# Modeling and forecasting bitumen sales using univariate and multivariate time series approaches: a case study of Algeria's NAFTAL corporation

**Youssouf Bouzir [1] *, Mouhamadou Djima Baranon [2], Mohamed Adam Suliman Ishag [3], Michael Arthur Ofori [4], Daniel Biftu Bekalo [5]**

[1]PhD Student, The Pan African University Institute for Basic Sciences, Technology and Innovation (PAUSTI), Kenya
youcefbouzir@gmail.com
http://orcid.org/0000-0002-8831-4244
[2]PhD, The Pan African University Institute for Basic Sciences, Technology and Innovation (PAUSTI), Kenya
djima.mouhamadou@gmail.com
http://orcid.org/0009-0005-7783-653X
[3] PhD, University of Kordofan, Sudan
mohamedas96068@gmail.com
http://orcid.org/0000-0002-7939-5097
[4]PhD, University of Cape Coast, Cape Coast, Ghana
mkyofori1920@gmail.com
http://orcid.org/0000-0002-4983-540X
[5]PhD, Haramaya University, Addis Ababa, Ethiopia
danibiftu@gmail.com
http://orcid.org/0000-0002-7935-2409

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* ***Corresponding Author***

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## Abstract

This study models and forecasts the NAFTAL Corporation's bitumen sales in Algeria using univariate and multivariate time series methods. This method uses the Box-Jenkins method to identify, estimate, diagnostic and predict. ANOVA and ADF tests showed seasonal patterns and stationary data. The best univariate models for bitumen (BTM) and pure bitumen (BTMP) were found to be SARIMAX(2,2,1) and SARIMAX(0,1,4), respectively. No volatility clustering or ARCH effects were captured via ARCH-LM tests. VAR(2) model used to explain dynamic interactions over time. Granger causality tests detected a significant unidirectional effect between BTM and BTMP ($p < 0.001$ at lag 2). According to the forecast error variance decomposition (FEVD), BTM accounts for 29.44% of the 12-month forecast error variance for BTMP and 98.25% of its own variation. These findings emphasize how crucial it is to take into account the overall bitumen trends when estimating product demand.

**Keywords:** Bitumen; Box-Jenkins; SARIMA; ARCH-LM; VAR.

**JEL classification codes:** C32; C51; C53; Q02; L71; L74

# نمذجة وتنبؤ مبيعات الزفت باستخدام أساليب السلاسل الزمنية أحادية المتغير ومتعددة المتغيرات: دراسة حالة مجمع نفطال الجزائري

[1] بوزير يوسف*، [2] محمدو جيما بارانون، [3] محمد أدم سليمان إسحاق، [4] مخاييل أرتور أوفوري، [5] دانييل بيفتو بكالو

[1] طالب دكتوراه، جامعة عموم إفريقيا للعلوم الأساسية، التكنولوجيا والابتكار (PAUSTI)، (كينيا)
✉ youcefbouzir@email.com
http://orcid.org/0000-0002-8831-4244
[2] طالب دكتوراه، جامعة عموم إفريقيا للعلوم الأساسية، التكنولوجيا والابتكار (PAUSTI)، (كينيا)
✉ djima.mouhamadou@email.com
http://orcid.org/0009-0005-7783-653X
[3] أستاذ جامعي، جامعة كردفان، (السودان)
✉ mohamedas96068@email.com
http://orcid.org/0000-0002-7939-5097
[4] أستاذ جامعي، جامعة كيب كوست، (غانا)
✉ mkyofori920@email.com
http://orcid.org/0000-0002-4983-540X
[5] أستاذ جامعي، جامعة هرمايا، (إثيوبيا)
✉ mkyofori920@email.com
http://orcid.org/0000-0002-7935-2409

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**الملخص:**

تقوم هذه الدراسة بنمذجة وتنبؤ مبيعات الزفت لمجمّع نفطال في الجزائر باستخدام أساليب السلاسل الزمنية أحادية ومتعددة المتغيرات، وذلك وفق منهجية بوكس-جينكينز في تحديد النماذج، تقدير المعلمات، التشخيص والتنبؤ. كشف اختبارا ANOVA و ADF عن أنماط موسمية وبيانات مستقرة. وقد تبيّن أن أفضل النماذج أحادية المتغير للزفت العادي (BTM) والزفت النقي(BTMP) هي على التوالي SARIMAX (2,2,1) و SARIMAX(0,1,4). ولم تُكشف أي تجمعات للتقلبات من خلال اختبارات ARCH-LM. كما وُظِّف نموذج VAR(2) لتفسير التفاعلات الديناميكية عبر الزمن، وكشفت اختبارات السببية لغرانجر عن تأثير أحادي الاتجاه ذو دلالة إحصائية بين BTM وBTMP عند مستوى ($p < 0.001$) عند التأخير الثاني. وبحسب تحليل تفكيك تباين خطأ التنبؤ (FEVD)، يُفسِّر BTM ما نسبته 29.44% من تباين خطأ التنبؤ الممتد لاثني عشر شهراً لـBTMP، فيما يُفسِّر 98.25% من تباينه الخاص. تؤكد هذه النتائج أهمية مراعاة الإتجاهات العامة لمبيعات الزفت عند تقدير الطلب على المنتجات.

