

Research Article

Research on Integrated Learning of Industrial Clusters in Self-Created Districts

Liyuan Pang , Yangmin Zhou, and Yingjing Chu

School of Business Department, Zhengzhou University, Zhengzhou, 450001 Henan, China

Correspondence should be addressed to Liyuan Pang; zzuply@gs.zzu.edu.cn

Received 27 July 2021; Accepted 25 August 2021; Published 15 September 2021

Academic Editor: Jian Su

Copyright © 2021 Liyuan Pang et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Under the premise of coordinated procurement bilateral and multi-issue negotiation, adaptive negotiation strategy has become an essential factor for multiagent conflict resolution. This paper studies an adaptive negotiation strategy based on selective integrated learning, which effectively improves negotiation. First, take the suppliers and purchasing companies in the cluster supply chain as the research objects and analyze the characteristics of multilateral negotiation of collaborative procurement. Secondly, the support vector machine algorithm performs adaptive learning for each evaluation data set to estimate the concession range. On this basis, remove the few submodels that perform poorly, recombine the calculation weights, and establish a multiagent clustered supply collaborative procurement negotiation model. The simulation experiment proves the feasibility of the adaptive negotiation strategy and the effectiveness of the adaptive coordination strategy based on selective ensemble learning proposed in this paper from the aspects of concession range prediction error rate, prediction accuracy rate, and negotiation utility.

1. Introduction

In recent years, with the rise of new technologies represented by artificial intelligence [1], blockchain [2], big data [3], and mobile Internet [4], the global economy [5] and information technology [6] have developed rapidly, and consumer demand has been escalating. In an open and competitive market environment, the industry's uncertainty factors [7] are multiplying day by day, and many companies cannot respond quickly to changes in market demand. They cannot face the complex and dynamic market environment alone. A large number of traditional enterprises are facing a competitive environment of industrial upgrading. Many companies, especially manufacturing companies, have adjusted their internal organizational structure, effective management, and cooperation. The rationale uses its resources and other methods to respond to dynamically changing market demands. Although this kind of change of the enterprise has achieved specific results, the actual effect is not significant in the face of dynamic market changes, and it is not the way of long-term survival and development of the enter-

prise. In order to quickly respond to the diverse needs of customers, companies need to cooperate with supply chain partners to develop relevant technologies, share information, and complementary resources to seek long-term sustainable and healthy development. Therefore, to adapt to market globalization and fierce competition pressure, the collaboration between upstream and downstream companies in the supply chain and between industries is required, especially in the procurement, production, logistics, and inventory links between partners in the supply chain [8].

The emergence of industrial clusters [9] has promoted the sound development of the regional economy. Industrial clusters refer to the combination of companies and institutions that are geographically concentrated and related to each other in a specific field [10, 11]. Its organizational form is the cooperation mode between enterprises in a fixed geographic space. Geographical aggregation can form a unique credit advantage, effectively reducing transaction costs and actively promoting the innovation and diffusion of knowledge, in developed countries, such as the machinery industry cluster in the Baden-Württemberg region in southern

Germany, the jewelry industry cluster in the Arezzo region of Italy, the electronics industry cluster in the US Silicon Valley, and Highway 128 and in developing countries, such as the information industry cluster in Bangalore, India, and the electronics industry cluster in Baja California, Mexico. Distinctive industrial clusters help the regional economy to proliferate in the country.

The shortcomings of industrial clusters [12] promote the development of the industrial cluster supply chain. Enterprises in the supply chain of an industrial cluster can collaborate to give play to the advantages of the industrial cluster's scale and reduce transaction costs. There are specific restraint schemes and codes of conduct [13] among enterprises in the cluster supply chain to prevent conflicts of interest between individual enterprises in the cluster and the overall industrial cluster and pursue the industrial cluster's long-term development. Given the ever-changing interactive behaviors among cluster enterprises [13], the cluster-type supply chain is also constantly changing. Based on their different technical capabilities and market needs, the node enterprises on the cluster supply chain will make targeted crosschain connections to form an agile supply chain network [14, 15]. In order to better adapt to rapidly changing market demands [16], reduce user search costs, improve service levels, and enhance customers' overall understanding and cognition of the cluster, business collaboration and coordinated development between the supply chains of industrial clusters are becoming more and more critical.

