

Optimization of Sugeno Fuzzy Inference System's Rules for Precipitation Predictions

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Submitted: July 01 2026 | Accepted: Sept 14 2026 | Published: Sept 28 2026

ABSTRACT

Precipitation information and forecasting play an important role in various fields, including agriculture, flood control, irrigation management, and water resource management. However, the stochastic characteristics of precipitation make accurate forecasting a complex task and require an approach capable of handling uncertainty. This study aims to optimize the rules of the Sugeno Fuzzy Inference System (FIS) to improve precipitation prediction accuracy. The dataset consists of historical precipitation data collected from four monitoring stations in Pasuruan, East Java, Indonesia, namely Puspo, Sumber, Tosari, and Tutar. The model employs eight input variables representing precipitation observations at several previous time points for each monitoring station. Rule optimization is performed using the Evolution Strategies Algorithm (ESA) to determine appropriate fuzzy rules and constant values in the Sugeno FIS. Several experimental scenarios are conducted, including fuzzy membership constraints, population and mutation ratios, recombination size, selection methods, and iteration settings. The experimental results identify the best configuration using membership constraints of 0 and 40, an initial population size (μ) of 200, a mutation size (m) of 5, a recombination size of 2μ , and Binary Tournament Selection. For the Puspo station, the optimized Sugeno FIS achieves an RMSE of 3.2639479683, compared with 7.2105862632 obtained using Linear Regression. In the test-data comparison, Sugeno FIS achieves an RMSE of 3.9867, while regression produces 8.89835. These results demonstrate that optimizing Sugeno FIS rules using ESA improves the model's ability to follow precipitation patterns and provides more accurate predictions than the regression approach. The main contribution of this study is the development of an optimized Sugeno FIS rule configuration as an alternative approach for precipitation prediction.

Keywords: Evolution Strategies, Optimization, Precipitation Prediction, Sugeno Fuzzy Inference System, Weather Forecasting.

ABSTRAK

Informasi dan prediksi presipitasi memiliki peran penting dalam berbagai bidang, seperti pertanian, pengendalian banjir, pengelolaan irigasi, serta pengelolaan sumber daya air. Namun, karakteristik presipitasi yang bersifat stokastik menyebabkan proses prediksi menjadi kompleks dan memerlukan metode yang mampu menangani ketidakpastian. Penelitian ini bertujuan mengoptimalkan aturan pada Sugeno Fuzzy Inference System (FIS) untuk meningkatkan akurasi prediksi presipitasi. Dataset yang digunakan merupakan data presipitasi historis dari empat stasiun pengamatan di Pasuruan, Jawa Timur, yaitu Puspo, Sumber, Tosari, dan Tutar. Model menggunakan delapan variabel masukan berupa data presipitasi pada beberapa waktu sebelumnya untuk setiap stasiun. Optimasi dilakukan menggunakan Evolution Strategies Algorithm (ESA) untuk menentukan konfigurasi aturan dan nilai konstanta pada model Sugeno FIS. Eksperimen dilakukan melalui beberapa skenario yang meliputi inisialisasi populasi, batas keanggotaan fuzzy, rasio populasi dan mutasi, ukuran rekombinasi, metode seleksi, serta jumlah iterasi. Hasil eksperimen menunjukkan konfigurasi terbaik menggunakan batas keanggotaan 0 dan 40, populasi awal (μ) sebesar 200, ukuran mutasi (m) sebesar 5, ukuran rekombinasi sebesar 2μ , serta Binary Tournament Selection. Pada pengujian stasiun Puspo, model Sugeno FIS teroptimasi menghasilkan RMSE sebesar 3,2639479683, lebih rendah dibandingkan Linear Regression sebesar 7,2105862632. Pada perbandingan data pengujian, RMSE Sugeno FIS sebesar 3,9867, sedangkan regresi sebesar 8,89835. Hasil tersebut menunjukkan bahwa optimasi aturan menggunakan ESA mampu meningkatkan kemampuan Sugeno FIS dalam

mengikuti pola presipitasi dan menghasilkan prediksi yang lebih akurat dibandingkan pendekatan regresi. Kontribusi penelitian ini adalah menghasilkan konfigurasi optimasi aturan Sugeno FIS yang dapat menjadi pendekatan alternatif untuk prediksi presipitasi.

Kata Kunci: *Evolution Strategies, Optimization, Precipitation Prediction, Sugeno Fuzzy Inference System, Weather Forecasting.*

INTRODUCTION

Precipitation forecasting is an important task in various fields, including agriculture, irrigation management, flood control, airport operations, shipping, and water resource management. Accurate precipitation information can support irrigation planning, soil moisture management, flood mitigation, and the management of water reservoirs and distribution systems. However, precipitation is a stochastic phenomenon influenced by multiple atmospheric conditions, making its temporal behavior difficult to represent accurately using conventional forecasting approaches. Forecasting uncertainty also tends to increase as the forecasting horizon becomes longer, which can lead to increasing prediction errors. Therefore, an appropriate forecasting approach is required to model the uncertain and nonlinear characteristics of precipitation and to provide reliable prediction results for practical decision-making.

Several previous studies have applied fuzzy-based and statistical approaches to precipitation and rainfall prediction. Tsukamoto fuzzy inference has been used for rainfall prediction, while Mamdani fuzzy inference has been applied to model rainfall based on weather and precipitation conditions. Other studies have employed Fuzzy Time Series, Adaptive Neuro-Fuzzy Inference System (ANFIS), Support Vector Regression, and hybrid machine-learning approaches. These studies demonstrate that fuzzy logic can effectively represent uncertainty in rainfall-related prediction problems. In particular, comparative research has indicated that Sugeno fuzzy inference can provide better performance than the Mamdani approach for rainfall prediction. Furthermore, previous research has explored optimization of Sugeno FIS using clustering and heuristic algorithms for different prediction and decision-making problems. The existing literature therefore provides evidence that fuzzy inference and optimization techniques have potential for improving prediction performance.

