Simulation Experiment on Optimization of New Energy Customer Value Model Based on Genetic algorithm

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ABSTRACT: *With the rapid development of the new energy industry, how to accurately evaluate and predict customer value to meet customer needs better and provide high-quality services has become an important issue the industry faces. To address this issue, we propose an optimization model based on genetic algorithms to improve the value and satisfaction of new energy customers. The model first collects relevant customer data, including historical electricity consumption, electricity consumption behaviour, complaints, etc. Then, we used genetic algorithms to process and analyze these data to find the optimal customer value evaluation model. A genetic algorithm is an optimization algorithm that simulates the evolution process of nature and can automatically search for and optimize solutions to problems. In model optimization, we used simulation experiments to evaluate the effectiveness and performance of different models. A simulation experiment is based on real data, which can simulate actual operations and predict future development trends. Through simulation experiments, we can compare the advantages and disadvantages of different models and select the optimal model for promotion and application.*

Keywords: Genetic Algorithm, Customer Value Model, Analysis

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1. Introduction

The genetic algorithm simulates the genetic process of adapting to the natural environment to survive in biological evolution [1]. The most representative results of the genetic algorithm are Darwin's evolutionism and Mendel's genetics. This algorithm provides an intelligent model for human work and life to find the internal law behind things [2]. The embryonic form of genetic algorithms is the study of natural and artificial adaptive systems proposed by Professor Holland in the 60s of last century. The United States pioneered the adaptive optimization genetic algorithm that can effectively solve complex systems and computing in the world [3]. After that, a large number of pure numerical optimization experiments were carried out by genetic algorithms. In the 80s of last century, the basic framework of the genetic algorithm was formed, which laid an important foundation for the subsequent genetic algorithm [4]. Compared with other artificial intelligence algorithms, the genetic algorithm has the advantage of autonomously organizing search after determining the parameters of a fixed coding scheme, fitness function and genetic operator. By selecting crossover, mutation and other operations, we can get a better sample of the next generation [5]. This algorithm effectively overcomes the problems of other algorithms; for example, when the search is limited by time and space, only the feasible solution space to select the initial point may fall into the local minimum and other issues. After introducing genetic factors, the genetic algorithm can search the overall situation so that the new population generation always maintains the optimal structure and finds the optimal solution. Therefore, this paper proposes a customer value model for new energy vehicles based on a genetic algorithm model.

2. State of the Art

Genetic algorithm has the characteristics of self-organization, self-adaptation and the ability to discover the laws and characteristics of the environment automatically. It is very suitable for continuous development and change [7]. The genetic algorithm adopts multi-iterations. According to the fitness value of individuals in different problem domains, this algorithm finds new approximate solutions through selection, crossover and optimization to simulate the evolution process of the population in a natural environment so that the new individual can better adapt to the environmental requirements than the old one [8]. Genetic factors can continuously improve the population and maintain a good structure for the next generation [9]. Genetic algorithms can respond to the change of data parameters, such as the number of customers. In the search for the best value customers, the local optimization problem can be effectively reduced. The biggest advantage of the genetic algorithm is the efficient implementation of the overall situation parallel search. In the search process, it can actively obtain and accumulate knowledge in the search space and adaptively control the search process to get the best solution [10]. Based on the genetic algorithm to study customer value, we can use a mathematical model and mathematical logic to help the value model change from experience-based qualitative analysis to the mathematical algorithm for quantitative analysis and let customer value model research to the direction of artificial intelligence.

The enterprises manage customer value mainly in this way: to get customers' basic information and data analysis according to customer orders and then to analyze customer feedback. Taking customer satisfaction and feedback issues as the guide, the enterprise can research and formulate measures to improve the main service and management issues. In customer management, the enterprises, through customer order, customer satisfaction, customer credit and other data, have evaluated the customer type, looking for the best customer. Currently, customer value management is mainly based on the analysis of customer parameters. However, under the background of increasing customer numbers and doubling parametric data, enterprises must establish an effective customer value model and find the best customers quickly. Based on the genetic algorithm to study customer value, this paper uses a genetic algorithm to search the advantages of the global optimal solution, to search the customer value database efficiently and quickly, and to help enterprises find the best value of customer types.

