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Research on Sales Prediction of New Energy Vehicles Based on BP Neural Network

Hao Zhang[1], Zhehua Zhang[1], Jun Jiang[1], Yu Gao[1] & Xinyan Wang[1]

[1] Tibet University, Lhasa, China

Correspondence: Jun Jiang, Tibet University, Lhasa 850000, Tibet, China.

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Abstract

Due to the depletion of traditional Chinese renewable energy sources such as crude oil, increased pollution and the endogenous transformation and upgrading of China's economy and society, the flourishing of China's new energy vehicle business is an inevitable requirement for a flourishing low-carbon and green economy. In the context of the global green transformation and the new double-cycle economic development, the flourishing of the new energy vehicle industry is an inevitable requirement for the development of a low-carbon and green economy, and is a necessary path for China to move from a large automotive nation to a strong automotive nation. China's new energy vehicle exports are growing steadily, mainly to Asian and European markets, especially Europe, where a major breakthrough has been made, mainly in the export of pure electric passenger cars and the rise of independent brands. The dividends from new energy vehicles are being used not only for international foreign trade, but also for road dust protection and landmark maintenance.

Keywords: electric vehicles, genetic algorithm, fuzzy integrated evaluation, Levenberg-Marquardt algorithm

1. Introduction

In recent years, with the price of joint venture brands down, the development of China's independent brands struggle, the China Association of Automobile Manufacturers data show that from January to October 2019, the Chinese brand car sales 8.65 million units, the market share of 41.88%, compared with the same period in 2018 fell by 0.6 percentage points. And the development of new energy vehicles is conducive to the transformation and upgrading of China's auto industry. Today's new energy vehicle's is to China's auto industry, just like the smartphone was to China's mobile phone industry 10 years ago, and is an additional path for China's auto industry to "change lanes and overtake" and achieve the overall catch-up of the industry. It can be said that the development of the new energy vehicle industry is a necessary path for China to move from being a large auto country to a strong auto country. With subsidies on the decline and competition intensifying, China's new energy vehicle industry has entered a period of transition "pain".

Floods in Europe, uncontrolled mountain fires in North America, abnormally high temperatures in Siberia and extreme weather in Zhengzhou, China ...... are a constant reminder of the urgency of addressing global climate change. The global energy shortage has also intensified, and many countries have announced bans on the sale of fuel vehicles, making the development of new energy vehicles an important step in addressing climate change and optimizing the energy structure. 2021 is the first year in which new energy vehicles have truly exploded, with China's new energy vehicle exports surging and performing brightly in the international market. In this context, to accelerate the realization of China's dream of becoming an automotive powerhouse, it is particularly important to analyze the current situation, opportunities and challenges of new energy vehicle exports, and explore strategies to cope with them.

2 Projected Use of New Energy Vehicles

2.1 Construction of BP Neural Network Model

In order to derive the factors influencing the sales of new energy vehicles, a neural network model was used to calculate the different indicators. In the neural network model, the neural network can be divided into feedforward neural network, feedback neural network and self-organising neural network according to the difference of interconnection methods of neuronal networks, and their structures are shown in Figures 1 to 2.

