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Study on the Robust Tolerance Design with Multiple Resource Suppliers on Cloud Manufacturing Platform

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Abstract

The robust tolerance design in the scenario with multiple resource suppliers is faced with greater uncertainty in the new manufacturing era. This paper studies the robust tolerance design on cloud manufacturing platform, in which a two-level game is put forward to reveal the relationship and behavior between the products and resource suppliers. According to the scenario with multiple resource suppliers, the multivariate process capability index has been introduced to solve the problem of robust tolerance design faced up with cloud manufacturing environment. A case study is used to illustrate the proposed model.

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Keywords: Robust Tolerance Design, Game theory, Multivariate process capability index

1. Introduction

With the development of intelligent manufacturing technology, socialization of resources sharing is an irresistible trend. Especially since the 21st century, the raise of Internet of Things (IoT) and logistics service provided an important supporting condition for service-oriented manufacturing, which brought out new manufacturing modes such as manufacturing grid[1], global manufacturing[2], cloud manufacturing[3] and so on. However, with the complexity of manufacturing system and socialization of resources sharing, how to ensure the stability of product quality under the environment of distributed intelligent manufacturing is the core of industry development. The manufacturing process with multiple resources reduces the stability of product quality. The robust tolerance design is studied in the scenario with multiple resource suppliers, such as cloud manufacturing (CMfg) in this article. CMfg is a new service-oriented grid manufacturing mode with the integration of cloud-computing and internet of things (IoT) to make the manufacturing resource virtualized with service oriented tendency. The internet of manufacturing things (IoMT) provides a new paradigm by extending the techniques of IoT to manufacturing field.

During the last few decades, the economic landscape has abandoned its local characteristics and evolved into a global and highly competitive economy.[4] Many suppliers and customers have accessed the internet to share the global manufacturing resources. Cloud manufacturing is emerging as a new manufacturing paradigm as well as an integrated technology, which is promising in transforming today's manufacturing industry towards service-oriented, highly collaborative and innovative manufacturing in the future.[5] Hao[6] proposes a concept of cloud future factory with distributed production lines and business departments and introduces an effective and dynamic information integration platform; Wei[7] put forwards a resource allocation model based on ant colony optimization algorithm to find the optimal solution based on a four-dimensional objective function (time, cost, quality of services and the load balance); Li[8] presents a QoS system model for sharing resource between different QoS-constrained users in Cloud Computing

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system and brings an optimizing chord algorithm to scheduling tasks submitted by users with lower QoS-constrained. Mourtzis[9] proposed a methodology for manufacturing networks design via a smart search algorithm Since the quality is the core competitiveness of manufacturing products, this topic need more attention in the scenario of CMfg. There are two kinds of participants in the CMfg process: the suppliers and demanders of resource service. The resource suppliers publish their idle resource, products, manufacturing and ability while the demanders of resource search the optimal manufacturing resources and select the corresponding partner to form a collaboration manufacturing net.[10]

In the early years, the quality control in the single part stage regarding accuracy and usability for the assembling stage will lead to a reduction of rework and scrap. Mechanical product reliability is an important product quality factor and is dependent on different parameters among which tolerance design is an important activity. Tolerance design is usually carried out on detailed geometric entities after structure design process[11]. With the development of computer technology, CAD/CAM (Computer Aided Design/ Computer Aided Manufacturing) plays an important role in modern industry and Computer Aided Tolerance (CAT) design is a key technology in the integration of CAx in the modern manufacturing system. In the past decades, the CAT researchers focus on the energy consumption at the customers` side and aim to improve the quality and reduce cost. There are several existing works on CAT in the literatures. The existing cost-tolerance model was built up by collecting enough statistical data of tolerance and cost and using least square method in the specific manufacturing process.[12] In order to improve the quality of products, researchers at home and abroad have applied robust thought to solve problems in the field of tolerance design. Tan put forward a robust tolerance design driven by the manufacturing knowledge based on intuitionistic fuzzy theory.[13] J Deng studied on a new robust tolerance design method for electromechanical device and consistency optimization for batch product of electromagnetic relay with improved robust tolerance design method.[14,15] Different from the existing cost-tolerance model, Zheng[16] proposes an assembly tolerance allocation method using coalitional game theory in an attempt to find a trade-off between the assembly cost and the assembly quality. Furthermore, Wu studies the tolerance design with multiple resource suppliers on cloud manufacturing based on game theory to find out the trade-off between the welfare of resource suppliers and resource demanders.[17]

