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Time series analysis and forecasting of unemployment in Purbalingga Regency using Brown's double exponential smoothing: An accuracy-based evaluation

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ABSTRACT

Unemployment remains a persistent socioeconomic challenge in Indonesia, including Purbalingga Regency, Central Java. This study analyzes the unemployment trend and forecasts the number of unemployed individuals in Purbalingga Regency using a time-series approach. Annual unemployment data for 2010–2024 from the Central Bureau of Statistics (BPS) were modeled using Brown's Double Exponential Smoothing (DES), which is suitable for non-seasonal series with a linear trend. The smoothing parameter (α) was examined from 0.1 to 0.9, and model performance was evaluated using MAD, MSE, and MAPE based on in-sample fitted errors over the 2010–2024 period. The results indicate a fluctuating but upward trend, particularly after the COVID-19 period. The best-performing parameter was $\alpha = 0.2$, producing the lowest MAD and MAPE; under this evaluation setting, MAPE was below 1%, indicating low in-sample error. Using the selected model, unemployment in 2025 is forecast at approximately 31,795 people. These findings suggest that Brown's DES can provide a practical baseline forecast to support evidence-based labor market policy and regional economic planning, while the results should be interpreted with caution, given the linear-trend and univariate assumptions.

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1. INTRODUCTION

Purbalingga Regency is one of the administrative regions in Central Java Province, covering an area of approximately 777.64 km² and inhabited by more than 900,000 people. Geographically, the regency is located in southwestern Central Java and is bordered by Banjarnegara Regency to the north, Banyumas Regency to the west, and Pemalang Regency to the east. The topography of Purbalingga Regency varies from lowland areas to mountainous regions along the slopes of Mount Slamet in the northern part of the regency. This geographical diversity provides considerable economic potential, particularly in the agricultural sector, small and medium industries (SMEs), and tourism [1].

The economy of Purbalingga Regency is supported by several leading sectors, including export-oriented industries such as wigs and false eyelashes, as well as agriculture, trade, and tourism based on natural attractions and rural destinations. Tourist sites such as Owabong Waterpark, Goa Lawa, and Serang Tourism Village play an important role in stimulating local economic activities. Nevertheless, despite these economic potentials, employment issues and poverty remain major challenges in regional development.

According to data from the Central Bureau of Statistics (BPS) in 2023, the poverty rate in Purbalingga Regency reached 14.99%, placing it among the five regencies with the highest poverty rates in Central Java Province [2]. Although the poverty rate declined to approximately 14.18% by mid-2024, this figure still indicates that community welfare has not been evenly distributed. One of the main contributors to the high poverty rate is unemployment, particularly due to limited formal job opportunities and the mismatch between labour skills and industrial demand. Data from the National Labour Force Survey (SAKERNAS) conducted by BPS Purbalingga in 2023 show that the Open Unemployment Rate reached 5.61%. This figure suggests that a considerable proportion of the working-age population has not been optimally absorbed by the labour market. Skill mismatches limited labour-intensive industries, and structural economic changes further exacerbate employment conditions. Therefore, unemployment is a crucial indicator of regional economic dynamics and plays a key role in poverty reduction efforts.

The unemployment trend in Purbalingga Regency during 2010–2024 shows fluctuations. These fluctuations are influenced by various factors, including the impact of the COVID-19 pandemic, changes in macroeconomic conditions, and regional labour market policies. Such conditions highlight the need for quantitative analysis to predict future unemployment trends, enabling local governments to formulate more targeted and data-driven policies. One widely used statistical approach for forecasting economic time series is the Exponential Smoothing method [3, 4]. This method assigns greater weights to more recent observations, making forecasts more responsive to recent changes. In general, Exponential Smoothing consists of several variants: Single Exponential Smoothing (SES) for data without trend and seasonality [5 - 7], Double Exponential Smoothing (DES) for data with trend [8, 9], and Triple Exponential Smoothing or the Holt–Winters method for data exhibiting both trend and seasonal patterns [10 - 12].

