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Research Article

Evaluation Model of Product Shape Design Scheme Based on Fuzzy Genetic Algorithm Mining Spatial Association Rules

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Put forward a kind of association rules mining method based on fuzzy genetic algorithm, this approach by building a mining model, the association rules and fuzzy genetic algorithm fuses in together, and then given to the fitness function of the mining space, and uses threshold to limit the fuzzy genetic algorithm will cross distribution and compile the fitness function, the improved method excavation stability is strong, the mining accuracy is high. The clustering analysis method of multidimensional fuzzy genetic algorithm mapping association network is studied, and the multidimensional module layout target is analyzed by using fuzzy hierarchical analysis technology and improved genetic algorithm combined with the clustering target of each angle, and the module division of each angle is realized. The main structure of the product is constructed with process model as the integration framework, style as the organization form, and feature list as the expression mechanism. The product characteristics based on fuzzy genetic algorithm are studied, the main structure configuration design process model mapping relation analysis, combined with the main structure of the joint model, together to achieve the fuzzy genetic algorithm (GA) variant design of fine-grained axiomatic mode, based on the associated network building and integration of new product design process, product structure of multidimensional optimization problem is solved.

1. Introduction

The purpose of manufacturing services oriented mass customization production mode is the efficiency in mass production mode and into the wood to provide customers with timely and satisfactory products and personalized service life cycle, the advantage of mass production and customization production organic union, in order to satisfy the demands of design and production efficiency and customer service requirements, It covers the whole life cycle process of the product [1]. Association rule in data mining technology is a method that can extract high-frequency feature clusters from modeling design data of network products and mine out key associated items [2]. Fuzzy genetic algorithm is a high energy and comprehensive item collection algorithm. Therefore, association rules and fuzzy genetic algorithm are combined by constructing mining model, and the model is studied.

Spatial data mining refers to the extraction of spatial patterns and features interested in product modeling design, the general relationship between spatial and nonspatial data and some other general data features hidden in the database from spatial database [3]. SDM is a branch of data mining, which is based on spatial database. It can automatically mine previously unknown and potentially useful knowledge from a large amount of spatial data, and extract nonexplicit spatial relations or other meaningful patterns, such as spatial association rules and spatial location distribution rules.

Multidimensional fuzzy genetic algorithm is used to mine the clustering analysis method of spatial association service mapping association network to realize module division based on multidimensional module layout objective analysis. Combined with complex network and product platform analysis technology, product platform construction oriented to the result of module division is realized. The main structure of the product is constructed with process

model as the integration framework, style as the organization form, and thing feature table as the expression mechanism. This paper proposes a method that combines adaptive and association rules, analyzes the advantages and disadvantages of traditional algorithms Apriori and FP-growth, and finally selects them for mining data association rules, and makes appropriate adaptive improvements to GA (genetic algorithm) according to its specific needs.

2. Related Work

As a random parallel search algorithm based on natural selection and genetic principles, genetic algorithm has been successfully applied in many fields [4]. However, traditional GA has defects of prematurity and low search efficiency. Adaptive GA can achieve the optimal balance between global optimization and convergence speed through appropriate adaptive adjustment of two important parameters, namely crossover operator and mutation operator [5]. The mining based on fuzzy GA has better mining performance through reasonable fusion of association rules and fuzzy GA, but it still has the problem of poor convergence. Some scholars proposed an automatic screening method based on clustering and expert experience, realizing the practical application of association rule data mining in traffic data [6]. The application of data mining combined with Bayesian algorithm in meteorological data also has good prediction effect [7]. In the automatic mining of fuzzy sets and fuzzy association rules, the automatic clustering method based on GA has remarkable efficiency circle. As the influence of GA two important parameters: the crossover and mutation probability, many scholars for its improved in order to improve the usability and applicability, to speed up the convergence rate, some scholars through nonlinear sorting genetic achieved good effect, reduce the relative convergence of the improved adaptive GA algorithm can take to protect the optimal preservation strategy [8], In addition, its crossover and mutation operators also have various improvements to ensure its global optimal advantages [9].

Fuzzy design (FD) theory realizes the design and analysis of similar products based on the concept of pattern [10]. According to the broad definition, similarity mode refers to concrete objective things, including concrete things, a certain system state in artificial system, etc. Similarity recognition is the process of identifying the specimen, benchmark or reference imitated by a specific object, setting the design reference or standard as a pattern class, and applying a series of analytical techniques supported by theories and methods such as similarity theory to classify the research object into the defined pattern class [11]. Due to the characteristics of the objective things with different degree of fuzziness, and the existence of the target environment interference and other factors, the target feature information conversion of feature information in the process of random overlapping [12], and people also reflect the process of fuzziness of objective things, makes the classic recognition method is more and more not adapt to the needs of reality. Fuzzy pattern recognition is produced and developed to meet this requirement. As the most classical algorithm, Apriori algorithm [13] is based on the prior knowledge of frequent item sets. The main problem of Apriori algorithm is that in order to search all frequent patterns, it is necessary to scan the transaction library repeatedly, and in order to obtain longer frequent patterns, a large number of candidate short frequent patterns are generated in the process, so it leads to a large time and space complexity of Apriori. When FP'-growth searches frequent item sets [14], it generates a large number of conditional pattern libraries and constructs conditional frequent pattern trees, which not only affects the mining efficiency of frequent item sets, but also increases the burden on database servers. For massive data, it still has great time and space complexity.