The remainder of this paper is organized as follows: Section 2 describes the system model and formulates the reaction and competition problem of resource suppliers in intelligent manufacturing process. In Section 3, the robust tolerance design on cloud manufacturing is given. The conclusion and future work is given in Section 4.

2. Model description

In the existing methods of tolerance design, the manufacturing scenario is given as a prerequisite, however, the information of manufacturing resources on CMfg platform is dynamic. A large number of candidate resources which meet the requirement of customers are available on the CMfg platform. Different resources combinations give different strategies of manufacturing process, which leads to a complicated scenario. In this paper, a tolerance design method with two level game model is proposed, including level of suppliers and level of demanders. The description of the method with multiple resource suppliers and multiple configuration units is shown in Fig. 1, as well as the relationship between the two levels in the game model.

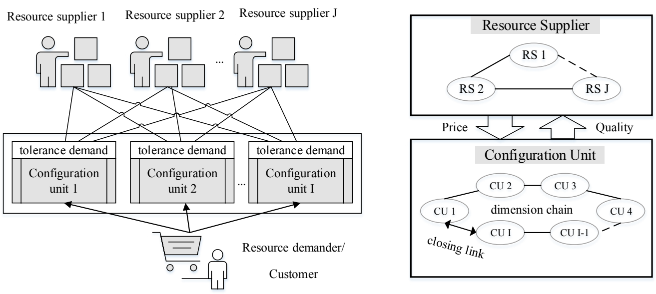

Fig. 1 The construction of system model and Interaction between two level

The demander level consists of I configuration units which have a precision requirement in a certain product from the customer. From the perspective of configuration unit (CU), the main objective is to select a resource supplier for manufacturing service of higher quality and lower cost. All the units affect the function requirement. The set of units could be regarded as a population in an evolutionary game in which each player could imitate other`s behaviour to maximize its profit. When the price and tolerance strategy of the resource supplier changes, CUs would change their choice to avoid more payoff in this trade.

The supplier level is made up of J candidate resources which are picked up by data mining to meet the requirement of customer.

The resource supplier (RS) aims at selling more service at higher price in a non-cooperation game with the relationship of competition. To win this competition, RS should reduce its price so that the CU would be more likely to make a choice on it. The strategy of a certain RS should consider its manufacturing cost as well as opportunity cost.

When RSs broadcast its strategy, the CUs make their decision to choose a RS to trade with. Observing the choices of CUs, the RSs would adjust their tolerance strategies and price strategies. By repeating the process of iteration, there would be no more adjustment in the strategies or choices. This stable point is the solution of our mathematic model.

Once a configuration unit i chooses a resource to supply the manufacturing service, the utility function could be described by quality. This paper use the quality loss concept to quantify the utility of configuration unit. Q_{Loss} could be described by

Eq.(1)

$$Q_{Loss}(T_i) = \frac{\propto}{2}(T_i)^2 \quad (1)$$

The unit must pay for the service of p_j when it chooses the resource j. So that the payoff function is shown in Eq. (2)

$$\omega_i(T_i) = Q_{Loss}(T_i) + p_i(T_i) \quad (2)$$

The objective of CU could be describe as follows.

