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A Novel T-S Fuzzy Robust Control for Part Transportation of Aircraft Carrier Considering Transportation Time and Stochastic Demand

Tiantian Luan, Mingxiao Sun *, Zhanyong Hu, Qiang Fu, Hao Wang

School of Automation, Harbin University of Science and Technology, No.52 Xuefu Road, Nangang District, Harbin City 150080, Heilongjiang Province, China; luantiantian@hrbust.edu.cn; 1328064801@qq.com; 1061000188@qq.com; 2718395372@qq.com

* Correspondence: sunmingxiao@hrbust.edu.cn

Abstract: The part transportation efficiency is a main factor of aircraft sortie generation rate. Part transportation is used to transport spare part from base to carrier. Transportation strategy depends on both demand on carrier and inventory in transportation base. The transportation time and stochastic demand will induce fluctuations of cost and inventory. Thus, a Takagi-Sugeno fuzzy system of dynamic part transportation is established considering transportation time and stochastic demand. And a novel Takagi-Sugeno fuzzy robust control is designed for dynamic part transportation, which will keep transportation cost and part inventory stable. First of all, a fuzzy model with stochastic demand and transportation time is proposed. Then, a novel robust control with cross rule groups is conducted according to production and transportation strategy, which will reduce fluctuations induced by strategies switch. Moreover, robust stability is guaranteed and part can be supplied in time under a low cost. Finally, simulation illustrates usefulness and quickness of the novel Takagi-Sugeno fuzzy robust control. Besides, the proposed method will be useful in other transportation electrification systems with delay time and uncertainty.

Keywords: part transportation; Takagi-Sugeno fuzzy control; carrier aircraft; transportation time; stochastic demand; cross rule group

1. Introduction

Ship transportation efficiency is an important factor of naval logistics support. Part transportation is a way to transport spare part of aircraft from base to carrier. Aircraft carrier is an important component of modern naval warfare. The way to improve warfare ability of aircraft carrier is worth studying with rapid development of navy [1-2]. The foundation of sustained warfare ability is readiness rate of carrier aircraft, which is mainly affected by part transportation. Data have showed that sortie generation rate of aircraft will increase by 10% - 20%, if the proportion of awaiting part can be reduced [3]. As a result, the research about part transportation considering stochastic demand and transportation time has a high theoretical and practical value.

There are two components of transportation time. When an aircraft is under Intermediate-level maintenance, a faulty device needs to be replaced. At this time, this aircraft will wait for maintenance personnel to deliver corresponding part from hangar. This waiting time is the first component of transportation time. When there is no corresponding part in hangar, this aircraft will wait for part on transportation base to be transported to carrier. This waiting time is another component of transportation time. Besides, due to randomness of failure, part demand is uncertain and stochastic.

At present, most researches have studied modeling of part transportation based on probability theory. Reference [4] and [5] applied METRIC model to part inventory management of aviation and vessels equipment. And two-level inventory allocation model of part transportation is established. Reference [6] and [7] used a network model to solve the problem of repair cost and resource allocation. Reference [8] discussed M/M/c queuing model used to solve the inventory allocation problem of multistage repairable part, in which maintenance time was negative exponential distribution and delivery time was constant. Reference [9] analyzed M/M/c model and M/G/c model in two-level inventory system with limited maintenance channels. The integer programming model of individual repairable part inventory was established based on limited maintenance channels in reference [10]. Reference [11] provided three fuzzy output feedback H ∞ controllers of the jacket platforms for irregular wave forces. The above literature applied probability theory to describe part transportation. When system was stable, probability theory can only obtain static indicators, such as shortage rate and cost. However, few literatures considered the impact of transportation time and stochastic demand during dynamic process. This paper will apply Takagi-Sugeno (T-S) method to model dynamic part transportation with less fuzzy rules.

In addition, stochastic demand and transportation time can cause fluctuation and instability. Robust control has the characteristic of guaranteeing robust stability [12-14]. Reference [15] applied robust control method to a group of closed-loop transportation chain system. Besides, the optimal control strategy of inventory replenishment was given, which can weaken the impact of demand uncertainty in the operation process. Besides, the robust optimization method was proposed for the flexible commitment contract issue between the customer and supplier in reference [16]. Reference [17] considered robust optimization method in transportation chain production and scheduling with uncertain boundaries. Reference [18] set up a class of remanufacturing dynamic models with uncertain parameters and delays, and presented a robust control strategy for these models. The impact of demand uncertainty was weakened through feedback control of inventory state. Reference [19] studied the inventory problem of transportation chain system considering the external disturbance. Then mini-max value method was applied to solve the robust optimal control of transportation chain inventory. The robust control has been applied in many areas. Reference [20] proposed a novel robust control system of ship fin stabilizer, which used force sensor to measure dynamic lift. Reference [21] proposed a novel controller for the secondary load frequency control. The suggested controller was based on the robust μ and mixed μ-synthesis in which the structured system uncertainties and external disturbance inputs were considered. Reference [22] designed a practical two-layer fuzzy control for the platooning, which applied two spacing policies to ensure robustness in different scenarios. Reference [23] proposed an enhanced robust controller based on high-order extended state observer for a dc-dc floating interleaved boost converter in fuel cell application to better deal with the unknown time-varying disturbance. Reference [24] proposed a fuzzy-observer-based composite feedback controller with a T-S model, which modified the transient performance. Reference [25] developed a T-S fuzzy sliding-mode control based constant-voltage charging control to guarantee both high performance and robust stability by combining the merits of T-S fuzzy technique with sliding-mode control method. Due to the uncertainty of transportation time and demand, it is necessary to reduce the shortage or excessive accumulation of part in the hangar. In order to maintain the stability and reliability of part transportation, a robust control method is adopted. In view of the stochastic demand, the robust control method can guarantee the robust stability and the smooth switching process. Although a lot of literatures have studied the robust control [26-27], few literatures considered both of transportation time and stochastic demand. In the part transportation process, the transportation time is long and stochastic demand is urgent. Thus, the factors of transportation time and stochastic demand play an important role. The proposed T-S fuzzy robust control can weaken the impacts of stochastic demand and transportation time. The transportation time is a kind of delay time. The stochastic demand is a kind of uncertainty and disturbance. The proposed T-S fuzzy robust control will not only be suitable for part transportation, but also be applied to the systems considering delay time, uncertainties and disturbances in transportation electrification field.

The organization of this paper is as follows. Firstly, the dynamic T-S model is established considering transportation time and stochastic demand. Secondly, the controls of cost and state variables (production rate and transportation rate) are realized by using the fuzzy robust control method. Finally, simulation illustrates usefulness and quickness of the novel T-S fuzzy robust control method (NTSFRC).

The contributions of this paper are as following:

1. As the transportation time is long and stochastic demand is always urgent, these two factors will decrease the transportation effectivity and readiness rate of carrier aircraft. The novel T-S fuzzy robust control applies cross fuzzy rules to control the dynamic process, which will avoid the influence of transportation time and stochastic demand on part transportation.
2. The goal of controlling part transportation is to ensure stability and timely part transportation at a low cost, which will be achieved by NTSFRC with robust principle. At the same time, the fluctuations of state variables and control variables are suppressed.
3. Since the model of NTSFRC is rearranged as fuzzy model, NTSFRC is faster and more robust than robust H∞ control strategy with particle swarm optimization (RHCS-PSO).

2. Modeling of Part Transportation

2.1. Description of Problem

The research object is part transportation of aircraft carrier "Nimitz" [1]. The average Intermediate-level (I-level) turnaround time of aircraft is shown in Figure 1. Figure 1 illustrates that I-level maintenance time is not due to insufficient staff, but the time of awaiting part. This indicates that part inventory cannot meet demand.

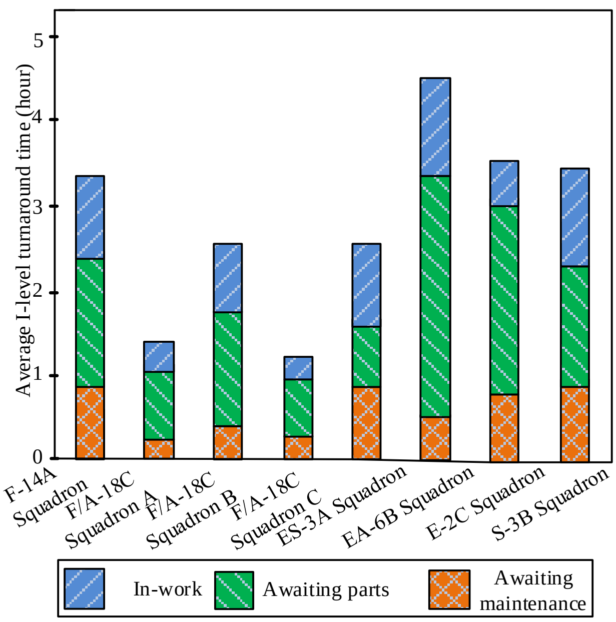


Figure 1. Components of I-level maintenance time.

During the period of USS Nimitz Surge Operations in 1997, the aircraft carrier carried a certain number of spare parts in initial state. After a certain kind of initial part was consumed, the aircraft carrier requested base to transport the corresponding part. If the base did not have corresponding part, it would inform parts production department for production. Otherwise, the base would transport the required part to carrier by carrier transporter. Thus, the part transportation of aircraft carrier "Nimitz" could be simplified into a system with a part transportation base and a part storage place on carrier. The dynamic process is given by Figure 2 and (1).

