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Cooperative Distribution Algorithm of Green Supply Chain Considering the Risk Aversion of Manufacturers

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Abstract

Considering production and marketing coordination between supply chain enterprises, this paper specifies a multi-agent supply chain concurrent negotiation model for two-stage supply chain in the supply chain environment. Coordinator is used to search optimal proposals based on particle swarm optimization (PSO) and send these proposals to other threads. Proposal strategies based on retention value and time are put forward by learning retention value of rivals through Parzen-window estimation. Simulation experiment is conducted to test negotiation performance of the model. Compared with ordinary models, the model makes two improvements as follows: (1)PSO is inserted into coordinator to improve negotiation efficiency; (2) Proposal strategies are effectively supported by Parzen-window estimation and enable agents to consider the retention values of rivals. Further researches need to be done to study trust relationship between agents and influence of external environment on supply chain negotiation solution.

***Keywords**: Particle swarm optimization (PSO); Estimation, supply chain; Coordination; Negotiation*

1. Introduction

Intelligent management of supply chains is an effective way for enterprises to save costs and improve competitiveness in the market environment of complicated competition and dynamic demands. Multi-agent system has advantages such as distributivity, interactivity and intellectuality, so it is suitable for enterprise-spanning management of supply chains in the complicated market environment. In an environment of distributive supply chain, enterprises hope to concurrently negotiate with more than one supplier to get better products, services and profits, meeting their own demands while improving collaborative efficiency of supply chains.

We found that most negotiation models require buyer agents to give counter-proposals after receiving proposals from all seller agents. This pattern restricts information exchange and flexibility of negotiation strategies. In addition, most models pay little attention to efficiency of coordinators. In the actual operation of supply chains, manufacturers look forward to consensus and win-win with sellers through timely negotiation. For this reason, this paper establishes a multi-agent concurrent model for two-stage supply chains. That means manufacturer agents can use mixed proposal strategies based on retention values and time to negotiate with seller agents through more than one concurrent threads. Meanwhile, PSO is used to coordinate each concurrent negotiation threads to support negotiation agents to reach agreements within limited time.

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2. Concurrent Negotiation Model

2.1. Model Framework

For accepting or refusing proposals and giving counter-proposals. This paper takes sellers and manufacturers as research objectives and supply chain as a production and marketing coordination network. In this model, manufacturers provides products and sellers need to purchase. A model framework describing that one manufacture agent concurrently negotiate with several seller agents is illustrated in Figure 1. Manufacturers and sellers have their own negotiation information (such as value range of negotiation issues and negotiation deadlines) and they do not know the information of each other. Manufacturer agents are decomposed into several sub-agents and one coordinator. The coordinator establishes negotiation threads at the same number with current seller agents and formulates different negotiation strategies for each thread. Each sub-agent is controlled through corresponding negotiation strategy. Coordinator needs to flexibly deal with negotiation thread information with different time and statues and timely update confidence values of other sub-agents because each seller agent may have different proposal strategies. Then sub-agents negotiate with seller agents based on updated confidence values. Negotiation threads include sub-agents and corresponding seller agents, and reserve negotiation information of manufacturer agents. They are also responsible

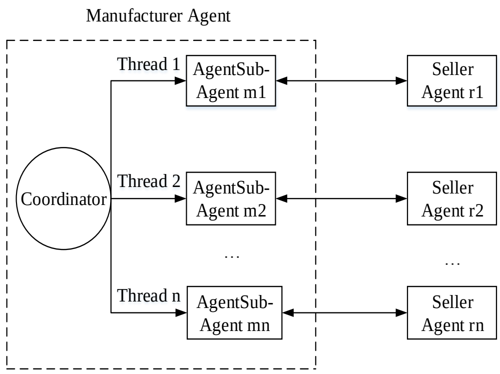

Figure 1. Framework of Supply Chain Concurrent Negotiation Model

The negotiation progress of single thread is shown in Figure 2. When negotiation starts, coordinator initializes negotiation thread according to the number of seller agents. Then it launches negotiation request and seller agents give response. All threads are carried out continuously. Check if there is the best proposal from coordinator before starting next round of proposing. If there is no best proposal, send out counter-proposals according to negotiation strategies. If there is the best proposal, judge whether utility value of the best proposal is bigger than that of current proposal. If yes, negotiation belief of manufacture agents need to be updated. If no, current negotiation strategy remains the base for giving proposal (counter-proposal). When sub-agents and supplier agent success or fail in negotiating, each thread will send negotiation results back to the coordinator.

