

Research Article

Application of Mathematical Economic Model in Financial System in Manufacturing Industry

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In the field of economic research, most of the sample data is not obtained based on controllable experiments but generated during the normal operation of the economic system. Therefore, the change of an economic variable is usually not caused by a single change of a cause variable. It is the result of a combination of multiple factors. Therefore, it is necessary to study the application of mathematical intelligent computing in computer intelligent manufacturing system. The purpose of this paper is to explore the application of mathematical intelligent computing in computer intelligent manufacturing system. For this reason, this paper uses the furnace temperature control model to carry out simulation experiment. In this simulation experiment, three algorithms of mathematical intelligent computing are mainly used, including BPES intelligent computing method, genetic algorithm, and MARS algorithm. The research results show that the superparameter optimization based on MARS has high efficiency, and the best result, the worst result, the average result, the variance, and the average time of multiple independent runs are controlled below 0.03 s. In this experiment, when the hidden layer node is 9, the prediction error value is the smallest, and the model simulation curve is basically consistent with the measured curve trend. In the simulation experiment of this paper, these three algorithms have shown good results in their respective links.

1. Introduction

Using economic principles to study the causal relationship between two economic variables is an important part of economics knowledge, and it is also an ability that economists should possess. There are a large number of simple causal relationships among various economic variables. The combination of some causal relationships constitutes a causal chain, and various causal chains can develop various complex causal relationships. However, due to the lack of specific technical guidelines for the development of smart manufacturing from digital manufacturing to the development of smart manufacturing, the progress of my country's smart manufacturing application promotion is slow, and there is still a big gap compared with industrialized countries. In this context, my country announced the "Made in China 2025" plan, which advocates innovation-driven intelligent transformation and accelerates the transition from manufacturing to creation.

Intelligent computing technology is to describe the problem object through a specific mathematical model, making it an operable, programmable, computable, and visualized subject. Mathematical intelligent computing technology is an interdisciplinary subject, including computer science, intelligent technology, neuroscience, physics, mathematics, physiology, and psychology [1]. Today, intelligent computing technology has been widely used in interdisciplinary fields, such as neuroinformatic, bioinformatics, and cheminformatics [2]. The advancement of this technology will further promote the development of interdisciplinary subjects such as neuroinformatic, bioinformatics, and cheminformatics. Secondly, the detailed research and further development of the latter will also greatly promote the development of intelligent computing technology [3].

In the current field of intelligent computing, many experts have conducted in-depth research on it. Kusiak proposed a network model and solved the traveling salesman problem. He successfully introduced the concept of "calcu-

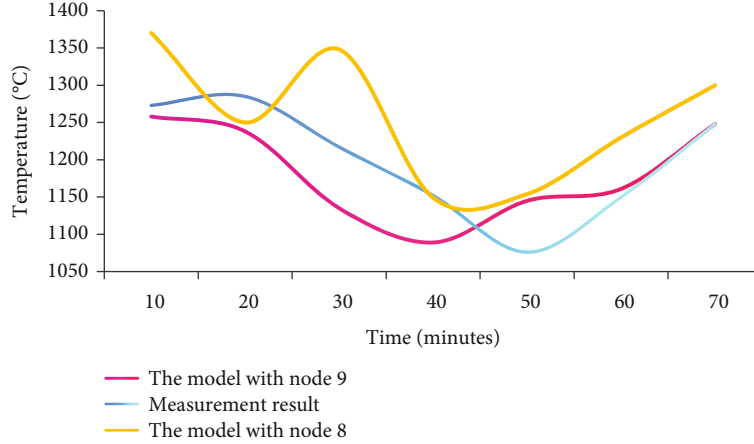


FIGURE 1: Genetic algorithm for furnace temperature prediction curve.

lated energy function” into the study of neural networks and provided a basis for determining the stability of the network [4]. Thoben et al. proposed a parallel distributed processing theory and at the same time proposed a multilayer network back propagation learning algorithm called BP algorithm [5]. On the basis of observing the activities and behaviors of the herd, Rehman et al. use the information sharing of individuals in the group to make the movement of the entire group produce an evolutionary process from disorder to order in the problem-solving space and obtain solutions [6]. Sprock and McGinnis pointed out that only through proper design and implementation of intelligent manufacturing system technology can the huge potential value be fully utilized [7]. Nagorny et al. pointed out that the intelligent manufacturing system is a system composed of computers, storage, and network resources. The overall analysis of the intelligent manufacturing system mainly comes from the software control level [8]. Lu and Ju proposed a new technology that describes the intelligent manufacturing system of small cars, which can completely change the implementation of manufacturing and supply chain management and prove the effectiveness of the method and evaluate it through case studies [9].

