

# Two-Stage Consensus Reaching Process for Two-Sided Matching Based on the Cloud Model in Large Sharing Platform

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## Research Article

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# Two-stage consensus reaching process for two-sided matching based on the cloud model in large sharing platform

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**Abstract:** The sharing economy plays an important role in economic development, and the sharing platform is the core point in the sharing economy. However, the large-scale sharing platform results in low-efficiencies and weak matching. To address the problem, we design a two-stage consensus reaching process for resources sharing in platform. Firstly, considering the time-consuming process of generating satisfaction, we design a new method to generate satisfaction based on large-scale mixed historical data, the cloud model is used to unify the mixed uncertain information. Then, we design a two-stage consensus reaching process to realize the stable matching. For the first stage, we maximize the total consensus of the two-sided individuals. For the second stage, to realize stable sharing, we focus on the individuals' requirement of consensus, the platform's strategies, such as discount and scheduling, are used to adjust their consensus. Finally, considering the hierarchy of the two-stage consensus reaching process, we establish bi-level programming to embody the features. We design an improved algorithm to deal with bi-level programming. Also, an industrial internet platform is used as an example to verify the method and algorithm.

**Keywords:** Sharing platform; Consensus reaching process; Two-sided matching; Mixed uncertain preferences; Cloud model

## 1. Introduction

The sharing economy, a new economic model, is being promoted by the rapid development of information technology, which has become a new economic growth point (Tian and Jiang 2018; Benjaafar et al. 2019; Choi et al. 2019). The scale of the global sharing economy will reach £241 billion by 2025, and it is still growing at an increasing rate (Basukie et al. 2020). In the sharing economy, the essence is to provide the idle goods or services of suppliers to demanders (Eloranta et al. 2016). The platform plays as the bridges role and has the responsibility to match demanders with suppliers. There are various types of sharing platforms, such as car-, knowledge-, and house-sharing platforms. In sharing platforms, to make more profit, the involved individuals, including suppliers, demanders, and platforms, require stable matching with high efficiency.

With the development of the sharing economy, the platform become larger and larger. Considering the new difficulties caused by the large-scale sharing, the previous methods (Liu and Ma 2015; Fan et al. 2018; Zhang et al. 2019a; Zhong and Bai 2019; Liang et al. 2020) may result in low-efficient matching in large sharing platform. According to the procedures of two-sided matching, we would like to introduce the new difficulties of realizing stable matching in large-scale sharing platform.

Firstly, the primary step of matching, which means generating the satisfaction through collecting the preferences (Li et al. 2019; Yu and Xu 2020), is time-consuming in large-scale sharing platform. Generally, the individuals' satisfaction is generated based on mutual assessment, kinds of uncertain information are considered, including preferences ordinals (Fan

et al. 2018), triangular intuitionistic fuzzy numbers (Yue et al. 2019), and incomplete fuzzy preference (Zhang et al. 2019a). However, in a sharing platform, mutual assessment is time-consuming because of the large-scale individuals. For example, CASICloud is a famous sharing platform. In 2019, there were 469,214 suppliers registered on the CASICloud, and the demanders released 1,123,528 requirements. Although the previous study creatively discussed how to classify large-scale groups into several manageable groups (Xu et al. 2018), the scale is still large. In the real case of CASICloud, the platform should match 168 suppliers with 324 demanders. Hence, considering the high-efficiency requirement of a sharing platform, it is urgent to detect an efficient method to generate mutual assessments.

Second, after obtaining the mutual assessment, the matching rule, like maximizing the satisfaction, is used to find the matching results, but may result in weak sharing. When aiming at maximizing satisfaction, some individuals in the matching results could not find the perfect matching couple, especially with large-scale matching problems in the platform. To solve this problem, a constraint, such as finding the perfect matching couple for each individual, is used to avoid the disadvantage (Zhang et al. 2019b). However, the constraint increases the difficulty of finding the solution and could even lead to no solution. Hence, in a sharing platform, it is meaningful to study how to find stable matching results in a large-scale matching problem.

To address the mentioned problems, we propose a two-stage consensus reaching process (CRP) to realize resources sharing based on the cloud model. To realize efficient matching, mixed historical evaluation information is adopted to generate individuals' satisfaction instead of time-consuming mutual assessment. It is known that a sharing platform stores a huge number of historical data, and the historical assessment is regarded as an important reference for individuals in practice. Hence, we use the historical assessment to generate the satisfaction. For the historical assessment, the assessment information could be drawn into two perspectives: scores or stars. To enhance the feasibility, we consider two types of information, we use the cloud model to unify the mixed uncertain information and generate the individuals' satisfaction.

Then, to realize stable sharing, we not only focused on the total consensus but also the individuals' requirements, and we establish a two-stage CRP for matching. For the first stage, we focus on the total consensus of two-sided individual. Consensus means that decision-makers fully discuss the issues to form a collective result after an interactive process of negotiation (Gong et al. 2021). Comparing maximizing the satisfaction, maximizing the consensus means the related individuals agree the matching result. Although maximizing the satisfaction could guarantee individuals' satisfaction, the rule could not represent individuals agreed the matching results. For the second stage, we focus on the individuals' requirement, the platform's strategies are used to adjust the individuals' low consensus. Because it is difficult to realize hard consensus, the soft consensus is adopted widely (Gou et al. 2018; Liu et al. 2019), we also adopt the soft consensus. To realize the CRP, we consider the influences of platforms' strategies on consensus, such as discount and scheduling. Regarding discounting, the platform provides a discount to suppliers or demanders, which is helpful in reducing the cost. For scheduling, because each supplier may serve several demanders, the serving sequences may influence demanders through the delivery time, and the serving sequences could be obtained by scheduling. For individual with low consensus, the platform could enhance the consensus by providing the on-time services through scheduling.

In our work, we study a two-stage CRP in a sharing platform. First, to avoid the time-

consuming mutual assessment, we design a new method to unify the mixed historical data based on the cloud mode and generate the satisfaction. Then, based on the satisfaction, to realize stable matching, the two-stage CRP are established. In the first stage, we aim at obtaining the matching results by maximizing the consensus. In the second stage, we adopt the adjusted strategies to adjust the individuals' low consensus. Considering the master-slave hierarchical structure of the two stages, we use bi-level programming to perform the features. Finally, we design an improved particle swarm optimization-genetic algorithm (PSO-GA) to find the optimal solution. The content is shown in Fig.1.

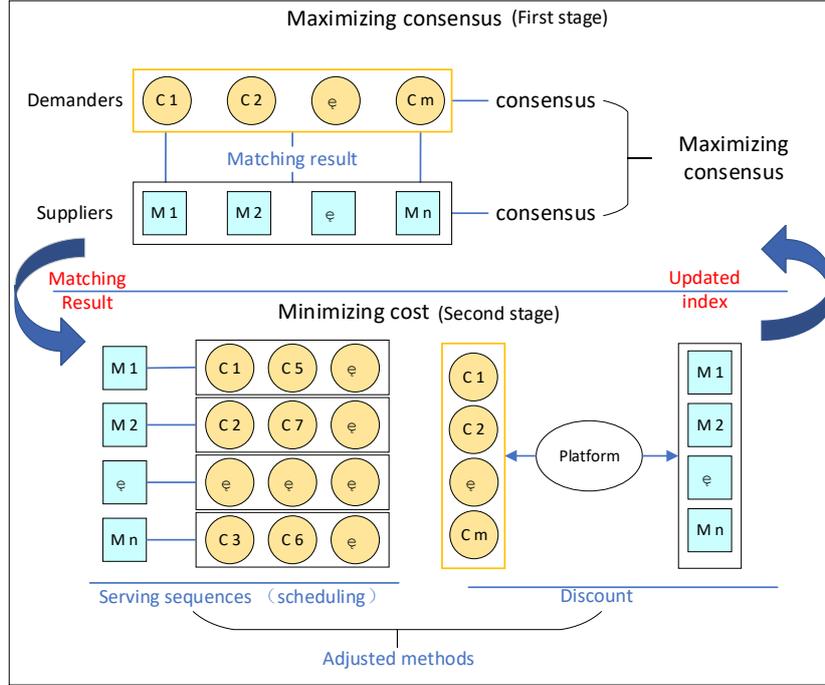


Figure 1 Procedure of the CRP

The remainder of our study is arranged as follows. Section 2 presents the recent literature on the CRP, and we compare our study with previous research. Section 3 presents the preliminaries of our study. Section 4 includes the details of the established mathematical model. Section 5 describes the procedures of our algorithm. Section 6 provides an example of industrial internet platform which provides the manufacturing capacity. In addition, we compare our study with the original method and other algorithms. Section 7 presents the contributions and future work.

## 2. The two-stage CRP model for two-sided matching

In our work, we studied a two-stage CRP based on the cloud model. First, given a large number of mixed historical data, we use the cloud model to unify the mixed data and generate the satisfaction. For the satisfaction, the similarity between the expected value and the matching object's historical value is regarded as the satisfaction. Then, because the adjusted method could only be determined after obtaining the matching, we design a two-stage CRP. The first stage aims to maximize consensus. In the second stage, to adjust the low consensus of individuals, we discuss the influences of platforms' strategies on consensus. In additional, because the strategies could increase the additional cost of the platform, it is necessary to minimise the cost. We set the objective, minimizing the cost, in the second stage.

The flow chart is shown in Fig.2.

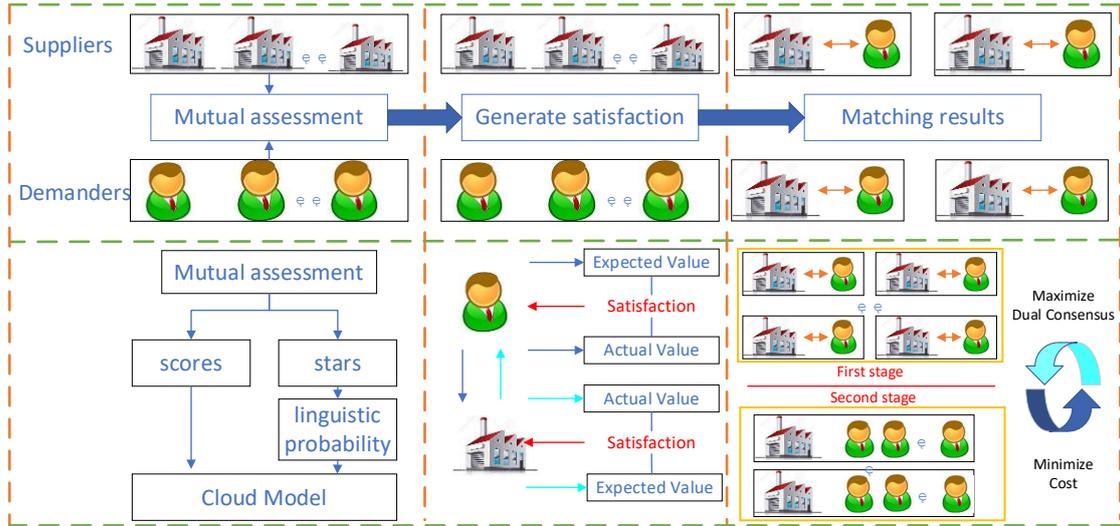


Figure 2 Flowchart of our study

## 2.1 The method for calculating satisfaction based cloud model through mixed historical data

In a sharing platform, satisfaction is generated by mutual assessment in previous studies, but the process of mutual assessment is time-consuming. Considering the platform's requirement of high efficiency, the previous methods are not suitable. Hence, we propose a highly efficient method to calculate satisfaction based on mixed historical data.

The platform has stored historical assessment values in a large scale, and we use historical data to generate satisfaction automatically instead of mutual assessment. In the sharing platform, there are two types of information: star information and score information. To enhance the feasibility, we consider two types of the most common historical data.

For score information, the historical scores represent the features of the individual, and the information formats should present the features of the whole score. Based on the scores, the reverse cloud generator could reflect the features of the whole score by generating the cloud model (Li and Du 2017). Hence, we convert the whole score information into the cloud model.

