Hindawi
Scientific Programming
Volume 2021, Article ID 6288679, 9 pages
https://doi.org/10.1155/2021/6288679

*Research Article*

# Research on Social Talent Governance Based on Genetic Algorithm

**Yan Zeng**

*Sichuan College of Architectural Technology, Deyang, Sichuan 618000, China*

Correspondence should be addressed to Yan Zeng; 631418020110@mails.cqjtu.edu.cn

Received 6 October 2021; Revised 21 November 2021; Accepted 29 November 2021; Published 13 December 2021

Academic Editor: Rahman Ali



The existing social talent governance algorithms have a number of issues such as slow convergence rate, relatively low data accuracy, recall rate, and low anti-interference. To address these problems, this paper proposes a research on social talent governance algorithm based on genetic algorithm. We discuss the difference between the traditional and the genetic algorithms and determine the implementation process of genetic algorithm. On this basis, the excellent individuals are determined by independent computing fitness, and the initialization population is designed according to the individual similarity threshold. After the population is defined, the roulette and deterministic sampling selection method are integrated to clarify the selection calculation process. Based on the calculation results, we design the crossover operator by segmented single-point crossover between individuals. The mutation operator is designed by segmented mutation of different gene segments according to the calculation results. The results are incorporated into the simulated annealing acceptance probability to conduct simulated annealing for the individuals after the cross-mutation operation and set relevant conditions after the end of the algorithm. We seek the optimal solution of the data within the number of iterations and finally realize the whole process of social talent governance algorithm. The experimental results show that the proposed algorithm has fast convergence rate, high data precision and recall, and has certain feasibility.

## 1. Introduction

Since the 18th National Congress, social governance has officially replaced social management and become one of the important aspects of the construction of socialism with Chinese characteristics. The Third Plenary Session of the 18th CPC Central Committee put forward the social governance concept of optimizing social management for the first time. "Innovating social governance, changing social governance methods and improving the overall governance level of society" has become the focus of social governance [1]. Promoting the construction of social governance system, innovating social governance methods, and effectively improving the level of public governance of the whole society have become the focus of social governance. The report of the 19th national congress attaches great importance to social governance, clearly points out the problems existing in China's current social governance, and puts forward "building a social governance pattern of co construction, CO governance and sharing" [2]. In the field of social governance, talent governance has also become the top priority of current social development, and fundamentally speaking, social governance is mainly the governance of "people" [3]. Talent has always been the core issue of economic and social development. At present, major countries in the world have gradually changed from factor driven and investment driven to innovation driven. Talent is the foundation of innovation, and innovation drive is essentially talent drive [4].

Due to the scarcity of talent resources, the global talent competition is becoming increasingly fierce. Since the eighteenth Congress of the Communist Party of China, general secretary Xi Jinping has made a series of speeches and instructions on talent work, reflecting rich governance ideas. Under the background of promoting the modernization of national governance system and governance capacity, how to build a talent development governance system to meet the requirements of innovation drive and promote the in-depth implementation of the strategy of strengthening the country with talents has become a frontier issue in

China's talent work practice and theoretical research [5]. In terms of social talent governance, the query and governance of talent information data are one of the important measures. It is imperative to have a scientific and efficient talent governance algorithm. Therefore, researchers in this field have done a lot of research and achieved some results.

Researchers see evolution's power as something to be emulated rather than envied. Genetic algorithm specifies the features of a problem in advance and may be able to solve complex problems whose structure cannot even be understood by humans. As compared to the traditional step-by-step procedures, genetic algorithms explore a greater range of solutions to a problem [6]. Genetic algorithms provide a search and optimization method that is based on natural selection and genetic mechanism of living organisms and are efficient in solving the complex optimization and industrial engineering problems [7]. A number of research studies focus on the use of genetic algorithms to present solution to complex problems. Some of these studies are summarized below.

In order to reveal this nonlinear relationship and predict the decision-making key of whether talents stay or not, literature [8] uses Python programming language and ID3 algorithm in machine learning to analyze the samples and construct a decision tree model based on the investigation and analysis of the attraction data of subjective and objective factors of talents staying in a second tier city and Wuhan. This paper analyzes the attractiveness of different factors from a microperspective and obtains the analysis results of the importance of various policy variables affecting the development of talents studying in Han. Compared with the existing policies for talents to stay in Wuhan, this paper analyzes the shortcomings of the existing policies for talents to stay in Wuhan and puts forward corresponding countermeasures and suggestions, but there are some problems such as relatively low recall and accuracy and low anti-interference. In order to identify the key factors affecting the knowledge management ability of international talents in construction enterprises, literature [9] built the evaluation model of knowledge management ability and influencing factors, designed the evaluation method of knowledge management ability and screened the key influencing factors, and verified the operability of the evaluation model by taking the international talents of a railway group company in South America and Africa as the empirical object. Combined with genetic algorithm and rough set, the key influencing factors of knowledge ability are selected, and the calculation results are verified to be reasonable by grey correlation analysis and project facts. This paper puts forward the strategy to improve the knowledge management ability of its employees. Even so, this method has the problem of slow convergence rate. Based on the theory of multiple intelligences, literature [10] constructed and empirically tested the four intelligence structure model of innovative scientific and technological talents in basic research by using the methods of literature research, questionnaire survey, and factor analysis. The model was evaluated and the talent intelligence structure map was drawn with the help of TOPSIS multi-index decision-making algorithm. Employers should customize and formulate more matching talent cultivation and development plans, but there are problems of relatively low recall and accuracy and low anti-interference.

