Sales Forecasting of Traditional Fuel Passenger Vehicles in China Based on BP Neural Network-SARIMA Combination Model

Minjing Peng[1], Jianjin Liao[2,*]

{peng.mj@wyu.edu.cn[1], kinjun6@163.com[2,*]}

School of Economics and Management, Wuyi University,Jiangmen, China

Abstract. Although the share of traditional fuel passenger vehicles and new energy passenger vehicles in the sales market changes frequently. However, few studies have explored the future development trend of traditional fuel passenger vehicles in the sales market. In this study, a combined BP neural network-SARIMA model is constructed to further improve the forecasting accuracy of the BP neural network model, and is used to forecast the monthly sales of traditional fuel-fired passenger vehicles in China in 2023. The results show that the combination model has better forecasting performance. This paper further observes the overall trend of monthly sales forecasts, and analyzes the abnormal fluctuations of sales in some months.

Keywords: BP neural network, SARIMA, BP neural network-SARIMA combination model, conventional fuel passenger vehicles, sales forecasting

1 Introduction

Due to the development of the automobile industry, changes in policy requirements and other factors, the sales market of traditional fuel passenger vehicles coexisting with new energy passenger vehicles is undergoing rapid changes. Therefore, the use of appropriate models to predict the trend of the overall or segmented passenger vehicles sales market can provide a reference basis for the strategic planning and decision-making of passenger vehicles companies. Previous scholars have conducted several studies on the overall development trend of the passenger car market, such as empirical simulation of the development of passenger car companies and market changes under the implementation of automotive industry policies [1]. Secondly, scholars have also paid attention to the refined new energy passenger vehicles market and have shown more positive views on its development and growth. Among them, one study directly based on the past sales time series data, adopting the Bass forecasting model to observe the overall upward trend of new energy passenger vehicles in the future [2].

However, the trend of change in the segmented traditional fuel passenger vehicles sales market has been largely ignored. The positive benefits of certain aspects of traditional fuel vehicles may become less favorable than those of new energy vehicles, such as environmental benefits, national policy advantages, and the advantages of the product's own qualities [3]–[5]. Based on the potential positive growth of new energy vehicles in the future, the future trend of traditional fuel passenger car market share has rarely been explored. In a previous study, Huang et al.

ICEMME 2023, November 17-19, Beijing, People's Republic of China
Copyright © 2024 EAI
DOI 10.4108/eai.17-11-2023.2342671

investigated the dynamic switching mechanism of consumers in choosing passenger cars based on the transition probability, and found that the economic advantages of new energy vehicles can cause consumers to deviate from the choice of fuel vehicles [6]. The development of new energy vehicles may have changed the sales market share of traditional fuel vehicles [7]. In addition, in recent years, In addition, in recent years, China has actively promoted the development of new energy vehicles [6], [8]. Therefore, focusing on the potentially more representative passenger vehicles sales market fluctuations in China, this study further explores the future development trend of China's traditional fuel-powered passenger vehicles in the sales market by adopting a scientific approach.

Forecasting sales trends has been proven to help companies adjust their sales strategies and make scientific decisions [9]. For example, based on the nonlinear regular mapping capability of BP neural networks [10], previous studies have utilized it to explore the demand for regional logistics [11]. However, each forecasting method has its optimal scope of application, and the time series data can be further decomposed into sequences with linear fluctuations and nonlinear stochastic fluctuations [12]. Further combination of SARIMA model suitable for predicting linear part of the series can improve the prediction accuracy of BP neural networks [13], [14]. Therefore, this study attempts to forecast and analyze the monthly sales volume of fuel passenger cars in China by using a combined forecasting model of BP neural network and SARIMA model, and then make suggestions for the development of fuel vehicle enterprises.

2 Models and Research Methods

The BP neural network model and SARIMA model are good at fitting the nonlinear and linear parts of the data, respectively. Therefore, firstly, the factor decomposition of the sequence of monthly sales of traditional fuel passenger vehicles in China is carried out with the help of the multiplication model. Subsequently, the BP neural network model and SARIMA model are built to fit and forecast the linear and nonlinear series in the time series, respectively. Finally, the multiplication model is used to synthesize the prediction results of the two models, so that the future monthly sales of China's traditional fuel passenger vehicles can be observed. The expression of the multiplication model is shown in (1):

$$x_t = T_t \cdot S_t \cdot I_t \tag{1}$$

T_t and S_t represent trend and seasonal fluctuations respectively, which are linear series in the data. I_t stands for stochastic fluctuation, which is a nonlinear series in the data.

