

Developing a Time Series Forecasting Model for Monthly Gasoline Consumption in Iran: An Application of the Seasonal Unit Root Test

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ABSTRACT

Energy consumption in Iran has risen sharply in recent decades, with the transportation sector as one of the largest consumers due to weak public transit and high reliance on gasoline. Limited refining capacity, sanctions, and rapid demand growth have widened the gap between production and consumption, making accurate forecasts critical for planning, budgeting, and policy design. This study forecasts monthly gasoline consumption in Iran using univariate seasonal time series models and data from April 1998 to March 2024. Seasonal unit root tests by Beaulieu–Miron and Taylor indicated a nonseasonal unit root but no seasonal unit roots, implying the need for first order differencing. Two models were then estimated: an autoregressive regression with monthly dummies and a seasonal autoregressive integrated moving average (SARIMA). out-of-sample forecasts (April 2023–March 2024) show that SARIMA outperformed the regression model with a Mean Absolute Percentage Error (MAPE) of 2.15% compared to 18.34%. Forecasts for April 2024–March 2027 indicate cumulative growth of 6.5% in gasoline consumption, averaging 2.15% annually over 115% higher than global energy growth projected by the International Energy Agency. These findings highlight the urgency of strengthening refining capacity, improving fuel efficiency, expanding public transport, and implementing rational pricing policies.

Keywords: Forecasting, Gasoline consumption, Iran, SARIMA, Seasonal unit root test.

INTRODUCTION

With the expansion of industry and globalization, along with population growth and development in the transportation sector worldwide, energy consumption has significantly increased. Today, it plays a crucial role in the economies of countries (Suganthi and Samuel, 2012). Reports from the International Energy Agency indicate that energy consumption has grown by more than 15% in the past decade (International Energy Agency, 2019), and it is projected to grow at least one percent per year until 2040 (Kim and Cho, 2019). Moreover, some studies believe that

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the share of developing countries, especially Asian countries, in the future increase in energy consumption will be greater than that of developed countries (Broadhead and Kilmann, 2008). comparison of energy data between Iran and the world shows that the per capita energy consumption in Iran is 1.8 times the global average. Therefore, energy wastage in Iran is significantly higher than the global average, highlighting the necessity for consumption management.

Energy consumption has grown with population, development, and higher living standards, with Iran's transport sector as a major consumer due to weak public transit and reliance on gasoline. Rising use of personal vehicles, inefficient engines, and aging fleets have pushed gasoline demand up, averaging 15% annual growth in recent years (Ministry of Energy, 2024). Limited and outdated refinery capacity, compounded by sanctions, has widened the production–consumption gap, forcing costly imports (Mehregan and Ghorbani, 2010). Thus, demand management is a key policy challenge, requiring reliable forecasts. This study develops a seasonal time series model to predict monthly gasoline use in Iran, supporting supply planning, pricing, efficiency reforms, and long-term policy.

Accurate forecasting of fuel consumption plays a vital role in energy policy and economic planning, particularly in economies experiencing rapid demand growth, subsidy reforms, and supply constraints. Reliable gasoline demand projections support pricing strategies, refinery capacity management, and infrastructure planning. Previous studies have employed either structural demand models or time series forecasting approaches. To provide a structured comparison and highlight the research gap addressed in this study, Table 1 summarizes the study context, energy type, methodology, key findings, and limitations of prior research.

Table 1. Comparative summary of previous studies on energy consumption forecasting.

Authors (Year)	Study Area	Energy Type	Methodology	Key Findings	Limitations
Rubia (2001)	Spain, Argentina, Australia	Electricity	Seasonal Unit Root Test (HEGY)	Identified stochastic seasonal patterns and showed that demand seasonality varies across markets.	Focused on electricity markets; did not extend forecasting performance comparison across alternative seasonal models.
Mishra and Smyth (2014)	United States	Natural Gas	GARCH Unit Root Test with Structural Breaks	Demonstrated that accounting for volatility and structural breaks can alter stationarity conclusions in energy demand series.	Emphasis on statistical properties rather than practical forecasting model comparison.
Sapnken et al. (2018)	Cameroon	Gasoline	Dynamic Regression Model	Estimated income and price elasticities and predicted long-term growth in gasoline consumption.	Structural demand model; limited attention to seasonal stochastic properties of demand.
Rosado et al. (2021)	Portugal	Fuel Sales	Seasonal Time Series Analysis	Found strong daily, weekly, and monthly seasonal demand variations.	Analysis mainly descriptive; limited evaluation of long-term forecasting models.
Ayyıldız and Murat (2024)	Turkey	Gasoline	Machine Learning (Lasso vs Ridge Regression)	Found Lasso regression improved forecast accuracy compared to Ridge regression.	Machine learning performance depends on large datasets; limited interpretability and seasonal stochastic testing.
Broni-Bediako et al. (2024)	Ghana	Natural Gas	ARIMA vs SARIMA Comparison	SARIMA slightly outperformed ARIMA in forecasting accuracy.	Did not evaluate pre-testing for seasonal unit roots or regression-based seasonal modeling.
Iatsyshyn et al. (2025)	Ukraine	Electricity	SARIMA	Demonstrated SARIMA effectively captures seasonal electricity demand with a MAPE of 12 %.	Focused on operational forecasting without comparison to regression models incorporating seasonal dummy structures.
Keshavarz Haddad and Mirbagheri Jam (2007)	Iran	Natural Gas	Econometric Structural Demand Model	Estimated short- and long-run demand elasticities and emphasized policy implications for pricing reforms.	Focused on macroeconomic determinants rather than stochastic seasonal behavior or high-frequency forecasting models.

63 Source: Research findings.

64

65 A review of international and Iranian literature reveals several research gaps in gasoline

66 demand forecasting. Many international studies apply seasonal models without formally testing

67 for seasonal unit roots, which may result in misspecification and reduced forecasting reliability. In

68 Iran, the use of stochastic seasonal unit root tests for gasoline consumption remains limited. This

69 study addresses this gap by employing the Beaulieu–Miron and Taylor seasonal unit root tests to

70 determine the appropriate differencing structure prior to model estimation. Substantively, prior

71 research has largely focused on electricity or natural gas consumption, while gasoline demand,

72 particularly using stochastic seasonal frameworks, has received comparatively less attention both

73 internationally and domestically. Methodologically, Iranian studies rarely provide systematic

74 comparisons between regression-based seasonal models and SARIMA models for gasoline

75 forecasting. This study contributes by conducting a structured out-of-sample comparison of these

76 approaches. Furthermore, while recent international literature increasingly emphasizes machine

77 learning techniques aimed primarily at maximizing predictive accuracy, such models often

78 prioritize forecasting performance over structural interpretation. In contrast, the present study not

79 only evaluates forecast accuracy but also explicitly investigates whether the monthly gasoline

80 series exhibits statistically identifiable seasonal stochastic patterns and whether such seasonality

81 can be formally modeled within a transparent econometric framework. Finally, medium-term

82 seasonal consumption projections remain relatively underexplored. By providing multi-year

forecasts based on rigorously tested seasonal dynamics, this study offers policy-relevant insights for energy planning within regulated fuel market environments.

