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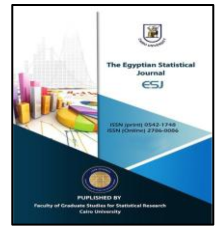

The Impact of Different Integration Methods on Using Hybrid Models in Forecasting Time Series

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Keywords

Time series forecasting, Hybrid Model, ARIMA, SVR, Integration methods, Oil price forecasting.

Abstract

This study evaluated the impact of different integration methods when using hybrid models for time series forecasting, employing monthly global oil price data from January 2004 to December 2023. The research included individual models of Autoregressive Integrated Moving Average (ARIMA) and Support Vector Regression (SVR) and a hybrid model (ARIMA-SVR) utilizing multiple integration techniques (additive, multiplicative, and regression). The results demonstrated the superiority of the additively integrated hybrid model, which achieved the lowest values for forecast accuracy metrics (MAE, MPE, MAPE, and MSE), significantly outperforming the other models. Specifically, this model showed a 46.4% improvement in MAE compared to the ARIMA model and a 29% improvement compared to the SVR model. The regression hybrid model followed in performance, followed by the multiplicatively integrated model, the SVR, and lastly, the ARIMA model. These findings highlight the effectiveness of hybrid models, particularly those with additive integration, in enhancing the forecasting accuracy of complex time series exhibiting both linear and nonlinear patterns. The study recommends exploring more sophisticated integration methods and expanding the scope of applications in future research.

1. Introduction

Forecasting time series data is a prominent area of research due to its extensive applications across various fields, including business, economics, government, social sciences, environmental science, medicine, politics, and finance. This widespread relevance has garnered significant attention. The inherent challenge in forecasting lies in the need to anticipate future events, a crucial element for effective planning and informed decision-making.

Numerous statistical methods are employed for forecasting diverse phenomena. Among these, time series analysis stands out as a key approach. Time series are characterized by continuous fluctuations, exhibiting linear and non-linear patterns. Analyzing such series with a single model, whether linear or non-linear, may not capture the full complexity of their behavior. Consequently, the need has arisen for advanced techniques, leading to the development of the hybrid model.

Many previous studies have harnessed the power of hybrid models to predict various phenomena across a broad spectrum of domains. These studies have consistently demonstrated the effectiveness of hybrid approaches in improving the accuracy of statistical forecasts. For example,

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Xu et al. (2020) employed hybrid models to predict drought rates for water stations in Henan Province, China, achieving superior performance compared to individual ARIMA and SVR models. Similarly, Farghaly, Ali, and El-Hafeez (2020) developed an innovative associative classifier that integrates association rule mining with a Support Vector Machine (SVM) and a Sequential Forward Selection (SFS) feature selection method. Their method focused on reducing the number of classification rules while improving accuracy. They employed the Gini index to select informative attributes and utilized an SFS wrapper approach to identify optimal feature subsets. Results on UCI datasets revealed that this hybrid approach significantly outperformed traditional classification techniques, demonstrating enhanced F-measure, balanced classification rate (BCR), and overall classification accuracy. In addition, the method improved computational efficiency by reducing rule generation, underscoring the value of integrating feature selection with associative rule mining and SVM techniques.

Building on the growing body of research utilizing hybrid models, Lai et al. (2021) compared SVR and ARIMA models with their hybrid counterparts to predict unemployment rates in five developing and five developed countries during the COVID-19 pandemic. Their findings demonstrated the superiority of the hybrid (ARIMA-SVR) model. Similarly, Zheng (2021) also found hybrid models to outperform individual SVR and ARIMA models when predicting daily coal prices at a port in China. Similarly, Nawi et al. (2021) observed a superior performance of hybrid models over single SVR and ARIMA models for predicting sea surface temperatures in the South China Sea.

Beyond time series forecasting, hybrid approaches have shown promise in other domains. Farghaly and Abd El-Hafeez (2022) introduced a novel feature selection method, FS-FAI, for text classification using frequent and associated item sets. This technique leverages association analysis to identify relevant features based on their frequency and relationships with the target variable. Specifically, the Apriori algorithm extracts frequent item sets, followed by pruning based on all-confidence. Experiments conducted on BBC and SMS spam datasets revealed that FS-FAI effectively reduces feature space and improves classification performance, especially when used with Naive Bayes and Random Forest classifiers. By incorporating feature interactions and eliminating redundancy, FS-FAI facilitates the creation of highly accurate text classification models using small feature sets.

Furthermore, Farghaly and Abd El-Hafeez (2023) further developed their feature selection approach, proposing a novel method based on frequent and correlated items (FS-FAI). Their approach utilizes association analysis to discern significant features by assessing relationships between features and the target variable. This method employs the Apriori algorithm for mining frequent item sets, which is also followed by pruning based on all-confidence. Testing on an SMS spam dataset showed that FS-FAI reduced redundant features and achieved high accuracy; the Naive Bayes and Decision Tree classifiers achieved 95.64% and 95.38% accuracy, respectively, while using only approximately 7% of the total features. The proposed methodology thus provides a viable means for improving text classification while increasing computational efficiency.

Kontopoulou et al. (2023) conducted an assessment ARIMA models and machine learning algorithms for time series forecasting, integrating these techniques into hybrid statistical-AI models. These hybrid models were applied to various applications, including finance, health, weather, utilities, and network traffic forecasting. The results generally indicated that AI algorithms provided improved forecasting accuracy compared to traditional statistical approaches.

Zhang and Zhou (2024) proposed a hybrid model, ARIMA-SVR-POT, which combines ARIMA, Support Vector Regression (SVR), and Peak Over Threshold (POT) techniques derived from extreme value theory. They assessed the performance of their hybrid model against three other established models: ARIMA-EGARCH, ARIMA-SVR, and ARIMA-EGARCH-POT. Their investigation, using WTI crude oil futures data from June 23, 2016, to September 30, 2022, demonstrated that the ARIMA-SVR-POT hybrid model accurately predicted returns and volatility.

Similarly, Huang and Li (2024) employed an ARIMA-SVR model to examine aggregated regional financial risk loan data. This approach integrated machine learning techniques within a traditional statistical regression framework. Specifically, they used the ARIMA model to fit the historical data, and the resulting error was then utilized as input for the SVR model to improve the non-linear error prediction. The experimental results showed that the advanced ARIMA-SVR method outperformed individual methods regarding both Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), demonstrating its superiority over the deep learning LSTM method.

Shams et al. (2024) developed an innovative deep-learning model called SACNN for detecting and classifying emergency vehicle sirens and traffic noise from extensive audio datasets. This model integrates the strengths of Efficient Net for feature extraction with One-Dimensional Convolutional Neural Networks (1D-CNN), utilizing a self-attention layer to enhance detection accuracy and efficiency. Experimental results indicated that SACNN outperformed other models, achieving superior scores in accuracy, precision, recall, and F1-score. Furthermore, the model showed computational efficiency, thus making it well-suited for real-time applications. This study provides a promising solution for enhancing traffic management, public safety, and noise pollution monitoring.

Eliwa et al. (2024) introduced an adaptive network-based fuzzy inference system (ANFIS) for forecasting gasoline prices. This study leveraged a comprehensive dataset from the U.S. Energy Information Administration, incorporating previous prices as an additional feature to enhance predictive performance. The ANFIS model demonstrated superior performance compared to traditional time series techniques such as VAR and ARIMA, achieving a score of 0.9970 and a correlation coefficient of 0.9985, which indicates a high level of accuracy and a strong positive relationship between predicted and actual values. The study also provided insights into the membership functions employed in the ANFIS model, visually demonstrating how input variables, including day, month, year, and previous price, are mapped to linguistic terms and fuzzy sets. These findings underscore the ANFIS model's potential as a robust and accurate method for gasoline price forecasting.

Mostafa et al. (2024a) conducted a scoping review exploring the role of deep learning in simplifying feature selection for hepatocellular carcinoma (HCC). Their review analyzed various studies that employed deep learning algorithms for HCC prediction, emphasizing methodologies, datasets, and performance metrics. Key findings highlighted the potential of techniques including (CNNs and RNNs) to enhance predictive accuracy and robustness while automating feature extraction. Additionally, the review addressed challenges related to data requirements, interpretability, and generalizability of deep learning models in medical applications. Furthermore, the study explored the importance of multimodal integration and ethical considerations for translating deep learning applications into clinical practice.