This article focuses on the research on collaborative procurement in the supply chain of industrial clusters driven by e-commerce. Procurement is the source of the production and marketing process of the supply chain and a critical link in the development of an enterprise. Statistics show that every 1% saving in raw material procurement costs is equivalent to an increase of 8% to 10% in sales. In the fiercely competitive market environment, the traditional independent procurement model faces low bargaining power, small quantity discounts, high procurement management costs and risks, inability to share information, and slow response to customer needs. Procurement costs have remained high. Cooperative procurement is a new procurement method developed in recent years. The above problems can be solved by establishing a complete information sharing mechanism and setting up suitable incentive measures and target constraints. Collaborative procurement can save a lot of time and economic costs for enterprises in the cluster and focus their energy on developing new products, marketing, and other business expansion.

This paper takes the suppliers and purchasing companies in the cluster supply chain as the primary research objects, analyzes the characteristics and processes of multi-lateral negotiation of collaborative procurement between the companies in the supply chain, and establishes a clustered supply chain based on multiagent solve the problem of collaborative procurement. The negotiation framework, combined with the objective constraint function of the best supplier selection problem, constructs a multiagent clustered supply chain collaborative procurement negotiation model [16], adopts efficient and intelligent adaptive negotiation

strategies based on selective integrated learning, and effectively resolves collaboration. During the procurement process, the negotiation issues between the procurement parties are conflicting. It assists the procurement enterprises in the industrial cluster to quickly, effectively, and economically select suitable suppliers, finally, through the simulation and function of the collaborative procurement adaptive negotiation strategy.

2. Related Works

Simply speaking, collaborative procurement [17] transforms the purchasing enterprises and suppliers from the traditional simple goods transaction to a strategic decision that considers the overall benefits of the cluster supply chain. Not only must the self-interest of each member company be considered but also the help of the entire supply chain. In the collaborative procurement process, PA and SA often conflict due to their different preferences and needs. Negotiation based on the relaxation of constraints is a meaningful way to resolve conflicts between supply chain members. The critical issue of autonegotiation [18] is how to quickly and effectively reach an agreement in an open and dynamic negotiation environment [19, 20]. Multiagent adaptive negotiation [21] can be regarded as a multistage decision-making process [22]. Although there may be conflicting preferences and goals between individual rational agents, to achieve the design goals, accept a specific agreement and find the best course of action. Agents participating in the negotiation have good intelligence and adaptability to cope with the current dynamically changing negotiation environment. Although researchers have successfully implemented technology-based multiagent systems [23], the agents in the system can only negotiate according to a predetermined negotiation strategy (or agreement). Multiagent intelligent systems [24] need to develop effective negotiation strategies suitable for autonomous agents. Negotiation strategies [25] constrain the irrational negotiation behaviors of companies participating in collaborative procurement, such as what strategies to adopt, determine the range of concessions, and maximize their effectiveness. In recent years, adaptive negotiation has gradually become an active research field in computing science, especially in e-commerce [26] and multiagent systems. Adaptive negotiation means that the agent adjusts stimulation parameters, assumptions, negotiation strategies, etc., in time according to changes in the environment, reduces manual intervention, and realizes automatic negotiation and consensus among members of the system. The critical issue of cluster supply chain collaborative procurement adaptive negotiation is how the multiagent system can reach an agreement in a dynamic and open negotiation environment. Most of the negotiation strategies proposed by previous scholars are carried out in a static negotiation environment. Therefore, when the negotiation environment is open and dynamic, the agent needs to provide a reasonable response in time according to the changes of the environment, and an adaptive intelligent negotiation strategy becomes particularly important.

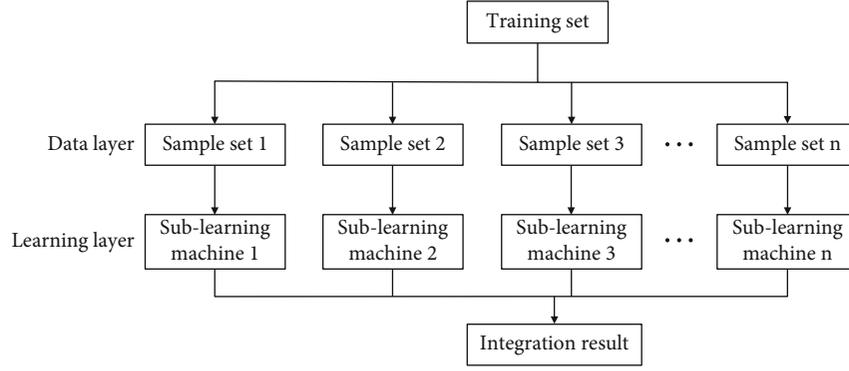


FIGURE 1: Integrated learning model.

