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Forecasting a museum visit in pandemic situation using double exponential smoothing model

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Abstract — The amount of visitors is a key performance indicator of a museum. This paper aims to evaluate the performance of a machine learning model for forecasting the number of visitors to a museum after the COVID-19 pandemic. The easing of policies that began to be implemented by the Palembang city government after the end of the pandemic at the end of 2022 became momentum in forecasting the number of visits to the Sultan Mahmud Badaruddin II (SMBII) Museum. During the pandemic, the museum experienced a very sharp decrease due to closures and restrictions on activities at the museum, and this had an impact on achieving the museum's targets in the fields of tourism and education. Museum managers need to establish a strategy to achieve the targets set during the post-pandemic period. This study predicts the number of visits to the SMBII Museum in post-pandemic years by applying the double exponential smoothing model (DESM). The dataset used is SMBII Museum visit data which is divided into three categories of visitors, namely student, local, and international. The evaluation results show that the DESM model has the best performance with MSE = 3.8 and α = 0.9. It has a better performance compared to the previous study using an additive decomposition model for forecasting museum visits. The phenomena that occurred in the student visitor category affected DESM's performance in predicting visits where MSE in the post-pandemic period had a 200 % higher value than before the pandemic which was influenced by the implementation of post-pandemic policies in museums. With the forecasting results in this study, it is hoped that it can become information in developing strategies and improving the performance of post-pandemic museums.

Keywords – exponential smoothing, forecasting, museum visit, pandemic, SMBII museum

I. Introduction

Visits to museums during the COVID-19 pandemic decreased sharply due to the policy of closing access to physical museums and limiting activities for tourism and educational activities. In Indonesia, there are 435 museums [1] which are spread across 37 provinces based on statistical data showing a low average visit and resulting in low museum performance in carrying out its role. For this reason, some museums in Indonesia have implemented a strategy by carrying out the process of transforming physical museums into digital museums by utilizing information and communication technology to increase their capabilities [2] and student learning experiences [3] as well as museum services and competitiveness [4], [5]. Digital museums have provided easy access for museum visitors to explore museums for recreational and educational purposes without having to directly access the physical museum, especially during a pandemic [6].

The ease and sophistication of technology provided by digital museums equipped with AR/VR features, games, guides, and learning have provided added value for museum visitors to learn about museum collections and history compared to traditional museum learning [7]. The sophistication of artificial intelligence embedded in smart museums makes digital museums more interactive and makes it easier for visitors to meet the needs of the museum as well as an attraction for visitors to take advantage of the latest digital service facilities [8].

After the pandemic ended, the museum opened wide access for visitors to the physical museum while still implementing health protocols. Digital museum service facilities are also still being utilized to support the performance of physical museums. With the efforts that have been made by museums, for example, the Sultan Mahmud Badaruddin II (SMBII) Palembang Museum, it is necessary to predict the number of post-pandemic museum visits so that strategies for activities and services related to the museum's duties for recreation and education can be formulated. Predictions of visits to the SMBII Museum had previously been carried out during the COVID-19 pandemic by applying a machine learning model to the SMBII Museum virtual tour application [9]. Machine learning has proven its effectiveness in predicting various cases in various fields during a pandemic. For museum applications, some forecasting models have been tested, including the exponential smoothing model, neural network, and support vector machine [10]–[13].

The additive decomposition model [14] has been proven to be effective in forecasting a museum visitor and will be evaluated in this study. Learning models with smart predictive abilities have been tested for their effectiveness in increasing interest in using smart virtual museum applications and having an impact on the cognitive abilities of museum visitors, especially students [15]. It is necessary to carry out further research regarding the use of forecasting models in predicting museum visits to be used in post-pandemic museum strategic planning.

Forecasting is a managerial strategic step in planning for the future to support decision-making. In determining the method to be used in forecasting, it must be based on past historical data from a transaction on the intended subject [16]. Judging from the period, forecasting can be divided into 3 types of forecasting; namely forecasting for the short term with a forecast $<$ 3 months, the second is forecasting with a span of 3 up to 18 months, and the third is forecasting for a long term with a span of $>$ 18 months. The measurement of forecasting accuracy is divided into 3 (three), namely the level of accuracy, forecasting costs, implementation, and resulting strategic impact [17].