A recent study by Mostafa et al. (2024b) investigated the impact of feature reduction techniques on machine learning models for hepatocellular carcinoma (HCC) prediction. The researchers utilized clinical data from the TCGA-LIHC dataset, employing methods like feature weighting, hidden feature correlation, and optimized selection to reduce data dimensionality. The study compared several algorithms, including Naive Bayes, Neural Networks, Decision Tree, SVM, and KNN, both before and after feature reduction. Results indicated that feature reduction significantly improved both the accuracy and execution time of the models, highlighting the importance of preprocessing data for medical prediction tasks. These findings suggest that an emphasis on optimal feature selection could enhance model efficiency for HCC diagnosis and treatment planning.

Lastly, El Koshiry (2024) investigated university ranking data from the QS World University Ranking, analyzing 4220 institutions and 25 attributes. The study examined the global distribution of universities, their size, research activity, and status, revealing that Europe is the continent with the most represented institutions. Linear regression and exponential smoothing techniques were then applied to project future university numbers across continents. The findings identified significant correlations between academic reputation, employer reputation, faculty citations, and overall scores. Machine learning algorithms, specifically random forest, and gradient boosting showed superior performance in predicting university rankings based on input parameters. These findings contribute valuable insights into global higher education trends and provide a framework for anticipating future shifts in the academic landscape.

Prior studies share a common thread in their application of diverse machine learning and artificial intelligence techniques, such as neural networks, support vector machines, association analysis, and time-series forecasting, to enhance performance across diverse domains. These domains range from acoustic pattern recognition and oil price prediction to text classification, feature selection, and cancer prognosis. These research endeavors underscore the significance of feature selection and the integration of hybrid models in achieving superior accuracy and efficiency in varied analytical tasks, thereby providing a robust foundation for the present study.

The distinctiveness of this research lies in its specific focus on integrating two models, ARIMA and SVR, to construct hybrid models, instead of analyzing them in isolation as is done in many other studies. Furthermore, this study compares different integration methods such as additive, multiplicative, and regression to determine the optimal approach for modeling global oil price data. Performance assessment is conducted using multiple metrics, leading to the formulation of practical recommendations for enhancing forecasting.

This systematic approach, centered on model integration and analyzing results within a specific context, differentiates the present study from others that often adopt a broader scope or concentrate on individual models.

2. Methodology

In this research, we focus on the individual models SVR and ARIMA, as well as the hybrid model "ARIMA - SVR". Here's a description of each model:

2.1 Autoregressive Integrated Moving Average (ARIMA) Model

The ARIMA model is generated by combining the autoregressive model AR(p) and the moving average model MA(q) after taking the necessary differences to make the time series stationary. This model is represented by ARIMA (p, d, q) (Box – Jenkins; 1970).

$$y_t = \emptyset_0 + \emptyset_1 \, y_{t-1} + \cdots \ldots + \emptyset_p \, y_{t-p} + e_t - \theta_1 e_{t-1} \ldots . -\theta_q e_{t-q} \qquad (1)$$

where;

$\emptyset_1, \emptyset_2 \ldots \ldots, \emptyset_p$: represent the parameters of the autoregressive model.

p: is the order of the autoregressive model.

$\theta_1, \theta_2 \ldots .. \theta_q$:represent the parameters of the moving average model.

q: is the order of the moving average.

e_t :represents the random error.

When the time series is non-stationary, it can be transformed into a stationary series by taking differences of order (d). In this case, the ARIMA model is denoted as ARIMA (p, d, q), and its equation is written as:

$$\emptyset_p(B)\nabla^d_{y_t=\theta_q(B)e_t} \tag{2}$$

$$\emptyset_p(B)(1-B)^d y_t = \theta_q(B)e_t \tag{3}$$

where;

d: denotes the differencing order for achieving stationarity in the time series.

B: denotes the backward shift operator.

Box-Jenkins Methodology:

The Box-Jenkins methodology consists of four main stages for obtaining the optimal model for forecasting the studied time series:

2.1.1 Identification

During this phase, we identify the model parameters p, d, and q. The Dickey-Fuller and Phillips-Perron tests are used to determine the value of d, which represents the number of differences needed to achieve stationarity in the time series. The p and q values are established through the autocorrelation function (ACF), partial autocorrelation function (PACF), and the Akaike information criterion (AIC). The AIC is computed to determine the model order, p, and q, in the following manner:

$$AIC = n\,Ln\,(\hat{\sigma}^2 n) + 2m \tag{4}$$

where;
m: Number of model parameters.
n: Number of observations.
$\widehat{\sigma}^2_n$: Variance of the residuals.

Schwarz Criterion (BIC)

Also known as the Bayesian Information Criterion (BIC), it is calculated as follows:

$$\mathrm{Bic(m)} = \mathrm{n\,Ln}\,(\widehat{\sigma}^2_n) + \mathrm{m\,Ln}\,(\mathrm{n}) \tag{5}$$

Therefore, the best model has the lowest BIC(m) and AIC(m) values.

2.1.2 Estimation

After identifying the proposed model to represent the time series data, the model parameters are estimated. There are several methods for parameter estimation, with the most important ones being the Maximum Likelihood method and the Ordinary Least Squares method.

2.1.3 Diagnostic

After identifying and estimating the proposed model to represent the time series data, the suitability of the model for the data is determined by analyzing the residuals obtained from applying the model. The residuals should be randomly distributed, and this is assessed based on the assumptions:

$$H_0: \rho = 0$$
$$H_1: \rho \neq 0$$

Two tests are used to assess how well the model fits the data:

Confidence Interval Test:

If the autocorrelation coefficient of the residuals $r_k\,(e_t)$ falls within the confidence interval with a probability of 95%.

$$-1.96\frac{1}{\sqrt{n}} \leq r_k(e_t) \leq 1.96\ \frac{1}{\sqrt{n}}$$

The errors are normally distributed, and the model is a good fit for the data.

Ljung – Box (Q) statistic:

- The test is done as follows:

H_0: The data fits the model.

H_1: The data does not fit the model.

Test statistic:

$$Q_m = n(n+2)\sum_{k=1}^{m}\frac{r_k^2(e)}{n-k} \tag{6}$$

$r_k(e)$: The autocorrelation coefficient for the residuals at lag (k).

n: represents the number of errors.

m: denotes the number of lag periods.

If the P-value < α, then the model is unfit for the data, and thus another model should be chosen.

2.1.4 Forecasting

Forecasting is the final stage of Box-Jenkins models and represents the primary objective of model building.

2.2 Support Vector Regression Model (SVR)

The Support Vector Regression (SVR) model is a powerful tool for data analysis and forecasting, notable for its high capability in handling non-linear data. SVR has been widely used for time series forecasting involving non-linear patterns, such as financial and economic data. The SVR model works by classifying and separating input data using an optimal hyperplane, regardless of whether the data is linearly separable (Cao and Tay, 2003).

$$f(x, w) = w^t\varphi(x_i) + b \tag{7}$$

where;

w: is the regression coefficients vector.

$\varphi(x_i)$: plots in a space with multiple dimensions.

b: is the bias term, and the prediction error is made using the loss function f(x). (Rosenbaum et al; 2013)

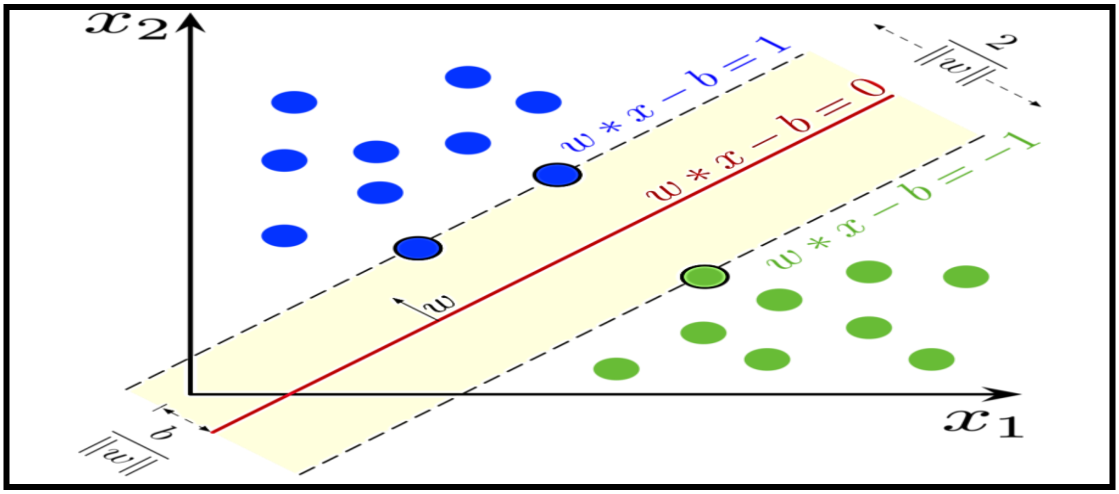

Figure 1. The algorithm of Support Vector Regression (SVR)

