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การเพิ่มความแม่นยำในการพยากรณ์การส่งออกเครื่องปรุงรสของไทยด้วยตัวแบบ SARIMA โดยใช้การค้นหากริดและช่วงคาดการณ์แบบบูตสแทร็ป

Enhancing Forecast Accuracy of Thailand's Seasoning Exports Using SARIMA Models with Grid Search and Bootstrap Prediction Intervals

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บทคัดย่อ

การพยากรณ์การส่งออกเครื่องปรุงรสของประเทศไทยไปยังกลุ่มประเทศอาเซียน+8 และตลาดโลกอย่างแม่นยำมีบทบาทสำคัญต่อการกำหนดกลยุทธ์ทางการค้าอย่างมีประสิทธิภาพ และการบริหารความเสี่ยงทางเศรษฐกิจ งานวิจัยนี้มุ่งเปรียบเทียบแบบจำลอง SARIMA ที่ใช้ในการพยากรณ์การส่งออก โดยอาศัยข้อมูลรายเดือนตั้งแต่ปี พ.ศ. 2556 ถึง พ.ศ. 2567 ทั้งนี้ได้ประเมินประสิทธิภาพของเทคนิคการเลือกแบบจำลอง SARIMA ระหว่างวิธี Grid Search (โดยพิจารณาจากค่า AIC และ BIC) กับการเลือกแบบจำลอง SARIMA อัตโนมัติด้วยฟังก์ชัน auto.arima() ในโปรแกรม R ผลการศึกษาพบว่า แบบจำลอง SARIMA ที่ได้จากการใช้ Grid Search มีความแม่นยำสูงกว่า โดยเฉพาะในการพยากรณ์ระยะสั้น ซึ่งสามารถลดค่าความคลาดเคลื่อนลงได้ประมาณร้อยละ 30 นอกจากนี้ การใช้ Bootstrap Prediction Intervals ยังให้ขอบเขตการพยากรณ์ที่มีความยืดหยุ่นและสมจริงมากกว่าการใช้ขอบเขตการพยากรณ์แบบมาตรฐาน ซึ่งเหมาะสมกับสภาวะตลาดที่มีความผันผวน เมื่อผสานการใช้แบบจำลอง SARIMA ที่เหมาะสมร่วมกับ Bootstrap Prediction Intervals จะช่วยเพิ่มความเชื่อมั่นให้แก่ผู้กำหนดนโยบายและผู้ประกอบการในการวางแผนกลยุทธ์และการตัดสินใจด้านการค้าระหว่างประเทศในบริบทเศรษฐกิจที่ไม่แน่นอน

ABSTRACT

Accurate forecasting of Thailand's seasoning exports to ASEAN+8 and global markets plays a vital role in developing effective trade strategies and managing economic risks. This research compares SARIMA models for export forecasting, utilizing monthly export data from 2013 to 2024. Specifically, we evaluate SARIMA model selection techniques-Grid Search (based on AIC and BIC) versus automatic SARIMA selection using the auto.arima() function in R. The results demonstrate that SARIMA models identified through Grid

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Search deliver superior accuracy, especially in short-term forecasting, where errors are reduced by approximately 30%. Additionally, the use of Bootstrap Prediction Intervals outperforms Standard Prediction Intervals, offering more flexible and realistic measures of uncertainty that are well-suited to volatile market environments. By integrating optimal SARIMA modeling with Bootstrap Prediction Intervals, policymakers and industry stakeholders gain enhanced reliability for strategic planning and risk management decisions in international trade. This approach significantly strengthens decision-making capabilities in an uncertain economic context.

คำสำคัญ: การพยากรณ์อนุกรมเวลา ตัวแบบ SARIMA การค้นหากริด ช่วงคาดการณ์แบบบูตสแทร็ป การส่งออกอาเซียน+8
Keywords: Time Series Forecasting, SARIMA Model, Grid Search Optimization, Bootstrap Prediction Intervals, ASEAN+8 Exports

INTRODUCTION

Thailand is a key player in the global seasoning market, ranking sixth among the world's exporters of seasoning products, with an average annual growth rate of 7.6% over the past five years. This steady expansion underscores the country's strong international position and the growing global demand for high-quality seasoning goods (Food Intelligence Center, National Food Institute, 2023). In 2024, Thailand's seasoning exports reached a total value of USD 1,064.70 million, marking a 9.67% increase from the previous year (Ministry of Commerce, Thailand, 2024). This upward trajectory highlights Thailand's competitive advantage in the international market and reinforces the rising global demand for high-quality seasoning products.

The primary export markets for Thai seasonings are the ASEAN+8 countries, which include the ten ASEAN nations, Thailand, Vietnam, Indonesia, Malaysia, Philippines, Singapore, Brunei, Cambodia, Laos, and Myanmar, along with China, Japan, South Korea, India, Australia, New Zealand, Russia, and the United States. This region alone accounts for over 65% of Thailand's total seasoning exports (Ministry of Commerce, Thailand, 2024).

The growing economic integration within ASEAN, coupled with evolving consumer preferences favoring Thai and Asian cuisine, has driven a sustained increase in demand for Thai seasoning products (Euromonitor International, 2023). Thailand's continued expansion in the global seasoning market is supported by its ability to adapt to shifting consumer preferences, maintain high production standards, and capitalize on emerging trade opportunities. These factors reinforce the country's position as a key exporter in the industry and highlight its potential for further growth in the coming years.

