Students' Performance Prediction in Higher Education During COVID-19 Pandemic Based on Recurrent Forecasting and Singular Spectrum Analysis

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Abstract

The COVID-19 pandemic is a virus that is changing habits in human life worldwide. The COVID-19 outbreaks in Indonesia have forced educational activities such as teaching and learning to be conducted online. Teaching and learning activities using the online method are familiar, but the effectiveness of this method still needs to be investigated to be applied in all educational systems. This study used the predictive modeling of Recurrent Forecasting (RF) derived from Singular Spectrum Analysis (SSA) to know the online learning method's practicality on the student's academic performance. The fundamental notion of the predictive fusion model is to improve the effectiveness of several forms of forecast models in SSA by employing a fusion method of two parameters, a window length (L), and a number of leading components (r). This study used undergraduate students' grade point averages (GPA) from a public university in Indonesia through online classes during the COVID-19 epidemic. The experiments unveiled that a parameter of L = 14 ($\mathbf{T/20}$) yielded the finest prediction using the RF-SSA model with a root mean square error (RMSE) value of 0.20. Such a finding signified the ability of the RF-SSA to project the students' academic performance according to the GPA for the forthcoming semester. Nonetheless, developing the RF-SSA algorithm for greater effectiveness is essential to acquiring more datasets, such as by gathering a bigger group of respondents from several Indonesian universities.

Keywords: Covid-19; RF-SSA; forecasting; GPA; SSA.

1. Introduction

COVID-19 was declared a pandemic on March 11, 2020, by the World Health Organization (WHO) (World Health Organization, 2020) [1]. The pandemic is a wide scale of spread of disease worldwide. This issue signaled various countries' governments to increase alertness and vigilance against this coronavirus. After finding many confirmed cases in Indonesia, the Indonesian

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government finally adopted a number of policies to break the COVID-19 transmission chain including in the educational systems.

According to circular No. 4 of 2020, upon the education policy execution during the emergency deployment of COVID-19, the learning process must be implemented from home through online or long-distance learning [2][3]. The Universitas Negeri Yogyakarta is among the universities implementing this policy in Indonesia. The teaching and learning activities with online systems are usually done via online platforms such as BeSmart, Google Classroom, or email [4][5].

The advantages of online learning are that in addition to students being able to take normal face-to-face lectures, they can study anywhere and anytime. However, online learning has disadvantages in that students are required to have an internet quota with a stable connection, students are easier to lose concentration in learning, and students tend to participate less actively. In terms of instructors, not all of them are familiar with online learning management systems, and stable connections are also an issue for both students and instructors. It is also difficult to conduct an online learning process that keeps the students on track.

Moreover, the learning motivation and environment may affect students' academic performances. Students' motivation may decrease if they do not have a supportive learning environment. The challenges faced are often the need for more motivation to learn from the students themselves, as it is common for students to attend only for attendance and then perform other activities unrelated to lecture activities. The success of online learning systems requires a good environment, motivation, and collaboration between instructors and students.

Numerous studies have used the Machine Learning (ML) approach to predict student academic performance at different points [6]. Such ML models, however, merely concentrate on projecting the students' performance instead of administering, attaining, and analyzing the students' performance trends and self-motivation levels. They also identify the contributory factors affecting the student's academic performance to ensure their keenness for online educational activities.

Singular Spectrum Analysis (SSA) is a superb and effective alternative to address trend components, substantially minimizing noise and unraveling the temporal data structure without preliminary manipulation [7]. The SSA is formed on the singular decomposition value on a special matrix constructed over a certain period [8][9]. Generally, the SSA represents univariate time series transformed into eigenvectors and eigenvalues of any trajectory matrix. The SSA refers to a multidimensional analog of principal component analysis (PCA), which is transformed into time series. One function of the SSA is separating the time series data into noise, trend, and seasonal categories by decomposing the time series Eigen and later reconstructing them into group selection [10].

The SSA, essentially, transforms a single-dimension time series into multidimensional trajectories via PCA (Singular Value Decomposition (SVD), as well as reconstruction (approximation) of the Principal Components chosen [11]. However, the separation of components in this fusion approach depends on the parameters used to select the window length of L, form the trajectory matrix, and identify the total of leading components of r based on the eigenvector plot. This separation is crucial in ensuring that the trend, seasonal, and noise components can be separated effortlessly in this model.

