Application of Multiple Linear Regression and Time-Series Models for Forecasting Sales of New Energy Vehicles

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Abstract—As one of the important means to reduce carbon dioxide emissions, new energy vehicles are developing rapidly in the Chinese market. In order to evaluate the future development situation, this paper predicts the sales volume of new energy vehicles by establishing a multiple linear regression model and time series based on the monthly data from 2016 to 2021. According to the fitting results, the multiple linear regression model can better reflect the sales of NEV than the ARIMA model. The ARIMA model predicts that sales of NEVs will continue to grow in the future. The multiple linear regression model makes an in-depth analysis of different influencing factors. In terms of economic factors, the rise in production costs caused by inflation may have a negative impact on sales. As for product factors, the improvement of supporting charging pile facilities is conducive to the increase in NEV sales. Regarding to competitive product analysis, the rise in oil prices is the main reason for purchase intention of NEV. However, they are still far less competitive than conventional cars while NEVs are growing fast. These results shed light on guiding further exploration of sales prediction for NEV.

Keywords- New Energy Vehicles, Sales Forecasting, Multiple Linear Regression Model, Time Series Model

1 INTRODUCTION

Environmental protection issues related to global warming have always been the focus of global attention. Since the birth of new energy vehicles (NEV) in the early 21st century, they have been attracting attention as one of the important innovative means to reduce carbon dioxide emissions. In November 2020, China called for the in-depth implementation of the national strategy for the development of new energy vehicles, to promote the high-quality and sustainable development of new energy vehicle industry, and to accelerate the construction of an automobile powerhouse.

In the Chinese market, new energy vehicles are usually divided into hybrid electric vehicles, battery electric vehicles and fuel cell vehicles. China has been promoting the commercialization of NEVs by formulating industry development strategies and became the world's largest NEV market in 2009 [1]. As of the end of May 2021, the number of new energy vehicles in China is about 5.8 million, accounting for about 50% of the global total of new energy vehicles. However, the proportion of NEV in the overall automobile market is still small, the industry chain still needs to be improved. In the future, the popularization potential and risks of China's new energy vehicles coexist [2]. Therefore, it is necessary to quantify and predict future sales data by analyzing the factors affecting the sales volume of the NEV market and establishing a model.

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Considering about influencing factors, policies (e.g., government subsidies and tax incentives) have affected consumers' purchasing choices and have played a very positive role in the development of new energy vehicles in the Chinese market [3]. Besides, the influencing factors of the industry itself will also affect the market development. The Multi-Level Perspective framework composed of landscapes, regimes and niches reflects the internal factors of the industry [4]. In addition, consumer' personal environmental awareness and acceptance of policies will also affect the consumption [5].

For establishing predicting model, several different forecasting methods have been used. According to the prediction results of the multiple linear regression model, the sales of new energy vehicles can be well fitted with factors, e.g., consumer income level, the number of charging stations, and policy subsidies [6]. Besides, both economic indicators (such as consumer price index, produce price index, fuel retail price) and search indicators reflecting the degree of consumer interest are included in the univariate time-series model and multi-variate model, reflecting that the sales volume of NEV will maintain a positive trend in the future [7]. The grey model has been applied to predict the sales of China's new energy vehicles from supply side and demand side, which shows that the growth rate of production and sales of NEV will be 27.53% and 30.49% separately from 2018 to 2020, indicating the promising growth of the market [8]. Additionally, a network externalities model combines different level of oil prices and of drivetrains to find that the sales of electric cars will rise up to 64% of the total sales of light-vehicle sales through 2030 in the United States [9]. Through BP neural network prediction, the effect of seasons, price of oil, technologies and polices on the sales of NEV in China to modify the fluctuation of data [10]. Considering about the regional factors, different cities in China are analyzed separately with BiLSTM (Bidirectional Long Short Term Memory) model by scenario analysis, predicting that the growth trend of NEV will not realize the target of 20% market share in 2025 [11].

