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Comparison of ARIMA and SARIMA Methods for Non-Oil and Gas Export Forecasting in East Java

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ABSTRACT

Abstract— Forecasting plays a pivotal role in economic planning, particularly in aligning supply with demand and informing production decisions. This study aims to compare the performance of the Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) models in forecasting the non-oil and gas export values of East Java, a region known for its dynamic trade activity. Using monthly time series data spanning from January 2007 to January 2024, sourced from the Central Statistics Agency (BPS) of East Java Province, this research conducts an in-depth analysis of forecasting accuracy and model suitability. Before model implementation, the dataset underwent several preprocessing steps to ensure its quality, including the handling of missing values and outlier adjustments. Both ARIMA and SARIMA models were developed, calibrated, and evaluated using standard forecasting performance metrics, namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The ARIMA model exhibited consistently lower error rates across all three metrics, indicating its robustness in capturing the underlying patterns within the export data. In contrast, while the SARIMA model incorporated seasonal components, its performance did not surpass that of ARIMA in this specific case. The comparative findings suggest that, despite the seasonal nature of trade, the ARIMA model is more suitable for short-term forecasting of East Java's non-oil and gas exports. This research contributes to the broader literature on economic forecasting by emphasizing the importance of selecting appropriate models based on data characteristics. Furthermore, the results provide valuable insights for policymakers and stakeholders engaged in export planning and regional trade development In this result the ARIMA model overcome the SARIMA with MAPE 0.116 to 0.983.

Keywords: ARIMA, export, forecasting, gas, SARIMA.

I. INTRODUCTION

Forecasting is essential for a company because it relates to the balance between exports and product demand. Forecasting is a prediction of future data values based on relevant historical data. This process greatly influences decisions regarding the amount of production of goods to be exported [1]. The forecasting uses data recorded by the Central Statistics Agency (BPS) of East Java Province for 14 years.

This forecast aims to ensure that non-oil and gas exports in East Java remain regular and adequate. If demand is lower than the available stock, exports can be adjusted, and vice versa, if demand increases, production must be increased to be sufficient. The most significant decline in non-oil and gas exports in East Java occurred in July 2016, which was 37.68% from the previous month, and an increase occurred

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in July 2018, by 53.34% from the previous month [2].

The solution can be found through forecasting or prediction to overcome this situation. Thus, the methods used to analyze data from January 2007 to January 2024 are Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA). Both methods are applied to predict future numbers and plan appropriate strategies. However, this study will compare the two methods and determine the most appropriate method for the existing data. In a previous study conducted by Herlena Bidi Astuti, et al. in an article entitled "ESTIMATION OF RETAIL PRICES OF CHICKEN EGGS IN BENGKULU CITY", it was concluded that the ARIMA model proved effective for forecasting with MSE and MAPE of 1,600 and 6.23, respectively [3]. Another study conducted by Laras Luthfiyyah Ibrahim and Eti Kurniati entitled "Forecasting the Number of Executive Train Passengers in Java Using the SARIMA Model" showed that the SARIMA(1,0,1)(1,1,0)12 model was used to estimate the number of train passengers in Java in March approaching the Eid al-Fitr holiday, with forecasting results reaching 4470 people [4]. The ARIMA method utilizes historical and current value data to produce accurate short-term predictions, allowing detailed analysis of data patterns and fluctuations, and providing reliable predictions for a limited period into the future [5]. Meanwhile, the SARIMA method forecasts data by considering seasonal components in its model, making it suitable for data analysis that shows specific patterns or cycles over a specific period.

Ref [6] using the ARIMA and SARIMA methods, tests were carried out to determine the stationarity of the variance and mean of the data, as well as to evaluate the significance of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The next step is to perform differencing to make the data stationary. After that, the calculation of Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) values is carried out to validate the model. This approach can predict the amount of non-oil and gas exports in several future periods, providing the information needed to determine the optimal value of non-oil and gas exports.

II. RESEARCH METHODOLOGIES

The methodology in research refers to a series of systematic steps to achieve the stated research objectives. This methodology is designed with a structured and scientific flow. This study begins with collecting data to be used, pre-processing data, exploring time series data, performing data modeling, predicting testing data, and evaluating the model. Researchers use RSME, MAE, and MAPE to measure the model’s accuracy.