**الكلمات المفتاحية:** الزفت؛ منهجية بوكس-جينكينز ؛ SARIMA؛ ARCH-LM؛ VAR

**تصنيف JEL:** L74؛ L71؛ Q02؛ C53؛ C51؛ C32

## 1. Introduction

The Bitumen is the binding agent in asphalt concrete, and virtually every paved road in the world depends on it. This basic fact gives bitumen an outsized role in infrastructure economics: when governments build roads, bitumen demand rises; when construction stalls, stockpiles accumulate. In developing economies, where rapid urbanization is straining existing transport networks, managing the relationship between supply and demand is not a minor logistics problem, it is a core function of national planning.

Africa clearly illustrates these stakes. The continent's bitumen market is projected to expand from USD 590.45 million in 2024 to USD 873.70 million by 2033 (Market Data Forecast, 2024), and road construction alone accounted for 80.47% of 2025 demand (Mordor Intelligence, 2025). Algeria sits at the center of this dynamic. Its vast geography makes transport infrastructure a prerequisite for economic integration, and the construction sector is expected to grow by 4.2% in real terms in 2026 on the back of sustained state investment in public works (Yahoo Finance, 2026). NAFTAL, the state corporation responsible for distributing fuels, lubricants, liquified petroleum gaz (LPG), and bitumen, is directly exposed to these pressures. Its five-year development plan (2022–2027), backed by projected investments exceeding 250 billion dinars (Algeria Invest, 2022), depends on the ability to anticipate demand accurately, optimize storage, and keep the supply chain from either running dry or accumulating costly surpluses.

The problem is that bitumen demand is genuinely difficult to forecast. Road construction is cyclical, project-dependent, and sensitive to budget releases and seasonal weather conditions. These features produce time series with pronounced seasonality, occasional volatility clusters, and complex interdependencies between related product categories. Getting the forecast wrong in either direction incurs real costs.

### 1.1 Univariate Forecasting in Energy and Petroleum Markets

The dominant analytical framework for this type of problem remains the Box-Jenkins ARIMA methodology (Box and Jenkins, 1976). Despite decades of competition from machine learning, ARIMA retains a strong empirical track record in energy markets, largely because of its statistical rigor, interpretability, and reliable performance on the kinds of structured temporal patterns found in commodity data (Zhang, 2024; Tsoku et al., 2024). Mensah (2015) demonstrated ARIMA's capacity to handle non-stationary Brent crude oil prices, and more recent work has paired it with neural networks to capture residual non-linearity (Tsoku et al., 2024). Tang (2026) confirmed its continued relevance as a baseline in comparative evaluations against GARCH and hybrid machine learning models.

When a series carries strong recurring seasonality, as energy consumption and construction material demand typically do, the Seasonal ARIMA (SARIMA) extension is the appropriate starting point. Zaim et al. (2023) used a SARIMA-GARCH hybrid to forecast Malaysian electricity demand under volatile seasonal conditions; Sigauke and Chikobvu (2011) applied the same combined structure to daily peak electricity demand in South Africa, showing that ignoring conditional variance alongside seasonality produces inferior results. In the developing-market context, most relevant here, Ndiaye et al. (2023) used SARIMA to assist Senegalese energy planners in matching supply capacity to demand projections. Thang et al. (2024) applied ARIMA models to forecast Vietnam's imports of petroleum and bituminous minerals, producing a directly analogous application to the present study.

### 1.2 Multivariate Approaches: VAR, VECM, and Causality Analysis.

Univariate models, by construction, treat each series in isolation. When the research question involves structural relationships between variables, whether one market drives another, or whether shocks in one series propagate to another, multivariate methods are necessary. Vector Autoregression (VAR) and Vector Error Correction Models (VECM) are standard tools for this purpose, as they model systems of interrelated variables without imposing a priori causal restrictions.

Within the Algerian context, these methods have been applied primarily at the macroeconomic level. Hadji and Abderrahmane (2024) used a VAR model with Granger causality testing to trace the influence of oil price fluctuations on Algerian economic growth. Bensafta (2023) applied a structural VAR to identify how discrete oil price shocks translate into long-run growth variations. Korso and Benbouziane (2025) extended this line of inquiry to Algeria's economic vulnerability and diversification challenges. At a broader scale, Olayungbo and Umechukwu (2022) used a global VAR to document how cross-country oil price dynamics affect domestic volatility in several African oil-exporting economies, Algeria among them. Balioz (2022) demonstrated VAR and VECM's utility for short-term forecasting of global energy and metal prices by exploiting cross-market feedback. These applications confirm the value of the VAR framework in petroleum-dependent economic structures, although they also suggest that its primary contribution is structural insight rather than predictive accuracy.

### 1.3 Volatility Modeling: ARCH/GARCH

Commodity markets frequently exhibit volatility clustering; large price or demand swings tend to arrive in groups, not randomly. Engle (1982) formalized this phenomenon with the ARCH model; Bollerslev (1986) generalized it into GARCH. Wang (2012) compared univariate and multivariate GARCH specifications across energy markets; and found that the GARCH family consistently accurate in capturing dynamic variance. Muşetescu et al. (2022) confirmed this for crude oil specifically. When volatility clustering is present in a demand series, ignoring it inflates forecast uncertainty intervals and can distort risk assessments.

