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Fish swarmed fuzzy time series for photovoltaic's forecasting in microgrid

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Abstract

Forecasting irradiation and temperature is important for designing photovoltaic systems because these two factors have a significant impact on system performance. Irradiation refers to the amount of solar radiation that reaches the earth's surface, and directly affects the amount of energy that can be generated by a photovoltaic system. Therefore, accurate irradiation forecasting is essential for estimating the amount of energy a photovoltaic system can produce, and can assist in determining the appropriate system size, configuration, and orientation to maximize energy output. Temperature also plays an important role in the performance of a photovoltaic system. With increasing temperature, the efficiency of the solar cell decreases, which means that the energy output of the system also decreases. Therefore, accurate temperature forecasts are essential for estimating system energy output, selecting suitable materials, and designing effective cooling systems to prevent overheating. In summary, forecasting irradiation and temperature is important for designing photovoltaic systems as it helps in determining suitable system size, configuration, orientation, material selection, and cooling system, which ultimately results in higher energy output and better system performance. In recent decades, many forecasting models have been built on the idea of fuzzy time series. There are several forecasting models proposed by integrating fuzzy time series with heuristic or evolutionary algorithms such as genetic algorithms, but the results are not satisfactory. To improve forecasting accuracy, a new hybrid forecasting model combines fish swarm optimization algorithm with fuzzy time series. The results of irradiance prediction/forecasting with the smallest error are using the type of Fuzzy Time Series prediction model optimized with FSOA with RMSE is 0.83832.

1. Introduction

Over the years, a variety of prediction models have been proposed to address the prediction issues in various fields. One of the most widely applied forecasting methods is the time series model. When historical data are illegible, incomplete, or contain uncertain information, the conventional model of time series can nevertheless handle many prediction issues. Fuzzy set theory was introduced by Zadeh in 1965. Song and Chissom first suggested a fuzzy time series approach based on fuzzy set theory. The three components of the fuzzy time series model are fuzzification, fuzzy relation finding, and defuzzification.

The choice of interval durations during the fuzzification process plays a significant role in the precision of the fuzzy time series model. In their experiments from 1993a, b, and 1994, Song and Chissom determined the lengths of random intervals. Forth two new methods based on the mean and distribution to find intervals and suggested that interval length was very important for forecasting accuracy [1]. Methods based on optimization were suggested [2]. Recently, methods using genetic algorithms have been suggested [3], [4], whereas methods using particle swarm optimization have been proposed [5], [6], and [7]. In addition, to calculate interval length, [8], [9], [10], [11] and [8] used the Gustafson-Kessel clustering algorithm. Examining all of these studies demonstrates how interval length determination can influence fuzzy time series techniques' ability to predict the future accurately.

Photovoltaic forecasting in microgrids involves predicting the power output of PV systems to facilitate efficient energy management within microgrid networks. Accurate PV forecasting enables microgrid operators to optimize resource allocation, storage management, and grid integration, thereby improving the overall efficiency and stability of the microgrid. Fuzzy time series forecasting is a technique that combines fuzzy logic and time series analysis to make predictions based on historical data. It is particularly useful when dealing with data that exhibits uncertainty or vagueness. Fuzzy time series models capture the linguistic relationships between variables and use fuzzy sets and rules to make predictions.

There are studies that have used optimization algorithms such as Particle Swarm Optimization (PSO) to optimize Fuzzy Time Series (FTS) for predicting various parameters, including air quality and power output of photovoltaic (PV) systems [15],[16]. FTS is a popular method for time series forecasting that uses fuzzy logic to handle uncertainty and imprecision in the data. The method involves dividing the data into fuzzy intervals and then using these intervals to generate fuzzy rules that can be used for prediction [15]. Optimization algorithms such as PSO can be used to optimize the parameters of FTS, such as the number and width of fuzzy intervals, to improve the accuracy of the predictions. These algorithms work by iteratively adjusting the parameters to minimize a cost function that measures the error between the predicted and actual values.

In the case of PV systems, FTS can be used to predict parameters such as radiation and temperature, which can then be used to optimize the power output of the system [17]. PSO can be used to optimize the parameters of the FTS model to improve the accuracy of the predictions and hence the power output of the system. The work of FIS-PSO after optimizing produced the good work with the smallest value that is better performance compared to other methods, which can increase the onset prediction of the rainy season [18], and improve neural network performance on univariate time series data [19].

