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Modelling and Simulation of Intelligent English Paper Generating based on Developed Genetic Algorithm

Limin Han[1*], Aiyun Chen[1], Rongjie Zhai[2]
[1]School of Foreign Studies, Anhui Polytechnic University, Wuhu, Anhui, China
[2]School of Artificial Intelligence, Anhui Polytechnic University, Wuhu, Anhui, China
*Corresponding Author.

Abstract:

In order to solve problems in generating paper for Test for English Majors (TEM) more effectively, a simplified generating model is proposed based on analyzing test features and requirements. Meanwhile, to improve the efficiency and quality of intelligent English paper generating, the normal genetic algorithm (GA) is improved. In addition, butterfly optimization algorithm is introduced to select the crossover rate and mutation rate for the genetic algorithm so that its optimization accuracy and speed are improved. Finally, the developed genetic algorithm is used to conduct the experiments of TEM paper generating and compared with the normal genetic algorithm. The simulation experimental results of generating TEM papers show that the developed genetic algorithm can work quickly with higher quality.

Keywords*: Test for English majors, Paper generating, Genetic algorithm, Modelling and simulation.*

I. INTRODUCTION

With the economical and social development of the whole world, the communication among countries is becoming increasingly extensive and popular. Hence, English has become one of the most important international languages in the world [1-3]. There are different kinds of English courses in the talent training systems of many countries, so conducting English tests and generating English papers automatically are becoming more and more essential and vital. The traditional method of generating English paper is manual or man-made generating. More specifically, based on a certain paper target and requirement, teachers or English paper generators tend to select test questions according to their own experiences in test databases to produce an English paper. The manual paper-generating process tends to be greatly influenced by personal experience of teachers or paper generators. Thus, the paper quality is far from desirable and the workload is very large. Luckily, with the rapid development of group intelligent algorithm, it is possible to use modern computer technology to generate English paper in an automatic and intelligent way. Thus, people can apply new group intelligent optimization algorithms and programs to generate English test papers that can meet high requirements. At present, many scholars at home and abroad have conducted rich study in this field.

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Du studied the method of generating examination paper through computers and made a template generator [4]. Yang Bo studied an online intelligent paper generation method and made a mathematical model of test paper generation. Improved particle swarm optimization algorithm was employed to solve the objective function of test paper generation [5]. Härtel Johannes designed an examination paper generating system on the basis of hybrid genetic algorithm, which could reduce the one-sided and subjective phenomenon in examination paper [6]. Abd El Rahman Sahar developed an examination paper generating system, including knowledge base of many questions' types linked to a test engine. The designed automated examination paper system could provide cost-saving and efficient solutions [7]. Zhang Haiyan designed a method which could randomly generate examination papers quickly [8]. Nguyen Minh Luan proposed a submodular memetic approximation algorithm which could jointly optimize the total quality maximization objective and the fairness quality maximization objective so that the quality of generated examination paper had been enhanced [9]. Zhang employed genetic algorithm to make the intelligent test paper generating system work well [10]. Huang analyzed constraint conditions of the auto-generating test paper and made related mathematical models so that the test paper generation was more intelligent and efficient [11]. MENG Jian designed the process of generating test paper in college English and the generation method had good quality and reflected students' real English proficiency [12]. Machine learning is used by Wu Tao to construct the CET-4 score prediction model and the diagnostic evaluation model. On this basis, the paper-generating algorithm which is verified from three perspectives of group paper time, test recommendation and score improvement is constructed [13]. Liu Dongyang put forward two paper-generating algorithms based on knowledge point association rules, which effectively provided better guidance and test recommendation for learners' knowledge points [14]. Lei Qian analyzed the overall evaluation objectives and the overall test parameters of the college English test paper, and put forward an automatic generating method of the college English test database based on invasive weed optimization algorithm, which could save human resources of English teaching in universities [15].

At present, some scholars have conducted some research on the intelligent paper-generating method, such as introducing genetic algorithms to automatically optimize test papers to meet the requirements of various test databases. However, although genetic algorithms are very suitable for multi-target optimization of intelligent paper generating, there are still many disadvantages, such as easily falling into local optimization and slow convergence, so there is a large research space in this field. In this paper, the butterfly optimization algorithm is introduced into the intelligent automatic paper generating to optimize the key parameters of the genetic algorithm, and use the improved algorithm to optimize and generate paper.

