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Research on the Optimization Model of the Supply Chain with Concurrent Negotiation Particle Swarm Optimization

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Abstract

In allusion to the production and marketing problems among the supply chain enterprises, the multi-agent technology is applied in the two-stage supply chain to establish a concurrent negotiation model under incomplete information constraint. The coordination strategy based on particle swarm optimization can update the belief value of the negotiating agents during the negotiation process, thus to further support the continuous negotiation. The simulation result not only verifies the feasibility and the effectiveness of this model, but also shows that this model is superior to other concurrent negotiation models in the aspects of negotiation result utility, negotiation time and negotiation success rate.

Keywords: *Concurrent Negotiation; Particle Swarm Optimization; Parzen Window Estimation; Multi-agent; Supply Chain*

1. Introduction

In the face of complex market competition and dynamic market requirement, the intelligent supply chain management is an effective approach for reducing enterprise cost and improving enterprise competitiveness [1]. With the advantages of distributivity, interactivity, intelligence, *etc.*, the multi-agent system is applicable to the multi-enterprise supply chain management in complex environment [2]. In the distributed supply chain environment, the member enterprises intend to obtain better products/services and benefits in the complex interactive activities, and the resource demanders expect to concurrently negotiate with multiple product/service resource providers in order to timely satisfy their own demands and meanwhile improve the coordination efficiency of the whole supply chain [3].

Due to the strong flexibility and wide applicability, the concurrent negotiation is concerned by many scholars at home and abroad [4-5]. Gu Chuanlong has proposed the business process oriented collaborative negotiation model for a single enterprise to negotiate with several upstream enterprises and one downstream enterprise at the same time, wherein this model aims at comprehensively coordinating the business processes of the negotiators to solve the conflicts [6]; Nguyen has proposed the concurrent negotiation threads coordination strategy on the basis of Rahwan's achievements to allow the buyer to apply different strategies to negotiate with several sellers at the same time, thus to select the optimal negotiation result [7-8]; Mansour K has considered the competitors' behavior factors and divided the negotiation objects into advantageous objects and disadvantageous objects through the first several rounds of negotiation from the angle of the buyer agent, and then he has adopted different negotiation strategies for the two types of negotiation objects and proposed the concurrent negotiation model with Meta strategy as the coordination mechanism [9]; Sun Tianhao has established the dynamic concurrent negotiation model which allows the agents to flexibly join and exit from the negotiation, wherein the transaction cost factor is also considered in this model and

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the coordination strategy based on relative utility is adopted to manage multiple concurrent one-to-one negotiations [10]; Chen Lu, *et. al.*, have discussed the competitors' preferences through fuzzy constraint method and similarity evaluation method and adopted Q learning algorithm of the reinforcement learning to generate the negotiation proposals in order to improve the multi-proposal multi-agent concurrent negotiation efficiency under the condition of incomplete information and negotiation time constraint [11-13]; Wu Yuying has proposed a fuzzy coordination strategy for a one-to-many automatic negotiation model, wherein such strategy can continue the negotiation process and is more consistent with the actual negotiation thought [14].

According to the above analysis, we can know that most negotiation models require the buyer agent to present the opposed proposal only after receiving the proposals of all seller agents. Such negotiation mode can restrict the information interaction during the negotiation process and the flexibility of the negotiation strategy. Additionally, most models are rarely focused on the working efficiency of the coordinators. In actual supply chain operation environment, the manufacturers more expect to timely reach a consensus with the retailer agents through negotiation, thus to achieve the win-win effect for the participants. Therefore, a multi-agent concurrent negotiation model under the two-stage supply chain background is established in this article, namely: the manufacturer agent adopts the mixing proposal strategy based on retention value and time to negotiate with the retailer agents through multiple concurrent negotiation threads, and meanwhile the particle swarm optimization algorithm is adopted to coordinate the concurrent negotiation threads in order to enable the negotiating agents to reach an agreement in finite time.