An optimization method called Fish Swarm Optimization (FSO) draws inspiration from how fish eat in their natural environment. It has been used to address a variety of issues, including finding effective network groups and resolving optimization issues. Fish Swarm Optimization (FSO) are a family of algorithms that were created and influenced by the ecological patterns of schooling fish in the wild. FSO has a relatively simpler implementation compared to PSO. It requires fewer parameters to tune, making it easier to implement and understand. In this research, Fish swarm optimization has been used for optimizing the fuzzy time series for forecasting purposes such as temperature and irradiance in photovoltaic.

2. Research Method

Fish Swarm Optimization (FSO) is one of the optimization techniques inspired by the behavior of fish in searching for food or moving in groups. FSO implements an algorithm to find the best solution to a problem by following a strategy similar to the movement of fish in a group. FSO utilizes the principle of collective intelligence in achieving the optimization goal. FSO consists of three main components, namely fish population, fish behavior, and selection criteria. The fish population consists of a collection of possible solutions. Fish behavior includes individual movements and social interactions between individuals in the fish population. Selection criteria are used to determine the best solution from the fish population.

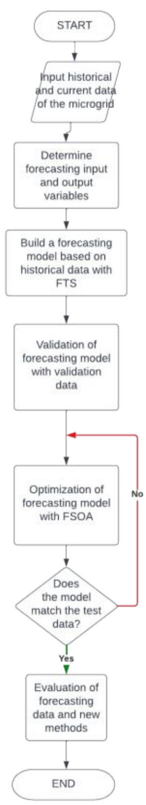


Figure 1. Flowchat of Forecasting using Fuzzy Time Series- FSOA

Fuzzy Time Series (FTS) is a prediction technique that uses fuzzy logic to handle uncertainty in time series data. FTS aims to develop a prediction model that can be used to predict future values of time series data based on past values. FTS utilizes linguistic variables in forming fuzzy rules to make predictions. These variables are used to describe the relationship between past data and future data. FTS has several stages in making prediction models, namely fuzzification of time series data, fuzzy rule formation, model testing, and model evaluation.

Figure 1 shows the flowchart of the Fish Swarm Optimization (FSO) algorithm for optimizing Fuzzy Time Series and the steps in forecasting are as follows:

(i) Initialization of FSO parameters

Determine Number of iterations (I), Number of fish (N), Fish Distance (Step_Size), then randomly determines the initial position of the fish (X) and the food (Y) in Equation 1.

$$\begin{aligned} X &= rand(Dx) \\ Y &= rand(Dy) \end{aligned} \tag{1}$$

(ii) Create an initial FSO weight matrix (w)

(iii) FSO iteration

Determine the objective function of the FSOA, in this case the fish swarm is used to determine the closest distance from the food (Y) as shown in Equation 2.

$$D \geq \sqrt{(X_i - X_j)^2 + (Y_i - Y_j)^2} \tag{2}$$

[bestPosition, bestFish] = max(distances)

As long as the iteration has not reached the maximum, repeat the following steps: update the position of the fish using the FSO's equation of motion, limit the position of the fish to stay within the search space, and evaluate the objective function value of each fish using Fuzzy Time Series. If the objective function value is better than the previous best value, save the objective function value and the best fish position.

(iv) Calculating fitness values and updating weights

(v) Output

- Output the best fish position as the optimal solution to optimize the Fuzzy Time Series.

The FSO motion equations are the same as those previously described. However, in evaluating the value of the objective function, Fuzzy Time Series is used as a method to build a prediction model. The following are the steps to create a prediction model using Fuzzy Time Series:

(i) Step 1: Fuzzy set formation

- Divide the historical data into time intervals is shown in Figure 2.
- Determine the membership function for each time interval. Membership function is divide to 5 MF and shown in Table 2 (Fuzzy parameter).
- Assign a membership level to each historical data.

(ii) Step 2: Fuzzy rule formation

- Define fuzzy rules based on the relationship pattern between input and output variables.
- Determine the degree of membership for each fuzzy rule.

(iii) Step 3: Fuzzification and Inference

- Convert input and output variables into fuzzy sets using predefined membership functions.
- Evaluate the degree of correctness of each fuzzy rule based on the fuzzy set of input variables.
- Combine relevant fuzzy rules to generate fuzzy outputs.

