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Research Article

Member Selection for the Collaborative New Product Innovation Teams Integrating Individual and Collaborative Attributions

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As the first stage of the formation of a collaborative new product innovation (CNPI) team, member selection is crucial for the effective operation of the CNPI team and the achievement of new product innovation goals. Considering comprehensively the individual and collaborative attributions, the individual knowledge competence, knowledge complementarity, and collaborative performance among candidates are chosen as the criteria to select CNPI team members in this paper. Moreover, using the fuzzy set and social network analysis method, the quantitative methods of the above criteria are proposed correspondingly. Then, by integrating the above criteria, a novel multiobjective decision model for member selection of the CNPI team is built from the view of individual and collaborative attributions. Since the proposed model is NP-hard, a double-population adaptive genetic algorithm is further developed to solve it. Finally, a real case is provided to illustrate the application and effectiveness of the proposed model and method in this paper.

1. Introduction

In order to adapt to the dramatic, changing market environment, enterprises are paying more and more attention to the adoption of a collaborative new product innovation (CNPI) mode for collaboration development advantages [1]. By adopting the CNPI mode, it is advantageous for enterprises to expand organization scale, improve utilization efficiency of internal and external resources, and decrease the costs and risks of new product development [2]. The CNPI team is the major and core organization to implement new product innovation and development activities, in which the complementary knowledge resources are shared by team members from various organizations in a more effective way, so as to inspire the thought of new product innovation [3–6]. At the formation stage of the CNPI team, member selection is an important decision-making issue. Selecting competent team members is of much significance to achieve knowledge complementarity, efficient collaboration and mutual inspiration, and maximize the collaborative performance of the team around the new product innovation goals [7, 8].

Currently, individual attribution of candidate member is much more considered as the decision-making information in most researches concerning member selection [9, 10], with less consideration on knowledge complementarity and collaborative attribution among team members. Actually, pursuing maximization of individual competence of team members will bring in a lot of disadvantages, among which the worst is the ignorance of collaborative performance and synergy among team members [10]. As a result, in order to stimulate the team synergy and collaboration performance, this paper focuses on member selection of CNPI team based on the individual and collaborative attributions of members, to construct a member selection decision model integrating individual knowledge competence, knowledge complementarity, and collaboration ability among members. In this paper, a new study perspective and method is expected to be provided for decision-makers in enterprises to select competent team members, so as to form a CNPI team with better performance.

2. Related Works

Member selection is a complicated decision-making issue and requires systematic consideration of multiple member selection attributions and indicators [11]. As proposed by [12], indicators such as individual traits, expertise, experience, knowledge learning and sharing abilities, communication skills and problem-solving skills, etc., should be taken into account as the major factors in taking a decision to select any member into the new product development team. Similarly, it is indicated in Antoniadis's [13] research that working experience, knowledge and skills, and individual traits of candidates should be deemed as the major indicators in selecting members for the project team. Chen and Lin [14] consider the knowledge domain width, teamwork ability, and good interpersonal relationship as the key indicators for team member selection. In addition, Leenders et al. [15] state that an efficient new product development team should consist of members with a sufficient knowledge reserve and a strong pioneering spirit. Wi et al. [11] insist that to better satisfy knowledge needs of projects or tasks, individual knowledge competency should be treated as the primary indicator for project team member selection. In all of the above researches, significance of individual attribution or indicators of candidates is emphasized for team member selection, especially the significance of individual knowledge competence. However, from the perspective of team synergy, it should not only emphasize individual knowledge competence but also the collaborative attribution among members, which is also a critical factor in the process of member selection. In the CNPI team, team members can break the traditional limit of organization to enter into a public and open platform for sharing and discussion of ideas and opinions. Besides, well complemented knowledge and cross collaboration play a significant role in improving team performance, since organizational performance relies on organic combination of knowledge and experience of all members [16]. What should be pointed out is that the collaboration involves not only co-work, complementarity, and consistency among members but also the effectiveness and depth of their collaboration relationships. Based on the above analysis, the collaborative attribution among members should be also taken as crucial indicator and be given sufficient importance in making decisions to select the desired member for the CNPI team. In this paper, the collaborative attributions among members are summarized as knowledge complementarity and knowledge collaboration performance.

Today, we step into a new era of knowledge explosion, where each individual can only master a very small part of human knowledge with the continuous refinement of social division of labor. The realization of the innovation goal is more and more inseparable from human knowledge division and collaboration. Knowledge complementarity has become a critical component for people to consider in knowledge collaborative innovation [17, 18]. In the collaborative environment of innovation alliance, [19] have proposed two dimensions of knowledge complementarity, relatedness and differences, and explored the role played by knowledge complementarity in the process of innovation alliance formation and member selection. Baum et al. [20] state that proper knowledge complementarity is helpful to establish efficient collaborative partnership. Besides, as proposed by [21], in the innovation cooperation network of industrial clusters, the main purpose of cross-level and cross-organization cooperation among nodes is to realize complementary advantages of innovation knowledge resources among organizations. Moreover, they've also investigated the influence of knowledge complementarity on the generation and change rules of innovation network structure. Meanwhile, it has been shown in a large number of researches that complementary knowledge resources among members are also of much help to stimulate members' enthusiasm for collaboration, bring about new product ideas and improve new product development performance [17, 22, 23].

Currently, collaborative innovation has become a major trend in new product development [1, 24, 25]. To complete a CNPI project or task, joint efforts and cooperation are required for members with different knowledge and expertise. Collaboration level and performance among team members are important considerations in CNPI team building and member selection. Scholars have conducted some researches on knowledge collaboration performance among members. For instance, Emden et al. [26] have shown that for member selection of cooperative research and development alliance, the good collaboration condition among members, such as nonconflict objectives, harmonious culture, etc., is conducive to communication, knowledge sharing, and mutually beneficial information exchange in the future alliance cooperation. Jiang et al. [27] point out that an excellent team is not a simple combination of team members, but rather requires deep collaboration of team members to integrate complementary advantages of all members and stimulate synergy. Furthermore, as Fan et al. [28] emphasized, good collaboration performance of members is able to promote communication among members effectively; enhance cohesion; improve mutual understanding, trust, and satisfaction; reduce conflicts and uncertainties in cooperation; shorten the time of mutual adaption; and ultimately lead to a great organizational cooperation performance. Meanwhile, the good collaboration performance among members is able to integrate interdisciplinary knowledge, which is quite critical for new product development, since such integration can decrease costs and risks of new product research and development, increase application opportunities of new technologies, and accelerate the speed of entering new markets. In summary, based on the perspective of individual and collaboration attributions of members, not only the individual knowledge competence of members but also the knowledge complementarity and knowledge collaboration performance among members should be taken into consideration in the selection of suitable and competent members for the CNPI team.

