Nash Negotiation Method of Conflict Resolution for MSC Production Marketing Coordination Based on Multi-Agent

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Abstract. In the face of increasingly market competition and diversified demand, manufacturers and dealers of Manufacturing Supply Chain （MSC） pay great effort to achieve production marketing coordination. However, it often generates conflicts in the process of production marketing coordination. For this kind of conflict problem, Multi-Agent technology is introduced. Enterprises of the supply chain are represented by Agents. The conflicts among Agents are resolved through Nash negotiation. A model of Nash Negotiation based on Agents is established. The conflict point of negotiation is determined by Stackelberg differential game. A Memetic Algorithm is proposed to solve the model. Finally, the validity of the algorithm and the model is verified by numerical experiment.

Keywords: Supply chain based on Multi-Agent, Production marketing coordination, Conflict, Nash negotiation, Memetic Algorithm, Differential game

1 Introduction

Production marketing coordination includes core businesses of supply chain, and it is the most important activity of manufacturing [1]. Because each member of the supply chain is independent individual, the operation among members in supply chain often has the characteristics of autonomy, distribution and so on, which leads to that conflicts in the process of production marketing coordination are hard to avoid [2]. If conflicts are not resolved in a timely and effective way, it will affect the effect of coordination and reduce the competitiveness of supply chain [3]. Traditional supply chain management can't resolve the problem of conflict in production marketing coordination effectively. With the development of the distributed object technology and artificial intelligence technology, it has been an important method to research and implement supply chain management that uses Multi-Agent technology to simulate, optimize and control the operation of supply chain [4].

The conflicts in production marketing coordination for supply chain based on Multi-Agent have drawn the attention of some scholars. Zhang establishes a coordination model of supply chain based on Multi-Agent to solve order conflicts, and puts forward a negotiation method based on fuzzy theory and Bayesian learning theory to solve the model [5]. For the problem of order fulfillment, Lin establishes a coordination model of Multi-Agent supply chain based on distributed constraint satisfaction, proposes a conflict resolution method based on the negotiation and analyzes the effect of constraint satisfaction algorithm under different form of demand [6]. Zheng analyzes the generating mechanism of conflict of supply chain from the aspect of information coordination, explores the application of multi-Agent system in supply chain management and establishes a supply chain model based on Multi-Agent which can solve the problem of asymmetric information [7]. Behzad considers the conflict between enterprises caused by the difference of goals and information asymmetry, and puts forward to a negotiation method based on Multi-Agent to resolve conflicts between enterprises for the problem of order acceptance in the case that demand is uncertain [8].

However, so far the existing research did not pay much attention on the combination between Game Theory and Multi-Agent. For the conflicts in production marketing coordination of supply chain, this paper introduces the method of Nash negotiation to resolve conflicts, establishes a model of Nash Negotiation based on Multi-Agent, and presents a method based on Memetic Algorithm to solve the model. The method is available to the case that objective function of Nash negotiation cannot be calculated by mathematical derivation.

2 Problem description and basic mathematics model

For convenience, we restrict that one manufacturer and one dealer in MSC is discussed in this paper. In order to meet the market demand *D(t)*, the dealer purchases a certain amount of products from manufacturer. The dealer decides the price of product *p(t)*, the manufacturer provides products for dealer at the wholesale price *w(t)*. The manufacturing cost of manufacturer is cm, the sales costs of dealer is cr. Let *A(t)* is manufacturer's advertising investment, $C_a(t)$ is the manufacturer's advertising costs, *h* is the advertising costs factor of manufacturer, manufacturer advertised to the market to promote product sale, the relation between the manufacturer's advertising cost and the manufacturer's advertising investment is [9]: $C_a(t) = hA(t)^2$.

According to advertising theory, the differential equation of reputation that changes over time is : $\frac{dG(t)}{dt} = kA(t) - \varphi G(t)$ .where $G(t)$ represents the reputation, k represents the impact degree on the reputation exerted by the advertising investment of manufacturer, φ represents the attenuation degree of the manufacturer's reputation. The reason of the reputation attenuation is that the consumer turn to other company's products because of the impact of their advertising activities.