(iv) Step 4: Defuzzification

- Convert fuzzy outputs to numerical values using defuzzification techniques (e.g. centroid or mean of max).

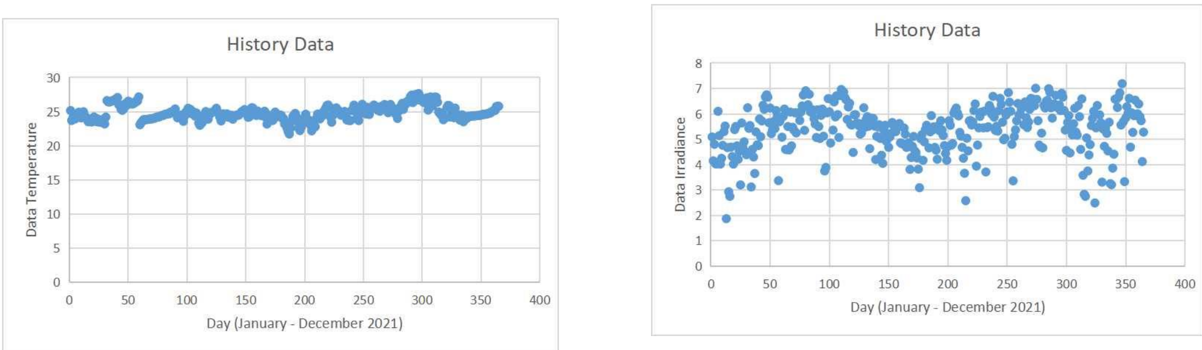
The FSOA algorithm works by generating a population of candidate solutions, where each solution corresponds to a set of FTS parameters. The algorithm then evaluates the fitness of each solution using a fitness function, which is typically based on the accuracy of the FTS model. In matlab, the fish swarm optimization algorithm program used as an optimization method for fuzzy time series with the parameters shown in Table 1. Data set for forecasting shown in Table 2 and Figure 2.

Table 1. Parameter of Forecasting using FTS-FSOA

Parameters	Values
Number of Fuzzy Sets	5
Fuzzy Parameters (temperature)	[45 50 55 60 65]
Fuzzy Parameters (irradiance)	[10 12 14 16 18]
Number of Iterations	100
Number of Particles	10
Number of Fish (N)	50
Step Size	3
Range (D)	3
Input data (NASA's data)	January - December, 2021

Table 2. Data Set of Input Data (Temperature and Irradiance)

Year	Month	Day	Temperature	Irradiance
2021	1	1	25.15	5.09
2021	1	2	23.7	4.15
2021	1	3	24.04	4.8
2021	1	4	23.98	4.03
2021	1	5	23,94	4.03
2021	1	6	24.19	6.1
…	…	…	…	…
2021	12	31	25.79	5.28



(a) (b)

Figure 2. Historical Data Set of (a) Temperature and (b) Irradiance

Once the prediction model is created, evaluation of the objective function value is carried out by comparing the predicted value with the actual value using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). RMSE and MAE are two common metrics used to measure the accuracy of forecasting models. Both of these metrics measure how close the predicted values are to the actual values of the data.

The formula for RMSE is as follows Equation 3.

$$RMSE = \sqrt{\frac{1}{n} \times \sum (predicted(i) - actual(i))^2} \tag{3}$$

where:

i. n is the number of data points in the sample
ii. predicted_i is the predicted value for data point i
iii. actual_i is the actual value for data point i
iv. ^2 denotes squaring the difference between the predicted and actual values
v. sum() calculates the sum of all data points

The formula for MAE is as follows Equation 4.

$$MAE = \frac{1}{n} \times \sum \left| (predicted(i) - actual(i)) \right| \tag{4}$$

where:
i. n is the number of data points in the sample
ii. predicted_i is the predicted value for data point i
iii. actual_i is the actual value for data point i
iv. abs() denotes taking the absolute value of the difference between the predicted and actual values
v. sum() calculates the sum of all data points

Both of these metrics yield numerical values that indicate the magnitude of the prediction error of the model. Smaller values of RMSE and MAE indicate a more accurate model, as the prediction error is smaller. However, RMSE tends to give more weight to larger errors than MAE, so it may give slightly different results depending on the case being analyzed.