3. Methodology

3.1. Genetic Algorithm

The main theoretical basis of the genetic algorithm is to use a mathematical model to simulate the biological evolution process. We can use the cross and variation of chromosomes in biological evolution to achieve population evolution. The genetic algorithm takes the process of selecting the optimal solution into the biological evolution process. The sample population is used as the problem representation, and the genetic factor is introduced into the sample population. A new population generation is obtained after the selection, crossover, mutation, and other operations. Multiple iterations of the reciprocating search training are carried out to ensure the optimality of the population. Finally, the individual with the maximum fitness is chosen as the optimal solution. The genetic algorithm uses binary encoding. Generally, binary symbols with fixed lengths represent different population individuals, and their corresponding genes are also composed of symbol sets. The individual tree encoding of the genetic algorithm is shown in Figure 1.

The core operation of the genetic algorithm is selection, crossover and mutation operation. The choice of operation is to allow individuals with better adaptability to the living environment to be inherited into a new generation and take care of the excellence of the population. Crossover is analogous to gene recombination between chromosomes in biological evolution. The mutation operation avoids omitting information that may occur in selection and crossover. The basic operation steps of the genetic algorithm are shown in Figure 2.

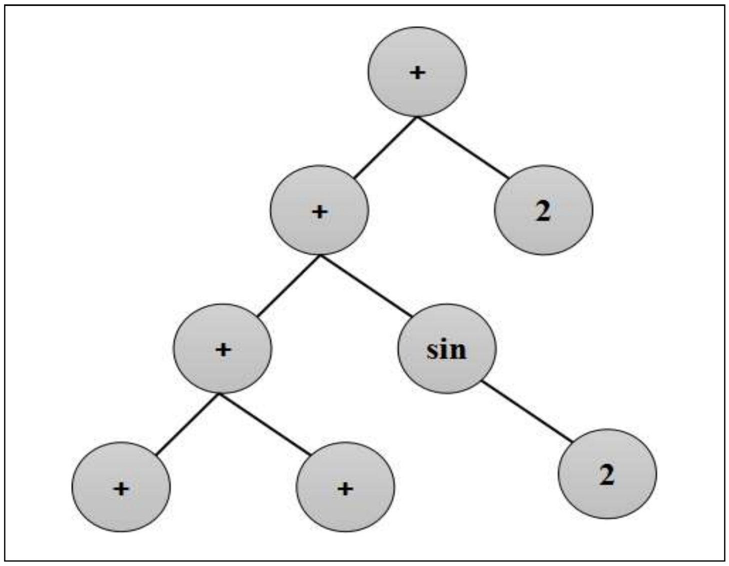


Figure 1. Individual Tree Structure Coding Graph of Genetic Algorithm

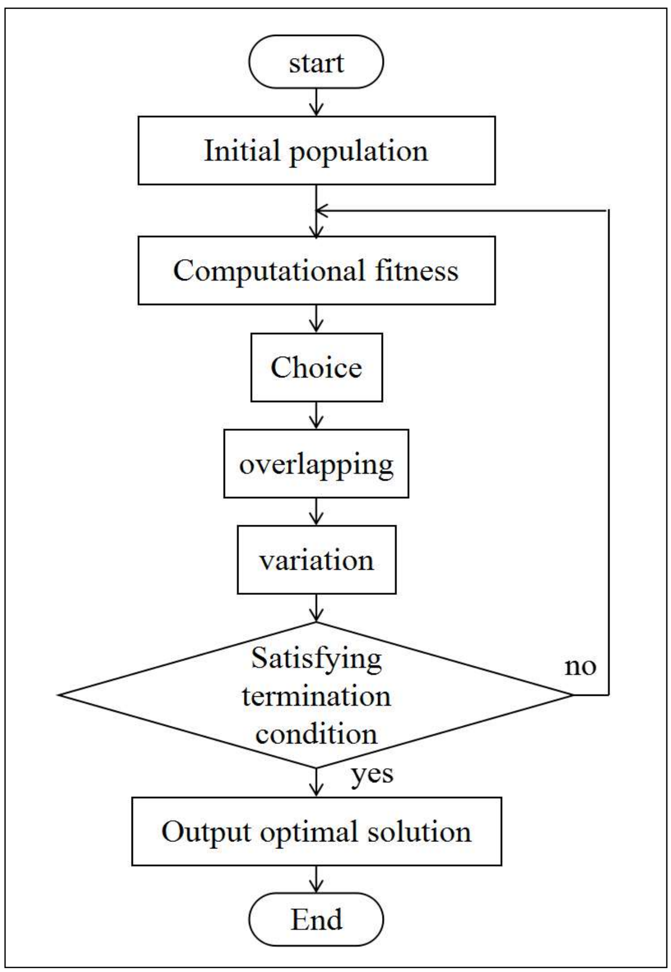


Figure 2. Operation diagram of genetic algorithm

In the selection of genetic algorithm, roulette is the main way, that is, through the proportion of choice. Cross operation crosses a single point and sets cross probability as a fixed value. The mutation operation is based on variation, and the crossover probability is also set as a fixed value. Before entering the genetic algorithm, the required parameters are set. Population size (*M*) represents the number of individuals, generally between 20-100. The iteration numerical range of termination of evolution in genetic operations is generally between 100-500. The crossover probability p_c is within the range of (0.4,0.9), and the variation probability is within (0,0.1). These four operating parameters will directly impact the final solution, the solution period and the efficiency of the genetic algorithm. The population size is *M*. The fitness value of individuals is f_1. And the probability of individual selection is calculated by the formula (1). The calculation process is firstly calculated for each individual fitness value f_1, $i = 1,2 , \dots , M$.

$$P_i = \frac{f_i}{\sum_{i=1}^{M} f_i} \tag{1}$$

The fitness of all individuals in a population is calculated by formula (2).

$$F = \sum_{i=1}^{M} f_i \tag{2}$$

The probability of individual selection is calculated by formula (3).

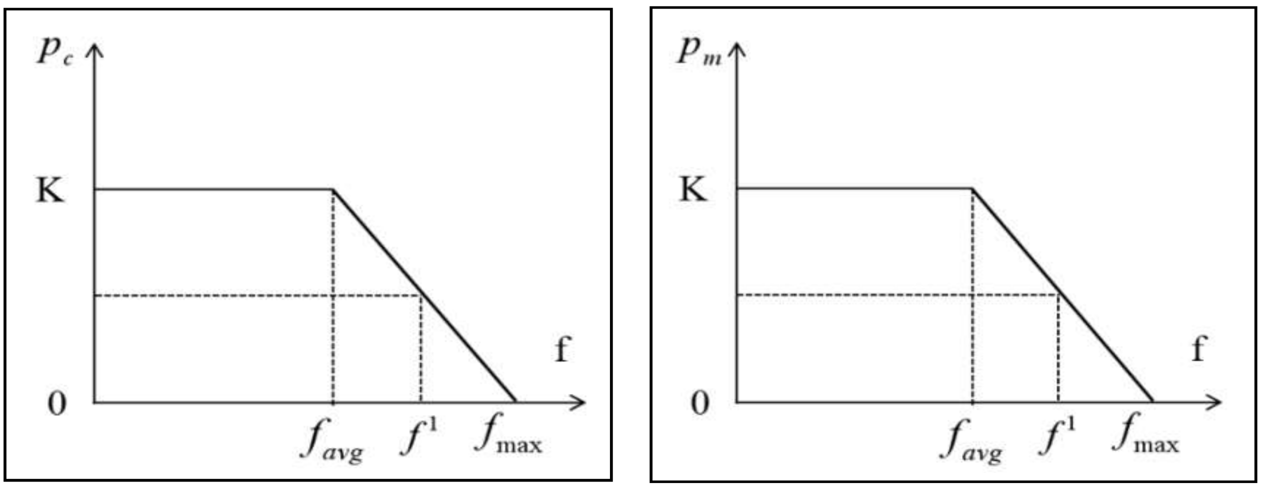
$$P_K = \frac{f_K}{\sum_{i=1}^{M} f_i}, K = 1, 2, L M \tag{3}$$