Supposed that the price demand function of dealer is[10]: $D(t) = \alpha - \beta P(t) + \eta G$. Where $D(t)$ is the product demand, α , β , η are all the constant number over zero. Among this, the α is the market capacity, the β is the price-sensitive factor. The higher the β value, the more sensitive the demand to price. If the price decreases, the demand increases. The η represents the advertisement-sensitive factor, the higher the η value, the more sensitive the demand to reputation.

Assumed that manufacturer and dealer have the same and positive discount rate μ, the goal of manufacturer is to find the wholesale price strategy and advertising strategy which can optimize itself profit in the infinite time. Then the manufacturer revenue function is as follow:

$$\Pi_m = \int_0^{\infty} e^{\mu t}[(w(t)-c)(\alpha - \beta P(t) + \eta G) - hA(t)^2]dt \tag{1}$$

The dealer revenue function:

$$\Pi_r = \int_0^{\infty} e^{\mu t}[(P(t)-w(t))(\alpha - \beta P(t) + \eta G)]dt \tag{2}$$

Both manufacturer and dealer make decision aiming to maximize their own benefits, which leads to inconsistencies in the decision variables, so conflicts occur. We resolve the conflicts by the method of Nash Negotiation.

3 Nash negotiation model based on Multi-Agent

3.1 Model of Nash negotiation

The Model of Nash negotiation based on Multi-Agent can be described by the following group with eight elements.

$$NM = < M, D, ME, x, u_m(x), u_r(x), d_m, d_r, S >$$

where M and D represent manufacturers and dealers respectively; ME negotiation coordination Agent; x the issue of negotiation, it is also the decision variable of production marketing coordination. $u_m(x)$ and $u_r(x)$ represent the utility function of manufacturers and dealers respectively. The utility function is represented by revenue function.

d_m and d_r is the conflict point of manufacturers and dealers respectively, which meet the condition $(u_m(x^*), u_r(x^*)) > (d_m, d_r)$, $(u_m(x^*), u_r(x^*)) = \arg\max \prod_{m,d}(u_i(x) - d_i)$, and $(u_m(x^*), u_r(x^*)) \in S$, S is strategy space. It is bottom line of decision maker which means utility of participant *i* cannot be less than d_i. When the participants are not come to an agreement, conflicts are unable to be resolved. Then d_i is conflict utility of participant *i*.

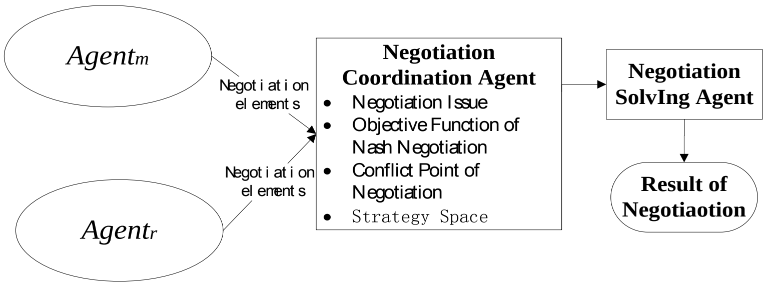

Fig. 1 Process of Nash negotiation based on Agent

Model of Nash negotiation can be solved by mathematical derivation if the object function is simple. We can get the solution to set the first derivative is equal to zero and the second derivative is less than zero. But when $\prod_i (u_i(x) - d_i)$ is not differentiable or the workload of derivation is huge with a very complex form, the mathematical derivation is not available. We can use computer algorithm to get optimal solution.

3.2 The determination of conflict point

The Stackelberg game result is applied as the conflict point of Nash negotiation. he process of Stackelberg game is as follow.

