Forecasting the Poverty Rates Using Holt's Exponential Smoothing

Riza Prapascatama Agusdin, Sylvert Prian Tahalea, Vynska Amalia Permadi
Universitas Pembangunan Nasional Veteran Yogyakarta, Yogyakarta, Indonesia

Article Info

Article history:

Received January 09, 2023
Revised February 20, 2024
Accepted March 14, 2024

Keywords:

Forecasting
Holt's Exponential Smoothing
Poverty Rates

ABSTRACT

As a developing country with many provinces, Indonesia has a poverty problem that needs to be overcome. This research aimed to predict the poverty level in the Special Region of Yogyakarta using poverty data provided by the Central Statistics Agency for the Special Region of Yogyakarta. The method used in this research was Holt exponential smoothing to predict poverty levels in Yogyakarta City and four districts (Sleman, Bantul, Kulon Progo, and Gunungkidul) in this province. Three performances were measured to evaluate forecast results: sum squared error, mean squared error, and root mean squared error. The research results showed that the best configuration for the cities of Yogyakarta and Bantul is α, β = 0.9, 0.4; Kulon Progo and Gunungkidul are α, β = 0.9, 0.9; and Sleman are α, β = 0.9, 0.6. The forecasting results for 2022 to 2024, using a 95% confidence interval, showed that the poverty rate will increase in every city and district in the Special Region of Yogyakarta.

Corresponding Author:

Vynska Amalia Permadi, +6281237233005
Faculty of Industrial Engineering, Department of Informatics,
Universitas Pembangunan Nasional Veteran Yogyakarta, Yogyakarta, Indonesia,
Email: vynspermadi@upnyk.ac.id

How to Cite:
R. Agusdin, S. Tahalea, and V. Permadi, "Forecasting the Poverty Rates using Holts Exponential Smoothing", *MATRIK: Jurnal Manajemen, Teknik Informatika, dan Rekayasa Komputer*, Vol. 23, No. 2, pp. 431-440, Mar, 2024.

1. INTRODUCTION

Poverty is a financial and non-financial deficiency covering social, cultural, political, and mental aspects [1], and it became one of the United Nations' Sustainable Development Goals [2]. As one of the developing countries, Indonesia has overcome poverty through several economic policies [3]. However, Indonesia's poverty trend is increasing with the rising petroleum prices and natural problems that have occurred in recent years. Therefore, the Indonesian government seeks to reduce poverty rates by implementing policies to carry out regional development in an integrated and continuous manner [4]. However, data on the poor in each area is needed to implement these policies successfully. Inaccurate data will cause poverty reduction to be less effective [5]. To overcome this, a method is needed that can accurately forecast poverty rates so the government can make and implement policies properly.

Forecasting is a technique for predicting the data trend to determine what will happen in the future based on previous data for decision-making [6]. It will be evaluated later to explain its accuracy and benefits [7, 8]. From this explanation, forecasting is a tool for foreseeing what will happen in the future, so it can be used in various sectors, especially in forecasting poverty in an area [9].

Statistics Indonesia stated that the poverty rate in the Special Region of Yogyakarta as of March 2022 was 454,760, or around 11.34% of the total population of the Special Region of Yogyakarta [10]. The number of poor people in Yogyakarta has decreased by 0.57% from 11.91% to 11.34% in March 2022, which is a pretty good achievement seeing the trend in 2019 - 2020, the number of poor people in Yogyakarta has increased by 14%. In the future, it is necessary to forecast the poverty rate in Yogyakarta, especially for each city and regency so that the government can make the right decision.

The forecasting methods in this study are selected by considering several things; several methods are often used, including Box-Jenkins, regression, and exponential smoothing [11]. The exponential smoothing method is one of the simple time-series forecasting methods popularly used for univariate data and can be used for data that only has trends or even data with a seasonal component [12]. The exponential smoothing method is defined in [13] as producing a weighted average of previous observations, with weights adjusted exponentially as the observational data increases. In other words, the higher the associated weight, the newer the observation. Thus, it can be concluded that, although it has similar characteristics to the ARIMA Box-Jenkins method, which produces a prediction model by calculating weighted linear summation [14], the exponential smoothing method has a different perspective of determining the weight, namely by establishing a weighting whose value explicitly decreases exponentially in the last observational data [15]. The exponential smoothing method is further divided into several methods, namely single exponential smoothing, double exponential smoothing, and triple exponential smoothing [16, 17, 12].

