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Research Article

Evaluation Model of Low-Carbon Circular Economy Coupling Development in Forest Area Based on Radial Basis Neural Network

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In this paper, we study the radial neural network algorithm for low-carbon circular economy in forest area, design a coupled development evaluation model, study its algorithmic ideas operation mode and the update formula obtained by standard algorithm, and finally optimize the RBF neural network by particle swarm algorithm. After an in-depth analysis of the particle swarm algorithm, an improved particle swarm algorithm is proposed to improve the search accuracy and capability of the algorithm by nonlinearly adjusting the inertia weights and introducing the average extreme value factor, in response to the problems of premature convergence and poor search capability that appear in the particle swarm algorithm. Through the analysis and evaluation of the interaction between industrial ecosystem and carbon emission, the main influencing factors of carbon emission are identified, and the size and magnitude of the influence of economic growth, industrial structure, energy intensity, and energy structure on carbon emission are determined; the current situation of the industrial ecological structure is evaluated, and the direction of optimization and adjustment of industrial economic structure, energy structure, and ecological structure is clarified. We construct a multidimensional multiconstraint multimodel industrial ecological structure optimization prediction model, set the development scenarios of economy and society, and optimize the prediction of low-carbon industrial ecological structure in forest areas; based on the simulation analysis of the prediction results, we propose the direction of industrial ecological structure adjustment and the path of industrial ecological system construction.

1. Introduction

The massive emission of greenhouse gases, mainly carbon dioxide, is the main culprit of global warming [1]. The international community is actively exploring a sustainable development path to effectively control carbon dioxide emissions (referred to as carbon emissions, hereafter the same) under the framework of the United Nations Framework Convention on Climate Change [2]. CO_2 is the main factor causing global warming, and vegetation absorbs CO_2 and produces oxygen to exchange carbon with the atmosphere to balance the CO_2 in the atmosphere, but the emergence of the industrial revolution has driven the change of land use pattern, and deforestation has weakened the carbon exchange function of vegetation [3]. At the same time, the extensive use of fossil fuels for economic development has led to a decrease in carbon uptake on the one hand and an increase in carbon emissions on the other, thus triggering global warming [4]. Industrialization is accelerating and the population is growing, bringing about massive exploitation and consumption of natural resources. There is a rapid increase of global wealth built on the premise of massive consumption of global resources [5]. According to statistics, three major energy sources, coal, oil, and natural gas, account for more than 80% of the energy consumed worldwide. The spread of the low-carbon concept has opened new horizons for solving global warming and energy problems. In the context of global climate change and energy shortage, the UK was the first to propose the concept of a "low-carbon economy" [6]. At the Copenhagen Summit, leaders from more than 190 countries attended the meeting and actively negotiated on the issue of carbon reduction [7]. Countries are actively taking measures to strengthen cooperation, establish energy saving and emission reduction targets, and vigorously develop clean energy sources such as tidal energy instead of fossil energy. There are many kinds of algorithms in use for radial-based neural networks, and, in general, each has its advantages and disadvantages, and researchers are struggling to find better algorithms [8]. After studying various algorithms, it is found that the algorithms almost all revolve around function network centre selection, basis function width, and weight adjustment to perform optimization. In the face of increasingly complex applications, classical algorithms have been difficult to meet the daily needs, resulting in many evolutionary algorithms, which belong to a bionic search algorithm with strong robustness, able to adapt to different problems and environments and to search for relatively efficient optimal solutions [9]. Based on different biological principles, evolutionary algorithms mainly include ant colony algorithms, particle swarm algorithms, and genetic algorithms. Combining evolutionary algorithms with neural networks is a relatively hot and current topic in artificial intelligence [10].

Tikhamarine et al. used urban planning in Malaysia as an example, and they found that a compact urban layout is beneficial to the reduction of energy consumption and carbon emissions [11]. The British scholar Lissak explored how to achieve low-carbon economic development goals from the perspective of spatial structure and argued that, in the construction of low-carbon cities, it is important to focus on the adaptation of urban development goals to low-carbon technologies [12]. Tamoffo constructed a VAR model to investigate the impact of GDP and energy consumption on carbon emissions [13]. The results showed that energy consumption is the main influencing factor and proposed to develop and utilize new energy sources such as wind energy and reduce the use of fossil energy to promote the development of a low-carbon economy [14]. Salam used the Lotka Volterra model and the PET model, respectively, and found that there is a positive correlation between population growth and the simultaneous increase in carbon emissions [15]. Yousefpoor analysed carbon emissions from a per capita perspective based on the fixed-effects model and concluded that industries such as energy and chemical industries have the highest correlation coefficients with per capita emissions and are the most important influencing factors of per capita emissions [16]. Regarding the countermeasures of carbon emission reduction, foreign scholars mainly focus on the macroeconomic policy of carbon emission reduction, carbon emission trading mechanism, the low-carbon legal system, and low-carbon financial policy. For example, there are three main types of macroeconomic research models on the intrinsic influence mechanism of carbon emissions on economic growth: optimal growth model, comprehensive evaluation model, and general equilibrium model [17]. The previous studies have provided rich experiences and results for later generations, which play a good reference role, especially on the measurement methods of carbon emissions, and the Intergovernmental Panel on Climate Change (IPCC) compiled the greenhouse gas. The IPCC Greenhouse Gas Inventory Guidelines have become a universal and common standard. Scholars at home and abroad have enriched the connotation and extension of low-carbon cities from different aspects [18]. In the research of low-carbon city development based on carbon emissions, most scholars have made an empirical analysis of carbon emissions from the end energy consumption, which provides the development direction of low-carbon cities to the latter. It has become a social consensus that the necessary path for the development of low-carbon cities is to develop low-carbon industries.