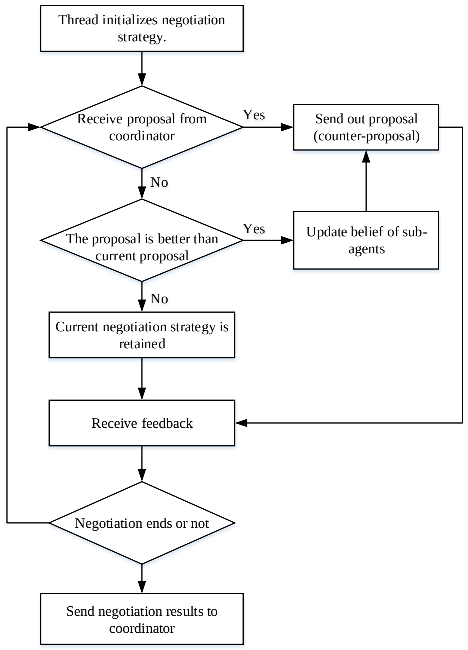

Figure 2. Negotiation Process of Single Thread

2.2. Setup of Major Parameters

$Ag = \{m, r_1, \cdots, r_n\}$ denotes a set of one manufacturer agent and several seller agents. For $a \in Ag$, $T^a_{\max}$ represents 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 topics, where $V_t^{a_i \to a_j}$ represents the proposal values the agent a_i sends to agent a_j at the time of t, and $[min_i^a, max_i^a]$ represents value range of agent a for topic i. W_i^a denotes the weight vector of agent a for topic i. A represents actions of negotiation. In $A \in \{\text{accept, reject, propose}\}$, "accept" means accepting proposal; "reject" means refusing proposal and "propose" means giving other proposals. U is utility function. Quantitative topic v_i is evaluation function

$$u^a(v_i) = \begin{cases} \dfrac{max_i^a - v_i}{max_i^a - min_i^a}, \\ \textit{Preference diminishing for topic i} \\ \dfrac{v_i - min_i^a}{max_i^a - min_i^a}, \\ \textit{Preference ascending for topic i} \end{cases} \tag{1}$$

Overall utility function of topics

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

Final united utility function is the utility sum of manufacturer and seller when a thread negotiate results. It can be expressed as:

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

If S is used to denote proposal strategy, multi-agent supply chain concurrent negotiation model is a six-tuple $\Gamma = \{Ag, X, T, A, U, S\}$.

2.3. Proposal Strategies

2.3.1. Time-based Proposal Strategy: Time-based concession strategy was proposed by Faratin who believed that time is one of the decisive factors to concession range. Time-based proposal strategy of manufacturer for the topic v_i at the time of t can be expressed as:

$$V^{m\to r}(t)_f = \begin{cases} \min_i^m + (t/T_{\max}^m)^B(\max_i^m - \min_i^m), \\ \textit{Preference diminishing for topic i} \\ \max_i^m - (t/T_{\max}^m)^B(\max_i^m - \min_i^m), \\ \textit{Preference ascending for topic i} \end{cases} \tag{4}$$

Time-based proposal strategy of seller for the topic v_i at the time of t can be expressed as:

$$V^{r\to m}(t)_f = \begin{cases} \min_i^r + (t/T_{\max}^r)^B(\max_i^r - \min_i^r), \\ \textit{Preference diminishing for topic i} \\ \max_i^r - (t/T_{\max}^r)^B(\max_i^r - \min_i^r), \\ \textit{Preference ascending for topic i} \end{cases} \tag{5}$$

2.3.2. Proposal Strategy based on Estimation of Rival Retention Value for Topics: Parzen window estimation is usually used to estimate probability density function of unknown distribution. The basic idea is to estimate the overall density function according to the average density of each point in a certain range. Taking manufacturer agents for example, calculate seller agents' retention values for topics. Assume $(x_1, x_2, \cdots, x_N)$ is the sample of unknown distribution and x_i is the proposed value of seller agent for a topic. The distribution can be estimated as follows:

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

Where N denotes the sample size, h is window width and $\varphi(\cdot)$ is window function. For the window function, it is usually uniform function, trigonometric function and gamma function. The model employs Gaussian function. Therefore, the probability density function of seller agent's proposal strategy can be expressed as:

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

Where d represents characteristic space dimension and p_{ri} denotes the proposed values of seller agent in the negotiation round i.

