Research on Supply-Demand Matching of Industrial Interconnection Based on Smart Contract in Digital Economy

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Abstract: Against the background of the digital economy, the conventional matching strategy of supply and demand is unable to meet the requirements of matching supply and demand industrial interconnection with digitalization as the core element. To solve the trust problem of supply and demand matching contract of digital industrial interconnection, a decision-making framework of supply and demand matching of industrial interconnection based on smart contract is proposed. Based on the massive resource data, a resource characteristic attribute matrix is constructed, and the Fuzzy C-Means algorithm is used to classify and reduce the dimension of massive resource data. Based on the attribute expectation of supply and demand, the objective function with maximum satisfaction is created to realise bidirectional matching. Finally, the effectiveness of the proposed method is demonstrated by an example.

Keywords: Digital Economy; Industrial Interconnection; Smart Contract; Fuzzy C-Means Algorithm; Two-Sided Matching

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1 Introduction

The digital economy is a new form of economy with the data resource as the key element and the modern information network as the main carrier. Through digital transformation, the global economic governance has entered a new era [15]. In the context of digital economy, the modernization degree of industrial and supply chains are promoted, and intelligent interconnection between chains, industries and enterprises is established. The data of industrial interconnection supply and demand network show a massive and multidimensional development trend. In this context, how to ensure the security of supply and demand transactions, and how to achieve a smarter, more efficient, and more reasonable matching of the resources of the industrial Internet supply and demand network emerges as a new proposal.

With the emergence of blockchain technology, smart contract has become widely known as one of its key technologies [20]. At its core is a set of computer protocols that execute transactions based on information, trigger the execution of transactions and settle them. Smart contract has the characteristics of weak centralisation, trust protection and is tamperproof. It can realise the non-differentiated recording of transactions between different nodes and promote the interconnection of information [17]. Currently, many scholars apply blockchain and smart contract to the energy and power grid, mainly solving the problem of information transparency and trust in energy transactions by establishing a cloud service platform [12, 16]. Some scholars also apply blockchain and smart contracts to supply chain management to reduce

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business risks and transaction costs [7, 12, 14]. The literature review revealed that in the context of the digital economy, applying blockchain and smart contract is one of the most important methods to realise the digital transformation of industrial and supply chain and ensure the security of digital transactions.

With the continuous cross-border cooperation between industries, the concept of industrial interconnection of supply and demand is constantly mentioned [9, 10]. Based on modern information technology, industrial interconnection realises the interconnection between the physical world and the virtual world of the network, and the regional distribution of resources is no longer an important factor affecting the cooperation between supply and demand between enterprises [6]. Industrial interconnection supply and demand matching transactions are evolving in a smarter, more efficient, and more reasonable direction, and all intelligent decisions are inextricably linked to data. In the past, scholars have conducted in-depth research on supply and demand transactions, e.g., considering the dynamics of supply and demand matching [4, 13], methods based on game theory [5], a multi-agent based supply and demand matching system [19], mathematical models and intelligent algorithms [1, 18], a data-driven supply and demand matching method for public transportation planning [8].

In summary, based on the literature review, the author finds that the research on the matching of supply and demand of industrial interconnection with data as a core element is still in its infancy in the context of the digital economy. The research contributions of this paper mainly focus on the following aspects:

(a) Considering the trust problem in supply and demand matching and transaction security, a transaction decision architecture based on smart contract is proposed. (b) For massive resource data, a resource characteristic attribute matrix is established, and the membership function of fuzzy clustering algorithm is improved to cluster and reduce the dimension of massive resource data.(c) Based on the attribute expectations of both the supplier and buyer, the satisfaction objective function is established to achieve bilateral matching. Considering that the service capability of resources in the industrial interconnection supply and demand network is differentiated, the method improves the operation efficiency and rationality of the matching result by reducing the dimension of resources and performing classification and re-matching.

2 Supply and Demand Transaction Decision Based on Smart Contract

2.1 Smart Contract Framework for Supply and Demand Transactions

By implementing smart contract technology, the resource transaction of the supply and demand network can be decentralised and transaction security can be ensured. The operation architecture of the industrial interconnection supply and demand network based on smart contract is shown in Figure 1. The overall operational structure is divided into four layers: user layer, application layer, executive module layer and basic support layer. The decision-making framework for matching supply and demand in the industrial interconnection based on smart contract is shown in Figure 1.

User layer: The user layer includes resource demanders, resource providers, and third-party supply and demand network cloud platform operators. Different users have different rights.

Application layer: Human-computer interaction interface between users and the platform, including transaction mode selection, demand task release, contract signing, order query, etc. Platform operator applications include resource management, contract management, authority management, credit management, etc.

Execution module layer: The execution module layer is composed of two modules, the operation module and information management module, which is the intermediate link connecting the application layer and resource layer. The main functions are system management module (including managers, authentication, user information registration, information editing, intelligent contract management, etc.), information tracking module (including resource information records, information query, liability allocation, supplier management, etc.), a trading decision module (including demand and resource selection, the resource allocation algorithm, etc.), service resource management module (including tube Management, order management, goods delivery management, capital management, etc.).

Basic support layer: This layer is composed of related technologies and servers that support the operation of the platform, including platform business server, cloud computing technology and blockchain database.