In order to further explore the future development of NEV and analyze the influencing factors that affect the sales, this research predicts the sales of NEV in the Chinese market by establishing a multiple linear regression model and a time series model. After exploring important influencing variables based on the results of data analysis, it combines them to provide recommendations for future policy formulation and NEV marketing. The rest part of the paper is organized as follows, the Sec. II will describe the data used to build the model and the two forecasting methods. The Sec. III will analyze the results of the multiple regression model and the time series model respectively, show the prediction results of the model, and analyze the limitations of the prediction model. The Sec. IV will summarize the content of the whole report and put forward the prospect of future research.

2 DATA AND METHOD

2.1 Data

To predict the sales of NEV, monthly data of sales of NEV in China and other variables are collected from 2016 to 2021, a total of 72 samples from Wind, China Association of Automobile Manufacturers, National Bureau of Statistics of China.

2.2 Method

This study predicts the development of NEV in the Chinese market by establishing a multiple linear regression model and a time series model. For the multiple linear regression model, on model variable selection, the variables affecting NEV sales can be mainly divided into three dimensions as shown in Fig. 1, which are policy factors, macroeconomic factors, and product factors. First, policy preferences can encourage product consumption, which is quantified by the cumulative number of relevant policies issued. Secondly, macroeconomic factors will affect the consumption level of consumers, thereby affecting their willingness to buy. Therefore, the consumer price index and consumer confidence index are included in the model for evaluation and analysis. Finally, product factors can be further subdivided into product own factors, complements factors, and substitute factors. According to economic theory, the sales of products in the market are largely influenced by their complements and substitutes [12]. The influence level of the product itself can be measured by NEV's search index (the total number of searches on Baidu for NEV-related search keywords); complementary factors include the number of charging piles and auto supplies price index in China; substitute factors include gasoline market prices (Octane-95 and Octane-92) and sales of non-new energy vehicles in the Chinese market.

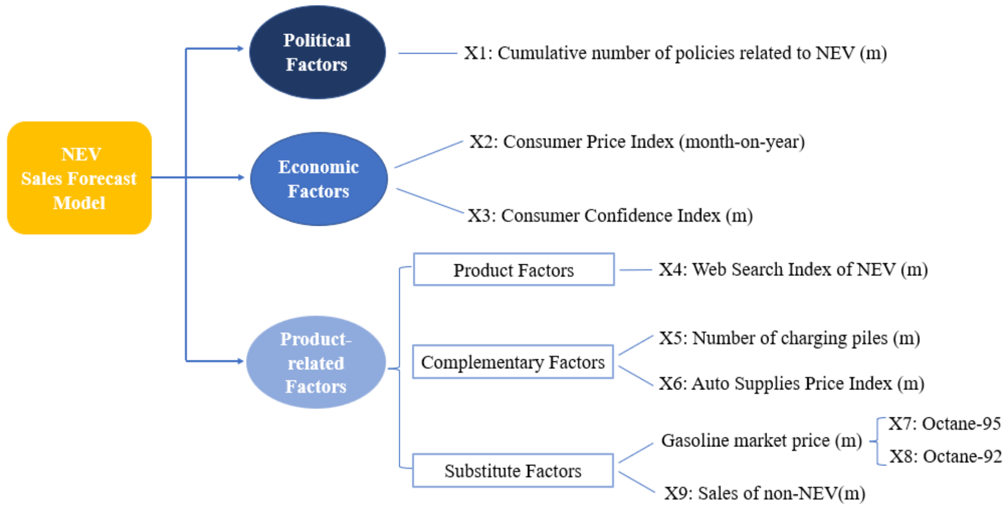

Figure 1. Variables included in mutiple linear regression models

According to the data trend of monthly sales volume, it can be seen that the sales volume of NEV will show a trend of exponential growth as a whole from 2016 to 2021. Therefore, a logarithmic model is selected for fitting.