This paper aims to project the undergraduate students' academic performance at a public university in Yogyakarta, Indonesia, with the Recurrent Forecasting algorithm- Singular Spectrum Analysis (RF-SSA). The forecasting models were employed to project these students' academic performance in the course of online learning according to the Grade Point Assessments (GPA). It is expected that the findings of this study will help the university to improve its online academic activities and to identify and further support academically-low student achievers in advance.

2. Methodology

A. Data

In this study, the data applied are the primary data obtained through an online questionnaire. The data contain the GPA of students from each department in the Faculty of Mathematics and Natural

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Sciences, Universitas Negeri Yogyakarta (UNY), in the odd and even semesters of the 2019/2020 academic year. The total respondents were 283 students in the third to seventh semesters. Figure 1 shows the distribution of the respondents, which was 7.8 percent from the Department of Science Education, 12 percent from the Department of Biology Education, 13.1 percent from the Department of Chemistry Education, 14.5 percent from the Department of Physics Education, and 52.7 percent from the Department of Mathematics Education.

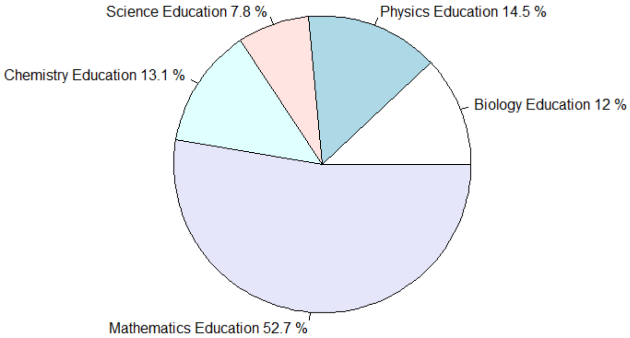

Figure 1: Distribution of the respondents in the Faculty of Mathematics and Natural Sciences UNY based on the departments

Figure 2 illustrates the academic performances of students based on GPA during online classes using boxplot charts. The median of the dataset is represented by the horizontal bar in the boxplot chart, while the top and bottom lines of boxes denote the 75th and 25th data percentiles. Figure 2 shows that students' achievement during Covid-19 was not influenced by where they lived during the implementation of online learning. Almost all students achieve excellent outcomes where the medians of the GPA students are between 3.50 and 3.60.

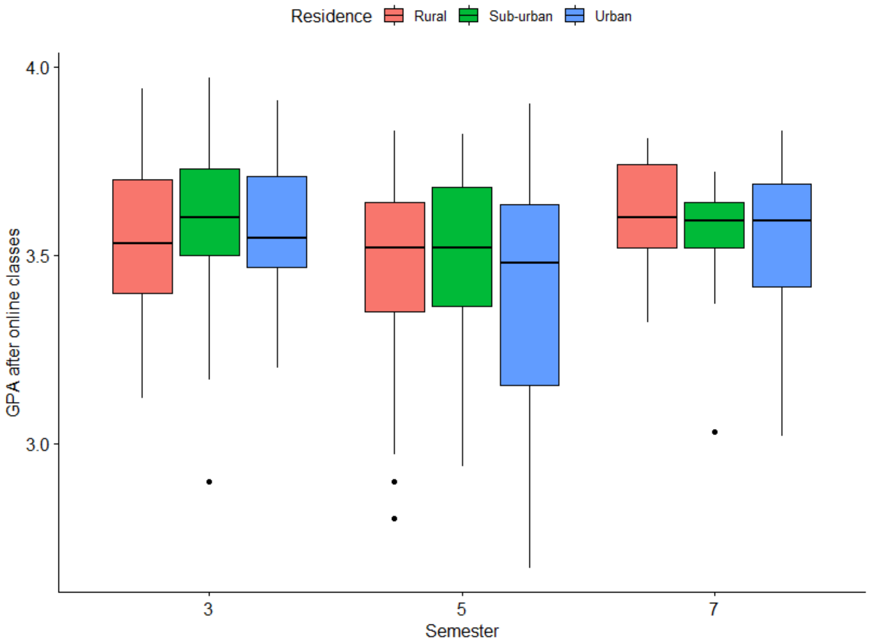

Figure 2: Boxplot of students' GPAs during online classes

Figure 3 shows the original GPA data of the students' performance. The increase in daily COVID-19 cases has limited students' academic activities to merely using online platforms at home. The solid black line demonstrates the students' GPAs before the online classes were implemented, while the red dashed line indicates the students' GPAs after the online classes were implemented. Evidently, the lines show that the GPA acquired by the students had increased after online learning compared

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to that of offline lectures. The average GPA after online classes is 3.51 (SD = 0.23), which is slightly higher than the average GPA before online classes of 3.43 (SD = 0.26).

