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Analyzing and Forecasting Admission Data using Time Series Model

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ABSTRACT

Problems that will be faced by higher education institutions, especially in the phase of new student admissions. Careful planning and strategies are needed in dealing with the process of admission of new students. The data for planning can be obtained using the forecasting method. The time series forecasting model is used to get forecasting data. Forecasting data is used for the decision making process. The data of new student admissions obtained is 3-period data (2017 - 2019). The data obtained is stationary. Because the data is stationary, the data does not need differentiation. The data obtained also has a sufficient correlation value, and has a loop on the 7th lag. Before making an application, a test is performed to find a time series model that is suitable for admission data. The tested models are the ARIMA model and the Autoregression model. In testing the forecast timespan, the ARIMA model gets a smaller error value in almost all tests. In the Cross-validation method, the ARIMA Model also gets a smaller RMSECV or MAECV value than the AR model. The ARIMA model was chosen to be implemented into the application. The auto_arima algorithm is used so that applications can adapt to different data. The ARIMA model is implemented into a prediction application using the Python programming language. Application development uses Django as a web-based web application framework. Bootstrap is used to create application interfaces. the result from forecasted data is acceptable for short period.

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1. INTRODUCTION

Higher education is the final level of formal academic education. Higher education institutions can include Colleges to Universities that cover a variety of levels starting from diploma to doctoral level. Higher education which is a formal educational institution has various problems. One of the most crucial is quality problems. Quality problems for an educational institution especially higher educations are almost always oriented to the achievement and prestige of an educational institution. Making educational institutions highly dependent on the quality of learning, supporting facilities, and lecturers. These problems also indirectly give birth to a competition. The current competition depends on the quality of graduates from these higher educational institutions. Graduates become the benchmark for the quality of an educational institution. Besides graduates, a variety of good supporting facilities can support a good learning process. As well as if supporting facilities are lacking or inappropriate. The learning process also becomes disrupted and less optimal. To avoid things like disruption to the learning process, quality improvement is needed. Improving the quality of a higher educational institution can begin with future planning. With great academic future planning, the problems that will be faced by educational institutions can be prevented [1] [2].

The making of academic planning requires estimating data that will be used to determine plans so that educational institutions can be better prepared to deal with future problems. These problems that will be faced, one of them is in the process of admitting new students. Admission of new students is a crucial moment for a higher educational institution in this phase. If the number of new students accepted cannot meet the admission target. They will find it difficult to develop and compete with others [3]. The number of applicants that changes each year requires different strategies in dealing with the process of admission of new students. Admission strategies also depend on how universities accept their students. There are many ways in the process of admission of new students. Ranging from national joint selection that is intended to accept students at State Universities in Indonesia. And there is the admission process is widely used by private universities which all processes can be done in one day, known as One Day Service (ODS)[4]. Registrant data in the ODS database form in daily data. It can be used to predict the number of registrants in the coming period with the forecasting method. Forecasting data is shown for decision making and application of priorities for the number of new students who will be accepted later [5]–[7] .

Based on the estimation of data in the past to predict a variable in the future that is called forecasting. Forecasting does not provide the same as data that will occur in the future. But forecasting looking for data as close as possible to the data that will occur. Forecasting itself is the science and art of predicting future events by using past data [8]. There are two kinds of forecasting, qualitative method, and the quantitative method. The qualitative method creates forecast data based on intuition or opinion. The quantitative method obtains forecast data using statistics and mathematical rules. In this research, we use a quantitative method. There are two models in quantitative method, Casual Model and time series model. Because admission data is a sequence data. We selected time series model. The time series model is based on a series of sequential data with the same sequence. This forecast model is a set of observational data measured based on time with the same interval. And measured over a certain period [9]. To obtain accurate prediction data using time series model. It takes a lot of reference of new student candidate data in previous years [7]. Forecasting with time series using a quantitative approach with past data which is a reference to get forecast data. Many time series models can be used such as Artificial Neural Network (ANN)[10], Single Exponential Smoothing [6], Auto Regression, Auto Regression Integrated Moving Average (ARIMA) [7] [11] [12].

