Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org

Volume 25, Issues 5, pp. 3603–3613, DOI 10.12694/scpe.v25i5.3184

MACHINE LEARNING ALGORITHMS IN SUPPLY CHAIN COORDINATION SIMULATION AND OPTIMIZATION

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Abstract. In response to the current situation of poor adaptive learning performance in Agent production and sales negotiation and dynamic changes in negotiation environment, the author proposes a method based on machine learning algorithms. Consider the impact of conflict level, cooperation possibility, and negotiation remaining time on negotiations in a dynamic negotiation environment, and use the entropy method to determine the weights of three influencing factors and perform linear weighting. Based on the differences in current negotiation topics, a concession amplitude prediction model based on dynamic selective ensemble learning is constructed, and an optimization strategy for supply chain production and sales negotiation is proposed. The experimental results indicate that, in the adaptive negotiation strategy of a regular SVM single learning machine, the joint utility of the most successfully negotiated agents falls within the interval [0.55, 0.70], while the author's ensemble learning strategy mainly focuses on [0.6, 0.8], the author's strategy is relatively superior to ordinary learning strategies in terms of both the number of successfully negotiated agents and the joint utility. Compared with the single learning machine negotiation strategy, this strategy improves the success rate and joint utility of Agent adaptive learning, and ensures the benefits of both production and sales in the supply chain, achieving a mutually beneficial situation for both parties in cooperation.

Key words: Dynamic selective ensemble learning, Dynamic negotiation environment, Agent production and sales negotiation, Adaptive learning, Entropy method

1. Introduction. Supply chain coordination is a key issue in supply chain management, which involves collaboration and coordination among different stakeholders. In the supply chain, due to the different goals and constraints of each participant, problems such as information asymmetry, order lag, and inventory backlog are prone to occur, leading to inefficiency and instability of the supply chain. In order to achieve efficient operation of the supply chain and maximize overall benefits, researchers have proposed various supply chain coordination models and algorithms. The core goal of supply chain coordination is to ensure effective coordination and cooperation among various links in the supply chain through reasonable decision-making and collaboration mechanisms, in order to optimize the efficiency of the entire supply chain system. In actual supply chain management, in order to solve the problem of information asymmetry, some measures can be taken to improve the flow and sharing of information. For example, establishing an information platform to improve the coordination and flexibility of various links in the supply chain through information sharing and transmission [1]. At the same time, adopting appropriate reward and punishment mechanisms to encourage all parties involved to work together and reduce the problems caused by information asymmetry.

In addition, order lag and inventory backlog are common issues in supply chain coordination. In order to address these issues, some supply chain coordination models and algorithms can be adopted. For example, by establishing a supply chain coordination model based on demand forecasting, it is possible to accurately predict demand and make corresponding adjustments according to changes in demand, avoiding the problems of order lag and inventory backlog [2]. In addition, reasonable inventory management strategies such as first in, first out (FIFO) and regular inventory can be adopted to control inventory backlog and improve the operational efficiency of the supply chain.

Supply chain coordination can also be achieved by optimizing logistics transportation and distribution. In the supply chain, logistics transportation and distribution play a crucial role. By optimizing logistics transportation and distribution plans, transportation costs can be reduced, transportation efficiency can be improved,

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and supply chain coordination and optimization can be achieved [3]. For example, centralized distribution can be adopted to reduce the frequency and distance of transportation, and lower transportation costs; At the same time, utilizing logistics technology and information systems to achieve visual management of logistics transportation and distribution, improving the efficiency and service quality of logistics transportation.