3. Results and Discussion

In performing temperature and irradiation forecasting optimization, it is important to understand the characteristics of the available historical data and select the forecasting method that best fits the data. In addition, factors that affect forecasting should be identified and considered in forecasting. By using the latest technologies, such as machine learning, forecasting can be optimized to improve accuracy.

Comparison of time series regression methods using Matlab as predictive analytics of the PV model. Model inputs are temperature and irradiance data in January - December 2021.To perform temperature and irradiance forecasting optimization, there are several factors that must be considered, such as the forecasting method used, the historical data used as a reference, and other factors that can affect the forecasting. In performing temperature and irradiation forecasting optimization, it is important to understand the characteristics of the available historical data and select the forecasting method that best fits the data. In addition, factors that affect forecasting should be identified and considered in forecasting. By using the latest technologies, such as machine learning, forecasting can be optimized to improve accuracy. There are several methods that can be used for forecasting including fuzzy time series, linear regression, fine tree regression, and FTS (fuzzy time series) with FSOA (fish swarm optimization algorithm).

Figure 3 shows irradiance's forecasting results using variations in forecasting methods and Figure 4 shows temperature's forecasting results using variations in forecasting methods.

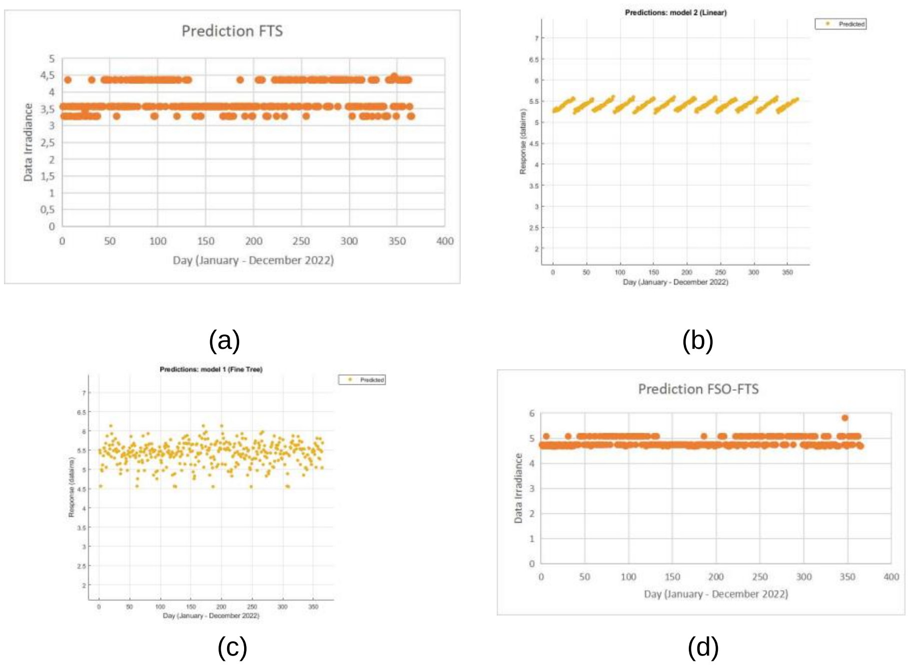


Figure 3. Irradiance's Forecasting Results using (a) Fuzzy Time Series, (b) Linear, (c) Fine Tree, (d) Fuzzy Time Series-FSOA