Since the 1990s, integrated learning [27] has become a research hotspot in machine learning due to its good stability and generalization performance and has been widely used in text analysis, data mining, pattern recognition, and intelligent prediction. Integrated learning uses multiple sub-learners to improve the generalization ability of the entire system and accurately classify or predict test samples as much as possible. Jiang [28] pointed out that the traditional self-adaptive negotiation based on a single learning machine is ineffective. Integrated learning obtains better prediction results by selectively combining multiple sublearning machines. Selective ensemble learning [29] can speed up the calculation speed, improve the algorithm's performance, and make breakthroughs in the research of machine learning. It has received extensive attention and interest from researchers at home and abroad. At the same time, selective ensemble learning [30] can improve the efficiency of adaptive learning and effectively improve the prediction accuracy of ordinary ensemble learning [31]. It can be achieved by eliminating some learning machines with poor prediction effects in the sublearning model. The ensemble learning theory is derived from the PAC learning model. This model is used to explore the equivalence of weak machine learning and robust machine learning algorithms. Integrated learning is not a single machine learning algorithm but to build multiple learning models for the same problem to learn and combine some rules to integrate the prediction results of each sublearning machine to complete the learning task. The integrated learning model is shown in Figure 1.

3. Method

For the low efficiency of a single learning machine in the adaptive negotiation of collaborative procurement in the cluster supply chain, we analyze the characteristics of multi-agent negotiation in collaborative procurement in the industrial cluster supply chain. It proposes a choice based on K -means clustering and support vector machine algorithm: an adaptive negotiation strategy for sexual ensemble learning. In the negotiation, first, perform K -means clustering for each negotiation issue to find the k sample subsets nearest to the current issue value; secondly, use the support vector machine algorithm to learn from each evaluation data set to estimate the concession range; third, using the root

mean square error as the screening criterion, directly delete the submodels with unsatisfactory prediction results, recalculate the combination weights, and build a selective integrated SVM model. Fourth, the utility function is used to determine whether to terminate the negotiation process; finally, the best supplier partner is selected based on the objective constraint function of the collaborative procurement strategy. The adaptive negotiation strategy is divided into selective integrated concession range learning, utility function optimization, and optimal cooperation.

3.1. Concession Range Learning Based on Selective Integration. The k -means algorithm divides clusters based on the distance similarity measure, which has the advantages of fast search and efficient classification. In addition, it can preprocess or analyze data. Among them, K represents the number of clusters of the sample. In each iteration of K -means clustering, the corresponding cluster center needs to be updated again, and the mean value of all samples in the cluster class is calculated. This paper uses European clustering as the similarity measure, and the calculation formula is as follows:

$$P_D(P_q, P_i) = \sqrt{\sum_{i \in S} (P_q - P_i)^2}. \quad (1)$$

In formula (1), P_q represents the sequence to be negotiated, P_i is the negotiation point of the data sample, and S is the sample data set.

The support vector machine algorithm evaluates the data set P_k and estimates the concession range. RMSE is used as an evaluation criterion to select the best-performing k sublearning machines as the ensemble submodel of the negotiation sequence P_q to be tested. The root means the square error of the output of the i th sublearner is as follows:

$$E_{ij} = \sqrt{\frac{\sum_{i=1}^k (A - c)^2}{k}}. \quad (2)$$

Among them, A_{ij} is the predicted magnitude of the concession of the i th learning model for j in the next round, and

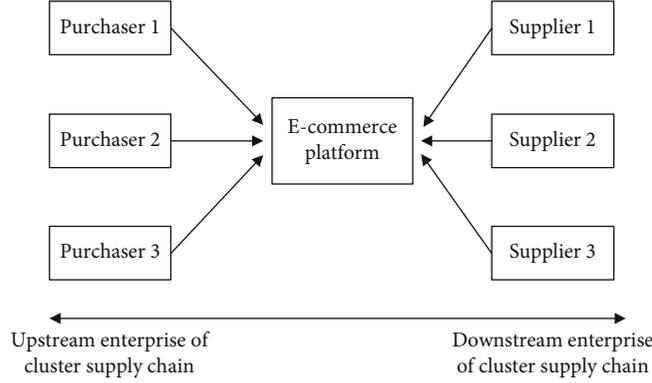


FIGURE 2: Supply-demand relationship structure of secondary cluster supply chain.

C_{ij} is the actual magnitude of the concession of j in the next round.