In addition to the above methods, supply chain coordination can also be achieved through reasonable partner selection and supplier management. In supply chain management, selecting suitable partners and suppliers is crucial for the coordination and stability of the supply chain. By evaluating and managing suppliers, we can ensure their quality and delivery time, and reduce the risks and problems they bring [4]. At the same time, establish long-term and stable cooperative relationships, strengthen communication and collaboration with suppliers, and improve the efficiency and stability of the supply chain. In short, supply chain coordination is a key issue in supply chain management. Through reasonable decision-making and collaboration mechanisms, problems such as information asymmetry, order lag, and inventory backlog can be solved, improving the efficiency and stability of the supply chain. In actual supply chain management, various means and methods can be adopted to achieve coordination and optimization of the supply chain, including information sharing, demand forecasting, inventory management, logistics transportation and distribution optimization, partner selection, and supplier management. Through continuous research and practice, supply chain coordination models and algorithms can be further improved, promoting the development and progress of supply chain management [5].

The author aims to study the application of machine learning algorithms in supply chain coordination simulation and optimization. By using machine learning algorithms to analyze a large amount of data in the supply chain, we can better understand the operational mechanisms and optimization methods of the supply chain. Specifically, the research objectives include the following aspects:

1. Analyze the characteristics and challenges of supply chain coordination problems: Through in-depth research on supply chain coordination problems, analyze the relationships and interactions between various links in the supply chain, and reveal the essence and challenges of supply chain coordination.
2. Explore the application of machine learning algorithms in supply chain coordination simulation: Using machine learning algorithms, construct a supply chain coordination simulation model, simulate the impact of different coordination strategies on supply chain performance, and further study the behavior and decision-making of all parties involved in the supply chain.
3. Propose a supply chain optimization method based on machine learning algorithms: Based on the analysis results of machine learning algorithms, design a supply chain optimization algorithm to improve the efficiency and stability of the supply chain by coordinating the decisions and actions of all parties involved.

Through the implementation of the above research objectives, the author aims to provide new ideas and methods for supply chain management, promote coordination and optimization of the supply chain, and improve overall operational effectiveness.

2. Agent Supply Chain Production and Sales Negotiation Model.

2.1. Production and sales negotiation framework. In negotiation, the entropy method is used to calculate the weight of the negotiation environment, and the impact factor of the negotiation environment on the concession amplitude of the issue is obtained through linear weighting. Using optimized strategies to predict the concession range of opponents and measuring the impact of other negotiating opponents on the current negotiation based on global utility, the proposal values for each issue in the next round are obtained[6]. After the negotiation, the negotiation agent selects the best partner based on their own wishes, as shown in Figure 2.1.

2.2. Negotiation parameters. The specific steps of a negotiation strategy based on dynamic selection ensemble learning are: 1) Description of the negotiation environment; 2) Define negotiation issues and essential elements; 3) Support adaptive learning, update concession amplitude, and propose counter proposals[7]. Therefore, an octet representation negotiation model is proposed, and the negotiation parameters are explained in Table 2.1.