### 1.4 Univariate vs. Multivariate Forecasting

Whether univariate or multivariate models produce better out-of-sample forecasts for petroleum products is genuinely unresolved. The theoretical case for multivariate models is intuitive; more information should help, but the practical reality is more complicated. Additional variables introduce additional parameters, and estimation error compounds. Li et al. (2024) found that simple univariate models consistently outperformed multivariate alternatives in forecasting crude oil basis volatility, attributing this to the lower estimation error of parsimonious structures. Rangga et al. (2024) reached similar conclusions in a comparative study of oil production forecasting, finding cases in which standalone historical trajectories outperformed interrelated system vectors. The implication is not that multivariate models are inferior, but that the two approaches answer different questions: VAR illuminates structural relationships, whereas ARIMA/SARIMA often forecasts more accurately. Running both in parallel is therefore the logical design choice.

### 1.5 Research Gap and Objectives

Despite extensive forecasting literature in the broader petroleum and construction sectors, product-specific bitumen demand forecasting at the sub-regional level in Africa, and Algeria in particular, has received minimal attention. Aggregate crude oil and general energy demand models are well-represented in the literature. The distinct seasonal patterns and volatility characteristics of pure bitumen and standard bitumen sales are not present.

This study addresses that gap using monthly sales data from NAFTAL. Four objectives guide the analysis. First, it identifies the best-fitting univariate SARIMA models for both standard bitumen (BTM) and pure bitumen (BTMP) sales, capturing their respective trend and seasonal structures. Second, it tests for ARCH effects to determine whether volatility clustering is present and whether risk management adjustments are warranted. Third, it uses a VAR model supplemented by Granger causality testing and variance decomposition to examine the dynamic relationship between BTM and BTMP sales. Fourth, it generates short-term forecasts from the selected models to directly support NAFTAL's operational and strategic planning.

## 2. Methodology

### 2.1 Data description

The analysis uses secondary time-series data from the sales records of Algeria's NAFTAL Corporation. The dataset comprises two primary product categories critical to road infrastructure: standard bitumen sales (denoted as BTM) and pure bitumen sales (denoted as BTMP) in metric tons (TM). The sample covers a monthly frequency spanning from January 2010 to December 2018, yielding a total of 108 observations (T = 108) for each series.

### 2.2 Univariate Approach: Box-Jenkins Methodology

The study applies the Box-Jenkins methodology for univariate modeling, executed across five phases: Preliminary Analysis, Stationarity Testing, Model Identification and Estimation, Diagnostic Checking, and ARCH Effect Testing.

**- Phase 1: Preliminary analysis**

The initial phase involves decomposing the time series to isolate underlying trends ($T_t$), seasonal components ($S_t$), and irregular residual components ($\varepsilon_t$). The series can be modeled as either an additive process:

$$X_t = T_t + S_t + \varepsilon_t$$

or a multiplicative process, as follows:

$$X_t = T_t \times S_t + \varepsilon_t$$

To mathematically detect and confirm the presence of seasonality, Analysis of Variance (ANOVA) using the Fisher test, alongside the Buys-Ballot decomposition method, is applied.

**- Phase 2: Stationarity testing**

The Augmented Dickey-Fuller (ADF) test is employed to formally test for the presence of unit roots. The ADF test is specified across three distinct regression models to account for potential deterministic elements:

- Model 1 (No constant, no trend):

$$\Delta x_t = \phi x_{t-1} + \Sigma \lambda_i \Delta x_{t-i} + \varepsilon_t$$

- Model 2 (With constant):

$$\Delta x_t = \phi x_{t-1} + c + \Sigma \lambda_i \Delta x_{t-i} + \varepsilon_t$$

- Model 3 (With constant and trend):

$$\Delta x_t = \phi x_{t-1} + b_t + c + \Sigma \lambda_i \Delta x_{t-i} + \varepsilon_t$$

If the null hypothesis of a unit root ($\phi = 0$) is not rejected, the series is deemed non-stationary. Stationarity is subsequently induced via seasonal differencing, mathematically denoted by the operator $(1 - B^s)^D$, and regular differencing, denoted by $(1 - B)^d$, where B is the backshift operator

**- Phase 3: Model identification and estimation**

Following stationarity confirmation, the optimal lag orders for the autoregressive (AR) and moving average (MA) components are identified via visual inspection of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) correlograms. The AR(p) process expresses current values as a linear combination of p past values:

$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \varepsilon_t$ and

$$\phi(B)X_t = \varepsilon_t$$

The MA(q) process expresses current values as a linear combination of current and q past stochastic error terms:

$X_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}$ and

$$X_t = \theta(B)\varepsilon_t$$

Combining these yields the ARMA(p,q) process for stationary data:

$$\phi(B)X_t = \theta(B)\varepsilon_t$$

For non-stationary data requiring d degrees of differencing, the ARIMA(p,d,q) model is employed:

$$\phi(B)(1 - B)^d X_t = \theta(B)\varepsilon_t$$

Given the seasonal nature of bitumen sales, the overarching seasonal ARIMA model, $SARIMA(p,d,q)(P,D,Q)_S$, is defined as:

$$\phi(B)\Phi_P(B^s)(1 - B)^d(1 - B^s)^D X_t = \theta(B)\Theta_Q(B^s)\varepsilon_t$$

Parameters are then robustly estimated utilizing the Maximum Likelihood Estimation (MLE) method.