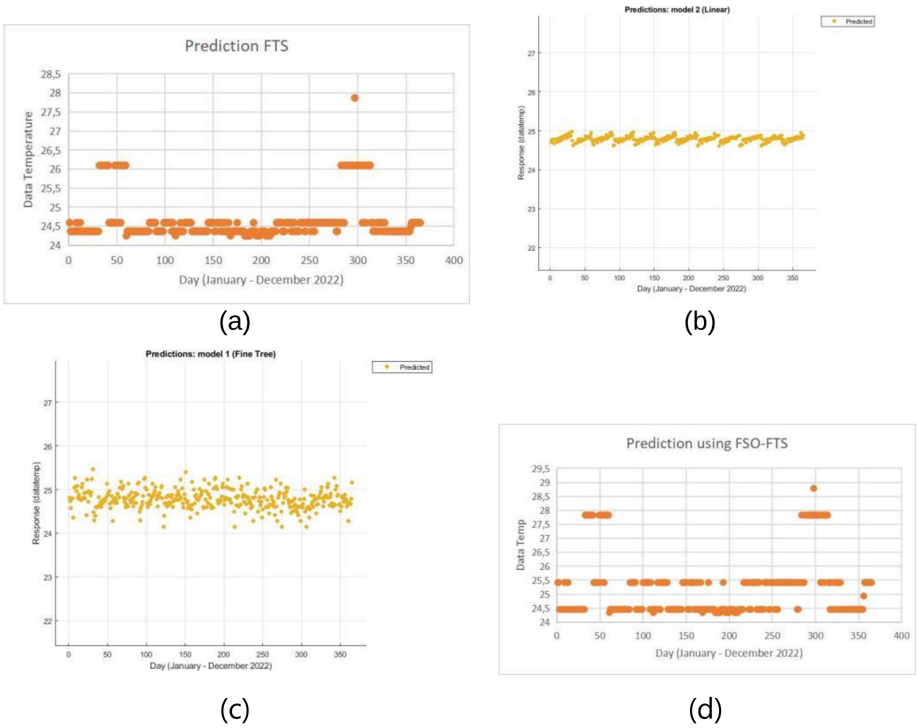


Figure 4. Temperature's Forecasting Results using (a) Fuzzy Time Series, (b) Linear, (c) Fine Tree, (d) Fuzzy Time Series-FSOA

Table 3. Comparison of RMSE and MAE with various forecasting methods

Model Type	Input PV	RMSE	MAE
Fuzzy Time Series-FSOA	Temperature	0.85511	0.63678
	Irradiance	0.83832	0.97074
Fuzzy Time Series	Temperature	0.707	0.5441
	Irradiance	1.71932	1.63155
Linear Regression	Temperature	1.0502	0.8285
	Irradiance	0.92136	0.72221
Fine Tree Regresion	Temperature	1.127	0.89048
	Irradiance	0.97566	0.7724

Based on the Table 3, it can be seen that the results of irradiance prediction/forecasting/forecasting with the smallest error are using the type of Fuzzy Time Series prediction model optimized with FSOA with RMSE is 0.83832. While the results of temperature prediction/forecasting/forecasting with the smallest error are using the Fuzzy Time Series prediction model type with RMSE is 0.707. This can occur because it uses the same FSOA parameters on different input data. For changes in input data, the optimization parameters in FSOA can be changed such as setting the range value or even the value of the fish population which will affect the error and fitness value of the forecasting results.

The use of Fish Swarm Optimization Algorithm (FSOA) in Fuzzy time series analysis is a popular technique for optimizing the parameters of a fuzzy time series model. FSOA is a metaheuristic optimization algorithm that is inspired by the collective behavior of fish schools in nature. It is a population-based algorithm that uses the movement of fish in the search for the optimal solution. Fuzzy time series analysis involves the use of fuzzy sets to model the behavior of a time series. The main challenge in fuzzy time series analysis is to determine the optimal values of the parameters that define the fuzzy sets. These parameters include the length of the interval, the number of intervals, and the degree of membership.

The use of FSOA in Fuzzy time series helps to improve the accuracy of the analysis by optimizing the parameters of the fuzzy sets. FSOA can effectively search the parameter space to find the optimal values that minimize the error between the predicted and actual values of the time series data. FSOA is particularly useful when dealing with large and complex time series data sets that are difficult to analyze using traditional statistical methods.

By mathematically modeling the irradiance shown in Equation 5 with the least squares method to obtain the Discrete-time Auto Regressive Model with fit to estimation data is 90.63%,FPE (final prediction error) is 0.001999, and MSE (mean square error): 0.001647.

$$A(z) = 1 - 0.9373z^{-1} - 0.6464z^{-2} + 0.5851z^{-3} \quad (5)$$

The mathematical equation of temperature based on forecasting results is shown in Equation 6 with fit to estimation data is 93.87%, FPE (final prediction error) is 0.0001299, and MSE (mean square error) is 0.0001069.