$$\mathrm{LnY_I} = \beta_0 + \beta_1 \mathrm{lnX_{i1}} + \beta_2 \mathrm{lnX_{i2}} + \cdots + \beta_p \mathrm{lnX_{ip}} + \varepsilon_i \tag{1}$$

where, $\beta_0, \beta_1, \ldots, \beta_p$ are parameters, ε_i are independent $N(0, \sigma^2)$. In the equation, LnY represents the logarithm of monthly NEV sales, and LnX are the factors that affect the dependent variable. In order to test the validity of the model, the hypothesis testing of the research includes unit root test, cointegration test, heteroscedasticity test and multicollinearity test.

For the time series model, ARIMA Model (Autoregressive Integrated Moving Average Model), which is one of the most common models used for time series forecasting, is adopted here. The variable X of the time series model is the logarithm of NEV monthly sales. The time series $\{x_t; t = 0, \pm1, \pm2, ...\}$ is an ARMA(p, q) model if it is stationary and satisfies:

$$x_t = \emptyset_1 x_{t-1} + \cdots + \emptyset_p x_{t-p} + \omega_t + \theta_1 \omega_{t-1} + \cdots + \theta_q \omega_{t-q} \tag{2}$$

Where $\emptyset_p \neq 0$, $\theta_q \neq 0, \sigma_w^2 > 0$. The parameters p and q are the order of autoregression and moving average, respectively. If the mean μ of x_i is nonzero, then $\alpha = \mu(1 - \emptyset_1 - \cdots - \emptyset_p)$, and the model (2) can be modified to:

$$x_t = \alpha + \emptyset_1 x_{t-1} + \cdots + \emptyset_p x_{t-p} + \omega_t + \theta_1 \omega_{t-1} + \cdots + \theta_q \omega_{t-q} \tag{3}$$

Where $\omega_t \sim wn(0, \sigma_w^2)$. When $q = 0$, the model is the p-order autoregressive model AR(p); when $p = 0$, the model is the q-order moving average model MA(q). Before the ARIMA model is established, the variables first need to pass the unit root test. Furthermore, after building the ARIMA model, this research performed a predictive analysis of the model results.

3 RESULTS AND DISCUSSION

The research mainly uses the multiple linear regression model to predict the sales volume, and uses the forecast results of the ARIMA model to assist the comparative analysis, so as to select a model with a higher goodness of fit.

3.1 Multiple Linear Regression Model

3.1.1 Correlation analysis

According to the Table 1., most of the relationships between explanatory variables and sales are consistent with the null hypothesis. From the analysis of political factors, there is a positive correlation between the cumulative number of policies issued (x_1) and the sales volume. For economic factors, the improvement of consumers' purchasing power (x_3) will also promote the increase in sales. From the perspective of product factors, the increase in the search index of products (x_4) is conducive to the expansion of sales; the improvement of charging piles (x_5) in complementary products will promote people's consumption of NEV; the rise in gasoline prices $(x_7\ and\ x_8)$ in substitutes is also one of the factors that affect people's choice to buy NEV. The results are also shown in the Fig. 3.

