Analysis of Marketing Forecasting Model Based on Genetic Neural Networks: Taking Clothing Marketing as an Example

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In this paper, according to the requirements of clothing sales forecast, the forecast model of clothing sales is constructed. Through the design of cyclic structure, the adverse effects of uncertainty, hysteresis, and time-varying factors of the predicted object are overcome, and the prediction procedure is theoretically standardized. Aiming at the shortcomings of traditional NN sales forecasting algorithm, such as low learning efficiency, slow convergence speed, and easy to fall into local minimum, this paper puts forward some improvement measures. Adaptive learning efficiency is used to improve the effectiveness and convergence of the algorithm, additional momentum method is used to improve the adaptability of the algorithm, and improved GA is used to optimize the weights of NN. Improve the global optimization characteristics of GA to achieve the purpose of fast optimization and accurate prediction. Finally, an example is used to verify the algorithm. On this basis, the correlation adaptability and prediction accuracy of clothing prediction methods are compared and analyzed, combined with the theoretical analysis of various methods, to explore the practical applicability of various methods under different prediction conditions. It provides an important basis for the decision-making of garment enterprises.

1. Introduction

China’s textile and garment industry is one of the industries that can best reflect international competitiveness. China’s total textile exports have maintained double-digit growth, but profits are constantly sliding [1]. With the development of economy, garment enterprises are facing a complex and changeable market environment. Only by ensuring the correct prediction of future sales can they make correct decisions and adapt to the changes of business environment [2]. The rapid development of China’s garment industry provides consumers with a free choice of products, and the industry competition is more intense. The competition among garment enterprises has developed from the initial purchase of raw materials, product design and production, sales channels, sales means, selection of sales venues to the promotion of grade effect, brand image design, and other in-depth links [3]. With the vigorous development of online shopping market, the application of artificial intelligence in clothing e-commerce has become a hot research field. Using machine learning methods to classify, retrieve, and match clothing products plays an important role in improving the clothing sales of e-commerce. The research time of sales forecasting in the field of clothing is not long. In practice, there is a lack of comprehensive understanding of the accuracy and applicability of forecasting procedures and methods, and many problems are encountered in the actual forecasting. Although much work has been accumulated in this field, they still have many shortcomings and need to be improved.

Clothing market prediction refers to the analysis of the supply and demand change law and development trend of the clothing market in a certain period in the future by using scientific methods and mathematical models on the basis of systematic investigation of the factors affecting the clothing market, so as to make a logical judgment and calculation of clothing sales [4]. With the increasingly fierce market competition, sales forecasting has been paid more and more attention by garment enterprises, and there are more and more methods for sales forecasting of garment products.
Clothing market share forecast, sales target forecast, clothing raw materials and product price forecast, clothing sales forecast, and so on are some of the main contents of clothing sales forecast research. Because of its characteristics of low cost, convenience, and rapidity, as well as its lack of time and space constraints, e-commerce is growing at an incredible rate [6]. With its strong adaptive learning ability, the back propagation neural network (BPNN) is now widely used and has achieved good results. However, in practice, its learning and training results can have significant errors. The main reason for this is that BPNN still has a number of flaws. This paper focuses on garment sales prediction because it can help garment businesses understand differences in consumer demand, accurately judge future sales prospects of garment commodities, and closely combine production and sales. In recent years, improved neural network (NN) technology [7] has been applied to actual enterprise sales forecasting, and the design process of network structure has been analyzed and studied to provide support for enterprise management decision-making.