Despite these developments, an important research gap remains in the optimization of Sugeno FIS rules specifically for precipitation forecasting. Previous rainfall studies have predominantly focused on Mamdani FIS, ANFIS, Fuzzy Time Series, statistical models, or machine-learning methods, while studies that explicitly optimize the rules and parameters of Sugeno FIS for precipitation prediction remain limited in the literature reviewed in this study. In addition, determining appropriate Sugeno rules is not straightforward because the model requires multiple rule-specific regression equations and constant parameters. In the present problem, the rule structure involves 16 constant values for each rule and a total of 256 numerical parameters that must be optimized. This large search space makes manual rule determination inefficient and creates a need for an automated optimization mechanism. Thus, the gap addressed by this study is not merely the use of Sugeno FIS for precipitation prediction, but the systematic optimization of its rule parameters to obtain a more suitable configuration for stochastic precipitation data.

To address this gap, this study proposes the use of the Evolution Strategies Algorithm (ESA) to optimize the rules and constant parameters of the Sugeno FIS. ESA is a heuristic optimization approach that can search a large solution space using population-based reproduction and recombination mechanisms. The optimization process in this study evaluates several experimental scenarios involving fuzzy membership constraints, population and mutation sizes, recombination size, selection method, and iteration settings. The resulting configuration is then applied to precipitation data from four monitoring stations in Pasuruan, namely Puspo, Sumber, Tosari, and Tutar, using precipitation observations at several previous time points as input variables. The novelty of this study lies in integrating Sugeno FIS with ESA specifically to optimize its rule parameters for precipitation prediction and in empirically determining an effective combination of ESA parameters rather than relying solely on manually specified fuzzy rules.

Therefore, the objective of this study is to develop and evaluate an optimized Sugeno FIS for precipitation prediction by determining an effective configuration of fuzzy membership constraints, population size, mutation size, recombination size, selection method, and iteration

process. The study also aims to compare the prediction performance of the optimized Sugeno FIS with the regression-based approach used as a comparison model. The contribution of this research is twofold: first, it provides an automated optimization strategy for determining Sugeno FIS rule parameters in a stochastic precipitation forecasting problem; and second, it identifies an experimentally supported ESA configuration for improving prediction accuracy. The expected output is an optimized Sugeno FIS model capable of following precipitation patterns more effectively and producing lower prediction errors, thereby providing an alternative computational approach for precipitation forecasting.

RESEARCH METHODOLOGY

Rahman (Rahman, 2020) and Janarthanan et al. (Janarthanan et al., 2021) have used Tsukamoto's fuzzy method to predict rainfall. However, the defuzzification process in these studies remains closely tied to the fuzzification process, making the resulting prediction relatively rigid. Susano and Anggraeni (Susano and Anggraeni, 2021) reported that the fuzzy time series method produced relatively poor accuracy. Novitasari et al. (Novitasari et al., 2020) and Talei et al. (Talei, Chua and Wong, 2010) proposed the Adaptive Neuro-Fuzzy Inference System (ANFIS) for rainfall prediction; however, this approach requires a relatively large amount of data for training and testing. Singla et al. (Singla, Kaur and Nijhawan, 2019), Damayanti et al. (Damayanti et al., 2022), and Kindhi et al. (Kindhi et al., 2022) applied Mamdani's fuzzy method to rainfall prediction. These studies demonstrate that fuzzy logic is a suitable approach for rainfall prediction, but its application remains relatively limited in addressing the statistical and time-series characteristics of rainfall data.

Ardi et al. (Ardi, Effendi and Nababan, 2021) demonstrated that Sugeno's fuzzy method can provide better performance than Mamdani's fuzzy method. Burhan et al. (Burhan, Mahmud and Bacht i ar, 2018) further proposed the use of Sugeno's fuzzy method combined with clustering optimization. Nevertheless, studies specifically addressing the optimization of Sugeno's fuzzy method for rainfall prediction remain relatively limited, particularly in recent years. Suparta and Samah (Suparta and Samah, 2020), for example, applied ANFIS for rainfall prediction in Tangerang, Indonesia. Gumilar et al. (Aditya Gumilar, Sri Suryani Prasetiowati and Yuliant Sibaroni, 2022) developed a hybrid machine-learning approach for rainfall classification using imbalanced data, while Morales et al. applied self-identification neuro-fuzzy optimization to model the relationship between rainfall and runoff. Optimization of Sugeno's fuzzy method has also been applied to other prediction and decision-making problems. Achnas et al. (Apsari Achnas, Cholissodin and Firdaus Mahmudy, 2015), for instance, optimized Sugeno's fuzzy method to determine house selling prices, while Kartikasari (Kartikasari, 2020) optimized Sugeno's fuzzy method for traffic-light control. These studies indicate the potential of Sugeno's fuzzy method for optimization, but its application to rainfall prediction remains insufficiently explored.

Sugeno's fuzzy method is particularly relevant because its inference process employs regression-based calculations (Salman and Kanigoro, 2021). The regression equations contain constant parameters that can be optimized to improve prediction performance and accuracy. This characteristic provides an opportunity to develop an optimized Sugeno fuzzy model specifically for rainfall prediction. Ridwan et al. (Ridwan et al., 2021) applied several regression methods to rainfall forecasting, while Farajzadeh et al. (Farajzadeh, Fakheri Fard and Lotfi, 2014) compared ARIMA and Artificial Neural Networks for modeling monthly rainfall and runoff and found comparable performance between the two approaches. Arumugam and Saranya (Arumugam and Saranya, 2018) proposed Seasonal ARIMA for detecting outliers and handling missing values, whereas Dwiasnati and Devianto (Dwiasnati and Yudo Devianto, 2022) optimized Support Vector Machine to identify flood-prone areas. These studies highlight the importance of statistical, regression, and optimization techniques in improving the reliability of rainfall-related prediction models.