In previous studies on the comparison of stock prices using the ARIMA model and the Artificial Neural Network (ANN) model, the level of Root Mean Square Error (RMSE) for ARIMA model was smaller than using the ANN model with a difference of more than double [13]. Next references refer to other research by Sismi and Darsyah. From their research, ARIMA Model is more optimal in producing forecasting compared to MA models [14]. Forecasting results with the ARIMA model are better than the two other forecasting methods, as evidenced by the results of the two studies above. The use of ARIMA to predict the number of new students has been used in a study from As'ad. in this study the level of differences in the number of registrants in 2017 and 2018 on actual data and the predicted data only around 5%, so the predicted results can be used for planning references [15]. Instead of predicting admission data yearly like other research in predicting a number of new students, we will predicting the data daily in which contain ODS system.

2. METHOD

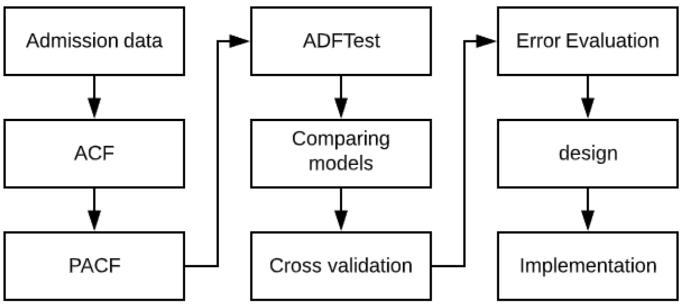

Figure 1. Research Method

In this study, there are several steps that we did these steps can be seen in Figure 1. the initial stage of this research is to collect data obtained from a related institution who process ODS data in UMS, the Data obtained is 3-period data (2017 - 2019) in the form of Excel, this data will be converted into CSV format to facilitate the processing of data using the Jupyter Notebook software which will then be processed by the pandas module in python so that it can be further analyzed using the Python programming language. To further analyze the data, the writer uses one department data as a sample, namely Mechanical Engineering department data.

The next stage is the stage to test whether the data to be analyzed has entered the time series criteria or not. This process includes ACF and PACF to see the correlation between the data. ACF is a function to calculate the correlation between data. And PACF is a function to calculate the partial correlation between data. These function also work to define the white noise of the data. To define the data stationary, we will use the Augmented Dickey-Fuller (ADF) test. The ADF test is a type of statistical test called a unit root test. it interprets this result using the p-value from the test. A p-value below a threshold (such as 5% or 1%) suggests we reject the null hypothesis (stationary). Otherwise, a p-value above the threshold suggests we fail to reject the null hypothesis (non-stationary).

The third stage is the analysis phase for testing between 2 models. At this stage, the researcher used the Auto Regression and ARIMA models to test the suitability of the model for Admission data in UMS. The Auto Regression Model is a model that looks for future predictive values based on a linear combination of the past values of a variable, or it can also be called a regression variable against itself. An autoregressive model can be stated as follows:

$$y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + e_t \quad (1)$$

Where y is the value or in this research y is the number of students, t is the time. The μ is the population mean that we get from the data. And this symbol ϕ, refer to the AR parameter, which we can find in PACF. The last variable is the error value. To find the forecast value from the formula above, we didn't include e_t variable or error variable. Because actually, we didn't know the error at that time yet. And the second model is ARIMA model. ARIMA has 3 main elements, namely: the Autoregression (AR), Moving Average (MA), and Integrated (I) models. The three elements can be modified so that they can form new models. For example, Autoregression and Moving Average (ARMA), if the data held, is already stationary. ARIMA is formed by 3 orders (p, d, q). p is an order from AR, d is an order from I, and q is an order from MA. Further explanation for each element in ARIMA. Auto Regression (AR), the explanation of AR can be seen in the previous explanation. Integrated (I), here I state the differentiation of data. To make the ARIMA model required to have stationary data, and if the data to be used by the ARIMA model is stationary, the value of I will be 0. Moving Average (MA), the value of the MA variable here is determined by the error of the variable itself. The ARIMA model is stated as follows:

$$y_t' = \mu + \phi_1 y_t' - 1 + \phi_p y_t' - p + \theta_1 e_t - 1 + \ldots + \theta_q e_t - q + e_t \quad (2)$$

Where y' is the Differenced data, differenced data calculated using simple term by reducing data by data before. Same as AR formula, μ is the population mean, e is the error value. And for θ_q is the Moving Average parameter, which reduced over time.