Some studies apply exponential smoothing, including research conducted by Fachrurrazi [18], which predicts the sale of drugs at the Bintang Geurugok Drug store using the single exponential smoothing method, Aminudin and Handoko [19], who conducted poverty line forecasting in West Java Province using the Double Exponential Smoothing method from Holt with West Java poverty line data from 2005 to 2017. Anggraeni, Mariani, and Ariadhy [20] conducted a study that predicted the poverty line in Purbalingga Regency from 2021 to 2023 using Brown's one-parameter Linear Double Exponential Smoothing method.

Inspired by previous research, this research uses the Double Exponential Smoothing forecasting method to forecast poverty rates in every city and regency in the Special Region of Yogyakarta from 2022 to 2024. The results of these predictions are expected to help each policymaker determine the right policy to overcome poverty.

2. RESEARCH METHOD

This study uses a quantitative approach to determine the calculation model of double exponential smoothing forecasting with the best performance and the lowest error rate. In addition, there will also be a prediction of the poverty rates from 2022 to 2024 for five cities and regencies in the Special Region of Yogyakarta. The data used is in the form of data on the poverty rate of cities and regencies in the Special Region of Yogyakarta from 2004 to 2021. The data was taken through the Statistics Indonesia website, Special Region of Yogyakarta Branch.

The first stage of research conducted in this study was to plot the poverty rate in each city and regency in the Special Region of Yogyakarta, namely Yogyakarta City, Sleman Regency, Bantul Regency, Gunungkidul Regency, and Kulon Progo Regency to visualize the poverty rates from 2004 to 2021. The double exponential smoothing forecasting calculation model was chosen in this study because the simplest exponential smoothing method, namely Simple Exponential Smoothing (SES) or the nave method, is more suitable for forecasting data without a clear trend or seasonal pattern [21]. Furthermore, with one sample data, namely data on the poverty rate of Yogyakarta city, a double exponential smoothing method with Holt's exponential smoothing (ES) was implemented to identify the best combination of alpha (α) and beta (β) parameters that have error rate values smallest with parameter combination scenarios as shown in Table 1.

Holt's [22] is one of the developments of a simple exponential smoothing forecasting method that can be used on data with trend characteristics. This method calculates forecasting (Equation 1) by involving two smoothing variable equations, namely level

(Equation 2) and trend (Equation 3), where l_t is an estimate of the value of a level variable at a time; t, b_t is an estimate of the value of the trend variable (slope) in the time sequence; t, α is a smoothing parameter or a level variable with a range of values $0 \leq \alpha \leq 1$; and β^* is the smoothing parameter for a trend variable whose range of values $0 \leq \beta^* \leq 1$.

$$\hat{y}_{t+h|t} = l_t + hb_t \tag{1}$$

$$l_t = ay_t + (1-\alpha)(l_{t-1} + b_{t-1}) \tag{2}$$

$$b_t = \beta * (l_t - l_{t-1}) + (1 - \beta*)b_{t-1} \tag{3}$$

Table 1. The Scenario of Testing the Combination of Alpha and Beta Parameters on the Poverty Rate of Yogyakarta City

Double Exponential Smoothing using Holt's ES				
Parameters		Evaluation Matrix		
Alpha (α)	Beta (β)	SSE	MSE	RMSE
0.1	0.1			
0.1	0.3			
0.3	0.1			
0.3	0.3			
0.5	0.1			
0.5	0.3			
0.7	0.1			
0.7	0.3			
0.9	0.1			
0.9	0.3			

In Equation (2), it is shown that the l_t value is the weighted average of the y_t observations, which is the predicted value for time t and depends on the $l_{t-1} + b_{(t-1)}$. Whereas in Equation (3), it is shown that b_t is the weighted average of the trend estimated at a certain time (t) based on $l_{t-l} - l_{(t-1)}$ and b_t, which is the estimated value of the previous trend. Unlike the forecast equation on SES, Holt's linear method does not produce a flat forecasting function value because it considers the trend. Based on Equation 1, the estimated forecast result with Holt's method is a linear function of h obtained by summing the estimated value of the level with the value of h multiplied by the estimated value of the last trend [21].