$$A(z) = 1 - 1.223z^{-1} - 0.3779z^{-2} + 0.601z^{-3} \quad (6)$$

The mathematical model obtained from forecasting results on photovoltaic (PV) is used to predict the future behavior of a PV system based on historical data and other relevant factors. PV forecasting models can be developed using various mathematical and statistical techniques such as time series analysis, artificial neural networks, fuzzy logic, and regression analysis. The mathematical model can be used for a variety of purposes, including:

a. Predicting the power output of a PV system: The mathematical model can be used to forecast the amount of electricity that will be generated by a PV system over a given period of time. This information can be used to optimize the use of the energy generated by the PV system and to plan for future energy needs.
b. Planning and scheduling: The mathematical model can be used to plan and schedule the use of a PV system. This can include determining the optimal times to use the system, as well as predicting the amount of energy that will be generated at different times of the day or year.
c. Energy trading: The mathematical model can be used to predict the price of energy in the market based on the amount of energy that is expected to be generated by the PV system. This can help energy traders to make informed decisions about buying and selling energy.
d. Design and optimization of PV systems: The mathematical model can be used to optimize the design of a PV system, including the size and orientation of the panels and the type of inverter used. This can help to maximize the energy output of the system and reduce costs.

4. Conclusion

From the results and discussions that have been carried out in the previous chapter, the conclusions that can be drawn from this research are the use of Fish Swarm Optimization Algorithm in Fuzzy time series analysis helps to improve the accuracy of the analysis and allows for the effective optimization of the parameters of the fuzzy time series model, and the mathematical model obtained from forecasting results on photovoltaic is used to predict the future behavior of a PV system and can be used for a variety of purposes, including predicting power output, planning and scheduling, energy trading, and design and optimization of PV systems.

References

[1] Kun-Huang Huarng. Effective lengths of intervals to improve forecasting in fuzzy time series. Fuzzy Sets and Systems 2001; 123(3), 387-394. https://doi.org/10.1016/S0165-0114(00)00057-9
[2] Erol Egrioglu, Cagdas Hakan Aladag, Ufuk Yolcu, Vedide R. Uslu, Murat A. Basaran. Finding an optimal interval length in high order fuzzy time series. Expert Systems with Applications. 2010; Vol 37 (7). https://doi.org/10.1016/j.eswa.2009.12.006
[3] Chen, S and Chung, N. Forecasting Enrollments of Students by Using Fuzzy Time Series and Genetic Algorithms. Information and Management Sciences. 2006; 17, (3), 1-17. http://dx.doi.org/10.1002/0470024569.ch1
[4] Lee, L.S. MultiCrossover Genetic Algorithms for Combinatorial Optimisation Problems. University of Southampton, United Kingdom. 2006.
[5] I-Hong Kuo, Shi-Jinn Horng, Tzong-Wann Kao, Tsung-Lieh Lin, Cheng-Ling Lee, Yi Pan. An improved method for forecasting enrollments based on fuzzy time series and particle swarm optimization. Expert Systems with Applications. 2009; Vol 36(3). https://doi.org/10.1016/j.eswa.2008.07.043
[6] R.J. Kuo, S.Y. Hong, Y.C. Huang. Integration of particle swarm optimization-based fuzzy neural network and artificial neural network for supplier selection. Applied Mathematical Modelling. 2010. Vol 34(2). https://doi.org/10.1016/j.apm.2010.03.033
[7] Kuang Yu Huang. A hybrid particle swarm optimization approach for clustering and classification of datasets. Knowledge-Based Systems. 2011. Vol 24(3). https://doi.org/10.1016/j.knosys.2010.12.003
[8] Cagdas Hakan Aladag, Erol Egrioglu, Cem Kadilar. Improvement in Forecasting Accuracy Using the Hybrid Model of ARFIMA and Feed Forward Neural Network. American Journal of Intelligent Systems. 2012; 2(2): 12-17.
[9] Cheng, C.-H., Chen, T., Teoh, H., & Chiang, C. Fuzzy time-series based on adaptive expectation model for TAIEX forecasting. Expert systems with applications. 2008;34.2 , 1126-1132. https://doi.org/10.1016/j.eswa.2006.12.021
[10] E. Egrioglu, C.H. Aladag, U. Yolcu, V.R. Uslu, N.A. Erilli. Fuzzy time series forecasting method based on Gustafson–Kessel fuzzy clustering. Expert Systems with Applications. 2011; 30(8). https://doi.org/10.1016/j.eswa.2011.02.052
[11] Yolcu, U., Egrioglu, E., & Aladag, C. H. A new linear & nonlinear artificial neural network model for time series forecasting. Decision Support Systems, 2013; 54(3), 1340–1347. https://doi.org/10.1016/j.dss.2012.12.006
[12] Musaed Alrashidi and Saifur Rahman, Short-term photovoltaic power production forecasting based on novel hybrid data-driven models. Journal of Big Data, 2023;10:26. https://doi.org/10.1186/s40537-023-00706-7