This research will evaluate the performance of DESM in predicting post-pandemic SMBII Museum visits. The dataset consists of museum visitor data for the period January-December 2018−2022. The dataset is divided into two parts, namely for the period before and during the pandemic for descriptive analysis. Meanwhile, for forecasting analysis, the dataset is divided into two, namely before the pandemic, and during the pandemic. The results obtained from the data processing will be discussed and concluded at the end of this paper. The output of this research will provide information that can be used in the formulation of strategic plans for museums after the COVID-19 pandemic.

II. Research Method

This study applies the steps as illustrated in Fig. 1. The research methodology consists of stages that are divided into three parts, data preparation, data processing, and performance analysis of machine learning models. Each stage applies the necessary methods in processing input data which will produce outputs to be evaluated in this study.

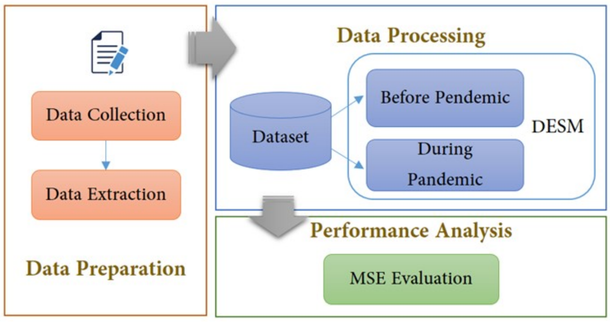

Fig. 1. System architectures.

A. Data Preparation

In the early stages of the research, data preparation was carried out to produce a good-quality dataset that represents the characteristics of the research object, namely the SMBII Museum. Good data will have an impact on the effectiveness of the model [18], [19]. The model is trained based on the dataset provided as the input model so that the quality of the prediction results will be greatly affected by the quality of the dataset. The larger and more representative the dataset, the better the prediction results.

1) Data Collection

Data collection was carried out from secondary data sources, namely the Palembang City Cultural Service and the management of the SMBII Museum. The dataset contains data on SMBII Museum visits in the January-December period for 2018-2022. The data collected contains the number of museum visitors according to classification, namely Student (S), Local (L), and International (I). Table 1 represents the dataset formed as a result of data collection.

Table 1. Water Quality Standards by WHO and EPA
(Source: The SMBI Museum, 2023)

Month	Museum Visitor Number		
	S	L	I
January	766	814	12
February	1201	788	53
March	922	757	51
April	1320	923	76
May	650	379	20
June	491	761	9
July	566	1068	89
September	866	776	31
October	1101	385	29
November	1611	561	41
December	1785	626	15

2) Data Extraction

The formed dataset is then extracted to obtain a dataset that can be processed with a machine learning model. This stage involves labeling and tabulation so that a dataset is produced which is stored in .csv file format. The data obtained is clean because it comes from secondary data from the SMBII Museum which has been validated by the Palembang City Culture Bureau. From the dataset, outliers were extracted from museum visit data to analyze the effectiveness or accuracy of the forecast results.

B. Data Processing

The dataset is then processed using the double exponential smoothing model (DESM). The output of this stage is the result of forecasting SMBII Museum visits based on the input dataset. DESM is a model developed to overcome differences that arise between actual data and predicted values when there is a trend in the data plot [20] trend shows the tendency to increase or decrease in data. The trend is a smoothed estimate of the average growth at the end of each period [21].

DESM is formulated with the following stages:

(a) Calculate a single exponential smoothing value

$$s_t^{'} = \alpha x_t + (1-\alpha)\, s_{t-1}^{'} \tag{1}$$

(b) Calculate double exponential smoothing value

$$s_t^{''} = \alpha s_t^{'} + (1-\alpha)\, s_{t-1}^{''} \tag{2}$$

(c) Calculate forecasting value

$$F_{t+m} = F_t + b_t m \tag{3}$$

where $s_t^{'}$ is single exponential smoothing value of *t*-period, $s_{t-1}^{'}$ is single exponential smoothing of $t-1$ period, $s_t^{''}$ is double exponential smoothing value of *t*-period, $s_{t-1}^{''}$ is double exponential smoothing value of $t-1$ period, α is parameter of exponential smoothing ($0 < \alpha < 1$), x_t is actual value *t*-period, *m* is forecasting period, and F_{t+m} is forecasting value for *m* periods.

