Research Article

Application of Multipopulation Genetic Algorithm in Industrial Special Clothing Design

Xianglei Zhang$^{1}$ and Cuiyu Yang$^{2}$

$^{1}$Guangdong Industry Polytechnic, Guangdong Guangzhou 510300, China
$^{2}$South China Agricultural University, Guangdong Guangzhou 510640, China

Correspondence should be addressed to Xianglei Zhang; 2006105094@gdip.edu.cn

Received 1 June 2022; Revised 9 July 2022; Accepted 12 July 2022; Published 20 July 2022

Abstract

Industrial special clothing refers to the clothing worn by employees of industrial enterprises and departments in order to dress uniformly, facilitate work, or protect their bodies from external injuries. They have the common characteristics of practicality and identification. This kind of clothing includes many styles, such as uniforms, shirts, jackets, overalls, skirts, aprons, and headscarves, which are also applicable in different fields. For example, the clothing for high-temperature operation requires high temperature resistance and comfort, while the clothing for high-altitude operation requires high clothing strength and can play a protective role. General interactive genetic algorithm only supports single user evaluation. The results can only reflect the preferences of a single user. The product designed by interactive genetic algorithm needs to meet the needs of as many users as possible, and a multiuser interactive genetic algorithm suitable for population design is proposed. The detailed design of three main modules of the algorithm, namely, population initialization module, single population module, and multipopulation module, is given. Finally, the algorithm and the general single user interactive genetic algorithm are applied to the garment design system for comparative experiments. The effectiveness of the algorithm in group design is verified.

1. Introduction

At present, the global industrial professional clothing market is in short supply, especially the demand for protective clothing will continue to grow. The total sales volume of German industrial clothing market increased from 33.5% in 1994 [1]. The annual growth rate was 2.9%, which increased from 4.2 billion Deutsche marks to 3.41 billion Deutsche marks in 1997 [2]. By 1999, the market sales will still maintain a stable growth [3]. In 1996, the sales volume of industrial protective clothing in Europe was US $3.13 billion, and it was expected to reach US $3.77 billion by 2003. In 1995, the consumption of synthetic fiber used in industrial clothing in Japan reached 3.5% 43.44 million tons, accounting for about 3% of its total synthetic fiber output [4]. In general, the industrial clothing market will have a large growth, and special industrial clothing will become the highest growth point in the market [5]. With the development of industry, the application scope of overalls is also expanding. Because the quality of work clothes has been improved, especially in wearing comfort and popular style. People are willing to wear work clothes in daily life, such as on the way to work, repair cars, and housework. It is easy to work. However, there are still great deficiencies in industrial clothing design in China [6]. Since the reform and opening up, China’s economy and society have achieved great development, and the people’s demand for textile and clothing consumer goods has increased. In 1994, China’s clothing production reached 7.8 billion pieces. In 1998, it reached more than 9 billion pieces, with a wide variety of fashion clothing styles, gradually in line with international fashion trends. In contrast, the domestic clothing industry does not pay enough attention to industrial clothing, generally poor quality, single performance, and old appearance, and the development level is significantly lower than the level of the whole clothing industry. In China, work uniforms are usually called professional clothes, while ordinary work clothes and protective clothing are usually
classified as labor insurance supplies, resulting that this part of the clothing does not get the attention of clothing design producers. The level improves slowly, and the users have gradually formed a simple understanding of industrial clothing [7].

In recent years, the international industrial clothing market, mainly in the United States and Europe, has developed greatly [8]. It not only puts forward new demands for industrial clothing in terms of characteristics but also requires close cooperation in basic processes in production [9]. The traditional understanding of industrial clothing can no longer meet the modern needs [10]. Industrial clothing has become a high-tech product and will become a high value-added product in the future clothing market, bringing huge economic benefits to enterprises [11]. However, it is difficult to meet the needs of customers in the design of industrial clothing, so this paper proposes a multipopulation genetic algorithm [12]. Multipopulation genetic algorithm is improved on the basis of genetic algorithm and introduces the concept of multi population. The main improvements are as follows: (1) Change a single population into multiple populations, and each population has controllable parameters, such as crossover and mutation probability. Giving different values can produce different search results. (2) By controlling the connection and coevolution between various groups through specific operation factors, we can get the optimal evolution results of all groups. (3) The convergence conditions of multiple populations can be determined according to the number of optimal individuals in each population evolution, and the optimal individuals in each population can be retained by adding artificial selection operators.