To determine the forecasting model used in this research, the best combination of model parameters is evaluated by the error rate in the formation of exponential smoothing. The most commonly used model performance measurement matrix for statistical analysis, specifically for forecasting methods, is Root Mean Square Error (RMSE) (Equation 4), which is the square root of the mean squared error of the prediction value. However, before obtaining the RMSE value, it takes the Mean Squared Error (MSE) value, which is the average of the squared difference between the original value (y_i) and the prediction $(\hat{y})$ (Equation 5). The MSE value is also a derivative of Sum Squared Error (SSE), which is the squared difference between the original value $(\hat{y})$ and the prediction $(\hat{y})$ (Equation 6) [23].

$$RMSE = \sqrt{MSE} \tag{4}$$

$$MSE = \frac{SSE}{N} \tag{5}$$

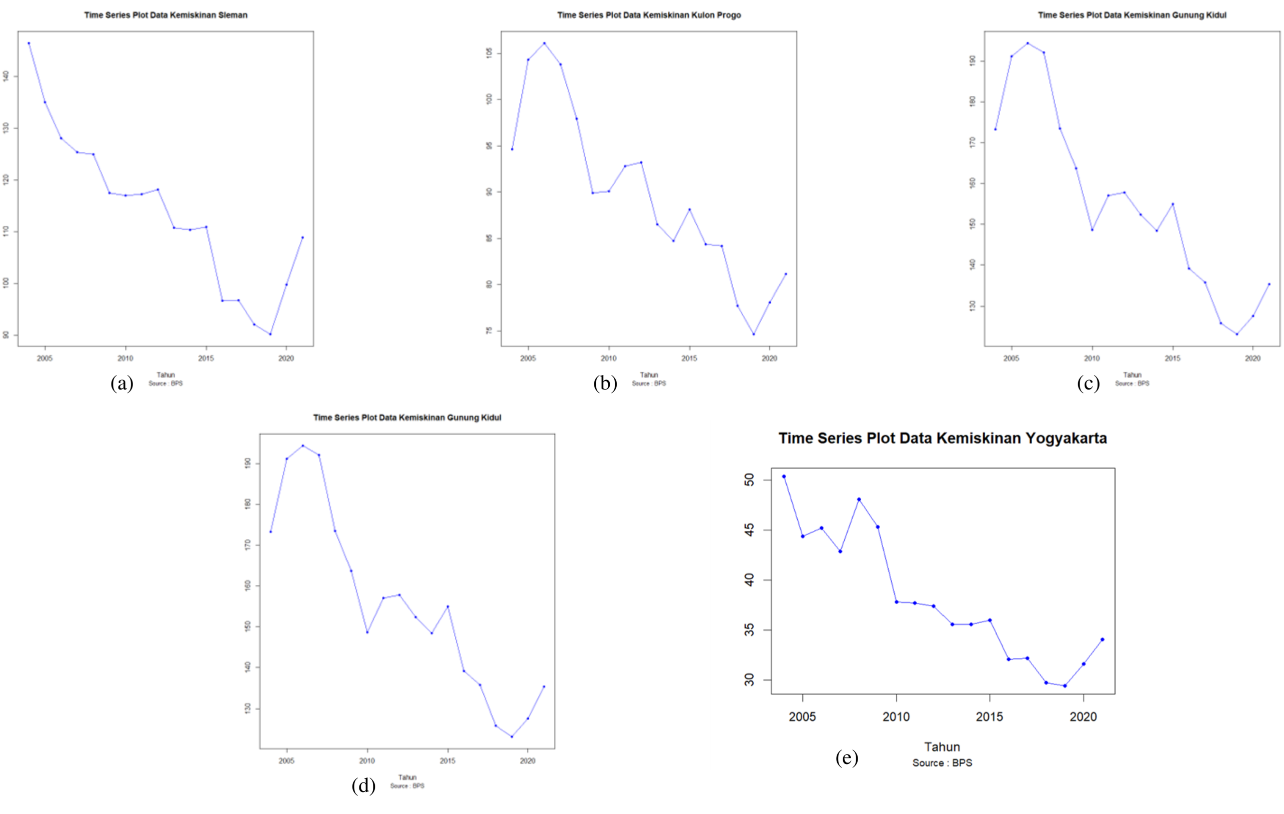
$$SSE = \sum_{i=1}^{N} (y_i - \hat{y})^2 \tag{6}$$

In addition to observing the three evaluation matrices, a plot or visualization of poverty rate data and exponential smoothing results was also made according to the parameters used to help conclude the best combination of parameters. Furthermore, the best-performing double exponential smoothing model will be used to predict the poverty rate for the next three years (2022-2024).