C. Performance Analysis

Forecasting aims to produce an estimated value with a minimum error value. DESM performance analysis was carried out to know the effectiveness of the model for forecasting post-pandemic SMBII Museum visits. The model evaluation indicator used to measure the storage of the estimated value against the actual value is the mean square error (MSE) [12], [21], [22]. MSE represents an overestimation or underestimation based on the percentage error resulting from the forecast against the actual demand in a period.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left[x_n - \hat{x}_n\right] \tag{4}$$

where x_n is actual data and $\hat{x}_n$ is forecast data of *n* sample.

III. Result

This paper discusses forecasting the number of post-pandemic visitors to the SMBII Museum based on time series data for the 2018−2022 period with DESM. Based on dataset processing with DESM, promising results were obtained to be utilized in the formulation of a post-pandemic museum strategic plan.

A. Dataset Descriptive Analysis

The dataset contains data on SMBII Museum visits for the 2018−2022 period. Descriptive statistical analysis was carried out on the dataset which was divided into two periods, namely the before-pandemic period (2018−2019) and during the pandemic period (2020−2022). The purpose of the descriptive analysis is to find out the descriptive characteristics of museum visit data for these two different periods so that you know the difference between visits before and during the pandemic. Table 2 and Table 3 describe the results of the descriptive statistics for the SMBII Museum visitor dataset for 2018−2022.

Table 2. Descriptive Statistics on SMBII Museum Visits before the Pandemic (2018−2019)

Month	Mean			Std. Deviation		
	S	L	I	S	L	I
January	679	716	14	123	139	2
February	867	569	41	472	310	18
March	755	620	40	236	194	16
April	970	768	44	496	220	46
May	387	239	12	372	198	11
June	246	381	5	347	538	6
July	333	701	59	330	519	42
September	682	887	33	260	157	3
October	681	516	37	595	185	11
November	1576	658	51	49	136	14
December	1332	497	21	641	183	8

hint: student (*S*), local (*L*), and international (*I*)

Table 3. Descriptive Statistics on SMBII Museum Visits during the Pandemic (2020−2022)

Month	Mean			Std. Deviation		
	S	L	I	S	L	I
January	501	388	7	542	427	0
February	471	212	16	654	266	0
March	554	223	7	240	103	0
April	335	106	1	442	96	3
May	176	296	0	305	513	0
June	374	225	0	324	195	0
July	218	194	0	197	178	0
September	196	275	0	339	476	0
October	487	168	0	671	124	0
November	458	185	2	538	76	4
December	777	296	2	1161	248	0

To illustrate the differences in SMBII Museum visits before and during the pandemic, Fig. 2 to Fig. 4 visualize the differences in the dataset for each group of SMBII Museum visitors, namely student, local, and international. Student (S) visitors are museum visitors with a student educational background. Local (L) visitors are Indonesian citizens with educational backgrounds other than students, and International (I) visitors are foreigners.

