

Integration of Double Exponential Smoothing Damped Trend with Metaheuristic Methods to Optimize Forecasting Rupiah Exchange Rate against USD during COVID-19 Pandemic

Maftahatul Hakimah, Muchamad Kurniawan*

Informatics Engineering Department
Institut Teknologi Adhi Tama Surabaya
Surabaya, Indonesia

*Correspondence: muchamad.kurniawan@itats.ac.id

Abstract-COVID-19 pandemic has brought great changes to the stability of the Indonesian state. The disease not only has an impact on public health but also has the effect of weakening the economic sector. One indicator is the weakening of the rupiah exchange rate against the USD. When the pandemic emerged, the rupiah exchange rate started to weaken, which may encourage investors to reduce investment in Indonesia. Therefore, it is necessary to predict the rupiah exchange rate during the COVID-19 pandemic for the coming period. This study applies the Double Exponential Smoothing forecasting method by adding a damped trend factor. The calculation of the parameters of the method becomes the research optimization problem. This optimization problem is then solved using metaheuristic methods, namely Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The performance of the forecasting model is measured based on the magnitude of the forecast error. This study shows that the PSO algorithm is better at obtaining the optimal parameters for predicting the rupiah exchange rate in the coming period compared to GA. The integration error rate of Double Exponential Smoothing damped trend with PSO is 0.70%, while the error rate for the same method with GA is 0.72%. Thus, the integrated performance of double exponential smoothing with metaheuristic optimization is a more excellent method in predicting the rupiah exchange rate against the USD during the period of the Coronavirus outbreak. Furthermore, the addition of a trend dampening factor to the DES method also significantly increases the forecast accuracy.

Keywords: double_exponential smoothing; genetic_algorithm; metaheuristic; particle_swarm_optimization; covid-19

Article info: submitted Jan 13th, 2020, revised: April 10, 2020, accepted June 19, 2020

1. Introduction

The Indonesian economy is affected by the emergence of the COVID-19 that began to plague in early 2020. The exchange rate of the rupiah against the USD is a major indicator of the economy in Indonesia. In January 2020 the rupiah strengthened to the level of Rp. 13,612, -. This month, Indonesia has not had the impact of the COVID-19 outbreak. However, the rupiah exchange rate against the USD began to weaken in February 2020 until March reached a value of Rp. 16,000, -. Along with the weakening of the rupiah exchange rate against the USD, the Government announced the COVID-19 pandemic in Indonesia. The ferocity of the COVID-19 greatly affects the level of investment decisions of some investors so that it has a very significant impact on the capital market [1]. All sectors of the economy experienced weakness. Looking

at the data on the rupiah exchange rate against the USD on the official website of Bank Indonesia, transactions experienced a quite high jump. With this condition, stakeholders must be able to understand the trend pattern of the rupiah exchange rate that occurred during the Pandemic. From the uncertainty of the rupiah exchange rate against the USD during the COVID-19 pandemic, it is necessary to predict the rupiah exchange rate for the coming period. The prediction only takes into account the pattern of the rupiah exchange rate against the USD in January to April 2020.

The forecasting method that can be applied to problems that contain trends is double exponential smoothing (DES). The DES method has two parameters that affect the accuracy of forecasting, namely the data smoothing parameter and the trend smoothing parameter. The values of these two Holt parameters must

be optimized so that the combination of the two can minimize forecasting errors [2]. There are no specific rules for getting the two optimal DES parameters. Generally, parameters are selected based on predictor intuition or by way of “trials” [3]. Zuhaimy Ismail, et al applied the Genetic Algorithm (GA) to estimate parameters from DES. The results of his research show that DES with parameter optimization using GA can improve forecasting accuracy on the Kuala Lumpur Composite Index and the daily Ringgit exchange rate against USD. In Nazim’s research, the best value of the two smoothing parameters was searched using the “solver” in Microsoft Excel [4]. Meanwhile, Ortiz optimized the DES parameters with the Particle Swarm Optimization (PSO) algorithm for forecasting the Philippine Peso exchange rate against other countries’ currencies [5]. The results showed that PSO was able to improve forecasting precision. On the other hand, Eusebio took a metaheuristic approach including GA, PSO and Simulated Annealing to optimize the parameters of the Holt-Winters method in predicting short term load forecasts [6]. His research concluded that the calculation of parameter optimization using an evolutionary approach is a fast and simple method of considering a large number of possible combinations for parameter values.