MATERIALS AND METHODS

Data Collection

The study uses monthly gasoline consumption in Iran from April 1998 to March 2024, drawn from the Statistical Yearbook of Energy-Producing Petroleum Products (NIOC, 2024). These official datasets provide consistent long-term coverage, enabling reliable analysis.

The empirical analyses were implemented in SHAZAM, with coding tailored to run the seasonal unit root tests and model estimations, since these procedures are not pre-programmed in common statistical packages. The SHAZAM code used for data processing, diagnostic testing, and model estimation is available from the corresponding author upon reasonable request.

Conceptual Framework

Although recent energy forecasting studies increasingly employ machine learning and deep learning techniques, these approaches primarily emphasize predictive accuracy rather than the explicit identification and modeling of stochastic seasonal structures. In contrast, classical econometric time series models such as SARIMA allow formal testing of seasonal properties and ensure consistency between the statistical characteristics of the data and model specification (Box et al., 2015; Hyndman and Athanasopoulos, 2021). Since the primary objective of this study is to detect and model seasonal stochastic behavior in monthly gasoline consumption using seasonal unit root tests, classical seasonal time series models were considered more appropriate for the analysis.

Modeling a time series requires first identifying its main components, which typically include trend, cyclical fluctuations, seasonal patterns, and irregular shocks (Lim and McAleer, 2000). The trend reflects long-term growth or decline, while cycles correspond to broader economic movements, and irregular components capture unexpected events. Seasonal variation is particularly important for monthly gasoline consumption, as factors such as weather and travel patterns create recurring fluctuations. Effective forecasting models must therefore incorporate the seasonal component to ensure reliable predictions.

Following the seminal work of Hylleberg et al. (1990), significant progress has been made in modeling seasonal components of time series (Franses, 1991; Beaulieu and Miron, 1993; Hylleberg, 1995; Ghysels et al., 1994; Taylor, 1998; Rodrigues and Osborne, 1999; Franses and Paap, 2004; Rodrigues and Franses, 2005). Seasonal behavior, such as that in monthly gasoline consumption, may be deterministic or stochastic (Darne and Diebolt, 2002). When seasonality is stochastic, it is referred to as a seasonal unit root or nonstationary stochastic seasonality (Ghysels and Osborn, 2001). Identifying such processes is essential, as it determines whether seasonal or regular differencing or both must be applied to achieve stationarity. Once stationarity is established, forecasting can proceed using methods such as the Box and Jenkins (1970) seasonal approach or regression models. Seasonal unit root tests provide a formal tool for detection. Initially proposed by Hylleberg et al. (1990) for quarterly data and extended to monthly data by Beaulieu and Miron (1993), these tests are now widely used to assess whether a time series like monthly gasoline consumption requires seasonal differencing. Let X_t be a monthly time series, such as the monthly gasoline consumption series, that behaves according to the following monthly self-explanatory process:

$$\varphi(L)X_t = \mu_t + \varepsilon_t \quad , \quad \mu_t = \alpha + \beta t + \sum_{s=1}^{11} \delta_s D_{s,t} \quad (1)$$

Where $\varphi(L)$ is a polynomial of degree 12 ($\varphi(L)=1-L^{12}$), L is the lag operator, ε_t is a white noise process meaning $\varepsilon_t \sim iid(0, \sigma^2)$ ¹, μ_t includes an intercept α , a linear trend (t), and monthly seasonal dummy variables $D_{(s,t)}$. The polynomial expression $\varphi(L)=1-L^{12}$ has 12 characteristic roots², which are (Beaulieu and Miron, 1993):

$$\pm 1; \pm i; -\frac{1}{2}(1 \pm \sqrt{3}i); \frac{1}{2}(1 \pm \sqrt{3}i); -\frac{1}{2}(\sqrt{3} \pm i); \frac{1}{2}(\sqrt{3} \pm i) \quad (2)$$

The frequency of each of these unit roots (k) is calculated using equation (3)³ (Taylor, 1998).

¹ iid means independent and identically distributed

² To obtain the characteristic roots of the equation $\varphi(L)=1-L^{12}$, the equation $(1-z^{12})=0$ must be solved for them. The general solution of this equation using sinusoidal functions is equal $\{1, \cos(2\pi k/12)+isin(2\pi k/12)\}$, $k=1,2,\dots,11$ which produces 12 distinct solutions, some of which are complex. All of these roots lie on a single unit circle (Franses, 1998).

³ The differential equation $\varphi(L)=1-L^{12}$ can be expressed based on sinusoidal functions as follows (Taylor, 1998). $1 - L_{12} = (1 - \lambda_0 L)(1 - \lambda_6 L) \prod_{j=1}^5 \{(1 - \lambda_j L)(1 - \lambda_{12-j} L)\}$, Which $\lambda_k = e^{i\omega_k}$, $k = 0,1,2, \dots,11$ and $\omega_k = 2\pi k/12$ where k is the unit root frequency.

$$\omega_k = 2\pi k/12, k = 0, 1, 2, \dots, 11 \quad (3)$$

Each of the unit roots in equation (2), from left to right, occurs at frequencies $0, \pi, \pm \frac{\pi}{2}, \pm \frac{2\pi}{3}, \pm \frac{\pi}{3}, \pm \frac{5\pi}{6}$ and $\pm \frac{\pi}{6}$ respectively. From this set, the first unit root (+1) corresponds to the non-seasonal or zero-frequency unit root, which represents long-term persistence without annual repetition (Taylor, 1998). The remaining roots represent seasonal unit roots occurring at 6, 3, 9, 8, 4, 2, 10, 7, 5, 1, and 11 cycles per year, respectively. A time series such as X_t may exhibit one or several of these roots, and the specific type determines the form of differencing required to achieve stationarity. Therefore, correctly identifying the unit root structure is a necessary first step in modeling.

Econometric Modelling and Analysis

To identify seasonal and non-seasonal unit roots in monthly time series, Beaulieu and Miron (1993) applied the seasonal difference unit root decomposition approach $\phi(L)=1-L^{12}$, originally introduced by Hylleberg et al. (1990). The HEGY test for monthly data relies on decomposing the roots of $(1-L^{12})$ in equation (4) (Rodrigues and Osborn, 1999).

$$\begin{aligned} (1 - L^{12}) &= (1 - L)(1 + L)(1 - iL)(1 + iL) \left[1 - \frac{1}{2} \left(1 - i3^{\frac{1}{2}} \right) L \right] \left[1 - \frac{1}{2} \left(1 + i3^{\frac{1}{2}} \right) L \right] \\ &\times \left[1 + \frac{1}{2} \left(1 + i3^{\frac{1}{2}} \right) L \right] \left[1 + \frac{1}{2} \left(1 - i3^{\frac{1}{2}} \right) L \right] \left[1 - \frac{1}{2} \left(3^{\frac{1}{2}} - i \right) L \right] \\ &\times \left[1 - \frac{1}{2} \left(3^{\frac{1}{2}} - i \right) L \right] \left[1 - \frac{1}{2} \left(3^{\frac{1}{2}} + i \right) L \right] \left[1 + \frac{1}{2} \left(3^{\frac{1}{2}} + i \right) L \right] \\ &\times \left[1 + \frac{1}{2} \left(3^{\frac{1}{2}} - i \right) L \right] \end{aligned} \quad (4)$$