The last stage is the stage to determine which model is having a better performance. To determine this, we use the Cross-validation method. In time-series data, the cross-validation method is slightly different from cross-validation in general. We use the Nested cross-validation method or commonly known as day forward chaining, which has been proven to be good for time series data[16]. To calculate the error measurement of each model, we used two error measurement method. The first one is Root Mean Square Error (RMSE) is an error measurement method that measures the average value of a model's error by squaring the error value and finding its root value. Error-values in the RMSE method have different weights. The RMSE method stated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \quad (3)$$

Where the n variable is the number of data, and e is the error that we got from reducing forecast value by real value. Afterwards, the error value is squared, and divided by the number of data. The last step is finding the root from a mean squared error. The second error measurement method is Mean Absolute Error (MAE), this method of measuring error that measures the average absolute error value of a model by reducing the predicted value to the original value of a variable and making it an absolute number. In the MAE error measurement method, the value of each error variable has the same weight. The MAE method stated as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |e_i| \quad (4)$$

The formula is similar to the RMSE, but instead of erasing negative value by squaring the error. In MAE to erasing negative value is by converting to absolute value. This method also used to find the percentage of error, usually called Mean absolute percentage error (MAPE). After finding the model with the best performance between those two methods. The last stage is the stage for designing the application and implementing the model. The model which obtained in the previous stage. This final stage is the process of making forecast applications that will be made using the Python programming language.

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The application will be developed using Django web framework for creating the web-based app. Django is a python based web framework. We choose python because python is remarkably easy to understand the programming language. And python itself has many libraries that support machine learning and statistical analysis. These libraries can be used to analyze the data and obtain forecast data. After obtaining a suitable model, the model is implemented to the application using a python programming language. If we got ARIMA model, we will use auto_arima function in python to determine PDQ order [17]. Because Bootstrap is integrated with Django in visual studio the user interface will be created using bootstrap framework.

This application will only have 2 main UI. In the first UI, the user will have to input the chosen department and number of days. A number of days is an input variable which is how many days will be forecast. The second UI will show the forecast result. To show the forecast result data, we will use Highchart for displaying the data as a chart. For the database, we use MySQL database to store the data. The database is used to store training data for the application.

3. RESULTS AND DISCUSSION

The entire data that the researcher got from the UMS database is 3-period data (2017 - 2019) of the Faculty of Engineering in UMS. In this study, the researchers used one of the majors as sample data, the chosen major was the Mechanical Engineering major. This data gathered using pandas library and saved as a data frame in python.