3. RESULT AND ANALYSIS

Implementation of Holt's ES visualization and modeling and error rate evaluation with three Evaluation matrices (SSE, MSE, and RMSE) in this study using RStudio tools and the R programming language. In all data plots in Figure 1, a downward trend in the poverty rate was identified, but there was also a trend of increasing the poverty rate in the range of 2020 to 2021 due to the COVID-19 pandemic.

The poverty rate data of Yogyakarta city was chosen as the first sample of time-series data will be analyzed for a combination of parameters using Holt's Double Exponential Smoothing method because this data has an obvious trend and the data fluctuations are quite small compared to other data. The poverty rate in Yogyakarta City has decreased relatively even though it has increased several times, with the number still below 5,000 people, as shown in Figure 1. However, the relatively small number of increases compared to other regencies cannot be justified as the local government's success in suppressing the poverty rate's growth, but rather because the number of people in the city of Yogyakarta is less than in other regencies.



(a) (b) (c) (d) (e)

Figure 1. Graph of city/ regency poverty rate in Yogyakarta Special Region Province 2004-2020 (unit: thousand inhabitants)

Model performance evaluation was carried out with various combinations of Alpha and Beta parameters using a data sample of Yogyakarta city to generate an Evaluation matrix, as shown in Table 2. From the RMSE value in the table, the Alpha parameter, which is the smoothing parameter for the level variable, gives the best result at a value of 0.9. In contrast, the Beta parameter, which is a smoothing parameter for the trend variable, shows a better RMSE result with a larger value of 0.3. Based on the time-series data, the trend direction is clearly seen to be decreasing. Therefore, it can be concluded that the smoothing parameter (β) is more dominant in determining the model.

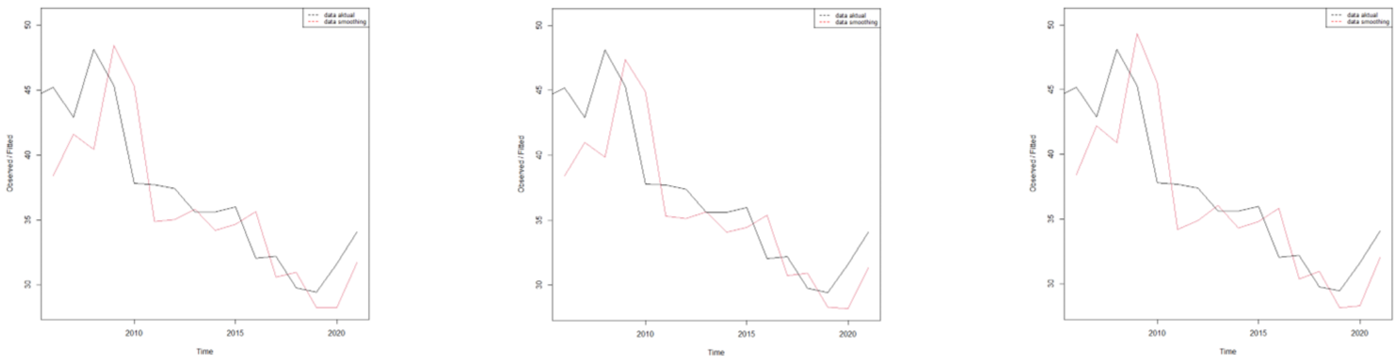
Table 2. Results of Testing the Combination of Alpha and Beta Parameters on Yogyakarta City Poverty Rate

Parameters		**Evaluation Matrices**		
Alpha (α)	**Beta** (β)	**SSE**	**MSE**	**RMSE**
0,1	0,1	8535.1682	474.17601	21.77558
0,1	0,3	3464.6818	192.4823	13.8738
0,3	0,1	1448.8676	80.492644	8.971769
0,3	0,3	568.5229	31.584606	5.620018
0,5	0,1	635.60241	35.311245	5.942327
0,5	0,3	331.19129	18.399516	4.289466
0,7	0,1	404.86228	22.49235	4.74261
0,7	0,3	256.16519	14.2314	3.772453
0,9	0,1	308.02086	17.11227	4.136698
0,9	0,3	224.15731	12.453184	3.528907

