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Time series data analysis to forecast the percentage of on-time graduates at Nusa Cendana university

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Abstract: The existence of information related to the estimated percentage of students graduating on time can certainly be one of the study materials that stakeholders can use to take strategies to increase the percentage of on-time graduates. One way that can be done is to use time series data related to the percentage of on-time graduates in the past year to predict the percentage of on-time graduates in the future. Forecasting can be done using ARIMA modeling. In addition, so that the solution used is also right on target, it is necessary to find out the factors that affect the study period of Undana students. The type of research used is mixed method research with sequential explanatory method where, in the first stage of research using quantitative methods, namely collecting data and quantitative analysis and in the second stage collecting and analyzing qualitative data. The quantitative data used is the percentage of on-time graduates at Nusa Cendana University in the last 5 years, while the qualitative data is the results of interviews with graduates of Nusa Cendana University related to factors that affect the length of study. The results showed that the best model for forecasting the percentage of on-time graduates of undergraduate students at Nusa Cendana University is the ARIMA (2, 2, 1) model with an AIC value of -125.64. The results of forecasting the percentage of on-time for the February, June, and September graduation periods in the next 5 years, namely 2024 to 2028, are 5.31%, 9.84%, 12.79%, 9.05%, 13.08%, 15.91%, 12.74%, 16.35%, 19.06%, 16.39%, 19.63%, 22.22%, 20%, 22.93%, and 25.41% respectively. Meanwhile, the factors that influence the study period of students are the curriculum applied in the study program, facilities and infrastructure, lecturers, and students themselves.
Keywords: *Academic performance, Arima, Data forecasting, Time series analysis.*

1. Introduction

Nusa Cendana University (Undana) is one of the first state universities established in East Nusa Tenggara province. Based on the Decree of the Minister of Higher Education and Science (MHES) Number 111 of 1962 dated August 28, 1962 (Universitas Nusa Cendana, 2024). (A brief History of Universitas Nusa Cendana, internet source), the establishment of the State University domiciled in Kupang was established starting from September 1, 1962, as well as the date of birth (Dies Natalis) of the State University in Kupang

Until now Undana has 1 (one) Postgraduate Program (PPs) and 9 (nine) Faculties, namely the Faculty of Teacher Training and Education (FKIP), Faculty of Animal Husbandry, Marine and Fisheries (FKKP), Faculty of Social and Political Sciences (FISIP), Faculty of Law (FH), Faculty of Agriculture (FAPERTA), Faculty of Science and Engineering (FST), Faculty of Public Health (FKM), Faculty of Medicine (Universitas Nusa Cendana, 2024) and Veterinary Medicine (FKKH), and Faculty

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of Economics and Business (FEB). The number of study programs consists of 2 S3 study programs, 8 S2 study programs and 47 SI study programs and 1 D3 study program.

Based on the Regulation of the Minister of Education and Culture of the Republic of Indonesia Number 49 of 2014 concerning National Higher Education Standards (Kurniawati, 2017), students of diploma four programs and undergraduate programs are required to take a learning load of at least 144 credits. The period of study used for students with the learning load as referred to above is 4 (four) to 5 (five) years for diploma four programs and undergraduate programs.

One of the criteria in the graduate competency standard is that the university leadership must ensure that the undergraduate study program (S1) has graduate competencies with a curriculum referring to KKNI and the Merdeka Learning Campus Merdeka policy, so that the average cumulative grade point average (GPA) of graduates is at least 3.40 consistently every year. Based on previous research by Ekowati, It was found that the student entrance selection pathway affects the first year GPA (Ekowati et al., 2021). In addition, the factors that influence GPA are environment and learning style with learning independence as an intervening variable (Ekowati et al., 2022). Therefore, both students and lecturers strive together to improve their students' GPA by paying attention to factors that affect students' GPA because GPA is one of the factors that affect the length of study of students (Aniswita et al., 2023).

The length of study of students is one of the criteria written in the graduate competency standards, namely university leaders, faculties and study programs with their respective authorities must ensure that students have learning outcomes so that at least 50% of students graduate on time in each batch (Andriansyah & Kamalia, 2021; R. Rosyid et al., 2023). Undergraduate students are said to graduate on time if they can complete their studies in less than or equal to four years and are categorized as graduating not on time if they complete their studies in more than four years (Moraga-Pumarino et al., 2023).

However, in an internal audit conducted by the Learning Development and Quality Assurance Institute of Nusa Cendana University, information was obtained that the on-time graduation of Undana students was very low. This is supported by the average length of study of Undana students from 2014 to 2019 which is more than 10 semesters or more than 5 years (Strategic Plan of Nusa Cendana University 2021-2025). In addition, educational performance is also measured through the Educational Efficiency Number (EEN). EEN is used as a measure of the level of efficiency of education delivery that provides an overview of the percentage of students who graduate on time. Although there has been an increase in the EEN score from 2014-2019, the average EEN is still below 25%. The low percentage of students who graduate on time will certainly affect the accreditation of study programs and universities.

The existence of information related to the estimated percentage of students graduating on time can certainly be one of the study materials that can be used by Nusa Cendana University stakeholders to take strategies to increase the percentage of on-time graduates. One way that can be done is to use time series data related to the percentage of on-time graduates in the past year to predict the percentage of on-time graduates in the future. Forecasting can be done using ARIMA modeling.

Research related to the use of ARIMA has been conducted by Alexander Karl Ferdinand Loder in 2023, to predict the number of active students. The results show that the combination of machine learning algorithms and ARIMA models is a valid model for predicting student status (Karl Ferdinand Loder, 2023). In addition, ARIMA has also been used by Rianto, et al., and As'ad, et al., to predict the number of new students (Muhamad, 2019). The analysis results show that the best model for (Melda Juliza & Puce Angreni, 2023) two consecutive studies is the ARIMA (2,1,1) model and the ARIMA (2,1,1) model (Teng, et al., 2017) (As'ad et al., 2017; Rianto & Yunis, 2021) .