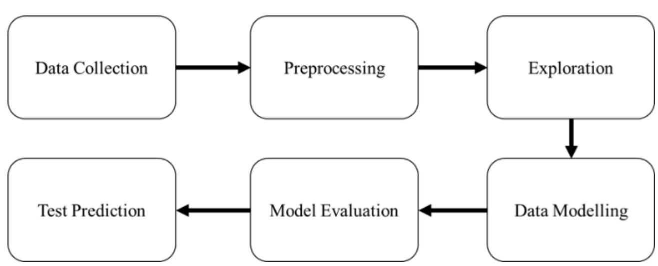

Figure 1. Research Flow

A. Data Collecting

The data we use in this study is monthly data from non-oil and gas exports in East Java, taken from the BPS East Java Province page. The data period used covers from January 2007 to January 2024. The selection of this period is based on the need to have a sufficient number of observations for time series analysis to identify patterns in the data.

B. Preprocessing

Data preprocessing is a crucial step in this study to ensure that the dataset is properly structured and ready for further analysis. The first task involves combining Excel files containing export data from the years 2007 to 2024 into a single dataset. This merging process creates a comprehensive and continuous data source. Following this, unnecessary rows—such as headers, footers, or empty rows that do not contribute meaningful information—are removed to clean the dataset.

Next, the column names are adjusted to represent the months of the year, from January to December, ensuring consistency and clarity. A new column labeled "Year" is then added to the far-left side of the dataset, containing the years 2007 to 2024. This "Year" column is subsequently set as the index of the DataFrame, which is essential for performing time-based operations and maintaining chronological order.

The dataset is then transposed to restructure the data, allowing the creation of a proper date range based on the number of columns. This transformation supports the conversion of the matrix-like format into a time series-friendly structure. The data is reshaped from a matrix into a series to facilitate easier manipulation and analysis. It is then transposed again to ensure the records are aligned in correct chronological order. This step helps preserve the temporal integrity of the dataset.

After restructuring, the data is reshaped into a columnar matrix format suitable for analytical models. A new DataFrame is created that focuses specifically on non-oil and gas export values, which are the primary subject of this study. To finalize the preprocessing, the index of the data is displayed to confirm that the date range is accurate, and the overall structure is verified. Finally, dataset information such as data types and missing values is reviewed, and any empty or null entries are removed to ensure the quality and completeness of the dataset.

C. Exploration

In the exploration of East Java's non-oil and gas export data from 2007 to 2024, the initial step is to create a time series plot to visualize trends throughout the time period. After that, a decomposition plot is carried out to identify the main components such as trends, seasonality, and residual components in the data. Furthermore, ACF and PACF analysis are used to evaluate the dependence between data values at previous times. A stationarity test is then carried out to verify whether the non-oil and gas export data has a constant mean and variance over time, so that the results indicate that the data is not stationary. Therefore, a differencing step is carried out to eliminate trends or seasonal patterns that may exist in the data, thus ensuring that the data is stationary and ready for further analysis using forecasting models such as ARIMA or SARIMA.

D. Data Modelling

Next, modeling is done using the ARIMA and SARIMA forecasting methods. Modeling using ARIMA will help identify patterns in non-stationary data, while SARIMA will consider seasonal effects that may affect export trends over time.

To carry out the modeling process, data that has gone through the pre-processing stage is required. Then, the researcher compares the results between the two methods that have been used. Then the data is separated into 2, namely as training data and testing data. After that, ARIMA and SARIMA modeling is carried out using training data until the best model is obtained.

E. Test Prediction

After performing data modeling using the ARIMA and SARIMA methods, the next step is to display the prediction results of the testing data from each method using a model that was previously created using training data.

F. Model Evaluation

Evaluation is an important stage to assess the performance or results of the developed model. In this context, metrics, RMSE, MAE, and MAPE are used to measure the level of model accuracy. After testing the model on the testing data, a comparison is made between the ARIMA and SARIMA methods. The best method will be selected based on the lowest MAPE results.

III. RESULT AND DISCUSSION

Researchers perform pre-processing using the help of the pandas and numpy libraries available in python used to combine excel then delete unnecessary rows and leave non-oil and gas data that will be used for modeling. The columns used are the non-oil and gas export report columns every month from January to December and the rows are the index years of non-oil and gas exports carried out, namely from 2007 to 2024. then transpose the data to create a date range that will later be used to sort the data by date. After that, change the data form into a column matrix until the data is shaped like the table below so that the data is ready to be carried out in the next stage.

TABLE I. EXPORT DATA NON-GAS IN EAST JAVA

Date	Data
2007-01-01	742.4
2007-02-01	793.83
2007-03-01	768.19
2007-04-01	955.19
2007-05-01	837.04
…	…
2023-08-01	1700.74
2023-09-01	1756.17
2023-10-01	1989.74
2023-11-01	2015.38
2023-12-01	2146.41

Based on the data obtained as in table 1, we will then process the data using the ARIMA and SARIMA methods to determine which method is most appropriate for use in forecasting non-oil and gas in East Java. The first step is to plot the data.

