Modeling the number of unemployed in South Sumatra Province using the exponential smoothing methods

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Abstract

The number of open unemployment in South Sumatra Province from year to year is found to be unstable. It can cause serious developmental problems. One solution to this problem is to build an early warning system by predicting the number of open unemployment in the future so that the Regional Government can establish relative policies to anticipate the negative impacts it will have on the environment, economy, social and politics. Therefore, this study discusses the best model to predict the number of unemployed in South Sumatra Province. The methods used to identify the best model are Single Exponential Smoothing (SES), Brown’s Exponential Smoothing (BES), and Holt’s Exponential Smoothing (HES). The Exponential Smoothing methods are compared to obtain forecasting results with a minimal error rate. Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) metrics are used to measure the performance of the forecasting model. Empirical results show that the SES model with the smoothing parameter value $\lambda = 0.7$ is the best significant model in predicting the number of open unemployment in South Sumatra Province with a MAPE value of 6.24% and an RMSE value of 23.058. Thus, this SES model can be a reference for the Government to predict the number of open unemployment in South Sumatra Province so that the Regional Government can anticipate the negative impacts it can cause.

Keywords The number of Unemployed · Single exponential smoothing (SES) · Brown’s exponential smoothing (BES) · Holt’s exponential smoothing (HES) · South Sumatra Province
Abbreviations

ES Exponential Smoothing.
SES Single Exponential Smoothing.
BES Brown’s Exponential Smoothing.
HES Holt’s Exponential Smoothing.
RMSE Root Mean Square Error.
MAPE Mean Absolute Percentage Error.
ILO International Labor Organization.
BPS Badan Pusat Statistik.

1 Introduction

According to the International Labor Organization (ILO), unemployment is a person belonging to the working-age population group who has not worked for a certain period and is willing to accept work and is looking for work (Resolution 2013). In other words, unemployment is a group of workers who want to work but have not had the opportunity to work. The increasing number of unemployed is generally caused by the growth in the number of available job opportunities that are not matched by the growth in the number of the labor force that continues to increase (Davidescu, Apostu, and Paul 2021). Unemployment that is already very chronic and structural in nature will generally have a negative impact on environmental, economic, social, and political development in a region. Unemployment that is already structural in nature is very influential on the achievement of community welfare and the development prospects of the area concerned. Therefore, the number of unemployed must be under control.

According to the BPS - Statistics Indonesia, the number of unemployed in South Sumatra Province in 2020 was 238,363 people. This condition illustrates that until the end of 2020, the number of residents in South Sumatra Province who do not have a job is 3.2% (Badan Pusat Statistik (BPS) 2020). However, this number of unemployed increased by 25.3% (higher) than the number of unemployed in 2019. The number of unemployed in 2019 was 190,204 people (Badan Pusat Statistik (BPS) 2020). In general, this condition represents a development problem.

Unemployment can have an impact on the national economy (Tesfaselassie and Wolters 2018). Unemployment causes the people’s prosperity level to decline so that tax revenues from the community will decrease. It will reduce funds for national economic activities that will eventually reduce development activities as well. Furthermore, because the level of people’s prosperity decreases, the purchasing power decreases so that the demand for manufactured goods decreases. This phenomenon will prevent investors (entrepreneurs) from expanding or establishing new industries. Thus, the level of investment will decrease so that economic growth will slow down.

Furthermore, unemployment can cause social and political conditions to become unstable (Davidescu, Apostu, and Paul 2021). The high unemployment rate illustrates the number of people who have lost their source of income. The loss of income sources will cause social vulnerabilities such as pickpocketing, robbery, homelessness, and other criminal acts because each individual is required to meet the needs of his life and his family. High unem-
ployment also causes public dissatisfaction (Chen and Hou 2019), so it can lead to demonstrations and even riots so that the political situation becomes unstable. The one way to anticipate this is to forecast the number of unemployed in the future so that the government can make the right and measurable decisions.

Several forecasting methods can be utilized to predict time series data according to the needs and data patterns. For that reason, a comparison process is needed between one forecasting method and another to obtain the best forecasting method with a minimal error rate. Meanwhile, the time series forecasting method that is often used is the exponential smoothing method (Ahmar, Fitmayanti, and Ruliana 2021). Therefore, this study will look for the most accurate Exponential Smoothing (ES) forecasting model in predicting the number of unemployed in South Sumatra province by comparing the error rate forecasting results from the Single Exponential Smoothing (SES), Brown’s Exponential Smoothing (BES) method, and Holt’s Exponential Smoothing (HES). The metrics used to measure the error rate of the forecasting model in this study are Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

This paper is structured as follows. The following section briefly describes the research methods used. In the Results and Discussion section, we present descriptive statistics, SES, BES, HES, and discuss the comparison of ES models. Finally, we provide conclusions and directions for future research in Sect. 4.