This paper establishes the theoretical framework and methodological system for the research on the construction of an industrial ecological system in low-carbon forest areas. From the perspective of the composite ecosystem in forest areas, this paper systematically analyses the carbon cycle process in forest areas by applying the theory of industrial ecology, puts forward the idea that industrial system and ecosystem are isomorphic to solve the carbon emission in forest areas, and establishes the methods and paths for the construction of the industrial ecological system in low-carbon forest areas, which provides a theoretical and methodological basis for the research on the construction of the industrial ecological system in low-carbon forest areas. It provides a theoretical and methodological basis for the study of industrial ecosystem construction in low-carbon forest areas. An industrial ecology analysis method for carbon emissions from forest complex ecosystems was established. In the framework of forest complex ecosystem, the carbon flow of industrial ecosystem and its interaction with carbon emission are quantitatively analysed, which provides a new way of thinking and analysis method to control carbon emission systematically from the root. There are two main ways to combine neural network and evolutionary algorithm, the first one is that the two algorithms are carried out collaboratively, and the evolutionary algorithm is used to select the topology and parameters of a neural network to solve the problem together; the other one is that evolutionary algorithm is used to preprocess the data first, and neural network is used to solve the problem at last. For the research of this topic, many scholars have proposed improved models, and they are widely used in various fields of society. How to choose a better way of combining algorithms to improve the accuracy and efficiency of the algorithm, which can greatly promote the use of artificial intelligence, is the background and significance of the research in this paper.

2. Radial-Based Neural Networks for Low-Carbon Circular Economy Coupled Development Evaluation Model Design in Forest Area

2.1. Improved Radial Basis Neural Network Design. RBF neural networks have good approximation performance for nonlinear networks and are gradually being widely used in different fields and industries. Biologists have found that neurons in the human brain produce local responses based on stimuli, and RBF neural networks were proposed on this basis [19]. RBF is a novel and effective neural network; scholars have invested a lot of research efforts to promote the development of this field. Like BP neural network, RBF neural network is a feed-forward neural network, which consists of 3 layers, including input layer, implicit layer, and output layer, among which the implicit layer is the key layer that learns and trains the data by using a radial basis function as the kernel function. In this way, the original linearly inseparable problem made linearly separable so that it can be solved by a linear system of equations, which largely speeds up the learning efficiency and avoids local minima in the process. The basic neurons and neural network structure of the radial basis neural network are first given below, as shown in Figure 1.

The radial basis function of the middle layer of the RBF network is consistent with the Cover theorem, in that the data from the low-dimensional space is transferred to the high-dimensional space. The core of the mapping relationship in RBF is the kernel function, and the corresponding mapping relationship will be determined once the kernel function is determined. Also, the mapping from the middle implicit layer to the final output layer of the network structure is linear. Thus, the nonlinear mapping from the initial input to the output is transformed into the final linear network output. A linear system of equations can directly solve the weights of each intermediate layer, thus reducing the training time of the RBF network and avoiding the problem of local minima. The generalization ability of RBF is better than BP network in many aspects, but when solving problems with the same accuracy requirements, the structure of BP network is simpler than RBF network. The approximation accuracy of the RBF network is significantly higher than that of the BP network. It can almost achieve complete approximation, and it is extremely convenient to design. The network can automatically increase neurons until the accuracy requirements are met. However, when the number of training samples increases, the number of hidden layer neurons of the RBF network is much higher than the former, which greatly increases the complexity of the RBF network, the structure is too large, and the amount of calculations also increases.

The design of RBF neural networks consists of two main aspects. One is the design of the network structure, that is, the problem of including several nodes between the input and output layers [20]. The second is the selection of a suitable method to solve the network parameters, which are mainly three: the centre of the radial basis function (generally Gaussian function), the sample variance, and the weight coefficients of the intermediate layers. When the centre of the radial basis function is selected, the common method is the self-organizing selection method, which consists of two parts: firstly, the centre and variance of the radial basis function are derived, and, secondly, the weight coefficients of the intermediate layer to the output layer are derived.

A Gaussian function is a commonly used radial basis function in RBF neural networks, and its activation function can be expressed as

$$R\left(x_p - c_i\right) = \exp\left(-\frac{1}{2\sigma^2 x_p}^{\left\|x_p - c_i\right\|^2}\right). \tag{1}$$

The output of the radial basis neural network is

$$y_i = \sum_{i,j=1}^{h} w_{i*j} \exp\left(-\frac{1}{2\sigma^2 x_p}^{\left\|x_p - c_i\right\|^2}\right). \tag{2}$$

The air quality standard levels are selected according to the specific air quality of the evaluated area, and the data between the levels are built as the input matrix X to be involved in the training, and the pollutant concentration data corresponding to each standard level is built as the output matrix Y. All the sample data are normalized. When the number of evaluated areas and pollutant indicators are p and q, respectively, the corresponding input and output matrices are shown in the following equation:

$$\begin{cases} X = \left[X_1, X_2, \ldots, X_h\right], Y = [1, 2, 3, \ldots, h], \\ X_i = \left[b_1, b_2, \ldots, b_h\right]^T, h = [1, 2, 3, \ldots, h], \\ a_{ij} = \left[a_1, a_2, \ldots, a_{ij}\right]^T, ij = [1, 2, 3, \ldots, h]. \end{cases} \tag{3}$$

The simulation function is used for air environment quality evaluation in the following format:

$$\begin{aligned} T &= \sin(\text{net}, H), \\ B &= \sin(\text{net}, X). \end{aligned} \tag{4}$$

The combination of models is an attempt to combine different individual models, the main purpose of which is to gather the advantages of every single model and obtain a combined model by using the information provided by various single models in the form of an appropriate weighted average [21]. The most important step after the model combination is to solve the weight coefficients of every single model, and after the weight coefficients of every single model are obtained, the single model is evaluated separately, and the weighted sum of the single evaluation results is obtained by using the obtained weight coefficients to obtain the evaluation results of the final combined model. This makes the combined model more effective than the single model in terms of accuracy and reliability and thus makes the final evaluation research work more convincing and valuable. The combination of combination models to single models can be classified from different perspectives according to the characteristics of different models, and the optimal combination prediction method is used in this paper to carry out the combination of methods. The basic idea is to construct the objective function according to the selected criteria and add a penalty to the equation; that is, the weight coefficient of every single model is solved under the constraints, and the optimal combination prediction model can be expressed as follows:

$$\begin{cases} \max \quad J = J\left(w_1, w_2, \ldots, w_n\right) \\ \text{s.t.} \quad \sum_{i,j=1}^{n} w_i^j = 1, w_i^j \geq 0. \end{cases} \tag{5}$$

In this paper, the principle of least-sum-of-squares error is chosen, where w_i is the weight of various single models. In practice, negative weights have not been agreed upon in