Based on some of the studies above, this study aims to predict the middle rupiah exchange rate against USD at the time of the COVID-19 outbreak using the DES forecasting method. and optimize its parameters using metaheuristic methods. The metaheuristic methods used are population-based, namely GA and PSO. However, another problem is the DES forecasting formula for the next period in the form of linear trend where the movement cannot be stopped. Therefore, the DES method in this study added a trend reduction factor (DES_{DT}). The trend damping factor is the same as the 2 parameters in DES which must be chosen so as to increase the accuracy of the forecast. So that GA and PSO performance will be measured in obtaining 3 parameters, namely the data smoothing parameter, the trend smoothing parameter and the damping factor. Next, the comparative GA and PSO performance is measured based on the magnitude of the forecast error obtained. The results of this study are expected to be a recommendation for a method to build a forecasting system for the rupiah exchange rate against the USD.

2. Theory

a. Double Exponential Smoothing Damped Trend

The results of forecasting the Holt’s Linear method or in this study are called double exponential smoothing, showing an indefinite constant trend into the future. This method tends to make excessive predictions especially for forecasting with long horizons [7]. DES forecast forecasting with a damping factor is calculated using the following recursive scheme [8], equation (1).

$$\begin{aligned} \hat{y}_{t+h|t} &= \ell_t + \sum_{j=1}^h \delta^j b_t \\ \ell_t &= \alpha y_t + (1-\alpha)(\ell_{t-1} + \delta b_{t-1}) \\ \ell_t &= \hat{a}(\ell_t - \ell_{t-1}) + (1-\hat{a})\delta b_{t-1} \end{aligned} \quad (1)$$

Where, $\hat{y}_{t+h|t}$ forecast value h the next period of t and y_t the actual value of the data. Estimated level for the period t , ℓ_t , greatly influenced by smoothing parameters α . Meanwhile, the trend estimates for the period t , b_t , greatly influenced by smoothing parameters β . The δ parameters is a trend dampening factor that indicates how quickly the local trend is damped. The α , β and δ parameters values range from 0 to 1. Apart from being influenced by the selection of the three parameters, the initial value for ℓ_t and b_t should also be considered [9]. This study adopted research [10] where the initial value was given ℓ_0 and b_0 , the *intercept* and *slope* values of the regression equation for the first one month of the dataset.

Metaheuristic Optimization

Metaheuristic optimization method is an optimization method that is able to handle complex and large-sized problems and produce satisfactory solutions in a reasonable time [11]. Metaheuristic methods explore the search space to find solutions that are close to optimal solutions. Metaheuristic algorithms incorporate mechanisms so as not to get trapped in the local search space [12]. There are 2 ways to solve optimization problems using metaheuristic methods, namely single solution-based metaheuristics and population-based metaheuristics. Single solution-based metaheuristics work iteratively through the search path, moving from the newest solution to the nearest neighbor in the search space. Meanwhile, population-based metaheuristics work iteratively in a population of solutions. First, the solution population is initialized, then a new solution population is sought. Then a selection procedure is applied to determine the most recent solution population. The iteration process stops until the criteria stop being met. This study uses a metaheuristic optimization method based on population.

b. Genetic Algorithm

Genetic Algorithm (GA) is a search technique adopted from the process of natural evolution. The computation process that occurs in this algorithm is analogous to the process of selecting living things in a population. Therefore, the search process in genetic algorithms is carried out at once for a number of possible solutions to problems [13]. The basic structure of GA is:

1. population initialization
2. population evaluation
3. population selection that will be subject to genetic operators
4. the process of crossing certain chromosome pairs
5. certain chromosome mutation processes