For star information, five-star evaluation information is similar to a linguistic evaluation, such as very good (five stars), good (four stars), general (three stars), poor (two stars), and very poor (one star). We regarded star information as linguistic information. To perform the whole assessment value, we first calculate the proportion of each star through historical data, and we convert the whole assessment value into probabilistic language based on the proportion. Star assessment is a type of natural language. Randomness and fuzziness are two important aspects of natural language (Li et al. 2009). In the past few decades, linguistic models were divided into the linguistic symbolic model, 2-tuple linguistic model, and linguistic computational model. Regarding the linguistic symbolic model and 2-tuple linguistic model, these two models could not present the randomness and fuzziness of natural language. The linguistic computational model could only perform fuzziness but not randomness (Wang et al. 2014b). However, the cloud model could perform the fuzziness and randomness of natural language. Meanwhile, we convert the score information into the cloud model, and we should unify the historical information. Hence, we convert star information into the cloud model.

Generally, there is five-level star information  $H = \{H_1 = \text{one star}, H_2 = \text{two star}, H_3 = \text{three star}, H_4 = \text{four star}, H_5 = \text{five star}\}$ , and we convert the star information into a

cloud model. As mentioned above, the star information is also a linguistic variable. We adopt a similar method to convert the star information into a cloud model. For cloud model, there are three necessary parameters in the cloud model: expectation ( $Ex$ ), entropy ( $En$ ), and super entropy ( $He$ ). The form of the cloud model is expressed in  $A = (Ex, En, He)$  (Li and Du 2017). After giving the range of the cloud model  $[X_{min}, X_{max}]$ , the three necessary parameters of the cloud model can be obtained based on Wang's study (Xiao and Wang 2019).

Considering the probabilistic linguistic term sets  $H(\rho) = \{H_\delta(\rho_\delta) | H_\delta \in H, \delta = 1, 2, 3 \dots 5, \sum_{\delta=1}^5 \rho_\delta \leq 1\}$ , the integrated method of probabilistic linguistic term sets is presented in formulas (4) and (5).

$$HB_{jk} = (Ex_{jk}, En_{jk}, He_{jk}) = (\sum_{\delta=1}^5 Ex_{jk\delta} p_{jk\delta}, \sqrt{\sum_{\zeta=1}^5 En_{jk\zeta}^2 p_{jk\zeta}^2}, \sqrt{\sum_{\zeta=1}^5 He_{jk\zeta}^2 p_{jk\zeta}^2}) \quad (1)$$

$$HA_{il} = (Ex_{il}, En_{il}, He_{il}) = (\sum_{\delta=1}^5 Ex_{il\delta} p_{il\delta}, \sqrt{\sum_{\delta=1}^5 En_{il\delta}^2 p_{il\delta}^2}, \sqrt{\sum_{\delta=1}^5 He_{il\delta}^2 p_{il\delta}^2}) \quad (2)$$

Finally, the satisfaction of each individual is calculated by the formula (3)–(4).

$$AB_{ij} = \sum_{k=1}^p \mu_k AB_{ijk} = \sum_{k=1}^p \mu_k Sim(EA_i, HB_{jk}) \quad (3)$$

$$BA_{ij} = \sum_{l=1}^q \mu'_l BA_{ijl} = \sum_{l=1}^q \mu'_l Sim(EB_j, HA_{il}) \quad (4)$$

$Sim(EA_i, HB_{jk})$  means the similarity between  $EA_i$  and  $HB_{jk}$ . The similarity proposed by Pei Wang was adopted (Wang et al. 2018) in our study. In Wang's study, given a cloud model  $A = (Ex, En, He)$ , if  $(x, y)$  is a droplet of  $A$ ,  $x$  satisfies  $x \sim N(Ex, En'^2)$ , and  $En' \sim N(En, He^2)$ . The estimated score can be obtained using formula (5).

$$\hat{s}(A) = \frac{1}{n} \sum_{i=1}^n x_i (\exp(-\frac{(x_i - Ex)^2}{2(En')^2})) \quad (5)$$

Given two cloud models  $A_1 = (Ex_1, En_1, He_1)$  and  $A_2 = (Ex_2, En_2, He_2)$ , the fuzzy distance is defined as formula (6).

$$D(A_1, A_2) = (|Ex_1 - Ex_2|, |En_1 - En_2|, |He_1 - He_2|) \quad (6)$$

Finally, the similarity between  $A_1$  and  $A_2$  is obtained using formula (7).

$$Sim(A_1, A_2) = 1 - \frac{\hat{s}(D(A_1, A_2))}{\hat{s}(A_1) + \hat{s}(A_2)} \quad (7)$$

## 2.2 The two-stage model for matching

In this section, we illustrate the two-stage CRP in detail. The first stage aims to obtain matching results by maximizing the consensus. The second stage aims to adjust the consensus to meet the requirement of the CRP, and minimizing the adjusted cost is set as the objective.

Before the construction, the notations should be defined, and they are presented in Table 1.

Table 1 Definition of notations

Notation	Explanation	Notation	Explanation
$m$	The number of demanders	$BA_{ij}^{C'}$	When $A_i$ match with $B_j$ , the $B_j$ 's updated satisfaction under cost index after the adjusted method
$n$	The number of suppliers	$\overline{BA}_C$	The updated decision matrix of B side under cost index
$p$	The number of suppliers' indexes	$ME_{ij}^{C'}$	When $A_i$ match with $B_j$ , the $B_j$ 's updated element consensus level under cost index after the adjusted

			method
$q$	The number of demanders' indexes	$CI'_i$	The updated decision matrix level of $A_i$
$w_i$	The degree of $i - th$ supplier's importance	$MI'_j$	The updated decision matrix level of $B_j$
$w'_j$	The degree of $j - th$ demander's importance	$FA_i$	The competing time of $i - th$ demander
$AB_{ijk}$	When $A_i$ match with $B_j$ , $AB_{ijk}$ means the satisfaction under $A_i$ 's $k - th$ index	$DA_i$	The delivery time of $i - th$ demander
$\overline{AB}_{jk}$	When $A_i$ match with $B_j$ , $\overline{AB}_{jk}$ means the element of $A_i$ 's decision matrix	$AC$	Adjustment cost
$AB_i$	The decision matrices of $i - th$ supplier	$IDC$	Inventory cost and delay cost
$\overline{AB}$	Collective decision matrix of supplier	$IC_i$	Inventory cost of $A_i$
$BA_{ijl}$	When $A_i$ match with $B_j$ , $BA_{ijl}$ means the satisfaction under $B_j$ 's $l - th$ index	$DC_i$	Delay cost of $A_i$
$\overline{BA}_{jl}$	When $A_i$ match with $B_j$ , $\overline{BA}_{jl}$ means the element of $B_j$ 's decision matrix	$FA_{ij}$	When $A_i$ match with $B_j$ , the completing time of $B_j$
$BA_j$	The decision matrices of $B_j$	$SA_{ij}$	When $A_i$ match with $B_j$ , the beginning of $B_j$ 's serving time
$\overline{BA}$	Collective decision matrix of demander	$Pt_{ij}$	When $A_i$ match with $B_j$ , the processing time of $B_j$
$CE_{ijk}$	When $A_i$ match with $B_j$ , $CE_{ijk}$ means the element consensus level under $A_i$ 's $k - th$ index	$TC$	Total cost
$ME_{ijl}$	When $A_i$ match with $B_j$ , $ME_{ijk}$ means the element consensus level under $B_j$ 's $l - th$ index	$Dis_{ij}$	When $A_i$ match with $B_j$ , the distance between $A_i$ and $B_j$
$CA_{ij}$	When $A_i$ match with $B_j$ , $A_i$ 's individual consensus level	$PC$	Total processing cost
$MA_{ij}$	When $A_i$ match with $B_j$ , $B_j$ 's individual consensus level	$Pc_{ij}$	When $A_i$ match with $B_j$ , $Pc_{ij}$ means $B_j$ 's processing cost
$CI_i$	$A_i$ 's decision matrix level	$A_i$	The $i - th$ supplier of A side
$MI_j$	$B_j$ 's decision matrix level	$B_j$	The $j - th$ demander of B side
$FB_{jo}$	The finishing time of the $o - th$ period free time of $B_j$	$k$	$k - th$ index
$SB_{jo}$	The start time of the $o - th$ period free time of $B_j$	$i$	The $i - th$ supplier
$Pt_{ij}$	When $A_i$ match with $B_j$ , $Pt_{ij}$ means the processing time.	$j$	The $j - th$ demander

$AB_{ij}^A$	When $A_i$ match with $B_j$ , the $A_i$ 's satisfaction under the availability index	$l$	$l - th$ index
$AB_{ij}^{A'}$	When $A_i$ match with $B_j$ , the $A_i$ 's updated satisfaction under the availability index after the adjusted method	$EAB_{ik}$	The expected value of $A_i$ 's $k - th$ index
$\overline{AB}_A'$	The updated decision matrix of A side under availability	$HAB_{jk}$	The historical value of $B_j$ 's $k - th$ index
$CE_{ij}^{A'}$	When $A_i$ match with $B_j$ , the $A_i$ 's updated element consensus level under availability index after the adjusted method	$EBA_{jl}$	The expected value of $B_j$ 's $k - th$ index
$AB_{ij}^C$	When $A_i$ match with $B_j$ , the $A_i$ 's satisfaction under cost index	$HBA_{il}$	The historical value of $A_i$ 's $l - th$ index
$AB_{ij}^{C'}$	When $A_i$ match with $B_j$ , the $A_i$ 's updated satisfaction under cost index after the adjusted method	$MSR$	The social relationship among the individuals
$\overline{AB}_C'$	The updated decision matrix of A side under cost index	$y_i$	The adjustment cost of $A_i$
$CE_{ij}^{C'}$	When $A_i$ match with $B_j$ , the $A_i$ 's updated element consensus level under cost index after the adjusted method	$y_j'$	The adjustment cost of $B_j$
$BA_{ij}^C$	When $A_i$ match with $B_j$ , the $B_j$ 's satisfaction under cost index	$x_{ij}$	Decision variables
$AB_{ij}$	When $A_i$ match with $B_j$ , $AB_{ij}$ indicates the $A_i$ 's satisfaction.	$BA_{ij}$	When $A_i$ match with $B_j$ , $BA_{ij}$ indicates the $B_j$ 's satisfaction.
$\mu_k$	The $k - th$ index's weight of suppliers	$\mu_l'$	The $l - th$ index's weight of demanders

### 2.2.1 The first stage: maximizing the total consensus

In this section, we illustrate how to establish a consensus model among demanders and suppliers. Comparing to previous studies, the CRP in our study is related to two groups named demanders and supplier, the relations of two groups are constructed based on the matching. Hence, in our study, we should establish the CRP of two groups.

Generally, the consensus level was formed based on the evaluation element, alternative, and decision matrix among the demanders and suppliers. In our study, because the consensus is established based on the interaction between two groups, we define the consensus level for suppliers and demanders. The consensus of each level is shown in Fig.3.

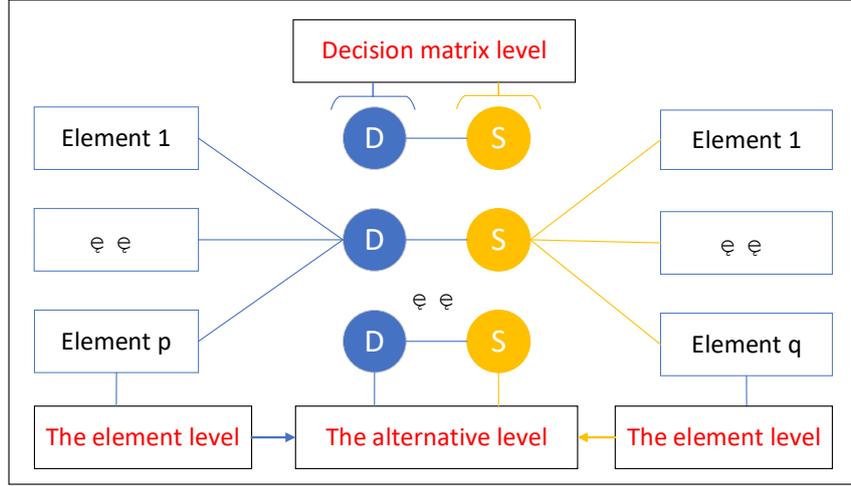


Figure 3 Consensus of each level

**Level 1. The evaluation element level.** The evaluation element level means the distance between the individual's value and the group's average value under indexes (Xiao et al. 2020). In our study, there exist two interactive groups named suppliers and demanders, and the individual's satisfaction is related to the matching object. Considering two interactive groups, we establish the element level for demanders and suppliers separately.