According to the root mean square error value E_{ij} , calculate the combined weight of the i th submodel as follows:

$$a_i = \frac{1/E_{ij}}{\sum_{i=1}^{k'} (1/(1/E_{ij}))}, \quad (3)$$

when all the training of the k th evaluation sample is completed, the first k' sublearning models with the minor error are selected, the prediction range $C_{t+1,j}^{p/s}$ of the concession of the purchasing enterprise A_p , and the supplier A_s in the $(t+1)$ th cluster is obtained.

$$C_{t+1,j}^{p/s} = \sum_{i=1}^{k'} a_i C_{ij}. \quad (4)$$

3.2. Utility Function Optimization. Utility orientation refers to a standard theory that uses utility as a basis for decision-making, proposed by Canadian scholar Kwang. In the agent negotiation process, agents exchange their intentions, beliefs, and preferences with each other and make corresponding assessments based on the utility theory to measure whether they accept the current negotiation issues. The adaptive negotiation strategy compares the two utility function differences before and after within the specified negotiation time to determine whether to terminate the current negotiation process, as shown in equation (5). Taking A_p as an example, according to the prediction range $C_{t+1,j}^{p/s}$ of the concession of j by the purchasing companies in the cluster in the previous stage $(t+1)$, the $P_{t,j}^p$ in the negotiation of j in the t th round further predicts the $P_{t+1,j}^{p/s}$ of the next round j , as shown in the formula 6.

$$U_t = \sum_{j=1}^m W_j P_{t,j}^p, \quad (5)$$

$$P_{t+1,j}^{p/s} = P_{t+1,j}^p + P_{t+1,j}^{p/s}. \quad (6)$$

W_j is the weight of j . Combining formulas (5) and (6), we can calculate the function difference between the predicted utility value of the procurement enterprise ap for round $t+1$ and the actual utility value for round t . After each round of negotiation, the purchasing enterprise agent in the cluster supply chain participating in collaborative purchasing must pass its negotiated value to the IA through the improve message with the difference $\Delta U_{t+1,t}$, and the IA will determine whether the purchasing enterprise agent will continue to increase the negotiation utility value. When the utility difference $\Delta U_{t+1,t} > 0$, the utility has not been maximized, and the next round of negotiation is continued; otherwise, the negotiation is stopped. Within the stipulated negotiation time, the procurement agent that has not reached a consensus can choose the maximum effect in the previous negotiation process to end the entire negotiation process.

3.3. Best Partnership Choice. After the adaptive negotiation is over, according to the objective constraint function of collaborative procurement, we can use the utility function in the second stage as the supplier evaluation satisfaction. The purchasing enterprise agent in the industrial cluster combines other procurement costs to select the best partner. The objective constraint function is shown in Equation (7), and the selection function is shown in Equation (8).

$$\max F = \alpha \sum_{K=1}^K \gamma(p, s, k) + (1 - \alpha) \frac{\beta}{\sum_{K=1}^K C_k}, \quad (7)$$

$$F = \alpha U_t + (1 - \alpha) \frac{1}{C_k}. \quad (8)$$

4. Results

In this article, taking the secondary supply chain of multiple parts purchasers and suppliers in a new energy automobile industry cluster as the negotiation background, the cluster supply chain's relationship structure is shown in Figure 2. The procurement enterprise agent in the industrial cluster integrates internal requirements, determines the attributes of procurement resources (such as price, quantity, and delivery time), develops a collaborative procurement plan, and

TABLE 1: Buyer and supplier issues.

Parameters	Buyer issue range	Supplier issue range	Supplier weight	Buyer weight
Price	[100, 150]	[100, 130]	0.4	0.35
Quantity	[800, 1000]	[850, 1200]	0.25	0.3
Delivery time	[1.5, 2]	[1, 2]	0.2	0.2
Warranty time	[17, 32]	[14, 23]	0.1	0.05
Defective rate	[80, 95]	[90, 96]	0.05	0.1

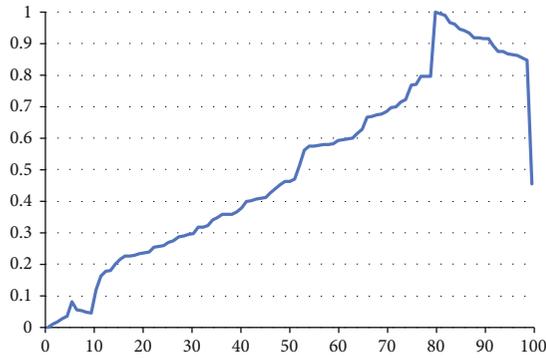


FIGURE 3: Data normalization result.

publishes it to the e-commerce information service agent of the cluster supply chain and has the supply of related resources. Merchant agent negotiates multiple attributes of procurement resources in a targeted manner based on its situation. All the attributes and issues of the procurement requirements are met, the procurement parties reach an agreement, and the collaborative procurement will be considered a successful negotiation. If there is no consensus on an issue within the stipulated negotiation time, the entire collaborative procurement negotiation will fail.