One of the primary objectives of the Support Vector Regression (SVR) model is prediction and classification. The concept is based on having two different datasets that can be separated using several lines. To find the optimal hyperplane, the distance between the closest point in the first group and the closest point in the second group should be maximized. These points are called "support vectors" or decision boundaries. The larger the distance between the nearest points in both groups, the more accurate the classification of new observations will be. The following equation represents the loss function.

$$\mathrm{L}(\mathrm{y}, \mathrm{f}(\mathrm{w}, \mathrm{x})) = \begin{cases} 0 & |\mathrm{f}| y_i - f(w, x)| \leq \epsilon \\ |y_i - f(w, x)| - \epsilon & otherwise \end{cases}$$

The point of using SVR is to find the function f (w, x) that agrees with the deviation ϵ for all training data in the prediction model. The problem is formulated as follows:

$$\text{Minimize: } \frac{1}{2} \; \|w\|^2$$

$$\text{Subject to } \begin{cases} y_i - f(x_i, w) - b \leq \epsilon + \delta_i \\ f\;(x_i, w) + b - y_i \leq \epsilon + \delta_i \end{cases}$$

Sometimes it is infeasible to predict all training data within the deviation ϵ. Therefore, slack variables are introduced. Consequently, the problem is reformulated as follows:

$$\text{Minimize: } \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} (\delta_i + \delta_i^*)$$

$$\text{Subject to } \begin{cases} y_i - f(x_i, w) - b \leq \epsilon + \delta_i^* \\ f(x_i, w) + b - y_i \leq \epsilon + \delta_i \end{cases}$$

$$\delta_i^*, \delta_i \geq 0$$

where;

C: is the regularization parameter, where C > 0, also known as the regularization term.

δ_i^*, δ_i: are variables that measure deviations larger than ϵ.

The Lagrange equation is used to solve the problem as follows:

$$f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*)\varphi(x_i, x) + b \quad (8)$$

where;
$(\alpha_i - \alpha_i^*)$: Lagrange multipliers.
and by using the kernel function, the solution becomes

$$f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*)k(x_i, x) + b \quad (9)$$

where;

$k(x_i, x)$: This function is known as Kernel, and it is used when linear separation of data is challenging. The data is transformed from the original domain to a high-dimensional space, allowing for better data separation. (Cosgun et al.; 2011).

2.3 Hybrid Model

The time series is assumed to be as follows:

$$y_t = L_t + N_t \quad (10)$$

where;
L_t: The time series' linear element.
N_t: The time series' nonlinear component.
The merging process is carried out in various ways:

2.3.1 Additive Hybrid Model (ARIMA-SVR)

The construction of the hybrid model follows these steps (Zhang, 2003):

1. Building the ARIMA model starting from the identification phase to prediction.
2. Obtaining the forecasted values from ARIMA to represent the linear part ($\hat{L}_t$).
3. Constructing the SVR model to model the residuals resulting from ARIMA.
4. Obtaining the forecasted values from the SVR model to represent the non-linear part ($\hat{N}_t$).
5. The hybrid model is as follows:

$$\hat{y}_t = \hat{L}_t + \hat{N}_t$$

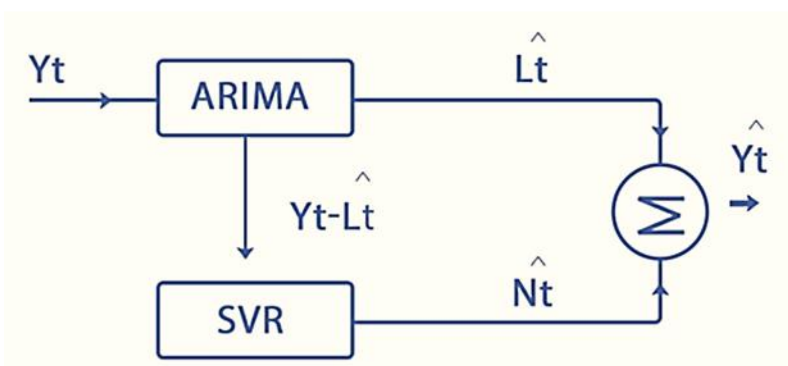

Figure 2. The additive hybrid model

Source: Prepared by the author.

2.3.2 Multiplicative Hybrid Model (ARIMA – SVR)

The multiplicative hybrid model (Wang et al; 2013) (Alsuwaylimi;2023). assumes that the series consists of two parts, linear and nonlinear, as shown in the following figure:

$$y_t = L_t \, . N_t$$

1. Obtaining the predicted values from ARIMA to represent the linear part ($\hat{L}_t$).
2. The nonlinear part is obtained as follows:

$$n_t = y_t / \hat{L}_t$$

3. It is estimated by using an SVR model to obtain ($\hat{N}_t$) to represent the nonlinear part.
4. The hybrid model is in the figure:

$$\hat{y}_t = \hat{L}_t \, . \hat{N}_t$$

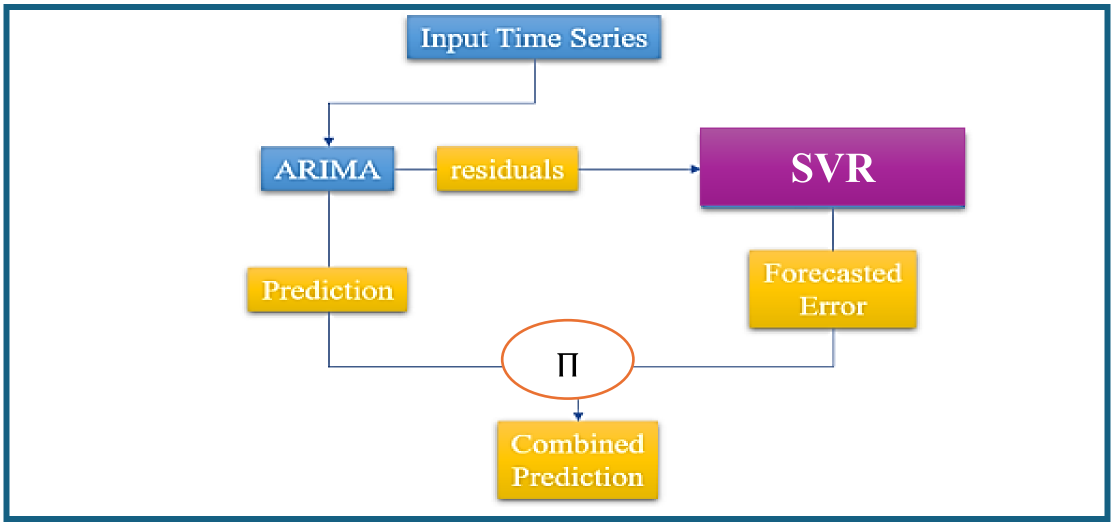

Figure 3. Multiplicative hybrid model

Source: Prepared by the author.

2.3.3 Hybrid regression model (ARIMA – SVR)

The hybrid model is built by utilizing the forecasted values generated by the ARIMA model and SVR as individual models, forming a multiple linear regression model to determine the integration weights as follows: (Watchareeporn & Chutatip; 2010)

$$y_t = \beta_0 + \beta_1 F_{ARIMA} + \beta_2 F_{SVR}$$

where;

y_t: Actual data (dependent variable).

F_{ARIMA}: Predicted values from the ARIMA model.

F_{SVR}: Predicted values from the SVR model.

β_1: First linear regression coefficient (first weight).

β_2: Second linear regression coefficient (second weight).

Considering $\beta_0 = 0$, the regression model will consist of the dependent variable being the real values of global oil prices and the independent variables being the predictions resulting from using SVR and ARIMA.

