

ARIMA (p, d, q) Modeling for Predicting Exports of Fresh and Chilled Fish Based on Market Conditions and Main Destination Countries : The Case of Indonesia 2012-2022

VITRI APRILLA HANDAYANI¹, EKO SULISTYONO², HERY SUNARSONO³, ADAMSYAM ARAFI⁴, DIANA SARI HARAHA⁵

^{1, 2, 4, 5}Department of Mathematics Faculty of Information Technology Batam Institute of Technology, Indonesia

³Department of Engineering Management Faculty Industrial Technology Batam Institute of Technology, Indonesia

e-mail: vitri@iteba.ac.id

ABSTRACT

Fresh and chilled fish are the largest contributor to Indonesia's fishery product exports, accounting for a share of 45% or around USD 2.2 billion in 2021. The main destination countries for Indonesia's fresh and chilled fish exports include China, the United States, Japan, and other European countries. This research aims to analyze the factors influencing the export value of Indonesia's fresh and chilled fish, as well as to identify and evaluate the ARIMA (p, d, q) model based on historical data from 2012-2022. The result is an ARIMA (4,2,2) model with a MAPE value of 2.208 and a predicted value for the 2023 period of 4351 tons. This is in line with the large exports of fresh fish from Indonesia to various destination countries.

Keywords: Exports, Fresh-Chilled Fish, Forecasting, ARIMA Model.

1. INTRODUCTION

Indonesia, as an archipelagic country with the second longest coastline in the world, has enormous fisheries potential. The capture and aquaculture sector is an important non-oil and gas foreign exchange contributor for Indonesia. Badan Pusat Statistik (BPS) data shows that the export value of Indonesian fishery products in 2021 was USD 4.8 billion (Lingkup & Dan, 2011). Fresh-chilled fish is the largest contributor to exports of Indonesian fishery products with a share reaching 45% or around USD 2.2 billion in 2021. The main destination countries for Indonesian fresh-chilled fish exports include China, the United States, Japan and other countries European (Febryanti & Utami, 2022). However, the values of Indonesia's fresh-chilled fish exports shows fluctuations from year to year, influenced by various factors. During 2012-2022, the average growth was only 2.3% per year. Fluctuations in export value are caused by the high dependence of exports on raw material supplies which are influenced by seasons and climate, as well as dynamic global market conditions influenced by economic turmoil, trade policies and demand from destination countries (Wicaksana et al., 2022) (Da Silva et al., 2023). Therefore, to maintain the performance and growth of fresh-chilled fish exports in the future, an appropriate prediction model is needed that takes into account the various factors mentioned previously (Asnawi et al., 2021). With accurate predictions, various policies and strategies can be implemented to support the availability of raw material supplies and increase market access so that export growth can be achieved optimally and sustainably (Febianah et al., 2021).

So far, not much research has been carried out regarding the prediction of the value of Indonesian fish exports by considering the main factors that influence it comprehensively. Several previous studies focused more on aspects of capture and aquaculture production (Irawati et al., 2019), Meanwhile, studies regarding export market prospects and the factors that influence them are still very limited. In fact, information regarding the projected future export value is very important

to direct efforts to increase the competitiveness of Indonesian fishery products in the global market. By modeling the main factors determining the value of fresh-chilled fish exports over the past few years, it is hoped that reliable projections regarding future export trends can be obtained. This projection information can be used as input for the preparation of various policy interventions to maintain the availability of raw material supplies, improve quality and competitiveness, develop new markets, and so on (Rahmah & Sitompul, 2023) (Yonvitner et al., 2020).

Thus, it is important to carry out this research to support efforts to increase the export performance of Indonesian fishery products through a comprehensive and reliable prediction model, where this is in line with the grouping of fish cultivation and will be linked to fish production in Indonesia and evaluating the optimization of the number of fish catches using stepped cages (Handayani et al., 2023)(Sunarsono et al., 2022). It is hoped that the predicted value of fresh-chilled fish exports in the future can be used to formulate policies for the development of export-oriented capture, cultivation and processing fisheries sectors.

The Autoregressive Integrated Moving Average (ARIMA) model is a popular method used for time series forecasting. ARIMA is capable of capturing patterns in data that contain autoregressive (AR) and moving average (MA) components, and can address non-stationarity issues through differencing (integrated). Several prior studies have successfully applied ARIMA in forecasting various types of time series data, such as economic data, weather data. In this research, ARIMA was chosen because the data satisfies the stationarity assumption after differencing and does not exhibit significant seasonal patterns. Nevertheless, this study has its own uniqueness by applying ARIMA to Exports of Fresh and Chilled Fish Based on Market Conditions and Main Destination Countries data, thus contributing a novel application of the ARIMA method for forecasting similar data types (Hernandez-Matamoros et al., 2020).

