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Retraction

Retracted: Optimization Calculation Method and Mathematical Modeling of Big Data Chaotic Model Based on Improved Genetic Algorithm

Journal of Function Spaces

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Z. Zhang and Y. Zhang, "Optimization Calculation Method and Mathematical Modeling of Big Data Chaotic Model Based on Improved Genetic Algorithm," *Journal of Function Spaces*, vol. 2022, Article ID 6983242, 9 pages, 2022.

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Research Article

Optimization Calculation Method and Mathematical Modeling of Big Data Chaotic Model Based on Improved Genetic Algorithm

Zhicheng Zhang [1] and Yan Zhang [2]

[1]*School of Science, Henan Institute of Technology, Xinxiang, Henan 453003, China*
[2]*College of Computer and Information Engineering, Henan Normal University, Xinxiang, Henan 453007, China*

Correspondence should be addressed to Zhicheng Zhang; zhangzc@hait.edu.cn

In order to find a chaotic trajectory sequence with strong global optimization ability to help the genetic selection of direction after the reversal of chemotaxis, an improved genetic algorithm based on chaos optimization is proposed by combining the characteristics of chaotic motion with the improved genetic algorithm. The optimal coverage problem in sensor networks can carry out fine optimization search on local areas. The results show that the overall trend of fitness and optimization efficiency is relatively stable. The optimization efficiency will be gradually improved with the continuous progress of time and genetics, and the error analysis will be reduced. This will greatly improve the impact of various adverse factors in the optimization process. In addition, the change rate of fitness is basically kept at a high change rate, which also reflects that the basic framework of the model is very excellent, and the whole algorithm structure and data processing are improved by 54%. The improved genetic algorithm proposed in this paper is used to adjust and optimize the controller parameters. When the uncertain parameters change greatly, the control system still has good control quality and strong robustness.

1. Introduction

For big data, efficient optimization calculation process is very important. The optimization process cannot be represented by any mathematical conditions [1]. With the development of computer technology, information technology, and system engineering technology, optimization technology has become an important branch of engineering and an important subject in applied mathematics [2]. Training data with sufficient data, proper distribution, and excellent performance is the premise for the above methods to successfully optimize fuzzy controllers, but the main training data are not always available [3]. Considering that the GA is suitable for multiparameter optimization, it does not need to know the local information of the object to be optimized, nor does it need good training data, but in practical control problems, uncertainty is ubiquitous [4]. The uncertainty may come from the modeling error of the described control object, or from the disturbance signal of the control system itself and the outside [5]. GA is a kind of global optimal probability search method, which is based on the evolutionary law of biology and evolved from the genetic mechanism of survival of the fittest.

The basic idea of GA starts from a population that represents the possible potential solutions of the problem, and a population is composed of a certain number of individuals encoded by genes, and each individual is actually an entity with characteristics of chromosomes [6]. Then, the genetic evolution process of these groups is simulated, and the evolution direction of the algorithm is known by the fitness value of the individual [7]. Although this method has solved the above problems well, the interpretability of the system is still not guaranteed [8]. The reason is that the goal of these algorithms is to obtain the optimal system response performance, but there is no effective guidance for the number of fuzzy set partitions and the selection of membership function parameters [9]. No matter which field the optimization technology is applied to, the optimization problem to be solved can generally be described in mathematical language, that is, to establish the corresponding mathematical model

[10]. Linear programming is one of the important fields in optimization problems. The linear optimization algorithm is applied to the optimal power flow problem of the power system. Usually, the whole problem is decomposed into two suboptimization problems of the active part and the reactive part and then iteratively solves them alternately or solves them separately. One of the more popular methods is the fusion of fuzzy logic and GA, resulting in genetic fuzzy algorithm.

