SELECTION OF MANUFACTURING AND LOGISTICS ALLIANCE MEMBERS BASED ON GENETIC ALGORITHM

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***ABSTRACT**: This paper aims to build a realistic M&LA member selection model based on the synergistic effect among the members. For this purpose, the core competence, task demand and synergist effect were detailed and determined as the dominant indices for member selection. Then, the author constructed the core competence matrix, task demand matrix and synergist matrix of candidate members. On this basis, a mathematical model was established for M&LA member selection based on the genetic algorithm (GA). Finally, the model was validated through simulation. This research provides a viable solution to the M&LA member selection under stable task demand*

***KEYWORDS**: core competence; task demand; synergist effect; genetic algorithm (GA)*

1 INTRODUCTION

The manufacturing and logistics alliance (M&LA) is the virtual integration of scattered manufacturing and logistics enterprises, aiming to complete their manufacturing tasks through collaboration. Focusing on synergism, the task-driven alliance integrates various organizations and resources into an organic whole. The centerpiece of the M&LA is a manufacturing and logistics service chain created against the task demand, resource level and capacity of each manufacturing and logistics enterprise. Once the task is completed or the resource is replenished, the close cooperation among the members will cease to exist, and return to the loosely coupled relationship.

The existing studies on the member selection of the M&LA mainly emphasize on supply chain (Yao, 2013), virtual enterprises (Huang et al., 2010, Jia et al., 2011), strategic alliance (Joshi and Lahiri, 2015), innovation cooperation (Liang and Han, 2010), team work (Feng and Fan, 2012, Zarvic et al., 2017), and industry-university- research cooperation (Mindruta et al., 2016). However, there is limited report on the collaboration among the members. To make up for the gap, this paper attempts to build a realistic M&LA member selection model based on the synergistic effect among the members. Then, the model was solved by the genetic algorithm (GA), providing a guarantee for the smooth collaboration among manufacturing and logistics enterprises

2 TERMINOLOGY

Three dominant indices, namely, core competence, task demand, and synergistic effect, were adopted for this research. These indices are both readily available and easily quantifiable.

(1) Core competence: the core competence refers the logistics strength unique to the M&LA members. In other words, no other enterprise in the manufacturing and logistics field enjoys the logistic strength. The logistic strength is either a specific type of logistics service ability, such as production, storage, and delivery, or a group of synergistic technical abilities combined in a certain pattern.

(2) Task demand: the task demand means the demand of M&LA members for certain raw materials or logistics services. When several enterprises in the alliance form a manufacturing and logistics service chain, they must consider the overall demand of each member, such that each enterprise could obtain the resource that it lacks from the other members.

(3) Synergist effect: the synergist effect stands for the enhancement of the cooperative effect among M&LA members, due to the previous cooperation, the highly-integrated communication, and the interpenetration of corporate culture and core competence. The stronger the synergist effect, the closer the cooperation among members in actual operation, and the more efficient the manufacturing and logistics activities.

3 MODEL CONSTRUCTION

3.1 Core competence matrix

According to the logistic strength required for the manufacturing and logistics activities, the core competence was measured by six primary indices: raw material storage, production and processing, transport, loading and handling, packaging, auxiliary equipment.

Then, all primary indices were quantified into corresponding secondary indices. Let the index system of core competence be $C = \{\boldsymbol{C}_1, \boldsymbol{C}_2, \cdots, \boldsymbol{C}_6\}$, where $\boldsymbol{C}_a$ ($a = 1,2,\cdots,6$) is the a-th primary index. For $\boldsymbol{C}_1$ (raw material storage), the secondary indices are $(C_{11}, C_{12}, \cdots, C_{1m_1})$, where C_{1b} ($b = 1,2,\cdots,m_1$) is the volume of the i-th raw material; For $\boldsymbol{C}_2$ (production and processing), the secondary indices are $(C_{21}, C_{22}, \cdots, C_{2m_2})$, where C_{2b} ($b = 1,2,\cdots,m_2$) is the production and processing speed of the i-th raw material; For $\boldsymbol{C}_3$ (transport), the secondary indices are $(C_{31}, C_{32}, \cdots, C_{3m_3})$, where C_{3b} ($b = 1,2,\cdots,m_3$) is the expected volume of raw materials that can be delivered to the i-th area per unit of time; For $\boldsymbol{C}_4$ (loading and handling), the secondary indices are $(C_{41}, C_{42}, \cdots, C_{4m_4})$, where C_{4b} ($b = 1,2,\cdots,m_4$) is the loading and handling speed of the i-th raw material; For $\boldsymbol{C}_5$ (packaging), the secondary indices are $(C_{51}, C_{52}, \cdots, C_{5m_5})$, where C_{5b} ($b = 1,2,\cdots,m_5$) is the packaging speed of the i-th raw material; For $\boldsymbol{C}_6$ (auxiliary equipment), the secondary indices are $(C_{61}, C_{62}, \cdots, C_{6m_6})$, where C_{6b} ($b = 1,2,\cdots,m_6$) is the number of auxiliary equipment for the i-th raw material.