In current researches, the quantitative decision-making method is mainly used to solve the problems of member selection. Among them, Chen and Lin [14] have established a mathematical model and a five-stage decision-making method to support the formation of the team, wherein they compared the competitiveness of team members using the AHP method, to select the desired members. Jiang et al. [27] have put forward a transformation method that can reduce the complexity of the member selection model and improve the solution efficiency of the member selection problem. In addition, Jian et al. [29] have proposed a nondominated sorting genetic algorithm II to solve the multi-objective partner selection problem in the context of collaborative product innovation. However, the decision-making methods proposed in the above works are mainly used to solve the member selection model based on individual attribution or indicator; however, it is difficult to directly use them for solving the member selection problem based on the individual and collaborative attributions. Therefore, a proper and effective member selection model is required to be proposed along with the solution algorithm to solve the member selection problem of a CNPI team based on individual and collaborative attributions.

3. Member Selection Model Integrating Individual and Collaborative Attributions

3.1. Problem Description. This paper aims to investigate the decision-making problem of member selection for the CNPI team based on individual and collaborative attributions of candidates, and construct a multi-objective decision model for member selection comprehensively integrating individual knowledge competence, knowledge complementarity, and knowledge collaboration performance among members. Firstly, the member selection problem of the CNPI team can be described as follows: in order to form a CNPI team, m members need to be selected from the candidate group $P = \{p_1, p_2, \ldots, p_i, \ldots, p_n\}$, where p_i represents the ith candidate, KC_i represents the individual knowledge competence of candidate p_i, while C_{ij} and CP_{ij} represent knowledge complementarity and knowledge collaboration performance among candidates p_i and p_j, respectively. The overall goal of this paper was to form a team with optimal individual and collaborative performance, under which three subgoals are considered: the first one is to optimize the individual knowledge competence of m members; the second one is to achieve proper knowledge complementarity among members; and the third one is to optimize the knowledge collaboration performance among members.

3.2. Individual Knowledge Competence of Members. CNPI is inherently a kind of knowledge-intensive activity. The individual knowledge competence of team members plays a key role in the success of product innovation [30–32]. A series of quantitative methods for individual knowledge competence has been put forward by many scholars, such as AHP, fuzzy mathematics, and text semantic method, etc [14, 33, 34]. Based on the existing researches, it has been found that direct monitoring and measuring of human knowledge competence are usually hard to be performed, and there are much fuzziness and uncertainty in the evaluation of individual knowledge competence. For these reasons, the fuzzy language variables are preferred for evaluation, such as "good knowledge competence," "moderate competence," and "poor competence." In order to deal with the fuzzy and uncertain information in the evaluation of individual knowledge competence, the fuzzy set theory [11, 35–37] is adopted in this paper for the evaluation of candidates' individual knowledge competence. For the purpose of determination of fuzzy evaluation results, the joint evaluation by candidates and experts from enterprises is considered in this paper to measure the individual knowledge competence of candidates under various attributions, with synthesis of evaluation results. Reasons for joint evaluation are listed as follows: firstly, members have the best understanding of their own knowledge competence under various attributions. Evaluation by members themselves not only reduces the impact of information "stickiness" generated by organizations in acquisition of individual information and knowledge competence but also decreases the work complexity and workload by direct self-evaluation of members compared with a series of works such as collection, acquisition, transformation, and quantification of members' information and knowledge competence. Secondly, in comparison with candidates, experts from enterprises are more aware of the knowledge requirements of product innovation projects or tasks, and thus are capable of providing necessary information support and professional assistance for candidates. Meanwhile, it is conducive to avoiding unreasonable evaluation results generated by candidates in their independent subjective evaluations. The fuzzy evaluation process of individual knowledge competence of candidates is shown in detail as follows:

Given that fuzzy language variables are mostly applied by candidates and experts from enterprises in the evaluation of individual knowledge competence, the triangular fuzzy data method is utilized in this paper for fuzzy quantification of the evaluation language variables. Assume a triangular fuzzy datum as $\widetilde{M} = (d^L, d^M, d^R)$, in which d^L, d^M, d^R represent the minimum value, the middle value, and the maximum value, respectively. The correspondence between language variables and fuzzy quantized values is shown in Table 1.

In addition, in order to meet the requirements of quantitative analysis of the problem, the fuzzy data converted from language variables are usually to be mapped to crisp scores. To this end, Oprcovic and Tzeng et al. [38] have proposed a method of converting the fuzzy data into crisp scores. As for the result obtained through this method, fuzzy data with a larger degree of membership functions will correspond to larger crisp scores, with two symmetrical triangular fuzzy data consistent with crisp scores after mapping. The triangular fuzzy datum $\widetilde{M} = (d^L, d^M, d^R)$ corresponds to a crisp score M, which can be defined as follows:

$$M = L + \frac{\Delta\left[\left(d_k^M - L\right)\left(\Delta + d_k^R - d_k^M\right)^2\left(R - d_k^L\right) + \left(d^R - L\right)\left(\Delta + d^M - d^L\right)^2\right]}{\left(\Delta + d^M - d^L\right)\left(\Delta + d^R - d^M\right)^2\left(R - d^L\right) + \left(d^R - L\right)\left(\Delta + d^M - d^L\right)^2\left(\Delta + d^R - d^M\right)}, \quad (1)$$

wherein $L = \min\{d^L\}$, $R = \max\{d^R\}$, $\Delta = R - L$.

Assume the set of knowledge points required for a CNPI project or task as $K = \{k_1, k_2, \ldots, k_\alpha, \ldots, k_U\}$ in which k_α represents the αth knowledge point, the set of candidates as $P = \{p_1, p_2, \ldots, p_i, \ldots, p_n\}$, and the set of experts from enterprises as $E = \{e_1, e_2, \ldots, e_k, \ldots, e_T\}$, in which e_k means the kth expert. Evaluations are conducted by candidates and experts from enterprises, respectively, using language variables to tacit knowledge competence under different attributions, which are assumed as the set $S = \{s_1, s_2, \ldots, s_\beta, \ldots, s_O\}$, wherein s_β means the βth evaluation attribution.

