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A Dynamic Selection Method for Equipment Resources in Cloud Manufacturing Environment

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ABSTRACT

Aiming at the problem that military equipment resources are easily affected by high-frequency random disturbances such as emergency order insertion, abnormal processing quality, equipment operation failure, etc. in the process of processing task execution in the cloud manufacturing environment, which causes the quality of service (QoS) of product processing to fail to meet the personalized needs of customers, a dynamic selection method of equipment resources in the cloud manufacturing environment is proposed. According to the running characteristics of cloud manufacturing services, a dynamic evolution model of service quality towards the process of processing task execution under cloud manufacturing environment is constructed. Taking the state vector and control vector in the dynamic evolution model as node variables, combined with Bayesian network, a decision model for dynamic selection of military equipment resources under random disturbance is established. By solving the model, the corresponding scheme of the optimal QoS value is obtained, and the dynamic selection of military equipment resources is realized. The experimental results show that this method can effectively and dynamically select military equipment resources, reduce the price and time cost of military equipment manufacturing, and improve the reliability of product processing, platform satisfaction and comprehensive QoS score.

Keywords: Cloud manufacturing environment, Military equipment resources, Dynamic selection, Machining quality of service, Dynamic evolutionary modeling, Bayesian networks

1. Introduction

As an important part of the core competitiveness of the country, the manufacturing industry plays a pivotal role in the development of the national economy [1]. With the continuous impact of the wave of economic globalization, the manufacturing industry is developing continuously in the direction of intelligence and digitalization. In this context, many countries around the world in order to seize the manufacturing market and enhance the international discourse, have put forward manufacturing revitalization plans from the national level in the hope that through the advanced manufacturing

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model and intelligent technology to rapidly accumulate competitive advantages [2-4]. With the continuous upgrading of market demand, the user's personalized demand is also increasing [5]. For enterprises, under the traditional manufacturing model, it becomes more and more difficult to complete customized products only through their own manufacturing resources, and only by continuously optimizing the resource allocation method and quickly adapting to the diversified market demands can they maintain their competitiveness in the fierce competition [6-8]. At present, a part of small and medium-sized manufacturing enterprises often fail to deliver on time in the face of a large number of customized orders because of limited manufacturing capacity [9-10]. And another part of enterprises are difficult to efficiently utilize the manufacturing resources due to the fixed source of orders, resulting in low equipment start-up rate, which leads to the idle and waste of resources [11-12]. Therefore, how to transform the current enterprise manufacturing model, effectively integrate manufacturing resources, and promote manufacturing enterprises to form a new organizational form of collaborative production and co-benefits has become an urgent problem for small and medium-sized enterprises [13-15].

Cloud manufacturing is a new model of networked manufacturing that integrates a variety of technologies such as networked manufacturing, cloud computing and the Internet of Things to achieve centralized, intelligent management and on-demand use of various manufacturing resources [16]. Dynamic selection of equipment resources in cloud manufacturing environment is a key technology in the operation of cloud manufacturing service platform, which is an important part of resource service management [17-18]. Compared with the traditional manufacturing model, the cloud manufacturing model breaks the barriers between enterprises, which can help enterprises with insufficient production capacity to solve the problem of shortage of manufacturing resources, and also empower enterprises with sufficient manufacturing capacity to improve the utilization efficiency of internal resources [19-21]. Through the centralized integration and elastic supply of manufacturing resources, the cloud manufacturing model effectively improves the cooperation and sharing ability between enterprise organizations, reduces resource consumption, and also plays a role in promoting the coordinated development of the manufacturing industry [22-24].

The above methods do not consider the impact of random disturbance on the service capability of military equipment resources, and lack the dynamic adjustment strategy of military equipment resources for random disturbance. Therefore, based on the previous research results, combined with the discrete Markov jump system theory, this paper constructs a Qos dynamic evolution model of the processing task execution process in the cloud manufacturing environment, studies the evolution path and mechanism of the military equipment resource complex dynamic network (CDN) in the cloud manufacturing environment, and explores the evolution law and characteristics of the CDN network. Analyze the impact of random disturbance on the robustness of military equipment resources CDN network, study the optimization decision method of military equipment resources under random disturbance, provide theoretical support for solving the problem of optimal configuration and stable operation of military equipment resources dynamic service under cloud manufacturing environment, promote the optimal configuration of military equipment resources, and realize the matching of military equipment price and quality, It helps to improve the use efficiency of military equipment, thus promoting the improvement of military equipment economy.

2. Resource selection for military equipment based on cloud manufacturing environment

2.1. Modeling the dynamic evolution of cloud processing tasks

In the military equipment resource processing task under the cloud manufacturing environment, the random disturbance will lead to the decline of the military equipment resource service ability to provide machining services, and ultimately the actual manufacturing service quality (QoS) of the cloud manufacturing task is unstable and deviates from the expected value. Therefore, based on Markov jump system theory, a dynamic evolution model of QoS in cloud manufacturing task execution process is established to characterize the impact of random production disturbances on military equipment resource service capability.

Markov jump system can effectively describe the production and service process of military equipment resources performing manufacturing tasks under cloud manufacturing environment, which is vulnerable to internal and external random disturbances and leads to random jump of military equipment service capability, as follows:

First, describe the process of military equipment resources performing processing tasks in the cloud manufacturing environment from the perspective of abstracting discrete time. It can be thought that the actual QoS of cloud processing tasks at each time is mainly determined by the actual QoS state at the previous time and the selection of military equipment resources between two times. Therefore, the discrete time Markov jump system is used to establish the QoS dynamic evolution model of cloud manufacturing task execution process, which can be expressed as:

$$\begin{aligned} x_{k+1} &= A\left(w_k P_r\right) x_k + O\left(w_k P_r\right) u_k + O_d\left(w_k P_r\right) d_k \\ x_k &= x_0, w_k = w_0, k = 0 \end{aligned} \tag{1}$$

Among them, x_k is the state vector of the system; the w_k is the mode in which the system is located, which follows the transfer probability matrix, the P_r jumps between modes. u_k is the control vector of the system; the d_k is the unknown input signal. x_0, r_0 are the initial state and initial mode of the system, respectively; the $A\left(r_k P_r\right)$, $O\left(r_k P_r\right)$, $O_d\left(r_k P_r\right)$ are known and the associated coefficient matrix associated with the system modes w_k, respectively.