2. Concurrent Negotiation Model

2.1. Model Framework

In this article, the retailer agent and the manufacturer agent in the supply chain are taken as the research objects, and the supply chain is regarded as a production and marketing coordination network composed of retailer agent and manufacturer agent. In this model, the party providing the product is regarded as the manufacturer agent while the party purchasing the product is regarded as the retailer agent. Figure 1, is the concurrent negotiation model framework for a manufacturer agent to negotiate with multiple retailer agents. Therein, the manufacturer agent and the retailer agents have their own negotiation information (negotiation topic scope, negotiation deadline, *etc.*,) and they do not know the negotiation information of the opposite party. Specifically, the manufacturer agent mainly includes two parts: multiple sub-manufacturer agents and one coordinator which is used to respectively create the negotiation thread for each retailer agent and coordinate different coordination strategies for the negotiation threads in order to control the sub-manufacturer agents through the coordination strategies. Since each retailer agent has different strategies for the proposals, thus the coordinator is required to flexibly process the negotiation thread information at different time and in different states and timely update the belief values of other sub-manufacturer agents, and the sub-manufacturer agents negotiate with the retailer agents on the basis of the continuously updated belief values. Additionally, the negotiation thread, which includes the sub-manufacturer agent and the corresponding retailer agent as well as the negotiation information of the manufacturer agent, is responsible for accepting or refusing the proposal and generating the opposed proposal.

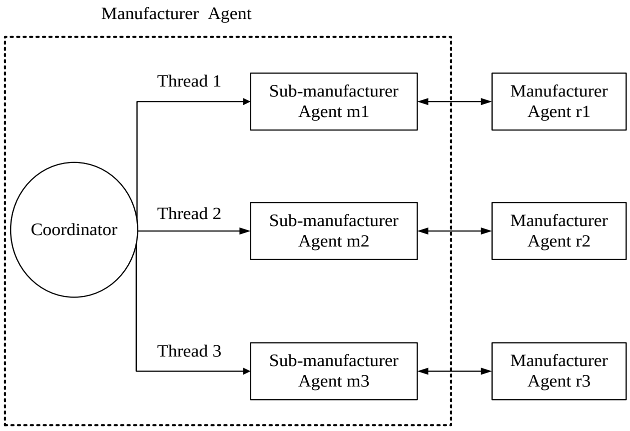

Figure 1. Concurrent Negotiation Model Framework of Multi-Agent Supply Chain

The negotiation process of a single thread is as shown in Figure 2. In the initial negotiation stage, the coordinator initializes the negotiation thread according to the number of the retailer agents and triggers the negotiation request, and then the corresponding retailer agent responds to the above request, wherein all negotiation threads are continuously executed. Before next proposal, it is necessary to check whether the optimal proposal is received from the coordinator; if not, it is necessary to present the opposed proposal according to the negotiation strategy; if yes, it is necessary to judge whether the utility of the proposal is greater than that of the present proposal: if yes, it is necessary to update the negotiation belief value of the manufacturer agent; if not, it is necessary to keep the present proposal and present the (opposed) proposal. When the sub-manufacturer agent and the supplier agent have successful or failed negotiation, each thread will send the negotiation result to the coordinator.