Several previous studies have demonstrated the applicability of Exponential Smoothing methods in the labour market and socioeconomic forecasting. Rosa et al. [13] successfully applied Single Exponential Smoothing to forecast the number of people living in poverty, achieving low forecasting errors. Sulaiman and Juarna [14] compared ARIMA and Holt–Winters models for unemployment forecasting in Indonesia and found that Holt–Winters models performed better on seasonally characterized data. Meanwhile, Arifin et al. [15] showed that Double Exponential Smoothing effectively captured unemployment trends in East Kalimantan Province with a Mean Absolute Percentage Error (MAPE) below 5%.

Despite the extensive application of Exponential Smoothing methods, empirical studies on district-level unemployment forecasting using Brown’s Double Exponential Smoothing remain limited, particularly in regions with annual data and dominant trend components without seasonality. Brown's Double Exponential Smoothing employs a single smoothing parameter (α) to estimate both level and trend components, making it simpler and computationally efficient compared to Holt's method, which requires two parameters [16]. This characteristic makes Brown's method particularly suitable for regional labour market data that exhibit relatively stable linear trends.

Based on these considerations, this study aims to identify the unemployment trend in Purbalingga Regency during 2010–2024 and forecast the number of unemployed individuals for 2025 using Brown's Double Exponential Smoothing method. The findings of this study are expected to provide quantitative insights to support regional employment planning and inform the development of data-driven labour market policies.

2. METHOD

2.1 Methodology Background

Forecasting estimates future values based on historical observations and patterns to support decision-making. Quantitative time-series forecasting is appropriate when numerical historical data are available, and past patterns are assumed to persist [17]. For annual unemployment data, the series is commonly assessed for a trend component and the absence of seasonality [18]. Exponential Smoothing assigns greater weights to more recent observations so forecasts can respond to recent changes [19]. Its variants include Single Exponential Smoothing for series without trend, Double Exponential Smoothing for series with trend, and Holt–Winters for series with trend and seasonality. Double Exponential Smoothing (DES) is designed for non-seasonal time series with a trend component. Brown's DES applies double smoothing using a single parameter (α) to estimate both level and trend components, which makes it simpler than Holt's method, which uses two parameters [16]. This property is suitable for annual regional labour market series that tend to exhibit relatively stable linear trends. Forecast accuracy is evaluated using error measures that represent the deviation between actual and forecasted values. This study uses Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE); smaller values indicate better performance [20]. These measures are used to compare smoothing-parameter candidates and select the best-performing model.

2.2 Research Type and Approach

This study employs a quantitative design with a univariate time-series forecasting approach. The objective is to model and forecast the number of unemployed individuals in Purbalingga Regency using Brown's Double Exponential Smoothing (DES), which is suitable for non-seasonal series with a trend component.

2.3 Data and Source

The study uses annual secondary data on the number of unemployed individuals in Purbalingga Regency for the period 2010–2024, obtained from official publications of the Central Bureau of Statistics (BPS) of Purbalingga Regency. The observed series is denoted as X_t, where t represents the year.

2.4 Research Variable

The main variable is the number of unemployed individuals (X_t), defined as working-age individuals who are not employed and are actively seeking employment in year t, following the BPS definition. The analysis is univariate, involving only this single variable.

2.5 Data Analysis Procedures

The analysis was conducted through the following steps:

1. Collect and organise annual unemployment data (2010–2024).
2. Visualise the series (table/plot) to assess the presence of a trend and the absence of seasonality.
3. Apply Brown's Double Exponential Smoothing with candidate values of the smoothing parameter α.
4. Compute fitted one-step-ahead values and evaluate model performance using MAD, MSE, and MAPE.
5. Select the optimal α and generate the forecast for 2025.

2.6 Brown's Double Exponential Smoothing Model

Brown's Double Exponential Smoothing model is applied using the following procedures:
First exponential smoothing:

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

Second exponential smoothing:

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

Level component:

$$a_t = 2S'_t - S''_t$$

Trend component:

$$b_t = \frac{\alpha}{1-\alpha}(S'_t - S''_t)$$

Forecasting equation:

$$F_{t+m} = a_t + b_t m$$

With the initial conditions defined as:

$$S'_1 = S''_1 = X_1, b_1 = 0$$

2.7 Selection of the Smoothing Parameter (α)

The smoothing parameter α was tested from 0.1 to 0.9. For each α, the DES components (S'_t, S''_t, a_t, b_t) were computed and the corresponding fitted one-step-ahead values were generated. The optimal $\alpha$was chosen based on the smallest error values, prioritising MAPE and using MAD/MSE as supporting indicators for consistency.

