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# Combined EEMD and ANN improved by GA for tourist visit forecasting

**Muhammad Latif[1], Sri Herawati[2]**
[1]Department of Mechatronics Engineering, University of Trunojoyo Madura, Bangkalan, Indonesia
[2]Department of Information Systems, University of Trunojoyo Madura, Bangkalan, Indonesia

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**ABSTRACT**

This study has proposed forecasting tourist visits use an ensemble empirical mode decomposition (EEMD) and optimized artificial neural networks (ANN) using genetic algorithms (GA). The data used is monthly data on tourist visits in Sumenep Regency. The data was obtained from the Sumenep district government from January 2015 to December 2019. EEMD algorithm breaks down tourist visit data into several intrinsic mode function (IMF) and residues. Then, EEMD results was normalized and then learned using ANN. GA is used to optimize weight and bias of the ANN. Experiments carried out to analyze performance in forecast results of proposed method compared with the EEMD-ANN without optimization of the GA. The experimental results show that the proposed method has better performance, namely the error value is reduced by 37%, 21% for MSE, RMSE, respectively.



***Corresponding Author:***

Muhammad Latif
Department of Mechantronics Engineering, Universitas of Trunojoyo Madura
Jl. Raya Telang PO BOX 2 Kamal, Bangkalan, Indonesia
Email: latif.utm@gmail.com

## 1. INTRODUCTION

Madura is one of the islands in East Java and has four districts, namely: Bangkalan, Sampang, Pamekasan, and Sumenep. Tourist spots in Madura are attractive for tourists. These areas consist of natural tourism, religious tourism, and culinary tourism. One of the religious tourism spots in Sumenep is Asta Tinggi. Asta Tinggi is a burial place for the kings of the Sumenep kingdom which was founded in 1644. This tourist spot is located in the village of Kebon Agung, the sub-district of Sumenep city. In addition, Sumenep has Gili Labak Island, which is a new natural tourist attraction which became famous in mid-2014. This island has underwater beauty and white sand which is very attractive to tourists. In 2019, data from the Sumenep government showed that the number of tourist visits was 840,950, consisting of 839,398 domestic tourists and 1,507 foreign tourists. Increased tourist visits are an important source of economic development [1]-[3], employment [4] and government revenues [5]. Forecasting tourist visits is necessary for planning and future decision making. Therefore, accurate forecasting is very important for related agencies and industries in the tourism sector, such as: hospitality [6] and transportation to monitor and anticipate trends in demand for tourist visits. In addition, this forecasting will also help planning new business opportunities in travel [7].

Forecasting tourist visits has been carried out by several previous studies, such as: forecasting uses the empirical mode decomposition (EMD) method which is integrated with artificial neural networks (ANN) [8]. Most of the fluctuation in tourist visits tends to be non-linear which is influenced by several factors, such as: economic, seasonal and political conditions. EMD can accommodate the fluctuation and complexity of these factors [9]. The EMD, which has been recently revisited in [10], has been applied to many different application fields [11], [12]. However, EMD often produces mixed mode which sometimes does not match the data pattern. This is a weakness of EMD. Ensemble empirical mode decomposition (EEMD) methods has been researched by [13], [14] to fix the weakness of EMD by adding white noise to the data. Forecasting using the integration of EEMD and artificial neural networks has been carried out to improve accuracy, as in research [15], [16]. The other research conducted by [17], that is predicted crude oil prices using EEMD and neural networks. The research compared the forecasting results of several learning methods of neural network. Combination of the feed-forward neural network (FNN) and the Polak-Ribiére conjugate gradient (PCG) learning process produce faster and good forecast accuracy compared to other learning methods. PCG looks for the non-positive value of the gradient in the network from the first iteration and searches according to the direction of the conjugation.