General interactive genetic algorithm only supports single user evaluation. The results can only reflect the preferences of a single user [13]. The product designed by interactive genetic algorithm needs to meet the needs of as many users as possible [14]. To this end, a multiuser interactive genetic algorithm for population design is proposed. In practical optimization problems, the optimization objectives of some problems cannot be expressed by explicit mathematical functions [15]. Such optimization objectives are called implicit objectives, and the corresponding optimization problems are called implicit objective optimization problems [16]. For example, if clothing design is regarded as an optimization problem, the optimization goal of the problem is to “design clothing that users are satisfied with.” Interactive evolutionary algorithm (IEA) is an evolutionary algorithm that obtains individual fitness based on human subjective evaluation [17]. It is an effective method to solve implicit objective optimization problems. Because human factors are added to the interactive evolutionary algorithm, how to reduce user fatigue and enhance the efficiency of the algorithm is a very urgent and meaningful topic [18].

2. State of the Art

Genetic algorithm is a kind of evolutionary algorithm [19]. It is an intelligent algorithm based on Darwin’s theory of natural selection—the survival of the fittest [20, 21]. The algorithm transforms the problem solving process into a process similar to the crossover and mutation of chromosome genes in biological evolution by mathematical means and computer simulation. When solving complex combinatorial optimization problems, compared with some conventional optimization algorithms, it can usually get better optimization results faster. Genetic algorithm has been widely used in combinatorial optimization, machine learning, signal processing, adaptive control, and artificial life. Genetic algorithm was first proposed in 1975. Once it was proposed, it received warm attention from the majority of scholars and carried out a more in-depth discussion on genetic algorithm. Darwin’s theory of natural selection holds that in nature, organisms can survive only through survival struggle. The struggle for existence consists of three aspects: intraspecific struggle, interspecific struggle, and the struggle between organism and environment. To some extent, the struggle for survival is a kind of natural selection. In the process of population continuation, there will be a variety of mutated individuals. The individuals with favorable mutations are relatively more likely to survive, while the individuals with unfavorable mutations are more likely to be eliminated. Darwin called the process of survival of favorable mutated individuals and elimination of unfavorable mutated individuals as natural selection. In the study of natural selection, it is found that the internal factors that determine biological evolution are biological heredity and variation. Heredity makes the species in nature continue and remain relatively stable; Variation makes biological traits more diversified and promotes the “advance with the times” of organisms. Genetic algorithm is a computational model to simulate the process of biological evolution. It is also a random search method with survival and detection. It takes all individuals in the population as the object, encodes all individuals, takes an objective function as the fitness, selects individuals through selection, crossover and mutation, and finally finds the optimal solution through continuous iteration. Figure 1 shows the specific flow chart of the algorithm.

In genetic algorithm, the core content is the coding of individual population, initialization of population, design of fitness function, design of genetic operation, and parameter setting. Genetic algorithm has been widely used in various fields, such as combinatorial optimization, machine learning, and adaptive control, and has gradually become an important modern intelligent algorithm. The basic calculation steps of genetic algorithm are as follows:

(1) Coding. In genetic algorithm, genes and chromosomes need to be encoded. Chromosomes are the arrangement of genes. Therefore, genes are encoded first, and then, the chromosome code is obtained according to the combination of genes. Adopt different coding methods according to different problems. (2) Population initialization. In general, a random function is used to generate an initial population, which is a set of hypothetical solutions of the problem. (3) After the population initialization is completed, the fitness value of each individual in the population can be calculated, and each individual has its corresponding fitness value. Generally speaking, the objective function in the mathematical model is the fitness function.
in the algorithm. (4) Select an action. Taking fitness as the selection principle, individuals with higher fitness values in the population are selected to reproduce the next generation. The commonly used selection strategies include roulette selection strategy, tournament selection strategy, and sorting-based selection strategy. Roulette selection strategy is a common and basic selection strategy, and the probability of individuals being selected in the population is directly proportional to their fitness value. (5) Cross operation. The same position of the selected individual is randomly selected, and the crossover operation is carried out with a certain crossover probability in order to generate a new individual. (7) When the optimal individual obtained in each iteration meets the termination conditions, or the fitness of the optimal individual does not change, it indicates that the iterative process of the algorithm has reached the convergence state, and the algorithm is over. Otherwise, replace the previous generation of population with the new population, return to the third step, and continue the cycle until the termination conditions are met. Figure 2 shows the evolution steps of the classical GA algorithm.