Therefore, researchers are interested in using the ARIMA model to forecast the percentage of on-time graduates at Nusa Cendana University with the title "Time Series Data Analysis to Forecast the Percentage of On-Time Graduates at Nusa Cendana University". In addition, in order for the solution to increase the percentage of on-time graduates by Undana stakeholders to be right on target, it is also necessary to find out the factors that affect the study period of Undana students through interviews.

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2. Literature Review

2.1. Time Series Data

Time series data is a type of data consisting of variables collected in time order within a certain time span for a certain category or individual (Lim & Zohren, 2021). If time is viewed as discrete (time can be viewed as continuous), the collection frequency is always the same. In the discrete case the frequency can be seconds, minutes, hours, days, weeks, months, or years (Anggraeni & Sutrasni, 2023) and others.

One of the groupings of time series models is (a) A stationary model is a model such that all its statistical properties do not change with time (i.e. it is time invariant). In applications, the statistical properties that are often of interest are mean, variance, and covariance. A time series model that satisfies the property that these three statistical measures are time invariant is called a weakly-stationary process. In a stationary model, its future statistical properties can be predicted based on historical data that has occurred in the past. Some stationary time series models are White Noise, Moving Average, Autoregressive Moving Average (ARMA) and ARMA (Muslihin & Ruchjana, 2023) models with exogenous variables (ARMAX); (b) Nonstationary models are models that do not fulfill the properties of stationary models, meaning that their statistical properties change with time. Some nonstationary models are trend models, Autoregressive Integrated Moving Average (ARIMA) models, seasonal ARIMA (SARIMA), ARIMAX models, and ARCH/GARCH heteroskedastic models.

2.2. ARIMA Model

ARIMA is a model used in statistics and econometrics, especially in time series analysis. The ARIMA model is a generalization of the Autoregressive Moving Average (ARMA) model with the Box Jenkins method which is used for forecasting future values in a time series of current and previous values (Pankratz, 1983).Therefore, ARIMA is often called the Box-Jenkins time series method (Slavia et al., 2019).

The ARIMA model is a model that completely ignores independent variables (Elif Bilginoglu, 2019) in making forecasts. The purpose of this model is to determine a good statistical relationship between the variable being forecasted and the historical values of the variable so that forecasting can be done with the model. ARIMA uses past and present values of the dependent variable to produce accurate short-term forecasts (Tiara Putri et al., 2019; Fathoni & Saputra, 2023; Jebb et al., 2015).

ARIMA is suitable if the observations from the time series are statistically related to each other (dependent) (Sri Rahayu et al., 2020). ARIMA has very good accuracy for short-term forecasting, while for long-term forecasting the accuracy of forecasting is not good (Slavia et al., 2019;Buchori & Sukmono, 2018; Ilmayasinta, 2021; Waluyo, 2019). The long-term forecasting results obtained will usually tend to flatten/constant (Styaningsih, 2020; Waluyo, 2019).

The representation of the ARIMA model is usually in the form of notation (p,d,q) with p being the autocorrelation, d being the differencing, and q being the moving average(Bakar & Rosbi, 2017; Safwandi, 2023). The ARIMA model consists of three basic steps, namely the identification stage (Dursun, 2023), the estimation and testing stage, and the diagnostic check (Hariadi, 2021; Ishak et al., 2023; Melda Juliza & Puce Angreni, 2023). Furthermore, the ARIMA model can be used for forecasting if the model obtained is adequate (Slavia et al., 2019; Putri et al., 2021).

The steps or stages in ARIMA Modelling, among others, can be explained as follows. *(a) Data Stationarity.* Stationary time series data is data whose average does not change with time. In the ARIMA model, the data used must be stationary or the average value of the data (Wirawan et al., 2019) does not change over time which can be seen through the data plot. If the data is not stationary (Mistawati et al., 2021), data conversion must be done using the differentiation method; *(b) Differentiation Method.* The differentiation method is used to convert non-stationary data into stationary data which is a requirement for ARIMA by calculating the difference between the current data value and the previous data value (Peng et al., 2024; Simanjuntak et al., 2023). Differentiation is d-ordered, if the data is stationary then the order is 0 so that it becomes ARIMA (p,0,q) or often referred to as ARMA. B

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notation (Backshift operator) is used in the differentiation process. The use of B notation in differentiation in general (Nuzulia, 1967:16) is:

$$B^d X_t = X_{t-d} \quad (1)$$

In general, for d-order differentiation is:

$$X^d = (1-B)^d X_t \quad (2)$$

(c) Model Identification. After the time series data to be processed is stationary, the next step is to determine the ARIMA (p,d,q) model that is suitable. In selecting and determining p and q can be seen through observing the Auto Correlation Function (ACF) and Partial Autocorrelation Function (PACF) (Mistawati et al., 2021) patterns, ACF and PACF patterns can have cut off and dies down patterns (Fathoni & Saputra, 2023; Syahrini et al., 2023). *First*, the ACF and PACF of time series data can have a cut off pattern. A cut off pattern is when the ACF and PACF lines are significant at the first or second lag but then there are no significant ACF and PACF lines at subsequent lags. *Secondly*, the ACF and PACF are said to have dies down behaviour if the two functions are not cut off, but rather decrease gradually. The shape of the decline can be without or with a sine wave. Determining whether a time series is modelled with AR, MA or ARIMA depends on the ACF and PACF patterns. The AR model is used if the ACF plot dies down while the PACF cuts off. The MA model is used if the ACF plot is cut off and the ACF plot dies down. Meanwhile, if both ACF and PACF plots die down, then the model used is the ARIMA model (Abbas Yakubu & Panji Agung Saputra, 2022). ***(d) Autoregressive (AR) model.*** The p-order autoregressive model is a model of regression results with itself at previous times defined. The general form of the AR model with order p (AR(p)) or ARIMA model (p,0,0) is as follows (Adi Soetrisno et al., 2019):

$$X_t = a_1 X_{t-1} + a_2 X_{t-2} + \cdots + a_P X_{t-P} + \varepsilon_t, t \in Z \quad (3)$$