Conventional genetic fuzzy system is to add a learning process based on evolutionary computation to a fuzzy system, and this evolutionary computation can be GA, genetic programming, or other evolutionary algorithms, and the system formed by it is called genetic optimization system [11]. This adaptive optimization controller is based on the conventional optimization controller, uses the neural network model to approach the actual controlled object, and uses the GA to continuously optimize the control rules of the controller online, even if these rules can keep up with changes. It can improve the control ability and control efficiency of the optimized controller [12]. Traditional GAs usually use time domain index, frequency domain index, error integral index, and their combination as the objective function. The optimization model is based on the design of nominal controlled object and does not consider the reality of parameter uncertainty of controlled object. Therefore, it is often difficult for the system to meet the requirements when the parameters of controlled object change [13]. In this paper, an optimization calculation method of big data chaotic model based on improved GA is proposed. The experimental results are analyzed and processed. After genetic operation of the original parameters, the error and performance indices of the parameters are set as important parameters, and the minimum objective function is introduced. After screening, the range data is obtained, and then, the optimal index and fitness function are calculated.

The innovative contribution of this paper is that the improved genetic algorithm is proposed to adjust and optimize the controller parameters. When the uncertain parameters change greatly, the control system still has good control quality and strong robustness. In addition, the algorithm does not destroy the structure and essence of traditional genetic algorithm, so it inherits the advantages of genetic algorithm and takes into account the advantages of random algorithm. In the improved genetic algorithm, the individuals in the new generation population only calculate the individuals involved in crossover and mutation operations, which shortens the calculation time to a certain extent. A chaotic trajectory sequence with strong global optimization ability is found to help reverse chemotaxis after genetic selection.

The research is divided into four sections. The first section describes the learning process of traditional genetic fuzzy system calculation and the fusion background of fuzzy logic and genetic algorithm. Section 2 describes the materials and methods. The analysis and research contents of genetic algorithm are improved. The chaos model based on big data is analyzed. The general analysis and mathematical modeling of the design are optimized. In the mechanism part of

optimization design, the establishment of mathematical model and the application of simulation algorithm are analyzed. The results are analyzed and discussed in Section 3. Finally, the full text is summarized. The results show that in the improved genetic algorithm, the individuals in the new generation population only calculate the individuals involved in crossover and mutation operations, which shortens the calculation time to a certain extent.

2. Materials and Methods

2.1. Analysis and Research of Improved GA. GA is a computational model that simulates the natural selection and population genetic mechanism of biological evolution [14]. Genetic operation in GA is based on coding mechanism. Coding has a great impact on the performance of the algorithm, such as search ability and population diversity. As a new global optimization algorithm, it has almost no restrictions on the optimization problems to be solved and does not need to involve the complex and cumbersome mathematical solution process like the conventional optimization algorithm [15]. According to different examples, it is only necessary to properly adjust the operator parameters and make minor modifications to adapt to new problems, and the program can be universal. The mapping system is very sensitive to the initial values and parameters, and the subtle differences between the initial values and parameters may make the final chaotic random sequences very different. The distribution diagram of the trajectory sequence generated by studying the trajectory of the chaotic motion is visually represented, and the random sequence of chaos is added at the beginning of the inheritance, which improves the search diversity of the genetic iteration and the ability to optimize the global region. GA does not require continuous variables, which is also convenient for dealing with discrete variables. At the same time, it can introduce various constraints, generate new solutions by random search, eliminate solutions with poor performance, avoid local optimal solutions by mutation, and search the global solution space to achieve global optimization or approximate global optimization. Figure 1 is the basic operation flow chart of GA.