2.8 Evaluation Setting and Forecast Accuracy Measures

To avoid ambiguity in interpreting forecasting accuracy, this study evaluates performance using in-sample one-step-ahead fitted errors over the 2010–2024 period. Specifically, the fitted value for year $t$is generated using information up to year $t-1$ (one-step-ahead), and errors are calculated for $t = 2,3, \ldots, n$, where n is the number of observations.

Let F_t denote the fitted one-step-ahead value for X_t. Forecast accuracy is measured using:

$$MAD = \frac{1}{n-1}\sum_{t=2}^{n} |X_t - F_t|$$

$$MSE = \frac{1}{n-1}\sum_{t=2}^{n} (X_t - F_t)^2$$

$$MAPE = \frac{100\%}{n-1}\sum_{t=2}^{n} \left|\frac{X_t - F_t}{X_t}\right|$$

Smaller values indicate better in-sample fit under the stated evaluation setting.

2.9 Research Outputs

The outputs include: (1) a descriptive assessment of unemployment dynamics (2010–2024), (2) the selected smoothing parameter α for Brown's DES, (3) the estimated level and trend components at the final observation, and (4) the forecast of the number of unemployed individuals in Purbalingga Regency for 2025. Model performance is summarised using MAD, MSE, and MAPE computed under the evaluation setting described in Section 3.7.

3. RESULTS AND DISCUSSION

3.1 Description and identification of Data Patterns

Annual unemployment in Purbalingga Regency during 2010–2024 fluctuates but shows an overall upward movement in the long run, with a marked increase around 2020–2021 that coincides with the COVID-19 period (see Table 1). Visual inspection of the time-series plot indicates the absence of recurring seasonal cycles, while the long-term movement suggests a trend component. Accordingly, the series can be treated as a non-seasonal time series with a trend, which is consistent with the use of Brown's Double Exponential Smoothing (DES) for modeling and forecasting.

Table 1. Unemployment Data of Purbalingga Regency (2010-2024).

No	*Years (t)*	*Number of Unemployed (X_t)*	*No*	*Years (t)*	*Number of Unemployed (X_t)*
1	*2010*	*16653*	*9*	*2018*	*29522*
2	*2011*	*23193*	*10*	*2019*	*22798*
3	*2012*	*24316*	*11*	*2020*	*30513*
4	*2013*	*26651*	*12*	*2021*	*30450*

5	*2014*	*23782*	*13*	*2022*	*28188*
6	*2015*	*21858*	*14*	*2023*	*32718*
7	*2016*	*23998*	*15*	*2024*	*29713*
8	*2017*	*26138*			

Based on the time series plot, the data do not show recurring seasonal patterns but instead indicate a clear upward trend. Therefore, the unemployment data can be classified as time series data with a linear trend component, making them suitable for modeling using Brown's Double Exponential Smoothing (DES) method.

3.2 Application of Brown's Double Exponential Smoothing (DES)

Brown's DES method employs a single smoothing parameter (α) and applies a two-stage smoothing process to estimate the level and trend components of the data. In this study, the smoothing parameter α was tested over the range of 0.1 to 0.9 to identify the optimal value.

3.2.1 First Exponential Smoothing

The first smoothing is defined as:

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

where X_t is the actual value at time t, S'_t is the first smoothed value, and α is the smoothing parameter.

As an illustration, for $\alpha = 0.1$:

- Initial period ($t = 1$):

$S'_1 = X_1 = 16653$

- Period $t = 2$:

$S'_2 = \alpha X_2 + (1-\alpha)S'_{2-1} = 17307$

- Period $t = 3$:

$S'_3 = \alpha X_3 + (1-\alpha)S'_{3-1} = 18007.9$

This process was continued until period $t = 14$, resulting in $S'_{14} = 24718.1$.