6. evaluation of the new population
7. Repeat from Step 3 until the stop conditions are met

Genetic Algorithm has characteristics in finding optimal solutions. GA tends to converge relatively long but is able to find solutions in a wide solution space [14].

c. Particle Swarm Optimization

Particle swarm optimization (PSO) is a population-based metaheuristic method that mimics the social behavior of living things such as flocks of birds, fish to find places that have enough food. The basic principle of the PSO algorithm, a swarm consisting of N flying particles represented by the vector x_i in the decision space. Every particle has a position and a velocity. Optimization takes advantage of cooperation between particles. The success of some particles will affect the behavior of other particles. Each particle adjusts its position towards the global (optimum) solution according to the following 2 factors: $pbest$ (the best solution so far achieved by several particles) and $gbest$ (the best solution achieved by all particles) [11]. The iteration process is carried out to update the position and velocity of the particles. Equation (2) is a mathematical equation used for the PSO iteration algorithm:

$$\begin{aligned} v[t,d] &= U(-1,1) * c_1 (pbest[d] - X[t-1,d]) + U(-1,1) * c_2 (gbest[d] - X[t-1,d]) \\ X[t,d] &= X[t-1] + v[t,d] \end{aligned} \quad (2)$$

In Equation (2), $U(-1,1)$ is a number generated randomly from -1 to 1 that is uniformly distributed. The coefficients c_1 and c_2 are the parameters defined by the researcher that push the particles towards $pbest$ and $gbest$ [5]. The PSO algorithm converges very quickly but it is still likely to be trapped in the local optimal solution because it cannot find a new solution space [14].

d. Evaluation of Forecasting Models

Evaluation of the performance of the DESDT forecasting model is carried out to determine the level of forecasting errors. The measurement of forecast error uses the following mean absolute percentage error (MAPE) formula, equation (3).

$$MAPE = \frac{1}{n} \sum \frac{|y_t - \hat{y}_t|}{y_t} \times 100 \quad (3)$$

The smaller the MAPE value, the better the forecasting accuracy and vice versa. Forecasting accuracy is very good if the MAPE value is below 10, whereas if the value is in the interval [10 - 20] then the forecasting is said to be good [15].

For algorithm comparisons, forecast error is also measured in the error formula, equation (4) [16].

$$\begin{aligned} \text{Mean Absolute Deviation} &: MAD = \frac{1}{n} \sum_{t=1}^n |y_t - \hat{y}_t| \\ \text{Mean Square Error} &: MSE = \frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2 \\ \text{Sum Square Error} &: SSE = \sum_{t=1}^n (y_t - \hat{y}_t)^2 \end{aligned} \quad (4)$$

with, \hat{y}_t is the forecast value for period t while y_t is the actual value of data for period t .

3. Method

The following are the stages of integration of DESDT with the metaheuristic method:

Stage 1. Data Preparation. The data used are daily data on the mean value of the rupiah exchange rate against USD for the period January 2 - April 30, 2020. This data is secondary data downloaded from the official website bi.go.id.

Stage 2. Divide the dataset. The dataset used in this study will be divided into 2 segments, namely training data and testing data. The best parameters from DESDT are obtained from the training process, while the testing process aims to measure the performance of PSO and GA in getting the best parameters.

Stage 3. Compile the parameter optimization model formulation. The parameter selection of the DESDT method is an optimization problem. So in this step it is important to determine the objective functions and constraints in accordance with the objectives of this study.

Stage 4. The training stage is to solve the parameter optimization problem using population-based metaheuristic methods. This solution will produce the best parameters for DESDT.

Stage 5. Testing phase. This stage is the forecasting stage for the next (daily) period. The best parameters obtained at the training stage are input at this testing stage.

Stage 6. DESDT integration performance measurement with metaheuristics. DESDT integration performance with metaheuristics is measured based on equation (3) - (4). From these performance measurements, GA and PSO can also be compared in finding optimal solutions.

a. Research data

The research data used in this study is secondary data downloaded from the official website of Bank Indonesia from January to May 2020. The features available in the data are the selling rate and the buying rate. In this research, the observed rupiah exchange rate is the middle rupiah exchange rate against the USD. The middle rate is the rate between the sell rate and the buy rate. The middle rate is calculated based on the number of selling and buying rates divided by two [17]. The rupiah middle rate is presented in Figure 1.