Accurate forecasting of Thailand's seasoning exports is crucial for businesses aiming to optimize production, improve supply chain management, and develop strategic trade policies. The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is widely recognized as an effective method for predicting data with seasonal patterns. Numerous studies have confirmed the effectiveness of SARIMA in export forecasting. For example, Adanacıoğlu and Yercan (2012) analyzed monthly tomato prices in Turkey and demonstrated that a SARIMA-based model effectively captured seasonal fluctuations. Similarly, Sabu and Kumar (2020) utilized SARIMA alongside other time series methods, such as Holt-Winters and Long Short-Term Memory (LSTM), to forecast are canut prices in Kerala and reported competitive results. Divisekara *et al.* (2020) also applied SARIMA to red lentil price data in Canada, showcasing its capability to manage weekly seasonality and volatility. In another study, Luo *et al*. (2013) highlighted the robustness of SARIMA in modeling cucumber price fluctuations, emphasizing its utility for short-term warnings in perishable product markets.

Furthermore, Makridakis *et al.* (2018) noted that machine learning methods can struggle with overfitting when historical data is limited, reinforcing the relevance of traditional forecasting models such as SARIMA. Klaharn *et al*. (2024) recently focused on Thailand's poultry meat sector, employing SARIMA and other forecasting models (such as NNAR, ETS, TBATS, STL, and THETA) to predict production and export volumes. Their findings indicated that SARIMA outperformed other methods in forecasting poultry production, while the THETA model excelled in export forecasting. Thus, SARIMA remains a powerful tool for forecasting Thailand's seasoning exports. However, selecting the most suitable model is critical to achieving high predictive accuracy. Traditional Grid Search methods, which use the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), systematically evaluate parameter combinations to identify the optimal SARIMA model.

While this approach is exhaustive and computationally intensive, it often yields more precise forecasts. In contrast, automatic SARIMA selection using the auto.arima() function in R automates the model selection process, reducing computational effort but potentially overlooking superior configurations that manual tuning could capture. Beyond model selection, understanding forecast uncertainty is equally vital. Standard SARIMA models assume that residuals follow a normal distribution and derive analytical prediction intervals (PI) based on this assumption. However, real-world export data frequently encounter structural changes, market disruptions, and external economic shocks, introducing unpredictable variability. These complexities often render standard prediction intervals insufficient for capturing the full range of possible future values. Bootstrap Prediction Interval (Bootstrap PI) offers a more adaptive and data-driven approach to quantifying forecast uncertainty, as it does not rely on strict distributional assumptions (Stine, 1985). Unlike traditional methods, Bootstrap PI captures both innovation and estimation errors, making it particularly suitable for time series forecasting (Pan and Politis, 2016).

By resampling residuals and constructing empirical prediction intervals, Bootstrap PI accommodates dynamic fluctuations in export trends, which is crucial in volatile trade environments. Additionally, Bootstrap PI has been effectively applied in complex anomaly detection tasks, demonstrating its robustness in real-world forecasting scenarios (Kumar and Srivastava, 2012). This flexibility allows for more precise risk assessments and enhances decision-making for industry stakeholders.

This study evaluates SARIMA models for forecasting Thailand's seasoning exports to ASEAN+8 and global markets. By comparing different model selection approaches and assessing the role of Bootstrap PI in enhancing forecast reliability, this research offers valuable insights for policymakers, exporters, and industry leaders. The findings contribute to improved trade decision-making, more effective risk management strategies, and enhanced predictive methodologies, thereby strengthening Thailand's competitive position in the global seasoning industry.

MATERIALS AND METHODS

1. Data Description

This study examines the monthly export values of seasoning products from Thailand to ASEAN+8 countries and global markets. The dataset spans from January 2013 to December 2024 and is sourced from the Ministry of Commerce of Thailand's Trade Statistics System (Ministry of Commerce, Thailand, 2024). We analyze both regional and global trade patterns, as ASEAN+8 serves as a significant market for Thailand's seasoning exports.

To develop reliable forecasts, the dataset was divided into training and testing sets. The training set covers a period of 120 months, from January 2013 to December 2022, and is used to estimate the SARIMA models. The testing set spans 24 months, from January 2023 to December 2024, and is reserved exclusively for out-of-sample evaluation. For evaluation purposes, the testing set is further segmented into three forecasting horizons: short-term (January 2023 to June 2023, 6 months), medium-term (January 2023 to December 2023, 12 months), and long-term (January 2023 to December 2024, 24 months). This partitioning ensures that the models are trained on sufficient historical data while enabling rigorous assessment of predictive accuracy across different time horizons.

Export values are measured in millions of Thai Baht (THB). Before fitting the models, we conducted exploratory data analysis (EDA) to examine long-term trends, seasonality, and potential non-stationarity. To formally assess stationarity, we applied both the Augmented Dickey–Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. The ADF test rejects the null hypothesis of a unit root (stationary) when the p-value is below 0.05, while the KPSS test rejects the null hypothesis of stationarity when the p-value is below 0.05. Interpreting the two results jointly provides a more reliable conclusion on whether differencing is required. Additionally, seasonal decomposition was performed to visualize the trend, seasonal, and irregular components of the time series. All data processing and statistical tests were carried out in R, using the tseries and forecast packages. Initial model insights were obtained using the auto.arima() function, while final model selection was conducted through AIC- and BIC-based Grid Search to ensure optimal SARIMA configurations.