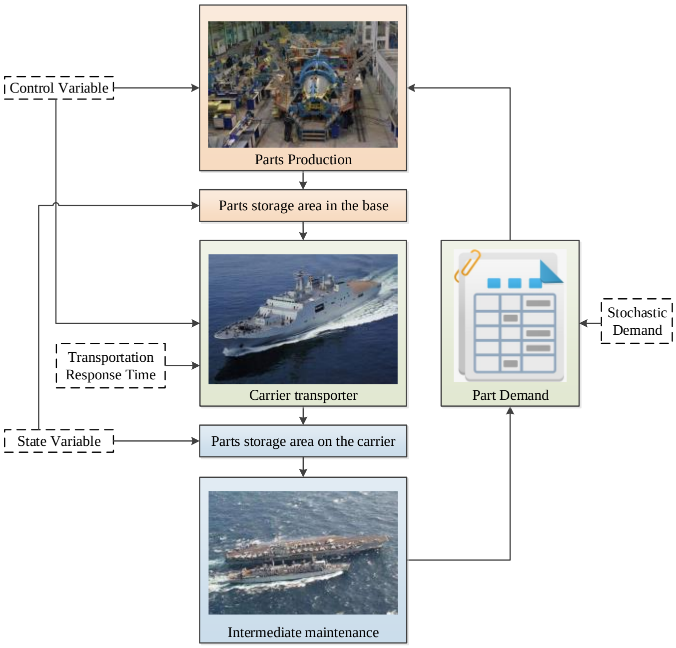


Figure 2. Dynamic process of part transportation.

$$\begin{cases} x_1(k+1) = x_1(k) + u_1(k) - u_{11}(k) \\ y_1(k+1) = y_1(k) + u_{11}(k) + u_{11}(k-\alpha_1) - v_1(k) \end{cases} \tag{1}$$

where, at the moment of k, $x_1(k)$ denotes the part inventory in transportation base and $y_1(k)$ denotes the part inventory on aircraft carrier, which are the state variables. $u_1(k)$ is the part production in transportation base, $u_{11}(k)$ is the part demand from aircraft carrier to transportation base and $u_{11}(k-\alpha_1)$ is the part transportation in response period, which are the control variables. α_1 denotes the response period. $v_1(k)$ denotes the uncertain part consumption on aircraft carrier, which is the stochastic disturbance variable.

In a word, the basic functions of part transportation comprise of a request process and a response process:

1. Request process: when aircraft carrier is short of part, parts are requested from transportation base.
2. Response process: the parts are transported to aircraft carrier, which will meet requirements.

2.2. T-S Model of Part Transportation

The T-S model of part transportation describing the dynamic and static processes is as shown:

$$
\begin{aligned}
&Plant\quad Rule\quad 1: if\quad x_1(k)\quad is\quad L_1^1,\ and\quad y_1(k)\quad is\quad L_2^1\quad then\\
&X(k+1)=\sum_{i=1}^{4}h_i(X(k))\left[A_1X(k)+B_1U(k)+B_{11}U(k-\alpha_1)+E_1V(k)\right],\\
&z(k)=\sum_{i=1}^{4}h_i(X(k))\left[C_1X(k)+D_1U(k)+D_{11}U(k-\alpha_1)\right]\\
&Plant\quad Rule\quad 2: if\quad x_1(k)\quad is\quad L_1^2,\ and\quad y_1(k)\quad is\quad L_2^2\quad then\\
&X(k+1)=\sum_{i=1}^{4}h_i(X(k))\left[A_2X(k)+B_2U(k)+B_{21}U(k-\alpha_1)+E_2V(k)\right],\\
&z(k)=\sum_{i=1}^{4}h_i(X(k))\left[C_2X(k)+D_2U(k)+D_{21}U(k-\alpha_1)\right]\\
&Plant\quad Rule\quad 3: if\quad x_1(k)\quad is\quad L_1^3,\ and\quad y_1(k)\quad is\quad L_2^3\quad then\\
&X(k+1)=\sum_{i=1}^{4}h_i(X(k))\left[A_3X(k)+B_3U(k)+B_{31}U(k-\alpha_1)+E_3V(k)\right],\\
&z(k)=\sum_{i=1}^{4}h_i(X(k))\left[C_3X(k)+D_3U(k)+D_{31}U(k-\alpha_1)\right]\\
&Plant\quad Rule\quad 4: if\quad x_1(k)\quad is\quad L_1^4,\ and\quad y_1(k)\quad is\quad L_2^4\quad then\\
&X(k+1)=\sum_{i=1}^{4}h_i(X(k))\left[A_4X(k)+B_4U(k)+B_{41}U(k-\alpha_1)+E_4V(k)\right],\\
&z(k)=\sum_{i=1}^{4}h_i(X(k))\left[C_4X(k)+D_4U(k)+D_{41}U(k-\alpha_1)\right]
\end{aligned}
\tag{2}
$$

where, $Plant\quad Rule\quad i(i=1,2,3,4)$ is the ith T-S fuzzy rule for the switch of part quantity. L is the T-S fuzzy set. $V(k)\in l_2[0,\infty)$ is the part consumption quantity. $X^T(k)=[x_1(k),y_1(k)]$ is the state variable of part quantity in each node. $U^T(k)=[u_1(k),u_{11}(k)]$ is the control variable of production quantity and transportation quantity. $U^T(k-\alpha_1)=[0,u_{11}(k-\alpha_1)]$ is the control variable of transportation quantity in response period. $V^T(k)=[0,v_1(k)]$ is the external request variable of stochastic consumption quantity. $z(k)$ is the output variable of cost. A_i is the inventory coefficient matrix. B_i is the coefficient matrix representing the production and transportation quantity of part. B_{i1} is the coefficient matrix representing the production and transportation quantity. C_i is the coefficient matrix representing the storage cost. D_i is the coefficient matrix representing production and transportation cost. D_{i1} is the coefficient matrix representing production and transportation cost in response period. E_i is the coefficient matrix representing consumption quantity. It is considered that A_i, B_i, B_{i1}, C_i, D_i, D_{i1} and E_i are constituted by two parts respectively, which are a certain term and an uncertain term. ΔA_i, ΔB_i, ΔB_{i1}, ΔC_i, ΔD_i, ΔD_{i1} and ΔE_i are uncertain terms. It is supposed that they satisfy $[\Delta A_i\quad \Delta B_i\quad \Delta E_i\quad \Delta C_i\quad \Delta D_i\quad \Delta F_i]=JWG$. J and G are constant matrices. W is a time varying uncertain matrix, which satisfies $W_{1i}^T(k)W_{1i}(k)\le I$, $W_{2i}^T(k)W_{2i}(k)\le I$, $i=1,2,\cdots,r$. I is the unit matrix. $h_i(X(k))=f_i(X(k))\Big/\sum_{i=1}^{r}f_i(X(k))$ is the membership of ith fuzzy rule. $f_i(X(k))=\prod_{j=1}^{n}L_j^i(x_j(k))$, $i=1,2,\cdots,r$. $L_j^i(x_j(k))$ is the membership function of $x_j(k)$.

Equation (2) shows the storage and cost of part transportation described by the deviation values, which are the differences between nominal values and actual values.

The number of Plant Rule depends on division number of $x_1(k)$ and $y_1(k)$, which are both double overlapping fuzzy division. $x_1(k)$ can be divided into L_1^1, L_1^2, L_1^3 and L_1^4. According to the character of double overlapping fuzzy division [12], the definition of fuzzy division is set that $L_1^1=L_1^2$ and $L_1^3=L_1^4$. The division number of $x_1(k)$ is 2.

$y_1(k)$ can be divided into L_2^1, L_2^2, L_2^3 and L_2^4. The definition of fuzzy division is set that $L_2^1 = L_2^3$ and $L_2^2 = L_2^4$. The division number of $y_1(k)$ is 2, too. Thus, the combination of $x_1(k)$ and $y_1(k)$ has 4 modes. In another word, Plant Rule is chosen as 4.

3. Novel T-S Fuzzy Robust Control Considering Transportation time and Stochastic Demand

3.1. Design of Novel T-S Fuzzy Robust Controller

The control cross rule groups of novel T-S fuzzy robust according to (2) is shown in (3). Since the Plant Rule is chosen as 4, the number of the novel fuzzy control rules is 4.

$$\begin{aligned}
&Control \quad Rule \quad 1: if \quad x_1(k) \quad is \quad L_1^1, \quad and \quad y_1(k) \quad is \quad L_2^1 \\
&then U(k) = -K_{11}X(k), U(k-\alpha_1) = -K_{111}X(k-\alpha_1) \\
&Control \quad Rule \quad 2: if \quad x_1(k) \quad is \quad L_1^2, \quad and \quad y_1(k) \quad is \quad L_2^2 \\
&then U(k) = -K_{21}X(k), U(k-\alpha_1) = -K_{211}X(k-\alpha_1) \\
&Control \quad Rule \quad 3: if \quad x_1(k) \quad is \quad L_1^3, \quad and \quad y_1(k) \quad is \quad L_2^3 \\
&then U(k) = -K_{31}X(k), U(k-\alpha_1) = -K_{311}X(k-\alpha_1) \\
&Control \quad Rule \quad 4: if \quad x_1(k) \quad is \quad L_1^4, \quad and \quad y_1(k) \quad is \quad L_2^4 \\
&then U(k) = -K_{41}X(k), U(k-\alpha_1) = -K_{411}X(k-\alpha_1)
\end{aligned} \tag{3}$$

where, K_{i1} and K_{i11} are the gain matrices of state feedback, $i = 1, 2, \cdots, r$, $r = 4$.

