ISSN: 3067-8307
Research Article

World Journal of Applied Mathematics and Statistics

# Sales Forecasting of Tesla New Energy Vehicles Based on VAR Model

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**Submitted:** 03 November 2025 **Accepted:** 10 November 2025 **Published:** 17 November 2025

https://doi.org/10.63620/MKWJAMS.2025.1022

***Citation:** Juntong, G. (2025). Sales Forecasting of Tesla New Energy Vehicles Based on VAR Model. Wor Jour of Appl Math and Sta, 1(4), 01-05.*

***Abstract***

*Based on the sales data of new energy vehicles in Hangzhou from January 2022 to December 2024, this paper uses the Vector Autoregression (VAR) model to model and forecast the sales volume of Tesla Model Y, and explores the impact of gasoline price data on its sales. Through unit root test, VAR model analysis and Impulse Response Function (IRF) analysis, it is found that the impact of gasoline price on Model Y sales is not statistically significant. The research results show that the sales of new energy vehicles are driven by multiple factors, and gasoline price is not the main determinant. The forecast indicates that the sales volume shows an overall upward trend. The conclusions of this study can provide reference for new energy vehicle enterprises to formulate production and sales strategies.*

**Keywords:** New Energy Vehicles, Tesla Model Y, Sales Forecasting, Gasoline Price Impact, Var Model.

## Problem Background

In recent years, the rapid transformation of the global energy structure and the implementation of "carbon peaking and carbon neutrality" goals have profoundly reshaped the automobile industry[1]. As one of the most dynamic sectors in the green economy, the new energy vehicle (NEV) industry has demonstrated remarkable growth. Particularly in China, NEVs have evolved from niche products into a mainstream choice for households, playing a vital role in promoting sustainable consumption and low-carbon economic transition.

Compared with traditional fuel vehicles, NEVs offer several distinctive advantages. First, their operating costs are significantly lower—the energy consumption per kilometer and maintenance expenses are both reduced, making them economically attractive in the long run. Second, their environmental benefits are substantial—the zero-emission feature aligns with national environmental protection goals and contributes to urban air quality improvement. Third, their user convenience and policy support—such as special license plate privileges, parking discounts, and right-of-way incentives—further enhance consumer appeal.

At the global level, the NEV market has entered a phase of accelerated expansion. According to the International Energy Agency (IEA), the global sales of electric vehicles exceeded 14 million units in 2023, accounting for nearly 18% of total automobile sales. China, Europe, and the United States remain the three major markets, with China contributing more than 60% of the total [2]. The penetration rate of NEVs in China surpassed 35% in 2024, reflecting not only the effectiveness of national industrial policies but also the growing maturity of consumer acceptance. In contrast, the U.S. market, dominated by Tesla, maintains a penetration rate of around 10%, suggesting substantial future growth potential. This global comparison highlights China's leading role in the diffusion of electric mobility.

Among NEV manufacturers, Tesla's Model Y stands out as a representative intelligent electric vehicle. Its continuous improvements in driving range, autonomous technology, and user experience have consolidated its brand influence and expanded its consumer base. In 2024, Model Y became one of the best-selling vehicles in the Chinese market, surpassing many domestic brands in monthly sales[3]. However, the sales performance of NEVs is influenced by multiple factors, including gasoline price fluctuations, government subsidies, infrastructure development, macroeconomic conditions, and consumer perception. Among these, gasoline price has traditionally been regarded as a key determinant in car purchase behavior, as it directly affects the operating costs of conventional vehicles[4] .

This study therefore focuses on the monthly sales data of Tesla Model Y in Hangzhou from January 2022 to December 2024, integrating gasoline price fluctuations to examine the dynamic relationship between the two variables. Using time-series econometric methods, particularly the Vector Autoregression (VAR) model, this paper aims to capture both short-term and long-term interactions through unit root tests, impulse response analysis, and variance decomposition. The purpose is to empirically evaluate whether gasoline price changes continue to shape consumer demand for NEVs, and to provide insights for both enterprises and policymakers in optimizing sales strategies and designing targeted policy support mechanisms.

