Simulation of Optimization Decision Model for Low-carbon Economy Schemes Based on Machine Learning Algorithms

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Abstract. Low-carbon economy (LCE) is a shift from high-carbon intensive industries and activities to low-emission or zero-emission industries and activities, which requires a lot of investment in new technologies and infrastructure, as well as changes in policies and regulations to promote sustainability and reduce emissions. In this article, the back propagation neural network (BPNN) algorithm in machine learning (ML) is applied to the construction of low-carbon economic scheme optimization decision model, and the performance of the model is simulated and tested. The results show that BPNN algorithm has higher accuracy and reliability in predicting the development level of LCE, which is 23.8% higher than Support Vector Machine (SVM) algorithm. Through the comparative study of BPNN algorithm and SVM algorithm in forecasting the development level of LCE, the advantages of BPNN algorithm in forecasting accuracy and application value are verified. BPNN algorithm can better adapt to and deal with the complex data patterns in the field of LCE, improve the accuracy and reliability of prediction, and provide strong technical support and guarantee for the growth of LCE.

Keywords: Machine learning; Low-carbon economy; Prediction accuracy.

1. Introduction

With the global warming and the increasingly serious environmental problems, LCE has become the common development direction of all countries in the world. In practice, LCE needs to rely on new technologies and new policies and regulations to achieve the goal of reducing emissions and promoting sustainable development [1]. However, how to formulate and implement LCE scheme effectively is a challenging problem. ML is a branch of artificial intelligence, which aims to make computers acquire knowledge and skills automatically through learning, and constantly improve their own performance [2-3]. In the past decades, ML has experienced rapid development and been widely used in many fields. For example, in the fields of image recognition, speech recognition, natural language processing and so on, ML algorithm has reached or even surpassed human performance [4].

In the field of LCE, ML algorithm also has a wide application prospect. Because the formulation and implementation of LCE scheme need to rely on a large quantity of data and complex calculations, the introduction of ML algorithm can help researchers to better process these data and make more accurate predictions [5]. For example, managers can predict the future energy demand through ML algorithm, so as to better plan the production and distribution of energy [6]. In addition, ML algorithm can be used to simulate and evaluate the effects of policies and regulations, so as to better formulate and implement low-carbon policies.

The purpose of this article is to build an LCE scheme optimization decision model based on ML algorithm, and to simulate the performance of the model. BPNN is a commonly used supervised learning algorithm, which can be used to solve classification and regression problems. The study will use BPNN algorithm to build the LCE scheme optimization decision model, simulate and evaluate the LCE scheme, and find out the optimal scheme combination.

The structure of the article is as follows: The first section is the introduction, which introduces the background of LCE and the application prospect of ML in LCE; The second section is the research purpose and method, which clarifies the research problems and methods adopted in this article; The third chapter is model construction, which introduces the construction process of BPNN model; The fourth section is performance evaluation, which evaluates the performance of BPNN model in detail;

The fifth chapter is the conclusion and prospect, summarizing the main conclusions of this article and the future research direction.

2. Theoretical basis

2.1 LCE

LCE is a new economic model that emerges at the historic moment under the background of global warming and increasingly serious environmental problems. By promoting new energy and new technologies, it advocates green consumption and sustainable development, realizes the decoupling between economic growth and carbon emissions, and promotes the coordinated growth of human economy, society and ecological environment [7].

The theoretical basis of LCE mainly involves many disciplines such as energy economics, environmental economics and ecological economics [8]. These disciplines have conducted in-depth research on the growth of LCE from different angles, which provides important theoretical support for the realization of LCE. Among them, energy economics mainly studies the supply, consumption and price of energy, and provides energy solutions for LCE; Environmental economics mainly studies the relationship between environment and economic article and discusses the optimal balance between environmental protection and economic article. Eco-economics mainly studies the economic value and sustainable growth of ecosystem, and provides enlightenment from the perspective of ecosystem for the growth of LCE.