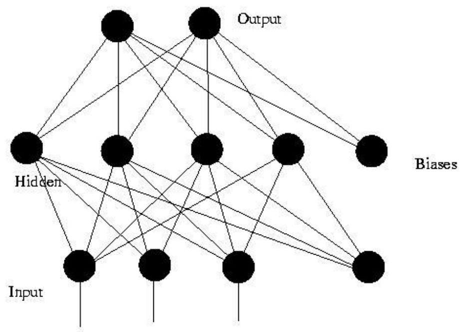

Figure 1. Feedforward neural network

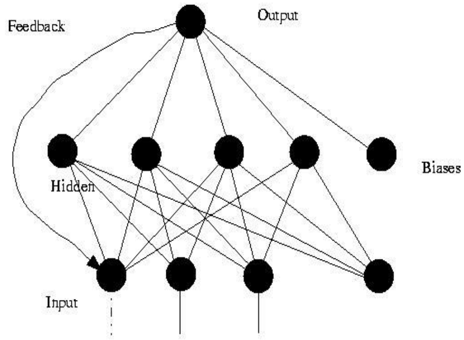

Figure 2. Feedback neural network

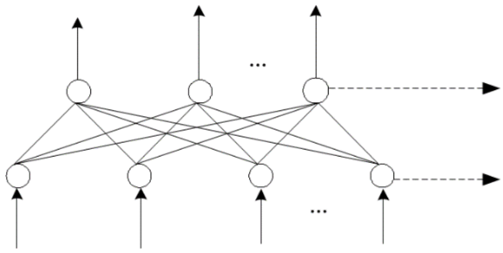

Figure 3. Self-organising neural network

This paper uses BP neural network, because in the neuronal network model, the neuronal network model with feedback has a stronger correction, in order to improve the accuracy of this model, this question selects the feed-forward neural network as the basis of the model construction, and its structure schematic diagram is shown in Figure.

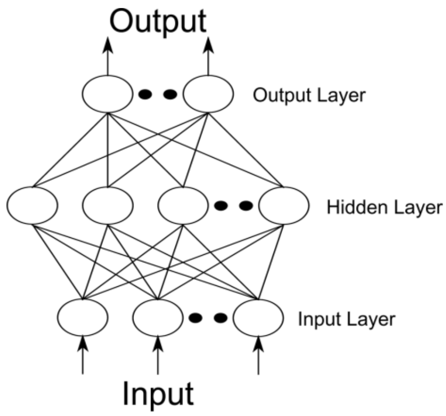

Figure 4. Schematic diagram of the feed-forward neural network structure

2.2 Applications of Neural Networks

We import the collected foreign trade data into a neural network model.

Step 1: Computation of neuron input and output

By defining the data information of each entry and output layer separately, the calculation results of neuron entry and output for each layer can be derived as follows:

(1) The implicit layer input vectors are;

$$hi_h(k) = \sum_{i=0}^{7} w_{hi} x_i(k) \qquad h = 1, 2, \cdots, 13$$

(2) The implied layer output vector is:

$$ho_h(k) = \mathrm{f}(hi_h(k)) \qquad h = 1, 2, \cdots, 13$$

(3) The output layer input vectors are:

$$yi_o(k) = \sum_{h=0}^{13} w_{oh} ho_h(k) \qquad o = 1$$

(4) The output vector of the output layer is:

$$yo_o(k) = \mathrm{f}(yi_o(k)) \qquad o = 1$$

Step 2: Calculation of the bias derivatives of the error function for each neuron in the output layer

After the input and output functions are obtained, the partial derivatives of the error function with respect to each neuron in the output layer need to be derived mathematically by solving for:

$$\frac{\partial e}{\partial w_{oh}} = \frac{\partial e}{\partial yi_o} \frac{\partial yi_o}{\partial w_{oh}}$$

where the partial derivative can be found by calculating

$$\frac{\partial e}{\partial yi_o} = \frac{\partial(\frac{1}{2}\sum_{o=1}^{1}(d_o(k) - yo_o(k)))^2}{\partial yi_o}$$
$$= -(d_o(k) - yo_o(k))yo'_o(k)$$
$$= -(d_o(k) - yo_o(k))\,\mathrm{f}'(yi_o(k)) \triangleq -\delta_o(k)$$

$$\frac{\partial yi_o(k)}{\partial w_{oh}} = \frac{\partial(\sum_{h}^{7} w_{oh}ho_h(k))}{\partial w_{oh}} = ho_h(k)$$

Step 3: Calculation of the bias derivatives of the error function for each neuron in the hidden layer