Let the set of candidate members be $P = \{P_1, P_2, \cdots, P_n\}$. Then the core competence of each member can be described by the core competence information matrix $\boldsymbol{S}$:

$$\boldsymbol{S} = \left[s_{i,ab}\right]_{n \times \sum_{a=1}^{6} m_a} = \begin{array}{c} \\ P_1 \\ P_2 \\ \vdots \\ P_n \end{array} \begin{array}{c} C_{11} \\ s_{1,11} \\ s_{2,11} \\ \vdots \\ s_{n,11} \end{array} \left[\begin{array}{cccccccc} C_{12} & \cdots & C_{1m_1} & C_{21} & \cdots & C_{2m_2} & \cdots & C_{6m_6} \\ s_{1,12} & \cdots & s_{1,1m_1} & s_{1,21} & \cdots & s_{1,2m_2} & \cdots & s_{1,6m_6} \\ s_{2,12} & \cdots & s_{2,1m_1} & s_{2,21} & \cdots & s_{2,2m_2} & \cdots & s_{2,6m_6} \\ \vdots & & \vdots & \vdots & & \vdots & & \vdots \\ s_{n,12} & \cdots & s_{n,1m_1} & s_{n,21} & \cdots & s_{n,2m_2} & \cdots & s_{n,6m_6} \end{array} \right] \quad (1)$$

where $s_{i,ab}$ ($i = 1,2,\cdots,n$; $a = 1,2,\cdots,6$; $b = 1,2,\cdots,m_a$) is the numerical information of member P_n under all secondary indices C_{ab}. All candidate members were subject to a preliminary selection to ensure that all of them strive towards the same goal.

3.2 Task demand matrix

The task demand was categorized into five basic levels depending on urgency. These levels are respectively denoted as I, II, III, IV and V in descending order. Each level has its unique requirement for every primary and secondary index. Considering the fuzziness of the categorization, the value of a secondary index is expressed as a range of values.

Let the task demand matrix $\boldsymbol{T}$ be:

$$\boldsymbol{T} = [t_{ab}^{x}]_{5 \times \sum_{a=1}^{6} m_a} = \begin{array}{c} \\ \text{I} \\ \text{II} \\ \text{III} \\ \text{IV} \\ \text{V} \end{array} \begin{array}{c} C_{11} \\ t_{11}^{1} \\ t_{11}^{2} \\ t_{11}^{3} \\ t_{11}^{4} \\ t_{11}^{5} \end{array} \left[\begin{array}{cccccccc} C_{12} & \cdots & C_{1m_1} & C_{21} & \cdots & C_{2m_2} & \cdots & C_{6m_6} \\ t_{12}^{1} & \cdots & t_{1m_1}^{1} & t_{21}^{1} & \cdots & t_{2m_2}^{1} & \cdots & t_{6m_6}^{1} \\ t_{12}^{2} & \cdots & t_{1m_1}^{2} & t_{21}^{2} & \cdots & t_{2m_2}^{2} & \cdots & t_{6m_6}^{2} \\ t_{12}^{3} & \cdots & t_{1m_1}^{3} & t_{21}^{3} & \cdots & t_{2m_2}^{3} & \cdots & t_{6m_6}^{3} \\ t_{12}^{4} & \cdots & t_{1m_1}^{4} & t_{21}^{4} & \cdots & t_{2m_2}^{4} & \cdots & t_{6m_6}^{4} \\ t_{12}^{5} & \cdots & t_{1m_1}^{5} & t_{21}^{5} & \cdots & t_{2m_2}^{5} & \cdots & t_{6m_6}^{5} \end{array} \right] \quad (2)$$

where x ($x = 1,2,\cdots,5$) is the level of urgency; t_{ab}^{x} ($a = 1,2,\cdots,6$; $b = 1,2,\cdots,m_a$) is the value range $({t_{ab}^{x}}^{-}, {t_{ab}^{x}}^{+})$ of secondary index C_{ab} on level x.