The above step is the runner method. Selection process is the process of selecting rotation *M* times. Each time a new individual is added to the new population by the following method. The pseudo-random number R is uniformly distributed in the interval [0,1]. When $r \le q_1$, selecting the first individual, otherwise selecting the *K* individual ($2 \le K \le M$), and letting the setting $q_{K-1} \le r \le q_K$ be established. In this way, the genetic operator is obtained after the selection process of *M* times. In the actual operation, it is necessary to set up the reasonable range and size of the parameters of the genetic algorithm through many experiments.

3.2. Improvement of Genetic Algorithm

The basic genetic algorithm adopts the method of fixed policy parameters, but the optimization result could be better. There is no way to solve the problem of change and dynamics of strategy parameters in genetic evolution, especially in the intersection probability, and mutation probability cannot be controlled. Therefore, the ordinary genetic algorithm cannot objectively reflect the individual evolution of the population in different periods of the state of change. This method ignores the evolutionary state of the population in the environmental change and ignores the adaptive characteristics of individual growth and genetic behaviour following change. It will cause the basic genetic algorithm parameters to remain unchanged, resulting in the performance and efficiency of the algorithm being low. After analyzing the principle, advantages and disadvantages of the basic genetic algorithm, we found that the performance of the genetic algorithm is greatly affected by parameters. If the parameters are fixed, then how to ensure the appropriateness of the choice is a major problem. If the parameter selection is inappropriate, the genetic algorithm will have different conclusions for different problems. In this context, an adaptive genetic algorithm (AGA) is proposed to solve the deficiency of the basic genetic algorithm.

The basic principle of adaptive genetic algorithm is that the adaptive degree of crossover probability p_c and mutation probability p_m can be dynamically changed. When the individual fitness of the population becomes consistent or the optimal state appears, increasing p_c and p_m. And when the fitness of population is not concentrated, reducing p_c and p_m . For those individuals whose fitness is better than the average fitness, the lower p_c and p_m, let the solution go into the next generation of sequences. If the fitness is less than the average fitness of individuals, the corresponding p_c and p_m is higher, directly eliminate the deletion of the individual. So the adaptive degree of cp_c and p_m here is the best states available for a particular solution of p_c and p_m. Thus, the adaptive heritage algorithm achieves global convergence on the basis of maintaining the diversity of the population. In Figure 3 (a) (b), the curve of crossover probability p_c and mutation probability p_m in adaptive genetic algorithm is expressed. The p_c and p_m in adaptive genetic algorithm is adjusted adaptively, and the formula is expressed as formula (4) and (5). In the formula, $f_{max} W$ represents the largest population fitness value; $f_{avg} W$ is evaluation of every population fitness value; $f_1 W$ is the larger fitness value of the two individuals to be crossed; f_W is a variation of the individual's fitness. Set the value k_1, k_2, k_3, k_4 between [0,1], so that p_c and p_m can be adjusted adaptively.