[13] Fran Sérgio Lobato, Valder Steffen Jr. Fish Swarm Optimization Algorithm Applied to Engineering System Design. Latin American Journal of Solids and Structures. 2014. 11, 143-156. https://doi.org/10.1590/S1679-78252014000100009
[14] Bogdan Oancea, Richard Pospíšil, Marius Nicolae Jula and Cosmin-Ionuț Imbrișcă. Experiments with Fuzzy Methods for Forecasting Time Series as Alternatives to Classical Methods. Mathematics 2021; 9, 2517. https://doi.org/10.3390/math9192517
[15] Rifandi, Angga Dwi Apria, Budi Darma Setiawan, Tibyani. Optimasi Interval Fuzzy Time Series Menggunakan Particle Swarm Optimization pada Peramalan Permintaan Darah : Studi Kasus Unit Transfusi Darah Cabang - PMI Kota Malang. Jurnal Pengembangan Teknologi Informasi dan Ilmu Komputer e-ISSN: 2548-964X, Vol. 2, No. 7, Juli 2018, pg. 2770-2779.
[16] Sari, Ade Puspita. Optimasi Interval Fuzzy Time Series menggunakan Particle Swarm Optimization Untuk Memprediksi Kualitas Udara Di Kota Pekanbaru. Skripsi thesis 2019, Universitas Islam Negeri Sultan Syarif Kasim Riau.
[17] Bahrudin, Muhammad Irfan . Optimisasi Daya Photovoltaic pada kondisi Partially Shaded dengan Maximum Power Point Tracker (MPPT) Menggunakan Metode Particle Swarm Optimization (PSO) Double Diode Model. Institut Teknologi Sepuluh Nopember. 2018
[18] Tyas, F. A., Setianama, M., Fadilatul Fajriyah, R., & Ilham, A. (2021). Implementation of Particle Swarm Optimization (PSO) to Improve Neural Network Performance in Univariate Time Series Prediction. Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control, 6(4). https://doi.org/10.22219/kinetik.v6i4.1330
[19] Noviandi, N., & Ilham, A. (2020). Optimization Fuzzy Inference System based Particle Swarm Optimization for Onset Prediction of the Rainy Season. Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control, 5(1). https://doi.org/10.22219/kinetik.v5i1.985
[20] Allen J. Wood, Power Generation Operation and Control, second edisi tahun 1996
[21] Frisk, M. (2017). Simulation and optimization of a hybrid renewable energy system for appli- cation on a cuban farm
[22] Saiprasad, N., Kalam, A., and Zayegh, A. (2018). Comparative study of optimization of hres using homer and ihoga software
[23] Akhter MN, Mekhilef S, Mokhlis H, Shah NM.(2019). Review on forecasting of photovoltaic power generation based on machine learning and metaheuristic techniques. IET Renew Power Gener. 2019;13(7):1009–23. https://doi.org/10.1049/iet-rpg.2018.5649
[24] Ahmed R, Sreeram V, Mishra Y, Arif D. (2020). A review and evaluation of the state-of-the-art in PV solar power forecasting: techniques and optimization. Renew Sustain Energy Rev. 2020;124:109792. https://doi.org/10.1016/j.rser.2020.109792
[25] Sharadga H, Hajimirza S, Balog RS.(2020). Time series forecasting of solar power generation for large-scale photovoltaic plants. Renew Energy. 2020;150:797–807. https://doi.org/10.1016/j.renene.2019.12.131
[26] Konstantinou M, Peratikou S, Charalambides AG.(2021). Solar photovoltaic forecasting of power outputusing LSTM net-works. Atmosphere. 2021;12(1):124. https://doi.org/10.3390/atmos12010124
[27] Miraftabzadeh SM, Longo M, Foiadelli F.(2020. A-day-ahead photovoltaic power prediction based on long short term memory algorithm. In: SEST 2020—3rd international conference on smart energy systems and technologies. 2020.p. 1–6. https://doi.org/10.1109/SEST48500.2020.9203481