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An effective service trust evaluation and preprocessing approach considering multi-user interests in cloud manufacturing

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ABSTRACT

In the cloud manufacturing (CMfg) platform, there are numerous manufacturing services with same or similar functions. Due to the inconsistency of service quality, how to effectively evaluate the quality of services is a fundamental problem in CMfg, and which aims to reduce risk and increase the benefits of users. Under these contexts, this study first constructs a comprehensive three-dimensional trust evaluation system that considers the trust of service demanders, resource providers, and cloud platform operators in CMfg. And then, a manufacturing services trust evaluation and preprocessing model is proposed, and the optimization process is described as following: (1) superior and inferior manufacturing services are identified by the first stage filtration; and (2) inferior manufacturing services are further classified by the second stage filtration. After that, to deal with the concerned problem, an improved multi-objective non-dominated sorting genetic algorithm III (IMO-NSGA-III) is developed to find the Pareto-optimal solutions. Furthermore, nine random instances are designed to show that the proposed IMO-NSGA-III outperforms other three state-of-the-art algorithms in terms of convergence and diversity. Finally, three case studies that comes from an automotive parts assembly company is employed, and the effectiveness of the proposed model and IMO-NSGA-III algorithm is further demonstrated.

1. Introduction

Cloud manufacturing (CMfg), as a new service-oriented manufacturing mode (Ren et al., 2017), has attracted wide attention from academia and industry because of its wide advantages, e.g., agile, customized, green, and intelligent (Lim et al., 2020, Mourtzis, 2022). As the CMfg platform grows in popularity, thousands of manufacturing services will be aggregated on the CMfg platform (Adamson et al., 2017). However, the quality of manufacturing services with the same or similar functions varies, and some services may be inferior or deceptive. Therefore, the key point is to evaluate the quality of CMfg services for ensuring the smooth implementation of CMfg.

As we known, the quality of CMfg services can be measured by service trust evaluation (Hu et al., 2021). Therefore, in recent years, many scholars have conducted multi-dimensional research on service trust evaluation, and majority of studies focus on trust evaluation based on quality of service (QoS) and user feedback (Huang et al., 2018, Xie et al., 2011, Lou et al., 2018, Yu and Huang, 2018). It is worth noting that some scholars suggested that the manufacturing services should be evaluated through a third-party evaluation platform so as to make the evaluation results more reliable and objective (Yan et al., 2016). However, to the best of our knowledge, few studies have evaluated trust from the perspective of the CMfg platform, and even fewer from the perspectives of QoS, user feedback, and the CMfg platform simultaneously. In other words, the trust evaluation of CMfg services will be more objective and comprehensive from the perspectives of service demanders, resource providers, and cloud platform operators simultaneously (Liu et al., 2019). Moreover, current studies mainly focus on establishing trust evaluation systems and selecting the superior services, but few studies focus on identifying the inferior services. In addition, most of the trust indicators considered nowadays did not distinguish the applicability of different kinds of services, e.g., hard manufacturing

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service and soft manufacturing service.

To fill the gap of existing research on trust evaluation of CMfg services, this study proposes a new trust evaluation and preprocessing method, and the main contributions are summarized as follows: (1) a comprehensive three-dimensional trust evaluation system is constructed, which considers the trust of three types of CMfg users; (2) a manufacturing service trust evaluation and preprocessing model based on the interests of service demanders, resource providers, and cloud platform operators (MSTEP-DPO) is constructed to identify the superior and inferior manufacturing services at the same time; (3) an improved multi-objective non-dominated sorting genetic algorithm III (IMO-NSGA-III) with several optimization strategies is proposed to solve the problem; and (4) nine random instances and three case studies are performed to verify the effectiveness of the proposed MSTEP-DPO model and IMO-NSGA-III algorithm.

The remainder of this paper is organized as follows. Section 2 reviews the related research and provides the research gap. Section 3 formulates a mathematical model for the trust evaluation and preprocessing of CMfg services. Next, an improved algorithm is proposed to solve the concerned problem in Section 4, and the effectiveness of the proposed algorithm is verified using nine random instances in Section 5. In Section 6, three case studies are performed and the validity of the proposed model and algorithm is further verified. Finally, conclusions and discussions of future research directions are given in Section 7.

2. Literature review

This study is related to three research streams: (1) trust evaluation methods of CMfg services; (2) trust evaluation indicators of CMfg services; and (3) equilibrium of user interests in CMfg.

2.1. Trust evaluation methods of CMfg services

As is known, high quality and reputable services are the foundation for ensuring the smooth process of service retrieval, invocation, and combination in CMfg (Huang et al., 2018). Therefore, the trust evaluation of CMfg services has received a lot of attention from scholars since the introduction of CMfg (Li et al., 2014). Some scholars focus on trust evaluation based on quality of services (QoS). For example, Zhao et al. (2014) proposed a credibility support mechanism for manufacturing cloud services based on classified QoS to ensure the reliability of manufacturing cloud service operation; Huang and Wu (2020) established a trust evaluation system based on five QoS-related indicators to provide a valid reference for manufacturing companies to select the appropriate CMfg resources. However, in reality, some resource providers may exaggerate the QoS scores of their services in order to increase their revenue. As a result, the authenticity and objectivity of QoS data published by resource providers cannot be effectively guaranteed (Huang et al., 2018). To fill this gap, some scholars began to design some trust evaluation systems based on user feedback. For example, Yu and Huang (2018) considered the user feedback data obtained by the users themselves as the QoS value of the services, and developed a trustworthy trust evaluation model; Huang et al. (2018) proposed a self-organizing evaluation method for manufacturing cloud services using user behavior data, which can effectively identify valuable services and professional users, thus encouraging widespread subscription and utilization; Xie et al. (2011) developed a trust model containing QoS information provided by the resource providers and feedback comments given by the service demanders, and the results showed that the model was more realistic in evaluating the quality of manufacturing services; Lou et al. (2018) introduced a comprehensive evaluation methodology that incorporates both objective (capability of services) and subjective (feedback of users) perspectives to evaluate trust of manufacturing services in CMfg. Furthermore, in order to make the evaluation results more objective and minimize the influence of human factors, some scholars suggested that the manufacturing services should be evaluated through a special evaluation platform. For example, Yan et al. (2016) proposed a new trust evaluation method that considers direct, indirect and third-party trust evaluation to make the transaction more practical and the trust evaluation value more useful. Nevertheless, to the best of our knowledge, there are relatively few studies on third-party trust evaluation, particularly from the perspective of the CMfg platform.

Meanwhile, by analyzing the above literature, it is found that these studies mainly focus on establishing trust evaluation systems and selecting the superior services, while there are fewer studies on identifying the inferior services. Based on previous studies, we extend this literature stream in three ways: (1) evaluate the trust of CMfg services from quality of service, feedback of users and transaction records of the CMfg platform simultaneously; (2) identify the superior and inferior cloud services at the same time based on trust; and (3) pre-process the inferior cloud services though two stage filtrations, e.g., the first stage filtration based on trust, and the second stage filtration based on historical warning information on the CMfg platform.

2.2. Trust evaluation indicators of CMfg service

Trust is a subjective judgment of the characteristics or behavior of the subject, which is characterized by vagueness, randomness, and uncertainty (Chen et al., 2011). Therefore, the construction of trust evaluation indicators is always the focus of trust evaluation of CMfg service. At early stages, fuzzy trust indicators were proposed to evaluate the trust between the two parties of a transaction (Jia and Duan, 2012). Then, more trust evaluation indicators were proposed to get closer to the real situation of the service, e.g., Zhao et al. (2014) proposed a trust evaluation method that includes reliability, timeliness, and cost indicator; Xie et al. (2011) proposed eight trust evaluation indicators: efficiency, cost, quality, reliability, security, maintainability, service level agreement (SLA), and service satisfaction index. With the increasing number of trust indicators, some scholars realized that the classification of indicators is more convenient for the measurement of trust. For example, Lou et al. (2018) divided the evaluation indicators into credit evaluation indicators and reliability evaluation indicators; Huang et al. (2018) proposed a trust evaluation system containing five primary indicators (i. e., time, cost, availability, reliability, and security) and thirteen secondary indicators; Yang et al. (2019a) divided the evaluation indicators into direct trust indicators (i.e., service response rate, service cost deviation, service reliability, delivery timeliness, and service success rate) and indirect trust indicators (i.e., service level, service cooperation rate, service energy efficiency, and recent activity); Based on direct and indirect trust indicators, Yan et al. (2016) increased third-party trust evaluation indicators. However, in the CMfg environment, trust evaluation indicators should be more in line with the characteristics of CMfg and the interests of CMfg users.

Through analysis of the aforementioned literature, it can be found that most of the above trust indicators do not distinguish the applicability of different kinds of services. However, in the actual CMfg platform, the types of services are diverse. Thus, the trust evaluation indicators for hard manufacturing services have gradually established, e.g., Li et al. (2014) proposed trust evaluation indicators for manufacturing resources in the field of machine building; Mubarok et al. (2018) constructed the trust evaluation indicators for machines and manufacturing equipment. Although this study also involves some of the same indicators in the previous research, this study has the following differences: (1) consider trust evaluation indicators from the perspective of three types of users in CMfg; (2) distinguish the indicator applicability for hard and soft manufacturing service; and (3) design some quantitative trust evaluation indicators based on real features of CMfg.

2.3. Equilibrium of user interests in CMfg

In the context of the ongoing industrial paradigm (e.g., Industry 4.0 and CMfg), many scholars realized that it is critical to consider the

Table 1
Definitions of the used notations.

Symbol	Descriptions
Indices	
i	Index for sub-demands
j	Index for candidate services of D_i
k	Index for similar sub-demands of D_i
l	Index for trust indicators of the service demander
J/K	Index for service demanders
m	Index for trust indicators of the resource provider
n	Index for trust indicators of the cloud platform operator
p	Index for transaction numbers
Parameters	
D_i	The i-th sub-demand
S_j	The j-th candidate services of D_i
N	Total number of candidate services of D_i
D_{ek}	The k-th similar sub-demand of D_i
M	Total number of similar sub-demands of D_i
R_{SR}	Service response rate
R_{SC}	Service cooperation rate
R_{SS}	Service success rate
T_{SD}	Service delivery timeliness
R_S	Service reliability
$R_{S_{hard}}$	Service reliability of hard manufacturing service
$R_{S_{soft}}$	Service reliability of soft manufacturing service
D_C	Service cost deviation
D_Q	Service quality deviation
D_T	Service time deviation
D_E	Service energy consumption deviation
A_R	Service recent activeness
E_{OF}	Service order fuzzy evaluation
N_{RB}	Number of requests sent to the cloud service by the service demander
N_R	Number of times that the cloud service responds to requests
N_T	Number of times that the service demander buys the cloud service
N_S	Number of times that the service demander successfully uses the cloud service (without returns)
N_{SD}	Number of times that the provider delivers the manufacturing service on time
t_S	Total service time of hard manufacturing service
t_{SF}	Service expiration time of hard manufacturing service
N_f	Number of times problems occurred while using the soft manufacturing service
N_U	Total number of times that the soft manufacturing service is used
C_{VP}	Cost of the cloud service
C_A	Average cost of similar cloud services in the CMfg platform
Q_{VP}	Quality of the cloud service
Q_A	Average quality of similar cloud services in the CMfg platform
T_{VP}	Time of the cloud service
T_A	Average time of similar cloud services in the CMfg platform
E_{VP}	Energy consumption of the cloud service
E_A	Average energy consumption of similar cloud services in the CMfg platform
N_C	Number of times the cloud service has been used recently in the CMfg platform
θ	The correction coefficient
E_{pof}	Evaluation score of the p-th transaction
E_{rank}	Evaluation grade of users
$SDTD$	Direct trust of the service demander based on their own experience
$SDTR$	Recommended trust of the service demander based on the experience of peers
w_{SDTD}	Weight of $SDTD$
w_{SDTR}	Weight of $SDTR$
$w_{lSDTD_{hard}}$	Weight of the l-th $SDTD$ indicator for hard manufacturing service
$w_{lSDTD_{soft}}$	Weight of the l-th $SDTD$ indicator for soft manufacturing service
SD	Service demander
τ	The threshold parameter
$CR_{J,K}$	Recommendation credibility between the J-th and the K-th SD
NF	Number of peers of the service demander
RPT_{hard}	Resource provider trust of hard manufacturing service
RPT_{soft}	Resource provider trust of soft manufacturing service
$w_{mRPT_{hard}}$	Weight of the m-th RPT indicator for hard manufacturing service
$w_{mRPT_{soft}}$	Weight of the m-th RPT indicator for soft manufacturing service
w_{nCPT}	Weight of the n-th CPT indicator
N_{all}	Total number of historical transactions of the cloud service
$\overline{RS_{after}}$	Average review score of the cloud service after the last warning
$\overline{RS_{before}}$	Average review score of the cloud service before the last warning
N_{after}	Total number of transactions after the last warning
N_{before}	Total number of transactions between the last warning and the penultimate warning
Decision variables	
SDT	Trust of the service demander
RPT	Trust of the resource provider
CPT	Trust of the cloud platform operator
$\overline{RS_{all}}$	Average review score of all transactions of the cloud service
Δ_{change}	Review score change of the cloud service after the last warning

interests of different users in order to ensure the continued participation of all users (Xu, 2012, Sokolov et al., 2020). At early stages, the interests of both service demanders and resource providers have been considered in some studies, e.g., service composition (Zhao et al., 2020), task scheduling (Mourtzis et al., 2022, Zhang et al., 2021), resource allocation (Carlucci et al., 2020), and security policy (Vatankhah Barenji, 2021). In recent years, some academics and practitioners have realized that it is also essential to consider the interests of three different types of users (service demanders, resource providers, and cloud platform operators) in CMfg. For example, Wang et al. (2021a) constructed an eight-objective CMfg service selection and scheduling model based on the interests of three types of users to improve the competitiveness of the service selection process and outcomes; Lim et al. (2021) incorporated user elements (cloud resource providers, cloud platform operators, and cloud service users) into the design of 3D printing CMfg platform architecture; Helo et al. (2021) considered the basic requirements of customers, designers and manufacturers when designing CMfg portals, so that the designed CMfg ecosystem is more competitive in the market; Lim et al. (2022) constructed a three-tier programming model of CMfg service composition considering the interests of service demanders, resource providers, and cloud platform operators to improve the manufacturing efficiency and reduces the cost. Based on the analysis of the above studies, it is found that there is a growing trend in research that considers the interests of three types of CMfg users, while such considerations are rare in the studies of trust evaluation. Therefore, we contribute to this literature by (1) establishing a comprehensive CMfg service trust evaluation system based on the trust of resource providers, cloud platform operators, and service demanders; and (2) constructing a multi-objective mathematical model to balance the trust of three types of users.

