Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control
Journal homepage: http://kinetik.umm.ac.id
ISSN: 2503-2267
Vol. 5, No. 1, February 2020, Pp. 61-70

Optimization fuzzy inference system based particle swarm optimization for onset prediction of the rainy season

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Article Info

Keywords:
Onset Prediction, Coefficient Correlation, Fuzzy Inference System

Article history:
Received 29 October 2019
Revised 22 November 2019
Accepted 02 December 2019
Published 12 February 2020

Cite:
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). doi:https://doi.org/10.22219/kinetik.v5i1.985

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Abstract

Rainfall which is occurred in an area explain the Onset Rainy Season (ORS). ORS is a characteristic of the rainy season which is important to know, but the characteristics of the rain itself is very difficult to predict. We use the method of Fuzzy Inference System (FIS) to predict ORS. Unfortunately, FIS is weak to determine parameters so that influences the working FIS method. In this study, we use PSO to optimize parameter of the FIS method to increase perform of the FIS method for onset prediction of the rainy season with the predictor Sea Surface Temperature Nino 3.4 and Index Ocean Dipole. We used coefficient correlation to determine the relationship between two variables as predictors and RMSE as evaluate to all methods. The experiment result has shown that the work of FIS-PSO after optimizing produced the good work with the coefficient correlation = 0.57 and RMSE = 2.96 that is the smallest value that is better performance if compared with other methods. It can be concluded that the method proposed can increase the onset prediction of the rainy season.

1. Introduction

The rainfall in an area will explain the onset prediction of the rainy season. The definition of every onset of the rainy season is always different, it depends on the climatology condition. The onset prediction of the rainy season is a characteristic of the rainy season that is important to know, but the characteristic of the rain itself is difficult to be predicted. Rain is a complex substance from the hydrologic cycle, so it is difficult to be formed and predicted [1]. The weather phenomenon has a big influence to make the onset of the rainy season. According to [2][3]. The phenomenon that affects climate is ENSO where it is an oceanic atmospheric interaction that occurs in the Pacific Ocean that causes global climate anomalies namely El-Nino and La Nina. One of the factors which have influenced the weather in Indonesia is the ENSO activities at the Pacific area. The ENSO Activities in Pacific can be measured by using the Sea Surface Temperature (SPL). The anomaly condition of the Nino Sea Surface Temperature (SST Nino 3.4) is one indicator that is used to see the ENSO phenomenon in the Pacific area which is happening or not by seeing the anomaly average happened [4].

Beside of the ENSO phenomenon, the IOD phenomenon has also affected ORS, which can affect the pattern of influence of rainfall anomalies in the tropics. Positive IOD is characterized by cold sea surface temperature. Negative IOD is characterized by the heat of the sea surface temperature [5].

The onset prediction of the rainy season is an information that has some roles because the information has become the basic to make a plan, decision, and the management business so the weather risk can be decreased. The onset prediction of the rainy season has been done so much with some methods. Previously, many researchers conducted the same research but used different approaches methods. For example, carried out by [6], used Ensemble Analysis Empirical Mode Decomposition (EEMD) to see the shortest and longest variations in rainfall time using three rainfall datasets from Kunming meteorology station, Lincang and Mengzi Yunnan province. The results of the analysis are predicted using short-term SVR methods and ANN for long-term prediction shows better performance compared to traditional methods. By [7], used three approaches, namely KNN, ANN, ELM for summer forecasting and rainfall prediction (2011-2016) for the State of Kerala India. The results of the percentage of KNN error for the summer were (3,075) and after the summer with the ANN method of (3,149). Different by [8], they compared the Adaptive Neuro Fuzzy Inference System (ANFIS) and the Artificial Neural Network (ANN) to predict the rainfall by seeing the five measurement criteria and ANFIS has shown the better result than ANN with the result of Root Mean Square Error (RMSE) 0.052, meanwhile ANN is 0.074.