The element level of demanders is presented in formulas (8) and (9).

$$CE_{ijk} = (1 - d(AB_{ijk}, \overline{AB}_{jk})) \quad (8)$$

$$\overline{AB}_{jk} = \sum_{i=1}^m w_i \times AB_{ijk} \quad (9)$$

$w_i$  indicates the importance degree of supplier  $i$ . In sharing platform, the consensus can be realized when all individuals in the two groups agree with the matching result. Considering the nonindependence of individuals, the individuals' decisions are mutually affected, and the degree of importance of each individual is different under the social networks (Dong et al. 2018). Generally, individuals with strong social relationships play an important role in the consensus reaching process. The degree of centrality is used to present the degree of importance under social networks (Wu et al. 2018).

In our study, considering the diverse social relationships among individuals, the degree of importance of individuals is different. Similarly, we use the in-degree centrality to calculate the degree of importance. We assume a directed graph  $G_1 = (M, L, R)$ ,  $MC = (M_1, M_2, \dots, M_n, C_1, C_2, \dots, C_m)$  represents the set of nodes,  $L = (l_1, l_2, \dots, l_\gamma)$  represents the set of directed lines, and  $R = (r_1^l, r_2^l, \dots, r_\gamma^l)$  represents the social relationship attached to the directed line.

Because the calculation of importance is similar for suppliers and demanders, we regard  $G_1 = (M, L, R)$  as an example to illustrate the calculation procedure.  $MCR = (MCR_{iu})_{(n+m) \times (n+m)}$  means the social relationship among demanders and suppliers, the centra degree of the supplier  $i$  is shown as formula (10).

$$CD^L(M_i) = \frac{1}{n+m-1} \sum_{u=1}^{n+m} MCR_{iu} \quad (10)$$

Then, importance degree of supplier  $i$  is expressed in formula (11).

$$w_i = \frac{CD^L(M_i)}{\sum_{v=1}^{\gamma} r_v^l} \quad (11)$$

The element level of demanders is presented in formulas (12) and (13).

$$ME_{ijl} = \left(1 - d(BA_{ijl}, \overline{BA}_{il})\right) \quad (12)$$

$$\overline{BA}_{il} = \sum_{j=1}^n w'_j \times BA_{ijl} \quad (13)$$

where  $w'_j$  means the degree of importance of demander  $j$ . The calculation is like  $w_i$ .

**Level 2. The alternatives level.** The alternatives level integrates diverse elements. Because the element level is determined by the matching object, the alternative level is also related to the matching object. Hence, the alternatives levels of the demanders and suppliers are expressed in formulas (14) and (15).

$$CA_{ij} = \frac{1}{p} \sum_{k=1}^p CE_{ijk} \quad (14)$$

$$MA_{ij} = \frac{1}{q} \sum_{l=1}^q ME_{ijl} \quad (15)$$

**Level 3. Decision matrix level.** The decision matrix level integrates different individuals. Similarly, the matrix level is related to the matching object. We establish two decision matrix levels for different groups, as indicated in formulas (16) and (17).

$$CI_i = \frac{1}{n} \sum_{j=1}^n CA_{ij} \quad (16)$$

$$MI_j = \frac{1}{m} \sum_{i=1}^m MA_{ij} \quad (17)$$

### (3) Constraints

Regarding formula (18), generally, the suppliers sell the remaining capacity in the sharing platform. When the supplier is assigned to the demander, the demander's required capacity should be lower than the supplier's remaining capacity. For example, for Airbnb, the required length of stay of the demander should be lower than the sharing time of the supplier. In an industrial internet platform, usually, the remaining capacity is regarded as the idle serving time, and thus, we set the constraint that the suppliers' remaining serving time should be greater than the demanders' required serving time. In our study, we consider a more complex situation, which is more realistic, and we assume that the serving time is discontinuous. We set constraints to ensure that the total intermittent time of suppliers is greater than the service time required by the demander. The constraint is presented in formula (18).

$$\sum_{o=1}^r (FB_{jo} - SB_{jo}) - \sum_{i=1}^m Pt_{ij} \times x_{ij} \geq 0 \quad (18)$$

In the matching couple, if the satisfaction difference between matched couples is large, the final matching result would also be unstable (Li et al. 2019). Hence, we set the constraint to guarantee that the differences in satisfaction between matching couples are lower than the threshold value. This is expressed in formula (19).

$$d(AB_{ij}, BA_{ij}) \leq d_1 \quad (19)$$

In sharing platform, considering the large remaining capacity of some suppliers, each supplier may serve multiple demanders. However, the platform cannot allocate the same task to two or more suppliers at the same time. For example, in Airbnb, the platform could not allocate the customer to two houses. Hence, we set the constraint to guarantee that each demander could only be assigned to one supplier in the matching result. This is indicated in the formula (20).

$$\sum_{j=1}^n x_{ij} = 1 \quad (20)$$

As mentioned above, the objective of our study is to find a matching couple that maximizes the consensus. Hence, the objective is expressed in formulas (21)–(24).

$$\max \cos = CI_i + MI_j \quad (21)$$

$$CI_i = \frac{1}{n} \sum_{j=1}^n CA_{ij} \quad MI_j = \frac{1}{m} \sum_{i=1}^m MA_{ij} \quad (22)$$

$$MA_{ij} = \frac{1}{q} \sum_{l=1}^q ME_{ijl} \quad CA_{ij} = \frac{1}{p} \sum_{k=1}^p CE_{ijk} \quad (23)$$

$$ME_{ijl} = \left(1 - d(BA_{ijl}, \overline{BA}_{il})\right) \quad CE_{ijk} = \left(1 - d(AB_{ijk}, \overline{AB}_{jk})\right) \quad (24)$$

$$\overline{BA}_{il} = \sum_{j=1}^n w'_j \times BA_{ijl} \quad \overline{AB}_{jk} = \sum_{i=1}^m w_i \times AB_{ijk} \quad (25)$$

$$\sum_{o=1}^r (FB_{jo} - SB_{jo}) - \sum_{i=1}^m Pt_{ij} \times x_{ij} \geq 0 \quad (26)$$

$$d(AB_{ij}, BA_{ij}) \leq d_1 \quad (27)$$

$$\sum_{j=1}^n x_{ij} = 1 \quad (28)$$

### 2.2.2 The two stage: adjusting the individuals' consensus

In the first stage, some individuals could not meet the constraint of consensus in the first stage, which means the value of consensus should be larger than a certain threshold value (Morente-Moliner et al. 2020), the platforms' strategies are adopted to enhance the consensus. However, the strategies not only enhance the consensus but also cause the additional cost, the additional cost is harmful to the operation of platform. To reduce the operational cost, we aim at minimizing the additional cost at the second stage.

(1) the influence of the strategies on consensus

Scheduling strategy could enhance the demanders' low satisfaction by providing on-demand services. In detail, scheduling could adjust the difference between the demanders' actual delivery time and expected delivery time. If the actual delivery time is greater than the expected delivery time, the satisfaction will decrease. In our study, we regarded  $g_i(\cdot)$  as a function that converts the differences of expected delivery time and the actual delivery time into satisfaction. The satisfaction of availability is changed, and the consensus level is also updated. This is presented in the updated formulas (29)–(31).

$$AB_{ij}^{A'} = AB_{ij}^A + g_i(\max(0, FA_i - DA_i)) \quad (29)$$

$$\overline{AB}_j^{A'} = \sum_{i=1}^m w_i \times AB_{ij}^{A'} \quad (30)$$

$$CE_{ij}^{A'} = 1 - d(AB_{ij}^{A'}, \overline{AB}_j^{A'}) \quad (31)$$

Discount strategy could improve the individuals' consensus. After obtaining the discount, the individuals' cost is decreased, and the satisfaction is increased.

Let  $f_i(\cdot)$  and  $f'_j(\cdot)$  be the demanders' and suppliers' conversion function. The input of the function is the cost that the platform must pay, and the output is the consensus that we could modify. After getting the discount, the satisfaction is increased, and the consensus is also changed. The mechanism of changing consensus of suppliers and demanders is expressed in formulas (32)–(37).

$$AB_{ij}^{C'} = AB_{ij}^C + f_i(y_i) \quad (32)$$

$$\overline{AB_j^{C'}} = \sum_{i=1}^m w_i \times AB_{ij}^{C'} \quad (33)$$

$$CE_{ij}^{C'} = \left(1 - d\left(AB_{ij}^{C'}, \overline{AB_j^{C'}}\right)\right) \quad (34)$$

$$BA_{ij}^{C'} = BA_{ij}^C + f_j'(y_j') \quad (35)$$

$$\overline{BA_j^{C'}} = \sum_{i=1}^m w_i \times BA_{ij}^{C'} \quad (36)$$

$$ME_{ij}^{C'} = 1 - d(BA_{ij}^{C'}, \overline{BA_j^{C'}}) \quad (37)$$

After conduction the two strategies, the updated consensus level of demanders and suppliers is presented as formulas (38)–(39).

$$CI_i' = \frac{1}{n} \sum_{j=1}^n \left( \frac{1}{p-2} \sum_{k=1}^{p-2} CE_{ijk} + CE_{ij}^{A'} + CE_{ij}^{C'} \right) \quad (38)$$

$$MI_j' = \frac{1}{m} \sum_{i=1}^m \left( \frac{1}{q-1} \sum_{l=1}^{q-1} ME_{ijl} + ME_{ij}^{C'} \right) \quad (39)$$

Also, to realize the consensus, the value should be larger than a certain threshold value. Generally, the value is 0.8. The constraints of consensus are presented in formulas (40) and (41).

$$CI_i' \geq 0.8 \quad (40)$$

$$MI_j' \geq 0.8 \quad (41)$$

(2) the mathematical model of the second stage

As mentioned above, the strategies may cause new additional cost. To reduce the burden of the cost, we should minimize the additional cost.

Firstly, the additional cost caused by the scheduling. The scheduling could influence the actual delivery time. If the actual delivery time is larger than the expected delivery time, the platform will pay for the delay cost  $DT_i$ , otherwise, there is vacancy cost  $VT_i$ . This is expressed in formulas (42)–(44).

$$IDC = \sum_{i=1}^m (IC_i + DC_i) \quad (42)$$

$$IC_i = \max(0, (FA_i - DA_i)) \times VT_i \quad (43)$$

$$DC_i = \max(0, (DA_i - FA_i)) \times DT_i \quad (44)$$

Secondly, the additional cost caused by the discount. Because the platform give the discount to the individuals, the profit of platform is decreased, we call the decreased profit as the discount cost.

$$AC = \sum_{i=1}^m y_i Pc_{ij} + \sum_{j=1}^n y_j' Pc_{ij}' \quad (44)$$

Thirdly, because there are kinds of sharing platform, to enhance the feasibility of our study, we assume there is an exit transportation cost between demanders and suppliers. For example, in manufacturing capacity sharing platform, because the demanders should transport the product to the suppliers, there exit the transportation cost. The transportation cost is determined by the distance between the matching couple. Therefore, the transportation cost is indicated in the formula (45).

$$TC = \sum_{i=1}^m \sum_{j=1}^n x_{ij} \times Dis_{ij} \quad (45)$$

As mentioned above, the mathematical model of the lower layer is presented as formulas (46)–(58).

$$\text{Min } TOC = AC + IDC + TC \quad (46)$$

$$AC = \sum_{i=1}^m y_i P c_{ij} + \sum_{j=1}^n y'_j P c'_{ij} \quad (47)$$

$$IDC = \sum_{i=1}^m (IC_i + DC_i) \quad TC = \sum_{i=1}^m \sum_{j=1}^n x_{ij} \times Dis_{ij} \quad (48)$$

$$IC_i = \max(0, (FA_i - DA_i)) \times VT_i \quad (49)$$

$$DC_i = \max(0, (DA_i - FA_i)) \times DT_i \quad (50)$$

$$AB_{ij}^{A'} = AB_{ij}^A + g_i(\max(0, FA_i - DA_i)) \quad (51)$$

$$\overline{AB_j^{A'}} = \sum_{i=1}^m w_i \times AB_{ij}^{A'} \quad CE_{ij}^{A'} = 1 - d(AB_{ij}^{A'}, \overline{AB_j^{A'}}) \quad (52)$$

$$AB_{ij}^{C'} = AB_{ij}^C + f_i(y_i) \quad \overline{AB_j^{C'}} = \sum_{i=1}^m w_i \times AB_{ij}^{C'} \quad (53)$$

$$CE_{ij}^{C'} = \left(1 - d(AB_{ij}^{C'}, \overline{AB_j^{C'}})\right) \quad BA_{ij}^{C'} = BA_{ij}^C + f'_j(y'_j) \quad (54)$$

$$\overline{BA_j^{C'}} = \sum_{i=1}^m w_i \times BA_{ij}^{C'} \quad ME_{ij}^{C'} = 1 - d(BA_{ij}^{C'}, \overline{BA_j^{C'}}) \quad (55)$$

$$CI_i' = \frac{1}{n} \sum_{j=1}^n \left( \frac{1}{p-2} \sum_{k=1}^{p-2} CE_{ijk} + CE_{ij}^{A'} + CE_{ij}^{C'} \right) \quad (56)$$

$$MI_j' = \frac{1}{m} \sum_{i=1}^m \left( \frac{1}{q-1} \sum_{l=1}^{q-1} ME_{ijl} + ME_{ij}^{C'} \right) \quad (57)$$

$$CI_i' \geq 0.8 \quad MI_j' \geq 0.8 \quad (58)$$

Bi-level programming is typically an NP-hard problem, and obtaining an optimal solution is difficult and time-consuming. The platform requires high efficiency, but the optimal solution could not meet this requirement. In our study, we adopt the satisfying solution, and a heuristic algorithm is suggested to solve the bi-level programming. Many algorithms can solve similar problems. Given the advantages of the PSO-GA algorithm, like simple operations and fast convergences (Hachimi et al. 2012), we use it to solve the problem.