The rest of this paper has the following parts: Section II describes models of generating TEM paper; Section III is about the development of normal GA; Section IV describes simulation experiments; Section V makes a conclusion of the paper.

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II. ANALYSIS AND MODELING OF TEST FOR ENGLISH MAJORS

A Test for English Majors is an English test targeted at undergraduates to examine the implementation of the English major teaching syllabus, mainly including the TEM-4 and TEM-8. A TEM-4 paper contains the following tasks, such as dictation, listening comprehension, language knowledge, cloze, reading comprehension and writing. TEM evaluates the comprehensive language application ability of English majors. Every year, a large number of students around the world use various professional English paper databases to prepare for the tests. Hence, if the question databases can be employed to quickly generate TEM papers that meet the assessment requirements, it will be of great benefit for test-takers across the world.

In TEM papers, there are some main attributes, such as question type, difficulty, reliability, ability differentiation, assessment of knowledge points, answering time, question exposure and so on. Therefore, the generating model of a TEM paper with n questions can be expressed with the following target matrix.

$$S(a_{i,j}) = \begin{cases} a_{1,1} & a_{1,2} & \cdots & a_{1,7} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,7} \\ \vdots & \vdots & \vdots & \vdots \\ a_{n,1} & a_{n,2} & \cdots & a_{n,7} \end{cases} \tag{1}$$

In this matrix, each column represents one attribute, with a total of 7 attributes; each row represents a test question meeting 7 attributes, with a total of n test questions. Therefore, the matrix S constitutes the target state matrix of the paper generating method in this paper. Accordingly, TEM paper generating problem is transformed into solution of the multi-objective constraint of the matrix S through this mathematical model. Each parameter in the test paper model is constrained and optimally solved, and then the algorithm design of TEM paper generating with multiple targets online is completed. The constraints of TEMs are mainly considered from the following aspects.

1) Question type and score constraints

$$\sum_{i=1}^{n} x_1 a_{i1} = g_j \tag{2}$$

Where, j is question type; g_j is the points of question type j. In TEM-4, j means dictation, listening comprehension, language knowledge, cloze, reading comprehension, writing and so on, $x_1 = \begin{cases} =1 & (a_{i1} = j) \\ =0 & (a_{i1} \neq j) \end{cases}$

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2) Difficulty coefficient constraint

$$\text{avg}\sum_{i=1}^{n} x_2 a_{i2} = b_j \tag{3}$$

Where, b_j is evaluation difficulty value of question type j, $x_2 = \begin{cases} =1 & (a_{i2} = j) \\ =0 & (a_{i2} \neq j) \end{cases}$

3) Test paper total score constraint

$$\sum_{i=1}^{n} a_{i3} = h \tag{4}$$

Where, h is total score of examination paper. In TEM-4, the total score is 100.

4) Test questions' exposure constraints

$$\sum_{i=1}^{n} a_{i4} = f \tag{5}$$

Where, f is test questions' exposure which should be as small as possible.

5) Test questions' knowledge point distribution constraints

$$\sum_{i=1}^{n} a_{i5} = x \tag{6}$$

Where, x is the number of knowledge points which should be as large as possible in test questions.

6) Test paper differentiation degree constraints

$$\sum_{i=1}^{n} a_{i6} / n = y \tag{7}$$

Where, y is the value of paper differentiation degree and is a sign of the differentiation power of a paper. It is used to measure the differentiation of students' different abilities in TEM tests. The larger the value is, the stronger the differentiation ability of the paper is.

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7) Test time constraints

$$\sum_{i=1}^{n} a_{i7} = u \tag{8}$$

Where, set value u is the total time of a test paper, and the total time of TEM-4 is 140 minutes. In the real process of paper generating, a TEM paper fitness is F, which truly reflects the above 7 indicators. It can be obtained by multiplying the absolute value of the required error by different weight coefficients, as is shown in Equation (9).

$$F = \sum_{i=1}^{i=7} F_i \beta_i \tag{9}$$

Where, F is the fitness of the whole paper; F_i is the corresponding error between the i^{th} index and the user request; β_i is the weight coefficient of the i^{th} index. The smaller the F value is, the higher quality a test paper has.

