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Modeling by Fuzzy Inference System of the Renewable Energy Quantity to Inject for Reinforcing the Under Voltage of Ambodivona Antananarivo

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ABSTRACT: *This research aims to model the hourly injected power to reinforce the under voltage Ambodivona Antananarivo using the fuzzy inference system model. Indeed, the Ambodivona sub voltage does not enough to feed the city center of Antananarivo permanently. In order to solve the problem of load shedding, the JIRAMA company uses renewable energy (wind and / or solar). When the electrical power is sufficient, there is no additional power injection. Otherwise, the injected power is calculated as needed. The fuzzy inference system model predicts the power to be injected to reinforce Ambodivona Antananarivo's under tension according to the hour of day. The model that we adopt have one input and one output. The input corresponds to the injected power at time t and the output corresponds to the injected power forecasted at time t+1 hour. The number of partitions is the only parameter of the model. We take 10 then 20 and 30 as the number of partition. At each number of partitions corresponds to a model. The three models obtained are evaluated by the MAE (Mean Absolute Error) metric which measures the average of the absolute values of the differences between the observed data and the output data from the model. A low MAE value indicates a small difference between the real data and the data from the model. As a result, if the partition number increases, the model becomes better. The best model is obtained with 30 partitions.*

Keywords: *Chen's method, Fuzzy Inference System, Injected Power, Mean Absolute Error, Number of Partition.*

I. Introduction

Load shedding is a major social problem in cities around the world. This is a sensitive point both politicians and people. In particular, the city of Antananarivo is also a victim of the load shedding; according to the newspaper Tribune Madagascar, published on December 04, 2020, [1] several districts of the city of Antananarivo such as Andoharanofotsy, Analakely, etc are victims. The causes of this load shedding are mainly explosion of transformers, failure of generator sets, and insufficient sources of electricity production in Ambodivona Antananarivo. The insufficient sources of production is the fundamental and permanent problem. For other causes, it is sufficient to replace or troubleshoot the defective equipment to resolve them.

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To eliminate load shedding, the JIRAMA company, which is the electricity supplier in the city of Antananarivo, uses renewable energy (wind and / or solar).

The resulting problem is what the power to inject is depending on the time of day to ensure the permanent continuity of electricity in the city of Antananarivo.

Many statistical models are able to make predictions. For this current studies, we use the fuzzy logic theory, invented by Lotfi Zadeh [2] to do the modeling. This theory have a great success in many fields. There are several fuzzy logic methods such as fuzzy inference systems [3], fuzzy time series [4] etc. In our paper, we use the Mamdani type fuzzy inference system model [5] to model the injected power into Ambodivona's under voltage according to the hour of day.

II. Materials and methods

2.1 Datasets

The hourly consumption data of Antananarivo during 2020 were collected from Ambodivona source substation. Then we compute the average that is shown on the Table 1 below.

Table 1: Hourly power under voltage during 2020 at Ambodivona

Hour(UTC+3)	Average Power(MW)	Hour(UTC+3)	Average Power(MW)
6h	34,44	18h	37,22
7h	41,33	19h	45,88
8h	46,00	20h	45,77
9h	48,11	21h	40,77
10h	49,22	22h	33,77
11h	48,88	23h	28,33
12h	47,44	00h	25,55
13h	46,66	01h	24,11
14h	40,22	02h	23,88
15h	39,55	03h	24,00
16h	40,33	04h	25,55
17h	40,22	05h	33,22

The threshold value was obtained by computing the average of the 24 values (table 1). If the power consumed is smaller than the threshold value, the hourly injected power is zero. Else, it is equals to the difference between the power consumed and the threshold value. The hourly power data to be injected are the data to be modeled by fuzzy inference system.