2. Principles of Mathematical Intelligent Computing and Intelligent Manufacturing System

2.1. The Principle of Mathematical Intelligent Computing. There are many different kinds of algorithms in mathematical intelligent computing. Typical intelligent algorithms include neural network, fuzzy logic, genetic algorithm, ant colony optimization algorithm, particle swarm optimization algorithm, immune algorithm, distribution estimation algorithm, memetic algorithm, and simulated annealing algorithm.

The first is neural network, and now, more is BP neural network, which is a widely used multilayer feedforward neural network. The training of BP neural network mainly depends on error back propagation [10]. Back propagation can adjust network weights and thresholds and solve many

nonlinear problems. The learning process of BP neural network is mainly divided into two stages: forward propagation and backward propagation. The first stage is the forward propagation process. The formula of forward propagation process of BP neural network is shown in the following formula.

$$I_h = \sum_n \omega_{hi} Y_i + b_h. \quad (1)$$

In this formula, I represent the input of neurons in the hidden layer and Y represents the output of neurons in output layer. ω represents the weight coefficient, B represents the vector of hidden layer neurons, and H and I represent the corresponding neurons.

At the beginning of training, multiple sample data sets are input into the network at the same time for processing and finally reach the output layer to output the results. Compare the output value of each set of input samples with the corresponding expected output value to calculate the total error of all samples [11]. If the error does not reach the ideal level or the number of iterations is insufficient, the second stage is back propagation. The original connection path will feed back information, so the network will readjust the connection weight and threshold of each neuron [12]. Then, the output error is adjusted to the minimum, so that the output value of the network is as close as possible to the value given by the actual sample. The most common BP neural structure has an input layer, hidden layer, and output layer, and the calculation formulas of each layer are shown in Figures 1-3.

$$\begin{aligned} Y_h &= f(I_h), \\ I_j &= \sum_n \omega_{hi} Y_h + b_j, \\ Y_j &= f(I_j), \end{aligned} \quad (2)$$

in which f stands for activation function, which is to judge whether a neuron is activated by receiving all the weighted sums of inputs. I represent the input of neurons in hidden

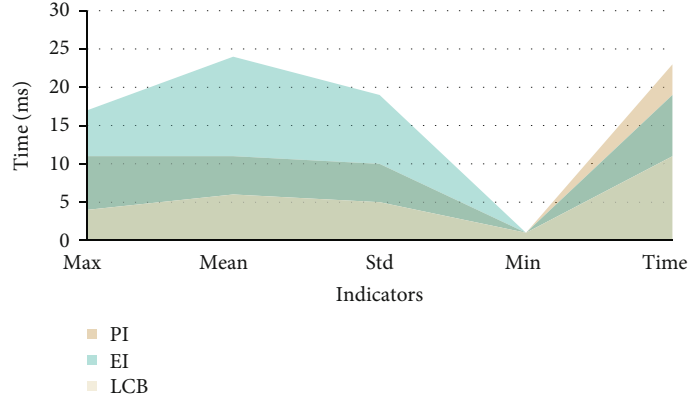


FIGURE 2: Changes in the efficiency of model simulation experiments.

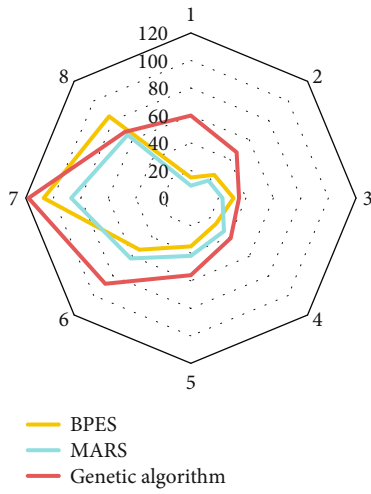


FIGURE 3: Comparison of the application range of intelligent computing.

layer, and y represents the output of neurons in output layer. ω represents the weight coefficient, B represents the vector of hidden layer neurons, and H and I represent the corresponding neurons.