The overall idea of modular design and implementation of complex products based on multidimensional programming is divided into four steps, including modular development and configuration of product structure, multi-factor modeling and module division, main structure construction of product platform, and module construction and optimization based on multidimensional coupling factors [15]. The modular development and configuration of product family are divided into two aspects, namely, the construction of complex product main structure, and the use of it to carry out configuration and optimization. Multi-factor modeling and module division include four aspects: the construction of correlation relations among views, the construction of fine-grained view model of products, the characterization of coupling factors and the correlation of multidimensional coupling factors, and the analysis of view ordered structure [16]. Modular design must plan product platform system structure by means of identification and analysis of multidimensional coupling factors or systematic coupling factors [17]. Through "domain stage-design view," mapping relationship, complex coupling factor requirements of product life cycle are integrated and expressed in product requirements, functions, structure and service view modules layout. The modular design method of complex products based on multidimensional programming has been evolving around the expression and analysis of multidimensional coupling factors and the construction and improvement of the main structure of products based on multidimensional coupling factor analysis, including: first, the stages and scope of product life cycle targeted by decision coupling factor analysis [18]; secondly, through the definition of coupling factors and their correlation, the multiangle ordered product module layout represented by multidimensional coupling factors is constructed. Thirdly, combined with the stages and scope involved in modularization, the product master structure based on the aggregation definition of multidimensional coupling factors was constructed [19] to provide standardized reference for configuration design. Fourth, carry out standardized configuration and variant design based on product structure, verify its systematicness and realize its improvement while applying multidimensional coupling factors [20–23], so as to promote the ability of modular ordered structure to meet the goals of corresponding life cycle stages and scope. According to the implementation process of modular design, the choice of specific implementation technology must also focus on the

establishment, application, and improvement of multidimensional coupling factors. First, the establishment, application and improvement of Browning factors must be based on the product model with formal association relationship representation as the core [24, 25]. Secondly, the establishment, application and improvement of coupling factors are the key of this method. Thirdly, the coupling factor and its multidimensional product master structure construction, expression and management technology are the means to achieve this method [26–28]. Finally, the systematic multidimensional coupling factors are gradually enriched and improved to realize the evolution of product structure, which is the guarantee of the implementation of this method.

In order to make full use of the useful information contained in these data, the modeling design of network products longs for the emergence of a technology that can efficiently extract data information. The above situation has inspired the emergence of data mining technology, and association rule is one of the most important branches of data mining technology. Network data usually appear in the form of explosive aggregation, resulting in poor mining performance of the proposed association rule mining method, and high-performance association rule mining method is still to be developed.

3. Fuzzy Genetic Algorithm Mining Spatial Association Rules for Complex Product Design

3.1. Mining Technology of Association Rules Based on Fuzzy Genetic Algorithm. Model based on constraint network view internal logical expression of product design stage, based on the fuzzy pattern recognition method of module partition technology, combined with improved genetic algorithm to realize the function/view structure design phase of module partition, combined with the correlation constraint network model in the mapping definition module layout, form, function, structure, demand service module layout mapping relation, Provide consistent module layout basis for multidimensional product family model construction. Figure 1 shows the model structure of mining method based on fuzzy genetic algorithm in the proposed association rules.

In Figure 1, the data to be mined of network products are input into the mining method model of the proposed association rules based on fuzzy genetic algorithm, and the database will receive it first and send mining signals to the structured query machine. Then, the processing chip in the model starts to calculate the support of the data to be mined using association rules, and the data list displays this calculation in the form of a digital code.

The probability of simultaneous occurrence in mapping cluster D can be expressed as

$$T\left(s_i s_j\right) = \left|\frac{\left|s_i s_j\right|}{|D|}\right|. \tag{1}$$

T can be used to represent the initial support of the data to be mined. In order to better conduct data mining, the initial support needs to be weighted to highlight the features of the data to be mined and enhance the mining accuracy of the mining method based on fuzzy genetic algorithm in the proposed association rules. Support degree, and its function expression is

$$T\left(s_i s_j\right) = \frac{1}{u}\left(y_1 T\left(s_i s_j\right) + y_2 T\left(s_1 s_2\right) + \ldots y_v T\left(s_i s_j\right)\right). \tag{2}$$