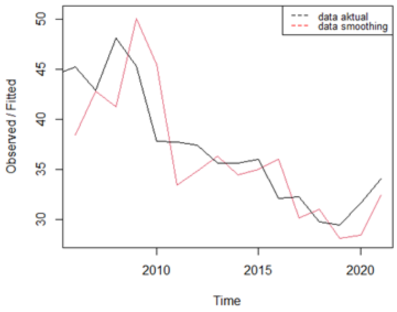
Table 3. Test Results of Beta Parameter Variations in Yogyakarta City Poverty Rate Data

Parameters		Evaluation Matrices		
Alpha (α)	Beta (β)	SSE	MSE	RMSE
0,9	**0,4**	**222.66215**	**12.370119**	**3.517118**
0,9	0,5	225.99084	12.55505	3.54331
0,9	0,6	231.70224	12.872347	3.587805
0,9	0,7	239.15297	13.286276	3.645034
0,9	0,8	248.39645	13.799803	3.714809

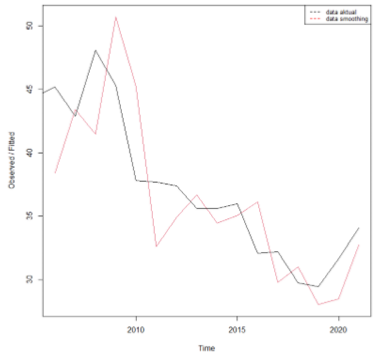
To confirm this, since the range of β is between 0 and 1, the next evaluation is carried out, namely, combining the Beta value = 0.4 to 0.8 with a constant Alpha value = 0.9. The test results are provided in the form of a performance evaluation with three evaluation matrices in Table 3. The combination of values α = 0.9 and β = 0.4 in Holt's model results in a decrease in error rate in the SSE, MSE, and RMSE compared to the combination of values α = 0.9 and β = 0.3 in Table 2. However, the error rate rises again, starting at the value of β = 0.5 to 0.8. To see the smoothing results formed with the corresponding parameter combinations in Table 3, a visualization of the results for each parameter combination is given in Figure 2.



(a) (b) (c)



(d)



(e)

Figure 2. The plot compares actual and smoothing data on Yogyakarta City poverty rates in 2004 -2020 with parameter combinations. (a) α, β = 0.9 and 0.4; (b) α, β = 0.9 and 0.5; (c) α, β = 0.9 and 0.6; (d) α, β = 0.9 and 0.7; and (e) α, β = 0.9 and 0.8.

From the results of implementing the double exponential smoothing method with Holt's on the time-series data on poverty rates in Yogyakarta city, the possible combination that produces a minimal error rate is α = 0.9 and β value between 0.3 and 0.9. So, the evaluation matrices for the test parameters used in Sleman, Gunungkidul, Kulon Progo, and Bantul regencies will only use a combination of these parameters. The results of testing variations in Beta parameters in the poverty rate data for the Sleman regency are given in Table 4. Like the smoothing results in the Yogyakarta city data, it is not always a large β value that gives the best smoothing results. In the poverty rate data in Sleman regency, after reaching the minimum error rate in the combination of variables α = 0.9 and β = 0.6. Furthermore, the error rate (RMSE value) of smoothing modeling will increase.

Table 4. Test Results of Beta Parameter Variations on Poverty Rate Data for Sleman Regency

Double Exponential Smoothing Method with Holt's ES				
Parameters		Evaluation Matrices		
Alpha (α)	Beta (β)	SSE	MSE	RMSE
0,9	0,3	732.39955	40.688864	6.378782
0,9	0,4	688.54546	38.252525	6.184863
0,9	0,5	664.29194	36.905108	6.074957
0,9	**0,6**	**654.1986**	**36.344366**	**6.028629**
0,9	0,7	657.14428	36.508016	6.042186
0,9	0,8	672.64098	37.368943	6.113014

Table 5. Test Results of Beta Parameter Variations in Poverty Rate Data for Gunungkidul Regency

Parameters		Evaluation Matrices		
Alpha (α)	Beta (β)	SSE	MSE	RMSE
0,9	0,3	615.54929	68.394366	8.270089
0,9	0,4	558.21776	31.012098	5.568851
0,9	0,5	524.70941	29.150523	5.399122
0,9	0,6	502.57386	27.92077	5.284011
0,9	0,7	486.63509	27.035283	5.199546
0,9	0,8	474.55169	26.363983	5.134587
0,9	**0,9**	**465.32198**	**25.85122**	**5.08441**

Table 6. Test Results of Beta Parameter Variations in Poverty Rate Data for Gunungkidul Regency