Therefore, this paper proposes a social talent governance algorithm based on genetic algorithm. The main contributions of the research work include the following:

(1) Firstly, the differences between traditional algorithm and genetic algorithm are analyzed to determine the implementation process of genetic algorithm. On this basis, the excellent individuals are determined by independent computing fitness, and the initialization population is designed according to the individual similarity threshold.

(2) After the population is defined, the roulette and deterministic sampling selection method are integrated to clarify the selection calculation process.

(3) Based on the calculation results, the crossover operator is designed by segmented single-point crossover between individuals, and the mutation operator is designed by segmented mutation of different gene segments according to the calculation results.

(4) The results are incorporated into the simulated annealing acceptance probability to conduct simulated annealing for the individuals after the cross-mutation operation, set relevant conditions after the end of the algorithm, seek the optimal solution of the data within the number of iterations, and finally realize the whole process of social talent governance algorithm.

Step 1: through comparative research, clarify the gap between traditional algorithms and the implementation process of genetic algorithm.
Step 2: determine the excellent individuals by independently calculating the fitness, and design the initialization population according to the individual similarity threshold.
Step 3: integrate roulette and deterministic sampling selection method to clarify the selection calculation process. Based on the calculation results, the crossover operator is designed by segmented single-point crossover between individuals, and the mutation operator is designed by segmented mutation of different gene segments according to the calculation results.
Step 4: integrate the results into the simulated annealing acceptance probability, conduct simulated annealing for the individuals after cross-mutation operation, set relevant conditions after the end of the algorithm, seek the optimal solution of the data within the number of iterations, and finally realize the whole process of social talent governance algorithm.
Step 5: do experimental analysis.
Step 6: present conclusion and future outlook.

## 2. Genetic Algorithm

A traditional algorithm is a step-by-step procedure to follow. Though it is widely used, it has certain shortcomings compared to the genetic algorithm which is based on the principle of genetics and natural selection for solving optimization problems [6, 7]. Compared with traditional evolutionary algorithms, genetic algorithm does not depend on the application field of the problem. It is a general algorithm framework that can solve combinatorial optimization problems and can be applied to many fields [11]. Genetic algorithm itself has strong robustness and fault tolerance, and the randomness of genetic operation is strong. It does not need strict requirements such as continuity and differentiability. It has simple operation and fast convergence rate. Compared with traditional evolutionary methods, genetic algorithm has obvious efficiency advantages [12]. Genetic algorithm does not operate the problem itself, but encodes the problem parameters and uses coding operation and evolution mechanism to reflect the complex process. Genetic algorithm is not constrained by search space and does not need complex derivation process. It uses fitness function to guide the whole search process and has little dependence on the problem itself [13].

The search process of genetic algorithm starts from the population in the solution space and operates several initial individuals in parallel, which can effectively prevent the locality of the search. Genetic algorithm expresses the solution of the problem as chromosomes and puts several chromosomes as parents in a specific problem environment to generate offspring individuals more suitable for the environment according to genetic operation [14]. Repeat this process until after several generations of evolution; the genetic operation will converge to the chromosome most suitable for the environment, that is, the optimal solution of the problem [15]. Comparison between genetic algorithm and traditional algorithm is shown in Table 1.

*2.1. Comparison between Genetic Algorithm and Traditional Algorithm.* sfgsdfgasfsdjfglsfsfhs.

*2.2. Genetic Algorithm Implementation Process.* The genetic algorithm implementation process mainly includes the following steps:

(1) Real number encoding: before using genetic algorithm for calculation, the solution of the actual problem to be solved shall be transformed into the mathematical language recognized by genetic algorithm; that is, the actual problem shall be transformed into string data [16], and each solution of the problem to be solved uniquely corresponds to a chromosome. The success of real number coding of chromosomes directly determines whether the operation can carry out the following genetic operations such as selection, crossover, and variation [17].

(2) Determine the initial population: according to the mechanism of real number coding in the previous step and the rules, the initial chromosome group [18], that is, the population, which is composed of chromosomes [19]. Each chromosome in the population is a unique individual. The number of individuals in the population is called population size (NP). The initial population is usually generated in a random way.

(3) Fitness calculation: determine the fitness calculation method of each individual in the population, and then calculate the fitness of each individual in the initial population [20].

(4) Genetic operation: genetic operation refers to the selection, crossover, and mutation of individuals in the population. The second step is the core step and essence of genetic algorithm [21]. Usually, after calculating the fitness value of each individual in the population, the proportional selection strategy is used to obtain the selection probability, and then the spinning wheel method is used to select the individuals in the population [22]. At present, single tangent point crossing and double tangent point crossing are most used in crossing operation. Gaussian mutation method is often used in mutation operation.