Virtual demand pool cloud platform: It connects physical resources such as manufacturing equipment, raw material and software with the network by using sensor technologies such as digital twin and IOT, realising the mapping of physical resources to virtual resources, and encapsulating their its services on the cloud platform to meet the needs of both supply and demand.

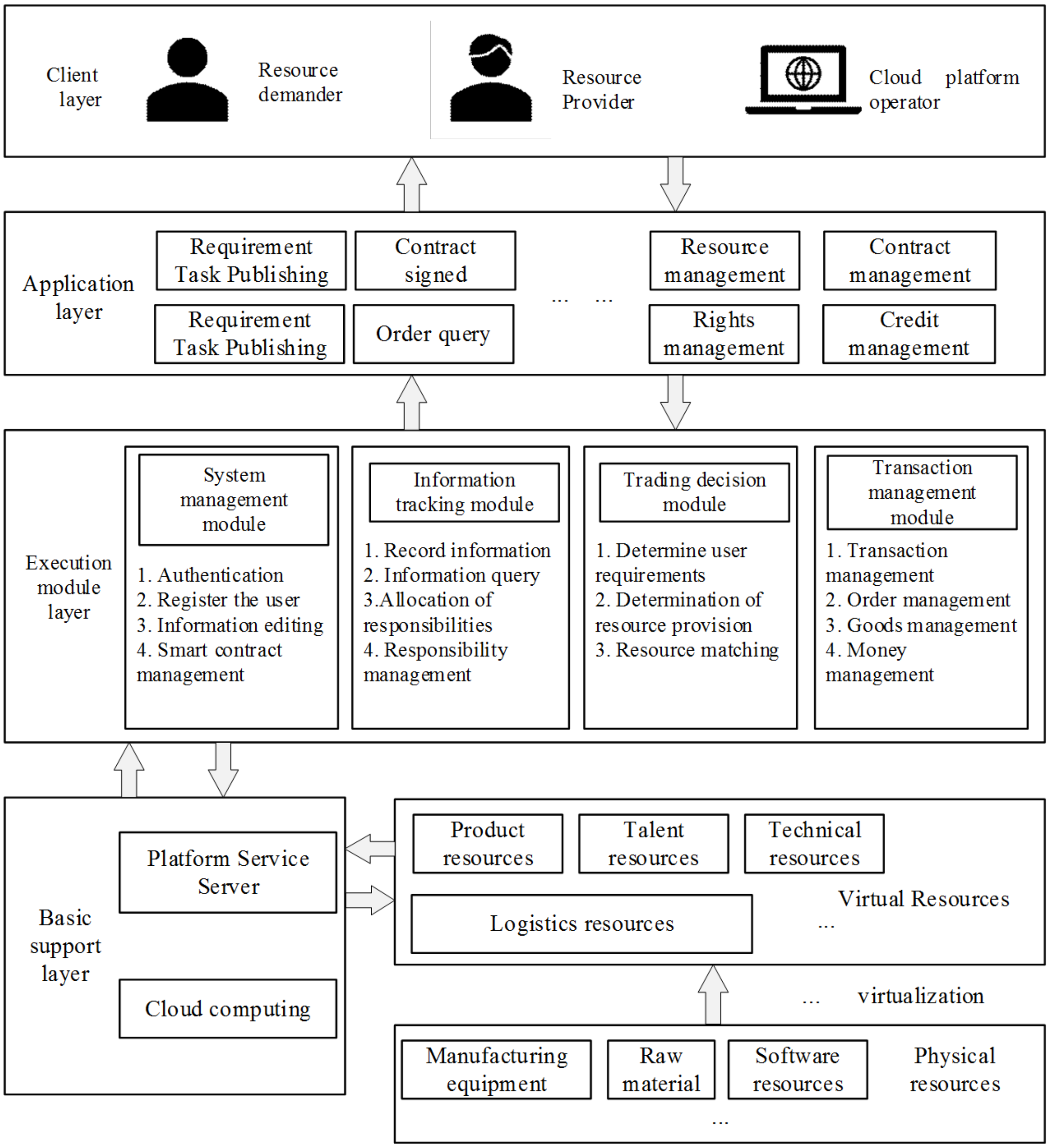

Figure 1 Operation architecture of an industrial interconnection supply and demand transaction based on smart contract

2.2 Transaction Process

According to the transaction operation architecture of industrial interconnection supply and demand network under the developed smart contract, the transaction process between the supply and demand sides of industrial interconnection is shown in Figure 2. It includes the task initiation stage, resource clustering stage, resource matching stage, contract formulation stage and contract execution stage.

Task initiation stage: On the industrial interconnection supply and demand cloud platform, both the supply and demand parties can upload their demand information, including the expectations of the transaction object. The resource demand party releases the demand information on the industrial interconnection supply and demand cloud platform to trigger the transaction.

Resource clustering stage: Based on Fuzzy C-means (FCM) [2] clustering algorithm, dimensionality of massive resources with different service capabilities is reduced, to reduce the difficulty of subsequent supply and demand matching and improve the rationality of matching results.

Resource matching stage: Based on the expected attribute values of the supply and demand sides, the maximum matching satisfaction is determined and the matching between supply and demand is completed.

Contract formulation stage: After the matching of supply and demand is successful, the transaction subject information of both parties is obtained, and the smart contract is formulated according to the agreed content of demand, time, price, etc. Both parties perform security verification using private keys, and the contract is signed after all security checks are passed.