To calculate the bias of the error function to each neuron in the hidden layer, it is necessary to use the connection weights from the hidden layer to the output layer, the function of the output layer and the function of the hidden layer to calculate the solution, and the specific solution is calculated as:

$$\frac{\partial e}{\partial w_{oh}} = \frac{\partial e}{\partial yi_o}\frac{\partial yi_o}{\partial w_{oh}} = -\delta_o(k)ho_h(k)$$

$$\frac{\partial e}{\partial w_{hi}} = \frac{\partial e}{\partial hi_h(k)}\frac{\partial hi_h(k)}{\partial w_{hi}}$$

$$\frac{\partial hi_h(k)}{\partial w_{hi}} = \frac{\partial(\sum_{i=0}^{7} w_{hi}x_i(k))}{\partial w_{hi}} = x_i(k)$$

$$\frac{\partial e}{\partial hi_h(k)} = \frac{\partial(\frac{1}{2}\sum_{o=1}^{1}((d_o(k) - \mathrm{f}(\sum_{h=0}^{7} w_{ho}ho_h(k))^2))}{\partial ho_h(k)}\frac{\partial ho_h(k)}{\partial hi_h(k)}$$

Step 4: Correction of connection weights using the output layer

By using the output of each neuron to make corrections to the connection weights, the specific solution is calculated as:

$$\Delta w_{oh}(k) = -\mu\frac{\partial e}{\partial w_{oh}} = \mu\delta_o(k)ho_h(k)$$
$$w_{oh}^{N+1} = w_{oh}^{N} + \mu\delta_o(k)ho_h(k)$$

Step 5: Correction of connection weights using the input layer

By using the individual neuron inputs to make corrections to the connection weights, the specific solution is calculated as:

$$\Delta w_{hi}(k) = -\mu\frac{\partial e}{\partial w_{hi}} = \delta_h(k)x_i(k)$$
$$w_{hi}^{N+1} = w_{hi}^{N} + \mu\delta_h(k)x_i(k)$$

Step 6: Calculation of global error

$$E = \frac{1}{2m}\sum_{k=1}^{m}\sum_{o=1}^{1}(d_o(k) - y_o(k))^2$$

Step 7: Judgement

In the judgement, the accuracy needs to be compared with the budgeted maximum number of times, and when the accuracy and budgeted number of times do not meet the requirements, the cycle of the above steps needs to be performed until the requirements are met.

2.3 BP Neural Network Prediction Results

After adjusting the neural network model established in this paper, the predictive regression graph of the neural network for new energy vehicles was obtained as shown in Figure 5 below.