where X_t is the observation value at time *t*, a_i for *i=1,2, ..., p* is the AR model parameter, and ε_t is the error at time t. *(e). Moving average (MA) model.* The general form of the MA model with order *q (MA(q))* or the ARIMA (0,0,q) model is as follows:

$$X_t = \varepsilon_t + b_1 \varepsilon_{t-1} + b_2 \varepsilon_{t-2} + \cdots + b_q \varepsilon_{t-q}, t \in Z \quad (4)$$

where X_t is the observation value at time t ,b_i for $i = 1,2, \dots, p$ is the AR model parameter, and ε_t is the error at time t. *(f) Mixed model ARMA and ARIMA process.* The ARMA model is a combination of AR and MA models (Wirawan et al., 2019). The ARMA function form is (p,q) or ARIMA model $(p, 0, q)$ and the model equation (Tarno et al., 2022) form is:

$$X_t = a_1 X_{t-1} + a_2 X_{t-2} + \cdots + a_P X_{t-P} + \varepsilon_t + b_1 \varepsilon_{t-1} + b_2 \varepsilon_{t-2} + \cdots + b_q \varepsilon_{t-q} \quad (5)$$

where X_t is the observation value at time t, a_i for $i = 1,2, \dots, p$ is the AR model parameter, b_i for $i = 1,2, \dots, p$ is the MA model parameter, and ε_{t-j} for $j = 0,1,2, \dots, p$ is the error at time $t - j$.

ARIMA *(p,d,q)* model where order p states the AR operator, order d states the result of differencing, and order q states the operator of MA (Wulandari R.A & Gernowo R, 2019), the general form of the ARIMA model (Mahrivandi et al., 2017) is:

$$a(B)(1-B)^d X_t = b(B)\varepsilon_t \quad (6)$$

where X_t is the observation value at time t, B the backward shift operator, and ε_t is the error value at time t.

The model equation is:

$$X_t = (1 + a_1) X_{t-1} + (a_1 - a_2) X_{t-2} + \cdots + (a_P - a_{P-1}) X_{t-P} + \varepsilon_t + b_q \varepsilon_{t-1} + \cdots + b_q \varepsilon_{t-q} \quad (7)$$

where X_t is the observation value at time t, a_i for $i = 1,2, \dots, p$ is the AR model parameter, b_i for $i = 1,2, \dots, p$ is the MA model parameter, and ε_t is the error at time t. ***(g) Model Parameter Testing.*** There are two types of model parameter testing carried out, namely partial testing and overall testing. 1)Testing each model parameter partially is done using the t-test; 2) Overall model testing (Overall F test). The model is said to be good if the error value is random, meaning that it no longer has a certain pattern (Jaoude, 2021). In other words, the model obtained can capture the existing (Jaoude, 2021) data

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pattern well. To see the randomness of the error value, the autocorrelation coefficient value of the error value is tested using the Ljung-Box method (Pradana et al., 2020).

$$Q = n'(n'+2)\sum_{k-1}^{m}\frac{r_k^2}{(n'-k)} \qquad (8)$$

Chi square distribution with degrees of freedom (Jabrah et al., 2016), $db = k - p - q - P - Q$,
Where:

n': $n - (d + SD)$
d: order of distinction is not a seasonal factor
D: order of seasonal factor differentiation
S: number of periods per season
M: seasonal time lag
r_k: autocorrelation for time $1,2,3,\dots,k$

Testing criteria:

If $Q \leq \mathrm{X}^2(a, db)$ or $p - value \geq 0{,}05$ the error value is random (acceptable model); If $Q > \mathrm{X}^2(a, db)$ or $p - value < 0{,}05$, the error value is not random (the model cannot be accepted).

(h) Selection of the Best Model. To determine the best model, the following AIC (Akaike information criterion) value can be used (Adi Soetrisno et al., 2019):

$$AIC = -2\log L(\hat{\theta}) + 2M \qquad (9)$$

with M being the number of parameters in the model. The best model is the one with the smallest AIC value.

Based on the background, namely the low timely graduation of Universitas Nusa Cendana students and the average length of study of Universitas Nusa Cendana students from 2014 to 2019 which is more than 10 semesters or more than 5 years and literature review, it is necessary to do forecasting related to the percentage of students who graduate on time in the next 5 years so that the right strategy can be determined to increase the percentage of timely graduation of Universitas Nusa Cendana students. In addition, it is also necessary to find out the factors that affect the study period so that the solution taken is right on target.

The method used for forecasting on-time graduate data is ARIMA. ARIMA is suitable if the observations from the time series are statistically related to each other (dependent) (Sri Rahayu et al., 2020). ARIMA is very good in accuracy for short-term forecasting, while for long-term forecasting the accuracy of forecasting is not good (Ilmayasinta, 2021). The long-term forecasting results obtained will usually tend to flatten/constant.

The steps in data analysis are identifying data stationarity, making ACF and PACF plots, identifying and estimating ARIMA models based on ACF and PACF plots, estimating parameters, testing the significance of parameters and assumptions on the models formed, calculating the AIC value to select the best model. Then, the best model will be used to do forecasting for the next 5 years with the best model.

3. Research Methods

3.1. Type of Research

The type of research used in this study is mixed method research. Mixed method research is a research approach that combines or associates qualitative forms and quantitative forms (Baran, 2019). This approach involves philosophical assumptions, the application of qualitative and quantitative approaches, and the mixing of the two approaches in one study (Suriviana et al., 2023). The quantitative-qualitative combination research method is a method that focuses on data (Creswell & Creswell, 2018) collection and analysis and combines quantitative and qualitative data (Sandelowski, 2000). Based on this, the purpose of this mixed methods research method is to find better research

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results than using only one approach, for example using a quantitative approach only or with a qualitative approach only. By using this method, more comprehensive, valid, reliable and objective data will be obtained (Irawan et al., 2024), so that a better understanding can be obtained when compared to one method. Meanwhile, the method used is sequential explanatory, namely the first stage of research using quantitative methods, namely collecting data and quantitative analysis and in the second stage collecting and analysing qualitative data. Thus, mixed methods sequential explanatory (combination) research is conducted to answer the formulation of (Ariswati, 2022) quantitative research problems and the formulation of qualitative research problems, or the formulation of different, but complementary problems.

