum_{i=1}^{n} y_i, \hat{z} = \overline{z} = \frac{1}{n}\sum_{i=1}^{n} z_i \tag{7}$$

Where, $\overline{y}, \overline{z}$is the arithmetic mean of $(\hat{y}, \hat{z})$sample value .

Meanwhile, we can also get an estimate of the random error $[(\widehat{\sigma}_y, \widehat{\sigma}_z)$, so we have

$$\widehat{\sigma}_y = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} (y_i - \overline{y_i})^2}, \widehat{\sigma}_z = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} (z_i - \overline{z_i})^2} \tag{8}$$

And estimation of covariance and correlation coefficient values

$$\mathrm{cov}(\hat{y}, \hat{z}) = \frac{1}{n-1}\sum_{i=1}^{n} (y_i - \overline{y_i})(z_i - \overline{z_i}) \tag{9}$$

$$\widehat{\rho}_{y,z} = \frac{\mathrm{cov}(\hat{y}, \hat{z})}{\widehat{\sigma}_y \widehat{\sigma}_z} \tag{10}$$

In order to estimate the estimated values$(\hat{y}, \hat{z})$ and $(\widehat{\sigma}_y, \widehat{\sigma}_z)$ precision, usually used as the approximate formula:

$$\widehat{\Delta}_y \approx \frac{\widehat{\sigma}_y}{\sqrt{n}}, \hat{\Delta}_z \approx \frac{\widehat{\sigma}_z}{\sqrt{n}} \tag{11}$$

By the formula (11) show that the sample size n increases, the more accurate the estimate. Obviously, in order to ensure the accuracy of the expected estimate

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must be a lot of shooting live ammunition, to do so would be very expensive and time consuming. For this reason, in order to simulate shooting test as an adjunct, statistics and determine the prior distribution, and then use the identification method based on Bayes statistics can be more reasonable guidance to determine the accuracy of the results by simulating the point of impact.

3.2 Fuzzy identification method

First, using fuzzy theory proposed the fuzzy model of the system , then structure identification and parameter identification by means of system identification methods. In this case, the performance of the prototype fuzzy model identification is very typical, this is an effective method of nonlinear dynamic model complex systems blur. In the performance of the prototype fuzzy model identification, performance prototype model consists of the following three parts:

(1) fuzzy rules For a multi-input single-output nonlinear system of a first bogey of the fuzzy rules for the performance of the prototype model is

$$\begin{aligned}&R_k : if\, X_1 is\ A_{1k}, X_2 is A_{2k}, \ldots, X_m is A_{mk}\\&then\, y_k = p_{0k} + p_{1k}X_1 + p_{2k}X_2 + \ldots + p_{mk}X_m\end{aligned}$$

Wherein, X_i is the i-th input variable (i = l, 2, ..., m), m is the number of input variables; $A_{ik}$is a fuzzy set, its membership function of the parameter is the rule premise Ministry identified parameters; $y_k$is the output of the K fuzzy rules; p_{ik} is the coefficient of variable X_i section K fuzzy rule conclusion linear polynomial function; p_{0k} is a constant term.

(2) reasoning algorithm

$$\begin{aligned}&|y = y_k| = \left| X_1 is\ A_{1k}, X_2 is A_{2k}, \ldots, X_m is A_{mk} \right| \wedge R_k\\&= A_{1k}(X_1^*) \wedge \ldots \wedge A_{mk}(X_m^*) R_k\end{aligned} \tag{12}$$

Where, $|*|$ is the true value of * fuzzy proposition; $\wedge$take small operations;

$|*|\ X_1 is\ A_{1k} = A_{ik}\,(X_i^*)(i = 1,2,\ldots,m) \rightarrow X_i^*$membership function grade; $R_k$is the corresponding fuzzy implication relation.