3. Problem statement and mathematical modeling

In this section, the notations and assumptions used in this study are first introduced, and then, the problem is formally defined. After that, a three-dimensional trust evaluation system based on the trust of three types of users is constructed. Finally, a comprehensive multi-objective mathematical model is developed.

3.1. Notations and assumptions

In this study, the definitions of the used notations are shown in Table 1, and the relevant assumptions are listed as follows:

(1) The operations of cloud platform operators are stable and timely. Thus, the trust of cloud platform operators will not be affected by service demanders and resource providers.

(2) The evaluations of service demanders and cloud platform operators are determined based on the current service quality of resource providers, and no false information. Thus, the trust of resource providers will not be affected by service demanders and cloud platform operators.

3.2. Problem statement

In the CMfg environment, all transaction activities of service are

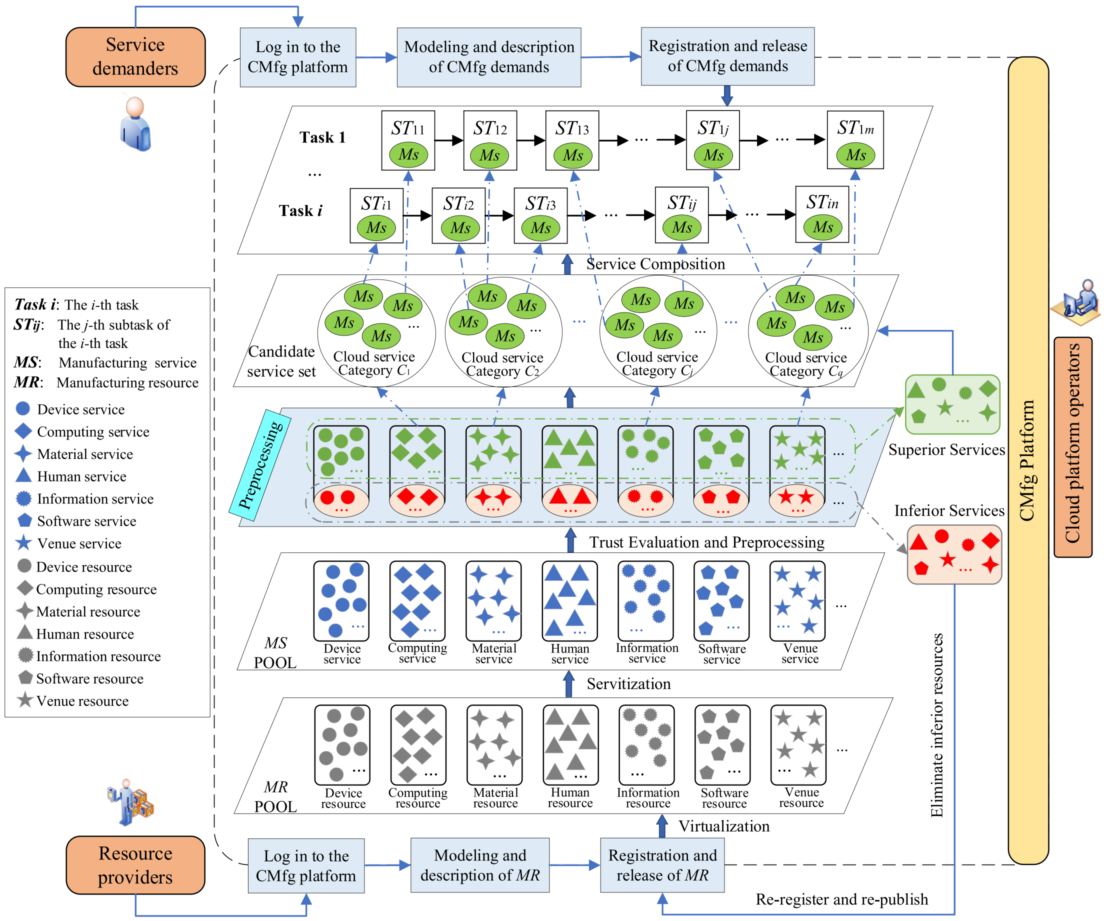


Fig. 1. Transaction flow of CMfg services.

completed on the CMfg platform. Resource providers register various types of manufacturing resources (MRs) on the CMfg platform. MRs are transformed into manufacturing services (MSs) after virtualization and servitization operations. These MSs are stored in the CMfg platform and managed by cloud platform operators efficiently. When service demanders submit manufacturing demands to the CMfg platform, the following steps are taken: (1) the demand is decomposed into many sub-demands (i.e., subtasks); (2) the CMfg platform searches potential services for each subtask and evaluates the quality of these candidate service; (3) the platform selects the optimal MS combination for all subtasks; and (4) each subtask is assigned to the corresponding resource provider to complete. For easy understanding, the transaction flow of CMfg services is shown in Fig. 1.

As can be seen from Fig. 1, the CMfg platform gathers a variety of heterogeneous manufacturing resources, and some manufacturing services perform the same or similar functions, but their quality differs. In this study, the purpose of trust evaluation and preprocessing is to evaluate the quality of these candidate service of each subtask before service composition. Meanwhile, considering the interests of all users (including service demanders, resource providers, and cloud platform operators) in the trust evaluation of cloud services is critical to ensuring the application and implementation of CMfg.

The specific steps of trust evaluation and preprocessing of CMfg services are displayed in Fig. 2, and which are explained as follows:

Step1: Decompose the demand of a service demander into multiple sub-demands. For each sub-demand D_i, search for its candidate services $\{S_1, S_2, \cdots, S_j, \cdots, S_N\}$;

Step2: Search similar sub-demands $\{D_{e1}, D_{e2}, \cdots, D_{ek}, \cdots, D_{eM}\}$ of D_i, and users or enterprises with similar sub-demands are defined as peers of the service demander;

Step3: Extract basic information and historical transaction data of candidate services $\{S_1, S_2, \cdots, S_j, \cdots, S_N\}$ from the CMfg platform;

Step4: Calculate trust evaluation values of service demanders, resource providers, and cloud platform operators according to the formulas of trust in Sections 3.3 and 3.4, and denoted as *SDT*, *RPT*, and *CPT*;

Step5: Find the Pareto-optimal solutions by the proposed algorithm in Section 4;

Step6: Pareto-optimal solutions with higher *SDT*, *RPT*, and *CPT* values are regarded as superior services, and these solutions are returned to the CMfg platform as potential services for service composition and optimization;

Step7: Pareto-optimal solutions with lower *SDT*, *RPT*, and *CPT* values are further classified to determine whether they are composed of inferior services;

Step8: Give warnings to these inferior services or remove them from the CMfg platform.

According to the procedures of trust evaluation and preprocessing of CMfg services, the purpose of this paper is to identify superior and inferior CMfg services by maximizing and minimizing the trust of the users.

3.3. Establishment of trust evaluation system

The trust of a cloud service can be assessed by the basic information, historical transaction data, and evaluation data of completed transactions from service demanders, resource providers, and cloud platform operators (Yang et al., 2019a).

In the CMfg platform, manufacturing services can be roughly classified into two types: hard manufacturing services (e.g., equipment

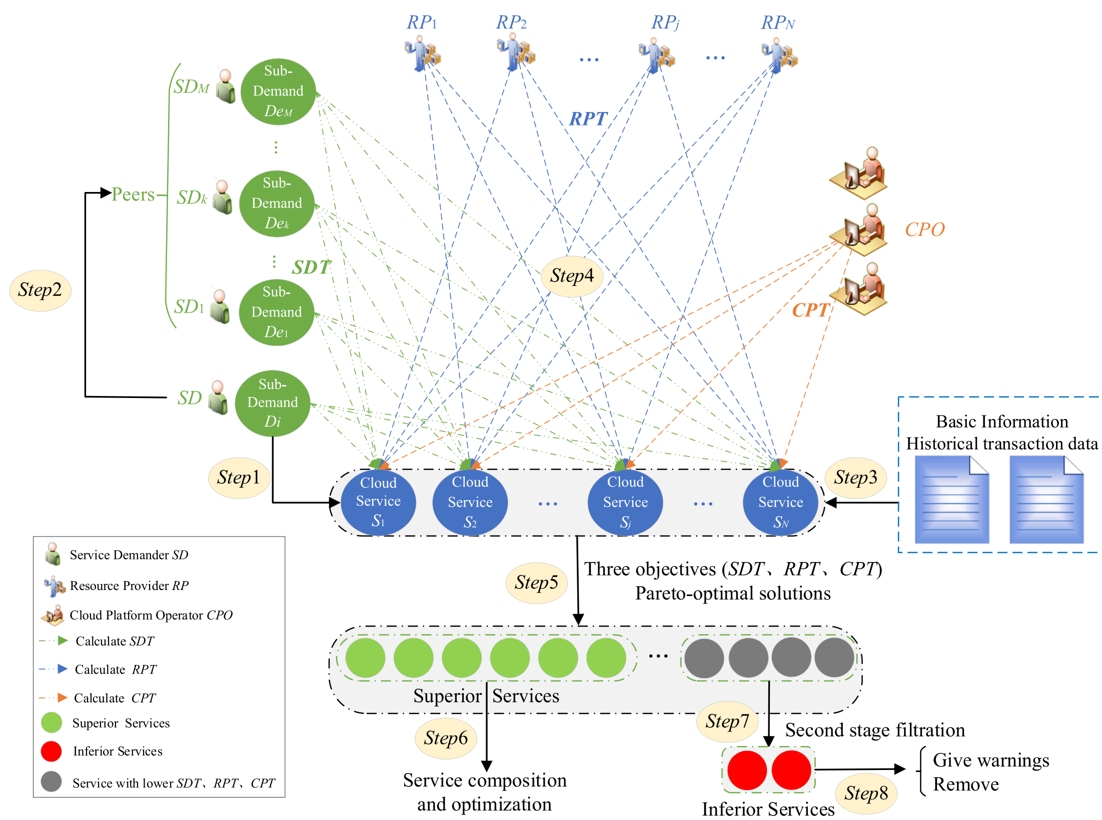


Fig. 2. Steps for cloud service trust evaluation and preprocessing.

Table 2
Trust indicators.

User categories	Hard manufacturing services	Soft manufacturing services
Service demanders	Service response rate $R_{SR} = N_R/N_{RB}$	
	Service cooperation rate $R_{SC} = N_T/N_R$	
	Service success rate $R_{SS} = N_S/N_T$	
	Service delivery timeliness $T_{SD} = N_{SD}/N_T$	-
	Service reliability $R_{S_{hard}} = (t_S - t_{SF})/t_S$	Service reliability $R_{S_{soft}} = (N_U - N_f)/N_U$
Resource providers	Service cost deviation $D_C = \lvert C_{VP} - C_A\rvert/C_A$	
	Service quality deviation $D_Q = \lvert Q_{VP} - Q_A\rvert/Q_A$	
	Service time deviation $D_T = \lvert T_{VP} - T_A\rvert/T_A$	-
	Service energy consumption deviation $D_E = \lvert E_{VP} - E_A\rvert/E_A$	-
Cloud platform operators	Service recent activeness $A_R = arctan(N_C - \theta)/\pi$	
	Service order fuzzy evaluation $E_{OF} = \sum_{p=1}^{N_C} E_{pof}/N_C$	

services, material services, and computing services) and soft manufacturing services (e.g., software services, model services, knowledge services, and data services). Among them, the two types of manufacturing services have different characteristics (Xu, 2012). Therefore, different trust indicators for hard manufacturing services and soft manufacturing services are proposed, and they are summarized in Table 2.