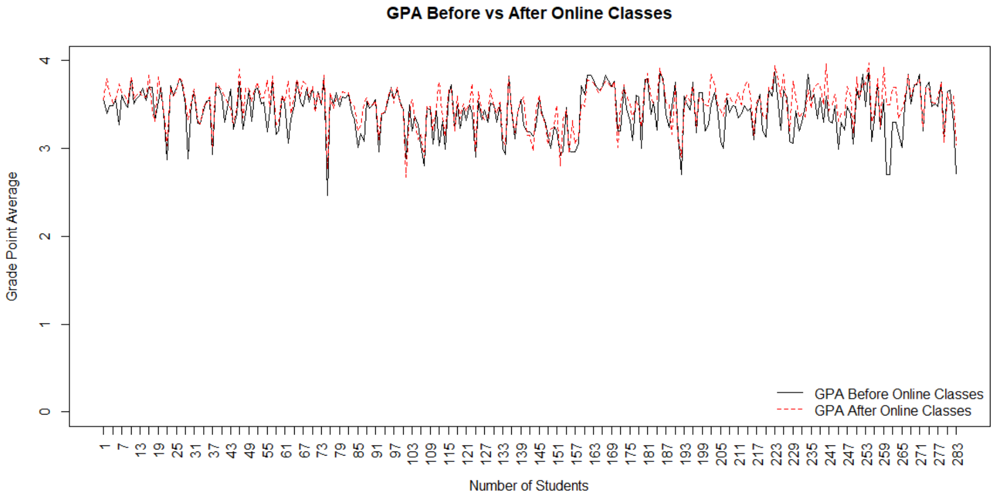

Figure 3: Comparison of GPA before and after online classes

B. Singular Spectrum Analysis

1. Decomposition

The first stage of the SSA is decomposition, which involves trend, seasonality, cyclicality, and error. The decomposition consists of two stages embedding and singular value decomposition (SVD). At the embedding stage, the window length (L) parameter is determined with a condition of $2 < L < \frac{N}{2}$, where N is the total observations. The embedding represents a stage for mapping or transferring the one-dimensional into multidimensional time series data, that $X_1, X_2, X_3, \dots, X_K$ with the lag vector of X_i are formed into the path matrix of L × K. The matrix **X** has the same anti−diagonal elements.

$$\mathbf{X} = \begin{pmatrix} f_0 & f_1 & \cdots & f_{K-1} \\ f_1 & f_2 & \cdots & f_K \\ \vdots & \cdots & \ddots & \vdots \\ f_{1-L} & f_L & \cdots & f_{N-1} \end{pmatrix} \tag{1}$$

In the next stage, the SDV is constructed using a path matrix. Suppose that the eigenvalues are $\lambda_1, \lambda_2, \dots, \lambda_L$ which are obtained from the multiplication of matrix $\mathbf{X}$ and its transpose, $\mathbf{S} = \mathbf{X}\mathbf{X}^{\mathrm{T}}$. The eigenvalues were in descending order $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_L \geq 0$ and $\mathbf{U}_1, \mathbf{U}_2, \dots, \mathbf{U}_L$ are the eigenvectors. It is defined that $\boldsymbol{V}_i = \frac{\mathbf{X}^T \mathbf{U}_i}{\sqrt{\lambda_i}}$ where $i = 1, \dots, d$, and $d = max\{i, \lambda_i > 0\}$), so the SDV of the path matrix can be obtained as follows,

$$\mathbf{X} = \mathbf{X}_1 + \mathbf{X}_2 + \mathbf{X}_3 + \cdots + \mathbf{X}_d \tag{2}$$

$$\mathbf{X} = \mathbf{U}_1\sqrt{\lambda_1 \mathbf{V}_1^T} + \mathbf{U}_2\sqrt{\lambda_2 \mathbf{V}_2^T} + \mathbf{U}_3\sqrt{\lambda_3 \mathbf{V}_3^T} + \cdots + \mathbf{U}_d\sqrt{\lambda_d \mathbf{V}_d^T} \tag{3}$$

$$\mathbf{X} = \sum_{i=1}^{d} \mathbf{U}_i\sqrt{\lambda_i \mathbf{V}_i^T} \tag{4}$$