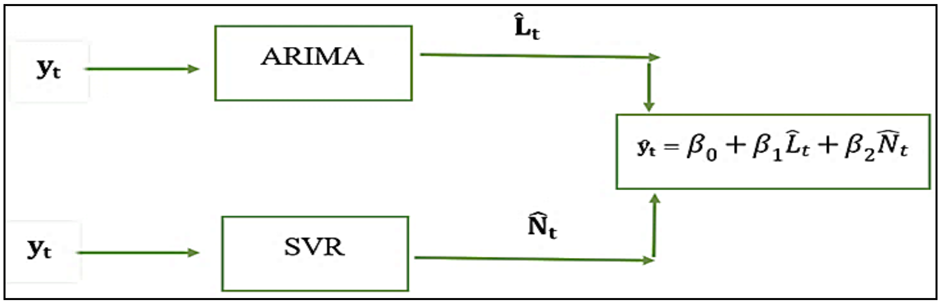

Figure 4. Hybrid regression model

Source: Prepared by the author.

2.4 Model Accuracy Efficiency Metrics

The efficiency of the performance of the models is measured to test the best model according to several statistical criteria (Wei, 2006), which are:

1. **Mean square error (MSE):**

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2$$

2. **Mean absolute percentage error:**

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|y_t - \hat{y}_t|}{y_t} \times 100$$

3. **Mean Absolute error:**

$$MAE = \sum_{t=1}^{n}\frac{|y_t - \hat{y}_t|}{n}$$

3. Applied Study

This study aims to forecast time series using individual models SVR and ARIMA, as well as the hybrid model "ARIMA – SVR" through different integration methods, applied to global oil price data from January 2004 to December 2023. The data used compares monthly observations totaling 240 data points, with 216 data points used as the training set, representing 90% of the total data, and the remaining 24 data points used as the test set, representing 10% of the total data. The study seeks to compare actual and predicted values to assess the model's forecasting capability.

The software programs EViews 12, Stat Graphic 19, and Python were utilized to analyze the time series data of global oil prices. We begin by conducting descriptive statistics for both the training and test sets as follows:

Table 1. Descriptive Statistics

Statistics	Value (Training)	Value (Test)
N	216	24
Mean	88.27	86.20
Median	63.83	83.7
Min.	16.6	70.25
Max.	133.8	114.8
Standard Division	22.47	12.83
Kurtosis	-0.44	-0.19
Skewness	0.45	0.86

This dataset analysis presented in Table (1) provides a comprehensive overview of the descriptive statistics for both the test and training values. Descriptive statistics serve as a fundamental tool in data analysis, offering insights into the central tendency, dispersion, and shape of data distribution. In this context, the dataset comprises two sets of values: the test values, with a mean of 86.20 and a median of 83.7, and the training values, which exhibit a higher mean of 88.27 and a median of 63.83. The range of values is notable, with the test set spanning from a minimum of 70.25 to a maximum of 114.8, while the training set ranges from 16.6 to 133.8.

Furthermore, the standard deviation indicates variability within each dataset, with the test values showing a standard deviation of 12.83 and the training values at 22.47, suggesting greater dispersion in the training data. The kurtosis values, recorded at 0.19 for the test and 0.44 for the training set, along with skewness values of 0.86 and 0.45 respectively, provide additional context regarding the distribution's peakness and asymmetry.

This descriptive framework lays the groundwork for further statistical analysis and interpretation, enabling researchers to draw meaningful conclusions from the observed data patterns. By understanding these basic measures, one can deepen their understanding of the fundamental characteristics of the data before proceeding to more complex analysis.

3.1 Autoregressive Integrated Moving Average (ARIMA) Model

To construct a better model for forecasting and estimating its parameters and to ensure the model's suitability for time series data of global oil prices, it is necessary to analyze the series according to the following steps:

3.1.1 Time Series Stationarity

Stationarity stands as a key concept in the analysis of time series data. The Box-Jenkins methodology can only be used if the analyzed time series is stationary. Checking the reliability of the time series is the initial step that must be examined. Hence, before implementing the method, the data needs to be ready to guarantee the time series' stability. The stability of a series can be visually assessed by examining the original plot and the plots of the autocorrelation function (ACF) and partial autocorrelation function (PACF). Additional statistical techniques like the ADF and KPSS tests can also be employed for this objective.

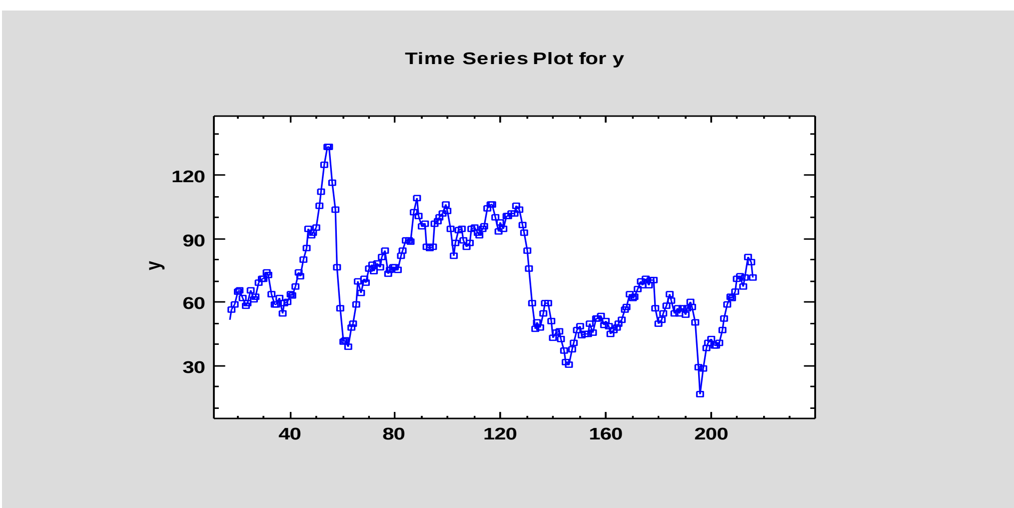

Figure 5. Time Series of Global Oil Prices

From Figure (5), we observed that there is no general trend in the time series of global oil prices, indicating that the series is stable over time. This stability is further confirmed by the shapes of both the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF)

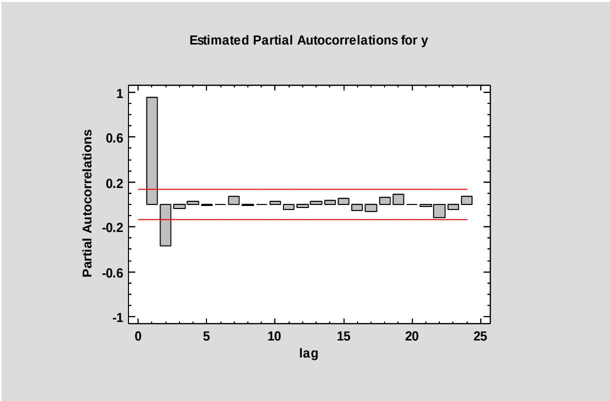

Figure 6. PACF

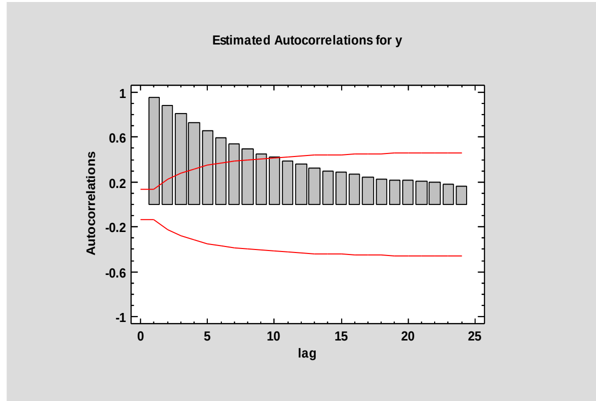

Figure 7. ACF

The initial phase of constructing the ARIMA model involves analyzing the shape of the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF). From Figures (2) and (3), it is observed that the ACF values are significant for many lags, and the series does not decay slowly. This indicates that the series is stable at its original level, i.e., it is integrated of order zero, I(0). To further validate the stability of the time series, unit root tests (ADF, PP, KPSS) were conducted, and the results are as follows:

Table 2. unit root tests

Test	Value	P – value	I (d)
ADF	-3.28	0.016	I (0)
PP	-2.86	0.04	I (0)
KPSS	0.344	0.344	I (0)

From Table (2), we observe that in both the ADF and PP tests, the p-value is lower than the significance threshold of 0.05. Therefore, we dismiss the null hypothesis and embrace the alternative hypothesis regarding the time series of global oil prices as stable at its original level. On the other hand, in the KPSS test, the p-value is greater than 0.05, leading to the acceptance of the null hypothesis that the series is stable at its original level, I (0).

