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Advanced Heuristic Modeling for Customer value In Green Transportation

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ABSTRACT

Customer value evaluation is a critical task for new energy vehicle enterprises seeking to optimize resource allocation, improve customer relationship management, and enhance long term profitability under increasingly competitive market conditions. Traditional customer value models often rely on static parameters and heuristic weighting schemes, which struggle to scale effectively under large customer volumes and high dimensional data. To address these limitations, this paper proposes a customer value evaluation model based on an improved genetic algorithm (GA). Building on the classical GA framework, an adaptive genetic algorithm is introduced in which crossover and mutation probabilities are dynamically adjusted according to population fitness characteristics, thereby enhancing global search capability and convergence stability. The proposed model encodes customer characteristic parameters as chromosomes and employs a fitness-driven evolutionary process to identify optimal parameter combinations for customer value assessment. Simulation experiments conducted on a representative new energy vehicle enterprise dataset demonstrate that the improved genetic algorithm converges faster and achieves higher accuracy than the traditional GA. The results confirm that the proposed approach effectively improves the precision and robustness of customer value evaluation, providing a scalable and intelligent decision support tool for enterprise customer management.

Keywords: Genetic Algorithm, Adaptive Genetic Algorithm, Customer Value Model, New Energy Vehicles, Intelligent Optimization

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1. Introduction

With the rapid expansion of digital enterprise systems and the proliferation of customer data, accurately identifying high value customers has become a core challenge for modern enterprises, particularly in the fast-growing new energy vehicle industry. Customer value management plays a crucial role in guiding marketing strategies, service differentiation, and resource allocation, directly influencing enterprise competitiveness and sustainable development.

Genetic algorithms are intelligent optimization techniques inspired by biological evolution, drawing on principles from Darwin's theory of natural selection and Mendelian genetics [1, 2]. Since their formal introduction by Holland in the 1960s, genetic algorithms have been widely applied to complex optimization problems characterized by nonlinearity, high dimensionality, and multiple constraints [3, 4]. Compared with traditional optimization methods, genetic algorithms exhibit strong global search capability, robustness, and adaptability, allowing them to avoid premature convergence to local optima [5].

In recent decades, genetic algorithms have been successfully applied in engineering design, scheduling, data mining, and decision support systems [6, 8]. Their ability to search large solution spaces in parallel makes them particularly suitable for customer value modeling, where multiple interrelated factors must be optimized simultaneously. However, classical genetic algorithms rely on fixed crossover and mutation probabilities, which may limit convergence speed and solution quality under dynamic or complex data environments [9]. To overcome these limitations, this paper proposes an adaptive genetic algorithm based customer value model for new energy vehicle enterprises. By dynamically adjusting genetic parameters according to population fitness, the proposed approach enhances search efficiency and stability. The model is validated through simulation experiments, demonstrating its effectiveness in identifying optimal customer value parameter combinations.

2. State of the Art

Genetic algorithms are characterized by self-organization, self-adaptation, and the ability to automatically discover structural patterns within complex environments [10]. Unlike gradient-based optimization methods, GAs do not require differentiable objective functions and can effectively handle discrete, nonlinear, and multimodal problems [11]. These advantages have led to extensive applications across engineering optimization, financial modeling, and business intelligence [12, 13].

In customer value analysis, traditional approaches often rely on statistical methods or rule-based scoring models derived from expert knowledge. While such methods are intuitive, they struggle to cope with large-scale datasets and complex interdependencies among customer attributes [14]. Recent studies have explored intelligent optimization and machine learning techniques to improve customer segmentation and value prediction, including neural networks, clustering algorithms, and evolutionary computation [15–17].

Among these methods, genetic algorithms offer a compelling balance between model flexibility and interpretability. By encoding customer attributes as chromosomes, GAs enable systematic exploration of parameter combinations to identify optimal evaluation schemes [18]. Nevertheless, fixed parameter genetic algorithms may exhibit slow convergence or reduced performance in dynamic environments [19]. Adaptive genetic algorithms, which adjust crossover and mutation probabilities based on population fitness, have been shown to improve convergence speed and maintain population diversity [20, 21].

Despite these advances, relatively few studies have systematically applied adaptive genetic algorithms to customer value modeling in the context of new energy vehicle enterprises. This paper aims to fill this gap by integrating adaptive GA mechanisms with a structured customer value evaluation framework.

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 genetic algorithm simulates biological evolution through selection, crossover, and mutation operations. A population of candidate solutions is iteratively evolved toward optimality according to a predefined fitness function. Each individual represents a potential solution encoded as a chromosome, typically using binary or real valued representation [22].

