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Forecasting and analysing the gap between Thailand's wood pellet supply and global demand

Phongsathon Koondee[1, 2], Jirawan Niemsakul[3], Tuangyot Supeekit[4], Tuanjai Somboonwiwat[5] and Wirachchaya Chanpuypetch*[1, 2]

[1]College of Maritime Studies and Management, Chiang Mai University, Samut Sakhon 74000, Thailand
[2]Graduate School, Chiang Mai University, Chiang Mai 50200, Thailand
[3]Faculty of Logistics and Supply Chain, Sripatum University, Chonburi Campus, Chonburi 20000, Thailand
[4]Department of Industrial Engineering, Faculty of Engineering, Mahidol University, Nakhon Pathom 73170, Thailand
[5]Department of Production Engineering, King Mongkut's University of Technology Thonburi, Bangkok 10140, Thailand

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Abstract

With the global concern for climate change on the rise, the use of biomass wood pellets as a sustainable alternative to fossil fuels is gaining popularity in numerous countries, such as the European Union (EU), the United States, Canada, Japan, and South Korea. In response, the Thai government has initiated a project to promote the cultivation of fast-growing trees, such as Acacia, which can serve as feedstock for biomass power plants both domestically and internationally. The objective of this study is to evaluate the demand-supply gap for wood pellets in Thailand. To predict future demand for wood pellets, historical import data from January 2017 to December 2021 were examined and analysed, with a variety of time-series forecasting techniques, including the Simple Moving Average (SMA), the Holt's Two-Parameter method, and the ARIMA method, being employed. The appropriate techniques were subsequently chosen based on the Mean Absolute Deviation (MAD), Mean Square Error (MSE), and Mean Absolute Percentage Error (MAPE). The results of the analysis can be utilised to identify market gaps and growth opportunities, and to develop a comprehensive supply chain strategy for wood pellets, ranging from upstream tree plantation to downstream demand.

Keywords: Wood pellets, Forecasting, Simple moving average, Holt's two-parameter, ARIMA

1. Introduction

The issue of global warming and climate change has gained widespread attention globally. The main contributor to this phenomenon is the emission of carbon dioxide as a result of the combustion of fossil fuels for heating and electricity generation. In response, many countries are turning towards biomass as a more sustainable option for electricity production in place of traditional fossil fuels.

The European Union (EU) leads in terms of global demand for biomass, accounting for over 50% of the total demand for biomass utilised for heat or electricity generation, such as wood pellets (classified under HS-Code: 440131). The demand for EU wood pellets is expected to see a substantial increase, ranging from 30-40% between 2021 and 2026 [1]. The top ten global importers of wood pellets in 2020 were the United Kingdom, Italy, Denmark, Germany, Sweden, South Korea, Belgium, France, and Austria. In terms of supply, the leading ten countries with the highest production were China, the United States, Canada, Vietnam, Germany, Sweden, Russia, Latvia, France, and Austria.

In Asia, South Korea and Japan have the largest consumption of wood pellets (excluding China). South Korea imported a total of 1,515,803 metric tons of wood pellets from countries such as Vietnam, Malaysia, Canada, Russia, Indonesia, and Thailand, with 97,597 metric tons being sourced from Thailand. Meanwhile, Japan imported wood pellets from countries like Canada, China, Indonesia, Malaysia, Vietnam, as well as Thailand.

In this context, Thailand's agricultural landscape presents a potential source of biomass feedstocks in the form of crops, fast and slow-growing trees, and agricultural waste products that can be processed into wood pellets. In recent years, Thailand has established itself as a supplier of wood pellets to several countries and has been ranked among the top 20 producers in Asia. During the period of 2017 to 2018, Thailand's wood pellet production capacity exceeded 200,000 tons. However, despite being a significant producer of wood pellets, Thailand is only able to meet one-third of the total demand for wood pellet feedstocks in its primary export markets, South Korea and Japan. This highlights the gap between Thailand's supply and the global demand for wood pellets.

The motivation for this study is grounded in the pressing issue of global warming and climate change, which has driven the search for sustainable alternatives to conventional fossil fuels. In this context, biomass, specifically wood pellets, have emerged as a more environmentally friendly option for electricity generation, gaining widespread recognition and acceptance. With expectations of a significant increase in the demand for wood pellets in the coming years, the aim of this research is to provide insights into the global demand trend for wood pellets and to develop forecasting models that can serve as a tool for identifying market gaps and expanding

*Corresponding author.
Email address: wirachchaya.c@cmu.ac.th
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the Thai wood pellet industry. The research will analyse international trade statistics data to identify the most promising market for Thailand and use the data to develop forecasting models that can be further employed to analyse market gaps, in order to enhance the industrial capacity of the Thai wood pellet industry. The information generated by this research can be highly beneficial for the Thai wood pellet industry, in terms of identifying potential markets and devising strategies for growth and expansion.

The structure of this paper is as follows. Section 2 reviews the relevant literature and consolidates the current state of knowledge on the topic under investigation. Section 3 elaborates on the methodology utilised in this research. The findings of the study are presented in Sections 4, followed by a discussion of the implications, contributions, and limitations of the research in Section 5. Finally, Section 6 presents the conclusions drawn from the research.

2. Literature review

2.1 Overview of global biomass feedstocks market

Recently, the consumption of biomass feedstocks and wood pellets has been increasing worldwide. It is also found that the demand for renewable energy is expanding, and the consumption trend for this energy is increasing as well. In the EU, the biofuel market is likely to grow from 2020 to 2030 in both the transportation and electric power sectors due to the energy targets policy [1]. According to the analysis of articles, literature, and other relevant documents, it was found that the wood pellet industry in Russia is growing rapidly, especially in terms of the export market [2]. The EU provides energy priority and accelerates the use of renewable energy to comply with EU energy laws and regulations. In line with the 2020 to 2030 energy targets, member states in the EU will likely increase the volume of biomass feedstock imports [3]. Several EU countries are moving closer to achieving the clean energy target 2020 and are ready to work towards achieving the 2030 goal. The development of biomass energy and the study of biomass mobilisation is a priority for EU countries [4].

In the case of heat energy used in Australia, it was found that power electric energy generation could be replaced by using biofuel as wood pellets by 2030. The rate of thermal energy consumption in this country produced from wood pellets has also increased [5]. In Brazil, they have studied and used a biomass resource model to assess and forecast its capabilities. It was found that Brazil has many biomass resources, and it is predicted that Brazil can be a potential feedstocks exporter [6]. Biomass buying and selling in Spain showed an increase in biomass feedstock imports and exports. Moreover, agricultural biomass is the main driver of biomass trade in the country [7]. Iran has studied the return on investment in using biomass energy, it was found that there is a large amount of wood waste that can be used to produce biomass energy [8].

The analysis of the performance of the biomass energy market and the prediction of wood pellet production and consumption brings out a set of trade and price data for wood pellets in the EU to show the market's capabilities [9]. The analysis presents the revenue from the growth of this industry. Additionally, the expansion of urban areas directly affects the increased volume of demand for biofuel [10].

2.2 Global demand for wood pellets from Thailand

Wood pellets are one form of biomass fuel made from compacted sawdust, wood shavings, or other wood waste. They are considered a renewable energy source providing a more sustainable alternative to traditional fossil fuels such as coal and natural gas. The production of wood pellets leads to lower greenhouse gas emission compared to the burning of fossil fuels making them an appealing choice for those seeking to reduce their carbon footprint. Wood pellets are cost-effective, efficient, and easy to store and transport, making them well suited for use in residential and commercial heating systems, as well as in large-scale power generation facilities.

In this section, import data for wood pellets was collected to analyse the demand trend in the global market and the key export markets of Thailand, namely South Korea and Japan. The analysis focused on the HS-Code 440131, which refers to wood for fuel, including sawdust, wood waste and scrap, that have been consolidated into wood pellets. By comparing the global import data from various regions with the import data from Thailand, opportunities for Thailand to enhance its competitiveness in the global market can be identified. The data was retrieved from the United Nations Commodity Trade Statistics Database (UN Comtrade) covering the period between 2015 and 2021. The statistics related to the import of wood pellets are presented in Table 1.