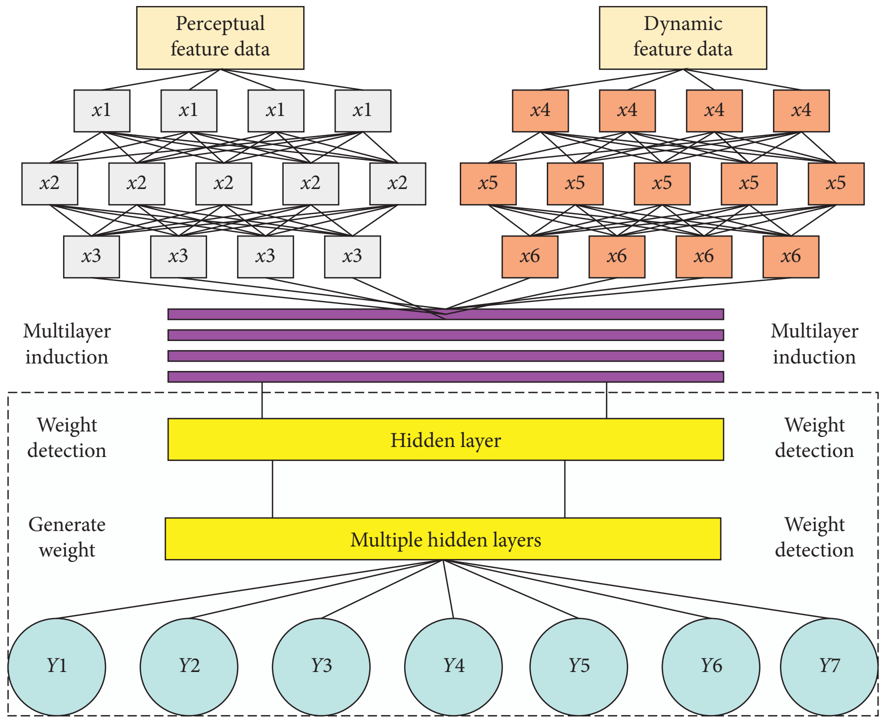

Figure 1: RBF neural network structure.

academia, so a nonnegative constraint is added to the model. The above equation is written in the matrix form as follows:

$$\begin{cases} \max J_1 = W^T EW, \\ RW^T = 1, \\ W \geq 0. \end{cases} \quad (6)$$

The nonlinear planning problem of minimizing the objective function is transformed into a linear planning problem by mathematical planning theory and the K-T condition, and the transformed model is shown in the following:

$$\begin{cases} \max J = v, \\ EW - (\alpha + \beta)W^T - P = 0, \\ RW^T + v = 1, \\ W \geq 0, P \geq 0, \\ \alpha, \beta \geq 0. \end{cases} \quad (7)$$

Third, the selected single model should apply to the application conditions required by the combined model. If the correlation between the selected single models is large, the solution of the respective model weights will encounter obstacles after the combination of the models, so the advantages and disadvantages of the single models should be considered comprehensively [22]. Otherwise, when the combined is the shortcomings of every single model selected, it cannot represent the problem characteristics well and will not reflect its superiority, which will also be contrary to our initial idea. Finally, the complexity of a single model and the difficulty of collecting sample data should be considered. In general, the more complex a single model is, the more relevant factors the model considers, the more sample information it contains, and the higher the accuracy of the corresponding combined model will be in the end. However, the more complex the model is, the better it will be, and the more complex the model is, the higher the workload will be. For cost consideration, sometimes a single model with moderate complexity and easy-to-collect sample data is selected for combination, not that the accuracy of the model will be improved after the combination compared with the single model. Therefore, the selection of a single model is the key to construct a combined model:

$$H_i(x) = \varphi\left(\frac{\left\| X - C_i^j \right\|}{\beta_i}\right). \quad (8)$$

In the whole RBF neural network model, the biggest difference between it and other feedforward neural networks is the implicit layer, because its implicit layer uses radial basis function as the basis function; then from this certain, it increases the diversity of the neural network, because this diversity is reflected not only in the structure of the neural network, but also in the selection of basis function, which increases the wide range of RBF neural network and applicability:

$$F(x_i) = d_i - \sum_{i,j=1}^{h} w_{i*j} \exp\left(-\frac{1}{2\sigma^2 x_p} \left\| x_p - c_i \right\|^2\right). \quad (9)$$

When building a portfolio model, the selection of individual models considers their applicability. Three aspects should be considered: first, every single model selected can be applied individually, that is, evaluated in a domain, and the model is the one we consider only if its theory fits the problem under study. Second, the data or assumptions between every single model need to be approximately the same or similar. For example, if the output of one model results in continuous values while the output of another model is discrete, then the combination of the results from these two single models will lose most of the information, which will greatly affect the final results and thus reduce the performance of the combined model. If only a single model is combined without considering the compatibility between models, the resulting combined model is meaningless, and then the evaluation results based on the model have no reference value, and the overall evaluation model is divided into two parts, the training phase and the inference phase. The training phase can also be referred to as the learning phase, where the RBF neural network is first trained based on the processed historical data so that the undetermined parameters can be determined through the training of the computer program. Once the model parameters are determined, this model can be used to make predictive inferences on new incoming data and provide decision support for managers, as shown in Figure 2.

The particle swarm algorithm simulates the birds in a flock of birds by designing a massless particle. The particle has only two attributes: speed and position. Speed represents the speed of movement, and position represents the direction of movement. Each particle searches for the optimal solution individually in the search space and records it as the current individual extreme value and shares the individual extreme value with other particles in the entire particle swarm and finds the optimal individual extreme value as the entire particle. All particles in the particle swarm adjust their speed and position according to the current individual extreme value they find and the current global optimal solution shared by the entire particle swarm. The selection of individual models for combination should be considered for individual model selection. In general, the overall modelling effort and cost is proportional to the number of individual models, and the performance of the combined model can be improved with the increase of the number. The fewer the number of models, the lower the prediction cost of individual models and the lower the value of integrating information from existing models, which affects the accuracy of the results of the combined model.

2.2. Evaluation Model Analysis of Low-Carbon Economy Coupled Development in Forest Areas. The process of carbon flow in a forest complex ecosystem is the process of decomposition, transformation, and transfer of carbon-containing substances. The input energy, food, and raw materials are mainly hydrocarbons (carbon chain organic substances), which are transformed into carbon-containing inorganic substances (e.g., carbon dioxide) or short carbon chain organic substances (e.g., methane) after the anthropogenic processes such as combustion process, industrial production process and residents living in the forest complex ecosystem [23]. Therefore, the carbon flow process is a carbon chain conversion process; the forest area is a forest area built on a carbon chain, which links the three subsystems of economic, social, and natural in the forest complex ecosystem, forming a carbon cycle system within the forest area, as shown in Figure 3.