**- Phase 4: Diagnostic checking**

Model adequacy is evaluated by ensuring residual white-noise properties and minimizing information loss. The optimal model minimizes the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) criteria:

$$AIC = log(\sigma^2_\varepsilon) + 2(ps+q)/T$$

$$SIC = log(\sigma^2\varepsilon) + (p+q)log(T)/T$$

**- Phase 5: ARCH effect testing**

To ensure the conditional variance of the residuals is constant over time, the Lagrange Multiplier (ARCH-LM) test for conditional heteroscedasticity is administered. If significant ARCH effects are detected, the variance is modeled using the ARCH(p) framework. The ARCH(p) variance equation models current variance ht as a function of past squared errors:

$$h_t = \alpha_0 + \Sigma\alpha_i\, \varepsilon^2_{t-i}$$

## 2.3 Multivariate Approach: Vector Autoregression (VAR)

To investigate potential dynamic transmission channels and joint predictability, a multivariate Vector Autoregression (VAR) approach was implemented. The VAR model extends the univariate AR structure to a system of interdependent equations. The standard VAR(p) mathematical specification is:

$$X_t = \Phi_0 + \Phi_1 X_{t-1} + \ldots + \Phi_p X_{t-p} + \varepsilon_t$$

where $X_t$ represents a K×1 vector of endogenous variables, $\Phi_i$ are K×K coefficient matrix capturing the system's dynamic feedback loops, and $\varepsilon_t$ is a K×1 vector of white noise error terms with zero mean and covariance matrix Σ. For the VAR model to be dynamically stable and valid for policy inference, the stationarity condition requires that all roots of the characteristic polynomial determinant $\det|I_n - \Phi_1 L - \ldots - \Phi_p L^p|$ lie strictly outside the unit circle.

The optimal lag length (p) is empirically determined by minimizing the multivariate information criteria, specifically the AIC and BIC. Once configured, the VAR framework facilitates critical post-estimation analytics. Specifically, the Granger Causality Test evaluates whether past historical observations of one variable provide statistically significant information to improve the predictive accuracy of the other variable beyond what is already contained in the latter's own history. Additionally, Impulse Response Functions (IRF) trace the temporal path of a dependent variable in response to a one-standard-deviation orthogonalized shock to another variable in the system. Finally, the Forecast Error Variance Decomposition (FEVD) quantifies the proportion of the forecast error variance of one variable that is attributable to shocks in each of the system's constituent variables across specific time horizons.

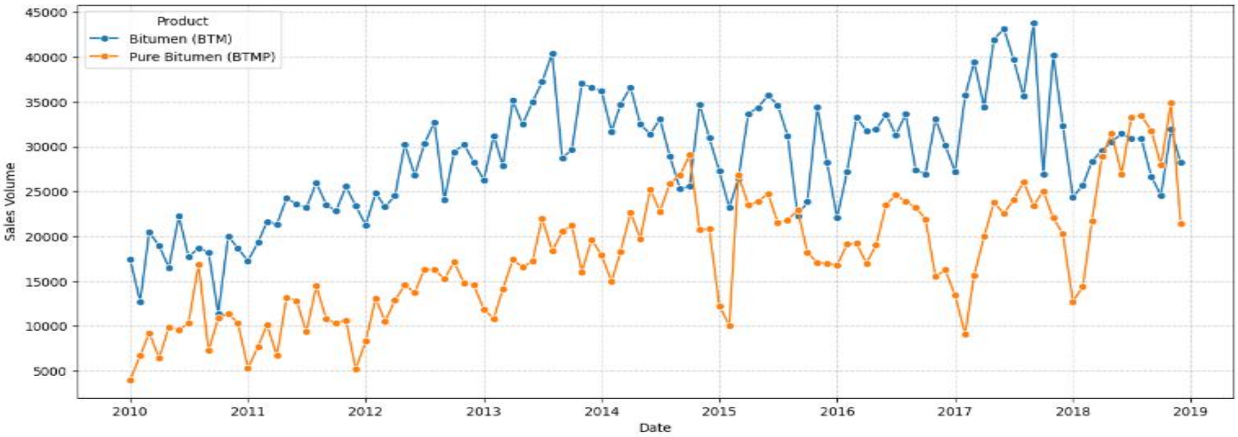
## 3. Empirical results

### 3.1 Descriptive statistics and preliminary analysis

Initial inspection of the monthly sales series for BTM and BTMP (Figure 1) showed clear cyclicality consistent with the operational patterns of the construction and public works sectors in Algeria. Bitumen demand typically escalates during the warmer, drier months optimal for asphalt paving, producing a distinct seasonal pattern within each year.