1.1 Literature Review

Forecasting is often classified as short-term, medium-term, and long-term forecasting. Short-term forecasting is operational with a period of days, weeks, months in the future. Medium-term forecasting is tactical with maturities of six months to two years, and long-term forecasting is strategic with a term of more than two years. This research is included in the type of medium-term forecasting.

Based on previous research, Gustriansyah (2019) has highlighted the application of the SES method to predict the number of sales of multi-products. The best SES model was obtained by using the smoothing parameter $\phi=0.9$ (Gustriansyah et al. 2019). Meanwhile, Nursyamsi (2018) implemented the BES method to predict the number of unemployed in Makassar city. The forecasting model produced a MAPE value of 23.6% (Nursyamsi 2018). His research was supported by the forecasting model of Syafwan et al. (2020) that resulted in a MAPE of 16.35% for the Province of North Sumatra (Syafwan et al. 2021). Their research was suitable for short-term forecasting.

Meanwhile, Sulaiman (2021) stated that the HES method could predict the open unemployment rate in Indonesia more accurately than using the ARIMA method (Sulaiman and Juarna 2021; Katris 2020) selected the best model to predict unemployment rates in several countries by comparing machine learning methods with ARIMA and Holt-Winters (Katris 2020). In addition, Mihaela (2020) tries another approach by forecasting the regional unemployment rate in Romania using Google Trends (Mihaela 2020). There is a gap because no research compares and measures the error rate of forecasting the number of unemployed using the three ES methods: SES, BES, and HES. Therefore, this study tries to bridge the research gap.
1.2 Single exponential smoothing

SES is a forecasting method that uses historical time-series data with a horizontal pattern without a trend or seasonality. SES utilizes a single smoothing parameter ($\alpha$). The $\alpha$ is between 0 and 1. The formulas for SES is as in (1) (Gustriansyah et al. 2019).

$$F_{t+1} = \alpha A_t + (1 - \alpha) F_t$$  \hspace{1cm} (1)

Where:

$F_{t+1}$ = the forecast value at period $t+1$.
$F_t$ = the forecast value at period $t$.
$A_t$ = the actual value at period $t$.
$F_2 = A_1$.

1.3 Brown’s exponential smoothing

BES is an SES derivative forecasting method utilized to overcome a trend. BES also uses $\alpha$ with values between 0 and 1. The formulas for BES is as in (2) (Hyndman and Athanasopoulos 2019).

$$S'_t = \alpha A_t + (1 - \alpha) S'_{t-1}$$  \hspace{1cm} (2).

$$S''_t = \alpha S'_t + (1 - \alpha) S''_{t-1}$$

$L_t = 2 S'_t - S''_t$

$T_t = \alpha / (1 - \alpha) (S'_t - S''_t)$

$F_{t+m} = L_t + m T_t$

$S'_1 = S''_1 = A_1$

Where:

$S'_t$ = the singly-smoothed series.
$A_{t-1}$ = the actual value at period $t-1$.
$S''_t$ = the doubly-smoothed series.
$L_t$ = the estimated level at period $t$.
$T_t$ = the estimated trend at period $t$.
$F_{t+m}$ = the forecast value at period $t+m$.
$m$ = number of periods.

1.4 Holt’s exponential smoothing

HES is a forecasting method that utilizes historical time series data with trending data patterns. The HES method uses two smoothing parameters: data ($\alpha$) and trend ($\beta$). The $\alpha$ and $\beta$ parameter intervals are between 0 and 1. The formulas for HES is as in (3) (Hyndman and Athanasopoulos 2019).

$$F_{t+m} = L_t + m T_t$$  \hspace{1cm} (3).

$L_t = \alpha A_t + (1 - \alpha) (L_{t-1} + T_{t-1})$

$T_t = \beta (L_t - L_{t-1}) + (1 - \beta) T_{t-1}$

$T_1 = 0, L_1 = A_1$. 