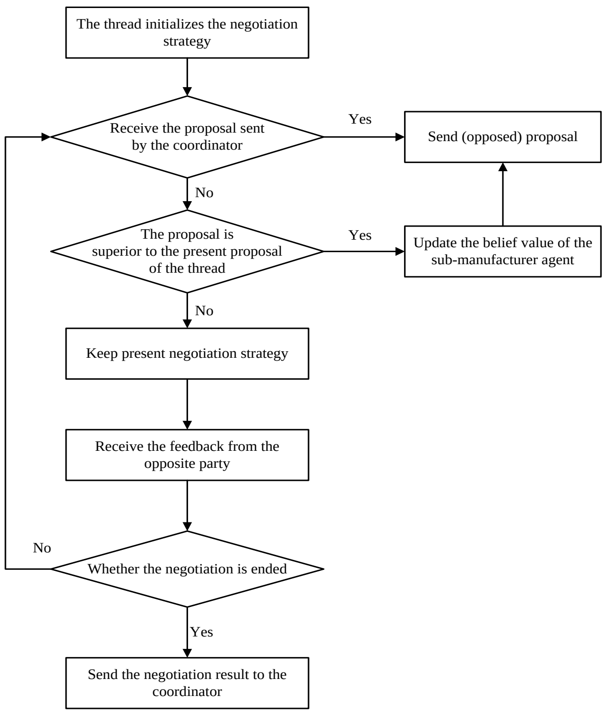

Figure 2. Negotiation Process of a Single Thread

2.2. Main Parameter Setting

$Ag = \{m, r_1, \cdots, r_n\}$ denotes the set composed of one manufacturer agent and multiple retailer agents. For $a \in Ag$, T^a_{max} denotes the deadline of Agent a ; $X \in \{V_t^{a_i \to a_j}, min_i^a, max_i^a, w_i^a\}$ denotes negotiation topic, wherein $V_t^{a_i \to a_j}$ denotes the proposal value sent from Agent a_i to the negotiation competitor Agent a_j at time t ; $[min_i^a, max_i^a]$ denotes the value range provided by Agent a for topic i ; W_i^a denotes the weight vector provided by Agent a for the topic i , $\sum_{i=1}^{n} w_i^a = 1$; A denotes the action adopted during the negotiation process, $A \in \{\text{accept, reject, propose}\}$, wherein "accept" denotes proposal acceptance, "reject" denotes proposal refusing, and "propose" denotes proposal presentation; U denotes the utility function, namely the evaluation function for quantitatively evaluating topic v_i .

$$u^a(v_i) = \begin{cases} \dfrac{max_i^a - v_i}{max_i^a - min_i^a}, \\ \text{Progressive decreasing of preference on topic i} \\ \dfrac{v_i - min_i^a}{max_i^a - min_i^a}, \\ \text{Progressive increasing of preference on topic i} \end{cases} \tag{1}$$

The overall utility function of the topic is as follows:

$$U^a = \sum_{i=1}^{n} w_i^a u^a(v_i) \tag{2}$$

The final integrated utility function is the utility sum of the manufacturer agent and the retailer agent when the thread has successful negotiation and can be expressed as follows:

$$U^{ALL} = \lambda U^m + (1-\lambda) U^r \tag{3}$$

If S is set to denote the proposal strategy, then concurrent negotiation model for the multi-agent supply chain is a sextuple set $\Gamma = \{Ag, X, T, A, U, S\}$.

2.3. Proposal Strategy

2.3.1. Time Based Proposal Strategy: For the time based concession strategy proposed by Faratin, time is believed as one of the factors determining the concession range [15]. At time t , the time based proposal strategy of the manufacturer agent for topic v_i can be expressed as follows:

$$V^{m \to r}(t)_f = \begin{cases} \min_i^m + (t / T^m_{max})^B (\max_i^m - \min_i^m), \\ \text{Progressive decreasing of preference on topic i} \\ \max_i^m - (t / T^m_{max})^B (\max_i^m - \min_i^m), \\ \text{Progressive increasing of preference on topic i} \end{cases} \tag{4}$$

At time t , the time based proposal strategy of the retailer agent for topic v_i can be expressed as follows:

$$V^{r\to m}(t)_f = \begin{cases} \min_i^r + (t/T_{\max}^r)^B(\max_i^r - \min_i^r), \\ \text{Progressive decreasing of preference on topic i} \\ \max_i^r - (t/T_{\max}^r)^B(\max_i^r - \min_i^r), \\ \text{Progressive increasing of preference on topic i} \end{cases} \tag{5}$$

2.3.2. Proposal Strategy Based on Competitor's Topic Retention Value Estimation: Parzen window estimation is usually adopted to estimate the probability density function with unknown distribution, and the basic thought thereof is to adopt the mean value of the densities of the points in a certain range to estimate the overall density function[16]. Here, the manufacturer agent is taken as an example to calculate the retailer agent's topic retention value. Specifically, if $(x_1, x_2, \cdots, x_N)$ is assumed as the samples with unknown distribution and x_i is assumed to denote the proposal value of the topic of the retailer agent, then the distribution is estimated as follows:

$$\hat{f}_h(x) = \frac{1}{N \cdot h}\sum_{i=1}^{N}\varphi(\frac{x - x_i}{h}) \tag{6}$$

In the above formula, N denotes sample size, h is window width and $\varphi(\cdot)$ is window function. Uniform function, trigonometric function and gamma function are usually adopted as the window function, but Gaussian function is adopted for the model. Therefore, the probability density function of the proposal strategy of the retailer agent is as follows:

$$P(x) = \frac{1}{N \cdot (2\pi)^{d/2} \cdot h}\sum_{i=1}^{N}\exp\{-\frac{(x - p_{ri})^2}{2h^2}\} \tag{7}$$

In the above formula, d denotes characteristic space dimensionality, p_{ri} denotes the proposal value of the retailer agent in the i th round of the negotiation.