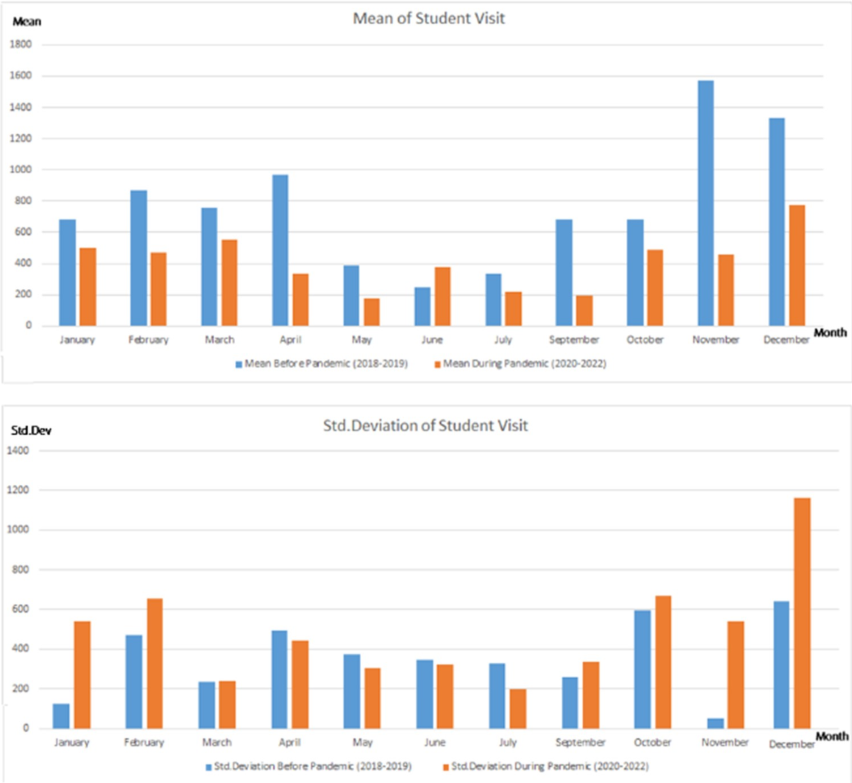

Fig. 2. Mean and std. deviation of student visit visualization.

Fig. 2 to Fig. 4 show a decline in the average visit to museums by students, local and international with a high standard deviation value during the pandemic period. This fact shows that there were differences in the number of museum visits before and during the pandemic due to the implementation of museum policies in dealing with the COVID-19 pandemic situation.

B. *Outlier Dataset Analysis*

Outliers in the dataset are extracted to eliminate data that can lead to high bias in forecasting results [23]. Fig. 5 to Fig. 7 illustrate the outlier boxplot in the dataset for each category of visitors to the SMBII Museum. Based on the outlier analysis, it is known that there are outlier data in the student visit dataset to the museum in November 2022. In the foreign tourist visit dataset, there are two outliers in April and July 2019. Meanwhile, there are no outliers in the local visit dataset.

C. *Forecasting Museum Visit*

Forecasting SMBII Museum visits with DESM is carried out with a dataset containing museum visit data in 2018−2022 which is divided into periods before the pandemic and during the pandemic. This study will predict the number of post-pandemic SMBII Museum visits which began in August 2022 when the Indonesian government began to relax health protocols in public spaces.

Fig. 8 illustrates the results of forecasting with DESM. To evaluate DESM performance for forecasting museum visits, the MSE and RMAE value indicators are used because there is a museum visit variable value of *0* which makes it impossible to use the MAPE indicator for DESM performance for forecasting museum visits which causes an infinite value. Table 4 describes the MSE value resulting from the predicted visit of the SMBII Museum for the 2018−2022 period which consists of 60 data. Changes to the alpha (α) and gamma (γ) = $(1 - \alpha)$ were conducted to find the best MSE value that represents the best results with DESM.

DESM was tested with parameter values $0 < \alpha < 1$ dan gamma $0 < \gamma < 1$ obtained the best MSE value with value $\alpha = 0.9$ dan $\gamma = 0.1$ where the MSE value for each category of museum visitors is $MSE_{Student}$ = 1,681.54; MSE_{Local} = 917.85; and $MSE_{International}$ = 3.80. To find out how DESM predicts student visits before, during, and after the pandemic, the MSE values are calculated for the student visit category as illustrated in Fig. 11. Previous research has applied the decomposition method to predict visits to the Aceh State Museum [12].

Therefore, this research compared the predictive results of the additive decomposition method with the DESM method using data on student visits for 5 years. The prediction results are shown in Table 5 which shows that the DESM method has results better MSE scores than the decomposition for predicting student visits to the SMBII Museum in the 2018−2022 period.