Beaulieu and Miron (1993), using the decomposition of seasonal differencing unit roots, have shown that equation (5) can be used to test for seasonal and non-seasonal unit roots.

$$(1 - L^{12})X_t = \alpha + \sum_{s=1}^{11} \delta_s D_{s,t} + \beta t + \sum_{i=1}^{12} \pi_i y_{i,t-1} + \sum_{j=1}^p \phi_j (1 - L^{12})X_{t-j} + \varepsilon_t \quad (5)$$

Here, α , $D_{(s,t)}$, and t retain their previous definitions, while p denotes the augmentation degree of equation (4) to ensure that the error terms satisfy the white noise property ($\varepsilon_t \sim iid(0, \sigma^2)$). According to Beaulieu and Miron (1993), the variables $y_{i,t}$ are linear transformations of the lagged

values of X_t , constructed so that the unit root at the frequency of interest is preserved while those at other frequencies are eliminated. These variables are used to test for unit roots at the corresponding frequencies, as shown in equation (6). Each of the twelve $y_{i,t}$ series isolates one root from equation (4). For instance, $y_{1,t}$ retains the zero-frequency root (+1), while $y_{2,t}$ preserves only the root at frequency π (bimonthly). Thus, the statistical significance of π_i confirms the existence of a unit root at its associated frequency.

In applying the BM test, the optimal lag p in equation (6) must be determined. Following Franses and Paap (2004), equation (5) is first estimated with a maximum lag length (p_{max}), typically 36 lags (three years). The residuals are then tested for seasonal autocorrelation and heteroscedasticity using LM(12) and ARCH(12). If these statistics are insignificant, one lag is removed and the equation is re-estimated, repeating the process until significance is achieved. Thus, if LM(12) and ARCH(12) are rejected at $k-1$ lags but not at k , the appropriate lag length is k . Once the initial lag is selected, the adequacy of the model is confirmed through residual diagnostics, including LM(1) for first order autocorrelation and ARCH(1) for first order heteroscedasticity.

$$\begin{aligned}
 y_{1t} &= (1 + L + L^2 + L^3 + L^4 + L^5 + L^6 + L^7 + L^8 + L^9 + L^{10} + L^{11})X_t, \\
 y_{2t} &= -(1 - L + L^2 - L^3 + L^4 - L^5 + L^6 - L^7 + L^8 - L^9 + L^{10} - L^{11})X_t, \\
 y_{3t} &= -(1 - L^3 + L^5 - L^7 + L^9 - L^{11})X_t, \\
 y_{4t} &= -(1 - L^2 + L^4 - L^6 + L^8 - L^{10})X_t, \\
 y_{5t} &= -\frac{1}{2}(1 + L - 2L^2 + L^3 + L^4 - 2L^5 + L^6 + L^7 - 2L^8 + L^9 + L^{10} - 2L^{11})X_t, \\
 y_{6t} &= \frac{\sqrt{3}}{2}(1 - L + L^3 - L^4 + L^6 - L^7 + L^9 - L^{10})X_t, \\
 y_{7t} &= \frac{1}{2}(1 - L - 2L^2 - L^3 + L^4 + 2L^5 + L^6 - L^7 - 2L^8 - L^9 + L^{10} + 2L^{11})X_t, \\
 y_{8t} &= -\frac{\sqrt{3}}{2}(1 + L - L^3 - L^4 + L^6 + L^7 - L^9 - L^{10})X_t, \\
 y_{9t} &= -\frac{1}{2}(\sqrt{3} - L + L^3 - \sqrt{3}L^4 + 2L^5 - \sqrt{3}L^6 + L^7 - L^9 + \sqrt{3}L^{10} - 2L^{11})X_t, \\
 y_{10t} &= \frac{1}{2}(1 - \sqrt{3}L + 2L^2 - \sqrt{3}L^3 + L^4 - L^6 + \sqrt{3}L^7 - 2L^8 + \sqrt{3}L^9 - L^{10})X_t, \\
 y_{11t} &= \frac{1}{2}(\sqrt{3} + L - L^3 - \sqrt{3}L^4 - 2L^5 - \sqrt{3}L^6 - L^7 + L^9 + \sqrt{3}L^{10} + 2L^{11})X_t, \\
 y_{12t} &= -\frac{1}{2}(1 + \sqrt{3}L + 2L^2 + \sqrt{3}L^3 + L^4 - L^6 - \sqrt{3}L^7 - 2L^8 - \sqrt{3}L^9 - L^{10})X_t,
 \end{aligned} \tag{6}$$

Once the optimal lag length is identified, equation (5) is estimated using OLS, and the parameters are tested with t and F statistics. The null hypothesis of a unit root at a given frequency

is tested against the alternative of stationarity. For zero and π frequencies, the hypotheses $H_{k0}: \pi_k = 0$ for $k=1,2$ are tested against $H_{k1}: \pi_k < 0$ using one-sided t-tests. For complex seasonal unit roots, the hypotheses $H_{k0}: \pi_k = \pi_{k+1} = 0$ for $k=3,5,7,9,11$ are tested against $H_{k1}: \pi_k \neq 0$ or $\pi_{k+1} \neq 0$ using F-tests. Specifically, $\pi_3=\pi_4=0$, $\pi_5=\pi_6=0$, $\pi_7=\pi_8=0$, $\pi_9=\pi_{10}=0$ and $\pi_{11}=\pi_{12}=0$ correspond to unit roots at frequencies $\pm \frac{\pi}{2}$ (quarterly), $\pm \frac{2\pi}{3}$ (trimonthly), $\pm \frac{\pi}{3}$ (semi-annual), $\pm \frac{5\pi}{6}$ (two and a half months), and $\pm \frac{\pi}{6}$ (annual), respectively (Table 2).

In the BM framework, the series X_t has no unit roots at zero or seasonal frequencies when π_1 and π_2 are non-zero and the F-tests for the seasonal frequency pairs $\{3,4\}, \{5,6\}, \{7,8\}, \{9,10\}, \{11,12\}$ are statistically different from zero. Under these conditions, X_t is trend stationary. If all unit roots are present simultaneously, the series follows a seasonal random walk, also referred to as seasonal integration of order one, $SI(1)$ (Rodrigues and Osborn, 1999). Failure to reject the null $H_0: \phi(L)=1-L^{12}$, or the insignificance of all test statistics, confirms the seasonal random walk process. In such cases, seasonal differencing $(1 - L^{12} = \Delta_{12})$ is applied to achieve stationarity. Table 2 summarizes the differencing filters for both seasonal and non-seasonal unit roots.