To some extent, the quality of fitness function determines the search range and global optimization ability of GA. The traditional GA takes a single objective function as the fitness function, so it is not comprehensive enough to consider the problem, and sometimes, it is impossible to find the optimal solution [16]. Generally, GA basically includes four main operations: chromosome encoding, population setting, calculation of fitness function value, and genetic operation. The quality of the coding method is very important to the GA. A good coding method may make the genetic operations such as crossover operation and mutation operation simply run [17]. A poor coding method may make genetic operation difficult to achieve. Therefore, this paper believes that the coding method largely determines how to carry out the genetic evolution operation of the population and its optimization efficiency [18]. Assuming that the value range of a parameter is $[U_{min}, U_{max}]$ and the parameter is
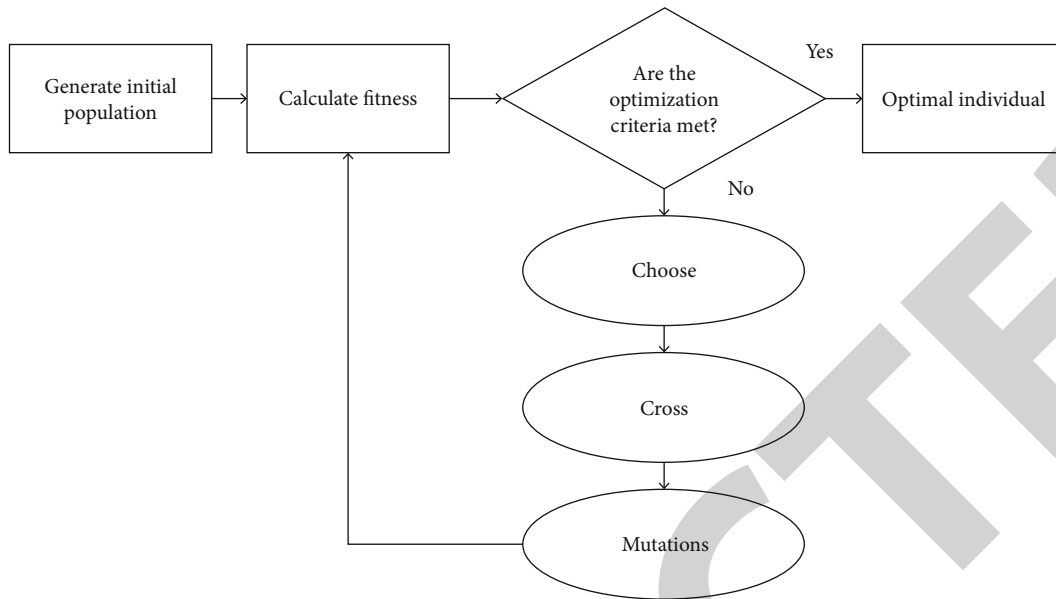
Figure 1: The basic operation flow chart of the GA.

represented by a string of binary coded symbols with length l, the coding accuracy of binary coding is as follows:

$$\delta = \frac{U_{\max} - U_{\min}}{2^l - 1}. \tag{1}$$

Assuming that the code of an individual is $X : b_l b_{l-1} \cdots b_2 b_1$, the corresponding decoding formula is

$$x = U_{\min} + \left(\sum_{l=1}^{l} b_l \bullet 2^{l-1} \right) \bullet \frac{U_{\max} - U_{\min}}{2^l - 1}. \tag{2}$$

The main processing data are shown in Table 1.

At present, there are usually two methods to generate the initial population. One is generated according to the completely random method, which is applicable to the case where there is no prior knowledge of the solution of the problem [19]. Another method is to transform some prior knowledge into a set of requirements that must be met and then randomly select samples from the solutions that meet these requirements. By selecting the initial population, the GA can avoid premature convergence and find the optimal solution faster.

Since the GA basically does not participate in the analysis of external information, when the fitness function is used as the judgment basis, the required value is nonnegative [20]. Therefore, the objective function to be solved is directly converted into a fitness function:

$$\mathrm{Fit}(f(x)) = f(x). \tag{3}$$

Maximum value when the objective function is negative:

$$\mathrm{Fit}(f(x)) = -f(x). \tag{4}$$

Minimum value when the objective function is negative:

$$\mathrm{Fit}(f(x)) = \begin{cases} f(x) - c_{\min}, f(x) > c_{\min}, \\ 0. \end{cases} \tag{5}$$

$c_{\max}, c_{\min}$ in the above formula is the maximum and minimum estimates of $f(x)$, respectively.

2.2. Chaos Model Based on Big Data. The calculation of this parameter is an important step to extract its chaotic characteristics. Differential action reflects the rate of change of the system deviation signal and has predictability, which can predict the trend of deviation change, so it has a superprevious control effect. It can reflect the change rate of system deviation signal through differential action, which is predictive, can predict the trend of deviation change, and can carry out advance control and improve the dynamic performance of the system. It can reduce overshoot and adjustment time. The Lyapunov exponent can describe the chaotic intensity of big data, which has various description forms [21]. This paper adopts the following description form: set β_{n1}, β_{n2} as two points close to the limit in space, and then, its distance is expressed as $\beta_{n1} - \beta_{n2} = \delta \leq 1$. After Δn time, the trajectory of the two points can be expressed as $\delta_{\Delta n} = \beta_{n1+\Delta n} - \beta_{n2+\Delta n}$ [22]. Then, the maximum Lyapunov exponent can be described as

$$\delta_{\Delta n} = \delta_{0e}^{\lambda \Delta n}. \tag{6}$$

If λ is set to a positive number, then the parameters between the ringing tracks are separated, which means chaos. However, because the two tracks are generally close to each other, the above formula is only valid when the distance value is relatively small. If the distance is large, the separation of the tracks will be greatly reduced [23].