3.2. Time and Place of Research

The research was conducted from March to August 2024. The research was conducted at Nusa Cendana University, Kupang, East Nusa Tenggara.

3.3. Research Data

In this study, the quantitative data used is the percentage of on-time graduates at Nusa Cendana University in the last 5 years. Meanwhile, the qualitative data is in the form of interview results with graduates of Nusa Cendana University related to factors that influence the length of study.

3.4. Data Collection Techniques and Instruments

In this study, researchers used data collection techniques in the form of (Arif & Sulistianah, 2019) documentation and interviews. ***(1) Documentation.*** Documentation is a data collection technique by collecting and analyzing documents, both written, pictorial, and electronic documents (Fadhilah, 2024). Documentation in this study was conducted to obtain data related to on-time graduates at Nusa Cendana University in the last 11 years. The instrument used was a USB drive, also called a flash drive or memory stick, which is a small portable device that plugs into a USB port on your computer. USB drives are commonly used for storage, data backup and file transfer between devices. Researchers used a USB drive to store data related to on-time graduates at Nusa Cendana University in the last 11 years, namely 2013 to 2023. ***(2) Interview.*** Interview is a data collection technique that is carried out by asking questions directly between researchers and sources. Structured interviews are used as a data collection technique, when the researcher or data collector already knows with certainty about what information will be obtained (Hutapea & Martanti, 2023). Therefore, in conducting interviews, data collectors have prepared research instruments in the form of written questions whose alternative answers have also been prepared. In this structured interview, each respondent is given the same questions, and the data collector records them. Semi-structured interviews are a type of interview that is included in the in-dept interview category, where the implementation is freer when compared to structured interviews (Aung et al., 2021). The purpose of this type of interview is to find problems more openly, where the interviewees are asked for their opinions and ideas. In conducting interviews, researchers need to listen carefully and record what informants say (Muslihin & Ruchjana, 2023). Unstructured interviews are free interviews where researchers do not use interview guidelines that have been arranged systematically and completely for data collection (Mahfuda, 2023; O'Brien & Tabaczynski, 2007). The interview guide used is only an outline of the problems to be asked. The type of interview used in this research is a semi-structured (Hutapea & Martanti, 2023) interview (Dursun, 2023). Interviews were conducted to obtain information from Nusa Cendana University graduates about the factors that influence the study period.

3.5. Data Analysis Technique

Quantitative data analysis is carried out using the ARIMA- Box Jenkins forecasting method. The research steps taken are as foll (As'ad et al., 2017): ***(1)*** Plot the time series data, in this case the data on the percentage of on-time graduates at Nusa Cendana University from 2013 to 2023; ***(2)*** Check the

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stationarity of the data. To determine the occurrence of data stationarity, a unit root test (Dickey Fuller Test) can be performed. The hypothesis used is:
H0: $\emptyset = 0$ *(there is a unit root, the data is not stationary)*
H1: $\emptyset \neq 0$ *(no unit root, stationary data)*
The test statistics are:

$$ADF_t = \frac{\hat{\emptyset}-1}{SE(\emptyset)}$$

The value of the test statistic is then compared with the critical value from the Mackinon table. In addition, we can also use the $p - value$ to decide the conclusion. If the $p - value < 0{,}05$, it can be concluded that the data is stationary. If the data is not stationary, then differencing needs to be done until the data is stationary. ***(3)*** Make ACF and PACF plots to determine the order of AR(p) and the order of MA(q). The analysis process to determine the order of AR(p) and the order of MA(q) can be labeled as follows:

Table 1.
Determination of order AR(p), MA(q) or ARMA(p,q).

Process	***Autocorelation function*** **(ACF)**	***Partial autocorelation function*** **(PACF)**
AR(p)	Decays to zero (exponentially) or follows a sine wave pattern (dies down)	Cuts off immediately to zero after lag p.
MA(q)	Decays to zero immediately after lag q (cuts off after lag q)	Decays to zero (Exponentially) or follows a sine wave pattern (Dies down).
ARMA(p,q)	Decays to 0 (zero)	Decays to 0 (zero)

(4) Perform tentative ARIMA model estimation according to the AR and MA orders obtained in step 3; ***(5)*** Perform model parameter testing consisting of partial model parameter tests, overall model parameter tests, and residual normality tests using the Kolmogorov Smirnov test; ***(6)*** Select the best model by looking at the smallest AIC value from several significant models in step 5; ***(7)*** Estimate the percentage of on-time graduates using the best model obtained in step 6. The research steps can be depicted in a flowchart based on Figure 1.