2. SARIMA Model Formulation

The Seasonal Auto-Regressive Integrated Moving Average (SARIMA) model extends ARIMA by incorporating seasonal components to capture periodic patterns in time series data. Box and Jenkins introduced this framework in 1970, laying the foundation for modern time series modeling (Box *et al*., 2015). Their work established the classical framework, which was later elaborated by Brockwell and Davis (2002) and applied in modern contexts by Hyndman and Athanasopoulos (2018). It is expressed as follows:

$$SARIMA(p, d, q) \times (P, D, Q)_m \tag{1}$$

where p = Order of the non-seasonal auto-regressive (AR) component, d = Degree of non-seasonal differencing, q = Order of the non-seasonal moving average (MA) component, P = Order of the seasonal auto-regressive (SAR) component, D = Degree of seasonal differencing, Q = Order of the seasonal moving average (SMA) component, m= Length of the seasonal cycle (e.g., m = 12 for monthly data with annual seasonality).

The general mathematical formulation is:

$$\Phi_P(B^m)\emptyset_p(B)(1-B)^d(1-B^m)^D Y_t = \Theta_Q(B^m)\theta_q(B)\epsilon_t \tag{2}$$

where B is the backward shift operator, Φ_P and $\emptyset_p$represent the seasonal and non-seasonal autoregressive components., Θ_Q and θ_q represent the seasonal and non-seasonal moving average components, ϵ_t is the white noise error term.

The SARIMA model can capture dependencies across multiple time horizons (short, medium, and seasonal), making it a robust choice for forecasting in various time series applications (Hyndman and Athanasopoulos, 2018).

3. Model Selection Criteria

This study compares two SARIMA model selection approaches: Grid Search with AIC and BIC, which involves manual tuning and systematically explores parameter combinations at a higher computational cost, and the AutoSARIMA function, which automates the search process through stepwise optimization for efficient model selection.

3.1 AIC and BIC

Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are commonly used to select models by balancing goodness-of-fit and complexity.

$$AIC = -2 \ln L + 2k \tag{3}$$

$$BIC = -2 \ln L + k \ln n \tag{4}$$

Where L is the likelihood function, k is the number of parameters, and n is the sample size. The model with the lowest AIC or BIC is preferred. BIC penalizes complex models more heavily than AIC, making it more conservative in selecting simpler models.

3.2 Grid Search for SARIMA

Grid Search is a brute-force method for finding the optimal SARIMA parameters by exhaustively evaluating all possible parameter combinations within a predefined range. The approach follows these steps:

(1) Define the search space: $p, d, q, P, Q \in \{0, 1, 2\}$ with $D \in \{0, 1\}$.

(2) Fit SARIMA models for each combination and compute AIC and BIC.

(3) Rank models based on AIC/BIC and present the top 5 best-performing models.

Grid Search ensures optimal parameter selection by systematically evaluating all possible parameter combinations. However, this exhaustive search process requires significant computational resources, making it time-consuming, particularly for large datasets or complex models.

3.3 AutoSARIMA (auto.arima in R)

AutoSARIMA performs automatic SARIMA selection using a stepwise search based on information criteria (typically AICc by default in R), while AIC and BIC values of the selected models are reported for comparison.

The function iteratively evaluates candidate models, applies heuristic refinements, and selects the specification with the lowest information criterion. While computationally efficient and faster than exhaustive search, this approach may not always yield the globally optimal model.

3.4 Comparison of model selection methods

Table 1 provides a comprehensive comparison of different model selection approaches, detailing their strengths and limitations. It emphasizes critical aspects such as accuracy, computational efficiency, and the risk of overfitting, thereby aiding in the selection of the most appropriate method for a given forecasting scenario.

Table 1 Comparison of SARIMA model selection approaches

Method	Search Strategy	Computation Time	Risk of Overfitting
Grid Search	Exhaustive	High	Low
AIC/BIC	Information Criterion	Moderate	Moderate
AutoSARIMA function	Stepwise Search	Low	Moderate

Grid Search provides the most comprehensive approach to model selection but is computationally intensive. AIC and BIC serve as reliable criteria for comparing competing models, while the AutoSARIMA function offers a faster alternative with reasonable accuracy. The choice of approach depends on the trade-off between computational cost and the need for optimality.

4. Model Evaluation Metrics

Two widely used error metrics are employed to evaluate the performance of the SARIMA models: Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

Root Mean Square Error (RMSE) measures the average magnitude of the error between predicted and actual values. It is calculated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2} \quad (5)$$

where Y_t = Actual value at time t, $\hat{Y}_t$ = Predicted value at time t, n = Number of observations

Mean Absolute Percentage Error (MAPE) evaluates the average percentage error between predicted and actual values, and is expressed as a percentage:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \times 100 \quad (6)$$

where $Y_t \neq 0$ for all t, to avoid division by zero, and other variables are defined as above.

Lower RMSE and MAPE values indicate better model performance, with RMSE emphasizing the magnitude of errors and MAPE offering a percentage-based measure of accuracy.