$$T_i = arg \min_{T_i} \omega_i(T_i) \quad (3)$$

The net payoff of the whole product is defined as the accumulated payoff when all the CUs choosing RS j ,which is shown in Eq. (4)

$$\pi_j = \sum_{i=1}^{I} \omega_i(T_i) \quad (4)$$

The replicator dynamics which depicts the selection of the population is shown in Eq. (5)

$$\frac{\partial y_j}{\partial t} = y_j(\pi_j - \bar{\pi}) \quad (5)$$

where

$$\bar{\pi}_j = \sum_1^J y_j \pi_j \quad (6)$$

The Eq. (5) could be dispersed as follows

$$y_j(n+1) = y_j(n) + \sigma_1 y_j(n)(\pi_j(n) - \bar{\pi}(n)) \quad (7)$$

Where n is the iteration number and σ_1 is the step length.

The terminal condition is express as

$$|\pi_j(n) - \bar{\pi}(n)| < \varepsilon_1 \quad (8)$$

where ε_1 is a small positive constant.

3. Robust tolerance design on Cloud Manufacturing Platform

The existing research on tolerance design has less considered the manufacturing environment, especially the intelligent manufacturing process such as CMfg. How to take the constraints of distribute resources in the intelligent manufacturing process into account in tolerance design is a very worthy question. Process capability is the key problem to build a bridge between tolerance and resources.

The process capability index is a statistical measure of process capability: the ability of a process to produce output within specification limits.[18] In stable production, the quality characteristic of most products obey normal distribution or approximate normal distribution. The concept of process capability only holds meaning for processes that are in a state of statistical control. Process capability indices measure how much "natural variation" a process experiences relative to its specification limits and allows different processes to be compared with respect to how well an organization controls them.

It is harder and more complicated to assess manufacturing process capability of the multivariate quality characteristics in the CMfg manufacturing mode known from the concept and principle of CMfg[19].

In some research of multivariate process capability index, assume that there are p quality characteristics in a product $X = (x_1, x_2, \dots, x_p)$ which are all distributed normally, $X \sim N_p(\mu, \Sigma)$.

$$MC_p = \frac{Vol(Tolerance\ area)}{Vol[(X-\mu)'\Sigma^{-1}(X-\mu) \ll \chi^2_{p,0.9973}]} \quad (9)$$

But this kind of definition has practicability only when the multi-variable environment is simple. In the process of CMfg which is complicated and multivariable, calculation of n-dimensional hyper-volume seems impossible.

According to a definition formula of univariate process capability index in Eq. (9), K.S.Chen[20] proposes a definition of multivariate process capability index shown in Eq. (9).

$$S_{pk} = \frac{1}{3}\Phi^{-1}\left[\frac{1}{2}\Phi\left(\frac{USL-\mu}{\sigma}\right) + \frac{1}{2}\Phi\left(\frac{\mu-LSL}{\sigma}\right)\right] \quad (10)$$

$$S_{pk}^T = \frac{1}{3}\Phi^{-1}\left\{\frac{\left[\prod_{j=1}^{p}(2\Phi(3S_{pkj})-1)+1\right]}{2}\right\} \quad (11)$$

This definition is based on existing manufacturing mode whose univariate process capability index S_{pkj} in Eq. (10) could be acquired in history data.

There are two kinds of resources selected by similar matching algorithm system (SMAs): old resource service (ORS) and new resource service (NRS).ORS is the resource service that has been invoked or used at least one time. NRS is the resource service that be published recently and has never been invoked or used since it was registered.[21] As time goes by, the stability of resource decline. In consequence, even though the data of multivariate process capability is given by the history database, it is necessary for some preprocessing. As for the NRS, missing initial value calls for appropriate preprocessing, too. A method based on IFS is given as follows.

The direct relationship between process capability index and percentage of nonconforming itemsp $= 2p_L = 1 - 2\Phi(3S_{pk})$ causes the fuzzy model that $E_j = (\mu_j, \upsilon_j)$, where E_j is the candidate of resource, μ_j is the fuzzy percentage of conforming items and υ_j is the fuzzy percentage of nonconforming items (%NC) in a certain period time. $\pi = 1 - \mu - \upsilon$ is the degree of indeterminacy.