(5) Stop the operation: judge the individuals generated in the above steps. When the individual fitness value reaches the preset conditions or the number of algorithm iterations reaches the preset times, the operation can be stopped and the optimal solution can be output. Otherwise, continue the above steps until the stop requirements are met [23]. The operation flow of genetic algorithm is shown in Figure 1.

## 3. Research on the Social Talent Governance Based on the Genetic Algorithm

*3.1. Initializing the Population Design.* In the process of social talent governance research based on genetic algorithm, in order to improve its convergence rate, the initialized population needs to add some setting conditions on the basis of random generation. For example, the initial population meeting the requirements of total number constraint, type total number constraint, and employment direction total number constraint of talent management needs can be randomly generated, so as to reduce the risk of falling into prematurity [24].

At the same time, after the initialization of the population, in order to avoid the situation of high similarity between related, resulting in poor governance quality, it is necessary to deal with the individuals with high similarity [25]. If the method of individual concentration similarity control is adopted, the population may fall into precocity. Therefore, this paper uses the method of deleting the individuals with high similarity in the initialized population, and only one similar individual needs to be retained. In the process of offspring genetic evolution, no matter which generation has individuals with high similarity, it is necessary to delete the redundant individuals and keep one [26]. This requires the calculation of the individual similarity $A_{PQ}$

Table 1: Comparison between genetic algorithm and traditional algorithm.

| Traditional algorithm | Genetic algorithm |
|---|---|
| All the characteristics of the problem should be described | Needless to describe the problem characteristics (self-organized, adaptive) |
| Operon the parameter itself | Encode the parameters |
| The results of the solution depend on the source value | The results of the solution are independent of the source value |
| Locally optimal solution | Globally optimal solution |
| Have a certain planting standards and determine the conversion rules | No definite termination criterion, the probabilistic conversion rule |
| Different forms of auxiliary information are required (continuous, micro, etc.) | No secondary information (just the fitness function) |
| Single-point search, run independently | Run in parallel |

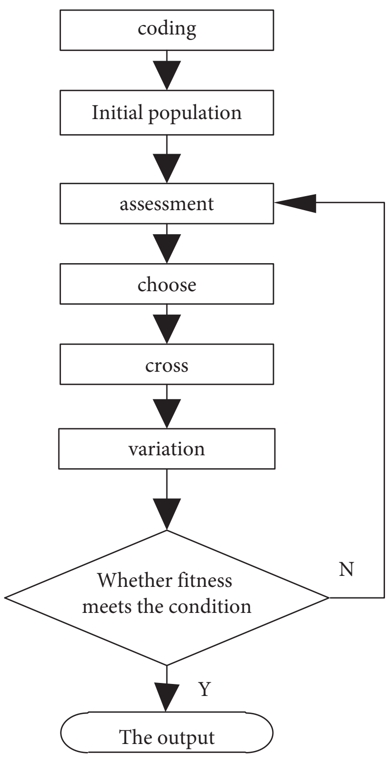


Figure 1: Operation flowchart of genetic algorithm.

and the advance setting of the individual similarity valve value $L$; generally $L$ is 35%.

When the calculated individual similarity is greater than the set threshold, the individual is deleted. When the calculated individual similarity is less than the set threshold, individual retention is performed. In this way, we can ensure that the individual similarity among the next generation population is lower than the set threshold and prevent the algorithm from falling into the early local convergence phenomenon. Individual gene information entropy is shown in Figure 2.

In the calculation of individual similarity, the specific calculation formula of population information entropy is obtained by using the method of information entropy, as shown in

$$H(M) = \left(-\frac{1}{N}\right)\sum_{i=1}^{N}\sum_{j=1}^{S} P_{ij}\log P_{ij}, \tag{1}$$

where $M$ is the number of individuals, $N$ is the number of individual genes, and $S$ indicates the number of alleles: $S\colon \{k_1, k_2, \ldots, k_S\}$. When a binary coding was applied, the allele is available to have only the probability that $\{0, 1\}$, $P_{ij}$ being the number $j$ allele being $K_i$ in $M$ individuals, $K_i \in \{k_i, k_2, \ldots, k_S\}$. Entropy of a variable is the average level of information or uncertainty inherent in the variable's possible outcomes. If an event has a higher probability to occur, it is no surprise when that event happens; hence transmission of such a message carries small amount of information. On the other hand, if an event is unlikely to occur, it is very informative to know the event happened or will happen.

Thus, there is similarity between individual $P$ and individual $Q$ for $A_{PQ}$ specific calculation formulas such as

$$A_{PQ} = \frac{1}{1 + H(2)}, \tag{2}$$

where $H(1)$ represents the information entropy between $P$ and $Q$.