Hence, the total control law is arranged to be (4).

$$\begin{aligned}
U(k) &= -\sum_{i=1}^{r} h_i K_{i1} X(k) \\
U(k-\alpha_1) &= -\sum_{i=1}^{r} h_i K_{i11} X(k-\alpha_1)
\end{aligned} \tag{4}$$

The control strategies are calculated from (5) - (8). When the following conditions can be met, there will be the state feedback control (4). $K_{i1} = Y_{i1} X_1^{-1}$ and $K_{i11} = Y_{i11} X_1^{-1}$, which can guarantee that the fuzzy system (2) is robust stable asymptotically with the performance indicator γ:

1. Inputs of fuzzy system (2) meet double overlapping fuzzy partition [28]. If the fuzzy sets overlap each other, it is called double overlapping fuzzy partition.
2. The given parameter γ is greater than zero.
3. P_1, Q_1 and X_1 are symmetric and positive definite matrices.
4. P_1, Q_1, X_1, Y_{i1} and Y_{i11} meet symmetric linear matrix inequality (5) - (8).

$$\begin{bmatrix}
-P_1 + Q_1 & 0 & 0 & A_i - B_i K_i & C_i - D_i K_i \\
0 & -Q_1 & 0 & -B_{i1} K_{i1} & -D_{i1} K_{i1} \\
0 & 0 & -\gamma^2 I & B_{wi} & 0 \\
A_i - B_i K_i & -B_{i1} K_{i1} & B_{wi} & -P_1 & 0 \\
C_i - D_i K_i & -D_{i1} K_{i1} & 0 & 0 & -I
\end{bmatrix} < 0, \quad i \in I_c \tag{5}$$

$$\begin{bmatrix}
-X_1 + X_1 Q_1 X_1 & 0 & 0 & A_i X_1 - B_i Y_{i1} & C_i X_1 - D_i Y_{i1} \\
0 & -X_1 Q_1 X_1 & 0 & -B_{i1} Y_{i11} & -D_{i1} Y_{i11} \\
0 & 0 & -\gamma^2 I & B_{wi} & 0 \\
A_i X_1 - B_i Y_{i1} & -B_{i1} Y_{i11} & B_{wi} & -X_1 & 0 \\
C_i X_1 - D_i Y_{i1} & -D_{i1} Y_{i11} & 0 & 0 & -I
\end{bmatrix} < 0, \quad i \in I_c \tag{6}$$

$$\begin{bmatrix} -4P_1+4Q_1 & 0 & 0 & A_i-B_iK_j+A_j-B_jK_i & C_i-D_iK_j+C_j-D_jK_i \\ 0 & -4Q_1 & 0 & -B_{i1}K_{j1}-B_{j1}K_{i1} & -D_{i1}K_{j1}-D_{j1}K_{i1} \\ 0 & 0 & -4\gamma^2 I & B_{wi}+B_{wj} & 0 \\ A_i-B_iK_j+A_j-B_jK_i & -B_{i1}K_{j1}-B_{j1}K_{i1} & B_{wi}+B_{wj} & -P_1 & 0 \\ C_i-D_iK_j+C_j-D_jK_i & -D_{i1}K_{j1}-D_{j1}K_{i1} & 0 & 0 & -I \end{bmatrix}<0, \tag{7}$$

$$i<j, i, j\in I_c$$

$$\begin{bmatrix} -4X_1+4X_1Q_1X_1 & 0 & 0 & A_iX_1-B_iY_{j1}+A_jX_1-B_jY_{i1} & C_iX_1-D_iY_{j1}+C_jX_1-D_jY_{i1} \\ 0 & -4X_1Q_1X_1 & 0 & -B_{i1}Y_{j11}-B_{j1}Y_{i11} & -D_{i1}Y_{j11}-D_{j1}Y_{i11} \\ 0 & 0 & -4\gamma^2 I & B_{wi}+B_{wj} & 0 \\ A_iX_1-B_iY_{j1}+A_jX_1-B_jY_{i1} & -B_{i1}Y_{j11}-B_{j1}Y_{i11} & B_{wi}+B_{wj} & -X_1 & 0 \\ C_iX_1-D_iY_{j1}+C_jX_1-D_jY_{i1} & -D_{i1}Y_{j11}-D_{j1}Y_{i11} & 0 & 0 & -I \end{bmatrix}<0, \tag{8}$$

$$i<j, i, j\in I_c$$

where, I_c is serial number set contained in O_c. O_c is the cth largest overlap rule group [28]. In all overlap rule groups, the overlap rule group with the largest number of rules is called the largest overlap rule group. $c=1,2,\cdots\prod_{j=1}^{n}(m_j-1)$. m_j is the fuzzy partition of the jth input variable.

3.2. Stability Proof of Part Transportation

When input vector is $X^T(k)=[x_1(k), y_1(k)]$, the system contains 4 cross rule groups, the local model on the cth cross rule group is

$$\begin{cases} X(k+1)=\sum_{i\in c}\sum_{j\in c}h_ih_jU_{ij}X(k) \\ z(k)=\sum_{i\in c}\sum_{j\in c}h_ih_jV_{ij}X(k) \end{cases} \tag{9}$$

where, $U_{ij}=\begin{bmatrix}A_i-B_iK_{j1} & -B_{i1}K_{i11} & E_i\end{bmatrix}$, $V_{ij}=\begin{bmatrix}C_i-D_iK_{j1} & -D_{i1}K_{i11} & 0\end{bmatrix}$, $X(k)=\begin{bmatrix}X(k) & v(k)\end{bmatrix}$.

The Lyapunov function is set as:

$$V_L(X(k))=X^T(k)P_1X(k)+X^T(k)Q_1X(k) \tag{10}$$

Then

$$\begin{aligned}
&\Delta V_L\left(X(k)\right)=V_L\left(X(k+1)\right)-V_L\left(X(k)\right)\\
&=X^T(k+1)P_1X(k+1)-X^T(k)P_1X(k)\\
&+X^T(k+1)Q_1X(k+1)-X^T(k)Q_1X(k)\\
&=\sum_{i\in c}\sum_{j\in c}h_ih_j\sum_{p\in c}\sum_{q\in c}h_ph_q\left[X^T(k)U_{ij}^TP_1U_{pq}X(k)-X^T(k)P_1X(k)\right]\\
&+X^T(k+1)Q_1X(k+1)-X^T(k)Q_1X(k)\\
&=\sum_{i\in c}\sum_{j\in c}h_ih_j\sum_{p\in c}\sum_{q\in c}h_ph_qX^T(k)\left[U_{ij}^TP_1U_{pq}-W\right]X(k)
\end{aligned}\tag{11}$$

where, $W=\begin{bmatrix}P_1-Q_1 & 0 & 0\\ 0 & Q_1 & 0\\ 0 & 0 & 0\end{bmatrix}$.

Then

$$\begin{aligned}
\Delta V_L\left(X(k)\right)&=\sum_{i=j}h_j^2\sum_{p=q}h_p^2X^T(k)\left[U_{ii}^TP_1U_{pp}-W\right]X(k)\\
&+2\sum_{i<j}h_ih_j\sum_{p<q}h_ph_qX^T(k)\left[U_{ij}^{'T}P_1U_{pq}^{'}-W\right]X(k)
\end{aligned}\tag{12}$$

where, $U_{ij}^{'}=\dfrac{U_{ij}+U_{ji}}{2}$, $U_{pq}^{'}=\dfrac{U_{pq}+U_{qp}}{2}$.

The performance index function is defined as:

$$J=\sum_{k=0}^{N-1}\left[z^T(k)z(k)-\gamma^2v^T(k)v(k)\right]\tag{13}$$

Then

$$\begin{aligned}
J&=\sum_{k=0}^{N-1}\left[z^T(k)z(k)-\gamma^2v^T(k)v(k)+\Delta V_L\left(X(k)\right)\right]-V_L\left(X(k)\right)\\
&\le\sum_{k=0}^{N-1}\left[z^T(k)z(k)-\gamma^2v^T(k)v(k)+\Delta V_L\left(X(k)\right)\right]
\end{aligned}\tag{14}$$

$$\begin{aligned}
J&\le\sum_{k=0}^{N-1}\left[\sum_{i=j}h_j^2\sum_{p=q}h_p^2X^T(k)\left(U_{ii}^TP_1U_{pp}-W^{'}+V_{ii}^TV_{pp}\right)X(k)\right]\\
&+2\sum_{k=0}^{N-1}\left[\sum_{i<j}h_ih_j\sum_{p<q}h_ph_qX^T(k)\left(U_{ij}^{'T}P_1U_{pq}^{'}-W^{'}+V_{ij}^{'T}V_{pq}^{'}\right)X(k)\right]
\end{aligned}\tag{15}$$

where, $W^{'}=\begin{bmatrix}P_1-Q_1 & 0 & 0\\ 0 & Q_1 & 0\\ 0 & 0 & \gamma^2I\end{bmatrix}$.

Then

$$\begin{aligned}
J&\le\sum_{k=0}^{N-1}\left[\sum_{i=j}h_j^2X^T(k)\left(U_{ii}^TP_1U_{pp}-W^{'}+V_{ii}^TV_{pp}\right)X(k)\right]\\
&+2\sum_{k=0}^{N-1}\left[\sum_{i<j}h_ih_jX^T(k)\left(U_{ij}^{'T}P_1U_{pq}^{'}-W^{'}+V_{ij}^{'T}V_{pq}^{'}\right)X(k)\right]
\end{aligned}\tag{16}$$

$U_{ii}^TP_1U_{pp}-W^{'}+V_{ii}^TV_{pp}<0$ and $U_{ij}^{'T}P_1U_{pq}^{'}-W^{'}+V_{ij}^{'T}V_{pq}^{'}<0$ can be obtained based on Schur Lemma. $J<0$ means $z^T(k)z(k)<\gamma^2v^T(k)v(k)$. When $N\to+\infty$, $\dfrac{\left\|z(k)\right\|_2}{\left\|v(k)\right\|_2}<\gamma$. Thus the system is stable under γ.