The input layer is used for data input, the hidden layer is used for processing data, and the output layer is used for outputting results. If the network has an input signal, the input signal is first sent to the hidden layer node and then sent to the output layer node of the next hidden layer [13]. When the signal reaches the output layer, the algorithm will correct the weights and thresholds, and the calculation process is shown in Formulas (3) and (4).

$$W_K(K+1) = W_K(K) + \delta_K^p t_t^p, \quad (3)$$

$$\theta_k(k+1) = \theta_k(k) + \delta_K^p t_t^p. \quad (4)$$

W denotes weight, θ denotes threshold, k denotes any neuron in output layer, p denotes sample, and δ denotes error.

In this process, the propagation of the input signal is carried out layer by layer. BP neural network has at least one hidden layer, but it is difficult to determine the number of

nodes [14]. In the actual network construction process, we mainly use the trial and error method to determine the optimal number of nodes, and the signals are sent layer by layer until the output layer is sent, so BP neural network is a parallel multilayer feedforward network.

Secondly, we will introduce the genetic algorithm in mathematical intelligent computing, which is an algorithm developed according to the biological evolution process and can find the optimal solution by simulating the natural evolution process. Genetic algorithm is a global optimization algorithm with random search. The basic principle of genetic algorithm is to simulate the evolution law of genetic selection and survival of the fittest [15]. The parameters solved in the problem are encoded as chromosomes. Through many iterations, selection, mutation, intersection, and so on, we use genetic manipulation to create and retain excellent individuals to ensure that individuals have the best adaptability. Genetic algorithm has three important operations: chromosome coding and decoding, design of fitting function and genetic manipulation, and parameter adjustment of genetic function [16]. Chromosome coding and decoding solve this problem. The process of constructing chromosomes in a specific order is called coding, and the process of decompiling the optimal single chromosome output by genetic algorithm to solve the problem is called decoding. Today, common coding techniques include binary coding and real coding. Among them, binary coding is a relatively simple and easy-to-use method, which follows the minimum character set coding principle of genetic algorithm [17]. Binary coding is the main choice for coding in genetic algorithm toolbox of MATLAB. The genetic algorithm is shown in the following formula:

$$\begin{cases} \max f(X), \\ X \in R, \\ R \subset U. \end{cases} \quad (5)$$

X is a decision variable, $\max f(x)$ is an objective function, u is a basic space, and r is a subset of u . The solution x satisfying the constraint conditions is called feasible

solution, and the set r represents the set composed of all solutions satisfying the constraint conditions, which is called feasible solution set.

The main parameters of genetic algorithm are population size, crossing probability, mutation probability, evolutionary algebra, and population initialization method. These parameters determine whether the population will mature prematurely [18]. If the parameter value is too small, it will cause the inbred lines to produce pathological genes. If it is too large, the algorithm will be inefficient. Therefore, the commonly used population size should be between 100 and 200. The execution of genetic algorithm does not depend on the characteristics of the optimization problem itself, and the optimization result can be completed by simple genetic operation. Genetic algorithm searches possible feature strings in space to find good matching strings [19]. In order to perform this search, the algorithm uses only the fitting values related to the inspected points in the search space. No matter how complex the problem itself is, genetic algorithm performs its search by performing the same crossover and accidental mutation operations. In practice, genetic algorithm can search complex and highly nonlinear multidimensional space quickly and effectively.

2.2. Principle and Function of Intelligent Manufacturing System. Intelligent manufacturing system applies mathematical intelligent calculation method to carry out intelligent perception, intelligent reasoning, intelligent decision-making, and intelligent control in the manufacturing process, thus greatly improving the automation and flexibility of the whole manufacturing system [20]. Intelligent manufacturing is the integration of intelligence and manufacturing technology, which uses intelligent technology to solve manufacturing problems. It refers to the representation and learning of manufacturing activity knowledge; the perception and analysis of product life cycle design, processing, assembly, and other linked information; and the realization of intelligent decision-making and execution, manufacturing system, manufacturing equipment knowledge reasoning, dynamic sensing, independent decision-making, and other functions [21]. Intelligent manufacturing is a manufacturing activity, including all links of the whole product life cycle, including some main links: intelligent design, intelligent processing, and intelligent assembly.