During the algorithm calculation, each subpopulation independently calculates its fitness to determine excellent individuals, with fitness calculation functions such as

$$F_i = a \times f_i + b. \tag{3}$$

When $f_{\min} \geq 2 \times f_p - f_{\max}$, we get results like

$$a = \frac{f_p}{f_{\max} - f_{\min}}, \tag{4}$$

$$b = \frac{f_p \times \left(f_{\max} - 2f_p\right)}{f_{\max} - f_p}. \tag{5}$$

When $f_{\min} \leq 2 \times f_p - f_{\max}$, we get results like

$$a = \frac{f_p}{f_p - f_{\min}}, \tag{6}$$

$$b = \frac{-f_{\min} \times f_p)}{f_p - f_{\min}}. \tag{7}$$

Among them, $f_p$, $f_{\max}$, and $f_{\min}$ represent the mean, maximum, and minimum values of genetic contemporary fitness values, respectively.

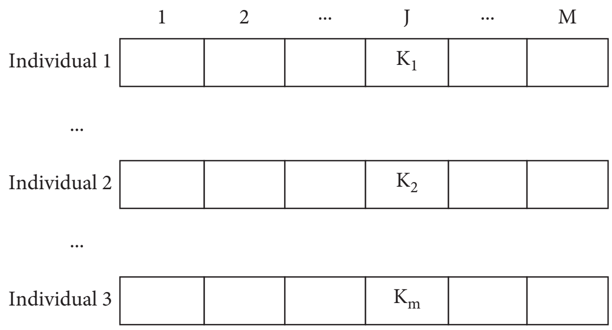


Figure 2: Individual gene information entropy.

*3.2. Selecting the Operator Design.* A genetic operator is used in genetic algorithms to guide the algorithm towards a solution. These operators are of three types including mutation, crossover, and selection that work in conjunction with one another to make the algorithm successful. These operators are used to create and maintain genetic diversity, combine existing solutions into new solutions, and select between solutions. The selection operator will determine the evolution direction of the population, so the quality of the selection operator method will greatly affect the efficiency of genetic algorithm.

*3.2.1. Wheel Bet Selection.* At present, in the process of selecting operators, the more commonly used method is roulette selection method. This method determines whether an individual can be inherited to the next generation according to the application of individual fitness value in probability. Therefore, its advantage is that the probability of genetic evolution is large for individuals with good fitness and small for individuals with poor fitness. However, its disadvantages are also obvious. Although excellent individuals have a high probability of being inherited, there will also be the possibility of not being inherited. The specific steps of roulette selection are as follows:

(1) The sum of values for all individual fitness functions was calculated as $F$, with specific calculation formulas such as

$$F = \sum_{i=1}^{n} f_i. \tag{8}$$

Among these, $f_i$ is the fitness function value of the $i$ th individual.

(2) Calculate individual selection probability $P_{si}$, such as

$$P_{si} = \frac{f_i}{F}. \tag{9}$$

(3) Make roulette selections. The optimal individual preservation method, that is, the optimal individual in the parent generation, is directly inherited to the child generation, so that the global optimal solution of the genetic algorithm must contain the local optimal solution, so as to ensure the convergence of the algorithm, but it is easy to fall into prematurity. The sorting selection method is to sort the fitness values of individuals and then set a certain proportion. The individuals included in the proportion are directly inherited in the offspring. For example, the first 15% of offspring with excellent individual fitness are set for direct inheritance [27].

Combined with the advantages and disadvantages of each method, the genetic algorithm selected in this paper adopts roulette selection method and sorting selection method to select offspring. Among them, in order to retain excellent individuals as much as possible, this paper sets the first 15% of excellent individuals for direct inheritance, and then the selection operator of the remaining individuals adopts roulette selection.

*3.2.2. Adaptive Selection.* In order to improve the convergence rate and recall of genetic algorithm, based on roulette selection, considering that the deterministic sampling selection method can ensure that some individuals with large fitness can be retained in the next generation, the deterministic sampling selection operator is adopted. Select according to the following improvement selection strategy:

(1) Compute the fitness function values and $f_{i-\text{sum}}$. for all the previous individuals in the population according to

$$f_{i-\text{sum}} = \sum_{i=1}^{M} fi, \ (i = 1, 2, 3 \ldots M). \tag{10}$$

(2) Divide the fitness function of all individuals in the population by removing this sum, where formula for (11) yields the expected survival number of $N_i$, for each individual in the next generation population, that is,

$$N_i = \frac{M f_i}{f_{i-\text{sum}}}, \ (i = 1, 2, 3 \ldots M). \tag{11}$$

In formula, $M$ is the population size and $f_i$ is the fitness value of the $i$ individual.

(3) Determine the number of survival of each corresponding individual in the next generation group according to the integer part of the $N_i$, and then choose by roulette.

*3.3. Crossover Operator Design.* Because the chromosome coding method in this paper is piecewise real coding, the crossover operator adopts piecewise single-point crossover between individuals, so the crossover result will show the form of multipoint crossover in the whole population. Because species cross inheritance in nature has a certain probability, it is necessary to set the cross probability $Pc$ before the cross operator.