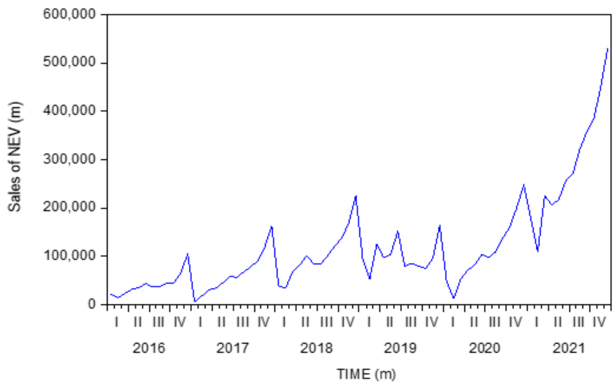

Figure 2. Line graph of NEV monthly sales

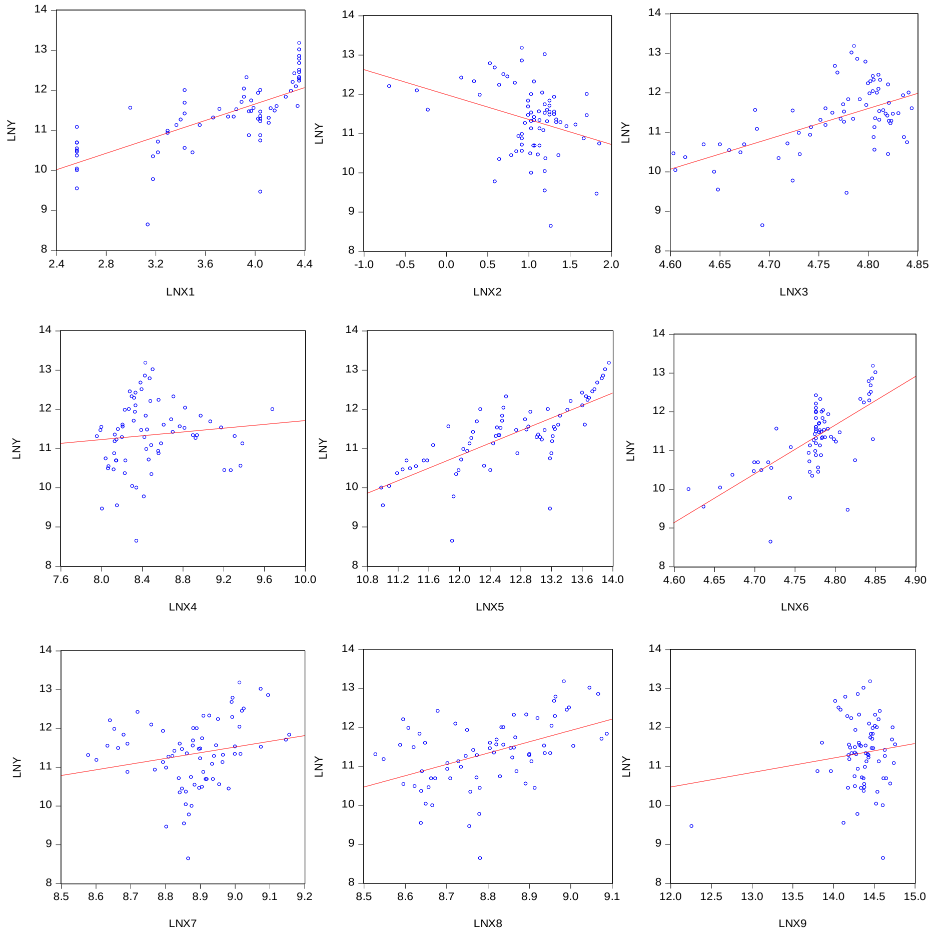

Figure 3. Correlation fit of each variable

Table 1 Pearson Correlation Coefficient

	LnY	LnX1	LnX2	LnX3	LnX4	LnX5	LnX6	LnX7	LnX8	LnX9
LnY	1.000	0.715	-0.321	0.561	0.106	0.746	0.692	0.209	0.464	0.197
LnX1	0.715	1.000	-0.166	0.825	-0.046	0.970	0.842	-0.048	0.408	-0.213
LnX2	-0.321	-0.166	1.000	-0.059	-0.095	-0.211	-0.064	0.096	0.039	-0.178
LnX3	0.561	0.825	-0.059	1.000	0.256	0.752	0.777	0.051	0.479	-0.097
LnX4	0.106	-0.046	-0.095	0.256	1.000	-0.125	0.125	0.353	0.425	0.306
LnX5	0.746	0.970	-0.211	0.752	-0.125	1.000	0.860	-0.044	0.374	-0.225
LnX6	0.692	0.842	-0.064	0.777	0.125	0.860	1.000	0.205	0.593	-0.213
LnX7	0.209	-0.048	0.096	0.051	0.353	-0.044	0.205	1.000	0.862	0.029
LnX8	0.464	0.408	0.039	0.479	0.425	0.374	0.593	0.862	1.000	-0.039
LnX9	0.197	-0.213	-0.178	-0.097	0.306	-0.225	-0.213	0.029	-0.039	1.000