However, neural network methods often experience over-fitting, local optima, and are sensitive to parameter selection. Useful alternative approaches include ANN and genetic algorithms (GA). The GA algorithm is used to optimize the weights and biases of the neural network. The combination of ANN and GA has been investigated for various fields, such as biology [18], traffic emissions [19] and construction [20]. This study aims to forecast tourist visits. The proposed novelty of this study is forecast tourist visits used EEMD and optimized artificial neural network use a GA. GA are used to optimize weight and bias of ANN. The remaining structure of this paper is given as; section 2 discusses the research method used in this study, section 3 presents the results and discussion of study, finally, the conclusion is discussed in section 4.

## 2. METHOD

In order to develop a good forecasting system in tourist visit, we propose a combination of the EEMD, ANN and GA methods. The complete proposed of tourist visit forecasting algorithm is shown in Figure 1. The data used is monthly data on tourist visits in Sumenep Regency. The data were obtained through the Sumenep district government from January 2015 to December 2019. The time series data of tourist visits are shown in Figure 2.

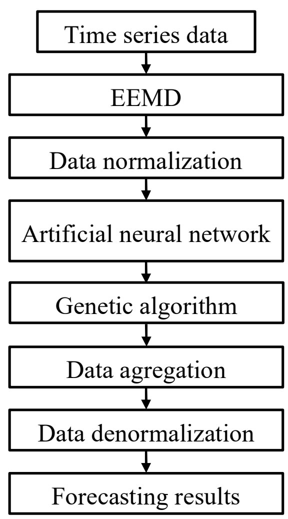


Figure 1. Tourist visit forecasting algorithm

### 2.1. Ensemble empirical mode decomposition

EEMD is a method to analyze data with the help of noise to eliminate mixing mode phenomenon and get the true frequency distribution of the original signal. EEMD is an improvement over the EMD method proposed by [13]. The principle of the EEMD is to add white noise to data, then distribute it evenly throughout frequency space. EEMD decomposed the data into a simple finite number of orthogonal oscillation modes. That is called intrinsic mode function (IMF). IMF requirements must be (1) the number of extrema and the number of zero-crossings must equal or at most differ by one, and (2) mean value of the upper envelope and the lower envelope is zero wherever. The EEMD algorithm decomposed the original data into several IMF and residues. The EEMD algorithm is as:

Step 1: Initialize M.

Step 2: Generate white noise.

Step 3: Adding white noise to the IMF in EMD.
Step 4: Back to steps (2) and (3), use different white noise until m=M.
Step 5: Find the ensemble mean for each IMF in experiment M using (1);
Step 6: Find the ensemble mean for the residue in experiment M using (2);

$$\bar{c}_i = \frac{1}{M}\sum_m^M c_{i,m} \rightarrow i = 1,\ldots\ldots,n \quad (1)$$

$$\bar{r}_n = \frac{1}{M}\sum_m^M r_{n,m} \quad (2)$$

Where $M$ is number of ensembles, $m$ is index of ensemble, $i$ is index of IMF, $n$ is index of residue, $c$ is IMF, $\bar{c}$ is mean of ensemble for each IMF, $r$ is residue and $\bar{r}$ is mean of ensemble for the residue.

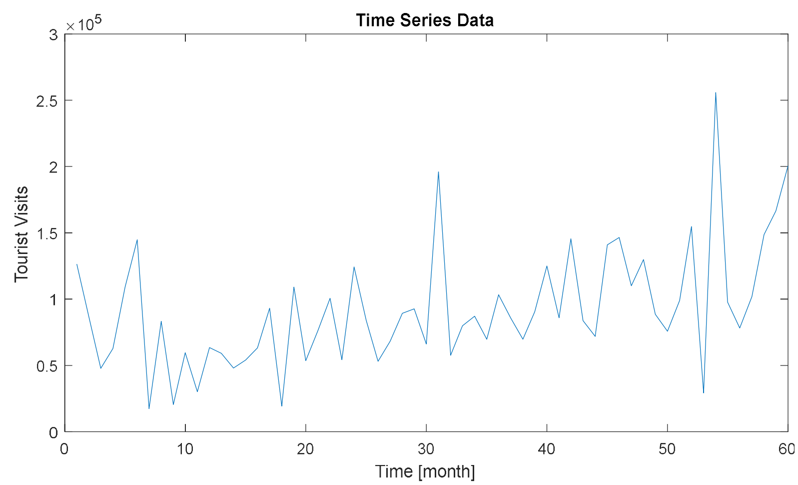


Figure 2. The original data of tourist visits

### 2.2. Data normalization

The decomposition of the data produces several IMFs and residue, then each data on the IMF and the residue is normalized using (3). Data normalization is a function of activating the input value in neural network training.