Parameters		Evaluation Matrices		
Alpha (α)	Beta (β)	SSE	MSE	RMSE
0,9	0,3	2554.7534	283.86149	16.84819
0,9	0,4	2312.2253	128.45696	11.33389
0,9	0,5	2152.9172	119.60651	10.93648
0,9	0,6	2039.4086	113.30048	10.64427
0,9	0,7	1960.6334	108.92408	10.43667
0,9	0,8	1914.0977	106.33876	10.31207
0,9	**0,9**	**1899.767**	**105.54261**	**10.27339**

With the same test scenario, the test results of the combination of Beta parameters for poverty rate data in Kulon Progo and Gunungkidul regencies are successively given in Table 5 and Table 6. The characteristics of the poverty rate data for these two regencies are almost similar in the evaluation results. Both only showed a minimum error rate in the combination of α, β = 0.9, and 0.9. Compared to other regency data, there is a very drastic downward trend in these two regency data, and there are fluctuations in several years as well. This more erratic trend certainly affects the smoothing results, so a minimum RMSE value is only obtained when the variables have the maximum value.

Table 7. Test Results of Beta Parameter Variations in Bantul Regency Poverty Rate Data

Parameters		Evaluation Matrices		
Alpha (α)	Beta (β)	SSE	MSE	RMSE
0,9	0,3	2098.1233	233.12481	15.26843
0,9	**0,4**	**2224.4121**	**123.57845**	**11.11658**
0,9	0,5	2349.4004	130.52224	11.42463
0,9	0,6	2478.9214	137.71785	11.73532
0,9	0,7	2620.0538	145.55855	12.06476
0,9	0,8	2780.3377	154.46321	12.42832

The last beta parameter variation test in this study was evaluated using the poverty rate data of the Bantul regencies; the results are given in Table 7. Alpha and Beta variable values with a minimum RMSE value are found in a combination of α = 0.9 and β = 0.4. Furthermore, at higher β values (ranging from 0.5 to 0.8), the RMSE value increases again. Here, it can be concluded that the best combination of parameters for smoothing the poverty rate data of the Bantul regencies is given in α, β = 0.9, and 0.4.

Table 8. Results of Forecasting Poverty Rate Data in City and Regencies in Special Region of Yogyakarta

City/ Regencies	**Forecasting Results**								
	2022			**2023**			**2024**		
	Point	**Lo 95**	**Hi 95**	**Point**	**Lo 95**	**Hi 95**	**Point**	**Lo 95**	**Hi 95**
Yogyakarta	34.86436	27.73276	41.99596	35.9287	24.4568	47.40061	36.99305	20.71174	53.27435
Sleman	115.7438	103.5776	127.91	123.2024	101.87301	144.5319	130.661	98.48607	162.836
Kulon Progo	84.49292	73.61929	95.36655	88.01234	66.4724	109.55227	91.53175	56.67758	126.38593
GunungKidul	142.4411	120.441	164.4413	150.0797	106.49888	193.6605	157.7183	87.19933	228.2372
Bantul	149.3666	125.5373	173.1958	152.7189	114.3871	191.0507	156.0712	101.6695	210.4729

After finding the best combination of smoothing parameters in various data on the poverty rate of a city and regencies in the Special Region of Yogyakarta, a short-term forecast (the next three years) was then carried out with the best model with the lowest error rate in each data. The forecasting results are the point estimate (Point) and interval estimate with a confidence interval of 95%. The forecasting results are given in Table 8. Because Holt's is a linear trend forecasting method and, in all data, has increased the number of poverty rates due to the COVID-19 pandemic, the forecasting results for the next three years in all cities and regencies in the Special Region of Yogyakarta will be increased.

4. CONCLUSION

By configuring some parameters, the poverty rates were forecasted using Holt's Exponential Smoothing. The result was evaluated using RMSE, MSE, and SSE as model performance measurements. The best parameters configuration is α = 0.9 for every region and β = 0.4 for Yogyakarta City and Bantul, β = 0.6 for Sleman, and β = 0.9 for Kulon Progo and Gunungkidul. The result shows that the best parameters configuration for Yogyakarta city is α = 0.9 and β =0.4 with SSE = 222.662150, MSE = 12.370119, and RMSE = 3.517118; the best parameters configuration for Sleman is α = 0.9 and β =0.6 with SSE = 654.198595, MSE= 36.344366, and RMSE = 6.028629; the best parameter configuration for Bantul is α = 0.9 and β = 0.4 with SSE = 2224.41210, MSE = 123.57845, and RMSE = 11.11658; the best parameter configuration for Kulon Progo is α = 0.9 and β = 0.9 with SSE = 465.32198, MSE = 25,85122, and RMSE = 5.08441; and the best parameter configuration for Gunungkidul is α = 0.9 and β = 0.9 with SSE = 1899.76701, MSE = 105.54261, and RMSE = 10.27339. Yogyakarta city, with the lowest RMSE value, shows a better-fit forecast model than other regencies, even though the difference in the number of inhabitants can also cause this.