2.1 Construction of BP neural network model

BP neural network is a multilayer feed-forward network based on the error back propagation algorithm, embodying the learning and mapping process between the input, hidden and output layers, and the relationship between the network structures is shown in (2):

$$y_t = w_0 + \sum_{j=1}^{Q} w_j \, g\left(w_{0j} + \sum_{i=1}^{P} w_{ij} y_{t-i} \right) + \varepsilon_t \tag{2}$$

The equation reflects the forward and back propagation process between input y_{t-i} and output y_t. w_{ij} is the connection weight vector. w_j is the threshold vector. The number of nodes in the input and hidden layers are P and Q, respectively. $g(\cdot)$ is the logistic transformation function. In this study, the nonlinear fluctuation series of the first six months is used to predict the series of the following month. Therefore, the constructed BP neural network has 6 nodes in the input layer and the number of nodes in the output layer is 1. In addition, the number of hidden layers was 1, the number of nodes was determined to be 10, and the mean square error function was set as the loss function. Subsequently, iteratively updating the weights and thresholds of the network structure through the gradient search technique was able to minimize the total error of the network output.

2.2 Metrics for model evaluation

The autoregressive moving average model, i.e., ARIMA (p , d , q) model, is able to transform a non-stationary time series into a stable one by means of differential transformation, and its structure is shown in (3):

$$\varphi_p (B) \nabla^d Y_t = \theta_q (B) \omega_t \tag{3}$$

In this case, φ_p is the autoregressive quantity, p is the autoregressive order, B is the backward shift, $\nabla^d = (1 - B)^d$ is the period-by-period difference of order d, Y_t is the time series, θ_q is the shift quantity, q is the autoregressive order, ω_t is the white noise.

The seasonal fluctuation characteristics in the time series may affect the fitting accuracy of the ARIMA model. The $SARIMA (p , d , q) (P , D , Q)_S$ model can make up for this shortcoming by further seasonal differencing, whose expression is shown in (4):

$$\varphi_p (B) \phi_P \left(B^S \right) \nabla^d \nabla_S^D Y_t = \theta_q \Theta_Q \left(B^S \right) \omega_t \tag{4}$$

In this case, ϕ_P is the seasonal regression quantity, P is the seasonal regression order, $\nabla_S^D = (1 - B^S)^D$ is the seasonal difference of order D, S is the seasonal period, Θ_Q is the seasonal shifting quantity, Q is the seasonal shifting order.

In the construction of the SARIMA forecasting model for the non-stochastic fluctuation series of monthly sales of traditional fuel vehicles, firstly, the 1st order 12-step differencing is used to convert it into a smooth series. Subsequently, the characteristics of the time series after differencing are observed, and the four indicators, namely, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), are combined to determine the parameters of the model. Finally, this study adopts $SARIMA (1 , 1 , 2) (0 , 1 , 1)_{12}$ as the optimal model for linear series forecasting.

2.3 Construction of the SARIMA model

In order to evaluate the prediction performance of the combination model, in addition to compare the model predicted values with the true values directly, it is also able to make a more effective comparison by the Root Mean Squared Error (RMSE) and the Mean Percentage Error (MAPE). The formulas for the two error values are shown in (5), (6):

$$RMSE = \sqrt{\frac{I}{N}\sum_{t=1}^{N}(observed_t - predicted_t)^2} \tag{5}$$

$$MAPE = \frac{100}{N} \times \sum_{t=1}^{N}\left|\frac{observed_t - predicted_t}{observed_t}\right| \tag{6}$$

Where N represents the number of true observations and predicted values, $observed_t$ represents true observations, and $predicted_t$ represents predicted values.