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1.5 Root Mean Square Error and Mean Absolute percentage error

The metric that is often used to measure the performance of forecasting model is the RMSE and in percentage is the MAPE. The formula for RMSE is as in (4) (Malsa, Vyas, and Gautam 2021), and MAPE is as in (5) (Gustriansyah et al. 2019).

\[
RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (A_t - F_t)^2}
\]

(4)

\[
MAPE = \frac{1}{n} \sum_{t=1}^{n} \frac{|A_t - F_t|}{A_t}
\]

(5)

2 Methods

This study uses a quantitative approach. The data set used was data on the number of open unemployment in the South Sumatra Province period February 2008 to August 2020. The data set consisted of 26 biannually data that was the data of secondary and was obtained from the Statistics Indonesia of South Sumatra Province (Badan Pusat Statistik (BPS) 2020). Furthermore, the data set was divided into two parts, namely 20 time-series data for modeling and six time-series data for testing. Then, the data set were analyzed and tested using the SES, BES, and HES methods with smoothing parameters to predict the number of unemployed in the future.

Sequentially, the stages of the research carried out are:
(1) Identifying data by plotting data on the number of unemployed in South Sumatra Province;
(2) Determine α and β by trial and error;
(3) Perform forecasting modeling using the SES (1), BES (2), and HES (3) methods;
(4) Evaluating forecasting results using RMSE (4) and MAPE (5) metrics;
(5) Selecting the best SES, BES, and HES model that produces the minimum RMSE and MAPE values;
(6) Forecasting the number of unemployed in the future using the best SES, BES, and HES models;
(7) Comparing forecasting results to determine the best forecasting model.

3 Results and discussion

3.1 Descriptive statistics

Based on data obtained from the Statistics Indonesia of South Sumatra Province (Badan Pusat Statistik (BPS) 2020), the average number of unemployed in South Sumatra Province from February 2008 to August 2020 was 212,495 people. The minimum number of
unemployed was 154,467 people recorded in February 2014, and the maximum number of unemployed was 292,234 as of February 2009. Table 1 presents the details of this data set.

Table 1  Data on the number of unemployed in South of Sumatra the period February 2008 - August 2020

| Month/Year | February | August |
|------------|----------|--------|
| 2008       | 292,054  | 280,657|
| 2009       | 292,234  | 263,471|
| 2010       | 237,118  | 243,851|
| 2011       | 239,276  | 241,577|
| 2012       | 221,934  | 214,730|
| 2013       | 213,638  | 179,249|
| 2014       | 154,467  | 192,868|
| 2015       | 202,199  | 238,921|
| 2016       | 159,525  | 180,157|
| 2017       | 161,152  | 181,135|
| 2018       | 180,354  | 178,847|
| 2019       | 176,328  | 190,204|
| 2020       | 170,531  | 238,363|

Source: BPS - Statistics Indonesia of South of Sumatera Province.

Fig. 1  The plot of the number of unemployed in South Sumatra Province for periods February 2008-August 2020

Fig. 2  The plot of decomposition of forecasting number of unemployed data in South Sumatra Province the period February 2008-August 2020
The standard deviation of the data on the number of unemployed is 41,335 people. The data forms a normal distribution. The standard deviation value that is smaller than the mean value indicates that the data fully explains the entire data. In other words, the distribution of the data to the mean is low. Figure 1 demonstrates a data plot on the number of unemployed in South Sumatra Province period February 2008 to August 2020.

Data on the number of unemployed in South Sumatra Province in Fig. 1 shows the trend data pattern (increasing/decreasing) at a certain period. The data pattern increased dramatically during the global economic slowdown (2014–2015) and the Covid-19 pandemic (2020–2021) but tends to be downward in the long term. Therefore, decomposition is carried out to identify the data pattern better. In addition, the data pattern in Fig. 1 includes a non-linear pattern so that multiplicative decomposition and Exponential Smoothing (ES) methods are the most appropriate for this research. Figure 2 demonstrates the results of the multiplicative decomposition of the data on the number of unemployed where the identified data patterns are in the form of trends and cycles/random.

### 3.2 Modelling Approach

The Single Exponential Smoothing (SES) method in this study uses 26 time-series data on the number of unemployed in South Sumatra Province and one smoothing parameter ($\alpha$). The determination of the best SES model is done by trial and error with various values of $\alpha$ and using 20 time-series data. In the initial experiment, the value of $\alpha=0.1$ and continues to increase until $\alpha=0.9$. The evaluation of this SES model uses RMSE and MAPE metrics. Table 2 shows the trial-and-error results of this SES model.