### 3. Improved PSO-GA

In our mathematical model, the first layer is integer programming. The GA can deal with the integer programming well because of the integer coding method, and the coding method could represent the solution directly. The second layer of the mathematical model is mixed-integer programming, which contains integer and continuous variables. To obtain the integer programming, we also use the GA, considering its advantages, to find the scheduling of each supplier. Meanwhile, to enhance the searching ability of the GA, in the crossover, we design an adaptive method to determine the number of genes based on the cloud model. Then, the discount is a continuing variable. As a simple and economic concept, with low computational cost, PSO has been shown to optimize successfully a wide range of continuous optimization problems (Hachimi et al. 2012). In addition, PSO has few control parameters, fast searching speed, and high efficiency. Therefore, we use PSO to deal with continuous problems.

#### 3.1 Improved GA for the upper layer

In this section, we describe improved GA. The original GA is always inefficient, and we propose an improved GA to solve the problem. Primarily, the basic rules of operations, such as mutation and operations, should be defined. We illustrate the main operation of the improved GA in detail.

(1) the coding method

The coding method is important for the efficiency of the algorithm. In GA, there are two types of coding methods. As the upper layer finds the matching couple, the method of binary coding is not suitable as it increases the difficulties of calculation. Therefore, we chose the integer coding method.

For integer coding, to reduce the complexity of our algorithm, we assume that the demanders are listed in stable sequences, we should only generate a number for each demander randomly, and the number represents a certain supplier. The generated number is less than the number of suppliers.

(2) Crossover

After the coding method is identified, we should identify the crossover and mutation. For the crossover, we first select a position randomly in the chromosome. Then, we generate a random number, and the range of the number is  $[-\max, +\max]$ . The number represents the selected genes, the minus sign means that the direction is left, and the positive sign means that the direction is right.

It is all known that the number of genes influences the global search ability of the algorithm in the crossover. In classic GA, the number of crossover genes is fixed, which reduces the searching ability of the algorithm. Generally, to enhance the searching ability, the number of cross genes is inversely proportional to the diversity. When the diversity of the population decreases, the number of crossover genes should be increased to improve the search range. In addition, the number of cross genes is inversely proportional to iterations. Hence, considering these features, we design an adaptive number  $Ex$ . This is expressed in formulas (59) and (60).

$$Ex = Ex_{max} \times \left(1 - \frac{e^\delta - e^{-\delta}}{e^\delta + e^{-\delta}}\right) \quad (59)$$

$$\delta = \frac{gen}{max_{gen} \times \left(\frac{f_{avg}}{f_{max}}\right)} \quad (60)$$

In formulas (82) and (83), the number of iterations is  $gen$ . Diversity can be represented by  $\frac{f_{avg}}{f_{max}}$ ,  $f_{avg}$  means the average value of all individuals, and  $f_{max}$  is the maximising value of all individuals. If  $\frac{f_{avg}}{f_{max}}$  increases, diversity decreases. Because when  $f_{avg} = f_{max}$ ,  $\frac{f_{avg}}{f_{max}} = 1$ , the value of all individuals is the same, and the diversity is poor.

Taking the derivative of  $\delta$  in formula (59), the derivative is less than 0. Certainly, we can infer that  $\delta$  increases as  $Ex$  decreases. According to (60), we know that  $gen$  increases as  $\delta$  decreases, and  $\frac{f_{avg}}{f_{max}}$  increases as  $Ex$  increases. Hence,  $Ex$  increases with the number of iterations and decreases with an increase in diversity.

To further increase the searching ability of our study, we conduct a disturbance on  $Ex$  because the disturbance is helpful to avoid local convergences. The cloud model can show more possible solutions than the normal distribution [55], and we use a cloud model to present the disturbance.

The number of cross genes that are generated by the adaptive method is used as the expected value  $Ex$  of the cloud model, and a forward cloud generator is used to generate the cloud

model. Subsequently, a point is randomly selected in the generated cloud model, and the abscissa of the point is used as the number of cross genes. Considering the distribution characteristics of the cloud model, our method can not only ensure that the number of crossover genes is like the number of crossover genes calculated by the adaptive method but also add a disturbance to the number of genes. The disturbance is helpful to avoid local convergence.

### (3) Mutation

After that, the mutation should be defined. For the procedure of mutation, we select a gene in the chromosome randomly. After that, we generate an integer randomly, which is less than the number of suppliers. Then, the selected gene is replaced by the integer.

## 3.2 PSO-GA algorithm for the lower layer

The lower layer aims to arrange the production sequences of the demanders' tasks for each supplier. As each supplier undertakes several demanders' tasks, it is necessary to detect how to schedule several tasks. Hence, we first consider the scheduling of the tasks. After that, we determine the adjustment cost. To address the problem,

First, for the scheduling part, we use the GA to find the optimal sequences of the demanders' task for each supplier. Also, we identify the coding method firstly, the integer coding method is adopted. For each supplier, because the demanders that are assigned to the suppliers are already determined on the upper layer, we could list the matching demanders as sequences, the sequences are the coding method. Then, for crossover, the original crossover is suitable, we use the traditional crossover. After that, for mutation, because the demanders are determined already, we exchange the two genes under one supplier, and the exchanging is regarded as the mutation.

Second, after determining the scheduling result, the availability is obtained. Then, we should determine the adjustment cost. We use PSO to identify the final adjustment cost.

The pseudocode of our algorithm is as follows:

Input: ( $P_c$ (crossover probability), $P_m$ (mutation probability), Population size and Max Generation, $\omega, v_{max}$ )
Output: The matching result and the total cost
1. Initiate the solution of the upper layer ( $X = (X_1, X_2, X_3, X_4, \dots, X_n)$ )
3. <b>While:</b> ( $t < Max\ Generation$ ) or ( <i>Stop Condition</i> ) do
4.     Input $X$ into the lower-level programming
5.     Obtain the scheduling results $Y$ and adjusted consensus $Adc$ by using PSO-GA
6.     Input $Adc$ into the upper-level programming
7.     Obtain the new matching result $X' = (X'_1, X'_2, X'_3, X'_4, \dots, X'_n)$ by IGA
8. $X = X'$
12. $t \leftarrow t + 1$
13. <b>End while</b>
14. <b>Return</b> $X, Y$
15. <b>End</b>

## 4. Case study in manufacturing capacity sharing platform

### 4.1 Background

XTMG is an industrial internet platform that shares manufacturing resources, such as

machine tools. In the platform, there exist nearly 13,000 machine tools and thousands of concurrent service requests per day. Hence, effective matching of machine tools and services is of great significance to the development of the platform.

In recent years, various policies, such as Industry 4.0, have been issued by governments. The number of two-sided individuals has increased dramatically. Certainly, low efficiency could not support the sustainable development of the platform. Demanders with low satisfaction would opt out of the platform, which hinders the development of the platform. In addition, the development of information technology has also broken the island effect of suppliers and demanders. The opinions of demanders with lower satisfaction will be quickly transmitted to other demanders, forming a chain reaction, leading to demander churn speed up. Meanwhile, demander churn has reduced the purchase rate of platform machine tool services, and machine tool services may abandon the platform due to low purchase rates. The decrease in the number of machine tool services has reduced the platform's competitiveness, reduced the ability to attract demanders, and further reduced the number of demanders. The vicious circle of both sides has greatly hindered the development of the platform. However, the substantial increase in the number of individuals results in low efficiency of the previous methods.

Hence, we adopt our method to realize highly efficient matching.

#### 4.2 Historic data

There are 11 demanders and 6 suppliers. As mentioned above, we count the cooperation before, and the final social relationship is obtained after standardization. The social relationships among the demanders are presented in Table 2.

Table 2 The social relationship between demanders

Demander	1	2	3	4	5	6	7	8	9	10	11
1	0	0.23		0.14							0.13
2	0.23	0			0.12				0.22		
3			0								0.12
4	0.14			0		0.23		0.21			
5		0.12			0		0.15				0.28
6				0.23		0				0.37	
7					0.15		0				0.11
8				0.21				0		0.15	
9		0.22							0		
10						0.37		0.15		0	
11	0.13		0.12		0.28		0.11				0

Notice: the blank means the no relationship between them

The social relationships of suppliers are shown in Table 3.

Table 3 The social relationship between suppliers

supplier	1	2	3	4	5	6
1	0	0.11	0.13			0.12
2	0.11	0	0.12		0.25	
3	0.13	0.12	0		0.10	
4				0	0.21	0.13
5		0.25	0.10	0.21	0	
6	0.12			0.13		0

The comprehensive form of the star rating and the score is adopted in our study. Although the processing of multiple forms of evaluation information is difficult, it can improve the versatility of the article. The star information of the demanders is presented in Table 4. The score information of the demanders is shown in Fig.4 and Fig.5.

The cloud model for linguistics variables is determined by the calculation method in reference (Wang et al. 2014b), specifically very poor (VP) (0, 10.30, 0.262), poor (P) (30.9, 6.37, 0.162), general (G) (50, 0.393, 0.1), good (G) (69.1, 6.37, 0.162), and very good (VG) (100, 10.30, 0.262).

Table 4 Star information of demanders

Demanders	Reliability					Reputation					Security				
	5	4	3	2	1	5	4	3	2	1	5	4	3	2	1
1	0.1	0.02	0.36	0.26	0.26	0.16	0.19	0.27	0.22	0.16	0.33	0.24	0.21	0.1	0.12
2	0.06	0.07	0.27	0.15	0.44	0.2	0.13	0.12	0.38	0.17	0.13	0.34	0.31	0.12	0.1
3	0.14	0.14	0.08	0.58	0.06	0.05	0.08	0.37	0.35	0.15	0.11	0.14	0.42	0.21	0.11
4	0	0.37	0.12	0.11	0.4	0.16	0.18	0.22	0.37	0.07	0.09	0.11	0.11	0.35	0.34
5	0.08	0.41	0.21	0.13	0.17	0.38	0.28	0.06	0.1	0.18	0.02	0.21	0.11	0.27	0.39
6	0.01	0.09	0.31	0.04	0.55	0.18	0.07	0.18	0.36	0.2	0.06	0.11	0.22	0.31	0.3
7	0.06	0.16	0.22	0.03	0.53	0.11	0.03	0.22	0.22	0.42	0.12	0.08	0.25	0.16	0.39
8	0.18	0.19	0.26	0.18	0.19	0.11	0.09	0.31	0.32	0.17	0.11	0.14	0.09	0.42	0.24
9	0.06	0.01	0.11	0.35	0.46	0.26	0.27	0.18	0.22	0.07	0.1	0.04	0.28	0.25	0.21
10	0.17	0.28	0.15	0.19	0.21	0.24	0.25	0.23	0.23	0.05	0.05	0.32	0.25	0.15	0.23
11	0	0.22	0.19	0.06	0.53	0.11	0.17	0.35	0.12	0.25	0.11	0.07	0.46	0.23	0.13

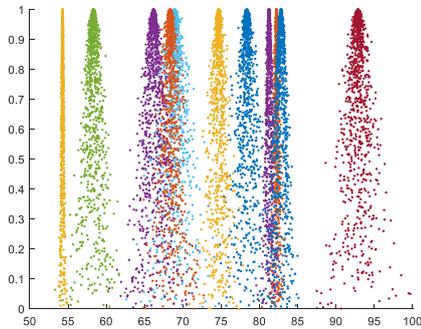


Figure 4 availability for demanders

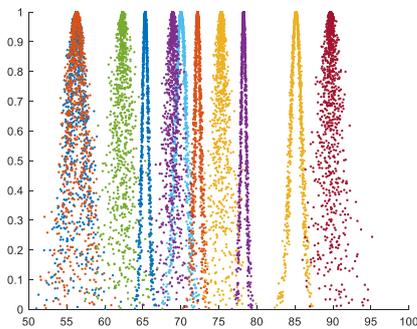


Figure 5 the price for demanders

Similarly, the star information of suppliers is presented in Table 5 and the score information of suppliers is shown in Fig.6–Fig.8.