3.3.1. Trust indicators of service demanders

From the perspective of service demanders, the trust of a cloud service consists of two aspects: (1) the direct service trust evaluation made by the service demander based on their own direct experience (*SDTD*); and (2) the recommended service trust evaluation based on the experience of peers (*SDTR*). The combination of *SDTD* and *SDTR* can make a more comprehensive evaluation of cloud services from the demand side (Yan et al., 2016).

For the measurement of trust of service demanders (*SDT*), the first step is to check whether service demanders have historical service transaction data with the cloud service. Then, let *SDT* be zero if there is no historical transaction data; otherwise, *SDT* can be measured by historical data from service demanders when historical transaction data is available. For hard manufacturing services, *SDT* consists of five aspects: service response rate R_{SR}, service cooperation rate R_{SC}, service success rate R_{SS}, service delivery timeliness T_{SD}, and service reliability $R_{S_{hard}}$. For soft manufacturing services, *SDT* consists of four aspects: service response rate R_{SR}, service cooperation rate R_{SC}, service success rate R_{SS}, and service reliability $R_{S_{soft}}$.

(1) Service response rate R_{SR}

$$R_{SR} = \frac{N_R}{N_{RB}} \tag{1}$$

where R_{SR} represents the willingness of cloud services to participate in cooperation, N_{RB} is the number of requests sent to the cloud service by the service demander, N_R is the number of times the cloud service responds to these requests, and R_{SR} is applicable to both hard and soft manufacturing services.

(2) Service cooperation rate R_{SC}

$$R_{SC} = \frac{N_T}{N_R} \tag{2}$$

where R_{SC} reflects the probability that the service demander prefers the cloud service, N_T is the number of times that the service demander buys the cloud service, and R_{SC} is applicable to both hard and soft manufacturing services.

(3) Service success rate R_{SS}

$$R_{SS} = \frac{N_S}{N_T} \tag{3}$$

where R_{SS} represents the likelihood of success of the cloud service, N_S is the number of times the service demander successfully used the cloud service (without returns), and R_{SS} is applicable to both hard and soft manufacturing services.

(4) Service delivery timeliness T_{SD}

$$T_{SD} = \frac{N_{SD}}{N_T} \tag{4}$$

where T_{SD} represents the probability that the cloud service can complete the manufacturing task on time, and N_{SD} is the number of times that the provider delivers the service on time within the specified delivery period, noted that T_{SD} is only applicable to hard manufacturing services because soft manufacturing services do not have manufacturing time.

(5) Service reliability R_S

For hard manufacturing services, service reliability $R_{S_{hard}}$ is measured by the probability that hard manufacturing services work normally. The failure of equipment services and computing services, and the expiration of material resources are examples of abnormal working conditions for hard manufacturing services. The service reliability of hard manufacturing services can be formulated as:

$$R_{S_{hard}} = \frac{t_S - t_{SF}}{t_S} \tag{5}$$

where $R_{S_{hard}}$ is the service reliability of hard manufacturing services, t_S is the total service time of the cloud service, and t_{SF} is the service expiration time.

For soft manufacturing services, service reliability $R_{S_{soft}}$ is measured by the probability that the soft manufacturing services are used without problems. Problems with the use of soft manufacturing services may include software incompatibility, software upgrade failure, and model, knowledge, or data services that are out of date. The service reliability of soft manufacturing services can be formulated as:

$$R_{S_{soft}} = \frac{N_U - N_f}{N_U} \tag{6}$$

where $R_{S_{soft}}$ is the service reliability of soft manufacturing services, N_U is the total number of times that the soft manufacturing service is used, and N_f is the number of times problems occurred while using the service.

3.3.2. Trust indicators of resource providers

To evaluate the trust of resource providers, QoS attributes (cost, time and quality) and energy consumption of this service are compared to other similar cloud services in the CMfg platform. Such comparisons help filter out false and invalid cloud services. For hard manufacturing services, trust of resource providers (*RPT*) consists of four aspects: service cost deviation D_C, service time deviation D_T, service quality deviation D_Q, and service energy consumption deviation D_E. For soft manufacturing services, they have no manufacturing time and negligible service energy consumption (Yang et al., 2019b), so *RPT* of soft manufacturing services only consists of D_C and D_Q.

(1) Service cost deviation D_C

$$D_C = \frac{|C_{VP} - C_A|}{C_A} \tag{7}$$

where D_C reflects the cost control level of the cloud service, C_{VP} is the cost of the cloud service, and C_A is the average cost of similar cloud services in the CMfg platform.

(2) Service time deviation D_T

$$D_T = \frac{|T_{VP} - T_A|}{T_A} \tag{8}$$

where D_T reflects the time control level of the cloud service, T_{VP} is the time of the cloud service, and T_A is the average time of similar cloud services in the CMfg platform.

(3) Service quality deviation D_Q

$$D_Q = \frac{|Q_{VP} - Q_A|}{Q_A} \tag{9}$$

where D_Q represents the quality control level of the cloud service, Q_{VP} is the quality of the cloud service, and Q_A is the average quality of similar cloud services in the CMfg platform.

(4) Service energy consumption deviation D_E

$$D_E = \frac{|E_{VP} - E_A|}{E_A} \tag{10}$$

where D_E represents the energy consumption control level of the cloud service, E_{VP} is the service energy consumption of the cloud service, and E_A is the average energy consumption of similar cloud services in the CMfg platform.

3.3.3. Trust indicators of cloud platform operators

To evaluate the trust of cloud platform operators, recent transaction records and user evaluations of the cloud service in the CMfg platform are used. To be more precise, trust of cloud platform operators (*CPT*) consists of service recent activeness A_R and service order fuzzy evaluation E_{OF}. A_R and E_{OF} are applicable to both hard and soft manufacturing services.

(1) Service recent activeness A_R

$$A_R = \frac{arctan(N_C - \theta)}{\pi} \tag{11}$$

where A_R indicates the frequency of the cloud service has interacted with other users recently, N_C is the number of times the cloud service has been used recently in the CMfg platform, π is a constant number, and θ is the correction coefficient (positive integer). Noted that, θ has a modulating effect, i.e., when the number of evaluations is less than θ, the evaluation times factor value increases slowly; otherwise, when the number of evaluations is greater than θ, the evaluation times factor value increases quickly, eventually approaching one.

(2) Service order fuzzy evaluation E_{OF}

$$E_{OF} = \frac{\sum_{p=1}^{N_C} E_{pof}}{N_C} \tag{12}$$

where E_{OF} reflects the evaluations of user recently of the cloud service in the CMfg platform, and E_{of} is the evaluation score of the cloud service after each transaction. Among them, E_{of} is determined by evaluation grade E_{rank}, and the evaluation results "Excellent", "Good", "Medium", "Qualified", and "Poor" of E_{rank} correspond to "1", "0.8", "0.6", "0.4", and "0.2" of E_{of}, respectively (Hu et al., 2021, Chu and Varma, 2012).

3.4. Multi-objective mathematical model

Based on the proposed trust evaluation indicators in Section 3.3, a three-objective trust evaluation and preprocessing model is developed.

3.4.1. Measurement of user trust

(1) Trust of service demanders

Each trust evaluation indicator has different measurement criteria and units, so the evaluation value of each indicator needs to be normalized to a value and located in $[0,1]$ before the overall trust value is calculated (Liu and Zhang, 2017). As described in Section 3.3.1, *SDT* consists of *SDTD* and *SDTR*, and the formula for calculating *SDT* is

$$SDT = w_{SDTD}SDTD + w_{SDTR}SDTR \tag{13}$$

where w_{SDTD} and w_{SDTR} are the weights corresponding to the trust of service demanders themselves and their peers (w_{SDTD}, $w_{SDTR} \in [0,1]$, $w_{SDTD} + w_{SDTR} = 1$).

1) Calculation of *SDTD*

For hard manufacturing services, record the normalized service demander trust evaluation indicators ($R_{SR}, R_{SC}, R_{SS}, T_{SD}, R_{S_{hard}}$) as $B = \{B_1, B_2, B_3, B_4, B_5\}$. For soft manufacturing services, record the normalized service demander trust evaluation indicators (R_{SR}, R_{SC}, R_{SS}, $R_{S_{soft}}$) as $B = \{B_1, B_2, B_3, B_4\}$. The formulas for calculating *SDTD* are

$$SDTD_{hard} = \sum_{l=1}^{5} w_{lSDTD_{hard}} B_l \tag{14}$$

$$SDTD_{soft} = \sum_{l=1}^{4} w_{lSDTD_{soft}} B_l \tag{15}$$

where $w_{lSDTD_{hard}}$ and $w_{lSDTD_{soft}}$ are the weights of *SDTD* indicators for hard and soft manufacturing service, in which $0 \le w_{lSDTD_{hard}} \le 1$, $0 \le w_{lSDTD_{soft}} \le 1$, $\sum_{l=1}^{5} w_{lSDTD_{hard}} = 1$, $\sum_{l=1}^{4} w_{lSDTD_{soft}} = 1$, and the values of the weights are obtained by the AHP method (Saaty, 1990, Dey et al., 2017).

2) Calculation of *SDTR*

The trust of service demander peers is the recommendation trust, and the recommendation trust depends on the similarity of the trust preferences between service demander and peers. The similarity between service demanders can be calculated by the Euclidean method (Chaves et al., 2018, Yang et al., 2019a):

$$Sim(J,K) = \sqrt{\sum (SDTD_J - SDTD_K)^2} \tag{16}$$

where $SDTD_J$ and $SDTD_K$ represent the direct trust of service demander SD_K and service demander SD_J. Meanwhile, the threshold parameter $\tau (0 < \tau < 1)$ is set to select reliable peers. If $Sim(J,K) \ge \tau$, service demander SD_K can be regarded as the peer of service demander SD_J; otherwise, service demander SD_K cannot be regarded as the peer of service demander SD_J. The calculation formula of recommendation credibility is described as:

$$CR_{J,K} = \frac{1}{1 + Sim(J,K)} \tag{17}$$

Therefore, *SDTR* can be calculated as:

$$SDTR = \frac{\sum_{k=1}^{NF} CR_{J,K} SDTD_K}{\sum_{k=1}^{NF} CR_{J,K}} \tag{18}$$

where *NF* is the number of peers of service demander SD_J.

(2) Trust of resource providers

For hard manufacturing services, record the normalized resource provider trust evaluation indicators (D_C, D_T, D_Q, D_E) as $P = \{P_1, P_2, P_3, P_4\}$. For soft manufacturing services, record the normalized resource provider trust evaluation indicators (D_C, D_Q) as $P = \{P_1, P_2\}$.

Therefore, *RPT* can be calculated as:

$$RPT = \begin{cases} \sum_{m=1}^{4} w_{mRPT_{hard}} P_m, & forRPT_{hard} \\ \sum_{m=1}^{2} w_{mRPT_{soft}} P_m, & forRPT_{soft} \end{cases} \tag{19}$$

where $w_{mRPT_{hard}}$ and $w_{mRPT_{soft}}$ are the weights of *RPT* indicators for hard and soft manufacturing service, in which $0 \le w_{mRPT_{hard}} \le 1$, $0 \le w_{mRPT_{soft}} \le 1$, $\sum_{m=1}^{4} w_{mRPT_{hard}} = 1$, $\sum_{m=1}^{2} w_{mRPT_{soft}} = 1$, and the values of the weights are obtained by AHP method.

(3) Trust of cloud platform operators

For both hard and soft manufacturing services, record the normalized cloud platform trust evaluation indicators (A_R,E_{OF}) as $C = \{C_1, C_2\}$. The historical evaluation indicator matrix of the cloud service on the CMfg platform is

$$C = \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \\ \vdots & \vdots \\ C_{p1} & C_{p1} \\ \vdots & \vdots \\ C_{N_c1} & C_{N_c2} \end{bmatrix} \tag{20}$$

where N_c is the number of times the cloud service is transacted recently in the CMfg platform. The trust formula for the *p*-th transaction of the cloud service is

$$T_p = \sum_{n=1}^{2} w_{nCPT} C_n \tag{21}$$

where w_{nCPT} corresponding to the weights of *CPT* indicators, in which $0 \le w_{nCPT} \le 1$, $\sum_{n=1}^{2} w_{nCPT} = 1$, and the value of the weights is obtained by the AHP method.

