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A NOVEL NPD TEAM FORMATION METHOD BASED ON SOCIAL NETWORK ANALYSIS APPROACH

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Abstract. *Forming an effective New Product Development (NPD) team is of great importance for the success of NPD. With this regard, this paper proposes a Social Network Analysis (SNA) based approach to NPD team formation and builds a corresponding multi-objective optimization model by integrating the multiple attributes of individual knowledge competence, knowledge similarity and knowledge collaboration performance. Secondly, a Genetic Algorithm (GA) is developed to solve the proposed model. Finally, a real NPD team formation case is given to verify the application and effectiveness of the proposed model, and the GA is implemented to select the competent NPD team members for the formation of an effective NPD team.*

Keywords: NPD team formation, Social network analysis, Knowledge and collaboration, Genetic algorithm

1. **Introduction.** Facing the intense competition in global market, New Product Development (NPD) is the vital source for firms' competition advantages [1]. For the success of NPD, firms should cooperate with broad partners to transcend the boundaries among different organizations, enhance the use ratio of innovation resources, lower the NPD cost and risk, and improve the innovation level of NPD [2,3]. During the NPD process, NPD team is the implement subject to carry out the NPD activities [4,5]. Particularly, the members of NPD team are always with different knowledge and organization backgrounds, which is helpful to share and exchange the diversified innovation resources (especially the knowledge resource), and inspire the innovative ideas [6-8]. It is of crucial importance to form an excellent NPD team with competent members in order to guarantee the successful operation of NPD process [9,10]. This work aims to develop a novel model of NPD team formation based on the Social Network Analysis (SNA) method, which can offer a beneficial decision-making support to establish an excellent NPD team with appropriate team members.

Currently, collaborative innovation is becoming an important trend in NPD, which makes NPD team formation a more complex decision problem, because it needs to consider more complicated requirements of NPD team and attributes of team members [6,9,11].

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Antoniadis [12] stated that the experience, knowledge, skill, and personality should be regarded as the main indicators to choose team members and form teams. Lee [13] obtained a conclusion that the NPD team with higher efficiency are always composed of qualified and fittest team members who master sufficient and suitable knowledge resources. Su et al. [14,15] stated that individual knowledge ability and knowledge complementarity among team members determine the innovation level and success probability of collaborative NPD teams. More recently, Jian et al. [16] stated that the collaborative product innovation team should call upon more members with a high level of knowledge and skill to carry out NPD activities more effectively. Therefore, enough attention should be paid to the importance of individual performance, especially knowledge competence for NPD team formation.

Existing literature mostly paid attention to the individual performance of team members, while the knowledge collaboration among members is seldom considered, which can help decision makers to build an excellent team with more collaborative innovation effect. In the context of NPD, the multiple attributions on knowledge and collaboration should be considered and integrated to establish an effective NPD team with more knowledge superiority and collaboration performance. First, the knowledge similarity between team members is an important factor. Jian et al. [17] pointed out that the appropriate level of knowledge similarity is conducive to forming a more valuable cooperation relationship. Furthermore, the befitting knowledge similarity level can inspire team members' cooperation motivation and improve collaboration performance of NPD [18]. On the other hand, the collaboration performance between team members is the second important factor. Good collaboration among team members can contribute to promoting the interpersonal interaction, mutual agreement and trust, avoiding the uncertainty and misunderstanding, and enhancing the team cohesiveness and performance [19,20]. Through investigating lots of excellent teams, Jiang et al. [21] implied that the excellent team is not a simple combination of team members but should depend more on the mutual collaboration among team members to stir up the collaborative innovation advantages. Furthermore, researchers increasingly introduced the Social Network Analysis (SNA) method to investigate the practical problems of collaborative organizations. Su et al. [6,15] adopted the SNA indexes, such as path length, degree centrality and closeness centrality, to analyze the cooperation relationships within NPD teams. Li et al. [22] developed a weighted SNA method to evaluate the cooperation relationships among members in NPD team. Wi et al. [23] proposed an SNA-Based method to measure the familiarity degree among NPD team members.