With the continuous popularization and maturity of e-commerce platform in the international and domestic market, more and more clothing commodity enterprises and consumer groups began to turn to the network, showing a more positive and good development trend. The research of NN has made progress and achievements in many aspects, proposed a large number of network models, found many learning algorithms, and successfully discussed and analyzed the system theory of NN [8]. On this basis, the artificial neural network (ANN) has also achieved fruitful applications in the fields of pattern classification, machine vision, machine hearing, robot control, signal processing, combinatorial optimization problem solving, associative memory, coding theory, medical diagnosis, financial decision-making, data mining, and so on [9]. The reason why NN technology has such a high exposure rate is inseparable from its many advantages. It can analyze a large amount of data at the same time and store relevant information, respectively. In addition, NN can also carry out self-learning and self-adaptation. What is more amazing is that it also has fault tolerance to a certain extent and can be close to complex nonlinear relationships in specific cases. It can process quantitative and qualitative data or information at the same time as the cloud model, and NN can also process nonlinear and uncertain data [10]. This paper establishes a prediction model based on genetic algorithm neural network (GANN). Genetic algorithm (GA) is used to optimize the initial weight and threshold of the network, and the feasibility of removing outliers and dimensionality reduction is proposed based on sample clustering and principal component analysis. Simulation experiments are carried out, respectively, and the results are compared to obtain the optimal solution. By comparing the model with the statistical prediction method, it is judged that the model is obviously superior to the statistical method in overcoming the adverse effects such as uncertainty and nonlinear change of the prediction object and the prediction accuracy. The feasibility and accuracy of the genetic BP network are verified by simulation experiments. It can be used in the sales forecast of garment enterprises.

2. Related Work

In the study of periodic time series forecasting, reference [11] used iterative ANN to model and compare the two methods of direct and iterative forecasting. Reference [12] used fuzzy NN to predict Taiwan’s manufacturing industry’s innovation performance and created an adaptive fuzzy NN inference system. A new automatic smooth integration model based on time series and ANN was proposed in reference [13]. Reference [14] proposed a maximum learning mechanism to optimize ANN, and it accurately predicted monthly clothing sales through the learning and training of a specific brand’s sales data. Reference [15] uses Sina Weibo data to predict movie box office using the BPNN prediction method. The number of hidden layer nodes, weights, and thresholds of BPNN is optimized using GA using a mixed coding of binary and real numbers in reference [16]. In reference [17], a GA with a three-layer chromosome structure was proposed for simultaneously optimizing the topological structure and weight space of the BP network. And the experiment validated the scheme’s viability. For the inherent flaws of nonlinear phenomena in statistical model prediction, reference [18] proposed a clothing sales prediction model based on NN. The implementation of NN in clothing sales forecasting is investigated, as well as the modeling steps and network parameter optimization. Reference [19] proposed an improved genetic BP algorithm for adaptive crossover and mutation operators, as well as multiple stepwise regression to reduce the number of variables in the BPNN input variables. For the premature flaws in the GA algorithm, reference [20] proposed improved crossover and mutation strategies, as well as the use of immigration operators to improve the algorithm’s performance. Reference [21] uses an improved GA algorithm to adjust the NN structure and parameters. The example of sunspot prediction shows the advantages of the improved GANN algorithm. Reference [22] uses GANN based on gene mutation to replace traditional BPNN. Gene mutation strategy can better adapt to evolutionary procedures and effectively optimize weights. Reference [23] improved and optimized ANN. And through empirical research, forecast the monthly sales of clothing products, and finally compared with traditional forecasting methods, and achieved better forecast results. Reference [23] proposed a scheme of using genetic BPNN to classify customers and verified the feasibility of this scheme through experiments. Compared with the classic decision tree classification model, its classification scheme has the advantages of simple modeling, good scalability, and strong fault tolerance. Reference [24] proposed a plan to use the smooth BPNN model to predict the time series of the commodity market share and through experiments proved that this model has a slightly higher prediction accuracy than the general BPNN model. Compared with the traditional state-space prediction model, it shows that this model has better flexibility and higher prediction accuracy than the state-space model.

In light of the complexity and uniqueness of product sales in apparel companies, this article proposes an effective GANN-based marketing forecasting model based on
previous studies. A sales forecast network model is established based on an analysis of the factors that influence clothing sales, and GA is used to optimize the calculation of each connection weight of the BPNN. The method combines the benefits of the backward propagation neural grid and GA, providing both NN’s powerful learning capabilities and GA’s global search capabilities. It can help businesses improve the efficiency and accuracy of their clothing sales forecasts.