## Data and Model

### Data Source and Description

The data used in this study mainly include two categories, both covering the time span from January 2022 to December 2024[5]:

1. Tesla Model Y sales data: Obtained from the China Association of Automobile Manufacturers and mainstream automotive information websites, reflecting the monthly sales in Hangzhou;
2. Gasoline price data: Referring to the refined gasoline price adjustment records released by the National Development and Reform Commission (NDRC) and third-party gasoline price monitoring platforms, with the monthly price of No. 92 gasoline as the core indicator.

To ensure the timeliness and accuracy of the data, the author sorted and screened the original data, eliminated outliers and missing values, and constructed a relatively complete time series sample. The specific monthly price data of No. 92 gasoline are shown in the table below:

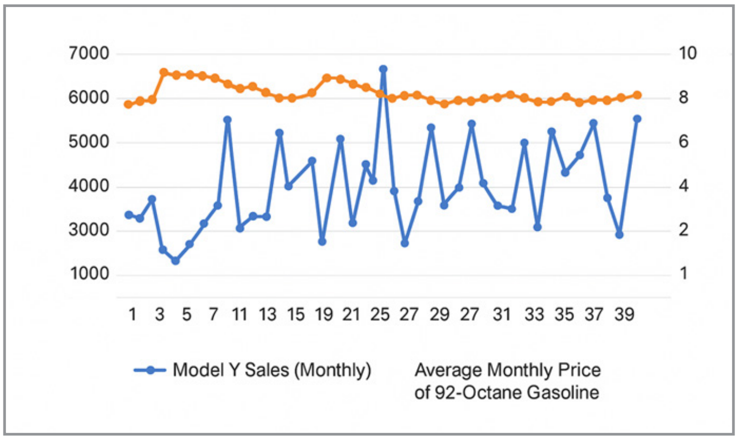


**Figure 1:** Monthly Sales of Tesla Model Y and Average Price of 92-Octane Gasoline in Hangzhou (2022–2024)

Figure 1 shows the trend of Model Y sales and the corresponding gasoline prices in Hangzhou. It can be observed from the figure that the fluctuation trends of the two are not significantly synchronized in most periods, which initially indicates that the impact of gasoline price changes on the sales of new energy vehicles is not linear or direct. Further analysis of their internal relationship with the help of econometric models is needed.

Before constructing the model, the data were subjected to stationarity diagnostics to satisfy the prerequisites of time-series modeling. The results indicated that the sales series was stationary at level, while the gasoline price series was non-stationary and became stationary after first-order differencing. Therefore, the original sales series and the first-order differenced gasoline price series were used in the VAR model estimation.

### Model Construction and Analysis Method

Given that both NEV sales and gasoline price are economic variables likely to exhibit dynamic interdependence, this study adopts the Vector Autoregression (VAR) framework for modeling. Unlike traditional single-equation regression models that assume strict exogeneity, the VAR model treats all variables as endogenous, allowing for mutual feedback effects among them. This property makes the VAR model particularly appropriate for capturing complex temporal linkages between Tesla Model Y sales and gasoline price fluctuations without imposing restrictive theoretical assumptions.

The general form of the VAR(p) model can be expressed as:

$$Y_t = c + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t \quad (1)$$

Where $Y_t$ represents the vector of endogenous variables (Model Y sales and the differenced gasoline price), $A_i$ are coefficient matrices,c is a constant term, and $\varepsilon_t$ denotes the vector of white-noise error terms.