3 Monthly Sales forecasting of Traditional Fuel Passenger Vehicles

Driven by the subsidy policy, new energy vehicles have seen accelerated growth since 2014 and continue to penetrate the market. As a result, the share of traditional fuel vehicles in the passenger car sales market has also begun to change at an accelerated pace. Therefore, this study selects the monthly sales of traditional fuel vehicles for each full year from January 2014 to December 2022 as the empirical dataset, and the data are obtained from the official website of Passenger Vehicle Market Information Consortium, which is a well-known platform for information exchange and market research of the automotive industry in China. First, the respective fitting and error values of the combined BP neural network-SARIMA model and the single BP neural network model are observed and compared, so as to validate the prediction effect of the combined model. Subsequently, the sales of conventional fuel passenger vehicles from January 2023 to December 2023 were predicted based on the integrated model with better accuracy.

3.1 Validation of BP Neural Network-SARIMA Combination Models

The respective prediction results of the BP neural network model and the combined BP neural network-SARIMA model for the empirical dataset are shown in Fig. 1. The combination model exhibits a better level of fit to the true value, which preliminarily validates its effectiveness for predicting the monthly sales trend of conventional fuel passenger vehicles.

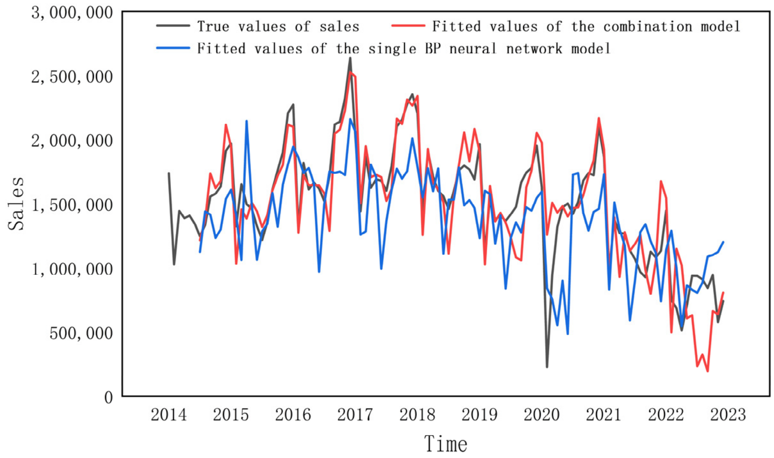

Fig. 1. Effectiveness of predictive fitting of different models to the true values

Secondly, the two models were further compared based on the root mean square error and mean percentage error, and the results were obtained as shown in Table 1. The RMSE and MAPE generated by the combined model for data fitting prediction are 235811 and 0.15, respectively, which are within acceptable error metrics, and both are improved relative to the single model. In summary, considering the potential impact of the development of new energy vehicles and the spread of new coronavirus pneumonia on the market share of traditional fuel vehicles in recent years, for the empirical dataset, the combined BP neural network-SARIMA model achieves a sizable forecasting performance, which is suitable for predicting the monthly sales of traditional fuel passenger vehicles.

Table 1. Predictive performance of different models

Models	Evaluation metrics for prediction performance	
	RMSE	MAPE
BP neural network-SARIMA combination model	235811	0.15
BP neural network model	353561	0.22

3.2 Forecasting using the BP neural network-SARIMA combination model

Based on the constructed BP neural network-SARIMA combination model, this study further forecasts the monthly sales volume of conventional fuel passenger vehicles from January 2023 to December 2023 in China, as shown in Fig. 2.