Based on this probability density function, manufacturer agent may give counter-proposal to seller while retaining estimation values on the premise of safeguarding own benefits.

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

2.3.3. Lineary Weighted Proposal Strategy: Above two proposals are complementary to each other to some extent. Time-based proposal strategy fails to take into account the rival retention values for topics though it considers the satisfaction degree of negotiation deadline; while the proposal strategy based on estimation of rival retention value for topics ignores the constraint of negotiation deadline. Thus these two proposal strategies are combined by dynamic linear weight:

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

$s_1, s_2 \in [0,1]$, 且 $s_1 + s_2 = 1$。

Where s_1、 s_2 denote integration coefficient under the condition of $s_1, s_2 \in [0,1]$ and $s_1 + s_2 = 1$.

3. PSO-based Coordination Strategy

In order to manage concurrent negotiation threads, PSO algorithm is inserted into the coordinator. Search the best proposal and send it to other threads still under negotiation until all threads are finished or reach the negotiation deadline. During concurrent negotiation, one thread is over when it reaches agreement.

PSO is a population search algorithm based on simulation of predation of bird flock. Unlike genetic algorithm, it has no crossover and mutation operators. It searches according to rate. In this algorithm, an individual searches the optimal solution for itself or for the near individuals. This population behavior also searches the globally optimal solution for the whole space. Assume x_k^t represents location of the individual k at the time of t and k moves at the rate of u_k^{t+1}. It can be expressed as:

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

Rate is an important parameter and expressed as:

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

Where $u_{k_j}^t$ denotes the rate of individual k at the time of t in dimension j; denotes location of individual k at the time of t in dimension j; c_1 and c_2 are used to accelerate and larger than 0; r_{1j}^t and r_{2j}^t represent random numbers in the internal [0,1]; y_{kj}^t is the optimal solution for individual and $\hat{y}_{kj}^t$ is the globally optimal solution. The optimal solution for the individual $t+1$ can be expressed in formula (5).

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

Where $f(\cdot)$ is fitness function, thus the optimal solution for the whole space is:

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

According to features of PSO algorithm and supply chain concurrent negotiation model, taking manufacturer agent as an example, negotiation threads can be taken as particles in PSO algorithm. Proposals between threads represent current location of particles, and proposal successfully negotiated through a thread is the optimal solution for particle. The optimal solution with highest utility value is the globally optimal solution among all successfully negotiated threads. Increment or decrement of proposal values is rate and the fitness function is utility function U^m.

4. Description of Negotiation Procedures

Based on methods above, negotiation procedures can be described as below:

Step 1: Coordinator establishes negotiation threads according to the number of sellers and initializes proposal strategies and PSO parameters of each thread. PSO is used to coordinate concurrent negotiation threads. Calculate the best proposal and send it to other sub-agents.

Step 2: When initializing, manufacturer agents and seller agents use time-based proposal strategy to negotiate with sellers according to the formula (4) and (5).

Step 3: When the two parties accumulate some history data of negotiation after a certain period, the formula (6) and (7) are used to calculate retention values. Linearly weighted proposal strategy can be used to conduct one-to-one negotiation according to the formula (9).

Step 4: After sub-agents receive the best proposal from coordinator, current proposal strategy can be retained if the utility value of the proposal is larger than that of their own proposal. Otherwise, is appointed as new rate to calculate the concession parameter of time-based proposal strategy $B' = \dfrac{\ln(\max_i^m - \min_i^m) - \ln u'}{\ln(t+1) - \ln t}$ through the formula (3) and (9). If negotiation is successful, move forward to Step 5; otherwise, return to Step 3.

Step 5: When one thread's negotiation is successful, send negotiation results to coordinator and wait until other threads complete negotiation.

Step 6: Coordinator chooses the optimal seller according to the formula (3) when all threads complete negotiation.