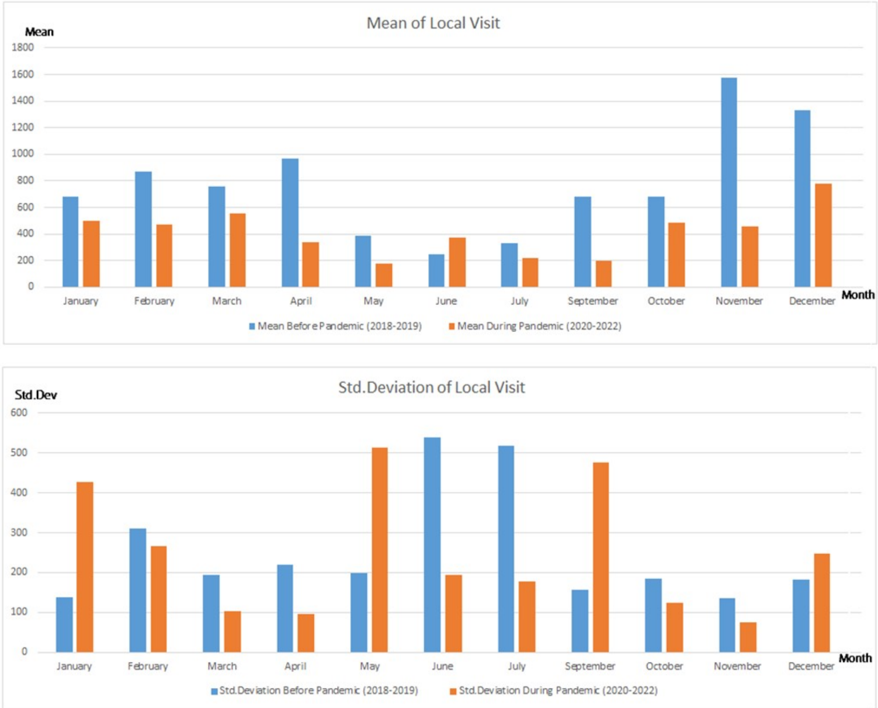

Fig. 3. Mean and std. deviation of local visit visualization.

Table 4. MSE of SMBII Museum Visits Forecasting using DESM

Visitor Category	α	γ	**MSE**
Student	0.1	0.1	265345.64
	0.2	0.1	144333.30
	0.3	0.1	91361.46
	0.4	0.1	60801.25
	0.5	0.1	39991.40
	0.6	0.1	25010.05
	0.7	0.1	14104.58
	0.8	0.1	6427.21
	0.9	0.1	1681.54
Local	0.1	0.1	563725.16
	0.2	0.1	159946.38
	0.3	0.1	73304.61
	0.4	0.1	41179.51
	0.5	0.1	24901.43
	0.6	0.1	14898.66
	0.7	0.1	8157.85
	0.8	0.1	3617.67
	0.9	0.1	917.85
International	0.1	0.1	1433.68
	0.2	0.1	368.99
	0.3	0.1	193.00
	0.4	0.1	124.26
	0.5	0.1	83.26
	0.6	0.1	53.64
	0.7	0.1	31.04
	0.8	0.1	14.40
	0.9	0.1	3.80

Table 5. MSE Score Comparison of Student Visit 2018−2022

Prediction Model	**MSE**
Additive Decomposition	545201.82
DESM	1681.54

IV. Discussion

Forecasting SMBII Museum visits with DESM shows high MSE results for the student visit category. The outlier data which has a value of 2114 is far above the average value of student visits in November, which is 580.7 or 360 % with a standard deviation of 510 which seems to affect the high MSE value of forecasting student visits to the SMBII Museum compared to the MSE prediction of visits by local and foreign tourists.

The outlier has an impact on the effectiveness of DESM in predicting museum visits but this value cannot be ignored because it is a time series data for the post-pandemic period. The outlier phenomenon of student visits to the museum was caused during the post-pandemic period when the policy of easing activities in public spaces began to take effect and many physical activities at the SMBII Museum attracted visitors, especially students, to SMBII Museum, including exhibitions, competitions and the National Heritage Network Association National Working Meeting *(Rapat Kerja Nasional Jaringan Kota Pusaka)* which was held at SMBII Museum in November 2022.

Visitors in the student category are the dominant visitors to the SMBII Museum, namely 58 % in the 2018−2022 period. Forecasting of student visits to museums during a pandemic period is divided into two, namely before the pandemic (2018−2019), and during the pandemic (2020−2022). It is known that during the pre−pandemic and the pandemic DESM produced forecast values with MSE that differed by more than 100 % while after the pandemic the MSE value increased by more than 200 %.