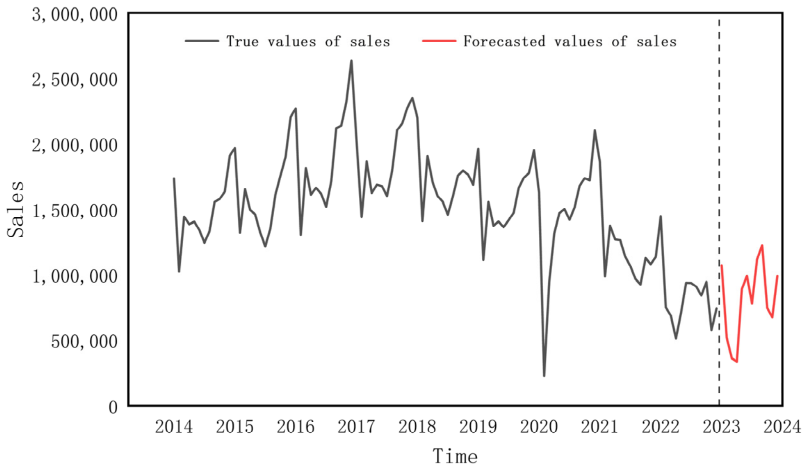

Fig. 2. Monthly Conventional Fuel Passenger Vehicle Sales Forecast to 2023

As shown by the forecast results, the monthly sales of conventional fuel passenger vehicles in 2023 have little fluctuation in change compared to the previous year. The forecast result for the whole year's sales is 9,724,200 units, which is a slight decrease compared to the actual sales in 2022 (10,009,000 units). Notably, the forecasted sales for both January and October show a significant downward trend from the previous year, at 1,074,000 units and 748,200 units, respectively. However, these two months are usually the peak points of sales volume for passenger vehicles manufacturers, as factors related to vehicles purchasing perceptions, economic efficiency, and other factors are likely to positively influence consumers' demand for vehicles at this time [15], [16]. Therefore, this study further analyzes this anomaly:

(1) Generally speaking, due to the concept of "ringing in the old and ringing in the new", abundant funds, and sufficient time, consumers' demand for vehicles increases at the beginning of the year. However, sales forecasts indicate that January 2023 will see a year-over-year decline in conventional passenger vehicles sales. This may be due not only to various policy measures gradually favoring the new energy passenger vehicles market, but also due to the newer technology of the new energy vehicles themselves and a change in consumer attitudes that may contribute to this phenomenon.

(2) At the end of the year, passenger vehicles manufacturers usually attract consumers through promotional campaigns and sales promotions. However, forecasts show that sales of conventional fuel vehicles will fall in October 2023 compared to the previous year. Information that is more relevant to the quality of the product itself is relatively more effective in changing consumers' purchase intentions [17]. The relatively declining sales trend reflects the fact that consumers may be concerned that the product power of traditional fuel vehicles themselves is gradually being surpassed, and thus publicity and promotions are gradually becoming less effective in promoting consumer purchases.

4 Conclusions

In this paper, based on the BP neural network-SARIMA combination model, the nonlinear fluctuation series and linear fluctuation series in the monthly sales of traditional fuel passenger vehicles are targeted for forecasting. Compared with the single BP neural network model, the combination model has better and acceptable forecasting performance, as shown in the two error metrics of RMSE and MAPE. Further forecasting of monthly sales for the whole year 2023 reveals a slight decrease in sales for the whole year and abnormal fluctuations in sales for individual months. This may be due to the fact that the attractiveness of traditional fuel passenger vehicles to consumers has been undermined by the new energy passenger vehicles in the market, and consumers' purchasing intentions have begun to change, resulting in the loss of market share for traditional fuel passenger vehicles.

Combining the results of the forecasts and analysis, the slight downward trend in annual sales reflects the loss of market share for traditional fuel passenger cars, which is most likely caused by competition with new energy passenger cars [8]. The analysis of the abnormal monthly fluctuations further verifies this reason: the policy preference for new energy passenger cars, their superiority in technology, and the shift in consumers' environmental awareness are gradually undermining the attractiveness of traditional fuel vehicles to consumers. Consumers are gradually losing demand for traditional fuel vehicles, resulting in a decline in their sales. The following recommendations are made to effectively address the development of traditional fuel vehicles:

(1) Traditional fuel passenger car companies need to strengthen the research and development of their own products and improve their level of service. For example, lower energy consumption and better service quality during purchase and use are the outstanding advantages of new energy passenger vehicles [18]. Traditional fuel vehicles companies can be committed to improving the fuel efficiency of passenger car products, and improve the customer's purchase and use experience through more comprehensive and humanized services.

(2) Strengthening the protection of the environment and the penetration of new energy passenger vehicles in the market is an irreversible trend. Traditional fuel passenger vehicles companies need to actively comply with the call for environmental protection. In addition to further improving the drive system so as to increase the fuel efficiency of passenger cars [19], traditional fuel passenger vehicles enterprises can further develop competitive new energy passenger car products based on consumers' concerns about their own products in terms of appearance and safety [18].