The system state vector x_k indicates the actual QoS state of the cloud manufacturing task at the k moment. Since there may be multiple random disturbances caused by different factors during the execution of cloud manufacturing tasks, and different types of random disturbances with different processing schedules will lead to continuous and diverse changes in the QoS of tasks, the real-time QoS state of each observation rather than the final QoS of the expected completed processing is used as the system state vector, describe the actual execution of cloud manufacturing tasks in a more granular way. It is usually composed of the evaluation index of the average price of military equipment per piece (C), time costs (T), processing quality (φ), reliability (R), platform satisfaction (E , so the QoS of manufacturing tasks can be expressed as:

$$x_k = \left(\overline{C}_k, \overline{T}_k, \overline{\varphi}_k, \overline{R}_k, \overline{E}_k\right) \tag{2}$$

The price of military equipment should take into account not only the processing costs, but also the logistics costs between the production and processing resources. Processing costs refers to the military equipment resource providers in order to complete a task, in the production process of raw materials, fuel, power, wages, rent, interest and other all the projected expenditures, $CF_{k,i,j}$ is used to indicate the production and processing of a batch task $Z_{k,j}$ of a candidate military equipment resource $Q_{k,i}$.

Logistics cost is the cost of the logistics connection between the front and back two candidate resources in the service of military equipment resources, using $CG_{k,i,j}$ indicate the logistics cost in the military equipment resource pool for military equipment resources $Q_{k,i}$. Among them, if the task immediately before the node is a resource user, the logistics cost of candidate resources for this type of task is the logistics cost from the location of the candidate resources to the location of the resource user; if the task immediately after the node is a resource user, its logistics cost not only includes the logistics cost from the location of the immediately preceding resource to its location, but also includes the logistics cost from its location to the place where the task is to be delivered.

As can be seen from the above, the price of military equipment for candidate military equipment resources $Q_{k,i}$ complete the mission $Z_{k,j}$ is:

$$C_{k,i,j} = CF_{k,i,j} + CG_{k,i,j} \tag{3}$$

In this case, the values of processing costs and logistics costs are committed by the resource providers according to their own circumstances.

As the production and processing tasks accepted by the cloud manufacturing model are mostly complex manufacturing tasks that require collaborative production and processing to complete the task, and its production and processing resources have the characteristics of decentralization and off-site, the execution time should not only consider the processing time, but also need to consider the impact of the task entity flow between production and processing resources on the time. Processing time refers to the resource provider in order to complete a task, the expected completion of the task time, $TF_{k,i,j}$ represents the production and processing time of the candidate military equipment resource $Q_{k,i}$ to complete a batch task $Z_{k,j}$.

Logistics time is defined as the logistics connection time between the front and back two candidate resources in the service of military equipment resources, using $TG_{k,i,j}$ denotes the logistics time for resources $Q_{k,i}$ to complete a batch of tasks in the military equipment resource set. Among them, if the immediate preceding node of the task is a resource user, the logistics time of the candidate resource for this type of task is the time from the location of the candidate resource to the location of the resource user; if the immediate after node of the task is a resource user, its logistics time includes not only the logistics time from its location to the location of the immediate candidate resource, but also the logistics time from its location to the place where the task is delivered.

As can be seen from the above, the time for candidate military equipment resources $Q_{k,i}$ to complete the mission $Z_{k,j}$ is:

$$T_{k,i,j} = TF_{k,i,j} + TG_{k,i,j} \tag{4}$$

The values of processing time and logistics time are committed values given by the resource provider according to its own situation.

Processing quality is a set of intrinsic characteristics of the product to meet the requirements of the product user and other related parties, its indicators are more complex to measure, generally use the pass rate as a basis for judging the quality of the product, $\varphi_{k,i,j}$ indicates the value of the pass rate for candidate military equipment resources $Q_{k,i}$ to complete the mission $Z_{k,j}$, which is based on the historical data recorded in the cloud manufacturing platform. The formula is:

$$\varphi_{k,i,j} = 1 - \frac{\hat{N}_{k,i,j}}{N_{k,i,j}} \tag{5}$$

Among them, $\hat{N}_{k,i,j}$ is the number of rejects in the production and processing of similar products for candidate military equipment resources $Q_{k,i}$. $N_{k,i,j}$ is the total amount of similar products produced and processed for candidate resources $Q_{k,i}$.

With the dynamic increase or decrease of military equipment resources and services in the cloud manufacturing system, changes in the state and quality of cloud services, changes in the correlation relationship between cloud services, and changes in user requirements, there are many uncertain factors affecting the execution of cloud manufacturing services, which makes it difficult for production and processing services to be completed safely and reliably. In order to ensure that the tasks can be completed safely and reliably, the cloud manufacturing service platform needs to assess the ability of each production and processing resource provider to complete the specified tasks under the specified conditions, and the reliability of the resource providers to complete the corresponding tasks as an important basis for the dynamic selection of the military equipment resources, in order to guide and incentivize the resource providers to provide more reliable services.

Use $R_{k,i,j}$ indicate the reliability for candidate military equipment resources $Q_{k,i}$ to complete the mission $Z_{k,j}$, i.e., the probability that the provider of the resource in a previous transaction will accomplish the same type of task as promised, which is calculated as follows:

$$R_{k,i,j} = 1 - \frac{\hat{M}_{k,i,j}}{M_{k,i,j}} \tag{6}$$

Among them, $\hat{M}_{k,i,j}$ is the number of failures to implement the mandate as promised; $M_{k,i,j}$ is the total number of times it has participated in the task. If the cloud manufacturing service platform has not yet accumulated a considerable history, an estimate can be given based on the combined capabilities such as the size of the resource provider and the service capability.