Then, based on the correspondence between language variables and the triangular fuzzy data as shown in Table 1, language evaluations by candidates and enterprise experts to knowledge point k_α under various attributions are converted into triangular fuzzy data, which are further converted into crisp scores for synthesis. Thus, the knowledge competence value of candidate p_i on knowledge point k_α is calculated as follows:

$$\mathrm{KC}_i^\alpha = w_C \sum_{\beta=1}^{O} w_{s_\beta} M_{i\alpha\beta} + w_E \sum_{\beta=1}^{O} \sum_{k=1}^{T} w_{s_\beta} M_{ki\alpha\beta}, \quad (2)$$

In the above formula, KC_i^α indicates knowledge competence value of candidate p_i on knowledge point k_α, $M_{i\alpha\beta}$ represents evaluation value of competence from candidate p_i on knowledge point k_α based on attribution s_β, $M_{ki\alpha\beta}$ represents evaluation values from expert e_k to the competence of candidate p_i on knowledge point k_α based on attribution s_β, w_C and w_E indicate the relative importance of candidates and experts, respectively, in the process of evaluation, where $w_C + w_E = 1$, and w_{s_β} indicates the relative importance of evaluation attributions, wherein, $\sum_{\beta=1}^{O} w_{s_\beta} = 1$.

Furthermore, the individual knowledge competence value of candidate p_i can be calculated by the following formula:

$$\mathrm{KC}_i' = \sum_{\alpha=1}^{M} \mathrm{KC}_i^\alpha. \quad (3)$$

To ensure that the individual knowledge competence of candidates is within the range of $[0, 1]$, the following formula is used for normalization:

$$\mathrm{KC}_i = \frac{\mathrm{KC}_i'}{\mathrm{KC}_{\max}'}, \quad (4)$$

where in $\mathrm{KC}_{\max}' = \max\{\mathrm{KC}_i' | i = 1, 2, \ldots, n\}$.

3.3. Knowledge Complementarity among Members. It is obvious that managers of enterprises expect, from their perspective, team members equipped with optimal individual knowledge competence to deal with the difficulties and challenges in CNPI. However, from the perspective of teamwork, the method to simply pursue the maximization of members' individual knowledge competence has brought about an obvious defect. In the CNPI team, too much similarity on knowledge or competence among members indicates too much overlap, which will hinder the mutual learning and collaboration performance among them. On the other hand, if there exist over-differences on knowledge or ability among members, they will find it hard to understand the knowledge of each other, leading to a great divide of knowledge communication and collaboration [20, 39]. Obviously, the synergy among team members is hard to be stimulated under the above two circumstances. As shown in the existing researches, whether a collaboration will be successful or not depends on to what extent the members' individual knowledge competence is matched and complemented [19]. In this paper, knowledge complementarity is measured from the perspective of comparative advantages of knowledge competence among members. Firstly, assume S_{ij} as the comparative advantages of the knowledge competence of candidate p_i over p_j, and $Sk^\alpha(ij)$ as the comparative advantages of knowledge competence of candidate p_i over p_j on knowledge point k_α. $Sk^\alpha(ij)$ can be calculated by the following formula:

$$Sk^\alpha(ij) = \begin{cases} \mathrm{KC}_i^\alpha - \mathrm{KC}_j^\alpha, & \text{if } \mathrm{KC}_i^\alpha \geq \mathrm{KC}_j^\alpha, \\ 0, & \text{if } \mathrm{KC}_i^\alpha < \mathrm{KC}_j^\alpha, \end{cases} \quad (5)$$

wherein, KC_i^α and KC_j^α represent knowledge competence of candidates p_i and p_j on knowledge point k_α, respectively.

Then S_{ij} can be figured out through the following formula:

$$S_{ij} = \sum_{\alpha=1}^{M} Sk^\alpha(ij), \quad i, j = 1, 2, \ldots, n. \quad (6)$$

Assume C_{ij} as knowledge complementarity coefficient between candidates p_i and p_j. Since the knowledge complementarity coefficients are symmetrical between them, then $C_{ij} = C_{ji}$. Thus, the knowledge complementarity between candidates p_i and p_j can be obtained by the following formula:

$$C_{ij} = C_{ji} = S_{ij} + S_{ji}. \quad (7)$$

It is obvious that C_{ij} is within the range of $[0, U]$, and U denotes the number of knowledge points. If $C_{ij} = 0$, candidates p_i and p_j have completely identical knowledge background and competence as expressed; if $C_{ij} = U$, it is indicated that candidates p_i and p_j have completely different knowledge background and competence. In accordance with the aforementioned analysis, neither the over-similarity nor the over-difference should appear among members on

Table 1: Correspondence between Language variables and Triangle fuzzy data.

Language variable	Triangle fuzzy data
Very poor (VP)	(0, 0, 0.2)
Poor (P)	(0, 0.2, 0.4)
Moderate (M)	(0.3, 0.5, 0.7)
Good (G)	(0.6, 0.8, 1.0)
Very good (VG)	(0.8, 1, 1)

knowledge background and competence. Hence, the appropriate knowledge complementarity among members should satisfy the following conditions:

$$\underline{\theta} \le C_{ij} \le \overline{\theta}, \tag{8}$$

wherein $\underline{\theta}$ and $\overline{\theta}$ represent the upper limit and lower limit of the reasonable knowledge complementarity interval, respectively.

3.4. Formal Knowledge Collaboration Performance. Typically, the formal knowledge collaboration relationship appears as the formal working relationship among candidates based on tasks or projects. As shown in many researches, the partner with whom we have cooperated once will be preferred to establish the next collaboration relationship, because the sound historical cooperation experience may decrease the uncertainty of understanding the competence of partners [40–42]. Therefore, it is assumed that partners with more sound cooperation experiences behave better than those with less cooperation experiences, with respect to collaboration performance. In reference to the method of Newman [43], the formal knowledge collaboration performance among candidates is measured using the task cooperation information and is calculated as FC_{ij} with the following formula:

$$\mathrm{FC}_{ij} = \sum_k \frac{\sigma_i^k \sigma_j^k}{n_k - 1}, \tag{9}$$

wherein σ_i^k is a Boolean variable used to determine if candidate p_i is involved in task k. If candidate p_i is involved in the task k, $\sigma_i^k = 1$; otherwise $\sigma_i^k = 0$. n_k refers to the number of members involved in task k. What needs to be noted in particular is that tasks undertaken by one single man are excluded here, for they do not work for a collaboration relationship among members and their introduction will lead to failure of the formula (9).