Table 1 Import statistics for wood pellets from Thailand 2015 – 2021 (Unit: tons).

Year	Global demand		Japan		South Korea	
	Global imports	Imports from Thailand	Total imports	Imports from Thailand	Total imports	Imports from Thailand
2015	14,924,520.42	25,428.79	232,425.00	197.09	1,470,684.61	18,953.14
2016	16,294,574.45	21,706.34	333,302.00	485.87	1,716,641.19	14,526.97
2017	18,505,907.25	128,031.98	506,383.78	1,078.88	2,431,165.73	126,724.57
2018	21,828,146.32	223,325.16	1,059,542.00	12,515.71	3,174,654.79	275,934.00
2019	22,502,293.86	122,616.65	1,614,057.04	42,790.93	3,002,318.84	129,395.46
2020	21,851,363.02	58,849.44	2,028,243.36	11,575.65	-	-
2021	23,364,496.39	-	3,116,797.95	-	-	-

Data source: UN Comtrade
Note: The HS-Code 440131, which refers to wood for fuel, including sawdust, wood waste and scrap, that have been consolidated into wood pellets.

We then created graphs to visualise the global demand trends for wood pellets imported from various regions and to compare it with the total exports from Thailand, as illustrated in Figure 1. The graph demonstrates a significant discrepancy between the global demand for wood pellets and the amount of supply from Thailand.

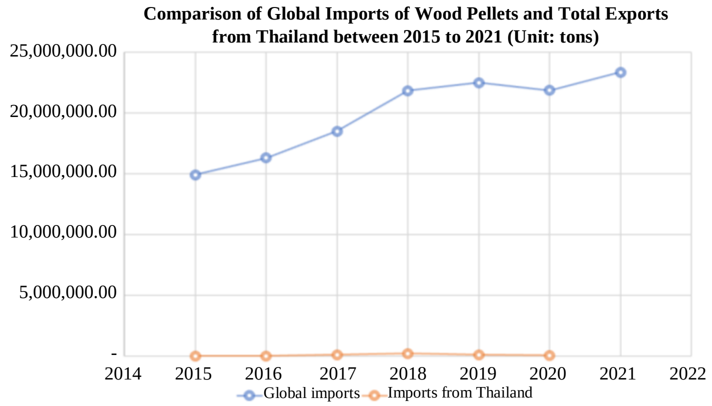


Figure 1 Comparison of global imports of wood pellets and total exports from Thailand between 2015 to 2021 (Unit: tons).

In out study, we took into consideration the primary markets for the export of wood pellets from Thailand, which including South Korea and Japan. Thailand is a significant producer of wood pellets and its exports to these countries have been increasing in recent time.

South Korea is one of the leading importers of wood pellets in the world and has been increasing its imports from Thailand in recent years. This is due to the government's efforts to reduce greenhouse gas emissions and enhance the use of renewable energy sources, such as wood pellets.

Similarly, Japan is another significant market for Thai wood pellets. The country has been increasing its imports of wood pellets in recent years to fulfil its energy needs and reduce its dependence on imported fossil fuels. Furthermore, Japan has a well-established infrastructure for importing and distributing wood pellets making it a convenient market for Thai exporters.

Therefore, South Korea and Japan are crucial markets for Thai wood pellets and play a significant role in the country's export trade. With the growing demand for renewable energy sources in these countries, it is expected that the demand for Thai wood pellets will continue to increase in the future. This demand is illustrated in Figures 2 and 3 for South Korea and Japan, respectively.

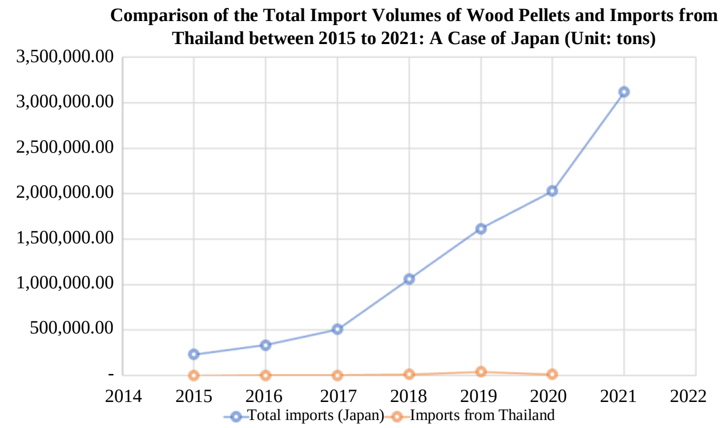
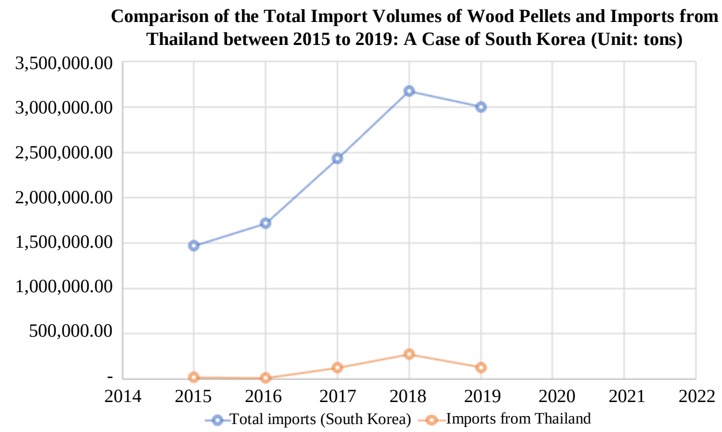


Figure 2 Comparison of the total import volumes for wood pellets and import volumes from Thailand in 2015 – 2021: A case of Japan (Unit: tons).

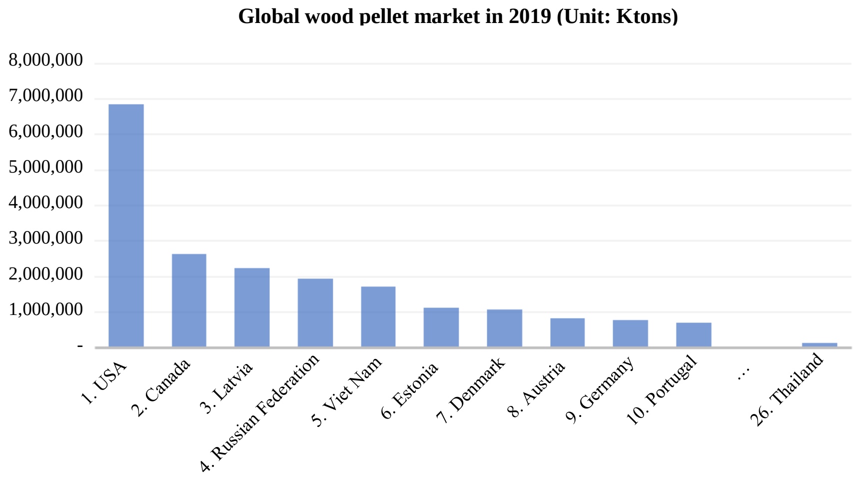


Figures 3 Comparison of the total import volumes for wood pellets and import volumes from Thailand in 2015 – 2019: A case of South Korea (Unit: tons).