The support given by fuzzy genetic algorithm is used to calculate the fitness of data 1 to be mined in modeling design of network products. The fitness calculation formula can be expressed as

$$M(I) = \beta C(I) + \alpha T_V\left(s_i s_j\right). \tag{3}$$

Then the association rules and fuzzy genetic algorithm can be used to optimize the fitness, and the association rules in the data to be mined in the modeling design of network products can be mined. Firstly, the fuzzy genetic algorithm is used to convert the data to be mined into genetic genes and encode them. At this time, fuzzy genetic items with the units digit n in Rn will be generated, and these items will be connected into a new cluster according to the rules of chromosomes. At this time, the fitness of the data to be mined can be expressed as

$$M(C) = y\left(\frac{T_v\left(s_i s_j\right)/T_{\max}}{C_{\max}}\right) + y_0\frac{C(I)}{C_{\max}}. \tag{4}$$

3.2. Product Design Model Mining of Spatial Association Rules Based on Fuzzy Genetic Algorithm. According to the characteristics of the proposed FGA (Fuzzy Genetic Algorithm), the extraction process of spatial association rules is generally divided into three steps:

(1) Determine the threshold of support and credibility of spatial association rules according to the needs of specific problems, and generate the fitness function in the FGA process. The spatial predicates of spatial objects that meet certain support degree are listed to form association rule table, namely association rule set.

(2) The association rule table is discretized and combined into spatial association rules to obtain the chromosomal transaction set arranged in a certain order as the object of spatial association rule mining.

(3) FGA parameters are integrated and the algorithm is started. The flow chart is shown in Figure 2.

The support degree and confidence degree of association rules are two measures of rule interest degree. Support is a measure of the usefulness of an association rule, which shows how often the rule appears in the entire database. Confidence is a measure of the reliability of association rules, which reflects the certainty of rules found. The disadvantage of using only support to design fitness function is that many

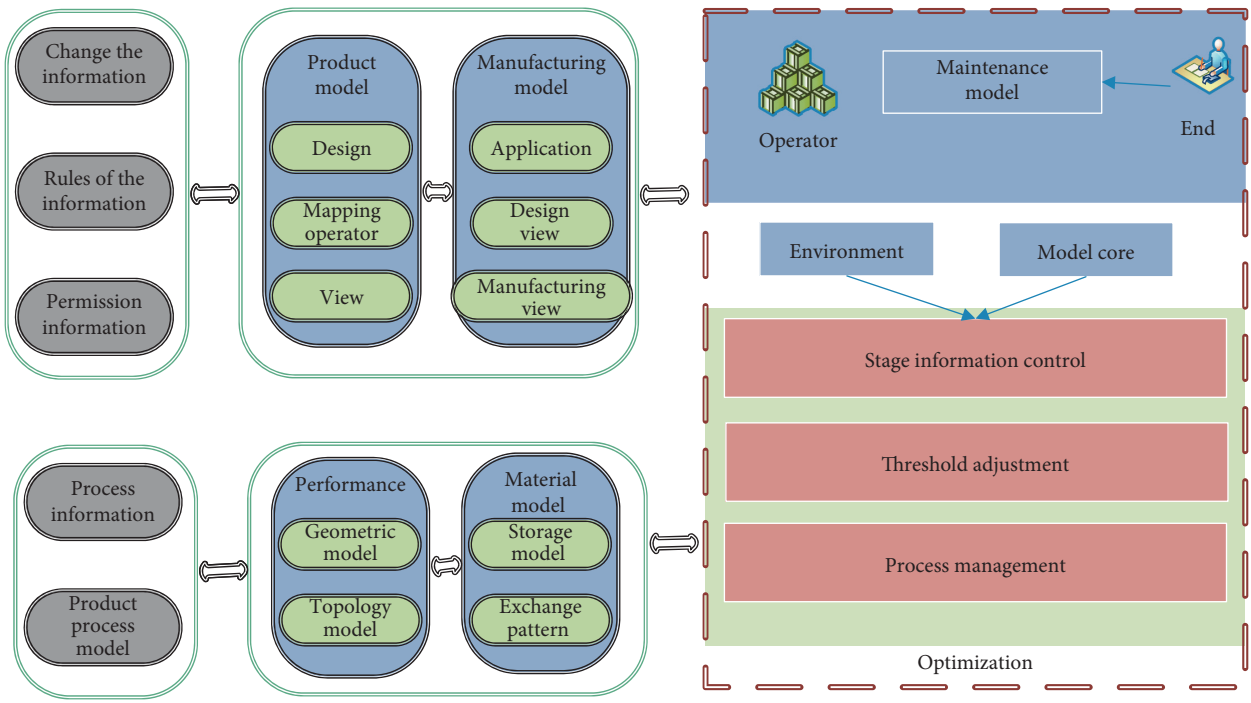

Figure 1: Structure diagram of fuzzy genetic mining spatial association rules product model.