Cloud manufacturing service platform is based on the relative relationship between the prior expectations of resource users for products and services and the actual feelings they get after actually getting them in previous transactions, and combined with the communication and collaboration of each production and processing resource provider in the production and processing process, and the support and enthusiasm of the service platform in dealing with related problems, it conducts a comprehensive evaluation of the resource providers, and gives the satisfaction value of the cloud manufacturing service platform. Using $E_{k,i,j}$ indicate the expected satisfaction level of the cloud manufacturing service platform for candidate military equipment resources $Q_{k,i}$ to complete the mission $Z_{k,j}$. The satisfaction value of cloud manufacturing service platform is 0~1, and the higher the value, the greater the contribution of resource providers to the QoS satisfaction performance of dynamic selection of military equipment resources. As with reliability indicators, if the cloud manufacturing service platform has not accumulated a considerable historical record, the estimated value can be given according to the scale of resource providers, service capabilities and other comprehensive capabilities.

By using the above equation to calculate $C_{k,i,j}$, $T_{k,i,j}$, $\varphi_{k,i,j}$, $R_{k,i,j}$, $E_{k,i,j}$, then the corresponding average value can be obtained.

In particular, x_0 refers to the QoS status of cloud manufacturing tasks before task execution, representing the optimal QoS status of cloud manufacturing tasks, that is, military equipment resources $Q_{k,i}$ obtained through initial optimization perform the QoS value of the entire cloud manufacturing task executed without any disturbance.

System model r_k describes the service capability state of the candidate military equipment resource set during the execution of cloud manufacturing tasks. When the number of resources in the candidate resource set is large, the combined service capability of each military equipment resource in the candidate resource set in the ideal operation state is weighted, take the first m resource with the highest capability to build the system mode to ensure the service capability of the candidate resource, and at the same time effectively control the system modal scale and reduce the time and space complexity. With $S_{k,i}$ represents the actual service capability of the candidate resource concentration i military equipment resource $Q_{k,i}$ at time k, using the following formula:

$$S_{k,i} = \left(C_{k,i}, T_{k,i}, Q_{k,i}, R_{k,i}, E_{k,i}\right) \tag{7}$$

It can be seen that the state combinations of all the resources in the candidate resource set will constitute the set of modes of the system, and follow a certain probability law to jump among the modes. Considering that the situation where two military equipment resources undergo random perturbations at the same time and are successively selected to execute the same cloud manufacturing task is a very small probability event, the system modes that are mainly considered during the execution of the cloud manufacturing task should be centered around the random perturbation situations (e.g., disappearance of perturbation, mitigation, maintenance, deterioration, etc.) occurring in the running military equipment resources. The system mode of k at any time can be represented by a matrix $S_k = \left[S_{k,1}, S_{k,2}, \cdots, S_{k,m}\right]$ composed of the service capability of each military equipment.

The dynamic evolution of QoS during the execution of cloud manufacturing tasks indicates that all cloud manufacturing tasks are initially optimized resources $Q_{k,i}$ without random disturbance the difference between the QoS status of the completed processing task and the QoS status of the processing task completed by the re optimized matching resources after the actual random disturbance. The difference between the two is related to the actual resource service capability $S_{*,i}$ of each processing task, which can be expressed as follows:

$$\overline{x} = Q_{k,i} + \frac{\sum_{i=1}^{n}\left(S_{*,i} - Q_{k,i}\right)}{n} \tag{8}$$

Among them, n is the total number of workpieces to be machined for this cloud manufacturing task. With x_0 represents the QoS status of the task without production disturbance, and can determine the coefficient matrix $A\left(w_k P_r\right)$, $O\left(w_k P_r\right)$, $O_d\left(w_k P_r r_k\right)$ of formula (1) as follows:

$$\begin{aligned} & A\left(w_k P_r\right) = 1 \\ & O\left(w_k P_r\right) = \frac{\begin{bmatrix} S_{k,1} - Q_{k,i} \\ S_{k,2} - Q_{k,i} \\ \vdots \\ S_{k,m} - Q_{k,i} \end{bmatrix}}{n} \\ & O_d\left(w_k P_r\right) = 0 \end{aligned} \tag{9}$$

System control vectors u_k is for moment k, the external inputs to the control system state vector changes, i.e., the results of the dynamic selection of military equipment resources. For the candidate resource set with a total number of candidate resources of m, a cloud manufacturing task in which the maximum number of artifacts is $\tau_{\max}$ and the remaining processing number is n_{remain} that allowed to be assigned at time k, the control vector can be expressed as follows:

$$u_k = \left(u_{k,1} \quad u_{k,2} \quad \cdots \quad u_{k,m}\right) \tag{10}$$

Among them, $\left\|u_k\right\|_1 \le \min\left(\tau_{\max}, n_{remain}\right)$.

2.2. *Design of military equipment selection methodology*

2.2.1. Description of the problem of dynamic selection of military equipment resources based on changes in cloud manufacturing tasks. The initial task set $Z = \left\{Z_1, Z_2, \cdots, Z_\eta\right\}$ in the cloud manufacturing service platform consists of η first-level manufacturing tasks, that is, Z_j indicates a first-level manufacturing task. Z_j can be decomposed, after task decomposition, into κ_j secondary manufacturing tasks, i.e $Z_j = \left\{Z_{j1}, Z_{j2}, \cdots, Z_{j\kappa_j}\right\}$, Z_{jl} denotes a secondary manufacturing task; for each secondary manufacturing task, the Z_{jl} there is multiple candidates for military equipment resources, secondary manufacturing tasks Z_{jl} can be randomly executed on the candidate military equipment resources. Due to the difference of resource attributes, the execution time, cost, and service quality of secondary manufacturing tasks on different resources will vary. Resources in cloud manufacturing environment are characterized by distribution, diversity, abstraction, dynamics and heterogeneity. Different resources may belong to different national defense industry departments, so the physical distance between resources will lead to the corresponding logistics time and cost in the execution of multiple secondary manufacturing tasks of primary manufacturing tasks. The essence of resource scheduling in the cloud manufacturing environment is to select the most appropriate resources for various tasks, and give the service order of resources on the task, as well as the start time and end time of each resource service, so as to optimize the QoS status of the dynamic selection scheme. In the whole