(1) ORS preprocessing

The ORS may be invoked for more than one time. The degenerate coefficient is given in Eq. (12).

$$h(t_k) = e^{-\frac{\Delta t_k}{\theta}}, h(t_k) \in [0,1], \Delta t_k = t_c - t_k, \theta = \frac{N_{date}}{1.95} \quad (12)$$

where N_{date} is the time that the reliable of information taken from 1 to 0, t_c is the time when the user is willing to invoke the resource. As the μ_j and υ_j are calculated from the data of the period time, t_k is the end moment of the certain period time.
Assume that there are m records in history data. The calculation method of fuzzy set E_j is given in Eq. (13).

$$E_j = \frac{1}{m}\sum_{i=1}^{m} h_j(t_i)\cdot E_j(t_i) \tag{13}$$

(2) NRS preprocessing
There are n resources similar to the resource which we want to speculate.

$$E = \frac{1}{N}E_1 \oplus E_2 \oplus \ldots \oplus E_N \tag{14}$$

For the purpose of accuracy, the t_k is factor causing the deviation in Eq. (14). Hence, the Eq. (14) could be developed into Eq. (15) when the t_k of different similar E is quite different.

$$E = \frac{1}{N}\mathbf{h}\,\Theta\,\mathbf{E} = \frac{1}{N}h_1\cdot E_1 \oplus \ldots \oplus h_n\cdot E_n \tag{15}$$

Eq. (15) discounts the information from their own invoked time to t_c.
The fuzzy model works well when we consider the degenerate coefficient caused by time or the speculating process of NRS, but to give a doubtless value of index of stability in multivariate process capability for optimal selecting, psychology index is introduced to solve this problem.
When using the function that $p = \upsilon_j = 1 - 2\Phi(3S_{pkj})$ to calculate S_{pkj}, the result maybe too upbeat. Hence, the fuzzy degree of indeterminacy π_j is allocated to the rate of qualified products $\mu_j{}'$ and the percentage of nonconforming items $\upsilon_j{}'$ in certain proportion to the users\` psychology index k shown in Eq. (16).

$$\mu' = \mu + k\cdot\pi, \upsilon' = \upsilon + (1-k)\pi \tag{16}$$

Table 1 the value range of *k* in different condition of allocation psychology

allocation psychology	k
pessimistic	[0,0.5]
adiaphorous	0.5
optimistic	(0.5,1)

So that $S_{pkj} = \frac{1}{3}\Phi^{-1}(\frac{1-\upsilon'}{2})$ could reflect the process capability index of one certain candidate resource j.
3.1 Objective function of robust tolerance design model
The objective of tolerance design is

$$\mathrm{Min(C)} \tag{17}$$

3.2 Constraint conditions of robust tolerance design model
For tolerance design, the assembly requirements are normally treated as constraint condition as follows:

$$\sigma_\Sigma^2 = \sigma_1^2 + \sigma_2^2 + \cdots + \sigma_n^2 < \sigma_{\Sigma 0}^2 \tag{18}$$

where
σ_i is the standard deviation of the component link i, i=1,2,3,…,n;
n is the number of component links;
σ_Σ is the standard deviation of the close link;
$\sigma_{\Sigma 0}$ is the limit standard deviation of the close link.

$$\sigma = \frac{T}{6C_p} \tag{19}$$

The Eq. (18) could be revised as follows:

$$\frac{T_1^2}{C_{p1}^2} + \frac{T_2^2}{C_{p2}^2} + \cdots + \frac{T_n^2}{C_{pn}^2} < 36\sigma_{\Sigma 0}^2 \tag{20}$$