III. DEVELOPMENT OF GENETIC ALGORITHM

In order to enhance the efficiency and quality of paper generating through genetic algorithm, the normal genetic algorithm is optimized and improved. The crossover rate and mutation rate of the genetic algorithm have an important influence on its execution efficiency. If the two parameters are not selected properly, the algorithm will have ill-function due to slow execution speed and low optimization accuracy [16-18]. The selection of these two parameters usually depends on experience of designers. Execution effectiveness of genetic algorithm designed by different designers at different levels is different and the algorithm robustness is poor [19,20].

The butterfly optimization algorithm, a novel bio-inspired group intelligent optimization algorithm proposed in 2018, studies the mutual behavior rules of foraging among individuals in butterfly groups by Sankalap Arora et al [21-24]. The proposed algorithm has a simple mathematical model and strong optimization ability, which can balance local search and global search well, so it is very suitable for parallel processing [25]. It has been successfully applied in a variety of engineering fields with desirable results, such as automatic voltage regulation, neural network algorithm training, dynamic path planning and other fields [26,27].

Therefore, the new butterfly optimization algorithm is employed in this paper to optimize the crossover rate and mutation rate of the genetic algorithm, thus making the genetic algorithm more suitable for search of the optimized objects. The flow chart of optimizing the crossover rate and mutation rate of genetic algorithm through butterfly optimization algorithm is shown in Fig 1. The accuracy of searching results by the genetic algorithms selecting different crossover rates and mutation rates is constantly compared. The optimal crossover rate and mutation rate after 100 generations of iteration of the butterfly optimization

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algorithm are selected and applied to the genetic algorithm.

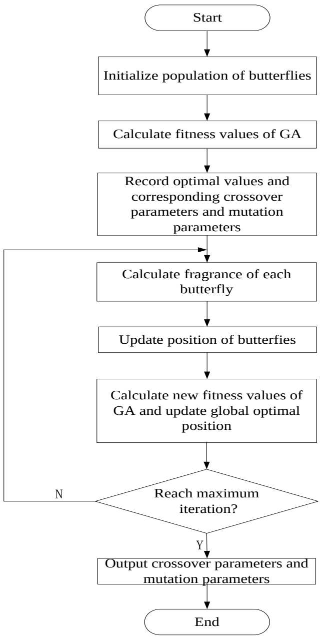

Fig 1. Flowchart of Developed GA

In order to verify the execution effect of the new genetic algorithm studied in this paper and test whether the crossover rate and mutation rate selected by the butterfly optimization algorithm can effectively improve the solution ability, the new genetic algorithm is used to search the optimal values of six standard test functions. The optimized results are also compared with the simulation results of normal genetic algorithms. The test functions of this optimization simulation experiments are shown in TABLE I. Because F1-F3 has only a global optimal value, they are unimodal functions which mainly evaluate exploitation capability of the studied meta-heuristic algorithm.

F4-F6 are polymodal functions, different from the unimodal function, which contain many local optimal solutions. The number of local optimal solutions increases exponentially with the design variables. Therefore, the stability of the algorithm can be verified by solving different types of functions. The local optimal solution is the most common problem of the optimization algorithm. By solving multiple multimodal functions, the ability of the algorithm to jump out of local optima is verified.

TABLE I. Description of 6 benchmark functions

Function	V_no	Range	f_{min}
$F_1(x)=\sum_{i=1}^{n} x_i^2$	30	[-100,100]	0
$F_2(x)=\sum_{i=1}^{n}(\sum_{j-1}^{n} x_j)^2$	30	[-100,100]	0
$F_3(x)=\max_i\{\lvert x_i\rvert,1\le i\le n\}$	30	[-100,100]	0