Based on the result above, the Research Questions (RQ) that will be studied in this research are: RQ 1, is there a relationship between the SSTA Nino 3.4 and how IOD find the onset prediction results of the rainy season?; RQ 2, how to make a prediction method of the onset of the rainy season use FIS based on SSTA Nino 3, 4 and IOD?; RQ 3, how good performance the prediction method rainy season after optimizing with PSO?.

In this research, we propose the optimizing of FIS with the Particle Swarm Optimization (PSO) method to predict the onset of the rainy season. FIS is a computation outline based on the theoretical concept of fuzzy is used to map the input to output based on IF-THEN rule given [9]. FIS consists of Sugeno, Mamdani and Tsukamoto's method. The difference method is to make output. In this study we will use Mamdani method. The Fuzzy Mamdani method is easier to use and accurate in producing a decision in the form of a fuzzy set that is easy to understand because its best suits human instincts [8][10].

Mamdani's method is the first method built and has succeeded to be implemented in the design of the control system building design uses the fuzzy group theory. Mamdani method is based on IF-THEN rules with fuzzy-antecedent and consequent predicates [11][12]. PSO will be used to optimize the fuzzy parameter. PSO's method is to make a potential solution to quicken the best solution [13][14]. The PSO works with initialized with a group of particles and then to find the best solution. Every particle has position vector and speech to initialize randomly at the beginning to reach the best swarm score (global best) and the best particle score [13].

In this study This paper is organized as follows. In section 2, the methodology of this study is explained including the proposed method. The experimental results and discussion of comparing the proposed method with other prior researches are presented in section 4. Finally, our work of this paper is summarized in the last section.

2. Research Method

2.1 Fuzzy Inference System

Fuzzy inference system (FIS) is based on fuzzy set theory and IF-THEN fuzzy rules. The basic structure of fuzzy is built based on the three components namely, (1) rule base (containing selected fuzzy rules), (2) database or data dictionary (defining membership functions to be used in the rule base) and (3) reasoning mechanism (performing inference procedures on a given rule base to get results which can be used) [10][15].

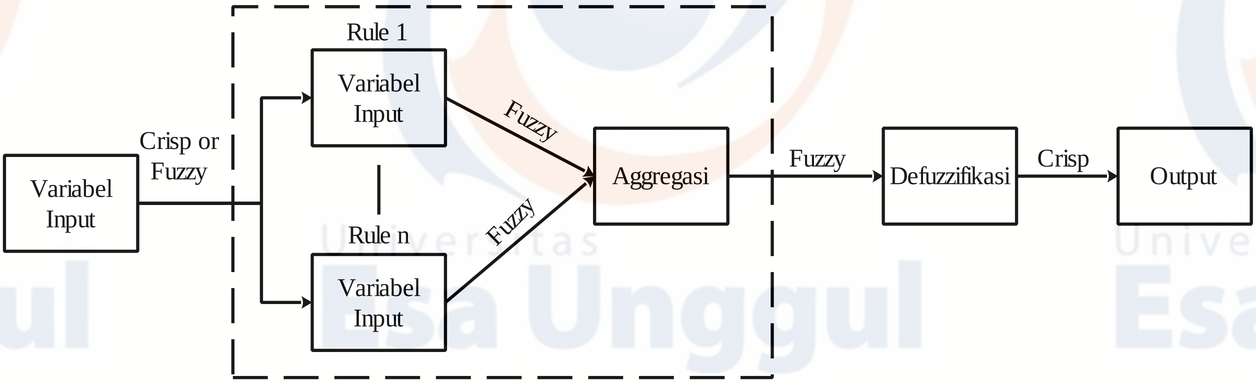


Figure 1. Block Design of Fuzzy Inference System Method (Compiled from [16])

The block design above explained that FIS there are several stages to produce output in the form of crisp values:

Stage 1. Each input and output variable are determined by the degree of membership

Stage 2. Fuzzy logic operations are performed if the antecedent part is more than one statement. The operator used is the AND operator for the MIN or OR function for the MAX function.