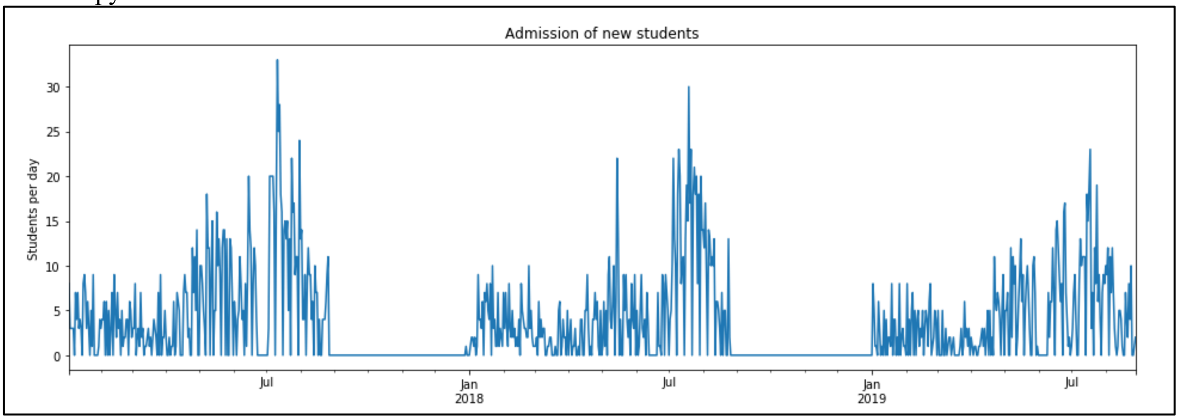


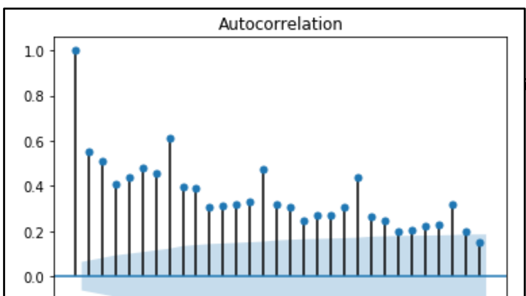
Figure 2. Mechanical Engineering Admission data

In Figure 2, it can be seen that from September to the end of December the data for the number of registrants remained at 0, this is because in previous periods the UMS opened new student admissions starting from January to late August. Before making a forecasting application, the researcher took 2-time series forecasting models that will be tested to find which model is more suitable for Admissions data which then will be implemented into forecasting applications.

3.1 ACF and PACF

This step is to determine the correlation between the data. ACF and PACF plot can be useful to see whether the data is stationary data or not. The horizontal axis indicates the lag, and the vertical axis indicates correlation. In figure 3 and 4, the first value (0th lag) is always 1. A sharp drop from lag 0 to lag 1 indicate the data is stationary. And from the 7th, 14th lag and so on, the value is rising. It indicates that the data has seasonality.

ACF also can be used to test whether the data is white noise or not. The white noise appears when the data in time series is random data and have no correlation. If the 95% of ACF is less than ((+/-) 2/sqrt(data length)) or (0.064/-0.064) it means that the data is white noise. In figure 3, it appears that more than 5% of the data is higher than (0.064/-0.064). So the data is not white noise [18].



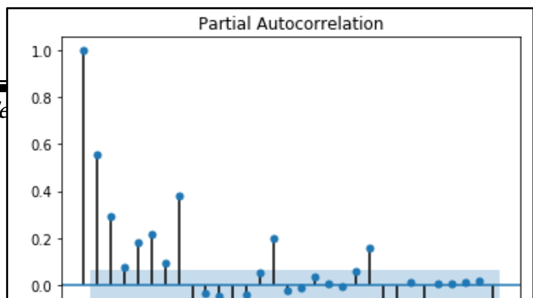


Figure 3. ACF Plot

Figure 4. PACF Plot

3.2 ADF Test

The results of the ADF Test can be seen in Figure 5, showing the data is stationary. To see the stationary data from the ADF test results can be seen in the p-value column, the results show that the p-value is less than 5% (1.1443%) it is shown that the data has no unit root and will reject the null hypothesis.

```
Augmented Dickey-Fuller Test:
ADF test statistic       -3.386082
p-value                   0.011443
```

Figure 5. ADF Test result

From the ADF test results above, it can be concluded that the data is not influenced by trends (Stationary).

3.3 Auto_arima

To determine the order of the ARIMA model the researcher uses the auto_arima function. Auto_arima can also be used to predict using the order contained in the auto_arima results. In figure 6, the model obtained from the auto_arima algorithm is SARIMA (5,0,5). It is because the data have seasonality. And also the data is stationary, variable I (d) on ARIMA is not needed.