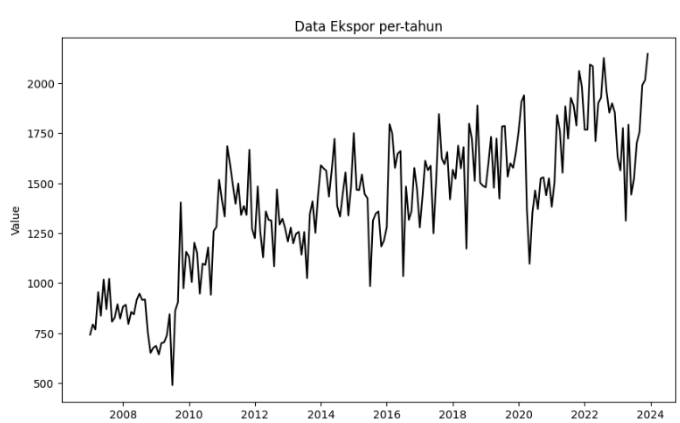

Figure 2. Data Plot

The sales data pattern obtained is a combination. In certain periods there is an increase and in certain periods there is also a decrease [7]. This data is not intermittent due to the graph from Figure 2, so it will be no problem to using an ARIMA or SARIMA model. A study comparing Croston, SES, and deep learning methods for intermittent demand forecasting found that RNN outperformed traditional models in empirical tests, with MAE proving to be a more robust evaluation metric than RMSSE [8].The highest increase occurred in July 2018 and the lowest decrease occurred in July 2016. The next stage is to display a decomposition plot containing trends, seasonality, and residual components in the data.

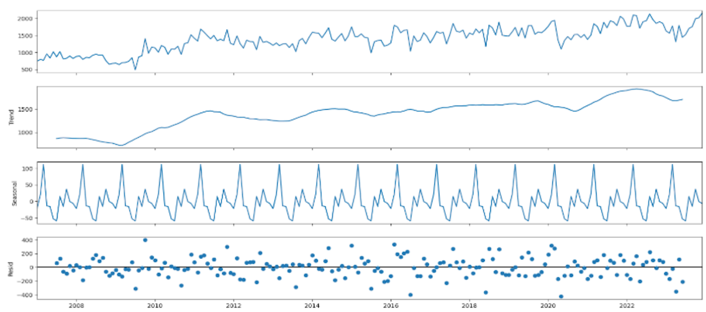

Figure 3. Decomposition Plot

From the illustration in Figure 3, it can be said that non-oil and gas export data in East Java has a long-term trend that increases over time, with significant annual and seasonal fluctuations. This indicates an increase in the value of non-oil and gas exports in East Java. The next step is to check the stationarity against the average value, using the ACF and PACF plots. This data look like can be solve using parametric instead non-parametric. Yet, a study proposed VGAMCV, a semi-parametric method combining Vector Generalized Additive Models with cross-validation, as a novel approach for multi-label classification, showing promising results compared to Random Forest, though without statistically significant improvements [9].