3.3 Synergist effect matrix

The synergist effect among the members depends on various factors. Besides, the effect is difficult to quantify in an accurate manner. To solve the problem, an evaluation index set was created to quantify the possible synergist effect between each pair of members.

3.3.1 Building the evaluation index set

By the previous definition on synergist effect, the author decided to evaluate synergist effect from such four dimensions as information exchange, cooperation experience, ability-task relevance, and business coordination. Moreover, ten indices were selected for the evaluation, including information communication, data sharing, historical cooperation, other project cooperation, cooperation with the government, core competence relevance, task unit relevance, similarity of corporate culture, conflict coordination, as well as planning and implementation (Table 1).

Table 1. Evaluation index set

Dimension	Name of index
Information exchange	Information communication
	Data sharing
Cooperation experience	Historical cooperation
	Other project cooperation
	Cooperation with the government
Ability-task relevance	Core competence relevance
	Task unit relevance
Business coordination	Similarity of corporate culture
	Conflict coordination
	Planning and implementation

3.3.2 Quantification of each synergist effect index

The possible synergist effect indices between each pair of members were quantified. The qualitative indices were scored by the M&LA members.

Let the synergist effect evaluation index set be $D = \{D_1, D_2, \cdots, D_{10}\}$, where D_r $(r = 1,2,\cdots,10)$ is the r-th index. Then, the synergist effect matrix $\boldsymbol{Q}^r$ between the members under index D_r can be expressed as:

$$\boldsymbol{Q}^r = \left[q_{ij}^r\right]_{n\times n} = \begin{matrix} & P_1 & P_2 & \cdots & P_n \\ P_1 & q_{11}^r & q_{12}^r & \cdots & q_{1n}^r \\ P_2 & q_{21}^r & q_{22}^r & \cdots & q_{2n}^r \\ \vdots & \vdots & \vdots & & \vdots \\ P_n & q_{n1}^r & q_{n2}^r & \cdots & q_{nn}^r \end{matrix} \quad (3)$$

where q_{ij}^r is the mean synergist effect between members P_i and P_j under index D_r; $q_{ij}^r = 0$ means there is no synergist effect between the two members; the value of q_{ij}^r is positively correlated with the quality of the synergist effect between the two members.

Since all candidate members share the same goal, there is no other benefit-based relationship to make the synergist effect negative. Hence, the q_{ij}^r was assumed to be equal to or greater than zero, and the synergist effect between P_i and itself was ignored.

For simplicity, $\boldsymbol{Q}^r$was normalized as $\widetilde{\boldsymbol{Q}}^r = \left[q_{ij}^r\right]_{n\times n}$, where

$$\tilde{q}_{ij}^r = q_{ij}^r / \max\{q_{ij}^r\} \ (i,j = 1,2,\cdots,n \text{ and } i \neq j; r = 1,2,\cdots,10) \quad (4)$$

Because the synergist effect indices have different importance's in the evaluation of the total synergist effect between P_i and P_j, a weight vector was introduced as $W = (w_1, w_2, \cdots, w_{10})^T$, with w_r being the weight of index D_r. It is obvious that $\sum_{r=1}^{10} w_r = 1$ $(0 \le w_r \le 1)$.

Based on the synergist effect matrix $\boldsymbol{Q}^r$ and weight vector W of each index, the overall synergist effect $\boldsymbol{Q} = \left[q_{ij}\right]_{n\times n}$ can be calculated as:

$$q_{ij} = \sum_{r=1}^{10} w_r \tilde{q}_{ij}^r \quad (5)$$

where q_{ij} is the overall synergist effect between P_i and P_j under index D_r. If $q_{ij}^r = 0$ $(i \neq j)$, there is no synergist effect between each member and itself.