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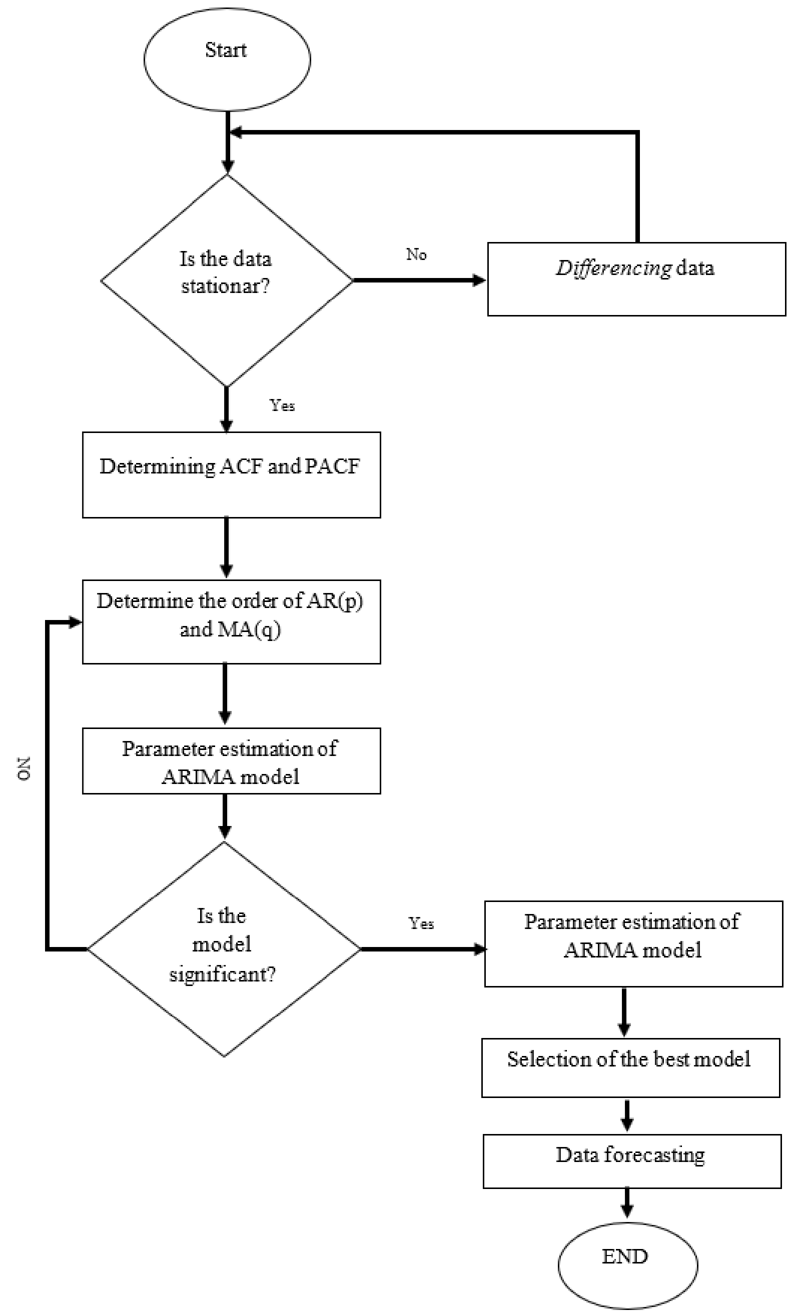

Figure 1.
ARIMA flowchart.

Meanwhile, qualitative data analysis was carried out by analysing data from interviews with Nusa Cendana University graduates to obtain factors that influence their study period.

4. Results

Research activities were carried out at Nusa Cendana University from January to June 2024. This activity is in the form of forecasting the percentage of on-time graduates at Nusa Cendana University based on graduate data in the last 11 years. In addition, interviews were also conducted to find out the

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factors that influence the length of study of students. The data used in this study are data on on-time graduates in the last 11 years, namely 2013-2023. Data for on-time graduates is calculated in three graduation periods, namely in February, June, and September so that the data totals 33. A summary of the data analysis can be presented in the following table.

Table 2.
The summary of the data.

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.005921	0.014117	0.032811	0.044656	0.066228	0.148936

4.1. Qualitative Data

The qualitative data is in the form of interviews with graduates of Nusa Cendana University related to factors that influence the length of study. There were 10 interviewees in this study, consisting of 5 on-time graduates and 5 untimely graduates who came from various faculties at Nusa Cendana University.

4.2. Data Analysis

4.2.1. Time Series Data

In this study, data analysis was carried out using the help of RStudio which can be downloaded for free through the website https://posit.co/download/rstudio-desktop/. The following are the stages of time series data analysis carried out in this study.

4.2.2. Data Plot

In the first stage, the data plot of the percentage of on-time graduates in the graduation period 2013 to 2023 is carried out.

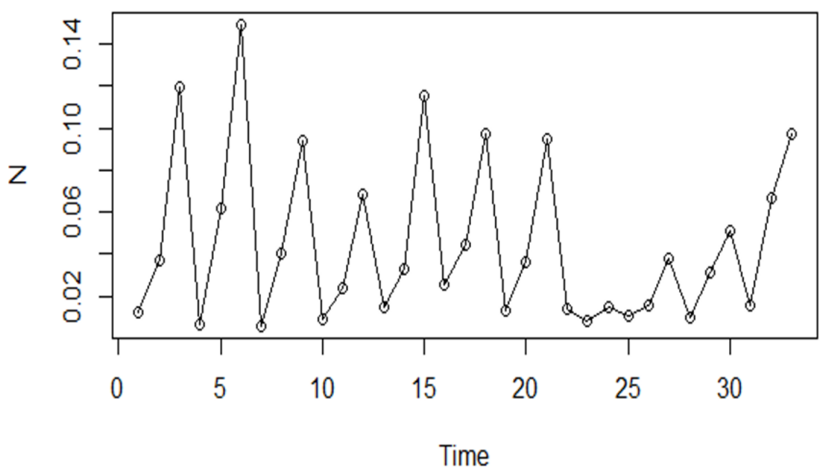

Figure 2.
Plot of on-time graduate data.

4.2.3. Identifying Data Stationarity

After plotting the data, the next step is to identify the stationary data. One of the requirements that must be met in ARIMA analysis is that the data used must be stationary or the average value of the data does not change over time which can be seen through the data plot. The test used to assess data stationarity is the Augmented Dickey-Fuller Test. The following are the results of stationarity testing of data on on-time graduates at Nusa Cendana University.

Augmented Dickey-Fuller Test

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data: PWTU

Dickey-Fuller = -1.979, Lag order = 3, p-value = 0.5811

alternative hypothesis: stationary

It is noted that the p$-value > 0{,}05$ so it is concluded that the data is not statistical. Therefore, it is necessary to differentiate the data. After differentiation, the stationarity test is conducted again on the data. The following are the results of the stationary test on the first differentiation data.