$$\boldsymbol{x' = y\left(ymin_{max} * \left(\frac{x - x_{min}}{xmin_{max}()}\right)\right)_{min}} \quad (3)$$

Where variable $x'$ is the result of normalization, $y_{min}$ and $y_{max}$ are the min and max of activation function values, $x$ is original data, $x_{min}$ and $x_{max}$ are the min and max of original data values.

### 2.3. Artificial neural network

Data learning in ANN is carried out using FNN which has been optimized using PCG. PCG is a type of learning that belongs to the neural network investigated by Polak and Ribiére. PCG find non-positive value of the network gradient starting from the first repetition and use conjugation direction [21]. The FNN learning algorithm with PCG optimization is:
Step 1: Initialize overall weights.
Step 2: Do step 3 through 6 while epoch <=10000 or learning rate >=0.1.
Step 3: Find hidden layer output; using (4), (5)
Step 4: Find the output of each output layer; using (6), (7)
Step 5: Find the error factor in the output layer; using (8), (9)
Step 6: Find the error factor in the hidden layer; using (10), (11), (12)
Step 7: Find the gradient on the output layer; using (13)
Step 8: Find the gradient on the hidden layer; using (14)
Step 9: Find the parameter β for all neurons; using (15)
Step 10: Find the directions for all neurons; using (16), (17)

Step 11: Determine the α parameter for all neurons.
Step 12: Update the weight using (18); using (18)

$$h\_net_j = v_{j0} + \sum_{i=1}^{n} x_i\, v_{ji} \tag{4}$$

$$h_j = f(h\_net_j) = \frac{1}{1+e^{-h\_net_j}} \tag{5}$$

$$y\_net_k = w_{k0} + \sum_{j=1}^{p} h_j\, w_{kj} \tag{6}$$

$$y_k = f(y\_net_k) = \frac{1}{1+e^{-y\_net_k}} \tag{7}$$

$$e_k = (t_k - y_k) f'(y\_net_k) \tag{8}$$

$$e_k = (t_k - y_k) y_k (1 - y_k) \tag{9}$$

$$e\_net_j = \sum_{k=1}^{m} e_k - w_{kj} \tag{10}$$

$$e_j = e\_net_j f'(h\_net_j) \tag{11}$$

$$e_j = e\_net_j h_j (1 - h_j) \tag{12}$$

$$m_{k+1} = \frac{1}{N} \sum_{n=1}^{p} e_{nk} y_{nk} \tag{13}$$

$$m_{j+1} = \frac{1}{N} \sum_{n=1}^{p} e_{nj} y_{nj} \tag{14}$$

$$\beta_{t+1} = \frac{m_{t+1}^T (m_{t+1} - m_{t+1})}{m_t^T m_t} \tag{15}$$

$$d_{t+1} = -m_{t+1} + \beta_t d_t \tag{16}$$

$$d_t = -m_t \tag{17}$$

$$w_{t+1} = w_t + \alpha_{t+1} d_{t+1} \tag{18}$$

### 2.3. Genetic algorithm

GA is used to improve weight values of artificial neural networks in forecasting tourist visits. The weight value of each layer on ANN becomes the chromosome value in GA. This weight data set becomes a population that will be optimized using GA [22]. The GA algorithm in optimizing the ANN architecture is presented in the following steps;

Step 1: Determine the population size by trial and error. Each chromosome has two sets of genes, that is represents the number of input layer neurons and hidden layer neurons. There are 4 input layers and 30 hidden layers and represent the population used in GA.
Step 2: For each individual evaluate fitness function in population.
Step 3: Select two individuals in the latest generation with highest fitness values.
Step 4: Do crossovers and mutations to reproduce individuals in the next generation.
Step 5: Back to step 2 until all individuals in the population reach 100 or the RMSE is less than 0.0001.
Step 6: Decode individuals who converged on the last generation.
Step 7: An optimized neural network architecture has been formed.