An important limitation of the BM test, as noted by Dickey and Fuller (1979), is that the multiple t_k and $F_{k,k+1}$ statistics cannot control the overall significance level for the null of seasonal integration. To resolve this, Taylor (1998) proposed two joint F-tests that allow simultaneous testing of all unit roots. The first tests the null $H_0: \pi_1 = \pi_2 = \dots = \pi_{12} = 0$ against the alternative of at least one non-zero root, using the statistic $F_{1\dots 12}$. The second tests the null $H_0: \pi_2 = \pi_3 = \dots = \pi_{12} = 0$ against its alternative, using $F_{2\dots 12}$. Critical values for these tests were provided by Taylor (1998).

Table 2. Differencing filters and unit roots in the seasonal random walk process for monthly data.

Filters	Roots	Frequencies	Number of cycles in a year	Duration of each cycle (months)
$(1 - L)$	1	0	0	--
$(1 + L)$	-1	π	6	2
$(1 + L^2)$	$\pm i$	$\frac{\pi}{2}$	3	4
$(1 + \sqrt{3}L + L^2)$	$-\frac{1}{2}(1 \pm \sqrt{3}i)$	$\frac{5\pi}{6}$	5	2.4
$(1 - \sqrt{3}L + L^2)$	$\frac{1}{2}(1 \pm \sqrt{3}i)$	$\frac{\pi}{6}$	1	12
$(1 + L + L^2)$	$-\frac{1}{2}(\sqrt{3} \pm i)$	$\frac{2\pi}{3}$	4	3
$(1 - L + L^2)$	$\frac{1}{2}(\sqrt{3} \pm i)$	$\frac{\pi}{3}$	2	6

Source: Rodriguez and Osborne (2005).

In summary, the BM test identifies the type and number of unit roots in the monthly gasoline consumption series, allowing the selection of an appropriate differencing filter (Δ_s) to achieve stationarity. Forecasting is then conducted using the stationary data. If the test results indicate a non-stationary seasonal random process, meaning at least one seasonal unit root is present, the suitable forecasting approach is an autoregressive specification, commonly referred to as the Regression-Based Model, expressed in equation (7).

$$\Delta_s x_t = \alpha_0 + \sum_{i=1}^p \phi_i \Delta_s X_{t-i} + \varepsilon_t \quad , \quad \Delta_s x_t = x_t - x_{t-s} \quad (7)$$

Here, $\Delta_s x_t$ denotes the stationary consumption series, α_0 is the intercept, p is the number of lags, ϕ_i are the parameters to be estimated, $\Delta_s x_{t-i}$ represents the i -th lag of the stationary series, and ε_t is the error term. If the BM test results show insignificance for all statistics except the t -statistic, the monthly gasoline consumption series contains no seasonal unit roots. In this case, seasonal changes are deterministic rather than random, and a differencing filter $(1-L)$ is applied to remove the stochastic trend. Forecasting can then be performed using a regression model with monthly seasonal dummy variables, expressed in equation (8).

$$\Delta x_t = \alpha_0 + \sum_{s=1}^{11} \varphi_s D_{st} + \sum_{i=1}^p \phi_i \Delta X_{t-i} + \varepsilon_t \quad , \quad \Delta x_t = x_t - x_{t-1} \quad (8)$$

Another approach for modeling seasonal time series such as gasoline consumption is the Seasonal Box-Jenkins method (Box and Jenkins, 1970), implemented through the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. This model combines seasonal and non-seasonal components, where seasonal autoregressive and moving average terms of lag 12 have orders P and Q , while non-seasonal terms follow the standard ARIMA structure with orders p and q (Enders, 2004). The general form, $ARIMA(p,d,q)(P,D,Q)$, includes non-seasonal differencing

(1-L)^d and seasonal differencing (1-L¹²)^D, typically with d=D=1 for economic variables (Brendstrup et al., 2004). Stationarity is first assessed using the ACF plot, after which the Box–Jenkins three stage procedure is applied to identify, estimate, and validate the appropriate SARIMA model (Franses, 1995). Forecasts are then generated from the estimated parameters. In forecasting-oriented time series analysis, ARIMA-type models are widely regarded as reliable baseline forecasting tools because their stochastic formulation and differencing filters enable them to capture evolving temporal dynamics and implicitly accommodate structural changes reflected in long historical datasets (Box et al., 2015; Hyndman and Athanasopoulos, 2021; Szostek et al., 2024; Hossain et al., 2025;). SARIMA models can take additive or multiplicative forms: in the additive case, seasonal terms enter separately, while in the multiplicative form they interact with non-seasonal terms, capturing cross effects between seasonal and non-seasonal lags.

As noted, multiple models can be used to forecast monthly gasoline consumption or other economic variables. To identify the superior forecasting model, prediction accuracy must be evaluated using appropriate forecast error measures. Forecast errors can be measured using several criteria, among which the MAPE and the Root Mean Square Error (RMSE) are widely applied in time series forecasting studies because they capture complementary aspects of model accuracy, defined in equation (9) and (10) (Wooldridge, 2003; Iatsyshyn et al., 2025).

$$MAPE = \frac{1}{T} \sum_{t=1}^T \left| \frac{P - A}{A} \right| \quad (9)$$

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^T (P - A)^2} \quad (10)$$

Here, t=1,2,...,T denotes the number of forecast observations, P the predicted values, and A the actual values of the variable. The MAPE measures the average percentage deviation between predicted and actual values and RMSE measures the square root of the average squared difference between predicted and actual values and places greater weight on larger forecast errors. Lower values of MAPE and RMSE indicate higher forecasting accuracy.

To calculate these error measures, the original dataset (April 1998–March 2024) was divided into a training period and a testing period. The training set comprises the gasoline consumption from April 1998 to March 2023, which were used to estimate the candidate models. The final 12

months of the sample, April 2023 to March 2024, were withheld from estimation and reserved exclusively for evaluating forecast accuracy.

In-sample errors were computed by comparing the fitted values generated by each model over the last 12 months of the estimation period (April 2022–March 2023) with the corresponding actual observed values. This measure reflects how well a model reproduces the data used in its own estimation.