5. Prediction Intervals for Forecast Uncertainty

Quantifying forecast uncertainty is essential for assessing the reliability of predictions in time series. Prediction intervals (PI) provide a confidence range within which future values are expected to fall. This section presents two approaches: (1) Standard Prediction Intervals, which assume normality in the residuals, and (2) Bootstrap Prediction Intervals, a data-driven alternative that does not rely on distributional assumptions.

5.1 Standard prediction intervals (PI)

Standard Prediction Intervals are derived under the assumption that the residuals in the SARIMA model follow a normal distribution. Given this assumption, the PI can be computed as follows:

$$PI_t = \hat{Y}_t \pm Z_{\propto/2} \cdot \hat{\sigma} \tag{7}$$

where $\hat{Y}_t$ = Point forecast at time t, $Z_{\propto/2}$ = Critical value from the standard normal distribution (e.g., 1.96 for a 95% confidence interval), $\hat{\sigma}$ = Standard deviation of forecast errors.

This method is computationally efficient and easy to implement. However, it assumes that the residuals are normally distributed, which may not hold in real-world data. If the residuals exhibit skewness, heteroskedasticity, or outliers, the resulting prediction intervals may be inaccurate and could underestimate forecast uncertainty (Hyndman and Athanasopoulos, 2018).

5.2 Bootstrap prediction intervals (PI)

Bootstrap Prediction Intervals provide a more flexible approach by estimating uncertainty directly from the data. Unlike standard PI, bootstrap-based intervals do not assume normality; instead, they rely on empirical resampling techniques. The procedure consists of the following steps:

(1) Extract the residuals $e_t = Y_t - \hat{Y}_t$ from the fitted SARIMA model.

(2) Resample these residuals with replacement to generate a new set e_t^*.

(3) Generate bootstrap forecasts using:

$$Y_t^{(b)} = \hat{Y}_t + e_t^{(b)}, \qquad b = 1, 2, \ldots, B \tag{8}$$

where $Y_t^{(b)}$ denotes the b-th bootstrap replicate of the forecast at time t; $\hat{Y}_t$ is the point forecast obtained from the fitted SARIMA model; $e_t^{(b)}$ is the resampled residual drawn with replacement from the model residuals; and B represents the total number of bootstrap replications. Note that in this context B refers to the number of replications and should not be confused with the backshift operator B used in the SARIMA model equations.

(4) Compute empirical prediction intervals using the percentiles of the bootstrap forecasts:

$$PI = \left[Percentile_{\propto/2}\left(Y_t^{(b)}\right), \qquad Percentile_{1-\propto/2}\left(Y_t^{(b)}\right)\right] \tag{9}$$

where typical values of α are 0.05 for a 95% confidence interval.

Bootstrap methods naturally adapt to non-Gaussian and heteroskedastic error structures, providing more robust prediction intervals, especially in the presence of structural changes or outliers. The utility of bootstrap techniques in constructing prediction intervals has been well documented in the literature (Stine, 1985; Efron and Tibshirani, 1994; Pan and Politis, 2016).

5.3 Comparison: Standard vs Bootstrap PI

The strengths and limitations of the two methods, Standard Prediction Intervals and Bootstrap Prediction Intervals, are summarized in Table 2, highlighting key differences in their assumptions, flexibility, and suitability for various forecasting scenarios.

Table 2 Comparison of standard and bootstrap prediction intervals

Method	Assumption	Flexibility
Standard PI	Residuals follow normal distribution	Low
Bootstrap PI	No distributional assumption	High

Bootstrap Prediction Intervals (PI) offer several advantages over standard methods. They are more flexible, as they do not require residuals to follow a normal distribution, making them suitable for a wide range of time series data. Being data-driven, they naturally adapt to non-Gaussian and heteroskedastic error structures, allowing for more accurate uncertainty estimation. Additionally, Bootstrap PI is robust to structural changes, making it a reliable choice when dealing with datasets containing outliers or exhibiting non-linearity, thereby ensuring more realistic forecast intervals in dynamic environments.

5.4 Evaluation of prediction intervals across forecasting horizons

Forecast uncertainty increases over time, making the assessment of both Standard and Bootstrap Prediction Intervals across different forecasting horizons essential. This study evaluates short-term (6 months) forecasts for immediate accuracy, medium-term (12 months) forecasts for seasonal performance, and long-term (24 months) forecasts for the robustness of SARIMA models in extended predictions. The comparison focuses on empirical coverage probability and interval width to determine the reliability of each method. The results indicate that Bootstrap PI generally produces broader and more reliable uncertainty bounds, particularly in long-term forecasts, where deviations from normality arise due to structural changes or evolving market dynamics.

RESULTS AND DISCUSSION

1. Stationarity Analysis and Differencing Selection

Stationarity is critical for SARIMA forecasting. To evaluate the ASIAN+8 and World datasets, we applied the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, as summarized in Table 3. Both tests indicated non-stationarity (p-values > 0.05 for ADF and p-values < 0.05 for KPSS), suggesting the presence of a unit root and confirming the need for differencing.

We applied first-order differencing ($d = 1$), which resulted in stationary series for both datasets, as confirmed by the ADF test (Table 4). For seasonal stationarity, the ASIAN+8 dataset required one seasonal difference (D = 1), whereas the World dataset required two (D = 2) because the first seasonal differencing was insufficient. Consequently, the final differencing parameters were d = 1, D = 1 for the ASIAN+8 dataset and d = 1 , D = 2 for the World dataset. These configurations were then used in the SARIMA grid search to identify the optimal forecasting model.