1.1 Time Series Model

Autoregressive Model (AR):

Autoregressive model (AR) is a statistical model that utilizes the relationship between variable values in a time period and variable values at a previous time. In the context of export value prediction, AR takes into account that the export value in a period can be predicted based on the export value in the previous period. Equation AR(p) shows the relationship between a variable and its previous values up to p lag:

$$X_t = c + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \dots + \phi_p X_{t-p} + \varepsilon_t \quad \dots (1)$$

X_t is the export value at time t , ϕ_1 is the regression coefficient, c is a constant, and ε is random error at time t .

Moving Average Model (MA):

Model moving average (MA) is a model that describes the relationship between variable values at a certain time and previous error values (Van Rossum, 2019). MA(q) consider the relationship between the export value and the previous finite error values q lag:

$$X_t = \mu + \varepsilon_t + \theta_1 + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} \quad \dots (2)$$

X_t is the export value at time t , ε_t was an error in timing t , θ_i is the coefficient in the MA model, and μ is the average export value.

ARIMA (Autoregressive Integrated Moving Average)

The ARIMA model is a combination of the AR and MA models which also takes into account the differentiation process to make the data stationary. ARIMA (p, d, q) consists of three main components: AR (p) for the autoregressive component, I(d) for differentiation components, and MA (q) for the moving average component. This model can be used to predict export values based on its own historical data after addressing seasonal trends and variations (Siami-Namini et al., 2018) (Fattah et al., 2018).

Stationarity Testing

Stationarity is a crucial requirement in ARIMA modeling. A time series data is considered stationary if there are no significant changes in the mean and variance over time. There are two types of stationarity: mean stationarity and variance stationarity. Stationarity testing can be done by examining the time series plot and the autocorrelation function (ACF) plot. If the data is non-stationary, the differencing process needs to be performed (Horváth et al., 2014).

Differencing Process

Differencing is the process of creating new data from the difference between the current and previous observations. The purpose is to obtain stationary data, both in mean and variance. The degree of differencing (d) is determined by the number of differencing processes required until the data becomes stationary. If the data is still non-stationary after the first differencing, a second differencing is performed, and so on until stationarity is achieved (McGonigle et al., 2022).

Model Validation

After the ARIMA model is formed, validation is necessary to ensure the model is suitable for use. Validation includes parameter significance testing, residual white noise testing, and residual normality testing.

Parameter Significance Testing

The ARIMA model parameters, p, d, and q, must be significant at a certain level of significance (α), such as 5% or 10%. If insignificant, other models should be considered.

Residual White Noise Testing

The residuals should be white noise, meaning there should be no specific pattern. This can be tested by examining the residual ACF plot, Ljung-Box Q-statistic values, or run tests.

Residual Normality Testing

The residuals are required to be normally distributed to ensure unbiased estimation. Normality testing can be performed using the Kolmogorov-Smirnov test, Anderson-Darling test, or others.

If the model passes all three tests above, the ARIMA model can be used for forecasting. However, if it fails, re-identification and re-estimation of the model are necessary (Liu & Zhou, 2024).

With ARIMA, we can combine information from export values in previous periods, consider seasonal patterns, and take into account changes in trends to produce more accurate predictions. (Majiid & Handayani, 2023). Through the use of these models, research on export value predictions can utilize historical analysis of export data to identify patterns, trends and fluctuations that influence export values. Comparison and testing of these models on relevant export data can help determine the most appropriate model for predicting future export values with a greater degree of accuracy.

2. RESEARCH METHOD

2.1 Research Design

This study employed the ARIMA modeling approach for time series forecasting of Export-Import data. The dataset consisted of 132 observations recorded from 2012 to 2022. To evaluate the model's performance, the dataset was divided into training and testing sets. The first ARIMA (p,d,q) of the observations, were used as the training set to estimate the ARIMA model parameters.

The training data was used to identify the optimal order of the ARIMA (p,d,q) model by analyzing the autocorrelation and partial autocorrelation functions. Several candidate models were fit to the training set and the best model was selected based on ACF and PACF Plot.

Once the final ARIMA model was specified, it was trained on the entire training dataset. The model's predictive accuracy on the testing set was then evaluated using performance metrics such as RMSE and MAPE. This train-test split allows us to simulate a realistic forecasting scenario and obtain an unbiased estimate of how well the model can generalize to new unseen data points.