2.2 Modeling approach

The approach adopted to perform the Mamdani type fuzzy inference system modeling is in four steps:
Step 1: Fuzzification
Step 2: Fuzzy inference engine
Step 3: Defuzzification
Step 4: Evaluation of the model

a) Step 1: Fuzzification

Fuzzification consists to convert each numerical value into fuzzy values. First, we partition the discourse universe of the input variable. This universe of discourse is the extent of the statistical series of the input variable with a safety margin. Create n-partitions is equivalent to creating n-fuzzy sets on the universe of discourse. We take as membership functions of fuzzy sets isosceles triangle functions and right triangle functions for fuzzy sets at the extremity of the discourse universe. In our research, we keep the same universe of discourse and the same partitioning for the input and output of the model. Practically, the operation of fuzzification consists in finding for each real value the fuzzy set having the highest degree of membership.

b) Step 2: Fuzzy inference engine

The fuzzy inference engine applies the fuzzy inference rules to the fuzzy value resulting from the fuzzification of the input variable. It makes operations on linguistics variables using fuzzy rules. A fuzzy rule is like:

IF <CONDITION> **THEN** <CONSEQUENCE>

In our study, the Chen's method [6] is implemented to obtain fuzzy rules in fuzzy time series. These rules are used into the fuzzy inference system.

Thus, the "CONDITION" is the fuzzy value of the input variable and the "CONSEQUENCE" is the fuzzy value of the output variable.

After fuzzifying the numerical value of the injected power, the fuzzy rules are applied to the fuzzy value of the input variable. The fuzzy inference engine aggregate fuzzy sets resulting from the application of fuzzy rules to a fuzzy values.

c) Step 3: Defuzzification

Defuzzification process is the reverse of fuzzification. It convert the fuzzy set from the previous fuzzy inference engine into a real value. The center of gravity method, also called the Barycenter method [7] is used to make the defuzzification.

X_0 is the defuzzified value of the fuzzy set $\widetilde{A_0}$ of membership function µ by the Barycenter method, an example is shown in Figure 1. Then, the value defuzzified is obtained by the formula:

$$X_0 = \frac{\int_U \mu(X_r) dX_r}{\int_U \mu(X_r) dX_r} \qquad (1)$$

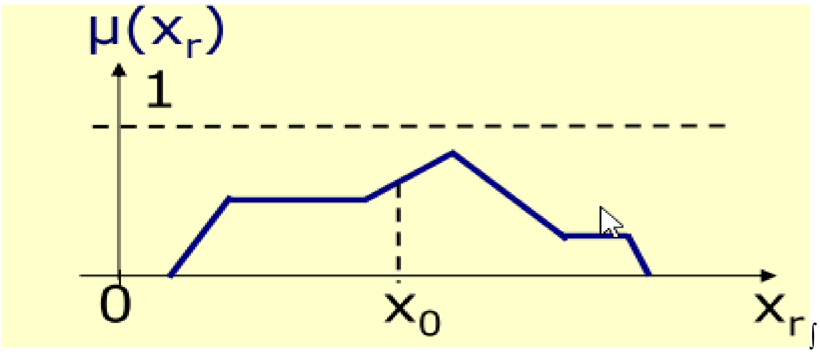

Figure 1: Example of a fuzzy set [7]

d) Step 4: Evaluation of the model

Each partition number of the universe of discourse corresponds to a forecast model. This study took as 10 then 20 then 30 partition numbers. Three forecast models of injected power were obtained. To choose the model to use, we assessed the difference between the observed and predicted data from the model. The MAE (Mean Absolute Error) metric is used to evaluate candidate models. The smaller value of MAE gave the better model.

The following formula gave the value of MAE:

$$MAE = \frac{1}{n} \times \sum_{t=1}^{n} |X_t - \overline{X_t}| \quad (2)$$

Where:
n: Number of observations
X_t: The observation
$\overline{X_t}$: The forecast

2.3 Structure of the model

The model designed was a Mamdani type fuzzy inference system model with one input and one output. The input was the injected power at time t and the output corresponded to the injected power predicted at time t+1. The partitioning of the input and output of the model was the same. The model mapping is shown on Figure 2.