The experimental data comes from the dataverse network platform. The original data is a double matrix of 150×5 . Each sample has five attributes: price, quantity, delivery time, warranty time, and defective rate. The experiment selects the first 100 samples as the training sample set and the last 50 samples as the test sample set. It is assumed that the issue ranges and weights of suppliers and purchasers participating in collaborative procurement in a cluster supply chain are shown in Table 1.

The maximum negotiation time for buyers in the cluster supply chain is 2 minutes, and the maximum negotiation time that suppliers can accept is 1.5 minutes. At the same time, in the windows ten operating system, the processor is Intel(R) core i5-9500M@3.4GHz, and the RAM is 8G. The adaptive negotiation strategy of selective integrated learning is realized.

In order to avoid the annihilation of the original data and reduce the sensitivity of the abnormal data to the algorithm, this article first normalizes the original sample data. The experimental results show that the original sample data is normalized, and support vector machine classification accuracy reaches 93%. Secondly, perform K -means clustering on the normalized experimental sample data, continuously iterate and update the cluster center, and repeatedly

TABLE 2: Sublearning machine training results.

Sublearning machine	Subtraining sample	Operation hours	RMSE	Combination weight
1	12	0.86	0.0974	0.15
2	14	0.94	0.0845	0.17
3	16	0.93	0.0821	0.16
4	18	0.95	0.0785	0.16
5	20	1.027	0.0854	0.18
6	22	1.23	0.0812	0.2

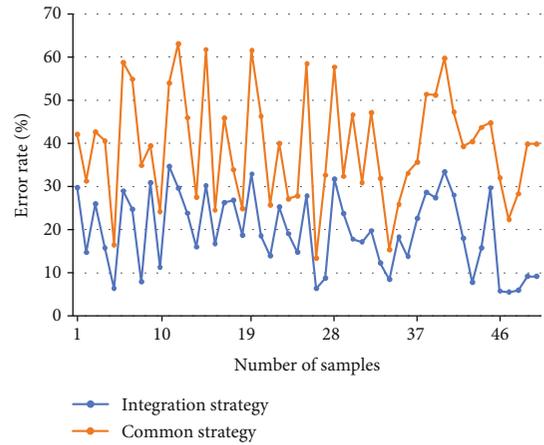


FIGURE 4: Comparison of the error rate results of the two strategies.

adjust the cluster center position and parameter K . In addition, when $k=6$, the clustering effect is the best. Figure 3 shows the result after normalization.

Construct six subtraining set matrices and then use the SVM sublearning machine to make predictions. Using the root mean square error as the criterion, recalculate the combination weights, remove a few sublearning models that perform poorly, and proceed to the next round of issue prediction results. The training results of each sublearning machine are shown in Table 2.

The main purpose of the cluster supply chain collaborative procurement negotiation in this article is to assist the purchasing enterprises in the cluster to economically and effectively select the appropriate supplier and complete the transaction as soon as possible. Therefore, to verify the effectiveness of the adaptive negotiation strategy based on selective ensemble learning, this paper sets up a control experiment. Specially selected 50 sets of test data sets for suppliers and purchasers, compared the traditional single

TABLE 3: Comparison of important parameters of two strategies.

Strategy	Minimum	Maximum	Median	Mean	Standard deviation	Accuracy
Common strategy	2.7	32.2	14.2	18.6	9.4	92.3%
Integration strategy	3.3	26.2	10.1	15.1	8.6	97%

TABLE 4: Comparison of negotiation utility value of two adaptive strategies.