2.2 ML

ML is a branch of artificial intelligence, which aims to make computers acquire knowledge and skills automatically through learning, and constantly improve their own performance. ML theory is developed on the basis of psychology, computer science, statistics and other disciplines. By learning a large quantity of data, it obtains the mapping relationship between input and output, and predicts and classifies unknown data [9].

In ML, neural network is an important algorithm, which constructs a multi-level calculation model by simulating human brain neurons, thus realizing the processing and analysis of complex data. Among them, BPNN is a commonly used supervised learning algorithm, which trains the neural network through the back propagation algorithm, thus obtaining the mapping relationship between input and output [10]. In this article, BPNN algorithm will be used to construct the optimization decision model of LCE scheme, so as to realize the simulation and evaluation of LCE scheme.

3. Optimization decision model of LCE scheme

The LCE scheme optimization decision model mainly includes three parts: data preprocessing, BPNN model construction and model evaluation. First, we need to determine the input and output of the model. In the optimization decision of LCE scheme, the input usually includes historical carbon emission data, energy consumption data, economic activity data, etc., while the output is the optimization decision result of LCE scheme, such as the future development trend of LCE, policy suggestions, etc. In the LCE scheme optimization decision model, a multi-layer perceptron model is constructed by BPNN algorithm, which has good nonlinear mapping ability and can deal with complex nonlinear problems [11]. After a series of weight adjustment and activation function processing, the input data is passed to the output layer, and the weight is continuously adjusted through the back propagation algorithm, so that the prediction result of the model is as close as possible to the actual output. When building the model, the appropriate quantity of hidden layers and hidden layer nodes are set according to the actual situation and demand, and the model is trained and learned by optimization algorithms such as gradient descent method. The neural network model in this article is shown in Figure 1.

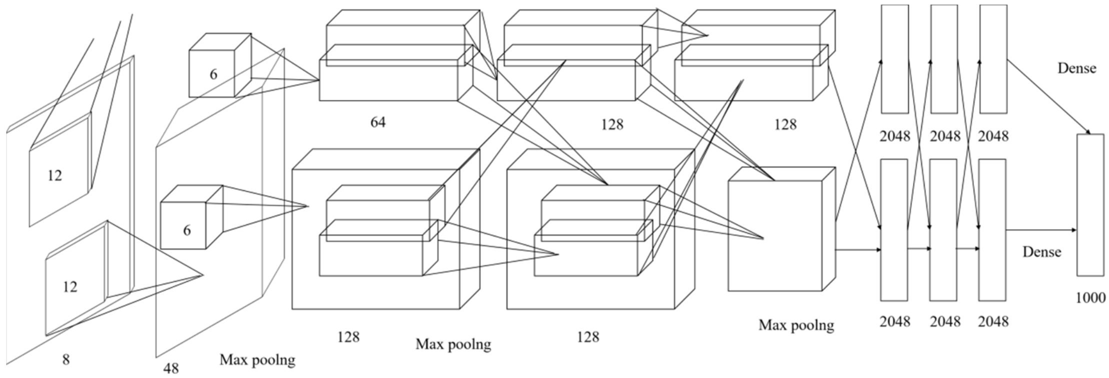

Figure 1 Neural network model

Economic data processing is very important in this study, and it is necessary to fully consider the source, quality, representativeness and reliability of the data, and adopt appropriate processing methods and technologies to process and analyze the data in order to obtain more accurate and reliable model performance evaluation results [12]. In order to make the model better learn and identify the features and laws in data, feature engineering is needed. Specifically, more effective features can be extracted through statistical analysis and transformation of data for model training.