$$NM = \{A, I, P, w, T, C, Lc, U\} \tag{2.1}$$

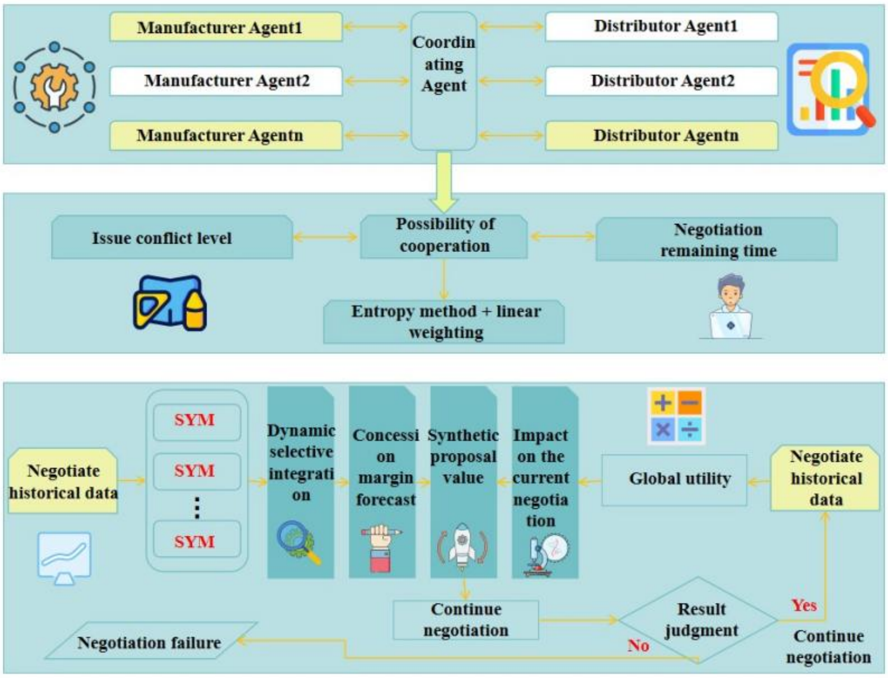


Fig. 2.1: Agent production and marketing negotiation framework

Table 2.1: Description of the negotiation parameters

Parameter	Describe
A	distributor manufacturer coordinator
I	Negotiation topic set
P	The agenda value for each round of negotiation
T	The remaining time for negotiation gradually decreases during the negotiation process
Lc	Conflict level between both parties
w	Participate in negotiating agent's weight vectors for each issue
C	The likelihood of cooperation between manufacturer and distributor agents
U	Evaluation of the proposed value of the opponent in the t-th round of negotiation on issue j

2.3. Negotiation Environment. For the expression of the negotiation environment, the author characterizes it using three factors: the level of issue conflict, remaining negotiation time, and the possibility of the best partner. Among them, the level of issue conflict is a positive indicator; The greater the remaining negotiation time and the possibility of the best partner, the smaller the concession made, which is a negative indicator.

Issue conflict level. The degree of conflict between the negotiating agent and the opponent on issue j, as shown in Equation 2.2.

$$Lc_t = \sum_{j=1}^{n} ep_j w_j \sqrt{|P_{t,j}^{s} - p_{t,j}^{opp}|^2} \tag{2.2}$$

Among them, $P_{t,j}^{s}$ represents the proposal value of our agent for issue j in round t, $P_{t,j}^{opp}$ represents the proposal value of our opponent for issue j in round t; ep_j represents the proportion of the number of opponents who are in conflict with the Agent regarding issue j in the total number of negotiations. Best partner possibility: decreases with the increase of competitors. A_i^t has A_c^t competitors and A_p^t trading parties in round t negotiation, and the possibility of A_i^t being considered as the preferred trading partner of the trading parties is shown in Equation 2.3.

$$c(A_i^t, A_p^t) = 1 - [(A_p^t - 1)/A_p^t]^{A_c^t} \tag{2.3}$$

Remaining negotiation time. The remaining time in the negotiation of round t is calculated as shown in Equation 2.4.

$$T(t, \tau, \lambda) = 1 - (t/\tau)^{\lambda} \tag{2.4}$$

Among them, τ is the deadline; λ is the optimal time limit for MDA.

2.4. Integration of negotiated environmental factors . The legitimate value method determines the weights of three factors in the negotiation environment, assuming that there are r agents participating in the negotiation, Amd calculates the conflict level of the manufacturer and distributor's own issues, the possibility of the best partner, and the remaining negotiation time in each round of negotiation[8]. The positive and negative indicators are dimensionless according to Equations 2.5 and 2.6, forming a matrix as shown in Equation 2.7.

$$s_{r,i} = (s_{r,i} - min\{s_i\})/(max\{s_i\} - min\{s_i\}) \tag{2.5}$$

$$s_{r,i} = (max\{s_i\} - s_{r,i})/(max\{s_i\} - min\{s_i\}) \tag{2.6}$$

$$R = \begin{bmatrix} s_{11} & s_{12} & s_{13} \\ s_{21} & s_{22} & s_{23} \\ \cdots & & \\ \cdots & & \\ \cdots & & \\ s_{r1} & s_{r2} & s_{r3} \end{bmatrix} \tag{2.7}$$