3.1.2 Model Estimation

After confirming the stationarity of the time series for global oil prices at the original level and observing the autocorrelation function, the proposed model is ARIMA (2,0,0), and its equation is written as follows:

$$y_t = \mu + \emptyset\, y_{t-1} + \emptyset\, y_{t-2} + e_t$$

To find the best model for the time series, we compare the proposed model with several other models to determine the most appropriate model for the data. The model with the lowest values for the following statistical measures is considered the best:

Table 3. Comparison of Candidate Models

Model	AIC	BIC	HQC
ARIMA (2,0,0)	3.4497	3.4966	3.4686
ARIMA (2,0,1)	3.4609	3.5223	3.48617
ARIMA (2,0,2)	3.471	3.5491	3.5029
ARIMA (1,1,0)	3.4729	3.4988	3.4790

Based on Table (3), the best model is ARIMA (2,0,0) as it has the lowest values for all statistical criteria.

Table 4. Estimation of the Proposed ARIMA (2,0,0) Model

Parameter	Estimate	St. error	P – value
AR (1)	1.3157	0.0625	0.000
AR (2)	-0.36898	0.0624	0.000
Mean	68.6703	6.4203	0.000
Constant	3.6585		

Therefore, the equation for the model is as follows:

$$\hat{y}_t = 3.65857 + 1.31571 y_{t-1} - 0.368983 y_{t-2}$$

3.1.3 Model Diagnosis

After estimating the model parameters and determining their order, it is essential to verify the model's adequacy and efficiency. This is done by calculating the residuals' autocorrelation coefficients and conducting the following tests:

Ljung-Box Test:

The results of the test were as follows:

Table 5. Ljung – Box

Test	Statistics (Q)	P – value
Ljung – Box	15.778	0.826

From Table (5), we noticed that the p-value for the test is greater than 0.05. Therefore, we accept the null hypothesis $H_0: \rho_i(e_t) = 0$, indicating that the errors are random and uncorrelated. Consequently, the model is adequate and efficient for representing the time series of global oil prices.

Residual Test:

When graphing the autocorrelation and partial autocorrelation coefficients of the residuals, we observe that all autocorrelation values fall within the 95% confidence interval. This indicates that the residual series consists of uncorrelated random variables, suggesting that the model used is appropriate and accurately represents the data.

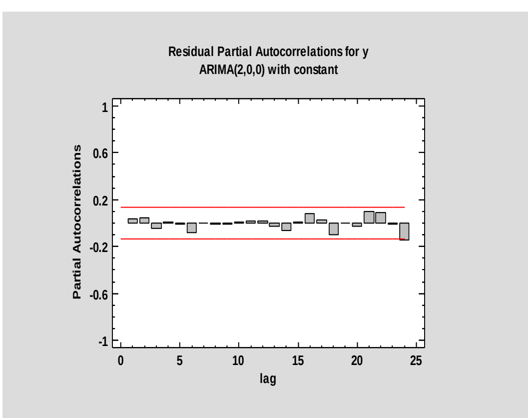

Figure 8. PACF of the Residuals

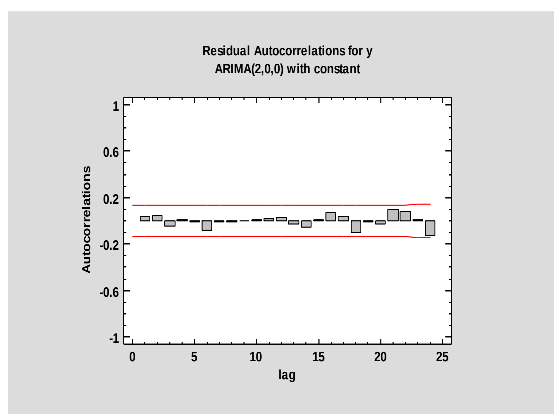

Figure 9. ACF of the Residuals

3.1.4 Forecasting

After the model passed the diagnostic tests, confirming its suitability for predicting global oil prices for 24 observations, which constitute the test set, the prediction results are shown in Table (11). The following figure illustrates the estimated and actual values for the ARIMA (2,0,0) model.

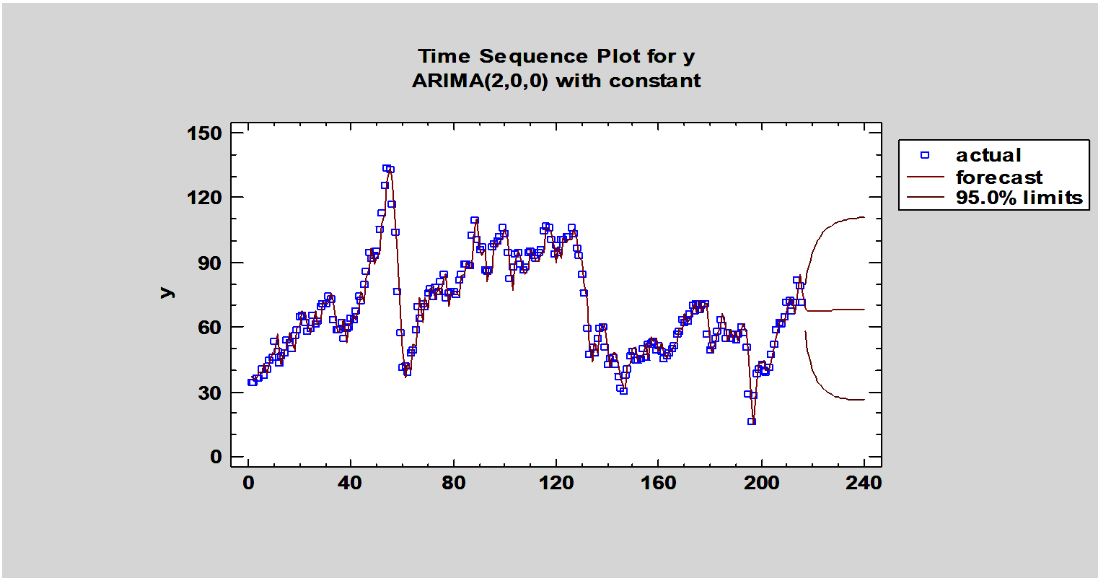

Figure 10. Plot of Estimated and Actual Values for ARIMA (2,0,0)

From Figure (10), it is observed that the performance of the ARIMA model in the forecasting process is unsatisfactory for monthly global oil prices.

3.2 Estimating the Support Vector Regression (SVR) Model

To estimate the Support Vector Regression (SVR) model for the global oil prices series, the data was divided into two groups: a training set consisting of 90% of the total data, which includes 216 observations, and a test set comprising 10% of the total data, which includes 24 observations. To estimate the model, the appropriate "Kernel" function must first be determined as follows:

Table 6. Types of Kernel Functions

Measure	Linear	Polynomial	RBF	Sigmoid
MSE	0.0000004	409.4	57.5	197.5
R^2(Training)	100%	18.58%	88.5%	60.6%

Based on Table (6), the linear Kernel function was selected for predicting global oil prices due to its lowest mean squared error and highest coefficient of determination (R-squared) for the training set. After applying several trial tests on the training data, C=1.0 and ε=0.1 were identified as the optimal parameters, providing the lowest mean squared error values. These parameters were employed to train the model, and predictions were made for the test set comprising 24 observations from January 2022 to December 2023 using Stat Graphics 19 software. The predicted values are shown alongside those from other models in Table (11).

Comparing actual and predicted values using the SVR model, it was observed that the SVR model outperformed the ARIMA model in terms of forecasting accuracy. This is proven by the strong correlation between the estimated and actual values, as depicted in the subsequent figure.