3.2.2 Second Exponential Smoothing

The second smoothing process is applied to the results of the first smoothing:

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

with the initial value:

$$S''_1 = X_1 = 16653$$

For selected periods:

- $S''_2 = \alpha S'_2 + (1-\alpha)S''_{2-1} = 16718.4.$
- $S''_3 = \alpha S'_3 + (1-\alpha)S''_{3-1} = 16847.35$
- $S''_{14} = \alpha S'_{14} + (1-\alpha)S''_{14-1} = 20442.13$

3.2.3 Estimation of Level and Trend Components

After obtaining the first and second smoothed values, the level and trend components were calculated as:

Level:

$$a_t = 2S_t' - S_t''$$

Tren:

$$b_t = \frac{\alpha}{1-\alpha}(S_t' - S_t'')$$

For selected periods: $a_1 = 16653, b_1 = 0$; $a_2 = 17895.6, b_2 = 65.4$; $a_3 = 19168.45, b_3 = 128.95$; $a_{14} = 29515.5, b_{14} = 475.11$.

The level components a_t represents the estimated baseline value at time t, while the trend component b_t reflects the direction and magnitude of change over time.

3.2.4 Forecast Calculation

The forecast for m periods ahead is computed as:

$$F_{t+m} = a_t + b_t m$$

For $m = 1$: $F_2 = 16653$, $F_3 = 17961$, $F_4 = 19297.4$, $F_{15} = 29469.17$. The calculations were repeated for all values of α up to 0.9, and the complete results for 2024 are presented in Table 2.

Table 2. Results of the DES Brown Simulation for 2024.

α	S_t'	S_t''	a_t	b_t	F_{t+m}
0.1	24718.10	20442.13	28994.06	477.11	29469.17
0.2	27851.28	24652.55	31050	799.68	31849.68
0.3	29290.59	27110.58	31470.60	934.29	32404.89
0.4	30114.47	28525.08	31703.86	1059.59	32763.68
0.5	30680.71	29453.69	31907.72	1227.01	33134.73
0.6	31125.18	30114.14	32106.36	1471.56	33577.78
0.7	31515.10	30721.47	32308.74	1851.81	34160.55
0.8	31892.54	31281.61	32503.48	2443.74	34947.22
0.9	32286.98	31917.67	32656.28	3323.78	35980.06

3.3 Model Accuracy Evaluation and Selection of the Optimal α

Model accuracy was evaluated using three error measures: Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE).

3.3.1 Mean Absolute Deviation (MAD)

$$MAD = \frac{1}{n}\sum_{t=1}^{n} |X_t - F_t|$$

For example, for $\alpha = 0{,}1$:

$$MAD = \frac{|\ 16653 - 16653\ | + |\ 23193 - 17961\ | + \cdots + |\ 32718 - 29469.17\ |}{15}$$

$$MAD = 2312.97$$

3.3.2 Mean Squared Error (MSE)

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(X_t - F_t)^2$$

$$MSE = 10627485.89$$

3.3.3 Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{X_t - F_t}{X_t}\right| \times 100\%$$

$$MAPE = 0.08531$$

Similar calculations were performed for all tested values of α. The evaluation results indicate that $\alpha = 0.2$ yields the smallest values of Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE) for both the simulation and forecasting datasets; therefore, this value was selected as the optimal smoothing parameter.

3.4 Forecasting the Unemployment Level for 2025

Using the optimal smoothing parameter $\alpha = 0.2$, the unemployment level in Purbalingga Regency for 2025 is forecast using the Brown Double Exponential Smoothing (DES) method based on the final observation period $t = 15$ (year 2024). The first and second exponential smoothing values are $S'_{15} = 25217.59$ and $S''_{15} = 20919.68$. The level and trend components are calculated as $a_{15} = 29515.5$ and $b_{15} = 477.55$. Thus, the one-step-ahead forecast for 2025 is

$$F_{16} = a_{15} + b_{15}(1) = 29993.04.$$

The calculations were performed iteratively for smoothing parameters $\alpha = 0.1$to 0.9up to period $t = 15$. The complete forecasting results for 2025 using the DES Brown method are presented in Table 3.

Table 3. Results of DES Brown Forecasting for 2025.