The legitimate weight of the jth environmental indicator is shown in Equation 2.8, with a legitimate weight of π_j. The entire negotiation environment should make concessions to the t-round negotiation agent θ_t. As follows:

$$H_j = -(1/lnr)\sum_{i=1}^{r}(\frac{s_{ij}}{\sum_{i=1}^{r}} s_{ij}) \tag{2.8}$$

$$\pi_j = \frac{(1 - H_j)}{r - \sum_{i=1}^{r} H_j} \tag{2.9}$$

$$\theta_t = \pi_1 lc_t + \pi_2 c_t + \pi_3 T_t \tag{2.10}$$

3. Adaptive negotiation optimization strategy based on multi-agent.

3.1. Concession amplitude learning based on dynamic selective ensemble SVM. The predictive performance of each sub SVM learning machine varies for different data, and it is not advisable to use the same model function to estimate the concession amplitude for different issues. Based on the current issue value in the negotiation, use the nearest neighbor sample set as the evaluation sample to evaluate the performance of each sub model, and retain the sub models with better performance for integration[9]. In the negotiation, the K-means nearest neighbor search algorithm is used for each negotiation topic. The validation dataset is used to find k subsets of samples that are closest to the current value of the topic to be predicted, and the root mean square error is used as the evaluation criterion for the predictive performance of each sub model. Some sub models with poor predictive performance are eliminated, and the combined weights of each sub model are calculated to establish the final dynamic selective ensemble SVM model.

1. Generate an evaluation dataset using K-means. In order to predict the negotiation sequence P_q, let the number of nearest negotiation samples in the validation dataset P_L be k, calculate the distance between P_q and each negotiation data sample point P_i in P_L, and obtain the first k sample sets P_k.

$$P_D(P_q, P_i) = \sqrt{\sum_{i \in L} (P_q - P_i)^2} \tag{3.1}$$

2. SVM sub learning machine filtering. Input P_k sample sets, use root mean square error as the screening criterion, and select the corresponding top $\overline{k}$ sub learning machine as the ensemble sub model of the predicted set P_q. The root mean square error of the i-th sub model is shown in Equation 3.2.

$$E_{ij} = \sqrt{\frac{\sum_{i=1}^{k} (\widetilde{c_{ij}} - C_{ij})^2}{k}} \tag{3.2}$$

   Among them, $\widetilde{c_{ij}}$ represents the predicted concession amplitude of the i-th sub learning machine for the next round of issue j; C_{ij} represents the actual concession amount for the next round of agenda item j.

3. Calculate the combined weights of each sub model. According to the root mean square error E_{ij} of the i-th sub model, the combined weight of this sub model is:

$$a_i = (\frac{1}{E_{ij}^2}) / (\sum_{i=1}^{\overline{k}} \frac{1}{E_{ij}^2}) \tag{3.3}$$

When all h sub learning machines are successfully trained, combined with the $\overline{k}$ sub learning model with the smallest selection error for the current issue, four variables are inputted: the average concession amplitude value of the manufacturer and distributor agents in the first t rounds to hedge against the sudden issue j, and the difference in the proposed values of the manufacturer and distributor agents in the t round[10]. The predicted concession amplitude values for A_{fac} and A_{dis} in the t+1 round are obtained. The predicted output for each issue's concession amplitude is:

$$C_{t+1,j}^{fac/dis} = a_1 C_{1j} + a_2 C_{2j} + ... + a_{\overline{k}} C_{\overline{k}j} \tag{3.4}$$

3.2. Utility Function Optimization. The global utility indicates that for positive issues, the larger the opponent's issue value is, the better, while for negative issues, the opposite is true. The utility evaluation functions for the negotiation object's issue value during t-round negotiation are shown in Equations 3.5 and 3.6, respectively.