Table 5 Star information of suppliers

	Reliability					Reputation				
	5	4	3	2	1	5	4	3	2	1
1	0.02	0.38	0.18	0.32	0.1	0.36	0.01	0.13	0.19	0.31
2	0.22	0.11	0.18	0.24	0.25	0.09	0.02	0.31	0.24	0.35
3	0.39	0.35	0.11	0.15	0	0.14	0.27	0.23	0.25	0.11
4	0.07	0.22	0.39	0.23	0.1	0.14	0.4	0.03	0.37	0.06
5	0.21	0.27	0.1	0.31	0.11	0.06	0.03	0.23	0.02	0.66
6	0.06	0.22	0.1	0.12	0.5	0.15	0.01	0.02	0.26	0.56

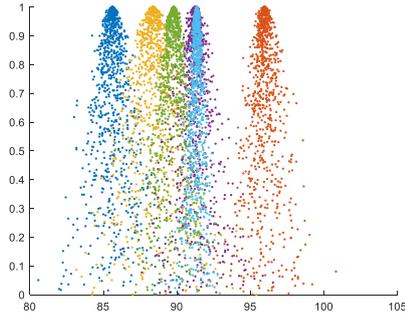


Figure 6 Cooperation intensity for suppliers

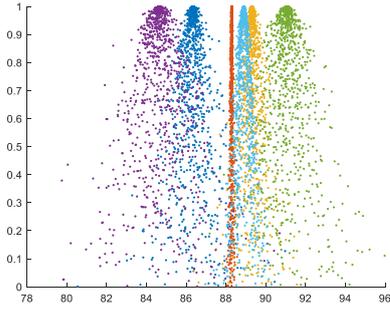


Figure 7 Security for suppliers

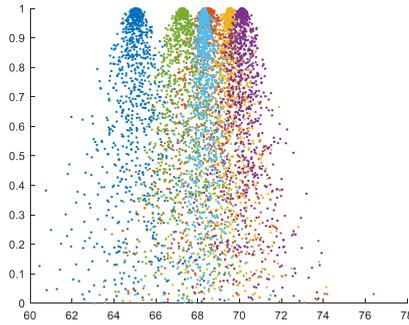


Figure 8 Cloud model of the price for suppliers

In general, it is difficult to determine the preferences of suppliers and demanders. In our study, we regard historical data as a reference point to calculate satisfaction. Hence, historical evaluation data are given as a standard to calculate preferences, as presented in Table 6.

Table 6 Historical data of demanders

Suppliers	Reliability	Reputation	Security	Availability	Prices
1	(53.29,6.76,0.15)	(47.51,9.31,0.24)	(89.49,0.66,0.7)	(80.81,0.19,0.74)	(63.58,0.03,1.02)
2	(51.3,5.89,0.23)	(69.29,4.67,0.18)	(98.01,0.37,0.71)	(81.86,0.01,0.05)	(71.57,0.81,0.88)
3	(26.08,7.28,0.21)	(52.81,6.35,0.16)	(94.23,1.04,0.93)	(89.91,0.12,0.39)	(62.93,0.22,0.69)
4	(53.11,5.4,0.17)	(42.24,6.68,0.18)	(89.46,0.51,0.62)	(87.85,0.68,0.95)	(65.81,0.53,0.59)
5	(48.5,6.78,0.19)	(87.74,3.3,0.21)	(92.66,0.69,0.47)	(95.8,0.47,0.91)	(67.33,0.69,0.62)
6	(72.5,4.67,0.22)	(70.29,4.86,0.26)	(97.86,0.33,0.21)	(92.99,0.32,0.16)	(69.47,0.16,0.53)

The processing time and delivery time of the demanders are listed in Table 7. Meanwhile, the transportation costs of different suppliers are listed in Table 8.

Table 7 Processing time and delivery time of the demanders

Demander	1	2	3	4	5	6	7	8	9	10	11
Processing Time	2.1	3.1	4.2	2.9	3.3	3.5	3.6	1.1	3	3.9	3.5
Delivery Time	7.3	9.7	10.7	7	6.5	11.1	5	8.4	8.8	6.7	4.8

The processing cost of suppliers for each demander is listed in Table 8.

Table 8 Transportation costs

Suppliers	1	2	3	4	5	6
1	33.8	32.2	29.8	33	32.6	31.5
2	33	36.2	37.8	32.8	37	34.2

3	31	35	38	32.1	35	35
4	22.1	23.2	25.8	21.2	24	26
5	26.5	27.4	29.8	31.2	32.8	33.7
6	27.4	26.6	29.1	31.2	32.3	31.4
7	27	26.8	25.1	27.2	25.6	24.9
8	25.8	29.8	24.5	25.3	26.6	28.2
9	31.2	28.2	22.9	23.5	22.7	28.1
10	27.2	29	32	31.4	24.5	29.3
11	31.8	32.5	31.2	33.5	32.1	28.2

### 4.3 Result

In our study, we use our improved algorithm to calculate the final result, which is shown in Fig.9.

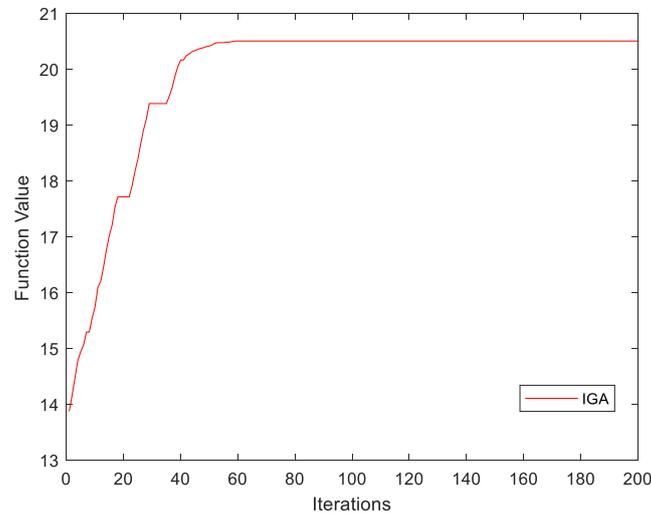


Figure 9 Running result of the algorithm

In addition, the matching couple is presented in Table 9.

Table 9 Matching couple

Suppliers	1	2	3	4	5	6
Demanders	4,2	5,6	7,11,8	3	10,9	1

According to the results, the total consensus is 20.52, and the individual's consensus is higher than 0.9. Meanwhile, the cost of scheduling is only 338.5, and the actual delivery time is close to the contact delivery time. The results prove that our method could improve the individual's consensus, and it is also helpful in producing on-time products.

### 4.4 Comparison of algorithms

In our study, we designed an improved PSO-GA algorithm. To verify the effectiveness of our algorithm, we compared our algorithm with the original bat algorithm (BA), cuckoo search (CS), and fireworks algorithm (FA). For comparison, to verify the advantage of our algorithm further, we added another two datasets, 15D8S (15 demanders and 10 suppliers) and 30D18S, which are generated by a random method. Hence, there are three data sets named 11D6S, 15D8S, and 30D18S. We compared the results of our algorithm with other algorithms based on these datasets. In addition, the parameters are determined by taguchi experimental design, we

provided the related parameters of these algorithms. The comparison results are shown in Fig.10–Fig.12.

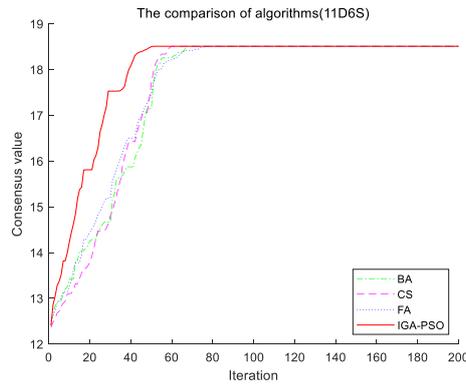


Figure 10 Comparison of algorithms (11D6S)

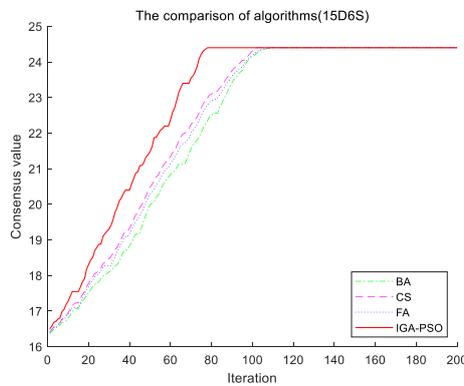


Figure 11 Comparison of algorithms (15D8S)

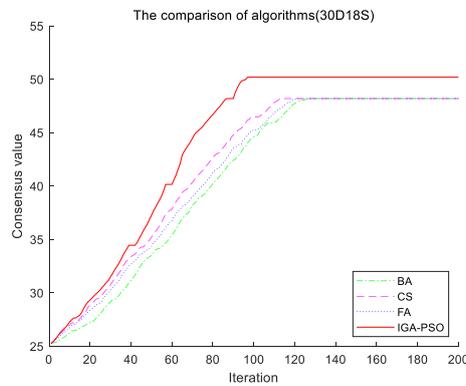


Figure 12 Comparison of algorithms (30D18S)

According to Fig.10–Fig.12, the results show that our algorithm has better performance, such as searching ability and convergence. In detail, we used three datasets to compare the performances with other similar algorithms. For 11D6S (11 demanders and 6 suppliers) and 15D8S, our algorithm has a faster convergence speed. For 30D18S, our algorithm finds a better solution and has a faster convergence speed. Hence, our algorithm has better performance and searching ability.

#### 4.5 Comparison of methods

To enhance the meaning of our study, we compare our study with existing studies of two-sided matching. Given the features of previous studies, we consider three impactors, namely

maximizing satisfaction, stable constraint, and peer effect. The comparing results are shown as Table 11.

Table 11 Related interviews of two-sided matching

Authors	Maximizing Satisfaction	Stable constraint	Peer effects
Li (Li et al. 2019)	√	√	
Gong(Gong et al. 2019) Chang(Chang et al. 2019) Han(Han et al. 2018) Victor (Sanchez-Anguix et al. 2019)	√		
Li(Li et al. 2020) Zhang(Zhang et al. 2019b)	√	√	
Elizabeth(Bodine-Baron et al. 2011)	√		√

1) Comparing the method with the previous method (maximizing the satisfaction)

To maximize satisfaction, considering the features of the industrial internet platform, we also establish a bi-level programming model. The first level aims at maximizing satisfaction, and the second level aims at minimizing the cost. The mathematical model is as formula (61)-(71).