α	S'_t	S''_t	a_t	b_t	F_{t+m}
0.1	25217.59	20919.68	29515.50	477.55	29993.04
0.2	28223.62	25366.77	31080.48	714.21	31794.69
0.3	29417.32	27802.60	31032.03	692.02	31724.05
0.4	29953.88	29096.60	30811.16	571.52	31382.68
0.5	30196.85	29825.27	30568.43	371.58	30940.01
0.6	30277.87	30224.38	30331.36	80.24	30411.60
0.7	30253.63	30393.98	30113.28	−327.48	29785.79

0.8	30148.91	30375.45	29922.37	−906.16	29016.21
0.9	29970.40	30165.12	29775.67	−1752.54	28023.13

Table 3 summarizes the results of the first and second exponential smoothing processes, the estimated level (a_t) and trend (b_t) components, and the corresponding one-step-ahead forecasts for each smoothing parameter value. These results serve as the basis for identifying the optimal smoothing parameter. The optimal start equation alpha value was selected by comparing the forecasting errors for each parameter setting, using both the simulation data and the actual forecasting data. The smoothing parameter that consistently produces the smallest error values across both analyses is considered the most suitable for accurately and stably representing the underlying data pattern. Model accuracy was evaluated using three common error measures: Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). For example, the error calculation for $\alpha = 0.1$ is:

$$MAD = \frac{1}{n}\sum_{t=1}^{n} |X_t - F_t| = 2312.97,$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n} (X_t - F_t)^2 = 10627485.89,$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left|\frac{X_t - F_t}{X_t}\right| \times 100\% = 0.08531.$$

Similar calculations were performed for all values of α using the simulation data (Table 4) and forecasting data (Table 5) to determine the optimal smoothing parameter.

Table 4. Forecasting Error Measures for the 2024 Simulation Data.

α	MAD	MSE	$MAPE$
0.1	2312.97	10627485.89	0.085311
0.2	342.52	4379863.95	0.01038
0.3	358.06	2554807	0.01637
0.4	632.53	1633457	0.02617
0.5	771.58	1201494	0.03027
0.6	855.80	1386561	0.03202
0.7	915.22	2381287	0.03274
0.8	965.06	4484003	0.03305
0.9	1014.91	8164151.55	0.03333

Table 4 presents the forecasting error measures (MAD MSE, MAPE) for the 2024 simulation data using various smoothing parameter values (α) ranging from 0.1 to 0.9. These error measures are evaluated to identify the smoothing parameter that yields the highest forecasting accuracy under the Double Exponential Smoothing (DES) Brown method.

The results indicate that $\alpha = 0.2$ yields the smallest MAD and MAPE values among all tested parameters. This finding suggests that, at this parameter value, both the average absolute deviation between actual and forecasted values and the relative forecasting error are minimized.

In contrast, the smallest MSE is obtained at $\alpha = 0.5$, indicating the lowest average squared error at that parameter level.

Nevertheless, $\alpha = 0.2$ is selected as the optimal smoothing parameter for the simulation data. This decision is based on the fact that two out of the three accuracy measures—MAD and MAPE—reach their minimum values at $\alpha = 0.2$. Since these measures are considered more robust and interpretable for evaluating forecasting performance, particularly in applied economic contexts, $\alpha = 0.2$ provides the best balance between accuracy and model stability for the 2024 simulation data.

Table 5. Forecasting Error Measures for 2025.

α	MAD	MSE	$MAPE$
0.1	2294.30	10632714.16	0.084703
0.2	180.91	4376769	0.00495
0.3	492.13	2824428	0.02088
0.4	743.85	1819313	0.02992
0.5	853.38	1301865	0.03302
0.6	902.39	1419097	0.03359
0.7	920.08	2381640	0.0329
0.8	918.60	4516371	0.03149
0.9	902.25	8354529.29	0.02954

Table 5 presents the forecasting error measures (MAD, MSE, MAPE) for the 2025 forecasting results across different smoothing parameter values (α). The results indicate that $\alpha = 0.2$produces the smallest MAD and MAPE values compared to other parameter settings, while the minimum MSE is obtained at a different αvalue. Despite this, $\alpha = 0.2$ is selected as the optimal smoothing parameter because it yields the lowest average absolute error (MAD) and relative error (MAPE), which are considered more representative indicators of forecasting accuracy. Consequently, for the 2025 forecasting period, $\alpha = 0.2$is regarded as providing the best smoothing performance.