The research design for this research activity includes: 1) Identify the problem that will be studied in this research by determining the problem and research gap. Based on research conducted previously on (Sunarsono et al., 2022) in an effort to optimize the type of net angle used as a medium for catching fish in the sea used by fishing communities. Apart from that, there are groupings of types of fish cultivation developed in Indonesia (Handayani et al., 2023). 2) Based on this and data sources related to the number of Fresh-Chilled Fish Exports Based on Market Conditions and Main Destination Country: Indonesian Case 2012-2022, the research that will be carried out is aimed at knowing the modeling and forecasting of Export-Import data. 3) The data was explored and analyzed using time series analysis and multivariate analysis to determine the existence of modeling and forecasting Export-Import data in Indonesia in 2012-2022.

2.2 Data Collection Techniques

Secondary data refers to the type of data collected by other parties or obtained from pre-existing sources. This data is not collected directly by researchers or data users to be used by other individuals or organizations for analysis, research or other purposes. Secondary data can be various types of information, including statistical data, research reports, surveys, business documents, government data, social media data, and more. This data can be obtained from sources such as government agencies, non-government organizations, private companies, research institutions, or public databases. In this research, secondary data derived from form of Fresh-Chilled Fish Export Data Based on Market Conditions and Main Destination Countries 2012-2022 was used (Source: <https://bps.go.id/>)

The research methodology to be carried out can be seen in Figure 1.

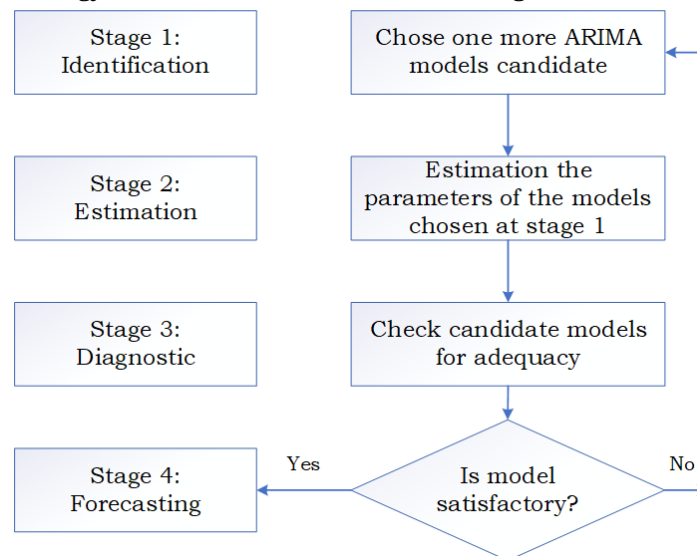


Figure 1. Research Flow Chart

Stage 1: The process of model identification involves ensuring that the variables are stationary (meaning their statistical properties like mean and variance do not change over time), detecting any seasonal patterns present in the data series, and analyzing the plots of the AutoCorrelation Function (ACF) and Partial AutoCorrelation Function (PACF) for the series. Examining these ACF and PACF plots helps determine whether an autoregressive component, a moving average component, or a combination of both should be incorporated into the model.

Stage 2: The model estimation step involves utilizing computational algorithms to determine the optimal coefficients or parameter values that provide the best fit for the selected ARIMA (Autoregressive Integrated Moving Average) model. The most widely used methods for this purpose are Maximum Likelihood Estimation (MLE) and non-linear least-squares estimation techniques. These algorithms iteratively adjust the model parameters until they converge to values that minimize the discrepancies between the predicted values from the model and the actual observations in the data.

Stage 3: The model checking stage involves evaluating whether the estimated ARIMA model adheres to the assumptions and specifications of a stationary univariate process. Specifically, it is crucial to verify that the residuals (the differences between the actual observations and the model's predictions) are independent of each other and exhibit constant mean and variance over time. Plotting the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals can help identify any misspecification in the model. If the estimated model proves inadequate, it is necessary to revisit the initial step and attempt to construct a better-fitting model. Additionally, the estimated model should be compared against other candidate ARIMA models to select the one that best captures the patterns present in the data. The criteria used in model selection: Mean Absolute Percentage Error (MAPE) value, which are defined by:

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{A_t - P_t}{A_t} \right| \times 100 \quad \dots (3)$$

Stage 4: Once an ARIMA model has been identified, estimated, and validated as conforming to the specifications of a stationary univariate process, it can be utilized for generating forecasts. If the model adequately captures the patterns and characteristics present in the historical data, it becomes a suitable tool for predicting future values of the time series variable of interest. The forecasting capabilities of the ARIMA model are leveraged by inputting the estimated parameters and applying the model's equations to project values into the future time periods.