$$U_{t,all}^{+} = \sum_{j=1}^{n} w_{t,j} (\frac{p_{t,j}^{opp} - p_{t,j}^{min}}{p_{t,j}^{max} - p_{t,j}^{min}}) \tag{3.5}$$

$$U_{t,all}^{-} = \sum_{j=1}^{n} w_{t,j} \left(\frac{p_{t,j}^{max} - p_{t,j}^{opp}}{p_{t,j}^{max} - p_{t,j}^{min}} \right) \tag{3.6}$$

$$U_{t,all} = U_{t,all}^{+} + U_{t,all}^{-} \tag{3.7}$$

Among them, $p_{t,j}^{opp}$ represents the current proposal value of the other party; $p_{t,j}^{max}$ represents the maximum value of the current proposal. Taking Afac as an example, in the t-round negotiation, the global utility with each Adis is calculated based on Equation 3.6. larger the $U_{t,all}$, the greater the utility obtained from the current A_{dis} negotiation, and the smaller the impact on the concession amplitude, making a larger concession[11].

The difference in local utility between the two rounds of negotiation is used to determine whether to stop the current negotiation process, as shown in Equation 3.8. According to the predicted concession range of A_{fac} on issue j in round t+1, the proposal value of distributor BB on issue j in round t of $C_{t+1}^{dis\to fac}$ negotiation is $p_{t,j}^{dis\to fac}$. The predicted proposal value of distributor $A_{t+1,j}^{dis\to fac}$ on issue j in round t+1 is shown in Equation 3.9.

$$U_{t,area} = \sum_{j=1}^{j} w^{j} p_{j}^{dis\to fac} \tag{3.8}$$

$$p_{t+1,j}^{dis\to fac} = p_{t,j}^{dis\to fac} + C_{t+i,j}^{dis\to fac} \tag{3.9}$$

Coordinate Amd with Equations 3.8 and 3.9 to calculate the difference between A_{dis}'s predicted utility value in round t+1 and the actual utility value in round t. When the difference is $\Delta U_{t+1,t} > 0$, continuing to negotiate A_{fac}'s utility will increase, but the utility has not been maximized yet. Otherwise, end the negotiation[12].

3.3. Topic proposal. Taking A_{fac} as an example, in multilateral adaptive negotiation, not only should the impact of the negotiation environment on the degree of concession be considered, but also the impact of other negotiation objects on the current negotiation. Therefore, the next round of proposal values for topic j are proposed by Equations 3.10 and 3.11.

$$p_{t+1,j}^{fac\to dis} = p_{t,j}^{dis\to fac} - p_{t,j}^{fac\to dis} \times (w_j) \times \left(a\theta + \beta C_{t+1}^{dir} + \frac{U_{t,all}^{i} - U_{t,all}^{min}}{U_{t,all}^{max} - U_{t,all}^{min}}\right) \tag{3.10}$$

$$p_{t+1,j}^{fac\to dis} = p_{t,j}^{dis\to fac} + p_{t,j}^{fac\to dis} \times (w_j) \times \left(a\theta + \beta C_{t+1}^{dir} + \frac{U_{t,all}^{i} - U_{t,all}^{min}}{U_{t,all}^{max} - U_{t,all}^{min}}\right) \tag{3.11}$$

Among them, Equation 3.10 represents cost based issues; Equation 3.11 represents profit oriented issues; θ Indicates the extent of concessions made under the influence of the negotiation environment; C_{t+1}^{fac} represents the concession amount of the opponent in the next round based on the ensemble learning algorithm; $U_{t,all}^{i}$ represents the global utility obtained from negotiating with the current negotiating party. The larger the value, the greater the concession, and vice versa[13].

3.4. Best Partner Selection. After the negotiation, the A_{fac} manufacturer makes a decision on the negotiation results, selects the appropriate A_{dis}, calculates the similarity of topics based on common neighbors according to the needs of the negotiation, and selects cooperation partners that are more suitable according to the similarity of topics, as shown in Equation 3.12.

$$S_{fac,dis} = (1 + e^{-D_{fac,dis}}) \times ||I_{fac} \cap I_{dis}|| \tag{3.12}$$

Among them, $D_{fac,dis}$ represents the issue gap between A_{fac} and A_{dis}; $I_{fac} \cap I_{dis}$ represents the number of topics that A_{fac} and A_{dis} are satisfied with after successful negotiations, and selects the best partner based on similarity.