**Figure 1**

Time series plots of monthly Bitumen (BTM) and Pure Bitumen (BTMP) sales volume (January 2010 – December 2018)




**Source**: result from Python data analysis

The Analysis of Variance (ANOVA) (Table 1, Appendix A) utilized the Fisher test (F=1.63 for BTM and F=2.44 for BTMP); while the seasonality for BTM was marginally significant (p=0.103), the BTMP series yielded a highly significant test statistic (p=0.0098), confirming the presence of rigorous seasonality in the Pure Bitumen. Moreover, the application of the Buys-Ballot decomposition diagnostic shows a strong direct proportionality between the periodic standard deviations and their respective means (correlations of 0.73 and 0.79, respectively), supporting a multiplicative decomposition scheme over an additive one.

### 3.2 Stationarity analysis

The Box-Jenkins methodology requires stationarity. Initial Augmented Dickey-Fuller (ADF) tests (Figure 2, Appendix A) applied to the raw level series indicate the presence of unit roots (p-value = 0.1390 > 0.05), thus failing the stationarity requirement.

To address this, appropriate differencing was applied to remove stochastic trend and seasonal variance. The BTM series required both a regular first difference and a seasonal difference (d=1, D=1), while the BTMP series was rendered stationary following analogous mathematical transformations. Subsequent post-transformation ADF testing (Figure 3,

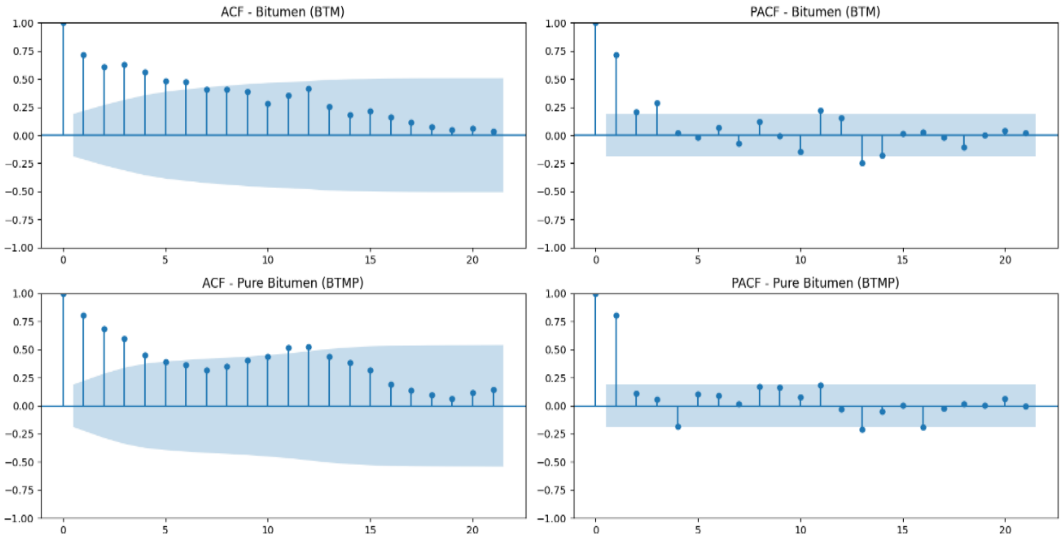
Appendix A) resulted in large negative test statistics that strongly rejected the null hypothesis of a unit root at the 1% significance level (p-values = 0.000), affirming that the differenced series (DBTMSA and BTMPSAT) possessed constant mean and variance, making them suitable for ARMA parameter estimation

### 3.3 Univariate model analysis

Through a systematic evaluation of the ACF and PACF correlograms (Figure 4), alongside rigorous minimization of information criteria, the optimal models for both series were determined and parameters successfully estimated.

**Figure 4**

ACF and PACF correlograms for BTM and BTMP (2010-2018)




**Source**: result from Python data analysis

The following table (Table 2) summarizes the estimation results.

**Table 2**

Estimation Results for DBTMSA and BTMPSAT Series

| Parameter | DBTMSA Estimate | DBTMSA z-stat | BTMPSAT Estimate | BTMPSAT z-stat |
|---|---|---|---|---|
| AR(1) | -0.4271 | -4.312 | N/A | - |
| AR(2) | -0.3063 | -3.008 | N/A | - |
| MA(1) | -0.9783 | -21.904 | -0.4058 | -3.759 |
| MA(2) | N/A | - | -0.1366 | -1.199 |
| MA(3) | N/A | - | -0.0293 | -0.260 |
| MA(4) | N/A | - | -0.3950 | -3.147 |
| Intercept | None | - | 174.1677 | 5.233 |
| Log Likelihood | -1041.961 | - | -1029.859 | - |
| AIC | 2091.921 | - | 2071.718 | - |
| BIC | 2102.575 | - | 2087.755 | - |
| Durbin-Watson | 2.064 | - | 1.985 | - |
| Jarque-Bera | 2.89 (p=0.24) | - | 2.98 (p=0.22) | - |

**Source**: result from Python data analysis

For the BTM series, a SARIMA(2,1,0)(0,1,1)12 specification yielded the best fit. The highly significant t-statistics for the AR(1) and AR(2) terms confirm the relevance of past short-term lags in forecasting current sales. The estimated mathematical equation for the differenced BTM series is displayed as:

$$DBTMSA_t = -0.4271\, DBTMSA_{t-1} - 0.3063\, DBTMSA_{t-2} + \varepsilon_t - 0.9783\, \varepsilon_{t-1}$$

In the case of BTMP series, the model selection process concluded that an ARIMA(0,1,4) structure on the stationarized series was optimal with the following estimated equation:

$$BTMPSAT_t = 174.17 + \varepsilon_t - 0.4058\, \varepsilon_{t-1} - 0.1366\, \varepsilon_{t-2} - 0.0293\, \varepsilon_{t-3} - 0.3950\, \varepsilon_{t-4}$$

Both models passed the diagnostic validation. Durbin-Watson statistics (2.016 and 1.948) are close to 2.0, ruling out first-order residual autocorrelation. Furthermore, the Jarque-Bera test results showed non-significant p-values (0.24 for BTM and 0.22 for BTMP).