5. Experiment

In order to verify the rationality and scientificity of the model, simulation experiment is conducted by setting corresponding parameters. For comparative purpose, experiment parameters are same with the reference [4] as shown in Table 1. The experiment should be repeated for 3 times under same condition with average values as experimental results. The experimental evaluation criteria include final united utility function, success rate of negotiation and average negotiation time (average ratio of actual time of successful negotiation to negotiation deadline)

Table 1. Experiment Parameter Setting

Parameter	Description	Value
n	Number of seller agents	[1,30]
N	Number of topics	[1,8]
T	Negotiation deadline	[150,600]
$\min_i^a$	Minimum value of agent a to topic i	[0,20]
$\max_i^a$	Maximum value of agent a to topic i	[30,50]
w_i^a	Weight of agent a to topic i	1/N

According to results of simulation experiment (as shown in Figure 3,4,5), the model achieves a total utility value of 0.452, an average negotiation time of 0.72 and a success rate of 78.5% when the number of sellers is 5. Ordinary models have total utility value of 0.395, average negotiation time of 0.79 and success rate of 70.9%. When the number of sellers is 10, the model achieves a total utility value of 0.516, an average negotiation time of 0.76 and a success rate of 84.6% while ordinary models have total utility value of 0.427, average negotiation time of 0.83

and success rate of 73.5%. The model also achieves better negotiation results than ordinary models when the number of sellers is 15, 20, 25 and 30. In addition, the proposal strategy used in this model provides the best proposal for other threads. As the negotiation goes on, the rest threads refuse to accept proposals that are beyond their own preference ranges. Therefore, average negotiation time reduces and growth of success rate decelerates with increasing number of sellers.

Analysis above gets following conclusions: (1) the model can achieve negotiation results with larger utility values compared with ordinary models, and utility value increases with rising number of sellers. This indicates that negotiation result will be better when negotiating with more sellers if costs are not considered. (2) The model takes less time to reach negotiation results than ordinary models. When negotiating with same number of sellers, the model achieves results more quickly. PSO algorithm is used to accelerate concession rate, shorten negotiation time and improve negotiation efficiency. (3) The model has a higher success rate of negotiation than ordinary models. Parzen window estimation is used to learn retention values of rivals for topics, to gain more negotiation information, to help own parties to choose more suitable negotiation strategies and to improve success rate.

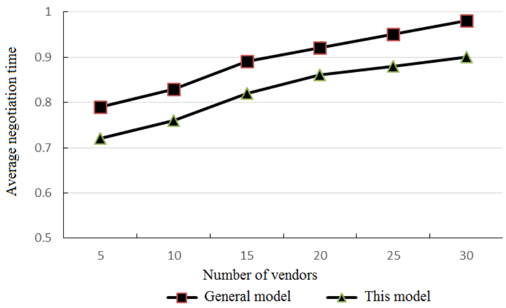

Figure 3. Final Total Utility Values for Different Number of Sellers

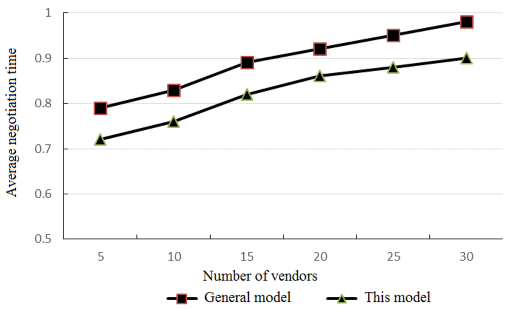

Figure 4. Average Negotiation Time for Different Number of Sellers

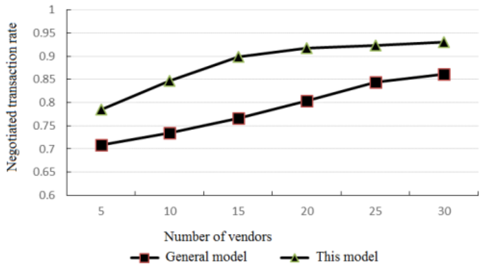

Figure 5. Negotiation Success Rate for Different Number of Sellers

6. Conclusion

Considering production and marketing coordination between supply chain enterprises, this paper specifies a concurrent negotiation model under constraint of poor information and applies multi-agent technology to two-stage supply chain. PSO-based negotiation strategy can update belief values of agents during negotiation so that negotiation can be carried out continuously. Simulation experiment results indicates that the model is feasible and efficient and has advantages in utility values of negotiation results, negotiation time and success rate compared with other concurrent negotiation models.

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