Augmented Dickey-Fuller Test

data: diff1

Dickey-Fuller = -2.693, Lag order = 3, p-value = 0.3055

alternative hypothesis: stationary

It is observed that the $p - value > 0{,}05$ so it is concluded that the first differentiation data is not yet stationary. Therefore, it is necessary to perform a second differentiation on the data. The following are the results of the second differentiation on the data. After differentiation, the stationarity test was conducted again on the data. The following are the results of the stationary test on the second differentiation data

Augmented Dickey-Fuller Test

data: diff2

Dickey-Fuller = -4.5772, Lag order = 3, p-value = 0.01

alternative hypothesis: stationary

It is noted that the p-value$< 0{,}05$ so it is concluded that the second differentiation data is stationary. The following is a plot of the second differentiation results on the data.

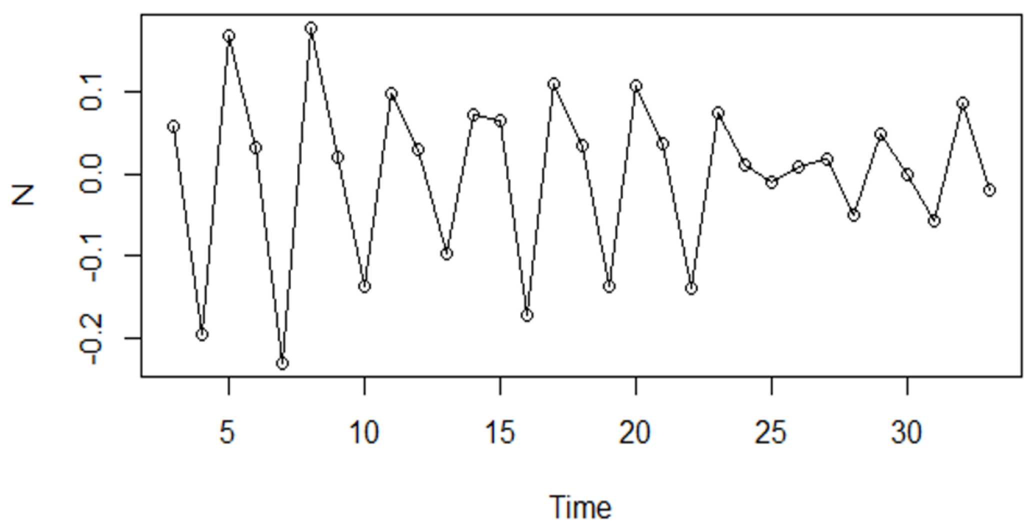

Figure 3.
Plot of differentiated result data.

4.2.4. Making ACF and PACF Plots.

The next step is to create ACF and PACF plots. ACF and PACF plots are used to determine the order of AR and MA. The following are the results of the ACF and PACF plots from the differentiation results of the two data.

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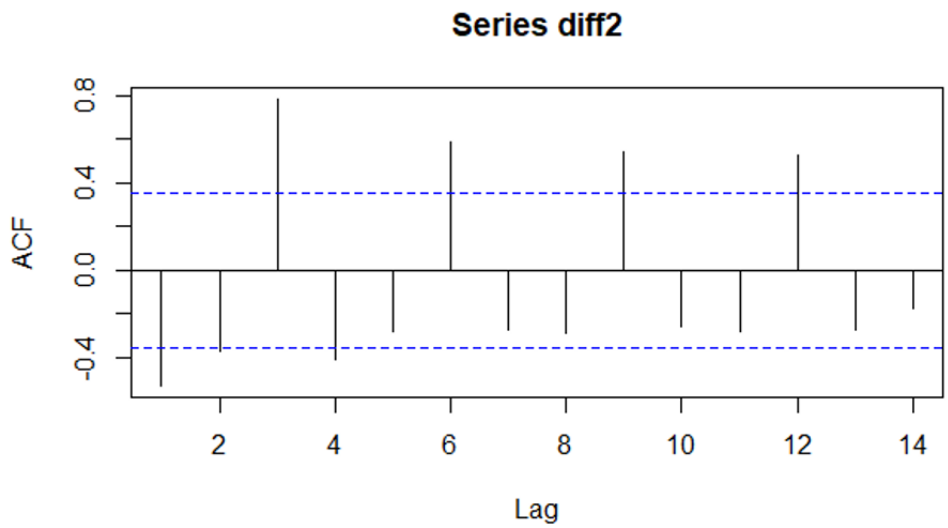

Figure 4.
ACF Plot of differentiated data results.

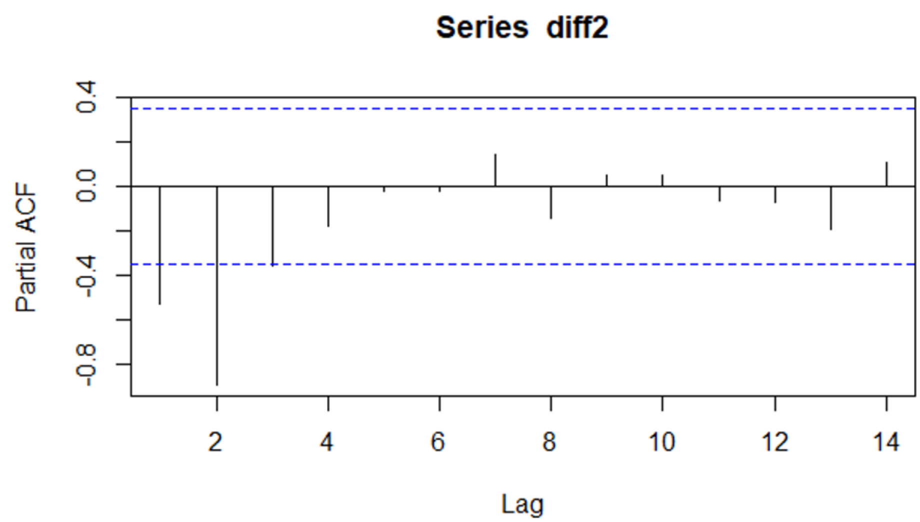

Figure 5.
PACF plot of differentiated data.