References

[1] L. Chen, “The Demand Estimation,Supply Analysis and Welfare Effect of Mergers Simulation in China’s Automobile Industry,” *China Soft Science*, no. 12, pp. 148–157, 2013.(In Chinese)

[2] Y. LIU, M. WANG, and J. WANG, “The Predictive Ｒesearch on China’s New Energy Vehicles Market,” *Research on Economics and Management*, vol. 37, no. 04, pp. 86–91, 2016. (In Chinese)

[3] K. Petrauskienė, M. Skvarnavičiūtė, and J. Dvarionienė, “Comparative environmental life cycle assessment of electric and conventional vehicles in Lithuania,” *Journal of Cleaner Production*, vol. 246, p. 119042, 2020.

[4] Z. Wang, C. Zhao, J. Yin, and B. Zhang, “Purchasing intentions of Chinese citizens on new energy vehicles: How should one respond to current preferential policy?,” *Journal of Cleaner Production*, vol. 161, pp. 1000–1010, 2017.

[5] Z. Wang, C. Wang, and Y. Hao, “Influencing factors of private purchasing intentions of new energy vehicles in China,” *Journal of Renewable and Sustainable Energy*, vol. 5, no. 6, p. 063133, 2013.

[6] Z. Huang, L. Zhang, and T. Zhi, “The Future of Traditional Fuel Vehicles (TFV) and New Energy Vehicles (NEV): Creative Destruction or Co-existence?,” *arXiv preprint*, p. arXiv:2207.03672, 2022.

[7] J. Earl and M. J. Fell, “Electric vehicle manufacturers’ perceptions of the market potential for demand-side flexibility using electric vehicles in the United Kingdom,” *Energy Policy*, vol. 129, pp. 646–652, 2019.

[8] H. Liao, S. Peng, L. Li, and Y. Zhu, “The role of governmental policy in game between traditional fuel and new energy vehicles,” *Computers & Industrial Engineering*, vol. 169, p. 108292, 2022.

[9] S. Mu, Y. Wang, F. Wang, and L. Ogiela, “Transformative computing for products sales forecast based on SCIM,” *Applied Soft Computing*, vol. 109, p. 107520, 2021.

[10] B. H. M. Sadeghi, “A BP-neural network predictor model for plastic injection molding process,” *Journal of Materials Processing Technology*, vol. 103, no. 3, pp. 411–416, 2000.

[11] L. Huang, G. Xie, W. Zhao, Y. Gu, and Y. Huang, “Regional logistics demand forecasting: a BP neural network approach,” *Complex Intell. Syst.*, vol. 9, no. 3, pp. 2297–2312, 2023.

[12] S. Li and B. Li, “Comparison of Prediction Method Based on SARIMA Model and X-12-ARIMA Seasonal Adjustment Method,” *Statistics & Decision*, vol. 34, no. 18, pp. 39–42, 2018. (In Chinese)

[13] M. Yonghong, W. Zhiyong, A. Mingye, and W. Wei, “The Construction and Application of a New Exchange Rate Forecast Model Combining ARIMA with a Chaotic BP Algorithm,” *Emerging Markets Finance and Trade*, vol. 52, no. 6, pp. 1481–1495, 2016.

[14] Y. WANG, B. HAN, Q. Zhang, and D. Li, “Forecasting of Entering Passenger Flow Volume in Beijing Subway Based on SARIMA Model,” *Journal of Transportation Systems Engineering and Information Technology*, vol. 15, no. 06, pp. 205–211, 2015. (In Chinese)

[15] C. Xia, “Calculation of Real Economic Time Series,Seasonal Adjustment and Some Economic Implications,” *Economic Research Journal*, no. 03, pp. 36-43+94, 2002. (In Chinese)

[16] M. Kaur and H. S. Sandhu, “Factors Influencing Buying Behaviour-A Study Of Passenger Car Market,” *Paradigm*, vol. 8, no. 2, pp. 26–30, 2004.

[17] M. Kukar-Kinney and L. Xia, “The effectiveness of number of deals purchased in influencing consumers’ response to daily deal promotions: A cue utilization approach,” *Journal of Business Research*, vol. 79, pp. 189–197, 2017.

[18] X. Wang, Y. Cheng, T. Lv, and R. Cai, “Fuel vehicles or new energy vehicles? A study on the differentiation of vehicle consumer demand based on online reviews,” *MIP*, 2023.

[19] D. Andress, S. Das, F. Joseck, and T. Dean Nguyen, “Status of advanced light-duty transportation technologies in the US,” *Energy Policy*, vol. 41, pp. 348–364, 2012.