Analysis to Predict the Number of New Students At UNU Pasuruan using Arima Method

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Abstract*—New student admission is an important aspect in higher education management, including Nahdlatul Ulama University (UNU) Pasuruan. Relevant prediction of total new students is needed to support resource planning such as teaching staff, facilities, and budget. This study aims to evaluate the historical pattern of new student admissions at UNU Pasuruan and predict the number of new students in the coming years using the ARIMA (Auto Regressive Integrated Moving Average) method. The data used is historical data on new student admissions in the last five years, which is analyzed to identify trends, seasonality, and fluctuation patterns. The analysis is performed using statistical software such as Python to improve the accuracy and efficiency of the process. This study approach includes several main steps, namely collecting historical data on the number of new students, testing stationarity using the Augmented Dickey-Fuller (ADF) test, identifying model parameters through ACF and PACF graphs, and estimating ARIMA model parameters. The resulting model is evaluated using prediction error metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The study findings describe that the ARIMA model (6,0,1) produces an RMSE value of 21.88 and a MAPE of 0.2%. In addition to having the smallest error score, the ARIMA model (6,0,1) also has the smallest AIC score of the various models that can be used for predictions, which is 447.44 and the largest log likelihood value, which is -214.72. The largest prediction of the number of new students is in July, which is 92.72 and the smallest in February, which is 24.43. This prediction is expected to help university management in optimizing resource planning, increasing management efficiency, and anticipating fluctuations in the number of new students in the future. This study offers new findings in the form of the use of predictive models based on historical data to support strategic decision-making, such as resource allocation and promotion planning. With these results, universities can anticipate changes in the number of enrollments more effectively, which were previously only done based on subjective estimates. The model built can also be applied to similar datasets in the future with appropriate parameter adjustments.

Keywords— New Student Prediction, ARIMA, Stationarity

I. INTRODUCTION

Higher education is an educational institution that aims to educate students to become productive members of society by acquiring knowledge and skills in various fields, including the world of work [1] In the context of higher education, students play a very important role in achieving educational goals [2]. In order to complete their education quickly and obtain a suitable career, prospective students tend to choose the best colleges. When choosing a college, they consider various factors such as the facilities offered, the academic performance of the college and the reputation of the institution [3]. To maximise academic services to students and even prospective students, the university needs to prepare various things both in terms of physical and non-physical, such as facilities in each study program, accreditation, teaching staff and other things.

In order to become one of the best universities that is the choice and destination of prospective students to come to study, the University of Nahdlatul Ulama (UNU) Pasuruan needs a strategy in order to prepare various things needed by the university to develop even better. It is also based on its goal to produce young people who excel in academics and have a strong moral and spiritual character. This university offers various study programs and continues to improve the quality of education and its competitiveness.

One of the strategies taken by UNU Pasuruan is predicting the number of new students each year, which is affected by external aspects including economic conditions and education policies, as well as internal factors such as campus reputation [4]. Forecasting the number of new students is essential to ensure that resource needs can be anticipated [5].

To take into account the forecasting of the number of new students we apply one of the data analysis technologies, namely the ARIMA method, which predicts trends based on historical data [2]. The use of ARIMA for prediction of the number of new students at UNU Pasuruan can help understand fluctuations in enrolment which is important for managerial decision making. In addition to researching and predicting the number of incoming students at UNU Pasuruan, by using ARIMA we also provide recommendations for human resource planning and management.

For the application of this arima method, commonly used time series analysis models are the Auto Regression (AR) model, Moving Average (MA) model, Autoregression Moving Average (ARMA) model, Auto Regression Integration Moving Average (ARIMA) model and SARIMA model [6]. Among these methods, ARIMA is an effective approach to analyzing time series data because of its ability to handle both stationary and non-stationary data [7]. ARIMA models can identify trends, seasonality, and fluctuations in data, and provide a solid

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foundation for accurate forecasting and decision making. ARIMA also has high flexibility in handling time series data with various characteristics [8]. ARIMA can be more reliable in time and resource-limited interval forecasting when compared to other forecasting methods [9].