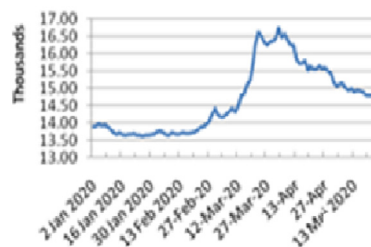


Figure 1. Graph of the rupiah exchange rate against USD January - May 2020

The rupiah transaction against the USD was seen to have strengthened in January and was relatively stable until February 2020. A hike in the trend in the exchange rate began to appear in March. In March Indonesia experienced the COVID-19 pandemic condition. The rupiah continued to weaken until early April. After two weeks, the rupiah exchange rate seems to have begun to strengthen again until early June 2020. In accordance with the research objectives, to test the DESDT integration with metaheuristic optimization, the rupiah middle exchange rate dataset is divided into two parts given in Table 1 below.

Table 1. Distribution of the dataset

Data Set	Period	Lots of Data
Training data	January 2 - April 30, 2020	84 days
Testing data	May 4 - May 29, 2020	16 days

The training data sample was taken until April 30 because during that period the rupiah exchange rate graph began to strengthen again. Here the integration performance of DESDT with metaheuristics is tested whether it can produce forecasts with small errors. Linear trends in training data are presented in Figure 2 below.

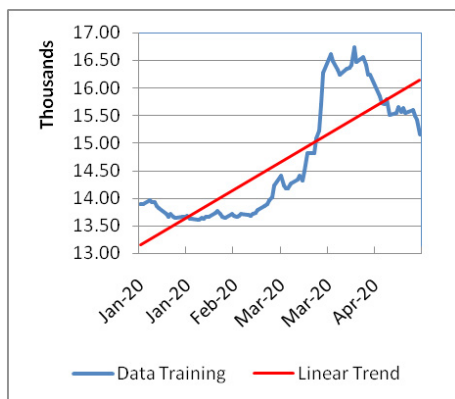


Figure 2. Linear trends in training data

The training data is processed using Equation (1) to obtain optimal DESDT parameters using GA and PSO. This stage is called the training stage. The output from the next training stage is used to predict the next period. This forecasting process is a testing phase. The results of forecasting the DESDT method with GA and PSO will be compared with testing data. The magnitude of forecasting errors is the difference between forecasting results with testing data. This forecasting error is measured based on Equation (3) - (4)

b. Parameter Optimization Model Formulation

The training phase begins with compiling a parameter optimization model. The parameter optimization problem

here is to get the best value from the DESDT parameter so that the forecast results are close to the actual value. So that the functional cost in this study is the magnitude of the training data forecasting error. While the limitation of this optimization problem is the forecasting formula of the DESDT method. The following is the formulation of the parameter optimization model:

Minimization Equation (3)
 Subject to (5)
 - Equation (1)
 - $0 \leq \alpha, \beta, \check{o} \leq 1$

The parameter optimization problem (5) will be solved using the GA and PSO metaheuristic methods which are implemented in the MATLAB program.

2. Results and Discussion

The results of this study describe the performance of the GA and PSO methods at the training and testing stages

a. Results of the Training Stage

The result of the training stage is the solution to Equation (5), namely the smoothing parameter values α , and the damping factor \check{o} that minimizes forecast errors. Because the metaheuristic method is a stochastic method, the optimal value of the three parameters is carried out up to 10 times running the program. The test results are summarized in Table 2.