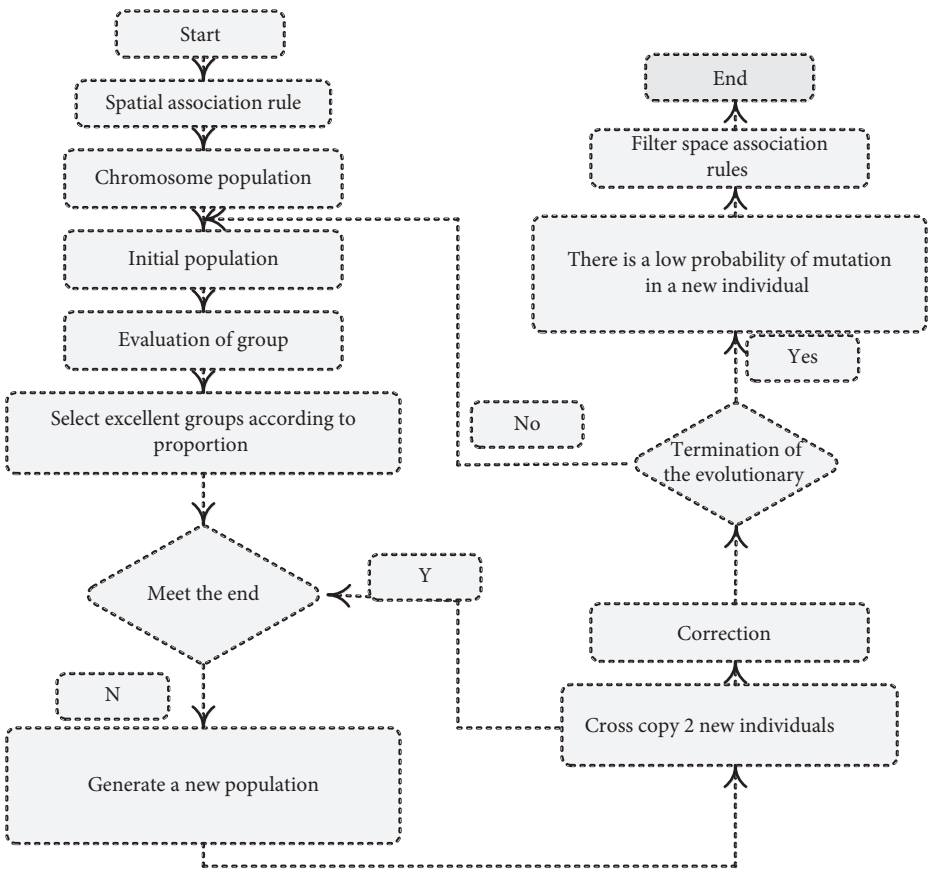

Figure 2: Flowchart of mining spatial association rules with fuzzy genetic algorithm.

potentially meaningful patterns will be deleted because of the items with low support, while the disadvantage of using only support confidence is that it ignores the support of category attribute item set, which may lead to misleading.

$$T\left(R_j\right) = \frac{\vartheta_c Su\left(R_j\right) + \vartheta_x Con\left(R_j\right)}{\min su}. \quad (5)$$

Based on the previous qualitative knowledge [13], fuzzy rules as shown in Table 1 can be summarized. This rule has strong experience and the size of specific values can be adjusted according to the actual situation.

The fuzzy reasoning algorithm adopts min-Max algorithm, and a fuzzy relation can be expressed as:

$$T = \cup t_c \times f_a \times p_c. \quad (6)$$

4. Construction of Complex Product Union Model for Fuzzy Genetic Algorithm Spatial Association Rules

For the hierarchical characteristics of product structure, Process Map Model (PMM) can be expressed in the following form:

$$TM = TC_0 \times D_0 \times T_0 + \ldots\ldots TC_m \times D_m \times T_m. \quad (7)$$

For product family structure of multidimensional information model, process factors with different resolutions can constitute processes of different levels and establish process styles. For the dynamic development process, the data model also needs to be able to describe the dynamic information and the dynamic association between the data in the process. By organizing data for process and adopting corresponding data organization mode for different product development stages, the characteristics of each stage of product development process information and the relationship between each stage can be well reflected.

The process based on assembly robustness optimization is shown in Figure 3: first, information such as tolerance and accuracy is obtained from the assembly model; Second, according to the product family range product requirements, design and distribution tolerance, precision, and size chain polymerization, that is, synthesis of size chain, determine the constituent ring and closed ring; Thirdly, the average assembly accuracy and success rate under various distribution aggregation conditions were simulated and analyzed to optimize the distribution scheme. Fourthly, the weight of each evaluation index in module division is determined by using grey normalization method. Fifth, evaluate the degree of compliance with the quality requirements of structural controllability and robustness, and optimize the scheme again. Sixth, evaluate the index distribution of each scheme comprehensively with multiple objectives. If the requirements are met, deconstruct the scheme according to the size chain structure to form the result of module division. Seventh, if it meets the requirements, reconstruct the size chain distribution scheme, and reconduct the second to the eighth process until the size chain structure design results that meet the requirements appear.

Table 1: Query table corresponding to the fuzzy rule table.

*f*0	f0							
	R1	R2	R3	R4	R5	R6	R7	R8
R7	R0	R0	R1	R2	R3	R4	R5	R6
R6	R0	R1	R2	R3	R4	R5	R6	--
R5	R0	R2	R3	R4	R5	R6	--	--
R4	R0	R3	R4	R5	R6	----	--	--
R3	R0	R4	R5	R6	---	-----	---	---
R2	R0	R5	R6	---	---	---	---	---
R1	R0	R6	-----	---	----	----	----	----

Step 1. Two initial populations are randomly generated according to the problem dimension. Population 1 (POP1) adopts particle swarm algorithm, and population 2 (POP2) adopts genetic algorithm for evolution. The two populations adopt the same coding rules, fitness function, population size and maximum evolution algebra.