3.4 Setting the objective function and constraint

3.4.1 Objective function

Suppose the member selection decision vector is $\boldsymbol{U} = (u_1, u_2, \cdots, u_n)^T$, where

$$u_i = \begin{cases} 1, & Member\ P_i\ is\ selected. \\ 0, & Member\ P_i\ is\ not\ selected \end{cases} \quad (6)$$

The foregoing analysis shows that the M&LA member selection model aims to select the members that can maximize the synergist effect while fulfilling the manufacturing tasks. Hence, the objective function Z can be established as:

$$max\ \mathrm{Z} = \sum_{i=1}^{n}\sum_{j=1}^{n} u_i u_j q_{ij} \quad (7)$$

3.4.2 Constraint

Let us define the selection vector as $\boldsymbol{V} = \left(v_{11}, v_{12}, \cdots, v_{1m_1}, v_{21}, \cdots, v_{6m_6}\right)^T$, where

$$v_{ab} = \begin{cases} 1, & Index\ C_{ab}\ is\ selected. \\ 0, & Index\ C_{ab}\ is\ not\ selected \end{cases} \quad (8)$$

Depending on the actual situation, the indices must satisfy the following constraint:

$$\lambda_{ab} v_{ab} t_{ab}^{x\ -} \le \sum_{i=1}^{n} u_i v_{ab} s_{i,ab} \le \lambda_{ab} v_{ab} t_{ab}^{x\ +} \quad (9)$$

where λ_{ab} is the correction factors for the standard value range of secondary index C_{ab}.

4 GA SOLUTION

In essence, the M&LA member selection is to perverse the suitable enterprises while eliminating the unsuitable ones. This process bears much resemblance to the “natural selection” in the GA. Therefore, the algorithm was designed as follows:

4.1 Coding

The binary coding was adopted. Each code stands for the state of a candidate member. 1 means selected and 0 means not selected.

4.2 Fitness function

The target parameters were nondimensionalized. Then, the corrected objective function can be obtained as:

$$min\ Z(U) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} q_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} u_i u_j q_{ij}} \quad (10)$$

The constraint in the established model was processed by the penalty function method. The penalty function can be expressed as:

$$W(U) = y_1^2 + y_2^2 \quad (11)$$

Where

$$y_1 = min\{0, v_{ab} t_{ab}^{x\,+} - \lambda_{ab} \sum_{i=1}^{n} u_i v_{ab} s_{i,ab}\} \quad (12)$$

$$y_2 = min\{0, \lambda_{ab} \sum_{i=1}^{n} u_i v_{ab} s_{i,ab} - v_{ab} t_{ab}^{x\,-}\} \quad (13)$$

After introducing the penalty function, the fitness function can be rewritten as:

$$F(U_m) = Z(U_m) + \omega(m) \cdot W(U_m) \quad (14)$$

where $\omega(m)$ is the penalty coefficient. However, the static penalty function may lead to the premature or slow convergence. Thus, the penalty coefficient was adjusted by the dynamic penalty function method (Hadj-Alouane, 1992), which treats the information obtained during the search as the feedback. The penalty coefficient was adjusted by the following formula:

$$\omega(m+1) = \begin{cases} \frac{\omega(m)}{\omega_1}, & Case(1) \\ \omega_2 \omega(m), & Case(2) \\ \omega(m), & Other\ cases \end{cases} \quad (15)$$

where $\omega_1 > \omega_2 > 1$; Case (1) means the proportion of feasible solutions to the best individual exceeds 80% in the past m generations; Case (2) means the proportion of infeasible solutions to the best individual exceeds 80% in the past m generations.

4.3 Selection

The roulette selection method is adopted here:

$$P_s = \frac{Z_{max} - F(U_m)}{\sum_{m=1}^{popsize} [Z_{max} - F(U_m)]} \quad (16)$$

where P_s is the probability that an individual is selected; Z_{max} is the estimated upper bound; *popsize* is the population size.

4.4 Crossover

To prevent premature and local convergence, the adaptive adjustment strategy was employed to control the probability of crossover and mutation.