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In this stage, the matrix $\mathbf{X}$ can be formed from the eigenvector component ($\mathbf{U}_i$), the singular value ($\sqrt{\lambda_i}$), and the principal component ($\mathbf{V}_i^T$). These three components are often referred to as an eigentriple, which describes the characteristics of each matrix.

2. Reconstruction

The second stage of SSA is a reconstruction of the original series and uses that to forecast new data points [12]. The reconstruction consists of two stages grouping and diagonal averaging.

The first stage is grouping. In this stage, the path matrix of order L×K was divided into several groups corresponding to trends, seasonal, and noise in the time series data. The splitting of matrix X is carried out into m disjoined subsets of $\mathrm{I} = \{I_1, I_2, I_3, \dots, I_m\}$. If $\mathrm{X} = \mathrm{X}_1 + \mathrm{X}_2 + \mathrm{X}_3 + \cdots + \mathrm{X}_d$ correspond with the groups of $\mathrm{I} = \{I_1, I_2, I_3, \dots, I_m\}$then it can be expanded into $\mathrm{X} = \mathrm{X}_{I1} + \mathrm{X}_{I2} + \mathrm{X}_{I3} + \cdots + \mathrm{X}_{Im}$.

The final stage of SSA is diagonal averaging. This stage rearranges $\mathrm{X}_{i,j}$ matrix obtained at the grouping stage into a series with a length of N. Let Y be a matrix of order $L \times K$, elements $y_{i,j}$ where $1 < i < L, 1 < j < K$. Suppose that $\min(L, K)$and $K^* = \max(L, K)$ so $N = L + K - 1$. The following equation can be used to find the average diagonal of the matrix.

$$g_k = \begin{cases} \frac{1}{k}\sum_{m=1}^{k} f_{m,k-m+1}^* & , for\ 1 \le k < L^* \\ \frac{1}{L^*-1}\sum_{m=1}^{L^*-1} f_{m,k-m+1}^* & for\ L^* \le k \le K^* + 1 \\ \frac{1}{N-k+1}\sum_{m=k-K^*+1}^{N-k+1} f_{m,k-m+1}^* & , for\ K^* + 1 \le k < N \end{cases} \quad (5)$$

The matrix $\mathbf{X}_{i,j}$ is then transformed into a function of g_k where the rows are as follows.

$$\tilde{Y}^{(k)} = (\tilde{y}_1{}^{(k)}, \tilde{y}_2{}^{(k)}, \tilde{y}_3{}^{(k)}, \dots, \tilde{y}_N{}^{(k)}) \quad (6)$$

The original series data is the sum of the m series as follows

$$y_n = \sum_{k=1}^{m} \tilde{y}_n{}^{(k)} \quad , n = 1,2,3, \dots, N \quad (7)$$

3. Forecasting Stage based on RF-SSA

In the SSA forecasting, the time series must fulfill the linear recurrent formula (LRF). Time series $Y_T = (y_1, \dots, y_T)$ satisfy the LRF of order d if:

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + \cdots + a_d y_{t-d},$$
$$t = d + 1, \dots, T \quad (8)$$

The RF-SSA was applied in this study for forecasting due to its effectiveness in predicting data. The algorithms are described below in detail [13]. Let us assume that U_j^∇ is the vector of the initial $L - 1$ components of eigenvector U_j, while π_j denotes the final component of $U_j (j = 1, \dots, r)$. By denoting $v^2 = \sum_{j-1}^{r} \pi_j^2$, the coefficient vector of $\mathfrak{R}$ is defined as follows:

$$\mathfrak{R} = \frac{1}{1 - v^2} \sum_{j=1}^{r} \pi_j \ U_j^\nabla \quad (9)$$

Considering the prior notation, the forecast of RF-SSA $(\hat{y}_{T+1}, \dots, \hat{y}_{T+M})$ can be attained by