Table 2. Training Results

Cost Function	MAPE (%)	α	β	\check{o}	
GA	Worst MAPE	0.619163	0.992003	0.875853	0.431585
	Best MAPE	0.612822	0.907839	0.910162	0.481209
	Mean MAPE	0.615051			
PSO	Worst MAPE	0.625930	0.997737	0.219646	0.493563
	Best MAPE	0.612380	0.867514	0.993331	0.503997
	Mean MAPE	0.615291			

The DESDT parameter optimization has been carried out by GA and PSO. The comparison of the results of the GA and PSO training methods to find the best DESDT parameters is shown in Table 2. In the 10 times running the program, overall GA is better than PSO shown by Mean MAPE with a very small difference of 0.0002%. MAPE PSO is smaller than Best MAPE GA. DESDT parameters taken at the training stage here are a combination of parameters with Best MAPE. The matching of the forecasting result curve at the training stage with the actual data on the rupiah exchange rate against the USD for Worst MAPE and Best MAPE is presented in Figures 3 and 4 below.

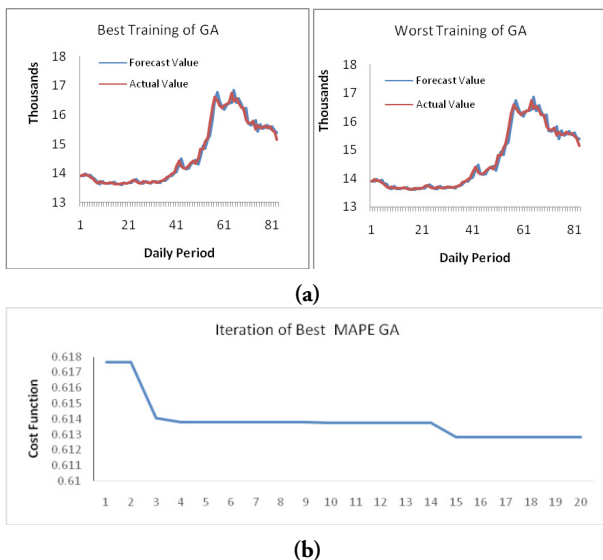


Figure 3. Graphic matching curve for the training stage and GA iteration on Best MAPE

Matching the curve of Figure 3a shows that the parameters produced by GA for both Best MAPE and Worst MAPE are very good with an average error of 0.61%. Figure 3c. is an iteration of GA to get optimal parameters for Best MAPE. It can be seen in iteration 15, GA begins to converge on the best solution. Meanwhile, a graph comparing the results of DESDT and PSO forecasting with actual data is presented below:

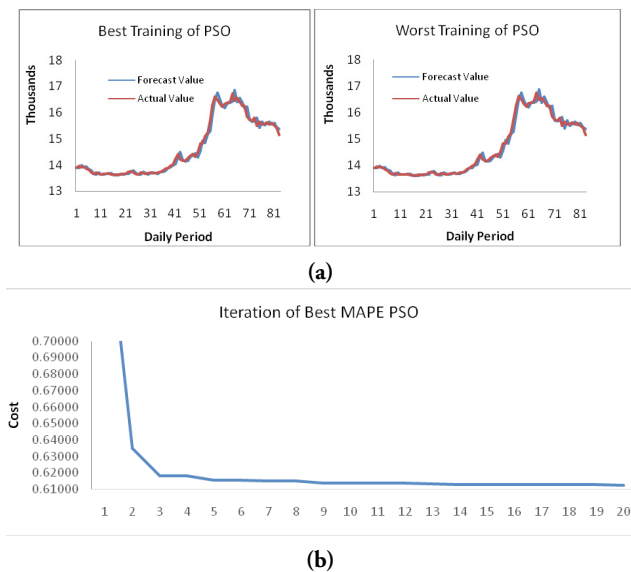


Figure 4. Graph of PSO training and iteration stage matching curve at Best MAPE

Figure 4a. shows that the training results from the PSO algorithm provide forecasting results that match the actual data well. Meanwhile, Figure 4b is the PSO iteration

to get the optimal solution with Best MAPE. The PSO algorithm begins to converge to the optimal solution at the 14th iteration. The search for optimal solutions for the GA and PSO methods is limited to 20 iterations.