In Indonesia, Iriany et al. (Iriany et al., 2015) predicted precipitation in Pasuruan, East Java, using the Generalized Space-Time Autoregressive (GSTAR) model. Subsequently, Utomo et al. (Utomo, Mahmudy and Anam, 2017) proposed an improved model by incorporating a Fuzzy Neural Network. Although these studies demonstrate the applicability of spatial-temporal and fuzzy-based approaches to rainfall prediction in Indonesia, the optimization of Sugeno's fuzzy inference parameters for rainfall prediction has received limited attention. Therefore, a research gap remains in developing an optimized Sugeno fuzzy model that combines the flexibility of fuzzy inference with regression-based parameter optimization for improving rainfall prediction

accuracy. This study addresses this gap by optimizing the constant parameters in Sugeno's fuzzy regression equations and evaluating whether the optimized model can provide more accurate and reliable rainfall predictions than conventional fuzzy approaches.

Sugeno's Fuzzy Inference System

A fuzzy logic inference proposed by Takagi and Sugeno (Takagi and Sugeno, 1985) is the right way to resolve the ambiguity that is often encountered in the field of forecasting meteorology. The method can easily incorporate expert knowledge in the form of mathematical model's standard in the form of Fuzzy Inference System (FIS). FIS is a non-linear cartography based on a specific input vector for a scalar vector output using fuzzy logic. A FIS simulates the process of human reasoning by allowing the computer to behave in a calculation less precise than the classical one. It is suitable to provide reasoning through the membership feature and a set of rules. It is also very good for modeling systems that are hard to accurately represent the mathematical model (Susano and Anggraeni, 2021).

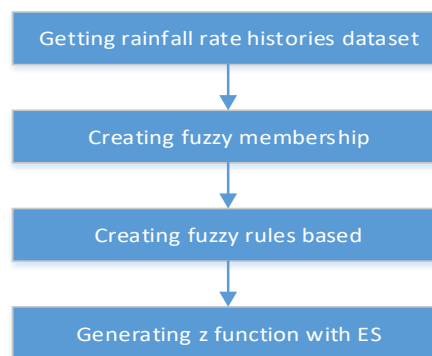


Figure 1: Steps to build the Fuzzy Inference System using Evolution Strategies Algorithm

Precipitation Forecasting is one of the most complex elements in the field. One of them because precipitation is a stochastic process. It is dependent on a variety of parameters such as sea surface temperature, surface pressure and atmospheric flow parameters (Aditya Gumilar, Sri Suryani Prasetyowati, and Yuliant Sibaroni, 2022). We use precipitation rate data for daily atmospheric. Steps to build the system of Fuzzy Inference System using Evolution Strategies Algorithm can be seen in Fig. 1. Evolution Strategies Algorithm is used to determine the appropriate fuzzy membership set and rules to get higher accuracy.



Figure 2: Puspo, Sumber, Tosari and Tutar area on Google Maps

Dataset

We have the precipitation dataset for this study belonging from Iriany, et al. (Iriany *et al.*, 2015) so it can make easier for us to do the comparison and accuracy calculation. We have a precipitation dataset from four Pasuruan stations namely Puspo, Sumber, Tosari, and Tutar. Each area can be seen in Fig. 2.

Rules Based

This study uses 8 input variables that are precipitation of yesterday (d-1), two days ago (d-2), etc. for each monitoring station that has been mentioned. Fig. 3 shows that the fourth station has a similar precipitation rate, so it is likely that the two stations influence each other. The conditions are sunny and rain conditions. The conditions rules are presented as Table 1 to be used in the fuzzification process. Between the variables of the table have AND relation as,

IF *state_1* AND *state_2* AND *state_3* AND AND *state_n* THEN *decision*

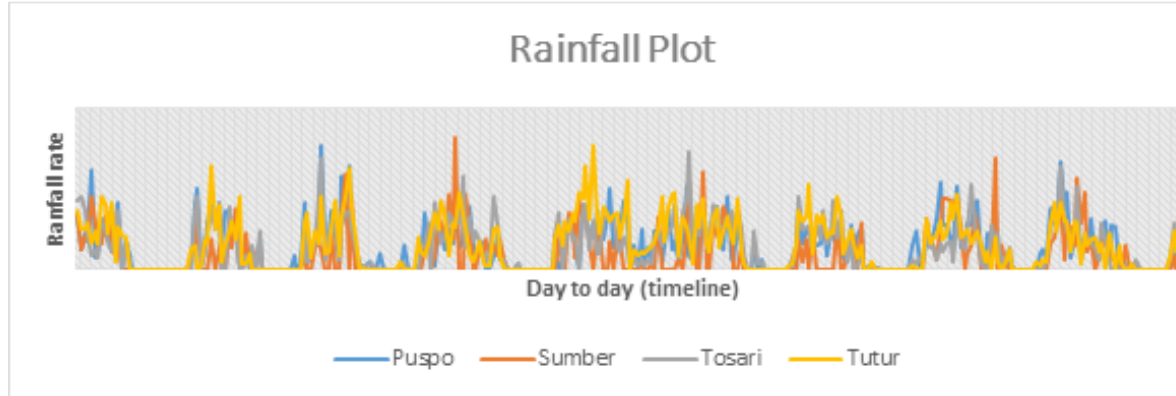


Figure 3: Rainfall Plot from Four Stations

On the table there is a number 0, which represents a sunny state and the number 1 representing the wet state, so on the third row can be read as.

IF Puspo (d-1)=sunny AND Puspo (d-2)=rain AND Puspo (d-18)=sunny AND Puspo (d-36)=sunny AND Sumber (d-1)=sunny AND Sumber (d-2)=rain AND Sumber (d-18)=sunny ANDetc.... THEN Puspo (d-0)=f3 (z1-16).