3. Methodology

3.1. GANN. Building a sales forecast model based on ANN is one of the most effective methods to forecast future sales. NN is widely used in intelligent control, system optimization, pattern recognition, sales forecast, and other fields [25]. BPNN algorithm is the most widely used NN algorithm. The learning algorithm of BPNN adopts error back propagation which is a supervised learning process. The advantages and disadvantages of NN structure affect the learning and training rate and convergence rate of the whole network. Too few network nodes may lead to large errors in output results, while too many network nodes may lead to prolonged learning time and slow convergence rate of the whole network.

ANN is a computational structure based on modern neurobiology research that simulates biological processes and reflects some human brain characteristics [26]. It is an abstraction, simplification, and simulation of the nervous system of the human brain, rather than a true description. Zheng has made remarkable progress in many disciplines and is widely used in intelligent control, signal processing, data prediction, optimization calculation, biomedical engineering, and pattern recognition because it is a new information processing model that imitates the biological nervous system and has a unique structure. Neurons are frequently referred to as “processing units” in ANN [27, 28]. It is sometimes referred to as a “node” in the context of a network. A basic artificial neuron is depicted in Figure 1.

A multilayer feedforward network made up of nonlinear transformation units is known as BPNN or error BPNN. The weight coefficients of each layer in the network can be adjusted and corrected by solving the minimum value of the error function and using the learning method of minimum mean square error. It has excellent self-learning and parallel processing abilities, as well as some generalization, generalization, and adaptive abilities. There are three layers in BPNN: an input layer, an output layer, and a hidden layer. There is no mutual connection between units in the same layer, and the layers are fully connected. Forward information transmission and backward error propagation are the two parts of the BP algorithm. Despite the fact that BPNN has been successfully applied, it still has some shortcomings in terms of practical operation, such as low learning efficiency, slow convergence rate, and network learning and memory instability [29]. The BPNN learning rate is slow, and there is a high risk of network training failure.

GA has the following characteristics: it has a wide range of fast searching ability in the search space. As a global optimization search algorithm, it can avoid local minima. In the evolution process, it does not need to provide gradient information of the problem to be solved. It does not rely on any external knowledge of the search space but only uses the fitness function to guide and optimize the search. According to the original algorithm flow and the improvement ideas in this paper, a new improved GANN algorithm flow is established, as shown in Figure 2.

Fitness is a numerical value that describes the degree of fit between each individual project and the required target, and fitness function is a function designed to calculate this numerical value, which directly determines the selection result. Before solving a problem with GA, we must first encode the solution space of the problem so that it can be operated by GA. The most commonly used coding method is binary coding. When the variables in the solution space are discrete variables, each variable can be directly encoded with a binary string of corresponding digits. For those continuous variables, it is necessary to discretize the continuous variables before encoding them.

The advantage of GA is that while using probability search technology, multipoint search of solution space can be carried out. It avoids falling into the local minimum, increases the flexibility of searching, and improves the calculation speed of the system. GA optimizes the parameters of each connection layer of BPNN, and through repeated training and adjustment, finally determines the optimal weight threshold of the network. Practice has proved that better results can be achieved by optimizing the initial weight threshold of BPNN with GA.

3.2. Marketing Forecast Model. The sales market of clothing industry includes both domestic and international markets. This paper mainly focuses on the clothing sales in domestic market. Clothing sales are influenced by various complicated factors, such as fashion trends, seasonal climate changes, product prices, holidays, shop decoration, regional consumption differences, and brand awareness. The above-mentioned influencing factors are used as inputs to construct the forecast.

Consumer demand is increasingly diversified. Modern consumers pay attention to individuality in dressing, and clothing has become the external display of expressing their individuality and self-pursuit. Color and style can best express people’s personality, and the personalized development of color matching and style has become a key factor affecting clothing sales. Personalized service of clothing products has also been further developed. Besides tailor-made and tailor-made, there are deep personalized services such as special design to meet different levels of consumer needs.