Contract execution stage: After the contract is signed, the platform tracks and monitors the transaction progress information (resource service progress, logistics information, customer service information, capital flow information, etc.), and generates real-time credits for the transaction information.

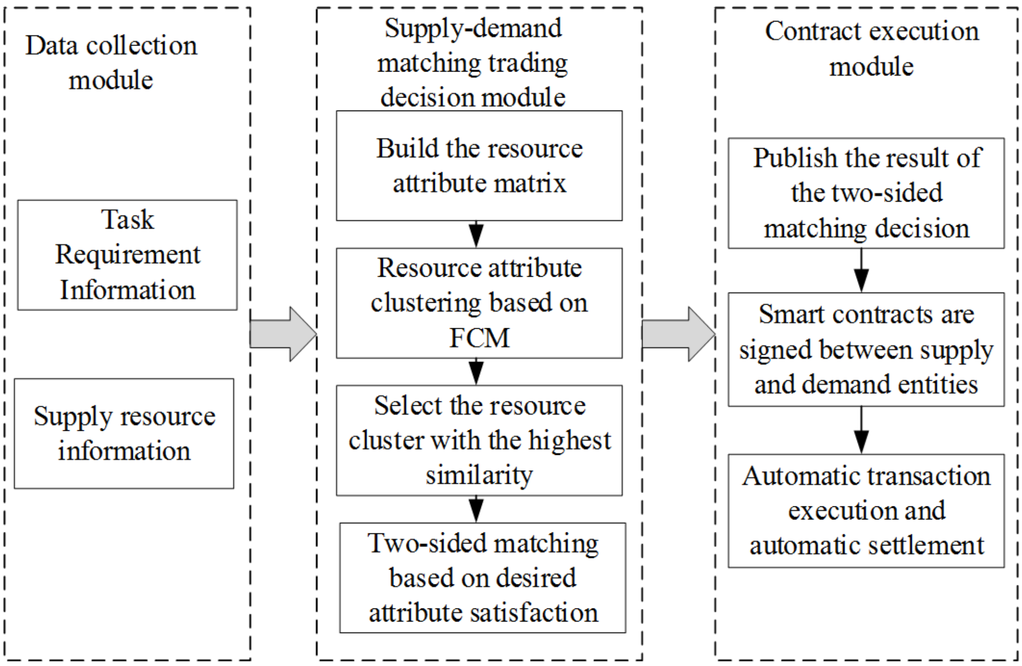

Figure 2 Transaction process based on smart contract

3 Resource Clustering Based on FCM

There is a large amount of resource data in the industrial interconnection supply and demand network, and the service contents and service capabilities offered by enterprises are different. In this case, the conventional direct supply and demand matching may lead to unreasonable matching results. Therefore, resources are clustered according to their features and characteristics before resource matching. Thus, for supply and demand matching, the class cluster with the most similarity to the demand is found. There are many clustering methods. Conventional clustering methods include methods based on grid, density, partitioning, and model and hierarchy [11]. In the actual clustering process, the classification of a certain attribute of resources is often uncertain, so in this study the fuzzy C-means algorithm is used as the resource clustering algorithm, and the classification is done by calculating the sample membership index.

3.1 Introduction of Algorithm

The FCM algorithm is the result of fusing the K-means algorithm and fuzzy thinking, which brings the fuzzy logic into the K-means algorithm. At the same time, FCM is an objective function-based fuzzy clustering method that classifies each sample by calculating its degree of membership to a certain class. For example, if the samples are divided into two classes, the probability that member A is in the sample may be 0.3 to A and 0.7 to B, to achieve fuzzy clustering.

Suppose there is a data set X, to be divided into C classes, there are C class centres c_i, and the membership degree of each sample j belonging to a certain class is u_{ij}. The objective function and constraints of FCM algorithm are as follows:

$$J=\sum_{i=1}^{C}\sum_{j=1}^{n}u_{ij}^{m}\left\|x_j-c_i\right\|^2 \tag{1}$$

$$\sum_{i=1}^{C}u_{ij}=1,\quad j=1,2,\dots,n \tag{2}$$

Eq. (1) is the objective function, which is composed of the membership degree of the corresponding sample multiplied by the distance of the sample to each type of centre. The smaller the sample is, the better the classification effect is. In Eq. (2) $u_{ij}\in[0,1]$, the more u_{ij} approaches 1, the higher the likelihood that the sample belongs to the class i. The sum of membership $\sum_{i=1}^{C}u_{ij}=1$; m is the fuzzy weight coefficient, and the smaller m is, the weaker the degree of ambiguity is. In general $m=2$; $\left\|x_j-c_i\right\|^2$ denotes the distance of the sample from the centre of class i.