Through continuous learning and training, BPNN can find out its regularity from a large quantity of economic data with unknown patterns, and is especially good at dealing with any type of data, which usually needs to meet the following requirements:

$$m = \sqrt{x + y} + R(10) \tag{1}$$

Where m is the quantity of neurons in the hidden layer, x is the quantity of neurons in the output layer, and y is the quantity of neurons in the input layer. The roughness calculation stage of the set X is:

$$R^{-}(X) = \{U_2, U_3, U_4, U_5, U_7\} \tag{2}$$

$$R_{-}(X) = \{U_2, U_4, U_5\} \neq \emptyset \tag{3}$$

Therefore:

$$\rho(X) = 1 - \frac{|POS_C(X)|}{|R^{-}(X)|} = 0.6 \tag{4}$$

The preprocessed economic data are input into the BPNN model, and the weights are constantly adjusted by the back propagation algorithm, so that the prediction results of the model are as close as possible to the actual output [13]. By constantly adjusting weights and training models, more accurate prediction results of LCE development trend can be obtained, which can provide reference for decision makers. Let y_t be a $k \times 1$-dimensional observable variable containing k low-carbon economy variables. These variables are related to $m \times 1$ dimension vector a_t. The measurement equation is defined as:

$$y_t = z_t \times a_t + d_t + \mu_t \quad t = 1,2,\ldots,T \tag{5}$$

Where T represents sample length, z_t represents $k \times m$ matrix, and d_t represents $k \times 1$ vector. μ_t represents $k \times 1$ vector, which is a continuous uncorrelated disturbance term with mean value of 0 and covariance matrix of H_t:

$$E(\mu_t) = 0, \quad var(u_t) = H \tag{6}$$

In general, the element of a_t is unobservable, and the equation of state is defined as:

$$a_t = T_t a_{t-1} + c_t + R_t \xi_t \quad t = 1,2,\ldots,T \tag{7}$$

Where, T_t represents the $m \times m$ matrix, c_t represents the vector of $m \times 1$, and R_t represents the $m \times g$ matrix. ξ_t represents the mean value 0 of $g \times 1$ vector, and the random uncorrelated disturbance term whose covariance is Q_t:

$$E(\xi_t) = 0, \quad var(\xi_t) = Q_t \tag{8}$$

4. Model testing and analysis

In order to verify the performance and application effect of LCE scheme optimization decision model, this section carries out simulation tests. Firstly, the actual LCE data of a certain area, including carbon emissions, energy consumption, economic growth and other indicators, are adopted and the data are preprocessed. Then, the BPNN model is constructed and the corresponding parameters are set. Through many experiments, the best training parameters and model performance are obtained. Finally, the model is tested with the test set, and the performance of the model is evaluated. The trained BPNN and SVM algorithms are used to predict the economic article level of LCE. The prediction results of BPNN algorithm are shown in Figure 2 and SVM algorithm are shown in Figure 3.