Upper layer:

$$\max S = \sum_{i=1}^m \sum_{j=1}^n x_{ij} \times AB_{ij} + \sum_{i=1}^m \sum_{j=1}^n x_{ij} \times BA_{ij} \quad (61)$$

$$\sum_{o=1}^r (FB_{jo} - SB_{jo}) - \sum_{i=1}^m Pt_{ij} \times x_{ij} \geq 0 \quad (62)$$

$$\sum_{j=1}^n x_{ij} = 1 \quad (63)$$

$$x_{ij} = 0 \text{ or } 1 \quad (64)$$

Lower layer:

$$\text{Min } TOC = IDC + TC \quad (65)$$

$$IDC = \sum_{i=1}^m (IC_i + DC_i) \quad (66)$$

$$IC_i = \max(0, (FA_i - DA_i)) \times VT_i \quad (67)$$

$$DC_i = \max(0, (DA_i - FA_i)) \times DT_i \quad (68)$$

$$TC = \sum_{i=1}^m \sum_{j=1}^n x_{ij} \times Dis_{ij} \quad (69)$$

$$FA_{ij} = SA_{ij} + Pt_{ij} + IT_{ij} \quad (70)$$

$$IDC + TC + PC \leq \lambda \quad (71)$$

We use the same algorithm to solve the mathematical model. After the calculation, the result is presented in Table 12.

Table 12 Matching results

Demander	1	2	3	4	5	6	7	8	9	10	11
Suppliers	1	5	4	5	3	3	2	1	1	2	6
A	0.77	0.74	0.77	0.80	0.76	0.74	0.77	0.83	0.76	0.74	0.79
B	0.77	0.72	0.77	0.79	0.75	0.73	0.79	0.83	0.77	0.77	0.75

According to the matching couple, the total satisfaction was 16.91. However, to maximize satisfaction, the results are not stable. For example, if the matching object of 10 is 4, the satisfaction of 10 is 0.78. Compared to Supplier 2, Demander 10 is inclined to cooperate with 4. Therefore, the results are not stable. In addition, the maximizing value of satisfaction is 0.83,

and the minimizing value of satisfaction is only 0.72. It is also harmful to match results because of the high frequency of communication.

### 2) Stable constraint

To avoid this disadvantage, we set a stable constraint that guarantees that the individual could match the preferred matching couple. The constraint is expressed in formula (72) (Li et al. 2019).

$$x_{ij} + \sum_{\varepsilon: AB_{i\varepsilon} \geq AB_{ij}} x_{i\varepsilon} + \sum_{\zeta: BA_{i\zeta} \geq BA_{ij}} x_{i\zeta} \geq 1 \quad (72)$$

After adding relevant constraints, for 11D6S, the algorithm found a stable solution in the 87th generation. For 15D8S and 30D18S, the algorithm could not find a stable solution. This shows that the constraints increase the difficulty of obtaining a solution, and even result in no solution.

Considering the features of the sharing platform, strategies such as discounts are neglected. In our study, we also consider platform strategies. Similarly, we add an adjusted mechanism to modify the satisfaction. After that, we use the same algorithm to solve the problem. After the calculation, the number of iterations was higher than that in our study. Moreover, for the 30D18S dataset, the algorithm could not find a stable solution in 200 generations. Therefore, the method of maximizing consensus is more helpful for finding a stable solution.

Table 13 Comparison of results (stable constraint)

Dataset	11D6S	15D8S	30D18S
Our study	59	78	97
Stable constraint	108	126	No solution

Table 13 indicates that our study could find a matching result in a shorter time. In addition, for large-scale datasets, it is difficult to find a stable solution for large-scale datasets.

### 3) Comparison of the method with the previous method (peer effect)

The peer effect indicates that the individuals' preferences are not only related to their own preferences but also to other individuals' decisions. However, the relationship between different individuals is different, and the degree of mutual influence is also different. In previous studies, only the connection between different individuals was considered, and the strength of the connection was not considered. In our study, we fully consider the strength of social relationships. We use the in-degree centrality to determine the importance of individuals.

Considering the influences of social relationships, we set the peer effect as an objective. The formula is in formula (73).

$$\min DIS = \sum_{i=1}^m \sum_{j=1}^n x_{ij} (\sum_{\omega \neq i, \omega=1}^m \sum_{\tau \neq j, \tau=1}^n x_{\omega\tau} (|AB_{ij} - AB_{\omega\tau}| + |BA_{ij} - BA_{\omega\tau}|)) \quad (73)$$

Similarly, the proposed algorithm in our study is adopted to deal with the mathematical model that sets the peer effect as objective. To express the influence of social relationships, we take the product of the difference in satisfaction between individuals and the strength of social relationships between individuals as the evaluation index. The comparison results are in Table 14.

Table 14 Comparison of results (peer effect)

Datasets	11D6S		15D8S		30D18S	
	Supplier	Demander	Supplier	Demander	Supplier	demander
Our study	0.144	0.165	0.225	0.246	0.473	0.512

Peer effect	0.156	0.201	0.258	0.312	0.53	0.731
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In social networks, the degree of importance of individuals is different in the social network. We use the in-degree of centrality to represent the importance of different individuals. In the CRP, individuals with higher importance can influence the preferences of other individuals through the CRP.

## 5. Conclusion and future study

To obtain the matching couple, we establish a two-stage dual-group consensus reaching model. Given many individuals on the platform, we use mixed historical data, such as stars and scores, to generate satisfaction. Then, given the frequent communication among individuals, we consider the influences of social relationships. To avoid the disadvantages found in previous studies, we find matching results through the CRP. However, in the sharing platform, not all indices, such as cost and availability, could be obtained at the same time. The CRP could not be realized immediately. Hence, we establish a bi-level mathematical model. The first layer maximizes the consensus, and the lower layer obtains the value of cost and availability by minimizing the total cost. We then design an improved PSO-GA algorithm to solve the bi-level programming. Finally, we take the manufacturing sharing platform as an example.

The following contributions can be drawn. (1) Historical data were adopted to present the preferences and assessment, and the mixed data, including score information and star information, are integrated by the cloud model. (2) The platforms' strategies, like discount and scheduling, are fully considered in two-sided matching. (3) Considering the interaction between the moderators and decision-makers, a two-stage CRP is used to realize matching. (4) We improve the original PSO-GA by integrating the cloud model.

There are areas that require further research. First, the social relationship is complex, and we encourage other scholars to study the social relationship with business meaning. Second, in the sharing platform, the platform is regarded as the moderator that provides the feedback and adjusted method. In the sharing platform, the final matching results were conducted using the platform. If the matching results are harmful to the platform's profit, the platform will reject these matching results. Hence, the platform's opinion also influences CRP. In future work, we encourage scholars to study the new CRP that moderates the process in the sharing platform. Third, considering the platform's high-efficiency requirements, we encourage other scholars to design an efficient algorithm to solve the mathematical model.

### Compliance with ethical standards

**Ethical approval** This article does not contain any studies with animals performed by any of the authors.

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**Conflict of Interest** The authors declare that they have no conflict of interest.

**Informed consent** Informed consent was obtained from all individual participants included in the study.

### **Authorship contributions**

Huagang Tong contributed to conceptualization, formal analysis and investigation, methodology, writing—original draft. Jianjun Zhu contributed to conceptualization, methodology, supervision, resources, writing—review & editing. Xiao Tan contributed to the formal analysis and investigation, writing - review and editing.