To sum up, from the view of knowledge and collaboration, the knowledge competence of individual member, the knowledge similarity and collaboration performance among team members should get great attention in the decision-making on NPD team formation. Nevertheless, the systematic integration of the above attributions in NPD team formation decision is not studied in the existing work. On the other hand, the team members and the cooperation relationships among them form a collaboration social network in the process of NPD. For the issue of NPD team formation, the SNA method can provide a new sight and methodology to investigate candidates' knowledge and collaboration attributions. The knowledge and collaboration attributions, including knowledge competence of individual member, the knowledge similarity and collaboration performance among team members, can be effectively integrated and investigated via SNA method. Based on the above analysis, this paper will develop a weighted SNA method to integrate the knowledge and collaboration attributions of candidates, and then propose a novel multi-objective optimization model for NPD team formation.

The reminder of the paper is organized as follows. In Section 2, the multi-objective model for NPD team formation is built using the attributions of individual knowledge competence, knowledge similarity and collaboration performance. Section 3 develops a genetic algorithm to solve the model. In Section 4, the application of the model and the algorithm are presented in a real case to show their practicality. Finally, the conclusions are summarized in Section 5.

2. **The NPD Team Formation Model.**

2.1. **Problem statement.** The problem of NPD team formation can be defined as follows: To form an NPD team, the decision makers need to select m members from n candidates, namely $P = \{P_1, P_2, \ldots, P_n\}$, where P_i represents the ith candidate. The knowledge competence of candidate P_i is set as KC_i. Let C_{ij} and CP_{ij} be the knowledge similarity and collaborative performance between candidates P_i and P_j. To choose the competent team members, from the perspective of knowledge and collaboration, decision makers should pick out m members with the optimal sum of the knowledge competence KC_i, and among these members, there should exist suitable knowledge similarity C_{ij} and the maximal collaboration performance CP_{ij}.

In the social network theory, the SNA method regards social organization and its structure as a social network with nodes representing the organization elements and ties denoting the relationship among the nodes. SNA method is a transdisciplinary methodology which puts emphasis upon how organization structural rules affect its elements' characteristics and behaviors [24,25]. The research perspective of social network regards the reality organizations or systems as clusters of interconnected nodes and their ties. Specifically, the nodes can denote subjects of diversiform levels, for instance, the individual level, organizational level and even country level. Furthermore, the ties among nodes can also be of many types, for instance, the interpersonal relationship, formal and informal collaboration, competition and partnership, and can be measured by different indexes, such as the distance frequency duration and closeness.

In this paper, we view the candidate group of NPD team as a social network, where the nodes denote the candidates of NPD team, and the ties among nodes represent the knowledge collaboration relationships among candidates. Based on the social network theory, the NPD team social network can be defined as a weighted-network $G = (P, E, W)$, where $P = \{P_1, P_2, \ldots, P_n\}$ denotes the set of candidates, $E = \{(P_i, P_j)\}$ denotes the set of collaboration ties between candidates P_i and P_j, and $W = \{w_i, w_{ij}\}$ represents the sets of nodes weight and ties weight which respectively represent the individual knowledge competence and knowledge collaboration performance among candidates. Next, we will put emphasis on discussing how to measure the individual knowledge competence, knowledge similarity and knowledge collaboration performance using the SNA method.

2.2. **Knowledge competence.** Knowledge competence refers to the crucial knowledge ability of team members to carry out the NPD tasks [17]. In this work, a decision matrix is proposed to calculate the individual knowledge competence. Suppose $T = \left[t_{ig}^k\right]_{n\times q}$ is the decision matrix, where t_{ig}^k is the value sequence for the kth ($k = 1, 2, \ldots, M$) knowledge of candidate P_i under the criterion R_g, $g = 1, 2, \ldots, q$. The criteria of knowledge competence are mainly set on the basis of NPD task's needs. Considering the criterion of knowledge competence is mainly subjective criterion, the value of R_g can be obtained by expert assessment with scores from 1 to 9 (1: very bad, 9: very good). Furthermore, regarding the commensurability between various criteria, elements in matrix $T = \left[t_{ig}^k\right]_{n\times q}$ should be normalized into corresponding elements in matrix $T' = \left[t_{ig}^{k'}\right]_{n\times q}$ via the following approach [26].