Table 3 Stationarity test results (before differencing)

Dataset	ADF Statistic	ADF p-value	KPSS Level	KPSS p-value
ASIAN+8	-3.0485	0.1411 (Unit Root)	2.2976	0.01 (Non-Stationary)
World	-2.8471	0.2247 (Unit Root)	2.3021	0.01 (Non-Stationary)

Table 4 Stationarity test results after differencing and final differencing parameters

Dataset	d	D	ADF Statistic	ADF p-value	Conclusion
ASIAN+8	1	1	-6.3910	0.01	No Unit Root / Stationary
World	1	2	-6.4183	0.01	No Unit Root / Stationary

2. Model Selection and Performance Evaluation

This study evaluates SARIMA models for Thailand’s seasoning exports using three selection approaches to ensure optimal forecasting accuracy. The Grid Search (AIC) method selects the model with the lowest Akaike Information Criterion (AIC), balancing model fit and complexity, as shown in Table 5. Similarly, the Grid Search (BIC) method prioritizes the model with the lowest Bayesian Information Criterion (BIC), which imposes a more substantial penalty on model complexity, with the selected models presented in Table 6. In contrast, the AutoSARIMA function employs an automated stepwise search that evaluates candidate models using information criteria (typically AICc by default in R), and Table 7 summarizes the models selected through this method.

While computationally efficient, the AutoSARIMA function relies on a stepwise heuristic that may converge to a local optimum rather than the global best specification. By contrast, Grid Search systematically explores all parameter combinations within the predefined range, thereby ensuring that the selected SARIMA model corresponds to the global optimum under AIC/BIC criteria. This design choice explains why the Grid Search models in this study consistently achieved lower AIC, BIC, RMSE, and MAPE than AutoSARIMA, demonstrating superior forecasting performance across horizons.

The selection process identifies the best SARIMA models for the ASIAN+8 and World datasets by minimizing AIC and BIC values, ensuring robust model performance across different forecasting scenarios. The top five SARIMA models selected based on AIC and BIC rankings exhibit variations; however, both criteria identify the same optimal model for each dataset. For the ASIAN+8 dataset, the best-performing model is SARIMA (0,1,1) $(1,1,1)_{12}$, with an AIC of 1296.89 and a BIC of 1307.58. Similarly, for the World dataset, the optimal model is SARIMA (2,1,2) $(1,2,1)_{12}$, with an AIC of 1270.05 and a BIC of 1287.93. Models selected through Grid Search consistently achieve lower AIC and BIC values than AutoSARIMA, highlighting their superior performance and suitability for forecasting these datasets.

The explicit model equations obtained from the Grid Search are presented below. For the ASEAN+8 dataset, the optimal specification corresponds to SARIMA(0,1,1)(1,1,1)$_{12}$ which can be expressed as:

$$(1-\Phi_1 B^{12})(1-B)(1-B^{12})y_t = (1+\theta_1 B)(1+\Theta_1 B^{12})\varepsilon_t$$

where B is the backshift operator ($By_t = y_{t-1}$), Φ_1 and Θ_1 are seasonal AR and MA coefficients, and θ_1 is the non-seasonal MA coefficient.

For the World dataset, the optimal model identified is SARIMA(2,1,2)(1,2,1)$_{12}$, which is formulated as:

$$(1-\phi_1 B-\phi_2 B^2)(1-\Phi_1 B^{12})(1-B)(1-B^{12})^2 y_t = (1+\theta_1 B+\theta_2 B^2)(1+\Theta_1 B^{12})\varepsilon_t$$

where ϕ_1, ϕ_2 are non-seasonal AR coefficients, θ_1, θ_2 are non-seasonal MA coefficients, Φ_1 is the seasonal AR coefficient, and Θ_1 is the seasonal MA coefficient.

Table 5 Top 5 SARIMA models based on AIC for ASIAN+8 and world

Dataset	Rank	p	d	q	P	D	Q	AIC
ASIAN+8	1	0	1	1	1	1	1	1296.89
	2	0	1	1	0	1	2	1297.15
	3	1	1	1	1	1	1	1297.73
	4	0	1	2	1	1	1	1297.99
	5	1	1	1	0	1	2	1298.04
World	1	2	1	2	1	2	1	1270.05
	2	2	1	2	1	2	2	1271.42
	3	2	1	2	2	2	1	1271.71
	4	2	1	2	0	2	2	1272.07
	5	2	1	2	2	2	2	1273.40

Table 6 Top 5 SARIMA models based on BIC for ASIAN+8 and world

Dataset	Rank	p	d	q	P	D	Q	BIC
ASIAN+8	1	0	1	1	1	1	1	1307.58
	2	0	1	1	0	1	2	1307.84
	3	0	1	1	0	1	1	1308.71
	4	1	1	1	1	1	1	1311.10
	5	0	1	2	1	1	1	1311.35
World	1	2	1	2	1	2	1	1287.93
	2	2	1	2	0	2	2	1289.95
	3	0	1	1	0	2	2	1290.96
	4	0	1	1	1	2	2	1291.28
	5	0	1	1	0	2	1	1291.48

Table 7 Best SARIMA models selected by the AutoSARIMA function for ASEAN+8 and World

Dataset	p	d	q	P	D	Q	AIC	BIC
ASIAN+8	0	1	1	1	0	0	1436.61	1447.73
World	0	1	1	0	0	2	1522.75	1533.87

3. Comparison of Forecasted and Actual Values

We compare the best SARIMA model, selected based on AIC and BIC criteria, with the forecasts from the AutoSARIMA function (auto.arima() in R) using actual export data from January 2023 to December 2024. Since both AIC and BIC selected the same model, Table 8 presents its forecasts alongside those obtained from AutoSARIMA for both datasets.