Today (t-0) column is the forecast results for Puspo from the condition variable of the line. Today (t-0) calculated using a linear regression (or called zero-order equation) as in (1). The equation contained in variable z1 to z16 is a constant value that needs to be optimized and will be discussed in chapter 7 of Optimization.

$$f(z_{1-16}) = z_1 + z_2 * Pu_{t-1} + z_3 * Su_{t-1} + z_4 * To_{t-1} + \dots + z_{15} * To_{t-34} + z_{16} * Tu_{t-34} \quad (1)$$

Table 1: Rules Based for Fuzzification and Interference

Puspo	Sumber								Tosari				Tutur			
$d-0$	$d-$	$d-$	$d-$	$d-$	$d-$	$d-$	$d-$	$d-$	$d-$	$d-$	$d-$	$d-$	$d-$	$d-$	$d-$	$d-$
	1	2	18	36	1	2	18	36	1	2	18	36	1	2	18	36
$f_1(Z_{1-16})$	F	F	F	F	F	F	F	F	F	F	F	F	F	F	F	F
$f_2(Z_{1-16})$	T	F	F	F	T	F	F	F	T	F	F	F	T	F	F	F
$f_3(Z_{1-16})$	F	T	F	F	F	T	F	F	F	T	F	F	F	T	F	F
$f_4(Z_{1-16})$	T	T	F	F	T	T	F	F	T	T	F	F	T	T	F	F
$f_5(Z_{1-16})$	F	F	T	F	F	F	T	F	F	F	T	F	F	F	T	F
$f_6(Z_{1-16})$	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F
$f_7(Z_{1-16})$	F	T	T	F	F	T	T	F	F	T	T	F	F	T	T	F
$f_8(Z_{1-16})$	T	T	T	F	T	T	T	F	T	T	T	F	T	T	T	F
$f_9(Z_{1-16})$	F	F	F	T	F	F	F	T	F	F	F	T	F	F	F	T
$f_{10}(Z_{1-16})$	T	F	F	T	T	F	F	T	T	F	F	T	T	F	F	T
$f_{11}(Z_{1-16})$	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T
$f_{12}(Z_{1-16})$	T	T	F	T	T	T	F	T	T	T	F	T	T	T	F	T
$f_{13}(Z_{1-16})$	F	F	T	T	F	F	T	T	F	F	T	T	F	F	T	T
$f_{14}(Z_{1-16})$	T	F	T	T	T	F	T	T	T	F	T	T	T	F	T	T
$f_{15}(Z_{1-16})$	F	T	T	T	F	T	T	T	F	T	T	T	F	T	T	T
$f_{16}(Z_{1-16})$	T	T	T	T	T	T	T	T	T	T	T	T	T	T	T	T

Fuzzification - Defuzzification

Not all precipitation decisions can be presented with definitely sunny or definitely rain. Sometimes precipitation is presented with thunderstorms, heavy rain or drizzle so the necessary statistical science presenting with a certain value accordance with certain precipitation levels. If definitely sunny presented with 0 and the definitely rain presented with 1 then rain at lower levels or almost sunny can be presented with decimal value between 1 and 0 as (2). Otherwise, if definitely sunny is presented with 1 and definitely rain is presented with 0 then sunny at higher level or almost rain can be presented with decimal value between 0 and 1 (3).

To change the precipitation statistical value of previous research into the fuzzy value requires a membership set as in Fig. 4. From the Fig. 4, it can be seen that there are three parts by two lines listed. These two lines are the fuzzy value described. The third part is the part with the statistical value less than 10, 10 to 40, and over 40. Under the rules based, the next calculation is defuzzification using (4).

$$f(x) = \begin{cases} 0 & x < 10 \\ \frac{x-10}{40-10} & 10 < x < 40 \\ 1 & 40 < x \end{cases} \quad (2)$$

$$f(x) = \begin{cases} 1 & x < 10 \\ \frac{40-x}{40-10} & 10 < x < 40 \\ 0 & 40 < x \end{cases} \quad (3)$$

$$Defuzzification = \frac{\sum \alpha f_{predicate} * f(z_{1-16})}{\sum \alpha f_{predicate}} \quad (4)$$

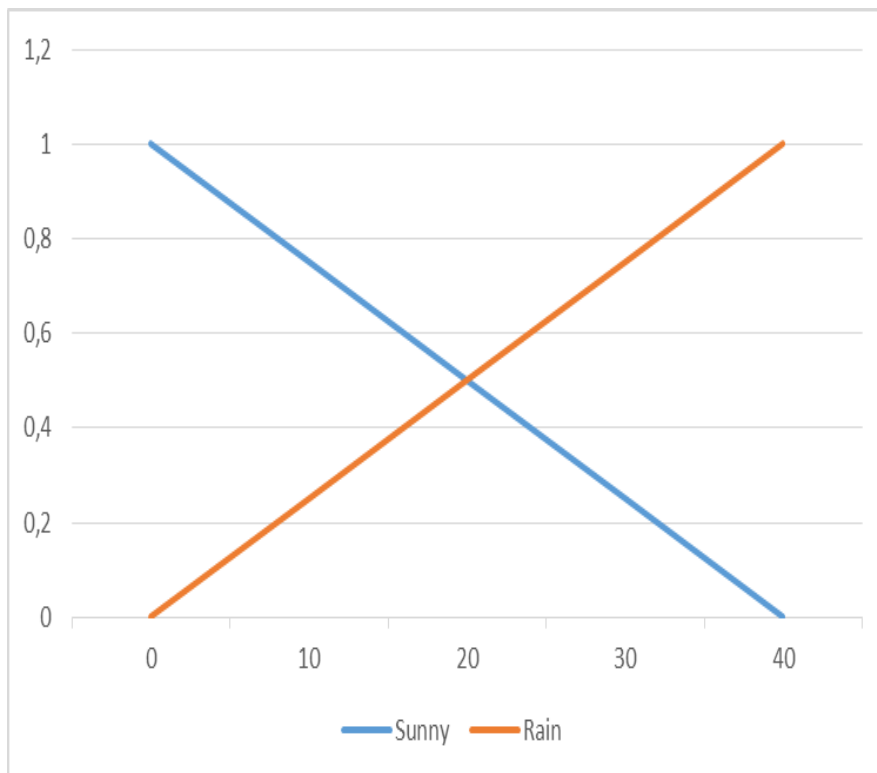


Figure 4: Fuzzy membership

Optimization

To find the rules of Fuzzy Inference System that are suitable for the precipitation case requires a very wide exploration. To shorten the time of exploration, we take one of heuristic algorithms. Evolution Strategies Algorithm is one of the heuristic algorithms that can come up with a better solution with more effective time. It can happen because not all search areas are explored.