$$t_{ih}^{k'} = \frac{t_g^{k\max} - t_{ig}^k}{t_g^{k\max} - t_g^{k\min}} \quad g = 1, 2, \ldots, q \text{ for cost criteria} \tag{1}$$

$$t_{ig}^{k'} = \frac{t_{ig}^k - t_g^{k\min}}{t_g^{k\max} - t_g^{k\min}} \quad g = 1, 2, \ldots, q \text{ for benefit criteria} \tag{2}$$

where $t_g^{k\max} = \max\left\{t_{ig}^k \middle| i = 1, 2, \ldots, n\right\}$, $t_g^{k\min} = \min\left\{t_{ig}^i \middle| i = 1, 2, \ldots, n\right\}$.

Next, the decision makers should set up weight w_g to each criterion, $\sum_{g=1}^q w_g = 1$, $g = 1, 2, \ldots, q$, by Analytic Hierarchy Process (AHP) method. Then, the individual knowledge competence for the kth knowledge of candidate P_i can be obtained by the following equation

$$KC_i^k = \sum_{g=1}^q w_g \cdot t_{ig}^k, \quad i = 1, 2, \ldots, n \tag{3}$$

Finally, the individual knowledge competence of candidate P_i can be obtained

$$KC_i = \sum_{k=1}^M KC_i^k \tag{4}$$

2.3. **Knowledge similarity.** In this work, knowledge similarity refers to the similarity degree among team members' knowledge content and structure. In the NPD process, the suitable knowledge similarity can be beneficial for team members' effective communicating and cooperation. In order to calculate the value of knowledge similarity, this work uses the measurement method of text similarity in Vector Space Model (VSM). Suppose that $\overrightarrow{PK_i} = \left(KC_i^1, KC_i^2, \ldots, KC_i^k\right)$ is the knowledge weight vector of member p_i, and $\overrightarrow{PK_j} = \left(KC_j^1, KC_j^2, \ldots, KC_j^k\right)$ is for member p_j. Then, the knowledge similarity C_{ij} between members p_i and p_j can be calculated by the inner product of PK_i and PK_j.

$$C_{ij} = \frac{\overrightarrow{PK_i} \cdot \overrightarrow{PK_j}}{|PK_i| \times |PK_j|} = \frac{\sum_{k=1}^M KC_i^k \times KC_j^k}{\sqrt{\sum_{k=1}^M \left(KC_i^k\right)^2} \times \sqrt{\sum_{k=1}^M \left(KC_j^k\right)^2}} \tag{5}$$

Notably, C_{ij} is within $[0, 1]$. Specifically, 1 reflects two members' knowledge content and structure is exactly the same, and 0 denotes there is no similarity between two team members' knowledge. To assure effective knowledge collaboration within NPD teams, the knowledge of different team members should be neither too dissimilar nor too similar, and it should be with appropriate value. Thus, the knowledge collaboration relationship is beneficial and valuable if and only if the knowledge similarity meets the following condition

$$\underline{\sigma} \le C_{ij} \le \overline{\sigma} \tag{6}$$

where $\overline{\sigma}$ and $\underline{\sigma}$ are respectively the ceiling and floor of the knowledge similarity degree.

2.4. **Knowledge collaboration performance.** Under the NPD context, there are mainly two kinds of knowledge collaboration relationships among the NPD team members, which are respectively the formal knowledge collaboration relationship and the informal collaboration relationship, and the formal and informal relationships both form the collaborative network among the NPD team members. In an NPD team, the formal knowledge collaboration relationship mainly resides in the formal cooperation on NPD task or project. On the other hand, the informal knowledge collaboration relationship reflects the interpersonal social relationship among team members. Based on the above analysis, this work tries to investigate the knowledge collaboration performance from the perspective of formal and informal knowledge collaboration relationships.