When dealing with the problem of clothing sales forecast, NN, as a new mathematical modeling method, can discover the mapping relationship between factors affecting clothing sales and sales volume by analyzing historical sales data. Pattern recognition and excitement extraction are the core elements of the mapping process. During the learning
process, patterns are extracted and saved. The next period’s sales output can be generated directly from the network’s input during the prediction stage. The accuracy of the prediction is determined by the network structure and algorithm, as well as whether the training data is sufficient and representative. The real number is used to encode during the encoding process. The randomization of the population increases as the crossover probability increases, the diversity of the population expands as the mutation probability increases, and the risk of the algorithm falling into a local optimal solution decreases with the continuous increase of population size.

In fact, fashion trends are characterized by constant dynamic changes, and popular elements include a wide range of factors such as fabrics, styles, and colors, making it difficult to extract typical characteristics data from historical sales data. Create a network model for the BPNN parameters that have been determined, and reassign the best individual to the initial weight threshold of each BPNN connection layer after GA optimization. Then, after sending the normalized sample data to BPNN for learning and repeated training, determine the network’s system parameters based on its performance, and finally, create the BP network model. The prediction model is built using the GANN algorithm, the global search is done using the GA algorithm, and the unknown areas are targeted. Although the processing speed is fast, the accuracy is low, and falling into local minima is difficult. To improve
search speed and accuracy, the BPNN algorithm is used to look for the areas with the most benefits.

As the smallest unit in NN, neuron is a model with input, output, and calculation functions. We can use a complex nonlinear function to represent neurons:

$$z(x) = f \left( \sum_{i=1}^{D} w_{ij} x_i + w_0 \right).$$

(1)

Among them, \( \{x_i\}_{i=1}^{D} \) is the input, \( \{w_{ij}\}_{i,j=0}^{D} \) is the weight coefficient of the neuron to be trained, and \( z \) is the output. Sigmoid function, the mathematical expression is

$$f(x) = \frac{1}{1 + e^{-x}}.$$ (2)

Tanh function, the mathematical expression is

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}.$$ (3)

Softmax function, the mathematical expression is

$$f(x)_j = \frac{e^{v_j}}{\sum_{i=1}^{D} e^{v_i}}, \quad j \in [1, D],$$ (4)

where \( M \) is the dimension of the vector \( x \) and \( x_j \) is the \( j \)-th element in \( x \). Through the function expression of the above neuron, we can easily describe a \( K \)-layer fully connected network:

$$z_{j}^{(k)} = f \left( \sum_{i=1}^{D} w_{ij}^{(k-1)} z_i^{(k-1)} + \xi_{ij}^{(k-1)} \right), \quad k \in [1, K], \quad z^{(0)} = x,$$ (5)

where \( z_{j}^{(k)} \) represents the \( k \)-th layer of the network and the \( j \)-th neuron.

Through the genetic coding operation, genetic coding is performed on the randomly assigned initial weight threshold to obtain a randomly distributed sequence string. The real number coding scheme is used. Compared with the traditional binary coding scheme, the optimal solution is directly listed by all the weights of the NN, thus omitting the encoding and decoding process between binary and real numbers and improving the accuracy of the solution and the learning of NN speed.

The code chain of the encoding is made up of the connection weights, hidden layer unit thresholds, and output layer unit thresholds between the network layer units. Arrange them in order to form a code chain, corresponding to the weights or thresholds on a specific connection in NN. A group of code chains represents a group of different weight values, and each code chain represents a type of weight or threshold distribution state of the network NN. Send the normalized prediction sample data to the trained BP network model, which will then predict the output data and denormalize it. Optimize the weight threshold of each BPNN connection layer using GA. To begin, genetically encode the initial weight threshold of each network connection layer, and then, use the sum of the absolute value of the error between predicted and actual sales volume as the individual fitness function. Calculate the individual fitness function value, then repeat the selection, crossover, and mutation operations to generate new genetic individuals, recalculating and comparing the individual fitness function values to obtain the optimal fitness function value, and use the optimal fitness value to locate its location. The formula for adaptive change of crossover probability and mutation probability with fitness value is as follows.