3. RESULT AND DISCUSSION

3.1 Evaluation of Factors Influencing The Value of Indonesian Fresh-Chilled Fish Exports

In (Latuheru, 2022) has assessed the consequences of the exchange rate on the number of Indonesian fresh/chilled fish exports to Singapore over the last five years, from 2016 to 2020, in the context of the Covid-19 pandemic, which is considered the main cause of global trade instability, including a decline in the total value of fishery product exports by 7%, Indonesia actually experienced an increase in exports of fishery products, thereby rising to the ranking as the world's main exporter of fishery products in 2020. Although the value of fresh fish in Indonesia has experienced fluctuations, especially declines, research shows that fish exports have also experienced a decline in volume due to bad weather and decreased production. Analysis of the impact of the US \$ exchange rate on fresh fish exports in Indonesia shows that changes in the exchange rate against the rupiah have an effect on the volume of fresh fish exports.

Research conducted by Regarding export market opportunities with a Bayesian analysis approach has identified market opportunities for Indonesian tuna in its export destination markets using a Bayesian approach (Yusuf et al., 2017). The research findings showed that the Indonesian tuna market is dominated by the Japanese market (54%), followed by the USA market (24%) and the EU market (23%). Canned tuna was the main commodity with a probability of 54%, followed by fresh tuna (26%) and frozen tuna (24%). To maintain the consistency of Indonesian tuna exports, an appropriate marketing strategy is needed, especially a market penetration strategy that focuses on tracking raw materials, fishing locations, number of fleets and fishing gear used in the fishing process. (Hikmah et al., 2021).

Based on a literature study conducted, several main factors influence fresh-chilled fish exports in Indonesia, including: Currency Exchange Rates, Weather and Seasonal Conditions, Trade and Sanitation Regulations, Infrastructure and Logistics, Technology and Innovation, Government Policy, International Market Demand, Quality Product. The following illustration of the distribution of fresh-chilled fish exports in Indonesia based on destination countries can be seen in Figure 2.

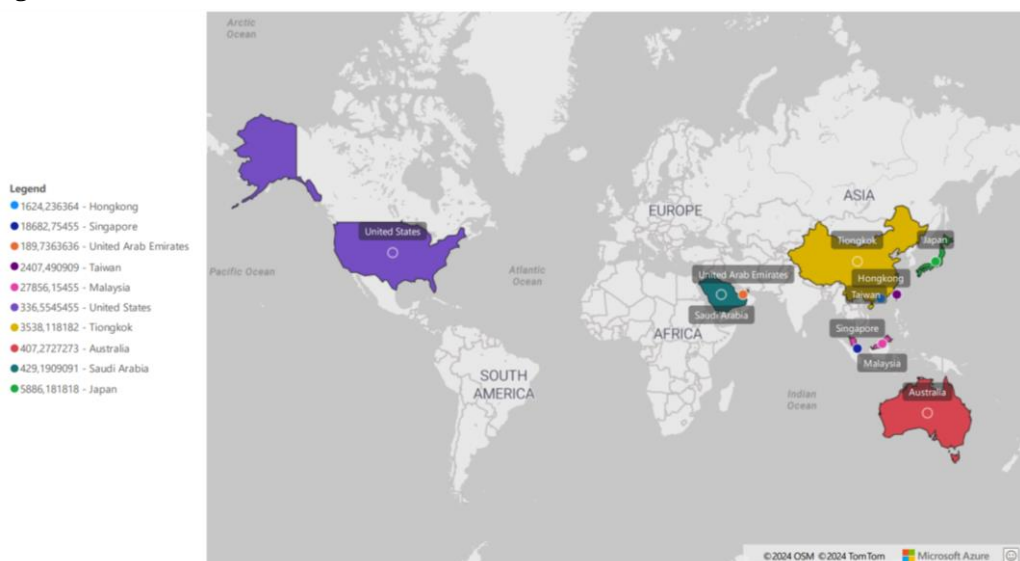


Figure 2. Distribution of the Number of Exports of Fresh Chilled Fish in Indonesia 2012-2022

3.2 Building a Prediction Model for The Value of Indonesian Fresh-Chilled Fish Exports

To forecast fresh-chilled fish export data for 2012 – 2022, we first check the stationary data as one of the conditions for forecasting. The time series plot to see the stationarity of the data can be seen in Figure 3.