Accordingly, *CPT* can be calculated as:

$$CPT = \frac{\sum_{p=1}^{N_c} T_p}{N_c} \tag{22}$$

3.4.2. Establishment of MSTEP-DPO

Based on the measurement of user trust in Section 3.4.1, a three-objective mathematical model is developed based on the trust of service demanders, resource providers, and cloud platform operators:

(1) Objectives for superior services

Objective1:

$$\max SDT = \max(w_{SDTD} SDTD + w_{SDTR} SDTR) \tag{23}$$

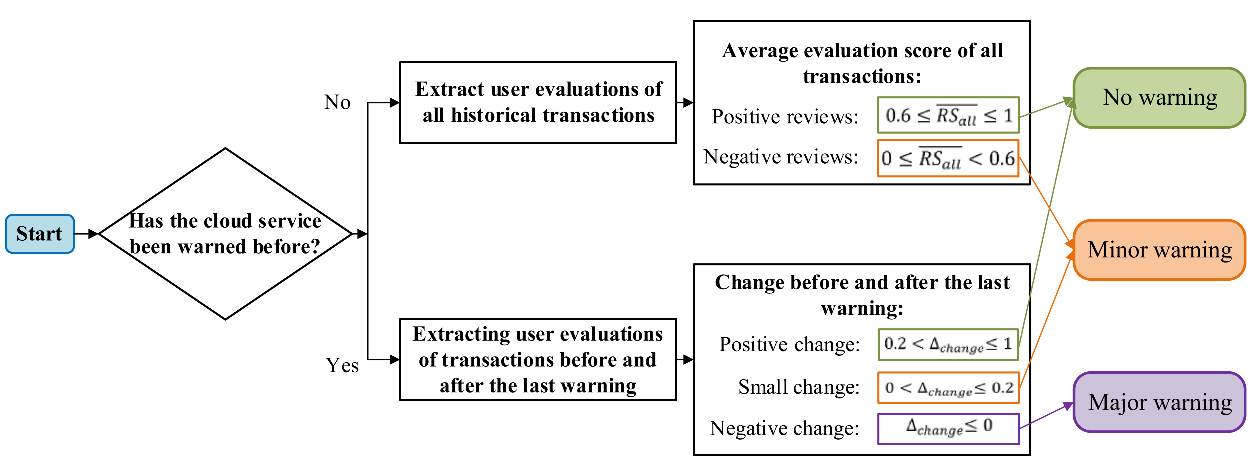


Fig. 3. Second stage filtration of inferior services.

Objective2:

$$\max RPT = \max\begin{cases}\sum_{m=1}^{4} w_{mRPT_{hard}} P_m, & for RPT_{hard}\\ \sum_{m=1}^{2} w_{mRPT_{soft}} P_m, & for RPT_{soft}\end{cases} \tag{24}$$

Objective3:

$$\max CPT = \max \frac{\sum_{p=1}^{N_c} T_p}{N_c} \tag{25}$$

(2) Objectives for inferior services
1) First stage filtration
Objective1:

$$\min SDT = \min(w_{SDTD} SDTD + w_{SDTR} SDTR) \tag{26}$$

Objective2:

$$\min RPT = \min\begin{cases}\sum_{m=1}^{4} w_{mRPT_{hard}} P_m, & for RPT_{hard}\\ \sum_{m=1}^{2} w_{mRPT_{soft}} P_m, & for RPT_{soft}\end{cases} \tag{27}$$

Objective3:

$$\min CPT = \min \frac{\sum_{p=1}^{N_c} T_p}{N_c} \tag{28}$$

2) Second stage filtration

After the first stage filtration, services with low trust values are gained. However, the reason for the low trust may be the high professionalism or the limited scope of adaptation of the service, but this is not sufficient to determine that a service is inferior. Therefore, in order to further judge whether these services are inferior or not, the second stage filtration based on historical warning data and user evaluations is proposed. The second stage filtration process of inferior services is designed as shown in Fig. 3, and the detailed steps are explained as follows:

Step1: For services with low trust values after the first stage filtration, check whether they have been warned before or not;

Step2: If a service has not been warned before, extract user evaluations from all historical transactions of this service. The average evaluation score $\overline{RS_{all}}$ of this service is calculated as:

$$\overline{RS_{all}} = \frac{\sum_{p=1}^{N_{all}} E_{pof}}{N_{all}} \tag{29}$$

where N_{all} is the total number of historical transactions, and E_{of} is the evaluation score of the cloud service after each transaction (similar to Eq. (12)). If $0.6 \le \overline{RS_{all}} \le 1$, it means that the user evaluations of the cloud service are positive, so the cloud service will not be warned. If $0 \le \overline{RS_{all}} < 0.6$, the user evaluations of the cloud service are negative, so the cloud service will receive a minor warning;

Step3: If a service has been warned before, extract user evaluations of transactions before and after the last warning of this service. The evaluation score changes Δ_{change} of this service can be calculated as:

$$\Delta_{change} = \overline{RS_{after}} - \overline{RS_{before}} = \frac{\sum_{p=1}^{N_{after}} E_{pof}}{N_{after}} - \frac{\sum_{p=1}^{N_{before}} E_{pof}}{N_{before}} \tag{30}$$

where $\overline{RS_{after}}$ and $\overline{RS_{before}}$ represent the average evaluation scores of the cloud service after and before the last warning, in which N_{after} is the total number of transactions after the last warning, and N_{before} is the total number of transactions between the last warning and the penultimate warning. If $\Delta_{change} \le 0$, it means that the user evaluations have not gotten better or even worse since the last warning, so the cloud service will receive a major warning. If $0 < \Delta_{change} \le 0.2$, it means that the user evaluations have changed less since the last warning, so the cloud service will receive a minor warning. If $0.2 < \Delta_{change} \le 1$, it means the user evaluations have changed better since the last warning, so the cloud service will not be warned.

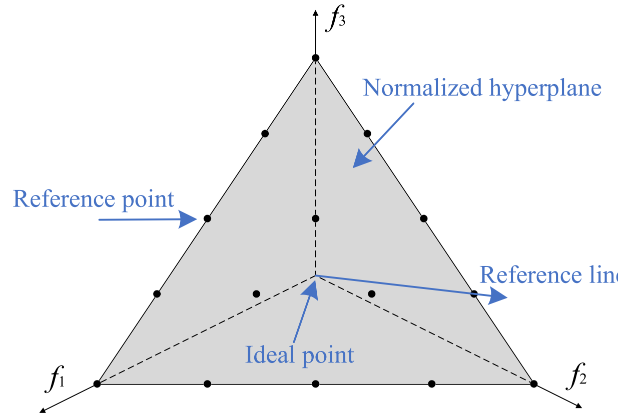


Fig. 4. Example of reference points construction.

If a cloud service receives three consecutive major warnings, it may be recommended for removal from the CMfg platform. If a cloud service receives three consecutive minor warnings, it may receive a major warning from the CMfg platform.

4. Proposed algorithm: IMO-NSGA-III

The MSTEP-DPO model includes three objectives, which belong to a multi-objective optimization problem (MOP). Intelligent optimization algorithms, such as multi-objective particle swarm optimization (MOPSO) (Coello et al., 2002), non-dominated sorting genetic algorithm II (NSGA-II) (Deb et al., 2002), and non-dominated sorting genetic algorithm III (NSGA-III) (Deb and Jain, 2014), can be employed as candidate to deal with the concerned problem. Among them, NSGA-III is widely used for solving high-dimensional optimization problems since it has an ability to maintain good diversity when solving MOPs with three or more objectives (Zhang et al., 2019, Ruan et al., 2019, Yuan et al., 2015, Rubaiee and Yildirim, 2019). According to the characteristics of the research problem, this study improves the standard NSGA-III and designs a novel algorithm, named the IMO-NSGA-III algorithm.

4.1. Generation of reference points

The NSGA-III algorithm uses the approach of constructing weights by boundary intersection to generate reference points on a normalized hyperplane (Das and Dennis, 1998). For M objectives and p dimensions, H reference points can be obtained, $H = \binom{M+p-1}{p}$. Fig. 4 is a schematic diagram of generating 15 reference points as an example. The objective number $M = 3$ and the dimensional number $p = 4$, thus $H = \binom{3+4-1}{4} = C_6^4 = 15$.

4.2. Dynamic encoding and initialization strategy

The algorithm selects individuals in the solution space randomly, it is still possible to miss some individuals (cloud services) in numerous iterations due to the large number of services in the CMfg platform. To avoid this situation, this study proposes a pre-optimization strategy in the initialization phase. As shown in Fig. 5, the specific operation of the pre-optimization strategy is as follows: (1) randomly select X individuals from the search space; (2) pre-optimization X individuals and get the individual (cloud service) with the best or worst trust; (3) put this individual into the initial population; and (4) repeat (1)-(3) until the initial population is N. Based on this, the quality of the initial solution will be improved and the global search capability of the algorithm will be enhanced.

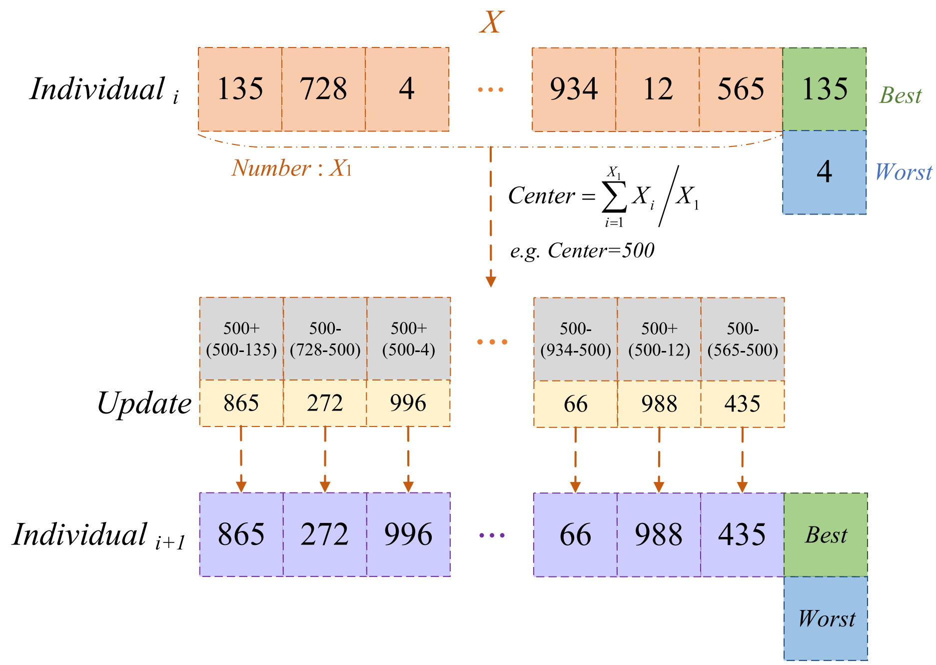


Fig. 5. Dynamic coding and symmetric updating mechanism.

Based on the pre-optimization strategy, this study proposes a dynamic coding method, denoted as $Individual = [X, Best]$ or $Individual = [X, Worst]$, where X represents the numbers of randomly selected X_1 solutions (cloud services), *Best* represents the number of the best cloud service after pre-optimization, and *Worst* represents the number of the worst cloud service after pre-optimization.

Taking the $Individual_i$ in Fig. 5 as an example, X is a randomly generated number vector $[135, 728, 4, \cdots, 934, 12, 565]$ of X_1 cloud services (bits 1 to X_1 of the $Individual_i$ code). The number vector of the best cloud service ($Best = [135]$) or the worst cloud service ($Worst = [4]$) is obtained through the non-dominated sorting of fitness values (the last bit of the $Individual_i$ code).

4.3. Individual update strategy

The standard NSGA-III generates offspring population by selection, crossover, and mutation operators. Due to the dynamic coding method of the proposed algorithm, the fitness values are constant after the crossover operation. Therefore, in order to enhance the global search capability of the algorithm, this study proposes an effective symmetric update strategy.

To avoid limitations in the range of cloud services selected, the distribution of X_1 cloud services across all cloud services should be maximized for each random selection of X_1 cloud services. By setting a central value [i.e., $Center = round(n/2)$], the number value of the original cloud service is symmetrically transferred to the other side of the central value. As shown in Fig. 5, assume $Center = 500$, the updated individual code is $X = [865, 272, 996, \cdots, 66, 988, 435]$. After that, the number of the best or worst cloud service can be obtained through the non-dominated sorting.

In addition, IMO-NSGA-III introduces a random perturbation strategy to avoid the algorithm falling into local optimum in the late iteration. Namely, randomly select P (determined by the random disturbance rate P_r) individuals as disturbance particles from the feasible solution set that was not selected in the early stage of the algorithm iteration. Meanwhile, this operation is used to check whether there is a better solution, so as to achieving the global development impact.

4.4. Dual fitness strategy

The model in this study needs to be solved for both superior cloud services and inferior cloud services, which have different fitness. For the problem of solving superior cloud services, the trust evaluation values of users need to be maximum and the fitness value mapped to $[1/z_1 \quad 1/z_2 \quad 1/z_3]$. For the problem of solving inferior cloud services, the trust evaluation values of users need to be minimum and the fitness value mapped to $[z_1 \quad z_2 \quad z_3]$, where z_1, z_2 and z_3 are the comprehensive trust values of service demanders, resource providers, and cloud platform operators, respectively. The Pareto-optimal solutions with the smaller fitness value are selected at each iteration and put into the next generation. Finally, the Pareto-optimal solutions are obtained after several iterations.

4.5. Niche-preservation operation

To associate individuals with reference points more easily, the multi-objective values must be adaptively normalized first, and then the specific operations are formulated as:

Compute ideal point:$z^{min} = (z_1^{min}, z_2^{min}, \cdots, z_M^{min})$

Translate objectives: $f_i'(x) = f_i(x) - z_i^{min}$, $i = 1, 2, \cdots, M$

Compute extreme points:$\min ASF(x, w) = max_{i=1}^{M} f_i'(x)/w_i$

Normalize objectives:$f_i^n(x) = \frac{f_i'(x)}{a_i - z_i^{min}}$

The extreme point ($z^{i,max}$) in the i-th objective is identified by finding the solution ($x \in S_t$) that makes the corresponding achievement scalarizing function (ASF, formed with $f_i'(x)$ and a weight vector w_i close to the i-th objective) minimum. a_i is the intercept of the i-th objective.