Step 2. initialize the two populations, including population size PopSize, genetic crossover, mutation probability Pe, Pm, particle swarm inertia factor W, learning factor C1, C2, maximum velocity Vmax, and maximum iteration number Tmax

Step 3. calculate the fitness values of all individuals in the two populations, and evaluate them. The optimal location Pbes and global optimal individuals of population 1 and Gga of population 2 were obtained. The fitness values of the optimal individuals of the two populations were compared, and the optimal individuals of the other population were replaced by individuals with larger fitness values, so as to continue evolution as the next generation.

Step 4. take the individual with a large fitness value as the optimal individual of this generation to judge whether the termination condition is met at this time. If the number of iterations has reached the maximum number of iterations, the algorithm ends and go to Step 6. Otherwise, go to the next step.

Step 5. The speed and location of POP 1 are updated respectively to generate the next generation population. For POP2, survival expectation selection method and optimal individual preservation method are used to select chromosomes, and then crossover and mutation operations are carried out to obtain the next generation population. Then, Step 3 is used to continue the fitness value evaluation.

Step 6. output the optimal individual as the optimal solution of the problem.

5. Example Verification

The curves of crossover probability and mutation probability are shown in Figure 4. It can be seen from Figure 4 that the crossover probability decreases with the increase of the evolutionary algebra and finally approaches 0.6. The variation probability increases with the increase of evolution

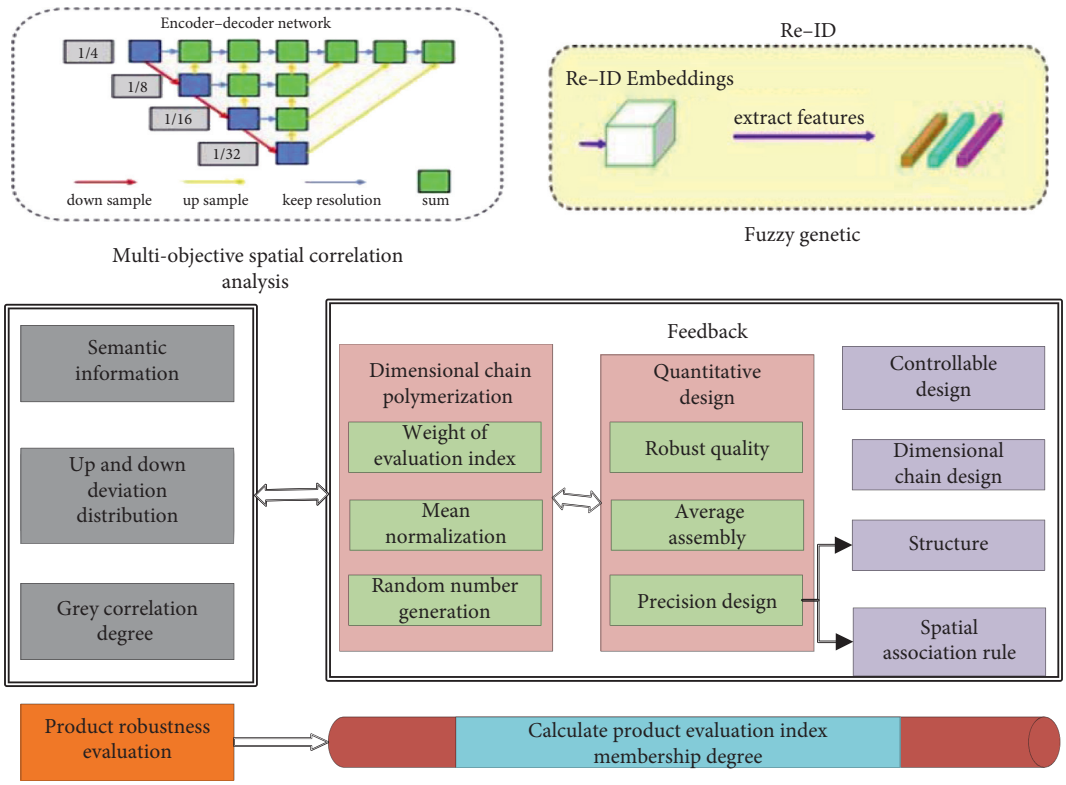

Figure 3: Spatial association mining based on fuzzy genetic algorithm for product robustness optimization.