3.3 Solution of robust tolerance design
It is assumed that p_j is the price the supplier charges the customers of the manufacturing service. Then the welfare function is given by

$$U_j(T_j) = p_j(T_j) - f_j(T_j) \tag{21}$$

It is common sense that when the precision gets higher, the tolerance is smaller, as a result the price of the manufacturing service gets more expensive. It is assumed that

$$p_j(T_j) = \delta(T_j^u - T_j) + C \tag{22}$$

where
T_j^u denotes the upper limit of the tolerance which the resource supplier j could supply in the manufacturing task;
δ is a coefficient which denotes the price of each tolerance degree as well as the price strategy.
For the resource j, the strategy for price and precision are shown as follows

$$T_j(n+1) = T_j(n) - \sigma_2 \tag{23}$$
$$\delta_j(m+1) = \delta_j(m) + \sigma_3 \tag{24}$$

where m is the iteration number and σ_2 and σ_3 are the step length. The initial value of T_j is the upper limit of the tolerance value range.
All the strategies of the iterative process must satisfy Eq. (3).
Let $W_j = \sum_{i=1}^{l} y_{ji}\, U_j(T_j)$ presents the whole welfare resource supplier j could receive in the process of resource selecting and tolerance design. The terminal criterion is

$$W_j = max W_j \tag{25}$$

4. Case study

To demonstrate the model and process in a concise way, it is assumed that there are two resource suppliers standby. The configuration unit is abstracted by auto-body manufacturing task. The assembly structure is shown in Fig. 4.[36] This assembly is made up of four components. In addition, $L_1 = L_2 = 370mm$, $L_3 = 850mm$, $\alpha = 60°$ The constraints are shown as follows

$$L_0 = \cos\alpha\,(L_1 + L_2) + L_3 \tag{26}$$
$$0.05 \le T_1 \le 0.2 \tag{27}$$
$$0.05 \le T_2 \le 0.2 \tag{28}$$
$$0.05 \le T_3 \le 0.2 \tag{29}$$
$$0.1 \le T_0 \le 0.3 \tag{30}$$

As L_1 L_2 and L_3 are planar features, each of them could observe and imitate other` choice. The assumption of the population for evolutionary game is proved to be tenable. It is obvious that RS 2 is cheaper at low precision service and more expensive at high precision than RS 1. The Cost-Tolerance curves of RS1 and RS2 are shown in Fig. 3. The initial information of RS in algorithm is shown in Table. 2.

Given the coefficient of quality loss (α=2000), the result of tolerance design is $T_1 = T_2 = T_3 = 0.05$.

Table 2 The initial information of RS

	RS 1	RS 2
$T_j(1)$	0.2	0.2
C_j	1.40228	1.06648
σ_2	0.05	

L_1 L_2 and L_3 are component links. It is assumed that a resource user looks for a manufacturing resource chain 30 days later for a multivariate-quality product whose manufacturing task could be decomposed into 6 subtasks in the platform of CMfg. The user publish this requirement in 12th, October, 2014. After the SMAs, some candidate resources are given as a result. The information of candidate is as follows:

$$QC_1 = \begin{bmatrix} RS_{11}(99.96, 0.03); (99.94, 0.04) \\ RS_{12}(99.99, 0.01); (99.98, 0.01) \\ RS_{13}(99.899, 0.011); (99.897, 0.011) \\ RS_{14}(99.94, 0.05); (99.92, 0.06) \end{bmatrix};$$

$$QC_2 = \begin{bmatrix} RS_{21}(99.997, 0.001); (99.996, 0.001) \\ RS_{22}(99.980, 0.005); (99.962, 0.006) \\ RS_{23}(99.975, 0.024); (99.964, 0.033) \end{bmatrix};$$

$$QC_3 = \begin{bmatrix} RS_{31}(99.83, 0.12); (99.81, 0.13) \\ RS_{32}(NULL) \end{bmatrix}.$$