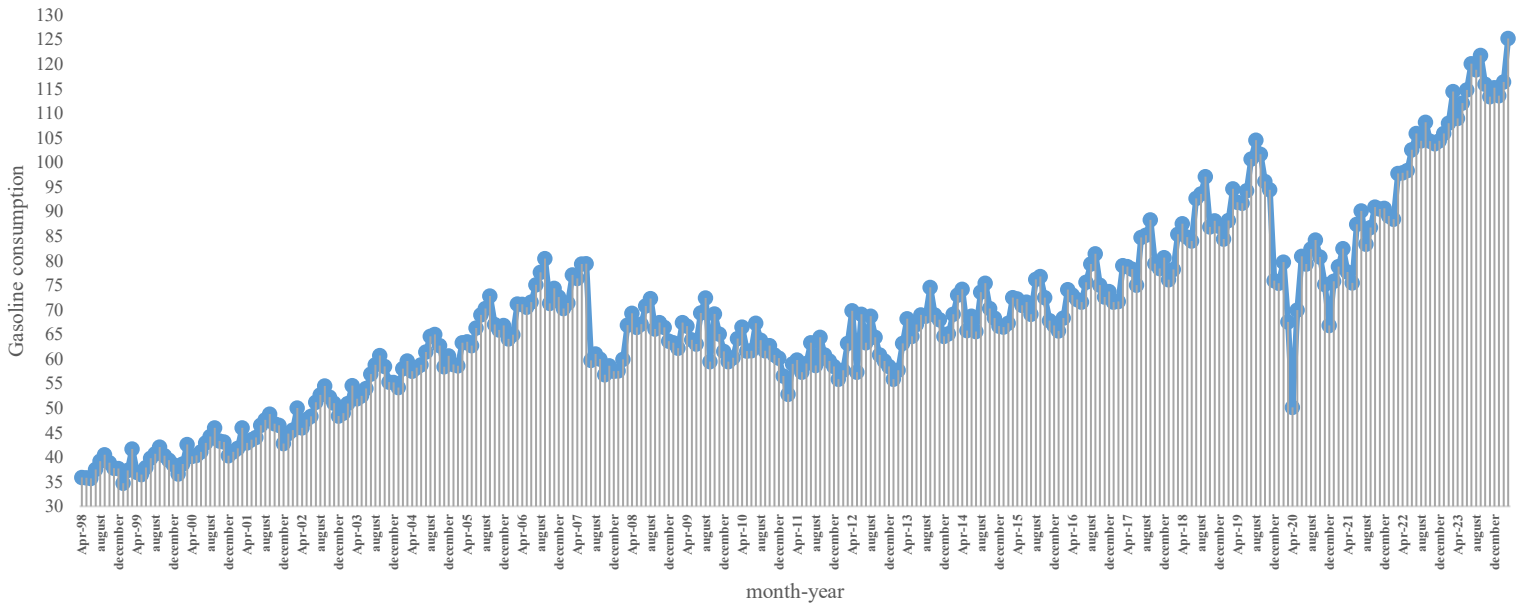
Out-of-sample errors were computed by generating forecasts for the 12-month testing period (April 2023 to March 2024) using models estimated only with observations available up to March 2023. The predicted values were then compared with the actual observed gasoline consumption values for the same period, which were not included in the estimation process. Because the out-of-sample test evaluates predictive performance on data the model has not previously encountered, it provides a more rigorous and realistic assessment of forecasting ability than the in-sample measure and was therefore given primary weight in model selection. MAPE and RMSE were calculated separately for the in-sample and out-of-sample periods using equations (9) and (10), and the model exhibiting the lowest MAPE and RMSE was selected as the preferred forecasting model.

Once the preferred model was identified through the in-sample/out-of-sample comparison described above, it was re-estimated using the original dataset (April 1998–March 2024), and this final re-estimated model was used to generate the out-of-sample forecasts for the period April 2024 to March 2027.

RESULTS AND DISCUSSION

Descriptive statistics

Figure 1 shows Iran's monthly gasoline consumption (1998–2024), which displays two main features. First, the series has an overall upward trend with structural breaks in July 2007 and December 2019 due to subsidy reforms and sharp price hikes. The COVID-19 outbreak in early 2020, coinciding with further price increases, caused consumption to drop by 15% and 40% in March–April 2020, reversing the usual holiday-driven rise. Second, the series exhibits clear seasonal fluctuations, though the seasonal pattern has shifted over time. Non-constant mean and variance confirm non-stationarity.



280 **Figure 1.** Average monthly gasoline consumption in Iran from April 1998 to March 2024 (Million
 281 liters per day).

282
 283 Figure 2 further indicates strong, slowly decaying autocorrelation with spikes at seasonal lags
 284 (12, 24, 36), suggesting seasonal non-stationarity.

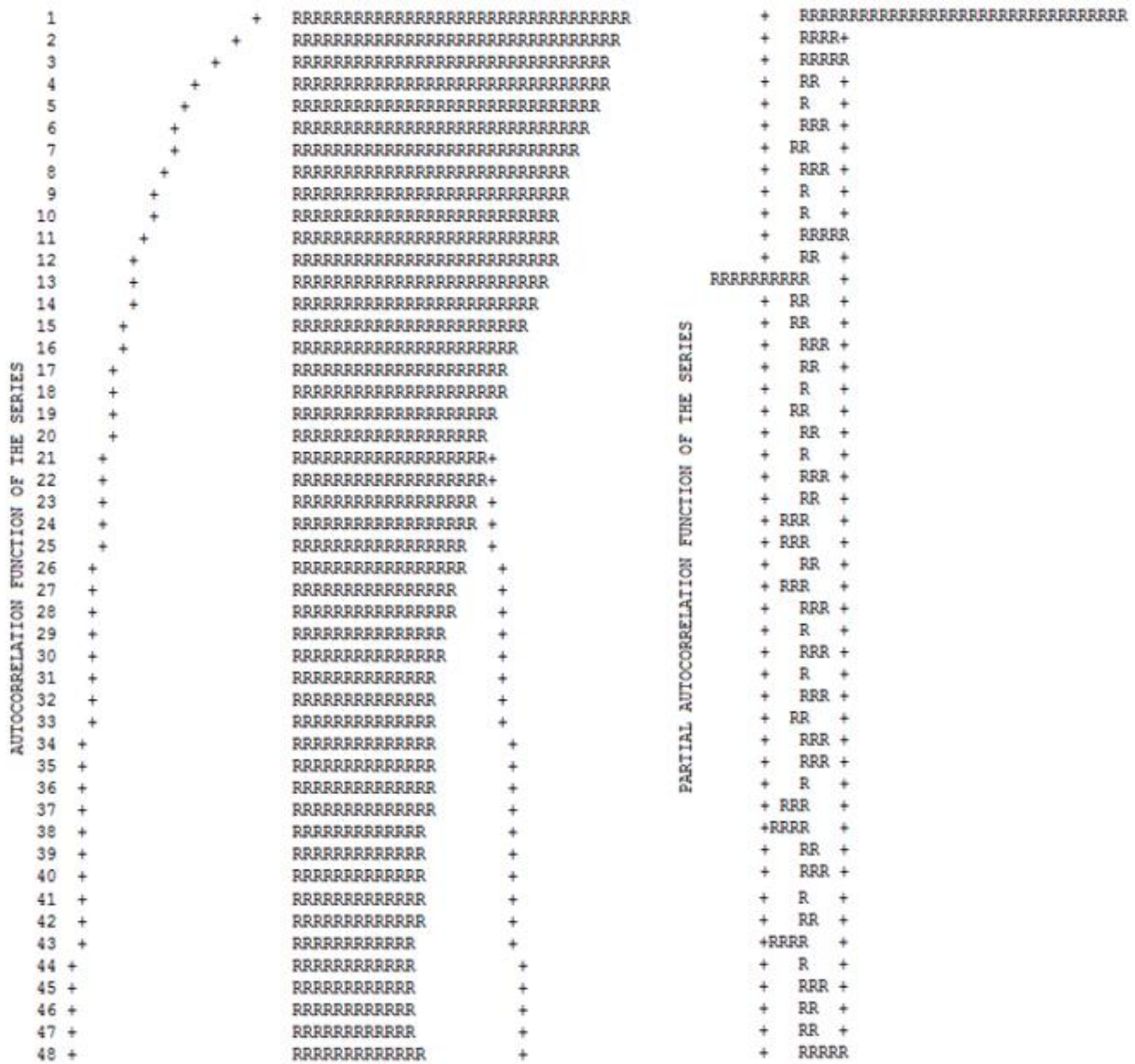


Figure 2. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the original monthly gasoline consumption series, April 1998–March 2024.