The reason we chose the ARIMA method for prediction analysis of the number of new students at UNU Pasuruan is because this method is very suitable for analysing time series data. ARIMA has the ability to identify patterns in historical data, including trends, seasonality, or random fluctuations, which often occur in new student enrolment data. In addition, ARIMA is flexible because its components (AR, I, MA) can be adjusted to the characteristics of the data, including nonstationary data [5] [8]. This ability allows the model to provide more accurate prediction results, which can help understand new student enrolment patterns in more depth [5].

In addition to flexibility and accuracy, the ARIMA method is also easy to implement with the help of statistical software such as Python that we used in this research, making it a practical choice for data-driven research [3]. ARIMA has been widely used in educational contexts, including student enrolment prediction, making it relevant for use in this study. With more precise prediction results, this research is expected to help UNU Pasuruan in resource planning, promotion strategies, and capacity management more effectively.

II. RESEARCH METHODS

The research method used uses the steps in the ARIMA method, with a flow as in Figure 1.

1) Time series data collection in the form of a dataset of the number of new students over 5 years.
2) Stationary inspection using Augmented Dickey-Fuller (ADF) test.
3) If the data is not stationary, differentiation must be carried out so that the data becomes stationary.
4) If the information is stationary, it will proceed to the next stage.
5) Using the pmdarima library in Python to identify the model to be analyzed.
6) The best model will be obtained based on the lowest AIC and BIC values.
7) Validation is performed to check the accuracy of the selected mathematical model.
8) If validation fails to meet the most appropriate model parameters, a repeat will be performed to select a different model using the appropriate lag.
9) If the validation is correct, proceed to the next stage.
10) Forecasting is done to evaluate the total number of incoming students in the coming period.

Stationary data is time series data that has statistical properties that are constant over time [5]. This means that the mean, variance and covariance of the data do not change significantly over time. In time series analysis, stationarity is an important prerequisite because many predictive methods, including ARIMA, assume that the data has statistically stable properties. Stationary data usually show no upward or downward trend patterns, and data fluctuations appear to be consistent around the average [10] [11].

Indicators of successful stationary data can be seen in several ways. Visually, a graph of stationary data will show a flat pattern with no clear trend, with uniform fluctuations [11]. Statistically, tests such as ADF can be used to confirm stationarity, where a p-value <0.05 indicates that the data is stationary. In addition, the Autocorrelation Function (ACF) graph for stationary data will show rapidly decreasing autocorrelation after a few lags. If the data is not stationary, differencing techniques are often applied to achieve stationarity, which is characterised by a more stable data pattern after the process. Stationarity is important to ensure the results of analyses and predictions are more accurate and reliable [12].

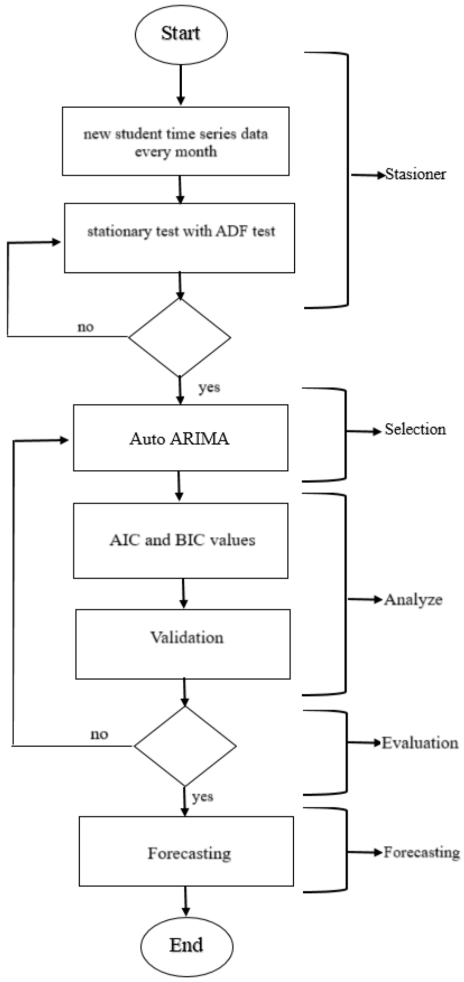

Fig. 1. Research Methods

A. Data and Variables

This research was conducted in the period from November 2024 to January 2025. The source of research data came from the New Student Admissions Bureau (PMB) located on Jl. Warungdowo, Pasuruan Regency, and connected to Nahdlatul Ulama Pasuruan University. The data collection technique in this study is a series of steps to collect relevant information to support the research objectives [11]. The methods used include document studies, surveys, interviews, literature reviews, and observations. Specifically, this study relies on document study methodology to collect findings from various media sources,

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such as books, images, videos, and databases. Data obtained from the PMB Bureau became the main basis in this study for further analysis.