According to the Lagrange multiplier method, the objective function J is expanded to obtain:

$$J=\sum_{i=1}^{C}\sum_{j=1}^{n}u_{ij}^{m}\left\|x_j-c_i\right\|^2+\lambda_1\left(\sum_{i=1}^{C}u_{i1}-1\right)+\dots+\lambda_j\left(\sum_{i=1}^{C}u_{ij}-1\right)+\dots+\lambda_n\left(\sum_{i=1}^{C}u_{in}-1\right) \tag{3}$$

In this case, the extremum problem of Eq. (1) can be transformed into the partial derivative of u_{ij} and c_i, and the iterative formula of A, u_{ij}, and c_i can be found as follows when u_{ij} and c_i are set to zero:

$$u_{ij}=\frac{1}{\sum_{k=1}^{C}\left(\frac{\left\|x_j-c_i\right\|}{\left\|x_j-c_k\right\|}\right)^{\left(\frac{2}{m-1}\right)}} \tag{4}$$

$$c_i=\sum_{j=1}^{m}\frac{u_{ij}^{m}}{\sum_{j=1}^{n}u_{ij}^{m}}x_j \tag{5}$$

3.2 Construct the Resource Attribute Matrix

The resource set of the supplier is $R=\{r_1,r_2,\dots,r_n\}$, $r_m\in R$ represents the number m resource in the set, each resource is composed of a series of resource attribute indicators, the resource attribute set is $A=\{a_1,a_2,\dots,a_s\}$, $a_k\in A$ represents the k item attribute in the set, from this, the resource attribute matrix can be calculated as $RA=[ra_{mk}]_{n\times s}$. The demand task set of the demander is $T=\left\{t_1,t_2,\dots,t_q\right\}$, where $t_j, j\in(1,q)$ represents the number j subtask, the attribute set of the demand task is $B=\left\{b_1,b_2,\dots,b_d\right\}$, $b_l\in B$ represents the attribute of the l item in the set. Thus, the resource matrix $TB=\left[tb_{jl}\right]_{q\times d}$ of the demand task can be obtained as follows:

$$RA=\begin{bmatrix} ra_{11} & \dots & ra_{1k} & \dots & ra_{1s}\\ ra_{m1} & \dots & ra_{mk} & \dots & ra_{ms}\\ ra_{n1} & \dots & ra_{nk} & \dots & ra_{ns}\end{bmatrix} \tag{6}$$

$$TB=\begin{bmatrix} tb_{11} & \dots & tb_{1l} & \dots & tb_{1d}\\ tb_{j1} & \dots & tb_{jl} & \dots & tb_{jd}\\ tb_{q1} & \dots & tb_{ql} & \dots & tb_{qd}\end{bmatrix} \tag{7}$$

The resource attributes are listed in Table 1. Resource matching based on the supply and demand network is about finding the optimal resources among many resources to meet the demand of the buyers. The determination of the resource attributes directly affects the clustering results. In the interconnected network of supply and demand in this paper, the design of the industry resources matching strategy is done based on intelligent contract. Intelligent contract will record the history of resource suppliers trading credibility, history of matching the quality, price, delivery time, delivery quality, and supplier of resources service capability is the important attribute index.

Table 1 Resource property table

Attribute	Attribute indicator	Attribute description	Attribute feature
a_1	$T_r = 1 - \frac{T_{actual}}{T_{contract}}$	Delivery time of the supplier's resources	Quantitative positive correlation
a_2	P_{quote}	Supplier resource delivery price	Quantitative negative correlation
a_3	$Q = 1 - \frac{N_{return}}{N_{sale}}$	Supplier resource delivery quality rate	Quantitative positive correlation
a_4	D	Resource distance from task	Quantitative negative correlation
a_5	$C_r \in [0,1]$	Supplier's contract performance credibility	Qualitative positive correlation
a_6	$SC \in [0,1]$	Supply side resource service capability	Qualitative positive correlation

Where, T_{actual} is the actual time required to complete the task, and $T_{contract}$ is the contracted delivery time. P_{quote} is the quotation from the resource supplier. N_{return} is the quantity of resource returned by the supplier, and N_{sale} is the total sales volume of the supplier.

Both supplier's contract performance credibility C_r and the supplier's resource service capability SC are qualitative attributes that are difficult to evaluate with objective quantitative data. In this paper, the triangular fuzzy number from fuzzy theory is used to quantitatively process the qualitative attributes of resources based on historical customer ratings and other linguistic information. The comparison between the value of the qualitative attribute and the triangular fuzzy number is shown in Table 2 below.

Table 2 Comparison table between qualitative attribute value and triangular fuzzy number

Evaluation type	Evaluation language	Triangular fuzzy number
Fuzzy language	lower	(0, 0.1, 0.25)
	low	(0.1, 0.25, 0.5)
	average	(0.25, 0.5, 0.75)
	high	(0.5, 0.75, 0.9)
	higher	(0.75, 0.9, 1)

Table 3 Task property table

Attribute	Attribute indicator	Attribute description	Attribute feature
b_1	$T_{demander}$	Task demand time	Quantitative positive correlation
b_2	$P_{demander}$	Task price	Quantitative negative correlation
b_3	C_t	Demand-side credibility	Qualitative positive correlation

The attribute nature of supply and demand resources determines the difference between unit and dimension. It is necessary to first remove dimension normalisation for all attribute data in the matrix, so that each element in the supply and demand attribute matrix is between [0,1]. The normalisation process is shown in Eq. (8). Then the quantitative negatively correlated properties a_2 and a_4 are positively correlated by $a = 1 - a$ to update the matrix. We get the new resource attribute matrix $RA' = \left[ra'_{mk}\right]_{s\times n}$, and we can get the demand task attribute matrix $TB' = \left[tb'_{jl}\right]_{q\times o}$ in a similar way. The solution of the task properties can be found in Table 3, which lists the resource properties.

$$ra'_{mk} = \frac{ra_{mk} - ra_{m\min}}{ra_{m\max} - ra_{m\min}} \tag{8}$$

Considering the different influence of each attribute feature on the clustering result, the feature weight coefficient of each dimension $\omega = (\omega_1, \omega_2, ..., \omega_n)$ is introduced to reduce the influence of the unique properties of attributes on the clustering results, and assign weight to the attribute of the resource supplier. The Euclidean distance after introducing the feature weight coefficient is expressed as follows:

$$u_{ij}=1/\omega\sum_{e=1}^{C}\sum_{k=1}^{S}\left(\frac{\|ra_{mk}-c_i\|}{\|ra_{mk}-c_e\|}\right)^{\frac{2}{m-1}} \tag{9}$$

When calculating the improved membership function, the Euclidean distance of the clustering centre of each attribute in the sample is taken into account, so as to obtain the membership degree of a certain kind of resource belonging to the clustering centre, and construct the membership matrix.