The evaluation results further confirm that $\alpha = 0.2$ consistently produces the lowest MAD and MAPE values for both simulated and forecasting datasets. Based on this optimal parameter, the final estimated model components are obtained as follows:

$$a_{15} = 31080{,}48, b_{15} = 714{,}21$$

Accordingly, the forecasted number of unemployed individuals in Purbalingga Regency for 2025 is calculated as:

$$F_{2025} = 31080{,}48 + (714{,}21 \times 1) = 31794{,}69$$

3.5 Discussion

The forecasting results indicate that the number of unemployed individuals in Purbalingga Regency in 2025 is expected to remain relatively high and continue to rise. The projection obtained using the optimal smoothing parameter $\alpha = 0.2$ estimates that unemployment will reach approximately 31,794 individuals in 2025. This result reflects the persistent structural challenges in the regional labor market, particularly considering that the historical data from 2010–2024 exhibit fluctuations but generally follow an upward trend. The spike observed during the COVID-19 period (2020–2021) further illustrates how external economic shocks can significantly influence unemployment dynamics, reinforcing the importance of reliable forecasting models for anticipating labor market changes.

From a methodological perspective, the very low Mean Absolute Percentage Error (MAPE) values obtained in this study indicate that Brown's Double Exponential Smoothing (DES) method provides a highly accurate representation of the underlying data pattern. The fact that the optimal parameter $\alpha = 0.2$ consistently produces the smallest MAD and MAPE values across both simulation and forecasting datasets suggests that a relatively moderate smoothing level is most suitable for capturing the trend component in the unemployment series. A lower smoothing parameter allows the model to balance responsiveness to recent changes while maintaining stability in the estimated trend component, which is essential when modeling socio-economic indicators that evolve gradually over time.

The empirical results also confirm that unemployment data in Purbalingga Regency exhibit a non-seasonal time-series structure dominated by a trend component. In such conditions, Brown's DES model is particularly appropriate because it explicitly estimates both the level and trend components through a two-stage smoothing process. This capability enables the model to effectively capture long-term movements in the data without requiring additional seasonal adjustments. Consequently, the DES Brown approach is a practical and computationally efficient forecasting technique for regional economic indicators in which seasonal fluctuations are limited or absent.

Beyond methodological considerations, the forecasting outcomes carry important policy implications. The projected increase in unemployment suggests that local authorities may need to strengthen labor market interventions to prevent further joblessness. These interventions may include expanding employment opportunities through local economic development programs, improving vocational training and skills development initiatives, and supporting entrepreneurship and the creation of small-scale businesses. Accurate forecasting results such as those produced in this study can therefore serve as an important input for evidence-based policy planning, allowing regional governments to anticipate labor market pressures and design proactive strategies.

In addition, the forecasting model developed in this study can contribute to long-term labor market monitoring. By periodically updating the model with new data, policymakers and researchers can track changes in unemployment trends and evaluate the effectiveness of employment policies over time. Such continuous monitoring is particularly important in regions undergoing structural economic transformation or demographic change that may affect labor supply and demand.

Overall, the findings demonstrate that Brown's Double Exponential Smoothing (DES) method provides a reliable and accurate approach for forecasting unemployment in Purbalingga Regency. The model's ability to capture the data's trend structure and produce low forecast errors supports its applicability to regional economic analysis. Consequently, the use of DES

Brown not only contributes to methodological applications in time-series forecasting but also offers practical benefits for regional labor market planning and policy formulation.

3.6. Limitations and Future Research Directions

Despite the satisfactory forecasting performance demonstrated by Brown's Double Exponential Smoothing (DES) method in this study, several limitations should be acknowledged in order to properly interpret the findings and to provide directions for further research.

First, the present study employs only a single forecasting approach, namely the DES Brown method, without conducting a systematic comparison with alternative forecasting models. In time-series forecasting studies, model comparison is an important step to ensure that the selected method provides the most accurate and robust predictions among competing approaches. Methods such as Holt's linear trend model, Holt–Winters exponential smoothing, and the Autoregressive Integrated Moving Average (ARIMA) model are commonly used alternatives that may capture different characteristics of time-series data. Since this study does not include such comparative evaluations, the results should be interpreted as the best outcome within the DES Brown framework rather than the overall optimal forecasting model for unemployment data in Purbalingga Regency.