Table 2 Multicollinearity Analysis of Model (1)

	B	Std	Beta	t	Sig.	Tolerance	VIF
(Constant)	-18.792	5.119		-3.671	0.001		
x1	1.345	0.537	0.937	2.503	0.015	0.022	45.591
x2	-0.168	0.126	-0.085	-1.328	0.189	0.751	1.331
x3	-1.764	1.711	-0.129	-1.031	0.306	0.196	5.095
x4	0.362	0.198	0.159	1.832	0.072	0.408	2.449
x5	0.296	0.362	0.277	0.819	0.416	0.027	37.206
x6	5.836	2.864	0.321	2.038	0.046	0.124	8.076
x7	8.824	2.054	1.255	4.295	0.000	0.036	27.773
x8	-8.030	2.212	-1.282	-3.630	0.001	0.025	40.623
x9	1.089	0.184	0.365	5.921	0.000	0.808	1.237

Table 3 Regression Result of Model (1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNX1	1.344	0.537	2.503	0.015
LNX2	-0.168	0.126	-1.327	0.189
LNX3	-1.764	1.711	-1.031	0.307
LNX4	0.362	0.198	1.832	0.072
LNX5	0.297	0.362	0.820	0.416
LNX6	5.836	2.864	2.038	0.046
LNX7	8.824	2.054	4.295	0.000
LNX8	-8.030	2.212	-3.630	0.001
LNX9	1.089	0.184	5.921	0.000
C	-43.271	11.788	-3.671	0.001
R-squared	0.810	Mean dependent var		11.347
Adjusted R-squared	0.782	S.D. dependent var		0.870
S.E. of regression	0.406	Akaike info criterion		1.165
Sum squared resid	10.235	Schwarz criterion		1.481
Log likelihood	-31.932	Hannan-Quinn criter.		1.291
F-statistic	29.278	Durbin-Watson stat		1.488
Prob(F-statistic)	0			

3.1.2 Preliminary regression results

The initial model can get Model (1) by including all 9 related variables into the model, and the regression results are as follows:

$$\mathrm{LnY} = \mathrm{C} + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \beta_3 \ln X_3 + \beta_4 \ln X_4 + \beta_5 \ln X_5 + \beta_6 \ln X_6 + \beta_7 \ln X_7 + \beta_8 \ln X_8 + \beta_9 \ln X_9 \tag{5}$$

The Adjusted R-squared of the preliminary model is about 0.782 as shown in Table 3., and the fitting effect of the model is great, indicating that the initial variables can better predict the sales volume. However, some variables are insignificant and need to be corrected.

Based on the multicollinearity analysis, the VIF values of some variables have multicollinearity according to the Table 2., which may lead to the insignificant variables. Since more sample data cannot be obtained, the model is corrected by excluding variables.

Table 4 Regression Result of Model (2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNX2	-0.217	0.125	-1.741	0.086
LNX5	0.904	0.070	12.960	0.000
LNX7	1.604	0.423	3.792	0.000
LNX9	0.984	0.176	5.594	0.000
C	-28.239	4.596	-6.144	0.000
R-squared	0.762	Mean dependent var		11.347
Adjusted R-squared	0.748	S.D. dependent var		0.870
S.E. of regression	0.437	Akaike info criterion		1.248
Sum squared resid	12.783	Schwarz criterion		1.406
Log likelihood	-39.935	Hannan-Quinn criter.		1.311
F-statistic	53.660	Durbin-Watson stat		1.308
Prob(F-statistic)	0			