TABLE 1: Computational comparison of main models.

Model	Improved GA model	Big data chaotic model	Optimization model
Objective function 1	0.021	0.012	0.047
Objective function 2	0.024	0.032	0.365
Objective function 3	0.024	0.014	0.235
Objective function 4	0.025	0.045	0.333
Objective function 5	0.036	0.022	0.452
Objective function 6	0.022	0.036	0.324

Therefore, the GA is improved on this basis, and the flow chart of the improved GA as shown in Figure 2 is obtained.

2.3. General Analysis and Mathematical Modeling of Optimization Design

2.3.1. Mechanism and Analysis of Optimization Design. This paper designs the optimization calculation model under the framework of big data chaos model. For the traditional deterministic system, the inertial motion produced by it will show some observable characteristics and eventually return to static. When the external system is excited by a deterministic rule, the response of the system fed back to the outside world should also be deterministic [24]. However, for chaotic systems, this phenomenon is not true, and it may produce unpredictable, irregular, and never-repeated chaotic phenomena after being stimulated by deterministic rules [25]. In the process of using GA to optimize fuzzy control rules, many papers use the method of randomly generating initial populations, which will generate many populations that are not reasonable and do not conform to the process control experience, thus increasing the optimization of GA. The algebra reduces its convergence speed and is not conducive to us finding the optimal solution. Chaos models are generally divided into continuous and discrete models, as shown in Figure 3 for a schematic diagram of the discrete model.

The continuous model is mainly expressed as follows:

$$
\begin{cases}
\dfrac{d_x}{d_\tau} = a(y - x), \\
\dfrac{d_y}{d_\tau} = cx - xz - y, \\
\dfrac{d_z}{d_\tau} = xy - bz.
\end{cases}
\tag{7}
$$

Discrete model uses difference equation to describe discrete chaotic system, which can generate discrete chaotic signal in time domain from an initial value and mapping formula and finally form digital chaotic sequence without the value of each sequence point, which is generally expressed in the form of nonlinear difference variance:

$$
Z_{i+1} = \rho Z_i (1 - Z_i).
\tag{8}
$$

For $\rho \in (0, 4]$, $Z_i \in [0, 1]$, the above formula will not be directly used and then improved:

$$
Z_{i+1} = 1 - \rho Z_i^2,
\tag{9}
$$

in which $\rho \in (0, 2)$ and $Z_i \in [-1, 1]$. The modified formula has the effect of simplifying calculation and has good practical significance in practical operation.