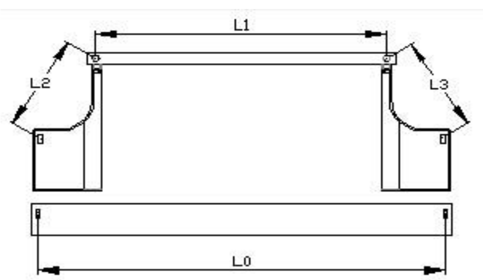

Fig. 2 The sketch map of assembly and dimensional

QC stands for quality characteristic, CR presents candidate resource. The data in each square bracket of a certain QC is the candidate resources which could undertake the manufacturing task. Such as the RS_{ij} presents the candidate resource j of subtask *i*. Because of the data`s randomness in one certain manufacturing task, we take the average value of a period time to mining the decay trend with time. To evaluate the multivariate process capability, the information from a certain period time is acquired. In every row of the data in the square bracket, the former parenthesis is the fuzzy average rate of qualified products and the fuzzy %NC from 12th, October, 2012 to 12th, October, 2013 while the latter parenthesis is the fuzzy average rate of qualified products and the fuzzy %NC from 12th, October, 2013 to 12th, October, 2014. As supplementary, the RS_{66}`s parenthesis contains the information from 12th, October, 2011 to 12th, October, 2014.

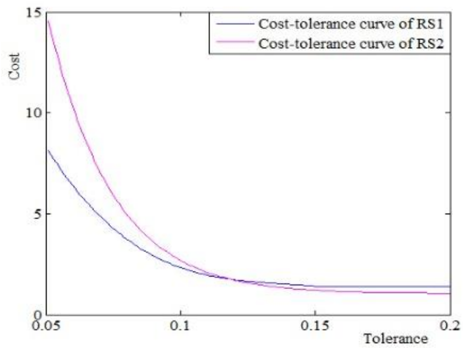

Fig. 3 the Cost-Tolerance curves of RS1 and RS2

The $RS_{32}(null)$ means the second candidate resource of the 4th subtask is NRS.

For the existing of NRS, the conjecture process is necessary.

A group of resources similar with the RS_{42} in engineering level, precision, detection method and so on, which could not provide the service at the requirement time, are picked up for the conjecture process. The information is shown in Table 3 and Table 4.

Table 3 the information from 12th, October, 2012 to 12th, October, 2013

	μ%	υ %	π%
$RS_{32}^{(1)}$	99.9929	0.0067	0.0004
$RS_{32}^{(2)}$	99.9971	0.0021	0.0008
$RS_{32}^{(3)}$	99.9983	0.0014	0.0003

Table 4 the information from 12th, October, 2013 to 12th, October, 2014

	μ%	υ %	π%
$RS_{42}^{(1)}$	99.9931	0.0066	0.0003
$RS_{42}^{(2)}$	99.9972	0.0021	0.0007
$RS_{42}^{(3)}$	99.9985	0.0013	0.0002

The conjectural information is shown in Table 5 after calculation and combining the accurate part of data in [0,99.99].

Table 5 the conjectural information of RS_{42}

	μ%	process capability index
2013.12.10~	99.993237	1.325294467

2014.12.10		
2012.12.10~ 2013.12.10	99.993217	1.325251667

We could calculate the capability index of every possible resources of which the information is shown in Table 6.

Table 6 the capability index of candidate resources

	CR1	CR2	CR3	CR4
QC1	1.162200	1.256365	1.144369	1.133707
QC2	1.402281	1.221178	1.188597	
QC3	1.320572	1.325245		

*QC stands for quality characteristic, CR presents candidate resource.

Given the limit standard deviation of the close link, the possible resource which could satisfy the assembly requirements could be picked up to undertake the manufacturing tasks.

5. Conclusion

This paper studies the robust tolerance design on cloud manufacturing platform, in which a two-level game is put forward to reveal the relationship and behavior between the products and resource suppliers. According to the scenario with multiple resource suppliers, the multivariate process capability index has been introduced to solve the problem of robust tolerance design faced up with cloud manufacturing environment. A case study is used to illustrate the proposed model.

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