3.3 Flow of the Algorithm

Step 1: Data preprocessing. The resource attribute matrix is initialised, the resource attributes are normalised according to Eq. (8), and the feature attributes are weighted.

Step 2: Initialise the basic parameters of the algorithm. Set the initial cluster centre c_0, set the iteration stop threshold ε, set the iteration counter $T_d=0$, and set the maximum number of iterations.

Step 3: Update the membership matrix U_f according to Eq. (4), and update the iteration count to $T_d=T_d+1$.

Step 4: Divide the membership degree and select a new cluster centre according to Eq. (5).

Step 5: Calculate the value of the objective function value for each node and cluster centre in the class cluster. If it is less than the given threshold ε, or if the change from the last objective function is less than the threshold, then the algorithm stops; if it is greater, then go to Step 6.

Step 6: Evaluate whether the number of iterations meets the specified maximum number of iterations. If yes, the algorithm stops; if not, return to Step 3 to update the membership matrix U_f.

Step 7: The algorithm stops, and the clustering result is determined.

4 Supply and Demand Bilateral Matching Decision Mechanism

In the exchange of supply and demand, the resource demand objective is to obtain the most satisfactory service with the lowest cost, and resource service suppliers of the resource demand satisfaction, and at the same time relatively high profits, or the supply and demand on both sides of the transaction is a typical not cross relationship. To match the two decisions for independent voluntary market operation, and ensure its cooperation characteristics meet the requirements of the bilateral matching theory basics, two-sided matching theory and matching decision method are applied for study and analysis.

In this study, from the perspective of the desired attributes, the subjects of the supply side and demand side have a psychological expected value for each attribute value of the other party, which is filled in by the subjects of the supply and demand sides on the cloud platform according to the historical experience and their own needs, and the range is [0,1]. Let the expected value of the task for the resource attribute be $\eta^r=\{\eta_1^r,...\eta_2^r,...,\eta_s^r\}$, and let the expected value matrix of the resource for the task be expressed as η^t, and $\eta^t=[\eta_{il}]_{g\times d}$. First, the optimal resource cluster is selected by the similarity of the attributes. Then, the satisfaction function can be obtained by the difference between the actual attribute value and the expected attribute value.

$$\delta_\eta=\sum_{k=1}^{s}\eta_k^r \tag{10}$$

$$\delta_{ra}=\sum_{h=1}\sum_{k=1}^{s}ra_{hk} \tag{11}$$

$$\phi=\delta_{ra}-h\delta_\eta \tag{12}$$

Eq. (10) represents the sum of the expected attributes of a single resource standard. Assuming that h belongs to a certain class of clusters, Eq. (11) represents the sum of the actual attribute values of that class of clusters. In Eq. (12), ϕ represents the similarity value, and the smaller ϕ is, the greater the similarity. In this way, the optimal resource cluster is found.

After the fuzzy clustering and attribute similarity calculation, the optimal resource class cluster is selected as $U=\{u_1,u_2,...u_g\}$, where $u_i\in U$ represents resource i in the resource set, and the attribute matrix of the optimal resource class cluster is $RA''=[ra''_{ik}]_{g\times n}$. Let the satisfaction of the demand task with the supplier's resource be α_{ij}, it represents the satisfaction of the task j with the resource

i. Let the satisfaction of the resources on the supplier side to the demand task be β_{ij}, it represents the satisfaction of the resource i with the task j. The bilateral matching decision of supply and demand based on expectation attributes is to select the task and resource that maximises the bilateral satisfaction for matching. The formula of the satisfaction of both sides is as follows:

$$\alpha_{ij} = \sum_{k=1}^{s} \begin{cases} 1 , & \eta_k^r \le a_k \\ 1-\left(\eta_k^r - a_k\right) , & \eta_k^r > a_k \end{cases} \tag{13}$$

$$\beta_{ij} = \sum_{l=1}^{d} \begin{cases} 1 , & \eta_l^t \le b_l \\ 1-\left(\eta_l^t - b_l\right) , & \eta_l^t > b_l \end{cases} \tag{14}$$

$$\eta_k^r \in [0,1], \quad \eta_l^t \in [0,1] \tag{15}$$

Let x_{ij} be a 0-1 variable, when $x_{ij} = 0$, it means that the resource i does not match task j, when $x_{ij} = 1$, it means that the resource i and task j match completely. According to the principle of maximising the satisfaction of both parties, the objective function is established as follows:

$$\max Z_1 = \sum_{i=1}^{g}\sum_{j=1}^{n} x_{ij}\alpha_{ij} \tag{16}$$

$$\max Z_2 = \sum_{i=1}^{g}\sum_{j=1}^{n} x_{ij}\beta_{ij} \tag{17}$$

$$s.t. \quad \sum_{j=1}^{n} x_{ij} = 1 \tag{18}$$

$$\sum_{i=1}^{g} x_{ij} \le 1 \tag{19}$$

Where, Eq. (16) and (17) represent the objective function that maximises the satisfaction of both parties, and Eq. (18) and (19) are objective constraints. Eq. (18) indicates that a resource can only match one task, and Eq. (19) indicates that a task can either match or not match a resource.