Stage 3. Implication. The purpose of the implication is to obtain an IF-THEN rule output based on the degree of antecedent correctness.

Stage 4. aggregation. Aggregation aims to combine the outputs of all the IF-THEN rules

Stage 5. Defuzzifcation.

Defuzzification input is a fuzzy set of results from aggregation and output in the form of a single number to be entered into the FIS output variable. There are several methods in Mamdani rule one of which is the centroid method. To calculate the area under the curve at the defuzzification stage is done using Equation 1 [8].

$$z^* = \frac{\int z\mu_a(x)\,dx}{\int \mu_a(x)\,dx} \tag{1}$$

Where, z is defuzzification value, x is a fuzzy zet member, and $\mu(x)$ is degree of membership of an element x in a set "a".

2.2 Particle Swarm Optimitation

Optimization is done to get the best results. There are several optimization methods among them but the popular papling at the moment is Particle Swarm Optimization (PSO). PSO was first proposed by Eberhart R and Kennedy J in 1995 [17]. PSO works by randomly initializing and finding optimal solutions by updating generation [12][18][19]. The optimization function of the PSO is seen by considering the global optimum function. The PSO algorithm search technique is a multi agent parallel by maintaining a swarm of particles and each particle is a potential solution where the best solution can be presented as a point or surface in an n-dimensional area.

PSO in performing optimization has two stages namely, representation of solutions and fitness functions. Learning Rates which are symbolized by C_1 and C_2 are constants for assessing the ability of particles, C_1 is a learning factor for particles and C_2 is a learning factor for swarm. The social ability of C_2 swarm which shows the weight of particles to their memory, together with r_1 and r_2 as random vector values. C_1 and C_2 values are between 0-2. In the PSO algorithm the balance of global and local exploration is mainly controlled by Inertia Weight (ϴ) and is a parameter of speed reduction to avoid stagnation of particle at the optimum locale [19].

The PSO algorithm process according to [19] consists of several processes, namely:

Stage 1. Determine the size of the swarm and determine the initial value of each particle randomly.
Stage 2. Evaluate the value of the objective function for each particle.
Stage 3. Determine initial velocity.
Stage 4. Calculating $Pbest$ and $Gbest$.
Stage 5. Calculate the velocity and position (x) of the particle using the following Equation 2.

$$v_{id}(t+1)=w.v_{id}(t)+c_1.r_1.(p_{id}-x_{id}(t))+c_2.r_2.(p_{gd}-x_{id}(t))$$
$$x_{id}(t+1)=x_{id}(t)+v_{id}(t+1) \quad (2)$$

Where,
$v_{id}(t+1)$ and $v_{id}(t)$ is the latest particle speed and current particle speed
$x_{id}(t+1)$ and $x_{id}(t)$ is the latest particle position and current particle position
r_1 and r_2 is random numbers are uniformly distributed in intervals 0 and 1
c_1 and c_2 is the coefficient of acceleration of personal influence and social influence
w is inertia weight

Stage 6. Evaluate the value of the objective function in the next iteration.
Stage 7. Update $Pbest$ and $Gbest$
Stage 8. Check, what the solution is optimal or not, if it is optimal then the algorithm process stops, but if it is not optimal then move back to stage 5

We proposed a fuzzy inference system optimization method optimized particle swarm optimization (PSO) for onset prediction. The proposed method tested using three datasets: 1) The rainfall dataset from Waingapu city by BMKG Waingapu dsitrict 1973-2013; 2) IOD dataset by Japan Marine Earth Science and Technology Center (JAMSTEC) from 1973-2013 (link: http://www.jamstec.go.jp/.); 3) SSTA Nino 3.4 datasets by dari National Oceanic Atmospheric Administration (NOAA) (link: http://www.cpc.ncep.noaa.gov/.) for onset prediction ORS. Figure 2 shows block design of the proposed method. As shown in Figure 2, the research stages such as:

- First of all, we do preprocess to know the beginning of the season by counting the value of the rainfall per year period of the year 1973-2013. Three datasets used are ORS, SSTA Nino 3.4 and IOD. We do cleanse the data missing from SSTA Nino 3,4 and IOD as following in Equation 3.

$$A(day)=\sum_{n=1}^{day}\left[R(n)-\bar{R}\right] \quad (3)$$

Where, A (day) is the accumulation of rainfall anomaly, R is the daily rainfall (mm/day) and n is the n-th day. R is the average rainfall per year. Then, count the rainfall anomaly accumulation value with the result from the addition of the rainfall anomaly beginning value after then count the minimum value.