With regard to the formal knowledge collaboration relationship, it is mainly generated among team members in the process of project or task collaboration. Researches have shown that partners who have collaborated on a lot of projects or tasks will obtain a better collaboration performance than those who have worked together on less projects or tasks [27]. To calculate the formal knowledge collaboration strength, this work accumulates the strengths of the ties among each pair of team members who have the projects cooperation experience. In detail, if P_i is a participant of project k, $\delta_i^k = 1$; otherwise, $\delta_i^k = 0$. Furthermore, let Fw_{ij} represent the formal knowledge collaboration strength between P_i and P_j, which can be denoted by the following equation:

$$Fw_{ij} = \sum_k \frac{\delta_i^k \delta_j^k}{n_k - 1} \tag{7}$$

where n_k represents the number of participants of project k. Especially, the values of Fw_{ij} calculated by Equation (7) is not necessarily within $[0, 1]$; thus, Fw_{ij} should be normalized by the following equation:

$$Fw'_{ij} = \frac{Fw_{ij}}{\max(Fw_{ij})} \tag{8}$$

As for the informal knowledge collaboration relationship, it typically occurs in the interpersonal social relationship among team members, which reflects the social relationship influence of members in the collaboration network. For the evaluation of social relationship influence in social networks, the classical indexes are mainly the closeness centrality, degree centrality and betweenness centrality [28]. Thereinto, the betweenness centrality is a comprehensive social relationship influence index, which implies the importance of node's position and reflects its influence on knowledge exchange in the network [29]. In the context of NPD team, the informal collaboration relationship between team members is often with the information and knowledge flow. With this consideration, this work chooses the index of betweenness centrality to evaluate members' social relationship influence, and defines it as the informal knowledge collaboration influence of team members. For the NPD team candidate network G, the informal collaboration influence of P_i can be calculated by Equation (9):

$$Be_i = \sum_{s \neq i \neq t \in G} \frac{\varphi_{st}(i)}{\varphi_{st}} \tag{9}$$

where φ_{st} denotes the shortest path length between P_s and P_t, and $\varphi_{st}(i)$ is the shortest path length between P_s and P_t which is via P_i. Karsai et al. stated that there is a positive relationship between the tie weight and the social influence of nodes at each end of the tie [30], which can be depicted by the equation of $w_{ij} \sim (k_i k_j)^\theta$, where k_i and k_j denote the nodes influence at each end, and θ is a characteristic parameter of certain network. Therefore, the weight Iw_{ij} which represents the strength of informal knowledge collaboration can be obtained by the following equation.

$$Iw_{ij} = \sqrt{Be_i \cdot Be_j} \tag{10}$$

In the same manner, the values of Iw_{ij} calculated by Equation (10) may also not be within $[0, 1]$, and then Iw_{ij} can be normalized by the following equation:

$$Iw'_{ij} = \frac{Iw_{ij}}{\max(Iw_{ij})} \tag{11}$$

By integrating the formal and informal knowledge collaborative performance, the knowledge collaboration performance between P_i and P_j, that is the tie weight can be calculated by the following formula:

$$w_{ij} = CP_{ij} = \alpha \times Fw'_{ij} + \beta \times Iw'_{ij} \tag{12}$$

where α and β are respectively the weights to balance the formal and informal knowledge collaboration performance, and there is $\alpha + \beta = 1$.

2.5. **The model for NPD team formation.** On the basis of the above definitions, in order to address NPD team formation problems by integrating synthetically the individual knowledge competence, knowledge similarity and knowledge collaboration performance, this paper proposes a multi-objective optimization model for NPD team formation.

$$\text{Max } Z_1 = \sum_{i=1}^{n} KC_i \cdot x_i \tag{13}$$

$$\text{Max } Z_2 = \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} CP_{ij} \cdot x_i x_j \tag{14}$$

$$\text{s.t. } \underline{\sigma} \leq C_{ij} \leq \overline{\sigma}, \quad i, j = 1, 2, \ldots, n \tag{15}$$

$$\sum_{i=1}^{n} x_i = m \tag{16}$$

$$x_i = \begin{cases} 1 & \text{if candidate } P_i \text{ is selected} \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

In the NPD team formation model, Z_1 and Z_2 respectively denote the objectives of individual knowledge competence and knowledge collaboration performance. Constraint (15) states that the knowledge similarity should fall within a reasonable range. Constraint (16) denotes that m desired members should be selected from n candidates. Constraint (17) states the rule for judging whether a candidate is selected as team member. For this model, it is a multi-objective 0-1 programming model, and it has been proved to be an NP-hard problem. Due to its nonlinearity and huge solution space, it is difficult to settle this problem by the common enumeration algorithm. Hence, this work will propose a Genetic Algorithm (GA) to deal with this model.