To ensure that the value of formal knowledge collaboration performance among members is within the range of $[0, 1]$, FC_{ij} should be normalized:

$$\mathrm{FC}_{ij}' = \frac{\mathrm{FC}_{ij}}{\mathrm{FC}_{ij\,\mathrm{max}}}, \tag{10}$$

where in $\mathrm{FC}_{ij\,\mathrm{max}} = \max\left\{\mathrm{FC}_{ij} | i = 1, 2, \ldots, n;\ j = 1, 2, \ldots, n\right\}$.

3.5. Informal Knowledge Collaboration Performance. The informal knowledge collaboration relationship mainly appears as social relations among candidates in information and knowledge communication. Currently, no unified quantification criteria have been developed for the measurement of informal knowledge collaboration relationship. The commonly used method is to measure by the frequency of communication among individuals or their joint participation [5]. However, to count the communications or activities among individuals is hard to achieve and involves a huge workload. Thus, based on the social network theory, the social relationship influence of team candidates is proposed to measure the informal knowledge collaboration performance among members in this paper. By this method, the social relationship influence of candidates with collaboration relationship is taken as the major reference. That is, the stronger the social relationship influence the candidates have, the stronger is the informal knowledge collaboration relationship among them.

To measure the social relationship influence of candidates, the commonly used indicators in social network analysis are intensity, closeness, and betweenness. Among them, the indicator of intensity is the simplest way. Used to describe the direct influence among network nodes in the static network, it reflects the direct social relationship strength of this member in a social network [44]. The indicator of closeness is utilized to illustrate the difficulty degree for a node to reach other nodes through the network, reflecting the indirect social relationship strength of this member in the social network [45]. As an indicator for measuring overall influence, the betweenness indicator reflects the importance of member position in the network and its influence in network information and knowledge flow [46]. In comprehensive consideration of direct and indirect relationship influence of members, the betweenness indicator is of great practical significance. As a result, the betweenness indicator is selected to evaluate the social relationship influence of candidates in social network, and is defined as the influence strength of informal knowledge collaboration relationship of candidates in this paper.

The betweenness of candidate p_i in the social network, also the influence strength of informal collaboration relationship, is represented by Be_i which is calculated as follows:

$$\mathrm{Be}_i = \sum_{s \ne i \ne t \in G} \frac{\xi_{\mathrm{st}}(i)}{\xi_{\mathrm{st}}}. \tag{11}$$

wherein ξ_{st} refers to the number of the shortest paths between candidates p_s and p_t, $\xi_{\mathrm{st}}(i)$ for the number of the shortest paths between candidates p_s and p_t that pass through candidate p_i. Then, Be_i should be normalized to ensure it within $[0, 1]$. If all of the shortest paths between any other candidates' nodes pass through candidate p_i, candidate p_i will get the highest value for the influence strength of the informal collaboration relationship, as shown in the following:

$$\mathrm{be}_{\mathrm{max}} = \frac{(n-1) \times (n-2)}{2}. \tag{12}$$

Thus, the normalized influence strength of informal collaboration relationship of the candidate is as follows:

$$\mathrm{Be}_i = \frac{\mathrm{be}_i}{\mathrm{be}_{\max}} = \frac{2b_i}{(n-1)\times(n-2)}, \quad 0 \le \mathrm{Be}_i \le 1. \tag{13}$$

Researches show a significant correlation between the relationship strength among nodes and the influence of nodes at both ends [47, 48], which can be expressed as $w_{ij} \sim (o_i o_j)^{\theta}$, wherein o_i and o_j stand for influence of nodes at both ends, respectively, and θ for the accommodation coefficient of a specific network. Therefore, the influence strength of informal knowledge collaboration relationship IC_{ij}' between candidates p_i and p_j is defined as:

$$\mathrm{IC}_{ij}' = \sqrt{\mathrm{Be}_i \cdot \mathrm{Be}_j}, \quad 0 \le \mathrm{IC}_{ij}' \le 1. \tag{14}$$

Combining the abovementioned formal and informal knowledge collaboration performance, the knowledge collaboration performance CP_{ij} between candidates p_i and p_j can be shown as follows:

$$\mathrm{CP}_{ij} = \mu \times \mathrm{FC}_{ij}' + \nu \times \mathrm{IC}_{ij}', \tag{15}$$

wherein μ and ν refer to the weights of formal and informal knowledge collaboration performance, respectively, with $\mu + \nu = 1$.

4. Decision-Making Model of Member Selection for the CNPI Team

Based on the above analysis, the attribution indicators including the individual knowledge competence, knowledge complementarity, and knowledge collaboration performance among candidates are integrated in this paper, so as to solve the member selection problem of the CNPI in comprehensive consideration of both individual and collaborative attributions. Then, a 0-1 multi-objective decision model is built as follows for the CNPI team member selection:

$$\mathrm{Max}\, Z_1 = \sum_{i=1}^{n} \mathrm{KC}_i \cdot x_i, \tag{16}$$

$$\mathrm{Max}\, Z_2 = \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \ne i}}^{n} \mathrm{CP}_{ij} \cdot x_i x_j, \tag{17}$$

$$\text{s.t. } \underline{\theta} \le C_{ij} \le \overline{\theta}, \quad i, j = 1, 2, \ldots, n, \tag{18}$$

$$\sum_{i=1}^{n} x_i = m, \tag{19}$$

$$x_i = \begin{cases} 1, & \text{candidate } p_i \text{ is selected}, \\ 0, & \text{otherwise}. \end{cases} \tag{20}$$

In models (16)–(20), objective (16) refers to the optimal individual knowledge competence of the member; objective (17) refers to the optimal knowledge collaboration performance among members; constraint (18) suggests that knowledge complementarity among members should be within the appropriate range, and constraint (19) indicates selection of m members from n candidates to form a team. Meanwhile, the member selection model is a 0-1 quadratic programming optimization model, similar to the difference maximization model of Kuo et al., which has proved that this problem is NP-hard [49]. Moreover, the member selection model proposed in this work comprehensively considered the individual knowledge competence, knowledge complementarity, and knowledge collaboration performance among candidates, which is more systematic and reasonable in the context of the CNPI than other member modes of selection or partner selection models [12, 29, 35]. Specifically, Zhang and Zhang's [12] member selection model considered the two goals of team members' personality and interpersonal relationships. Jian et al. [29] established an evaluation index model integrating knowledge matching degree and overall revenue of innovation alliance. The above models are difficult to deal with the complex requirements for the CNPI team member selection, while it is the advantage of the proposed member selection model of this work. Then, to solve the member selection problem in a more effective way, a Double-Population Adaptive Genetic Algorithm is proposed in this paper.