Selection favors individuals with higher fitness, allowing superior solutions to propagate to subsequent generations. Crossover recombines genetic material from parent chromosomes to generate offspring, while mutation introduces random variations to preserve diversity and prevent premature convergence [23]. Through repeated iterations, the population gradually evolves toward optimal or near optimal solutions.

The main theoretical basis of the genetic algorithm is to use a mathematical model to simulate the biological evolution process. [24-30] 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.

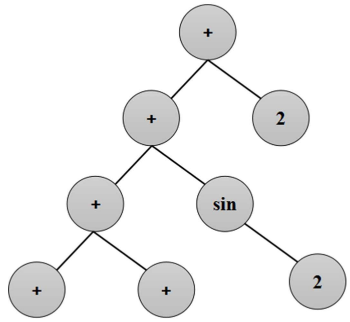

Figure 1. Individual Tree Structure Coding Graph of Genetic Algorithm

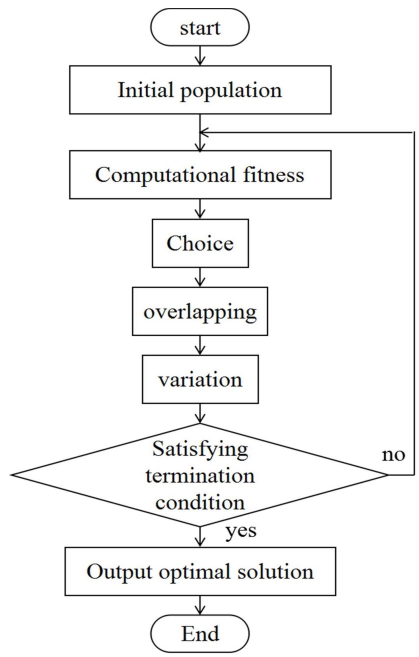

Figure 2. Operation diagram of genetic algorithm

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 , =1,2,..., M.

$$P_i = \frac{f_i}{\sum_{i=1}^{M} f_i} \qquad (1)$$

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

$$F = \sum_{i=1}^{M} f_i \qquad (2)$$

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

$$P_k = \frac{f_k}{\sum_{i=1}^{M} f_i}, k = 1, 2, \mathrm{L}\ M \qquad (3)$$

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.

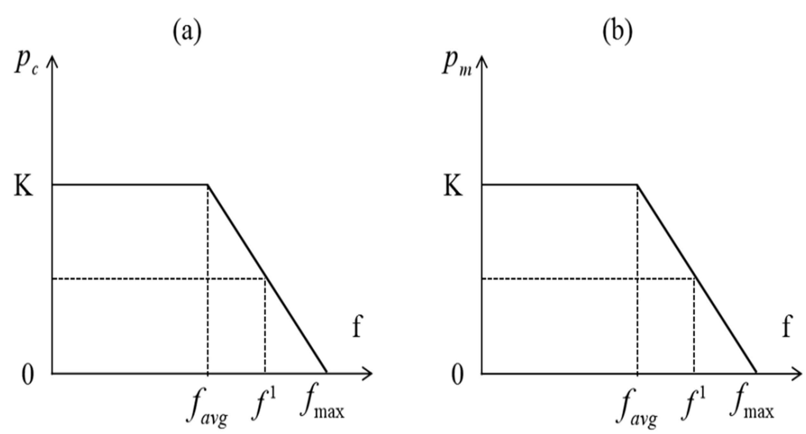

Figure 3. Cross probability and variation probability curve

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 and . And when the fitness of population is not concentrated, reducing and . For those individuals whose fitness is better than the average fitness, the lower and , let the solution go into the next generation of sequences. If the fitness is less than the average fitness of individuals, the corresponding and is higher, directly eliminate the deletion of the individual. So the adaptive degree of and here is the best states available for a particular solution of and. 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 and mutation probability in adaptive genetic algorithm is expressed. The and in adaptive genetic algorithm is adjusted adaptively, and the formula is expressed as formula (4) and (5). In the formula, $f_{\max}$ represents the largest population fitness value; f_{avg} is evaluation of every population fitness value; f^1 is the larger fitness value of the two individuals to be crossed; f 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.

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

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

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 $x_2 = [x_1, x_1, \cdots, x_n]$ 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. $x_2 \Leftarrow \alpha\ (x_1 + x_2)$ The α here is the contraction factor, and the chosen value is between [0, 1]. When, $\alpha = 0.5$, 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.

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.