3. Genetic Algorithm for the Team Formation Model.

3.1. **Coding and initialization.** Binary coding is the most commonly used coding method in genetic algorithms. An individual, which is $[1, 0, 0, \ldots, 1, 0]$ of n genes, is represented by binary code, where 1 or 0 indicates whether a candidate is selected for the team. For the proposed model, we need to select m members from n candidates, so that each individual has m genes encoded as 1. Then, individuals with parameters of m and n are randomly generated for initialization according to the proposed coding rule.

3.2. **Fitness function.** The fitness function is an indicator used to judge the quality of individuals in a group. It is difficult to obtain the best solution for the problem of NPD team formation at the same time. However, it is easy to obtain the positive ideal point and negative ideal point of each target. Thus, the ideal point method is used to set the fitness function.

In the ideal point method, the criterion of assessing the plan is the distance between each target value and the ideal point. In other words, the smaller the distance shortens, the better the plan becomes. Therefore, the fitness function in this work is set as

$$Fitness = M - \sqrt{\gamma_1 \left(\frac{Z_1 - Z_1^*}{Z_1^*}\right)^2 + \gamma_2 \left(\frac{Z_2 - Z_2^*}{Z_2^*}\right)^2} \tag{18}$$

where (Z_1^*, Z_2^*) = the ideal point, which consists of the optimal values of targets. (Z_1, Z_2) = the target value. M denotes a very large positive integer. γ_1 and γ_2 are respectively the weights of Z_1 and Z_2, $\gamma_1 + \gamma_2 = 1$.

3.3. **Selection strategy.** The purpose of the selection is to directly pass the optimized solution to the next generation or to generate new solutions through pairing to regenerate to the next generation. To improve the performance of the algorithm, a tournament selection mechanism based on genetic algorithm is proposed. The tournament selection method has invariance to the nonlinear transformation of the fitness value. It can control the selection pressure more stably, and has a high escape probability even if it falls into local optimum. Firstly, randomly select r individuals from the population. Then, choose the optimal individuals from the r individuals to survive to the next generation according to the fitness function. At last, repeat the aforementioned steps to obtain the new population.

3.4. **Crossover operation.** Crossover operation is a key step in genetic algorithm. In this work, the two-point crossover is adopted in order to improve the convergence speed in the model. Nevertheless, this two-point crossover operator may produce infeasible solutions, which do not meet the constraint (16) in the model. Hereby, this paper proposes a reparation strategy to repair the infeasible offspring. To be specific, for the infeasible offspring, the number of genes encoded as 1 should be decreased or increased until the constraint (16) is met. At the same time, the number of genes encoded as 0 also needs to be modified accordingly. In summary, the reparation strategy not only ensures that the constraint (16) can be met by the number of genes encoded as 1, but also the offspring feasible.

3.5. **Mutation operation.** There are two purposes in the process of mutation operation. Firstly, genetic algorithm can own the ability of local random search; secondly, genetic algorithms can also maintain population diversity to prevent immature convergence. Hereby, the inversion mutation operator is adopted to the individual. This method requires that two reversal points in the chromosome are selected randomly, and then reverse the order of the genes between the two reversal points. Obviously, the inversion operator cannot change the number of the genes encoded as 1, but only change the order of the genes. Hence, it is easily known that all the generated solutions by this operation meet the constraint (16).

4. **Case Study.** To present the application and effectiveness of the proposed method, this work presents a case of NPD team formation for *mobile phone interfaces design*, which is a project carried out by *FX Technology Co., Ltd.*

To carry out the project of *mobile phone interfaces design*, an NPD team will be established. The needed knowledge for this NPD project can be summarized by the following keywords, i.e., body style (k_1), body dimension (k_2), body color (k_3), body material (k_4) and body artistic (k_5). The decision makers need to select 8 desired members from 23 candidates to form this NPD team, and 4 criteria of individual knowledge competence are introduced to get the node weight of the candidate network, as shown in Table 1.