After that, the vertical distance of each individual to the corresponding reference line is calculated. Based on this, the reference point whose reference line is closest to a population member is considered relevant to the population member. Finally, the Niche-preservation operation (Deb and Jain, 2014) is used to retain the population diversity and create an offspring population.

4.6. Framework of IMO-NSGA-III

As stated previously, through the introduction of improvement

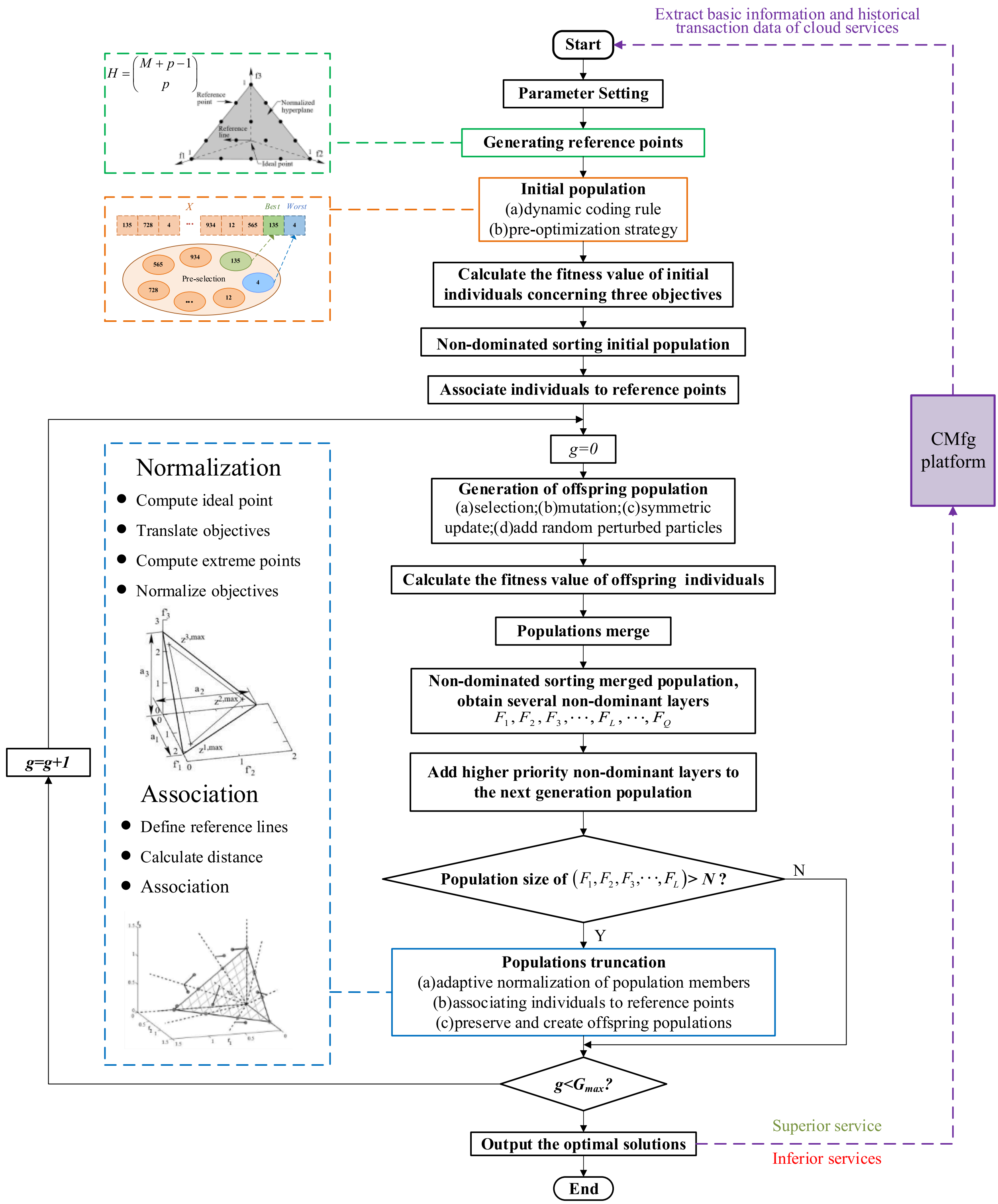


Fig. 6. Flowchart of IMO-NSGA-III.

strategies, this study designs an improved algorithm IMO-NSGA-III to address the trust evaluation and preprocessing model. The Pseudo-code is displayed in Algorithm 1. The flowchart of IMO-NSGA-III is displayed in Fig. 6, and the specific steps are as follows:

Step1: Extract basic information and historical transaction data for functionally similar cloud services from the CMfg platform;

Step2: Initialize algorithm parameters, including the total number of iterations G_{max}, population size N, objective number M, the number of pre-optimization feasible solutions X_1, the update rate P_c, the mutation rate P_m, the random disturbance rate P_r and other parameters;

Step3: Calculate the number of reference points H based on the objective number M and the dimension number p. Generate a uniformly distributed reference point set Z_r;

Step4: Generate an initial population P_g with N individuals according to the proposed dynamic coding rule and pre-optimization strategy in Section 4.2;

Step5: Calculate the fitness values of each individual in P_g according to the "Dual fitness strategy";

Step6: Individuals in P_g with $Rank = 1$ are selected as the offspring population S_g. Symmetric update and mutation operations are performed to generate offspring populations C_g and M_g numbered at N_c and N_m, respectively. Generate an offspring population R_g with N_r randomly disturbed particles, and the fitness of individuals in each offspring population is calculated;

Step7: Populations S_g, C_g, M_g and R_g are merged to get a combined population T_g, and then the fitness values of each individual in T_g is calculated;

Step8: Sort the population T_g by the fast, nondominant sorting method and obtain several sorted layers $F_1, F_2, F_3, \cdots, F_L, \cdots, F_Q$;

Step9: Individuals in higher priority layers are added to the next generation until all individuals in the critical layer F_L are selected into the next generation. If the population size of the next generation is equal to N, execute **Step12**; otherwise, execute Step10;

Step10: Normalize the individuals in the first L layers;

Step11: Calculate the vertical distance between all individuals in the first L layers and the reference points. Find the reference point associated with each individual. An individual is considered to be associated with a reference point if its vertical distance from the reference point is the smallest. Calculate the niche of the j-th reference point, and select K individuals from the L-th layer to enter the next generation population (P_{g+1}) with the population size equal to N;

Step12: Let $g = g + 1$, repeat **Steps 7** to **11** until the termination is met, and the obtained *Pareto* front Q is the solutions of the MSTEP-DPO model.

Algorithm 1 Pseudo-code of IMO-NSGA-III

Inputs: Data of cloud services, algorithm parameters.
Outputs: The Pareto-optimal solutions.
1: Generate reference point set Z_r2: Initialize the population $P_g (g = 0)$
3: Calculate the fitness of all individuals in P_g
4: Fast, non-dominant sorting of all individuals in P_g
5: Associate individuals to reference points
6: **while** ($g <$ Max number of iterations) **do**
7: Select individuals in P_g with $Rank = 1$ to obtain population S_g
8: Generate offspring population C_g by symmetric update
9: Generate offspring population M_g by mutation10: Generate offspring population R_g by adding perturbed individuals
11: Combine populations S_g, C_g, M_g and R_g to obtain T_g
12: Calculate the fitness of each individual in T_g
13: Fast, non-dominant sorting of population T_g and obtain several non-dominated layers $F_1, F_2, F_3, \cdots, F_L, \cdots, F_Q$14: **while** (the number of the next generation $< N$) **do**
15: Add F_i (from higher priority to lower priority) to the next generation16: **end while**
17: **if** (the number of $\{F_1, F_2, F_3, \cdots, F_L\} = N$)
18:$P_{g+1} = \{F_1, F_2, F_3, \cdots, F_L\}$19: **else if** (the number of $\{F_1, F_2, F_3, \cdots, F_L\}\rangle N$)20: Normalize individuals in $\{F_1, F_2, F_3, \cdots, F_L\}$21: Calculate vertical distances between all individuals and reference points22: Find the reference point associated with each individual23: Calculate the niche of the j-th reference point24: Select K individuals from F_L to the next generation $F_{L(K)}$25:$P_{g+1} = \{F_1, F_2, F_3, \cdots, F_{L(K)}\}$26: **end if**
27:$g = g + 1$
28: **end while**
29: Obtain the *Pareto* front Q
30: **end procedure**

5. Performance analysis of the IMO-NSGA-III algorithm

In this section, nine random instances are designed to verify the effectiveness of the proposed algorithm in solving the MSTEP-DPO model. More precisely, IMO-NSGA-III is compared with other common and advanced multi-objective intelligent optimization algorithms, which are: MOPSO, standard NSGA-II, and standard NSGA-III.

5.1. Experimental settings

There is presently no universal standard test set since the autonomy and diversity in the description and definition of manufacturing services across different CMfg platforms (Wang et al., 2021b, Wang et al., 2019). In this study, nine test instances (200 × 5, 200 × 10, 200 × 20, 500 × 5, 500 × 10, 500 × 20, 1000 × 5, 1000 × 10, and 1000 × 20) are autonomously designed for testing the proposed algorithm. Among them, the size of the problem consists of the numbers of cloud services and service demander peers, e.g., 200 × 5 means that there are 200 cloud services and 5 service demander peers. Since the optimization steps for solving superior cloud services and inferior cloud services are the same, only the fitness functions are different. Therefore, we use the evaluation of superior cloud services as an example for comparative analysis. Note that, the parameter setting is described in Table 3, and some parameters obey different ranges of uniform distribution. For example, U [0,1200] means that parameter t_S follows a uniform distribution between [0,1200].

Table 3
Parameter setting of the IMO-NSGA-III algorithm.

Description/Definition	Parameter	Value/ distribution
Number of cloud services	N_{CS}	200, 500, 1000
Number of demanders	N_{demand}	5, 10, 20
Number of requests sent to the cloud service by the service demander	N_{RB}	U [0,50]
Number of times the cloud service responds to these requests	N_R	U [0,50]
Number of times that the service demander buys the cloud service	N_T	U [0,50]
Number of times that the provider delivers the service in time	N_{SD}	U [0,50]
Number of times the service demander successfully used the cloud service	N_S	U [0,50]
Total service time of the cloud service	t_S	U [0,1200]
Service expiration time	t_{SF}	U [0,80]
Cost of the cloud service	C_{VP}	U [400,500]
Time of the cloud service	T_{VP}	U [18,30]
Quality of the cloud service	Q_{VP}	U [0.90,0.99]
Energy consumption of the cloud service	E_{VP}	U [20,40]
Number of times the cloud service has been used recently	N_C	U [0,50]
The correction coefficient	θ	20
Evaluation score of the cloud service after each transaction	E_{Rank}	1, 2, 3, 4, 5
Weight corresponding to the trust of service demanders themselves	w_{SDTR}	0.8
Weight corresponding to the trust of service demanders peers	w_{SDTD}	0.2

Note: $N_{RB} > N_R > N_T > N_{SD} > N_S$, $t_S > t_{SF}$

Additionally, all programs are coded and implemented in MATLAB R2016b and run on a 1.6 GHz Intel Core i5-8250U CPU with 16 GB of RAM and a 64-bit Windows 10 1909 operating system.

5.2. Performance metrics

To assess the solution performance of different algorithms, three evaluation metrics are employed, which are: (1) Generational distance (GD). GD is used to evaluate the convergence of the algorithm (Schutze et al., 2012). The smaller the GD value, implying the solved solutions are closer to the true *Pareto* front, and the algorithm has a better convergence. (2) Maximum spread (MS). MS is used to measure the diversity of the algorithm (Zitzler et al., 2000). The higher the MS value, implying superior extension performance of the solved solutions, and the algorithm has a better diversity. (3) Inverted generational distance (IGD). IGD is utilized to measure the comprehensive performance of the algorithm (Bosman and Thierens, 2003). The smaller the IGD value, implying superior comprehensive performance of the algorithm.

To obtain the true *Pareto* front, enumeration method is employed to find the non-dominated solutions of each scenario, and these non-dominated solutions are regarded as the true *Pareto* front of each instance.

Table 4
Parameters settings of four algorithms.

Parameters	MOPSO	NSGA-II	NSGA-III	IMO-NSGA-III
Population size n_{Pop}	100	100	100	100
Maximum number of iterations G_{max}	100	100	100	100
Variable size X_1	5	1	1	20
Reference point division size $n_{Division}$	-	-	10	10
Symmetrical update rate $P_{Crossover}$	-	0.5	0.5	0.5
Mutation percentage $P_{mutation}$	-	0.5	0.5	0.5
Mutation rate m_u	0.02	0.02	0.02	0.02
Inertia weight w	0.5	-	-	-
Intertia weight damping rate w_{damp}	0.99	-	-	-
Personal learning coefficient c_1	1	-	-	-
Global learning coefficient c_2	2	-	-	-
Number of grids per dimension n_{Grid}	7	-	-	-
Inflation rate α	0.1	-	-	-
Leader selection pressure β	2	-	-	-
Deletion selection pressure γ	2	-	-	-

5.3. Comparison with other intelligent algorithms

To provide a comprehensive and reliable comparison, the proposed IMO-NSGA-III algorithm is compared with MOPSO, NSGA-II, and NSGA-III. To ensure fair comparisons, the basic parameters of the other algorithms are kept consistent with IMO-NSGA-III, which are displayed in Table 4.