The best parameter configuration of each city and regency used to forecast poverty rates for three years, from 2022 to 2024. The result shows increasing trends for all the cities and regencies using a confidence interval of 95%. Even though this research shows increasing trends in forecasting, it can give different results when using different configurations or forecasting models. The data used in this research was annual poverty rate data. Further research using monthly and seasonal data can bring new forecast results. Some forecast methods, like Bayesian Linear Regression or Bayesian Diffusion Modelling, can be applied to this data, which will bring different results and insight.

5. ACKNOWLEDGEMENTS

The Acknowledgments section is optional. Research sources can be included in this section.

6. DECLARATIONS

AUTHOR CONTIBUTION

The first author coordinated the research, including data collection and visualization. The second author was responsible for pattern analysis and forecasting. The third author served as the corresponding author and handled parameter testing to identify the best-fit model.

FUNDING STATEMENT

This research uses private funds from researchers.

COMPETING INTEREST

The authors declare no conflict of interest

REFERENCES

[1] S. Idrus and L. Rosida, "Poverty in Indonesia: Critical Review," *Archives of Business Research*, vol. 8, no. 6, pp. 127–132, Jun. 2020, number: 6. [Online]. Available: https://journals.scholarpublishing.org/index.php/ABR/article/view/8326

[2] C. Lakner, D. G. Mahler, M. Negre, and E. B. Prydz, "How much does reducing inequality matter for global poverty?" *The Journal of Economic Inequality*, vol. 20, no. 3, pp. 559–585, Sep. 2022. [Online]. Available: https://link.springer.com/10.1007/s10888-021-09510-w

[3] K. D. Hartomo, S. Yulianto, and A. Valentina, "A New Model of Poverty Index Prediction Using Triple Exponential Smoothing Method," in *2020 7th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE)*. Semarang, Indonesia: IEEE, Sep. 2020, pp. 76–79. [Online]. Available: https://ieeexplore.ieee.org/document/9239205/

[4] World Bank, *Indonesia Poverty Assessment - Pathways towards Economic Security*. World Bank, May 2023. [Online]. Available: http://elibrary.worldbank.org/doi/book/10.1596/39799

[5] G. Hurulle, S. Bamaramannage, and H. Galpaya, "Data for Poverty Measurement," *LIRNEasia*, Sep. 2023. [Online]. Available: https://lirneasia.net/2023/09/data-for-poverty-measurement

[6] F. Riandari, H. T. Sihotang, and H. Husain, "Forecasting the Number of Students in Multiple Linear Regressions," *MATRIK : Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 21, no. 2, pp. 249–256, Mar. 2022. [Online]. Available: https://journal.universitasbumigora.ac.id/index.php/matrik/article/view/1348

[7] D. Rajapaksha, C. Bergmeir, and R. J. Hyndman, "LoMEF: A framework to produce local explanations for global model time series forecasts," *International Journal of Forecasting*, vol. 39, no. 3, pp. 1424–1447, Jul. 2023. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0169207022000978

[8] A. Wanto, N. L. W. S. R. Ginantra, S. Hendraputra, I. O. Kirana, and A. R. Damanik, "Optimization of Performance Traditional Back-propagation with Cyclical Rule for Forecasting Model," *MATRIK : Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 22, no. 1, pp. 51–82, Nov. 2022, number: 1. [Online]. Available: https://journal.universitasbumigora.ac.id/index.php/matrik/article/view/1826

[9] V. N. Markova, K. I. Alekseeva, A. B. Neustroeva, and E. V. Potravnaya, "Analysis and Forecast of the Poverty Rate in the Arctic Zone of the Republic of Sakha (Yakutia)," *Studies on Russian Economic Development*, vol. 32, no. 4, pp. 415–423, Jul. 2021. [Online]. Available: https://link.springer.com/10.1134/S1075700721040109

[10] B. P. S. D. I. Yogyakarta, *Survei Sosial Ekonomi Nasional*, 2022.