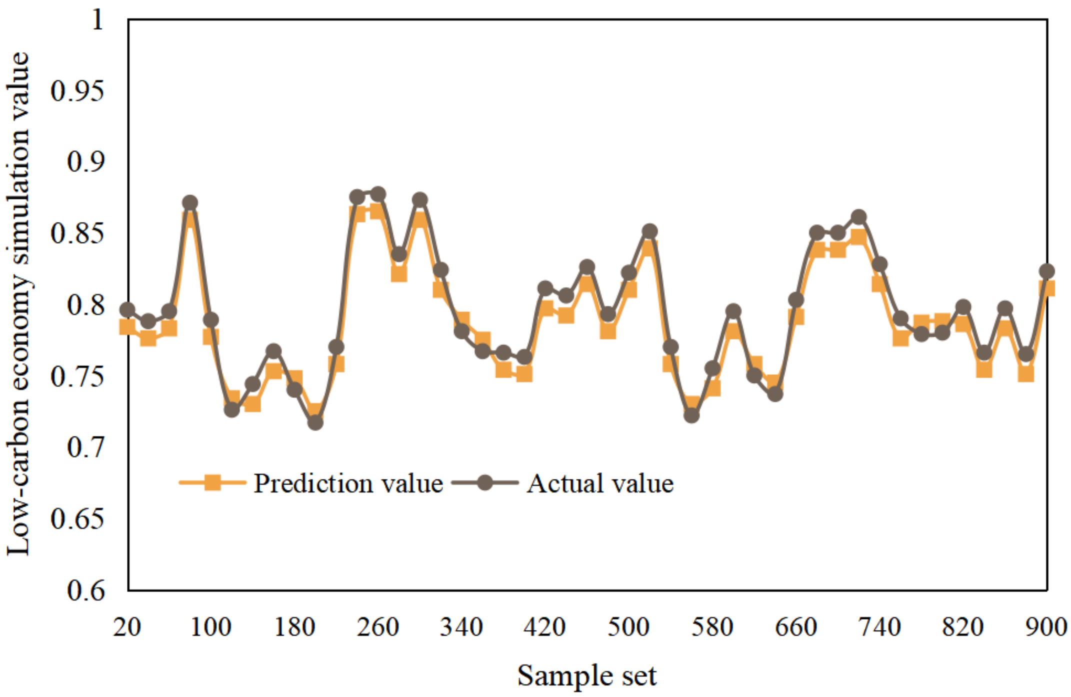

Figure 2 Simulation value and actual value of BPNN algorithm

According to the results of Figure 2, the predicted value of BPNN algorithm is closer to the actual value, which shows that BPNN algorithm can better fit the data and has higher prediction accuracy. In the LCE scheme optimization decision model, BPNN algorithm can learn the characteristics and laws of historical data and establish the mapping relationship between input and output.

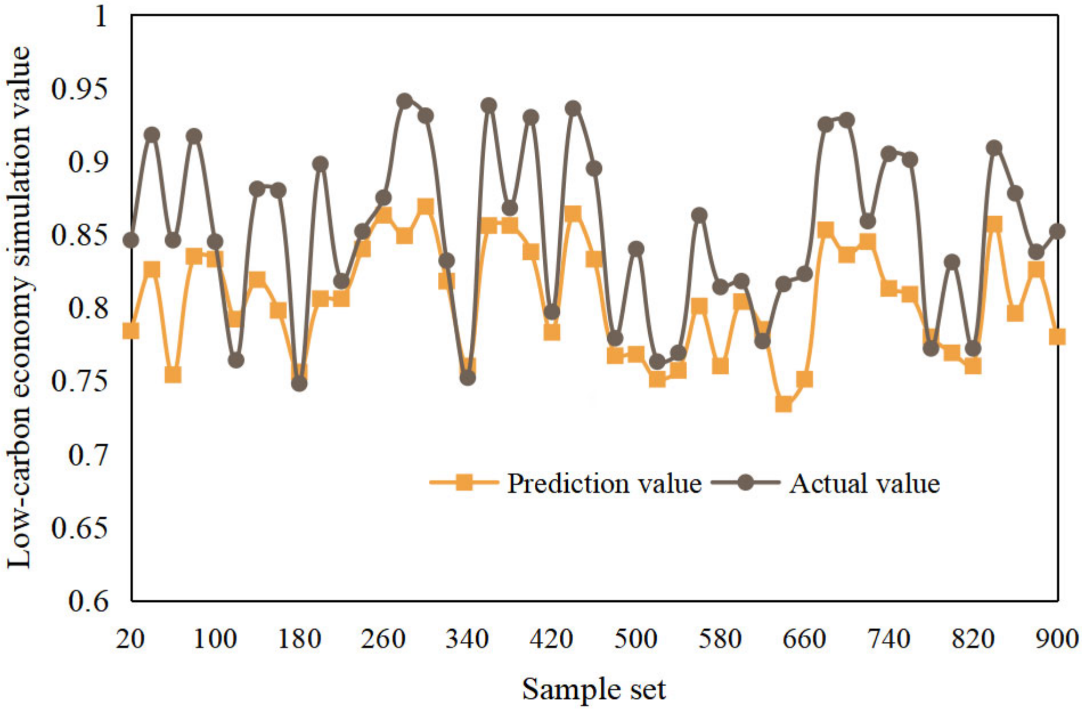

Figure 3 Simulation value and actual value of SVM algorithm

SVM algorithm is a commonly used ML algorithm, which classifies or regresses data by constructing a hyperplane. In the LCE scheme optimization decision model, SVM algorithm can learn the characteristics and laws of historical data and establish the mapping relationship between input and output. According to the results of Figure 3, there is a certain gap between the predicted value of SVM algorithm and the actual value, which may be because SVM algorithm is not good enough in dealing with nonlinear problems, or the quality and representativeness of data sets are not high enough.