S/N	Common strategy		S/N	Integration strategy		S/N	Utility value
	Utility value	Utility value		Utility value	Utility value		
1	0.51	26	0.63	1	0.80	26	0.89
2	0.54	27	0.74	2	0.70	27	0.78
3	0.68	28	0.64	3	0.74	28	0.88
4	0.61	29	0.67	4	0.87	29	0.54
5	0.88	30	0.78	5	0.56	30	0.75
6	0.67	31	0.59	6	0.87	31	0.64
7	0.83	32	0.63	7	0.77	32	0.51
8	0.70	33	0.81	8	0.55	33	0.57
9	0.89	34	0.65	9	0.84	34	0.81
10	0.71	35	0.68	10	0.70	35	0.89
11	0.71	36	0.73	11	0.64	36	0.70
12	0.69	37	0.75	12	0.62	37	0.79
13	0.53	38	0.70	13	0.84	38	0.59
14	0.55	39	0.79	14	0.76	39	0.62
15	0.75	40	0.81	15	0.65	40	0.51
16	0.79	41	0.76	16	0.67	41	0.84
17	0.52	42	0.73	17	0.71	42	0.85
18	0.84	43	0.69	18	0.57	43	0.50
19	0.81	44	0.66	19	0.88	44	0.56
20	0.83	45	0.62	20	0.65	45	0.76
21	0.85	46	0.81	21	0.52	46	0.89
22	0.50	47	0.80	22	0.59	47	0.60
23	0.67	48	0.65	23	0.87	48	0.64
24	0.76	49	0.66	24	0.83	49	0.87
25	0.57	50	0.81	25	0.71	50	0.89

learning machine model based on support vector machines, predicted the opponent's concession range and used negotiation effectiveness as an evaluation indicator to resolve conflicts in collaborative procurement multi-issue negotiation. Explore the practicality and effectiveness of the adaptive negotiation strategy based on selective ensemble learning proposed in this research.

After each round of negotiation, the purchasing enterprise agent in the cluster supply chain participating in collaborative purchasing must send its negotiation utility difference $\Delta U_{t+1,t}$ to the e-commerce information service agent through the improve message, and the IA will determine whether the purchasing enterprise agent will continue to increase negotiate the utility value. If the utility increases, the next negotiation round will continue; if the utility decreases or the maximum negotiation time T_{\max}^p is exceeded, the negotiation will be stopped immediately. Procurement agents that have not reached a consensus can

choose the greatest effect in the previous negotiation process to end the entire negotiation process.

The error rate of the adaptive negotiation strategy based on selective ensemble learning and the common SVM single learning machine adaptive negotiation strategy (referred to as the common strategy) on the price issue's concession range prediction value is shown in Figure 4. It is not difficult to see that, in most cases, in the collaborative procurement process of the cluster supply chain, the error rate of the predicted value of the concession range based on the integrated strategy is significantly lower than that of the ordinary negotiation strategy. The specific analysis of the error rate of the two strategies is shown in Table 3. Among them, the average error rate of the negotiation strategy based on selective ensemble learning is 11%, and the standard deviation is 6.35%, which outperforms the ordinary strategies of 15.66% and 8.56%. In addition, in comparing four essential indicators, the maximum value of the adaptive negotiation

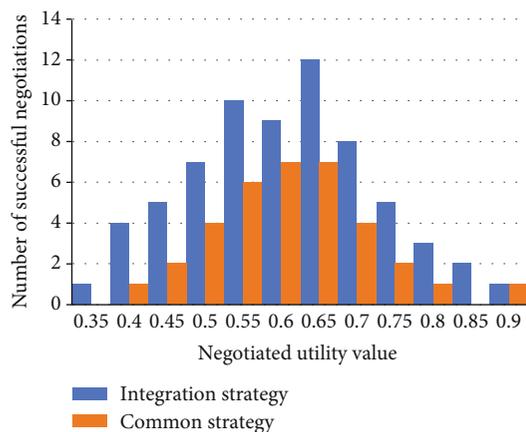


FIGURE 5: Comparison of negotiation utility value and successful agent.

strategy based on selective ensemble learning was reduced by 6%, the median was reduced by 4%, and the average was reduced by 3.99%.

In the collaborative procurement adaptive negotiation process of conflict resolution, the final detailed utility values of the integrated negotiation strategy and the ordinary negotiation strategy are shown in Table 4. After interval processing, the statistical results of negotiation utility are shown in Figure 5. The negotiation utility value based on the integrated optimization strategy is mainly in the interval [0.5, 0.75], while the common SVM single learning machine negotiation strategy is mainly concentrated in [0.4, 0.7]. The average utility value of the integrated negotiation strategy is 0.641, and the utility value of 60% of successful agents is higher than the average. In contrast, the relevant data of the common negotiation strategy based on a single SVM learning machine is 0.56 and 445%. The procurement enterprise agent on the cluster supply chain accepts the supplier agent's proposal, selectively integrates and learns the negotiation issues in the collaborative procurement process, dynamically adjusts its negotiation strategy, and makes appropriate concessions, which is conducive to collaborative procurement—the successful negotiation results in higher negotiation effectiveness and better negotiation results. This article is aimed at realizing multiagent adaptive negotiation to effectively resolve conflicts in the collaborative procurement process. Since the original experimental data does not involve procurement negotiation costs, storage costs, goods costs, and logistics costs, it is temporarily unable to select the final supplier based on the collaborative procurement objective constraint function.