5. Improved Double-Population Adaptive Genetic Algorithm

As discussed in the last section, to solve the member selection model proposed in this paper is NP-hard. It is not possible to promptly and effectively get the optimal solution of a NP-hard problem using the traditional optimization algorithm, such as the minimum–maximum boundary method, weighted sum method, ε-constraint method, etc. [10]. For NP-hard problems, genetic algorithm is a common solution. However, the traditional genetic algorithm tends to fall into a dilemma such as local optimum, poor local optimization ability, and prematurity [12]. Thus, improvement of the standard genetic algorithm is required in the application process, and double-population genetic algorithm and adaptive genetic algorithm are two major improvement solutions. In terms of the former algorithm, two different populations evolve at the same time, where excellent individuals in the different populations exchange genetic information to achieve a higher equilibrium, so as to increase the probability of jumping out of the local optimum. With respect to the adaptive genetic algorithm, adaptive adjustment is performed to the crossover and mutation probability of individuals in accordance with the fitness of the individuals, so that the problems existing in the traditional genetic algorithm, such as a slow rate of convergence and poor local optimization ability caused by the fixed crossover and mutation probability of individuals, can be better handled. In the paper, the advantages of these two algorithms are combined, and a Double-Population Adaptive Genetic Algorithm (DPAGA) is proposed to solve the team member selection problem.

5.1. Chromosome Encoding. In accordance with the characteristics of member selection model, the chromosome is encoded with 0-1 binary coding method. Thus, each individual (e.g. member selection scheme) in a population is encoded as $[1, 0, 0, \ldots, 1, 0]$ in form, with total n-loci in the coding (gene). However, 1 indicates that candidates are selected, while 0 indicates that candidates are not selected. m members need to be selected from n candidates to form a knowledge network, so m genes should be encoded as 1 in each chromosome. According to the above encoding rules, multiple feasible chromosomes are randomly generated after n and m are defined, and two initial populations are formed.

5.2. Construction of a Fitness Function. Since team member selection is a nonlinear, multi-objective combination optimization problem, it's difficult to give the optimal values of two objectives simultaneously. However, the maximum and minimum values of the two objectives are easy to acquire. Thus, the ideal point method is used to convert the multi-objective into a single objective in this paper, so that the fitness function is constructed for the member selection model.

In terms of the ideal point method, a decision scheme is evaluated through the gap between its actual objective value and its ideal objective value. Namely, the smaller the gap is, the better the scheme is. As the set of ideal solutions of each objective, the ideal point can be subjectively determined by decision-makers or in accordance with the optimal value of a single objective [50]. Therefore, by using the ideal point method, the evaluation function for member selection is obtained as follows:

$$\min Z = \sqrt{\left(Z_1 - Z_1^*\right)^2 + \left(Z_2 - Z_2^*\right)^2}, \tag{21}$$

wherein (Z_1^*, Z_2^*) = ideal point; it consists of optimal values of two sub-objectives, Z_1^* for the optimal value of the first objective function and Z_2^* for the optimal value of the second objective function. (Z_1, Z_2) = current objective value, wherein Z_1 represents the current value of the first objective function and Z_2 means the current value of the second objective function. Z = gap between current objective value and the ideal point.

Moreover, considering that the two objective functions have different dimensions and importance, it is necessary to normalize the two objectives and allocate them different weights, so as to construct the fitness function as follows:

$$\text{Fitness} = H - \sqrt{\gamma_1 \left(\frac{Z_1 - Z_1^*}{Z_1^*}\right)^2 + \gamma_2 \left(\frac{Z_2 - Z_2^*}{Z_2^*}\right)^2}, \tag{22}$$

wherein H is a sufficiently large positive integer, γ_1 and γ_2 refer to the weight of objective Z_1 and Z_2, respectively, with $\gamma_1 + \gamma_2 = 1$.

5.3. Selection Operation. The Roulette method is used as the selection strategy for algorithms. Firstly, the fitness value of each individual is obtained in accordance with the fitness function, followed by selection operation to both populations using the Roulette method. Based on the fitness value, each generation of individuals is determined for its probability of being selected to enter the next generation. Assume ψ_i as the probability of individual i to be selected to enter the next generation, then:

$$\psi_i = \frac{\text{Fitness}(i)}{\sum_{i=1}^{n} \text{Fitness}(i)}. \tag{23}$$

5.4. Adaptive Crossover and Mutation Operations. DPAGA is an algorithm where two populations evolve independently and synchronously, with different crossover and mutation operations for different populations who will communicate mutually with certain rules at the right time. Independent evolution, crossover, and mutation operations of two populations ensure their diversity, while exchange of excellent individuals among populations ensures the rate of convergence of feasible solutions. For the population construction in the DPAGA algorithm, the method proposed in reference [51] in this paper refers to: assume population 1 as a detection sub-population, used for local search and providing new hyperplanes in the evolution process to avoid premature convergence; assume population 2 as a development sub-population, used for local search and retention of outstanding individuals. In relation to crossover and mutation operations between the two populations, the two-point crossover and two-point mutation are adopted, respectively.

With regard to the two-point crossover, two individuals are chosen randomly from the selected populations as crossover objects, with random generation of two intersection location points. Then, genes at these two intersection location points are exchanged with the rest remaining unchanged, as shown in Figure 1.

By using the two-point mutation operation, two location points with different gene values are generated randomly for an individual, followed by the exchange of gene values at these two location points using their alleles, as shown in Figure 2.