(3)Model output

All of the rules by the k (k = l, 2, ..., N) and the weighted average of the output $y_k$obtained. If you take the weight of $|y = y_k|$, the model output is

$$y = \frac{\sum\limits_{k=1}^{N} |y = y_k| \cdot y_k}{\sum\limits_{k=1}^{N} y = y_k} \tag{13}$$

Structure identification and parameter identification performance of prototype models usually includes the premise and conclusion[15]. Parameter identification, model performance index $y(p)$ and the choice of estimate RMS $y^*(p)$ squared error value is minimum as the system output, it is given by:

$$J = \min\left\{ \frac{1}{h} \sum_{j=1}^{n} [y(p) - y^*(p)]^2 \right\}^{\frac{1}{2}} \tag{14}$$

Performance digital mock-up fuzzy model as predictive model, combined with the rolling optimization and feedback correction algorithms, fuzzy predictive control is an advanced control strategy[16], the key lies in the fuzzy identification method for predicting the performance of a prototype fuzzy model identification.

Set the nonlinear model of the controlled object is given by:

$$y(k+1) = \frac{y(k)}{1 + y(k)^2} + u(k) \tag{15}$$

Its performance prototype fuzzy prediction model is given by:

$$y(k+1) = \sum_{i=1}^{N} \lambda_i \rho_i y(k) + \sum_{i=1}^{N} \lambda q_i(k) u(k-1) \tag{16}$$

Set Λ_i is the i-th row vector Λ, y_i is the i-th element of Y, using recursive least squares algorithms for parameter identification of fuzzy rules conclusions ministry, so we have

$$L_i = \frac{Q_{i+1}\Lambda_i}{1 + \Lambda_i^T Q_{i-1} \Lambda_i}, Q_i = Q_{i-1} - L_i \Lambda_i^T Q_{i-1} \tag{17}$$

$$P_i^* = P_{i-1}^* + L_i \left[y_i - \Lambda_i^T P_{i-1}^* \right] \tag{18}$$

At the same time, the quantization level given a set of data of $X = \{x_1, x_2, \ldots, x_n\}$ and performance of prototype fuzzy forecasting model inputs $u(k+1)$ and $y(k)$ are respectively $\{B_1, B_2, B_3, B_4, B_5, B_6\}$and $\{A_1, A_2, A_3, A_4, A_5, A_6\}$, the membership function is shown in figure 3.

In the identification of model, fuzzy rule premise parameter and conclusion parameters alternately, the specific process is as follows:

Step 1: the initial value given the number of clusters C.

Step 2:using fuzzy C clustering computing partition algorithm on the existing sample data, obtains the performance prototype fuzzy membership function of premise variables model.

Step 3: using the formula (17) and (18) the identification of fuzzy rule conclusion parameter vector P_i^*.

Step 4:performance index calculation of $J = \sum\limits_{i=1}^{n} \frac{|y_i - y_i^*|^2}{n}$, if J meet the identification accuracy requirements, then identification set into, or increase the number of cluster C, return to the step 2.

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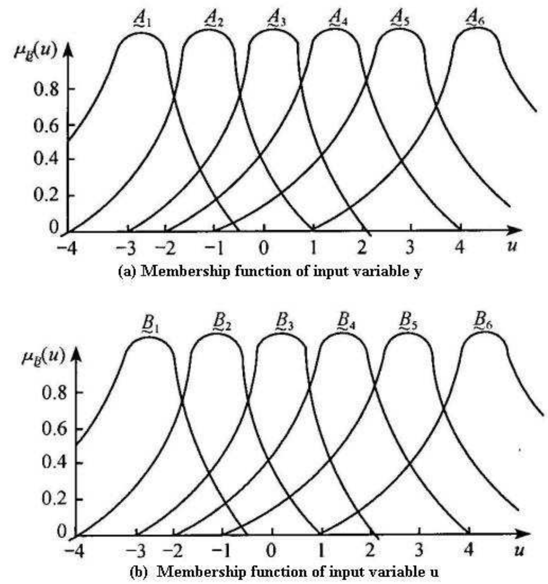