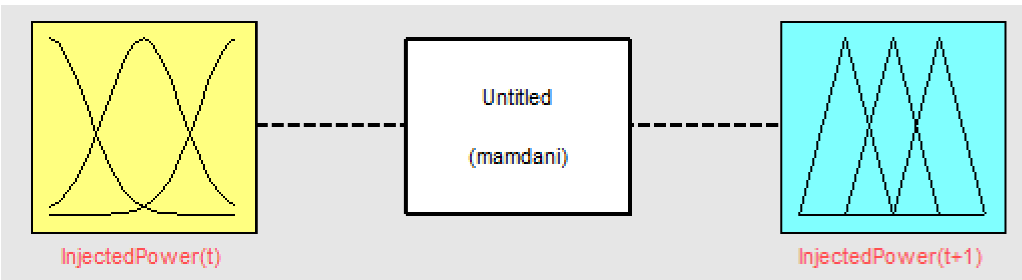

Figure 2: Structure of the model

III. Results

3.1 Results of injected power data

The first step consists to compute the power to be injected to reinforce the under voltage at Ambodivona from the hourly power consumption data (Table 1).

The hourly power data consumed by the city of Antananarivo (during 2020) as well as its average value and the threshold value are represented on Figure 3.

The hourly power consumed is:

➢ Below the threshold value between 9:40 p.m and 6:45 a.m:

During these hours, the majority of users do not work hence they consume less electricity. Around 6 p.m, we noticed a little drop in consumption compared to the threshold value. During these moments, the majority of the consumers left their workplaces. Thus, the injection of additional power to increase Ambodivona's energization is unnecessary. And the hourly injected power is zero during these hours.

➢ Above the threshold value between 6:45 a.m to 5:55 p.m and 6:05 p.m to 9:40 p.m:

During these hours, the consumers need more electricity than the threshold value. The JIRAMA company must inject additional power from renewable energy (wind and / or solar). The quantity of injected power is the difference between the power consumed and the threshold value.

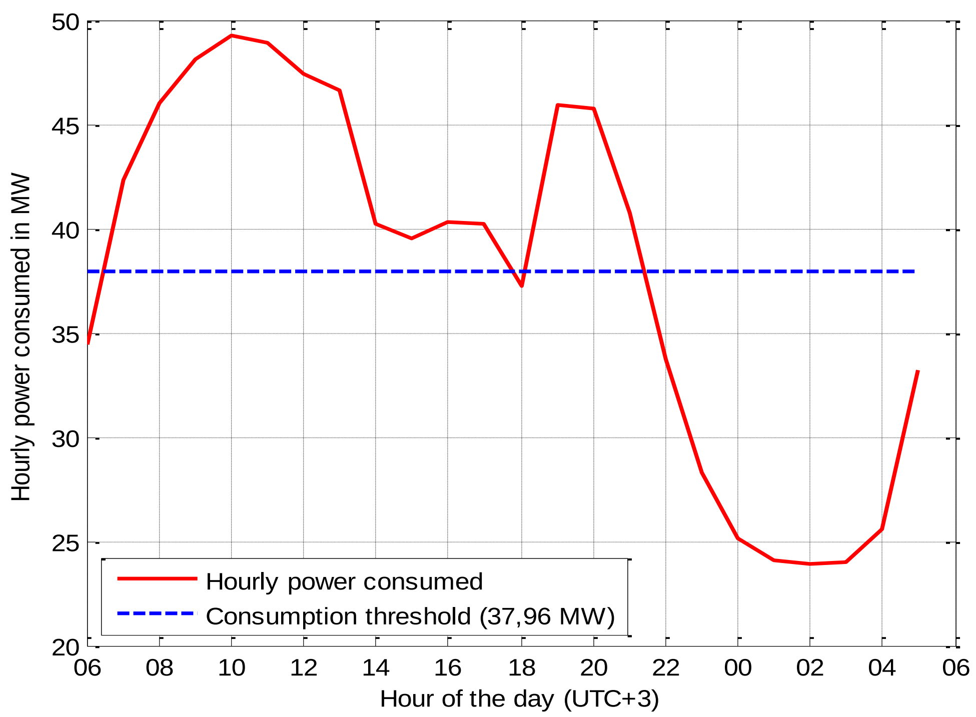

Figure 3 : Hourly power consumed and consumption threshold

The value of the injected power is obtained by applying the following rules:

➢ The injected power is zero if the hourly power consumed is less than the threshold value.