It is a master-slave relationship between manufacturer and dealer when they play Stackelberg game. Manufacturer is master and dealer is slave. We first solve the problem of dealer's optimal control. The optimal function of dealer $V_r(G)$ has to satisfy the HJB equation:

$$\mu V_r(G) = \max_{P(t)}\{(P(t) - w(t))(\alpha - \beta P(t) + \eta G) + \lambda_r (kA(t) - \varphi G)\} \quad (3)$$

where $\lambda_r = \frac{dV_r(G)}{dG}$. Let the first derivative about $P(t)$ at the right side is zero, we get $P^*(t) = \frac{\beta w(t) + \eta G + \alpha}{2\beta}$.

HJB equation of manufacturer：

$$\mu V_m(G) = \max_{w(t),A(t)}\{(w(t) - c)(\alpha - \beta P(t) + \eta G) - hA(t)^2 + \lambda_m (kA(t) - \varphi G)\} \quad (4)$$

Take $P^*(t)$ into (4) and solve the optimal problem about $A(t)$ and $w(t)$: $w^*(t) = \frac{\eta G + \alpha + \beta c}{2\beta}$, $A^*(t) = \frac{k\lambda_m}{2h}$.

We assume that $V_m(G) = \frac{B_1}{2}G^2 + B_2 G + B_3$, so $\lambda_m = B_1 G + B_2$. Take λ_m, $P^*(t)$, $w^*(t)$, $A^*(t)$ into right side of (4), take $V_m(G)$ into the left side of

(4).Then we compare the coefficient about G of the both side of (4), and get the equation set about B_1, B_2, B_3.

$$\begin{cases} \frac{\mu B_1}{2} = \frac{3h\eta^2 - 2\beta(k^2-2k)B_1^2 - 8\beta h\varphi B_1}{8\beta h} \\ \mu B_2 = \frac{4h\eta(\alpha-\beta c) - 4\beta(k^2-2k)B_1 B_2 - 8\beta h\varphi B_2}{8\beta h} \\ \mu B_3 = \frac{h(\alpha-\beta c)^2 - 2\beta(k^2-2k)B_2^2}{8\beta h} \end{cases} \quad (5)$$

We get B_1, B_2, B_3 by equation set (5). C_1, C_2, C_3 can be derived in a similar way under the assumption that $V_r(G) = \frac{C_1}{2}G^2 + C_2 G + C_3$.Then we solve differential equation of G about *t*.

$$\frac{dG}{dt} = k\frac{kB_1G + kB_2}{2h} - \varphi G \Rightarrow \frac{dG}{dt} + \frac{2h\varphi - k^2B_1}{2h}G = \frac{k^2B_2}{2h},$$

$$\Rightarrow G = \mathbf{e}^{-\int\frac{2h\varphi-k^2B_1}{2h}\mathbf{d}t}[C_0 + \int\frac{k^2B_2}{2h}e^{\int\frac{2h\varphi-k^2B_1}{2h}dt}dt] = C_0\mathbf{e}^{-\frac{2h\varphi-k^2B_1}{2h}\mathbf{t}} + \frac{k^2B_2}{2h\varphi - k^2B_1}$$

$$G(0) = 0 \quad \Rightarrow C_0 = -\frac{k^2B_2}{2h\varphi - k^2B_1}$$

Lemma: the optimal decision under Stackelberg Game is as follow:

$$P^*(t) = \frac{3\eta G + 3\alpha + \beta c}{4\beta}, w^*(t) = \frac{\eta G + \alpha + \beta c}{2\beta}, A^*(t) = \frac{k(B_1G + B_2)}{2h}$$

$G = -\frac{k^2B_2}{2h\varphi - k^2B_1}\mathbf{e}^{-\frac{2h\varphi-k^2B_1}{2h}\mathbf{t}} + \frac{k^2B_2}{2h\varphi - k^2B_1}$ and B_1, B_2, B_3 satisfy the equation set of (4), $B_1, B_2, B_3 > 0$.

Proof: Take B_1, B_2, B_3 to G, we get above expression about G. Then take G into $P^*(t)$, $w^*(t)$, $A^*(t)$, we get relevant sales price, wholesale price and advertising.