- Next, do the correlation analyse between the onset of the rainy season with IOD and SSTA Nino 3.4 which will be used to find the predictor. The correlation coefficient value which is measured by using the equality (2) [8] as follow Equation 4.

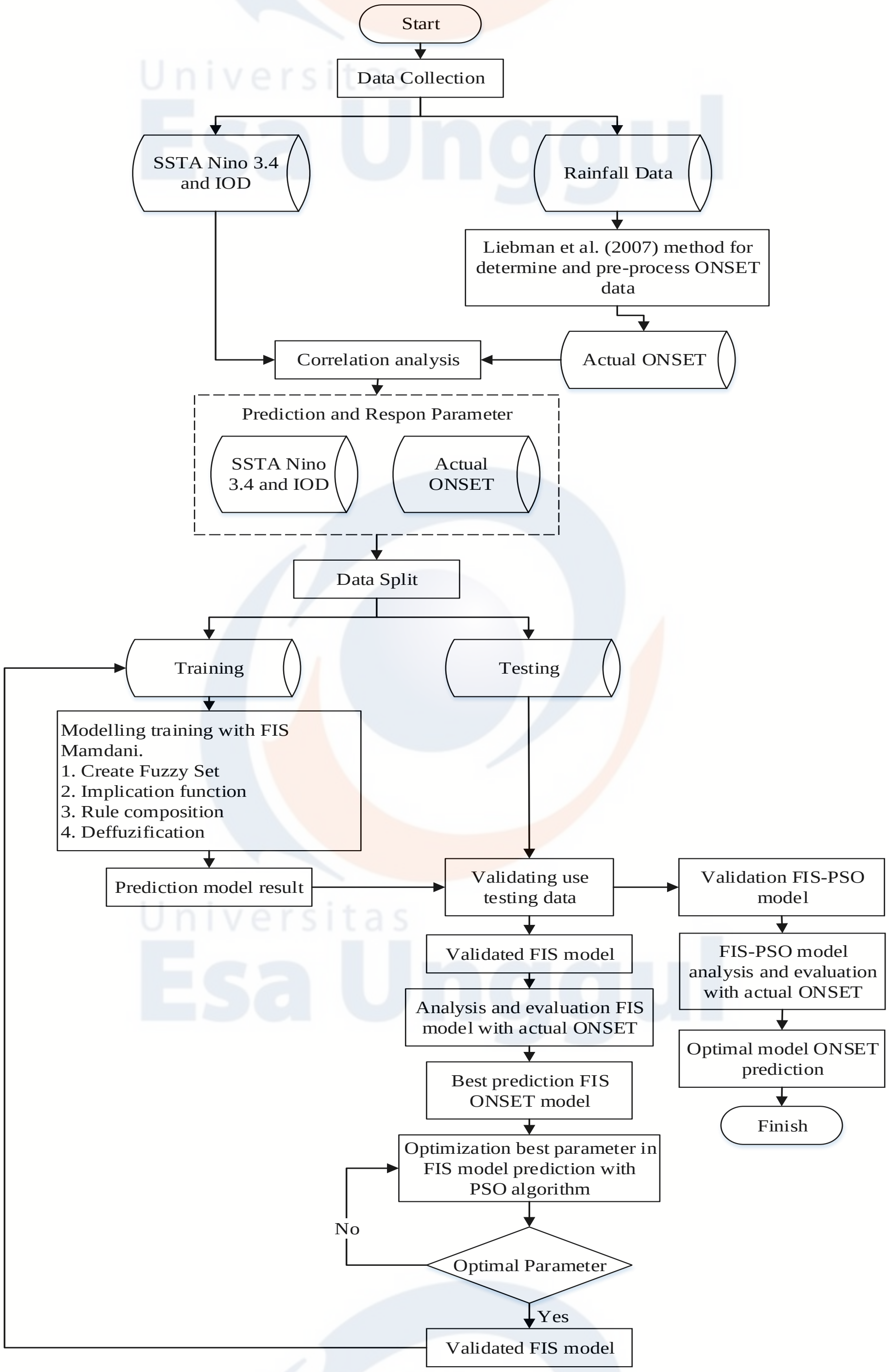


Figure 2. Block Design of the Proposed Method

$$r = \frac{n\sum_{i=1}^{n} x_i y_i - \left(\sum_{i=1}^{n} y_i\right)}{\sqrt{\left[n\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2\right]\left[n\sum_{i=1}^{n} y_i^2 - \left(\sum_{i=1}^{n} y_i\right)^2\right]}} \quad (4)$$

where, r is the value of the correlation between the onset of the rainy season with IOD and SSTA Nino 3.4, n is the amount of the pair of IOD, SSTA Nino 3.4 and the onset of the rainy season data, $\sum X_i$ is the total amount from the IOD variable or SSTA Nino 3.4, $\sum Y_i$ is the total amount of the onset of the rainy season variable. The correlation coefficient r shows the power of the relation between two with the space of the correlation value $-1 \le r \le 1$.

- The next stage we do training and testing. In this stage, the correlation result between the onset of the rainy season with SSTA Nino 3.4 and IOD data are used technic k-fold cross validation that to share data randomly to be k-subset which are free to each other in using the review as much as k. We used k=1 to k=5 for producing 5 prediction methods. At the first iteration, the first group of the predictor data as the test data, the second predictor data to the fifth group as the practice