4.2.5. Identification and Estimation of ARIMA Models Based on ACF and PACF Plots

Determining whether a time series data is modelled with AR, MA or ARIMA depends on the ACF and PACF patterns. The AR model is used if the ACF plot dies down while the PACF is cut off. The MA model is used if the ACF plot is cut off and the ACF plot dies down. Meanwhile, if both ACF and PACF plots are equally dies down, then the model used is the ARIMA model (Rosyid et al., 2019). Based on the results of the ACF and PACF plots above, the possible order choices for AR are AR (1) and AR (2). While the possible order choices for MA are MA (1), MA (3), MA (6), MA (9), and MA (2). Here are the choices of ARIMA models that will be used to estimate the parameters.

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Table 1.
ARIMA model selection.

Model	ARIMA (p, d, q)
Model 1	ARIMA (1, 2, 1)
Model 2	ARIMA (2, 2, 1)
Model 3	ARIMA (1, 2, 3)
Model 4	ARIMA (2, 2, 3)
Model 5	ARIMA (1, 2, 6)
Model 6	ARIMA (2, 2, 6)
Model 7	ARIMA (1, 2, 9)
Model 8	ARIMA (2, 2, 9)
Model 9	ARIMA (1, 2, 12)
Model 10	ARIMA (2, 2, 12)

4.2.6. Parameter Estimation, Parameter Significance Testing, and Assumptions on the Models Formed.

4.2.6.1. Testing Each Model Parameter Partially

Partial model significance testing can be done by looking at the p-value of each parameter. If the p-value <0.05, it can be concluded that the parameter is significant. Based on the p-value results above, it is concluded that the parameters are significant in each model.

Table 4.
Partial model parameter test results.

ARIMA (p, d, q)	Significant parameters
ARIMA (1, 2, 1)	All significant
ARIMA (2, 2, 1)	All significant
ARIMA (1, 2, 3)	All significant
ARIMA (2, 2, 3)	MA(1), MA(2), MA(3)
ARIMA (1, 2, 6)	MA(4)
ARIMA (2, 2, 6)	MA(2), MA(3), MA(5)
ARIMA (1, 2, 9)	AR(1), MA(1), MA(2), MA(3), MA(4), MA(5), MA(7), MA(8), MA(9)
ARIMA (2, 2, 9)	AR(2), MA(2), MA(5), MA(8), MA(9)
ARIMA (1, 2, 12)	Nothing significant
ARIMA (2, 2, 12)	MA(1), MA(2), MA(3), MA(4), MA(5), MA(6), MA(7), MA(8), MA(9), MA(10), MA(11), MA(12)

4.2.6.2. Overall F Test

The model is said to be good if the residual value is random, meaning that it does not have a certain pattern anymore, in other words, the model obtained can capture the existing data pattern well. To see the randomness of the error value, the autocorrelation coefficient value of the error value is tested using the Ljung-Box method. If the p-value> 0.05, it can be concluded that the residuals are random. The following are the results of the Ljung-Box test for 10 ARIMA models.

Table 5.
Ljung-box test results.

ARIMA (p, d, q)	Ljung-box result	Conclusion
ARIMA (1, 2, 1)	1.53e-11	Model is not significant
ARIMA (2, 2, 1)	0.7307	Significant model
ARIMA (1, 2, 3)	3.325e-06	Model is not significant
ARIMA (2, 2, 3)	0.4074	Significant model

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ARIMA (p,d,q)	Ljung-box result	Conclusion
ARIMA (1, 2, 6)	0.393	Significant model
ARIMA (2, 2, 6)	0.7823	Significant model
ARIMA (1, 2, 9)	0.9557	Significant model
ARIMA (2, 2, 9)	0.9823	Significant model
ARIMA (1, 2, 12)	0.9918	Significant model
ARIMA (2, 2, 12)	0.9394	Significant model

Based on the results in Table 4. above, it is noted that the ARIMA (1, 2, 1) and ARIMA (1, 2, 3) models are not significant so that the model is no longer used at the next stage. In addition to testing the overall model, a residual normality test was also conducted using the Kolmogorov-Smirnov Test. If the p-value> 0.05, it can be concluded that the residuals are normally distributed. The following test results from the Kolmogorov-Smirnov Test determine the residual normality of the remaining 8 models.

Table 6.
Kolmogorov-Smirnov result.

ARIMA (p,d,q)	Kolmogorov-Smirnov	Conclusion
ARIMA (2, 2, 1)	0.9729	Residuals are normally distributed
ARIMA (2, 2, 3)	0.997	Residuals are normally distributed
ARIMA (1, 2, 6)	0.865	Residuals are normally distributed
ARIMA (2, 2, 6)	0.9103	Residuals are normally distributed
ARIMA (1, 2, 9)	0.4142	Residuals are normally distributed
ARIMA (2, 2, 9)	0.9281	Residuals are normally distributed
ARIMA (1, 2, 12)	0.9918	Residuals are normally distributed
ARIMA (2, 2, 12)	0.9352	Residuals are normally distributed

4.2.7. Selecting the Best Model

The best model selection is done by paying attention to the smallest AIC value of the ARIMA model. The following are the AIC values of the 7 significant ARIMA models based on Table 4 and Table 5 above.

Table 7.
AIC value of each model.

ARIMA (p,d,q)	AIC
ARIMA (2, 2, 1)	-125.64
ARIMA (2, 2, 3)	-125.13
ARIMA (1, 2, 6)	-109.75
ARIMA (2, 2, 6)	-118.08
ARIMA (1, 2, 9)	-115.19
ARIMA (2, 2, 9)	-114.3
ARIMA (1, 2, 12)	-109.99
ARIMA (2, 2, 12)	-114.7

Based on the AIC value in Table 6 above, it is obtained that the best model is the ARIMA (2, 2, 1) model with an AIC value of -125.64. Therefore, this model will be used to forecast on-time graduates in the next 12 graduation periods.

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4.3. Perform Forecasting for The Next 15 Periods with the Best Model

From the previous step, the best model is the ARIMA (2, 2, 1) model. At this stage, we will use this model to perform on-time graduate forecasting for the next 5 years. The following are the forecasting results.

Table 8.
Forecasting results of percentage of on-time graduates.