### 2.4. Data aggregation

The data has been decomposed into several IMFs and the residues are recombined into a single data. The adaptive linear neural network (Adaline) method is used to recombine the data. Recombine the data is called data aggregation. The Adaline method is shown in (19);

$$y = \sum_{i=1}^{n} x_i . w_i + b \tag{19}$$

### 2.5. Data denormalization

Data denormalization aims to return the processed data into real values. Denormalization can be done by modifying (3) to produce the value of Variable $x$. We used two error measurement techniques to evaluate achievement model of tourist visit forecasting, namely mean square error (MSE) and root mean squared error (RMSE). The MSE and RMSE equations are shown in (20) and (21). Besides the forecasting error measurement technique, we also use the forecast movement direction value to develop the model. The direction of forecasting movement can be used to assist decision making. The direction of the forecast movement can be measured using a directional statistic (Dstat) which is stated in (22).

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_t - x_t)^2 \quad (20)$$

$$RMSE = \sqrt{\sum_{t=1}^{n}(y_t - x_t)^2} \quad (21)$$

$$Dstat = \frac{1}{n}\sum_{t=1}^{n} a_t x\, 100\% \quad (22)$$

Where $n$ is the amount of actual data, $x$ is actual data, $t$ is the i-th time, $y_t$ is the forecast data and $a$ is constant variable. $a_t$=1 if $(y_t+1-y_t)\ (\hat{y}_t+1-y_t) \geq 0$, and $a_t$=0 if $(y_t+1-y_t)\ (\hat{y}_t+1-y_t) < 0$.

## 3. RESULTS AND DISCUSSION

In the EEMD method, the experiment in forecasting tourist visits is carried out using 100 ensembles, the standard deviation is 0.2, lower threshold is 0.05, upper threshold is 0.5 and tolerance is 0.05. Experimental results show that the data is spell out into 4 IMFs and one residue as shown in Figure 3. Each component in the IMF has a different frequency. This decomposition assumes that each data set consists of various intrinsic oscillation models. Each intrinsic mode (linear or nonlinear) is an oscillation that will have the same number of extremes symmetrically to the local mean value.