The linear weighting method is used to transform the above multi-objective model into a single objective model, as shown in Eq. (20).

$$\max Z = \mu_1\alpha_{mi} + \mu_2\beta_{im} \tag{20}$$

$$st. \quad \mu_1 \ge 0, \mu_2 \ge 0, \mu_1 + \mu_2 = 1 \tag{21}$$

μ_1 and μ_2 are the weights of objective function satisfaction, which are usually assigned according to the importance of the supply and demand subjects. Considering the fairness of subjects in the two-sided matching process, take $\mu_1 = \mu_2 = 0.5$. The single objective model corresponds to the assignment problem model in operations research and can be solved with the Hungarian algorithm.

5 Analysis of Examples

In this study, data from an industrial interconnection cloud platform is used as an example to perform an experimental analysis. For the processing tasks of a batch of parts, 1000 groups of data resources of the service provider are randomly selected from the cloud platform database. The original data matrix is shown in Table 4 after preliminary calculation and the normalised data is shown in Table 5.

Table 4 Raw resource attribute matrix

Service resources	a_1	a_2	a_3	a_4
r_1	0.8564	356	0.9631	68
r_2	0.6522	280	0.8435	53
r_3	0.7894	308	0.8783	75
....	...	...	...	...
r_{998}	0.9581	280	0.9861	113
r_{999}	0.8635	180	0.9486	150
r_{1000}	0.6428	270	0.9834	89

By the evaluation information, attributes a_5 and a_6 are added to the matrix, based on the fuzzy triangular number in Table 2. Based on Eq. (8), the original matrix of resource attributes is processed dimensionlessly. In addition, the two attributes of a_2 and a_4 are positively processed, and the attributes of the resources are weighted. The weights here are $\omega_1 = 0.8$, $\omega_2 = 0.8$, $\omega_3 = 0.9$, $\omega_4 = 0.8$, $\omega_5 = 1$, $\omega_6 = 0.9$. The new dimensionless resource attribute matrix is shown in Table 5.

Table 5 Dimensionless resource attribute matrix

Service resources	a_1	a_2	a_3	a_4	a_5	a_6
r_1	0.6851	0.7531	0.8668	0.4359	0.2500	0.6750
r_2	0.5218	0.6634	0.7592	0.3984	0.9000	0.6750
r_3	0.6315	0.6815	0.7905	0.4976	0.7500	0.8100
....	....	...	...	...	...	....

Service resources	a_1	a_2	a_3	a_4	a_5	a_6
r_{998}	0.7665	0.6634	0.8875	0.6435	1.000	0.9000
r_{999}	0.6908	0.4751	0.8537	0.7324	1.000	0.4500
r_{1000}	0.51424	0.6389	0.8851	0.5648	0.500	0.2250

In this study, the elbow method [3] is used to determine the optimal number of classifications by determining the sum of the squared errors (SSE) from the sample point to the centroid. From Figure 3, it can be seen that the optimal number of clusters is 6. The clustering results are shown in Figure 4, indicating that the clustering method proposed in this study is feasible.