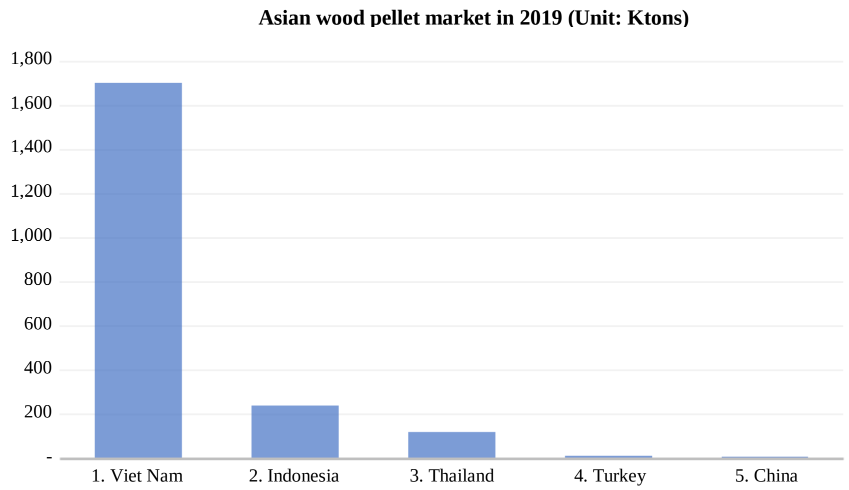
As depicted in Figures 2 and 3, the demand for wood pellets in both Japan and South Korea has been steadily increasing, mirroring the global trend. Unfortunately, Thailand is unable to meet the demand for wood pellets, resulting in a growing gap between supply and demand since 2015. By comparing the total import volumes of wood pellets and the import volumes from Thailand between 2015 to 2021 in Japan and South Korea, it is possible to analyse the demand trend for wood pellets globally and highlight the gap in supply. The subsequent section presents an analysis of Thailand's share in the international wood pellet market.

2.3 Wood pellet market

In this section, the market share of the wood pellet export industry was thoroughly evaluated to assess Thailand's market position and competitiveness within the sector. This analysis is crucial as it provides a comprehensive understanding of current market trends and enables companies to determine their strengths and weaknesses, thereby identifying new opportunities and formulating strategies to enhance their market share. The market shares of both the global and Asian wood pellet industries in 2019 are displayed in Figures 4 and 5, respectively.



Figures 4 Global wood pellet market in 2019.



Figures 5 Asian wood pellet market in 2019.

As indicated by the UN Comtrade statistics data report for the global market, the United State of America has established itself as the market leader, with a reported market share of 27% in the year 2019. In the Asian region, Vietnam emerged as the largest exporter of wood pellets, boasting a market share of 81.12% of market share. Meanwhile, Thailand holds a 5.82% market share in Asia, which ranks it third in the region and 26th globally with a mere 1% market share worldwide.

2.4 Overview of the applications of forecasting techniques

Previous market analysis reveals a substantial gap between the demand for wood pellets and the supply from Thailand. There is a rapidly growing demand for wood pellets, particularly in Japan, but Thailand's supply has not yet been able to keep up. Despite the potential for biomass feedstocks in Thailand's agricultural sector, the production of wood pellets has not increased accordingly. Additionally, Thailand is moving towards biomass as a more environmentally friendly option for electricity generation, instead of relying on traditional fossil fuels. Thus, the goal of this study is to analyse recent international trade data of the primary wood pellet market in Thailand in order to develop the most suitable forecasting model, which will be used to predict the growth of the market gap and compare it with the capacity of the Thai wood pellet industry.

Consequently, an overview of various applications of forecasting techniques are provides in this section. Torphon and Phoonsakhoo [11] conducted a study in which they employed three forecasting techniques to predict the sales of paper products. These techniques were the Weighted Moving Average (WMA), Exponential Smoothing (ES), and trend analysis, with the trend analysis, with the trend analysis method resulting in the lowest forecasts error. Likewise, Pinthong [12] applied three approaches to create sales forecasts for five rubber products in Thailand. These were the forecast with seasonality, trend analysis, and the multiplication between trend value and seasonal change index (TxS). The trend forecasting method was deemed the most suitable for this industry. Theeranaew and Worarat [13] used time series forecasting methods to predict the number of new S-curve factories that would be established. They applied the decomposition, Holt-winters, and regression methods, with the decomposition procedure producing the lowest values for Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD). Next, Jatuporn and Sukprasert [14] created a forecast for the production and export volume of Thai rubber products using statistical data. The Box-Jenkins model and Simple Seasonal Exponential Smoothing were applied, with the Box-Jenkins time series model determined to be the most appropriate forecasting model. In the corn industry, a sales forecast of corn exports was presented by [15]. This study utilised the Holt-Winters Exponential Smoothing and Box-Jenkins forecasting methods on export data from the past 20 years (2000 – 2020) and found that both methods were suitable for forecasting the export volume of corn.

Typically, in forecasting analysis, the assessment of forecast accuracy is an important component. The accuracy of a forecast provides insight into its reliability and enables informed decisions to be made based on the results. A range of metrics are used to measure forecast accuracy, including Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). These metrics quantify the degree to which forecasts match actual values. By evaluating the accuracy of various forecasting models, stakeholders can determine which model provides the most precise predictions for their particular application [16, 17].

3. Research methodology

3.1 Forecasting process

The objective of this study was to provide a projection of the global demand for wood pellets, with a particular emphasis on the primary export markets for Thailand. To commence, the study gathered historical market data, which served as the input for the selected forecasting methods. The data was then subjected to analysis to uncover trends, patterns, and interrelationships among variables. This stage incorporated the utilisation of descriptive statistics and data visualisation techniques to grasp the data. Subsequently, based on the data analysis, appropriate forecasting models were selected. These models were then estimated by utilising the data to determine the parameters that fit the data best. The estimated model was then utilised to generate predictions for the future, which may have been based on extrapolating historical trends. Finally, the accuracy of the forecast was evaluated by comparing actual values with the predictions made by the model. The accuracy of the forecasts could be measured using a variety of metrics, including MAD, MAPE, MSE, or RMSE [18, 19].

The results of this study indicated the expected market growth or decline of the wood pellet industry. An accurate projection of the market's future, produced through the most suitable forecasting model, can provide valuable information to guide decision-making and planning within the industry. The steps involved in the forecasting process are illustrated in Figure 6.

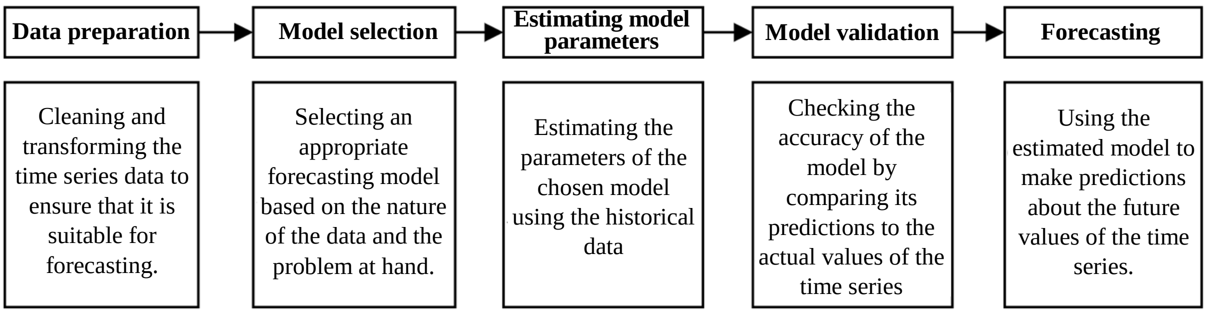


Figure 6 Steps in the forecasting process.

3.2 Dataset

As indicated by the literature review, the primary markets for the export of wood pellets from Thailand are Japan and South Korea. In order to assess the situation, this study conducted an analysis of international trade statistics, with a primary focus on these two countries. Data on the total volume of wood pellets imported globally between 2015 and 2021 was obtained from the UN Comtrade database, as depicted in Figures 2 and 3, respectively, for Japan and South Korea. It was observed that South Korea experienced irregular import volumes, with a lack of imported data available since 2019. On the other hand, Japan's import data is both continuous and up-to-date, and the country has policies that promote the import of biomass and wood pellets from overseas.

Given these considerations, this study places a central emphasis on Japan's demand for wood pellets, in order to forecast the overall trend of demand. This will permit the establishment of a market gap between Thailand and its primary export markets. The study used five years' monthly worth of Japan's total import statistics data for wood pellets, 2017 to 2021 (totally 60-month period, sourced from the UN Comtrade database. It is a collection of data recorded over period of time. This data set consists of trending factors without any recurring trends, as illustrated in Figure 7.