3. Methodology

3.1. Interactive Genetic Algorithm. Interactive genetic algorithm can also be called human-computer interactive evolutionary optimization algorithm, that is, in the process of evolutionary computing, people can intervene and guide the evolutionary process through interaction with computers, so as to solve a class of implicit performance index optimization problems that cannot be solved by traditional genetic algorithm. Because of human participation, genetic algorithm has been well expanded, and it no longer simply depends on fitness function, which greatly broadens the application field of traditional genetic algorithm. In the interactive genetic algorithm, the characteristics of the search space are different in different evolution periods. Therefore, it is difficult to ensure the approximation accuracy of the agent model by using the same model to approximate the fitness function evaluated by users in the whole evolution cycle. In this paper, a multiagent model algorithm based on adaptive partition is proposed. According to the evolution process, the search space is adaptively partitioned, and a multiclass agent model is established in each subspace according to its characteristics and updated online. In the evolution process, the agent model is used to evaluate all or part of the individuals instead of people, so as to reduce user fatigue. Or when people evaluate the same number of individuals, the evolutionary algebra and population size are increased, so as to improve the performance of interactive genetic algorithm.

3.2. Multiuser Interactive Genetic Algorithm. The multiuser interactive genetic algorithm mainly includes three modules: population initialization module, single population module, and multipopulation module.

3.2.1. Population Initialization Module. Suppose the population size is $n$ and the user size is $u$. The population...
initialization is completed in the following two steps: (i) randomly generate a population size of \( n \) for \( u \) users, and display the individuals in various groups to the corresponding users. Each user scores them according to their preference for individuals; (2) after each user has completed the evaluation, the corresponding individuals of all users will be formed into a set and sorted according to individual scores. The initial population of muiga is composed of the \( n \) individuals with the highest score. After the population initialization is completed, the algorithm enters the single population module.

3.2.2. Single Population Module. When the algorithm enters the single population module, it is said that the algorithm is in the single population mode. In this mode, the corresponding population of each user is the same. Under the common guidance of all users, the population uses genetic operations (selection, crossover, and mutation) to continuously evolve a new generation of population until the end condition of the algorithm is reached or the population diversity is lower than a set lower limit. In the process of evolution, elitist retention strategy is adopted.

(1) Individual fitness function in single population model, individual fitness should depend on the scores of all users. Record \( f_i(x) \) as the evaluation value of user \( I \) on individual \( x \), \( i = 1, 2U \). Then, the fitness function \( fit(x) \) of individual \( x \) can be expressed as follows:

\[
fit(x) = \sqrt{\frac{1}{U} \sum_{i=1}^{U} f_i^2(x)},
\]

of which, \( f_i(x) \in [f_{\text{min}}, f_{\text{max}}] \), where \( f_{\text{min}} \) and \( f_{\text{max}} \) are the lower and upper bounds of the user evaluation value, respectively. Then, the maximum value of individual fitness is as follows:

\[
fit_{\text{max}} = \sqrt{\frac{1}{U} \sum_{i=1}^{U} f_{\text{max}}^2} = f_{\text{max}}.
\]

Compared with the general single user IgA, which directly assigns the user score as the individual fitness, using equation (1) to calculate the individual fitness will increase the computational complexity. However, in the IgA execution process, the user’s evaluation process is the most time-consuming, and the calculation time is negligible compared with the evaluation time. Therefore, the increase of calculation complexity here has little impact on the algorithm execution time.

(2) Convergence condition of algorithm

When muiga is in multipopulation mode, the corresponding population of each user is different (see Section 1.3), and it is impossible to determine an individual that all users are satisfied with in this mode. Therefore, muiga can
only converge in a single population model. It is specified that when the following conditions are true, the algorithm converges: muiga is in a single population mode, and there is an individual \(x\) in the current population so that

\[
\text{Fit}(x) \geq a\text{fit}_{\max},
\]

where \(a\) is the user satisfaction factor, which is generally acceptable \(a \in [0.8, 1]\). \(x\) is the result of muiga. The larger \(a\), the more difficult the algorithm is to converge, but the better the quality of the results. For specific application, a maximum evolution algebra can be set. When the evolution algebra exceeds this value, muiga forces to enter the single population mode, takes the optimal individual in this mode as the design result, and terminates the algorithm.