The minimum RMSE value obtained using $\alpha=0.7$ is 26,258, and the minimum MAPE value obtained using $\alpha=0.7$ is 9.96%. Therefore, the SES model that uses the parameter $\alpha=0.7$ is the best model to forecast the number of unemployed with a data pattern like this.

### Table 2
The error rate of SES modeling with various values of $\alpha$

| $\alpha$ | RMSE  | MAPE (%) |
|---------|--------|----------|
| 0.1     | 48,498 | 22.46    |
| 0.3     | 30,123 | 12.59    |
| 0.5     | 26,722 | 11.14    |
| 0.6     | 26,309 | 10.74    |
| 0.7     | **26,258** | **10.42** |
| 0.9     | 26,909 | 10.66    |

### Table 3
The results of the SES modeling use $\alpha=0.7$ with $F_t$ as the forecast result and $A_t$ as the actual data

| $t$ | $A_t$ | $F_t$ | $A_tF_t$ | $|A_t-F_t|/A_t$ | $(A_tF_t)^2$ |
|-----|-------|-------|----------|----------------|--------------|
| 1   | 292,054 |       |          |                |              |
| 2   | 280,657 | 292,054 | -11,397  | 0.041          | 129,891,609  |
| 3   | 292,234 | 284,076 | 8,158    | 0.028          | 66,551,332   |
| ... | ...    | ...    | ...      | ...            | ...          |
| 19  | 161,152 | 179,797 | -18,827  | 0.117          | 354,453,812  |
| 20  | 181,135 | 166,800 | 14,335   | 0.079          | 205,489,842  |
| Sum |       |        |          | 1.981          | 13,099,999,794 |

$A_t$ and $F_t$ are the actual data and forecast result, respectively.
Table 3 shows a sample of SES modeling results using the smoothing parameter $\alpha = 0.7$. This calculation process was carried out sequentially from August 2008 to August 2017.

The next stage is forecasting the number of unemployed using the SES model with smoothing parameter $\alpha = 0.7$. The data used are six time-series data for the period February 2018-August 2020. Evaluation of the error rate of the forecasting model uses RMSE and MAPE metrics. Table 4 shows the results of forecasting using the SES model with $\alpha = 0.7$. Forecasting results showed that the data in the August 2018 period has the minimum error rate, which is -451. It means that the forecasting results for that period are the most accurate.

Figure 3 demonstrates the SES model forecasting results plot with smoothing parameter $\alpha = 0.7$. This plot illustrates that the SES model is accurate enough to predict fluctuating data patterns. However, the forecast data shows a lag time-series value because the SES model only uses actual and predicted values from the previous period without considering data trends.

### Table 4
Comparison of forecasting results ($F_t$) with actual data ($A_t$) for periods February 2018-August 2020 with $\alpha = 0.7$

| $A_t$  | $F_t$  | Error |
|--------|--------|--------|
| 180,354| 176,835| 3,519  |
| 178,847| 179,298| -451   |
| 176,328| 178,982| -2,654 |
| 190,204| 177,124| 13,080 |
| 170,531| 186,280| -15,749|
| 238,363| 175,256| 63,107 |

|        | RMSE     | MAPE (%) |
|--------|----------|----------|
| $\alpha$ |          |          |
| 0.1    | 31,804   | 13.33    |
| **0.3**| **26,149**| **10.03**|
| 0.5    | 28,856   | 11.22    |
| 0.6    | 30,701   | 11.69    |
| 0.7    | 32,919   | 12.12    |
| 0.9    | 39,437   | 14.63    |

**Fig. 3** The data plot for forecasting the number of unemployed in South Sumatra Province uses the SES model with $\alpha = 0.7$ for the periods February 2008-August 2020.
Similar to the SES model, the determination of the best BES model is also done by trial and error with various values of $\alpha$ and using 20 time-series data. In the initial experiment, the value of $\alpha=0.1$ and continued to increase until $\alpha=0.9$. The evaluation of this BES model also uses RMSE and MAPE metrics. Table 5 shows the trial-and-error results of this BES model.

The minimum RMSE value obtained using $\alpha=0.3$ is 26,149, and the minimum MAPE value also obtained using $\alpha=0.3$ is 10.03%. So, the BES model that uses the parameter $\alpha=0.3$ is the best model to forecast the number of unemployed.