As shown in (1), there are 16 (z1 to z16) constant variables that need to be optimized. If at one table of rules based there are 16 rows, then 16 constant variables multiply by 16 rows, obtained 256 total of constants variable that needs to be optimized. Evolution Strategies Algorithm works to represent a solution to a string and a string that represented by real numerical support. The string can be called by individual or chromosome. At the beginning of the formation of a string, the numerical formed randomly. If the table of rules based, there are 256 total of variable so there are 256 numerical formed randomly. All 256 numeric values are formed randomly in the range -10 to 10.

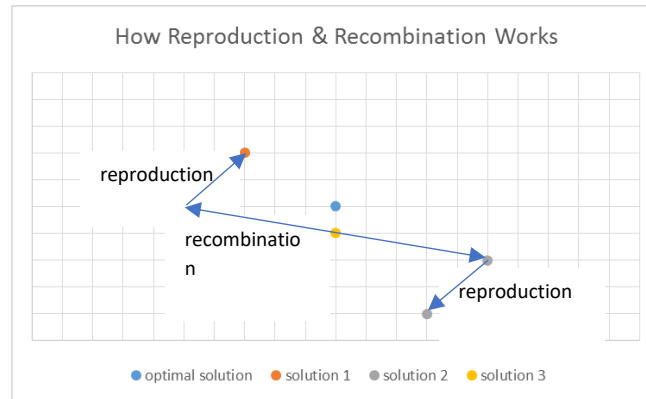


Figure 5: How Reproduction and Recombination Method works

At each iteration, Evolution Strategies Algorithm has the primary operations called reproduction methods to improve the solution. As an example, consider Fig. 5. The reproduction method works by increasing the value of (x) and (y) as in solution 1 or lower the value of (x) and (y) as in solution 2. Naturally, reproduction method which tends to move diagonally is often obtained local optimum. So, to fix, it requires secondary operations called recombination method. Recombination method works by taking the average value of two or more solutions. In Fig. 5, solution 3 derived from the recombination operation between solution 1 and solution 2.

Regression

The Sugeno Fuzzy Inference System has more complex calculations than Linear Regression, so Sugeno FIS should be better and more accurate than the regression. The rules based on Sugeno FIS have several equations for several conditions than Linear Regression that have only one equation for all conditions. From previous research, we obtain the predicted results for Puspo as in Fig. 6. These Fig. will be used as an accurate comparison.

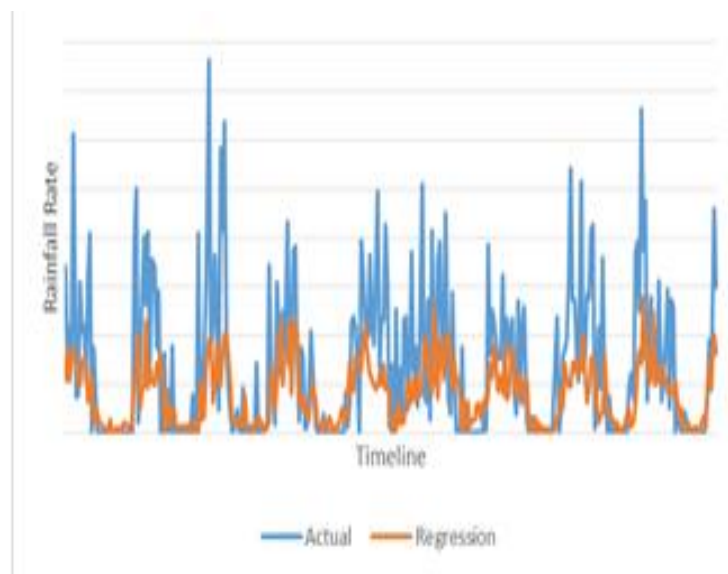


Figure 6: Comparison with previous

Numerical Example

This study used several phases. The first scenario is optimized with full random initialization. The base parameter used is population = 100, mutation = 5 and without recombination. The phase has obtained worse Root Mean Square (RMSE) result than Regression. RMSE is a formula for getting error distance. The RMSE formula follows is stated in (5). The next phase is optimized with Linear Regression with one of string initialization, and the other string was randomized. The phase successfully has obtained better RMSE results than Regression.

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^T (Y_t^s - Y_t^a)^2} \quad (5)$$

The next phase is optimized with several different fuzzy memberships. Fuzzy membership is divided by two constraints. The examples of scenarios of phase along with each constraint are shown in Table 2. Nan (Not a Number) result means that the operation obtains undefined RMSE. We thought it because the completeness of rules based, so the alpha predicate variable as divider has zero value. Referring to Chapter VI, the third part is the most part with the statistical value less than 1st constraint, the constraint 1st to 2nd constraint, and over 2nd constraint. From Table 2, we obtained the best constraints is 0 for 1st constraint and 40 for 2nd constraint. From the table we have known that by narrowing the gap between the 1st to the 2nd constraint can improve accuracy but need more rules or ends with NaN.

The next phase is getting the best ratio of initial population size (μ) and mutation size (m) to get the best solution. This phase uses several ratios of μ and m scenarios to obtain the total population (λ) size near 1,000 solutions. Evolution Strategies Algorithm belongs to the class of stochastic algorithms. Every run may produce different result (Mahmudy, 2015). Thus, to obtain fair results the algorithm runs 10 times and the average RMSE is calculated. This phase results are shown in Table 3. The μ is the initial population size was used, m is the mutation operation size, while the RMSE is the quality solution that has been obtained from ratio μ : m scenarios.