The crossover probability can be calculated as:

$$P_c = \begin{cases} P_{c1} - \frac{(P_{c1} - P_{c2})(\acute{F} - \bar{F})}{F_{max} - \bar{F}}, & \acute{F} \geq \bar{F} \\ P_{c1}, & \acute{F} < \bar{F} \end{cases} \quad (17)$$

where P_{c1} and P_{c2} are control parameters between 0 and 1; F_{max} is the maximum fitness of the current population; $\bar{F}$ is the mean fitness; $\acute{F}$ is the one with the greater fitness out of the two individuals involved in crossover.

4.5 Mutation

The adaptive mutation probability can be calculated as:

$$P_m = \begin{cases} P_{m1} - \frac{(P_{m1} - P_{m2})(F_{max} - \bar{F})}{F_{max} - \bar{F}}, & F \geq \bar{F} \\ P_{m1}, & F < \bar{F} \end{cases} \quad (18)$$

where P_{m1} and P_{m2} are control parameters between 0 and 1; F is the fitness of mutated individuals.

4.6 Termination

The iteration was terminated in one of the following two conditions: (1) the algorithm solving reaches the maximum number of iterations; (2) the range of the mean fitness of population satisfies the pre-set precision range.

5 SIMULATION

The proposed method was verified with a member selection problem. Suppose 20 enterprises need to be selected from a M&LA to form a manufacturing and logistics service chain, with the aim to complete a manufacturing task. Due to space limitations, 3 primary indices (raw material storage, production and processing, and transport) and their corresponding 12 secondary indices were selected for further discussion. The core competence of the 20 members is listed in Table 2. The index data were normalized. The synergist effect and task demand of these members are depicted in Tables 3 and 4, respectively.

Table 2. Core competence of the 20 members

Candidate members	**Raw material storage C1**				**Production and processing C2**				**Transport C3**			
	the i-th raw material				**the i-th raw material**				**the i-th raw material**			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Enterprise 1	0.339	0.845	0.382	0.625	0.510	0.599	0.067	0.771	0.604	0.564	0.537	0.531
Enterprise 2	0.167	0.742	0.979	0.025	0.393	0.212	0.727	0.447	0.564	0.661	0.542	0.000
Enterprise 3	0.000	0.040	0.531	0.661	0.918	0.855	0.352	0.223	0.291	0.636	0.000	0.757
Enterprise 4	0.319	0.290	0.857	0.644	0.413	0.689	0.000	0.806	0.637	0.000	0.171	0.000

Enterprise 5	0.350	0.606	0.000	0.851	0.090	0.050	0.319	0.391	0.570	0.282	0.334	0.978
Enterprise 6	0.850	0.457	0.108	0.172	0.596	0.022	0.888	0.537	0.376	0.069	0.466	0.245
Enterprise 7	0.032	0.000	1.000	0.895	0.812	0.620	0.370	0.273	0.000	0.000	0.562	0.524
Enterprise 8	0.629	0.669	0.664	0.000	0.778	0.438	0.910	0.395	0.059	0.352	0.726	0.127
Enterprise 9	0.000	0.932	0.242	0.672	0.658	0.000	0.066	1.000	0.561	0.835	0.119	0.728
Enterprise 10	0.649	0.029	0.540	0.579	0.179	0.770	0.353	0.640	0.250	0.662	0.151	0.613
Enterprise 11	0.198	0.403	0.000	0.000	0.129	0.268	0.905	0.329	0.000	0.005	0.472	0.182
Enterprise 12	0.213	0.059	0.078	0.215	0.641	0.000	0.525	0.275	0.899	0.000	0.038	0.000
Enterprise 13	0.935	0.419	0.812	0.199	0.000	0.000	0.902	0.061	0.049	0.018	0.000	1.000
Enterprise 14	0.000	0.913	0.835	0.000	0.961	0.894	0.442	0.000	0.000	0.100	0.079	0.473
Enterprise 15	0.390	0.381	0.286	1.000	1.000	0.600	0.000	0.430	0.839	0.000	0.739	0.547
Enterprise 16	0.464	0.000	0.881	0.309	0.425	0.489	0.000	0.000	0.000	0.243	0.089	0.673
Enterprise 17	0.599	1.000	0.021	0.460	0.890	0.000	0.808	0.839	0.000	0.755	0.873	0.059
Enterprise 18	0.000	0.965	0.890	0.000	0.807	0.965	0.077	0.496	0.069	0.543	0.710	0.634
Enterprise 19	0.841	0.000	0.069	0.000	0.000	0.085	0.000	0.754	0.038	0.000	0.000	0.760
Enterprise 20	0.836	0.580	0.000	0.936	0.961	0.316	0.999	0.612	1.000	0.344	0.281	0.000