NTSFRC can weaken fluctuations of part quantity and total cost induced by transportation time and stochastic demand, which will maintain stability of total cost. γ denotes weaken degree of transportation time and stochastic demand:

$$\frac{\|\text{Total cost of part transportation}\|_2}{\|\text{Consumption request of parts}\|_2} \leq \gamma \tag{17}$$

where, $\|\cdot\|_2$ is the norm of $l_2[0,\infty)$.

Equation (17) describes the system gain between consumption request variables $V(k)$ and total cost $z(k)$.

The stability conditions are as follows:

1. T-S system (2) is asymptotically stable: $V(k)$ is zero.
2. T-S system (2) is robust stable: $V(k)$ is not zero, the initial conditions are zero, and any external disturbance meets $\|z(k)\|_2^2 \leq \gamma^2 \|V(k)\|_2^2$.

4. Simulations of Part Transportation

4.1. Parameter Settings

The experimental environment is GenTai high performance computing simulation platform system, which has two Intel Xeon scalable gold 6226r CPUs(16 Core, 32 Thread, 2.9 GHz, Turbo 3.9 GHz, 22 MB). This platform system is based on GenTai gts2-tis2000 series. It is integrated with 6-channel DDR4 memory controller with new Intel c621 chipset. Its memory is 128GBDDR4 RECC Shared Memory. The simulation software is MATLAB, and its version is R2016b. The results of T-S fuzzy control strategy are validated by simulations. Hypothesizes are as followed:

1. Part inventories in transportation base and on aircraft carrier are measurable.
2. Fuzzy partitions of $x_1(k)$ and $y_1(k)$ are respectively $Q_1^1(x_1(k))$, $Q_1^2(x_1(k))$ and $Q_2^1(y_1(k))$, $Q_2^2(y_1(k))$. According production and request strategies in section II, the expressions of $Q_1^1(x_1(k))$, $Q_1^2(x_1(k))$, $Q_2^1(y_1(k))$ and $Q_2^2(y_1(k))$ can be obtained. $Q_1^1(x_1(k))=\begin{cases} 1, & x_1(k)<0 \\ 1-x_1(k)/S_1, & 0\leq x_1(k)<S_1 \\ 0, & x_1(k)\geq S_1 \end{cases}$, $Q_1^2(x_1(k))=\begin{cases} 1, & S_1\leq x_1(k)<S_{\max} \\ x_1(k)/S_1, & 0\leq x_1(k)<S_1 \\ 0, & x_1(k)<0 \end{cases}$, $Q_2^1(y_1(k))=\begin{cases} 1, & y_1(k)<0 \\ 1-y_1(k)/T_1, & 0\leq y_1(k)<T_1 \\ 0, & y_1(k)\geq T_1 \end{cases}$ and $Q_2^2(y_1(k))=\begin{cases} 1, & T_1\leq y_1(k)<T_{\max} \\ y_1(k)/T_1, & 0\leq y_1(k)<T_1 \\ 0, & y_1(k)<0 \end{cases}$. S_1 and $S_{\max}$ are respectively the desired quantity and maximum quantity in transportation base. T_1 and $T_{\max}$ are respectively the desired quantity and maximum quantity on aircraft carrier. S_1 is 1000 sets and $S_{\max}$ is 5000 sets. T_1 is 500 sets and $T_{\max}$ is 1500 sets. It can be obtained from the Surge Operation of Nimitz in 1997 that the carrier can carry about part of 500-1500 sets and the transportation base can store part of 1000-5000 sets.
3. According to the cross rule groups designed in section II, $Q_1^1(x_1(k))$, $Q_1^2(x_1(k))$, $Q_2^1(y_1(k))$ and $Q_2^2(y_1(k))$ meet double overlapping fuzzy divisions, which are as shown in Figure 3.

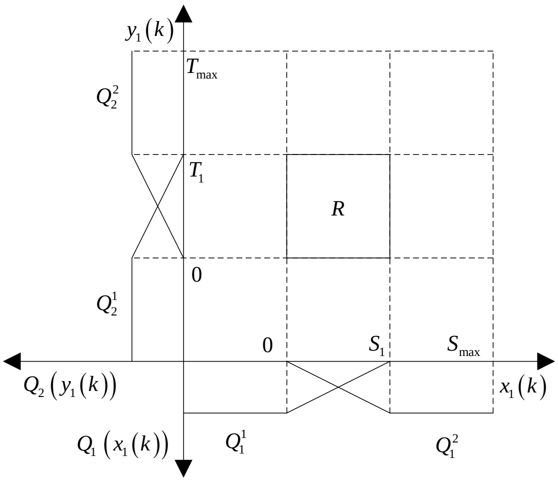


Figure 3. Fuzzy membership functions of inventories.

In Figure 3, S_1 is 1000 sets and $S_{\max}$ is 5000 sets. T_1 is 500 sets and $T_{\max}$ is 1500 sets. $L_1^1 = L_1^2 = Q_1^1$, $L_1^3 = L_1^4 = Q_1^2$, $L_2^1 = L_2^3 = Q_2^1$ and $L_2^2 = L_2^4 = Q_2^2$. The number of fuzzy rules is four in system (2).

As a result, the values of coefficient matrices are obtained from (1) as follows: $A_1 = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$, $A_2 = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$, $A_3 = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$, $A_4 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$, $B_1 = B_3 = \begin{bmatrix} 1 & -1 \\ 0 & 1+\beta \end{bmatrix}$, $B_2 = B_4 = \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix}$, $C_1 = [0 \quad 0]$, $C_2 = [0 \quad c_{s2}]$, $C_3 = [c_{s1} \quad 0]$, $C_4 = [c_{s1} \quad c_{s2}]$, $D_1 = [c_n \quad c_o + c_{oo}]$, $D_2 = [c_n \quad c_o]$, $D_3 = [c_p \quad c_o + c_{oo}]$, $D_4 = [c_p \quad c_o]$, $E_1 = E_2 = E_3 = E_4 = \begin{bmatrix} 0 & 0 \\ 0 & -1 \end{bmatrix}$, $B_{11} = B_{21} = B_{31} = B_{41} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$, $D_{11} = D_{31} = [0 \quad c_{o1}]$, $D_{21} = D_{41} = [0 \quad c_o]$, $W_{1i}(k) = W_{2i}(k) = \sin(k), i = 1,2,3,4$. c_{s1} is storage cost in base and its value is 50 dollars/set. c_{s2} is storage cost on carrier and its value is 100 dollars/set. c_o is transport cost in normal request mode and its value is 600 dollars/set. c_{o1} is transport cost depending on request quantity and its value is 1000 dollars/set. c_p is production cost in normal request mode and its value is 500 dollars/set. c_n is production cost depending on request quantity and its value is 900 dollars/set. c_{oo} is transport cost from other bases and its value is 800 dollars/set. β is proportion of part from other bases and its value is 0.4. α_1 is transportation time and its value is 3 days.

Let the parameter γ is 0.8 (0.8 is the best value of γ, which obtained from many tests under different values of γ), the following results can be obtained by solving (5) - (8): $X_1 = \begin{bmatrix} 83.4539 & -0.6958 \\ -0.6958 & 66.4010 \end{bmatrix}$, $P_1 = \begin{bmatrix} 91.8836 & 2.8329 \\ 2.8329 & 96.6113 \end{bmatrix}$, $Q_1 = \begin{bmatrix} 26.8640 & -6.6267 \\ -6.6267 & 11.8017 \end{bmatrix}$, $Y_{11} = \begin{bmatrix} 7.7338 & -5.8215 \\ -12.7970 & 6.6531 \end{bmatrix}$, $Y_{21} = \begin{bmatrix} 4.5493 & -7.6542 \\ -1.3133 & 11.3498 \end{bmatrix}$, $Y_{31} = \begin{bmatrix} 20.1847 & -5.4040 \\ -11.0482 & 3.6473 \end{bmatrix}$, $Y_{41} = \begin{bmatrix} 16.1918 & -6.8391 \\ 1.5352 & 9.5066 \end{bmatrix}$, $K_{11} = \begin{bmatrix} 0.0911 & -0.1918 \\ -0.0689 & 0.0995 \end{bmatrix}$, $K_{21} = \begin{bmatrix} 0.0544 & -0.0192 \\ -0.0903 & 0.1700 \end{bmatrix}$, $K_{31} = \begin{bmatrix} 0.2405 & -0.1639 \\ -0.0643 & 0.0543 \end{bmatrix}$, $K_{41} = \begin{bmatrix} 0.1942 & 0.0252 \\ -0.0808 & 0.1423 \end{bmatrix}$, $Y_{111} = \begin{bmatrix} 1.2934 & -2.0483 \\ -4.5001 & 1.1863 \end{bmatrix}$, $Y_{211} = \begin{bmatrix} 0.2845 & -3.6482 \\ -0.3762 & 5.7381 \end{bmatrix}$, $Y_{311} = \begin{bmatrix} 6.7392 & -2.5731 \\ -5.0383 & 0.3428 \end{bmatrix}$, $Y_{411} = \begin{bmatrix} 4.5271 & -1.6435 \\ 0.3520 & 3.0735 \end{bmatrix}$,

$K_{111}=\begin{bmatrix}0.0152 & -0.0307\\ -0.0538 & 0.0173\end{bmatrix}$, $K_{211}=\begin{bmatrix}0.0030 & -0.0549\\ -0.0038 & 0.0864\end{bmatrix}$, $K_{311}=\begin{bmatrix}0.0804 & -0.0379\\ -0.0603 & 0.0045\end{bmatrix}$, $K_{411}=\begin{bmatrix}0.0540 & -0.0242\\ 0.0046 & 0.0463\end{bmatrix}$.