Among them, the first subsystem is the natural subsystem, consisting of water, air, soil, biology, and mineral resources, whose function is to provide the ecological environment and natural resources necessary for human survival and production life and at the same time to consume the waste discharged from the economic and social subsystems; the second subsystem is the economic subsystem, consisting of the production system, circulation system, consumption system, reduction system, and regulation system. The third subsystem is the social subsystem, which consists of politics, institutions, science and technology, and culture. The core of this subsystem is human, and the main function of this subsystem is human spiritual, cultural, and orderly social activities.

According to the above analysis of the function and carbon emission activities of forest complex ecosystem, the carbon emission activities categorized and reorganized into subsystems of forest complex ecosystem according to the carbon flow route of carbon emission generation and consumption. For example, the carbon sink part shared by the natural environment system and built environment system of forest area is composed of the ecological support system of forest area; the burning of energy is grouped into different activity categories; then the forest area operation guarantee system can be divided into energy production and supply system and waste treatment system; private cars and public transportation, logistics, and transportation are all transportation activities grouped into service system; production system refers to industrial production system alone.

Each type of activity is classified as industrial activity, and each carbon emission industrial activity is placed in the forest complex ecosystem, which constitutes the industrial system of carbon emission in the forest area. According to the above reclassification of forest complex ecosystem functions, forest complex ecosystem functions can be divided into 6 subsystems corresponding to forest industrial carbon emission activities: forest energy production system, industrial production system, forest living system, forest service system, forest waste treatment system, and forest ecological support system. We use 80% of the data as the training dataset and 20% of the data as the test dataset, where the data is randomly allocated. Then, the coupling relationship between the forest complex ecosystem and forest industrial carbon emission activities is shown in Table 1.

According to ecological principles, ecosystems are composed of producers, consumers, and decomposers. Natural ecosystem plants are producers, animals are consumers, and microorganisms are decomposers. This structure of the natural ecosystem ensures the balance and stability of the natural ecosystem. This structure of the natural ecosystem ensures the balance and stability of the natural ecosystem [24]. The ecosystem of the carbon emission industry also has the characteristics of such an

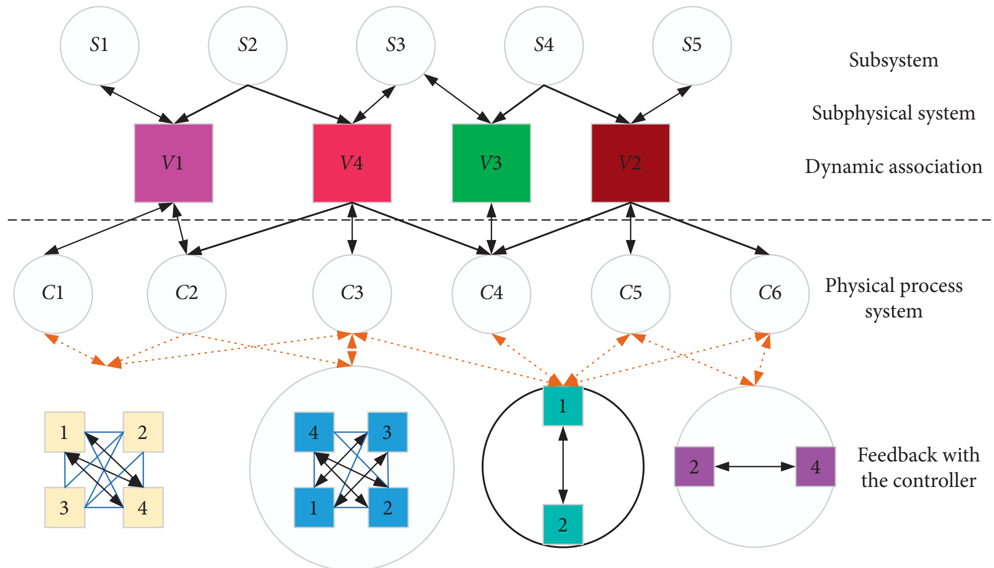

FIGURE 2: Evaluation model design.

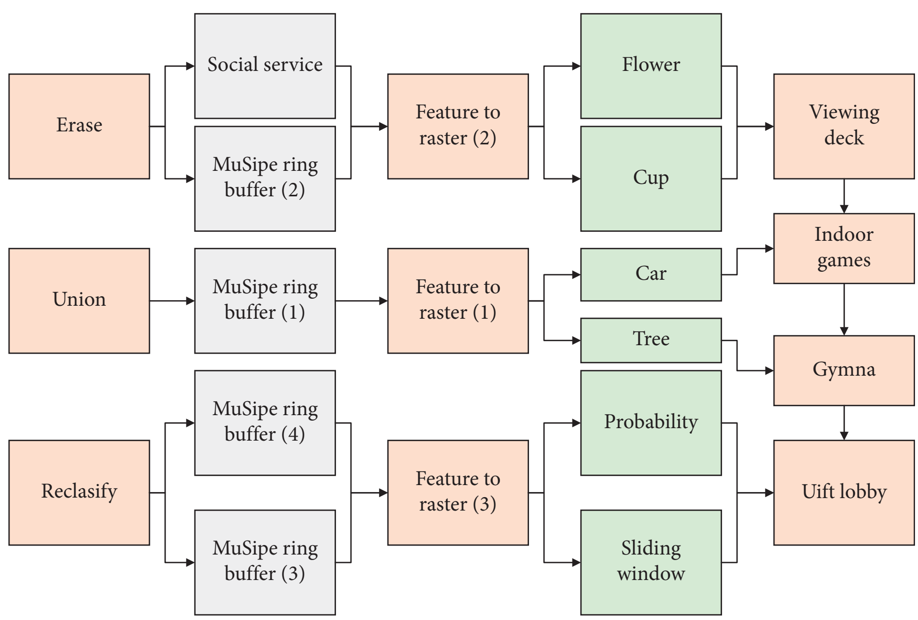

FIGURE 3: Carbon chain of a complex ecosystem.

TABLE 1: Analysis of the coupling relationship between the forest complex ecosystem and forest industry carbon emission activities.