(a) (b)

Figure 3. Cross probability and variation probability curve

$$P_c = \begin{cases} \dfrac{k_1(f_{max} - f^1)}{f_{max} - f_{avg}} & f^1 \geq f_{avg} \\ k_2 & f^1 < f_{avg} \end{cases} \tag{4}$$

$$P_c = \begin{cases} \dfrac{k_3(f_{max} - f^1)}{f_{max} - f_{avg}} & f^1 \geq f_{avg} \\ k_4 & f^1 < f_{avg} \end{cases} \tag{5}$$

In the initial population selection, the genetic algorithm will randomly select the initial population of the object at the beginning, and the selection value is between 20 ~ 100. In constrained optimization issues, the initial population must ensure the feasibility of individuals based on diversity, randomicity and uniformity. It is difficult for the randomly selected population to reach the target under this requirement. Under the condition of many dimensions and many constraints, only applying the stochastic algorithm will prolong the selection time of the initial population, and directly affect the efficiency of the genetic algorithm. Therefore, this paper proposes two aspects to study the initial population. One is that the initial population is generated by the method of internal correction on the basis of the points in the feasible region. The two is to find an internal point by using scientific search methods when people cannot give an initial point. The search process for the initial population is shown in figure 4. Here $x_1^{(1)}$ is the interior point of the feasible domain, which is the initial point required to be taken. After the initial population searching for the first individual x_1, the subsequent individual $x_2 = [x_1, x_1, \ldots, x_n]$ was randomly generated. If x_2 is a viable individual, it continues to transmit the next individual x_3. If x_2 is not a viable individual, adjust it according to $x_2 \Leftarrow x_1 + \alpha\,(x_1 + x_2)$. The α here is the contraction factor, and the chosen value is between [0, 1]. When $\alpha = 5.0$, the new point can be positioned between x_1 and x_2 then, in the same way, you can find all the points in the initial population you need.

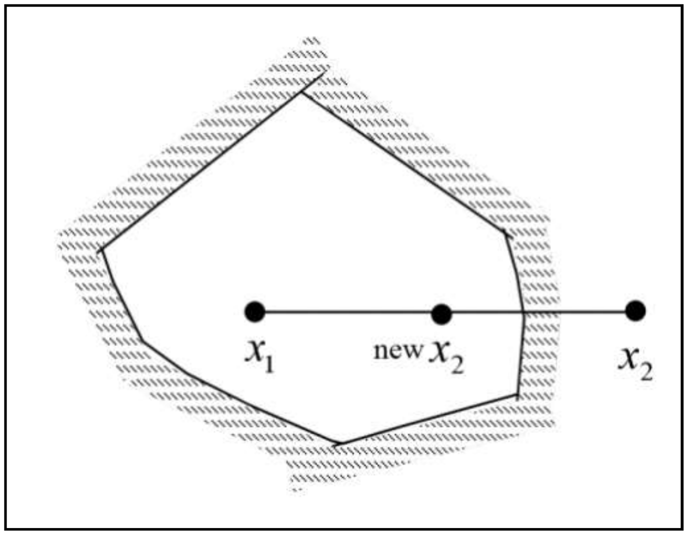


Figure 4. The relationship between the new individual and the original individual