### 3.4 ARCH effect analysis

For both the BTM and BTMP series, the p-values from the ARCH-LM test are significantly greater than the conventional significance level of 0.05:

- Bitumen (BTM) Residuals: p-value = 0.7379

- Pure Bitumen (BTMP) Residuals: p-value = 0.6676

Hence, there is no statistically significant evidence of ARCH effects in the residuals. The residual variance is constant over time, and the remaining errors are consistent with white noise.

### 3.5 Multivariate VAR analysis

To specify the VAR, optimal lag selection was executed utilizing the Akaike and Schwarz information criteria. As detailed in Table 3, a two-lag system without a deterministic constant, denoted as VAR(2), minimized both criterion functions and was thus selected as the optimal multivariate baseline.

**Table 3**
VAR model selection criteria

| | With constant | | Without constant | |
|---|---|---|---|---|
| Lag | AIC | BIC | AIC | BIC |
| P=1 | 33.457899 | 33.620237 | 33.421440 | 33.529666 |
| P=2 | 33.260025 | 33.532348 | 33.222418 | 33.440276 |
| P=3 | 33.302769 | 33.686519 | 33.265865 | 33.594794 |
| P=4 | 33.283757 | 33.780411 | 33.246877 | 33.688347 |

**Source**: result from Python data analysis

The estimated VAR(2) for the NAFTAL Bitumen series can be expressed in the general matrix form:

$$Z_t = C + \Phi_1 Z_{t-1} + \Phi_2 Z_{t-2} + \varepsilon_t$$

Substituting the estimated coefficients (Figure 6, Appendix A) from our analysis:

$$\begin{bmatrix} DBTMSA_t \\ BTMPSAT_t \end{bmatrix} = \begin{bmatrix} -240.9505 \\ 161.2733 \end{bmatrix} + \begin{bmatrix} -0.6037 & 0.1920 \\ -0.0295 & -0.1231 \end{bmatrix} \begin{bmatrix} DBTMSA_{t-1} \\ BTMPSAT_{t-1} \end{bmatrix} + \begin{bmatrix} -0.2004 & 0.1117 \\ -0.4241 & -0.0761 \end{bmatrix} \begin{bmatrix} DBTMSA_{t-2} \\ BTMPSAT_{t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}$$

To ascertain whether one bitumen product acts as a leading indicator for the other, formal Granger causality testing was conducted within the specified VAR(2) framework. The results, summarized in Table 4, evaluate the predictive power of past observations across variables.

**Table 4**

Granger causality test result

| Null Hypothesis $H_0$ | Lag | F-Statistic | p-value | Decision ($\alpha = 0.05$) |
|---|---|---|---|---|
| BTM does not Granger-cause BTMP | 1 | 5.421 | 0.0221 | Reject $H_0$ |
| BTM does not Granger-cause BTMP | 2 | 11.234 | 0.0000 | Reject $H_0$ |
| BTMP does not Granger-cause BTM | 1 | 0.941 | 0.3342 | Fail to Reject |
| BTMP does not Granger-cause BTM | 2 | 1.372 | 0.2593 | Fail to Reject |

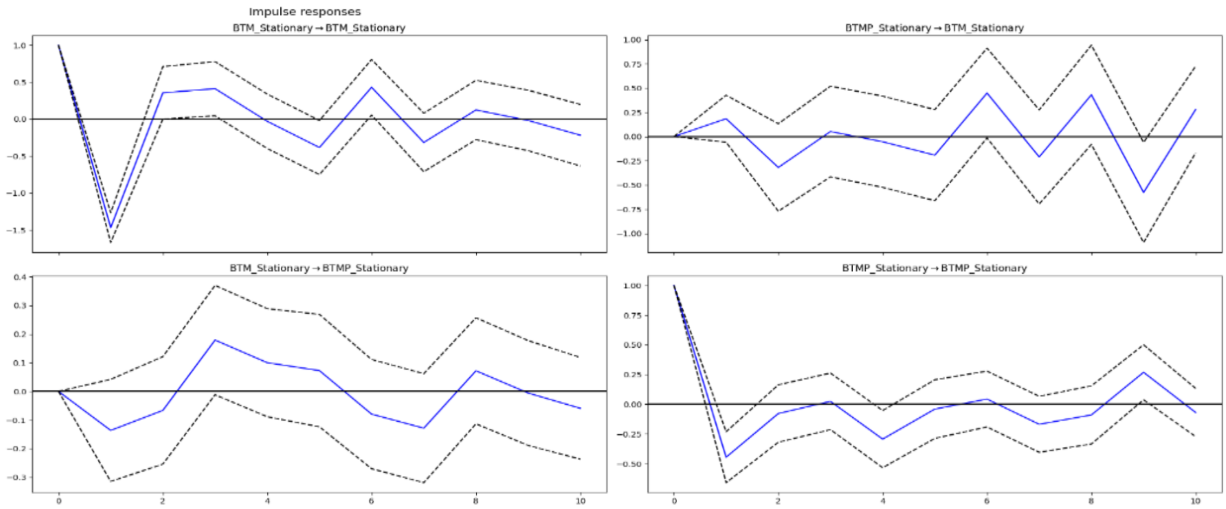
**Source**: result from Python data analysis