Intelligent manufacturing can be divided into three different levels: manufacturing object or product intelligence, manufacturing process intelligence, and manufacturing tool intelligence. Knowledge base/knowledge engineering, dynamic sensing, and independent decision-making constitute the three cores of intelligent manufacturing. Intelligent manufacturing is a higher development stage based on digital manufacturing. Its realization cannot be separated from the foundation of digital manufacturing [22]. Therefore, digital manufacturing technology includes product data management technology, virtual manufacturing technology, rapid prototyping technology, computer-aided inspection technology, and digital manufacturing technology. Control technology is the basic technology of intelligent manufacturing. However, the intelli-

gent manufacturing process focuses on knowledge and reasoning, while the digital manufacturing process focuses on data and information processing. There are essential differences between them. Digital manufacturing system deals with data, but intelligent manufacturing system deals with objects [23]. The processing method of digital manufacturing system mainly stays at the data processing level, while the processing method of intelligent manufacturing system is based on the new generation of artificial intelligence. The mathematical method of digital manufacturing system modeling is a classical mathematical (arithmetic) method. The mathematical method of intelligent manufacturing system modeling is nonclassical mathematics (intelligent mathematics). The performance of digital manufacturing system is declining in use, while intelligent manufacturing system is self-optimizing, and its performance will decline in use. Intelligent manufacturing system has fault tolerance. When the environment is abnormal or abused, the digital manufacturing system will not work normally. Intelligent manufacturing is the result of continuous integration, development, and application of intelligent manufacturing technology. Data mining, machine learning, expert system, neural network, computer vision, Internet of Things, and other intelligent methods are integrated with manufacturing technology to form knowledge representation and modeling technology [24]. Knowledge base construction search technology, heterogeneous knowledge transfer and sharing technology, real-time positioning technology, wireless sensor technology, dynamic navigation technology, autonomous reasoning technology, autonomous compensation technology, autonomous early warning technology, and other types of intelligent manufacturing technologies play an important role in intelligent manufacturing.

The key functions of intelligent manufacturing system are as follows: (1) intelligent perception. Manufacturing equipment of intelligent manufacturing system has the ability to identify unique conditions and environment and supports intelligent analysis and decision-making by identifying and analyzing unique working conditions in real time; (2) intelligent decision. Intelligent manufacturing system has the ability of sensing analysis, making decisions, making decisions, and collecting information. Strong knowledge base is an important element to support intelligent decision; (3) intelligent learning. Intelligent manufacturing system can perform data analysis and mining based on manufacturing operation data or user usage data, so as to continuously improve knowledge base through learning; (4) intelligent diagnosis. Intelligent manufacturing system can automatically diagnose and predict faults based on real-time monitoring of operational data, so as to carry out intelligent troubleshooting and repair; and (5) intelligent optimization. Intelligent manufacturing system can adaptively adjust the organizational structure and operation mode according to the perceived information, so the system performance and efficiency are always the best.

The application models in intelligent manufacturing system can be divided into two types in depth. The first is the traditional shallow learning model, and the second is the deep learning model. The key feature of the shallow model is to use artificial experience to extract the features of samples,

but the focus of the model is mainly on complete classification or prediction. Assuming that there is no error in the application of the model, the quality of functions will become the bottleneck affecting the performance of the whole system [25]. Therefore, R&D teams usually spend a lot of time looking for better functions, which requires R&D personnel to have a deep understanding of the problems to be solved. In order to reach this level, it is usually necessary to repeatedly explore even years of sharpening. Therefore, the function of manually designing samples is not an extensible method [26]. The essence of deep learning is to build a machine learning model with many hidden layers and a large amount of training data, so as to learn more useful functions and ultimately improve the accuracy of classification or prediction. Different from traditional shallow learning, deep learning has the following differences: emphasizing the depth of model structure. There are usually 5, 6, or even 10 hidden nodes. Clearly emphasize the importance of feature learning, that is, the feature transformation of each layer transforms the feature representation of samples in the original space into a new feature space, which is beneficial to classification and prediction. Compared with the way of constructing features by artificial features, deep learning with the features of big data can better explain the rich interior of data. Therefore, in the next few years, more and more examples will use deep learning models with big data instead of traditional shallow models.