Table 3. Synergist effect of the 20 members

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
1	0.00	0.30	0.00	0.89	0.33	0.00	0.89	0.74	0.96	0.34	0.00	0.24	0.00	0.18	0.20	0.59	0.63	0.00	0.35	0.33
2	0.30	0.00	0.00	0.19	0.78	0.79	0.04	0.03	0.64	0.76	0.39	0.00	0.33	0.41	0.43	0.00	0.79	0.73	0.00	0.37
3	0.00	0.00	0.00	0.29	0.80	0.42	0.00	0.15	0.88	0.61	0.49	0.66	0.00	0.49	0.00	0.66	0.28	0.03	0.24	0.00
4	0.89	0.19	0.29	0.00	0.30	0.66	0.60	0.41	0.72	0.00	0.61	0.20	0.85	0.38	0.76	0.00	0.47	0.40	0.35	0.83
5	0.33	0.78	0.80	0.30	0.00	0.91	0.07	0.11	0.61	0.66	0.08	0.00	0.52	0.94	0.38	0.03	0.00	0.10	0.76	0.00
6	0.00	0.79	0.42	0.66	0.91	0.00	0.22	0.69	0.62	0.21	0.81	0.44	0.00	0.40	0.20	0.72	0.00	0.00	0.84	0.00
7	0.89	0.04	0.00	0.60	0.07	0.22	0.00	0.23	0.00	0.28	0.14	0.50	0.00	0.29	0.93	0.36	0.20	0.00	0.16	0.00
8	0.74	0.03	0.15	0.41	0.11	0.69	0.23	0.00	0.18	0.39	0.00	0.89	0.42	0.14	0.89	0.00	0.56	0.24	0.00	0.79
9	0.96	0.64	0.88	0.72	0.61	0.62	0.00	0.18	0.00	0.00	0.21	0.44	0.00	0.21	0.80	0.56	0.22	0.28	0.89	0.39
10	0.34	0.76	0.61	0.00	0.66	0.21	0.28	0.39	0.00	0.00	0.75	0.40	0.18	0.52	0.30	0.45	0.55	0.00	0.88	0.00
11	0.00	0.39	0.49	0.61	0.08	0.81	0.14	0.00	0.21	0.75	0.00	0.30	0.44	0.00	0.46	0.00	0.08	0.27	0.97	0.00
12	0.24	0.00	0.66	0.20	0.00	0.44	0.50	0.89	0.44	0.40	0.30	0.00	0.70	0.00	0.55	0.74	0.12	0.00	0.00	0.87
13	0.00	0.33	0.00	0.85	0.52	0.00	0.00	0.42	0.00	0.18	0.44	0.70	0.00	0.49	0.30	0.86	0.00	0.00	0.77	0.81

14	0.18	0.41	0.49	0.38	0.94	0.40	0.29	0.14	0.21	0.52	0.00	0.00	0.49	0.00	0.00	0.05	0.37	0.03	0.36	0.60
15	0.20	0.43	0.00	0.76	0.38	0.20	0.93	0.89	0.80	0.30	0.46	0.55	0.30	0.00	0.00	0.50	0.00	0.69	0.66	0.54
16	0.59	0.00	0.66	0.00	0.03	0.72	0.36	0.00	0.56	0.45	0.00	0.74	0.86	0.05	0.50	0.00	0.52	0.31	0.91	0.00
17	0.63	0.79	0.28	0.47	0.00	0.00	0.20	0.56	0.22	0.55	0.08	0.12	0.00	0.37	0.00	0.52	0.00	0.60	0.08	0.11
18	0.00	0.73	0.03	0.40	0.10	0.00	0.00	0.24	0.28	0.00	0.27	0.00	0.00	0.03	0.69	0.31	0.60	0.00	0.27	0.00
19	0.35	0.00	0.24	0.35	0.76	0.84	0.16	0.00	0.89	0.88	0.97	0.00	0.77	0.36	0.66	0.91	0.08	0.27	0.00	0.84
20	0.33	0.37	0.00	0.83	0.00	0.00	0.00	0.79	0.39	0.00	0.00	0.87	0.81	0.60	0.54	0.00	0.11	0.00	0.84	0.00