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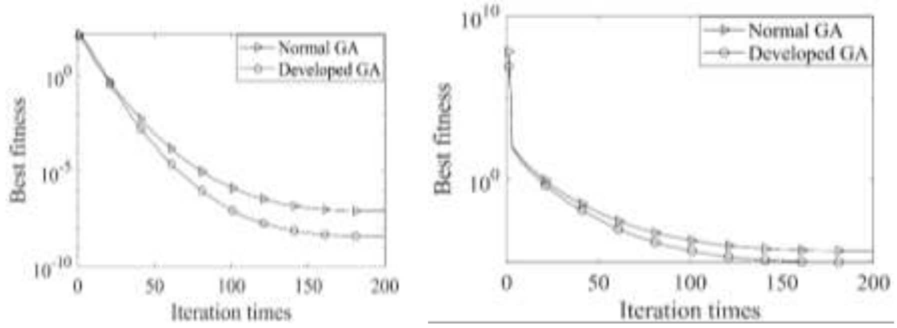
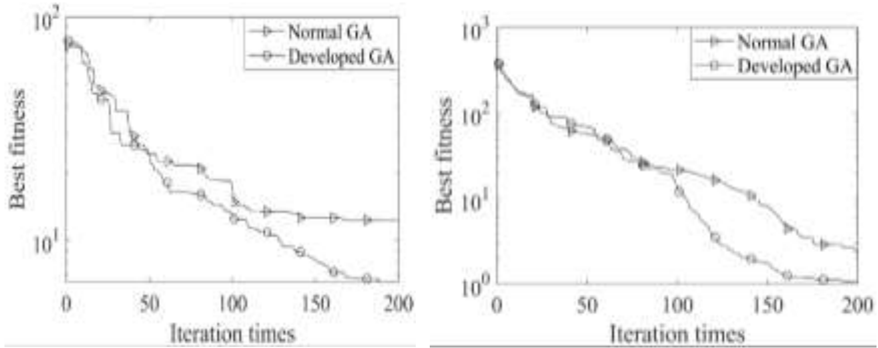
$F_4(x)=\sum_{i=1}^{n}[x_i^2-10\cos(2\pi x_i)+10]$	30	[-5.12,5.12]	0
$F_5(x)=-20\exp(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x^2})-e(\frac{1}{n}\sum_{i=1}^{n}cos(2\pi x_i))+2+e$	30	[-32,32]	0
$F_6(x)=\sum_{i=1}^{11}\left[a_i-\frac{x_1(b_i^2+b_i x_2)}{b_i^2+b_i x_3+x_4}\right]^2$	4	[-5,5]	0.00030

Fig 2 is the iterative process of solving the test function in this study. Normal GA is a normal genetic algorithm with a crossover rate of 0.2 and a mutation rate of 0.2. Developed GA is the improved genetic whose crossover rate and a mutation rate are selected by the butterfly optimization algorithm. Genetic algorithm crossover rate and mutation rate selected by the butterfly optimization algorithm are 0.24997 and 0.55983, respectively. In Figure 2, to better display the differences in the convergence process of the two algorithms, the ordinate adopts the log coordinate axis with base 10.

The developed GA adopting the crossover rate and mutation rate selected by the butterfly optimization algorithm shows faster convergence rate and higher solution accuracy in solving different test functions, which verifies that the genetic algorithm optimized by the butterfly optimization algorithm has stronger solution ability and higher solution accuracy. In particular, through the process of solving the multimodal function F4-F6, it can be seen that the mutation rate and crossover rate optimized by the butterfly optimization algorithm can obviously help the genetic algorithm jump out of the local optimal solution and converge quickly. Therefore, the solution ability of the genetic algorithm has been significantly improved.



(a) Comparison of test function F1 (b) Comparison of test function F2



(c) Comparison of test function F3 (d) Comparison of test function F4

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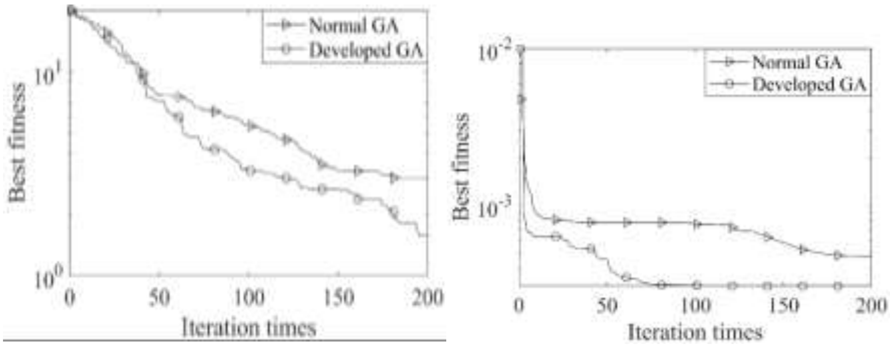

(e) Comparison of test function F5 (f) Comparison of test function F6

Fig 2. Comparison of test function F1-F6 of the optimization algorithm.

In order to verify that the developed GA has higher optimizing accuracy and more stable optimizing performance, average values and standard deviation of 20 optimizing results are calculated and shown in TABLE II.