3.1.3 Modified regression model

According to the correlation coefficient and T-value, 5 variables were excluded from the initial model. The four remaining variables are the consumer price index(x_2), the number of charging piles in the country(x_5), the price of Octane-95(x_7), and the sales volume of non-new energy vehicles(x_9). The model results are as follows:

$$\mathrm{LnY} = -28.239 - 0.217\ln X_2 + 0.904\ln X_5 + 1.604\ln X_7 + 0.984\ln X_9 \tag{6}$$

After revising the model, the Adjusted R-squared of model (2) is about 0.748 as listed in Table 4. The goodness of fit is still good, so excluding variables have no great impact on the model. In addition, the model reserved variables are all significant at the level of α=10%, which is more optimized than model (1).

3.1.4 Hypothetical test

a) Unit root test: According to the result of Augmented Dickey-Fuller Tested, as shown in Table 5., the null hypothesis is rejected at the 5% significance level, so there is no unit root in the time series data, which means all variables are stationary at the first-order difference.

b) Cointegration test: The cointegration relationship can be interpreted as a long-term stable equilibrium relationship between variables. The research uses the E-G two-step method to test the residual sequence.

Table 5 Unit Root Test Results

Variables	**(C,T,K)**	**ADF-Test Value**	**Test Value (α=5%)**	**P-Value**	**Result**
DLnY	(C,N,11)	-3.350	-2.912	0.017	Stable**
DLnX1	(C,N,11)	-6.383	-2.904	0	Stable**
DLnX2	(N,N,11)	-9.303	-1.946	0	Stable**
DLnX3	(N,N,11)	-10.524	-1.946	0	Stable**
DLnX4	(N,N,11)	-9.034	-1.946	0	Stable**
DLnX5	(C,T,11)	-7.509	-3.475	0	Stable**
DLnX6	(C,N,11)	-10.679	-2.904	0	Stable**
DLnX7	(N,N,11)	-5.695	-1.946	0	Stable**
DLnX8	(N,N,11)	-5.762	-1.946	0	Stable**
DLnX9	(N,N,11)	-11.781	-1.946	0	Stable**

**Reject the null hypothesis at the 5% significanc level

The sequence e rejects the null hypothesis of the existence of a unit root as shown in Table 6., indicating that the sequence e is stationary, so there is a cointegration relationship in the model.

Table 6 Cointegration Test Results

Augmented Dickey-Fuller test statistic	t-Statistic	Prob.*
Test critical values	-5.814	0.000
1% level	-2.598	
5% level	-1.945	
10% level	-1.614	

*MacKinnon (1996) one-sided p-values.

c) Heteroskedasticity test: According to the test results shown in Table 7., the null hypothesis is rejected, which mean there is no heteroscedasticity problem in the model.

Table 7 Heteroskedasticity Test: White

F-statistic	0.645	Prob. F(14,57)	0.816
Obs*R-squared	9.845	Prob. Chi-Square(14)	0.773
Scaled explained SS	46.393	Prob. Chi-Square(14)	0

d) Multicollinearity test: According to the test results in Table 8., the VIF of all variables is around 1, so one can conclude that there is no multicollinearity problem.

Table 8 Multicollinearity Analysis of Model (2)

	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
(Constant)	-28.238	4.596		-6.144	0.000		
LnX2	-0.217	0.125	-0.110	-1.742	0.086	0.893	1.120
LnX5	0.904	0.070	0.844	12.962	0.000	0.837	1.195
LnX7	1.604	0.423	0.228	3.792	0.000	0.981	1.019
LnX9	0.984	0.176	0.362	5.594	0.000	0.848	1.179

3.1.5 Prediction

According to the fitting curve shown in Fig. 4 of the prediction model, the optimized model uses fewer variables and better fits the sales of new energy vehicles in China.

3.1.6 Unit root test

Before building an ARIMA model, it is first necessary to perform a unit root test on the predictors. By performing unit root test on the sales data from January 2016 to December 2021, it can be seen from the Table 9. that the original data of the series are stable.