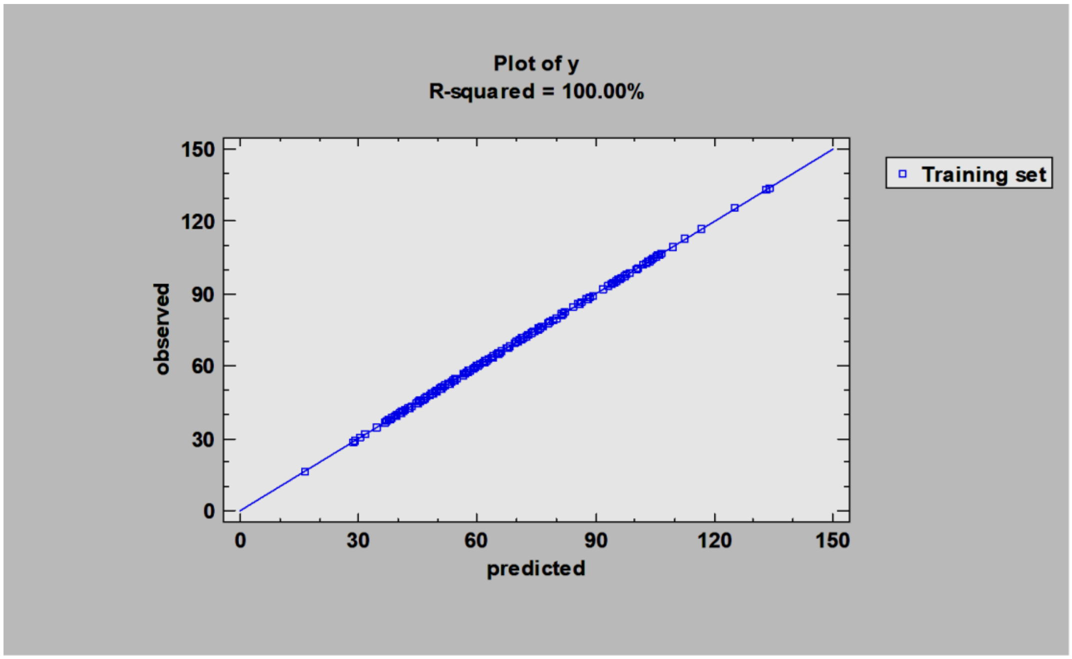

Figure 11. Estimated and Actual Values for the SVR Model

To test the adequacy of the model for monthly time series data of global oil prices using the Ljung-Box test, the results are as follows:

Table 7. Ljung-Box Test

Test	Q	P – value
Ljung – Box	11.32	0.713

The results of the Ljung-Box test indicated a p-value of 0.713, which is greater than 0.05. Consequently, we accept the null hypothesis that the errors are random and uncorrelated, confirming that the model is adequate and efficient for representing the monthly time series of global oil prices. Additionally, we observed that the autocorrelation coefficients fall within the 95% confidence interval and there is no autocorrelation among the residuals. This further supports the quality of the SVR model.

3.3 Estimation of the Hybrid Model (ARIMA-SVR)

To estimate the hybrid model (ARIMA-SVR), different integration methods are employed. These include the additive and multiplicative hybrid models and the regression hybrid model. These methods are utilized to determine the most appropriate model for oil price data.

3.3.1 The Additive Hybrid Model (ARIMA-SVR)

To estimate the hybrid model, estimated values from the ARIMA model representing the linear part of the series ($\hat{L}_t$) are obtained. Then, an SVR model is constructed based on the residuals from ARIMA, and the predicted values from the SVR model represent the nonlinear part ($\hat{N}_t$). Thus, the hybrid model series is obtained as follows:

$$\hat{y}_t = \hat{L}_t + \hat{N}_t$$

Then, the hybrid model is used to forecast 24 observations, which constitute the test set, as illustrated in Table (12). By comparing the predicted values with the actual ones using the hybrid model, we noticed a strong convergence between them. This is evident in Figure (12), indicating a significant improvement in the performance and predictive ability of the hybrid model for monthly global oil prices.

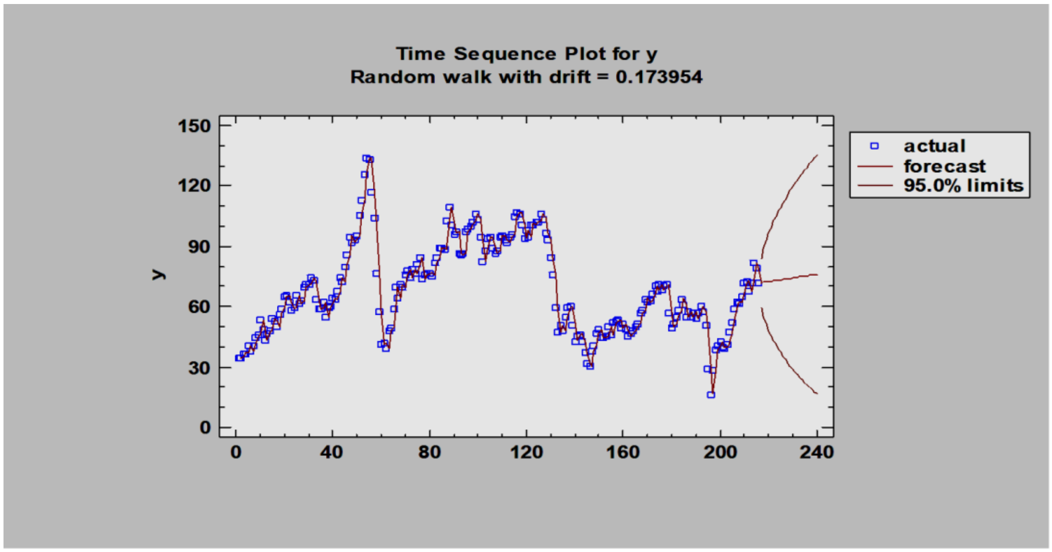

Figure 12. Actual and Estimated Values using the Additive Hybrid Model (ARIMA-SVR)

To verify the adequacy of the model for the global oil price time series data, the Ljung-Box test was conducted with the following results:

Table 8. Ljung-Box Test

Test	Q	P – value
Ljung – Box	10.13	0.297

As the p-value equals 0.297, we accept the null hypothesis, implying that the additive hybrid model is suitable for representing the monthly time series of global oil prices.

3.3.2 The Multiplicative Hybrid Model (ARIMA-SVR)

This model assumes that the series is composed of a multiplicative product of two components: one linear and the other nonlinear, as follows:

$$y_t = l_t \,.\, N_t$$

The estimated values of the ARIMA model represent the linear part of the series $(\hat{L}_t)$By dividing the actual values of the series by the linear part, we obtain the values of the nonlinear part, which are then input into the SVR model. By obtaining the estimates of the values from the SVR model to represent the nonlinear part $(\widehat{N}_t)$, the new hybrid model becomes:

$$\hat{y}_t = \hat{L}_t \,.\, \widehat{N}_t$$

Using the hybrid model to forecast a set of 24 test observations yielded results as shown in Table (12). It is noticeable that there is an enhancement in the multiplicative hybrid model's ability to forecast monthly global oil prices, as depicted in Figure (13).