$$p_c = p_c^0 + \frac{k_1 \left( f_{\text{avg}} \right)_{n_i}}{\left( f_{\text{max}} - f' \right)^{\eta_i}}.$$ (6)

$$p_m = p_m^0 + \frac{k_2 \left( f_{\text{avg}} \right)_{n_m}}{\left( f_{\text{max}} - f' \right)^{\eta_m}},$$ (7)

where \( f_{\text{max}} \) is the largest fitness value in the group; \( f_{\text{avg}} \) is the average fitness value of each generation group; \( f' \) is the larger fitness value of the two individuals to be crossed; \( f \) is the fitness value of the individual to be mutated. \( p_c^0 \) and \( p_m^0 \) are the initial crossover and mutation probabilities; and \( k_1, k_2, n_c, \) and \( n_m \) are coefficient factors. Use the following normalization method to transform the data into the \([0,1]\) interval.

$$x_i = \frac{(x_i - x_{\text{min}})}{(x_{\text{max}} - x_{\text{min}})}, \quad i = 1, 2, \ldots, m,$$ (8)

where \( x_i \) represents the input or output data, \( x_{\text{max}} \) represents the minimum value of the data change range, and \( x_{\text{max}} \) represents the maximum value of the data change range.

When using the BPNN algorithm to train the network, the larger the \( \eta \), the greater the weight change, but if the weight changes too much, oscillations will occur in the learning process. In order to avoid this phenomenon, the method of adding momentum term can be adopted. According to the actual needs, this paper designs the crossover and mutation formulas that adaptively change with the fitness and the number of iterations.

4. Result Analysis and Discussion

BPNN is used for sales forecasting. Aiming at the defects of BPNN algorithm, improvement measures are adopted to improve its convergence speed and overcome local extreme phenomenon. Through the analysis of the influence factors of sales forecast and the establishment of the forecasting program, the forecast stability and forecasting effect of apparel companies have been improved. However, in the method selection stage of the forecasting program, the appropriateness of the initial selection method affects the efficiency of the entire program. In the prediction experiment of sample data, we plan to use the typical prediction method selected above to predict the sample data according
to the established prediction program, verify the applicability of the clothing sales prediction program, and compare and analyze various prediction methods based on the prediction results.

The GA algorithm is a global optimization algorithm. The training problem of BPNN is actually an optimization problem, that is, finding the optimal connection weight so that the difference between the output of the NN and the target output is extremely small. Therefore, GA can be used to train the connection weights of BPNN. Compared with the nonlinear activation function of the hidden unit, the linear weights connected to the network output units are updated on a different “time scale.” When the activation function of the hidden layer is slowly updated according to a certain nonlinear optimal strategy, the output weight is adjusted quickly according to the linear optimal strategy. Therefore, for the training of the hidden layer and the output layer, different optimal strategies can be used, and perhaps, different time scales can be used.

This article focuses on the influence of seasonal and category factors on product sales based on the sales characteristics of clothing products. Numerical experiments must address the inconsistency between model prediction accuracy and precision, reduce network redundancy as much as
possible, and improve generalization ability while ensuring fault tolerance. The average absolute error, square error, and mean square error are used to compare and analyze the predicted output result with the actual value of the target output, as well as summarize and evaluate the system model’s performance, after network model learning, training, and prediction. Figure 3 shows the prediction results of XX brand men’s/women’s clothes using ordinary BP network.

Identifying outliers is because clothing sales have a certain contingency. The relationship between sales volume and input variables in a certain period may deviate from the normal data structure, and it is reflected in the data as outliers. Common discriminant models include maximum entropy model, conditional random field, and so on. These models directly model the conditional probability distribution. Although it cannot describe the overall distribution of the data set, when faced with multiple classification tasks, the classification effect is usually better than the generative model. The average absolute error of using unoptimized ordinary BPNN and GA optimized BPNN model is shown in Figure 4. The squared difference is shown in Figure 5. The mean square error is shown in Figure 6.