cycle of resource scheduling in the cloud manufacturing environment, there are many different disturbance factors based on the change of manufacturing tasks, which are mainly reflected in the access of new tasks, the change of task attributes of manufacturing tasks, and the cancellation of tasks.
1) The inclusion of new task. In the process of cloud manufacturing service processing, each manufacturing task in the initial task set Z provides orderly service on different resource nodes under the unified selection of the cloud manufacturing service platform. At time t_1 of the cloud manufacturing service manufacturing cycle, the manufacturing task set $\hat{Z} = \{Z_{\eta+1}, Z_{\eta+2}, \cdots, Z_{\eta+r}\}$ reaches the cloud manufacturing service platform, part of the unfinished tasks in the initial task set $Z = \{Z_1, Z_2, \cdots, Z_\eta\}$ at time t_1 constitute the manufacturing task set $Z_{unfinished}$, at which point the task set will be manufactured $Z_{unfinished}$ with the newly accessed set of tasks $\hat{Z}$ combining to form a new set of manufacturing tasks $Z' = \{Z_{unfinished}, \hat{Z}\}$, the cloud manufacturing services platform for a new collection of tasks $Z' = \{Z_{unfinished}, \hat{Z}\}$ continue with the dynamic selection service for military equipment resources.
2) Task revocation. At the t_2 time of the cloud manufacturing services manufacturing cycle, the user undoes some manufacturing tasks, and the resources occupied by the undone tasks are unblocked and can be used to serve other manufacturing tasks, the unfinished tasks in the manufacturing task set Z' at time t_2 constitute the manufacturing task set $Z'_{unfinished}$, order the assembly of manufacturing tasks $Z'_{unfinished} = Z''$, the cloud manufacturing services platform based on a collection of manufacturing tasks Z'' continuing the dynamic selection of military equipment resources.
3) Changes in task attributes. At the t_3 moment of the cloud manufacturing services manufacturing scheduling, the user modifies the expected goals of the service for a number of tasks in the set of manufacturing tasks in$H$3, the unfinished tasks in the manufacturing task set Z'' at time t_3 constitute the manufacturing task set $Z''_{unfinished}$, order the assembly of manufacturing tasks $Z''_{unfinished} = Z'''$, the cloud manufacturing services platform, based on the set of manufacturing tasks with changed attributes Z''' continuing the dynamic selection of military equipment resources.

For analytical purposes, the following dynamic selection rules for military equipment resources are relevant.

Rule 1: Each manufacturing resource can independently complete one or more secondary manufacturing tasks, and the same secondary manufacturing task cannot be processed by different manufacturing resources at the same time;

Rule 2: The first level manufacturing task is decomposed to form a second level manufacturing task, which is the smallest unit to be served;

Rule 3: The processing and manufacturing of the second level manufacturing task and the next second level manufacturing task between different manufacturing resources will generate certain logistics costs and logistics time;

Rule 4: The service mode of the task is to receive services in order according to the sequence of the second level manufacturing tasks. The start time of the next second level manufacturing task is not less than the sum of the logistics time between the end time of the previous second level manufacturing task and the selected resources of the two second level manufacturing tasks;

Rule 5: Logistics cost between different resources is proportional to logistics time and logistics distance;

Rule 6: Different types of first level manufacturing tasks have the same execution priority;

Rule 7: All cloud manufacturing resources are available at zero time;

Rule 8: Once the secondary manufacturing task starts processing until its manufacturing service is completed, it cannot be interrupted.

2.2.2. Dynamic selection decision modeling of military equipment resources in cloud manufacturing environment. According to the dynamic selection rules of military equipment resources formulated in subsection 2.1, a Bayesian network is selected to establish a decision model for the dynamic selection of military equipment resources under stochastic perturbation. The network structure is used to express the information and interrelationships related to the decision-making problem, and the modeling process needs to take into account the dynamic selection rules of military equipment resources, as well as the relationship between the current node and its parent node, so as to reduce the parameter scale, and the model uses the ternary group $\langle X,V,W\rangle$ to express.

The system state vector x_k and the control vector u_k in the dynamic evolution model of the cloud processing task are used as the node variables, the $X=\{x_k,u_k\}$, node variables are the set of node variables in the network that express information relevant to the decision task, i.e., decision variables, nodes X which can be further categorized into sets of decision environment nodes based on variable characteristics I, the set of decision-making choice nodes D, the set of decision target nodes H, the set of decision passing nodes O and the set of decision value nodes Y several subsets, and $X=I\cup D\cup H\cup O\cup Y$.

The set of decision environment nodes I, which represents the set of all external information collected prior to making an optimal choice $I=\{I_1,I_2,\cdots,I_f\}$, which are not under the control of the decision maker, are direct observations and estimations, and are represented by circles in the structure of the decision network.

The set of decision-selective nodes D, representing the set of choice nodes for which decisions need to be made $D=\{D_1,D_2,\cdots,D_g\}$, which is the alternative feasible options, controlled by the decision maker and represented by squares in the decision network structure.

The set of decision target nodes H, representing the set of objectives for decision-making on dynamic selection of military equipment resources in a cloud environment $H=\{H_1,H_2,\cdots,H_{n'}\}$, which is represented by a hexagon in the decision network structure;

The set of decision-passing nodes B, which represents the consequences of the decision choices made in the previous stages of a multi-stage decision problem $B=\{B_1,B_2,\cdots,B_b\}$, which is used to provide better information for decision-making choices at the next stage and is represented by a pentagon in the structure of the decision network.