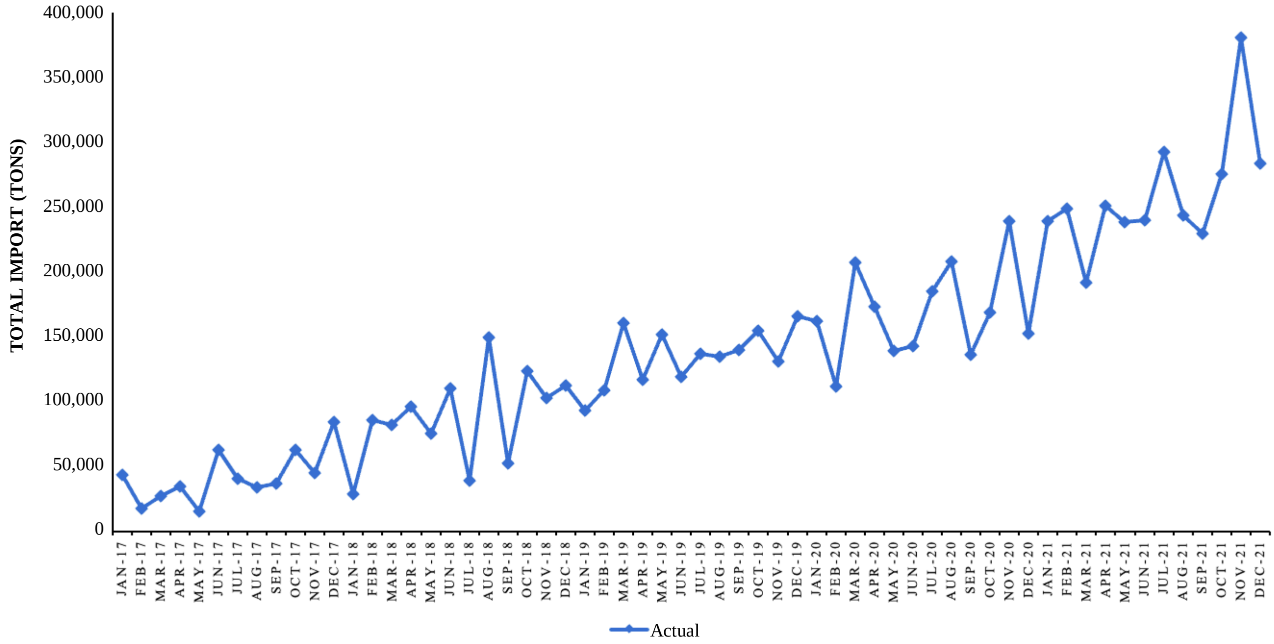


Figure 7 Time series with trend data: Japan's wood pellet total imports from 2017 to 2021.

From the time series plot, it is evident that there is a clear upward trend. This trend is a long-term increase in the data values. Additionally, there appears to be a slight curve in the data, suggesting that the rate of increase in the data values seem to accelerate over time. Given the presence of a trend in the dataset, it is necessary to employ time series analysis to model the data and generate forecasts.

3.3 Forecasting techniques

In the preceding section, it was observed that the time series plot exhibits a significant upward trend, which suggests that exponential smoothing (ES) could be a suitable method for forecasting. ES is a time series forecasting technique that utilises weighted averages to predict future points, and is advantageous for time series with a long-term upward or downward trend as it can effectively capture the trend and make accurate forecasts of future values.

In addition, a Simple Moving Average (SMA) and ARIMA are popular forecasting techniques that can be applied to time series data with an upward trend. The SMA is a simple forecasting method that involves calculating the average of a set of past observations and using this average to predict future values. The number of past observations utilised to compute the average is referred to as the "window size." SMA can be helpful in smoothing out short-term fluctuations in the data and identifying the underlying trend.

On the other hand, ARIMA is a more advanced time series forecasting method that models the autoregression and the moving average components of a time series. Autoregression pertains to the correlation between an observation and multiple lagged observations, while the moving average represents the relationship between the residual errors from the time series model and the mean value of the residual errors. ARIMA models can predict time series data with an upward trend by modelling and capturing the trend in the data and forecasting future values accordingly.

Therefore, all three techniques can be effective forecasting methods for an upward trend in a time series. Thus, this study employed three time series forecasting techniques, namely SMA, ES, and ARIMA, to predict the future demand for wood pellets in Japan. The analysis was conducted using EViews version 12, which is widely used software by economists for creating time-series forecasting [20]. The three forecasting techniques are briefly explained in Sections 3.3.1 to 3.3.3.

3.3.1 Simple Moving Average (SMA)

The Simple Moving Average (SMA) is a fundamental technique for smoothing out a time series data by averaging a selected subset of previous observations. The window size or the number of past observations used for the calculation is pre-determined and remains fixed throughout the analysis. It is contingent on the data's specifics and the desired objectives [21-23]. To compute the SMA for a given time period, the most recent k values, where k represents the window size, are summed up and divided by k. This calculation produces the SMA for that particular time period. As new data becomes available, the window shifts forward in time, and the SMA is re-calculated using the updated set of past observations [24, 25]. If the time series data points are represented as $p_1, p_2, \ldots, p_n$, then the SMA can be computed using Equation 1:

$$SMA_k = \frac{1}{k}\sum_{i=n-k+1}^{n} p_i \tag{1}$$

3.3.2 Holt's Two-Parameter method

Holt's Two-Parameter method was employed in this investigation for forecasting purposes. It is a variation of the exponential smoothing method suitable for time series that exhibit trends but not seasonality, and is frequently utilised for smoothing models to forecast trend data. The approach incorporates a trend component to the simple exponential smoothing method and involves two smoothing parameters, namely the level smoothing parameter (alpha, α) and the trend smoothing parameter (beta, β). The level smoothing parameter regulates the weight assigned to the most recent observation in the forecast, while the trend smoothing parameter controls the weight assigned to the estimated trend [26, 27]. A higher alpha value prioritises the most recent observation, while a higher beta value results in a more consistent trend estimation. Both parameters range from 0 to 1 [28, 29]. The equation for Holt's Two-Parameter method is shown below:

$$F_{t+m} = L_t + mb_t \tag{2}$$

where:

$L_t = \alpha y_t + (1-\alpha)(L_{t-1} + b_{t-1})$ (level series)
$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1}$ (trend estimate)
α = smoothing constant for the level ($0 \leq \alpha \leq 1$)
β = smoothing constant for the trend ($0 \leq \beta \leq 1$)
m = periods to be forecast into the future

3.3.3 Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model is a widely used statistical model for forecasting future values of a time series based on its historical data. The primary purpose of the ARIMA model is to generate stable, interference-free data based on the Box-Jenkins approach. The model consists of three main components, including Autoregression (AR), Integration (I), and Moving Average (MA) [30-32].

To use an ARIMA model for forecasting, the appropriate parameters of the model, denoted by ARIMA(p,d,q), must be identified. The p parameter represents the number of autoregressive terms, d represents the degree of differencing required to make the time series stationary, and q represents the number of MA terms [33, 34]. Initially, we test whether the time series is stationary or not using statistical tests such as the Augmented Dickey-Fuller (ADF) test or the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. If the time series is non-stationary, we apply the differencing method to make it stationary by removing trends [35, 36].

After making the time series stationary, we can identify the degree of differencing (d) required for the ARIMA model. We can then use Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to identify the different ARIMA models [37, 38]. By comparing the ACF and PACF graphs, the appropriate parameters of the ARIMA model can be selected [18, 39, 40], as detailed in Table 2.

Table 2 Characteristics of theoretical ACF and PACF for stationary process.

Model	ACF	PACF
AR(p)	Tails off exponential decay or damped sine wave	Cuts off after lag p
MA (q)	Cut off after lag q	Tails off exponential decay or damped sine wave

Once the optimal parameters of the ARIMA model have been identified, we can estimate the model's parameters and select the most suitable model for prediction based on statistical measures such as the Akaike Information Criterion (AIC) and the Schwarz Criterion, also known as the Bayesian Information Criterion (BIC). These measures compare the goodness-of-fit of different ARIMA models, allowing to choose the most suitable model for time series. In summary, the ARIMA model is a valuable tool for forecasting future values of time series data, and the selection of appropriate parameters is crucial for accurate predictions [40].