The results indicate that the selected SARIMA model consistently outperforms the AutoSARIMA forecasts, especially during months with higher volatility. The selected model effectively captures seasonal patterns and underlying trends, resulting in more accurate forecasts than AutoSARIMA. This demonstrates that the selected SARIMA model is the preferred choice for forecasting Thailand's seasoning exports.

4. Forecasting Accuracy Evaluation

To evaluate the forecasting performance of the selected SARIMA models, we compare the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) across different forecasting horizons: short-term (6 months), medium-term (12 months), and long-term (24 months). These metrics quantify predictive accuracy, with lower values indicating better performance. As shown in Table 9, the results indicate that the selected SARIMA model consistently outperforms the AutoSARIMA forecasts across all horizons, achieving the lowest RMSE and MAPE values. These performance metrics highlight the model's effectiveness in capturing seasonal trends in Thailand's seasoning export data.

For short-term forecasting (6 months), the selected SARIMA model demonstrates superior predictive accuracy, reducing RMSE by 51.0 for the ASEAN+8 dataset and by 24.72 for the World dataset, compared to the AutoSARIMA forecasts. These improvements underscore the model's ability to capture short-term fluctuations in export volumes.

In the medium-term forecasting scenario (12 months), the SARIMA model continues to deliver higher accuracy, with an RMSE reduction of 15.76 in the World dataset. This suggests improved handling of seasonal patterns and mid-range variations in export values.

Over the long-term forecasting horizon (24 months), the selected SARIMA model exhibits greater stability and reliability. It consistently achieves lower RMSE values than AutoSARIMA for both ASEAN+8 and World datasets, indicating its suitability for strategic export planning and long-term decision-making.

Overall, the selected SARIMA model yields better forecasting performance than AutoSARIMA across all timeframes, with notably lower RMSE and MAPE values. The short-term forecasting scenario yields particularly strong results, with MAPE improving to 6.69. These findings confirm the model's robustness and practical applicability in forecasting export trends under seasonal and volatile conditions.

Interestingly, the results show that long-term forecasts occasionally yield lower MAPE values than short-term forecasts. This finding contrasts with the typical expectation that short-term predictions are more accurate. A plausible explanation is that the initial months of the testing period exhibited higher volatility, which disproportionately affected short-term forecasts. In contrast, long-term horizons averaged out these fluctuations, resulting in comparatively lower error rates. While the selected SARIMA model demonstrates overall robustness, this anomaly highlights potential limitations of the model under conditions of abrupt short-term variations. Future studies could investigate this issue further by incorporating alternative models (e.g., SARIMAX with exogenous variables or volatility models such as GARCH) to enhance short-term forecasting performance.

5. Prediction Intervals for Forecast Uncertainty

Forecast uncertainty is central to the reliability of time series forecasts. In this study, we construct 95% prediction intervals (PI) for SARIMA models using both standard and bootstrap approaches. Standard PI assumes normally distributed residuals, while bootstrap PI provides a more flexible, data-driven estimate by resampling residuals. To generate bootstrap PIs, we use B = 1000 replications, which is a widely adopted choice in time series forecasting as it balances accuracy and computational efficiency. As noted by Lima *et al.* (2024), bootstrap replications in the order of 1000 are typically sufficient to yield stable interval estimates, while larger values may improve precision at the cost of additional computation.

Table 10 and Table 11 present the 24-month forecasts and the corresponding 95% prediction intervals (PI) for the ASEAN+8 and World markets, respectively. Although the structure of results is identical, the datasets differ by region. Figures 1 and 2 provide visual comparisons between the standard and bootstrap approaches across both markets. The results show that the standard PIs are generally wider than the bootstrap PIs, particularly at longer horizons, indicating the conservative nature of the normal-theory intervals. By contrast, bootstrap PIs yield narrower ranges that more closely reflect the empirical distribution of residuals. This suggests that the standard approach may overstate forecast uncertainty, while the bootstrap method provides a more data-driven and practical representation of risk, offering policymakers and exporters uncertainty ranges that are realistic without being overly conservative.