Combining mathematical intelligent computing with manufacturing system, various intelligent manufacturing technologies are formed, such as intelligent CAD/CAM technology (ICAD/ICAM), intelligent computer aided process planning technology (ICAPP), intelligent numerical control technology (INC), intelligent database technology (IDB), and intelligent computer integrated manufacturing system (ICIMS). The combination of intelligent methods and manufacturing system models and technologies is very flexible. It can be combined through the commonness of disciplines, levels, and methods, such as knowledge-based digital product/process design, knowledge-based virtual enterprise, illusory virtual technology, and agent-based manufacturing technology. In addition, remote network manufacturing technology, smart grid technology, intelligent Internet of Things technology, intelligent cloud computing technology, intelligent mass data processing technology, and so on have also appeared.

3. General Database Construction Experiment

3.1. Experiment Preparation

3.1.1. Determine Different Mathematical Intelligent Calculation Methods. For big data, the data can be processed and utilized based on intelligent algorithms (such as deep learning) to actively predict output and control all aspects of production. In the absence of data, production can be completed through independent learning. Therefore, different intelligent computing methods are compared to better study them. The situation of multiple algorithms is shown in Table 1.

TABLE 1: The situation of multiple intelligent calculation methods.

	The first algorithm	The second algorithm	The third algorithm
Algorithm	BPES	Genetic algorithm	MARS

3.1.2. Construction of BPES Intelligent Calculation Method. The application of BP neural network in deterministic expert system is called neural network expert system (BPES). According to the rules in the rule base, BPNN is generated, and CF value is used as network weight. Then, BPNN trains and learns according to the training data to form BPES. BPES system extracts IF-THEN rules from knowledge base and generates graphics according to the rules. Deterministic values are used as connection values between nodes of a graph. The specific algorithm is as follows: initialization: rule record parameter $I = 0$, graph record number $k = 0$, rule number in knowledge base KD is m , if it is greater than 0, $m > 0$. Put the first rule r into the knowledge base KD, and then, place d . Otherwise, it ends; select a new rule. Exit if $I = M$, otherwise, determine whether k is the predecessor or successor of R . If so, please increase r to d , otherwise, create a new subgraph. When constructing a BPES intelligent computing method, an empirical formula is needed, as shown in the following formula:

$$h = a + \sqrt{(m + n)}, \quad (6)$$

where a is an adjustment constant between 1 and 10, h is the number of hidden layer nodes, m is the number of input layer nodes, and n is the number of output layer nodes.

The BP algorithm is divided into two steps, namely, forward propagation and backward propagation. Forward propagation passes through all hidden layers and then transmits to the output layer. In the process of layer-by-layer processing, the state of neurons in each layer only affects the state of neurons in the next layer. At the output layer, the current output is compared with the expected output, and if the current output is not equal to the expected output, the BP process is entered. Back propagation used is to transmit the error signal back according to the original forward propagation path and modify the weight coefficient of each neuron in each hidden layer in order to minimize the error signal. In back propagation, an error function is needed, as shown in the following equation:

$$e = \frac{1}{2} \sum_{i=1}^M (X_i - Y_i)^2, \quad (7)$$

in which e represents error, X_i represents sample, and Y_i represents expected output. This learning process should be performed for any given sample and expected output until all input and output requirements are met.

3.1.3. The Construction of Genetic Intelligence Algorithm. Genetic algorithm needs to design fitness function. It can be used to evaluate personal strengths and weaknesses and

often changes from the objective function of optimization problems. If the standard function is a maximization problem, it can be used as a direct fitting function. Objective function is a minimization problem, which needs to be transformed into fitness function. Typical methods include converting opposites or each other. The process of optimization calculation using genetic algorithm is as follows: Step 1: determine the solution space and single phenotype X of the problem, and establish an optimization model; Step 2: when executing genetic algorithm, it is necessary to determine the search space and genotype X of individuals in the population. Therefore, the corresponding relationship between x and z should be made clear; Step 3: different mapping relationships will affect, depending on whether genetic algorithm can find the best solution. Therefore, it is necessary to determine the transformation rules from objective function to individual fitness function; Step 4: design gene operator; and Step 5: determine the operation parameters of genetic algorithm: m , h , p , c , and m . In the construction of genetic algorithm, covariance matrix is needed, and the specific formulas are shown in (8), (9), and (10).

$$\sigma_x^2 = \frac{1}{N} \sum_{i=1}^N (x_i - \mu_x)^2, \quad (8)$$

$$\sigma_y^2 = \frac{1}{N} \sum_{i=1}^N (y_i - \mu_y)^2, \quad (9)$$

$$\sigma_{xy} = \frac{1}{N} \sum_{i=1}^N (x_i - \mu_x)(y_i - \mu_y), \quad (10)$$

in which σ_x , σ_y , and σ_{xy} represent covariance, μ_x and μ_y represent average value, and x_i and y_i represent sample data.