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$$\hat{y}_i = \begin{cases} \tilde{y}_i, & i = 1, \dots, T \\ \mathfrak{R}^T Z_i, & i = T+1, \dots, T+M \end{cases} \tag{10}$$

where $Z_i = [\hat{y}_{i-L+1}, \dots, \hat{y}_{i-1}]^T$ and $\tilde{y}_1, \dots, \tilde{y}_T$ signify the reconstructed time series values that could be retrieved from the formerly depicted ones at the reconstruction stage.

3. Result and Discussion

A. Decomposition and Reconstruction

Figure 4 shows the plot of fourteen leading eigenvectors. The eigenvector plot helps select the suitable group for the time series data components, particularly in separating trend, seasonal, and noise components [14]. This information is applicable for more detailed analysis in the RF-SSA grouping step. To identify the trend components through the eigenvector plot, the trend component and the seasonality component using sine waves are denoted by the slow cycles that are demonstrated in the graph with higher frequencies. The noise component is denoted by the saw-tooth of the graph with lower frequencies. The coordinates of the leading eigenvector are almost continuous, which corresponds to Bartlett filter's pure smoothing [15]. The reconstruction results by the 14 Eigentriples are displayed in Figure 4, respectively. Both figures demonstrate how the first and second Eigentriple are trend-compatible, while other Eigentriples comprise the noise components and therefore are unrelated to the trend. In addition, it had verified that UNY's GPA data are unbiased by the seasonality as the eigenvectors plot does not illustrate the plot.

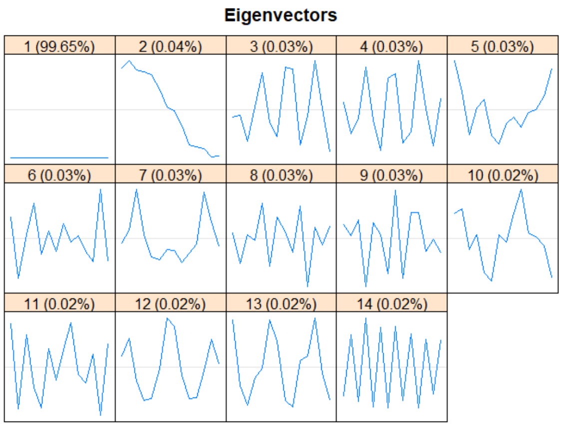

Figure 4: Eigenvectors plot using SSA

After identifying the components, the next step is reconstructing the fourteen series, as shown in Figure 5. In Figure 5, the first and second plots contain trends, while other plots contain noise components irrelevant to trends.

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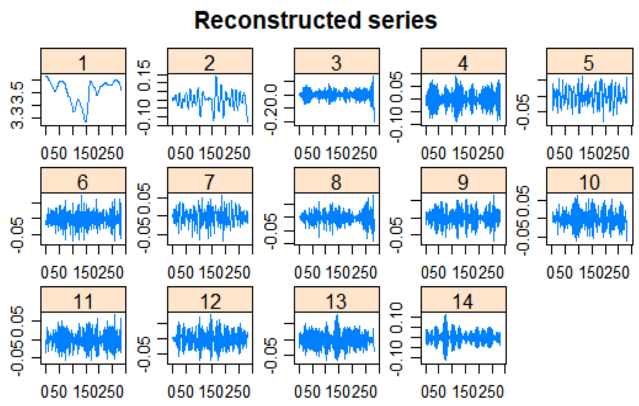
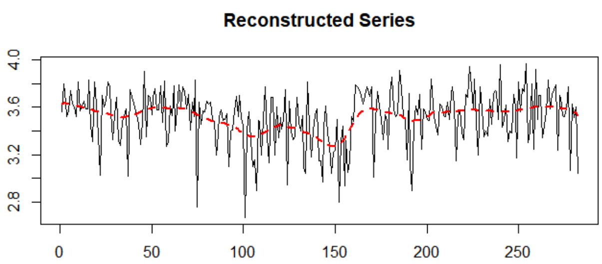
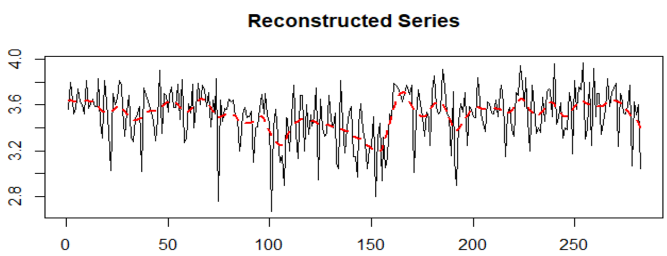