Content	M	Meaning
Result set header	25.4	Returns the number of data columns
Field	33.5	Return data column information (multiple)
EOF	125.47	End of column
Row data	21.47	Row data (multiple)
EOF	18.65	End of data
END	20.25	Data

ecological structure. The extraction, processing, and supply of fossil energy, raw materials, and food are the producers; the use and utilization of fossil energy, raw materials, and food are the consumers; the waste treatment system and ecological support system are the decomposers. However, the carbon emission industrial ecosystem is not a natural ecosystem, but an artificial ecosystem is dominated by human activities. This artificial ecosystem is in a state of ecological imbalance due to the increasing intensity of human activities, which is manifested by the fact that the natural ecological support system is insufficient to absorb or offset the increasing carbon emissions from the production and consumption systems, thus causing climate warming. The carbon emission industrial ecosystem consists of six subsystems, the functions of which coupled with the functions of forest areas. Among the 6 subsystems of the industrial ecosystem, energy production system, industrial production system, living system, service system, and comprehensive waste treatment system are the decomposition of the functions of the economic subsystem and social subsystem in the composite ecosystem of forest area; therefore, the carbon emission industrial system is also a subsystem of the social-economic-natural composite ecosystem, which reflects the carbon emission status of the composite ecosystem of forest area. Therefore, to analyse the carbon emission status of carbon emission industrial ecosystem, it is necessary to analyse the carbon emission status of carbon emission industrial ecosystem in the context of carbon emission industrial ecosystem consists of 6 subsystems, the functions of which are coupled with the functions of forest area. Among the 6 subsystems of the industrial ecosystem, energy production system, industrial production system, living system, service system, and comprehensive waste treatment system are the decomposition of the functions of the economic subsystem and social subsystem in the composite ecosystem of forest area; therefore, carbon emission industrial system is also the subsystem of the social-economic-natural composite ecosystem, which reflects the carbon emission status of the composite ecosystem of forest area. Therefore, the analysis of the carbon emission status of the carbon emission industry ecosystem should be analysed under the general framework of the social-economic-natural composite ecosystem in the forest area. The analysis under the general framework of the social-economic-natural composite ecosystem of forest area is shown in Figure 4.

The carbon source of the forest complex ecosystem is mainly the input of fossil energy, the economic and social subsystems consume fossil energy to produce carbon emissions, and the natural subsystem absorbs carbon dioxide; the increase of carbon emissions is the result of the large consumption of fossil energy and thus breaking the carbon balance of the economic-social-natural complex ecosystem; the industrial system is the source of carbon emissions. The carbon emission of the industrial system relates to the function of the forest complex ecosystem by carbon chain, which constitutes an industrial ecosystem. The goal of low-carbon forest area construction is to control carbon emissions, and the construction of an industrial ecosystem is the fundamental way to achieve the goal of low-carbon forest area construction. The components of the industrial ecological system in low-carbon forest area include industrial ecological spatial pattern, industrial ecological structure, and industrial decolonization and ecological industrialization; the methods of construction mainly include the analysis of carbon emission of the composite ecosystem in forest area, the analysis of the

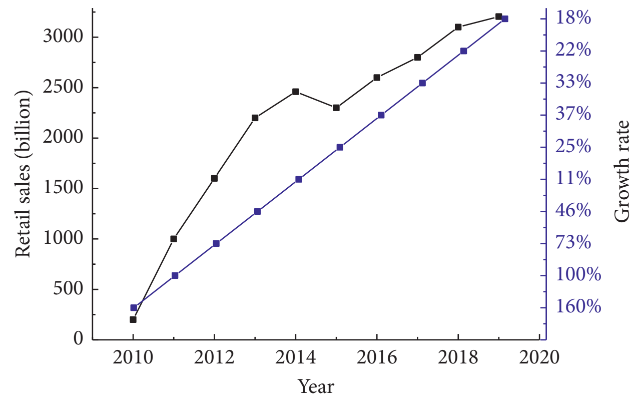

Figure 4: Change in emissions.

interaction between industrial ecosystem and carbon emission, and the prediction of industrial ecological structure optimization and other main research steps.

Since the carbon emission industrial ecosystem is an artificial ecosystem dominated by human activities, it has dynamic characteristics; that is, its ecosystem equilibrium state will change with the development of the economy and society. At present, it is due to the continuous increase in the intensity of human activities, especially in China, the fossil energy-based energy structure, and the rough and unreasonable industrial structure, coupled with the serious destruction of the natural ecological environment, thus causing a serious imbalance of the carbon emission industrial ecosystem in forest areas. Therefore, considering the dynamic characteristics of the carbon emission industrial ecosystem, how to ensure economic growth while effectively controlling carbon emission is a topic that must be solved in front of us.

3. Analysis of Results

3.1. Network Node Number Determination and Result Analysis. In this paper, the improved PSO-RBF algorithm is applied to the water quality evaluation of Laban Lake in Santa County, and the test data are obtained from the local water quality monitoring station, and the monitored data are used as the test samples. The RBF neural network was set up as 3 layers, and the 6 input nodes of the input layer consisted of 6 evaluation parameters of water quality including (dissolved oxygen, permanganate index, total phosphorus, total nitrogen, chemical oxygen demand, and ammonia nitrogen). In RBF neural networks, the number of nodes in the hidden layer has been a difficult problem in the study of this network. At present, the determination of the number of nodes of the hidden layer is mainly based on experimental methods and practical experience, which essentially determines the number of nodes of the hidden layer by experience and then adjusts the nodes of the hidden layer by simulation experiments and finally selects the optimal number of nodes, and the performance of the neural network reflected by different hidden layer nodes is different, and this chapter also uses practical experience and experimental methods to determine the number of nodes of the hidden layer, and Figure 5 gives the mean square error corresponding to different hidden layer nodes.