TABLE II indicates that the average values of developed GA are much closer to the correct results, which verifies that developed GA has higher optimizing accuracy than normal GA. TABLE II also indicates that the standard deviation of developed GA are smaller than that of normal GA, which verifies that developed GA has more stable optimizing performance. To sum up, the above analysis can verify that developed GA has higher comprehensive properties.

TABLE II. The calculating results of average value and standard deviation

F	Normal GA		Developed GA	
	ave	std	ave	std
F1	2.5049e-07	1.1202e-09	8.4132e-10	2.2515E-11
F2	0.032599	5.3922 e-02	0.0076905	1.7139E-02
F3	5.5036	2.1809 E-02	3.2643	3.1615E-03
F4	0.54231	7.9086 E-03	0.0019214	1.5847 E-05
F5	4.3938	6.6274 E-02	1.6088	7.8546 E-04
F6	0.00062119	1.6902 E-04	0.00030749	1.6686E-07

IV. INTELLIGENT PAPER-GENERATING EXPERIMENTS BASED ON THE DEVELOPED GA

On the basis of constructed English test databases, simulation experiments of TEM-4 paper generating through developed genetic algorithm and normal genetic algorithm, are carried out respectively. In the simulation experiments, the Host operating system is Windows 7, the CPU is Intel Core i5 and internal storage is 8G. The English test database includes dictation text database, listening comprehension

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database, language knowledge database, cloze database and writing database, etc, with each branch database containing 3000 questions. The generated paper includes 1 dictation essay, 20 listening comprehension questions, 20 language knowledge points (vocabulary and grammar questions), 20 cloze questions, 15 reading comprehension questions, 1 writing task and so on. The specific question types and their corresponding score of TEM-4 papers are shown in TABLE III.

The crossover and mutation rates of the paper-generating genetic algorithm were optimized by the butterfly algorithm with values of 0.27449 and 0.28652, respectively. The number of population individuals and iteration generations is 60 and 200, respectively. The TEM paper generation experiments of the two algorithms are carried out 100 times and produced 100 TEM papers.

The optimal convergence curves of the two algorithms in the experiment are shown in Fig 3. The analysis of the optimal convergence curve in the experiment can find that the normal GA has some advantages in the early stage. But after 40 iterations, the fitness function values change slowly. The developed GA can help to better jump out of local optimum and conduct better evolution. The normal GA is exceeded quickly and the developed GA fitness value reaches the optimum rapidly.

TABLE III. Question type, number of questions and score share in generated TEM paper

Question type	Number of questions	Score share in paper
Dictation text	1	10
Listening comprehension	10	20
Language knowledge	20	20
Cloze	10	10
Reading comprehension	15	20
Writing	1	20

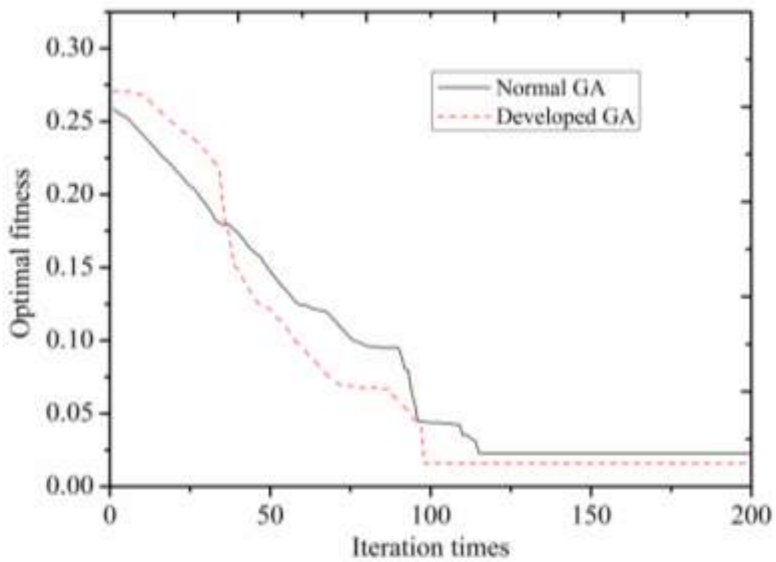

Fig 3. The optimal convergence curves of the two algorithms in the experiment

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Meanwhile, relation curves between two algorithms' average fitness changing with iteration shown in Fig 4 are achieved. Fig 4 indicates that as the iterative process continues, the developed GA has obvious advantages. Average fitness of 50, 100, 150 and 200 iterations is calculated and shown in TABLE IV. TABLE IV indicates that compared with normal GA, average fitness of developed GA of 50, 100, 150 and 200 iterations is improved by 16.49%, 24.2%, 17.94% and 20.98%, respectively

In order to further test the performance of developed GA and normal GA, the consuming time of TEM papers generating is calculated and shown in Fig 5. Fig 5 indicates that with the same English test database size, with the same times of iteration, the developed GA takes less time than the normal GA, and the advantage becomes more obvious with the number of iterations increasing.