TABLE 1. Criteria for team formation of *mobile phone interfaces design* project

Objective	Criteria	Descriptions
Individual knowledge competence	Publications (R_1)	Quantity of publications about certain knowledge
	Experience (R_2)	The experience on certain knowledge in practice
	Knowledge capability (R_3)	Total number of problems solved by co-work with others
	Know-who knowledge (R_4)	The ability to get others' knowledge help

TABLE 2. The result of node weights

	P_1	P_2	P_3	P_4	P_5	$\ldots$	P_{21}	P_{22}	P_{23}
P_1	**0.626**	0.42	0.86	0.95	0.50	$\ldots$	0.80	0.28	0.94
P_2	0.42	**0.767**	0.99	0.98	0.54	$\ldots$	0.74	0.55	0.97
P_3	0.86	0.99	**0.308**	0.55	0.61	$\ldots$	0.31	0.96	0.15
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
P_{22}	0.28	0.21	0.94	0.89	0.43	$\ldots$	0.70	**0.925**	0.76
P_{23}	0.94	0.97	0.15	0.71	0.61	$\ldots$	0.51	0.99	**0.898**

Among them, R_1 and R_3 are the objective criteria, and its data can be acquired from the publication database. R_2 and R_4 are the subjective criteria, and their values can be set by the experts using the score from 1 to 9 (9: very good, 1: very bad). Furthermore, the weights of R_1, R_2, R_3, and R_4 are set as $W = (0.30, 0.20, 0.30, 0.20)$ by the AHP method. Considering comprehensively the proper knowledge similarity and the enough candidates, the decision makers set up the ceiling and floor values as $(\bar{\sigma}, \underline{\sigma}) = (0.74, 0.42)$. Then, the results of node weights are presented in Table 2.

As for the weight of knowledge collaboration relationship between candidates, it depends on candidates' formal and informal knowledge collaboration information. The information about knowledge collaboration relationship among candidates can be extracted from the Knowledge Management System (KMS) of *FX*. Using the tie weight method developed in this paper, the tie weights can be obtained and the weighted NPD team network can be further produced using the software of UCINET, as shown in Figure 1.

On the basis of the above results, the model for *mobile phone interfaces design* team formation in this case can be further proposed as follows:

$$\begin{aligned}
&\text{Max } Z_1 = 0.626x_1 + 0.767x_2 + \cdots + 0.925x_{22} + 0.898x_{23} \\
&\text{Max } Z_2 = 0.506x_1x_2 + 0.473x_1x_4 + \cdots + 0.616x_{14}x_{23} + 0.748x_{18}x_{23} \\
&\quad \text{s.t. } 0.42 \leq C_{ij} \leq 0.74 \\
&\qquad \sum_{i=1}^{23} x_i = 8 \\
&\qquad x_i = 1 \text{ or } 0 \\
&\qquad i, j = 1, 2, \ldots, 23
\end{aligned}$$

The GA is operated to settle the above team formation model. The GA is written using the MATLAB R2016a and operated 50 times to obtain the best solution. Finally, the best solution obtained by the GA is $[1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0]$, that is, the 1st, 2nd, 5th, 7th, 15th, 19th, 20th, 22nd candidates are chosen to build the NPD