Table 2: Fuzzy Membership Scenario

1 st constraint	2 nd constraint	RMSE
5	35	NaN
5	40	5.667239042982774
0	35	NaN
0	40	5.369717701944091
0	45	5.474279464319255

Table 3. Best Population Scenario

μ	M	RMSE
100	10	5.990903
111	9	5.972572
125	8	5.95405
142	7	5.951296
166	6	5.956416
200	5	5.894698
250	4	5.907833
333	3	5.950036
500	2	4.115387
1000	1	4.378221

If the iterations size is added to both of this ratio, the results are shown as in Fig. 8. The Fig. 8 shows that each ratio 500:2 and 1000:1 has a similar pattern but the ratio 500:2 is still better than the ratio of 1000:1. Ratio 200:5 is able to provide the best results in the first 20 iteration, but afterward has unable to get better result again. A proper ratio enables the algorithm to explore the search space while maintaining population diversity.

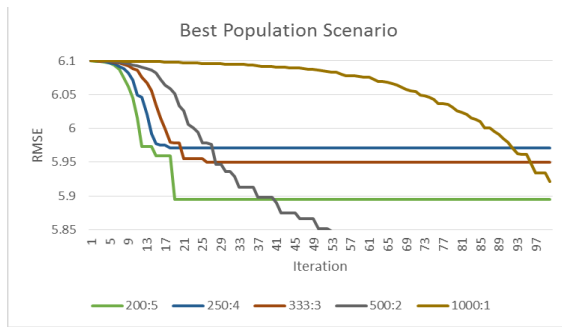


Figure 7. Best Population Scenario

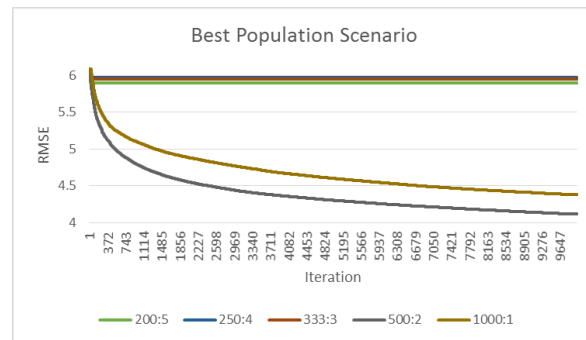


Figure 8. Best Population Scenario with long iteration

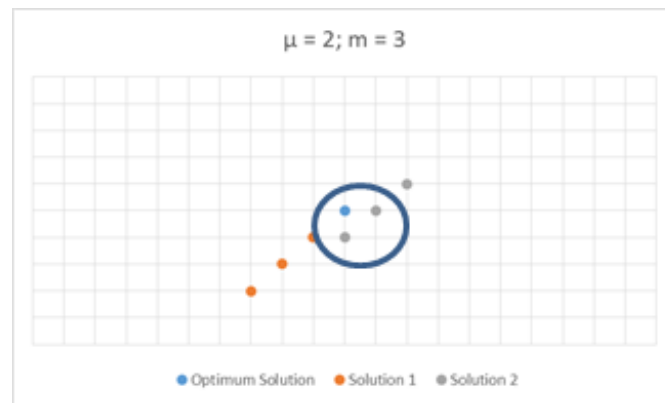


Figure 9. Scenario with $\mu = 2$ and $m = 3$

Note that on the Fig. 9, has known of one optimum solution is looking for, and we have six of new solutions. The new solutions were generated from solution 1 and solution 2. Because $\mu = 2$ then the selection method would select only two solutions from solution 2 where we're closest to the optimum solution. On the Fig. 9, the selection method was selected only new solution from solution 2 while the new solution from selection 1 were more potentially to find the optimum solution hasn't selected. Otherwise, on the Fig. 10, has known of one optimum solution is looking for, and we have six of new solutions. The six of new solutions were from each of solution 1, solution 2, and solution 3 produced two new solutions. Because $\mu = 3$ then the selection method would select three solutions with one of them was from solution 1 where more potentially to find the optimum solution.

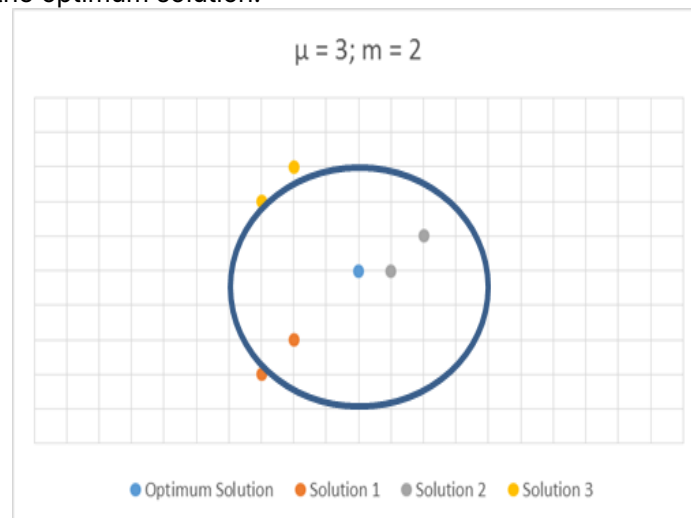


Figure 10. Scenario with $\mu = 3$ and $m = 2$

The next phase is getting the best size of recombination to get the best solution. This phase uses several ratio scenarios between the sizes of recombination with sizes of μ . Each of these scenarios carried out ten times and an average RMSE has obtained. This phase results are shown as in Table IV. Recombination column is the ratio between the sizes of recombination with size of μ ; and the RMSE is the quality of solution that has been obtained by the ratio of recombination size was performed.