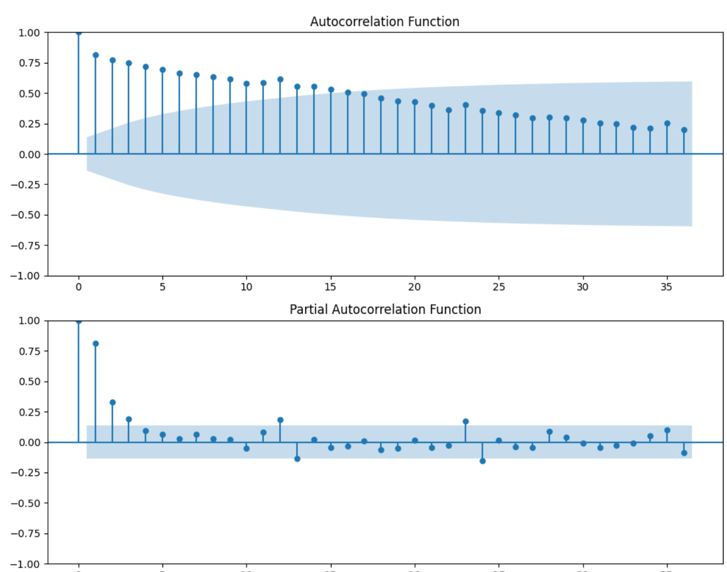

Figure 4. Plot ACF and PACF

It can be seen that in Figure 4 the ACF and PACF values at lag 0 are always 1 because they represent the correlation between the data value at lag 0 and itself. In the ACF plot, it can be seen that the ACF value decreases gradually (dies down) as the lag increases. This indicates that there is a dependency between the current value and the previous value in the data, but the dependency becomes weaker as the time interval increases. Data at lag 1 to lag 5 significantly affect the current data value. Data values at lag 1 and lag 2 have a significant partial effect on the current data value, regardless of the effect of data values at lag 0. Thus, data needs to be differencing so that the data becomes stationary.

TABLE II. DIFFERENCING RESULT

	adf	kpss
Test Statistic	-6.610145	0.056647
p-value	0.0	0.1
Numbers of lags	10	19
decision	Stationary	Stationary
Critical Value (1%)	-3.464875	0.739
Critical Value (5%)	-2.876714	0.463
Critical Value (10%)	-2.574859	0.347
Critical Value (2.5%)	NaN	0.574

Based on the results of differencing using the ADF test, it can be seen that the test statistic (-6.610145) is much lower than the critical value, as well as the p-value which is small from 0.05, this means that the data does not have a unit root (stationary) at that level of significance. While the KPSS test with a p-value of 0.1 and a test statistic (0.056647) which is much lower than the critical value, which means that the data does not have a trend that changes over time. So from the results of the stationarity test using the ADF and KPSS tests, it can be concluded that the non-oil and gas export data in East Java after differencing has become stationary.

Next, modeling is done using the ARIMA and SARIMA forecasting methods. Modeling using ARIMA will help identify patterns in non-stationary data, while SARIMA will consider seasonal effects that may affect export trends over time.

To perform modeling, data that has gone through the pre-processing stage is required. Researchers compare the results of the two models used. Then the data is separated into 2 types, namely used as training data and testing data. After that, ARIMA and SARIMA modeling is carried out using training data to obtain the best model.

When modeling data, the first thing to do is transform the data to make it stationary. This process is carried out by data differentiation, namely reducing each observation with the previous observation to eliminate trends and keep the variance constant. After that, the best parameter search is carried out for the ARIMA and SARIMA models using the auto_arima function.

TABLE III. BEST MODEL

Best Model	ARIMA(0, 0, 1)(0, 0, 1)[12]
Total Fit Time	16.235 seconds

From Table III, it is known that the output of the ARIMA model, the best parameters selected for the model are ARIMA(0,0,1)(0,0,1)[12]. This shows that the best ARIMA model has a seasonal component with an order of (0,0,1) and a period of 12 months. The recorded AIC value shows that the selected model has sufficient goodness of fit, with a low AIC value. Interpretation of this output helps to understand how the ARIMA model is selected based on the best parameters. Model coefficients, such as ma.L1 and ma.S.L12, show the influence of the previous period error and seasonal error on the value of non-oil and gas exports in East Java. The predictions generated from this model can provide insight into possible fluctuations in non-oil and gas exports in the future, although it should be noted that these predictions can vary from month to month. Thus, the output provides an overview of how the ARIMA model is selected and how the interpretation of these parameters helps in understanding data patterns and behavior.

TABLE IV. BEST MODEL

Best Model	ARIMA(0, 0, 1)(0, 0, 1)[12]
Total Fit Time	38.693 seconds

From Table IV, it is known that the SARIMA model output, the best parameters selected for the model are ARIMA (0,0,1) (0,0,1) [12]. This shows that the best SARIMA model has a seasonal component with an order of (0,0,1) and a period of 12 months. The recorded AIC value shows that the selected model has sufficient goodness of fit, with a low AIC value.

From this output, it helps to understand how the SARIMA model is selected based on the best parameters. The model coefficients, such as ma.L1 and ma.S.L12, show the influence of the previous period error and seasonal error on the value of non-oil and gas exports in East Java. The predictions generated from this model can provide insight into possible fluctuations in non-oil and gas exports in the future, although it should be noted that these predictions can vary from month to month. Thus, the output provides an overview of how the SARIMA model is selected and how the interpretation of these parameters helps in understanding data patterns and behavior.

After modeling the data using the ARIMA and SARIMA methods, the next step is to display the prediction results of the testing data from each method using a model that has been created previously using training data.