3.4 Evaluating forecast accuracy

The evaluation of forecast accuracy is an essential final stage in the forecasting process where the forecasted values are compared against actual values to gauge the effectiveness of the forecast model. The primary objective of this step is to establish the forecast's accuracy and highlight areas that require further improvement. Several forecast accuracy tests can be utilised to assess the performance of various forecasting models. Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Error (MSE) are commonly used forecast accuracy metrics for SMA, Holt's two-parameter, and ARIMA models [16, 17, 41, 42].

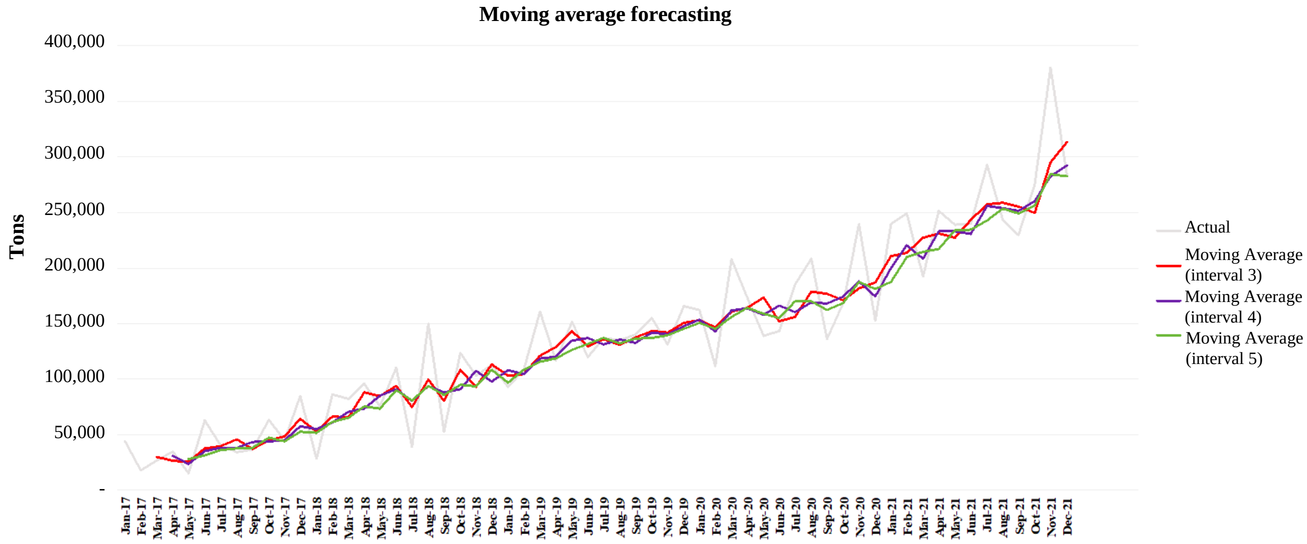
MAPE is often used to determine forecast accuracy by computing the average percentage difference between the forecasted and actual values, where lower values indicate higher forecast accuracy. However, this metric has limitations, such as sensitivity to extreme values and difficulties in handling zero or near-zero actual values [43]. MAD is another commonly used metric that determines the average absolute difference between the forecasted and actual values, with lower values indicating higher forecast accuracy. However, MAD is prone to the influence of outliers from the average, leading to skewed results when extreme values are present in the data. Similarly, MSE measures the average squared difference between the forecasted and actual values and is commonly used to evaluate the three forecast models, with lower values indicating higher forecast accuracy. Nonetheless, MSE, like MAD, is also sensitive to outliers from the average, which can skew results when extreme values are present in the data [44, 45].

As all these metrics have limitations, a combination of multiple metrics is recommended to provide a more comprehensive assessment of forecast accuracy. This study utilises three metrics, namely MAD, MSE, and MAPE, to measure forecast error [46, 47].

4. Results

4.1 Forecasting models using SMA

Initially, this study applied SMA-based forecasting models to analyse Japan's wood pellet imports data from 2017 to 2021, which included a trend component. The models were generated with intervals of 3, 4, and 5 months for data analysis, and the forecast data from each interval was presented in Figure 8. SMA-based forecasting models involve computing rolling averages over a specified interval, and are commonly employed in time series analysis to predict future trends or values. Figure 8 provides visual representations of the forecasted trends in Japan's wood pellet imports based on the different intervals of the SMA-based forecasting models.



Figures 8 SMA-based forecasting models for the time series data of Japan's wood pellet total imports from 2017 to 2021.

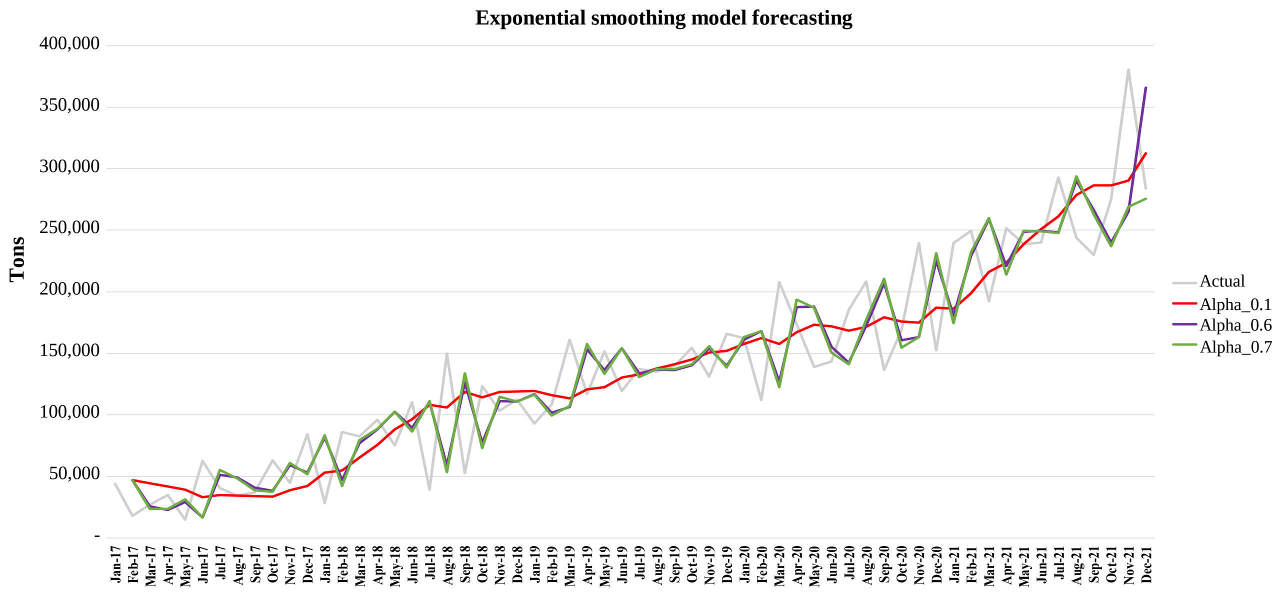
Subsequently, we conducted an analysis of the forecast accuracy of the various SMA-based models. This analysis involved computing forecast accuracy measures, namely Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE), and comparing the forecast values obtained from each model. The results of the analysis are presented in Table 3. The findings revealed that the forecast accuracy varied significantly among the different intervals of the SMA model, with the 3-month SMA forecast exhibiting the lowest error. This outcome suggests that the 3-month SMA model may be the most accurate for predicting future trends in Japan's wood pellet imports data from 2017 to 2021.

Table 3 The forecast accuracy of the SMA-based models.

SMA	MAD	MSE	MAPE
3-month SMA	19,872.93	661,427,329.25	17.78%
4-month SMA	20,558.65	711,778,751.01	18.61%
5-month SMA	20,952.60	788,779,016.08	18.49%

4.2 Forecasting models using Holt's Two Parameter method

In order to enhance the accuracy of our forecasting analysis of Japan's wood pellet imports from 2017 to 2021, we also utilised Holt's Two Parameter method, which is a double exponential smoothing method that takes into account both trend and level components of time series data. This method provides more precise forecasts than simple models by adjusting the smoothing parameters, alpha (α) and beta (β). In this study, we evaluated three different Holt's Two Parameter-based models with specific alpha and beta values, namely 1) alpha 0.1 beta 0.9 , 2) alpha 0.6 beta 0.4, and 3) alpha 0.7 beta 0.3. The forecasting results for each model are illustrated in Figure 9.