This fact is due to the sharp increase in student visits to museums after the pandemic due to the easing of post-pandemic health protocol policies students starting to have physical activities no longer studying from home and the many museum activities that attracted students to come to the museum after the pandemic had

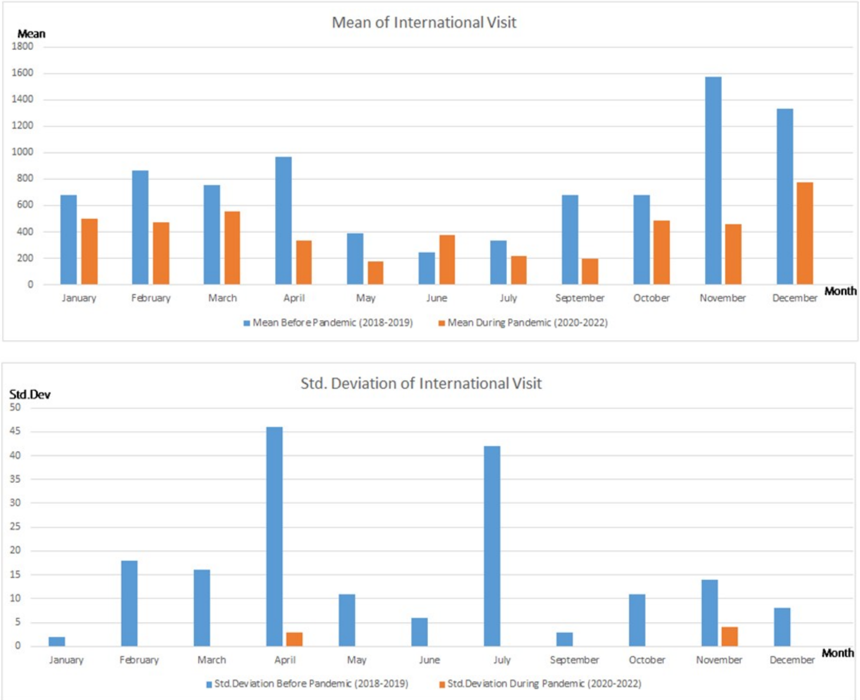

Fig. 4. Mean and std.deviation of international visit visualization.

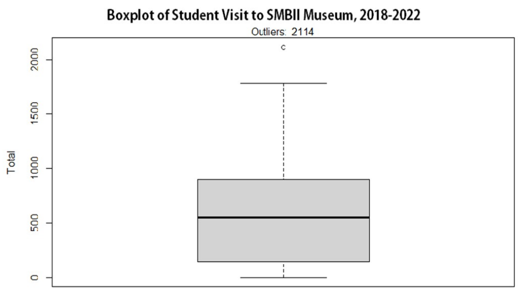

Fig. 5. Boxplot of student visit.

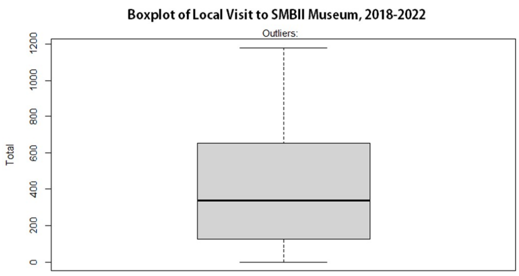

Fig. 6. Boxplot of local visit.

Fig. 7. Boxplot of international visit.

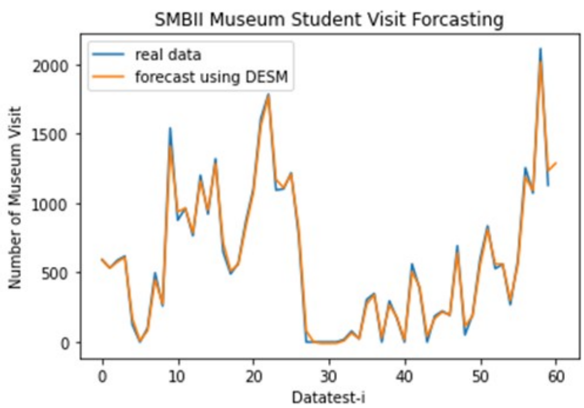

Fig. 8. Student visit forecasting result.

an impact on forecasting results. In addition, the amount of data in the data set for the post-pandemic period also had an effect where it only consisted of six data. It is necessary to increase the amount of post−pandemic data to further analyze the effectiveness of DESM in forecasting post-pandemic SMBII Museum visits.