The estimation process proceeds through several key stages:

1. Stationarity Testing – Before estimation, all variables must satisfy the weak stationarity condition to avoid spurious regression. The Augmented Dickey–Fuller (ADF) test is employed to determine the order of integration for each series. Non-stationary variables are differenced until stationarity is achieved.
2. Lag Order Selection – Selecting an appropriate lag length (p) is essential to balance model parsimony and explanatory power. Lag order is determined based on multiple information criteria, including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan–Quinn Criterion (HQIC). The lag that minimizes these statistics is considered optimal.
3. Model Estimation and Diagnostic Checking – After determining p, the VAR model parameters are estimated using the Ordinary Least Squares (OLS) method equation-by-equation. Diagnostic tests such as the Ljung–Box Q-test for serial correlation and the White test for heteroskedasticity are then performed to verify the adequacy and stability of the model.
4. Impulse Response Function (IRF) Analysis – The IRF examines how one variable responds to an exogenous

one-standard-deviation shock in another variable over time while holding all other innovations constant. This enables tracing the temporal transmission of gasoline price shocks on Tesla Model Y sales and helps interpret both the magnitude and persistence of such effects.

5. Forecast Error Variance Decomposition (FEVD) – The FEVD decomposes the forecast variance of each variable into portions attributable to its own innovations and those of other variables. This provides quantitative evidence on the relative importance of gasoline price shocks compared to internal sales dynamics in explaining forecast errors.
6. Stability and Structural Analysis (optional extension) – To ensure the robustness of the dynamic system, the study also checks the inverse roots of the characteristic polynomial to confirm that all roots lie within the unit circle, indicating system stability. Although the baseline model is a reduced-form VAR, potential structural relationships could be further explored using a Structural VAR (SVAR) framework in future work[6].

All computations are conducted in the Stata 17 environment, ensuring analytical transparency and replicability. The results derived from the VAR framework provide a basis for interpreting the temporal transmission mechanisms between gasoline prices and new energy vehicle sales[7].

## Empirical Analysis

### Unit Root Test and Stationarity Analysis

To ensure the validity of time series modeling, this paper first conducts a stationarity test on the two core variables: Model Y sales in Hangzhou and gasoline price. The Augmented Dickey-Fuller (ADF) test method is used to judge whether the variables have unit roots, i.e., whether they are non-stationary series.

The test results are summarized in Table 1. The ADF statistic for Model Y sales is 5.398, which is less than the 1%, 5%, and 10% critical values, with a p-value of 0.0000, thereby rejecting the null hypothesis of a unit root. This indicates that the sales series is stationary in levels. In contrast, the gasoline price series fails to reject the null hypothesis at the level form (ADF=2.437; p=0.1314), implying non-stationarity. However, after first-order differencing, the series becomes stationary (ADF =6.306; p = 0.0000).

Therefore, in the subsequent VAR modeling, the original series of Model Y sales and the first-order differenced series of gasoline price are used as input variables, which meets the stationarity premise.

**Table 1:** Results of the Augmented Dickey–Fuller (ADF) Test

| Variable name | Lag order | ADF statistic | 1%critical value | 5%critical value | 10%critical value | P value | Stationarity |
|---|---|---|---|---|---|---|---|
| Model Y Sales(Level) | 0 | -5.398 | -3.662 | -2.964 | -2.614 | 0 | Stationary |
| Gasoline Price (Level) | 0 | -2.437 | -3.662 | -2.964 | -2.614 | 0.1314 | Non-stationary |
| Gasoline Price (1st Diff.) | 1 | -6.306 | -3.668 | -2.966 | -2.616 | 0 | Stationary |

### Var Model Specification and Estimation

After confirming the stationarity of the variables, the optimal lag length for the VAR model is determined using multiple information criteria, including the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The results consistently support a lag order of one (VAR(1)), which balances model parsimony and dynamic adequacy.

The estimated VAR(1) model captures the short-run interactions between Tesla Model Y sales and gasoline price fluctuations. Diagnostic checks confirm the absence of serial correlation and heteroskedasticity in the residuals, validating the robustness of the model for dynamic analysis.