Granger causality tests establish a unidirectional relationship from BTM to BTMP, identifying BTM as a leading indicator. With a p-value below 0.001 (p-value = 0.000) at the second lag, past BTM sales contain predictive information for future BTMP trajectories, while the reverse does not hold (p = 0.2593), confirming that pure bitumen does not predict BTM.

The Impulse Response Functions (Figure 5) confirm these findings. A one-standard-deviation shock to BTM produces a positive response in BTMP that peaks around the second month and fades over several periods. In contrast, BTM sales remain largely unresponsive to shocks in the BTMP segment.

**Figure 5**

Impulse Response Functions from the optimized VAR(2) model




**Source**: result from Python data analysis

The Forecast Error Variance Decomposition confirms a unidirectional dependency between the two series over a 12-month horizon. While BTM remains almost entirely exogenous, with approximately 98.25% of its forecast error variance explained by its own internal shocks, BTMP demonstrates increasing endogeneity, with nearly 30% of its variance attributable to innovations in the broader BTM market.

### 3.6 Forecasting

The fitted SARIMA and ARIMA models were used to generate out-of-sample forecasts for a 12-month horizon. The projected volumetric demands are listed in Table 5.

**Table 5**

12-Month Projected Volumetric Demands (2019)

| Series | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sept | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| BTM | 23017 | 23738 | 25882 | 26800 | 26959 | 27362 | 26504 | 26200 | 21140 | 19448 | 25686 | 22231 |
| BTMP | 23617 | 26398 | 23649 | 27368 | 27543 | 27717 | 27891 | 28065 | 28239 | 28413 | 28588 | 28762 |

**Source**: result from Python data analysis

The 2019 forecasts indicate that bitumen (BTM) will continue its established seasonal patterns with a mid-year peak, while Pure Bitumen (BTMP) is projected to follow a steady upward linear growth trend.

## 3. Discussion

The results carry practical weight beyond their statistical properties. Taken together, they paint a coherent picture of how bitumen demand behaves in Algeria, one that is structurally seasonal, causally linked across product segments, and reassuringly stable in its variance. Each of these findings has direct implications for how NAFTAL plans, procures, and manages inventory.

The strong performance of the SARIMA framework confirms what several comparative studies have found in adjacent commodity contexts: when a series has a stable seasonal structure and a clear autoregressive memory, a well-specified univariate model is hard to beat. Li et al. (2024) documented this pattern for crude oil basis volatility, noting that the lower estimation error of parsimonious models often offsets any informational advantage multivariate systems might theoretically provide. Rangga et al. (2024) reached similar conclusions for oil production forecasting. The BTM and BTMP series fit this profile well. Seasonal differencing was necessary, and the high-order MA components reflect the lumpy, project-driven rhythm of Algerian road construction, paving schedules that compress into weather-permissible windows, and then go quiet. A model that captures this structure does not need additional variables to forecast accurately; the history of the series itself carries most of the relevant signal.

The VAR results complicate the picture in a useful way. Standard and pure bitumen sales are not independent. Granger causality runs from BTM to BTMP ($p < 0.001$), and the lag structure suggests that BTM movements lead BTMP by roughly two months. This makes sense operationally: large national highway projects, which consume standard bitumen in bulk, are awarded and mobilized before specialized applications requiring pure bitumen begin. The aggregate market effectively announces what the specialized segment will need. For procurement planning, this means NAFTAL does not need to treat BTM and BTMP inventories as separate problems.

The ARCH-LM diagnostics are perhaps the most operationally reassuring findings in this study. Both series return p-values well above conventional significance thresholds (0.74 for BTM, 0.67 for BTMP), confirming that demand shocks are homoscedastic, their variance does not cluster or escalate following large disturbances. This stands in contrast to what one might expect from a commodity market exposed to oil price fluctuations and project-cycle uncertainty. The implication is that the forecast error bounds produced by the SARIMA models are reliable across the planning horizon, not just near the estimation sample. Budget allocations and inventory targets built on these forecasts do not require additional buffers for volatility risk.

NAFTAL's 250 billion dinar expansion plan and Africa's growing bitumen market leave little room for reactive procurement in the future. Decisions regarding import contracts, storage, and refinery output have to be made before demand peaks, not after. These forecasts, imperfect like any model, at least reflect how these specific series actually behave, which puts them ahead of planning done on instinct alone.