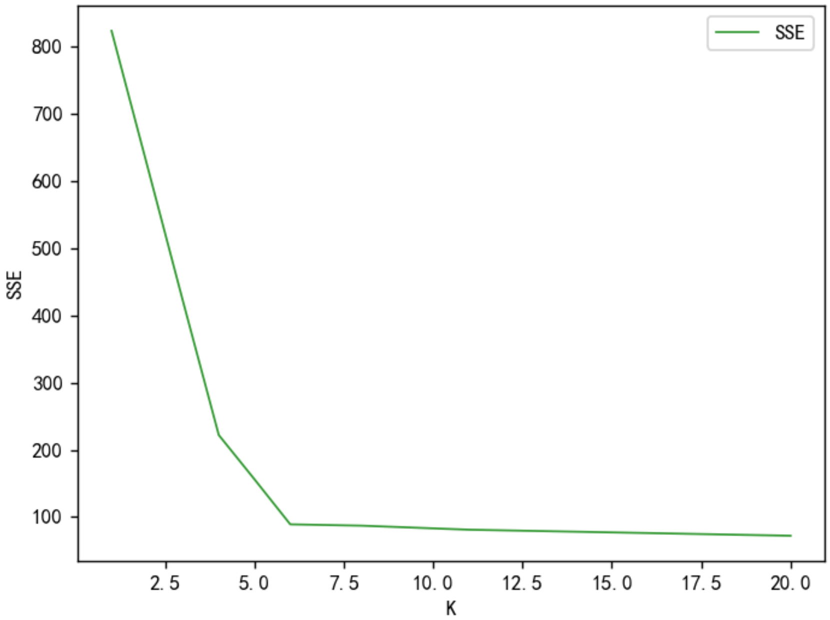

Figure 3 Optimal number of classifications

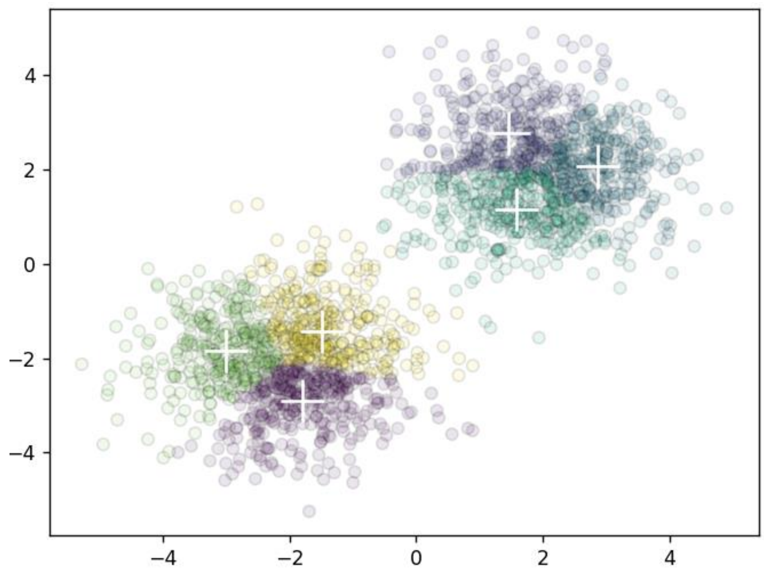

Figure 4 Clustering results

The optimal cluster U contains 113 resources, determined by Eq. (10)-(12). Assuming that there are 20 parts to be processed in this task, the resource cluster results are matched bilaterally with the task based on Eq. (13) - (20). In Tables 6 and 7, we first find the satisfaction matrix $A_s = [\alpha_{ij}]_{20\times113}$ of tasks to resources and the satisfaction matrix $B_s = [\beta_{ij}]_{20\times113}$ of resources to tasks can be determined. The matching results are shown in Table 8.

Table 6 Satisfaction matrix A_s of tasks to resources

α_{ij}	u_1	u_2	u_3	...	u_{112}	u_{113}
t_1	0.35	0.20	0.50	...	0.25	1.00
t_2	1.00	0.33	0.25	...	0.50	0.50
t_3	0.45	0.66	0.20	...	1.00	0.50
...	...	...	...	...	...	...
t_{18}	0.20	1.00	0.17	...	0.33	0.33
t_{19}	0.50	0.80	1.00	...	0.50	0.25
t_{20}	0.45	0.15	0.35	...	0.75	0.20

Table 7 Satisfaction matrix B_s of resources to tasks

β_{ij}	u_1	u_2	u_3	...	u_{112}	u_{113}
t_1	0.25	1.00	0.33	...	0.17	0.55
t_2	0.50	0.33	0.20	...	0.66	0.25
t_3	1.00	0.20	0.50	...	0.75	0.33
...	...	...	...	...	...	...
t_{18}	0.25	0.50	1.00	...	0.80	0.75
t_{19}	0.50	0.25	0.20	...	0.33	0.66
t_{20}	0.20	1.00	0.33	...	0.50	0.25

Table 8 Matching results

Task	Resource	Task	Resource	Task	Resource	Task	Resource
t_1	r_{22}	t_6	r_{34}	t_{11}	r_{391}	t_{16}	r_9
t_2	r_{385}	t_7	r_{23}	t_{12}	r_{954}	t_{17}	r_{75}
t_3	r_{237}	t_8	r_{286}	t_{13}	r_{248}	t_{18}	r_{124}
t_4	r_{82}	t_9	r_{868}	t_{14}	r_{15}	t_{19}	r_{535}
t_5	r_{153}	t_{10}	r_{712}	t_{15}	r_{86}	t_{20}	r_{169}

Table 9 Comparison of runtimes

Methods	Time
FCM-BM	168
BM	216

As shown in Table 9, we compare the proposed FCM+ two-sided matching method (BM) with the method for directly searching 1000 resources, and find that although the FCM+ two-sided matching method requires more steps, its final running time is less than that of the search for 1000 resources. We believe that in the actual supply and demand matching network, the sample size of resources is larger, so the direct matching of resource optimization takes more time, and matching results may appear unreasonable due to the large differences between resource types and service capability. In this study, the resources are first clustered, and their dimensions are reduced. Some resources, that do not meet the requirements are eliminated, and by selecting the optimal resource cluster for matching, the time is significantly reduced.

6 Conclusion

In this study, a new resource matching method for industrial interconnection supply and demand transaction based on smart contract is presented. First, the smart contract framework and the whole process of supply and demand transaction are analysed. Based on the characteristics of the attributes of the resources, the fuzzy C-means algorithm for resources is used to consider the fit of supply and demand on both sides, the expected properties of the main body are considered, the optimal resource class cluster is selected, the exact matching of resources is realised based on the bilateral matching theory, and the transaction of supply and demand is settled. Finally, the rationality and effectiveness of the proposed method are demonstrated by a case study. Compared with the conventional supply and demand matching model, this method takes into account the role of data in matching supply and demand in the modern industrial interconnection, and is more in line with the concept of data-driven core against the background of digital economy.

The main work for the future includes two aspects: 1. Further improve the clustering method in this study to achieve better classification. 2. Reducing some theoretical assumptions to bring the research closer to reality.

Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

[1] Altiparmak, F., Gen, M., Lin, L., & Paksoy, T. (2006). A genetic algorithm approach for multi-objective optimization of supply chain networks. *Computers and Industrial Engineering*, *51*(1), 196–215. https://doi.org/10.1016/j.cie.2006.07.011

[2] Bezdek, J. C., Ehrlich, R., & Full, W. (1984). FCM: The fuzzy c-means clustering algorithm. *Computers and Geosciences*, *10*(2–3), 191–203. https://doi.org/10.1016/0098-3004(84)90020-7

[3] Bholowalia, P., & Kumar, A. (2014). EBK-means: A clustering technique based on elbow method and k-means in WSN. *International Journal of Computers and Applications*, *105*(9).

[4] Chen, Q., Xu, Q., & Wu, C. (2019). Dynamic matching in cloud manufacturing considering matching costs. *Complexity*, *2019*, 1–16. https://doi.org/10.1155/2019/8398356

[5] Chen, Q., Xu, Q., & Wu, C. (2019, September). Optimal sharing strategies of idle manufacturing resource considering the effect of supply-demand matching. In International Conference on Industrial Engineering and Systems Management (IESM), *2019* (pp. 1–6). IEEE Publications.

[6] Cheng, Y., Xie, Y., Wang, D., Tao, F., & Ji, P. (2020). Manufacturing services scheduling with supply demand dual dynamic uncertainties toward industrial Internet platforms. *IEEE Transactions on Industrial Informatics*, *17*(5), 2997–3010. https://doi.org/10.1109/TII.2020.3004248

[7] De Giovanni, P. (2020). Blockchain and smart contracts in supply chain management: A game theoretic model. *International Journal of Production Economics*, *228*, 107855. https://doi.org/10.1016/j.ijpe.2020.107855

[8] Hadjidimitriou, N. S., Lippi, M., & Mamei, M. (2020). A data driven approach to match demand and supply for public transport planning. *IEEE Transactions on Intelligent Transportation Systems*, *22*(10), 6384–6394. https://doi.org/10.1109/TITS.2020.2991834

[9] Hao, R., Cheng, Y., Zhang, Y., & Tao, F. (2021). Manufacturing service supply-demand optimization with dual diversities for industrial internet platforms. *Computers and Industrial Engineering*, *156*, 107237. https://doi.org/10.1016/j.cie.2021.107237

[10] He, J., & Zhang, N. (2022). Design of a blockchain-based service platform for industrial interconnection supply and demand networks. *Journal of Theoretical and Applied Electronic Commerce Research*, *17*(2), 773–788. https://doi.org/10.3390/jtaer17020040

[11] Iwata, T., Hirao, T., & Ueda, N. (2018). Topic models for unsupervised cluster matching. *IEEE Transactions on Knowledge and Data Engineering*, *30*(4), 786–795. https://doi.org/10.1109/TKDE.2017.2778720

[12] Law, A. (2017), *Smart contracts and their application in supply chain management* ((Doctoral Dissertation). Massachusetts Institute of Technology).

[13] Long, T., & Jia, Q. S. (2021). Matching uncertain renewable supply with electric vehicle charging demand—A bi-level event-based optimization method. *Complex System Modeling and Simulation*, *1*(1), 33–44. https://doi.org/10.23919/CSMS.2021.0001

[14] Omar, I. A., Jayaraman, R., Debe, M. S., Salah, K., Yaqoob, I., & Omar, M. (2021). Automating procurement contracts in the healthcare supply chain using blockchain smart contracts. *IEEE Access*, *9*, 37397–37409. https://doi.org/10.1109/ACCESS.2021.3062471

[15] Paradise, J. F. (2019). China's quest for global economic governance reform. *Journal of Chinese Political Science*, 24(3), 471–493. https://doi.org/10.1007/s11366-019-09610-5

[16] Wang, L., Ma, Y., Zhu, L., Wang, X., Cong, H., & Shi, T. (2022). Design of integrated energy market cloud service platform based on blockchain smart contract. *International Journal of Electrical Power and Energy Systems*, *135*, 107515. https://doi.org/10.1016/j.ijepes.2021.107515

[17] Wang, S., Yuan, Y., Wang, X., Li, J., Qin, R., & Wang, F. Y. (2018, June). An overview of smart contract: Architecture, applications, and future trends. In *IEEE intelligent vehicles symposium (IV)*, *2018* (pp. 108–113). IEEE Publications.

[18] Xu, J., Chen, Y., Wang, J., Lund, P. D., & Wang, D. (2022). Ideal scheme selection of an integrated conventional and renewable energy system combining multi-objective optimization and matching performance analysis. *Energy Conversion and Management*, *251*, 114989. https://doi.org/10.1016/j.enconman.2021.114989

[19] Zhang, X., Yuan, X. M., & Wei, F. L. (2020). The dynamic broker dominant supply-demand matching decision using multiagent system. *Mathematical Problems in Engineering*, *2020*, 1–11. https://doi.org/10.1155/2020/4073273

[20] Zheng, Z., Xie, S., Dai, H. N., Chen, W., Chen, X., Weng, J., & Imran, M. (2020). An overview on smart contracts: Challenges, advances and platforms. *Future Generation Computer Systems*, *105*, 475–491. https://doi.org/10.1016/j.future.2019.12.019