Meanwhile, due to the strong randomness of the four algorithms, this study uses Wilcoxon signed-rank test (Woolson, 2007) with a significance level of 0.05 to test the significance of these algorithms. The symbols '>', '<', and '≈' indicate the proposed IMO-NSGA-III performs much better than, much worse than, and similar to the comparison algorithms, respectively. Each experiment independently runs 50 times in all algorithms, and the statistical results (mean and standard deviation) of GD, MS, and IGD are shown in Table 5. For easy comparison, the best performance values for each experiment are bolded in the table, and the error bars of the GD, MS, and IGD are plotted in Fig. 7.

In terms of the convergence of the *Pareto* front, it can be seen from Fig. 7(a) that the red line is generally lower than the other three lines, which indicates that the mean of GD values for IMO-NSGA-III is smaller than those of other three algorithms. The same trend can be seen in Table 5, where IMO-NSGA-III has seven GD values with the smallest mean and eight GD values with the smallest standard deviation among the nine test instances. It is noteworthy that IMO-NSGA-III has both the smallest mean and standard deviation of GD value in Instances 4-9. The above results show that the convergence of IMO-NSGA-III is superior to the other three algorithms, and this trend is more pronounced for larger service numbers (i.e., middle- and large-scale problems). The reason behind this is that IMO-NSGA-III improves the initialization method of the population, and the optimal individuals are selected by pre-optimization generation strategy to improve the quality of the initial population. Based on this, the high-quality solutions become more and more superior as the iterations proceed, resulting in better convergence of the algorithm.

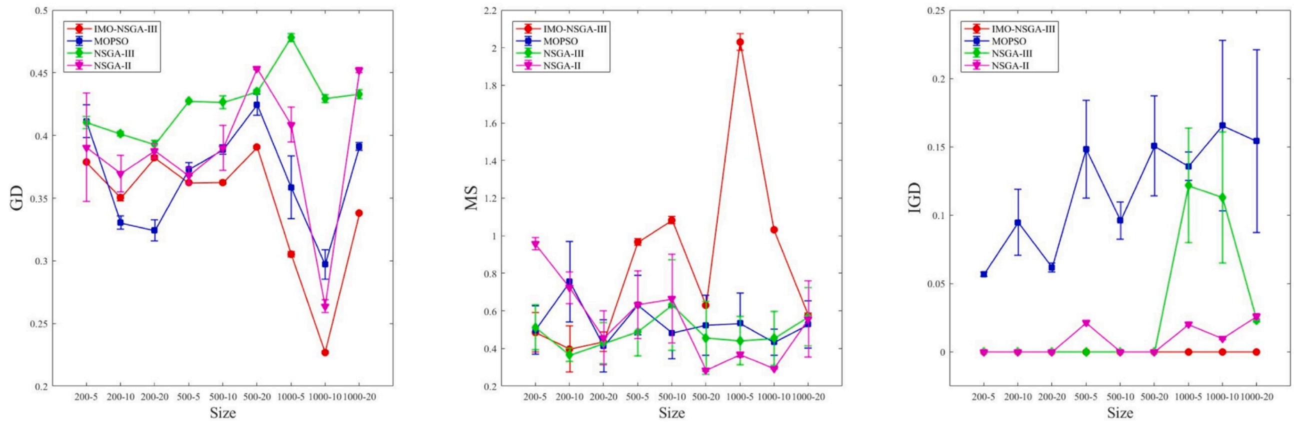
In terms of the diversity of the *Pareto* front, it can be seen from Table 5 that six out of the nine test instances of IMO-NSGA-III results have the largest MS means and the smallest MS standard deviation. The same trend can be seen from Fig. 7(b) that the MS mean and variance of IMO-NSGA-III are also superior. In addition, similar to the trend in GD values, the advantage of MS is more pronounced for larger numbers of services. That is to say, the diversity of IMO-NSGA-III is superior to the other three algorithms. The reason behind this is that IMO-NSGA-III improves the population update mechanism by adding a symmetric update strategy to give the algorithm a greater chance of traversing the feasible space, thus enhancing the global search capability of the algorithm and making it more versatile.

In terms of the comprehensive performance of the *Pareto* front, it can be seen from Table 5 and Fig. 7(c) that the IGD values obtained by the IMO-NSGA-III algorithm are zero for all nine test instances. IGD value equal to zero means that the optimal solution set obtained by the IMO-NSGA-III algorithm is part of the true *Pareto* front, namely, the optimal cloud services obtained by the IMO-NSGA-III algorithm belong to the optimal cloud services that is found by the enumeration method.

In summary, the numerical experimental results show that the IMO-

Table 5
GD, MS, and IGD values of four algorithms.

Problem sizes	Metrics	MOPSO (Mean/Std)	NSGA-II (Mean/Std)	NSGA-III (Mean/Std)	IMO-NSGA-III (Mean/Std)
200 × 5	GD	0.41135/0.114496194	0.39051/0.207531558	0.41033/0.069616266	**0.37868/0.023696967** (≈, ≈, ≈)
	MS	0.39742/0.358149168	**0.9575/0.180256126**	0.51197/0.345663845	0.48573/0.324338979 (>,<,≈)
	IGD	0.05682/0.041928532	**0/0**	**0/0**	**0/0** (>,≈, ≈)
200 × 10	GD	**0.33049**/0.072569039	0.36964/0.120716437	0.40129/**0.042873469**	0.35031/0.048826597 (<,≈, ≈)
	MS	0.55576/0.461980072	0.72359/0.289878861	**0.7668/0.189521309**	0.59749/0.349707466 (>,≈, <)
	IGD	0.09471/0.155644013	**0/0**	**0/0**	**0/0** (>,≈, ≈)
200 × 20	GD	**0.32424**/0.092496657	0.38779/0.076433943	0.3928/0.05655654	0.38233/**0.042583958** (<,≈, ≈)
	MS	0.31353/0.372264288	**0.45656**/0.378885545	0.32849/0.331876863	0.43567/**0.226033975** (>,≈, >)
	IGD	0.06177/0.056818249	**0/0**	**0/0**	**0/0** (>,≈, ≈)
500 × 5	GD	0.37295/0.072530105	0.36805/0.079463776	0.42753/0.02758051	**0.36234/0.023667568** (≈, ≈, >)
	MS	0.63175/0.398668393	0.63282/0.48872	0.423588831/0.355433838	**0.96586/0.133928963** (>,>,>)
	IGD	0.14825/0.188729114	0.02144/0.043281769	**0/0**	**0/0** (>,>,≈)
500 × 10	GD	0.38866/0.06161207	0.38999/0.133660827	0.42647/0.070806764	**0.36253/0.04044302** (≈, ≈, ≈)
	MS	0.48346/0.372224762	0.66465/0.486589714	0.63168/0.490840318	**1.08268/0.140399191** (>,>,>)
	IGD	0.09616/0.116846901	**0/0**	**0/0**	**0/0** (>,≈, ≈)
500 × 20	GD	0.42445/0.091685116	0.45333/0.033444132	0.43498/0.040096794	**0.39069/0.033419105** (≈, >,>)
	MS	0.52374/0.399574143	0.28472/0.080975234	0.45639/0.440342598	**0.6288/0.067820056** (>,>,>)
	IGD	0.15068/0.190907679	**0/0**	**0/0**	**0/0** (>,≈, ≈)
1000 × 5	GD	0.35856/0.158316471	0.4087/0.117430783	0.47819/0.055825869	**0.30533/0.045706188** (≈, >,>)
	MS	0.53413/0.402018482	0.36852/**0.115068065**	0.44155/0.359292293	**2.03078**/0.210326127 (>,>,>)
	IGD	0.13585/0.101373712	0.02029/0.03351744	0.12169/0.204651066	**0/0** (>,>,>)
1000 × 10	GD	0.39705/0.10768027	0.26377/0.070325119	0.42943/0.056603849	**0.22693/0.031507496** (>,≈, >)
	MS	0.43433/0.263808719	0.29327/0.063710195	0.45461/0.378803122	**1.03036/0.051279933** (>,>,>)
	IGD	0.16566/0.249611161	0.00987/0.028215679	0.11297/0.219090707	**0/0** (>,>,>)
1000 × 20	GD	0.39126/0.05561503	0.45214/0.045354412	0.4329/0.059797622	**0.33806/0.02422034** (>,>,>)
	MS	0.52901/0.353862354	0.55721/0.451174798	0.56876/0.392643435	**0.67389/0.116699276** (>,>,>)
	IGD	0.1542/0.258315032	0.02599/0.043004637	0.02311/0.03732278	**0/0** (>,>,>)



(a) GD (b) MS (c) IGD

Fig. 7. Error bars of GD, MS, and IGD value.

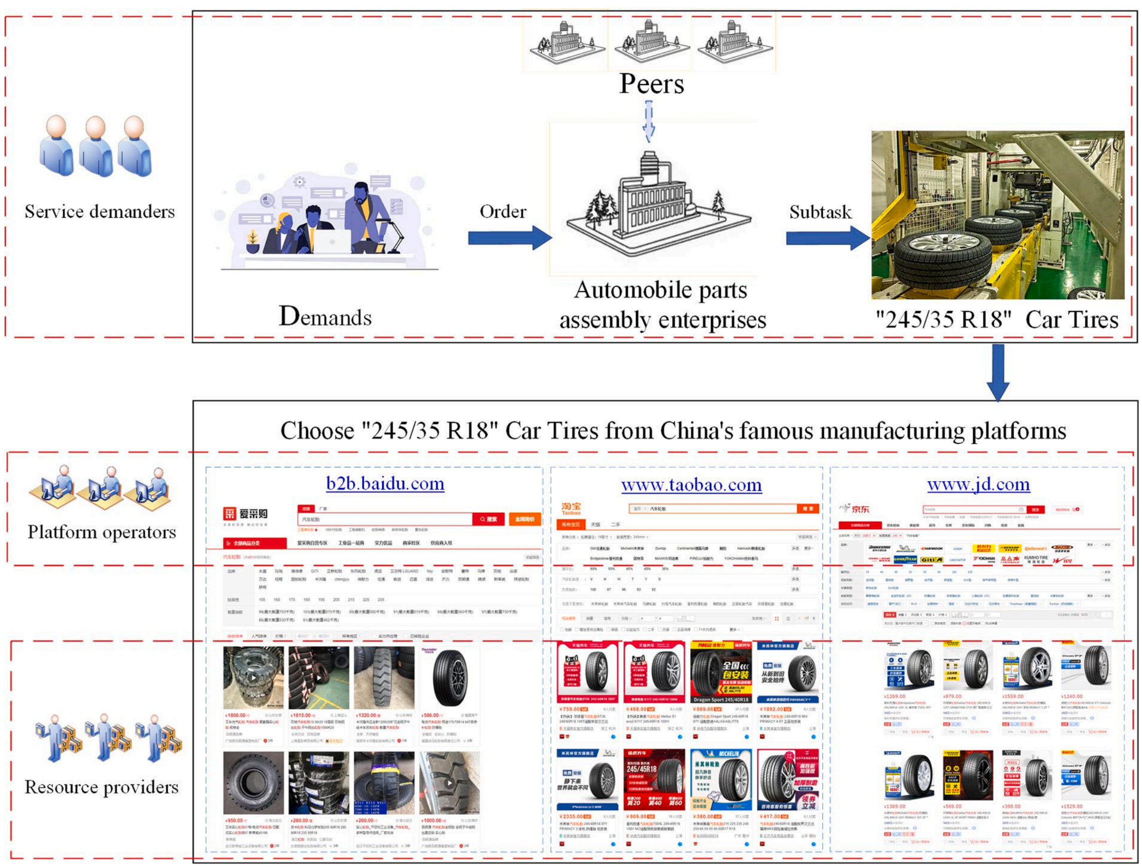


Fig. 8. Flowchart of case studies.

NSGA-III algorithm effectively solves the trust evaluation and pre-processing problem in CMfg. However, further testing of the approach in practical application cases is still required.

6. Applications in an automotive parts assembly company

In this section, three case studies that come from an automotive parts assembly company in Chongqing of China are employed, and then the effectiveness and superiority of the proposed MSTEP-DPO model and IMO-NSGA-III algorithm are demonstrated.

6.1. Description of the three case studies

In these application cases, the automotive parts assembly company receives a custom order, and this customer order can be split into many subtasks. For the subtask of configuring tires (medium-sized car tires with the specification of '245/35 R18'), it needs to be done through the outsourcing in the CMfg platform. Limited by the fact that there is no mature and large-scale open source CMfg platform, and the retrieval process of CMfg services is mainly based on relevant resources and service information. Therefore, the company needs to select medium-sized car tires from three reputable platforms of Chinese manufacturing industry (www.taobao.com, b2b.baidu.com, www.jd.