Table 6 shows a sample of BES modeling results using $\alpha=0.3$. This calculation process is carried out sequentially for periods August 2008 to August 2017.

Next is the process of forecasting the number of unemployed using the BES model with $\alpha=0.3$. The data used are six time-series data for the period February 2018-August 2020.

Table 6  The results of the BES modeling use $\alpha=0.3$ with $F_t$ as the forecast result and $A_t$ is the actual data

| $t$ | $A_t$ | $L_t$ | $T_t$ | $F_t$ | $A_t-F_t$ | $|A_t-F_t|/A_t$ | $(A_t-F_t)^2$ |
|-----|-------|-------|-------|-------|-----------|---------------|---------------|
| 1   | 292,054 | 292,054 | 0     |       |           | 0.041         | 129,891,609   |
| 2   | 280,657 | 288,242 | -1,026| 292,054| -11,397   | 0.024         | 49,255,131    |
| 3   | 292,234 | 288,795 | -394  | 285,216| 7,018     |               |               |
| ... | ...    | ...    | ...   | ...   | ...       |               |               |
| 19  | 161,152 | 168,239 | -5,690| 175,615| -21,704   | 0.090         | 209,169,523   |
| 20  | 181,135 | 172,028 | -4,017| 162,549| 6,397     | 0.103         | 345,451,700   |
| Sum | 1,905  |        |       |       | 12,991,418,229 |

Table 7  Comparison of forecasting results ($F_t$) with actual data ($A_t$) for periods February 2018-August 2020 with $\alpha=0.3$

| $A_t$ | $F_t$ | Error |
|-------|-------|-------|
| 180,354 | 168,010 | 12,344 |
| 178,847 | 171,399 | 7,448  |
| 176,328 | 172,962 | 3,366  |
| 190,204 | 172,745 | 17,459 |
| 170,531 | 181,287 | -10,756|
| 238,363 | 174,472 | 63,891 |
| Sum    |       | 28,053 |

RMSE=28,053  MAPE=9.20

Fig. 4  The data plot for forecasting the number of unemployed in South Sumatra Province uses the BES model with $\alpha=0.3$ for the periods February 2008-August 2020
Table 7 shows the results of forecasting using the BES model with $\alpha=0.3$. Forecasting results showed that the data for the February 2019 period has a minimum error rate of 3,366. It means that the forecasting results for that period are the most accurate.

Figure 4 demonstrates the plot of forecasting results from the BES model with $\alpha=0.3$. This plot illustrates that the BES model is smoother and accurate enough to predict fluctuating data patterns. However, this result is not optimal because the BES model does not involve smoothing trend parameters.

Furthermore, the best HES model is also obtained by trial and error. However, it uses various values of $\alpha$ and $\beta$ and 20 time-series data. In the initial experiment, the value of $\alpha$ and $\beta$ were 0.1 and continued to increase until $\alpha$ and $\beta$ were 0.9. The evaluation of this HES model also uses RMSE and MAPE metrics. Table 8 shows the trial-and-error results of the HES model using several different values of $\alpha$ and $\beta$.

The minimum RMSE value obtained using $\alpha=0.3$ and $\beta=0.3$ is 26,534. Meanwhile, the minimum MAPE value obtained using $\alpha=0.3$ and $\beta=0.3$ is 9.81% as well. Thus, the HES model that uses the parameters $\alpha=0.3$ and $\beta=0.3$ is the best model to forecast the number of unemployed.

| $\alpha$ | $\beta$ | RMSE  | MAPE (%) |
|----------|---------|-------|----------|
| 0.1      | 0.1     | 38,835| 16.72    |
| 0.3      | 0.3     | 32,788| 13.41    |
| 0.6      | 0.6     | 32,510| 12.58    |
| 0.9      | 0.9     | 30,992| 10.32    |
| 0.3      | 0.3     | 26,534| 9.81     |
| 0.6      | 0.6     | 27,381| 10.54    |
| 0.9      | 0.9     | 29,447| 11.79    |
| 0.3      | 0.3     | 26,534| 9.81     |
| 0.6      | 0.6     | 27,512| 10.70    |
| 0.9      | 0.9     | 33,551| 12.28    |

Table 8 The error rate of HES modeling with various values of $\alpha$ and $\beta$