Dep. Variable:	y
Model:	SARIMAX(5, 0, 5)

Figure 6. Auto_arima result

To determine the order that we got from auto_arima is acceptable or it's not white noise. We check the ACF plot from the predictions using auto_arima (SARIMA (5,0,5)). If 95% of the data is less than 0.365. The prediction data is white noise. As we can see in figure 7, more than 5% of the autocorrelation data is higher than (0.365/-0.365). So prediction data which generated by auto_arima is not white noise, and acceptable.

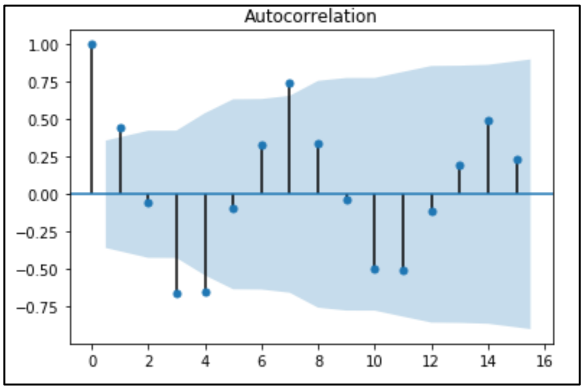


Figure 7. Auto_arima ACF Plot

3.4 1-Month Testing

The graph that is formed from the prediction results using the Auto Regression model and the ARIMA model can be seen in Figure 7. In figure 7 there are 3 lines representing the real value of the new students, predicted value using AR, and predicted value using ARIMA model. Using 938 data as training data and 30 data are used as testing data. And for the error measurement, it can be seen in table 2, which is the result of error testing using RMSE and MAE on both models. The data table above shows the error rate from the prediction data and the original data for the last 1 month (End of July - August). The results of the error test show that the error value from the ARIMA model is smaller than the error value from the Auto Regression model. The smaller error value is shown better-predicted value. Same as error measurement using the MAE method, which gets the results that the ARIMA model is smaller than the AR model.

Table 2. 1-Month error result

Model	RMSE	MAE
AutoRegression	4.392	3.849
SARIMA	3.747	2.894

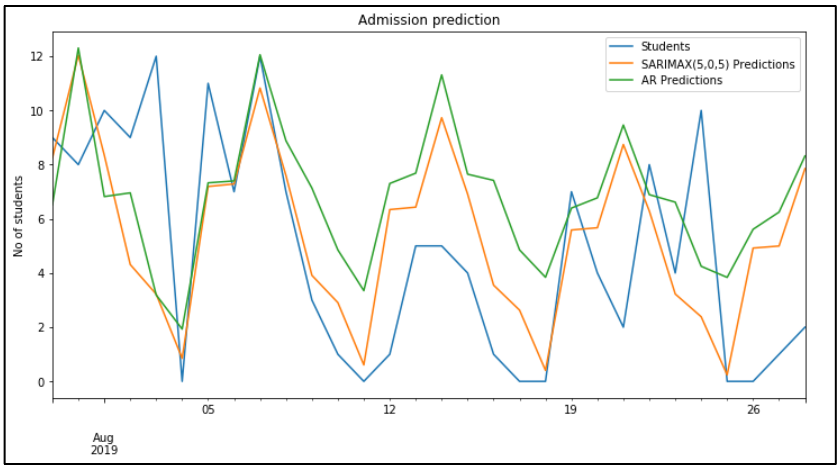


Figure 7. 1-Month test result

In Figure 7, it can also be seen the pattern of prediction results, both Auto Regression and SARIMA have repeated the same pattern and it shrunk, where every 7 days the prediction value of the two models will approach the value of 0, which every once a week the UMS also dismiss the ODS committee which falls on Sunday. And for both model, the value that approaches the value of 0 appears also on Sunday. The graph that is formed from the SARIMA model is also more integrated with the testing data graph than the graph that is formed from the Auto Regression model.

The distribution of error values can be seen on a graph that displays the error values of each model displayed in one graph, which can be seen in Figure 8.