data, and the second onset of the rainy season data to the fifth group as the targets. The second iteration, the second group predictor data as the test data, the others are the practice data the same process has been done until fifth iteration.
- For learning method, we use FIS mamdani because this method is intuitive and fixed to be given to human input [20]. There are four stage on FIS method:
  - **Fuzzification**. The input and output variables are divided into some fuzzy group, then find the affiliate function from each category. In this study, the affiliation functions are used zmf (Equation 5), Gaussian (Equation 6) and smf (Equation 7) by (wolframmathworld, (link: mathworld.wolfram.com)). Gaussian curve is found with two parameters (c, σ) followed Equation 8.

$$f\left(x;a,b\right)=\begin{cases}1, x\le a\\ 1-2\left(\dfrac{x-a}{b-a}\right)^2, a\le x\le \dfrac{a+b}{2}\\ 2\left(\dfrac{x-a}{b-a}\right)^2, \dfrac{a+b}{2}\le x\le b\\ 0, x\ge b\end{cases} \tag{5}$$

$$f\left(x;a,b\right)=\begin{cases}0, x\le a\\ 2\left(\dfrac{x-a}{b-a}\right)^2, a\le x\le \dfrac{a+b}{2}\\ 1-2\left(\dfrac{x-a}{b-a}\right)^2, \dfrac{a+b}{2}\le x\le b\\ 1, x\ge b\end{cases} \tag{6}$$

$$b=\frac{3\left(Mean-Median\right)}{\sigma} \tag{7}$$

Where, b is skewness and σ is standard deviation.

$$Gaussian\left(x;c,\sigma\right)=e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{8}$$

Where, c presents the middle point, σ presents the width of the component function and x is curve domain. Table 1, shows the space of the fuzzy variable value.