Table 6
Data information in case studies.

Symbol	Description	Data information in the platforms	Data source
N_{RB}	Number of inquiries sent to the cloud service by the service demander	Number of times the service demander (company or its peer) consulted the car tire	User behavior databases
N_R	Number of times the cloud service responds to these requests	Number of times the customer service of car tire responded to inquiries	User behavior databases
N_T	Number of times the service demander buys the cloud service	Number of times the service demander (company or its peer) purchased the car tire	User behavior databases
N_{SD}	Number of times the provider delivers the service in time	Number of times the service demander received the car tire in the expected time	User behavior databases
N_S	Number of times the service demander successfully used the cloud service	Number of times the service demander successfully used the car tire (without return)	User behavior databases
C_{VP}	Cost of the cloud service	Cost of the car tire	Product information databases
T_{VP}	Time of the cloud service	Average receipt time of the car tire over all historical transactions	Product information databases
Q_{VP}	Quality of the cloud service	Average evaluation score of the car tire over all historical transactions	Product information databases
N_C	Number of times the cloud service has been used recently	Number of times the car tire has been used within one year	Product information databases
E_{Rank}	Evaluation grade of the cloud service after each transaction	Evaluation grades ('excellent', 'good', 'medium', 'qualified', and 'poor') of the car tire for all historical transactions	Product information databases

com). In these application cases, the service demanders are corresponding to the automotive parts assembly company and users or enterprises that have the same product demand; the cloud platform operators are corresponding to the operators in each platform; and the resource providers are corresponding to the providers offering candidate tires. For easy understanding, the flowchart of case study is provided in Fig. 8.

In the company, Python 3.10.4 is used as the data crawling software to collect the service information. The scenarios in these application cases are the product information databases and the user behavior databases of the three platforms. The search parameters are car tires with a wheel diameter of 18 inches, a tread width of 245mm and a flat ratio of 35. The car tire belongs to the hard manufacturing service. The specific data information is described in Table 6.

Due to the lack of user feedback on the failure time t_{SF} of the car tire during use, the reliability $[R_S = (t_S - t_{SF})/t_S]$ of the car tire is set as a random value between [0, 1]. Energy consumption E_{VP} is calculated according to the tire pressure information of the car tire (Pearce and Hanlon, 2007, Alfieri et al., 2020). The obtained data are manually screened to remove duplicates and car tires with obvious misinformation, and the final number of services found from www.taobao.com, b2b.baidu.com, and www.jd.com is 336, 447, and 1212.

6.2. Computational results and analysis

To verify the effectiveness and superiority of the proposed model and algorithm, the analysis is conducted from three aspects: (1) verify the performance of IMO-NSGA-III; (2) verify the solution quality of MSTEP-DPO; and (3) compare MSTEP-DPO to single-objective models.

6.2.1. Verification of the performance of IMO-NSGA-III

Similar to Section 5, four algorithms (MOPSO, NSGA-II, NSGA-III, and IMO-NSGA-III) are used to solve the MSTEP-DPO model. Each platform case independently runs 50 times by the four algorithms, and the parameters are the same as the parameter settings in Section 5. The statistical results of GD, MS, and IGD are reported in Table 7 and Fig. 9. According to the case results, it can be observed that IMO-NSGA-III has smaller GD values, larger MS values, and smaller IGD values in all cases, which implies that IMO-NSGA-III has better convergence, diversity, and overall performance. The calculated results are in line with the analysis reported in Section 5.3.

6.2.2. Verification of the solution quality of MSTEP-DPO

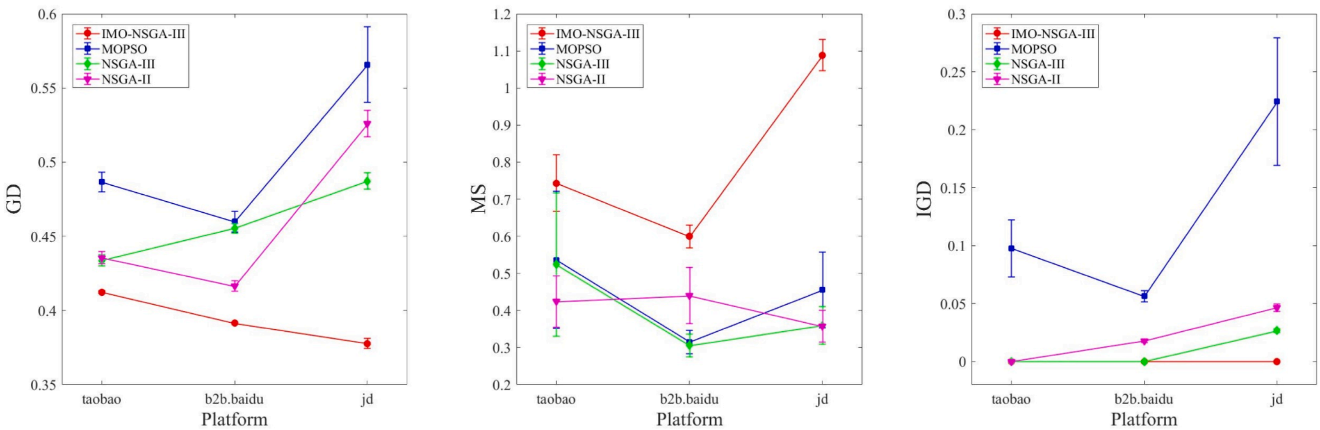
Fig. 10 shows the solutions of the superior tire cloud services and Fig. 11 shows the solutions of the inferior tire cloud services after first stage filtration in the three platforms. The light blue scatters in Fig. 10(a) and Fig. 11(a) represent all cloud services in each platform. The red scatters in Fig. 10(b)-(e) are the superior tire cloud services and the navy-blue scatters in Fig. 11(b)-(e) are the inferior tire cloud services after first stage filtration obtained by each of the four algorithms. In general, scatters with larger objective values are solved as superior services (red scatters), and scatters with smaller objective values and more dispersed distribution are solved as inferior services (navy-blue scatters). This indicates that the MSTEP-DPO model identifies superior and inferior services effectively.

It can be seen that the red scatters in Fig. 10(b)-(d) are more dispersed, while the red scatters in Fig. 10(e) are more concentrated. That is to say, the superior tire cloud services obtained by MOPSO, NSGA-II, and NSGA-III algorithms are more dispersed, while the superior tire cloud services obtained by IMO-NSGA-III algorithm is more concentrated. In addition, if a scatter has a small objective value on one coordinate, it means that the trust value for one type of user is low. The red scatters obtained by the IMO-NSGA-III algorithm are mostly concentrated in the larger range of the three coordinates, this means that the trust values of the obtained solutions are larger for all three types of users. Therefore, the superior tire cloud services obtained by IMO-NSGA-III have better trust of three types of CMfg users.

As can be seen from Fig. 11, IMO-NSGA-III can find more navy-blue scatters that are more distantly distributed by comparing with other three algorithms, indicating that the proposed algorithm can find the

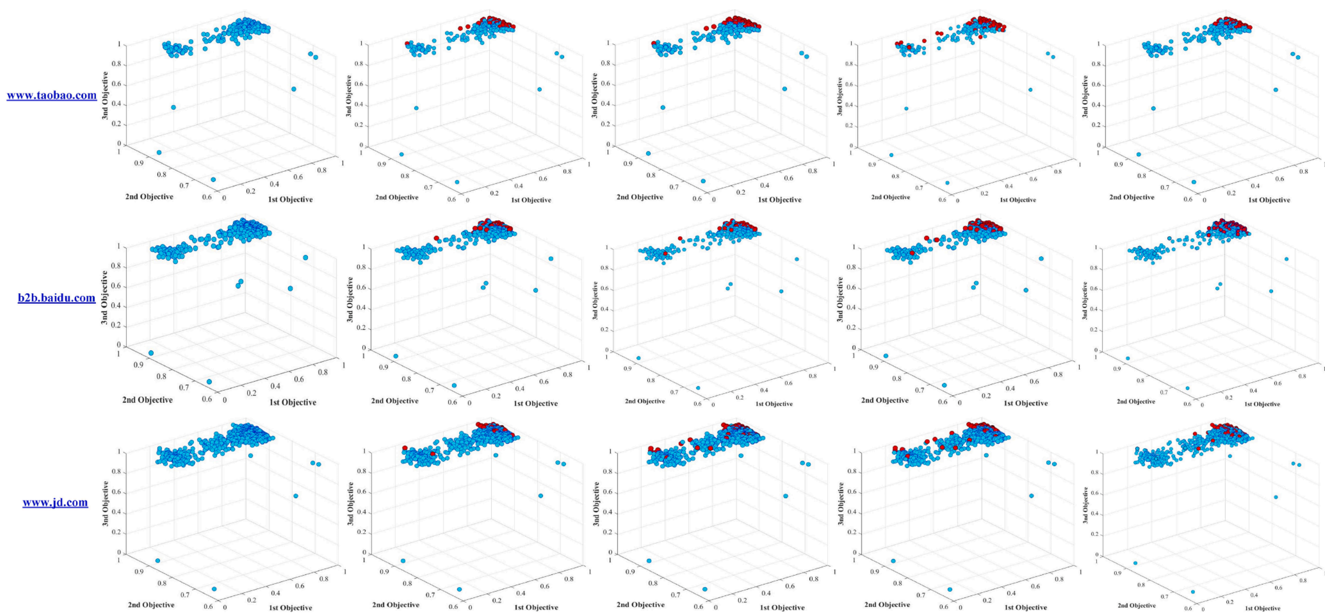
Table 7
GD, MS, and IGD values of case studies.

Platforms (Service number)	Metrics	MOPSO (Mean/Std)	NSGA-II (Mean/Std)	NSGA-III (Mean/Std)	IMO-NSGA-III (Mean/Std)
www.taobao.com(336)	GD	0.4867/0.081492863	0.43548/0.064165737	0.43368/0.061517582	**0.41241**/**0.027126226** (>,>,>)
	MS	0.53656/0.429969395	0.42397/**0.263213733**	0.5243/0.439582034	**0.74339**/0.275422542 (>,>,>)
	IGD	0.09759/0.157116754	**0/0**	**0/0**	**0/0** (>,≈, ≈)
b2b.baidu.com(447)	GD	0.45988/0.08278349	0.41648/0.059291517	0.45546/0.056710575	**0.39147**/**0.024917689** (>,>,>)
	MS	0.31512/0.17760125	0.44024/0.274374894	0.30563/0.17574723	**0.59977**/**0.174596755** (>,>,>)
	IGD	0.05633/0.06921087	0.01775/0.037701496	**0/0**	**0/0** (>,>,≈)
www.jd.com(1212)	GD	0.56571/0.159574117	0.52589/0.094172566	0.4873/0.073205783	**0.37768**/**0.058384107** (>,>,>)
	MS	0.45579/0.319751589	0.35762/0.207594251	0.35971/0.224906561	**1.08828**/**0.205198136** (>,>,>)
	IGD	0.22431/0.234711807	0.04658/0.056154189	0.02658/0.041955897	**0/0** (>,>,>)



(a)GD (b)MS (c)IGD

Fig. 9. Error bars of GD, MS, and IGD value in case studies.



(a) All (b) MOPSO (c) NSGA-II (d) NSGA-III (e) IMO-NSGA-III

Fig. 10. Scatters of the superior tire cloud services in the three platforms.

inferior cloud services more completely and accurately. To illustrate this more clearly, Fig. 12(a) shows the three-dimensional fitted surfaces for all cloud services in the three platforms and Fig. 12(b)-(e) show the three-dimensional fitted surfaces of the remaining cloud services after the inferior cloud services have been removed by the four algorithms. It is easy to see that the three-dimensional fitted surfaces obtained after excluding the inferior cloud services by IMO-NSGA-III algorithm are flatter (the remaining cloud services are more concentrated), indicating that the IMO-NSGA-III algorithm is more complete in finding the inferior cloud services.

Furthermore, to demonstrate the effectiveness of the second stage filtration, we take inferior tire cloud services after the first stage filtration on Taobao platform solved by IMO-NSGA-III algorithm as an example, and the eleven services after the second stage filtration are displayed in Table 8.

As can be seen in Table 8, seven out of eleven services have not received a warning before. The average evaluation scores of all historical transactions $\overline{RS_{all}}$ for these seven services are calculated, and it can be found that the $\overline{RS_{all}}$ values of Services 1, 8, 10 and 11 are greater than 0.6 and they will not receive a warning, while the $\overline{RS_{all}}$ values of Services 2, 5 and 7 are less than 0.6 and they will receive a minor warning. It is worth noting that the $\overline{RS_{all}}$ value of Service 7 is equal to 0, because it has no transaction records in the platform since its registration.

Four out of eleven services have received a warning before. The average evaluation scores of historical transactions after and before the last warning are calculated. For Services 4 and 6, the evaluation scores have improved significantly since the last warning, so no warnings will be received in this time. For Service 3, the evaluation scores have changed little since the last warning, so a minor warning will be received. For Service 9, the evaluation scores have gotten worse since the last warning, so a major warning will be received. Service 9 has been given 2 major warnings before and this service will be recommended to be removed from the platform in this time. Judging from the evaluation scores on the platform, it has more poor reviews and its $\overline{RS_{all}}$ is only 0.1346.