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# Figures

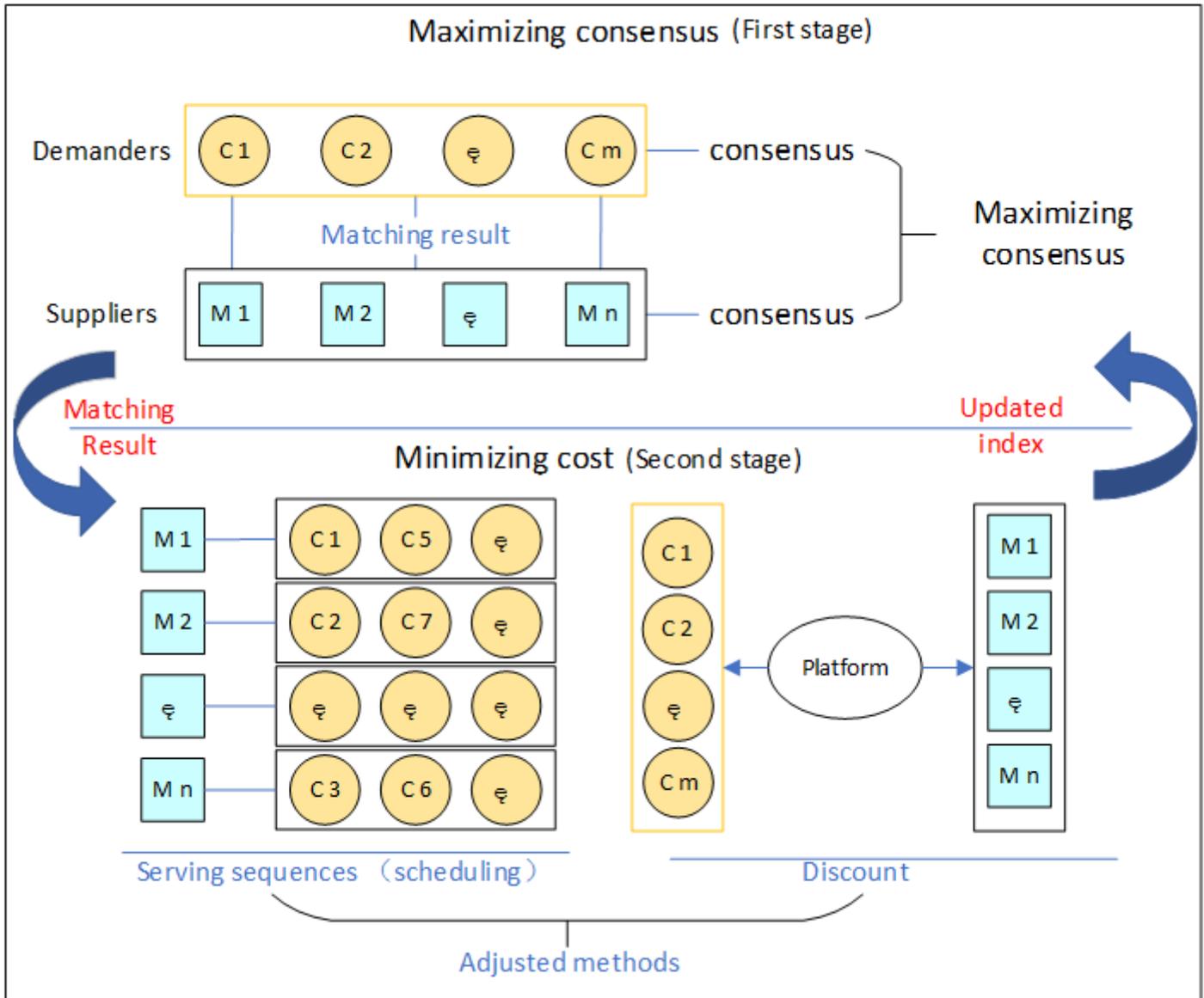


Figure 1

Procedure of the CRP

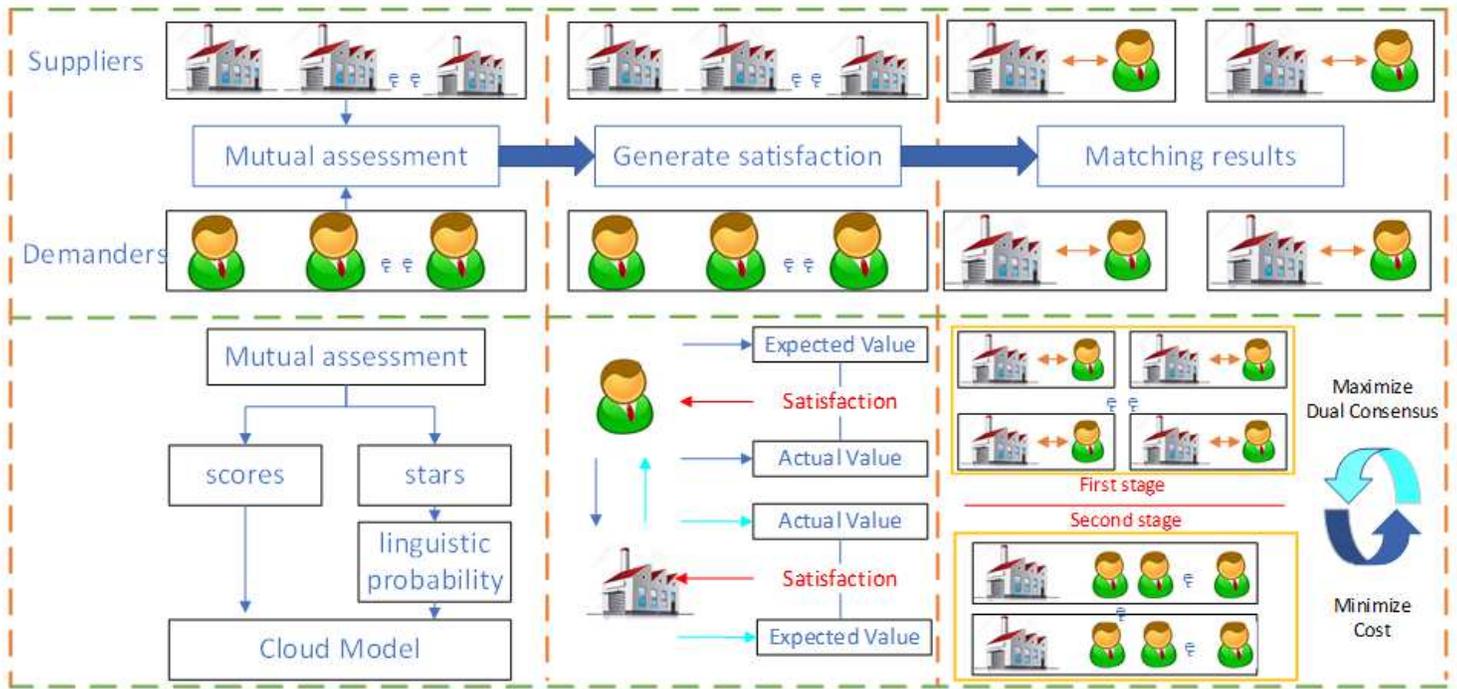


Figure 2

Flowchart of our study

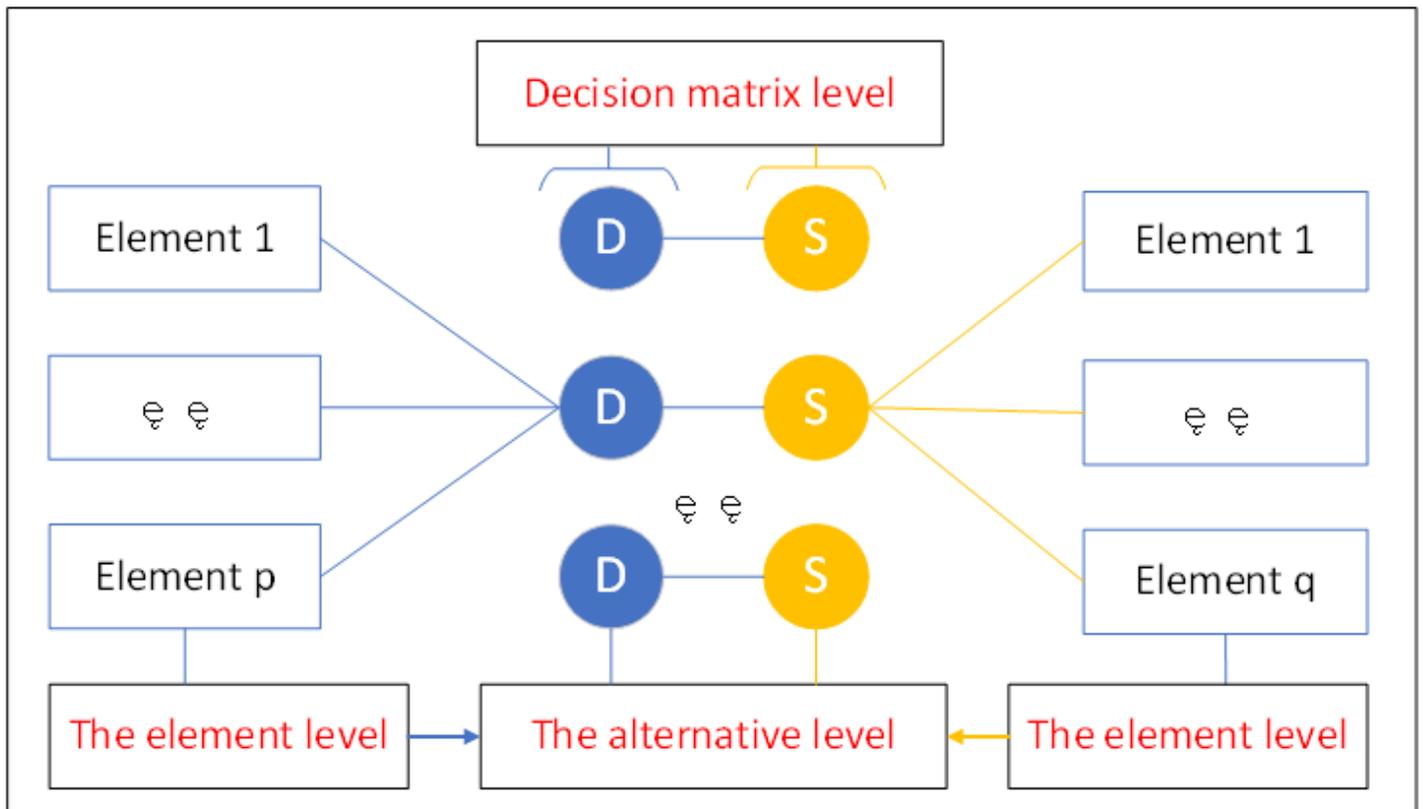
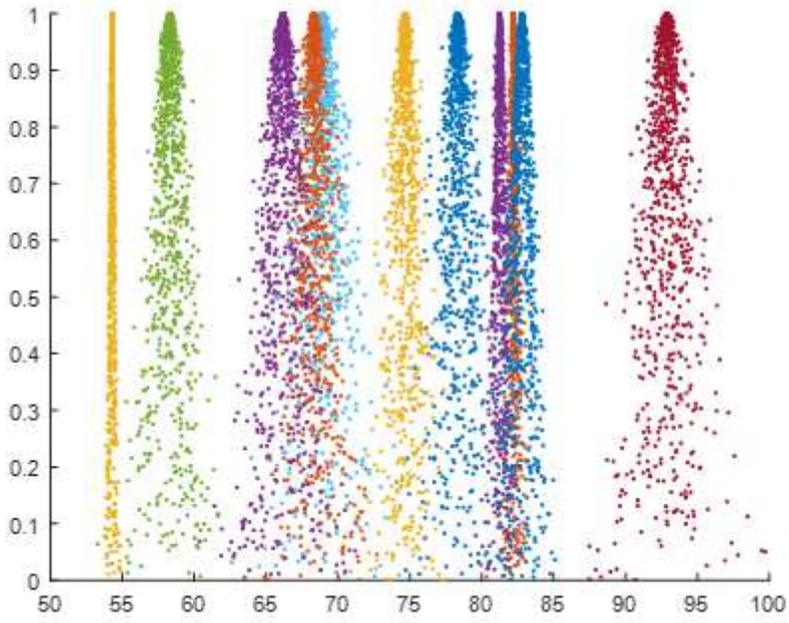