➢ The injected power is the difference between the hourly power consumed and the threshold value.

Table 2 show the result of the injected power values that will be used for the rest of the modeling.

Table 2: Injected power data

Schedule	Injected Power(MW)
6h	0
7h	4,37
8h	8,04
9h	10,15
10h	11,26
11h	10,92
12h	9,48
13h	8,7
14h	2,26
15h	1,59
16h	2,37
17h	2,26

schedule	Injected Power(MW)
18h	0
19h	7,92
20h	7,92
21h	2,81
22h	0
23h	0
00h	0
01h	0
02h	0
03h	0
04h	0
05h	0

3.2 Results of the modeling

Each partitions number chosen (10; 20; 30 partitions) corresponded to a model. According to the partitions number, we keep the same universe of discourse for input and output. The universe of discourse is:

$$U = [0\ MW, 12MW] \qquad (3)$$

a) Results of the modelization with 10 partitions

- **Results of step 1: fuzzification with 10 partitions**

For 10 partitions, we create 10 fuzzy sets called: $\widetilde{A_1}$, $\widetilde{A_2}$, $\widetilde{A_3}$, $\widetilde{A_4}$, $\widetilde{A_5}$, $\widetilde{A_6}$, $\widetilde{A_7}$, $\widetilde{A_8}$, $\widetilde{A_9}$, $\widetilde{A_{10}}$. The membership functions of these fuzzy sets are shown in Figures 4-a and 4-b.

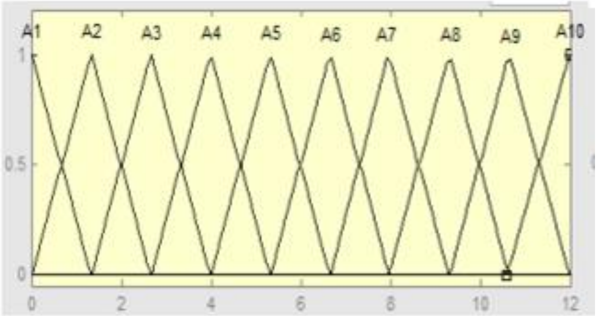

Figure 4-a: Partitioning of the discourse universe for input's model (10 partitions)

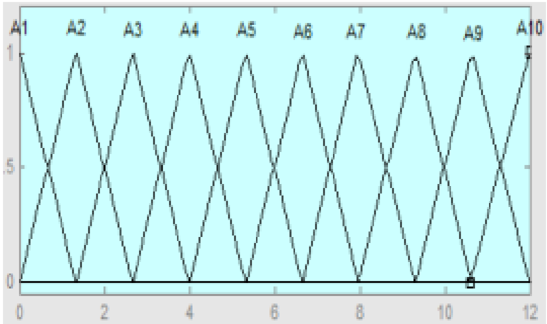

Figure 4-b: Partitioning of the discourse universe for output's model (10 partitions)

Table 3 summarized the results of the fuzzification with 10 partitions

Table 3: Results of fuzzification with 10 partitions

Schedule	Injected power (MW)	Blurred set
06h	0	$\widetilde{A}_1$
07h	4,37	$\widetilde{A}_4$
08h	8,04	$\widetilde{A}_7$
09h	10,15	$\widetilde{A}_9$
10h	11,26	$\widetilde{A}_9$
11h	10,92	$\widetilde{A}_8$
12h	9,48	$\widetilde{A}_7$
13h	8,7	$\widetilde{A}_7$
14h	2,26	$\widetilde{A}_3$
15h	1,59	$\widetilde{A}_2$
16h	2,37	$\widetilde{A}_3$
17h	2,26	$\widetilde{A}_3$

Schedule	Injected power (MW)	Blurred set
18h	0	$\widetilde{A}_1$
19h	7,92	$\widetilde{A}_7$
20h	7,92	$\widetilde{A}_7$
21h	2,81	$\widetilde{A}_3$
22h	0	$\widetilde{A}_1$
23h	0	$\widetilde{A}_1$
00h	0	$\widetilde{A}_1$
01h	0	$\widetilde{A}_1$
02h	0	$\widetilde{A}_1$
03h	0	$\widetilde{A}_1$
04h	0	$\widetilde{A}_1$
05h	0	$\widetilde{A}_1$

- **Results of step 2: The fuzzy inference rules used by the fuzzy inference engine**

The fuzzy inference engine applied the fuzzy rules to the fuzzy variable obtained by fuzzifying the input variable value.