Fig. 3: The input variables of Y and u membership function

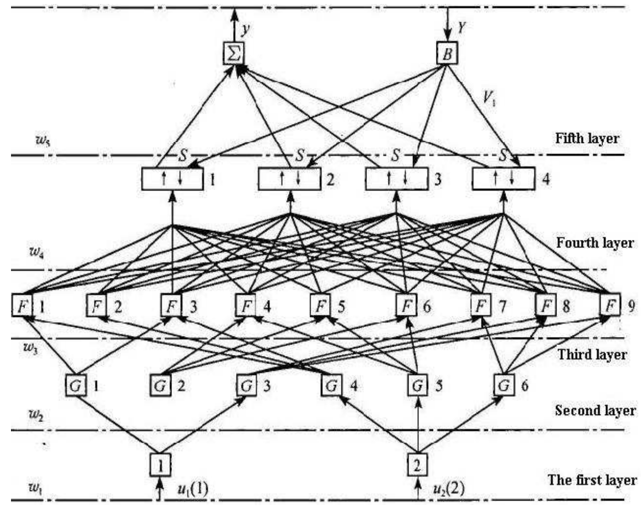

Fig. 4: Dual input fuzzy neural network structure

The identification results can be described by the control object type (12) performance prototype fuzzy forecasting model,it is given by:

$$\mathrm{R_i}\text{: if } \mathrm{Y}(\mathrm{k}-1) \text{ is } \mathrm{A_i} \text{ and } \mathrm{u}(\mathrm{k}) \text{is } \mathrm{B_i}, \text{then}$$

Where

$$\begin{aligned}
&\mathrm{R_1}\text{: if } \mathrm{y}(\mathrm{k}-1) \text{ is } \mathrm{A_1} \text{ and } \mathrm{u}(\mathrm{k}) \text{ is } \mathrm{B_i}, \text{then } \mathrm{y}(\mathrm{k}) \\
&\quad = -0.0177\mathrm{y}(\mathrm{k}-1)+1.127\mathrm{u}(\mathrm{k}) \\
&\mathrm{R_2}\text{: if } \mathrm{y}(\mathrm{k}-1) \text{ is } \mathrm{A_2} \text{ and } \mathrm{u}(\mathrm{k}) \text{ is } \mathrm{B_2}, \text{then } \mathrm{y}(\mathrm{k}) \\
&\quad = -0.0786\mathrm{y}(\mathrm{k}-1)+1.2516\mathrm{u}(\mathrm{k}) \\
&\mathrm{R_3}\text{: if } \mathrm{y}(\mathrm{k}-\mathrm{l}) \text{ is} \mathrm{A_3} \text{ and } \mathrm{u}(\mathrm{k}) \text{ is } \mathrm{B_3}, \text{then } \mathrm{y}(\mathrm{k}) \\
&\quad = -0.8273\mathrm{y}(\mathrm{k}-1)+1.023\mathrm{u}(\mathrm{k})
\end{aligned}$$

3.3 Model identification based on Fuzzy Neural Network

Using the combination of fuzzy logic and neural networks fuzzy neural network, as shown in Figure 4 of the DIFNN with the adaptive, self-learning, self-organizing and multi fuzzy inference function and can approach any nonlinear function. Mapping ability, provide powerful modeling way for modeling complex systems, and in this form the basis of fuzzy neural network model, identification of similar to the performance of prototype fuzzy model, finally get the identification model based on fuzzy neural network.

4 Performance tests

Based on the model identification DIFNN, set nonlinear object model:

$$y = 0.6\sin(\pi u) + 0.3\sin(3\pi u) + 0.1\sin(5\pi u) \tag{19}$$

Using DIFNN five nodes of the network structure (15,1,1,15,1), system input variables corresponding fuzzy random collection of $A_i(i = 1,2)$, the initial value of its membership function is: [-1, -0.9, -0.75 , -0.6, -0.45, -. 0.3,0.15,0,0.15,0.3,0.45, 0.6,0.75,0.9,1], $b_1(i)$ = 0 15, $b_2(i)$ = 0.2, i = 1,2, ..., 15.

Specific identification consists of two parts, that is the model parameter identification and structure identification DIFNN's. For the parameter identification are usually two algorithms: the mean and statistical analysis. If the selection of statistical analysis are:

Step 1: read the N sample data.