Table 9 Unit Root Test Results

Augmented Dickey-Fuller test statistic	t-Statistic	Prob.*
Test critical values	-4.735849	0.0014
1% level	-4.092547	
5% level	-3.474363	
10% level	-3.164499	

*MacKinnon (1996) one-sided p-values.

3.1.7 Result of model

According to the autocorrelation and partial correlation diagrams shown in Fig.5 and Fig. 6, this paper selects AR (1) as the prediction model:

$$LnY = 11.370 + 0.794LnY_{t-1} + \epsilon_t \quad (7)$$

Figure 4. Prediction curve of model (2).

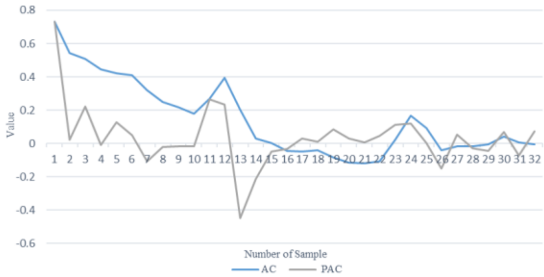

Figure 5. The distrtibution of autocorrelation and partial correlation

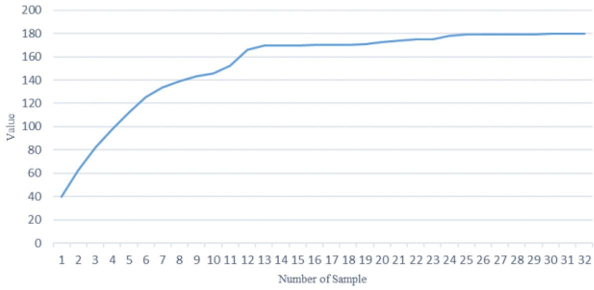

Figure 6. The distrtibution of Q-Stat

The adjusted R-square of the AR (1) model is 0.577 as shown in Table 10., which is smaller than that of the multiple regression model, but the results of the model are still significant. The model reflects that the sales volume of new energy vehicles will continue to increase in the future.

Table 10 Regression Result of AR(1)

Variable	Coefficient	Std.	t-Statistic	Prob.
C	11.370	0.393	28.898	0.000
AR(1)	0.794	0.087	9.114	0.000
SIGMASQ	0.307	0.031	9.955	0.000
R-squared	0.589	Mean dependent var		11.347
Adjusted R-squared	0.577	S.D. dependent var		0.870
S.E. of regression	0.566	Akaike info criterion		1.753
Sum squared resid	22.078	Schwarz criterion		1.848
Log likelihood	-60.107	Hannan-Quinn criter.		1.791
F-statistic	49.464	Durbin-Watson stat		2.102
Prob(F-statistic)	0			
Inverted AR Roots	.79			

3.1.8 Prediction

Based on the Fig. 7 and Fig. 8, the model can predict the sales well. As shown in Table 11., the Theil inequality coefficient of 0.024 is small, indicating that the model has good predictive ability; a small variance ratio of 0.115 denotes that the fluctuation of the sequence is better simulated, and a large covariance ratio of 0.881 indicates that the prediction result is ideal.

Table 11 Static forecast results of AR(1)

Root Mean Squared Error	0.549
Mean Absolute Error	0.357
Mean Abs. Percent Error	3.288
Theil Inequality Coefficient	0.024
Bias Proportion	0.004
Variance Proportion	0.115
Covariance Proportion	0.881
Theil U2 Coefficient	0.911
Symmetric MAPE	3.209