Quantitative data and qualitative data are the two main categories of information collection used in research [10]. The main difference between the two lies in the form and method of processing: quantitative data is presented in numerical form, which allows for more precise and measurable processing and analysis, while qualitative data is descriptive and cannot be measured with numbers [13]. For example, in this study, the materials used are quantitative data, and can be seen in Table 1, which contains information in the form of numbers and statistics that will be analyzed in more detail.

TABLE I. STUDENT DATA PER MONTH FOR 5 YEARS

No	Number of New Students
1	8
2	24
3	34
4	55
5	72
6	75
7	79
8	82
9	88
10	90
……..	………
59	89
60	118

B. ARIMA Model

ARIMA is a technique used to predict future events by utilizing past data to produce short-term forecasts [2]. ARIMA has the advantage of being able to predict with an effective level of accuracy for use in short-term forecasting. In addition, ARIMA is also flexible and fast [14]. Arima combines AR and MA models to be able to make predictions on time series data. AR explains the model regarding the dependent variable that is affected by the variable in the previous time. The AR model is described with AR(p) or ARIMA (p,0,0) through the stage of forming equation (1)

$$Y_t = \emptyset_1 . Y_{t-1} + \emptyset_2 . Y_{t-2} + \cdots + \emptyset_p . Y_{t-p} + w_t \quad (1)$$

Where:
Yt: *value of variable X at time t*
$\emptyset$: *p-th Autoregressive Parameter*
wt : *error value at time t*

Moving Average (MA) is a stage that describes in an explicit context the correlation of dependence on error scores in sequence. The MA model is described with MA(q) or Arima (0,0,q) by forming equation (2).

$$Y_t = w_t + \theta_1 . w_{t-1} + \theta_2 . w_{t-2} + \cdots + \theta_q . w_{t-p} \quad (2)$$

Where :
Yt: *value of variable X at time t*
θq: *qth moving average parameter*
wt: *error value at time t*

AR and MA can be combined into ARMA, namely (p,q) or Arima (p,0,q) by forming equation (3).

$$Y_t = \emptyset_1 . Y_{t-1} + \emptyset_2 . Y_{t-2} + \cdots + \emptyset_p . Y_{t-p} + w_t + \theta_1 . w_{t-1} + \theta_2 . w_{t-2} + \cdots + \theta_q . w_{t-p} \quad (3)$$

Where :
Yt: *Value of variable Z at time t*
$\emptyset p$: *p-th AR parameter*
θq: *qth MA parameter*
wt: *error value at time t*

Meanwhile, the ARIMA model is a technique that integrates the AR model and the MA model with the form ARIMA (p, d, q) where the order p represents the AR operator, the order d represents differencing, and the order q represents the MA operator. The ARIMA (p, d, q) model forms equation (4).

$$Y_t = (1 + \emptyset_1) \cdot_{t-1} + (\emptyset_1 - \emptyset_2) \cdot_{t-2} + \cdots + (\emptyset_p - \emptyset_{p-1}) \cdot_{t-p} + w_t - \theta_q . w_{t-1} - \cdots - \theta_q . w_{t-p} \quad (4)$$

Where :
Yt: *Value of variable Z at time t*
$\emptyset p$: *p-th AR parameter*
θq: *qth MA parameter*
wt: *error value at time t*

The forecasting carried out in this study uses the ARIMA method using Python, with several libraries in it to assist in this study, namely the Matplotlib, PMdarima, SicklitLearn, Pandas, Numpy and other libraries. [12]. The steps of applying the ARIMA method in this study are described in Figure 1.