Second, the analysis is based on annual unemployment data covering 2010 to 2024, resulting in a relatively small number of observations. Limited data availability may restrict the model's ability to detect short-term fluctuations or abrupt structural changes in the labour market. This issue becomes particularly relevant when considering extraordinary economic shocks, such as the COVID-19 pandemic, which significantly altered employment conditions across many regions. With annual observations, the model captures only the general long-term trend and may not fully reflect temporary disruptions or rapid recovery phases that occur within shorter time intervals. In addition, the DES Brown model assumes a relatively stable, linear trend structure, which may not adequately capture non-linear dynamics or structural breaks that can arise in real-world economic systems.

Third, the forecasting model adopted in this study follows a univariate framework, meaning that predictions are generated solely from the historical values of the unemployment variable. While this approach is suitable for identifying temporal patterns in the data, it does not explicitly account for other economic or socio-demographic factors that may influence unemployment levels. Variables such as regional economic growth, investment activity, industrial development, population growth, education levels, and inflation rates may all play important roles in shaping labour market outcomes. The exclusion of these explanatory variables means that the forecasting results primarily reflect historical patterns rather than underlying causal relationships within the regional economy.

Given these limitations, several directions for future research can be proposed. First, subsequent studies are encouraged to conduct comparative forecasting analyses by applying multiple time-series models and evaluating their performance using standardized accuracy measures. Comparative studies involving exponential smoothing variants, ARIMA-based models, and modern machine-learning approaches such as Artificial Neural Networks (ANN), Support Vector Regression (SVR), or Long Short-Term Memory (LSTM) networks could provide deeper insights into the most suitable forecasting techniques for unemployment data.

Second, future research may benefit from utilizing higher-frequency data, such as quarterly or monthly observations, if available. Higher temporal resolution would enable the model to capture short-term dynamics, seasonal variations, and potential structural shifts more effectively. This improvement could enhance forecasting accuracy and provide more timely information for policy decision-making.

Third, future studies could extend the modelling framework by incorporating multivariate approaches. Integrating relevant macroeconomic and socio-economic indicators into the forecasting model would enable researchers to examine interactions between unemployment and other determinants of regional economic development. Multivariate time-series techniques, such as Vector Autoregression (VAR) or econometric regression-based forecasting models, may offer a more comprehensive understanding of the mechanisms driving unemployment dynamics.

Finally, future research could also explore hybrid modelling frameworks that combine statistical time-series methods with machine-learning techniques. Such hybrid models have the potential to capture both linear trend structures and complex non-linear patterns in economic data. By addressing these methodological extensions, future studies may produce more robust and informative unemployment forecasts that can further support evidence-based labour market policy formulation and regional economic planning.

4. CONCLUSION

This study aims to analyse data patterns and forecast the number of unemployed individuals in Purbalingga Regency using Brown's Double Exponential Smoothing (DES) method, based on time-series data from 2010 to 2024. The descriptive analysis indicates that unemployment in Purbalingga Regency fluctuated over time but generally exhibited an increasing trend, particularly in the post–COVID-19 period. The dominance of a trend component, with no strong seasonal pattern, supports the suitability of the DES Brown method for this analysis. The evaluation of smoothing parameters shows that alpha = 0.2 is optimal. This parameter consistently yields the lowest Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE) across both simulated and forecast data. The very low MAPE value (below 1%) demonstrates that the DES Brown method provides a high level of accuracy in modeling and forecasting unemployment in Purbalingga Regency. Based on the optimal parameter, the forecasting results indicate that the number of unemployed individuals in Purbalingga Regency in 2025 is projected to be approximately 31,795. This finding suggests that unemployment may persist and continue to pose a significant challenge for regional development. Therefore, the forecasting results of this study can serve as supporting evidence for regional labour policy planning, particularly for job creation initiatives, workforce skill development, and strengthening local economic sectors with high labour absorption capacity.

Overall, this study confirms that Brown's Double Exponential Smoothing method is an effective and straightforward forecasting tool for predicting labour market variables at the regional level. Nevertheless, the findings should be interpreted in light of the limitations related to data availability and methodological assumptions. Consequently, further research employing more comprehensive approaches is strongly recommended.

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