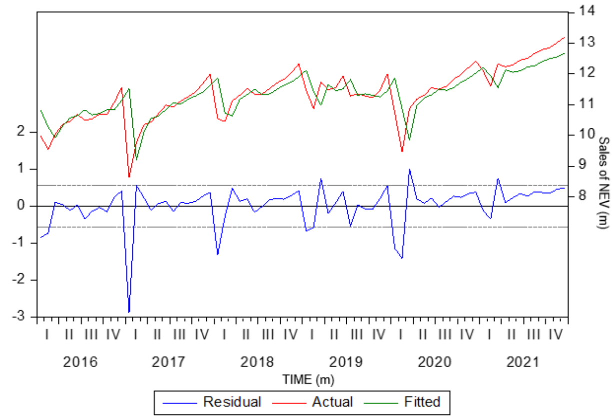

Figure 7. Prediction curve of AR(1)

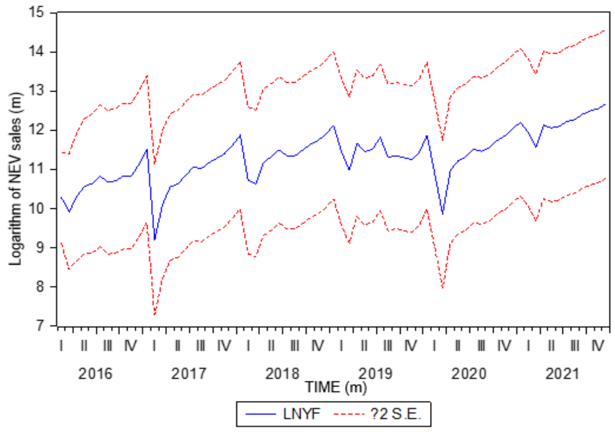

Figure 8. Static forecast curve of AR(1)

3.2 Limitations

In terms of data selection, since some data indicators are missing, some influencing factors can only be replaced by existing variables, which will have a certain impact on the goodness of fit of the model. Meanwhile, the sales volume and related data of new energy vehicles in 2013-2015 are missing, and the minimum statistical unit is monthly sales, which reduces the number of samples. Besides, with regard to model establishment, there may be some situations where the selection of some variables is not optimal. In the test of the multiple regression model, the model did not significantly reject the hypothesis of autocorrelation. The reason may be that some economic series have autocorrelation problems themselves, and the length of the observation period in this paper may not be enough to eliminate the autocorrelation of the data. In addition, owing to the missing data of some existing indicators in the period 2016-2021, and the existence of some data indicators that have not been quantified, the model may not cover all variables, causing autocorrelation problems. Moreover, the model may fluctuate greatly in the short term, causing it to fail the error correction model.

4 CONCLUSION

In summary, this paper carries out the sales volume prediction of new energy vehicles by establishing multiple regression models and time series models based on the data from 2016 to 2021 in the Chinese market. The prediction results of the multiple regression model are more in line with the actual situation, reflecting that the relevant infrastructure such as charging columns has a strong role in promoting the consumption of new energy vehicles, and the increase in gasoline prices is also the reason why more consumers buy new energy vehicles. Nevertheless, consumers' spending power and price level have a weak impact on overall sales. Meanwhile, rising inflation may lead to an increase in automobile manufacturing costs, resulting in price fluctuations and a decrease in sales. In addition, although the sales volume of new energy vehicles continues to increase, it still does not play a role in replacing non-new energy vehicles, and the expansion in the future market still needs to be vigorously promoted

For the future study, the research will optimize the model structure by collecting more detailed and comprehensive data metrics. In the meantime, it will validate the predictive power of the model against the latest data. Last but not least, through dynamic analysis of various indicators, a plan is proposed for further promoting the sales of new energy vehicles. The research analyzes and puts forward the key factors affecting the sales of new energy vehicles, including the facilities such as charging posts and the price of gasoline. At the same time, it indicates that new energy vehicles still have a lot of potential growth space in the Chinese market. In the future, only by improving supporting facilities and optimizing the design of new energy vehicles, can they truly become a substitute for traditional vehicles and further achieve the strategic goal of reducing carbon dioxide emissions. Overall, these results offer a guideline for promoting the popularization of new energy vehicles in China.

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