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III. RESULTS AND DISCUSSION

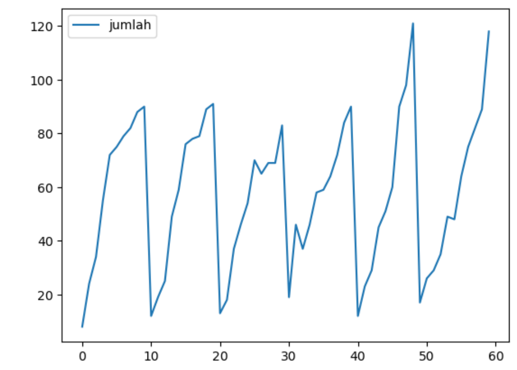

Fig. 2. New Student Time Series Graph

In Figure 2, the time series graph shows the number of students per month throughout the period 2019 - 2023 with a total of 60 datasets on the (X) axis and 120 students on the (Y) axis. Figure 2 shows that the data needs to be ensured to be stationary in mean and variance, this is done to see whether the ARIMA method has been fulfilled to be carried out in this study. This test is useful for finding out whether a time series has a unit root, which indicates whether or not there is a trend or pattern in the data. The ADF test carried out with Drift and Trend produces a low p-value score (<= 0.1) with a value of 0.044, these findings illustrate stationary data. Because the p-value score is very low (<= 0.01) for testing, it can be concluded.

The ACF or Autocorrelation Function test in Figure 4 is used to calculate and display the autocorrelation function of the time series stored from the decade rainfall data. 17.5 iterations were performed looking at the ACF value. The ACF value helps in identifying patterns or correlation structures in the time series, which can provide insight into the nature of the data and help in modeling and prediction. From the results of the ACF value, 2 lags are seen that are out of the standard significance of the values 1.00 and 0.50 which means they contain MA (1) and MA (2).

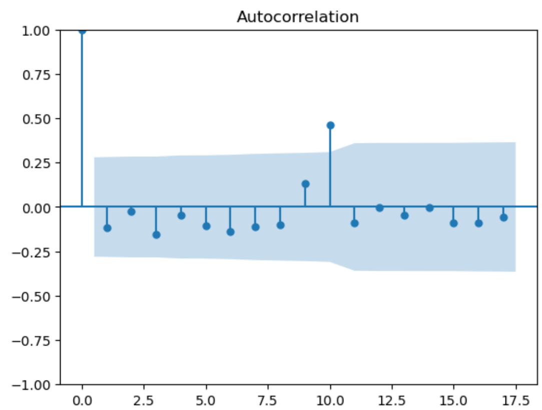

Fig. 3. ACF Plot of New Student Data

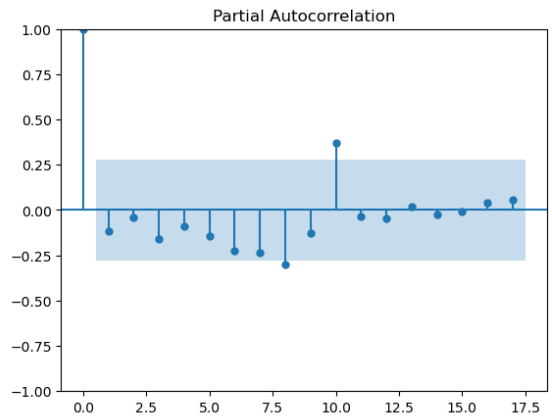

Fig. 4. PACF Plot of New Student Data

The PACF or Partial Autocorrelation Function test in Table 1 is used to calculate and display the partial correlation function of the time series stored in the Data object of the number of new students. The results of this test will provide a partial correlation value for each lag. PACF is a method used to identify a direct relationship between one time point and a specific time point in a time series, after eliminating the influence of correlation on previous lags. PACF analysis is useful in determining the optimal order of the ARIMA model, which is often applied to time series modeling. From the results of this PACF test, it can be seen that there are 3 lags that are outside the significance limits of the values 1.00, -0.25 and 0.35 which have the meaning of autoregressive or AR (1) AR (2) AR (3).