Based on the probability density function, the manufacturer agent presents the opposed proposal according to the retailer agent's retention estimation value under the precondition of retaining his/her own benefits.

$$V^{m\to r}(t)_s = \begin{cases} \min_i^m, & \min_i^m < \int P(x)xdx \\ e^{t/T} \times \int P(x)xdx, & otherwise \end{cases} \tag{8}$$

2.3.3. Linearly Weighted Proposal Strategy: The above two proposal strategies are more or less complementary to each other. Although the negotiation deadline satisfaction is considered in the time based proposal strategy, yet the topic retention value of the opposite party is not considered; although the retention value of the opposite party is considered in the proposal strategy based on topic retention value, yet the negotiation deadline constraint is not considered. Therefore, it is necessary to adopt the dynamic linear weighting method to integrate the two proposal strategies:

$$V^{m\to r}(t) = s_1 \times V^{m\to r}(t)_s + s_2 \times V^{m\to r}(t)_f \tag{9}$$

In the above formula, s_1 and s_2 denotes the integration coefficient, $s_1, s_2 \in [0,1]$, $s_1 + s_2 = 1$.

3. Coordination Strategy Based on Particle Swarm Optimization (PSO)

In order to manage multiple concurrent negotiation threads, the particle swarm optimization algorithm is embedded into the coordinator to find current optimal proposal and send it to other threads in the negotiating state till all negotiation threads are ended or reach the maximum negotiation time. During the concurrent negotiation process, if a negotiation thread reaches an agreement, then the thread will stop the negotiating activity.

As a swarm search algorithm based on bird flock predation simulation [17], PSO algorithm aims at searching the targets according to the speed, without including any crossover and mutation operations in the genetic algorithm. In this algorithm, the individual intends to find its optimal solution or the optimal solution of the neighborhood individual so as to find the optimal solution of the whole search space through such swarm behaviors. If x_k^t is assumed to denote the position of the k th individual at time t, then the movement of the individual k at the speed u_k^{t+1} can be expressed as follows:

$$x_k^{t+1} = x_k^t + u_k^{t+1} \tag{10}$$

The speed is an important parameter and is expressed as follows:

$$u_{k_j}^{t+1} = u_{k_j}^t + c_1 \cdot r_{1j}^t \cdot (y_{kj}^t - x_{kj}^t) + c_2 \cdot r_{2j}^t \cdot (\hat{y}_{kj}^t - x_{kj}^t) \tag{11}$$

In the above formula, $u_{k_j}^t$ denotes the speed of the individual k at time t in j -dimension space, x_{kj}^t denotes the position of the individual k at time t in j -dimension space, c_1 and c_2 (c_1 >0, c_2 >0) are used for acceleration, r_{1j}^t and r_{2j}^t are random numbers in the interval [0,1], y_{kj}^t denotes the individual optimal solution, and $\hat{y}_{kj}^t$ denotes the global optimal solution. The individual optimal solution in step ($t+1$) can be obtained through Formula (5):

$$y_k^{t+1} = \begin{cases} y_k^t & \text{if } f(x_k^{t+1}) \le f(y_k^t) \\ x_k^{t+1} & \text{if } f(x_k^{t+1}) > f(y_k^t) \end{cases} \tag{12}$$

In the above formula, $f(\cdot)$ is the fitness function. Therefore, the global optimal solution is as follows:

$$f(\hat{y}_k^t) = \max\{f(y_1^t), f(y_2^t), \cdots, f(y_N^t)\} \tag{13}$$

According to the characteristics of the particle swarm optimization algorithm and the concurrent negotiation model for the supply chain, the manufacturer agent is taken as an example in this article, wherein the negotiation threads can be regarded as the particles in the particle swarm optimization algorithm, the proposal of the present thread is the present position of the particle, the successfully negotiated proposal of the present thread is the individual optimal solution of the particle, the proposal with maximum utility among the present successfully negotiated threads is the global optimal solution, the proposal value increase or reduction amount is the speed, and the fitness function is the utility function U^m .