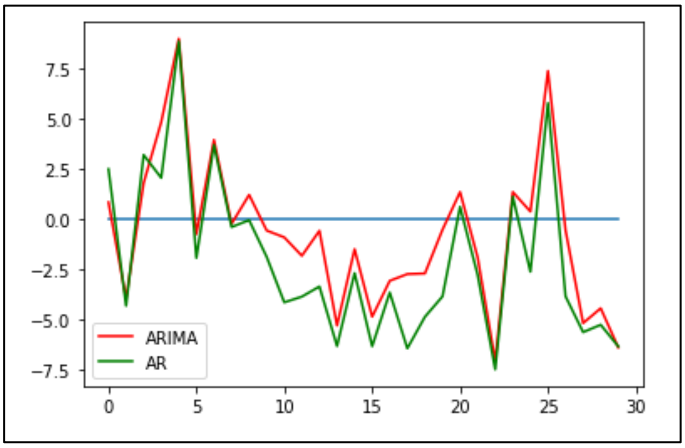


Figure 8. Error Distribution

The distribution of error values of each model has the same value ARIMA (-7.5 - 9) and AR (-7.5 - 9). However, the spread of error from the SARIMA model is closer to zero than the spread of error in the AR model which is more away from the value of 0.

3.5 2-Weeks Testing

The total of training same as the previous experiment (938 data) and for the testing data it reduced to 14 data (2 weeks). The prediction of the SARIMA and AR model produces a graph that can be seen in Figure 9. In Figure 9 the predictive data pattern of AR still has the same low point as the testing data on Sunday, but the resulting low point pattern of AR model is still far from zero value. The graphs formed by the SARIMA model have low point deviations that still fall on Sunday. The pattern formed by each model has a similar pattern.

Table 3. 2-Week error result

Model	RMSE	MAE
AutoRegression	3.967	3.313
SARIMA	3.513	2.542

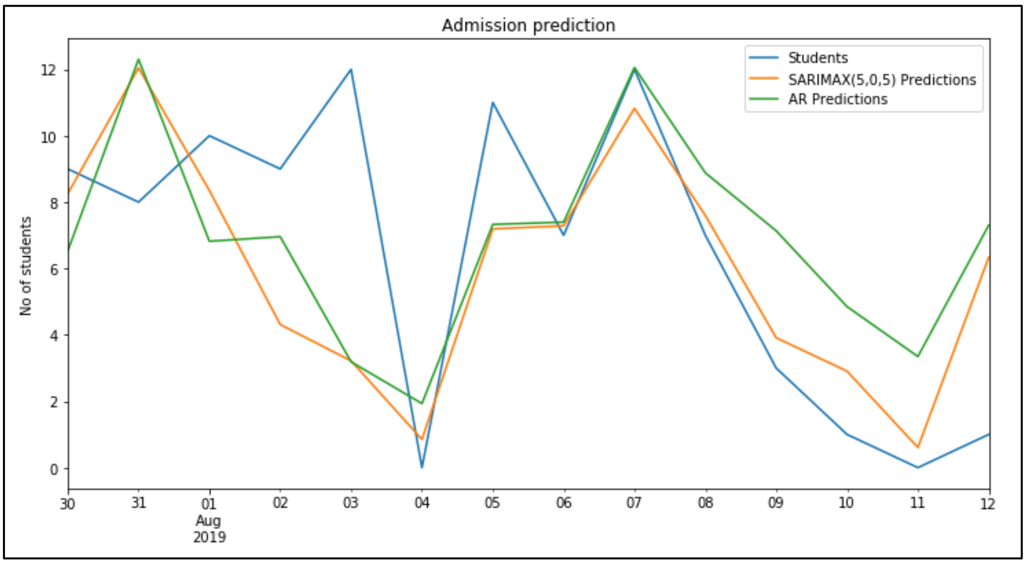


Figure 9. 2-Week test result

In table 3, the value of the measurement error generated by the AR model to predict data 2 weeks is greater than the error value of the SARIMA model, with a large difference. Error value using a span of 2 weeks has a smaller error value than the predicted results with a data span of 1 month.