3.1.4. Construction of MARS Intelligent Algorithm. The basic idea of MARS is to partition the entire data area first and then fit the data by fitting a spline function to each truncated area. The modeling process is usually divided into three steps. The first step is the forwarding process. The forward process is a weighted combination process of different basis functions, giving different basis functions different weights. The transmission process is basically the process of dividing the data area and selecting nodes. Each time a node is selected, a smaller area is divided and a pair of spline functions are generated. The second step is the backward trimming process. The forward process will produce many truncated spline function groups, and the model obtained at this time is overfitting. At present, some basic functions have been deleted and the model complexity has been reduced to prevent overfitting. The third step is model selection. Different models will be generated during the pruning process. People need to find the best model according to certain conditions.

3.2. Experiment Content. After obtaining the input feature vectors and corresponding labels of various algorithms, a network design is needed, including network type, topology, hyperparameters, and optimization algorithm. In order

TABLE 2: Parameter settings.

Parameter	Number of hidden neurons	Initial learning rate	Regularization coefficient
Interval	[10, -625]	[0.00000001, 1.0]	[0.00000001, 1.0]

to ensure the independence of design and verification, network design and optimization are based on the cross-validation set in the data set, network training is based on the training set, and the final network test is based on the test set.

The model used in this paper is the furnace temperature control model, which has many links, including power data processing, heating furnace predictive control, and superparameter optimization. BPES intelligent computing method, genetic algorithm, and MARS algorithm are applied to this model. BPES intelligent calculation method is mainly used in power data processing, genetic algorithm is mainly used in predictive control of heating furnace, and MARS algorithm is mainly used in superparameter optimization. The details are as follows:

3.2.1. Application Process of BPES Intelligent Calculation Method in Power Data Processing. The power data processing process has many complicated processes, and it is more difficult to operate stably for a long time. Over the years, operators have often managed power data based on years of experience, and accumulating such experience requires long-term operating experience and extensive knowledge. Therefore, a neural network is used based on the deterministic expert system. The training and learning expert system are used to supplement the knowledge base of the power 0 data fault diagnosis system and improve the learning ability and diagnosis accuracy of the system.

The application process is as follows: initial training: according to the generated network diagram, the training is carried out according to the BP algorithm. When the error is met or the number of training times is reached, the training ends; learning process: the network is fully connected, and the initial weight of the new connection is set to -1; retraining: train a fully connected network, and the training encounters errors or reaches the end of the training time.

3.2.2. Parameter Setting of MARS in Hyperparameter Optimization. In the Internet age, methods and technologies for handling large amounts of data are particularly important. Multivariate adaptive regression spline is a regression method that can handle high-dimensional data. The experimental parameters are set as follows. The initial random number of points is set to $2d + 1$. d is the dimension of the optimization problem. Due to the optimization of functions, the number of iterations set in the experiment is 500. For the hyperparameter optimization of the machine learning model, the number of iterations set in the experiment is 100. In the hyperparameter optimization based on MARS, the adaptive sampling method used is CAND.

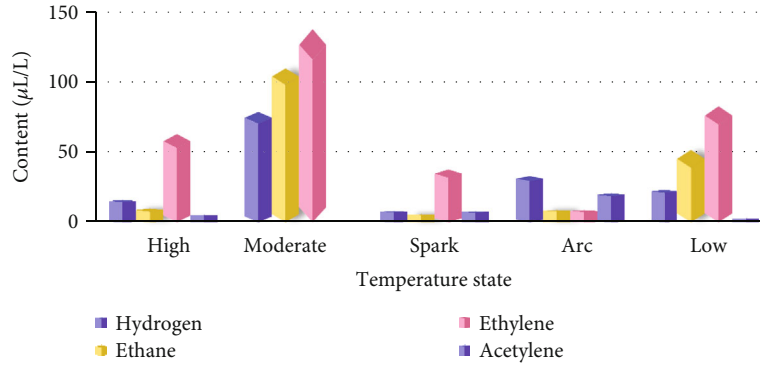


FIGURE 4: Comparison of transformer sample data.