Table 8 Comparison of actual values vs. forecasts from the selected SARIMA model and the AutoSARIMA function for ASIAN+8 and World (Jan 2023 – Dec 2024)

Date	ASIAN+8			World		
	Actual	Selected	AutoSARIMA	Actual	Selected	AutoSARIMA
2023-01	1641.56	1740.97	1826.09	2239.41	2231.05	2475.48
2023-02	1651.92	1837.05	1911.85	2443.56	2560.64	2552.57
2023-03	2014.21	2002.57	1984.09	2889.64	2702.73	2703.42
2023-04	1476.01	1732.10	1797.19	2205.04	2249.42	2373.57
2023-05	1912.96	1832.15	1809.34	2859.52	2507.48	2517.32
2023-06	1896.81	1911.12	1930.19	2838.32	2619.49	2649.87
2023-07	2035.37	1867.48	1868.85	3026.69	2449.69	2529.34
2023-08	2188.06	1849.51	1866.02	3161.73	2498.80	2483.64
2023-09	2067.44	1804.21	1822.14	3150.19	2329.26	2435.44
2023-10	2121.12	1846.88	1856.65	3125.72	2556.13	2431.83
2023-11	2097.47	1933.28	1939.37	3243.64	2847.46	2628.83
2023-12	1747.62	1820.12	1833.02	2794.40	2386.68	2441.21
2024-01	1829.42	1793.53	1898.06	2767.31	2329.81	2466.17
2024-02	1861.67	1867.50	1942.34	2893.64	2622.66	2525.46
2024-03	2131.86	2038.76	1980.28	3297.36	2643.41	2546.24
2024-04	1812.27	1806.86	1896.53	2864.89	2311.56	2390.88
2024-05	2118.62	1930.36	1906.25	3254.71	2415.43	2414.86
2024-06	1865.71	1961.19	1967.01	2969.82	2506.97	2443.50
2024-07	2221.60	1944.63	1942.22	3515.06	2491.82	2419.81
2024-08	2207.15	1925.70	1944.91	3422.93	2422.42	2437.15
2024-09	1993.47	1896.47	1928.32	3121.18	2196.19	2350.76
2024-10	2031.17	1932.82	1948.54	3096.95	2528.88	2307.16
2024-11	2135.60	1996.21	1991.39	3122.13	2696.92	2392.23
2024-12	1924.98	1917.58	1945.47	2938.47	2217.87	2285.56

Table 9 Forecast accuracy comparison (RMSE and MAPE)

Horizon	Dataset	Selected SARIMA		AutoSARIMA	
		RMSE	MAPE (%)	RMSE	MAPE (%)
Short-term (6m)	ASIAN+8	139.41	6.69	190.41	9.57
	World	192.57	5.61	217.29	7.95
Medium-term (12m)	ASIAN+8	190.64	8.46	206.43	9.76
	World	439.36	12.07	455.12	13.50
Long-term (24m)	ASIAN+8	168.97	6.85	181.10	7.99
	World	583.10	16.46	606.59	17.68

Table 10 Forecast and prediction intervals for ASIAN+8 (24 months)

Month	Forecast	Standard PI (95%)		Bootstrap PI (95%)	
		Lower	Upper	Lower	Upper
1	1740.97	1553.33	1928.60	1583.31	1932.39
2	1837.05	1640.24	2033.86	1650.51	2028.28
3	2002.57	1796.99	2208.15	1844.78	2193.99
4	1732.10	1518.11	1946.09	1574.31	1923.33
5	1832.15	1610.06	2054.23	1674.49	2023.38
6	1911.12	1681.24	2141.01	1753.33	2102.54
7	1867.48	1630.04	2104.92	1709.82	2058.71
8	1849.51	1604.75	2094.27	1691.85	2040.74
9	1804.21	1552.35	2056.08	1646.42	1995.44
10	1846.88	1588.10	2105.65	1689.08	2038.30
11	1933.28	1667.78	2198.78	1775.49	2124.51
12	1820.12	1548.05	2092.18	1662.32	2011.35
13	1793.53	1491.98	2095.07	1635.73	1984.94
14	1867.50	1555.23	2179.77	1709.85	2058.92
15	2038.76	1716.13	2361.39	1880.97	2230.18
16	1806.87	1474.19	2139.54	1649.07	1998.28
17	1930.36	1587.94	2272.78	1772.70	2121.59
18	1961.19	1609.29	2313.10	1803.54	2152.42
19	1944.63	1583.50	2305.76	1786.84	2135.86
20	1925.70	1555.57	2295.82	1767.90	2117.11
21	1896.47	1517.56	2275.39	1738.68	2087.89
22	1932.82	1545.32	2320.32	1775.03	2124.05
23	1996.21	1600.30	2392.11	1838.55	2187.63
24	1917.58	1513.45	2321.71	1759.79	2098.40

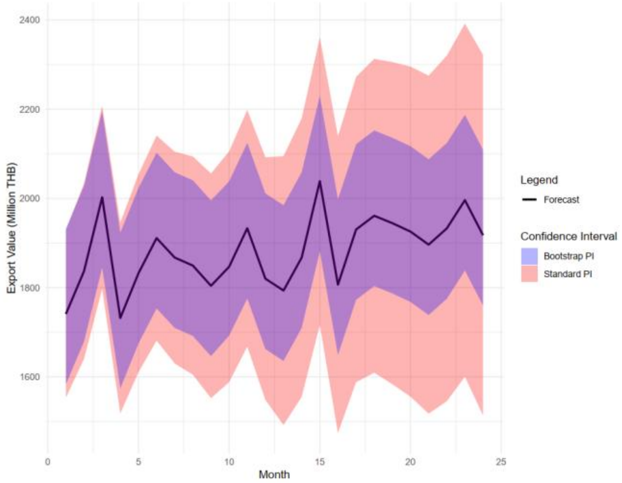

Figure 1 Prediction intervals (95%) for ASIAN+8 over a 24-month horizon

Table 11 Forecast and prediction intervals for the world (24 months)