For the problem that fixed crossover and mutation probability might lead to prematurity and local optimum, the adaptive selection method is adopted in this paper to optimize the crossover and mutation probability of the two populations. The fitness values are to be compared when two chromosomes are performing the crossover operation. If the larger fitness value between them is less than or equal to the average fitness value of the population, the crossover probability will increase adaptively; otherwise, it will decrease in an adaptive way. Similarly, if the fitness value of chromosomes performing mutation operation is less than or equal to the average fitness value of the population, the mutation probability will increase adaptively; otherwise, it will decrease in an adaptive way. In this way, individuals of each generation have varied crossover and mutation probabilities, and adaptive crossover and mutation are achieved. The adaptive crossover and mutation probabilities are obtained, respectively, as follows:

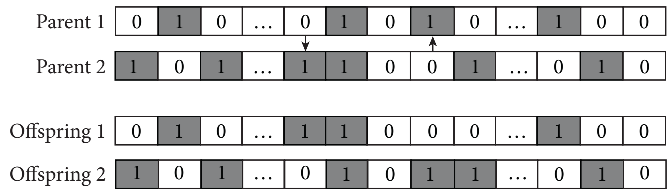

Figure 1: Two-point crossover operation.

$$p_c = \begin{cases} p_{c_{\min}} - \dfrac{f_{\max} - f}{f_{\max} - f_{\min}} \left(p_{c_{\max}} - p_{c_{\min}} \right), & f > \overline{f}, \\[2ex] p_{c_{\min}} + \dfrac{f_{\max} - f}{f_{\max} - f_{\min}} \left(p_{c_{\max}} - p_{c_{\min}} \right), & f \le \overline{f}, \end{cases}$$

$$p_m = \begin{cases} p_{m_{\min}} - \dfrac{f_{\max} - f}{f_{\max} - f_{\min}} \left(p_{m_{\max}} - p_{m_{\min}} \right), & f' > \overline{f}, \\[2ex] p_{m_{\min}} + \dfrac{f_{\max} - f}{f_{\max} - f_{\min}} \left(p_{m_{\max}} - p_{m_{\min}} \right), & f' \le \overline{f}, \end{cases} \tag{24}$$

wherein p_c, p_m refer to the adaptive crossover and mutation probabilities, respectively, $p_{c_{\max}}$, $p_{c_{\min}}$ indicate the maximum and minimum crossover probability, respectively, $p_{m_{\max}}$, $p_{m_{\min}}$ indicate the maximum and minimum mutation probability, respectively, $f_{\max}$, $f_{\min}$, $\overline{f}$ represent the maximum, minimum, and average fitness values in a population, respectively, and f, f' refer to the fitness values of individuals performing the crossover and mutation operations, respectively.

5.5. Migration Operation. After the next generation of population is produced through selection, crossover, and mutation of two populations, a random number num is generated. Then, the optimal solution is taken out from the two populations and hybridized with num chromosomes to integrate into counterpart population, so as to achieve an exchange of genetic information carried by outstanding individuals between populations and break the balance within the populations to avoid local optimal solution.

6. Case Study

To illustrate the feasibility and effectiveness of the method and the model proposed in this paper, a member selection decision for a team of smart phone appearance design project in X Technology Co., Ltd is taken as the case. X is one of the most creative companies in China, focusing on the development of intelligent electronic products. It has made great success in designing, manufacturing, and developing smartphones. X adopts the CPIN as important strategy to hold on to its core competence in NPD. Through CPIN, X aims at: (i) decreasing the NPD cost, (ii) reducing the NPD risk, and (iii) integrating partners' complementary competence to fill the knowledge gap.

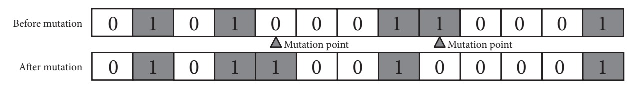

Figure 2: Two-point mutation operation.

To form a CNPI team for smart phone appearance design project, 18 members are to be selected from 42 candidates. Knowledge points of the smart phone appearance design project are mainly body style design (k_1), size design (k_2), color design (k_3), material design (k_4), and artistic design (k_5). Evaluation attributions shown in Table 2 are to be used for the measurement of individual knowledge competence of candidates. Three experts in the product innovation field are organized by X for the evaluation of individual knowledge competence of candidates, represented as $\{e_1, e_2, e_3\}$. The original data and fuzzy evaluation information of individual knowledge competence attribution of candidates are obtained as shown in Tables 3–8:

With regard to individual knowledge competence, decision-makers set the weights of self-evaluation and expert evaluation as (0.5, 0.5), respectively, and the weights of indicator s_1, s_2, and s_3 as (0.3, 0.4, 0.3), respectively. With formulas (1)–(4), the individual knowledge competence of members is obtained. On this basis, the knowledge complementarity coefficient is further obtained by formulas (5)–(7) (see Table 9). Comprehensively considering the requirements of knowledge complementarity among members and enough qualified candidates, decision-makers determine the appropriate interval of knowledge complementarity as $(\underline{\theta}, \overline{\theta}) = (1.00, 2.50)$. Accordingly, based on data in Table 9, it is derived that a set of 37 pairs of candidates incompliant with knowledge complementarity requirements are represented as $\text{INF} = \{(p_1, p_3), (p_1, p$ $13), (p_1, p_{33}), \ldots, (p_{37}, p_{42}), (p_{41}, p_{42})\}$.

Based on the task cooperation information of candidates, the formal knowledge collaboration competence among candidates can be obtained by formulas (9) and (10). With formulas (11)–(15), the informal knowledge collaboration performance among candidates is acquired. Furthermore, decision-makers confirm the relative importance weights of formal and informal collaboration performances as $\mu = 0.65, \nu = 0.35$. Thus, the knowledge collaboration performance among candidates is further obtained, as shown in Table 10.

Table 2: Indicators for member selection of CPIN team.

	Attribution	Description
Individual knowledge competence	Working experience (s_1)	Working experience in specific knowledge field
	Ability to solve problem (s_2)	Ability to solve practical problems with specific knowledge
	Ability to acquire help (s_3)	Ability to get help from others in specific knowledge field

Table 3: Fuzzy information of self-evaluation under attribution S_1.

	k_1	k_2	k_3	k_4	k_5		k_1	k_2	k_3	k_4	k_5
p_1	G	G	P	P	G	…	…	…	…	…	…
p_2	G	G	P	M	VP	p_{39}	P	P	VG	M	G
p_3	P	P	M	M	G	p_{40}	P	P	VP	G	G
p_4	M	G	G	P	M	p_{41}	P	VP	VG	VP	M
…	…	…	…	…	…	p_{42}	G	M	P	VG	G

Table 4: Fuzzy information of expert evaluation under attribution S_1.

	k_1	k_2	k_3	k_4	k_5		k_1	k_2	k_3	k_4	k_5
p_1	G/M/G	M/G/M	VP/P/M	P/P/M	M/G/G	…	…	…	…	…	…
p_2	M/P/M	G/M/G	VP/P/P	M/M/M	P/P/M	p_{39}	P/P/P	VP/P/P	G/M/G	M/G/G	G/G/M
p_3	P/M/P	VP/P/P	M/G/G	M/M/G	M/P/M	p_{40}	P/M/P	P/P/M	VP/P/P	G/M/G	G/G/M
p_4	M/M/P	M/M/M	G/M/G	VP/P/P	G/M/G	p_{41}	P/P/M	P/P/VP	G/M/M	VP/P/P	M/M/P
…	…	…	…	…	…	p_{42}	G/G/G	G/M/M	P/P/M	G/M/G	G/M/G