(3) Conditions for converting to multigroup modules

In the single population model, individuals can evolve under the guidance of multiple users. Thus, the final result can meet the requirements of multiple users. However, due to the small population size, population diversity is difficult to guarantee. Therefore, the algorithm is prone to premature convergence and fall into local optimization. The algorithm needs to be transferred into the multigroup module. Without losing generality, it is assumed that the individual is represented by binary code. The population is recorded as \(x\), and the population diversity \(D(x)\) is calculated as follows:

\[
D(x) = \frac{2}{N(N-1)L} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} h(x_i, x_j),
\]

where \(n\) is the population size, \(L\) is the individual coding length, \(x_i\) and \(x_j\) are the \(i\)th and \(j\)th individuals of population \(x\), respectively, and \(h(x_i, x_j)\) is the Hamming distance encoded by two individuals. If the algorithm is in the single population mode and the current population is \(x\), the algorithm enters the multigroup module when the following conditions are met:

\[
D(x) \leq \delta,
\]

of which, \(\delta\) is the population mode conversion threshold, and its default value is 0.25.

3.2.3. Multiple Group Modules. When the algorithm enters the multigroup module, it is said that the algorithm is in the multigroup mode. The main purpose of this module is to increase the diversity of the population. Two measures are taken to achieve this purpose: (1) the population corresponding to each user evolves independently; (2) increase the probability of variation. In this mode, the user score is directly assigned to the individual fitness value.

When all populations have evolved into a new generation of populations, the following operations are carried out: the individuals in all populations are formed into a set and sorted according to individual scores. The \(n\) individuals with the highest scores form a new population \(x_{\text{new}}\). If \(D(x_{\text{new}}) \leq \delta\), then the algorithm is still in multigroup mode. Otherwise, the algorithm enters the single population mode, and the corresponding population of each user is \(x_{\text{new}}\). Under the objective function, the optimization of the population is shown in Figure 3.

4. Result Analysis and Discussion

4.1. Training Data and Test Data Acquisition. Consider the following implicit performance index optimization problem:

\[
\begin{align*}
\max & \quad f(x), \\
\text{s.t.} & \quad x = (x_1, x_2, \ldots, x_D) \in S \subseteq \mathbb{R}^D, \\
& \quad x_d \in [a_d, b_d], d = 1, 2, \ldots, D,
\end{align*}
\]

where \(f(x)\) is the optimized implicit performance index, \(x\) is the \(d\)-dimensional decision variable, and \([a_d, b_d]\) is the value range of each dimensional variable. The interactive genetic algorithm is used to optimize the above problems. The decision variables are coded by real numbers. Without causing confusion, the corresponding individual in the evolutionary population of the interactive genetic algorithm is \(x\), and its fitness value is \(f(x)\). The process of using functions to optimize the algorithm is shown in Figure 4.

After the interactive genetic algorithm evolves the \(T\) generation, it saves the individuals and their fitness values evaluated by the users during the evolution process. There are \(n\) groups, which are recorded as follows:

\[
\text{Data} = \{ (x', f(x')) | i = 1, 2, \ldots, N \}. 
\]

The data in the save set is divided into two types, namely, training set and test set, which are used for the construction of agent model and the test of model approximation performance, respectively. The selection of training set will greatly affect the approximation performance of agent model. Generally speaking, the better the distribution of training set data, the stronger the generalization ability of the agent model.