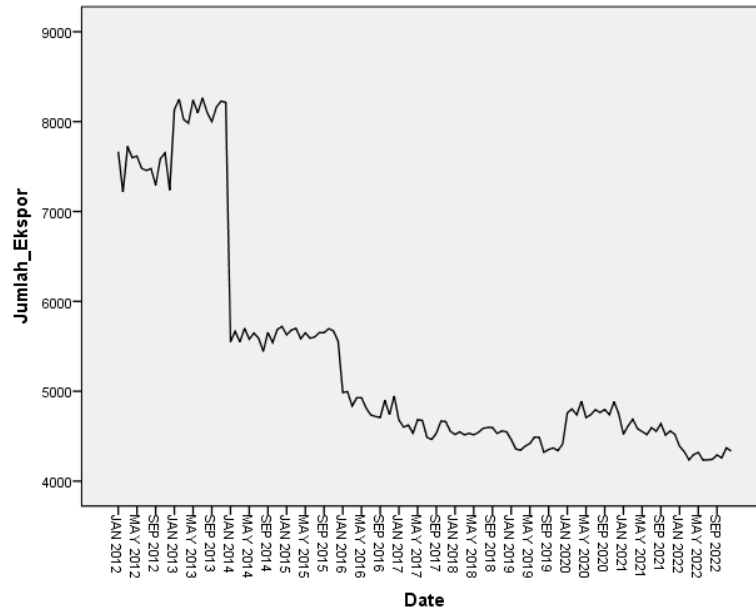


Figure 3. Time Series Plot of Fresh Fish Export Data for 2012-2022

Base on Figure 3, it can be seen that fres-chilled fish export data has a seasonal pattern, so the data is not stationary in terms of average or variance. To carry out forecasting, data must meet stationary assumptions in both mean and variance. Therefore, differencing is carried out so that the data is stationary. The results of the differencing carried out can be seen in Figure 4.

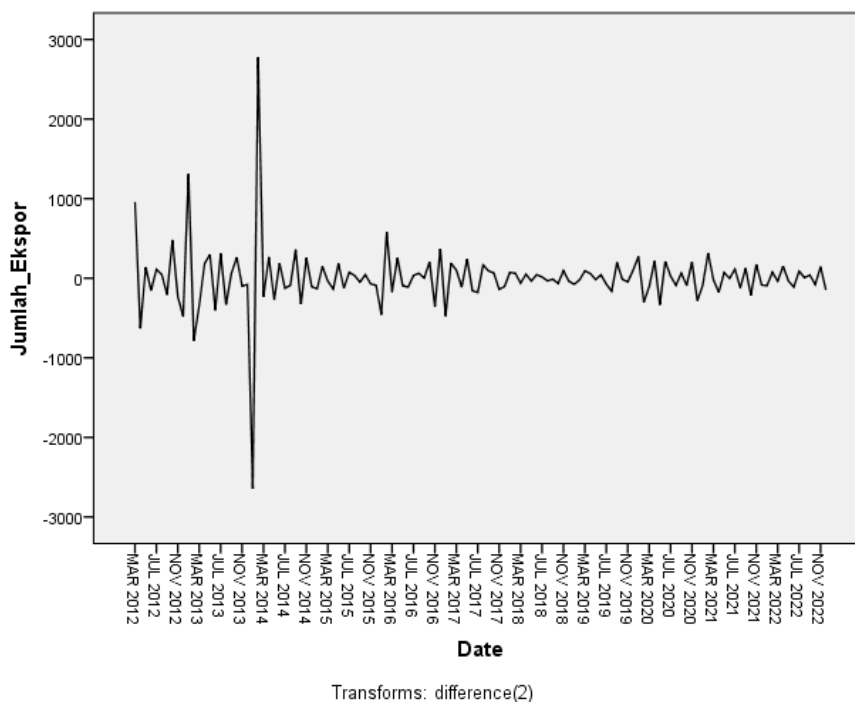


Figure 4. Time series plot of differencing results of fresh fish export data

In Figure 4, it can be seen that the time series plot of fish export data has a stationary pattern in the average. The data was differentiated twice, because when differencing once the data pattern was not stationary so the assumptions for forecasting were not met. After the stationarity assumption is met, we first check the Autocorrelation (ACF) and Partial Autocorrelation (PACF) to find out the number of Lags to support the ARIMA Model (p, d, q). The ACF and PACF plots can be seen in Figure 5.