It can be seen that the error value of BP network optimized by GA is smaller than that of ordinary BPNN. It shows that the genetic BP network model is superior to the ordinary BP network model. Experiments show that, compared with the nonoptimized BPNN, the GA-optimized BPNN has higher prediction accuracy, while avoiding the shortcomings of slow convergence speed.

![Figure 5: Comparison of the squared difference of the two models.](image)

![Figure 6: Comparison of the mean square error of the two models.](image)
and easy falling into local minimum in the learning and training of the ordinary BPNN, and can more accurately reflect the product sales trend in the actual sales forecast.

In the clothing sales forecast, there are many indicators that sample data can collect, among which there may be variables unrelated to the basic data structure. When establishing the prediction model, principal component analysis can be used to identify the index data with strong linear correlation with other factors in the input sample data, which can be regarded as removable factors, so as to explore the feasibility of dimension reduction of the input vector. And principal component analysis can be used to identify possible outliers in the data set. NN algorithm, BPNN algorithm, and improved GANN model are used to forecast, respectively. The data from January 2019 to December 2020 were taken as the training data of NN model and normalized. The data from January to May 2021 are used as test data. The training data is organized by time series window method. That is, every five data in sequence is taken as an input sample, and the sixth data is taken as an output sample. The average prediction error of each model is shown in Figure 7. The prediction accuracy of each model is shown in Figure 8.

It can be seen from the figure that the prediction accuracy of BPNN algorithm is not ideal enough. The prediction error is high, while the prediction accuracy of the improved GANN algorithm has been greatly improved, the absolute error is much smaller, and the prediction result is very ideal. This shows that the mathematical model established by GANN algorithm can correctly reflect the future trend and change rule of customer sales.

The network prediction model used in this paper has a strong ability to identify the trend value in the clothing sales prediction, especially the prediction accuracy of the fluctuation change of sales volume is very high, while seasonal index method and multiple regression method have certain errors and lags in identifying the fluctuation of sales volume and the peaks and valleys. Comparatively speaking, the results of this paper’s network prediction are objective, and the effect is unmatched by statistical methods. Therefore, whether using this paper’s NN prediction model to simulate or predict clothing sales, it will have a predictable and good application prospect. Experiments show that the prediction accuracy of BPNN optimized by GA is higher. With the help of the characteristics of GA, it can effectively avoid the shortcomings of BP network and combine the advantages of the two algorithms to improve the prediction accuracy and convergence speed when it is applied to the modeling and prediction process of BPNN.
5. Conclusions
Clothing sales forecasting accuracy is critical to the healthy marketing activities of clothing businesses. Clothing sales, on the other hand, are a multi-industry and multidepartment activity, and the rapid and diverse changes in consumption make forecasting clothing sales more difficult. We must pay attention to the standardization of the forecasting process, the reliability of data mining, and the scientificity of forecasting methods in order to achieve high accuracy. In this paper, improvement measures are proposed to address the shortcomings of traditional NN algorithms, namely, GA is used to optimize NN, and the characteristics of global optimization of GA algorithm are used to compensate for the shortcomings of BPNN algorithms, such as slow convergence speed and easy falling into local minima, in order to achieve the goal of fast optimization and accurate prediction. This paper proposes a clothing sales prediction procedure, theoretically standardizes the prediction's implementation procedure, and empirically verifies its rationality and superiority. The modeling steps and parameter optimization methods are investigated based on the characteristics of clothing sales forecast and GANN. The traditional GA algorithm has been improved, and the improved GA algorithm has better convergence than the preimproved GA algorithm, resolving the premature convergence problem more effectively. Finally, an example demonstrates that the improved GANN prediction algorithm has greatly improved prediction accuracy, providing a scientific and effective technical means for enterprise sales prediction that is also practical.

Data Availability
The data used to support the findings of this study are included within the article.

Conflicts of Interest
All the authors do not have any possible conflicts of interest.

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