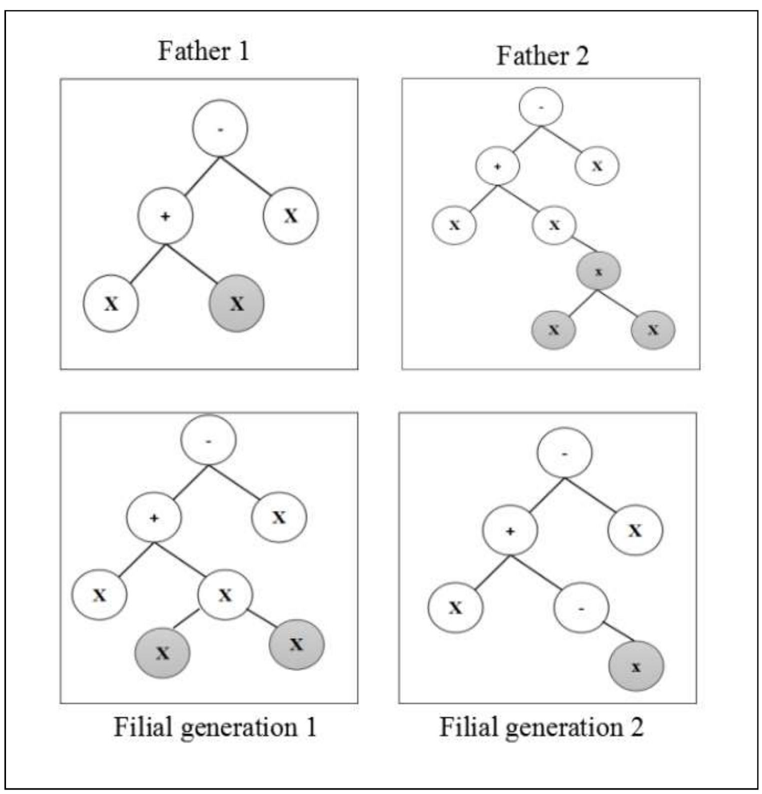


Figure 5. Schematic diagram of cross operator operation

The adaptive genetic algorithm can make the crossover probability and mutation probability of individuals change linearly with the average fitness and maximum fitness according to the fitness of individuals. This is a strategy to retain elite populations to ensure that each generation of elite individuals is not destroyed and copied to the next generation. This elitist strategy allows the best individuals in the current generation not to disrupt performance because of variations, crossover, and other operations. Cross operation is the core of the algorithm in genetic algorithm. Crossover operator is the crossover after selected two male parents in the current population randomly. How to choose the male parent is the key to genetic evolution. The representative strategies for selection of male parents are population improvement selection and competitive selection. In this paper, the competition selection method is adopted. We selected male parent with large fitting degree to do random crossover of the crossover probability. The operation principle of the crossover operator is shown in figure 5.

4. Result Analysis and Discussion

Now the enterprise management information system is popular, and the large automobile enterprises have established the customer information system. This has laid a good foundation for the establishment of customer value evaluation model by using the basic data of information system. Let the enterprises to quantitatively evaluate the value of the customer to the enterprise, allocate effective resources according to customer value, and achieve the goal of minimum cost and maximum profit. This paper proposes a customer value model based on genetic algorithm. On the basis of the above analysis and optimization of genetic algorithm, a new energy automobile enterprise M is selected to simulate the effect of genetic algorithm. Before the test starts, the first is to configure the parameters of the sample space. Then we use evaluation function to measure the possible combination of parameters in the parameter system. Finally, we use the genetic algorithm to select the optimal combination of parameters.