4. Digital Intelligent Computing Application Results

4.1. Analysis on Application Effect of Mathematical Intelligent Calculation in Computer Intelligent Manufacturing System. Based on the above configuration, the experiment of MARS for hyperparameter optimization mainly optimizes the following hyperparameters. That is, the size of hidden layer neurons, the type of optimization algorithm (solver), the type of activation function, the initial learning rate, and the regularization coefficient. The parameters are shown in Table 2.

As shown in Table 2, the number of hidden layer neurons is set to [10-625], and the initial learning rate and regularization coefficient are both set to [0.00000001, 1.0]. This ensures that MARS can have a good effect comparison when applied to hyperparameter optimization. If the parameters change after optimization, the application effect of MARS can be evaluated. If the parameters are not set in advance, there is no good standard for proceeding.

The BPES intelligent calculation method is applied to power data processing. More than 1,000 rules have been obtained from the actual data of the power supply design laboratory, of which more than 600 are related to transformer failures as shown in Figure 4.

4.2. Analysis on the Efficiency of Mathematical Intelligent Computing in Computer Intelligent Manufacturing System. Use MARS to screen and sort on hyperparameter optimization. Min, Max, Mean, Std, and time, respectively, represent the best result, worst result, average result, variance, and multiple times when various data-driven optimization algorithms perform multiple minimums on the same optimization problem. In the average time of independent operation, GP-PI, GP-EI, and GP-LCB represent optimization based on the acquisition functions PI, EI, and LCB, respectively. It is very important to observe its work efficiency, because hyperparameter optimization is to find a set of suitable hyperparameters in a limited time.

As shown in Figure 2, the efficiency of hyperparameter optimization based on MARS is very high. The best results, worst results, average results, variance, and average time of multiple independent runs are all controlled below 0.03 s. Of course, this is also related to the lack of sample data. The computational complexity of the data-driven hyperpara-

meter optimization algorithm involves two main aspects. On the one hand, it comes from functional evaluation, involving the training and testing of machine learning models. Another aspect is the establishment and update of regression models.

The era of big data puts forward higher requirements on intelligent computing technology. With the in-depth research and development of deep models such as deep learning, the widespread use of GPUs and other computing devices, and the rapid development of distributed parallel algorithms, intelligent computing technologies for big data have now been applied to speech recognition, facial recognition, image recognition, search engine, and other fields. A horizontal comparison of three intelligent computing technology application fields: MARS, genetic algorithm, and BPES, was performed.

As shown in Figure 3, the application interval similarity of MARS, genetic algorithm, and BPES is above 67%. Not only that, the application of BPES intelligent computing technology is more extensive than the other two groups, but in general, the three groups of algorithms. There are many intersections in the application. This shows that the three sets of algorithms have good optimization performance and play an important role in many fields.

5. Conclusions

- (1) With the rapid development of economics, people are not only concerned about the qualitative economic relationship in practical problems but also more concerned about the quantitative relationship between various economic variables, so as to maximize their own benefits with better decisions. The requirements for digital intelligence in various fields are getting higher and higher, and the application scope of intelligent manufacturing systems is expanding, it is urgent to solve this problem. And mathematical intelligent computing technology plays an important role in integrating data and improving efficiency. Through the research on the application of mathematical intelligent calculation in computer intelligent manufacturing system, it is found that mathematical intelligent calculation has significant application effects in many fields

- (2) The purpose of this article is to explore the application research of mathematical intelligent calculation in the computer intelligent manufacturing system; construct BPES, genetic algorithm, and MARS intelligent calculation methods; and carry out the in-power data processing, heating furnace predictive control, and hyperparameter optimization. In application, to measure the application effect of BPES, genetic algorithm, and MARS, it is found that the application effect of mathematical intelligent calculation is very good, and the effect is significant in big data processing and temperature prediction

Data Availability

The data used to support the finding of the article are available upon the author's reasonable request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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