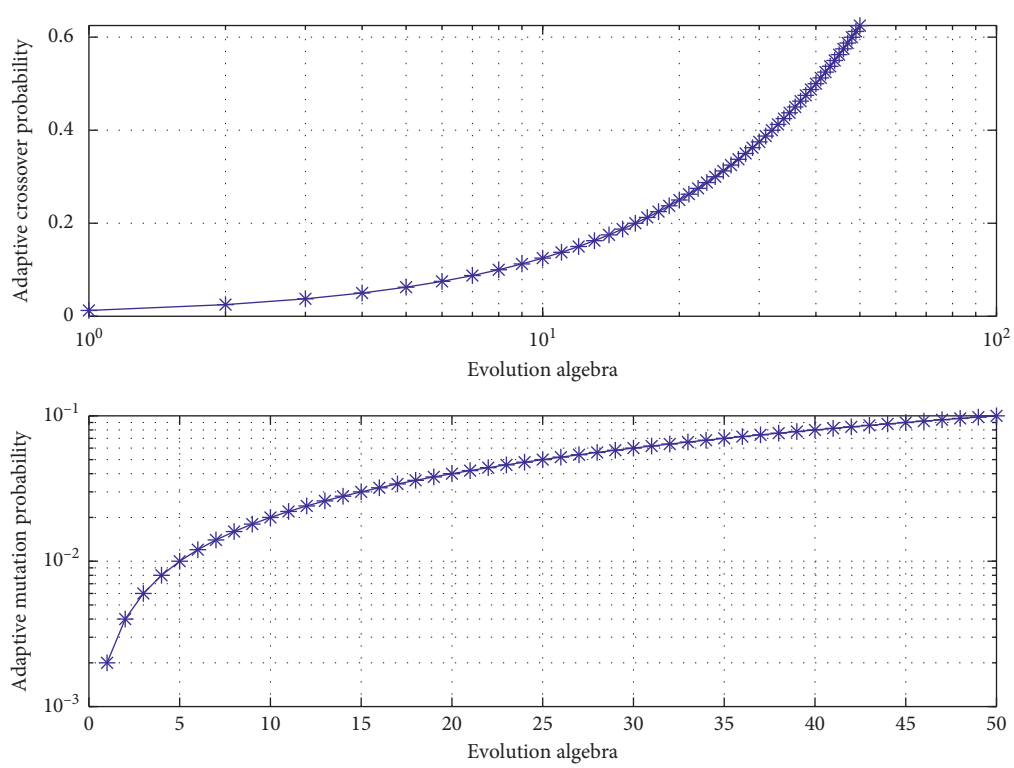

Figure 4: Improved adaptive crossover probability and mutation probability curves.

algebra, and finally tends to 0.09. In the initial stage of evolution, the generation of new individuals is mainly affected by crossover operators, but then the crossover probability tends to a certain value, so that good genes can be protected. Similarly, getting bigger initially can help it get out of local optimality and create new individuals.

Table 2: Comparison table of linear state of membership degree of the three methods.

Methods	Degree of dispersion/level	Number of lines/piece
Fuzzy genetic algorithm	4	7
Structured research method	3	5
Feature weighted mining method	2	4