Years	Months	On-time graduates
2024	February	5.31%
	June	9.84%
	September	12.79%
2025	February	9.05%
	June	13.08%
	September	15.91%
2026	February	12.74%
	June	16.35%
	September	19.06%
2027	February	16.39%
	June	19.63%
	September	22.22%
2028	February	20.00%
	June	22.93%
	September	25.41%

4.4. Interview Data

The following are the results of the analysis of interview data conducted with 10 respondents related to the factors that influence the study period of students: (1) Curriculum Factors. Based on the results of the interview, curriculum factors such as the distribution of courses set by the study program affect the length of study. This is because in the first few semesters courses that must be taken have been determined so that in the final semester students can focus on completing the final project. (2) Facilities and infrastructure factors. Based on the results of the interview, the facilities and infrastructure factor affect the length of study. If the facilities are complete, it will certainly help students in completing their studies. Conversely, if the facilities owned are not good, it can hinder student studies. One example highlighted by respondents is that the references available in the library are still inadequate, which makes it difficult for students to complete their final project. (3) Lecturer Factors. Lecturer factors such as lecturer qualifications, communication established with thesis supervisors, lecturer professionalism, and the length of time for correction of thesis supervisors greatly affect the completion of student studies. The longer the lecturer takes to correct the student's final project, the longer it will take students to make revisions, making students late in completing their final project. A good relationship with the lecturer is also considered a determining factor in the length of study of students, which if the student does not have good communication with the lecturer, the process of completing his studies will also not go well. (4) Student factors. Based on the results of interviews, there are several factors from students that affect the length of their studies, namely commitment, motivation, priority scale, mastery of the chosen topic and discipline. In addition, the length of time to complete the thesis assignment also affects graduating on time. The student factor is the factor that most influences the length of study of students. The level of awareness in students not to be lazy in completing the final project is still very low which ultimately makes the student take a long time ranging from 6-12 months to be able to complete the final project. (5) Economic factors. Based on the results of interviews, some students have side jobs. However, this does not affect their studies and they can still graduate on time. In addition, some of them received scholarships during college, which motivated them to graduate on time.

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5. Discussion

The ARIMA model is a model that completely ignores independent variables (Sri Rahayu et al., 2020) in making forecasts. The purpose of this model is to determine a good statistical relationship between the variable being forecasted and the historical values of the variable so that forecasting can be done with the model. ARIMA uses past and present values of the dependent variable to produce accurate short-term forecasts (Ishak et al., 2023; Permata & Habibi, 2023).

In this study, the ARIMA model is used to predict the percentage of on-time graduates of undergraduate programs at Nusa Cendana University. The length of study of students is one of the criteria written in the graduate competency standards. University leaders to study programs must ensure that at least 50% of students graduate on time in each batch (Cendana, Strategic Plan of Nusa Cendana University 2021-2025). The existence of information related to the estimated percentage of students graduating on time can certainly be one of the study materials that can be used by Nusa Cendana University stakeholders to take strategies to increase the percentage of on-time graduates.

Time series data on the percentage of on-time graduates in undergraduate programs in the last 11 years are divided into 33 periods and analyzed using the ARIMA model. Based on the analysis, the best model is the ARIMA (2, 2, 1) model with an AIC value of -125.64. This model is then used to predict graduates in the next 5 years, from 2024 to 2028. The forecasting results for the next 15 periods are 5.31%, 9.84%, 12.79%, 9.05%, 13.08%, 15.91%, 12.74%, 16.35%, 19.06%, 16.39%, 19.63%, 22.22%, 20%, 22.93%, and 25.41%. If you add up each prediction each year, you will see that there is an increase in the percentage of on-time graduates in the next 5 years. In fact, in 2027 the percentage of on-time graduates reached more than 50%, which is in accordance with the criteria written in the graduate competency standards (Cendana, Strategic Plan of Nusa Cendana University 2021-2025).

There are many factors that support efforts to increase the percentage of on-time graduates of postgraduate programs at Nusa Cendana University. One of them is the implementation of the Independent Learning Campus Merdeka curriculum, for example, with various alternative final assignments that can replace the thesis. Based on interviews, it is also found that curriculum factors such as the distribution of courses set by study programs affect the length of study. This is in line with the research of Dewanti & Pramono where the study program curriculum is the factor that has the greatest influence on student final project completion, namely 75.7% (Dewanti & Pramono, 2023). The length of task completion certainly affects the study period.

Another factor that also affects the study period of students is the availability of facilities in the campus environments such as classrooms, libraries, laboratories to the internet network. If the facilities are complete, it will certainly support students to be able to study well. besides that, lecturers also have an influence on the study period of students (Cerinda Sianipar et al., 2023; Hardiana et al., 2023). Adequate lecturer qualifications will certainly help students in understanding lecture material. In addition, the role of lecturers is also very important in guiding students in completing their final assignments.

One of the factors that also plays the most important role in influencing the study period of students is the internal factors of the students themselves (Ramli et al., 2018). This can be in the form of commitment, motivation, priority scale, mastery of the chosen topic and discipline from students to be able to complete their studies on time. This is in accordance with research by Jedvaj and Skrbinjek which states that motivation to complete studies affects the study period (Jedvaj & Skrbinjek, 2022). In addition, based on the results of interviews, it was found that the awareness within students to immediately complete the final project was still very low. This ultimately makes them take a long time to complete their final project until it exceeds the time limit of 4 years or 8 semesters.

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6. Conclusion

Based on the results and discussions that have been carried out, it is concluded that the best model for forecasting the percentage of on-time graduates of undergraduate students at Nusa Cendana University is the ARIMA (2, 2, 1) model with an AIC value of -125, 64 and The results of forecasting the percentage of on-time for the February, June, and September graduation periods in the next 5 years, namely 2024 to 2028 are 5.31%, 9.84%, 12.79%, 9.05%, 13.08%, 15.91%, 12.74%, 16.35%, 19.06%, 16.39%, 19.63%, 22.22%, 20%, 22.93%, and 25.41% respectively; and Factors that influence the study period of students are the curriculum applied in the study program, facilities and infrastructure, lecturers, and students themselves.

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