4. Negotiation Step Description

According to the above method thought, the whole negotiation steps are described as follows:

Step 1 The coordinator creates the negotiation threads one-to-one corresponding to the retailer agents, then initializes the proposal strategy of each negotiation thread and the parameters of the particle swarm optimization algorithm, then adopts the particle swarm optimization algorithm to coordinate the concurrent negotiation threads, then calculates the present optimal proposal and send it to other sub-manufacturer agents;

Step 2 At the initial time, the manufacturer agent and the retailer agent adopt the time based proposal strategy respectively according to Formula (4) and Formula (5);

Step 3 After both parties accumulate a certain amount of negotiation history data at certain time, it is necessary to calculate the topic retention values according to Formula (6) and Formula (7) and then adopt the linearly weighted proposal strategy for one-to-one negotiation according to Formula (9);

Step 4 After the sub-manufacturer agent receives the optimal proposal sent from the coordinator, if the utility of this optimal proposal is less than that of the present proposal, then the present proposal strategy will be retained; or else, it is necessary to change the concession parameter of the time based proposal strategy as $B' = \frac{\ln(\max_i^m - \min_i^m) - \ln u'}{\ln(t+1) - \ln t}$ (u' denotes the new speed) according to Formula (3) and Formula (9); for successful negotiation, please enter Step 5; or else, please return to Step 3;

Step 5 The thread with successful negotiation sends the corresponding result to the coordinator and waits for other threads to finish the negotiation;

Step 6 After all negotiation threads are ended, the coordinator will select the most suitable retailer agent according to Formula (3)

5. Experiment

In the manufacturing and marketing links of the supply chain in the manufacturing industry, the manufacturer agents and the retailer agents often negotiate with each other upon the production-marketing coordination plan. Generally speaking, the manufacturer agent seeks for sufficient orders, suitable prices, enough delivery time, new samples, rich varieties, complete models, *etc.*, as much as possible in the production capacity thereof; however, the retailer agent, standing for the market consumption capability, usually seeks for suitable orders, reasonable prices, timely delivery, new style, good quality, guaranteed services, *etc.*, In this article, one manufacturer agent and n retailer agents (i=1,2,…, n) are taken as the simulation experiment objects of the negotiation for N transaction topics, and the simulation negotiation results of the common model and the concurrent negotiation model are compared and analyzed. Therein, MATLABR 2012a is adopted to implement the negotiation model and compile the main program Opt_pso.m of the particle swarm optimization algorithm, thus to obtain current optimal negotiation result. In order to verify the feasibility and the effectiveness of the model, the experiment is carried out in the following two conditions:

(1) n=5，N=3

Namely: one manufacturer agent concurrently negotiates with 5 retailer agents upon the three negotiation topics - product price, order quantity and delivery time. The parameter settings of the manufacturer agent and the retailer agents are as shown in Table 1.

Table 1. Negotiation Topics of Negotiating Agents and Value Range

Negotiation Topic	Value Range		Weight	
	Manufacturer Agent	Retailer Agents	Manufacturer Agent	Retailer Agents
Product Price	[10,50]	[5,40]	0.334	0.333
Product Quantity	[10,50]	[10,50]	0.333	0.333
Delivery Date	[10,40]	[5,30]	0.333	0.334

The parameters of the particle swarm optimization algorithm are as follows: $c_1 = c_2 = 1.8$, $x \in [0.1, 0.9]$, $u_{max} = 3$, particle swarm scale = 50, and iteration times = 100. 100 experiments are independently carried out in each condition, and the experiment results are averaged, as shown in Table 2. Figure 3 shows the integrated utilities of the proposed negotiation model and the common negotiation model respectively adopted by the negotiating parties under the condition of different deadlines.

Table 2. Comparison of Results of Different Negotiation models

Negotiation Model Type	Integrated Utility	Mean Negotiation Time	Negotiation Success Rate
Common Model	0.358	0.792	0.709
Proposed Model	0.452	0.724	0.785