[11] C. L. Karmaker, "Determination of Optimum Smoothing Constant of Single Exponential Smoothing Method: A Case Study," *International Journal of Research in Industrial Engineering*, no. Online First, Aug. 2017. [Online]. Available: https://doi.org/10.22105/riej.2017.49603

[12] P. Montero-Manso and R. J. Hyndman, "Principles and algorithms for forecasting groups of time series: Locality and globality," *International Journal of Forecasting*, vol. 37, no. 4, pp. 1632–1653, Oct. 2021. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0169207021000558

[13] R. J. Hyndman and G. Athanasopoulos, *Forecasting: principles and practice*, 1st ed. Lexington, Ky: Otexts, 2014.

[14] L. F. Laurente Blanco and R. W. Machaca Hancco, "Modelamiento y proyeccin de la demanda de turismo internacional en Puno-Per," *Revista Brasileira de Pesquisa em Turismo*, vol. 14, no. 1, pp. 34–55, Jan. 2020. [Online]. Available: https://rbtur.org.br/rbtur/article/view/1606

[15] A. S. Ahmar, F. Fitmayanti, and R. Ruliana, "Modeling of inflation cases in South Sulawesi Province using single exponential smoothing and double exponential smoothing methods," *Quality & Quantity*, vol. 56, no. 1, pp. 227–237, Feb. 2022. [Online]. Available: https://link.springer.com/10.1007/s11135-021-01132-8

[16] J. Vimala and A. Nugroho, "Forecasting Penjualan Obat Menggunakan Metode Single, Double, dan Triple Exponential Smoothing (Studi Kasus: Apotek Mandiri Medika)," *IT-Explore: Jurnal Penerapan Teknologi Informasi dan Komunikasi*, vol. 1, no. 2, pp. 90–99, Jun. 2022. [Online]. Available: https://ejournal.uksw.edu/itexplore/article/view/6289

[17] M. Mirdaolivia and A. Amelia, "Metode Exponential Smoothing untuk Forecasting Jumlah Penduduk Miskin di Kota Langsa," *JURNAL GAMMA-PI*, vol. 3, no. 1, pp. 47–52, Aug. 2021. [Online]. Available: https://ejurnalunsam.id/index.php/jgp/article/view/3771

[18] S. Fachrurrazi, "Peramalan Penjualan Obat Menggunakan Metode Single Exponential Smoothing pada Toko Obat Bintang Geurugok," *TECHSI - Jurnal Teknik Informatika*, vol. 7, no. 1, pp. 19–30, Mar. 2019, number: 1. [Online]. Available: https://ojs.unimal.ac.id/techsi/article/view/178

[19] R. Aminudin and Y. Handoko, "Model Peramalan Garis Kemiskinan Menggunakan Metode Double Exponential Smoothing dari Holt," *Jurnal Tata Kelola dan Kerangka Kerja Teknologi Informasi*, vol. 5, no. 1, Jan. 2019. [Online]. Available: https://ojs.unikom.ac.id/index.php/jtk3ti/article/view/2295

[20] D. Anggraeni, S. Maryani, and S. Ariadhy, "Peramalan Garis Kemiskinan di Kabupaten Purbalingga Tahun 2021-2023 dengan Metode Double Exponential Smoothing Linier Satu Parameter dari Brown," *Jurnal Ilmiah Matematika dan Pendidikan Matematika*, vol. 13, no. 2, p. 155, Dec. 2021. [Online]. Available: http://jos.unsoed.ac.id/index.php/jmp/article/view/4548

[21] R. J. Hyndman and G. Athanasopoulos, *Forecasting: principles and practice*, 2nd ed. Lexington, Ky.: Otexts, online, open-access textbook, 2018.

[22] I. Djakaria and S. E. Saleh, "Covid-19 forecast using Holt-Winters exponential smoothing," *Journal of Physics: Conference Series*, vol. 1882, no. 1, p. 012033, May 2021. [Online]. Available: https://iopscience.iop.org/article/10.1088/1742-6596/1882/1/012033

[23] P. C. Bruce and A. Bruce, *Practical statistics for data scientists: 50 essential concepts*, first edition ed. Sebastopol, CA: O'Reilly, 2017, oCLC: ocn936003166.