Table 5: Fuzzy information of self-evaluation under attribution S_2.

	k_1	k_2	k_3	k_4	k_5		k_1	k_2	k_3	k_4	k_5
p_1	VG	G	M	G	M	…	…	…	…	…	…
p_2	G	G	M	G	VG	p_{39}	G	VP	M	G	VG
p_3	G	P	VG	M	G	p_{40}	M	VP	P	G	M
p_4	G	G	M	P	VG	p_{41}	M	M	G	P	VP
…	…	…	…	…	…	p_{42}	VG	G	M	G	G

Table 6: Fuzzy information of expert evaluation under attribution S_2.

	k_1	k_2	k_3	k_4	k_5		k_1	k_2	k_3	k_4	k_5
p_1	P/P/M	M/G/G	P/P/VP	P/M/M	M/M/G	…	…	…	…	…	…
p_2	P/P/VP	M/M/M	M/M/P	M/P/P	G/M/M	p_{39}	VP/P/P	M/P/M	G/G/G	G/M/G	G/G/M
p_3	G/M/G	VG/G/G	M/M/G	P/M/P	G/M/M	p_{40}	P/M/P	P/M/M	P/P/M	G/G/G	P/P/M
p_4	P/P/VP	G/M/M	G/G/G	M/G/G	M/M/P	p_{41}	P/M/M	P/P/VP	G/G/M	P/P/P	M/P/P
…	…	…	…	…	…	p_{42}	M/P/M	G/G/G	P/M/M	P/M/P	P/M/M

Table 7: Fuzzy information of self-evaluation under attribution S_3.

	k_1	k_2	k_3	k_4	k_5		k_1	k_2	k_3	k_4	k_5
p_1	G	G	P	VG	G	…	…	…	…	…	…
p_2	G	VG	M	G	G	p_{39}	G	P	G	G	VG
p_3	G	P	VG	M	VG	p_{40}	M	VP	M	VG	M
p_4	G	G	VG	VP	G	p_{41}	G	G	VG	P	G
…	…	…	…	…	…	p_{42}	VG	G	M	M	G

Table 8: Fuzzy information of expert evaluation under attribution S_3.

	k_1	k_2	k_3	k_4	k_5		k_1	k_2	k_3	k_4	k_5
p_1	M/M/M	P/P/P	G/M/M	P/M/P	M/M/P	…	…	…	…	…	…
p_2	M/P/M	G/G/VG	VP/P/P	M/M/M	P/P/M	p_{39}	P/P/P	VP/P/P	G/M/G	M/G/G	G/G/M
p_3	P/M/P	VP/P/VP	M/G/G	M/M/G	M/P/M	p_{40}	P/M/P	P/M/M	VP/P/P	G/M/G	G/G/M
p_4	M/P/P	M/M/M	G/M/G	P/P/P	G/M/G	p_{41}	P/M/P	P/M/M	P/M/M	G/M/G	P/M/M
…	…	…	…	…	…	p_{42}	G/M/G	G/G/G	M/M/G	P/M/P	G/M/G

Table 9: Individual knowledge competence and knowledge complementarity.

	p_1	p_2	p_3	p_4	…	…	…	p_{39}	p_{40}	p_{41}	p_{42}
p_1	**0.79**	0.84	3.07	1.87	…	…	…	1.67	0.77	0.68	3.01
p_2	0.84	**0.91**	2.01	1.98	…	…	…	1.44	1.31	0.62	2.27
p_3	3.07	2.01	**0.75**	1.23	…	…	…	0.69	2.00	1.87	0.58
p_4	1.87	1.98	1.23	**0.88**	…	…	…	0.89	1.86	1.65	1.52
…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…
p_{39}	1.67	1.44	0.69	0.89	…	…	…	**0.59**	1.35	1.60	1.21
p_{40}	0.77	1.31	2.00	1.86	…	…	…	1.35	**0.86**	1.24	1.80
p_{41}	0.68	0.62	1.87	1.65	…	…	…	1.60	1.24	**0.94**	3.21
p_{42}	3.01	2.27	0.58	1.52	…	…	…	1.21	1.80	3.21	**0.63**

Note: Data on the diagonals represent individual knowledge competence values of candidates.

Based on models (16)–(20), the member selection model in the case is obtained as:

$$\begin{aligned}
\text{Max } Z_1 &= 0.79x_1 + 0.91x_2 + 0.75x_3 \\
&\quad + 0.88x_4 + \cdots + 0.59x_{39} \\
&\quad + 0.86x_{40} + 0.94x_{41} + 0.63x_{42}, \\
\text{Max } Z_2 &= 0.67x_1x_2 + 0.32x_1x_3 \\
&\quad + 0.66x_1x_4 + \cdots + 0.51x_{42}x_{39} \\
&\quad + 0.79x_{42}x_{40} + 0.54x_{42}x_{41}, \\
\text{s.t. } & 0.40 \le C_{ij} \le 1.00, \\
& \sum_{i=1}^{42} x_i = 18, \\
& x_i = 1 \text{ or } 0, \\
& i, j = 1, 2, \ldots, 42.
\end{aligned} \tag{25}$$

Subsequently, the DPAGA is applied to solve the above member selection model. In DPAGA, the initial population size is generally made as 10~200, and 0.4~0.99 and 0.0001~0.1 as crossover and mutation probabilities, respectively. Moreover, population 1 differed from population 2 in terms of crossover and mutation probabilities, with larger crossover and mutation probabilities for the former while less for the latter. By considering the fact that population size is of direct influence in the calculation efficiency and rate of convergence of an algorithm (too large a size will lead to excessively long calculation time, while too small a size will cause more of a chance to fall into the local optimum), the initial population size of the two populations is made as 100 in this chapter with the maximum number of iterations as 300 and $H = 100$. The maximum and minimum crossover and mutation probabilities of population 1 are made as $p_{c_{1\max}} = 0.9$, $p_{c_{1\min}} = 0.7$, $p_{m_{1\max}} = 0.08$, $p_{m_{1\min}} = 0.06$, respectively. The maximum and minimum crossover and mutation probabilities of population 2 are made as $p_{c_{2\max}} = 0.6$, $p_{c_{2\min}} = 0.4$, $p_{m_{2\max}} = 0.05$, $p_{m_{2\min}} = 0.03$, respectively. Decision-makers attach the same importance to the two objective functions, namely, setting $\omega_1 = \omega_2 = 0.5$. The optimal values of the two single objective functions are calculated, respectively, and regarded as the ideal point of the final objective function (13.89, 21.77). Matlab R2010a is used to program and run the abovementioned algorithm, and the optimal scheme of team member selection is as follows upon the 103th iteration:

$$[0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0,]. \tag{26}$$

Table 10: Overall values of knowledge collaboration performance among candidates.