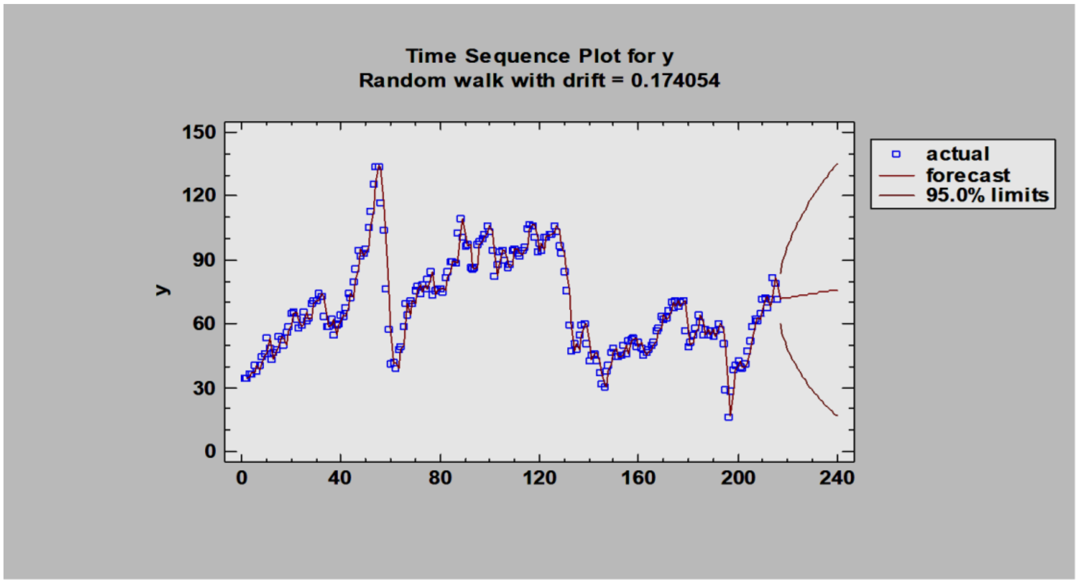

Figure 13. Actual and Estimated Values using the Multiplicative Hybrid Model (ARIMA-SVR)

By conducting the Ljung-Box test to verify the adequacy and suitability of the model for representing the global oil price time series, the results were as follows:

Table 9. Ljung-Box Test

Test	Q	P – value
Ljung – Box	13.20	0.651

It is observed that the p-value is greater than 0.05, thus accepting the null hypothesis that the multiplicative hybrid model is valid and efficient for representing the monthly time series of global oil prices.

3.3.3 Hybrid Regression Model (ARIMA – SVR)

This model results from a multiple regression equation representing the actual values of the training set, which consists of 216 observations. The dependent variable is predicted by the first independent variable, comprising of the predicted values by the ARIMA model, and the second independent variable is the predicted values by the SVR model. Therefore, the estimated regression equation without a constant is:

$$\hat{y}_t = 0.989\ F_{ARIMA} + 1.493\ F_{SVR}$$

Thus, the estimated and actual values by the multiple regression hybrid model, as shown in Table (12) indicate high performance in the prediction process. This is evident from the convergence between the actual and predicted values, as illustrated in the following figure:

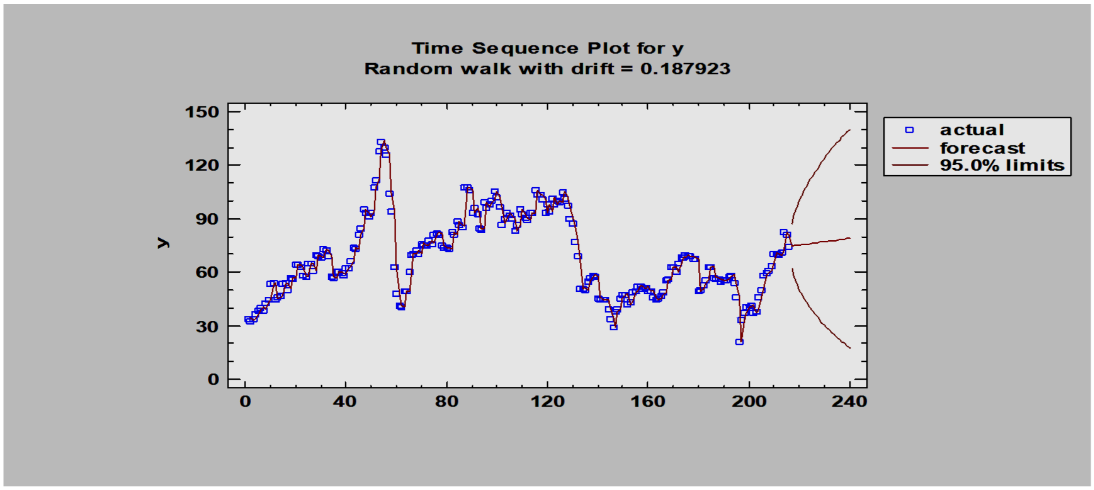

Figure 14. Actual and Predicted Values by the Hybrid Regression Model (ARIMA – SVR)

Using the Ljung-Box test for the resulting series, the test results are as follows:

Table 10. Ljung-Box Test

Test	Q	P – value
Ljung – Box	7.125	0.1754

The p-value is greater than 0.05, thus accepting the null hypothesis that the regression hybrid model is correct for the global oil price time series data.

Table 11. The predicted values of the ARIMA and SVR model:

	ARIMA			SVR	
	Actual values	**Predicted values**	**Residuals**	**Predicted values**	**Residuals**
1/2022	83.32	80.11	3.21	83.15	0.07
2/2022	91.47	90.24	1.23	90.11	1.35
3/2022	108.7	106.91	1.79	104.54	3.95
4/2022	101.79	97.34	4.45	101.10	0.67
5/2022	109.54	102.32	7.22	100.73	8.8
6/2022	114.82	109.10	5.72	111.64	3.18
7/2022	101.61	100.68	0.93	102.01	-0.39
8/2022	93.65	90.51	3.14	90.60	3.07
9/2022	84.36	82.62	1.63	83.30	0.93
10/2022	87.55	89	-1.45	85.31	2.24
11/2022	84.35	80.23	4.12	80.15	4.22
12/2022	76.45	71.22	5.23	77.5	-1.06
1/2023	78.11	77.01	1.1	79.20	-1.08
2/2023	76.80	73.60	3.2	70.6	6.23
3/2023	73.25	70.55	2.7	72.16	1.11
4/2023	79.46	72.96	6.40	79.01	0.44
5/2023	71.55	70.62	0.93	68.85	2.71
6/2023	70.21	65.06	5.15	71.2	-0.95
7/2023	76.07	79.01	-2.94	73.71	2.36
8/2023	81.38	79.08	2.30	80.16	1.2
9/2023	89.44	88.22	1.22	85.34	4.19
10/2023	85.65	80.11	5.54	86.05	-0.41
11/2023	77.62	73.35	4.32	76.10	1.59
12/2023	71.9	73.69	-1.79	65.9	6.1

From Table (11), the statistical predictions for the individual models ARIMA and SVR are closely aligned. Comparing the actual and predicted values using the SVR model, it is evident that the SVR model is better than the ARIMA model in forecasting.

Table 12. Predicted and Actual Values for Hybrid Models

	(ARIMA-SVR) Additive		ARIMA-SVR Multiple		ARIMA-SVR Regression	
	Predicted values	Residuals	Predicted values	Residuals	Predicted values	Residuals
1/2022	82.21	1.001	79.37	3.85	82.05	1.18
2/2022	90.32	1.15	89.36	2.14	89.001	2.44
3/2022	108.93	-0.43	105.35	3.14	99.61	8.86
4/2022	101.75	0.02	99.07	2.71	99.72	2.08
5/2022	105.52	4.04	110.01	-0.46	107.3	2.20
6/2022	112.71	2.13	107.30	7.52	115.9	-1.01
7/2022	101.62	0.01	99.15	2.47	101.69	-0.07
8/2022	91.63	2.05	93.01	0.66	89.01	4.64
9/2022	83.25	1.01	83.17	1.1	84.25	0.03
10/2022	85.55	2.02	86.17	1.38	87.19	0.36
11/2022	83.36	1.01	82.45	1.91	83.45	0.94
12/2022	76.46	-0.01	77.22	-0.78	75.49	0.93
1/2023	77.12	1	79.15	-1.03	76.15	1.97
2/2023	75.80	1.04	70.82	6.01	75.8	1.03
3/2023	70.13	3.1	72.17	1.15	72.91	0.35
4/2023	74.14	5.31	77.23	2.22	77.11	3.36
5/2023	71.50	0.08	70.68	0.89	68.32	3.26
6/2023	69.12	1.16	69.11	1.16	69.19	1.06
7/2023	72.05	4.02	78.15	-2.08	75.13	0.95
8/2023	80.13	1.27	80.24	1.16	79.65	1.73
9/2023	87.50	1.87	84.12	5.32	88.09	1.34
10/2023	82.45	3.18	82.38	3.26	82.31	3.33
11/2023	73.82	3.87	75.11	2.69	72.11	7.55
12/2023	71.39	0.56	69.12	2.89	72.13	-0.26

From Table (12), a comparison between the actual and predicted values for the three hybrid models is provided. The statistical measures from the various hybrid models show closely aligned results, indicating consistent performance across the different models.

3.4 Comparison Between Single Models and Hybrid Models Using Different Integration Methods.

The test set, comprising 24 observations, is now being employed, and the results are outlined in Table (13).