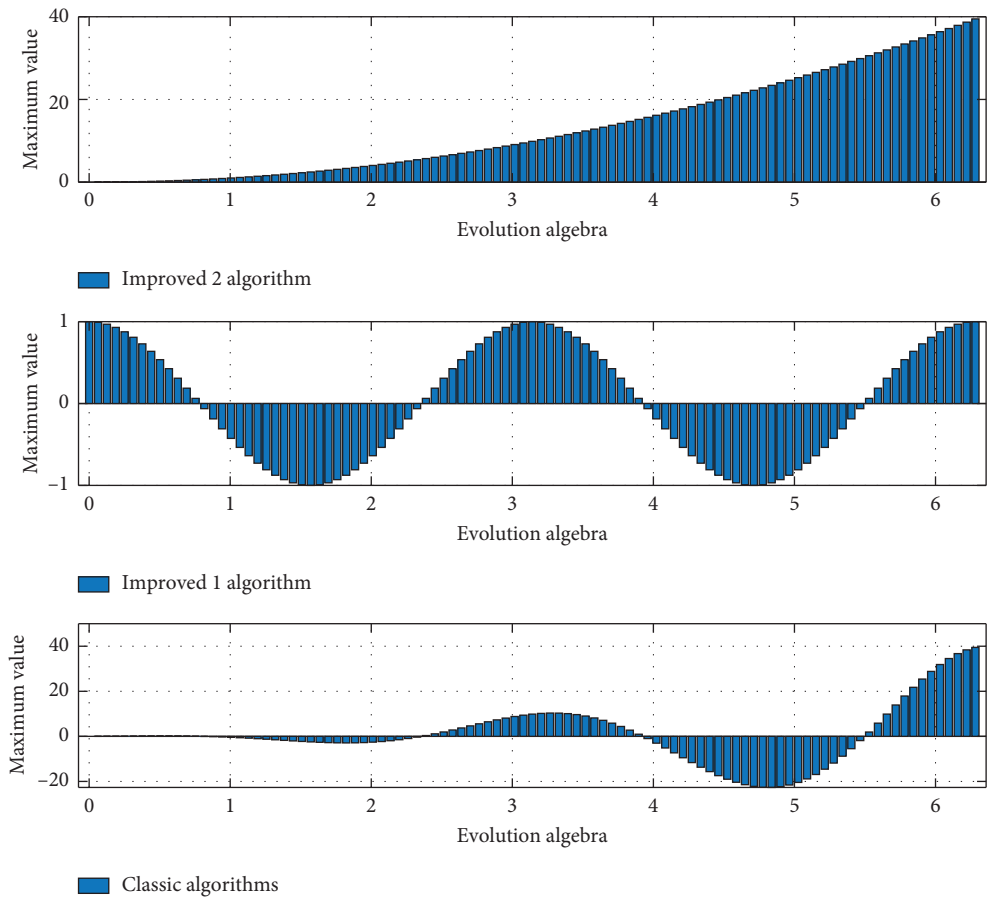

Figure 5: Comparison between the improved adaptive GA algorithm and the classical GA algorithm.

The mining stability of the association rule mining method is mainly reflected in the linear state of the membership degree of the method. The linear state of the membership degree that is too scattered and unevenly distributed is not good, so the mining stability of the method can be determined. This paper uses the improved method, the mining method based on structured research in association rules, and the mining method based on feature weighting in association rules to mine large natural noise data clusters.

In order to facilitate recording, the degree of dispersion of the linear state of membership in the experimental results was marked as level 1, level 2, level 3, level 4 and level 5. The higher the level is, the more dispersed the linear state of membership is "67", and the stronger the mining stability of the method is, the best degree of dispersion is level 4. The more the number of lines in the linear state of membership, the stronger the mining stability of the method will be. Table 2 is a comparison table of linear state of membership degree of the three methods.

As can be seen from Table 2, compared with the other two methods, the improved method in this paper has the best dispersion degree of membership linear state and the largest number of lines, proving that the improved method in this paper has the advantages of strong mining stability.

In the experiment, processing chips of the same specification and model are used to compare the noise features mined by the three methods with those inherent in large natural noise data clusters, and output the comparison curves of mining accuracy (unit: 1) of the three methods, as shown in Figure 5. At the same time, the mining work of the three methods was timed using a timer and recorded in Table 3.

As can be seen from Figure 6 and Table 3, compared with the other two methods, the improved method in this paper has higher mining accuracy and less mining time. By

Table 3: Mining time statistics of the three methods.

Three ways to compare	Mining time
Improvement method in this paper	37.8
Mining methods based on structured research	45.7
Mining method based on feature weighting	67.8

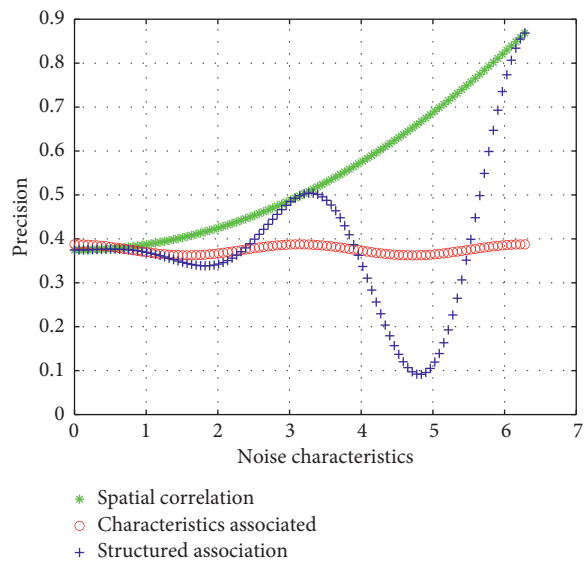

Figure 6: Comparison curves of mining accuracy of the three methods.

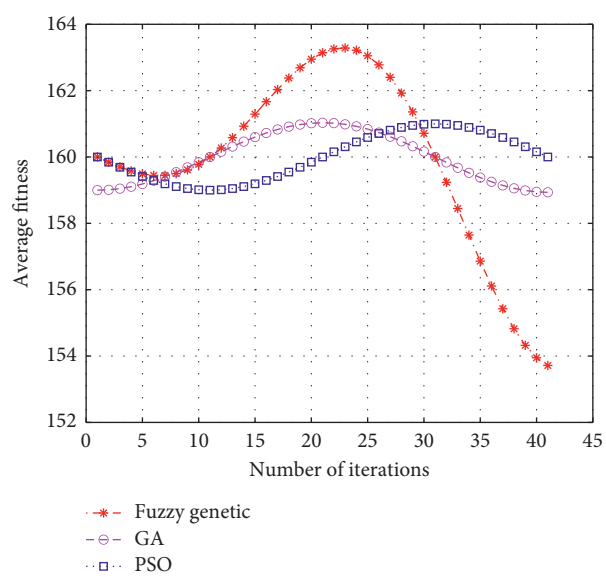

Figure 7: Comparison diagram of fuzzy genetic, GA and PSO (Particle swarm optimization) applied to Chess data set.

analyzing the experimental results, it can be seen that the improved method in this paper has a higher level of mining performance.

The experimental results are shown in Figure 5 after the application of the classical GA algorithm (Improvement 1) and the improved algorithm (improvement 2) in this paper to association rule mining. As can be seen from Figure 5, the improved algorithm in this paper has some improvement in solution quality compared with the classical algorithm and the improved Algorithm 1.