$A_t$ is the forecast result and $A_t$ is the actual data

| $t$ | $A_t$ | $L_t$ | $T_t$ | $F_t$ | $A_tF_t$ | $|A_tF_t|/A_t$ | $(A_tF_t)^2$ |
|-----|-------|------|------|------|--------|---------------|-------------|
| 1   | 292,054 | 292,054 | 0 | | | | |
| 2   | 280,657 | 288,635 | -1,026 | 292,054 | -11,397 | 0.041 | 129,891,609 |
| 3   | 292,234 | 288,997 | 609 | 287,609 | 4,625 | 0.016 | 21,389,053 |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 19  | 161,152 | 171,019 | -3,730 | 175,248 | -14,096 | 0.087 | 198,686,662 |
| 20  | 181,135 | 171,443 | -2,484 | 167,289 | 13,846 | 0.076 | 191,711,191 |
| Sum | 1.863 | 13,376,826,508 | | | | | |

Table 9 The results of the HES modeling use $\alpha=0.3$ and $\beta=0.3$ with $F_t$ as the forecast result and $A_t$ is the actual data
Table 9 shows a sample of the calculation results of the HES model using $\alpha=0.3$ and $\beta=0.3$. This calculation process is carried out sequentially for periods August 2008 to August 2017.

Next is forecasting the number of unemployed using the HES model with $\alpha=0.3$ and $\beta=0.3$. The data used are six time-series data for the period February 2018-August 2020. Table 10 shows the comparison between the actual data and the forecast results from the HES model with parameters $\alpha=0.3$ and $\beta=0.3$. The forecast results show that the data for the February 2019 period has a minimum error rate of 3.775. It means that the forecasting results for that period are the most accurate.

Figure 5 demonstrates the actual data plot and forecasting results from the HES model with $\alpha=0.3$ and $\beta=0.3$ periods February 2008 to August 2020. The evaluation results show that the HES forecasting model can follow the descending pattern of the actual data so that it can obtain an error rate minimally.

| $A_t$ | $F_t$ | Error |
|-------|-------|-------|
| 180,354 | 168,959 | 11,395 |
| 178,847 | 170,919 | 7,928 |
| 176,328 | 172,553 | 3,775 |
| 190,204 | 173,280 | 16,924 |
| 170,531 | 179,476 | -8,945 |
| 238,363 | 177,105 | 61,258 |

RMSE = 26,851 \hspace{1cm} MAPE = 8.79

Table 10 Comparison of forecasting results ($F_t$) with actual data ($A_t$) for periods February 2018-August 2020 with $\alpha=0.3$ dan $\beta=0.3$

Fig. 5 The data plot for forecasting the number of unemployed in South Sumatra Province uses the HES model with $\alpha=0.3$ and $\beta=0.3$ for the periods February 2008-August 2020

Table 11 Comparison of the Evaluation Results of Exponential Smoothing Model

| Model | RMSE | MAPE (%) |
|-------|------|----------|
| SES ($\alpha=0.7$) | 23,058 | 6.24 |
| BES ($\alpha=0.3$) | 28,053 | 9.20 |
| HES ($\alpha=0.3$ and $\beta=0.3$) | 26,851 | 8.79 |
3.3 The comparison of Exponential Smoothing Model

The comparison of the error rates of the three forecasting models, namely SES, BES, and HES is shown in Table 11.

Table 11 shows that the smallest RMSE value generated by the SES model with $\alpha=0.7$ is 23,058, and the smallest MAPE value is 6.24%. Hence, the Single Exponential Smoothing (SES) model is considered the most appropriate model to forecast the number of unemployed in South Sumatram Province period February 2018 to August 2020.

4 Conclusions

The results of this study indicate that the MAPE value of the SES, BES, and HES models is low (MAPE < 10%). Even the MAPE value for the SES model with $\alpha=0.7$ is only 6.24%. In general, this indicates that the ES model is a model with high accuracy for forecasting the number of unemployed in South Sumatra Province, especially the SES model with $\alpha=0.7$. This SES model can be a benchmark model for the South Sumatra Provincial Government to predict the unemployment rate in the future.

Future research can compare the results of this study with other methods such as the deep learning method, system dynamics, or actor-based models to obtain a more accurate method for predicting the number of unemployed in South Sumatra Province, or it can also be applied to Indonesia.

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Declarations

Conflict of interest The Authors declare that there are no conflicts of interest regarding the publication of this paper.

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