3.6 1-Week Testing

In testing with testing data for 1 week, the error value in both models is higher than the error value in the previous test. The patterns that are formed from the SARIMA and AR models are almost the same to each other. And for the resulting graph, it can be seen in Figure 10. The error measurement value generated from the SARIMA model with the MAE error measurement method is also smaller than the error measurement value in the AR model. But for error measurement using the RMSE error measurement method, the error rate of the AR model is lower than the SARIMA model.

Table 4. 1-Week error result

Model	RMSE	MAE
AutoRegression	4.372	3.773
SARIMA	4.45	3.57

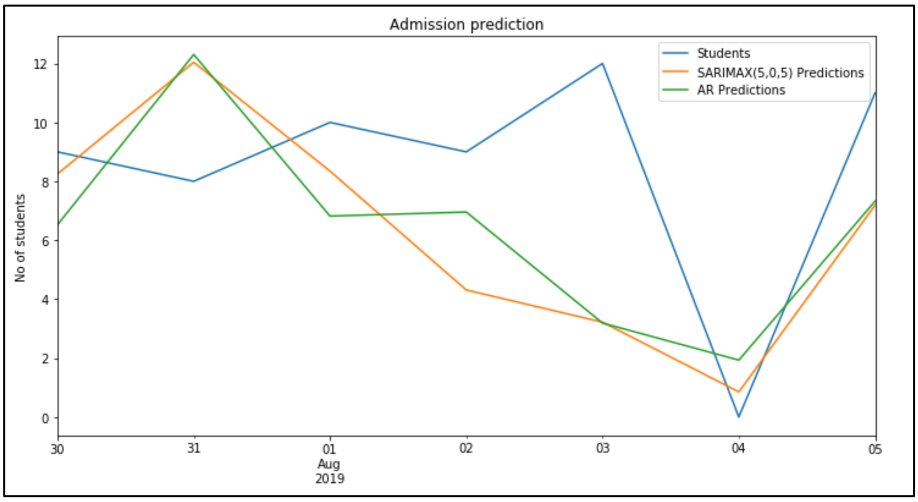


Figure 10. 1-Week test results

In table 4, the difference in error result happened because MAE measures the absolute error for each value. Absolute error gives each error same weight, and RMSE measures the error value by squaring the error value. Squaring the error value have an impact on different weight to each error value in RMSE [19]. From the 3 tests (1 month, 2 weeks, 1 week). Commonly ARIMA or AR can not forecast with a longer period. Because the more data ARIMA or AR will forecast, it only will get from the forecast value. Which is the forecast value itself has an error. Therefore the more data need to be forecast the more error it willl be getting.

3.7 Cross-Validation

Here we used grouping data for day forward-chaining of 10 groups, and each group contained 14 data (2 weeks). Researchers used data as much as 14 data because, in the previous experiment, the smallest error value was generated in the 2-week trial. This day forward chaining method aims to compare between AR and ARIMA, which are more suitable to be applied in forecasting applications. In table 5 can be seen is the value of the measurement error of each group of data.

Table 5. Cross-validation result

Data	Auto Regression		ARIMA	
	RMSE	MAE	RMSE	MAE
945 – 959	5.66	5.03	4.22	3.63
946 – 960	5.34	4.68	4.01	3.41
947 – 961	5.55	5.03	4.45	3.88
948 – 962	4.71	4.09	3.85	3.22
949 – 963	3.9	3.23	3.36	2.62
950 – 964	3.2	2.54	3.3	2.47
951 – 965	3.29	2.74	3.31	2.49
952 – 966	2.96	2.34	3.1	2.45
953 - 967	3.19	2.67	3.21	2.58
954 - 968	3.32	2.73	3.22	2.63

To see more clearly the error rate of each model in day forward chaining. Values from each model are grouped and calculate the average error value. Mean error in the cross validation of each model can be seen in Table 6. It can be seen that the ARIMA model has smaller Root Mean Square Error Cross Validation (RMSECV) and Mean Absolute Error Cross Validation (MAECV) values than the AR model.