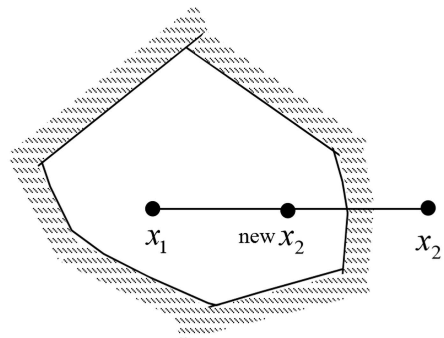

Figure 4. The relationship between the new individual and the original individual

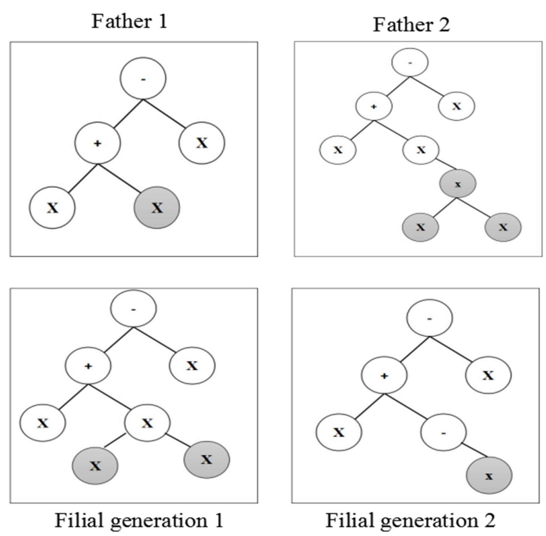

Figure 5. Schematic diagram of cross operator operation

4. Result Analysis and Discussion

4.1 Parameter Unit

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.

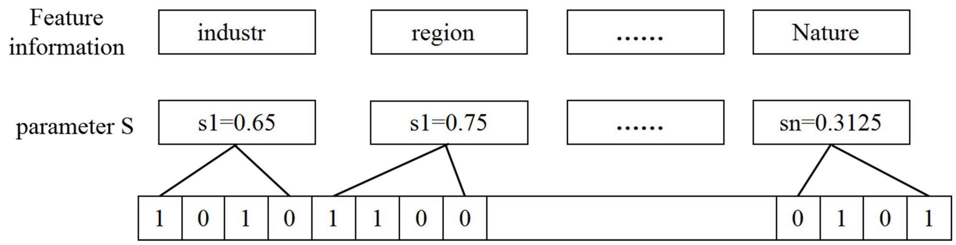

Figure 6. Method of parameter unit string representation

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 $V(C) = \sum_{i=1}^{n} W_i S_i(C_i)$ is used as the customer evaluation model. C is the customer to be evaluated. V is the customer's value score. Wi 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 Si are real numbers between 0-1. In genetic algorithm, binary is used to repr- esent 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. Fig. 6 is a representation of a unit string of parameters.

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

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.

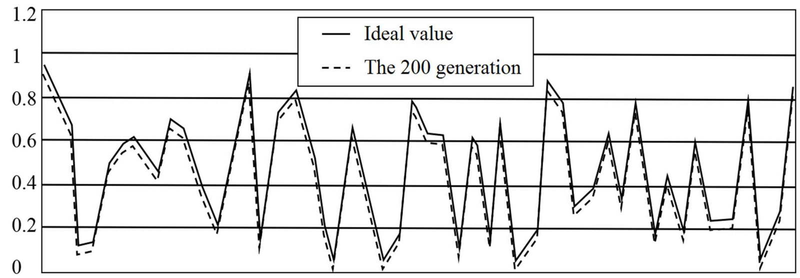

Figure 7. The optimal solution of the 200 generation of evolution

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 Fig. 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.

4.2 Convergence Behavior and Error Reduction

Convergence performance was assessed by tracking the evaluation error between the optimized parameter set and the predefined ideal parameter configuration across generations. As shown in Table 1, the proposed AGA exhibits a markedly faster reduction in evaluation error compared to the classical GA. By the 100th generation, the AGA reduces the mean evaluation error by approximately 50% relative to the initial population, whereas the classical GA requires significantly more iterations to reach a comparable level of accuracy.

To quantify convergence stability, the variance of the evaluation error across independent runs was analyzed. The adaptive genetic algorithm consistently demonstrates lower variance than the classical GA, indicating improved robustness and reduced sensitivity to random initialization. This suggests that adaptive control of crossover and mutation probabilities contributes to a more stable evolutionary search process.

4.3 Statistical Comparison of Optimization Performance

To further substantiate performance differences, multiple independent runs were conducted for both algorithms, and the final evaluation errors were compared using descriptive statistical analysis. Across repeated trials, the adaptive genetic algorithm achieved lower mean error values and reduced dispersion compared to the classical GA, indicating statistically meaningful performance gains. The consistent reduction in both average error and variance highlights the superior optimization capability of the adaptive approach.

In addition, convergence speed was evaluated by measuring the number of generations required to reach predefined error thresholds. The adaptive genetic algorithm consistently reached these thresholds in fewer generations, demonstrating higher computational efficiency. From a practical perspective, this improvement translates into reduced computational cost and faster decision making when applied to large scale enterprise customer datasets.