Table 1. Value Range

Function	Variable Name	Fuzzy Set/Class	Range of Value of Each Variable
Input	IOD	Positive	[> 0.4]
		Normal	[-0.4 0.4]
		Negative	[<-0.4]
	ASPL Nino 3.4	Strong	[>0.5]
		Moderate	[-0.5 0.5]
		Weak	[<-0.5]

Every parameter value is used to find the component level for each fold. Example the September IOD input variable parameter value with the negative fuzzy group (a = -1.13 and b= 0.08), normal (c = -0.06 and = 0.22), positive (a = 0.47 and b= 0.01). The July SSTA Nino 3.4 Variable with the weak fuzzy group (a = -0.57 and b= 0.67), middle (c = -0.104 and = 0.32), strong (a = 0.99 and b= -0.79). The August SSTA Nino 3.4 variable with the weak fuzzy group (a = -1.27 and b= 0.04), middle (c = -0.09 and = 0.32), strong (a = 0.18 and b = -1.15). The September SSTA Nino 3.4 variable with the weak fuzzy group (a = -1.39 and b= 0.23), middle (c = 0.04 and = 0.34), strong (a = 0.24 and b = -0.63). The onset of the rainy season output variable with the forward fuzzy group (c = 1.01 and = 0.02) and backward (c = 0.79 and = 0.06).

- **Implication**. We will define the component level (w) to every fuzzy group. The implication process will be done for all rules. So, the minimum value in every rule will be used to the aggregation process.
- **Aggregation**. This stage does process to combine all of the output rules if – then to be the single fuzzy group, so can be defined by every fuzzy group which is entered. To produce the single set fuzzy group, this stage uses maximum method. The maximum method is used to modify fuzzy area and apply to the output by using the OR operator.
- **Defuzzification**. This stage is using the centroid method to get the crisp value by taking the fuzzy area center point [16]. To count the under-curve scope will be done by following Equation 9. On the other hand, to get the curve limit value by following Equation 10.

$$z^* = \frac{\sum_{t=1}^{M} z_t w_t}{\sum_{t=1}^{M} w_t} \quad (9)$$

where, z^* is center average defuzzifier, z_t set fuzzy centroid t-th with w_t and w_t is the membership function.

$$y^* = \frac{z_1 w_1 + z_2 w_2 + z_3 w_3 + z_4 w_4}{w_1 + w_2 + w_3 + w_4} \quad (10)$$

The next stage for optimizing the component function from every input and output variables used PSO. For this research, the PSO process is used refer to [21]. Next the parameter explanation that is used to PSO. The particle amount used is 28,24 particles from the input variables and 4 particles from the output variables. The particle used is the component function in every variable. The dimension of the particle is defined from the problem that will be optimizing. C1 (learning factor for particle), C2 (learning factor for swarm). The value used is 2. The particle maximum change while the iteration is happening, with the limit used is -1 to 1. The condition will stop while the maximum iteration can be reached. The iteration used is 100 times. The weight inertia (w) is used to keep the balance between the global and local exploration capability.

- Method evaluated
- End

PSO, when optimization has two stages namely solution of representation and fitness function. Learning Rates symbolized by c_1 and c_2 are constants for assessing the ability of particles, c_1 learning factors for particles and c_2 learning factors for swarm. The social capability of c_2 swarm which shows the weight of particles to their memory, together with r_1 and r_2 as random vector values. The c_1 and c_2 values are between 0-2. In PSO the balance of global and local exploration is mainly controlled by Inertia Weight (θ) is a parameter of speed reduction to avoid particle stagnation to locale optimum [21].