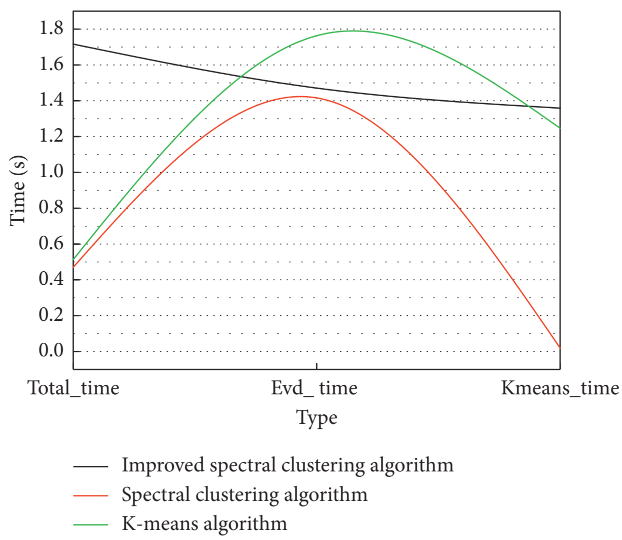

FIGURE 5: Network characteristics corresponding to the number of implied nodes.

To ensure the best performance of the algorithm, max is set to 0.95, min is set to 0.4, the maximum number of iterations T is set to 200, the acceleration factor is set to 2, the position and velocity range is set to [−1, 1], the number of dimensions is set to 40, and the control parameter of (3) is set to 8 according to the results of Shi's study. The RBF neural network structure is selected as 6 input nodes, 10 hidden layer nodes, and one output layer, and the training termination criterion is defined as the sum of squared errors, and the training is terminated when it is 0.001. The parameters obtained from the optimization of the PSO algorithm were used as parameters of the RBF neural network to model the water quality prediction and thus evaluate the water quality. The usefulness of the improved PSO-RBF neural network for water quality evaluation was demonstrated by 20 test samples. The simulation by MATLAB, software version MATLAB-2014b, was obtained as shown in Figure 6.

Considering the influence of past data on the predicted data, according to the characteristics of the exponential smoothing prediction model, the first 380 consecutive water quality samples were selected to calculate the smoothing value and smoothing coefficient to predict 20 test samples by MATLAB2014b simulation. Figure 7 gives the fit curve and relative error curve of the exponential smoothing water quality evaluation model and the actual measured value. The data of the whole process of a comprehensive evaluation of project benefits is composed of two parts, one is the scoring data of experts according to the basic indicators of this project; the other is the theoretical data generated randomly by using a computer according to the basic idea of hierarchical analysis method and using comprehensive evaluation method. Since the expert scoring data used in the calculation of this paper does not require quantitative processing, but attention should be paid to whether the size of the numerical interval is appropriate; otherwise, the interval is too large to seriously affect the learning process of the neural network, and the interval value is too small to reflect the role of the size of the feature values. In the expert scoring stage, the scoring range is set within [0, 1], which eliminates the step of normalizing the data, and the range of ownership values of the network model is not too large, which reduces the difficulty of network training and improves the accuracy of network model training.

The number of input units is 9, the number of output units is 1, the training error is set to 0.0001, and the maximum number of neurons is set to 1000. The MATLAB program is used for training, and the network model with 24 neurons is finally obtained. The training results of RBF neural network for financial efficiency evaluation of refining projects are compared by the improved PSO-RBF neural network model with the experimental results of other evaluation models for water quality, and the performance curve and prediction results can be intuitively found that the former is significantly better than the latter. This can be obtained, the improved model is suitable for water quality analysis research, and there are great advantages. Through simulation and analysis comparison, the effectiveness of this evaluation method is verified, and it provides an effective analysis method for water quality analysis.

The evaluation accuracy of this neural network model is over 95%. The use of the RBF neural network can make a quick evaluation of the investment benefits, especially in the operation phase of the project, which can give investors an overall grasp of the overall operation of the project. It provides a more convenient and reliable analysis and evaluation method for decision-makers. Considering the actual situation of the project, the project data we have collected may not be perfect, and the analysis only for these rough data may be somewhat biased in the expert scoring results. Since the input sample data play a rather important role in the model prediction accuracy, therefore, to obtain more accurate evaluation results more accurate raw data should be collected as the basis, and then the sample data are deeply standardized in two aspects.

3.2. Analysis of Economic Coupling Evaluation Model Results. In the industrial ecosystem of carbon emissions, the urban ecological support system includes forests, offshore waters, farmlands, river wetlands, and urban gardens, whose important ecological function is to absorb carbon dioxide; the other five subsystems all emit carbon dioxide, among which the energy industry subsystem is mainly the production and supply of electricity and heat. The industrial industry subsystem refers to the mining and manufacturing industries in the secondary industry.

The industrial subsystem refers to the main service industries such as transportation, construction, wholesale and retail, accommodation and catering, tourism, and so on, while other service industries belonging to the tertiary sector are classified as residential life; the urban waste treatment subsystem here mainly refers to the carbon dioxide generated by the waste resource treatment industry and the incineration of municipal domestic waste. According to the calculation method of total carbon emission, the CO_2

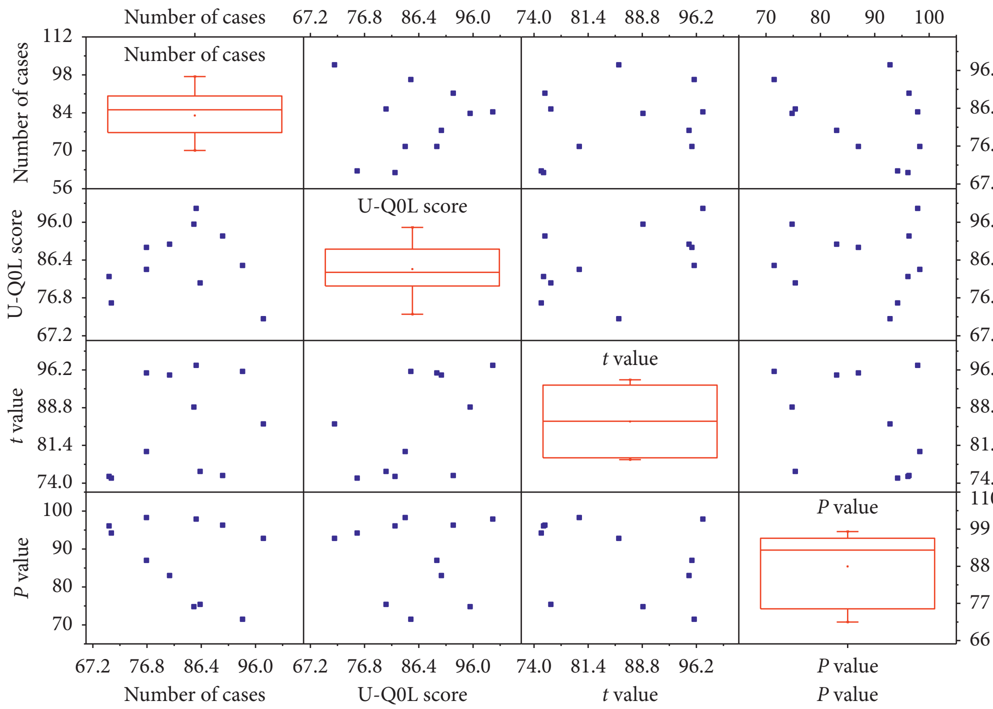

FIGURE 6: Predicted and actual values of the improved PSO-RBF neural network.