## 4. Conclusion

These findings demonstrate the complementary roles of univariate and multivariate approaches. The univariate models provided the predictive accuracy needed for operational planning, while the VAR model showed that NAFTAL could use aggregate BTM trends to anticipate pure bitumen demand roughly two months ahead.

Several policy and management implications follow for NAFTAL. Given the projected growth in demand and identified seasonal peaks, BTM trends should serve as a primary reference when planning BTMP inventory levels. To guard against supply shortages during peak paving periods, NAFTAL should develop international import arrangements to bridge domestic refinery shortfalls. In addition, forecasted demand peaks should be used to schedule production, refinery orders, and logistics ahead of time, before seasonal tightness translates into higher ordering and transport costs.

Despite the strength of the empirical strategy, certain limitations remain. The data ended in 2018; updating the models with more recent data could capture post-pandemic structural changes and the bivariate VAR omits macroeconomic drivers such as infrastructure spending or real oil prices.

Future work should focus on expanding this variable framework. Incorporating macroeconomic covariates into a VAR-X or VECM framework, where cointegration exists, is a natural next step. Combining SARIMA with machine learning methods could also improve forecasting accuracy as construction and energy markets become increasingly complex.

**Author's Contributions:** Equal contribution of all to authors.

**Data availability:** The datasets supporting these findings are available from the corresponding author upon reasonable request, Yet the python scripts handling the analysis were made publicly accessible on the GitHub repository at https://github.com/YossoufBouzir/SARIMA-VAR-ARCH-LM-MODELING

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# Appendix A

**Table 1.** ANOVA test for BTM vs BTMP

| Product | F-Statistic | p-value | Significant (alpha=0.05) |
|---|---|---|---|
| Bitumen (BTM) | 24.73896089 | 0.000 | Yes |
| Pure Bitumen (BTMP) | 20.30877217 | 0.000 | Yes |

**Figure 2.** ADF test on raw series BTM and BTMP

```
--- ADF Test for Raw Bitumen (BTM) ---
Augmented Dickey-Fuller Test for: Raw BTM
ADF Statistic: -2.4099
p-value: 0.1390
Critical Values:
   1%: -3.5019
   5%: -2.8928
   10%: -2.5835
Result: The series is non-stationary (fail to reject H0)

--- ADF Test for Raw Pure Bitumen (BTMP) ---
Augmented Dickey-Fuller Test for: Raw BTMP
ADF Statistic: -0.2285
p-value: 0.9350
Critical Values:
   1%: -3.4996
   5%: -2.8918
   10%: -2.5829
Result: The series is non-stationary (fail to reject H0)
```

**Figure 3.** ADF test on stationarized series DBTMSA AND BTMPSAT

```
--- ADF Test for Stationarized Bitumen (DBTMSA) ---
Augmented Dickey-Fuller Test for: Stationarized DBTMSA
ADF Statistic: -16.8059
p-value: 0.0000
Critical Values:
   1%: -3.5019
   5%: -2.8928
   10%: -2.5835
Result: The series is stationary (reject H0)

--- ADF Test for Stationarized Pure Bitumen (BTMPSAT) ---
Augmented Dickey-Fuller Test for: BTMPSAT
ADF Statistic: -7.4263
p-value: 0.0000
Critical Values:
   1%: -3.4996
   5%: -2.8918
   10%: -2.5829
Result: The series is stationary (reject H0)
```

# Appendix A

**Figure 6.** Multivariate Vector Autoregression (VAR) Estimation Results

STRATEGIC RESULTS: VAR MODEL PARAMETER ESTIMATES

| | Equation | Variable | Coefficient | Std. Error | t-stat | p-value |
|---|---|---|---|---|---|---|
| 0 | DBTMSA | const | -240.9505 | (469.7184) | -0.5130 | 0.6080 |
| 1 | DBTMSA | L1.DBTMSA | -0.6037*** | (0.1050) | -5.7469 | 0.0000 |
| 2 | DBTMSA | L1.BTMPSAT | 0.1920 | (0.1254) | 1.5313 | 0.1257 |
| 3 | DBTMSA | L2.DBTMSA | -0.2004* | (0.1070) | -1.8737 | 0.0610 |
| 4 | DBTMSA | L2.BTMPSAT | 0.1117 | (0.1244) | 0.8980 | 0.3692 |
| 5 | BTMPSAT | const | 161.2733 | (368.4928) | 0.4377 | 0.6616 |
| 6 | BTMPSAT | L1.DBTMSA | -0.0295 | (0.0824) | -0.3584 | 0.7201 |
| 7 | BTMPSAT | L1.BTMPSAT | -0.1231 | (0.0984) | -1.2508 | 0.2110 |
| 8 | BTMPSAT | L2.DBTMSA | -0.4241*** | (0.0839) | -5.0536 | 0.0000 |
| 9 | BTMPSAT | L2.BTMPSAT | -0.0761 | (0.0976) | -0.7800 | 0.4354 |

MODEL SELECTION CRITERIA AND DIAGNOSTICS

| Metric | Value |
|---|---|
| Log Likelihood | -1800.514 |
| AIC | 33.260 |
| BIC | 33.532 |
| HQIC | 33.370 |
| FPE | 2.784e+14 |
| Observations | 93 |