Step 2: optional T_1 an initial cluster centers: $r'_1, r'_2, ..., r'_{T1}$. Sampling is usually set before the T_1 samples as initial cluster centers.

Step 3: assuming that the clustering process has entered the K iteration, if there is a $\left|u - r_j^k\right| < \left|u - r_j^k\right|$ for a sample U (on the corner that find the cluster center when the iteration times), $u \in s_j^k$,where s_j^k is with r_j^k as the cluster center of sample set. Then all specimens assigned to T1 clustering.

Step 4: calculate the value of a new generation of multi-cluster center vector,it is given by:

$$r_j^{k+1} = \sum_{u \in s_j^k} \frac{u}{n_i}$$

Where, j = l, 2, ..., T_1, n_i is the number of samples included in S_j.

Step 5: If $r_j^{k+1} \neq r_j^k, j = 1,2,...,T_1$, then return step 3, the entire sample reclassified repeated iteration; if $r_j^{k+1} = r_j^k, j = 1,2,...,T_1$, then continue step 6.

The r_j^k is arranged from small to large, from the antecedent part parameter,it is given by:

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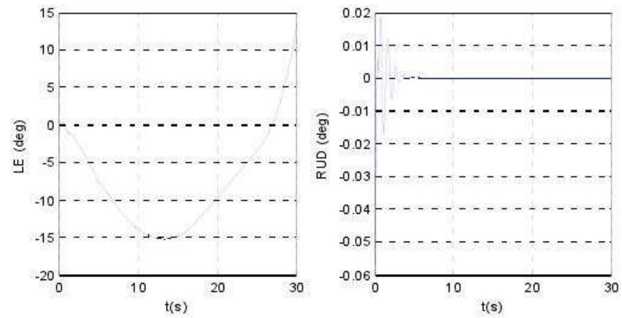

Fig. 5: Compare FNN network identification based simulation model output and the actual output of the system

$$a_1(i)\sum_{u\in s_j^k}\frac{u}{n_j}$$

Where, $i = 1,2,...,T_1$. Between the value of various types of computing centers,it is given by:

$$d_i(i) = \frac{a_1(i+1)+a_1(i)}{2}$$

According to equation, we can write

$$\exp = \left\{-\frac{d(i)-a_1(i)}{b_1(i)^2}\right\} = 0.5$$

Get the variance component parameters,it is given by:

$$b_1(i) = \frac{|a_1(i)-d_1(i)|}{\sqrt{\ln 2}}$$

For structure identification are:

Step 1: disposed intermediate storage unit $p(i,j) = 0$, where $i = 1,2,...,n(3), j = 1,2,...,n$, and $k = 0$;

Step 2:$k = k+1$,for DIFNN network consists of the first k training data were calculated

$$z_3(i), u_4^*(j), i = 1,2,...,n(3), j = 1,2,...,n(4), k = 0$$

Step 3: computing

$$C_{ml}(n) = \max[z_3(i)], u_h(m) = \max[u_4^*(j)]$$

Step 4: set $p(m,n) = p(n,m)+1$

Step 5:If $k \neq N$, then go to step 2; otherwise go to the next step Step 6.

Step 6: for $i = 1,2,...,n(3), j = 1,2,...,n(4)$, if $P(i,j) \geq \tau$, then $\omega_4 = (i,j) = 1$, else $\omega_4 = (i,j) = 0$;

Step 7: end.

After the above identification of network parameters can be shown in the simulation results shown in Figure 5, the method has high modeling accuracy is generally recognized or fuzzy neural networks can not match.

5 Conclusions

Hybrid modeling method is proposed in this paper, modeling method of hybrid modeling method using a variety of forms in the process of modeling of soft computing, avoids the shortcomings of single modeling method, this modeling method is not the superposition effect, easy to implement in engineering. In addition, hybrid modeling method for external disturbance and parameter changes of controlled object has a strong robustness, suitable for hypersonic complex flight condition and the large range of aerodynamic parameters. Finally, the Matlab simulation tool Simulink, in a hypersonic vehicle performance digital mock-up model as the simulation object, the hypersonic vehicle simulation model identification based on fuzzy neural network, the identification result is satisfactory.

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