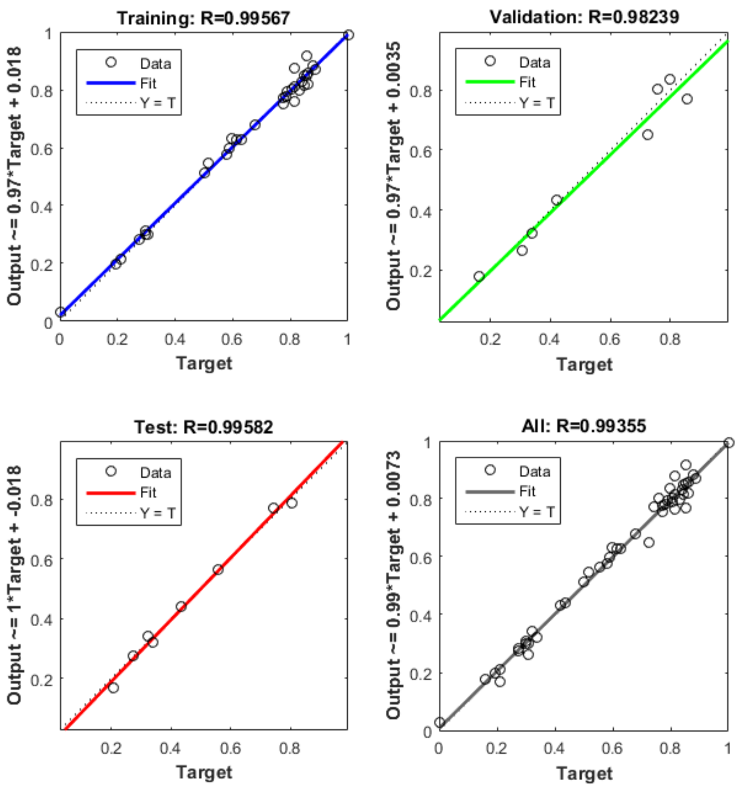

Figure 5. Regression image

3. Model Improvement Based on the Levenberg-Marquardt Algorithm

In order to improve the accuracy of model prediction and the speed of computation, this section applies an alternative algorithm for BP neural network model solving, which is dedicated to reducing the residuals and the number of iterations. Therefore, the Levenberg-Marquardt algorithm is introduced in this paper for model solving.

LM function calculation based on numerical optimization method not only uses the first derivative information of the objective function, but also uses the last second derivative information of the objective function.The iterative formula of LM algorithm can be:

$$X_{k+1} = X_k - (J^{T}{}_{k} J_k + \mu I)^{-1} * J_k * F(X_k)$$

The LM algorithm dynamically adjusts the damping factor according to the results of the iterations so that the value of the error function decreases at each iteration, which is a combination of the gradient descent method and the Newton method with faster convergence.

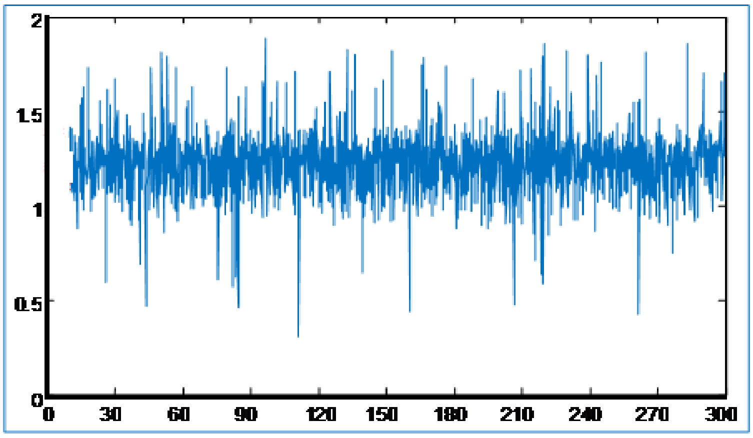

Figure 6. Output results

The improved BP neural network model is solved according to the above steps, based on the corresponding higher accuracy weights and thresholds, and the resulting residuals are shown in the upper panel of the figure. It can be seen that the residuals are more convergent than before and the residual values are also smaller. The BP neural network model based on the Levenberg-Marquardt algorithm in this paper is more accurate than the BP neural network model based on the genetic algorithm.

4. Conclusion

(1) Focus on plug-in hybrid new energy passenger vehicles

At present, the product strategy of ignoring plug-in hybrids and focusing on pure electric vehicles for new energy vehicles has reduced product width. Under the current situation of imperfect charging piles and other infrastructure construction, new energy vehicle consumers generally have

(2) PPO approach to meet consumers' individual needs

Consumers of new energy vehicles are still mainly the tasting type, they pursue individuality, fashion and manifestation of self, and this is also the case in vehicle selection. Therefore, while launching new models, customised modifications are made through PPO to further meet the differentiated needs of consumers in different market segments. At the same time, by launching different range versions of the same model, the length of the new energy passenger car product line will be increased to further meet the differentiated needs of different new energy passenger car segments.

(3) Combined product mix strategy of volume and image products

The policy requirement of double points makes it necessary for automotive companies to produce enough new energy vehicles to offset the current negative points for oil vehicle energy consumption. Therefore, when considering the product portfolio, it is important to have a product that can currently be produced at the lowest cost and in rapid volume. At the same time, for sustainable and healthy development, enterprises must have products that represent the high-end image of the enterprise. On the one hand, high-end products can give consumers a choice when it comes to consumer upgrading, on the other hand, high-end products can bring more profit to the enterprise, provide a source of profit for the enterprise, enhance the brand image of the enterprise, improve investor confidence and lay a solid user base for new platform products in the future.

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