4.2. Results and Discussions

The consumption requests are set as follows considering the different requests in practice.

1. Step type: $v_1(k)=\begin{cases}500, 0<k\le 100\\ 200, k>100\end{cases}$.
2. Normal distribution: $v_1(k)$ is $N(300,10^2)$.

A RHCS-PSO in reference [15] for part transportation is selected as a comparison object. RHCS-PSO considered transportation time and stochastic demand. The difference is that the model in reference [15] is not established by T-S fuzzy system.

The model established by reference [15] is

$$\begin{aligned}X(k+1)&=AX(k)+BU(k)+B_dU(k-\alpha_1)+EV(k)\\ z(k)&=CX(k)+DU(k)+D_dU(k-\alpha_1)\end{aligned} \tag{18}$$

where, $V(k)\in l_2[0,\infty)$ is the consumption quantity of part. $X^T(k)=[x_1(k),y_1(k)]$ is the state variable of part quantity in each node. $U^T(k)=[u_1(k),u_{11}(k)]$ is the control variable of production and transportation quantity. $U^T(k-\alpha_1)=[0,u_{11}(k-\alpha_1)]$ is the control variable of transportation quantity in response period. $V^T(k)=[0,v_1(k)]$ is the external request variable of consumption quantity. $z(k)$ is the output variable of cost. A is the inventory coefficient matrix. B is the coefficient matrix representing the production and transportation quantity. B_d is the coefficient matrix representing production and transportation quantity in response period. C is the coefficient matrix representing storage cost. D is the coefficient matrix representing production and request cost. D_d is the coefficient matrix representing production and request cost in response period. E is the coefficient matrix representing consumption quantity.

The control variable of production quantity and transportation quantity $U(k)$ is expressed as

$$U(k)=MQ^{-1}X(k) \tag{19}$$

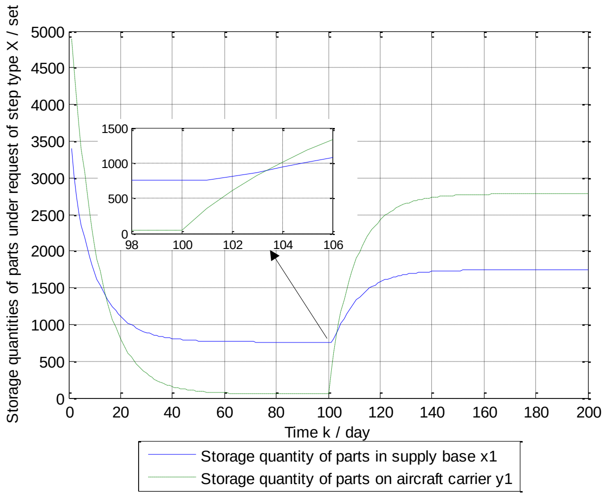
where, M and Q are obtained from below. For a given γ, if there exist positive-definite matrices Q, S_1, S_2 and M:

$$\begin{bmatrix}-Q & AQ+BM & E & 0 & 0 & 0\\ QA^T+M^TB^T & -Q & 0 & QC^T+M^TD^T & M^T & Q\\ E^T & 0 & -\gamma^2 I & 0 & 0 & 0\\ 0 & CQ+DM & 0 & -I & 0 & 0\\ 0 & M & 0 & 0 & -S_2 & 0\\ 0 & Q & 0 & 0 & 0 & -S_1\end{bmatrix}<0 \tag{20}$$

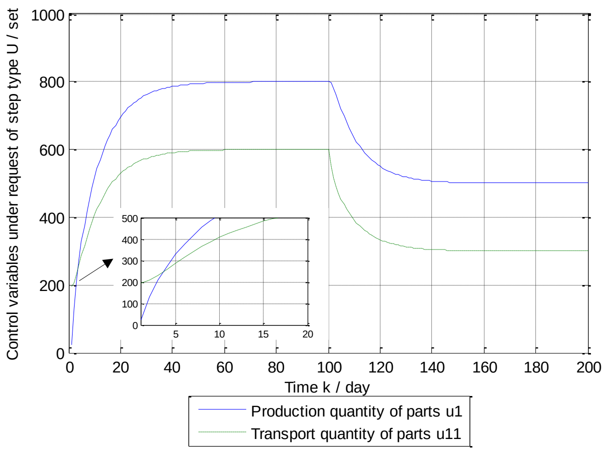
Equation (20) can hold, then it is quadratically stable with an H∞ norm bound γ. It also optimizes the H∞ norm bound γ by particle swarm optimization.

The input parameters of reference [15] are same as those of NTSFRC. Then, in reference [15], $M=\begin{bmatrix}-14.7409 & -11.8204\\ 18.1827 & 19.3753\end{bmatrix}$, $Q=\begin{bmatrix}28.5184 & 22.2745\\ 22.2745 & 27.1862\end{bmatrix}$ and $U(k)=\begin{bmatrix}-0.4924 & -0.0314\\ 0.2248 & 0.5285\end{bmatrix}X(k)$.

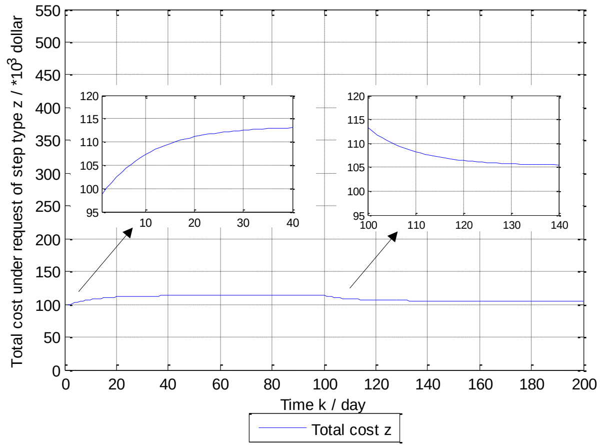
The results applying RHCS-PSO [15] and NTSFRC are shown in Figure 4 - 7.



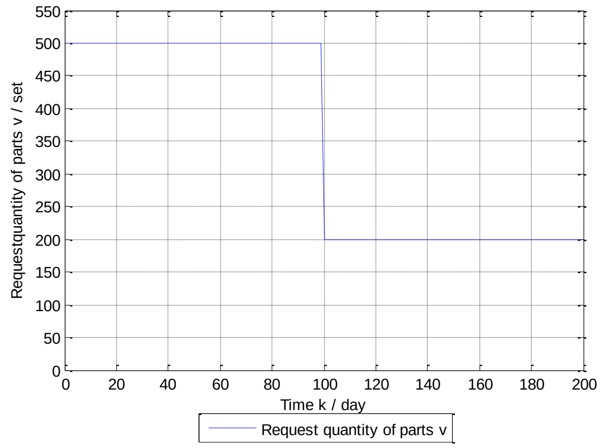
(a)



(b)

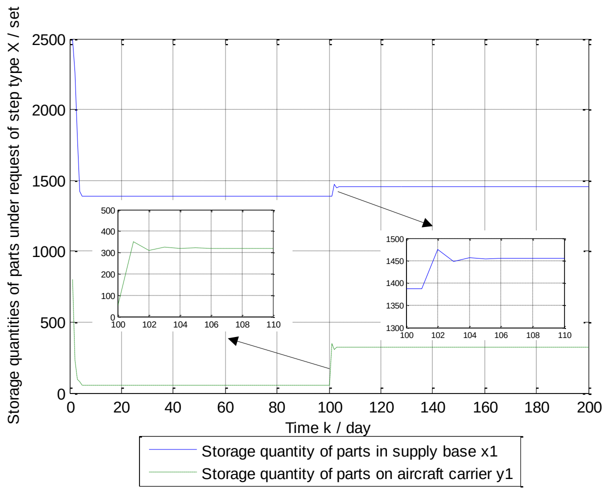


(c)

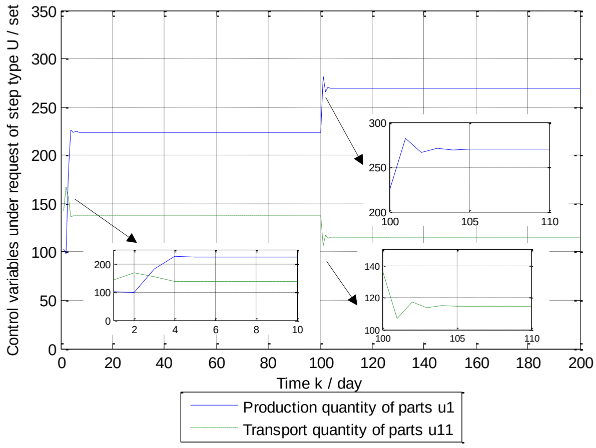


(d)

Figure 4. RHCS-PSO under request of step type: (a) Part inventories; (b) Production and transport quantities; (c) Total cost; (d) Request quantity of part.