The evolution process of the three algorithms on the Chess data set and Solar Flare data set is shown in Figure 7. The dimensions of these two datasets are 6 and 10 dimensions respectively, which belong to low-dimensional datasets. As can be seen from the figure, the convergence speed and individual quality of the coevolutionary algorithm

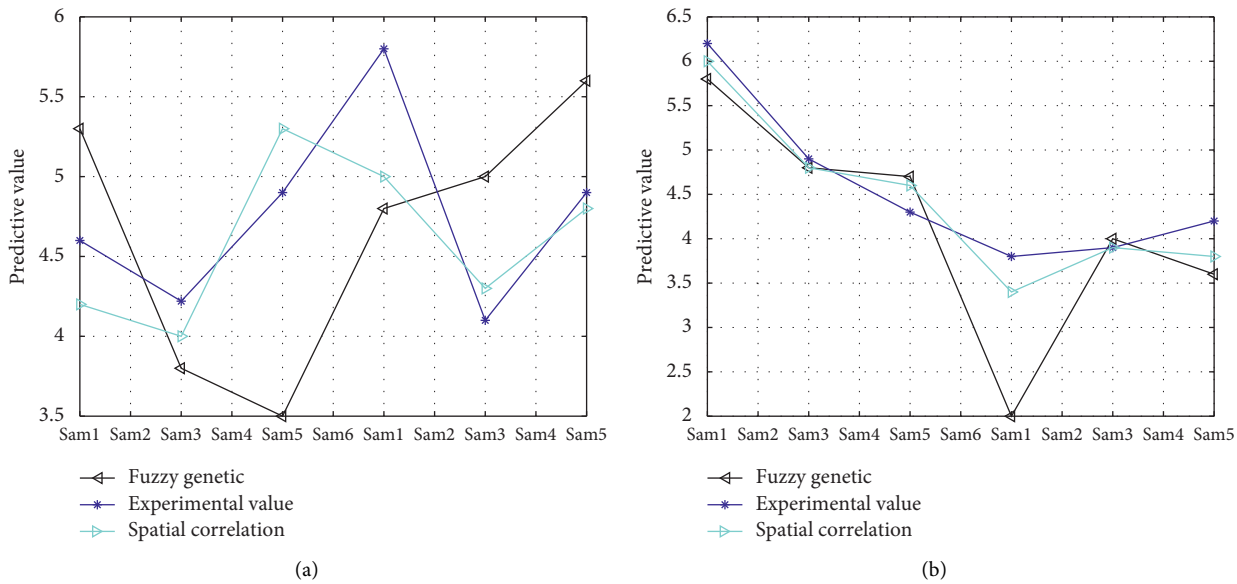

Figure 8: Broken line comparison of predicted values of fuzzy genetic model with one-dimensional variables, predicted values of spatial association rule model and experimental values. (a) "symmetric vs. asymmetric" comparison diagram. (b) "Precision vs. Roughness" comparison.

are slightly better than those of the other two algorithms in the early stage of evolution. As the number of iterations increases, the three algorithms converge. The experimental results show that there is little difference in the mining quality of association rules on low-dimensional data sets, and fuzzy genetic algorithm is slightly better than genetic algorithm and particle swarm optimization.

Use has built based on a one-dimensional variable tacit knowledge mapping model calculation above six samples of emotion predicted value, as shown in Figure 8, 6 groups of image, word of six experimental samples under one-dimensional variable fuzzy genetic algorithm model prediction, the spatial association rules model line comparison chart of the predicted values and experimental values, among them a is "symmetric asymmetric" contrast figure, B is the contrast of "precision to roughness". The results in Figure 8(a) show that the predicted value of the product design model of spatial association rules based on fuzzy genetic algorithm is closer to the experimental value.

6. Conclusion

This paper presents a method of mining association rules based on fuzzy genetic algorithm. Association rule in data mining technology is a method that can extract high frequency feature clusters from network product modeling design data and mine out key associated items. Fuzzy genetic algorithm is a high energy and comprehensive item collection algorithm. In this paper, association rules and fuzzy genetic algorithm are combined by constructing mining model, and the model is studied emphatically. The linear state of membership degree is improved by fuzzy genetic algorithm. By comparing the mining performance of the improved method in this paper, the mining method based on structured research in association rules and the mining method based on feature weighting in association rules, the experiment proves that the improved method in this paper has a high level of mining performance. Spatial association rules are an important result form of SDM. Mining spatial association rules from spatial database is a good method to transform data into knowledge. Research shows that FGA's self-organization, self-adaptability and self-learning characteristics can greatly optimize the mining of spatial association rules, and make spatial database mining have higher robustness, global, optimality and higher efficiency. The functional design and structure design of fuzzy genetic algorithm spatial rule product conceptual design are not considered, so the research on fuzzy genetic algorithm spatial rule product functional design and structure design will be the focus of future research direction.

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 there are no conflicts of interest.

Acknowledgments

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