Now consider the \(j\)th bisection space of the \(d\)-dimensional variable, where the point value is written as \(c_d^j\). It can be expressed as follows:

\[
c_d^j = a_d + \frac{(2j-1)(b_d - a_d)}{2m},
\]

\(d = 1, 2, \ldots, D, j = 1, 2, \ldots, m\). (9)

Arrange and combine these median values, and select \(m\) groups from them to obtain the reference sampling point set, which may be recorded as \(\text{SP}\); then, \(\text{SP}\) can be expressed as follows:

\[
\text{SP} = \begin{bmatrix}
C_1 \\
C_2 \\
\vdots \\
C_m
\end{bmatrix} = \begin{bmatrix}
c_1^1, & c_1^2, & \cdots, & c_1^D \\
c_2^1, & c_2^2, & \cdots, & c_2^D \\
\vdots & \vdots & \ddots & \vdots \\
c_m^1, & c_m^2, & \cdots, & c_m^D
\end{bmatrix}.
\]
Multifunctional optimization process

**Figure 3:** Population optimization.

Generation vs. F_value of f1

**Figure 4:** Function optimization genetic algorithm.
Thus, the training set can be expressed as follows:

\[
TR = \left\{ \left( x^k_i, f(x^k_i) \right) \right\} \mid x^k_i = \arg \min_{j \in \{1, 2, \ldots, N\}} d(C^j, x^i), i = 1, 2, \ldots, m\right\},
\]

(11)

Among, \( d(C^j, x^i) = \| C^j - x^i \|_2 \).

(12)

It is easy to see that the training set tr contains \( M \) data; then, the remaining \( N-M \) data in the save set data constitute the test set.

In order to ensure that the agent model has a certain approximation accuracy and balance with the computational complexity, the number of training data can change adaptively according to the evolution process, but in order to ensure the accuracy of the model, the training data should not be less than the test data at least. Therefore, this paper takes the following:

\[
m = a(t)N, 0.5 < a(t) < 1.
\]

(13)

4.2. Spatial Segmentation at the Initial Stage of Evolution.

The increase of the number of agent models will increase the computational complexity, so the number of agent models should be as small as possible. On the other hand, different decision variables have different effects on user evaluation. This paper hopes that the spatial segmentation of decision variables that have a greater impact on users will be more detailed. Such decision variables are called key dimensions. The determination of key dimension can be based on user’s subjective cognition or correlation coefficient method. The so-called correlation coefficient method takes the decision variables that have the greatest correlation with the fitness value of the evolutionary individual as the key dimension.

Let the size of the \( T \) generation evolutionary population be \( n(T) \), and the fitness value of individual \( X_i(T) \) be the following:

\[
f(x^i(t)), i = 1, 2, \ldots, n(t).
\]

(14)

The value of the gene locus corresponding to the decision variable \( x_d \) of the population is as follows:

\[
x_d(t) = \left( x^1_d(t), x^2_d(t), \ldots, x^T_d(t) \right)^T, \quad d = 1, 2, \ldots.
\]

(15)

\( x_d \) is the correlation coefficient with individual fitness is \( \rho(f, x_d, t) \), which can be expressed as follows:

\[
\rho(f, x_d, t) = \frac{1}{n(t)} \sum_{i=1}^{n(t)} \frac{(f(x^i(t)) - x_d(t))(f(x^i(t)) - f(t))}{\sqrt{\sum_{i=1}^{n(t)} (f(x^i(t)) - f(t))^2}}.
\]

(16)

among, \( x_d(t) = \frac{1}{n(t)} \sum_{i=1}^{n(t)} x^i_d(t), f(t) = \frac{1}{n(t)} \sum_{i=1}^{n(t)} f(x^i(t)) \).

(17)

4.3. Experimental Design and Result Analysis

4.3.1. Experimental Setup. The goal of the fashion design system is to design clothes that conform to users’ aesthetic views. In the fashion design system, each set of clothes can be represented by a quadruple: \( \{u, top \text{ style}, top \text{ color}, skirt \text{ style}, skirt \text{ color} \} \). Each suit is an individual in the population. Individuals are represented by 28 bit binary code, in which the 1st–5th bits represent the top style, the 6th–14th bits represent the top color, the 15th–19th bits represent the skirt style, and the 20th–28th bits represent the skirt color. Therefore, there are \( 2 = 32 \) styles and \( 2 = 512 \) colors for tops and skirts. When decoding, the 5-bit binary number representing the style is converted to decimal, and the corresponding style is read according to the decimal number. The 9-bit binary number representing the color is converted to an RGB value, and each component of the RGB value corresponds to a 3-bit binary number.

The genetic operation of single user IgA is the same as that of muiga. Relevant parameter settings are shown in Table 1: population size 8, crossover probability 0.8, and mutation probability 0.02, which specifies that the single user IgA converges when there is an individual satisfying the user.