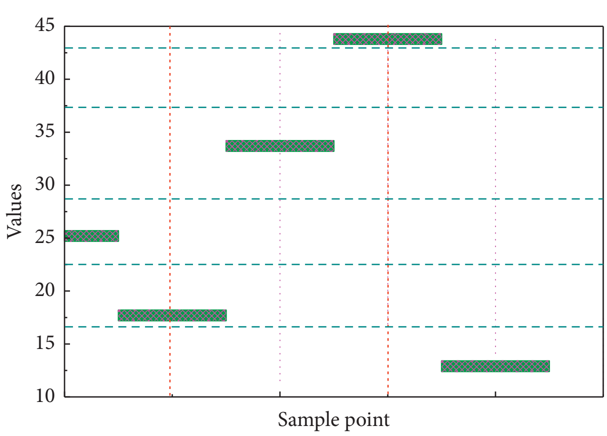

FIGURE 7: Relative error of exponential smoothing prediction model.

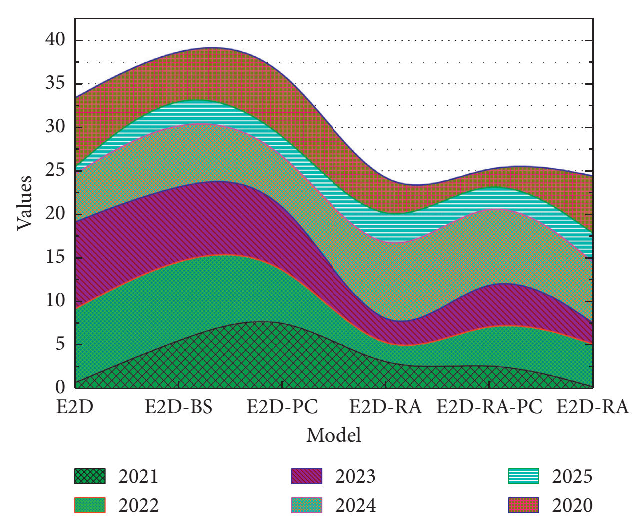

FIGURE 8: Total CO_2 emissions.

emission activities in Qinhuangdao City are divided into four parts, energy activities, industrial production process, land-use change and forestry, and waste treatment, while the agricultural and livestock production process is calculated in the Guide as the amount of CH_4, which is no longer used as the calculation content here. According to the calculation method in the Guide, the total carbon emissions from energy activities are measured as the total carbon emissions from the combustion process of all kinds of fossil fuels used in all production and living activities; the total carbon emissions from industrial production processes are measured as the carbon generated from the use of carbon-containing raw materials in the production process, excluding the combustion process of fuels, mainly from the iron and steel industry and the building materials industry; the total carbon emissions from waste treatment are measured. The total carbon emission measurement of waste treatment is mainly the carbon dioxide produced by waste incineration, and the total carbon emission measurement of land-use change and forestry mainly calculates the amount of carbon absorbed by forest and land change formation. The carbon emissions in 2020–2025 are shown in Figure 8.

When the concentration values of both PM2.5 and O_3 are low, they correspond to the light blue as well as yellow areas, whose air quality levels are below the level 3 standard and belong to the acceptable range; when the concentration values of both PM2.5 and O_3 are large or the concentration values of one pollutant are large, they correspond to the

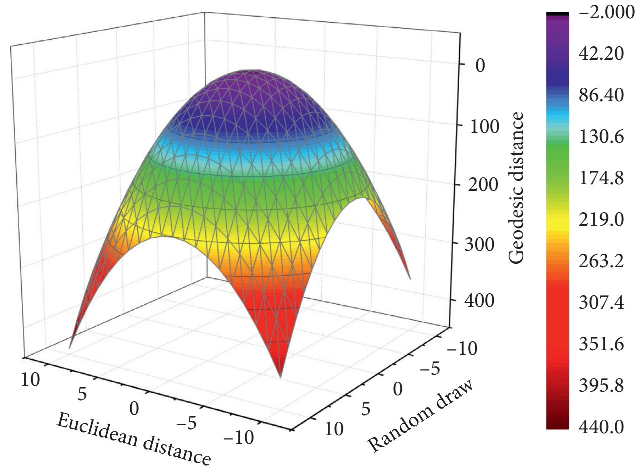

Figure 9: Effect of variables on model predicted values.