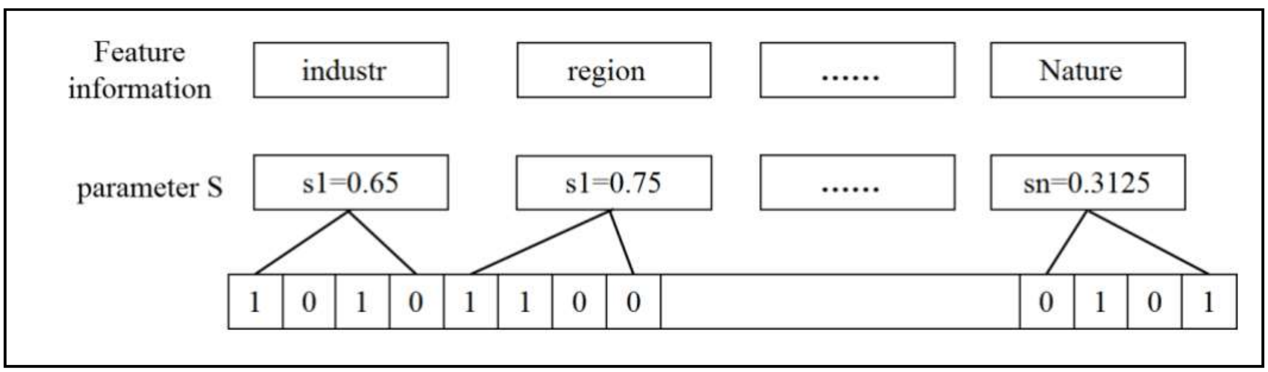


Figure 6. Method of parameter unit string representation

First of all, we need establish the customer value evaluation model. The parameters of a customer value model are the scoring criteria for all kinds of customer information. In this paper, the linear function model $V(C) = \sum_{i=1}^{n} W_i S_i$ is used as the customer evaluation model. C is the customer to be evaluated. V is the customer's value score. W_i is the corresponding weight of customer information. C is the customer's characteristic information value. And Si is the parameter we need to optimize, which is the score of each characteristic information of the customer. Here we use a set of parameters (S_1), ... S_i, ... S_n, to represent a group of candidate parameter combinations S. In order to facilitate the subsequent data processing, the model is normalized so that the values of S_i are real numbers between 0-1. In genetic algorithm, binary is used to represent parameter S. The length of the unit string is determined according to the accuracy of the model, so that the string corresponding to all the parameters represents the candidate parameter combination, that is, an individual in the genetic algorithm. Figure 6 is a representation of a unit string of parameters.

Then, each candidate parameter, in other word, the individual in the population, is evaluated. The standard of evaluation is calculated by fitness function, and then judged whether it can be selected into the next generation according to the result of calculation. According to the needs of customer value model, if the model is used to evaluate the quantitative value of the customer group, it is necessary to substitute the larger weight in the evaluation function. If it is used to predict the relative value between the individual customers, a smaller weight value should be used. The simulation experiment of the value model with 50 parameters is carried out in this paper. The ideal parameters are set, and the simulated customer samples are generated according to the set of ideal parameters. Then the genetic algorithm is used to optimize the sample data and compare with the pre-set ideal parameters to verify the effectiveness of the algorithm proposed in this paper. In this experiment, the population is 100. The number of parameters is 50. The length of the string is 8. The mutation probability is 0.4. The crossover probability is 0.3. The weight is 0.5. And the sample number of customers is 100000. Some of the data generated in the experiment is shown in Table 1.

Generation	Evaluation error of optimal solution and ideal value	Evaluation variance of optimal solution and ideal value
0	0.237801	0.304212
60	0.064619	0.079817
100	0.031789	0.037737
160	0.013713	0.017816
200	0.008341	0.011675

Table 1. Optimal Solution Error

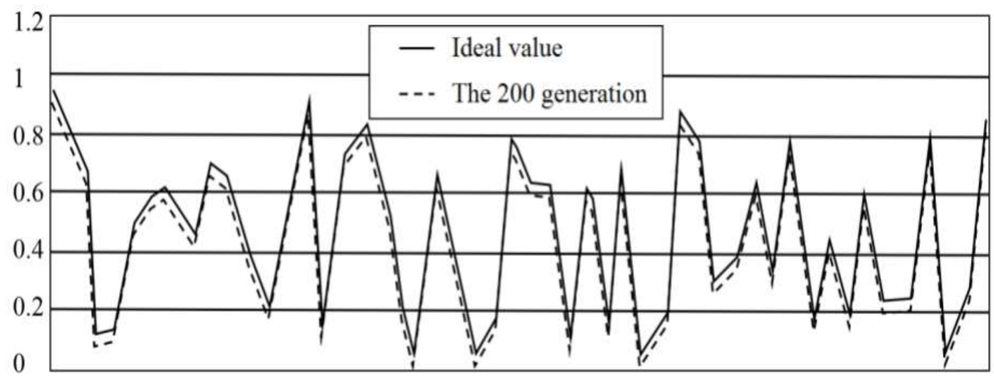


Figure 7. The optimal solution of the 200 generation of evolution

It can be seen from the table that the 200th iterations are in good agreement with the ideal parameters. This can also be seen from the optimal solution graph of the 200 iterations of evolution. As shown in Figure 7, the genetic algorithm can achieve rapid convergence and find the best combination of parameters with high degree of fit of ideal parameters, that is to say, the customer value model achieves the search for the best customers.