The optimal parameters with Best MAPE obtained by each GA and PSO method then become input in the forecasting process for May 2020

b. Testing Phase Results

The integration of the DESDT method with GA (DESDTGA) and DESDT with PSO (DESDT PSO) is measured for its performance based on the forecast error for May 2020. Forecasting errors in the testing phase are the difference between the forecasting results of the DESDTGA and DESDT PSO methods with testing data. The matching of the forecasting result curve for DES integration with Metaheuristics is given in Figure (5).

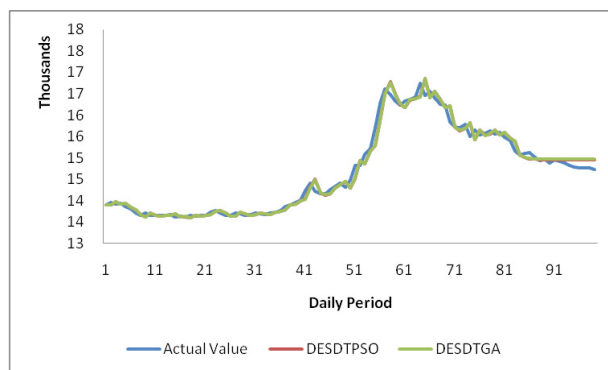


Figure 5. Matching curve forecasting result of DES integration with metaheuristics to actual data

The forecast period starts at the 85th period of the data set. The DESDT PSO forecast curve is closer to the actual data. As a comparison of the two methods, the measurement of forecast error is not only based on MAPE but is also measured based on Equation (4). Measurement errors for the DESDTGA and DESDT PSO methods and their competing methods are summarized in Table 3.

DESDT PSO method performs better than DESDTGA in all forecast error measurements. For DESDT PSO, the average forecast error against the actual data is IDR 105,119 which is shown in the MAD measurement. MAPE measurement shows the average forecast error ratio to actual data in each period of 0.7%. The integration of the DESDT method with the metaheuristic method both provides better forecasting than the Solver program. Whereas in the 4th method, the DES method is given to determine the effect of the damping factor on the forecasting results. It turns out that all types of forecast error measurements show that the damping factor can improve the DES forecasting results.

Table 3. Results of Measurement Error Forecasting Methods

Methods	α^*	β^*	δ^*	MAPE	MAD	MSE	SSE
DESDTGA	0.907839	0.910162	0.481209	0.723373	108.3304915	17729.467	283671.47
DESDTPSO	0.867514	0.993331	0.503997	0.706112	105.1197506	16635.617	282805.491
DESDT + Solver	0.972602	0.729724	0.449050	0.876080	129.956134	24579.494	393271.91
DES + Solver	0.947969	0.311962	-	4.546026	674.582524	607932.83	9726925.415

3. Conclusion

Calculation of optimal parameters from the DESDT method is important to improve forecast accuracy. Through the metaheuristic approach, the optimal parameters of the DESDT forecasting method are obtained quickly and simply because the combinations of the three parameters are very abundant. Based on the results of the testing phase, the optimal solution of the PSO method provides a forecast error of 0.017% smaller than the GA method. The DESDTPSO method's forecasting error is 0.706% with optimal parameters for DESDT are $\alpha^*=0.867514$, $\beta^*=0.993331$ and $\delta^* = 0.503997$.

It is necessary to understand the trend pattern of the rupiah exchange rate against the USD at the time of the Corona outbreak. Thus, future investment planning can be designed properly. The DES forecasting method was chosen as a consideration for the trend pattern in the rupiah exchange rate against the USD by adding a dampening factor. The measurement of forecast errors using the DES method with DESDT shows that the addition of trend dampening factors can significantly improve the forecast results of the rupiah exchange rate against the USD. Therefore, the integration of the DESDT method with metaheuristics can be recommended for the construction of a forecasting system for the rupiah exchange rate against the USD.

Forecasting the rupiah exchange rate in this study only considering historical data patterns during the Corona pandemic without considering the influence of the Indonesian Government's efforts to reduce the adverse effects of Corona. Related research should add the factors that influence the fluctuation of the rupiah exchange rate so that it becomes a better prediction.