2.3.2. Construction of Mathematical Model and Application of Simulation Algorithm. Since the above parameters selected in this paper belong to the basic range, the overall design of the optimal algorithm is required in the specific mathematical model design, so that the subsequent experimental simulation can be registered to achieve the purpose [26]. Chaotic motion exists widely in nonlinear systems, it has excellent properties such as ergodicity and randomness, and it can go to each state in a certain domain irreproducibly; this feature makes chaotic search inherently random and orbital history. It can ensure that all possible states can be traversed without repetition in the global scope, which is conducive to overcome the limitations of the general random algorithm with distributed traversal as the search mechanism, which will be more conducive to the optimization of the chaotic model of byte big data, and solve the problem [27]. In order to overcome the convergence problem of the basic GA, this paper also adopts the elite selection strategy. That is, after crossing and mutation, the optimal individual in the new generation population is generated and compared with the optimal individual of the previous generation. If the former is less than the latter, the poor individual of this generation will be replaced with the optimal individual of the previous generation; otherwise, no operation will be carried out. It realizes the communication and cooperation between individual information and group information by simulating various excellent characteristics of different biological groups, so that the algorithm can constantly revise its own optimization conditions through the interactive information between individuals, in order to find the optimal solution or approximate optimal solution of the optimization algorithm, and at the same time, it also improves the search accuracy of the intelligent algorithm. First of all, on the initialization population, an evaluation needs to be performed. At this time, the average error, mean square error, and determination coefficient R^2 need to be used
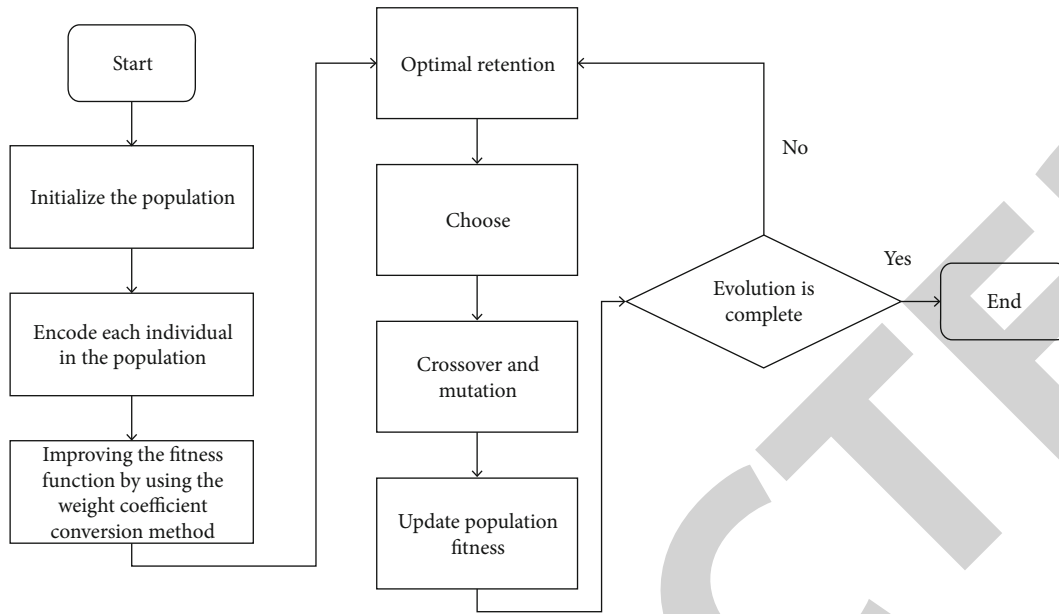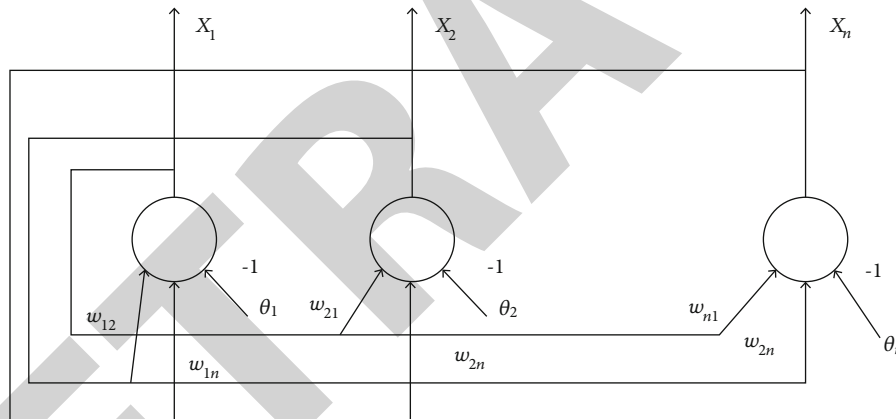
Figure 2: The basic flow chart of the improved GA.