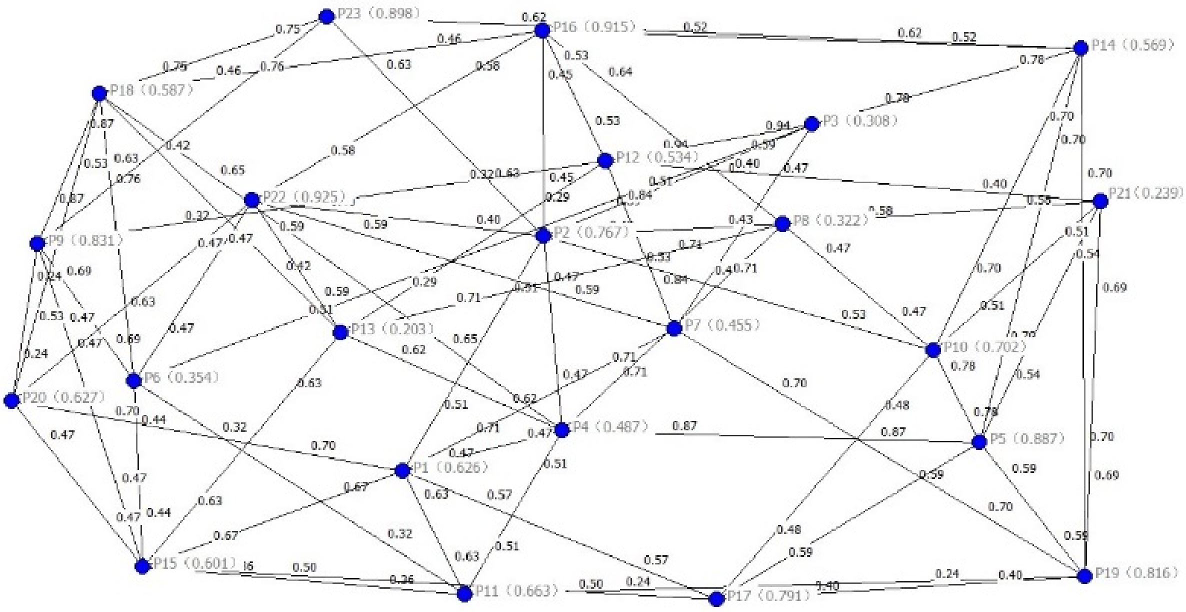

FIGURE 1. The weighted NPD team networks

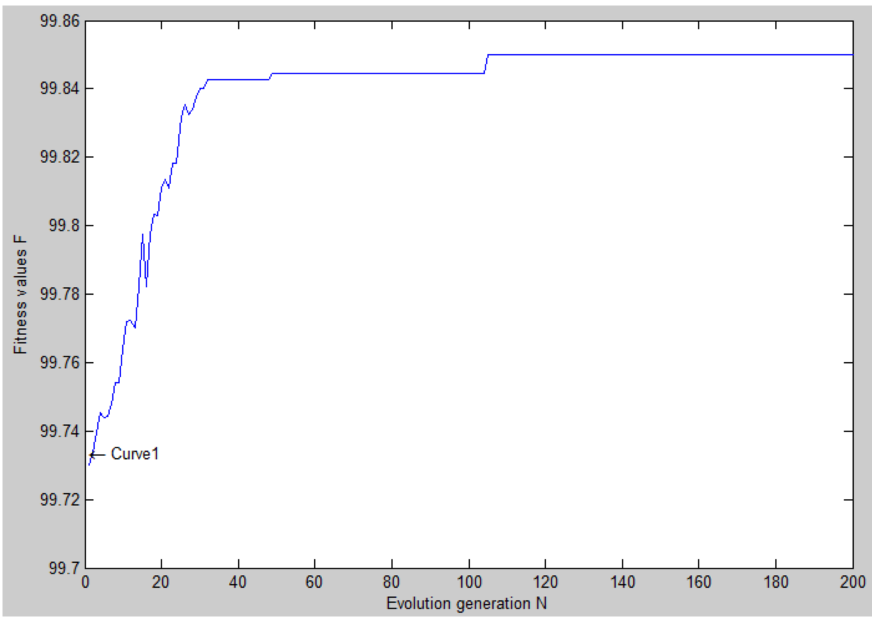

FIGURE 2. The running processes of GA

team of *mobile phone interfaces design*. In this solution, the best fitness value is 99.776, and the optimized solution is got at the 109th time step as shown in Figure 2.

5. **Conclusions.** There is no doubt that it is crucial to build an effective and efficient NPD team which can combine the individual knowledge competence, knowledge similarity and the knowledge collaboration performance among team members. Using the SNA method, a new NPD team formation model integrating both the knowledge and collaboration attributions of candidates is built. Furthermore, the proposed model is NP-hard which is difficult to be solved by the conventional optimization approach. Hence, a Genetic Algorithm (GA), which can effectively select the desired team members to form an

efficient NPD team, is presented to solve the model. In the case study, this paper applies the presented model and algorithm to NPD team for *mobile phone interfaces design* in *FX* company to test the effectiveness of the proposed method. According to the result, this method can effectively select competent team members with integrated quality for the NPD team formation. For more complex team formation problems, more attributions should be considered in the decision process, such as the personality of member and the knowledge complementarity among members. In the future, we will investigate more attributions to solve more complex team formation problems and to make more interesting decisions.

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