The main idea of chromosome segmentation in this paper is to assume that a test paper chromosome contains $M$ genes, that is, $M$ talent data and total $N$ segment genes, namely, different types of $N$ fields. Single-point crossover was performed within the segment, first with a crossover $i$, randomly selected within the segment; secondly, the gene value of the two segments after the $i$ intersection is exchanged, so that the single-point crossover within the segment is realized; and the other segments are modeled in the same way.

If the offspring obtained after the crossover operator operation have the same gene at the same gene, it indicates that there is duplicate data, the crossover is unsuccessful, and the duplicate gene needs to be replaced. The replaced data gene should be in the same type field as the original data gene. Finally, the individual fitness of chromosomes operated by crossover operator is calculated to eliminate individuals who do not meet the requirements of fitness.

*3.4. Mutation Operator Design.* According on the segmented real number coding of the chromosome, the improvement in variant operator is segmented variation in different gene segments. The specific idea is as follows: assume that a paper chromosome contains $M$ genes, that is, $M$ talent data, total $N$ segments, or different types of $N$ fields.

Since gene variation belongs to a small probability event, the probability $P_m$ of gene variation should be set in advance while setting a real number array of length 1, with a real number, selected at random by the system.

In the real number array, randomly select a real number $m$; by the system if $m < Pm$, the talent sequence number will undergo genetic variation; otherwise the gene variation will not occur in the talent sequence number.

The specific variation method is to first set two arrays; the first is the gene segment array as

$$R = [0, N-1], R_i (i \le N-1). \tag{12}$$

The second array is the formula for

$$K = [0, M-1], K_j (i \le M-1). \tag{13}$$

The system then randomly selects an integer $r$, in the $R$ array if $r \le N-1$ performs gene variation within the $y$ gene segment. Gene variation operation is performed within the $y$ gene segment, and the system continues to randomly select an integer $K$, in the $k$ array. If $k \le M-1$, the gene variation operation is performed at the $K_k$ gene; that is, the gene variation occurs at the gene value of the $r$ gene segment.

Finally, select a data that has the same type characteristics as the original talent data and belongs to the same type at the same time to replace and complete the mutation, so that the original data type structure will not be changed after the mutation operator is completed.

*3.5. Combined with Simulated Annealing Design.* In order to solve the problems of premature and weak local search ability of genetic algorithm, the genetic algorithm in this paper integrates simulated annealing acceptance probability to simulate the individuals after cross-mutation operation, so as to enhance the local search ability of the algorithm.

The specific calculation formula of simulated annealing acceptance probability is as follows:

$$p = \left\{ \begin{array}{cc} 1, & f(\text{old}) < f(\text{new}) \\ \exp\left(-\dfrac{f(\text{old}) - f(\text{new})}{T_t}\right), & f(\text{old}) \ge f(\text{new}) \end{array} \right\}. \tag{14}$$

Among these, $f(\text{old})$ indicates old individuals, $f(\text{new})$ indicates new individuals, and $T_t$ is the temperature at the $t$ moment. If the new individual is superior, the new individual is selected for iteration; if the new individual is poor, then iterative operation is with a certain probability $P$.

To ensure that the temperature $T$ gradually decreases with time $t$, the initial temperature $T_0$ is 100°C and the design temperature drop is such as:

$$T_{t+1} = \alpha T_t. \tag{15}$$

Among them, $\alpha$ is constant, generally 0.95; the temperature of $t$ time is

$$T_t = 100 * 0.95^t. \tag{16}$$

*3.6. End Condition Design.* Because the improved genetic algorithm belongs to evolutionary algorithm, two conditions are set for the end of the algorithm, and only one of them needs to be met to complete the operation of the algorithm. Condition 1: set a maximum number of iterations. If no suitable talent data is found after the algorithm reaches the maximum number of iterations, it indicates that the data search fails and the algorithm operation is completed. Condition 2: when the algorithm finds the optimal data solution within the maximum number of iterations, it indicates that the data retrieval volume is successful.

## 4. Experimental Analysis

*4.1. Experimental Scheme Design.* In order to verify the performance of the proposed evaluation method, an experimental analysis is carried out in this paper. The experiment takes a city's talent management database as the object, takes the current different talent categories and talent needs as the data conditions, and carries out the research to collect the data in the database. In order to ensure the accuracy of the experiment, the relevant results obtained in the experiment are processed by professional software.

*4.2. Experimental Index Design.* On the basis of the experimental scheme designed above, the indexes of this experiment are set as convergence rate, precision rate, duplicate check rate, and anti-interference. In order to promote the effectiveness of the experiment, the experiment is carried out in the form of comparison, which compares the methods in this paper, the key factor identification method of knowledge and ability based on genetic algorithm rough set, and the multiple intelligence structure and evaluation method of innovative scientific and technological talents. Many iterations are carried out in the comparison process to improve the accuracy of the experiment.

*4.3. Analysis of Experimental Results.* In order to verify the effectiveness of the design method in this paper, the experiment compares the method in this paper, the key factor identification method of knowledge capability based on genetic algorithm rough set, and the multiple intelligence structure and evaluation method of innovative scientific and technological talents. The recall and precision are compared. The results are shown in Figure 3.