The set of decision-value nodes Y, which is the result of the harmonization of decision-making objectives $Y=\{Y_1,Y_2,\cdots,Y_{n'}\}$, indicating that the value brought by each decision goal can be calculated based on the combination probability of its parent node and the corresponding weight of the goal, which is represented by a diamond in the decision network structure.

Before making multi-stage and multi-objective decisions, decision makers need to determine the selection of each decision stage in order based on the collected decision environment variables and the results of the completed decision stage. Then judge and select the QoS value of different decision schemes, and finally select the decision scheme with the largest QoS value.

Military equipment resource dynamic selection decision-making model under random perturbation will determine the model directed edge direction according to the type of subset to which the node belongs, in which the decision environment node belongs to the a priori information, there is no parent node; the decision selection node is guided by the decision environment node, and at the same time, it also affects the decision target node and the decision transfer node; the decision transfer node will affect the operation of the decision selection node in the next stage; the decision value node is the unified quantitative result of the decision target, and it is only affected by the decision target node. Define the directed edge, the $V=[v_{i'j'}]$ as the set of directed edges connecting the nodes, the $v_{i'j'}$ denotes a directed edges from node $X_{i'}$ to $X_{j'}$.

For each node, the $X_{i'}$ and the set of its parents $Pa(X_{i'})$, they are all corresponding to a conditional probability distribution $\rho=\{\rho(X_{i'}|Pa(X_{i'}))\}$, denotes the strength of the connection between the nodes.

2.3. *Realize the dynamic selection of military equipment resources in the cloud manufacturing environment*

The solution process of the Bayesian network-based decision model for dynamic selection of military equipment resources is as follows:

1) Determine the decision-making environment, according to the specific cloud manufacturing environment, production and processing task requirements, military equipment resource information and military equipment resource dynamic selection rules, change the decision-making environment node for the current real state distribution $I_{now}=\left(I_1=I_1^{\alpha},I_2=I_2^{\alpha},\cdots,I_{\beta}=I_{\beta}^{\alpha}\right)$, of which $I_{\beta}=I_{\beta}^{\alpha}$ indicates that the decision environment node β is in the α state. If some of the environmental variables in the cloud manufacturing environment have uncertainty, they can be represented by probability distributions.

2) Setting the decision selection node as an evidence node, calculating the corresponding value of the decision target node, and establishing a decision scheme $\psi_{i'}$ by sequentially determining the state of the decision selection point at each stage, e.g., a dynamic selection scheme for military equipment resources in a certain cloud manufacturing environment is $\psi_{i'}=\left(D_1=D_1^{\alpha},D_2=D_2^{\alpha},\cdots,D_g=D_g^{\alpha}\right)$, of which $D_g=D_g^{\alpha}$ indicates the g decision choice node select variable α.

3) Utilizing the previously established decision model for dynamic selection of military equipment resources for reasoning, we obtain the probability of each state of the target node in the I_{now} decision environment when using the decision scheme $\psi_{i'}$:

$$\rho=\left(H_{j'}=H_{j'}^{\alpha}\left|\psi_{i'},I_{now}\right.\right)=\rho\left(H_{j'}=H_{j'}^{\alpha}\left|Pa\left(H_{j'}\right)\right.\right)\times\rho\left(H_{j'}=Pa\left(H_{j'}\right)\left|\psi_{i'},I_{now}\right.\right) \tag{11}$$

4) Based on the above posterior probabilities, using $\rho=\left(H_{j'}=H_{j'}^{\alpha}\left|\psi_{i'},I_{now}\right.\right)$ replace the transfer probability matrix P_r in Eq. (1), calculate the sum of values of all decision value nodes, that is, the QoS value of the scheme.

5) The scheme corresponding to the optimal QoS value is used as the dynamic selection scheme of military equipment resources in the final cloud manufacturing environment.

3. Testing and analysis

3.1. *Determination of test indicators and data sources*

In order to verify the effectiveness of the proposed method, this paper takes the cloud service application cases in the military equipment cloud manufacturing service platform developed by the group to verify. At present, 15 sets of finning machine, 6 sets of assembly machine access to the military equipment cloud manufacturing service platform, and continue to carry out the military equipment processing, process parameter optimization decision-making, production quality online optimization and equipment remote operation and maintenance of various types of military equipment processing cloud services. This paper takes the military equipment processing cloud service as the experimental object to carry out verification. By calling the historical service records in the platform, it can be seen that the service has processed a total of 1,500 pieces of military equipment, and the minimum military equipment resource dynamic selection requirements for a single fin are shown in Table 1.

Table 1. Minimum military equipment resource dynamic selection requirements for a single fin

Index	Numerical value
Service price/yuan	Less than160
Time cost /min	Less than30

Processing quality	Greater than0.85
Reliability	Greater than0.70
Platform satisfaction	Greater than0.60
Comprehensive QoS	Greater than0.80

According to the statistical analysis of the cloud service platform, at present, the random disturbances of various finders mainly include two types: abnormal processing quality and equipment failure shutdown. After these two types of random disturbances, the processing time increases by 14.8% and 53.2% respectively, and the processing quality decreases by 14.8% and 53.2% respectively. Before the start of production, A1 fin machine was designated to complete the processing service after the production capacity balance, but when the 100th fin was processed, there was an equipment fault disturbance, so A2 fin machine was changed to complete the processing of the remaining 1400 parts. In order to analyze and compare the actual effect of the proposed method and the current strategy adopted by the enterprise, 15 finned machine resources with the same service capacity were screened in the platform to support the application of the proposed method. The initial service capacity of each finned machine is shown in Table 2.