V. Conclusion

This study analyzes the application of the double exponential smoothing (DESM) model in forecasting visits to museums after the COVID-19 pandemic. This research uses a dataset of tourist visits to the SMBII Museum in the 2018−2022 period. Based on the pandemic situation, the dataset is divided into two for descriptive statistical analysis, before the pandemic (2018−2019) and during the pandemic (2021−2022). For forecasting purposes with DESM, the dataset is divided into two which are before the pandemic (2018−2019), and during the pandemic (2019−2022).

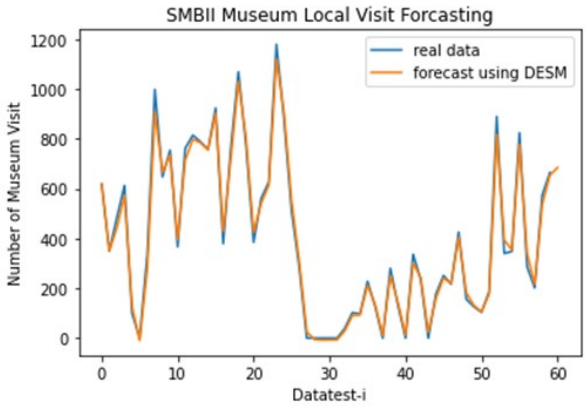

Fig. 9. Local visit forecasting result.

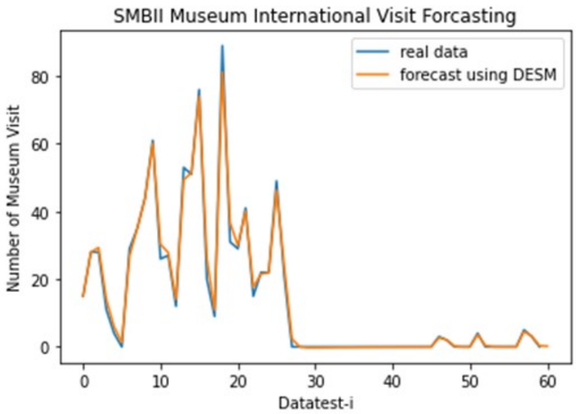

Fig. 10. International visit forecasting result.

The results showed that DESM was effective for forecasting with the best MSE value obtained for forecasting international tourist visits of 3.8 where $\alpha = 0.9$ and $\alpha = 0.1$. Meanwhile, for forecasting student visits as dominant visitors to museums, the best MSE values were obtained during the pandemic period when visits to museums were smaller than before the pandemic but there were no data outliers and the average monthly visit was also stable where museums limited visits to museums and were even required to close for visitors during the pandemic.

The highest MSE when forecasting the post−pandemic period was due to an outlier in November 2022. This data cannot be ignored because it is part of the time serial in the post-pandemic period. It is necessary to preprocess the dataset so that it can be processed using other indicators in measuring

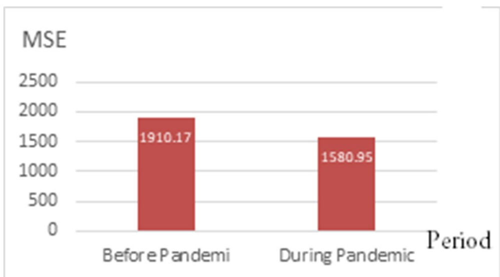

Fig. 11. MSE student visits for two categories of the pandemic period.

the effectiveness of DESM due to the presence of $0-$valued data which has an impact on calculations.

Further research can be carried out by comparing the performance of DESM with other models and adding data in the post-pandemic dataset so that the effectiveness of the DESM model can be increased and the best model in forecasting post-pandemic museum visits can be identified as information for various parties in developing post-pandemic museum recovery strategies.

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