4.3.2. Result Analysis. This section will take a muiga operation process as an example. Explain the basic process of group design. Figure 5 is the curve drawn according to the relevant data of this operation process.

It can be seen from the figure that the algorithm from generation 0 to generation 1 is in the population initialization module and the algorithm from generation 2 to generation 5. At this time, the algorithm is in the single population module, generation 6–7. The algorithm enters the multipopulation module, (IV) generation 8. When the algorithm runs to the 8th generation, the population diversity becomes 0.291, greater than \( \delta \). The algorithm reverts to the single population model.

In order to compare the differences of different algorithms in population size, population diversity, user fatigue,
and user satisfaction with the final results, GA algorithm is first used to run under the condition that the population number is 10 and the algebra is 1000. The running results are shown in Figure 6.

Then, set various algorithms to run 20 times and take the average value. Since GS IgA does not partition the space, when the global agent model is established, the population size is increased to 200. The population size change of the algorithm is shown in Figure 7. For clarity, only the results of the first 30 generations of evolution are given.

As can be seen from Figure 3, the population size of the algorithm in this paper is constantly changing, which indicates that the size of each subspace changes during the evolution process, that is, the space segmentation is dynamically changing. Using this algorithm, because the population size changes dynamically with evolution, and some individuals are randomly generated when the population size increases, the population diversity is good. In several generations when users do not participate in the evaluation, the population diversity decreases, but with the reuse of the agent model, the population diversity increases again, which is conducive to expanding the search space and greatly increasing the probability of providing users with more implicit satisfactory solutions, so as to facilitate the design of user satisfactory products for industrial clothing.

5. Conclusion

Due to the influence of user evaluation fatigue, the population size and evolution time of interactive genetic algorithm are small, which makes it difficult to guarantee the search performance of the algorithm. In this paper, a fitness approximation method based on spatial adaptive segmentation and multiclass agent model is proposed to effectively reduce user fatigue and improve the performance of the algorithm. While defining the user evaluation sensitivity, combined with the model approximation accuracy and search performance, an adaptive segmentation method of search space is proposed. According to a large number of experimental results, the quadratic polynomial and RBF neural network are selected to construct the proxy model, and the principle of using the proxy model is given. Finally, the evolutionary optimization system of industrial clothing is used to verify the effectiveness of the algorithm.

At the same time, this paper proposes a multiuser interactive genetic algorithm model and gives the implementation technology of the three main modules of the algorithm in detail: population initialization module, single population module, and multipopulation module. Muiga and single user IgA are applied to the industrial garment design system, respectively. The experimental results show that muiga has better results, can better meet the preferences and requirements of multiple users, and is an effective group design model.

Data Availability

The figures and tables used to support the findings of this study are included in the article.
Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported by 20190 School Level Humanities and Social Research Project of Guangdong Light Industry Polytechnic (SK2019-036). The authors would like to show sincere thanks to those techniques who have contributed to this research.

References

[1] E. K. Susanto, R. Fachruddin, M. I. Diputra, D. Herumurti, and A. A. Yunanto, “Maze generation based on difficulty using genetic algorithm with gene pool,” in 2020 International Seminar on Application for Technology of Information and Communication (Semicom), pp. 554–559, Semarang, Indonesia, September 2020.

[2] B. Justine and K. D. Wood, “Primary hyperoxaluria type 1: time for prime time?,” Clinical Kidney Journal, vol. 13, no. 5, pp. 41–50, 2022.

[3] S. Harris, G. Tsalidis, J. J. Espi Gallart, and F. Tegstedt, “Application of LCA and LCC in the early stages of wastewater treatment design: a multiple case study of brine effluents,” Journal of Cleaner Production, vol. 307, no. 6, article 127298, 2021.

[4] K. Khayanying and S. Anantawaraskul, “Application of genetic algorithm in simultaneous deconvolution: case studies of ethylene/1-butene copolymers with direct and inverse MW/CC relationships,” Macromolecular Symposia, vol. 390, no. 1, article 1900024, 2020.

[5] T. Orankitanun and S. Yaowiwat, “Application of genetic algorithm in tri-band U-slot microstrip antenna design,” in 2020 17th international conference on electrical engineering/electronics, computer, Telecommunications and Information Technology (ECTI-CON), pp. 127–130, Phuket, Thailand, June 2020.