Table 4.1: Issue range and corresponding weights of manufacturers and distributors

Parameter type	Manufacturer Issue Range	Distributor Issue Range	Manufacturer weight	Distributor weight
Price/yuan	[3 000,3 800]	[3 000,3 300]	0 25	0 25
Quantity	[800,1 000]	[850,1 200]	0 25	0 25
Delivery time/month	[2 5,3]	[1,3]	0 25	0 25
Warranty period/month	[12,24]	[15,48]	0 15	0 10
Defective rate/%	[80,95]	[0,95]	0 10	0 15

4. Adaptive negotiation steps and examples.

4.1. Negotiation Steps. The specific steps for adaptive negotiation are as follows:

Step 1: Negotiate initialization. Based on the negotiation targets of A_{fac} and A_{dis}, determine issue I, initialize issue weight W, maximum negotiation time T, and acceptable range of the issue, and normalize the issue.

Step 2: A_{md} determines if the remaining negotiation time T has been exceeded. If it has been exceeded, the negotiation will be concluded; On the contrary, proceed to step 3.

Step 3: A_{md} evaluates the negotiation environment and calculates according to Equation 2.10 θ and provide feedback to A_{fac} and A_{dis} who are currently negotiating [14].

Step 4: A_{md} adds the new proposal to the negotiation history database. A_{fac} and A_{dis} divide the negotiation data into multiple samples, adjust the parameters of each sub learning model, and calculate the root mean square error E_{ij} of each model according to equation (12).

Step 5: A_{fac}, A_{dis} calculates the weight of each sub learning model according to Equation 3.3 α, output the final strong combination learner, combined with the current proposal, to determine the next round of concession amplitude and measure $C_{t+1}^{fac/dis}$.

Step 6: A_{md} calculates the current global utility based on Equation 3.7 and provides feedback to A_{fac} and A_{dis} who are currently negotiating.

Step 7: Calculate the impact of the negotiation environment on the concession level of A_{fac} and A_{dis} being negotiated θ, based on the predicted concession amplitude in step 5, derive the counter proposal for each issue according to Equations 3.10 and 3.11, update the current utility value, negotiate the environmental conditions, and provide feedback to A_{md}.

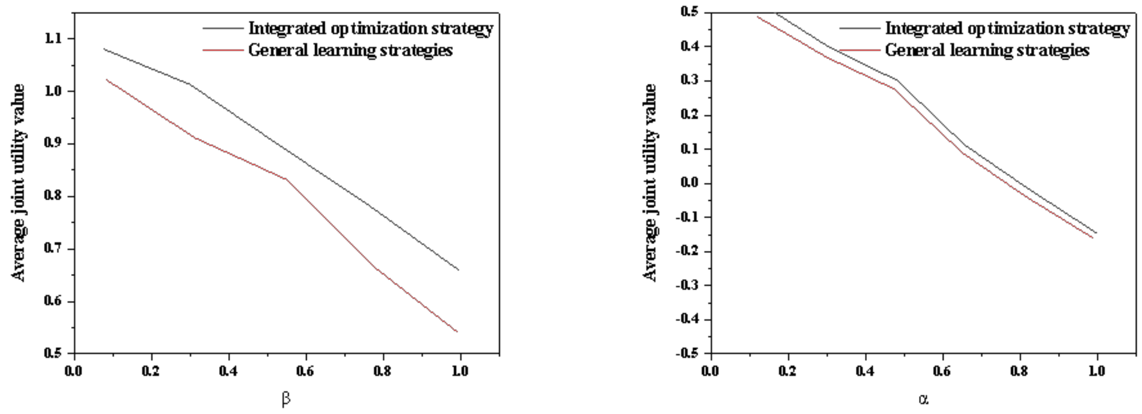
Step 8: A_{fac}, A_{dis} proposes a counter proposal. If the negotiating opponent accepts it, proceed to Step 9; Otherwise, proceed to step 3.