Proposition: If $2h\varphi - k^2B_1 > 0$, then the optimal decision under Stackelberg game tends to a stable state, by this time $G = \frac{k^2B_2}{2h\varphi - k^2B_1}$

Proof: $2h\varphi - k^2B_1 > 0 \Rightarrow -\frac{2h\varphi - k^2B_1}{2h} < 0$

$$\lim_{t\to\infty} G = \lim_{t\to\infty}\left(-\frac{k^2B_2}{2h\varphi - k^2B_1}\mathbf{e}^{-\frac{2h\varphi-k^2B_1}{2h}\mathbf{t}} + \frac{k^2B_2}{2h\varphi - k^2B_1}\right) \Rightarrow \lim_{t\to\infty} G = \frac{k^2B_2}{2h\varphi - k^2B_1}$$

Reputation cannot increase unlimited in real life. Otherwise demand will not increase without limit with the increase of reputation.

3.3 The method of solving the Nash negotiation model

This paper set conflict point as the result of Stackelberg game. Profit of manufacturer and dealer is as follow:

$$\prod_m^* = \int_0^\infty e^{\mu t}[(w^*(t)-c)(\alpha-\beta P^*(t)+\eta G)-hA^*(t)^2]dt \quad \prod_r^* = \int_0^\infty e^{\mu t}[(P^*(t)-w^*(t))(\alpha-\beta P^*(t)+\eta G)]dt$$

Model of Nash negotiation can be described as follow:

$$\begin{aligned} &\max \ (\prod_m - \prod_m^*)(\prod_r - \prod_r^*) \\ &\textit{s.t.} \quad (\prod_m, \prod_r) > (\prod_m^*, \prod_r^*) \end{aligned} \tag{6}$$

As a result that we use differential game to study dynamic decision problems, the model is difficult to solve by the method of mathematical derivation. We can know that the function form of $P(t)$, $w(t)$, $A(t)$ is as $-K_1\mathbf{e}^{-K_3\mathbf{t}}+K_2$.So we assume that $P(t)=-X_1\mathbf{e}^{-X_3\mathbf{t}}+X_2$, $w(t)=-Y_1\mathbf{e}^{-Y_3\mathbf{t}}+Y_2$, $A(t)=-Z_1\mathbf{e}^{-Z_3\mathbf{t}}+Z_2$, then we transfer the solving problem to search 9 d vector $(X_1, X_2, X_3, Y_1, Y_2, Y_3, Z_1, Z_2, Z_3)$ which satisfies the condition of $(\prod_m, \prod_r) > (\prod_m^*, \prod_r^*)$ and the vector can maximize $(\prod_m, \prod_r) > (\prod_m^*, \prod_r^*)$. So the key problem is the design and implementation of algorithm.

4 Memetic Algorithm

4.1 Local search of MA

The local search process occurs after the evolutionary operation. Because the basic Powell algorithm is quadratic termination, so it uses an improved algorithm [11]. The specific process of algorithm is as follow.

Step 1： Setting the initial point $x^{(1)}$, n linearly independent directions $d^{(1)}, d^{(2)}, \cdots, d^{(n)}$, Accuracy demand ε ,generation of search $k=1$, max generation K；

Step 2： Let f is fitness function, solving the one-dimensional problem : $\min \phi_i(\alpha)=f(x^{(i)}+\alpha d^{(i)})$ get α_i , define $x^{(i+1)}=x^{(i)}+\alpha d^{(i)}$, $(i=1,2,\cdots,n)$.

Step 3： Defining $\mu=\max\{f(x^{(i)})-f(x^{(i+1)}) \mid i=1,2,\cdots n\} = f(x^{(m)})-f(x^{(m+1)})$

Step 4： Setting $u=x^{(n+1)}-x^{(1)}$, solving the one-dimensional problem: $\min \phi(\alpha)=f(x^{(1)}+\alpha u)$, get $\bar{\alpha}$, setting $x^{(n+2)}=x^{(1)}+\bar{\alpha} u$.

Step5： Let $k=k+1$, if $k>K$ or $\| x^{(n+2)}-x^{(1)} \| \le \varepsilon$, stop calculating (set $x^{(n+2)}$ as the solution of problem)

Step6 ： If $|\bar{\alpha}| > \sqrt{\frac{f(x^{(1)}) - f(x^{n+2})}{\mu}}$, then calculating $d^{(i)} = d^{(i+1)}$, $i = m, m+1, \cdots n-1$ and $d^{(n)} = u$.