6.2.3. Comparison of multi-objective and single-objective models

To validate the effectiveness of the proposed multi-objective model,

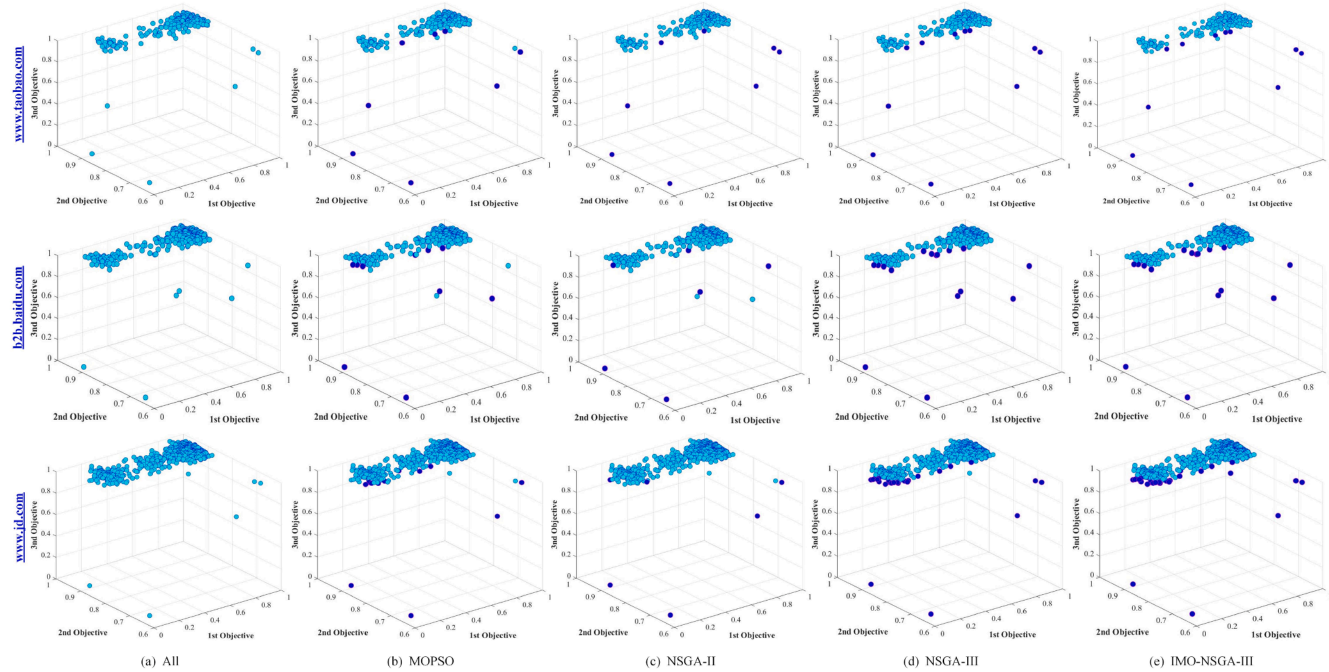


Fig. 11. Scatters of the inferior tire cloud services after first stage filtration in the three platforms.

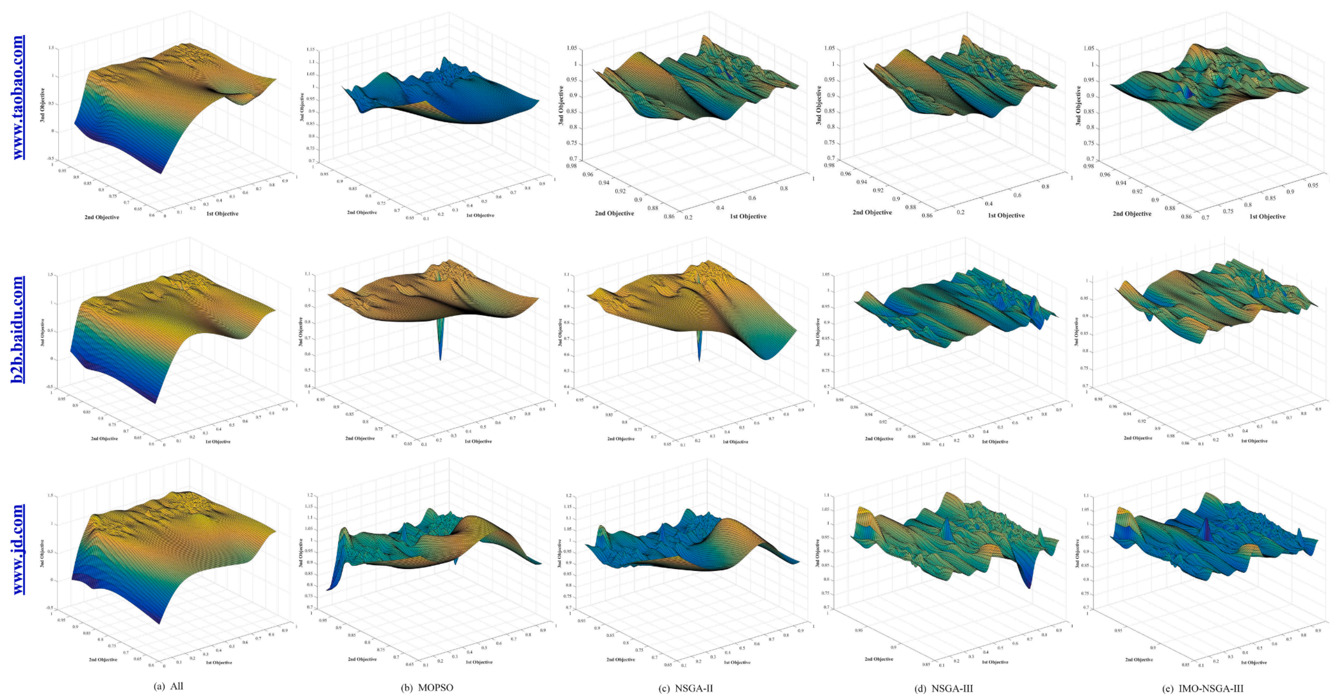


Fig. 12. Three-dimensional fitted surfaces of the remaining cloud services.

we compare it with single-objective models with different weights. More precisely, four preference-based weighting schemes are considered to avoid the interference of different weight values. Among them, w_1, w_2, and w_3 are the weights of trust of service demanders, resource providers, and cloud platform operators. The average statistical results of the trust value and repetition rate after 50 independent runs of each case are shown in Table 9. Noted that, the best values of the trust evaluation in each case are marked by the bold, and the "repetition rate" is defined as the overlap proportion between the cloud services obtained by the model (the number is X_1) and the top X_1 services on the platform based on page rank.

It can be seen that the comprehensive trust evaluation values of the superior cloud services obtained by the multi-objective model (MSTEP-DPO) in the three platforms are higher than that obtained by other single-objective models with preference. In the Baidu and JD platforms, the comprehensive trust evaluation values of the inferior cloud services obtained by the multi-objective model (MSTEP-DPO) are lower than that obtained by other single-objective models with preference, and results are not much different in Taobao platform. Moreover, it can be seen from the last column of Table 9 that the repetition rate of the MSTEP-

Table 8
Inferior tire cloud services after the second stage filtration.

Service	Been warned before?	$\overline{RS_{all}}$	$\overline{RS_{after}}$	$\overline{RS_{before}}$	Δ_{change}	Warning	Number of historical Major warnings
1	No	0.6000	-	-	-	No	0
2	No	0.4750	-	-	-	Minor	0
3	Yes	-	0.5067	0.3933	0.1134	Minor	0
4	Yes	-	0.8167	0.4469	0.3698	No	1
5	No	0.4182	-	-	-	Minor	0
6	Yes	-	0.7423	0.5034	0.2389	No	0
7	No	0.0000	-	-	-	Minor	0
8	No	0.6833	-	-	-	No	0
9	Yes	-	0.1275	0.1364	-0.0089	Major	2
10	No	0.6222	-	-	-	No	0
11	No	0.7714	-	-	-	No	0

Table 9
Results of for different models.

Platform (Service number)	Cloud service set	Model	Weights			Trust values				Repetition rate
			w_1	w_2	w_3	Service Demanders (SDT)	Resource Providers (RPT)	Cloud Platform (CPT)	Integrate	
www.taobao.com (336)	Optimal	Single-objective	0.3334	0.3333	0.3333	0.9605			0.9605	0.7345
			0.5000	0.2500	0.2500	0.9594			0.9594	0.5364
			0.2500	0.5000	0.2500	0.9618			0.9618	0.5412
			0.2500	0.2500	0.5000	**0.9632**			**0.9632**	0.6323
		MSTEP-DPO	-			**0.9606**	**0.9644**	**0.9645**	**0.9632**	**0.8645**
	Worst	Single-objective	0.3334	0.3333	0.3333	0.2569			0.2569	0.6428
			0.5000	0.2500	0.2500	**0.2179**			**0.2179**	0.7345
			0.2500	0.5000	0.2500	0.3601			0.3601	0.5345
			0.2500	0.2500	0.5000	0.3359			0.3359	0.6636
		MSTEP-DPO	-			0.1008	0.6699	0	0.2569	**0.7656**
b2b.baidu.com (447)	Optimal	Single-objective	0.3334	0.3333	0.3333	0.9644			0.9644	0.6435
			0.5000	0.2500	0.2500	0.9663			0.9663	0.5253
			0.2500	0.5000	0.2500	0.9643			0.9643	0.6698
			0.2500	0.2500	0.5000	0.9632			0.9632	0.5253
		MSTEP-DPO	-			**0.9733**	**0.9499**	**0.9766**	**0.9666**	**0.7434**
	Worst	Single-objective	0.3334	0.3333	0.3333	0.3309			0.3309	0.6791
			0.5000	0.2500	0.2500	0.2649			0.2649	0.4657
			0.2500	0.500	0.2500	0.3526			0.3526	0.5545
			0.2500	0.2500	0.5000	0.2462			0.2462	0.4566
		MSTEP-DPO	-			**0.0675**	**0.6715**	**0**	**0.2463**	**0.8325**
www.jd.com (1212)	Optimal	Single-objective	0.3334	0.3333	0.3333	0.9662			0.9662	0.5737
			0.5000	0.2500	0.2500	0.9664			0.9664	0.4579
			0.2500	0.500	0.2500	0.9683			0.9683	0.5326
			0.2500	0.2500	0.5000	0.9687			0.9687	0.4456
		MSTEP-DPO	-			**0.9786**	**0.9648**	**0.9632**	**0.9689**	**0.7456**
	Worst	Single-objective	0.3334	0.3333	0.3333	0.3379			0.3379	0.6563
			0.5000	0.2500	0.2500	0.2785			0.2785	0.5479
			0.2500	0.500	0.2500	0.3599			0.3599	0.6633
			0.2500	0.2500	0.5000	0.2926			0.2926	0.5563
		MSTEP-DPO	-			**0.1008**	**0.6695**	**0**	**0.2567**	**0.8456**

DPO model is generally higher than that of single-objective models, which proves that the trust evaluation results of the MSTEP-DPO model are closer to the real service situation in CMfg. In summary, the above comparison results are sufficient to show that the trust evaluation values derived using the MSTEP-DPO model are superior and better serve the interests of all users in the CMfg platform.

7. Conclusions and future works

In this study, the problem of trust evaluation and preprocessing of manufacturing services in CMfg environment is studied to ensure the quality of the CMfg service. More precisely, a comprehensive three-dimensional trust evaluation system is first constructed, which is more closely match the real situation of resources in CMfg. Then, a manufacturing service trust evaluation and preprocessing model based on the interests of service demanders, resource providers, and cloud platform operators (MSTEP-DPO) is constructed to identify the superior and inferior manufacturing services at the same time. After that, a multi-objective algorithm with improved strategies is designed to solve the proposed model. Furthermore, through nine random instances and three case studies, this study finds that (1) the superior and inferior cloud services are identified completely and accurately through the MSTEP-DPO model; (2) compared to the preference-based single-objective models, the overall trust of three type of users obtained by the MSTEP-DPO model is higher; (3) the inferior cloud services obtained after the second stage filtration are closer to the real condition of inferior services in the real platform; and (4) the IMO-NSGA-III algorithm is better than the comparison algorithms for solving the MSTEP-DPO model.

Regarding future research, there are several directions that can be further studied: (1) apply more sustainable indicators to the trust evaluation system under the green and low-consumption CMfg environment; (2) analyze the interplay between the trust or trust indicators of the three types of users; and (3) conduct follow-up research after the identified superior and inferior cloud services, such as service combination and scheduling of the selected superior cloud services, as well as the enhancement of the selected inferior cloud services.

CRediT authorship contribution statement

Weiqing Xiong: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Ming K. Lim:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – review & editing, Supervision, Project administration. **Ming-Lang Tseng:** Conceptualization, Methodology, Validation, Writing – original draft, Writing – review & editing. **Chao Wang:** Validation, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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