Step 9: A_{md} will write the successfully negotiated agent to the database. After the quick negotiation activity, A_{fac} and A_{dis} determine their partners based on Equation 3.11.

4.2. Example analysis. In order to demonstrate the differences between the two algorithms, simulation experiments were conducted. Assuming that there are conflicts between multiple manufacturers and distributors in the mobile phone production and sales chain when formulating collaborative plans, negotiations should be conducted according to common learning strategies and integrated optimization strategies. Consider the price, quantity, delivery time, warranty time, and defect rate of the plan as negotiation topics [15]. According to expert experience, manufacturers are most concerned about price, quantity, and delivery time, followed by warranty time and defect rate; Distributors are most concerned about price, quantity, and delivery time, followed by defect rate and warranty time. Therefore, the issue range and weight of manufacturers and distributors are shown in Table 4.1.

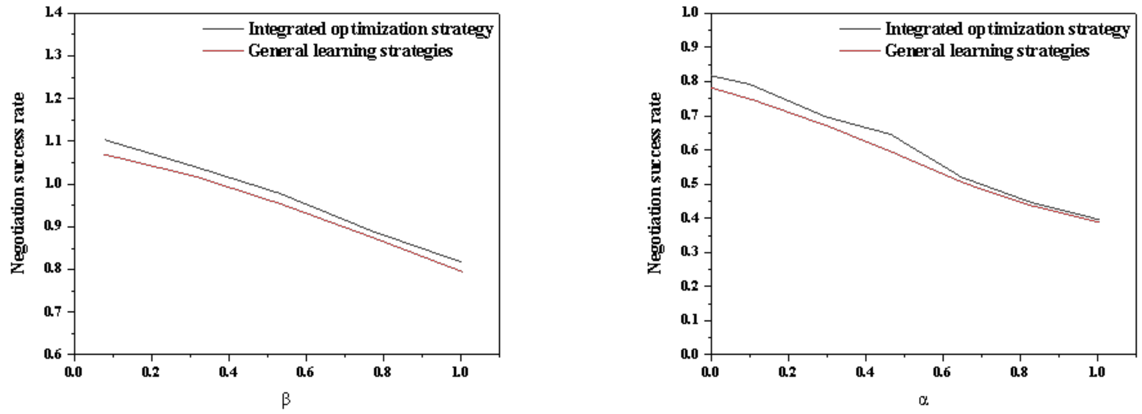
Generate 50 manufacturers and 50 distributors for the two adaptive negotiation strategies proposed by the author, and simulate the conflict resolution of collaborative plans. Based on existing experience, it is assumed that the maximum negotiation time τ_{fac} is 25 and τ_{dis} is 20.

In Figures 4.1(a)-(b), the x-axis and x-axis represent respectively α, β. The y-axis represents the average joint utility value of manufacturers and distributors at the time of successful negotiation, with different combinations of values [16]. It can be seen that as Increase in size The difference between the average joint utility



(a) (b)

Fig. 4.1: Meverage joint utility simulation results for 2 strategies



(a) (b)

Fig. 4.2: Negotiated success rate simulation results for 2 strategies

of the two negotiation strategies is increasing as the decrease in 0.4 When it is 0.6, the average combined utility of the two reaches its maximum. Therefore, the ensemble learning optimization strategy proposed in this article has better negotiation effectiveness than ordinary single learning machine adaptive strategies.

In Figures 4.2(a)-(b), the x-axis and y-axis represent respectively , The y-axis represents the negotiation success rate of manufacturers and distributors with different value combinations. It can be seen that in general, the integrated learning optimization strategy proposed in this paper has a higher negotiation success rate than the ordinary single learning machine adaptive strategy. Therefore, the integrated learning optimization strategy can improve the success rate of production and sales negotiations to a certain extent [17].