In the results of Figure 4 and Figure 5, the recall rate and accuracy of BPNN algorithm are higher than that of SVM algorithm, which shows that BPNN algorithm can better identify real positive samples (that is, more accurate predictions) when predicting the development level of LCE, and there are more real positive samples (that is, fewer false positives) for all positive samples.

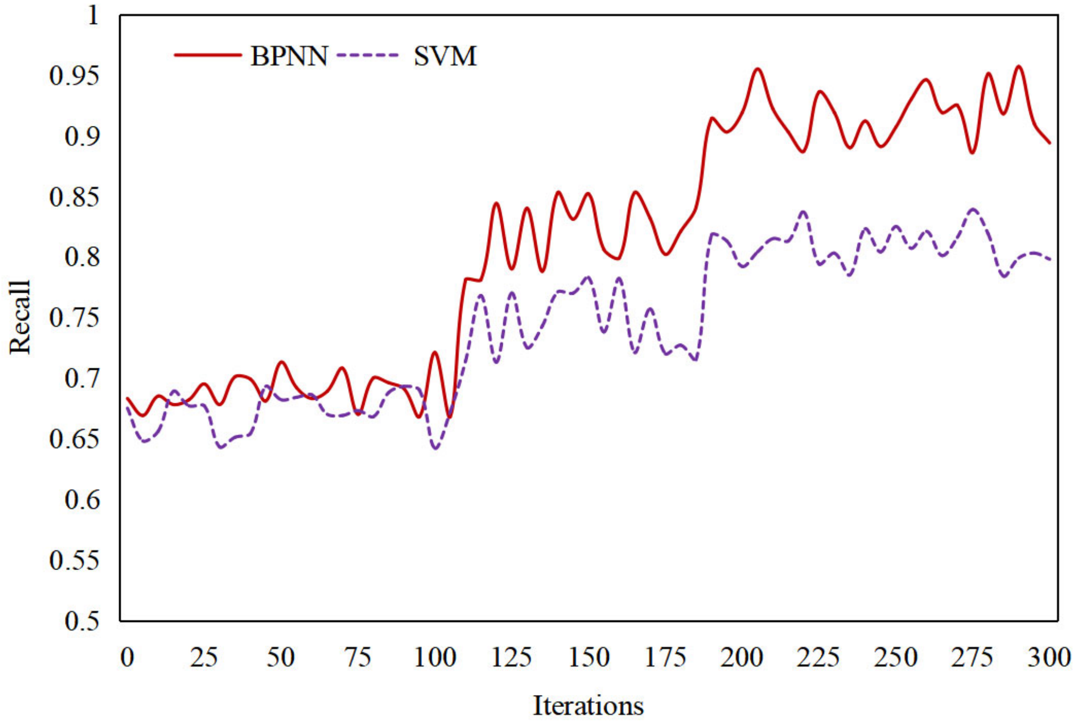

Figure 4 Comparison of recall rates predicted by LCE

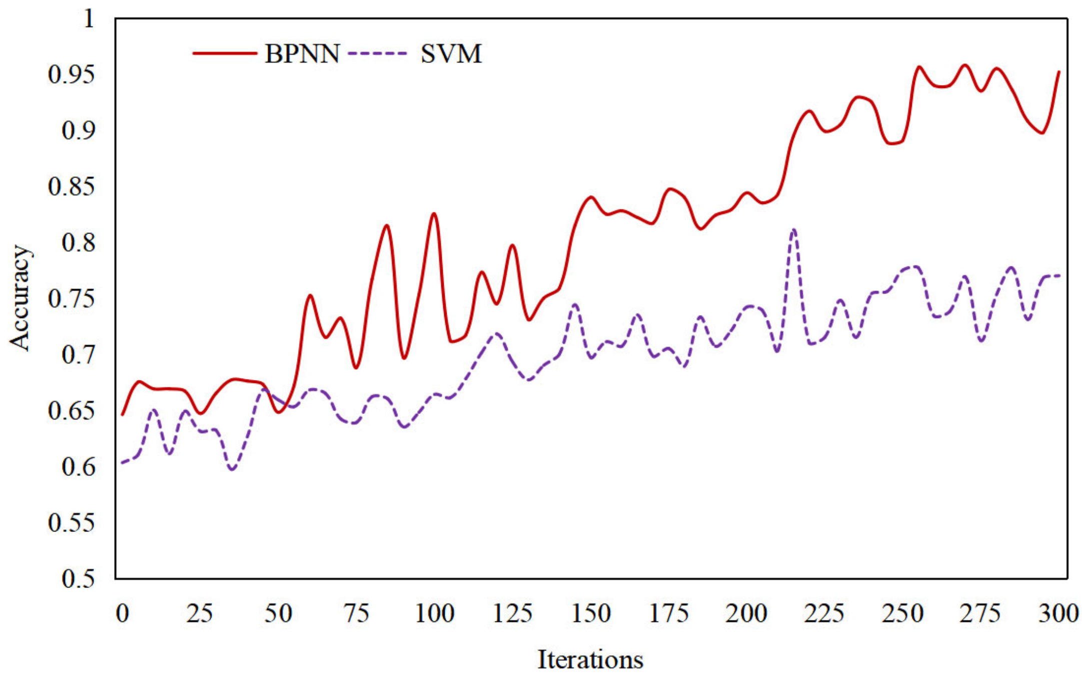

Figure 5 Comparison of accuracy of LCE prediction

BPNN algorithm often shows advantages in dealing with complex and nonlinear problems, which may be the reason why it performs better in predicting the development level of LCE. It can find the mapping relationship between input and output by learning and adjusting the weights and thresholds of neural networks, which makes it better understand and predict complex LCE phenomena. SVM algorithm is excellent in dealing with linear separable problems, but it may be limited in dealing with complex and nonlinear problems.

The growth of LCE needs to start with the optimization of energy structure, and increase the utilization of clean energy by adjusting the energy structure. At the same time, improve the efficiency of energy utilization and realize the sustainable growth of energy. The government can promote the growth of LCE by formulating relevant policies and regulations. For example, the establishment of carbon emissions trading system, the introduction of carbon tax, etc., to encourage enterprises to adopt low-carbon technologies and measures to promote the transformation of the whole society to a low-carbon direction. When making LCE scheme, we need to comprehensively consider many aspects, including using ML algorithm to forecast, optimizing energy structure, promoting low-carbon technology innovation, formulating relevant policies and regulations, and improving public awareness and participation in environmental protection. Through the cooperation and efforts of these measures, we can achieve the development goals of LCE and promote the realization of sustainable development.

5. Conclusion

With the global warming and the increasingly serious environmental problems, LCE has become the common development direction of all countries in the world. In this article, the BPNN algorithm in ML is applied to the construction of LCE scheme optimization decision model, and the performance of the model is simulated and tested. It can be seen from the prediction result diagram that the predicted value of BPNN algorithm is closer to the actual value, which means that BPNN algorithm can better capture the dynamic change pattern of historical data and better predict the future development trend. In addition, by comparing the prediction error indexes of different algorithms, it is found that the prediction accuracy of BPNN algorithm is 23.8% higher than that of SVM algorithm. This may be because BPNN algorithm has stronger nonlinear mapping ability and self-learning ability, and can better adapt to and deal with the complex and changeable nonlinear relationship in LCE field. Through the comparative study of BPNN algorithm and SVM algorithm, the advantages and application value of BPNN algorithm in LCE development level prediction are verified. This provides a strong theoretical support and technical guarantee for the growth of LCE field.

With the continuous growth of ML technology, more advanced algorithms and technologies, such as deep learning, can be further explored and applied to improve the accuracy and efficiency of LCE scheme optimization decision. In addition, I can combine the knowledge and technology in other fields, such as operational research and economics, to further improve and improve the model and method of LCE scheme optimization decision.

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