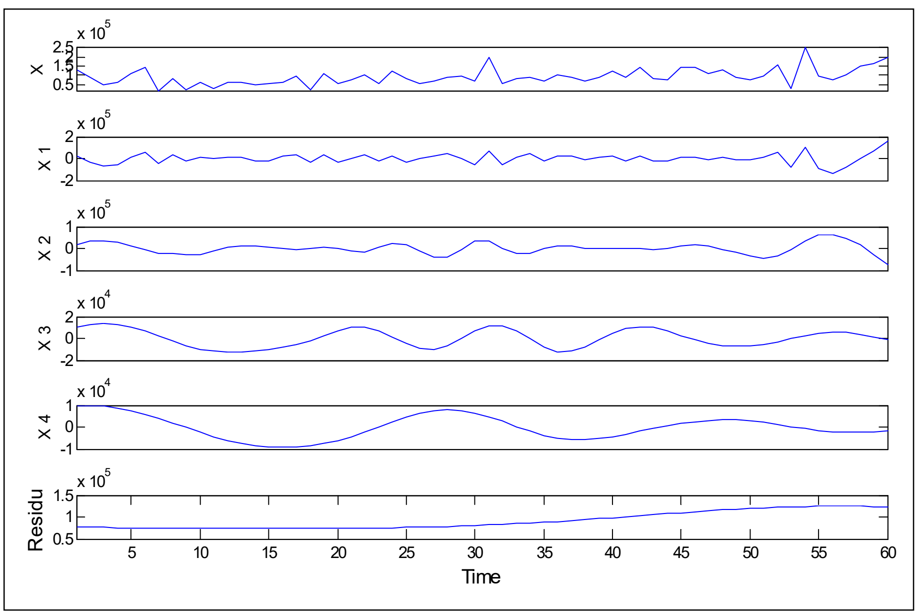


Figure 3. Results of data decomposition

After the tourist visit data is decomposed, then the data is normalized and processed using ANN. After conducting several experiments to determine the structure of ANN, then the best ones were selected, namely, 4 input layers, 30 hidden layers and one output layer. The parameters used in the experiment are as; error tolerance is 0.0001, epoch is 10,000 and learning rate is 0.1. The best performance measurement for forecast value generated from ANN before optimization using GA is MSE and RMSE. MSE is 0.02130 and RMSE is 0.14591 as shown in Table 1. The performance will be compared with the forecast performance after the weight value is optimized using GA.

Table 1. The performance ANN before optimization using GA

| Data patterns | MSE | RMSE | Dstat |
|---|---|---|---|
| 4-30-1 | 0.02130 | 0.14591 | 64.29% |

GA are used to improve weight values of neurons in input layer and hidden layer of ANN. The first experiment is done by tuning the population so that it gets the best performance. The best population is used in the next experiment, namely tuning the crossover and mutation probabilities to get the best performance. The best performance will be used in the next test. Tuning by varying the number of populations showed the best performance in a population of 45 with MSE 0.01334, MRSE 0.11552 and Dstat 78.57%. The experimental results are shown in Table 2. The next test is to vary the probability values of crossovers and mutations. In this test, the best performance is obtained when the crossover probability value is 0.9. and the mutation probability is 0.2. From a series of experiments, the best performance was obtained in a population of 45, crossover probability is 0.9. and mutation probability is 0.2. with MSE is 0.01334, MRSE is 0.11552 and Dstat is 78.57% as shown in Table 3.

Table 2. Experimental results by tuning population value

| Population | gen | Generation | Cros. Prob. | Mut. Prob. | MSE | RMSE | Dstat |
|---|---|---|---|---|---|---|---|
| 5 | 6 | 100 | 0.9 | 0.2 | 0.01563 | 0.12501 | 78.57% |
| 15 | 6 | 100 | 0.9 | 0.2 | 0.01398 | 0.11825 | 78.57% |
| 30 | 6 | 100 | 0.9 | 0.2 | 0.01469 | 0.12119 | 78.57% |
| 45 | 6 | 100 | 0.9 | 0.2 | 0.01334 | 0.11552 | 78.57% |
| 60 | 6 | 100 | 0.9 | 0.2 | 0.01388 | 0.11783 | 78.57% |

Table 3. Experimental results by tuning crossover probability value

| Population | gen | Generation | Cros. Prob. | Mut. Prob. | MSE | RMSE | Dstat |
|---|---|---|---|---|---|---|---|
| 45 | 6 | 100 | 0.1 | 0.2 | 0.01456 | 0.12067 | 78.57% |
| 45 | 6 | 100 | 0.2 | 0.2 | 0.01556 | 0.12475 | 78.57% |
| 45 | 6 | 100 | 0.3 | 0.2 | 0.01543 | 0.12421 | 78.57% |
| 45 | 6 | 100 | 0.4 | 0.2 | 0.01509 | 0.12283 | 85.71% |
| 45 | 6 | 100 | 0.5 | 0.2 | 0.01444 | 0.12016 | 78.57% |
| 45 | 6 | 100 | 0.6 | 0.2 | 0.01373 | 0.11716 | 78.57% |
| 45 | 6 | 100 | 0.7 | 0.2 | 0.01544 | 0.12426 | 78.57% |
| 45 | 6 | 100 | 0.8 | 0.2 | 0.01421 | 0.11919 | 78.57% |
| 45 | 6 | 100 | 0.9 | 0.2 | 0.01334 | 0.11552 | 78.57% |

It is worth mentioning that ANNs, as a machine learning (ML) technique inspired by the human brain [23], are a good choice for forecasting tasks because of their ability to generalise and find temporal patterns in the training data. Although we chose an FNN, we could have chosen a recurrent neural network (RNN) which might have produced better results as it takes into account time aspects that are intrinsic in time series data [24], [25]. However, we wanted to make use of best of ANNs and GAs by taking a GA as an optimiser for the weights of the neural network as it accelerates the learning process by better optimising hyper-parameters [26].