TABLE II. AUTO ARIMA RESULTS

ARIMA (0,0,0) (0,0,0) [0]	: AIC=670.794, Time=0.01 sec
ARIMA (0,0,1)(0,0,0)[0]	: AIC=626.368, Time=0.03 sec
ARIMA (0,0,2)(0,0,0)[0]	: AIC=601.122, Time=0.05 sec
ARIMA (0,0,3)(0,0,0)[0]	: AIC=592.650, Time=0.13 sec
ARIMA (0,0,4)(0,0,0)[0]	: AIC=588.802, Time=0.18 sec
ARIMA (0,0,5)(0,0,0)[0]	: AIC=infc, Time=0.21 sec
ARIMA (1,0,0)(0,0,0)[0]	: AIC=567.388, Time=0.02 sec
ARIMA (1,0,1)(0,0,0)[0]	: AIC=568.932, Time=0.04 sec
ARIMA (1,0,2)(0,0,0)[0]	: AIC=570.915, Time=0.05 sec
ARIMA (1,0,3)(0,0,0)[0]	: AIC=infc, Time=0.13 sec
ARIMA (1,0,4)(0,0,0)[0]	: AIC=infc, Time=0.18 sec
ARIMA (2,0,0)(0,0,0)[0]	: AIC=568.936, Time=0.03 sec
ARIMA (2,0,1)(0,0,0)[0]	: AIC= infc, Time=0.13 sec
ARIMA (2,0,2)(0,0,0)[0]	: AIC= infc, Time=0.15 sec
ARIMA (2,0,3)(0,0,0)[0]	: AIC= infc, Time=0.17 sec
ARIMA (3,0,0)(0,0,0)[0]	: AIC=570.935, Time=0.04 sec
ARIMA (3,0,1)(0,0,0)[0]	: AIC=572.655, Time=0.16 sec
ARIMA (3,0,2)(0,0,0)[0]	: AIC=infc, Time=0.17 sec
ARIMA (4,0,0)(0,0,0)[0]	: AIC=572.061, Time=0.04 sec

SARIMAX Result			
Dep. Vaiable:	jumlah	No. Observations:	50
Model:	ARIMA (6,0,1)	Log Likehood	-214.732
Date:	Sat, 04 Jan 2025	AIC	447.446
Time:	07:39:50	BIC	464.654
Sample:	0	HQIC	453.999

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In Figure 6, Auto Arima is run to create an Arima model to predict the number of new students. From this command, several iterations are carried out which are used to find the most optimal model based on the AIC score. Several models that were tried include ARIMA (2,0,2), ARIMA (0,0,0), ARIMA (1,0,0), ARIMA (0,0,1), ARIMA (0,0,0) (without mean), ARIMA (2,0,0), ARIMA (3,0,0), ARIMA (6,0,1), and so on. The model that has a smaller AIC score is declared better. The best model is obtained with the smallest AIC value among the other orders, namely ARIMA (6,0,1) with parameters ARIMA (6,0,1) with non-zero mean, Model coefficient ar1 = 0.6015, ma2 = -0.6801, std err = 0.833, mean = 163.524 with model performance Residual variance (sigma ^ 2) = 286.1147, Log likelihood = -214.72, AIC = 447.44 and BIC = 464.65.

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                 jumlah   No. Observations:                   50
Model:               ARIMA(6, 0, 1)   Log Likelihood                -214.723
Date:              Sat, 04 Jan 2025   AIC                            447.446
Time:                      07:39:50   BIC                            464.654
Sample:                           0   HQIC                           453.999
                               - 50
Covariance Type:                opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         56.5149      0.833     67.879      0.000      54.883      58.147
ar.L1          0.6015      0.265      2.273      0.023       0.083       1.120
ar.L2         -0.2384      0.359     -0.664      0.507      -0.942       0.465
ar.L3         -0.2913      0.311     -0.938      0.348      -0.900       0.318
ar.L4         -0.0112      0.372     -0.030      0.976      -0.740       0.718
ar.L5         -0.1609      0.362     -0.444      0.657      -0.870       0.549
ar.L6         -0.3418      0.286     -1.194      0.232      -0.903       0.219
ma.L1         -0.6801      0.251     -2.710      0.007      -1.172      -0.188
sigma2       286.1147     62.547      4.574      0.000     163.524     408.705
===================================================================================
Ljung-Box (L1) (Q):                   0.20   Jarque-Bera (JB):                 1.20
Prob(Q):                              0.66   Prob(JB):                         0.55
Heteroskedasticity (H):               1.49   Skew:                             0.31
Prob(H) (two-sided):                  0.42   Kurtosis:                         3.44
===================================================================================
```

Fig. 5. ARIMA (6,0,1) Results

This model also has a small AIC and BIC value so that the better the model is in explaining the data, then the high Log likelihood value indicates that the model can explain the data well. So overall, this model provides a good representation of the data on the number of new students, and the coefficients obtained can be used to make predictions or for further analysis. The last step in time series analysis to predict the number of new students is to forecast. Forecasting is done as much as 10 Prediction data or about 10 months into the future. This is done to find out the predicted number of new students in the following year.

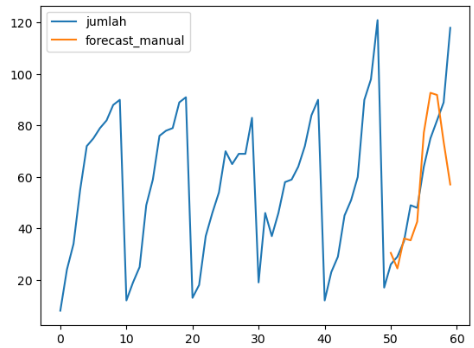

Fig. 6. Results of Forecasting the Number of New Students

Previous studies have shown that the ARIMA model can be effectively used to predict the number of new students with various parameters, such as ARIMA (2,1,1) and ARIMA (11,0,12), which were selected based on the lowest accuracy and error rates [15][16]. However, recent studies using the ARIMA (6,0,1) model show higher AIC and BIC values, indicating that parameter selection can still be optimized. In addition, the low statistical significance of some lags in this model can affect the accuracy of the prediction results. This difference emphasizes the need for a more optimal development model to improve the accuracy of estimating the number of new students. Meanwhile, the results of forecasting the number of new students show that the estimation of the new student registration period can follow the pattern of the training data used. In addition, the ten test data shown in Table 2 show an increasing trend that is in accordance with the movement pattern of the graph, so that the validity of the model in describing historical trends can be confirmed.