Table 6. Cross validation mean

Model	RMSECV	MAECV
Auto Regression	4.11	3.51
ARIMA	3.6	2.94

3.8 User Interface

After testing the error values of the two models, the ARIMA model was chosen because it produced an error value smaller than the error value obtained from the AR model on almost all tests. However, the error value of the AR model in the 1-week test is smaller in the RMSE test using 938 training data. Overall the ARIMA model gets a smaller error value than the AR model. As well as for grouping data, researchers use daily data grouping.

After getting a suitable model to be implemented into forecasting applications for admission in UMS, we implement the ARIMA model by using the auto_arima algorithm as an order finder. Auto_arima also used so the application can adapt to different data. The system model in this application is quite simple, and the database is used as a container for training data. And the input received by the system is only the department that will be predicted, and the number of days that will be predicted. The output of the application in the form of a graph that displays predictive data. This website based prediction application was developed using the Python and Django programming languages as web framework.

Figure 11, is the initial display of the application that will receive input in the form of majors and the number of days to be predicted, for the display of the research application using Bootstrap as a framework. And in Figure 12, the display of forecast data using Highchart framework as a graphical chart viewer.

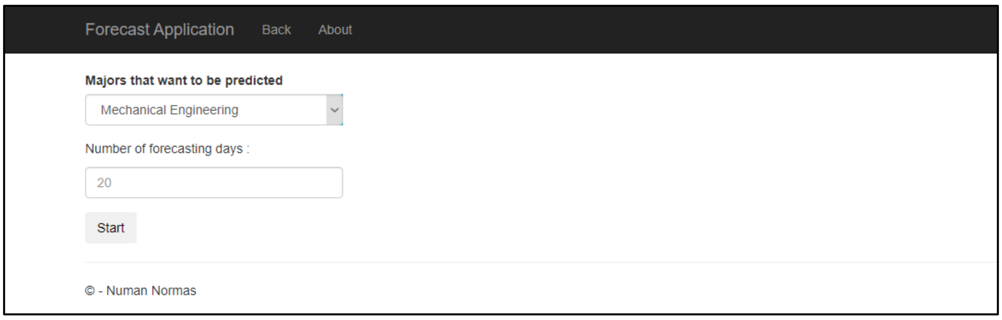


Figure 11. First user interface

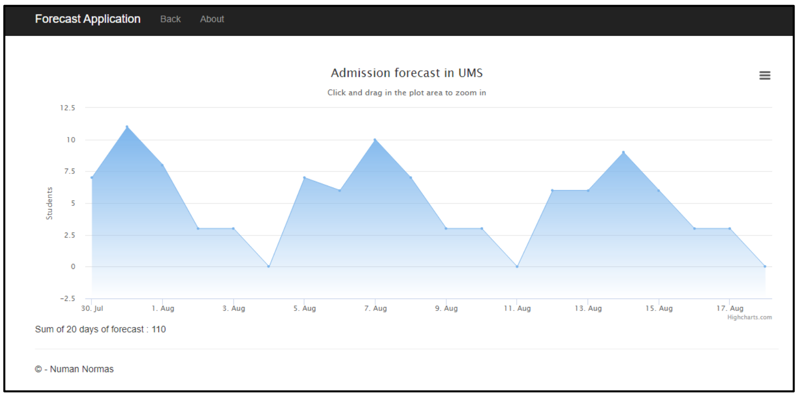


Figure 12. Second user interface

4. CONCLUSION

Based on the research, admission data can be forecasted using ARIMA or AR model. Forecast with a longer period is not suitable with ARIMA nor AR, because the ARIMA take value for forecasting is getting from the forecast value. The more data ARIMA need to forecast, more error will be generated. ARIMA model has higher accuracy to be applied into forecasting applications compared to AR models. Because the level of error measurements performed on almost all error tests show, ARIMA has a smaller error measurement value than the AR model. Either AR or ARIMA is bad at long-term forecasting, it will just repeating the same pattern. ARIMA can be used to forecast short period of data, and time series model creation of ARIMA is also swift.

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