5. Conclusion

The industrial cluster supply chain is a new network organization formed by the coupling of industrial cluster and supply chain. It mainly meets the flexible and changing needs of customers by dynamically configuring resources. Node companies on the cluster supply chain can selectively connect across chains according to their technical capabilities and market needs, forming an agile supply chain network and

continuously improving the operational efficiency of the entire industrial cluster supply chain. Therefore, industrial cluster supply chain collaboration is a comprehensive management model. The member companies within the cluster collaborate and coordinate with each other, give full play to their respective strengths to achieve efficient information sharing and resource optimization, and form a good trust and cooperation relationship. This article is mainly to study the problem of collaborative procurement in a cluster supply chain. Procurement is the source of the production and marketing process of the supply chain and a key link in the development of an enterprise. In a highly competitive market environment, the traditional independent procurement model faces low bargaining power, small quantity discounts, high procurement management costs, and slow response to customer needs. Procurement costs have always been high. Cooperative procurement is a new type of procurement method developed in recent years. By establishing a complete information-sharing mechanism and setting up sound incentive measures, target constraints, etc., the above problems can be better solved.

Data Availability

The processed data required to reproduce these findings cannot be shared at this time as the data also forms part of an ongoing study.

Conflicts of Interest

We declare that there is no conflict of interest.

References

- [1] B. Alhayani, H. Jasim Mohammed, I. Zeghaiton Chalooob, and J. Saleh Ahmed, "Effectiveness of artificial intelligence techniques against cyber security risks apply of it industry," *Materials Today: Proceedings*, 2021.
- [2] D. Berdik, S. Otoum, N. Schmidt, D. Porter, and Y. Jararweh, "A survey on blockchain for information systems management and security," *Information Processing & Management*, vol. 58, no. 1, article 102397, 2021.
- [3] K. Zhong, Y. Wang, J. Pei, S. Tang, and Z. Han, "Super efficiency SBM-DEA and neural network for performance evaluation," *Information Processing & Management*, vol. 58, no. 6, article 102728, 2021.
- [4] M. Chae and J. Kim, "What's so different about the mobile internet?," *Communications of the ACM*, vol. 46, no. 12, pp. 240–247, 2003.
- [5] P. Carlsson-Szlezak, M. Reeves, and P. Swartz, *What coronavirus could mean for the global economy*, vol. 3, no. 10, 2020Harvard Business Review, 2020.
- [6] T. M. Muhammedisaevna, R. F. Mubinovna, and M. N. U. Kizi, *The role of information technology in organization and management in tourism*, vol. 4, no. 55, 2020Academy, 2020.
- [7] H. Peng, N. Shen, H. Liao, H. Xue, and Q. Wang, "Uncertainty factors, methods, and solutions of closed-loop supply chain – a review for current situation and future prospects," *Journal of Cleaner Production*, vol. 254, article 120032, 2020.