Based on testing the proposed method shows that forecasting with ANN optimization using GA results in better forecasting than ANN without GA optimization. Forecasting with GA optimization, error value of forecasting is reduced by 37%, 21% for MSE and RMSE as shown in Table 4. This shows that the effect of optimization with GA has a very significant improvement in producing accurate forecasting. Comparison of actual data and tourist visit forecasting data using the EEMD, NN and GA methods. shown in Figure 4.

Table 4. Performance comparison

| | With GA | Without GA | Reduce% |
|---|---|---|---|
| MSE | 0.01334 | 0.02130 | 37 |
| RMSE | 0.11552 | 0.14591 | 21 |

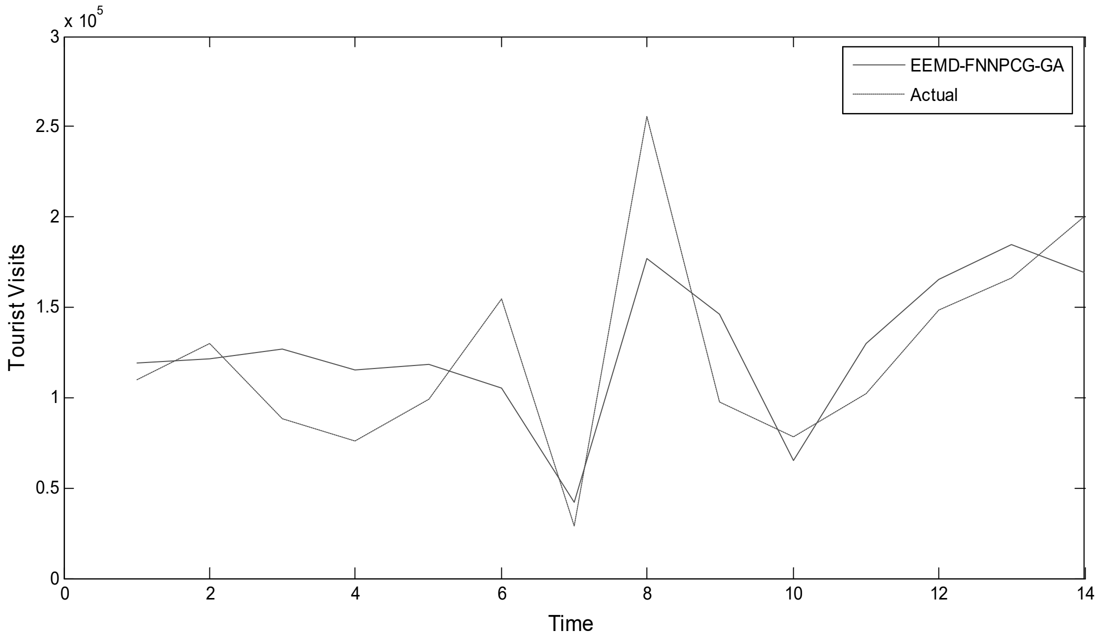


Figure 4. Comparison of actual data and tourist visit forecasting

## 4. CONCLUSION

This study has proposed forecasting tourist visits use combination an ensemble empirical mode decomposition and an optimized artificial neural network using GA. GA are used to optimize weight values in artificial neural networks. The model was tested on tourist visit data in Sumenep Regency, Indonesia. Experiments were carried out by analyze differences in forecast results of proposed method compared with the EEMD-ANN method without GA optimization. Based on the experimental results, it shows that the investigated method has better performance, error value of forecasting is reduced by 37%, 21% for MSE, RMSE, respectively. For better forecasting development, optimization can be improved using other new methods in future research.