Month	Forecast	Standard PI (95%)		Bootstrap PI (95%)	
		Lower	Upper	Lower	Upper
1	2231.05	1933.60	2528.50	1913.23	2425.86
2	2560.64	2158.30	2962.98	2270.04	2756.01
3	2702.73	2206.26	3199.20	2412.14	2936.37
4	2249.42	1673.31	2825.53	1958.83	2444.79
5	2507.48	1870.90	3144.06	2189.66	2702.85
6	2619.49	1918.26	3320.72	2301.67	2814.30
7	2449.69	1691.36	3208.03	2159.10	2644.51
8	2498.81	1693.27	3304.34	2180.98	2694.17
9	2329.26	1470.85	3187.67	2011.43	2562.90
10	2556.13	1651.68	3460.59	2265.54	2751.50
11	2847.46	1902.54	3792.38	2529.64	3042.83
12	2386.68	1395.81	3377.55	2096.08	2582.05
13	2329.81	1224.55	3435.08	2039.22	2525.18
14	2622.66	1425.23	3820.09	2331.39	2818.03
15	2643.40	1346.63	3940.18	2352.81	2838.77
16	2311.56	929.94	3693.18	2020.96	2506.93
17	2415.43	957.97	3872.89	2097.61	2610.80
18	2506.97	966.27	4047.67	2216.38	2740.61
19	2491.82	880.63	4102.99	2173.99	2725.46
20	2422.42	744.52	4100.31	2188.52	2617.23
21	2196.18	445.42	3946.95	1905.59	2391.56
22	2528.88	717.01	4340.76	2238.29	2724.25
23	2696.92	824.17	4569.67	2379.10	2892.29
24	2217.87	279.87	4155.86	1983.97	2451.51

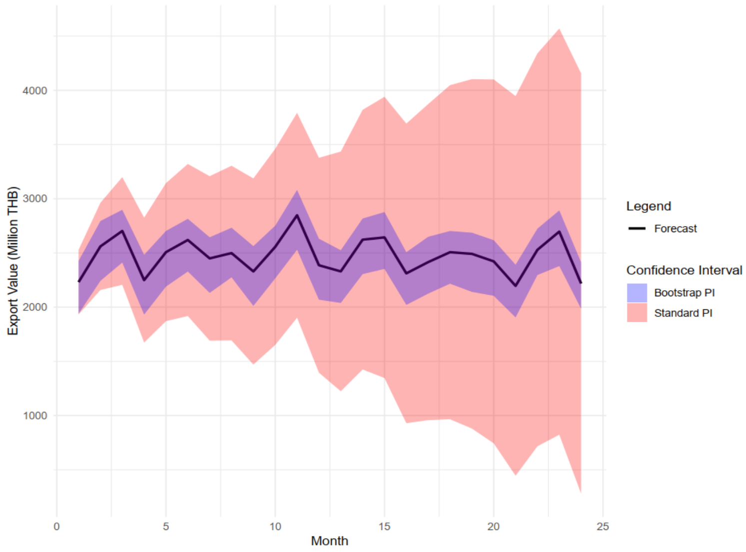

Figure 2 Prediction intervals (95%) for World over a 24-month horizon

CONCLUSIONS

This study evaluates the effectiveness of SARIMA models for forecasting Thailand's seasoning export values to ASEAN+8 and global markets. A comparative analysis of model selection techniques, specifically, grid search using AIC/BIC versus the AutoSARIMA function, provides valuable insights for optimizing forecasting accuracy. Forecast reliability is assessed by comparing Standard Prediction Intervals with Bootstrap-based PI.

Results indicate that grid search with AIC consistently outperforms AutoSARIMA, with the optimal SARIMA models yielding significantly lower RMSE and MAPE across short-, medium-, and long-term horizons. This demonstrates the advantage of manual tuning over fully automated approaches in various practical applications. Moreover, Bootstrap PI provide more robust and adaptive uncertainty quantification than Standard PI, an essential flexibility for international trade forecasting under structural changes and external shocks.

These findings have significant practical implications for policymakers, exporters, and industry professionals. By integrating an optimized SARIMA model with Bootstrap PI, businesses can enhance forecasting reliability, facilitating more informed decision-making in supply chain planning and market expansion.

Beyond methodological contributions, the proposed approach has several practical applications, particularly in supply chain planning, trade policy design, and risk management under volatile market conditions. Its key strengths include improved short-term accuracy through Grid Search and more robust uncertainty quantification using Bootstrap PI. However, limitations remain, such as higher computational cost and sensitivity to data quality. For successful implementation, practitioners should carefully determine the number of bootstrap replications, ensure reliable input data, and account for potential structural changes in the market. These considerations are critical to maximize the method's effectiveness in real-world applications.

Future research could further enhance SARIMA-based forecasting by integrating additional external macroeconomic indicators such as exchange rates and global trade policies to improve predictive precision and reliability. Moreover, addressing challenges like heteroskedasticity in residuals using models such as GARCH may further strengthen forecasting robustness in dynamic market environments. These improvements would significantly advance time series forecasting methodologies, especially in the context of global trade and economic planning.

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