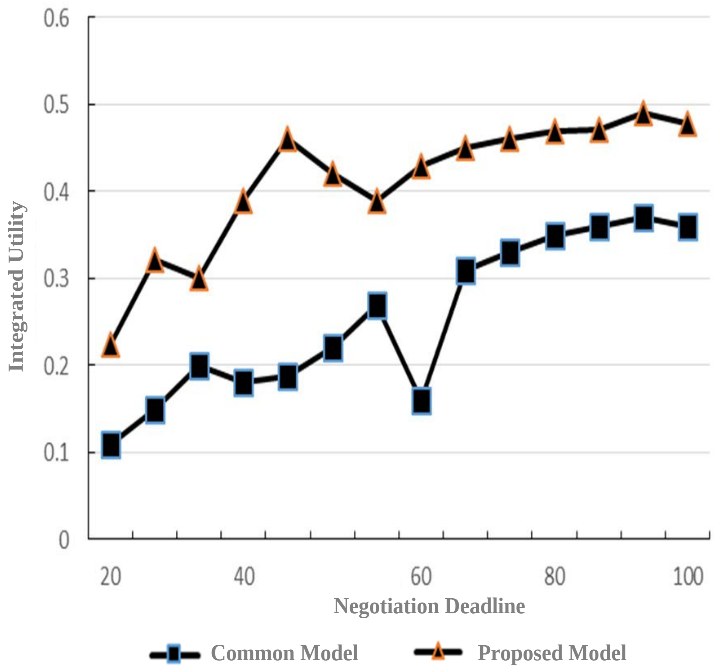

Figure 3. Utilities of Different Negotiation Models

According to the experiment result comparison as shown in Table 2 and Figure 3, under the condition of n=5 and N=3, compared with common negotiation model, the concurrent negotiation model has greater integrated utility, shorter negotiation time and higher success rate.

(2) n=10,15,20,25,30；N=3

Namely: one manufacturer agent concurrently negotiates with 10, 15, 20, 25 and 30 retailer agents upon the three negotiation topics - product price, order quantity and delivery time. The parameter settings of the manufacturer agent and the retailer agents are as shown in Table 3.

Table 3. Experiment Parameter Setting

Parameter	Parameter Description	Value
n	Number of Retailer Agents	10,15,20,25,30
w_i^a	Weight of Retailer Agent for Topic	1/N
T	Negotiation Deadline (Times)	[100,600]
$\min_i^a$	Minimum Value for the ith Topic	[0,20]
$\max_i^a$	Maximum Value for the ith Topic	[30,50]

When the number of the retailer agents is increased from 10 to 30, the integrated utilities, the negotiation time and the negotiation success rates are respectively as shown in Figures 4, 5 and 6.

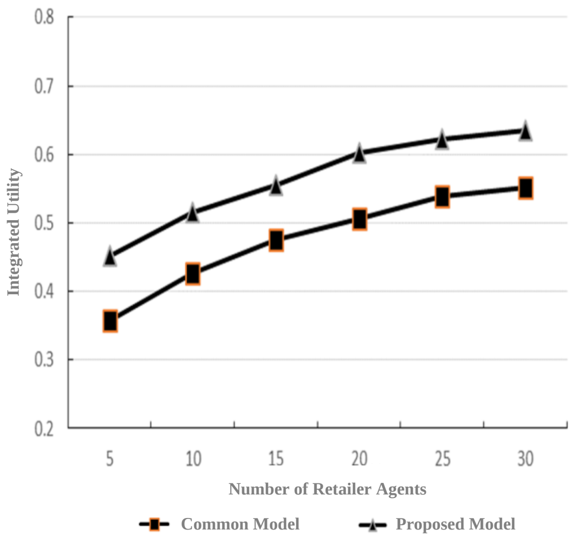

Figure 4. Integrated Utilities Under Different Numbers of Retailer Agents

According to Figure 4, under the condition of the same number of retailer agents, compared with the common negotiation model, the proposed concurrent negotiation model for the supply chain can obtain higher utility value. In the proposed model, the particle swarm optimization algorithm is adopted to search current optimal proposal and accordingly provide more possibly acceptable proposals, namely: better negotiation solution can be found, and this is also the reason for the higher integrated utility value. Additionally, when the number of the retailer agents is increased, the utility value is also increased, thus indicating that better negotiation result can be obtained through negotiating with more retailer agents under the condition of not considering the cost consumption.