- [8] A. Wieland, "Dancing the supply chain: toward transformative supply chain management," *Journal of Supply Chain Management*, vol. 57, no. 1, pp. 58–73, 2021.
- [9] F. Mazzoni, "Circular economy and eco-innovation in Italian industrial clusters. Best practices from Prato textile cluster," *Insights into Regional Development*, vol. 2, no. 3, pp. 661–676, 2020.
- [10] J. Pei, "Solving the problem of charging and discharging of electric vehicles based on particle swarm algorithm," in *2019 2nd international conference on information systems and computer aided education (ICISCAE)*, pp. 534–538, Dalian, 2019.
- [11] J. Pei, J. Li, H. Zhang, B. Zhou, M. Gao, and Q. Dat, "A recommendation algorithm about choosing travel means for urban residents in intelligent traffic system," in *2021 IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, vol. 5, pp. 2553–2556, Chongqing, China, 2021.
- [12] B. Garrod and D. A. Fennell, "An analysis of whalewatching codes of conduct," *Annals of Tourism Research*, vol. 31, no. 2, pp. 334–352, 2004.
- [13] M. Vedernikov, M. Zelena, L. Volianska-Savchuk, V. Litinska, and J. Boiko, "Management of the social package structure at industrial enterprises on the basis of cluster analysis," *TEM Journal*, vol. 9, no. 1, pp. 249–260, 2020.
- [14] M. M. Ehlenz, D. Pfeiffer, and G. Pearthree, "Downtown revitalization in the era of millennials: how developer perceptions of millennial market demands are shaping urban landscapes," *Urban Geography*, vol. 41, no. 1, pp. 79–102, 2020.
- [15] Y. Li and C. W. Zobel, "Exploring supply chain network resilience in the presence of the ripple effect," *International Journal of Production Economics*, vol. 228, article 107693, 2020.
- [16] M. Herrera, M. Pérez-Hernández, A. K. Parlikad, and J. Izquierdo, "Multi-agent systems and complex networks: review and applications in systems engineering," *Processes*, vol. 8, no. 3, p. 312, 2020.
- [17] Y. Sayyed, M. T. Hatamleh, and A. Alaya, "Investigating the influence of procurement management in construction projects on the innovation level and the overall project performance in developing countries," *International Journal of Construction Management*, pp. 1–30, 2021.
- [18] W. Liu, C. Ma, Z. Tu, X. Xu, and Z. Wang, "A multi-thread auto-negotiation method for value conflict resolution in transboundary service design," *Journal of Service Science and Management*, vol. 14, no. 3, pp. 262–280, 2021.
- [19] V. Jain, S. Wadhwa, and S. G. Deshmukh, "A negotiation-to-coordinate (n2c) mechanism for modeling buyer-supplier relationship in dynamic environment," *International Journal of Enterprise Information Systems (IJEIS)*, vol. 3, no. 2, pp. 1–22, 2007.
- [20] W. Liang, W. Huang, J. Long, K. Zhang, K. Li, and D. Zhang, "Deep reinforcement learning for resource protection and real-time detection in IoT environment," *IEEE Internet of Things Journal*, vol. 7, no. 7, pp. 6392–6401, 2020.
- [21] F. C. Sampaio, R. P. S. Leão, R. F. Sampaio, L. S. Melo, and G. C. Barroso, "A multi-agent-based integrated self-healing and adaptive protection system for power distribution systems with distributed generation," *Electric Power Systems Research*, vol. 188, article 106525, 2020.
- [22] C. M. Raio, A. B. Konova, and A. R. Otto, "Trait impulsivity and acute stress interact to influence choice and decision speed during multi-stage decision-making," *Scientific Reports*, vol. 10, no. 1, article 7754, pp. 1–12, 2020.
- [23] R. Olfati-Saber, J. A. Fax, and R. M. Murray, "Consensus and cooperation in networked multi-agent systems," *Proceedings of the IEEE*, vol. 95, no. 1, pp. 215–233, 2007.
- [24] V. O. Karasev and V. A. Sukhanov, "Product lifecycle management using multi-agent systems models," *Procedia Computer Science*, vol. 103, pp. 142–147, 2017.
- [25] H. B. Nguyen, C. Thomson, N. N. Jarjour et al., "Leading change and negotiation strategies for division leaders in clinical medicine," *Chest*, vol. 156, no. 6, pp. 1246–1253, 2019.
- [26] A. Bhatti, H. Akram, H. M. Basit, A. U. Khan, S. M. Raza, and M. B. Naqvi, "E-commerce trends during COVID-19 pandemic," *International Journal of Future Generation Communication and Networking*, vol. 13, no. 2, pp. 1449–1452, 2020.
- [27] D. Jiang, K. Wu, D. Chen et al., "A probability and integrated learning based classification algorithm for high-level human emotion recognition problems," *Measurement*, vol. 150, article 107049, 2020.
- [28] G. Jiang and T. Pang, "Self-adaptive negotiation method based on multi-agent supply chain collaboration," *Computer Engineering*, vol. 3, 2014.
- [29] H. Hong, C. Jiang, X. Peng, and W. Zhong, "Concurrent monitoring strategy for static and dynamic deviations based on selective ensemble learning using slow feature analysis," *Industrial & Engineering Chemistry Research*, vol. 59, no. 10, pp. 4620–4635, 2020.
- [30] T. Xie, T. Tan, and J. Li, "An extensive search trends-based analysis of public attention on social media in the early outbreak of COVID-19 in China," *Risk management and health-care policy*, vol. 13, pp. 1353–1364, 2020.
- [31] Y. Wang, T. Han, X. Han, and P. Liu, "Ensemble-learning-based hardware Trojans detection method by detecting the trigger nets," in *2019 IEEE international symposium on circuits and systems (ISCAS)*, pp. 1–5, 2019.
- [32] J. Rincón-Moreno, M. Ormazabal, M. J. Álvarez, and C. Jaca, "Shortcomings of transforming a local circular economy system through industrial symbiosis: a case study in Spanish SMEs," *Sustainability*, vol. 12, no. 20, p. 8423, 2020.