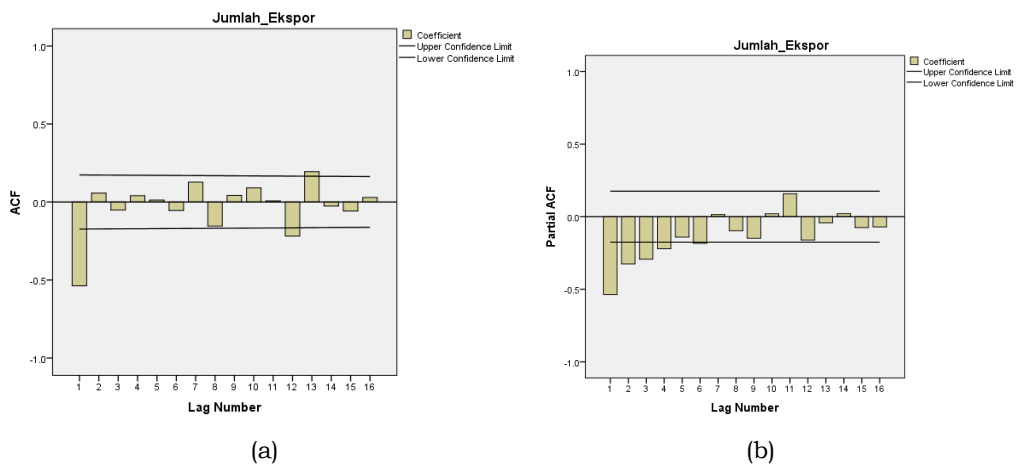


Figure 5. Plot ACF & PACF

Based on the ACF plot in Figure 5(a), it can be seen that the number of lines crossing the Upper Confidence and Lower Confidence boundaries is 3 lines, then this is used as a baseline for estimating the q model. Meanwhile, in the PACF plot in Figure 5(b), it can be seen that the number of lines crossing the Upper Confidence and Lower Confidence boundaries is 3 lines. This is then used as a baseline for estimating the p model. The ARIMA (p,d,q) model that will be combined is ARIMA (5,2,2), In accordance with the number of Lags that exceed the confidence interval limit in figure 5(a) and 5(b).

3.3 Evaluation of the Prediction Model for the Export Value of Fresh-Chilled Fish

ARIMA Model (p, d, q) which will be combined to find the best model in forecasting the Export Value of Fresh-Chilled Fish in Indonesia is the ARIMA model (5,2,2). The accuracy of each model will be evaluated to find the minimum Mean Absolute Percentage Error (MAPE). Evaluation of the prediction accuracy of the fish export value can be seen in Table 1.

Table 1. Model Evaluation Based on MAPE Values

No	Estimate ARIMA Models (p, d, q)	MAPE
1	ARIMA (5, 2,2)	2.217
2	ARIMA (5, 2,1)	2.231
3	ARIMA (5, 2,0)	2.593
4	ARIMA (4, 2,2)	2.208
5	ARIMA (4, 2,1)	2.231
6	ARIMA (4, 2,0)	2.643
7	ARIMA (3, 2,2)	2.214
8	ARIMA (3, 2,1)	2.219
9	ARIMA (3, 2,0)	2.756
10	ARIMA (4, 3,2)	3.027

The Mean Absolute Percentage Error (MAPE) value is an evaluation metric used to measure the level of accuracy of a forecasting or prediction model. The MAPE value measures the average percentage of the absolute difference between the actual value and the predicted value compared to the actual value. MAPE provides an illustration of the extent to which a forecasting model approaches the actual value in percentage form. The lower the MAPE value, the better the performance of the forecasting model.

To all the models built from combinations referring to the ACF and PACF values, it can be seen that the lowest MAPE the ARIMA model (4,2,2) with a MAPE value of 2,208 the predicted value in the next period in 2023 will be 4351 tons of fresh fish exported to destination countries. The plot of prediction results can be seen in Figure 6.