Figures 9 Holt's Two Parameter-based forecasting models for the time series data of Japan's wood pellet total imports from 2017 to 2021.

After generating forecast values using the Holt's Two Parameter method for the Japan's wood pellet imports data from 2017 to 2021, the accuracy of each model was assessed using MAD, MSE, and MAPE measures. The obtained error data were compared and presented in Table 4. The analysis revealed that the model with alpha and beta 0.9 had the least volatility, indicating the highest accuracy of prediction among the three Holt's Two Parameter-based models tested.

Table 4 The forecast accuracy of the Holt's Two Parameter-based models.

α	β	MAD	MSE	MAPE
0.1	0.9	25,384	1.04E+09	28.20%
0.6	0.4	33,348	1.83E+09	33.95%
0.7	0.3	33,401	1.83E+09	35.04%

4.3 Forecasting models using ARIMA

A further forecasting method was implemented to analyze Japan's wood pellet import data from 2017 to 2021 using the ARIMA time series forecasting technique. ARIMA is a widely used approach that involves multiple computation steps were performed in the following order.

4.3.1. Stationary test

The concept of stationarity in time series data refers to the stability of statistical properties, such as mean, variance, and autocovariance, over time. This is a fundamental assumption for numerous time series analysis methods, including ARIMA modelling and cointegration analysis. In cases where a time series is identified as non-stationary, it can be transformed into a stationary series through techniques such as differencing or de-seasonalising [48, 49].

This study assessed the stationarity of the time series data by using the Augmented Dickey-Fuller (ADF) test. The ADF test is a widely used unit root test in econometrics and time series analysis that enables researchers to determine the existence or absence of a unit root in the data and select the most appropriate methods for modelling and forecasting.

The null hypothesis of the ADF test asserts the existence of a unit root in the time series dataset. The ADF statistic is a negative value, with a more negative result indicating a stronger rejection of the null hypothesis at a given confidence level. If the test statistic is lower than the critical value, the null hypothesis is rejected, implying that the time series is stationary. Conversely, if the test statistic is greater than the critical value, the null hypothesis is not rejected, meaning the time series is non-stationary [50, 51].

In this study, the ADF test was implemented through Python programing. The results showed that the ADF test statistic of the original time series data was positive (2.1829) with a *p*-value of 0.9989. Comparing the test statistic to the critical values, it appears that the null hypothesis could not be rejected, suggesting that the time series is non-stationary and has a time-dependent structure.

As a result of the non-stationary, differencing was performed in this study. Differencing is a commonly used method to transform a non-stationary time series into a stationary one by subtracting the value of the time series at a given point from the value at previous point. After performing the first-ordered difference time series, the ADF test statistic became more negative (-6.6161) with a *p*-value of $6.2020e^{-09}$, allowing for the rejection of the null hypothesis. This implies that the first-ordered difference time series is stationary and does not contain a unit root. The results of the unit root test for the time series data are shown in Table 5, with the smooth series of the first-ordered difference time series of Japan's wood pellet imports illustrated in Figure 10.

Table 5 The results of the unit root test for the time series data of Japan's wood pellet total imports.

Time series data	ADF value	Critical value	*p*-value	Stability
Original time series	2.1829	1%: -3.558 5%: -2.917 10%: -2.596	0.9989	Nonstationary
The first-order differenced time series	-6.6161	1%: -3.555 5%: -2.916 10%: -2.596	$6.2020e^{-09}$	stationary

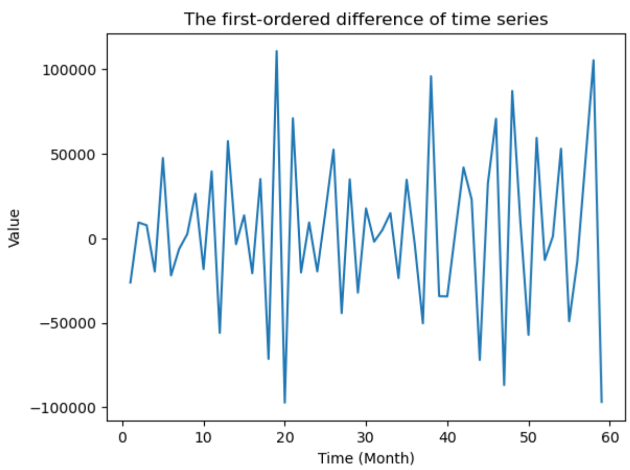


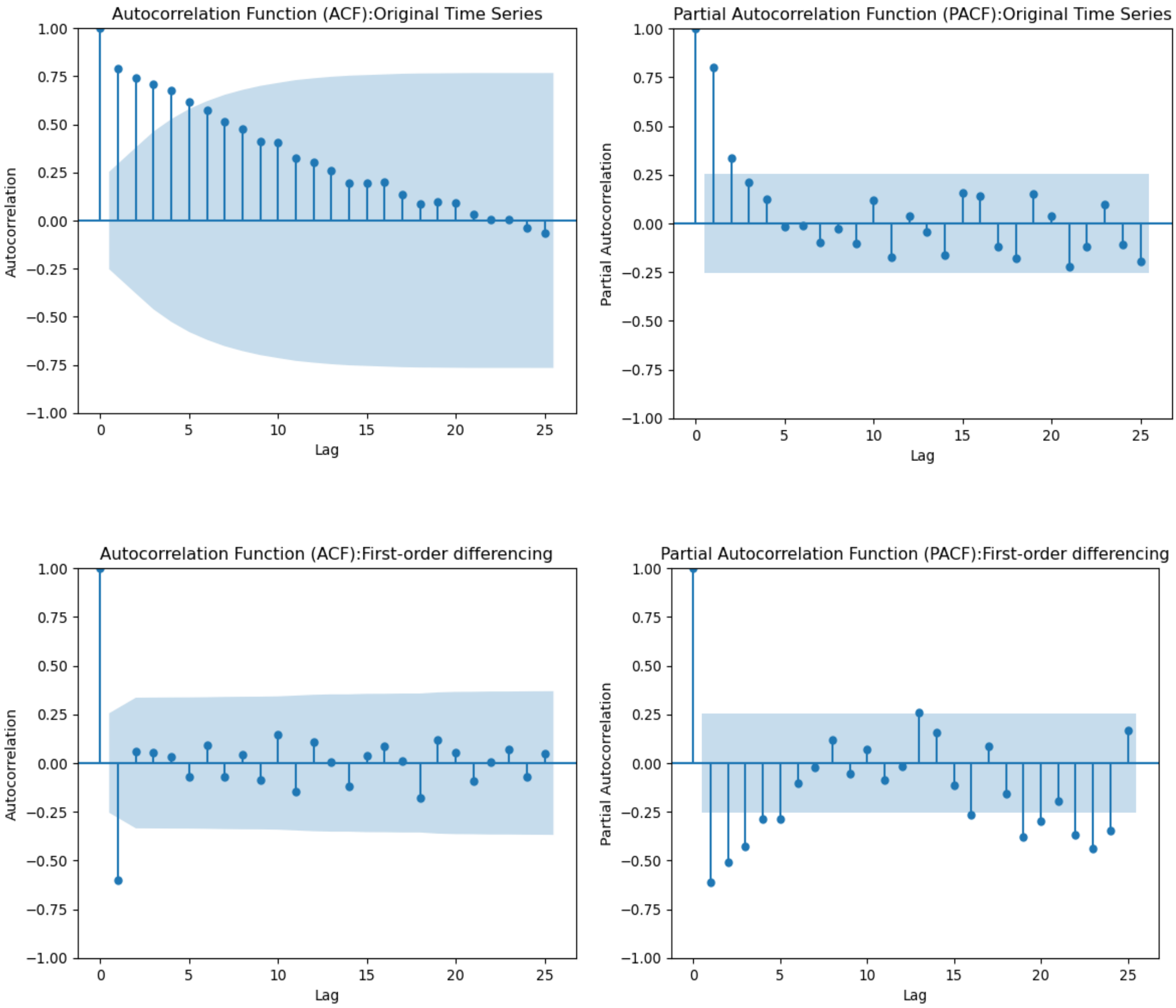
Figure 10 The smooth series of the first-ordered difference time series of Japan's wood pellet total imports.