In this study, the proposed method evaluated using Root Mean Square Error (RMSE). A good prediction method is correlation coefficient value is close to -1 and 1 and the RMSE value is close to zero [8]. Error value (error) is used to determine the value of deviation of the predicted value of the actual value. The value of the correlation coefficient is calculated by using Equation 4, while RMSE follow Equation 11.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} \left(X_t - F_t\right)^2}{n}} \quad (11)$$

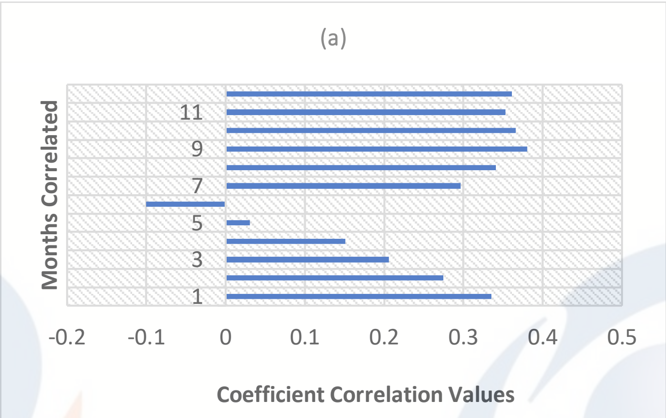
where, X_t is ORS actual and F_t is ORS value prediction.

3. Results and Dicussion

The experiments are tested using computing platform based on Intel Celeron 2.16 GHz CPU, 8 GB RAM and Microsoft Windows 10 64-bit operating system, and MATLAB R2008a as data analytics tool. MATLAB will be used to measure RMSE and graphic analysis.

3.1 Data Preprocessing

First of all, we combine three datasets (ORS with IOD and SSTA Nino 3.4), then do preprocessing using correlation analysis to determine the label of data as predictor. Determination of predictors was performed using a correlation analysis approach between IOD - ORS actual and SSTA Nino 3.4 - ORS actual. Figure 3, shown the results of the correlation calculations of two samples. As shown in Figure 3 the correlation value of SSTA Nino 3.4 in July, August, September, and IOD in September are 0.296, 0.342, 0.381 and 0.285 respectively.



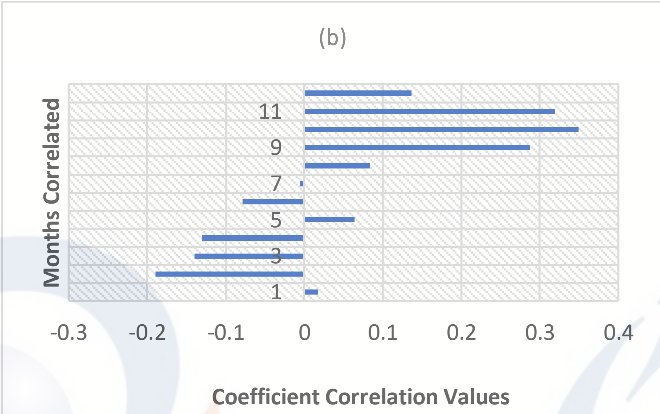


Figure 3. (a) Correlation Values SSTA Nino 3.4 with ORS Actual, (b) Correlation Values IOD with ORS Actual

3.2 Fuzzy inference system without particle swarm optimization

In the second experiment, we implemented fuzzy inference system (FIS) to predict ORS. The training and testing data were determined using a correlated predictor value. The training data is used to obtain the method and testing data used to determine the RMSE level of the method that has been produced. The k-fold cross validation method is used to separate the testing and training data, k-fold used is k=5. The experiment results shown in Table 2. In this result 5-fold can be told as the best FIS method because it has the highest correlation value around 5 kinds folded with the value 0.57 with the lowest RMSE value from the five kinds folded with the value 2.96.

Table 2. Correlation Coefficient and RMSE Results on FIS Method Only

1-Fold			2-Fold			3-Fold			4-Fold			5-Fold		
Years	(1)	(2)	Years	(1)	(2)	Years	(1)	(2)	Years	(1)	(2)	Years	(1)	(2)
1973	330	302	1981	316	292	1989	334	304	1997	343	341	2005	292	319
1974	325	301	1982	343	297	1990	338	338	1998	318	305	2006	357	336
1975	295	300	1983	321	305	1991	323	339	1999	320	305	2007	345	336
1976	338	303	1984	338	298	1992	324	305	2000	292	304	2008	329	336
1977	336	303	1985	325	300	1993	346	340	2001	314	305	2009	350	331
1978	339	303	1986	340	300	1994	336	345	2002	328	305	2010	259	319
1979	333	303	1987	320	297	1995	333	300	2003	318	306	2011	350	336
1980	341	306	1988	332	297	1996	322	288	2004	352	342	2012	343	336
Correlation		0.81	Correlation		0.05	Correlation		0.52	Correlation		0.84	Correlation		0.91
RMSE		76.56	RMSE		88.58	RMSE		34.18	RMSE		24.85	RMSE		8.46