Econometric model results

To develop the forecasting model, seasonal and non-seasonal unit roots in monthly gasoline consumption were tested using the Beaulieu–Miron (BM) method. The logarithmic series was estimated with OLS, and lag order determined via LM and ARCH tests, which identified the first lag as optimal. Diagnostic checks (Table 3) confirmed white-noise residuals.

Table 3. Results of diagnostic tests for the model with the optimal lag.

Type of Test	LM(1)	LM(12)	ARCH (1)	ARCH (12)
Calculated Statistic	0.07	1.29	0.07	11.66
Critical Statistic (5% Probability Level)	3.84	21.03	3.84	21.03

Source: Rodriguez and Osborne (2005).

BM test results (Table 4) showed a non-seasonal unit root at zero frequency, but no seasonal unit roots. Thus, a single non-seasonal differencing was sufficient to achieve stationarity. Re-estimation on first-differenced data confirmed these results (Table 5). ACF and PACF plots (Fig. 3) supported this, showing that trend non-stationarity was removed, though seasonal spikes persisted.

Table 4. Results of the seasonal unit root test for the monthly gasoline consumption.

Null Hypothesis	Calculated Statistic	Critical Value Significance Level			Unit Root at the Specified Frequency
		0.01	0.05	0.10	
π_1	-1.47	-3.73	-3.19	-2.91	✓
π_2	-4.16	-3.21	-2.65	-2.36	×
$\pi_3 = \pi_4$	10.24	7.86	5.77	4.86	×
$\pi_5 = \pi_6$	10.98	7.88	5.77	4.86	×
$\pi_7 = \pi_8$	19.14	7.86	5.77	4.86	×
$\pi_9 = \pi_{10}$	18.57	7.82	5.84	4.9	×
$\pi_{11} = \pi_{12}$	16.13	7.92	5.82	4.9	×

Source: Research findings.

Table 5. Results of the seasonal unit root test for the monthly gasoline consumption after non-seasonal filtering of the data.

Null Hypothesis	Calculated Statistic	Critical Value Significance Level			Unit Root at the Specified Frequency
		0.01	0.05	0.10	
π_1	-4.83	-3.73	-3.19	-2.91	×
π_2	-3.91	-3.21	-2.65	-2.36	×
$\pi_3 = \pi_4$	10.37	7.86	5.77	4.86	×
$\pi_5 = \pi_6$	10.99	7.88	5.77	4.86	×
$\pi_7 = \pi_8$	17.79	7.86	5.77	4.86	×
$\pi_9 = \pi_{10}$	18.09	7.82	5.84	4.9	×
$\pi_{11} = \pi_{12}$	15.52	7.92	5.82	4.9	×

Source: Research findings.

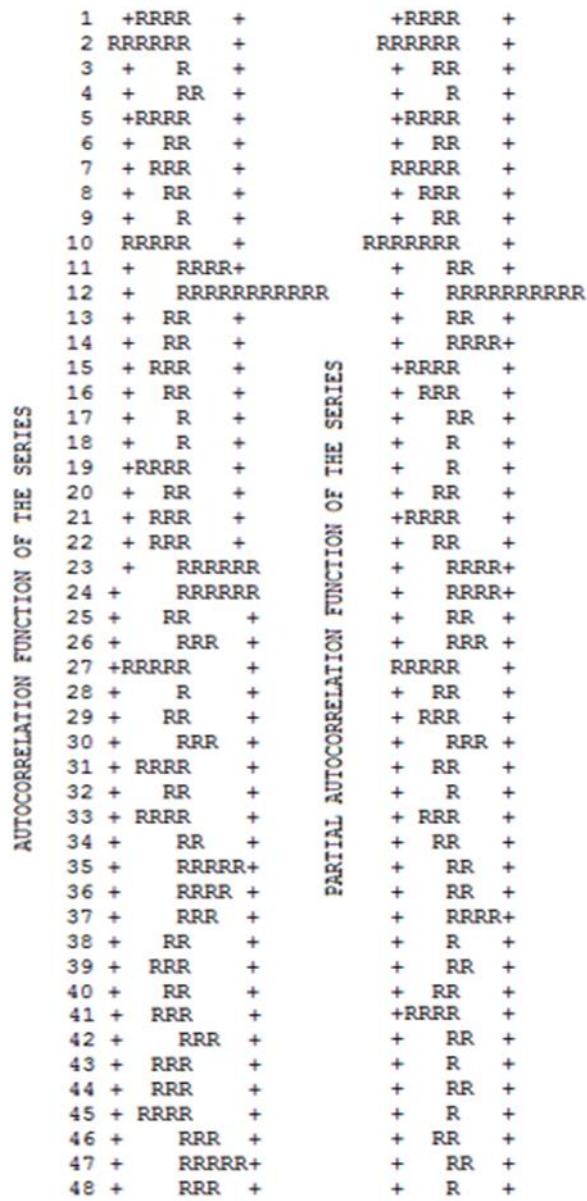


Figure 3. Autocorrelation (ACF) and Partial Autocorrelation (PACF) plots related to the time series of monthly gasoline consumption after non-seasonal filtering of the data.

Given these properties, the SARIMA model was identified as appropriate for capturing seasonal behavior. In parallel, an autoregressive regression with monthly dummy variables (equation (8)) was also estimated, with lag selection as described earlier in the research methodology section. Results of this specification are reported in Table 6.

Table 6. Estimated parameters of the model for monthly gasoline consumption.

$\Delta x_t = x_t - x_{t-1}$				
Description	Variable	Coefficients	Standard Error	t-statistic
April	D1	-5.37	1.08	-4.91
May	D2	-6.08	1.08	-5.64
June	D3	-2.98	1.07	-2.78
July	D4	-2.64	1.06	-2.49
August	D5	-3.30	1.06	-3.12
September	D6	-4.03	1.06	-3.82
October	D7	-8.16	1.06	-7.72
November	D8	-7.26	1.09	-6.66
December	D9	-7.26	1.07	-6.79
January	D10	-6.42	1.07	-5.99
February	D11	-3.78	1.07	-3.55
First lag (optimal) of the dependent variable	Δx_{t-1}	-0.22	0.06	-3.88
Intercept	c	5.12	0.75	6.81
LM(1)=0.71		ARCH (1)=0.08		
LM(12)=1.18		ARCH (12)=18.73		

Source: Research findings.

Note: Model estimation is based on the original dataset (April 1998–March 2024).