Table 2. Initial service capacity of each fin machine

Equipment resource number	Service price/yuan	Time cost /min	Processing quality	Reliability	Platform satisfaction	Comprehensive QoS
A1	160	26	0.86	0.72	0.65	0.91
A2	150	27	0.88	0.71	0.62	0.89
A3	159	30	0.87	0.73	0.61	0.88
A4	158	27	0.85	0.74	0.66	0.84
A5	157	25	0.89	0.76	0.64	0.87
A6	159	28	0.86	0.75	0.63	0.88
A7	160	29	0.88	0.73	0.66	0.81
A8	156	27	0.87	0.77	0.62	0.82
A9	159	30	0.89	0.74	0.64	0.86
A10	158	29	0.87	0.73	0.67	0.83
A11	157	26	0.88	0.75	0.65	0.90
A12	160	28	0.86	0.74	0.63	0.85
A13	158	27	0.89	0.76	0.64	0.87
A14	159	29	0.87	0.73	0.66	0.84
A15	156	30	0.88	0.77	0.62	0.86

3.2. Analysis of the effectiveness of dynamic selection methods for military equipment resources in cloud manufacturing environment

When using this method to dynamically select military equipment resources in the cloud manufacturing environment, A1 fin machine is responsible for completing the manufacturing task of 100 fins. When equipment disturbance occurs, this method is used to dynamically select equipment resources. The manufacturing task of each fin machine is shown in Table 3.

Table 3. Manufacturing tasks of each fin machine

Primary manufacturing task	Number of Level 1 manufacturing tasks per unit	Number of first level 2 manufacturing tasks/units	Number of second level 2 manufacturing tasks/units	Number of third level 2 manufacturing tasks/units
A1	1	2	1	3
A2	1	3	2	1
A3	1	1	2	3

A4	1	3	1	2
A5	1	2	3	1
A6	1	2	1	3
A7	1	3	1	2
A8	1	1	2	3
A9	1	2	3	1
A10	1	1	3	2
A11	1	2	2	2
A12	1	3	1	2
A13	1	1	3	2
A14	1	2	2	2
A15	1	3	1	2

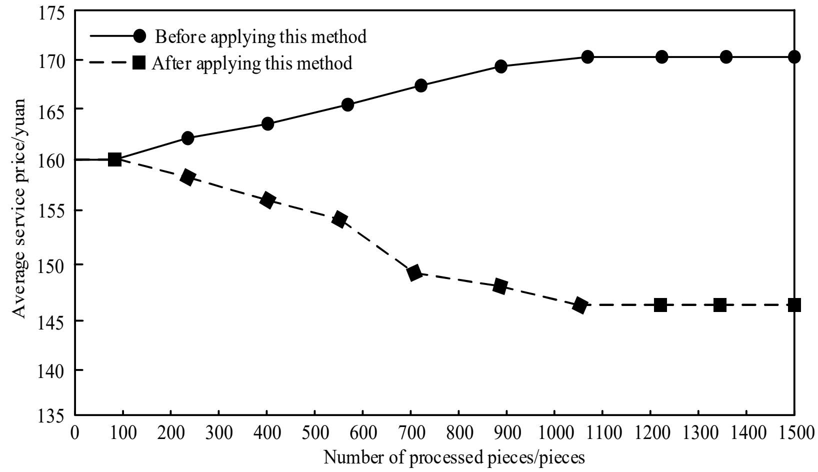
It can be seen from Table 3 that 100 fins are manufactured through three types of secondary manufacturing tasks in primary manufacturing task A1; After the disturbance of Deppon equipment, fourteen primary manufacturing tasks from A2 to A15 were used to complete the manufacturing tasks of the remaining 1400 fins. Each primary manufacturing task included three types of secondary manufacturing tasks, and each primary manufacturing task included six secondary manufacturing tasks. Since the manufacturing of 100 fins is completed in A1 task, the processing time of a single fin needs to be less than 30min, so the processing time of a single secondary task needs to be less than 500min.

Using the method of this paper for the military equipment cloud manufacturing service platform, military equipment resource dynamic selection, dynamic selection results are shown in Table 4.

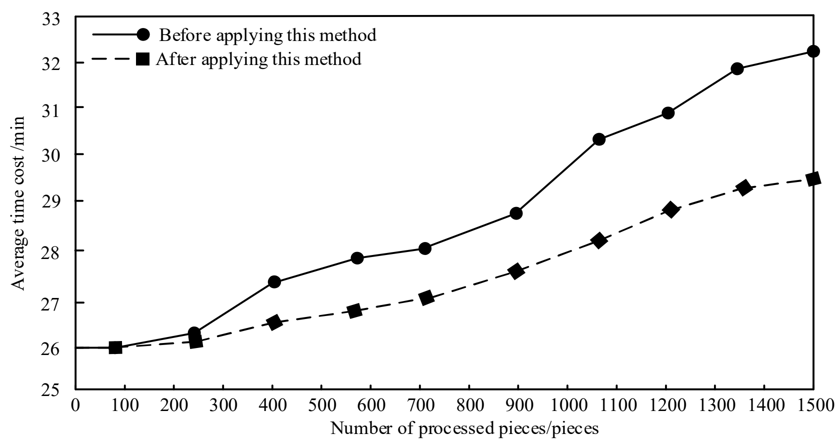
Table 4. Results of dynamic selection of equipment resources in cloud manufacturing environment

Equipment resource number	Number of first-level manufacturing tasks processed/piece	Number of processes for the first secondary manufacturing task/piece	Number of second level manufacturing tasks processed/piece	Number of third secondary manufacturing tasks processed/piece
A1	100	32	17	51
A2	100	51	32	17
A3	100	17	32	51
A4	100	51	17	32
A5	100	32	51	17
A6	100	32	17	51
A7	100	51	17	32
A8	100	17	32	51
A9	100	32	51	17
A10	100	17	51	32
A11	100	32	32	32
A12	100	51	17	32
A13	100	17	51	32
A14	100	32	32	32
A15	100	51	17	32