(1)ORS actual, (2)ORS prediction

3.3. Fuzzy inference system + particle swarm optimization

In the last experiment, we implement PSO+FIS to predict ORS. PSO used to parameter optimize the FIS method. This method is applied 5-fold as the best previous FIS method. The experiment result is shown in Table 3. Based on FIS parameter values in 5-fold optimized using PSO results, there was a significant improvement in performance compared to FIS method without previous PSO can seen Table 4, that is the correlation coefficient amount 0.91 and the lowest value on RMSE is 8.46.

Table 3. Correlation Coefficient and RMSE Results on FIS Method Only

1-Fold			2-Fold			3-Fold			4-Fold			5-Fold		
Years	(1)	(2)	Years	(1)	(2)	Years	(1)	(2)	Years	(1)	(2)	Years	(1)	(2)
1993	330	310	1981	316	309	1989	334	314	1997	343	337	2005	292	321
1994	325	312	1982	343	305	1990	338	306	1998	318	336	2006	357	333
1995	295	331	1983	321	314	1991	323	308	1999	320	328	2007	345	329
1996	338	315	1984	338	312	1992	324	309	2000	292	305	2008	329	325
1997	336	314	1985	325	311	1993	346	311	2001	314	314	2009	350	322
1998	339	315	1986	340	311	1994	336	305	2002	328	319	2010	259	322
1999	333	313	1987	320	315	1995	333	310	2003	318	310	2011	350	328
1980	341	312	1988	332	314	1996	322	309	2004	352	305	2012	343	336
Correlation		-0.84	Correlation		-0.46	Correlation		0.10	Correlation		0.22	Correlation		0.57
RMSE		40.66	RMSE		50.31	RMSE		64.95	RMSE		10.59	RMSE		2.96

$^{(1)}$ORS actual, $^{(2)}$ORS prediction

Table 4. Correlation Coefficient and RMSE Results on FIS Only VS PSO+FIS

	1-Fold		2-Fold		3-Fold		4-Fold		5-Fold	
	FIS	*FIS+PSO*	*FIS*	*FIS+PSO*	*FIS*	*FIS+PSO*	*FIS*	*FIS+PSO*	*FIS*	*FOS+PSO*
Correlation	0.81	-0.84	0.05	-0.46	0.52	0.10	0.84	0.22	0.91	0.57
RMSE	76.56	40.66	88.68	50.31	34.18	64.95	24.85	10.59	8.46	2.96

4. Conclussions

In this study, we have proposed a new scheme for optimizing parameters developed to improve the performance of the FIS method, in which PSO used to optimize parameters of FIS used to onset prediction of the rainy season. From the experiment results, show that FIS+PSO with use 5-fold yields excellent coefficient correlation and RMSE to onset prediction. PSO used to parameter optimize on FIS is proved to lower the coefficient correlation. RMSE evaluation also shows FIS+PSO gets better performance compared to FIS methods. It can be concluded that applied PSO is able to increase the correlation of data and better perform of FIS method. For the future research will be a concern on compare traditional evolutionary computation such as genetic algorithm (GA) and differential evolution (DE) for the same data to choose the best performance method.

Acknowledgement

Thank you to Department of Health Information Management, Esa Unggul University and Intelligent Computing Research Group by Department of Informatics at Universitas Muhammadiyah Semarang and which has become a place for researchers to develop this journal research. Hopefully, this research can make a major contribution to the advancement of technology in Indonesia.

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