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## REFERENCES

[1] J. T. Coshall and R. Charlesworth, "A management orientated approach to combination forecasting of tourism demand," *Tourism Management*, vol. 32, no. 4, pp. 759-769, 2011, doi: 10.1016/j.tourman.2010.06.011.
[2] K. Y. Chen, "Combining linear and nonlinear model in forecasting tourism demand," *Expert Systems Applications,* vol. 38, no. 8, pp. 10368-10376, 2011, doi: 10.1016/j.eswa.2011.02.049.
[3] R. R. Andrawis, A. F. Atiya, and H. El-Shishiny, "Combination of long term and short term forecasts, with application to tourism demand forecasting," *International Journal Forecasting*, vol. 27, no. 3, pp. 870-886, 2011, doi: 10.1016/j.ijforecast.2010.05.019.
[4] P. F. Pai, K. C. Hung, and K. P. Lin, "Tourism demand forecasting using novel hybrid system," *Expert Systems Application,* vol. 41, no. 8, pp. 3691-3702, 2014, doi: 10.1016/j.eswa.2013.12.007.
[5] O. Claveria and S. Torra, "Forecasting tourism demand to Catalonia: Neural networks vs. time series models," *EconomicModelling*, vol. 36, pp. 220-228, 2014, doi: 10.1016/j.econmod.2013.09.024.
[6] A. Guizzardi and A. Stacchini, "Real-time forecasting regional tourism with business sentiment surveys," *Tourism Management*, vol. 47, pp. 213-223, 2015, doi: 10.1016/j.tourman.2014.09.022.
[7] R. Law, G. Li, D. K. C. Fong, and X. Han, "Tourism demand forecasting: A deep learning approach," *Annals of Tourism Research,* vol. 75, pp. 410-423, 2019, doi: 0.1016/j.annals.2019.01.014.
[8] C. F. Chen, M. C. Lai, and C. C. Yeh, "Forecasting tourism demand based on empirical mode decomposition and neural network," *Knowledge-Based Systems*, vol. 26, pp. 281-287, 2012, doi: 10.1016/j.knosys.2011.09.002.
[9] N. E. Huang *et al.*, "The empirical mode decomposition and the Hubert spectrum for nonlinear and non-stationary time series analysis," *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 1998, vol. 454, no. 1971, pp. 903-995, doi: 10.1098/rspa.1998.0193.

[10] X. Hu, S. Peng and W. Hwang, "EMD Revisited: A New Understanding of the Envelope and Resolving the Mode-Mixing Problem in AM-FM Signals," *IEEE Transactions on Signal Processing*, vol. 60, no. 3, pp. 1075-1086, 2012, doi: 10.1109/TSP.2011.2179650.

[11] H. Xie and Z. Wang, "Mean frequency derived via Hilbert-Huang transform with application to fatigue EMG signal analysis," *Computer Methods and Programs in Biomedicine*, vol. 82, no. 2, pp. 114-120, 2006, doi: 10.1016/j.cmpb.2006.02.009.

[12] G. Biagetti, P. Crippa, A. Curzi, S. Orcioni and C. Turchetti, "Analysis of the EMG Signal During Cyclic Movements Using Multicomponent AM–FM Decomposition," *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 5, pp. 1672-1681, 2015, doi: 10.1109/JBHI.2014.2356340.

[13] Z. Wu and N. E. Huang, "Ensemble Empirical Mode Decomposition: a Noise-Assisted Data Analysis Method," *Advances in Adaptive Data Analysis*, vol. 1 no.1, pp. 1-41, 2009, doi: 10.1142/S1793536909000047.

[14] K. M. Chang, "Ensemble empirical mode decomposition for high frequency ECG noise reduction," *Biomedizinische Technik/Biomedical Engineering*, vol. 55, no. 4, pp. 193-201, 2010, doi: 10.1515/bmt.2010.030.