5. Conclusion

The genetic algorithm mainly studies the biological evolution and genetic advantage, which can help people find the best solution to solve the problem, and give the best prediction, made a positive contribution to the development and progress of society. Although the genetic algorithm has some shortcomings, such as falling into local minimum, but the improved algorithm has achieved remarkable results. Therefore, this paper proposes to optimize the genetic algorithm model, and applies it to the research of customer value model of new energy automotive enterprises. After analyzing the traditional genetic algorithm's operation process and model structure, we propose optimization and improvement of the algorithm and obtain the new formula of crossover probability and mutation probability in the adaptive state. Then, the improved genetic algorithm mathematical model is applied to the customer value evaluation of '*M*' new energy automobile enterprise. By establishing the data model and selecting samples, we use the improved genetic algorithm to design the customer model, testing and comparing the data under different iterations of the genetic algorithm. From the test results, we can see that the precision and accuracy of the customer value model based on the improved genetic algorithm have been improved, proving that the research is successful Of course. The results of the study also show that the system still has room for improvement, so as further improving data encoding genetic algorithm is one of the directions of future research.

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References

[1] Sudira, I. G. N., Hadi, B. K., Moelyadi, M. A., et al. (2016). Application of Genetic Algorithm for the Design Optimization of Geodesic Beam Structure. *Applied Mechanics & Materials, 842*, 266-272.

[2] Xiao, H., Xu, Z. Z., Kim, L. S., et al. (2015). Optimization scheme of genetic algorithm and its application on aeroengine fault diagnosis. *International Journal of Precision Engineering* and *Manufacturing, 16*(4), 735-741.

[3] Corso, L. L., Gasparin, A. L., Martins Gomes, H. (2016). Reliability based design optimization using a genetic algorithm: application to bonded thin films areas of copper/polypropylene. *Ingeniare Revista Chilena De Ingeniería, 24*(3), 510-519.

[4] Schoonover, P. L., Crossley, W. A., Heister, S. D. (2015). Application of a Genetic Algorithm to the Optimization of Hybrid Rockets. *Journal of Spacecraft* and *Rockets, 37*(5), 622-629.

[5] Manu, V. S., Veglia, G. (2016). Optimization of identity operation in NMR spectroscopy via genetic algorithm: Application to the TEDOR experiment. *Journal of Magnetic Resonance, 273*, 40.

[6] Babatunde, O., Armstrong, L., Diepeenveen, D., et al. (2015). Comparative analysis of Genetic Algorithm and Particle Swarm Optimization: An application in precision agriculture. *International Journal of Agricultural Sustainability, 12*(1), 71-88.

[7] Adams, L. J., Bello, G., Dumancas, G. G. (2015). Development and Application of a Genetic Algorithm for Variable Optimization and Predictive Modeling of Five-Year Mortality Using Questionnaire Data. *Bioinformatics* and *Biology Insights, 9*(Suppl 3), 31-41.

[8] Davis, J. B. A., Horswell, S. L., Johnston, R. L. (2016). Application of a Parallel Genetic Algorithm to the Global Optimization of Gas-Phase and Supported Gold–Iridium Sub-Nanoalloys. *Journal of Physical Chemistry C, 120*(7), 224-238.

[9] Jiang, P., Li, X., Dong, Y. (2015). Research and Application of a New Hybrid Forecasting Model Based on Genetic Algorithm Optimization: A Case Study of Shandong Wind Farm in China. *Mathematical Problems in Engineering, (2015-1-8), 2015, 215*, 1-14.

[10] Lim, T. Y., Al-Betar, M. A., Khader, A. T. (2015). Adaptive pair bonds in genetic algorithm: An application to real-parameter optimization. *Applied Mathematics* and *Computation, 252*(C), 503-519.