Estimation results (Table 6) show all coefficients are significant, and LM and ARCH tests confirm no serial correlation or heteroskedasticity in the residuals. The significance of monthly dummy variables indicates that gasoline consumption differs across months, and their coefficients quantify these differences. Differencing also shows that monthly growth depends on the previous month's growth.

Alongside the autoregressive regression model, several SARIMA specifications were estimated to capture the seasonal dynamics of monthly gasoline consumption in Iran. Consistent with the results of the seasonal unit root tests, first-order non-seasonal differencing was applied ($d=1$, $D=0$). Model identification followed the Box–Jenkins methodology, relying on the examination of autocorrelation and partial autocorrelation functions (ACF/PACF), maximum likelihood estimation, and residual diagnostic checks using the Box–Pierce Q-statistic. Accordingly, a range of alternative seasonal SARIMA structures, including $SARIMA(p,1,q)(3,0,0)_{12}$, $SARIMA(p,1,q)(0,0,2)_{12}$, and $SARIMA(p,1,q)(2,0,1)_{12}$, were systematically estimated. For each candidate specification, model selection was guided by standard information criteria, namely the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC/BIC), alongside residual diagnostic testing to ensure the absence of serial correlation and model adequacy. Among the competing specifications, the multiplicative $SARIMA(p,1,q)(2,0,1)_{12}$ model produced the

lowest AIC and SBC values and exhibited well-behaved residuals with no evidence of remaining serial correlation. Therefore, this specification was selected as the preferred model for forecasting monthly gasoline consumption in Iran (Table 7).

Table 7. Estimation of coefficients for the multiplicative SARIMA model for monthly gasoline consumption.

Model	Variable	Coefficients	t-statistic
SARIMA(p,1,q)(2,0,1) ₁₂	AR(1)	-0.12	-0.52
	AR(2)	-0.19	-2.33
	MA(1)	0.16	0.65
	SAR(1)	0.99	237.0
	SMA(1)	0.94	69.43
	C	-0.0005	-0.06
			Q(6)=4.41 (0/306)
			Q(12)=9.58 (0/130)
	SBC=2.79	AIC=2.71	
SARIMA(p,1,q)(3,0,0) ₁₂	SBC=2.83	AIC=2.74	
SARIMA(p,1,q)(0,0,2) ₁₂	SBC=2.85	AIC=2.76	

Source: Research findings.

Note: Model estimation is based on the original dataset (April 1998–March 2024).

It is important to note that all estimations and diagnostic tests conducted up to this stage are based on the original monthly gasoline consumption data covering April 1998 to March 2024. Model performance was evaluated using the MAPE and RMSE. The models were estimated using observations from April 1998 to March 2023 as the training (in-sample) period, while observations from April 2023 to March 2024 were reserved as the testing (out-of-sample) period. Comparison of predicted and actual values (Eq. 9 and 10) showed, based on Table 8, that the SARIMA model produced lower MAPE and RMSE than the autoregressive regression with monthly dummies.

The higher RMSE and MAPE obtained for the autoregressive regression model with monthly dummy variables reflect structural limitations of deterministic seasonal specifications rather than estimation deficiencies. While both models rely solely on historical gasoline consumption data and exclude exogenous variables, the regression model represents seasonality through fixed monthly effects and a restricted lag structure, implicitly assuming stable seasonal patterns over time. In practice, gasoline consumption in Iran exhibits evolving seasonal behavior and strong persistence that cannot be fully captured by deterministic dummy variables. By contrast, the SARIMA model explicitly incorporates stochastic non-seasonal and seasonal autoregressive and moving average components, allowing greater flexibility in modeling time varying seasonal dynamics and serial

dependence. Consequently, SARIMA produces substantially lower forecasting errors, while the regression model is retained as a benchmark for comparative evaluation.

Table 8. Comparison of in-sample and out-of-sample forecasting performance of SARIMA and autoregressive regression models based on MAPE and RMSE criteria.

Forecasting model	In-sample forecasting errors		Out-of-sample forecasting errors	
	MAPE(%)	RMSE	MAPE(%)	RMSE
SARIMA(p,1,q)(2,0,1) ₁₂	1.81	7.63	2.15	10.79
Autoregressive regression model with monthly dummy variables	12.25	63.72	18.34	89.53

Source: Research findings.

Forecasting Results

SARIMA demonstrated superior predictive accuracy. Using this model, monthly gasoline consumption was forecasted for April 2024 to March 2027, with results reported in Table 9.

Table 9. Prediction of monthly gasoline consumption (Million liters per day) in Iran (2024-2027).

Month \ Year	January	February	March	April	May	June	July	August	September	October	November	December
2024	-	-	-	122.03	121.25	124.19	126.68	127.62	128.69	125.16	123.60	121.86
2025	121.15	122.75	127.54	125.79	125.61	128.20	130.61	131.63	132.70	129.16	127.61	125.87
2026	125.16	126.75	131.54	129.79	129.61	132.19	134.60	135.62	136.69	133.16	131.60	129.87
2027	129.15	130.75	135.53	-	-	-	-	-	-	-	-	-

Source: Research findings.

Figure 4 compares actual and predicted monthly gasoline consumption from 1998 to 2027. The dashed line represents actual data (1998–2024), while the solid line shows forecasts (2024–2027). The predicted trend closely aligns with the historical pattern, indicating that the model reliably captures the consumption trajectory for the coming years.