By analyzing the data in Figure 3, it can be seen that, under the same amount of data, there will be some differences in recall and precision in this method, the key factor identification method of knowledge and ability based on genetic algorithm rough set, and the multiple intelligence structure and evaluation method of innovative scientific and technological talents. Among them, when using this method to query social talent governance data, the balance point of recall and precision is relatively high, while the balance point of recall and precision of the other two methods is always lower than this method. This is because this method has processed the use of genetic algorithm to verify the effectiveness of this method.

In order to further verify the performance of this method, this method, the key factor identification method of knowledge capability based on genetic algorithm rough set, and the multiple intelligence structure and evaluation method of innovative scientific and technological talents are experimentally analyzed to analyze the convergence rate of data query related to social talent governance. The results are shown in Figures 4–6.

By analyzing the data in Figures 4–6, it can be seen that there is a certain difference in the convergence rate of social talent governance related data query of this method, the key factor identification method of knowledge capability based on genetic algorithm rough set, and the multiple intelligence structure and evaluation method of innovative scientific and technological talents. Among them, the convergence rate of the proposed method is the highest. Even if the number of sample tasks and running time are increasing, the convergence rate is still relatively high and stable. The other two methods not only have unstable convergence rate, but also are very unstable. This is because this method integrates roulette and deterministic sampling selection method, defines the selection calculation process, designs the crossover operator through segmented single-point crossover between individuals, designs the mutation operator by segmented mutation of different gene segments according to the calculation results, obtains the search results, and then improves the effectiveness of the proposed method.

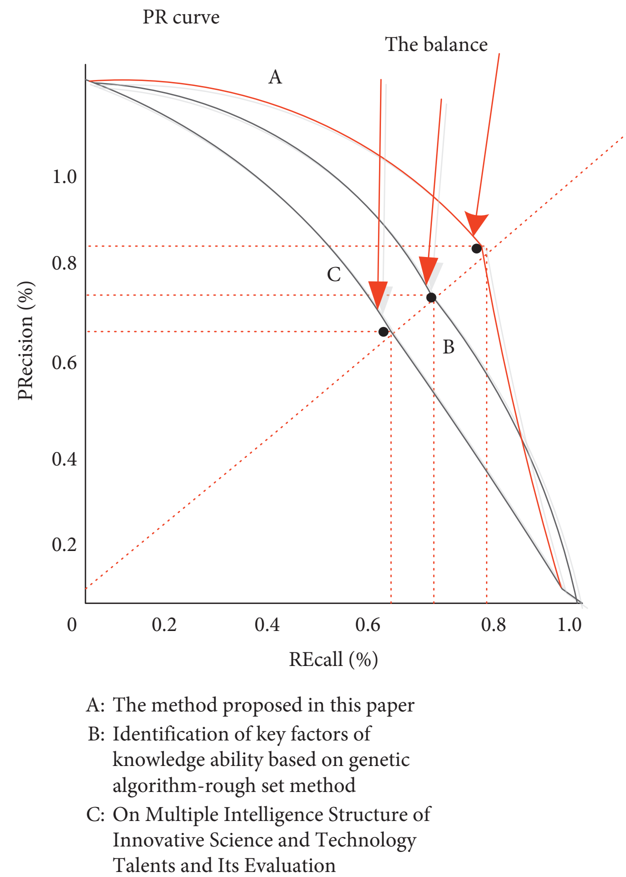


FIGURE 3: Comparison of recall and precision of different methods.

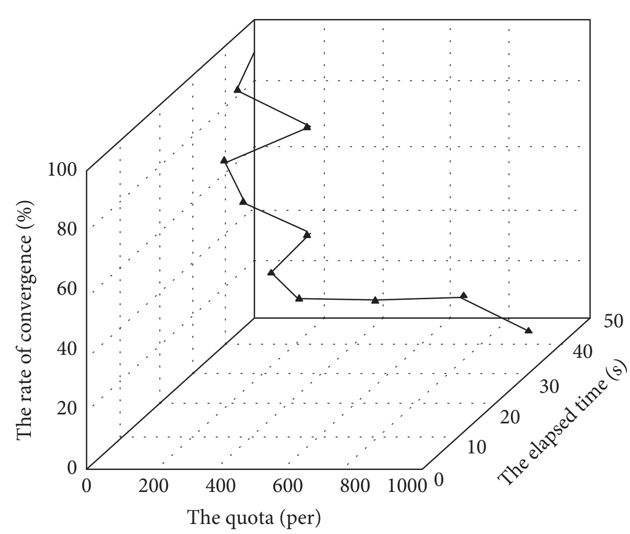


FIGURE 4: Convergence rate of knowledge capability key factor identification method based on genetic algorithm rough set.