4.3.2 Autocorrelation analysis

In ARIMA modelling, the parameters "*p*", "*d*", and "*q*" denote the autoregression (AR), integration (I), and moving average (MA) components, respectively. As previously determined through the ADF test, the original time series data was found to be non-stationary. To address this, a first-ordered differencing was performed, resulting in a new time series data that was deemed stationary and free of a unit root. Hence, the order of the differencing parameter "*d*" was established as 1.

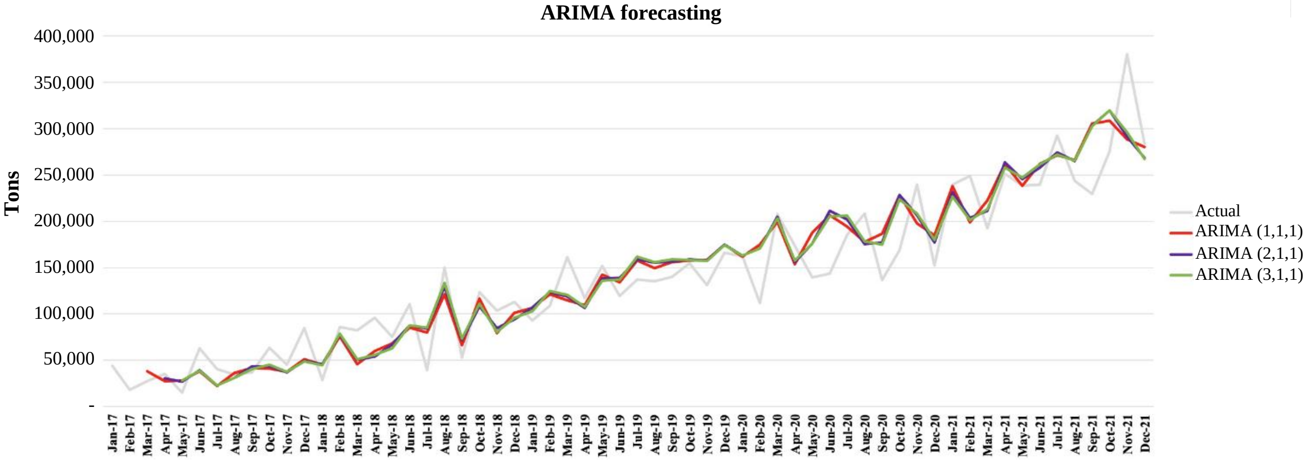
In order to determine the order of the AR term "*p*" and MA term "*q*" parameters, autocorrelation analysis was performed. This involved utilising the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. The order of the AR (*p*) was identified by the number of significant spikes in the PACF plot, while the order of MA (*q*) was determined by the number of significant spikes in the ACF plot that fall to zero after a few lags [40, 48].

The ACF and PACF plots for the original time series data and the first-differenced time series data of Japan's wood pellet total imports from January 2017 to December 2021 were presented in Figure 11 at a 95% confidence level. The purpose of these plots was to determine the order of the autoregression (AR) and moving average (MA) terms in the ARIMA model through an autocorrelation analysis.



Figures 11 The ACF and PACF plots for the original time series data and the first-ordered difference time series data of Japan's wood pellet total imports from January 2017 to December 2021.

In accordance with Figure 10, the ACF and PACF were analysed in order to determine the parameters "*p*" and "*q*" of the ARIMA model for the first-ordered difference time series data. A careful examination was conducted to determine whether the spikes were situated above or below the confidence interval (depicted by the blue area) prior to the emergence of the next spike within the blue area. The ACF of the first-ordered difference time series data revealed a single significant autocorrelation spike at the first "*q*" lag, thus implying an MA (*q*) value of 1. To establish the value of "*p*" in the AR (*p*) model, a scrutiny of the PACF plot was performed, which led to an estimation of using 3 AR terms. The parameter AR (1), AR (2), and AR (3) were accordingly established. Subsequently, the dataset was forecasted using the ARIMA (1,1,1), ARIMA (2,1,1), and ARIMA (3,1,1) models as demonstrated in Figure 12.

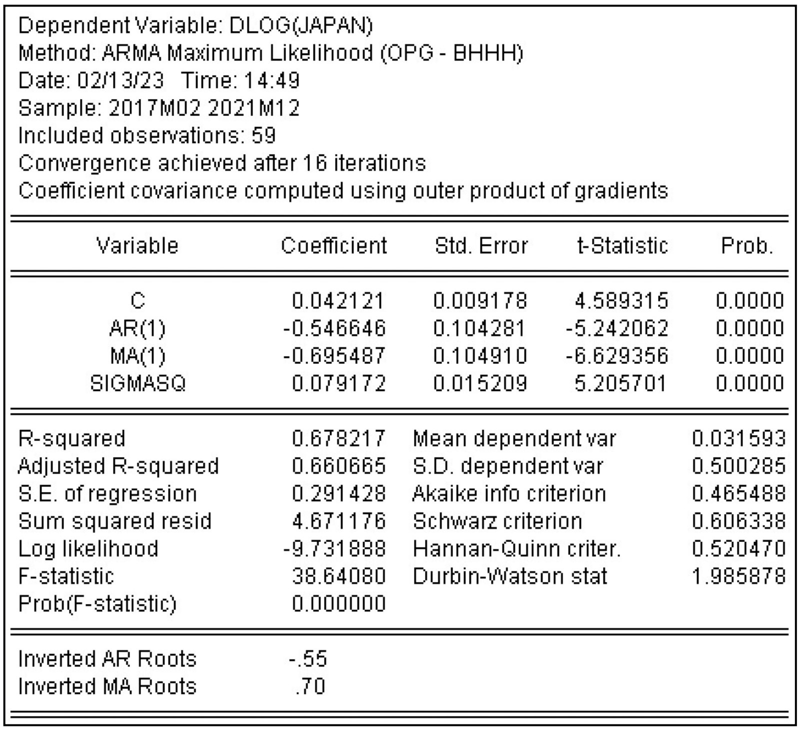


Figures 12 The results of ARIMA forecasting.

Subsequently, the optimal ARIMA model is determined by evaluating the Akaike Information Criterion (AIC) and the Schwarz Criterion, which is also known as the Bayesian Information Criterion (BIC). These two methods are widely used for selecting the most appropriate ARIMA model for a given time series dataset [40, 48]. The selection process involves comparing the AIC and BIC values of various ARIMA models and selecting the one with the lowest AIC and BIC values. Table 6 presents the fit test results for the first-ordered difference time series data of Japan's global imports of wood pellets from the years 2017 to 2021.

Table 6 The fit tests for the first-ordered difference time series data of Japan's wood pellet total imports from 2017 to 2021.

	ARIMA(1,1,1)	ARIMA(2,1,1)	ARIMA(3,1,1)
AIC	0.4655	0.4714	0.4982
BIC	0.6063	0.6475	0.7095



Dependent Variable: DLOG(JAPAN)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 02/13/23 Time: 14:49
Sample: 2017M02 2021M12
Included observations: 59
Convergence achieved after 16 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.042121	0.009178	4.589315	0.0000
AR(1)	-0.546646	0.104281	-5.242062	0.0000
MA(1)	-0.695487	0.104910	-6.629356	0.0000
SIGMASQ	0.079172	0.015209	5.205701	0.0000

R-squared	0.678217	Mean dependent var	0.031593
Adjusted R-squared	0.660665	S.D. dependent var	0.500285
S.E. of regression	0.291428	Akaike info criterion	0.465488
Sum squared resid	4.671176	Schwarz criterion	0.606338
Log likelihood	-9.731888	Hannan-Quinn criter.	0.520470
F-statistic	38.64080	Durbin-Watson stat	1.985878
Prob(F-statistic)	0.000000		

Inverted AR Roots	-.55
Inverted MA Roots	.70

Figure 13 Statistical analysis of ARIMA (1,1,1) fitting results for the first-ordered difference time series data of Japan's wood pellet total imports from 2017 to 2021.