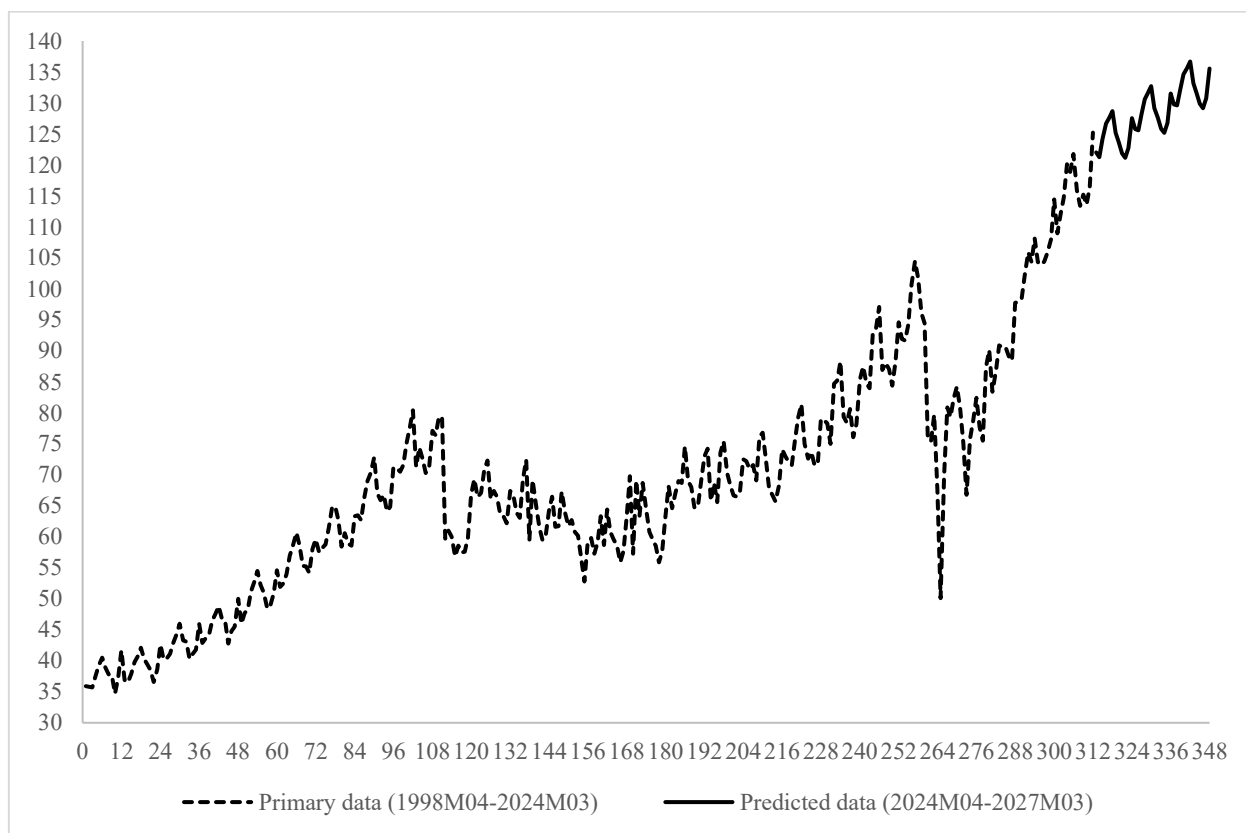


Figure 4. Average monthly gasoline consumption in Iran from April 1998 to March 2027 (Million liters per day).

LIMITATIONS

Although this study makes valuable contributions, it also faces certain limitations that provide directions for future research. The models rely solely on historical gasoline consumption data and do not include explanatory variables such as income, demographic trends, or fuel prices. Incorporating these factors in future studies could enhance predictive accuracy and provide a deeper understanding of consumption drivers. The analysis also depends on official statistics, which may not fully capture informal fuel use or cross-border smuggling, suggesting the need for more comprehensive data sources in subsequent research. Furthermore, while this study emphasizes important policy implications, it does not simulate alternative scenarios such as subsidy reforms or efficiency improvements. Future work could address this gap by testing different policy interventions to provide more detailed guidance for decision-makers.

CONCLUSIONS

This study investigates the seasonal and non-seasonal stochastic properties of monthly gasoline consumption in Iran using the Beaulieu–Miron test and compares autoregressive regression with monthly dummy variables and SARIMA models. The results demonstrate the superior performance of SARIMA in capturing long-term trends and seasonal fluctuations. Forecasts for April 2024–March 2027 indicate 2.15% average annual and 6.5% cumulative consumption growth, highlighting the need for effective gasoline demand management. The long dataset covering 1998–2024 and formal seasonal testing strengthen model specification and provide valuable insights for medium-term energy planning and policy formulation. Table 10 summarizes the main policy implications of the forecasted gasoline consumption.

Table 10. Policy implications of forecasted gasoline consumption growth in Iran.

Forecast Finding	Policy Challenge	Suggested Policy Response	Expected Policy Outcome
Average annual gasoline consumption growth of 2.15% (2024–2027)	Expansion of gap between domestic refining capacity and consumption	Expansion and modernization of refinery capacity and investment in downstream petroleum infrastructure	Reduced reliance on gasoline imports and improved energy supply security
Strong seasonal consumption fluctuations	Risk of temporary supply shortages during peak travel seasons	Development of strategic fuel reserves and improved seasonal fuel distribution planning	Improved supply stability and reduction in short-term market disruptions
Persistent long-term upward consumption trend	Increased fiscal burden from fuel subsidies and regulated pricing mechanisms	Gradual implementation of rational fuel pricing policies and targeted subsidy reforms	Improved demand management and reduction of inefficient fuel consumption
Rising transportation fuel demand	Increasing environmental and congestion pressures	Promotion of fuel efficiency standards, modernization of vehicle fleets, and development of public transportation infrastructure	Reduced per-capita gasoline consumption and improved environmental sustainability
Continued dependence on fossil fuels in transportation	Energy vulnerability to external shocks and price volatility	Investment in alternative fuels and renewable energy for transportation	Diversification of energy sources and improved long-term energy resilience

Source: Research findings.

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تدوین الگوی پیش بینی سری زمانی مصرف ماهانه بنزین در ایران: کاربردی از آزمون ریشه واحد فصلی

ابراهیم انسان، امیرحسین چنذری، و عاطفه کریمی

چکیده

مصرف انرژی در ایران طی دهه‌های اخیر به‌طور چشمگیری افزایش یافته است و بخش حمل‌ونقل به‌دلیل ضعف در سیستم حمل‌ونقل عمومی و اتکای شدید به بنزین، یکی از بزرگترین مصرف‌کنندگان به شمار می‌رود. محدودیت ظرفیت پالایشگاهی، تحریم‌ها و رشد سریع تقاضا شکاف میان تولید و مصرف را گسترش داده است و از این‌رو، پیش‌بینی دقیق مصرف بنزین برای برنامه‌ریزی، بودجه‌بندی و سیاست‌گذاری ضرورت دارد. در این پژوهش، با بهره‌گیری از داده‌های ماهانه مصرف بنزین طی دوره فروردین 1377 تا اسفند 1402 و با استفاده از مدل‌های تک‌متغیره سری‌های زمانی فصلی، روند مصرف مورد پیش‌بینی قرار گرفت. آزمون‌های ریشه واحد فصلی بویلیو-میرون و تیلور نشان دادند که این سری زمانی دارای یک ریشه واحد غیرفصلی و فاقد ریشه واحد فصلی است و بنابراین، تفاضل‌گیری مرتبه اول برای ایستاسازی کافی است. در ادامه دو مدل شامل رگرسیون خودرگرسیو با متغیرهای مجازی ماهانه و مدل خودرگرسیو یکپارچه میانگین متحرک فصلی (SARIMA) برآورد شدند. نتایج پیش‌بینی خارج از نمونه (فروردین 1402 تا اسفند 1402) نشان داد که مدل SARIMA با میانگین درصد قدر مطلق خطا (MAPE) معادل 2.15 درصد نسبت به 18.34 درصد در مدل رگرسیون عملکرد بهتری دارد. همچنین پیش‌بینی‌ها برای فروردین 1403 تا اسفند 1406 بیانگر رشد تجمعی 6.5 درصدی مصرف بنزین با میانگین رشد سالانه 2.15 درصد است که بیش از 115 درصد بالاتر از رشد جهانی انرژی پیش‌بینی‌شده توسط آژانس بین‌المللی انرژی می‌باشد. یافته‌های پژوهش ضرورت تقویت ظرفیت پالایشی، ارتقای بهره‌وری سوخت، توسعه حمل‌ونقل عمومی و اجرای سیاست‌های قیمتی منطقه‌ای را برجسته می‌سازد.