From the prediction results using the ARIMA model, the estimated value of non-oil and gas exports in East Java Province for the testing data period has been obtained. This prediction describes the data pattern that has been identified during the modeling process, taking into account the autoregressive and moving average effects in the data. Thus, this prediction provides an overview of the fluctuations in the value of non-oil and gas exports in the future based on the ARIMA model. This prediction is generated using the ARIMA code function, namely by modeling using the 'auto_arima' command on the training data and then making predictions for the testing data.

Meanwhile, the prediction using the SARIMA model also produces an estimate of the value of non-oil and gas exports in East Java Province for the testing data period. The SARIMA model considers seasonal effects that may affect export trends over time. Therefore, this prediction provides a more complete picture of the data pattern by taking seasonal factors into account.

To evaluate the performance of both models, plots of actual data and predictions from ARIMA and SARIMA have been presented. The plot of actual data and predictions generated from the ARIMA and SARIMA models provides a visual representation of how well the two models are able to predict the value of non-oil and gas exports in East Java.

The forecasting was conducted using data that has been collected by the BPS of East Java Province for 14 years.

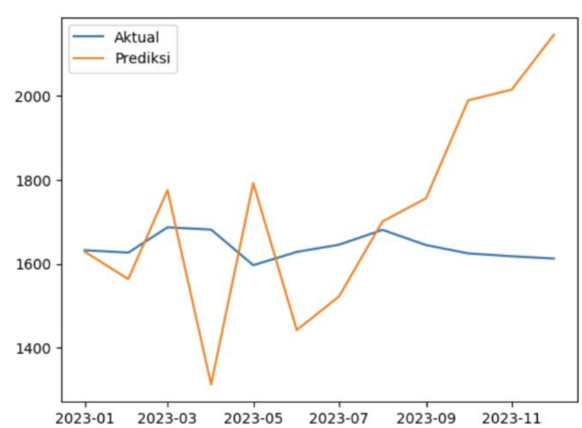

Figure 5. Example of a figure caption. *(figure caption)*

From Figure 5, it is known that the plot shows that the actual line (which represents the actual value) and the predicted line (which represents the value predicted by the model) have quite significant differences. This difference indicates that the two models may have different levels of accuracy in predicting the value of non-oil and gas exports.

In the ARIMA model, the difference between the actual and predicted lines may vary more from month to month. This shows that the ARIMA model may have fluctuating levels of accuracy in predicting the value of non-oil and gas exports at different times.

Figure 6. Example of a figure caption. *(figure caption)*

Meanwhile, in Figure 6, it is known that in the SARIMA model, it can be seen that the difference between the actual and predicted lines tends to be more stable or less variable from month to month. This may indicate that the SARIMA model has a more consistent level of accuracy in predicting the value of non-oil and gas exports in East Java. From the plot, a significant difference occurs between the actual and predicted lines. This illustrates that the models have different levels of accuracy in predicting the value of non-oil and gas exports in East Java Province. Further evaluation of the performance of the two models can be done by comparing evaluation matrices such as RMSE or MAE.

Evaluation is an important stage to assess the performance of the developed model. The best prediction or forecast is seen based on its level of accuracy, the smaller the error rate, the more accurate a model is in predicting. In this study, there are several evaluation metrics used to estimate the level of accuracy of the prediction results, such as RMSE, MAE, and MAPE. In this study, the two models can be compared based on the RMSE, MAE, and MAPE values to determine the best model. The smaller the RMSE, MAE and MAPE values mean that the model is the best model to use in predicting the value of non-oil and gas exports in East Java Province. Table V will show the results of the ARIMA and SARIMA model performance tests.

TABLE V. EVALUATION MODEL RESULTS

Model	RMSE	MAE	MAPE
ARIMA(0,0,1)	262.32	204.85	0.116
SARIMA(0,0,1)[12]	271.84	210.15	0.983

Based on Table V, it shows that the RMSE, MAE, and MAPE values of the ARIMA model are lower than the SARIMA model. So the ARIMA model is the best model that can be used for the analysis of non-oil and gas export values in East Java.

CONCLUSION

Based on the comparison of ARIMA and SARIMA forecasting methods in forecasting Non-Oil and Gas Exports in East Java for January 2007 to January 2024, the best method that can be used for forecasting non-oil and gas exports in East Java Province is the ARIMA method. This is because the ARIMA method shows lower RMSE, MAE, and MAPE values compared to the SARIMA method, namely RMSE: 262.32, MAE: 204.85, and MAPE: 0.116. Thus, this study recommends the use of the ARIMA model as the main forecasting tool for non-oil and gas exports in East Java, given its proven ability to produce predictions with smaller errors compared to the SARIMA model.

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