(a)



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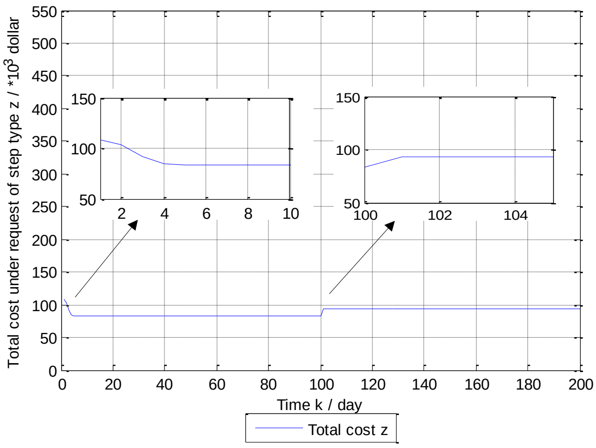
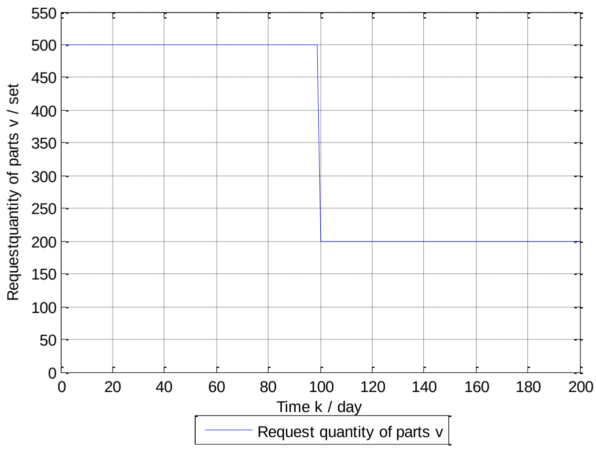


(c)



(d)

Figure 5. NTSFRC under request of step type: (a) Part inventories; (b) Production and transport quantities; (c) Total cost; (d) Request quantity of part.

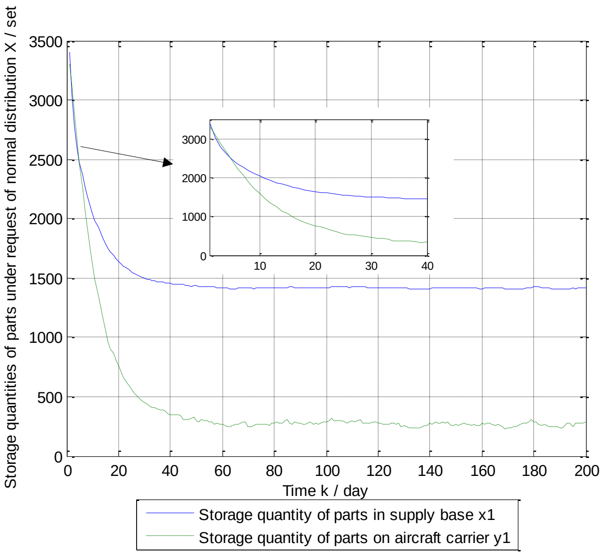
In the simulations of step-type request of part, Figure 4 and 5 switch at the moment of $k = 100$. The step response times are as shown in Table 1.

Table 1. Step response time under robust RHCS-PSO and NTSFRC.

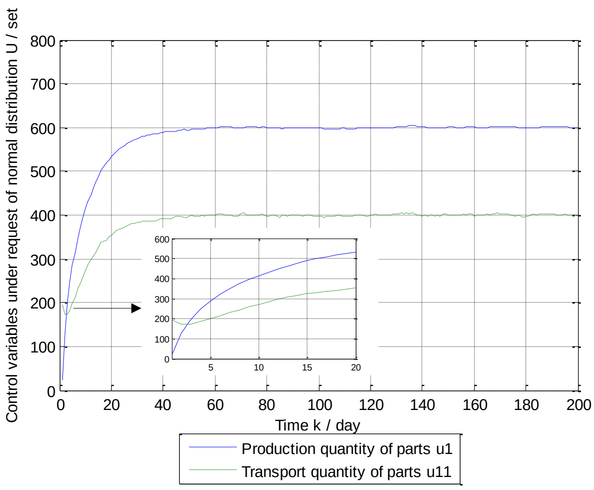
Moment of step response period(day)	RHCS-PSO (days)	NTSFRC (days)
$k = 0$	76	7
$k = 100$	76	7

The following results can be obtained:

1. RHCS-PSO and NTSFRC both make system stable gradually.
2. Fluctuations of total cost under two control methods are about 10000 dollars. It verifies usefulness of RHCS-PSO and NTSFRC.
3. Fluctuations of inventories $x_1(k)$ and $y_1(k)$ under RHCS-PSO are about 1000 sets and 2700 sets. In contrast, fluctuations of $x_1(k)$ and $y_1(k)$ under NTSFRC are about 500 sets and 300 sets. Meanwhile, production and transport quantities $u_1(k)$ and $u_{11}(k)$ under RHCS-PSO are about 300 sets and 300 sets. In contrast, $u_1(k)$ and $u_{11}(k)$ under NTSFRC are about 50 sets and 25 sets. The results illustrate robustness of NTSFRC is stronger.
4. Step response time of RHCS-PSO is 76 days and step response time of NTSFRC is 7 days, which proves rapidity of NTSFRC is superior to that of RHCS-PSO.



(a)



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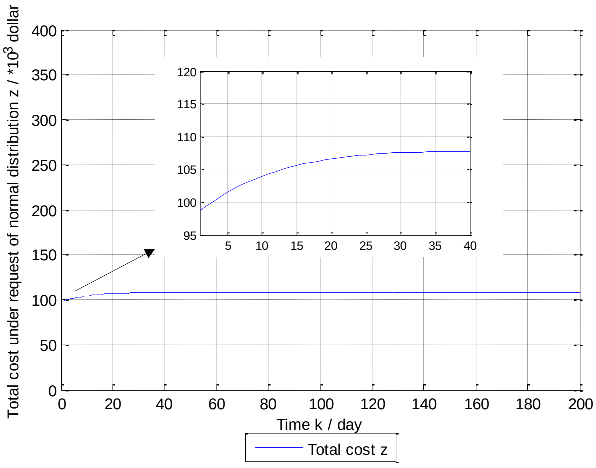

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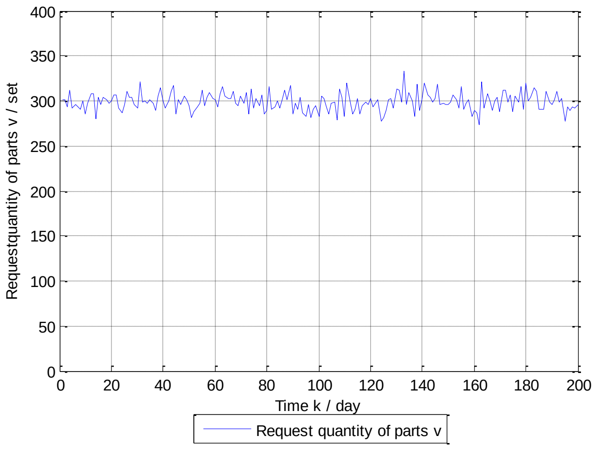
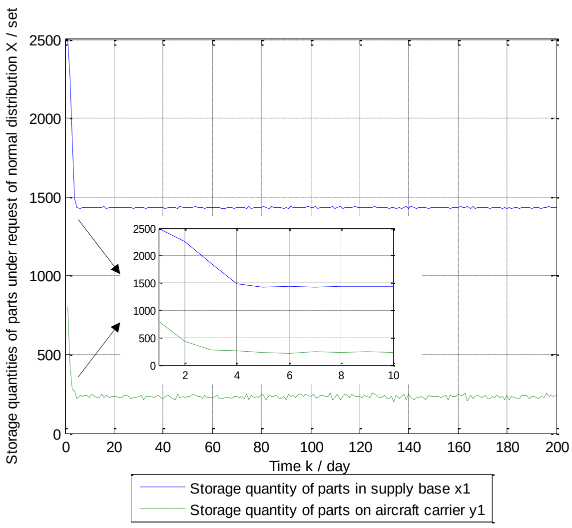
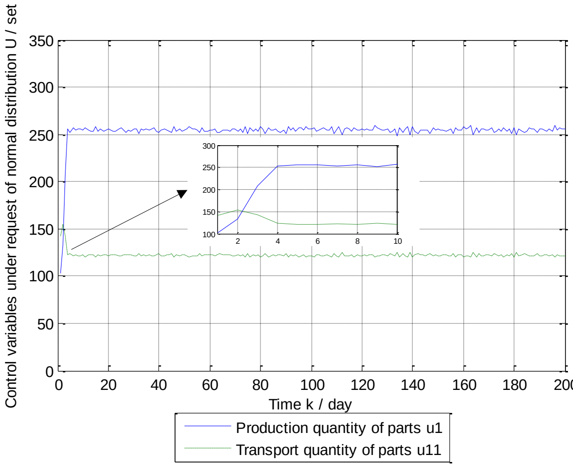


(d)

Figure 6. RHCS-PSO under request of normal distribution: (a) Part inventories; (b) Production and transport quantities; (c) Total cost; (d) Request quantity of part.