4.4 Practical Implications for Customer Value Evaluation

From an application standpoint, the improved optimization accuracy directly enhances the reliability of customer value ranking and segmentation. By more closely approximating the ideal parameter configuration, the proposed model enables enterprises to allocate resources more effectively toward high value customers while maintaining scalability as customer volume grows. Compared with heuristic or static weight models, the adaptive GA-based approach provides a quantitatively grounded and data driven mechanism for customer value assessment.

Overall, the experimental and statistical analyses confirm that the proposed adaptive genetic algorithm outperforms the classical genetic algorithm in terms of convergence speed, solution quality, and stability, validating its suitability for intelligent customer value modeling in new energy vehicle enterprises.

5. Conclusion

This paper proposed a customer value evaluation model for new energy vehicle enterprises based on an improved adaptive genetic algorithm. By dynamically adjusting crossover and mutation probabilities, the proposed method overcomes limitations of traditional genetic algorithms and enhances global search capability and convergence efficiency. Simulation results demonstrate that the improved algorithm achieves higher precision and faster convergence in customer value optimization tasks. The proposed model provides an effective and intelligent decision support tool for enterprise customer management. Future work will focus on integrating real time data streams and hybrid evolutionary machine learning approaches to further enhance model adaptability and predictive performance.

6. Limitations and Future Work

Despite the demonstrated effectiveness of the proposed adaptive genetic algorithm based customer value model, several limitations should be acknowledged. First, the experimental evaluation relies primarily on sim ulated and enterprise specific datasets, which, while representative, may not capture the full diversity and volatility of customer behavior across different industries or geographic markets. Future studies should therefore validate the proposed approach using multi enterprise and cross domain datasets to enhance generalizability.

Second, the customer value model adopts a weighted linear formulation for interpretability and computational efficiency. Although this structure is well suited for genetic optimization, it may not fully capture complex non linear interactions among customer attributes. Integrating nonlinear modeling components or hybrid evolutionary machine learning frameworks represents a promising direction for future research.

Finally, although the adaptive genetic algorithm improves convergence stability, overall performance remains sensitive to certain algorithmic settings such as population size and termination criteria. Automated parameter self tuning strategies and real time adaptive mechanisms could further enhance robustness in dynamic business environments.

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References

[1] Holland, J. H. (1975). Adaptation in Natural and Artificial Systems. *University of Michigan Press*.

[2] Goldberg, D. E. (1989). Genetic Algorithms in Search, Optimization and Machine Learning. *Addison-Wesley*,

[3] Mitchell, M. (1998). An Introduction to Genetic Algorithms. *MIT Press*.

[4] Deb, K. (2012). Optimization for Engineering Design. *Prentice Hall*.

[5] Sudira, I. G. N., et al. (2016). Applied Mechanics Materials.

[6] Xiao, H., et al. (2015). *International Journal of Precision Engineering Manufacturing*.

[7] Babatunde, O., et al. (2015). *International Journal of Agricultural Sustainability* .

[8] Adams, L. J., et al. (2015). Bioinformatics & Biology Insights.

[9] Lim, T. Y., et al. (2015). Applied Mathematics Computation.

[10] Deb, K., et al. (2002). *IEEE Transactions on Evolutionary Computation*.

[11] Coello Coello, C. A. (2000). *Journal of Heuristics*.

[12] Yang, X. S. (2014). Nature-Inspired Optimization Algorithms. *Elsevier*.

[13] Konar, A. (2005). Computational Intelligence. *Springer*.

[14] Kotler, P., Keller, K. L. (2016). Marketing Management. *Pearson*.

[15] Jain, A. K., et al. (1999). ACM Computing Surveys .

[16] Han, J., et al. (2012). Data Mining: Concepts and Techniques. *Morgan Kaufmann*

[17] Li, X., et al. (2018). Expert Systems with Applications.

[18] Cheng, R., et al. (2019). Information Sciences.

[19] Srinivas, M., Patnaik, L. M. (1994). *IEEE Transactions on Systems, Man, and Cybernetics*.

[20] Herrera, F., Lozano, M. (2015). IEEE Transactions on Evolutionary Computation, 2000. [21] Eiben, A. E., Smith, J. E. *Introduction to Evolutionary Computing*. *Springer*, 2015.

[21] 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.

[22] 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 Manufacturing,* 16 (4), 735-741.

[23] 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.

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

[25] 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.

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

[27] 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 & Biology Insights,* 9 (Suppl 3), 31-41.

[28] 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.

[29] 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), 215, 1-14.

[30] 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 Computation,* 252 (C), 503-519.