Table 4. Best Recombination Scenario

Recombination	RMSE
$\frac{1}{4} \mu$	5.748378
$\frac{1}{2} \mu$	5.730535
μ	5.719833
2μ	5.707863
4μ	5.715799

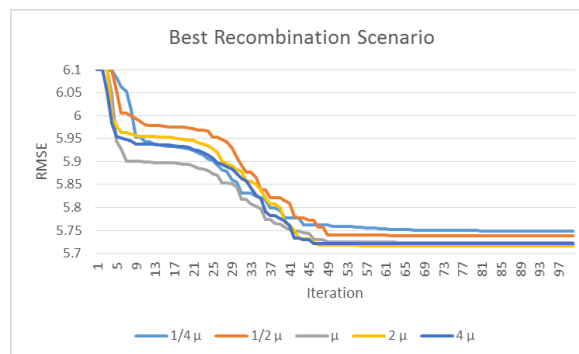


Figure 11. Best Recombination Scenario

Based on Table 4 has known that the best ratio for recombination size is 2μ or double size of the initial population. The RMSE of this ratio is 5.707863. This phase performance on each iteration is shown in Fig. 11. On the Fig. 11 has known that there is not a significant difference between the recombination scenarios. Each recombination scenario showed that significant RMSE has obtained on the first of 10 iterations, then sloped a while, then after 25 iterations RMSE increase again, and after the 50th iteration sloped again and forever.

We also assumed that the significant result was due to the diversity of string solutions. The small size of recombination with the big size of μ causes the optimum solution is difficult to obtain because the search area is still too wide. Conversely, if large size of recombination with the small size of μ causes the optimum solution is impossible to obtain due to the rapidly narrows of the search area and misses an optimum solution. Note that, the recombination method is the way of Evolution Strategies Algorithm to get out of local optimum.

To increase the diversity of solutions, Mahmudy, et al. (Mahmudy, Marian and Luong, 2013) used the random injection method to add a string with random solutions to the population. The diversity of solutions also can be influenced by choose selection method to be used. In previous scenarios, we used an Elitist Selection method, but at this step we tried to compare it with the Binary Tournament Selection method. Each of these scenarios conducted ten times and an average RMSE has obtained. This phase results are shown as in Table 5.

Table 5. Best Selection Scenario

Selection Method	RMSE
Elitist Selection	5.788117
Tournament Selection	4.924308

At the table has known that the Binary Tournament Selection has obtained better solved with RMSE 4.924308 compared to Elitism Selection with the RMSE 5.788117. This phase is increasingly proving that the assumption of more diversity of solution can improve the result of optimization. This phase performance on each iteration is shown as in Fig. 12. On the Fig. 12 has known that a better solution can be obtained by increasing the iteration on Binary Tournament Selection while Elitist Selection stacked after 40 iterations.



Figure 12. Best Selection Scenario

The next phase is finding the best number of iterations. The theory is more iteration means better solution can be obtained, but if solution not significantly obtained and then the iteration will only be a waste of time process.

On the Fig. 7 known that the best iteration of scenario 200:5 is as much as 20 iterations since it has been impossible to obtain better results. Otherwise, the scenario of 500:2 was difficult to determine the best number of iterations especially if you want to find the most optimal results. The difficulty was due to RMSE differences at each iteration may affect a satisfaction of end user, then the addition of iterations is needed. Iteration ends when the difference RMSE of each iteration is very small and does not affect end user satisfaction.

Many scenarios in this chapter are concluded with 1st fuzzy membership constraint is 0 and 2nd fuzzy membership constraint is 40; μ ESA is 200 and m ESA is 5; ESA Recombination is (2μ) ; Selection method is binary Tournament; and iteration is as much as RMSE difference is too small.

RESULT AND DISCUSSION

After a numerical experiment in the previous chapter with a small parameter, then we do the actual experiment with large parameter and long iteration of Sugeno FIS rule of Puspo station. This experiment uses the parameters that have been obtained in the previous chapter. The results of this experiment for Sugeno FIS rule of Puspo station are shown in Fig. 13.

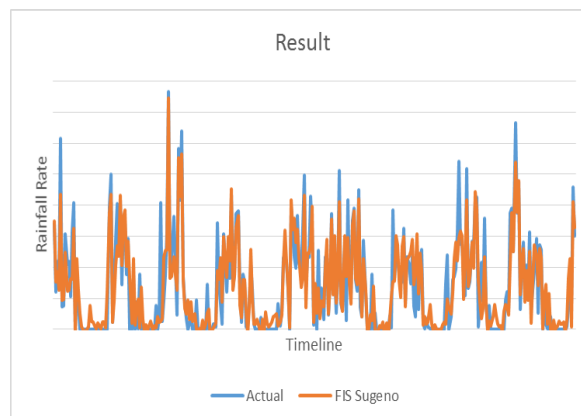


Figure 13. Result with Sugeno FIS

In Fig. 6 the prediction using Linear Regression showed the result that tends to be sunny (best case) with the RMSE amount as 7.21058626323459 for Puspo station whereas in Fig. 13 the prediction using Sugeno FIS showed the result that tends to be average between sunny and rainy (average case) with the RMSE amount as 3.2639479683204895 for Puspo station.

Figure 13 shows that the Sugeno Fuzzy Inference System (FIS) is able to follow the variation in precipitation rates more closely than the Linear Regression model. This result is also reflected in Table VI, which compares the actual precipitation rate with the predictions generated by Sugeno FIS and Linear Regression. The prediction pattern indicates that Sugeno FIS is more responsive to changes in precipitation, particularly when the rainfall rate fluctuates across

different observation periods. In contrast, Linear Regression tends to produce smoother predictions because it estimates the dependent variable based on a global linear relationship between the input variables and precipitation. Consequently, the Linear Regression predictions may not sufficiently represent nonlinear changes in rainfall patterns.