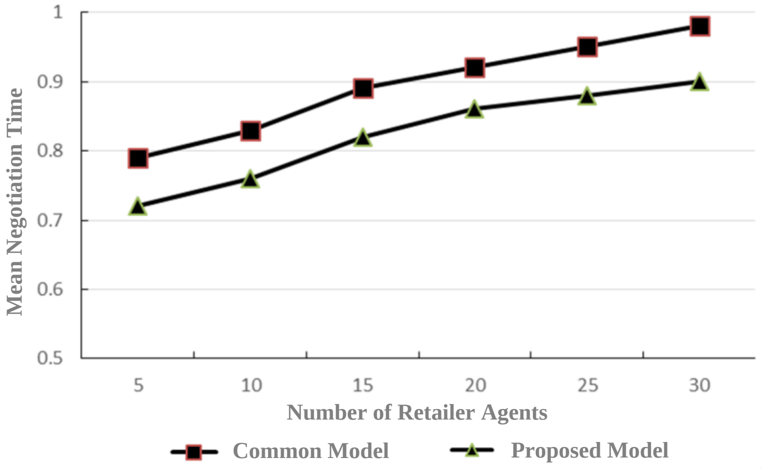

Figure 5. Mean Negotiation Time Under Different Numbers of Retailer Agents

According to Figure 5, compared with the common negotiation mode, the proposed negotiation model has shorter negotiation time. Under the condition of the same number of retailer agents, the proposed negotiation model can rapidly obtain the successful negotiation result. In the proposed negotiation model, Parzen window estimation algorithm is adopted to roughly estimate the competitor's topic retention value in order to generate better opposed proposal strategy. Meanwhile, due to the introduction of the particle swarm optimization algorithm into the proposed negotiation model, the negotiation threads are not executed in an completely independent way. Since the intermediate search results will be sent to other negotiation threads, thus the negotiation process is accelerated.

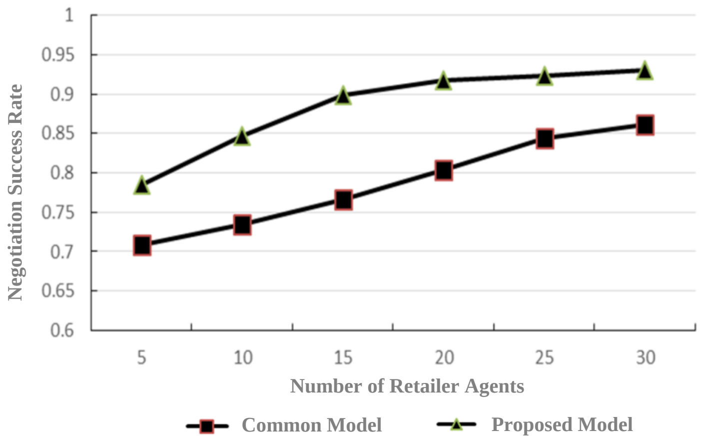

Figure 6. Negotiation Success Rates under Different Numbers of Retailer Agents

According to Figure 6, compared with common negotiation model, the proposed negotiation model has higher negotiation success rate. In the proposed negotiation model, Parzen window estimation algorithm is adopted to learn the competitor's topic retention value and obtain more negotiation information so as to make more reasonable negotiation strategy and improve the negotiation success rate. Additionally, the coordination strategy is adopted for the proposed negotiation model to provide optimal proposal to other threads, but along with the negotiation, it is difficult for the remaining negotiation threads to accept their proposals not in the competitor's preference scope, so the mean negotiation time is shortened but the growth rate of the negotiation success rate is reduced when the number of the retailer agents is increased.

6. Conclusion

In this article, the two-stage supply chain in the supply chain environment is taken as the research object to establish the concurrent negotiation model for the multi-agent supply chain, and the particle swarm optimization algorithm is adopted for the coordinator to search the optimal proposal and send it to other threads, and Parzen window estimation algorithm is also combined to learn the competitor's retention value, thus to propose the two strategies: the proposal strategy based on retention value and the time based proposal strategy. Meanwhile, the simulation experiment is carried out to verify the negotiation performance of the proposed model. Compared with common negotiation model, the proposed model is improved in the following two aspects: (1) Particle swarm optimization algorithm is embedded into the coordinator to improve the negotiation efficiency; (2) Parzen window estimation algorithm is adopted to support relevant proposal strategies in order to enable the negotiating agents to have the ability of considering the competitor's topic retention value. On the basis of this research, the influence of the trust relationship between the agents and the external environment of the supply chain on the negotiation solution will be considered in future research.

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