Table 4. Task demand of the 20 members

Level	**Raw material storage C1**				**Production and processing C2**				**Transport C3**			
	the i-th raw material				**the i-th raw material**				**the i-th raw material**			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
I	(4.2,4.8)	(4.0,4.7)	(4.5,5.2)	(4.6,5.3)	(4,5.5.2)	(4.7,5.0)	(4.2,4.9)	(5.0,5.5)	(3.2,4.0)	(4.0,4.6)	(3.7,4.2)	(3.5,4.1)
II	(3.2,3.8)	(3.0,3.7)	(3.5,4.2)	(3.6,4.2)	(3,5.4.2)	(3.7,4.0)	(2,4.3.1)	(4.0,4.5)	(2.5,3.1)	(3.0,3.6)	(2.7,3.2)	(3.0,3.6)
III	(2.2,2.8)	(2.0,2.7)	(2.5,3.2)	(2.6,3.2)	(2,4.3.1)	(3.0,3.6)	(1,5.2.1)	(3.0,3.5)	(2.0,2.5)	(2.7,3.2)	(2.1,2.6)	(2.5,3.1)
IV	(1.6,2.0)	(1.4,1.9)	(2.0,2.6)	(2.0,2.6)	(1,5.2.1)	(2.7,3.3)	(0,9.1.6)	(2.0,2.5)	(1.5,2.0)	(2.2,2.7)	(1.6,2.2)	(2.1,3.7)
V	(0.8,1.4)	(1.0,1.5)	(1.0,1.6)	(1.0,1.6)	(0,9.1.6)	(2.0,2.6)	(1.6,2.3)	(1.0,1.5)	(1.0,1.5)	(1.2,1.7)	(1.0,1.7)	(1.5,2.1)

Taking the level III task demand for example, the members were selected by the above-mentioned GA. The algorithm was compiled on the Matlab with the following parameters: initial population size=60; maximum number of iterations=200; initial penalty coefficient=0.1; $\omega_1 = 5$; $\omega_2 = 2$ correction factors=1.0. The computing process and results are illustrated in Figure 1.

It can be seen that the minimum fitness stabilized after 157 iterations, putting the optimal fitness at 0.0675 and the mean fitness at 0.176862. The optimal solution of the member selection decision vector $\boldsymbol{U} = (u_1, u_2, \cdots, u_{20})^T$ was $\boldsymbol{U} =$ [1,1,0,1,0,0,0,0,1,1,0,1,1,0,1,0,0,1,1,1], that is, enterprises 1, 2, 4, 9, 10, 12, 13, 15, 18, 19 and 20 were selected for the manufacturing and logistics service chain.

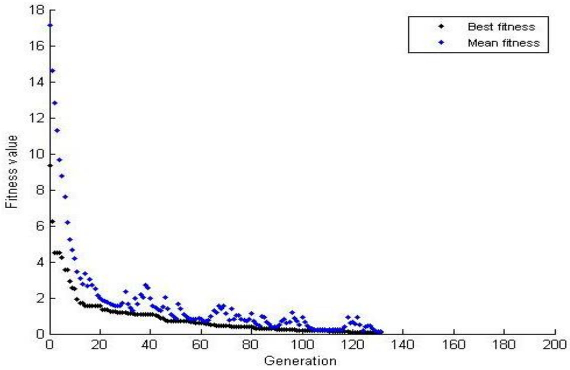

Figure 1. Computing process and results

6 CONCLUSION

The selection of M&LA members is an important decision-making process. The rationality of member selection directly bears on the synergist effect of the M&LA. Therefore, this paper establishes a M&LA member selection model, considering the relevance between ability and demand and the synergist effect among the members, and solves the model by the GA. In light of the constraint in the model, a penalty function was designed to optimize the search process; the adaptive crossover and mutation probabilities were introduced to overcome the premature and local convergence in the search. The experimental results demonstrate that the proposed algorithm has an excellent effect on M&LA member selection. This research mainly tackles the M&LA member selection under stable task demand. The future research will discuss the uncertainties resulted from the task demand variation after the member selection, and the dynamic adjustment in response to these uncertainties.

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