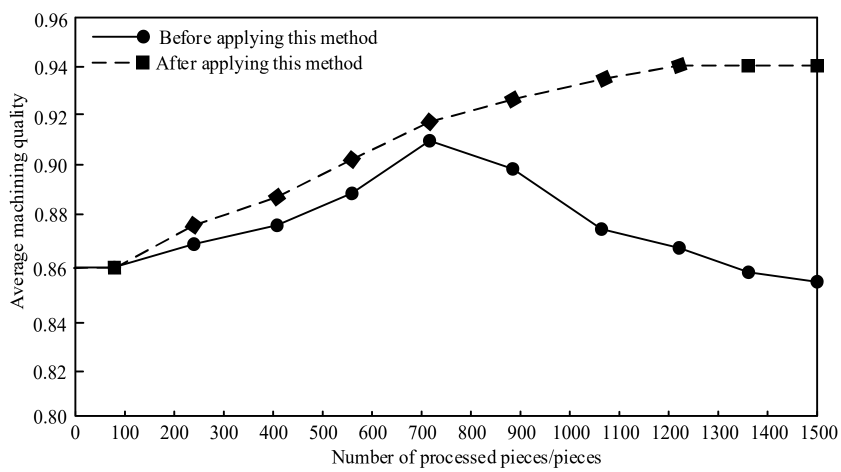
Analysis of Table 4 shows that the method of this paper can effectively and dynamically select the military equipment resources to complete the processing of workpieces, in which each military equipment resources are required to complete the processing of 100 workpieces. Using the method of this paper to analyze the military equipment cloud manufacturing service platform cloud manufacturing task of each evaluation index in different processing workpiece number of the evolution of the situation, as shown in Figure 1.



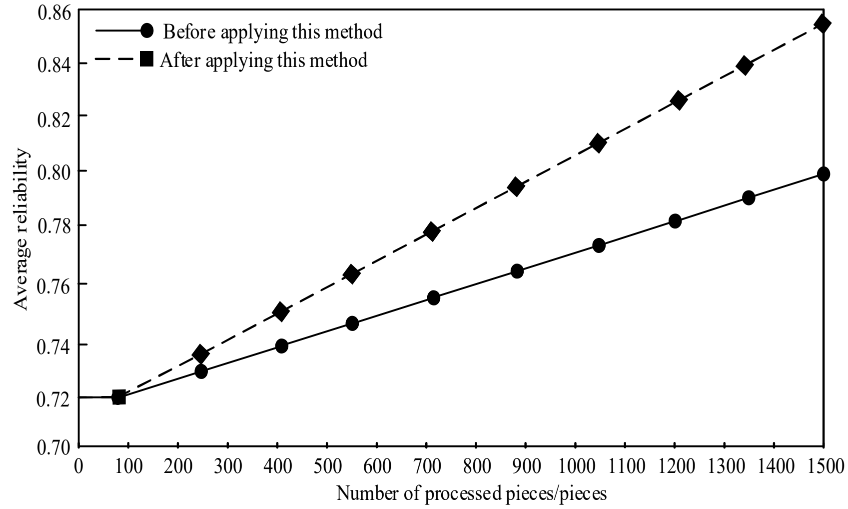
(a) Dynamic evolution of average service price



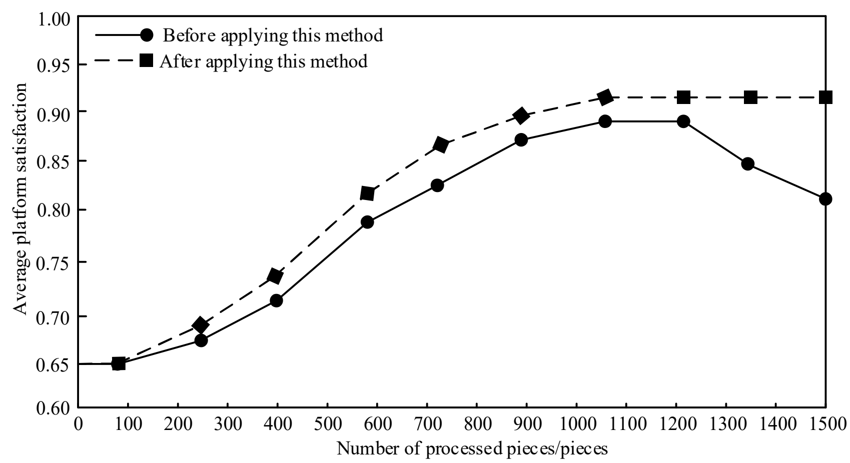
(b) Dynamic evolution of average time cost



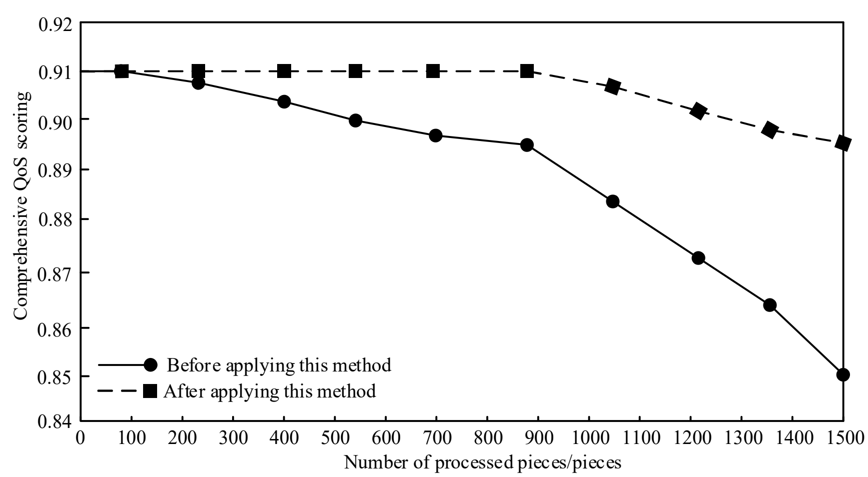
(c) Dynamic evolution of average machining quality