[6] S. Mitrovi, M. Stani, and S. Maovi, “Application of genetic algorithm in design of arch bridge,” in Contemporary achievements in civil engineering 22-23, pp. 67–74, Subotica, Serbia, April 2021.

[7] E. Y. Y. Chan, W. B. Goggins, Z. Huang, and C. S. Wong, "Hong Kong: Climatic Application in Urban Planning and Design at Multiple Scales for Creating a Healthy Living Environment," in Urban Climate Science for Planning Healthy Cities, pp. 151–166, Springer, Cham, 2021.

[8] M. Hirata, M. Wittayarat, Z. Namula et al., “Evaluation of multiple gene targeting in porcine embryos by the CRISPR/Cas 9 system using electroporation,” Molecular Biology Reports, vol. 47, no. 7, pp. 5073–5079, 2020.

[9] P. Khanal, L. He, A. J. Herbert et al., “The association of multiple gene variants with ageing skeletal muscle phenotypes in elderly women,” Genes, vol. 11, no. 12, pp. 1459–1466, 2020.

[10] E. Wulan and N. Apriiani, “The application of genetic algorithm in solving traveling salesman problem,” in Proceedings of the 1st international conference on Islam, science and technology, pp. 100–111, Bandung, Indonesia, July 2019.

[11] Z. Zhang, L. Gao, and Y. Xiang, “Application of optimized BP neural network based on genetic algorithm in rugby tackle action recognition,” in 2020 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA), pp. 95–99, Dalian, China, June 2020.

[12] H. Mai, B. Y. Cao, and X. G. Zhou, “The Application of Fuzzy Relational Equations and Genetic Algorithm in Fault Diagnosis Problem,” in Fuzzy Information and Engineering-2019, pp. 197–205, Springer, Singapore, 2020.

[13] E. H. Houssein, D. S. Abdelminaam, H. N. Hassan, M. M. Al-Sayed, and E. Nabil, “A hybrid barnacles mating optimizer algorithm with support vector machines for gene selection of microarray cancer classification,” IEEE Access, vol. 9, pp. 6652–6673, 2021.

[14] C. Guo, “Application of computer technology in optimal design of overall structure of special machinery,” Mathematical Problems in Engineering, vol. 2021, Article ID 6619485, 9 pages, 2021.

[15] D. H. Kang, S. C. Ko, Y. B. Heo, H. J. Lee, and H. M. Woo, “Robo MoClo: a robotics-assisted modular cloning framework for multiple gene assembly in biofoundry,” ACS Synthetic Biology, vol. 11, no. 3, pp. 1336–1348, 2022.

[16] Y. Zhao, “The application of immune genetic algorithm in BP neural network,” in 2021 6th International Conference on Intelligent Computing and Signal Processing (ICSP), pp. 115–118, Xi’an, China, April 2021.

[17] J. Lim, Y. S. Jang, H. S. Chang, J. C. Park, and J. Lee, “Multi-objective genetic algorithm in reliability-based design optimization with sequential statistical modeling: an application to design of engine mounting,” Structural and Multidisciplinary Optimization, vol. 61, no. 3, pp. 1253–1271, 2020.

[18] C. Hua and N. Liu, “A Quantum-Inspired Genetic K-Means Algorithm for Gene Clustering,” in International Symposium on Neural Networksp. 13–24, Springer, Cham.

[19] K. C. Onyelowe, F. E. Jalal, M. E. Onyia, I. C. Onuoha, and G. U. Alaneme, “Application of gene expression programming to evaluate strength characteristics of hydrated-lime-activated rice husk ash-treated expansive soil,” Applied Computational Intelligence and Soft Computing, vol. 2021, Article ID 6686347, 17 pages, 2021.

[20] L. Fatahi, “Vibration-based material properties identification of a car seat frame in time and frequency domains using multi-objective genetic algorithm,” Structural and Multidisciplinary Optimization, vol. 65, no. 1, pp. 1–14, 2022.

[21] J. Han, H. Cheng, Y. Shi, L. Wang, Y. Song, and W. Zhng, “Connectivity analysis and application of fracture cave carbonate reservoir in Tazhong,” Science Technology and Engineering, vol. 16, no. 5, pp. 147–152, 2016.