Table 13. Comparison between Single Models and Hybrid Models

Model	MSE	MAPE	MPE	MAE
ARIMA	13.737	0.03754	0.03080	3.2145
SVR	10.4859	0.02793	0.0237	2.41916
"ARIMA-SVR" Additive	5.05906	0.02039	0.02005	1.71920
"ARIMA-SVR" Multiplicative	8.87285	0.02773	0.02315	2.41
"ARIMA-SVR" Regression	7.9467	0.02279	0.02170	2.00166

The results, as shown in Table (13), indicate that the ARIMA model is the least efficient in predicting monthly global oil prices, as it presents weak performance with large errors. In contrast, the SVR model performs better in predicting monthly global oil prices due to its lower error rates. However, the additive hybrid model (ARIMA – SVR) is the most efficient, represented by the lowest values in statistical measures such as MAE, MPE, MAPE, and MSE. Following in efficiency is the regression hybrid model, then the multiplicative hybrid model, followed by the SVR model, and finally the ARIMA model.

4. Discussion

This research begins with an empirical analysis of global oil price time series data, focusing on the comparative performance of individual and hybrid time series models. Crucially, initial unit root tests confirmed the stationarity of the oil price series at its original level, thereby validating the application of stationarity-based time series modeling techniques and establishing a necessary foundation for subsequent analysis.

Building on this foundation, the investigation first assessed individual models, identifying ARIMA (2,0,0) as the most appropriate for modeling the monthly oil price data based on its superior fit indicated by BIC and AIC. However, despite its statistical significance, the ARIMA model demonstrated limited forecasting accuracy over a 24-period test set, highlighting the inherent challenges of relying solely on linear models when dealing with complex, real-world datasets. In contrast, the Support Vector Regression (SVR) model, using a linear kernel function, exhibited superior forecasting performance, effectively capturing the nonlinear dynamics often overlooked by traditional linear models.

This contrast then led the investigation to explore hybrid modeling structures, specifically combinations of ARIMA and SVR. These hybrid models, across various integration methods, demonstrated a marked improvement in forecasting performance compared to the individual models. Notably, the additive integration approach yielded the lowest error metrics (MAE, MPE, MAPE, and MSE), underscoring the effectiveness of additive decomposition in harnessing the linear components captured by ARIMA alongside the nonlinear patterns extracted by SVR, resulting in a more robust model. While other hybrid approaches employing multiple regression and multiplicative integration showed acceptable results; they proved less efficient.

The findings collectively demonstrate the advantage of using hybrid modeling frameworks when forecasting complex time series displaying linear and nonlinear dynamics. While individual models like ARIMA or SVR can perform adequately under certain circumstances, their effectiveness is limited by inherent assumptions, as evidenced by the comparatively higher error rates of ARIMA. Consequently, the proposed hybrid ARIMA-SVR model, utilizing additive integration, provides a robust and effective solution for forecasting global oil prices.

This research, therefore, builds upon and complements existing literature dedicated to enhancing model performance across various disciplines. Previous studies, which developed models like SACNN, FS-FAI, and ANFIS, focused on exceeding classification accuracy, resource efficiency, and predictive power through feature reduction, dimensionality reduction, and optimization algorithms. These efforts, alongside the present study, share the common goal of enhancing the statistical performance of predictive models via improved accuracy, efficient resource utilization, and reduced error, reflecting the consistent adoption of statistical metrics like F1-score, correlation coefficients, and error measures. The findings strongly advocate for hybrid modeling as a potent approach to forecasting time series that exhibit both linear and nonlinear dynamics.

5. Limitation

This study, while offering valuable insights into time series forecasting using hybrid models, is subject to several limitations. These limitations arise from various factors including the scope of the data, choices in model selection, methodological decisions, generalizability, and dependence on specific software.

The analysis was restricted in terms of data scope. First, the temporal range was limited to monthly global oil price data from January 2004 to December 2023. Consequently, the models' performance may not be generalizable to different periods or varying economic conditions. Second, the study focused exclusively on oil prices. The efficacy of the models might vary when applied to other types of data or different economic indicators.

The research relies on secondary data, with a primary emphasis on datasets from the World Bank and OPEC. Monthly global oil price data covering January 2004 to December 2023 was retrieved from the World Bank's commodity price database (www.worldbank.org), along with other relevant economic indicators. Additionally, OPEC's monthly and annual reports, accessed via their website (www.opec.org), provided further insights into the oil market. These data sources are fully cited to ensure transparency and reliability.

Finally, the reliance on specific software packages—namely EViews, Stat Graphics, and Python—presents a limitation. Different software packages or varying versions of the same software might produce slightly different results, which could influence the study's findings.

6. Conclusion

This research aims to forecast time series data by employing individual Support Vector Regression (SVR) and Autoregressive Integrated Moving Average (ARIMA) models, as well as their hybrid combination. Various integration techniques were explored for the hybrid model, which was applied to monthly global oil price time series data from January 2004 to December 2023. The study evaluates these models using several accuracy metrics to identify the optimal forecasting approach.

The results indicate that the global oil price time series exhibits stability at its original level. Based on the Box-Jenkins methodology, the ARIMA (2,0,0) model was identified as the most suitable for representing the monthly price series, achieving the lowest values for the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC). This ARIMA model was then used to forecast 24 future values. Similarly, for the SVR model, a linear kernel function was selected due to its lowest mean squared error (MSE) value. This SVR model was also used to forecast 24 future values.

Following the estimation of the hybrid ARIMA-SVR model using different integration methods—including additive, multiplicative, and regression-based approaches—a comparative analysis was conducted. This comparison between the individual models (SVR and ARIMA) and the hybrid models demonstrated the superiority of the additive hybrid model. This model achieved the lowest values across various statistical measures: Mean Absolute Error (MAE), Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE), and Mean Squared Error (MSE). The regression hybrid model exhibited the second-best performance, subsequently followed by the multiplicative hybrid model, then the SVR model, and finally, the ARIMA model.

The next step in the analysis will focus on determining the percentage improvement achieved by the superior models

Table 14. Comparison of Forecasting Model Performance (Detailed)

Forecasting Model	Mean Absolute Error (MAE) (Unit Undefined)	Comparison with Other Models	Percentage Improvement Compared to ARIMA	Percentage Improvement Compared to SVR	Estimated approximate MAE Value (Based on Percentages)
ARIMA	3.2145 (Reference)	Weakest in Forecasting	-	-	3.2145
SVR	2.41916	Better than ARIMA, but less than hybrid models	24.74%	-	2.41916
ARIMA-SVR (Additive)	Undefined (Best)	Best among all models	46.4%	29%	Approximately 1.71925
ARIMA-SVR (Regression)	Undefined	Better than ARIMA and SVR	37.7%	Not Available	Approximately 2.00016
ARIMA-SVR (Multiplicative)	Undefined	Better than ARIMA and SVR	25%	Not Available	Approximately 2.41088

1-The Best Model: The additive hybrid model (ARIMA-SVR) is the best-performing model without question, based on the significant improvement it achieved in forecasting accuracy (MAE), with an estimated MAE of 1.71925.

2-SVR Performance: The SVR model performed better than ARIMA but was less efficient than all the hybrid models.

3-Performance of Hybrid Models: All the hybrid models (additive, regression, and multiplicative) outperformed the individual ARIMA and SVR models, with the additive hybrid model significantly superior.

4-ARIMA Performance: The ARIMA model had the least forecasting accuracy.

Recommendations for Future Research

Building on these limitations, the following are suggestions for future research:

1. Data Expansion: Employ data from varying temporal ranges and alternative data modalities.
2. Exploration of Novel Models: Test more advanced modeling techniques, such as deep learning and reinforcement learning.
3. Advanced Hybrid Integration: Examine more complex methods of combining models for higher accuracy.

4. Comprehensive Evaluation: Implement a broader range of metrics and benchmark against non-traditional models.
5. Economic Impact Analysis: Investigate the influence of economic shifts on model performance.
6. Multivariate Models Development: Integrate additional variables along with oil prices to improve forecasting accuracy.
7. By acknowledging the existing constraints and suggesting future research avenues, this study facilitates more robust and applicable insights into time series forecasting using a hybrid model Exploring diverse techniques for evaluating the efficiency of hybrid models and contrasting them with conventional models across different scenarios.

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