(a)



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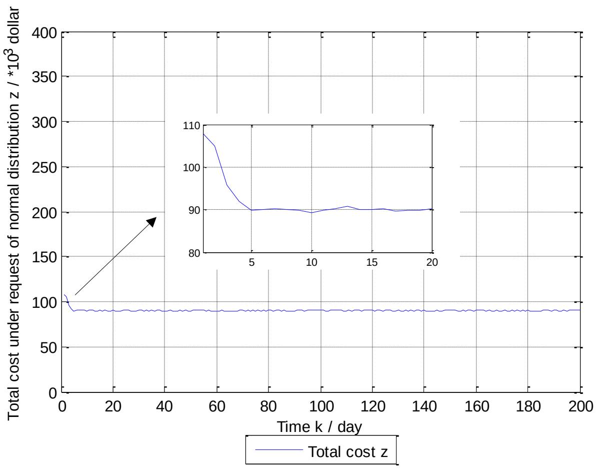

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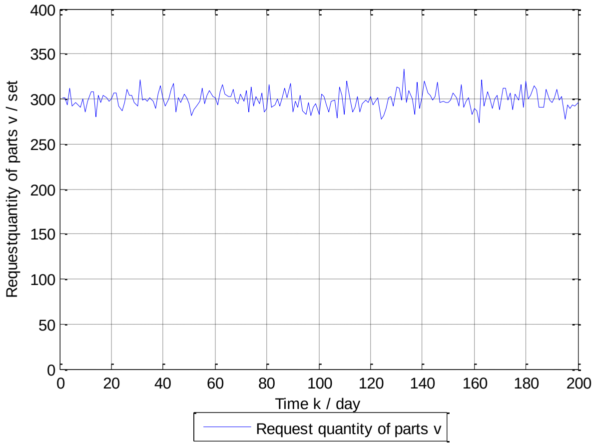
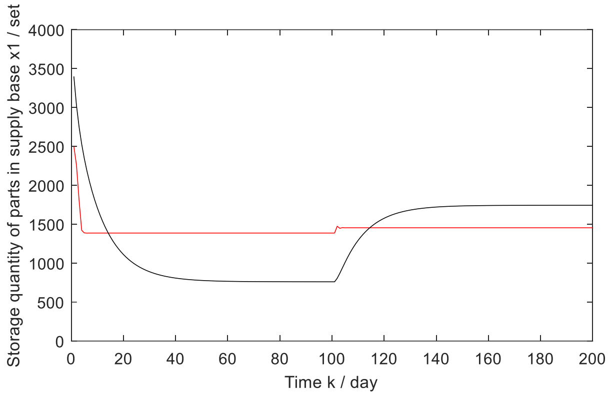


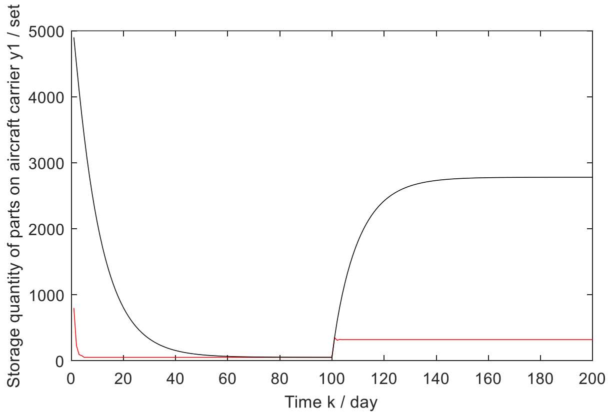
(d)

Figure 7. NTSFRC under request of normal distribution: (a) Part inventories; (b) Production and transport quantities; (c) Total cost; (d) Request quantity of part.

The compared results of different variables under RHCS-PSO and NTSFRC are shown in Figure 8 - 9. The difference of control effect is more obvious. In Figure 8 and 9, the red line denotes NTSFRC and the black line denotes RHCS-PSO.



(a)



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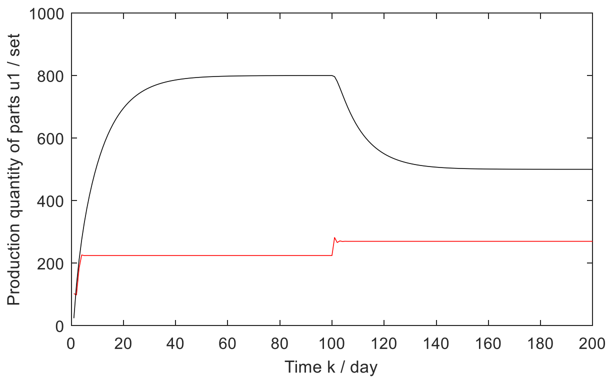
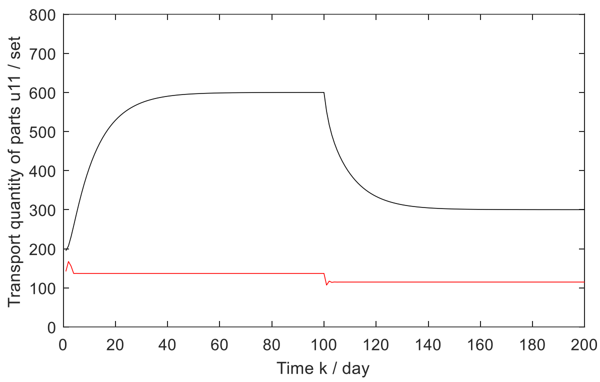


(c)



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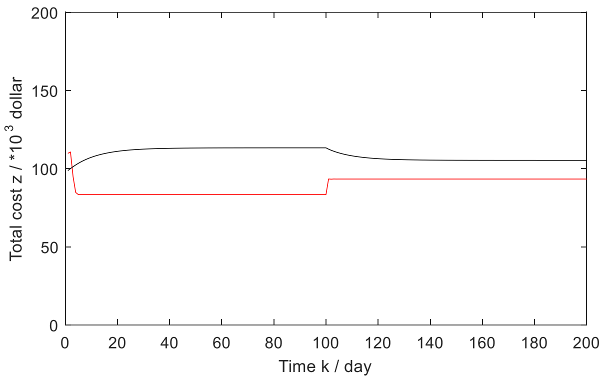
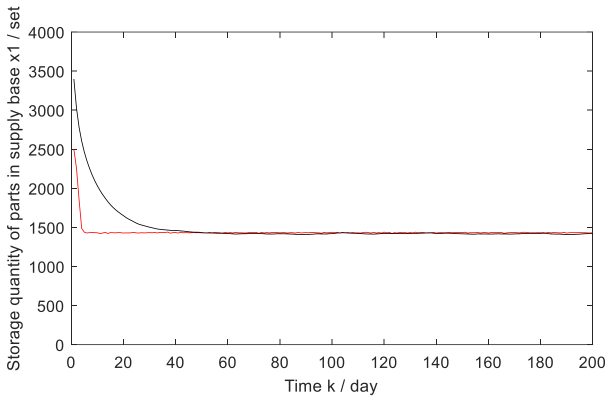
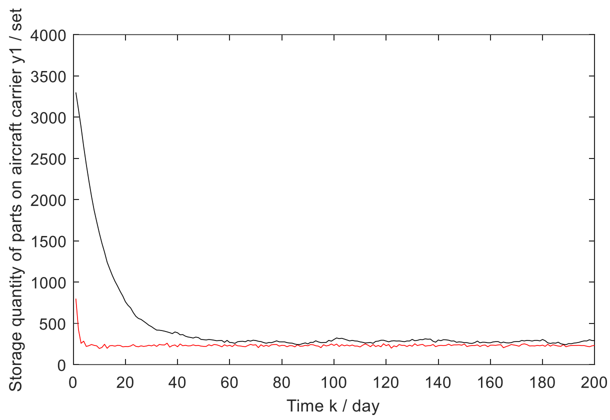


(e)

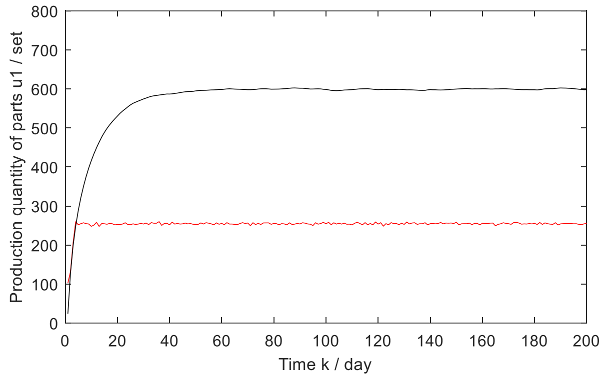
Figure 8. NTSFRC and RHCS-PSO under request of step type: (a) Storage quantity of parts in supply base; (b) Storage quantity of parts on aircraft carrier; (c) Production quantity of parts; (d) Transport quantity of parts; (e) Total cost.



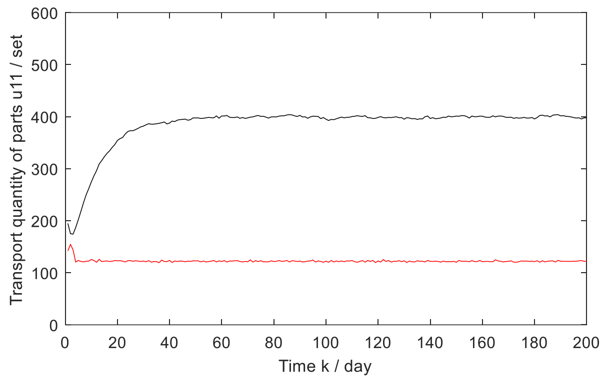
(a)


Storage quantity of parts on aircraft carrier y1 / set
4000
3500
3000
2500
2000
1500
1000
500
0
0 20 40 60 80 100 120 140 160 180 200
Time k / day

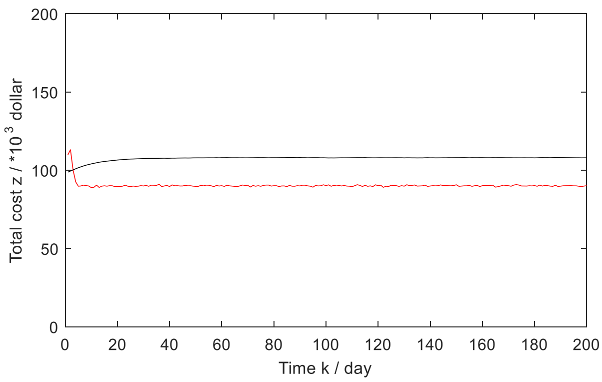
(b)


Production quantity of parts u1 / set
800
700
600
500
400
300
200
100
0
0 20 40 60 80 100 120 140 160 180 200
Time k / day

(c)


Transport quantity of parts u11 / set
600
500
400
300
200
100
0
0 20 40 60 80 100 120 140 160 180 200
Time k / day

(d)


Total cost z / *10^3 dollar
200
150
100
50
0
0 20 40 60 80 100 120 140 160 180 200
Time k / day

(e)

Figure 9. NTSFRC and RHCS-PSO under request of normal distribution: (a) Storage quantity of parts in supply base; (b) Storage quantity of parts on aircraft carrier; (c) Production quantity of parts; (d) Transport quantity of parts; (e) Total cost.