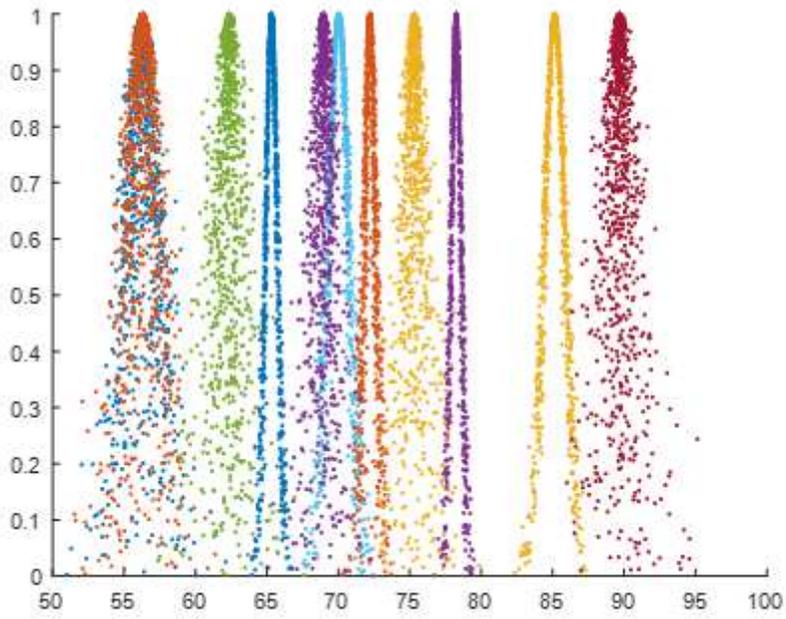
Figure 3

Consensus of each level



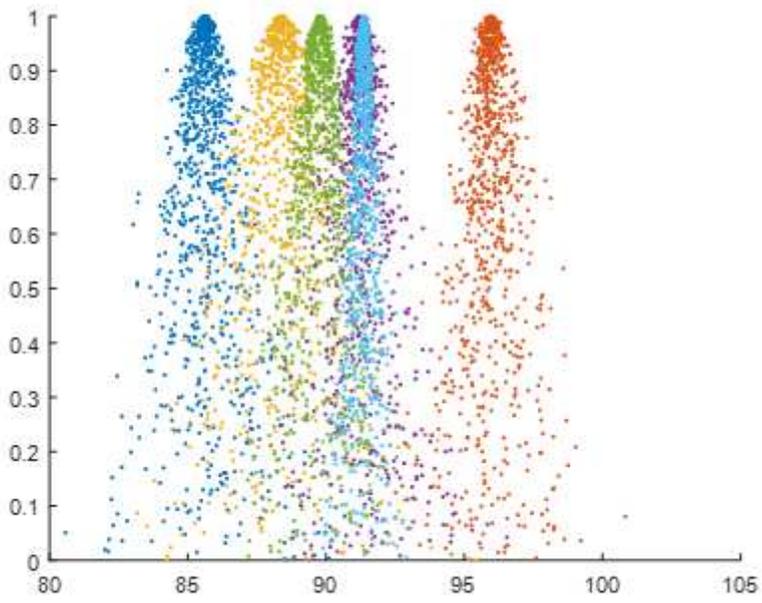
**Figure 4**

availability for demanders



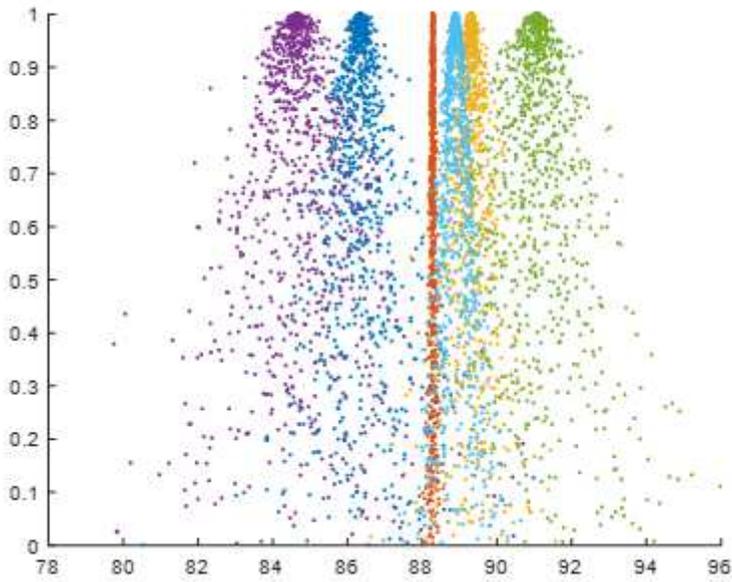
**Figure 5**

the price for demanders



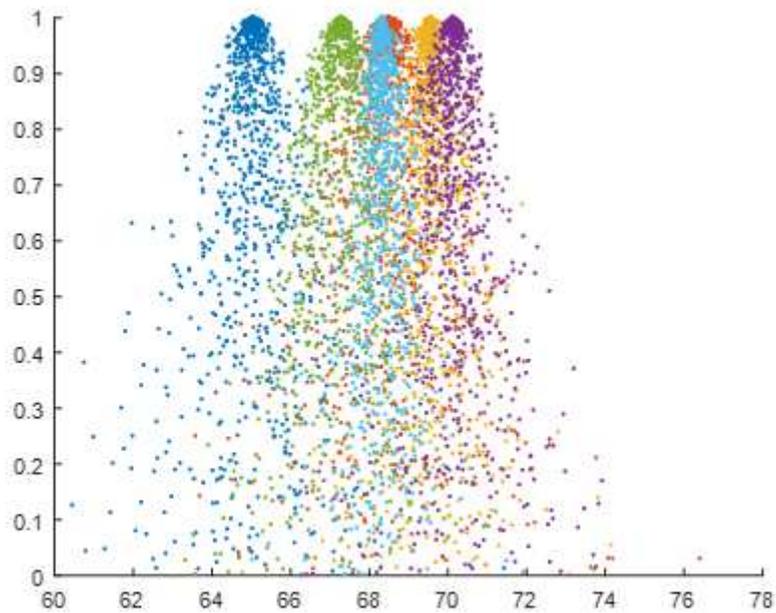
**Figure 6**

Cooperation intensity for suppliers



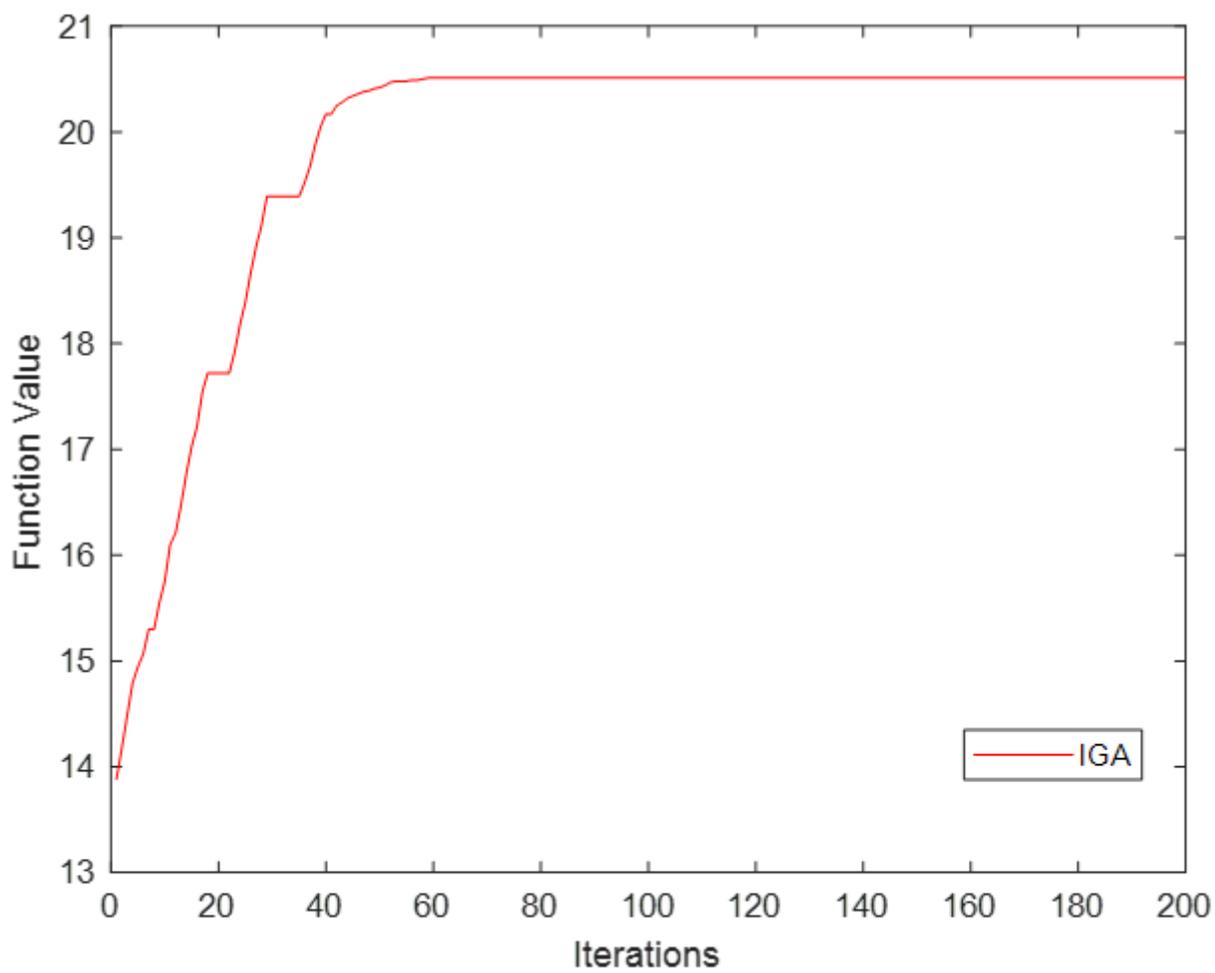
**Figure 7**

Security for suppliers



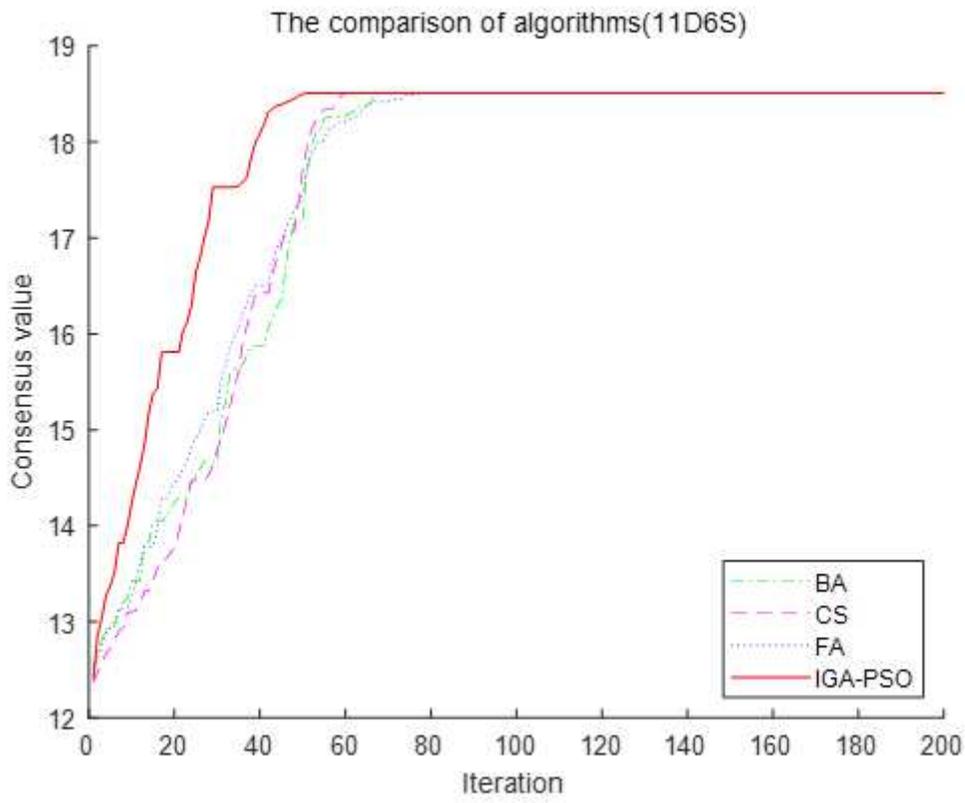
**Figure 8**

Cloud model of the price for suppliers



**Figure 9**

Running result of the algorithm



**Figure 10**

Comparison of algorithms (11D6S)

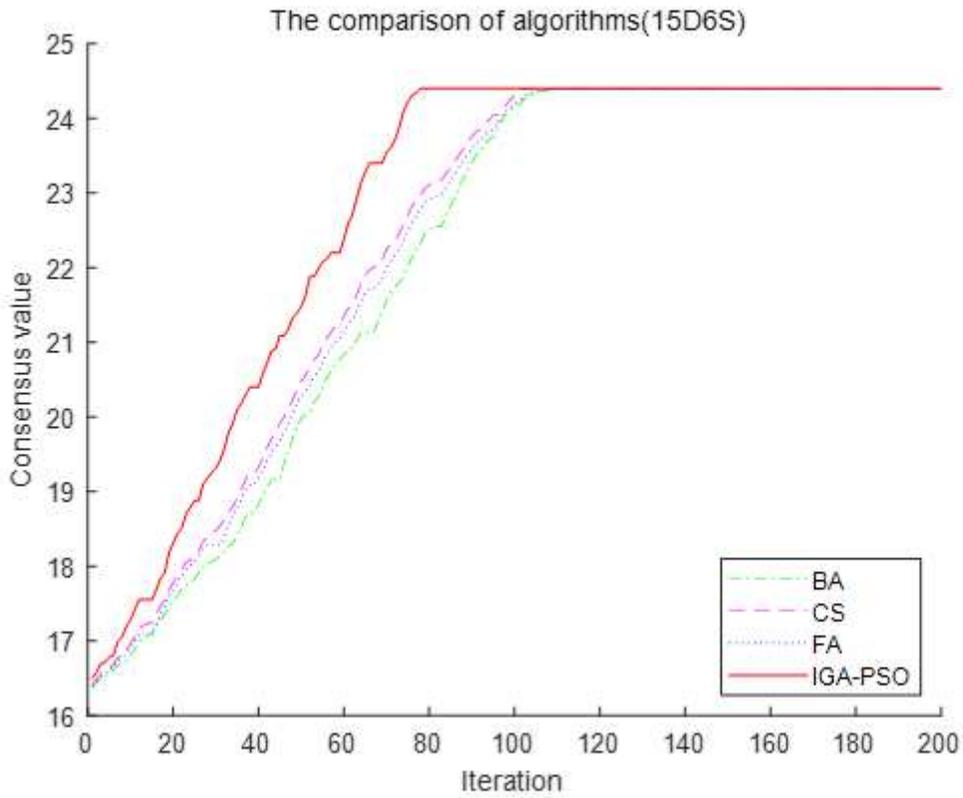


Figure 11

Comparison of algorithms (15D8S)

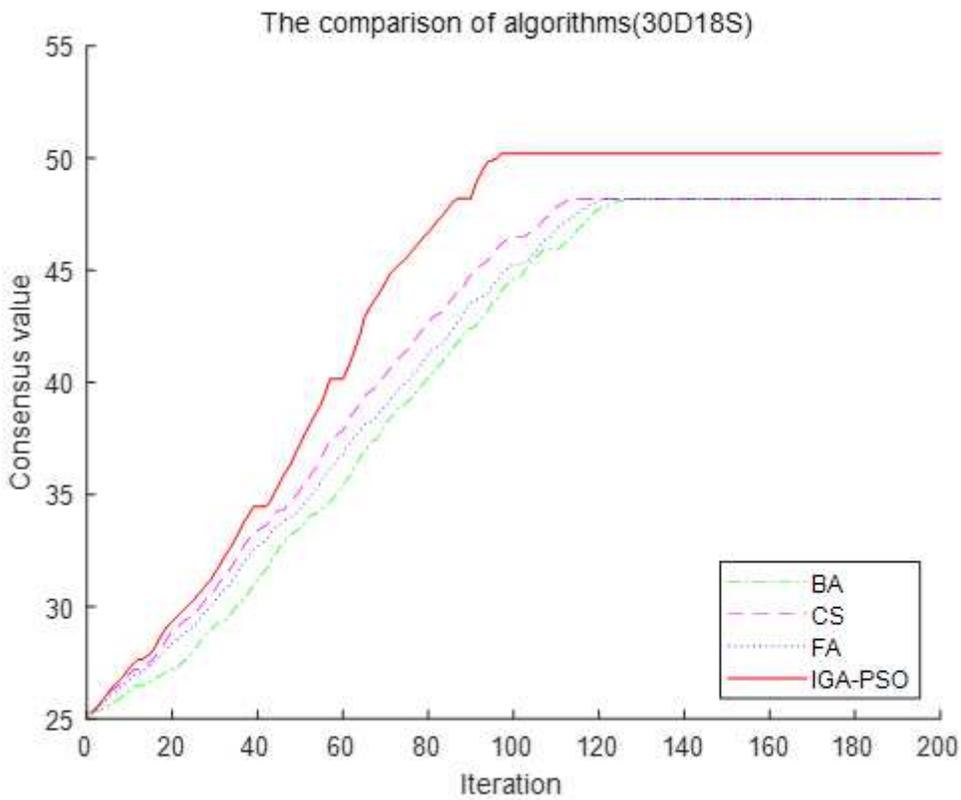


Figure 12

## Comparison of algorithms (30D18S)