### Impulse Response Analysis

To assess the dynamic impact of gasoline price shocks on Tesla Model Y sales, Impulse Response Functions (IRFs) are computed based on the estimated VAR(1) model. The IRF traces the response path of one variable when the other is subjected to a one-standard-deviation shock, while holding all other innovations constant(Klier & Linn, 2010).

Figure 2 shows the response path of sales volume to gasoline price changes. It can be seen from the figure that within the first 2 periods after the shock occurs, the sales volume fluctuates slightly, but the overall response amplitude is small, and its confidence interval generally covers the zero axis, indicating that it is not statistically significant. In addition, the direction of the response changes slightly in different periods, reflecting that the impact of gasoline price on sales volume is neither significant nor stable. This result indicates that gasoline price does not constitute a major driving factor for the sales of new energy vehicles in the short term.

This finding suggests that short-term gasoline price volatility exerts limited influence on consumer decisions regarding electric vehicle purchases.

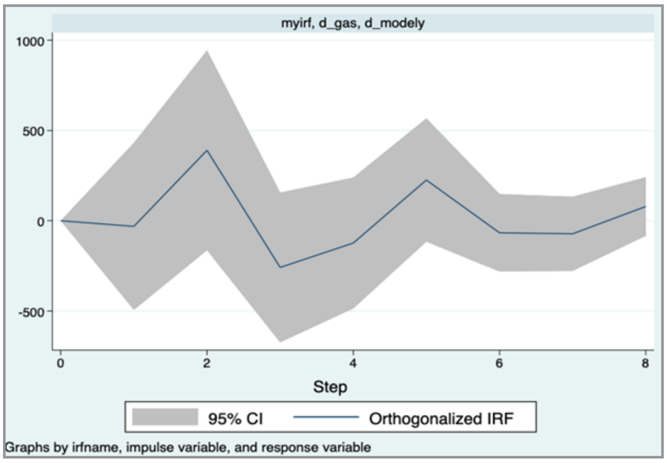


**Figure 2:** Impulse Response of Model Y Sales to Gasoline Price Shocks
(**Note:** The shaded area represents the 95% confidence interval.)

**Forecast Error Variance Decomposition (FEVD)**

To further quantify the relative importance of each variable in explaining forecast variations, Forecast Error Variance Decomposition (FEVD) is conducted. The FEVD partitions the variance of forecast errors for each variable into proportions attributable to its own innovations and those of other variables within the system.

The results, presented in Figure 3, reveal that the self-contribution of Model Y sales dominates across all forecast horizons, accounting for over 90% of the total forecast variance. The explanatory power of gasoline price shocks remains consistently low, peaking at approximately 8% in the second period before declining thereafter. Importantly, the confidence interval of this contribution also encompasses zero, reinforcing the conclusion that gasoline price changes have a negligible role in driving Tesla Model Y sales dynamics.

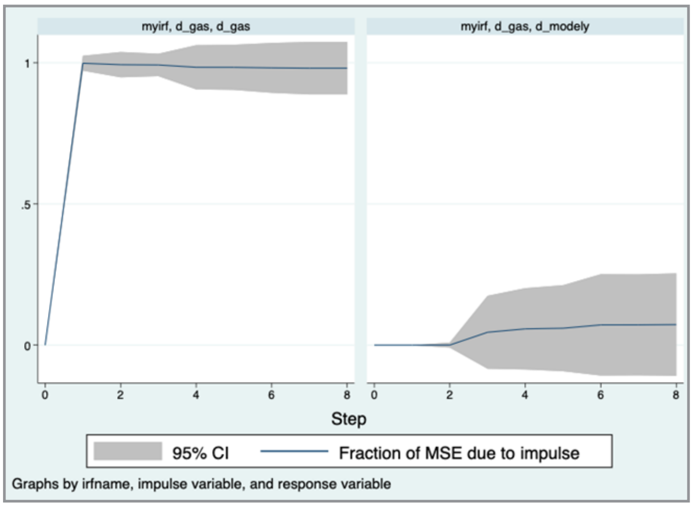


**Figure 3:** Forecast Error Variance Decomposition of Model Y Sales
(**Note:** The variance contribution of gasoline price remains below 10% across all periods.)