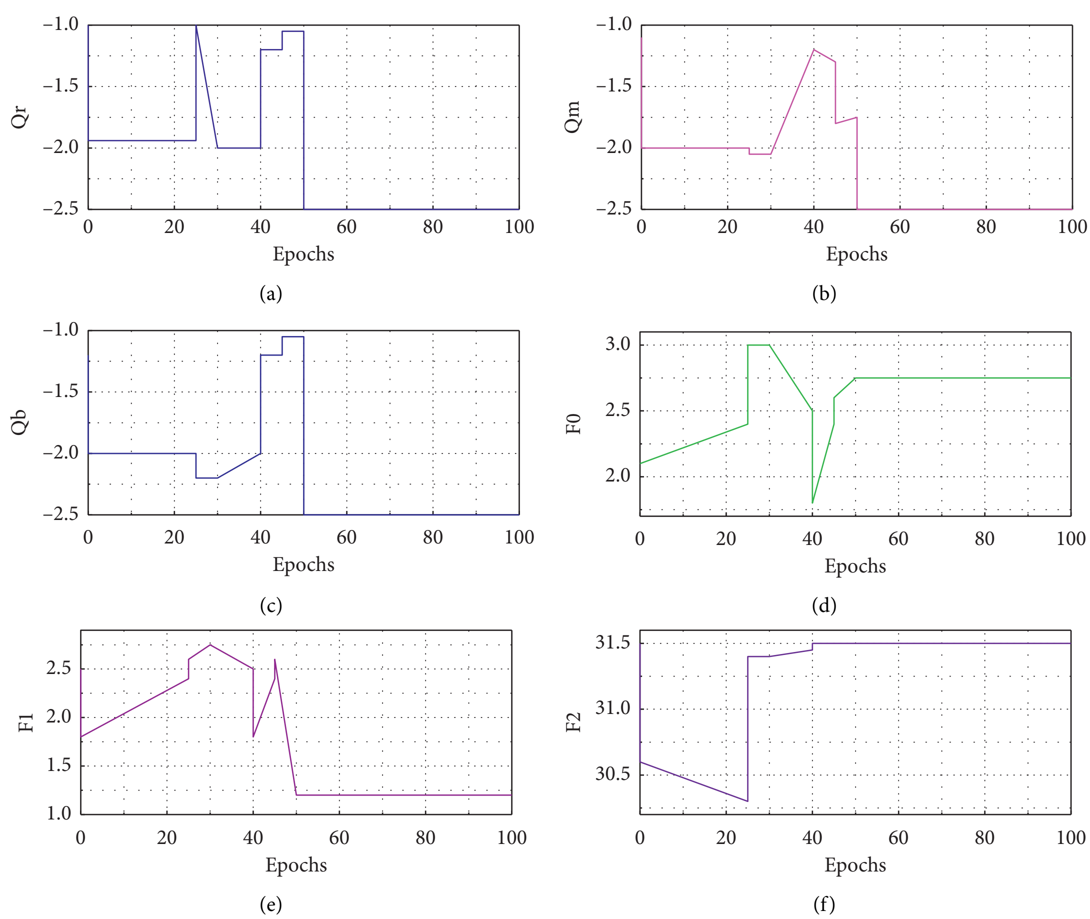

Figure 10: Fitting results.

purple and dark blue parts, whose air quality levels are above the level 4 standard and belong to moderate or severe pollution. Therefore, Figure 9 can well portray the influence of the concentration values of each variable on the final air quality, which is also consistent with the nature shown by the positive and negative of the parameters finally fitted by the model.

The 100 datasets were divided into the training set, validation set, and test set in proportion 75%, 15%, and 15%, respectively. As shown by the training error in Figure 6 and the fitting effect in Figure 7, after 28 stops of training, the test set R-value is 0.98, which is very satisfactory. The results of the evaluation of the sample environmental quality index values using two single models are shown in Figure 10.

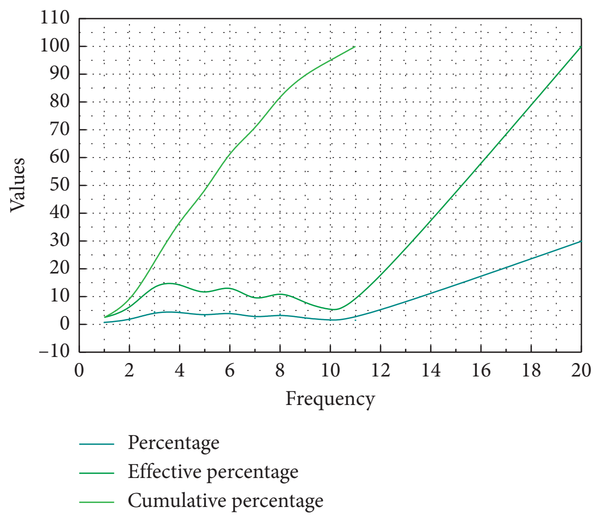

Figure 11: The whole taken image.

The improved PSO-RBF neural network is used in the evaluation to establish the prediction model, and the evaluation results are compared with other evaluation models, and the simulation results show that the improved algorithm is better than the ordinary algorithm in terms of prediction accuracy, and it has good effect for such nonlinear problems as water quality evaluation, and the use value is high. This paper makes good use of the advantages of the particle swarm algorithm in finding the best, combined with a radial basis neural network to solve complex nonlinear problems, as shown in Figure 11.

For each particle, we compare its fitness with the fitness of its best position. If it is better, we update it to the best. The theory is used in water quality evaluation, and good results are obtained. However, with continuous research work, further research work is also inevitable.

4. Conclusion

For the prediction object associated with many influencing factors, strong policy constraints, and dynamic change characteristics, a multidimensional multiconstraint multimodel fusion model is constructed to predict the state of industrial ecological structure through the situation setting, and the path of industrial ecological structure optimization is obtained through simulation analysis. The prediction model of multidimensional multiconstraint multimodel fusion for industrial ecological structure optimization is constructed, and the simulation analysis of the prediction results shows that the development state of 8.4% economic growth rate, 69.7% cumulative decrease in carbon emission intensity, and 73.0% cumulative decrease in energy intensity by 2030 requires industrial ecological structure adjustment, in which the ratio of primary, secondary, and tertiary industries is adjusted to 6.5 : 15.5 : 78.0, developing low-carbon industries mainly in tourism, with the output value of tourism reaching 51.0%, and limiting the development of high-carbon industries such as building materials, iron and steel, and petrochemicals; vigorously promoting clean energy, reducing the use of coal, with the proportion of nonfossil energy reaching 22.6% and the proportion of coal use falling to 53.9%; and increasing ecological environmental protection, with the forest coverage rate reaching over 65%. Also, we will build a clean, low-carbon, and efficient energy system, a green, low-carbon, and recycling industrial system, a green service industry system, a green consumption system, a waste resource treatment system, and an ecological support system in six aspects of the industrial ecological spatial pattern. Low-carbon economy is an economic model based on low energy consumption, low pollution, and low emissions. It is another major advancement of human society after agricultural civilization and industrial civilization. It is a new energy concept proposed by the international community to respond to the catastrophic changes in the global climate caused by the massive consumption of chemical energy and the massive emission of carbon dioxide (CO_2) and sulphur dioxide (SO_2). The essence is to solve the problem of improving energy efficiency and clean energy structure. The core is energy technology innovation and a fundamental change in the concept of human survival and development. The path of industrial ecology includes the construction of low-carbon recycling industrial parks and the low-carbon transformation of high-carbon industries, and the focus of eco-industrialization is on ecological construction and ecological protection at the same time.

Data Availability

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

Conflicts of Interest

The author declares no conflicts of interest in this paper.

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