Step7：Setting $x^{(1)} = x^{(n+2)}$, then transfer to step 2.

4.2 Global search of MA

A global search algorithm is a kind of adaptive genetic algorithm. Algorithm is detailed as follows. *Coding*：Using binary encoding, $[lb_i, ub_i]$ is the range of issue i , $lb_i^{'}$ is the biggest integer that is not more than lb_i, $ub_i^{'}$ is the most small integer that is not less than ub_i. The value of issue i is represented by binary. The length of binary code is $NI_i + MI_i$. NI_i is the length of the binary code $ub_i^{'} - lb_i^{'}$. MI_i is accuracy which means correct to $1/2^{MI_i}$ in the process of Algorithm implementation. *Population initialization:* Generating initial population in a random way. *Fitness function:* in the interaction negotiation, fitness function is the objective function of Nash negotiation. *Selection rules:* adopting Roulette method to select individual which is the most commonly used in genetic algorithm. *Crossover:* Use the simplest way of single-point crossover. Cross point is selected randomly. Crossover probability changed automatically along with the parent fitness and has the feature of nonlinear variation. The adaptive crossover probability:

$$pc = \begin{cases} \dfrac{(pc_{\max} - pc_{\min})}{(1 + \lambda_c \sqrt{\dfrac{fit' - fit_{avg}}{fit_{\max} - fit_{avg}}})} + pc_{\min} & fit' > fit_{avg} \\ pc_{\max} & fit' \le fit_{avg} \end{cases} \tag{7}$$

Where $fit_{\max}$ is the fitness of the best individual in a population, fit_{avg} is the average fitness of the generation population. fit' is the fitness of the better individual in crossover. $pc_{\max}$ and $pc_{\min}$ are respectively upper limit and lower limit of crossover probability. λ_c is a fixed constant. **Mutation:** we introduce new gene can keep the population diversity and avoid precocity to some extent. Mutation point is selected randomly. Mutation probability has the feature of nonlinear variation

$$pm = \begin{cases} \dfrac{(pm_{\max} - pm_{\min})}{(1 + \lambda_m \sqrt{\dfrac{fit'' - fit_{avg}}{fit_{\max} - fit_{avg}}})} + pm_{\min} & fit'' > fit_{avg} \\ pm_{\max} & fit'' \le fit_{avg} \end{cases} \tag{8}$$

Where $pm_{\max}$ and $pm_{\min}$ are respectively upper limit and lower limit of mutation probability, λ_m is a fixed constant. fit'' is the fitness of mutation individual.

5 Example

5.1 The conflict point

The values of parameter listed below：advertising coefficient cost is 20, advertising sensitive coefficient is 2, the attenuation degree of reputation is 0.3, market capacity is 80, price sensitive coefficient is 5, the discount rate is 0.6, unit cost of production is 7. According to the above parameters, we can achieve function graph of reputation about time and advertising sensitive coefficient. The graph shows the conclusions as follow. When advertising sensitive coefficient is fixed, reputation increases over time. But when time increases to a certain value, the increase of reputation becomes very slow. Reputation tends to a constant when time tends to infinity. When time is fixed, reputation increases with the increasing of advertising sensitive coefficient at an accelerating speed.

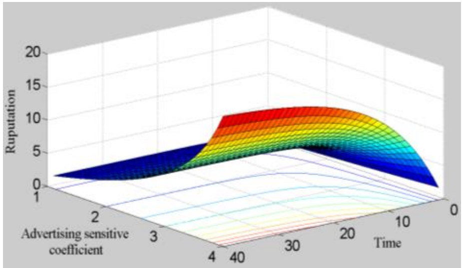

Figure 2 Function graph of reputation about time and advertising sensitive coefficient.