## Economic Interpretation and Discussion

The empirical results indicate that gasoline price fluctuations do not significantly affect Tesla Model Y sales in Hangzhou. Several economic explanations may account for this finding:

1. Structural Cost Differences: The long-term savings in energy and maintenance costs of electric vehicles offset the uncertainty associated with gasoline price volatility.
2. Strong Policy Support: Local governments provide substantial incentives for NEV adoption, including purchase subsidies, license plate privileges, and preferential road access, which weaken the sensitivity of consumers to gasoline price changes.
3. Technological Advancements: Continuous improvements in battery efficiency, driving range, and charging infrastructure enhance the intrinsic competitiveness of NEVs.
4. Consumer Perception Shift: Environmental awareness and preference for sustainable mobility have become dominant behavioral drivers, diminishing the traditional linkage between gasoline price and car purchase decisions.

These findings collectively suggest that the determinants of NEV demand have shifted from fuel cost sensitivity to technological and policy-driven factors. The results also highlight the necessity for manufacturers to emphasize innovation, performance improvement, and service quality rather than relying on fuel cost advantages in their market strategies.

## Conclusion

This study investigates the dynamic relationship between gasoline price fluctuations and Tesla Model Y sales in Hangzhou from January 2022 to December 2024 by employing a Vector Autoregression (VAR) model. Through a combination of unit root tests, impulse response analysis, and forecast error variance decomposition, the empirical evidence reveals that changes in gasoline prices exert an insignificant and unstable impact on the sales of Tesla Model Y. The confidence intervals of the impulse responses consistently include zero, and the variance contribution of gasoline price shocks remains below 10 percent across all forecast horizons.

These findings demonstrate that gasoline price are no longer a dominant determinant of new energy vehicle (NEV) consumption. The structure of consumer decision-making has shifted fundamentally in recent years. Rather than being driven by short-term energy cost considerations, NEV purchases are increasingly influenced by technological innovation, policy incentives, and environmental awareness. Consumers now prioritize vehicle performance, charging convenience, and long-term cost efficiency over fuel price volatility.

From a policy perspective, the results imply that government efforts to expand NEV adoption should focus less on temporary fuel-price-linked incentives and more on supporting technological progress, improving charging infrastructure, and sustaining consumer confidence in the long-term environmental benefits of electrification. Local authorities can also design differentiated policies—such as urban parking privileges or green-mobility credits—to further consolidate consumer preference for NEVs.

From an industrial perspective, manufacturers such as Tesla and domestic automakers should prioritize innovation and service optimization to strengthen market competitiveness. As the marginal impact of gasoline prices declines, firms'strategic advantages will increasingly depend on brand differentiation, battery technology, and post-sales ecosystem development.

Nevertheless, this study has several limitations. First, the available dataset covers a relatively short time span and a single regional market, which may constrain the generalizability of the results. Second, the model includes only gasoline prices as the external explanatory variable, while other relevant determinants—such as government subsidies, consumer income levels, or charging-infrastructure density—were not incorporated due to data limitations.

Future research could extend the model in three directions:
1. introducing more variables into a multivariate VAR or SVAR framework to capture a broader range of influences;
2. comparing results with alternative forecasting methods such as ARIMA, GARCH, or machine-learning-based hybrid models to improve predictive accuracy; and
3. expanding the empirical scope to multi-city or national datasets to verify the spatial robustness of the findings.

In conclusion, this study provides new empirical evidence on the weakening link between fuel prices and NEV market behavior in China's rapidly evolving automotive sector. By demonstrating that gasoline price shocks have only marginal effects on Tesla Model Y sales, the research contributes to a better understanding of the behavioral and structural transformation of the NEV market and offers valuable insights for policy makers and industry practitioners seeking to promote sustainable and innovation-driven mobility.

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