Figure 5: First stage: Elementary reconstructed series (L=14)

Figure 6 illustrates the reconstructed time series plot components from the extracted trend through the SSA for the students' GPAs. This reconstructed series is the latest noise-free dataset that is the derivative of the original data. It is crucial for SSA to ensure that the forecast results are precise and accurate [16]. The trend component in the time series data was employed to monitor the trend and pattern that occur since it goes through random tabulation according to the number of students' GPAs [17,18]. The straight and dashed plot lines correspondingly refer to the original students' GPA data and the reconstructed series based on the extracted trend components from SSA. In Figure 6(a), the trend was accurately produced by a leading eigentriple that concurred with the original reconstructed component shown in Figure 5. In Figure 6(b), both leading eigentriples accurately generate the trend illustration, concurring with the first and second reconstructed components exhibited in Figure 5. The plot of reconstructed time series components which was constructed by both leading eigentriple, complied with the initial students' GPA data in UNY even though the noise component was eliminated for $L = 14$.



(a)



(b)

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Figure 6: The students' GPAs performances of the reconstructed components from the extracted trends using SSA at L=14

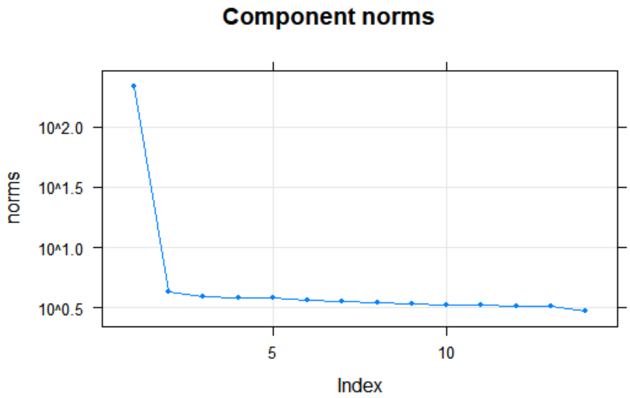

Figure 7: Logarithms of 14 eigenvalues

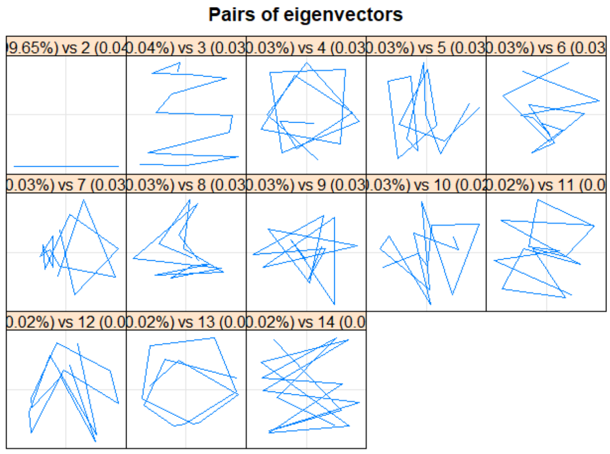

Figure 8: Plots of eigenvectors (EV) pairs for the students' GPA

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The eigenvalues graph and eigenvectors scatterplots were employed for the seasonal series components to be appropriately identified. In establishing the seasonal series components with a plot of eigenvalues, some steps were created using nearly equivalent eigenvalues. Figure 7 represents the plot of the logarithms of the 14 singular values for UNY students' GPA data. Evidently, no step produced with a corresponding sine wave was generated by approximately equal eigenvalues. The eigenvectors scatterplot exhibits the common polygons produced by a pair of eigenvectors to determine the seasonality components that had constructed the series components. From Figure 8, the regular polygons were not constructed by any pair of eigenvectors. Such a finding confirms that the students' GPAs are not influenced by seasonality, as no sinus waves are found in Figure 8.