The better performance of Sugeno FIS can be attributed to its fuzzy inference mechanism and the regression consequents embedded in the Sugeno rules. Unlike conventional linear regression, which applies a single global regression equation, Sugeno FIS divides the input space into several fuzzy regions and generates a local regression function for each rule. The diversity of fuzzy rules therefore enables the model to represent different rainfall conditions more flexibly. In addition, the parameters of the consequent equations influence the prediction generated by each rule. Optimization of these parameters allows the model to adjust the contribution of each rule according to the observed rainfall pattern. Thus, the improvement in prediction accuracy is not merely caused by the use of fuzzy logic, but also by the ability to optimize the parameters associated with the Sugeno inference process.

This finding is consistent with Ardi et al. (Ardi, Effendi and Nababan, 2021), who reported that Sugeno FIS can provide better performance than Mamdani FIS because its consequent component uses mathematical functions that can represent numerical relationships more directly. The present result extends this finding by demonstrating that the flexibility of the Sugeno model can be further exploited through parameter optimization for rainfall prediction. Similarly, Burhan et al. (Burhan, Mahmudy and Bacht i ar, 2018) demonstrated the potential of combining Sugeno fuzzy inference with optimization techniques. However, their approach focused on clustering optimization, whereas the present study emphasizes the optimization of parameters within the Sugeno inference mechanism for precipitation prediction. This distinction represents an important contribution because the optimization process directly addresses the parameters that determine the numerical output of the Sugeno rules.

The findings can also be compared with the GSTAR-based approach proposed by Iriany et al. (Iriany et al., 2015) for precipitation prediction in Pasuruan, Indonesia. GSTAR has an advantage in representing temporal and spatial dependencies among rainfall observations. However, its performance depends strongly on the underlying statistical structure and assumptions concerning spatial-temporal relationships. In contrast, Sugeno FIS does not require the rainfall relationship to be represented exclusively through a predefined linear statistical structure. Instead, it can accommodate nonlinear relationships through fuzzy rules while maintaining numerical regression functions in its consequents. Therefore, the present approach provides a complementary perspective to the GSTAR model by emphasizing nonlinear inference and parameter optimization rather than primarily spatial-temporal dependence.

The results are also relevant to the improved fuzzy neural approach proposed by Utomo, Mahmudy and Anam (2017), which incorporated a Fuzzy Neural Network into rainfall prediction in Pasuruan. The use of a neural component provides strong learning capabilities, but it generally requires an adequate amount of training data and appropriate parameter tuning. The proposed optimized Sugeno FIS offers a comparatively more interpretable structure because each fuzzy rule represents a specific rainfall condition and its consequent equation can be directly examined. This interpretability is particularly important when the objective is not only to obtain accurate predictions but also to understand how different rainfall conditions contribute to the resulting prediction.

Overall, the comparison in Figure 13 and Table VI indicates that the optimized Sugeno FIS provides a more flexible representation of precipitation variability than Linear Regression. The diversity of fuzzy rules enables the model to respond to different rainfall conditions, while parameter optimization improves the numerical output of the consequent functions. The results therefore strengthen previous evidence regarding the suitability of Sugeno-based approaches for numerical prediction while extending earlier studies by explicitly incorporating parameter optimization into rainfall prediction. Nevertheless, the superiority of the proposed approach should be evaluated using quantitative performance measures, such as MAE, MSE, RMSE, or MAPE, rather than visual comparison alone. Such evaluation is necessary to determine whether the closer visual correspondence between the Sugeno FIS predictions and actual precipitation rates is statistically supported by lower prediction errors. Error column is a simple error as (6).

$$Error = Predict - Actual \quad (6)$$

Table 6. Comparison Between Sugeno FIS and Regression

	Actual Rate	Sugeno FIS		Regression	
		<i>Predict</i>	<i>Error</i>	<i>Predict</i>	<i>Error</i>
1	0,6	5,764	5,164	3,7943	3,194
2	2,9	10,378	7,478	7,115	4,215
3	11,5	12,612	1,112	4,364	-7,136
4	11,909	13,085	1,176	4,358	-7,551
5	10,8	11,108	0,308	7,711	-3,089
6	6,4	9,575	3,175	7,282	0,882
7	0	0,822	0,822	7,607	7,607
8	19,7	17,124	-2,576	6,432	-13,268
9	16,8	14,265	-2,535	9,277	-7,523
10	11,625	14,927	3,302	11,041	-0,584
11	9,9	13,202	3,302	7,434	-2,466
12	18,3	16,327	-1,973	6,023	-12,277
13	10,727	10,062	-0,665	5,585	-5,142
14	9,1	9,359	0,259	4,934	-4,166
15	16,6	12,167	-4,433	4,468	-12,132
16	24,8	18,603	-6,197	4,990	-19,81
17	6,5	10,555	4,055	6,17	-0,33
18	11,8	9,712	-2,088	4,944	-6,856
19	11,636	11,625	-0,011	6,946	-4,69
20	21,4	10,727	-10,67	4,464	-16,936
21	15,9	13,521	-2,379	4,517	-11,383
	RMSE		3,9867		8,89835

CONCLUSION

The results demonstrate that the proposed Sugeno Fuzzy Inference System (FIS) provides better rainfall prediction performance than the Generalized Space-Time Autoregressive (GSTAR) and Linear Regression-based approaches. Quantitatively, the proposed Sugeno FIS achieved an error value of [insert error value], compared with [insert error value] obtained by the GSTAR/Linear Regression model, representing an improvement of [insert percentage]%. This improvement indicates that the use of multiple regression equations associated with specific fuzzy patterns enables Sugeno FIS to capture variations in rainfall conditions more effectively than a single global regression equation. The main contribution of this study is therefore the development of an optimized Sugeno FIS framework that combines fuzzy rule diversity with regression-based parameter optimization for rainfall prediction. Nevertheless, the study is limited by the characteristics, size, and temporal coverage of the rainfall dataset and by the variables included in the model, which may restrict the generalizability of the findings to other regions and climatic conditions. Future research should therefore evaluate the proposed model using larger and multi-location datasets, incorporate additional meteorological and spatial-temporal variables, and investigate hybrid optimization or machine-learning techniques to further improve prediction accuracy and model robustness.

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