Figure 3: Schematic diagram of discrete model.

as the objective function. The specific calculation formula is as follows:

$$\text{MAE}(\widehat{y}_i, y_i) = \frac{1}{n}\sum_{i=1}^{n}|\widehat{y}_i - y_i|,$$

$$\text{MSE}(\widehat{y}_i, y_i) = \frac{1}{n}\sum_{i=1}^{n}(\widehat{y}_i - y_i)^2, \qquad (10)$$

$$R^2(\widehat{y}_i, y_i) = 1 - \frac{\sum_{i=1}^{n}(\widehat{y}_i - y_i)^2}{\sum_{i=1}^{n}(\bar{y}_i - y_i)^2},$$

where $\widehat{y}_i$ is the predicted value, y_i is the actual value, and $\bar{y}_i$ is the center value of y_i. After comprehensively evaluating the whole initial population, the above formulas are cited as the multiobjective function, and the weight coefficient is added to the calculation to give weight to each

objective function. After getting the fitness of an individual, it is necessary to start screening the probability of being selected and determine whether the individual can inherit the next generation according to this item. Therefore, assuming that the fitness of individual i is the above objective function value f_i and the population size is PS, the probability of the individual i being selected is

$$P_i = \frac{f_i}{\sum_{i=1}^{\text{PS}}f_i}. \qquad (11)$$

The last step is the crossover mutation process, in which the purpose of crossover operation is to retain genes with excellent traits, while the purpose of mutation operation is to increase the diversity of genes and improve the probability of finding the global optimal solution in the solution space. The range of variation probability used in this paper is between thousandths and percentiles. In
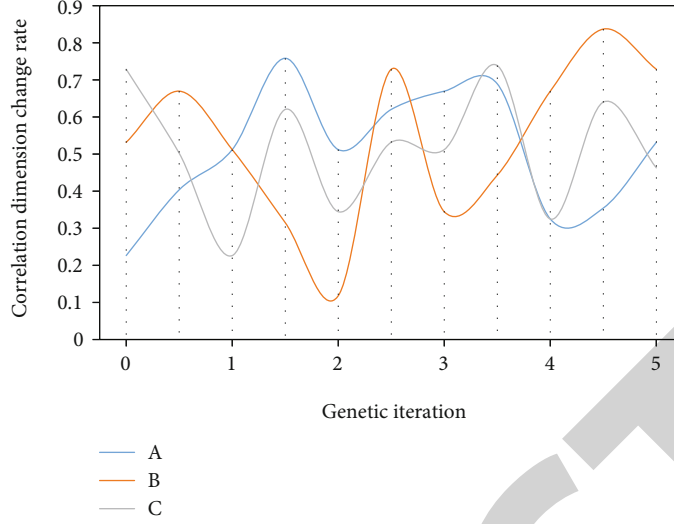
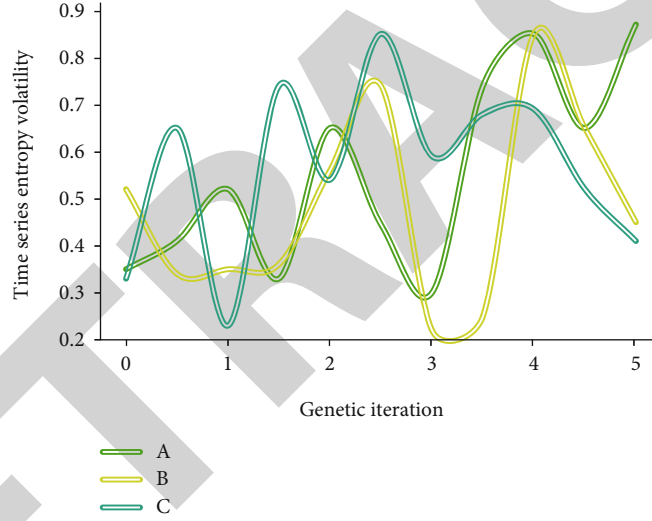Figure 4: Genetic analysis of association dimension.

Figure 5: Genetic analysis of the volatility of time series entropy.

order to avoid deleting individuals with high fitness value, this paper stipulates that individuals with high fitness value in each generation do not need genetic operation and can directly enter the next generation, so as to improve the over-all operation efficiency. Therefore, in the basic algorithm framework, the optimal selection is very effective.