Reference

- [1] C. I. Burhanuddin and M. N. Abdi, "AkMen AkMen," *Krisis, Ancaman Glob. Ekon. Dampak, Dari*, vol. 17, pp. 710–718, 2020.
- [2] E. Lesmana *et al.*, "Comparison of Double Exponential Smoothing Holt and Fuzzy Time Series Methods in Forecasting Stock Prices (Case Study : PT Bank Central Asia Tbk)," pp. 1615–1625, 2019.
- [3] Z. Ismail and F. F. Yeng, "Genetic algorithm for parameter estimation in double exponential smoothing," *Aust. J. Basic Appl. Sci.*, vol. 5, no. 7, pp. 1174–1180, 2011.
- [4] A. N. Aimran and A. Afthanorhan, "A comparison between single exponential smoothing (SES), double exponential smoothing (DES), holt (brown) and adaptive response rate exponential smoothing (ARRES) techniques in forecasting Malaysia population," *Glob. J. Math. Anal.*, vol. 2, no. 4, p. 276, 2014.
- [5] R. R. L. Ortiz, "The Accuracy Rate of Holt-Winters Model with Particle Swarm Optimization in Forecasting Exchange Rates," *J. Comput.*, vol. 11, no. 3, pp. 216–224, 2016.
- [6] E. Eusébio, C. Camus, and C. Curvelo, "Metaheuristic approach to the holt-winters optimal short term load forecast," *Renew. Energy Power Qual. J.*, vol. 1, no. 13, pp. 708–713, 2015.
- [7] R. J. Hyndman and G. Athanasopoulos, *Forecasting : Principles and Practice*, 2nd ed. Melbourne, Australia: OTexts, 2018.
- [8] R. Crevits and C. Croux, *Forecasting using robust exponential smoothing with damped trend and seasonal components.*
- [9] D. C. Montgomery, C. L. Jennings, and M. Kulahci, *Introduction to Time Series Analysis and Forecasting*. Hoboken, New Jersey: John Wiley & Sons, Inc., 2008.
- [10] M. Hakimah, W. M. Rahmawati, and A. Y. Afandi, "PENGUKURAN KINERJA METODE PERAMALAN TIPE EXPONENTIAL SMOOTHING DALAM PARAMETER TERBAIKNYA," vol. 5, no. 1, pp. 44–50, 2020.
- [11] E.-G. Talbi, *Metaheuristics From Design To Implementation*. New Jersey: John Wiley & Sons, Inc., 2009.
- [12] C. Blum and A. Roli, "Metaheuristics in Combinatorial Optimization: Overview and Conceptual Comparison," *ACM Comput. Surv.*, vol. 35, no. 3, pp. 268–308, 2003.
- [13] Z. Zuhri, *Algoritma Genetika*. Yogyakarta: C.V ANDI OFFSET, 2014.
- [14] M. Kurniawan and N. Suciati, "Premise Parameter Optimization on Adaptive Network Based Fuzzy Inference System Using Modification Hybrid Particle Swarm Optimization and Genetic Algorithm," *IPTEK*, vol. 22 Nomer 2, pp. 27–34, 2018.
- [15] J. J. Montaña Moreno, A. Palmer Pol, A. Sesé Abad,

- and B. Cajal Blasco, "El índice R-MAPE como medida resistente del ajuste en la previsión," *Psicothema*, vol. 25, no. 4, pp. 500–506, 2013.
- [16] L. T. Zhao, Y. Wang, S. Q. Guo, and G. R. Zeng, "A novel method based on numerical fitting for oil price trend forecasting," *Appl. Energy*, vol. 220, no. March, pp. 154–163, 2018.
- [17] A. Kosasih, "Memahami Kurs Tengah Bank Indonesia, Apa dan Bagaimana?" *PT Mid Solusi Nusantara*, 2018. [Online]. Available: <https://klikpajak.id/blog/tips-pajak/kurs-tengah-bank-indonesia/>. [Accessed: 01-Jun-2020].