When the request is the normal distribution in Figure 6 and 7, the means and variances of the inventories ($x_1(k)$ and $y_1(k)$), the production and transport quantities ($u_1(k)$ and $u_{11}(k)$) and the total cost ($z(k)$) are shown in Table 2.

In order to compare the effectiveness of RHCS-PSO and NTSFRC, the numerical results under normal distribution demand are statistically validated using the statistical tests. Since the initial stage is a dynamic response process, samples in the stable stage are selected as the analysis samples. The 81 th - 201 th sample values are selected from the 201 sample values as the object of analysis. The number of samples n is 121.

Firstly, the skewness and kurtosis test is used to analyze whether the numerical simulation results still satisfy normal distribution. The confidence level α is 0.1. The test hypothesis H_0 is that the sample satisfies the normal distribution. The denial of domain is the observation $|u_1| \geq z_{\alpha/4}$ or $|u_2| \geq z_{\alpha/4}$. And $z_{\alpha/4} = 1.96$ .The observations of variables are shown in Table 3. As shown in Table 3, the observations of all variables are less than 1.96. Thus, the test hypothesis is accepted, and all samples satisfy normal distribution.

Table 2. Means and variance of variables under RHCS-PSO and NTSFRC.

Mode	Type	RHCS-PSO	NTSFRC
Inventory in transportation base x_1	Mean (set)	1 420	1 432
	Variance (set²)	73	10
	Covariance(set²)	-1.1423	
	95% confidence interval	(1 419,1 421)	(1 431,1 433)
Inventory on aircraft carrier y_1	Mean (set)	282	232
	Variance (set²)	710	106
	Covariance(set²)	2.8735	
	95% confidence interval	(279,285)	(230,234)
Production quantity u_1	Mean (set)	599	255
	Variance (set²)	6.76	4.17
	Covariance(set²)	-0.0857	
	95% confidence interval	(598,600)	(254,256)

Transport quantity u_{11}	Mean (set)	399	122
	Variance (set²)	11	1.17
	Covariance(set²)	3.4876	
	95% confidence interval	(398,400)	(121,123)
Total cost z	Mean (dollar)	107 971	90 084
	Variance (dollar²)	0.006	0.014
	Covariance(set²)	0.0020	
	95% confidence interval	(107 961,107 980)	(90 018,90 151)

Secondly, significance level test is realized by t test method. The confidence level α is 0.05. The difference between RHCS-PSO and NTSFRC sample is d. The test hypothesis H_0 is that the mean value of d is equal to or greater than 0. The refusal of domain is $\bar{x}_d/\left(s_d/\sqrt{n}\right)<-t_{\alpha/2}\left(n-1\right)$. $\bar{x}_d$ is the mean of difference between two samples. s_d is the standard deviation of difference between two samples. n is sample size. And $t_{\alpha/2}\left(n-1\right)=t_{0.05}\left(120\right)=1.658$. $\bar{x}_d/\left(s_d/\sqrt{n}\right)$ of differences are shown in Table 4. As shown in Table 4, $\bar{x}_d/\left(s_d/\sqrt{n}\right)$ of all variables differences are less than 1.658. Therefore, the test hypothesis is rejected. The mean values of differences are less than 0. The effect of NTS-FRC is better than that of RHCS-PSO.

Table 3. Results of skewness and kurtosis Test.

Mode	Observation	RHCS-PSO	NTSFRC
Inventory in transportation base x_1	$\lvert u_1\rvert$	0.25	0.82
	$\lvert u_2\rvert$	0.45	0.60
Inventory on aircraft carrier y_1	$\lvert u_1\rvert$	0.52	0.34
	$\lvert u_2\rvert$	0.86	0.42
Production quantity u_1	$\lvert u_1\rvert$	0.45	0.47
	$\lvert u_2\rvert$	0.78	0.78
Transport quantity u_{11}	$\lvert u_1\rvert$	0.38	0.32
	$\lvert u_2\rvert$	0.66	0.71
Total cost z	$\lvert u_1\rvert$	0.59	0.64

$\lvert u_2 \rvert$	0.52	0.42

Table 4. Discriminant of t test $\bar{x}_d / \left(s_d / \sqrt{n} \right)$.

Mode	$\bar{x}_d / \left(s_d / \sqrt{n} \right)$
Inventory in transportation base x_1	-3.51
Inventory on aircraft carrier y_1	-4.73
Production quantity u_1	-5.32
Transport quantity u_{11}	-4.11
Total cost z	-6.18

In numerical results, the proposed method is benchmarked in realm of runtime, which are shown in Table 5 and Table 6. In order to get more accurate running time, each case is simulated 10 times. And the mean of running time is obtained. In Table 5, the mean running time of RHCS-PSO and NTSFRC under step demand are 0.83s and 0.84s respectively. In Table 6, the mean running time of RHCS-PSO and NTSFRC under normal distribution demand are 0.83s and 0.86s respectively. The running time of two methods is approximately equal.

The following results can be obtained from Figure 6 - 9 and Table 2 - 6:

1. The variance of total cost under RHCS-PSO is 0.006, and that under NTSFRC is 0.014. This means that robustness under RHCS-PSO is stronger slightly.
2. The variances of state variables ($x_1(k)$ and $y_1(k)$) under RHCS-PSO are about seven times of that under NTSFRC. The variance of control variable $u_1(k)$ under RHCS-PSO is about two times of that under NTSFRC. The variance of control variable $u_{11}(k)$ under RHCS-PSO is about ten times of that under NTSFRC. The results show that weakens degree of state variables and control variables under NTSFRC is much stronger.

Table 5. Benchmark result under step type.

NO.	RHCS-PSO (s)	NTSFRC (s)
1	0.94	0.83
2	0.90	0.85
3	0.79	0.82
4	0.79	0.81
5	0.82	0.87
6	0.86	0.85
7	0.79	0.85
8	0.80	0.88
9	0.79	0.82
10	0.79	0.81
Mean	0.83	0.84

Table 6. Benchmark result under normal distribution.

NO.	RHCS-PSO (s)	NTSFRC (s)
1	0.87	0.94
2	0.84	0.85

3	0.83	0.95
4	0.79	0.82
5	0.81	0.83
6	0.84	0.85
7	0.85	0.83
8	0.80	0.89
9	0.81	0.85
10	0.82	0.83
Mean	0.83	0.86

To sum up, the weaken degrees of total cost under RHCS-PSO and NTSFRC are similar. The response time of NTSFRC is much shorter than that of RHCS-PSO. Moreover, weaken degrees of state variables and control variables under NTSFRC are much stronger than those under RHCS-PSO. The simulation demonstrates NTSFRC can not only weaken fluctuation of total cost, but also weaken fluctuations of state variables and control variables.

The simulations show that NTSFRC can make production rate meet expected consumption rate. On the one hand, the shortage of part on carrier induced by low production rate will be avoided. On the other hand, the crowd storage places induced by high production rate will be avoided. What is more, the response time is shorter and fluctuations of inventories are smaller under NTSFRC, which will ensure sufficient part on carrier and improve readiness of aircraft.

Although the proposed method has above advantages, there are still some limitations:

1. When the multivariable are coupling, the control effect of the proposed method will not be ideal.
2. When the number of system variables is large, the curse of dimensionality makes the control effect decrease.
3. The proposed method does not achieve the adaptive change of fuzzy rules. When the parameters of the model change greatly, the control effect of the system will also decrease.

In the future, data-driven framework can be used to achieve more industrial oriented results, which will make the test data and test behavior completely separated. And the results will be more credible.

5. Conclusions

This paper takes the stochastic demand and transportation time into account. The fuzzy model of part transportation system is established. A NTSFRC strategy is designed for the model. Simulations demonstrate the effect of NTSFRC is superior to that of RHCS-PSO.

1. The response time of the proposed method is 69 days shorter than that of RHCS-PSO. Response time is reduced by about 90%.
2. The fluctuations of total cost and inventories are weakened through NTSFRC under the stochastic demand and transportation time. The total cost of the proposed method is 17887 dollars less than that of RHCS-PSO. The fluctuation range of the total cost of the system is reduced by about 95%.
3. The absolute values of covariance in the two methods are small, which means that the correlation between them is weak.

Thus, the proposed method can not only guarantee a stable transportation in time, but also improve the readiness and sortie generation rate of aircraft. Besides, NTSFRC will be useful in other systems with stochastic demand and transportation time.

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