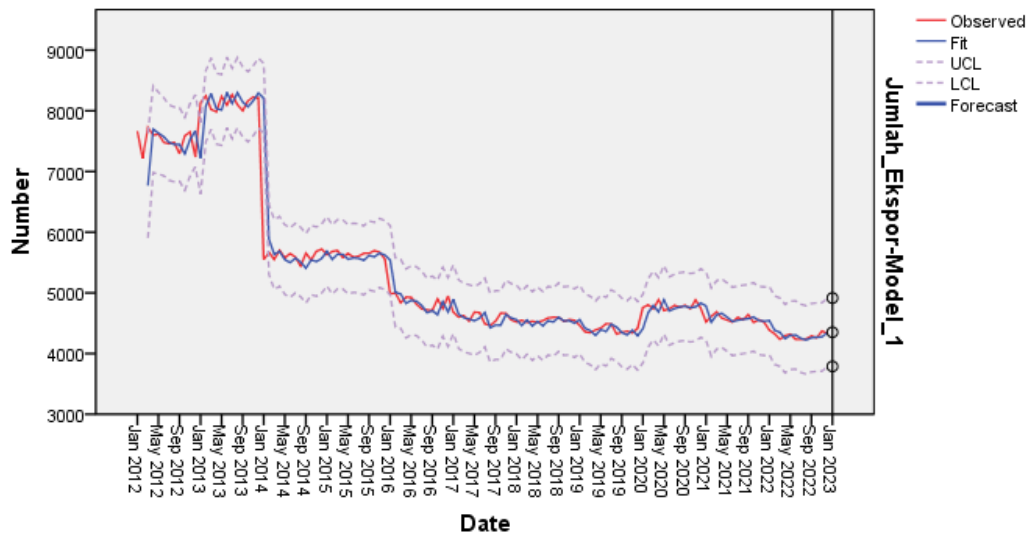


Figure 6. Prediction Plot of Fresh Fish Exports in 2023

In Figure 6, it can be seen that the predicted amount of exports in 2023 will be between the upper and lower limits of the confidence interval. This is in line with the number of fresh fish exports from Indonesia to various destination countries. According to information taken from the Indonesian Statistics publication by the Central Statistics Agency (BPS), in 2022, exports of fresh/cold caught fish will reach more than 52 thousand tons, with a value of more than 111 million US\$. The countries that are the largest export destinations include Malaysia, Singapore and Japan.

4. CONCLUSIONS

The lowest MAPE of all developed models the ARIMA model (4,2,2) with a MAPE value of 2,208 with a predicted value in the next period will be 4351 tons of fresh fish exported to destination countries. The predicted amount of exports in 2023 was between the upper and lower limits of the confidence interval. This is in line with the number of fresh fish exports from Indonesia to various destination countries. According to information taken from the Indonesian Statistics publication by the Central Statistics Agency (BPS), in 2022, exports of fresh/cold caught fish will reach more than 52 thousand tons, with a value of more than 111 million US\$. The countries that are the largest export destinations include Malaysia, Singapore and Japan.