In order to check the separability between the grouping, a W-correlation is used in the SSA approach. Large correlation values among the reconstructed components revealed a potential group formation by the components and the same component correspondence. In trend extrication, the trend-noise correlations ought to be close to zero. The correlation with L=14 is small at 0.003, nearly 0.

Table 1: RF-SSA Prediction Performance

SSA Forecasting Models	RMSE	MAE	MFE	Decision

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Recurrent	0.20	0.15	0.00	MFE = 0, model on target
Vector	0.29	0.21	-0.22	MFE<0, the model tends to forecast over

As previously stated, the SSA model had initially decomposed and reconstructed the GPA data. Consequently, the following step is projecting the future GPA data in UNY. At this point, the SSA forecasting algorithm named the RF-SSA was employed correspondingly. Table 1 displays the RF-SSA and VF-SSA forecasting model performances. The experimental results indicated that the RF-SSA model outperformed the VF-SSA model, as it had the lowest RMSE and the highest r values. The experimental findings patently indicated that the RF-SSA model functioned well with the small root mean square error (RMSE) and meant absolute error (MAE) of 0.20 and 0.15, respectively. The model predicts the outcomes perfectly on the data set as the result of the MFE value is zero (the ideal value). Besides promising statistics and findings, the RF-SSA is undeniably capable of fully catering to the variations in the performance of the students' academics. It can be extensively proven by performing an analysis based on Figure 9. The plot of the RF-SSA seemed to adhere to the original students' GPA data pattern even by excluding the noise components, specifically for $L = T/20$.

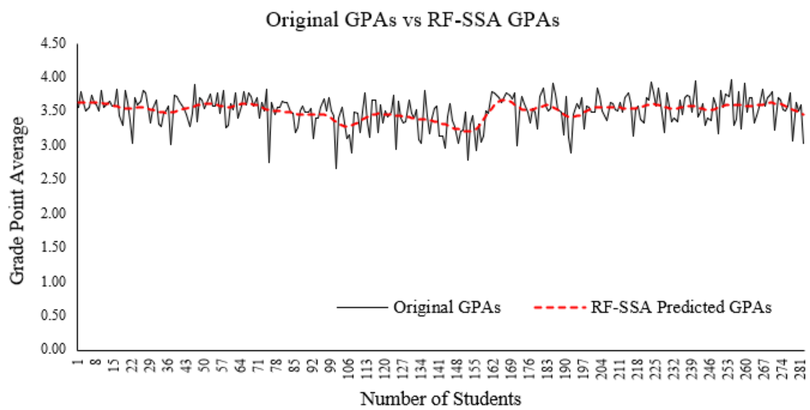

Figure 9: Predicted RF-SSA versus original data for GPA results for UNY

4. Conclusion

This paper studies the RF-SSA model's applicability in projecting students' academic performance at the Faculty of Mathematics and Natural Sciences UNY, Indonesia. These study findings provide an understanding and guidance for lecturers and universities to find improved approaches to improve online learning and teaching, develop an appropriate online assessment platform, develop an efficient teaching method, and so on. It was found that the pattern follows the RF-SSA model that can be applied to forecast the academic performance of students' patterns at the Faculty of Mathematics and Natural Sciences UNY, Indonesia. Using this model, it was suggested that the appropriate window length (L) and total eigentriples (r) parameters should be used for the same data set characteristics. The precise prediction result in this study shows that the parameters of L= 14 ($T/20$) and $r = 14$ were suitable for the use of the GPA data in short time series. Overall, the results showed that the RF-SSA model could accurately project the students' GPA as the model was at the target with an ideal value of zero for the MFE value. For future research, it is recommended that the two models be combined with different models for a hybrid prediction model, namely the Artificial Neural Networks, k-Nearest Neighbor, Decision Tree, Self-Organizing Maps, etc. By studying different types of prediction models, the precision, superiority, and drawbacks of these models, respectively, could be identified, and the best model to predict the students' academic performance from different angles could be determined. Hence, a fitting conclusion could be drawn.

A. Conflict of Interest Statement

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The authors agree that this research was conducted without any self-benefits or commercial or financial conflicts and declare the absence of conflicting interests with the funders.

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