```
50    30.465696
51    24.437012
52    36.102347
53    35.364126
54    42.616382
55    77.199688
56    92.724535
57    91.896221
58    73.671824
59    57.082380
```

Fig. 7. 10 data on forecasting the number of new students

The final step in forecasting is to evaluate the model used by measuring MAE, MAPE and RMSE. In Figure 10, it is known that the ARIMA (6,0,1) model produces MAE = 14,621, MAPE = 0.2 and RMSE = 21,884.

TABLE III. MAE, MAPE AND RMSE EVALUATION RESULTS

MAE – manual	14.62167618080127
MAPE – manual	0.20027750011448164
RMSE – manual	21.8840908325154497

IV. CONCLUSION

This study proves that the ARIMA method is effective in predicting the number of new students based on historical new student admission data. This prediction provides a strong foundation for UNU Pasuruan in developing new student admission strategies and better resource management. The resulting model is Model (6,0,1) based on auto ARIMA which is known to have the smallest AIC score of various models that can be applied in making predictions, namely 447.44 and the highest log likelihood score, namely -214.723. So the ARIMA model (6,0,1) is considered to be the most optimal step in carrying out the estimation in the context of the analysis carried out with the prediction results for the next period from the data obtained by the researcher, namely: January (30.46), February (24.43), March (36.10), April (35.36), May (42.61), June (77.19), July (92.72), August (91.89), September (73.67), October (57.08).

ARIMA models have advantages in analysing and predicting time series data, but their application to different

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datasets or longer periods has limitations that need to be considered [17][18]. One of the main challenges is the **sensitivity of ARIMA to non-stationary data**[19]. ARIMA requires the data to be stationary before the model is built, so if the new dataset has complex patterns of trends, seasonality, or fluctuations that cannot be normalised through differencing, the model may not provide optimal results. This can be a problem when the data used has a highly dynamic pattern or is influenced by significant external factors [20].

In addition, ARIMA is less able to capture non-linear patterns that may exist in time series data. The model is based on linear relationships between historical data, so complex patterns of relationships, such as variable interactions or sudden changes, are often poorly represented. In the context of longer periods, ARIMA also tends to become less accurate as the assumption that past patterns will continue may not hold in the future. As a result, these models need to be evaluated and updated regularly to ensure their performance remains relevant to the latest data. For very different datasets or longer periods, combining ARIMA with other models, such as machine learning-based models, can help capture more complex patterns.

For further research, it is recommended that researchers consider external factors that may affect the results, such as changes in education policy and economic conditions. Both of these factors have the potential to have a significant impact on the variables studied, so by including these factors, the accuracy of predictions in the study can be improved. Taking these external factors into account will provide a more comprehensive and realistic picture, and help in producing more relevant and applicable findings in a broader context.

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