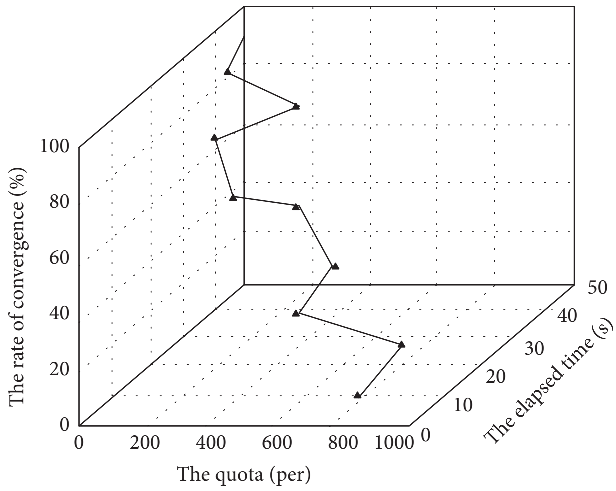


FIGURE 5: Convergence rate of multiple intelligences structure and evaluation method of innovative scientific and technological talents.

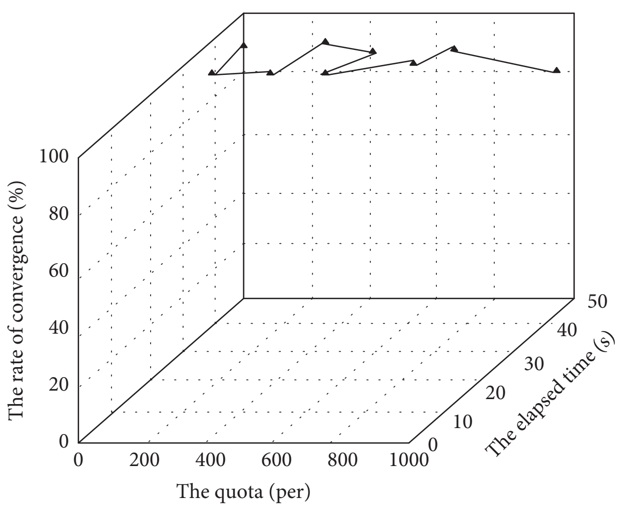


FIGURE 6: Convergence rate of the method proposed in this paper.

## 5. Conclusion

This paper presents the research on social talent governance algorithm based on genetic algorithm. The differences between traditional algorithm and genetic algorithm are analyzed, and the implementation process of genetic algorithm is determined. On this basis, the excellent individuals are determined by independent computing fitness, and the initialization population is designed according to the individual similarity threshold. After the population is defined, the roulette and deterministic sampling selection method are integrated to clarify the selection calculation process. Based on the calculation results, the crossover operator is designed by segmented single-point crossover between individuals, and the mutation operator is designed by segmented mutation of different gene segments according to the calculation results. The results are incorporated into the simulated annealing acceptance probability to conduct simulated annealing for the individuals after the cross-mutation operation, set relevant conditions after the end of the algorithm, seek the optimal solution of the data within the number of iterations, and finally realize the whole process of social talent governance algorithm. The experimental results show that the proposed algorithm has fast convergence rate, high data precision and recall, and certain feasibility.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The author declares that he has no conflicts of interest.

## References

[1] B. Crane and C. J. Hartwell, "Global talent management: a life cycle view of the interaction between human and social capital," *Journal of World Business*, vol. 54, no. 2, pp. 82–92, 2019.

[2] A. A. Mohammed, A. H. Baig, and R. Gururajan, "Talent management as a core source of innovation and social development in higher education," *Chapters:Innovation in Higher Education-Cases on Transforming and Advancing Practice*, IntechOpen, vol. 14, no. 2, , pp. 45–53, London, UK, 2020.

[3] K. Fu, "Investigation and analysis on social needs of early childhood development and health management specialty in higher vocational colleges," *Journal of Nanjing Radio & TV University*, vol. 7, no. 20, pp. 1145–1152, 2019.

[4] X. Peng, "The application of the fine idea in the management of the logistics and human resources in colleges and universities," *Modern Agriculture Research*, vol. 4, no. 3, pp. 145–153, 2019.

[5] W. Wikhamn, K. Asplund, and N. Dries, "Identification with management and the organisation as key mechanisms in explaining employee reactions to talent status," *Human Resource Management Journal*, vol. 5, no. 12, pp. 63–70, 2020.

[6] J. H. Holland, "Genetic algorithms," *Scientific American*, vol. 267, no. 1, pp. 66–72, 1992.

[7] J. Genlin, "Survey on genetic algorithm," *Computer Applications and Software*, vol. 2, no. 1, pp. 69–73, 2004.

[8] X. A. Chen, P. J. I. A. Xiang, F. Cheng, and J. Zhang, "Policy research on talents staying in Wuhan based on decision tree ID3 algorithm," *Journal of Wuhan University of Technology*, vol. 41, no. 2, pp. 1147–1153, 2019.

[9] Y. Wang, Y. Chen, X. Sha, Shouwei, and J. Li, "Identification of key factors of knowledge ability based on genetic algorithm-rough set: study on internationalization of construction industry," *Science and Technology Management Research*, vol. 39, no. 3, pp. 86–90, 2019.