As indicated in Table 6, upon comparing the established models of ARIMA(1,1,1), ARIMA(2,1,1), and ARIMA(3,1,1), it is evident that the AIC and BIC values of ARIMA(1,1,1) are lowest at 0.4655 and 0.6063, respectively. As a result, as illustrated in Figure 13, ARIMA(1,1,1) is deemed the optimal model and its specific equation is

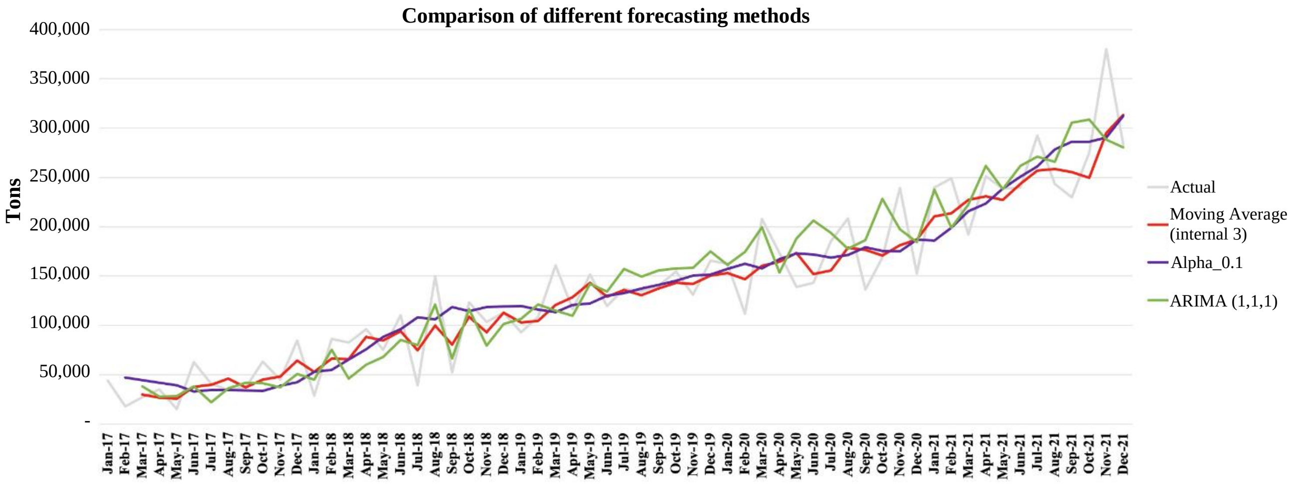
$$Y_t = 0.042121 - 0.546646Y_{t-1} - 0.695487\varepsilon_{t-1} + \varepsilon_t \quad (3)$$

4.4 Comparing the different forecasting models

Based on the presented forecasting results using various methods, the models with the least amount of error were selected for comparison. These include the 3-month SMA, Holt's Two Parameter model (with α=0.1 and β=0.9), and ARIMA (1,1,1). The comparison was made using forecast accuracy measures, namely MAD, MSE, and MAPE, as presented in Table 7. In addition, differences in forecast values and a comparison of the forecasting models can be displayed in the form of graphs, as illustrated in Figure 14.

Table 7 Comparison of forecast accuracy

Forecasting models	MAD	MSE	MAPE
3-month SMA	19,873	6.61E+08	17.78%
Holt's Two Parameter (α=0.1, β=0.9)	25,654	1.00E+09	28.19%
ARIMA (1,1,1)	23,867	9.59E+08	21.98%



Figures 14 Comparison of different forecasting methods.

The analysis showed that the 3-month SMA method had the lowest forecast errors with MAD = 19,873, MSE = 6.61E+08, and MAPE = 17.78%. This model was identified as the most appropriate due to the presence of an upward trend in the time series dataset [18]. Therefore, for wood pellet market demand forecasting based on the input data, the 3-month SMA method is the recommended alternative.

5. Discussion, strategic implications, and limitations

5.1 Discussion and strategic implications

The present study has significant strategic implications for the Thai wood pellet industry. Firstly, it provides valuable insights into the global trend in demand for wood pellets (HS-Code 440131), which can assist the industry in planning its production and expansion strategies. The study identifies an increasing demand for wood pellets, a trend that is likely to continue in the future, thereby presenting an opportunity for the Thai wood pellet industry to expand its production capacity and market share. Additionally, the study highlights the Japanese market as an important market for Thai wood pellets, with Japan's demand for wood pellets having increased in recent years, and Thailand having met a considerable proportion of this demand.

Furthermore, the study recommends the 3-month SMA forecasting model as the best fit model for predicting the future demand for wood pellets in Japan. This finding enablers the Thai wood pellet industry to plan and expand its production and marketing strategies accordingly, and to focus on meeting the demand from the Japanese market. Moreover, the study suggests that the application of SMA, Holt's Two-Parameter method, and ARIMA method could be extended to other countries that show potential for wood pellet markets. Future research should explore the potential for wood pellet demand in other countries and develop more accurate forecasting models. However, it should be noted that the study relied solely on historical data to construct the forecasting model, and potential shifts in demand and market conditions could impact its accuracy. Therefore, the study emphasises the importance of regularly monitoring and updating forecasting models and production strategies based on changes in market conditions [52, 53].

In summary, the study's findings offer valuable strategic implications for the Thai wood pellet industry. By focusing on expanding production capacity, meeting the demand from the Japanese market, and continually monitoring and updating strategies based on changing market conditions, the Thai wood pellet industry can establish itself for long-term success and growth. Furthermore, the research outcomes may inform the development of strategies for the supply chain of wood pellets, from upstream tree plantation to downstream demand, contributing to the transition to more sustainable forms of energy.

5.2 Limitations of the study

This research has certain limitations that should be acknowledged. Firstly, the investigation solely focuses on the Japanese wood pellet market and does not examine the demand for wood pellets in other potential markets. Therefore, the forecasting model formulated in this study may not be generalisable to other markets with different characteristics. Further research should explore additional markets and their demand for wood pellets to enhance the applicability of the forecasting model.

Secondly, the forecasting models developed in this study rely on historical statistical data from HS-Code 440131, which represents wood pellets. Other HS-Codes that may contain wood pellets were disregarded. Future research should explore more relevant products to develop more accurate demand forecasts. The range of data should be expanded further to encompass HS-Code 440132 - woods for fuel, sawdust, wood chips, and wood chips that coagulate in lumps of wood. This is critical as briquettes may provide more economic value and could be a significant input for data analysis of biomass supply.

Moreover, unforeseen events, such as changes in government policies, natural disasters, or global pandemics, could influence the wood pellet industry and affect the accuracy of the forecasting models. Future research should consider these factors and their impact on demand forecasts.

6. Conclusions and further research

In conclusion, this study provides valuable insights for the Thai wood pellet industry and highlights the potential of the industry to increase its production capacity and expand its market share. By focusing on meeting the demand from the Japanese market, stakeholders in the industry can use a suitable forecasting model to forecast future market demand and plan production and expansion strategies accordingly. The study also identifies the need for ongoing monitoring and updating of forecasting models and production strategies based on changing market conditions.

It is important to note that the study has limitations, including the focus on only the Japanese market and the use of only historical statistical data for the forecasting model. Further research is needed to explore other potential markets and to include more relevant products for more accurate demand forecasts. Additionally, addressing the challenge of raw material supply in the biomass industry in Thailand requires further research, such as cost-benefit analyses of fast-growing tree plantations. This can provide valuable guidance for investment in the industry and contribute to the country's long-term economic development while mitigating the adverse effects of climate change.

Further research is also needed to consider the sustainability of wood pellet production and transportation and to explore the potential for the development of more environmentally-friendly production processes. The findings of this study can inform the development of strategies for the supply chain of wood pellets from upstream tree plantation to downstream demand and contribute to the transition to more sustainable forms of energy. Overall, this study provides valuable insights for the Thai wood pellet industry and can inform strategic decision-making for the industry's long-term success and growth.

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