(d) Dynamic evolution of average reliability



(e) Dynamic evolution of average platform satisfaction



(f) Comprehensive dynamic evolution of QoS scores

Fig. 1. The evolution of each evaluation index of cloud manufacturing task under different number of workpieces processed

It can be seen from the analysis of Figure 1 (a) that when the number of workpieces processed exceeds 100, before the application of the method in this paper, the A2 fin machine completes the processing of the remaining 1400 pieces of parts, and the average price of military equipment starts to rise continuously. When the number of workpieces processed reaches 1100, it tends to stabilize at about 170 yuan; After the application of this method, the remaining 1400 parts are processed by A2 to A10 finned machines, and the average price of military equipment shows a downward trend. When the number of processed parts reaches 1100, it tends to stabilize at about 147 yuan; It shows that the average military equipment price of workpiece manufacturing can be reduced by using this method to dynamically select military equipment resources.

It can be seen from the analysis of Figure 1 (b) that when the number of processed workpieces exceeds 100, the average time cost before and after the application of this method shows an upward trend, and the maximum average time cost before the application of this method is about 32.2min; The highest average time cost after applying the method in this paper is about 29.5 minutes; The average time cost before the application of this method has exceeded the minimum requirements, which does not meet the processing requirements; The average time cost after the application of this method does not exceed the minimum requirements, which meets the processing requirements; It shows that the method can reduce the average time cost of the workpiece under random disturbance.

Analysis of Figure 1 (c) shows that before the application of this method, the average processing quality shows an upward trend and then a downward trend. After the application of this method, the average processing quality shows an upward trend. Although the average processing quality before and after the application of this method is higher than the minimum requirements, the average processing quality after the application of this method is higher than that before the application of this method in different workpiece quantities; It shows that the average processing quality of the workpiece can be improved after the application of this method.

It can be seen from the analysis of Figure 1 (d) that, with the increase of the number of processed workpieces, the average reliability of workpiece processing before and after the application of this method shows a linear growth trend. Among them, the average reliability after the application of this method is larger, which is significantly higher than that before the application of this method, indicating that the application of this method can improve the average reliability of workpiece processing.

Analysis of Figure 1 (e) shows that before the application of this method, with the increase of the number of workpieces, the average platform satisfaction first rises, then stabilizes, and then decreases. The lowest average platform satisfaction is higher than the minimum requirement, which meets the processing requirements of workpieces; After the application of this method, with the increase of the number of workpieces, the average platform satisfaction first rises and then tends to stabilize at about 0.92. The average platform satisfaction after the application of this method is significantly higher than that before the application of this method, which indicates that the application of this method can improve the platform satisfaction of workpiece processing.

It can be seen from the analysis of Figure 1 (f) that, with the increase of the number of processed workpieces, the comprehensive QoS score before the application of this method shows a downward trend. When the number of workpieces is less than 900, the decline rate of the comprehensive QoS score is relatively slow. When the number of workpieces exceeds 900, the decline rate of the comprehensive QoS score is relatively fast. The minimum comprehensive QoS score is about 0.85, which is not lower than the minimum demand and meets the workpiece processing requirements. The comprehensive QoS score after the application of this method does not change when the number of workpieces is less than 900. When the number of workpieces exceeds 900, the comprehensive QoS score starts to decline slowly, and the lowest QoS comprehensive score is about 0.895, which is significantly higher than that before the application of this method.

It can be seen from comprehensive analysis that the dynamic optimization method of military equipment resources designed in this paper can reduce the decline in service quality of cloud manufacturing tasks caused by random production disturbances, reduce the price of military equipment for workpiece manufacturing time cost, improve the reliability of workpiece processing, platform satisfaction and comprehensive QoS score.

4. Summary and outlook

4.1. Main work and conclusions

It is of great significance to deepen the cloud manufacturing service model into military equipment manufacturing, realize the sharing and collaboration of military equipment resources, support the development of production and processing cloud services, and promote the modernization of military equipment. Aiming at the problem that military equipment resources are prone to random disturbance in the task execution process under the cloud manufacturing environment, which causes the actual QoS of cloud manufacturing tasks to fail to meet the user's expectations, this paper constructs a dynamic evolution model of QoS in the cloud manufacturing task execution process based on discrete Markov jump system; Based on the dynamic evolution model, a dynamic selection model and solution method of military equipment resources under random disturbance based on Bayesian network are proposed, which provides a solution to the problem of random disturbance processing. The experimental results show that this method can effectively and dynamically select military equipment resources, reduce manufacturing costs, improve processing quality, and provide scientific basis for military equipment construction, promote the improvement of military equipment economy, optimize military equipment procurement and supply and demand relations, strengthen military equipment resource management and allocation, and promote equipment innovation and upgrading.

4.2. Prospects for follow-up

The above research results will further enrich the cloud manufacturing theory and enabling technology system, and provide technical support for the application of the cloud manufacturing model to the bottom of the workshop. However, the construction and evolution of dynamic service network of military equipment resources under cloud manufacturing environment is a complex process with the characteristics of dynamics, openness, uncertainty, etc. Although this paper has made a little useful exploration around this research topic, there are still some deficiencies and more content that can be further studied.

1) This paper focuses on the evolution characteristics of military equipment resource service network and the impact of random perturbation on network robustness in cloud manufacturing environment, but there are random perturbation, human abort, virus invasion, and other uncertain factors that cause cooperation interruption in cloud manufacturing environment, and the occurrence of these uncertain factors will cause the "butterfly effect" of the network, and how to quantify the impact of uncertain factors on the network needs to be further researched in combination with the robust optimization and robust operation of the network.

2) The dynamic selection method of military equipment resources under cloud manufacturing environment studied in this paper is still in the preliminary application stage, and it is still necessary to explore and study the key technologies such as the accurate dynamic acquisition of evaluation index parameter values, the automatic decomposition of cloud service tasks, and the collection of information on cloud service process, etc.

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