[10] Y. Yang and Q. Ge, "On multiple intelligence structure of innovative science and technology talents and its evaluation—taking talents of the basic research type as examples," *Journal of ChangZhou University (Social Science Edition)*, vol. 21, no. 1, pp. 63–72, 2020.

[11] X. Xia, "Evaluation of university talents based on K-means clustering algorithm: a case study of Luzhou Vocational and Technical College," *Digital Technology and Applications*, vol. 12, no. 1, p. 60, 2019.

[12] H. Linjing, A. Y. Tong, H. B. Liu, and X. C. Lin, "Modeling and control of combustion temperature system of circulating fluidized bed boiler," *Computer Simulation*, vol. 36, no. 1, pp. 112–116, 2019.
[13] E. P. O'Connor and M. C. Henry, "Exploring the relationship between exclusive talent management, perceived organizational justice and employee engagement: bridging the literature," *Journal of Business Ethics*, vol. 156, no. 1, pp. 1–15, 2019.
[14] A. T. Al-Rawashdeh, "The impact of applying talent management strategies in achieving competitive advantage in commercial banks in southern Jordan," *International Journal of Academic Research in Accounting, Finance and Management Sciences*, vol. 9, no. 4, pp. 56–63, 2019.
[15] W. Zheng, Y. J. Wu, C. Shen, and H. Wen, "Social media for talent selection? a validity test of inter-judge agreement and behavioural prediction," *Information Technology and Management*, vol. 45, no. 2, pp. 32–38, 2021.
[16] T. Kicheva, "145 Corporate social responsibility as an element of building an organization's employer brand," in *Proceedings of the International Scientific And Practical Conference "Human Resource Management"*, University of Economics-Varna, Varna, Bulgaria, 2019.
[17] K. C. Lui, Y. H. Fung, and Y. H. Chan, "Predictive study of ultra-low emissions from dual-fuel engine using artificial neural networks combined with genetic algorithm," *Advanced Materials Research*, vol. 6, Article ID 105047, 2020.
[18] V. K. Veeramsetty, G. V. N. Lakshmi, and A. Jayalaxmi, "Optimal allocation and contingency analysis of embedded generation deployment in distribution network using genetic algorithm," in *Proceedings of the 2012 International Conference on Computing, Electronics and Electrical Technologies (ICCEET)*, March 2020.
[19] D. E. Holland, R. J. Olesen, and J. E. Bevins, "Multi-objective genetic algorithm optimization of a directionally sensitive radiation detection system using a surrogate transport model," *Engineering Applications of Artificial Intelligence*, vol. 104, no. 1, Article ID 104357, 2021.
[20] R. M. Kakhki, M. Mohammadpoor, R. Faridi, and M. Bahadoria, "The development of an artificial neural network–genetic algorithm model (ANN-GA) for the adsorption and photocatalysis of methylene blue on a novel sulfur–nitrogen co-doped $Fe_2O_3$ nanostructure surface," *RSC Advances*, vol. 10, no. 2, pp. 69–74, 2020.
[21] A. Yl, S. Jafari, and T. Nikolaidis, "Advanced optimization of gas turbine aero-engine transient performance using linkage-learning genetic algorithm: part I, building blocks detection and optimization in runway," *Chinese Journal of Aeronautics*, vol. 34, no. 4, pp. 526–539, 2020.
[22] N. Dhibi and C. B. Amar, "Performance of genetic algorithm and levenberg marquardt method on multi-mother wavelet neural network training for 3D huge meshes deformation: a comparative study," *Neural Processing Letters*, vol. 53, 2021.
[23] Z. Liang, S. Shao, Z. Lv et al., "Onstructing a consciousness meter based on the combination of non-linear measurements and genetic algorithm-based support vector machine," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 15, no. 9, p. 1, 2020.
[24] M. M. Farizhendy, E. Noorzai, and M. Golabchi, "Implementing the NSGA-II genetic algorithm to select the optimal repair and maintenance method of jack-up drilling rigs in Iranian shipyards," *Ocean Engineering*, vol. 211, no. 13, Article ID 107548, 2020.
[25] X. Meng, R. Wang, Y. Xu, L. Zhang, and Z. Wei, "Genetic algorithm optimization for electromechanical composite braking force control based on the driver-vehicle-road closed-loop system," in *Proceedings of the 2019 IEEE 4th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, December 2020.
[26] E. Ardjmand, I. Ghalehkhondabi, W. A. Young, A. Sadeghi, G. R. Weckman, and H. Shakerid, "A hybrid artificial neural network, genetic algorithm and column generation heuristic for minimizing makespan in manual order picking operations," *Expert Systems with Applications*, vol. 159, no. 2, pp. 17–23, 2020.
[27] M. M. Salim, M. Sharkasy, M. Walash, and F. Belal, "Genetic algorithm with model-updating-based PLS regression for the spectrophotometric determination of clopidogrel, atorvastatin, and aspirin in the presence of its degradation product," *Journal of European Economy*, vol. 63, no. 2, pp. 46–53, 2020.