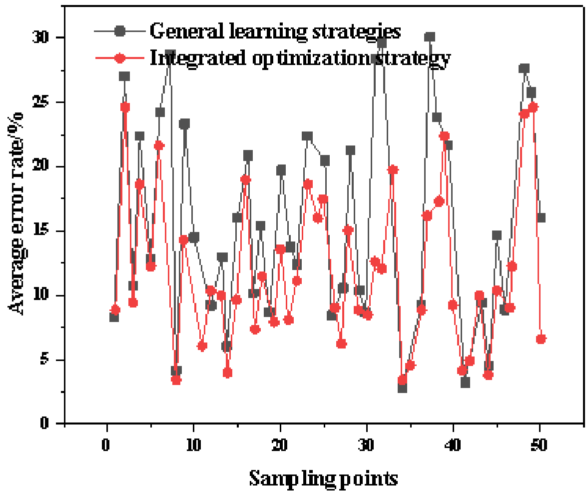


Fig. 4.3: Meverage error rate simulation results for 2 strategies

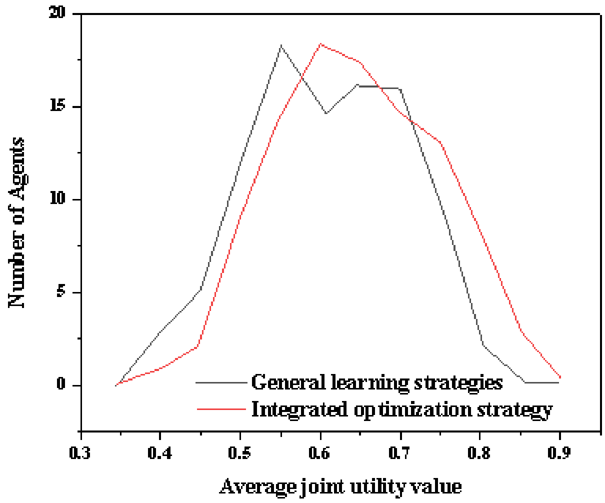


Fig. 4.4: Relationship between joint utility and successfully negotiated Agent

Figure 4.3 selects 50 manufacturers in the experiment to predict the average error rate of the opponent's concession amplitude on the same issue. Comparing the performance of the two strategies, it can be seen that in most cases, the author's ensemble learning strategy has lower error rates than the ordinary SVM single learning machine adaptive strategy [18].

From Figure 4.4, it can be seen that in the adaptive negotiation strategy of a regular SVM single learning machine, when the most successful agents are negotiated, their joint utility falls within the interval [0.55, 0.70], while the author's ensemble learning strategy mainly focuses on [0.6, 0.8], the author's strategy is relatively superior to ordinary learning strategies in terms of both the number of successfully negotiated agents and the joint utility [19,20]. The conclusion drawn from the above is that the negotiation strategy based on dynamic selective ensemble learning performs relatively better than ordinary single learning machine adaptive negotiation strategies in terms of joint utility, negotiation success rate, average error rate, etc.

5. Conclusion. Resolving conflicts in supply chain production and sales collaboration is beneficial for improving the operational efficiency of the supply chain. On the basis of considering the impact of the environment on negotiation, the author proposes an adaptive negotiation strategy based on dynamic selective ensemble SVM, which can reduce the error of opponent prediction information and also consider the impact of other negotiation processes in multilateral negotiation. The experimental results show that compared with the adaptive negotiation strategy of ordinary single learning machines, this strategy can to some extent improve the negotiation success rate, conflict resolution efficiency, and the joint utility of manufacturers and distributors. The next step will be to study adaptive negotiation methods for resolving conflicts in supply chain production and sales collaboration based on multilateral negotiations, in order to improve the intelligence level of the supply chain.

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Edited by: Zhigao Zheng
Special issue on: Graph Powered Big Aerospace Data Processing
Received: Jan 15, 2024
Accepted: Feb 18, 2024