Make advertising sensitive coefficient is equal to 2. Put the parameter of table 1 into equation (12), and we can get: $B_1 = 0.5$, $B_2 = 10$, $B_3 = 225$.According to B_1, B_2, B_3, we can get the expression of reputation(the initial reputation is zero): $G = -4\mathbf{e}^{-\frac{1}{4}\mathbf{t}} + 4$ .It can be seen from ***Fig.1*** that the change of reputation is very small when *t* is more than 20. Reputation is very close to the limit value. Decision will reach a relatively stable situation which is expressed in the proposition in section 2. $\prod_m^*$ and $\prod_r^*$ are the integral in the infinite time. It is easy to know that the value is infinity. So we choose a larger value to replace the original upper limit of integral which is positive infinity. We set $T = 100$. The approximation of conflict point can be expressed as:

$$\Pi_m^* = \int_0^{100} [\frac{112\mathbf{e}^{0.1\mathbf{t}} + 5024e^{0.6*t} - 1504 * \mathbf{e}^{0.35\mathbf{t}}}{80}]dt, \quad \Pi_r^* = \int_0^{100} [\frac{64\mathbf{e}^{0.1\mathbf{t}} + 2809e^{0.6t} - 848\mathbf{e}^{0.35\mathbf{t}}}{80}]dt$$

5.2 The process and results of Nash negotiation based on Memetic Algorithm

$\prod_m$ and $\prod_r$ can be expressed by the expression which contain $P(t)$,

$w(t)$， $A(t)$.So we can get the expression of $(\prod_m - \prod_m^*)(\prod_r - \prod_r^*)$. We use MATLAB programming to implement the negotiation process. The key part of code for getting conflict point is as follow.

```
% the expression of conflict point
    my=exp(0.6*t)*((W-7)*(80-5*P+2*G)-20*A*A);
    ry=exp(0.6*t)*(P-W)*(80-5*P+2*G);
%To solve the definite integral, (Fun1, Fun2) is conflict point
   fun1=int(my,t,0,50);
   Fun1=double(vpa(fun1)/10^14);
   fun2=int(ry,t,0,50);
   Fun2=double(vpa(fun2)/10^14);
```

We use integral solving function int() of MATLAB to get the conflict point $(\prod_m^*, \prod_r^*) = \mathbf{(11.2,6.3)}$ (Numerical narrow 10^{14} times). Then we apply Memetic Algorithm to get the optimal value of the fitness (objective function of Nash negotiation). $fitness = (\prod_m - \prod_m^*)(\prod_r - \prod_r^*)/10^{28}$.

Parameters of Memetic Algorithm are as follows: the largest iterative algebra of Powell algorithm is 50, and accuracy is 0.01. 12 linearly independent initial directions are chosen randomly. The population size of adaptive genetic algorithm is 20. The largest evolution algebra is 50. Initialization, selection, crossover and mutation process are as described in 4.2. The program of negotiation implement on the computer with the hardware configuration: Intel Pentium Dual T3200，2.00GHz，2GB. Final result is as ***table 1***.

Table 1 Result of Nash Negotiation

	A_i	B_i	C_i	$\prod_m$	$\prod_r$	*fitness*	*runtime*
1	1.25	1.64	2.42				
2	14.47	12.56	2.61	18.69	13.55	54.49	59.4s
3	0.12	0.57	1.16				

Table 1 shows that Memetic Algorithm can effectively solve the model of Nash negotiation in this paper. The result of Nash negotiation is superior to the conflict point. After negotiation, the manufacturer' profit increase by 66.9%, dealers' profit increased by 115%. From the aspect of distribution of profit, the manufacturers always occupy dominant position. In addition, the runtime is within tolerable range.

6 Conclusion

For the problem of coordinated decision of manufacturer and dealer in the downstream of supply chain, we take use of Nash negotiation to resolve conflicts and establish a model of Nash negotiation based on multi-Agent. We get conflict point by the master-slave differential game. Because the objective function of Nash Negotiation contains integral which makes that solution is difficult to get by the method of mathematical derivation, so we put forward a method based on Memetic Algorithm to solve the model. Finally we use a numerical experiment to validate the effectiveness of proposed model and algorithm.

Acknowledgments

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