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REFERENCES

- Asnawi, A., Luhur, E. S., & Suryawati, S. H. (2021). Model Permintaan Ekspor Udang Olahan Indonesia Oleh Pasar Jepang, Amerika Serikat Dan Uni Eropa Pendekatan Error Correction Model (Ecm). *Jurnal Sosial Ekonomi Kelautan Dan Perikanan*, 16(2), 193. <https://doi.org/10.15578/jsekp.v16i2.9768>
- Da Silva, V. do C., Krisnamurthi, B., & Harmini. (2023). Analisis Faktor-Faktor Yang Memengaruhi Ekspor Ikan Tuna Beku Indonesia. *Forum Agribisnis*, 13(2), 164–178. <https://doi.org/10.29244/fagb.13.2.164-178>
- Fattah, J., Ezzine, L., Aman, Z., El Moussami, H., & Lachhab, A. (2018). Forecasting of demand using ARIMA model. *International Journal of Engineering Business Management*, 10, 1–9. <https://doi.org/10.1177/1847979018808673>
- Febianah, M., Tyas, S. J. S., Solikhah, F., Herviansyah, F., Rosalia, A. A., & Minsaris, L. O. A. (2021). Model Peramalan Produksi Perikanan Tangkap di Pelabuhan Perikanan Kejawan Cirebon Jawa Barat. *Jurnal Vokasi Ilmu-Ilmu Perikanan (Jvip)*, 2(1), 1. <https://doi.org/10.35726/jvip.v2i1.545>
- Febryanti, D. I., & Utami, D. A. (2022). Pemanfaatan Platform Digital dalam Pemasaran Produk Perikanan dan Kelautan (Studi Kasus Aruna Indonesia). *Growth Dan Manajemen Lingkungan*, 12(1), 66–83.
- Handayani, V. A., Sulistyono, E., Hernando, L., Majiid, A., & Sunar-, H. (2023). Data exploration of marine cultivation types using cluster analysis with complete-linkage method. *JURTEKSI (Jurnal Teknologi Dan Sistem Informasi)*, X(1).
- Hernandez-Matamoros, A., Fujita, H., Hayashi, T., & Perez-Meana, H. (2020). Forecasting of COVID19 per regions using ARIMA models and polynomial functions. *Applied Soft Computing Journal*, 96, 106610. <https://doi.org/10.1016/j.asoc.2020.106610>
- Hikmah, H., Shafitri, N., Zulham, A., & Purnomo, A. H. (2021). Strategi Pengembangan Pasar Ikan Demersal di Kabupaten Merauke. *Buletin Ilmiah Marina Sosial Ekonomi Kelautan Dan Perikanan*, 7(1), 43. <https://doi.org/10.15578/marina.v7i1.9000>
- Horváth, L., Kokoszka, P., & Rice, G. (2014). Testing stationarity of functional time series. *Journal of Econometrics*, 179(1), 66–82. <https://doi.org/10.1016/j.jeconom.2013.11.002>
- Irawati, H., Kusnandar, F., & D Kusumaningrum, H. (2019). Analisis Penyebab Penolakan Produk Perikanan Indonesia Oleh Uni Eropa Periode 2007 – 2017 Dengan Pendekatan Root Cause Analysis. *Jurnal Standardisasi*, 21(2), 149. <https://doi.org/10.31153/js.v21i2.757>
- Latuheru, A. (2022). Pengaruh Nilai Tukar Terhadap Volume Ekspor Ikan Segar Dari Indonesia Ke Singapura. *Journal of Economics Review (JOER)*, 2(1), 31–39. <https://doi.org/10.55098/joer.2.1.31-39>
- Lingkup, D. I., & Dan, A. (2011). Daya Saing Ekspor Produk Perikanan Indonesia. *Journal of Agricultural and Resource Economics*, 10(Meningkatkan daya saing ekspor produk perikanan dilingkup ASEAN), 1–10.
- Liu, S., & Zhou, D. J. (2024). Using cross-validation methods to select time series models: Promises and pitfalls. *British Journal of Mathematical and Statistical Psychology*, 77(2), 337–355. <https://doi.org/10.1111/bmsp.12330>
- Majiid, A., & Handayani, V. A. (2023). Forecasting Data Inflasi Years on Years Kota Batam Tahun 2017-2020. *Jurnal Sintak*, 1(2), 29–34. <https://doi.org/>
- McGonigle, E. T., Killick, R., & Nunes, M. A. (2022). Modelling time-varying first and second-order structure of time series via wavelets and differencing*. *Electronic Journal of Statistics*, 16(2), 4398–4448. <https://doi.org/10.1214/22-EJS2044>
- Rahmah, A., & Sitompul, K. (2023). Proyeksi Ketersediaan Produksi Ikan Tuna , Cakalang Dan Tongkol Di Pelabuhan Perikanan Nusantara Sibolga. *Jurnal Penelitian Perikanan Indonesia*, 28(September 2022), 157–165.
- Siami-Namini, S., Tavakoli, N., & Siami Namin, A. (2018). A Comparison of ARIMA and LSTM in Forecasting Time Series. *Proceedings - 17th IEEE International Conference on Machine Learning and Applications, ICMLA 2018*, 1394–1401. <https://doi.org/10.1109/ICMLA.2018.00227>
- Sunarsono, H., Rahmiati, S., & Handayani, V. A. (2022). Analisa Sudut Jaring untuk Mengoptimalkan Hasil Tangkapan Ikan pada Keramba Tancap Nelayan Tradisional.

SITEKIN: Jurnal Sains, Teknologi Dan Industri, 20(1), 248–254.

- Van Rossum, H. H. (2019). Moving average quality control: Principles, practical application and future perspectives. *Clinical Chemistry and Laboratory Medicine*, 57(6), 773–782. <https://doi.org/10.1515/cclm-2018-0795>
- Wicaksana, I., Wijaya, I. P. E., Suhaeni, S., & Syahputra, A. Fahmi. (2022). Analisis Faktor-Faktor yang Memengaruhi Ekspor Komoditas Perikanan: Pendekatan Gravity Model. *Jurnal Agrimanex: Agribusiness, Rural Management, and Development Extension*, 3(1), 1–13. <https://doi.org/10.35706/agrimanex.v3i1.6966>
- Yonvitner, Boer, M., Taryono, Riyanto, M., Kurnia, R., Setyobudiandi, I., Santoso, J., Sukri, N., & Abdul Aziz, K. (2020). Estimasi Stok Suplai Kebutuhan Bahan Baku untuk Industri Pengolahan Ikan. *Jurnal Pengolahan Hasil Perikanan Indonesia*, 23(1), 158–165. <https://doi.org/10.17844/jphpi.v23i1.31058>
- Yusuf, R., Arthatiani, F. Y., & Putri, H. M. (2017). Peluang Pasar Ekspor Tuna Indonesia: Suatu Pendekatan Analisis Bayesian. *Kebijakan Sosial Ekonomi Kelautan Dan Perikanan*, 7(1), 39–50.