Assuming a subset S of the initial rule set, the number of rules it contains is $N(S)$, and the classification accuracy is $E(S)$. Then, the simplified objectives can be considered as $N(S)$ and $E(S)$. This is a two-objective combinatorial optimization problem. Introducing the weight $0 < \omega < 1$, the fitness S of the rule set $f(S)$ is defined as

$$f(S) = \begin{cases} \omega \dfrac{E(S)}{E_0} + (1 - \omega) \dfrac{N(S)}{N_0}, & E_0 \neq 0, \\[2ex] \omega E(S) + (1 - \omega) \dfrac{N(S)}{N_0}, & E_0 \neq 0, \end{cases} \tag{12}$$

Table 2: Comparison results of the three parameters with traditional methods.

Parameter	Method	Mean and standard deviation
Associative dimension	Traditional method	7.12 ± 0.32
	The method of this paper	7.12 ± 0.112
Lyapunov index	Traditional method	210 ± 0
	The method of this paper	210 ± 0
Time series entropy	Traditional method	3 ± 0
	The method of this paper	1.36 ± 8.745

where E_0 is the classification accuracy using the initial rule base and N_0 is the number of rules contained in the initial rule base. The above fitness function is used to evaluate the
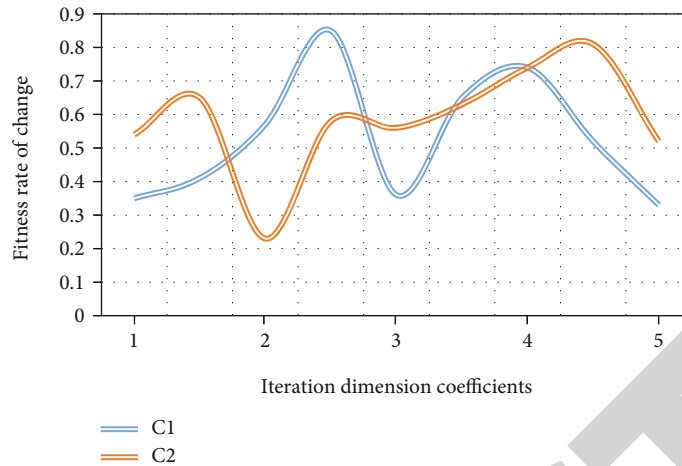
Figure 6: Iterative relationship diagram of fitness change rate.

individuals in the contemporary population. If the initial population is set as the initial matrix, in order to ensure the correlation and accuracy of each inheritance, in the process of optimal selection of circular inheritance, this paper makes a unified division in the objective function. Almost all machine learning algorithms come down to solving the optimization problem in order to achieve the goal we want the algorithm to achieve. In order to achieve a certain goal, it is necessary to construct an objective function, and then, let the function take the maximum or minimum value (that is, optimization), so as to obtain the model parameters of the machine learning algorithm. Constructing a reasonable objective function is the key to establish machine learning algorithm.

$$\min_{H \in \mathfrak{J}_\mu} \|G - H\|_F^2 \tag{13}$$

where H is the update matrix and G is the fixed matrix. After the above approximate problem of the initial matrix is calculated, a convex set projection can be obtained. At this time, it is willing to replace the off-diagonal elements of the matrix:

$$h_{ij} = \begin{cases} g_{ij}, & |g_{ij}| \leq \mu, \\ \mu \cdot \text{sign}\left(g_{ij}\right). \end{cases} \tag{14}$$

According to the above calculation, the elements can be arranged one by one in order, which can ensure that the matrix can be well iterated in the next update, and all the nondiagonal elements in the matrix that are greater than the threshold will be constrained. In this way, the optimal item can be obtained in the sequence. Of course, because interference items or coordinate items sometimes appear in genetics, it is necessary to pay attention to the different transformation of genetic matrix in actual calculation. Originally, the whole population evolved and decomposed into independent subpopulations. Each subpopulation evolves independently and cooperates to obtain the optimization target value. Because the dimension of each suboptimization problem is reduced, the burden on the subpopulation is reduced, and the optimization efficiency is improved.

3. Result Analysis and Discussion

In order to verify that the model designed in this paper has the characteristics of scientific, feasible, and efficient, this paper designs some relevant experiments again for analysis. Based on the characteristics of the chaotic model under big data, the improved GA can obtain the accurate global optimal value on all parameters. At the same time, the optimization performance is extremely stable. The experiments designed for this purpose also verify the practical operability of the model from the aspects of correlation dimension, time series entropy, fitness change rate, and optimization efficiency. Figures 4 and 5 are the analysis diagrams of correlation dimension and time series entropy under three different heritages: A, B, and C.