	p_1	p_2	p_3	p_4	…	…	…	p_{39}	p_{40}	p_{41}	p_{42}
p_1	–	0.67	0.32	0.66	…	…	…	0.53	0.91	0.43	0
p_2	0.67	–	0.93	0.72	…	…	…	0.67	0.42	0.53	0
p_3	0.32	0.93	–	0	…	…	…	0	0.71	0.66	0.55
p_4	0.66	0.72	0	–	…	…	…	0.41	0.60	0.40	0.75
…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…
p_{39}	0.53	0.67	0	0.41	…	…	…	–	0.74	0.70	0.51
p_{40}	0.91	0.42	0.71	0.60	…	…	…	0.74	–	0	0.79
p_{41}	0.43	0.53	0.66	0.40	…	…	…	0.70	0	–	0.54
p_{42}	0	0	0.55	0.75	…	…	…	0.51	0.79	0.54	–

Note: The mark "–" on the diagonals represents that no knowledge collaboration exists between candidates and themselves.

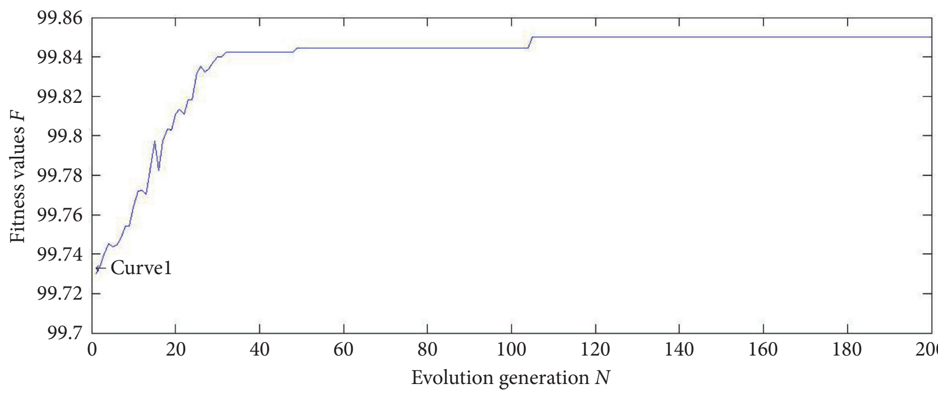

Figure 3: Optimal fitness value of each iteration of DPAGA

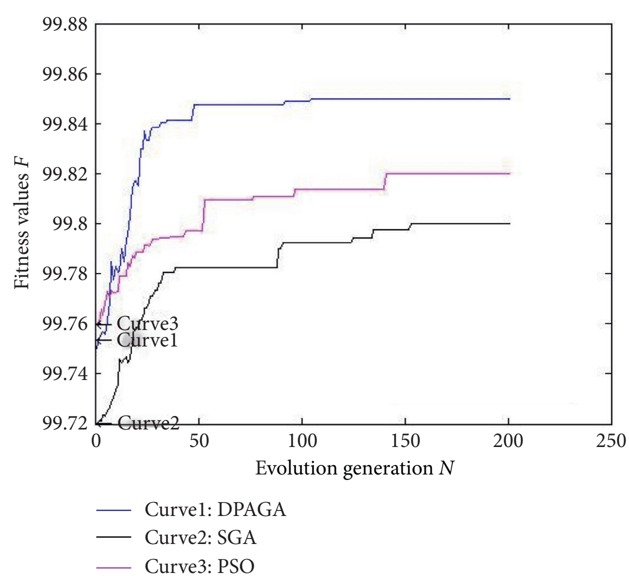

Figure 4: Comparison of DPAGA, SGA, and PSO.

Table 11: Comparison of DPAGA, SGA, and PSO.

Algorithm	Optimal result	Computing frequency	Computing time
DPAGA	99.8529	105	1.13
SGA	99.8177	156	2.24
PSO	99.7914	145	2.07

Namely, candidates $\{p_2, p_4, p_5, p_7, p_9, p_{12}, p_{13}, p_{15}, p_{17}, p_{18}, p_{20}, p_{22}, p_{25}, p_{27}, p_{30}, p_{39}, p_{40}\}$ are selected to form the smart phone appearance design team, wherein the overall knowledge competence of members selected by the scheme is 12.35, and the total knowledge collaboration performance among members is 19.18, with running results shown as Figure 3.

Moreover, for the purpose of verifying the effectiveness and advantage of DPAGA as proposed in solving the team member selection problem, DPAGA is compared with Standard Genetic Algorithm (SGA) and Particle Swarm Optimization (PSO) for analysis. The same population number and parameter of maximum iteration number are applied for all of the three algorithms which run for 30 times each, with the running results shown in Figure 4 and Table 11. It can be seen from Figure 4 and Table 11 that compared with SGA and PSO, DPAGA is capable of generating a better result with a faster solution speed. Its average iteration number is 105, less than SGA of 156 and PSO of 145; DPAGA also takes less time to get the optimal solution than SGA and PSO. In summary, the proposed DPAGA performs better than SGA and PSO in solving the member selection problem for the collaboration of new product innovation teams.

7. Conclusions

For the purpose of forming an efficient CNPI team, this paper suggests a member selection decision model and method for CNPI teams by integrating individual and collaborative attributions. The indicators for team member selection used in the method, including individual knowledge competence of candidates, knowledge complementarity, and knowledge collaboration performance among candidates, are quantified by the fuzzy theory and social network method. Then, a multi-objective optimization model is established by integrating those indicators for member selection of the CNPI teams and a double-population adaptive genetic algorithm (DPAGA) is proposed to solve the model. Meanwhile, real cases and comparative studies have confirmed the feasibility and effectiveness of the proposed member selection model and method in this paper.

It requires to be noted in particular that circumstances where might be short of individual and collaborative information of members should be taken into consideration in future researches. In addition, how to extend the research method proposed in the paper to other types of teams such as concurrent engineering teams, cross-functional teams, etc., should also be emphasized in future studies.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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