[15] W. C. Wang, K. W. Chau, L. Qiu, and Y. B Chen, "Improving forecasting accuracy of medium and long-term run off using artificial neural network based on EEMD decomposition," *Environmental Research*, vol. 139, pp. 46-54, 2015, doi: 10.1016/j.envres.2015.02.002.

[16] Y. X. Wu, Q. B. Wu and J.Q. Zhu, "Improved EEMD-based crude oil price forecasting using LSTM networks," *Physica A: Statistical Mechanics and its Applications*, vol. 516, pp. 114-124, 2019, doi: 10.1016/j.physa.2018.09.120.

[17] M. Latif and S. Herawati, "The application of EEMD and neural network based on Polak-Ribiére Conjugate Gradient algorithm for crude oil prices forecasting," *MATEC Web of Conferences*, 2016, vol. 58, pp. 1-5, doi:10.1051/matecconf/20165803013.

[18] Z. Lan, C. Zhao, W. Guo, X. Guan and X. Zhang, "Optimization of Culture Medium for Maximal Production of Spinosad Using an Artificial Neural Network - Genetic Algorithm Modeling," *Journal Molecular Microbiology Biotechnology*, vol. 25, no. 4, pp. 253-261, 2015, doi: 10.1159/000381312.

[19] A. M. Abdullah, R. S. A. Usmani, T. R. Pillai, M. Marjani and I. A. T. Hashem, "An Optimized Artificial Neural Network Model using Genetic Algorithm for Prediction of Traffic Emission Concentrations," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 6, pp. 794-803, 2021.

[20] E. T. Mohamad, R. S. Faradonbeh, D. J. Armaghani, M. Monjezi and M. Z. A. Majid, "An optimized ANN model based on genetic algorithm for predicting ripping production," *Neural Computing & Applications,* vol. 28, pp. 393-406, 2017.

[21] M. Ghasemi-Fard, K. Ansari-Asl, L. Albera, A. Kachenoura and L. Senhadji, "A low cost and reliable Polak-Ribiere conjugate gradient deflation ICA algorithm for real signals," *21st Iranian Conference on Electrical Engineering (ICEE*), 2013, pp. 1-5, doi: 10.1109/IranianCEE.2013.6599835.

[22] K. Pandey, S. Kumar, A. Malik and A. Kuriqi, "Artificial Neural Network Optimized with a Genetic Algorithm for Seasonal Groundwater Table Depth Prediction in Uttar Pradesh, India," *Sustainability*, vol. 12, no. 21, pp. 1-24, 2020, doi: 10.3390/su12218932.

[23] O. H. Hamid and J. Braun, "Reinforcement Learning and Attractor Neural Network Models of Associative Learning," *Computational Intelligence*, vol. 829, pp. 327-349, Springer, Cham, 2019.

[24] S. Glüge, O. H. Hamid, and A. Wendemuth, "A simple recurrent network for implicit learning of temporal sequences," *Cognitive Computation*, vol. 2, no. 4, pp. 265-271, 2010.

[25] D. Brezak, T. Bacek, D. Majetic, J. Kasac and B. Novakovic, "A comparison of feed-forward and recurrent neural networks in time series forecasting," *IEEE Conference on Computational Intelligence for Financial Engineering & Economics (CIFEr)*, 2012, pp. 1-6, doi: 10.1109/CIFEr.2012.6327793.

[26] C. D. Francescomarino, "Genetic algorithms for hyperparameter optimization in predictive business process monitoring," *Information Systems*, vol. 74, pp. 67-83, 2018, doi: 10.1016/j.is.2018.01.003.


## BIOGRAPHIES OF AUTHORS

**Muhammad Latif** is currently a lecturer in Department of Mechatronics Engineering, University of Trunojoyo Madura. His research interests are in intelligent system and robotic. He can be contacted at email: m.latif@trunojoyo.ac.id.

**Sri Herawati** is currently a lecturer in Department of Information Systems, University of Trunojoyo Madura. Her research interests are in forecasting, business intelligent, decision support system and expert system. She can be contacted at email: sriherawati@trunojoyo.ac.id.