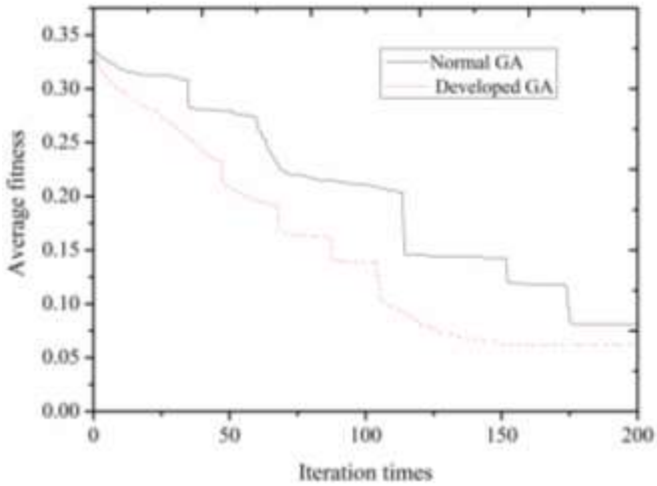

Fig 4. Average convergence curves of the two algorithms in the experiment

TABLE IV. Average fitness comparison of different iteration times

Iteration	Normal GA	Developed GA
50	0.285	0.238
100	0.219	0.166
150	0.156	0.128
200	0.081	0.064

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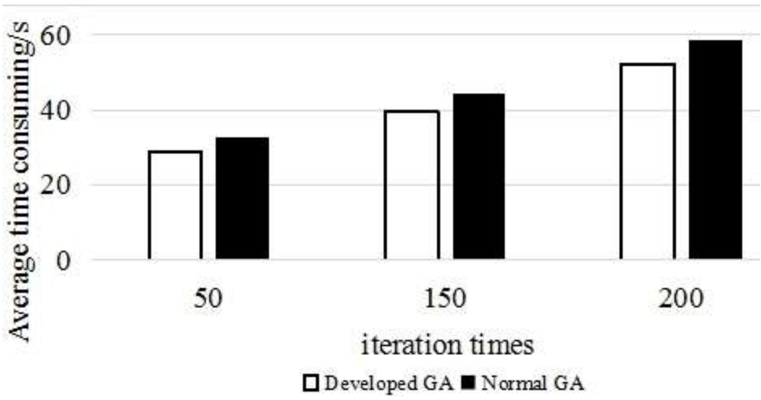

Fig 5. Average time consuming of generating TEM papers

Test questions' exposure is one of the important factors for assessing the quality of a test paper. The higher the questions' exposure is, the lower the test quality will be, and more similar test papers will be generated. Therefore, this paper calculates the exposure and success rate of the two algorithms, as is shown in TABLE V. It can be discovered from this table that questions' exposure and success rate of generated TEM papers of developed GA are smaller than those of normal GA, which indicates that the developed GA is more suitable than normal GA for TEM paper generating. Hence, the quality of TEM papers generated by developed GA is higher than that of normal GA

TABLE V. Result comparison of paper generating

Algorithm	Exposure rate	Success rate
Normal GA	3.94%	93%
Developed GA	2.51%	99%

V. CONCLUSION

On the basis of analyzing the characteristics and requirements of TEM-4, this paper establishes a reasonable and simplified mathematical model of intelligent paper-generating model. In order to improve the efficiency and quality of group volume, the normal genetic algorithm is developed. The newly-designed butterfly optimization algorithm is introduced to optimize the crossover rate and mutation rate of the genetic algorithm, so that it is more suitable for the searching calculation of generating TEM papers. 100 simulation tests suggest that the developed genetic algorithm can conduct intelligent TEM paper generating, greatly enhancing the efficiency and quality of paper generating.

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