Each subpopulation evolves independently and cooperates to obtain the optimization target value. As the dimension of each suboptimization problem is reduced, the burden on the subpopulation is reduced, and the optimization efficiency can be seen from the analysis of the above figure. It can be seen from the analysis of the above figure that the trend is unstable in three different heredity, whether in the correlation dimension or in the entropy of time series, which also directly shows that there will be great differences in the search for the optimal term in different heredity due to different genetic methods, genetic algebra, and other factors. Table 2 is the result data of correlation dimension, Lyapunov exponent, and time series entropy compared with traditional methods.

To improve, in terms of correlation dimension, if the correlation dimension is large, the overall trend will tend to be stable. This is because the amount and accuracy of correlation will be greatly enhanced when the algebra increases. The richness will also reduce errors. On the entropy of time series, because each matrix is different for time inheritance and there are too many uncertainties on the time axis, the objective function Jin Xu should be discussed and distinguished in concrete operation, and the algorithm designed
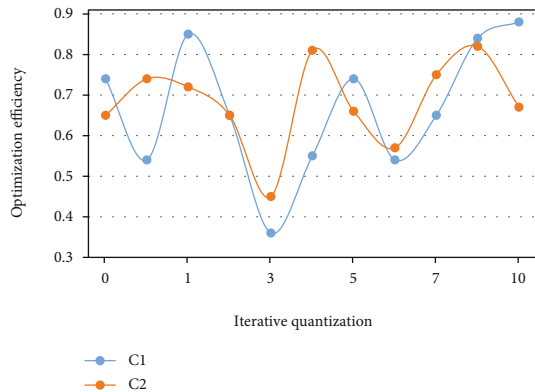
FIGURE 7: Optimization efficiency analysis diagram.

in this paper will optimize and deal with this problem. Figures 6 and 7 are the analysis figures of fitness change rate and optimization efficiency under two different dimensional coefficients $C1$ and $C2$.

It can be seen from experiments that the overall trend of fitness and optimization efficiency is relatively stable, and with the continuous progress of time and inheritance, the optimization efficiency will gradually increase, and the error analysis will be reduced by 75.4%, which will greatly improve the influence of various unfavorable factors in the optimization process, and because the rate of change of fitness basically maintains a high rate of change, it also reflects that the basic framework of the model is extremely excellent, for the entire algorithm structure and data processing soy sauce 54%. promote. The optimization process of GA is to force the penalty term to gradually approach 0, so that the penalty function reaches the minimum value, which also gradually approximates the originally out-of-bounds variable until it is pulled back to the constraint range of the variable. The whole algorithm spends most of its time on the calculation of the objective function, which reduces the calculation time. In the improved GA, only the individuals involved in crossover and mutation operations are calculated for the individuals in the new generation population, which shortens the calculation time to some extent.

4. Conclusions

Aiming at the disadvantage of premature GA, an improved GA is proposed. The improved GA introduces the population differentiation mechanism, adopts the dynamic adaptive crossover mutation operator, organically combines the improved heuristic crossover method and the chaotic mutation method degenerated with the number of iterations, and designs a mechanism to make the algorithm jump out of the local optimization. It can be seen from the experiment that the intelligent controller optimized by GA shows good dynamic and static characteristics when dealing with time-varying, time-delay, nonlinear, and model-uncertain systems. However, it should be pointed out that GA can find the global optimal solution when solving simple systems or some functions. The improved GA proposed in this paper is used to adjust and optimize the controller parameters.

When the uncertain parameters change greatly, the control system can still have good control quality and strong robustness. In addition, the algorithm does not destroy the structure and essence of traditional GA, so it inherits the advantages of GA and takes into account the advantages of random algorithm.

However, there are some limitations in this paper. In practical application, genetic algorithm is prone to premature convergence. We should not only keep the excellent individuals but also maintain the diversity of the group. Therefore, it is necessary to analyze the genetic algorithm in the future research.

Data Availability

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

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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