We obtained the following 16 fuzzy rules in the case of 10 partitions (when additional power injection is necessary) from Chen's method:

Rule N°1: If "A1" then "A4"
Rule N°2: If "A4" then "A7"
Rule N°3: If "A7" then "A9"
Rule N°4: If "A9" then "A9"

Rule N°5: If "A9" then "A8"
Rule N°6: If "A8" then "A7"
Rule N°7: If "A7" then "A7"
Rule N°8: If "A7" then "A3"
Rule N°9: If "A3" then "A2"
Rule N°10: If "A2" then "A3"
Rule N°11: If "A3" then "A3"
Rule N°12: If "A3" then "A1"
Rule N°13: If "A1" then "A7"
Rule N°14: If "A7" then "A3"
Rule N°15: If "A3" then "A1"
Rule N°16: If "A1" then "A1"

- **Results of step 3: defuzzification**

The Barycenter method is applied for the fuzzy set resulting from the aggregation of possible "consequences".

As example of defuzzification, input is 4.94 MW. The correspondent fuzzy set is A4 (Figure 5). The fuzzy inference rules applied is rule N°2: If "A4" then "A7".

The "consequence" fuzzy sets is A7. Applying the Barycenter method, we got the value 7.98 MW. This value corresponded to the injected power predicted by the model at time t+1 hour.

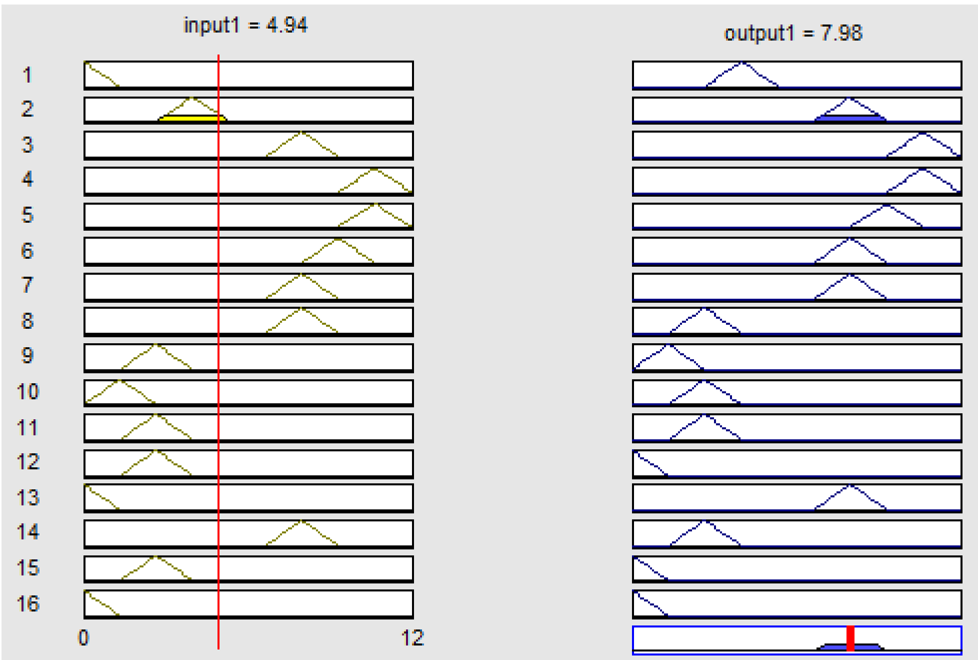

Figure 5: Defuzzification by the Barycenter method (10 partitions)

The Figure 6 showed the result of the modeling for 10 partitions. The red curve is the injected power and the blue curve is the injected power predicted by the model.

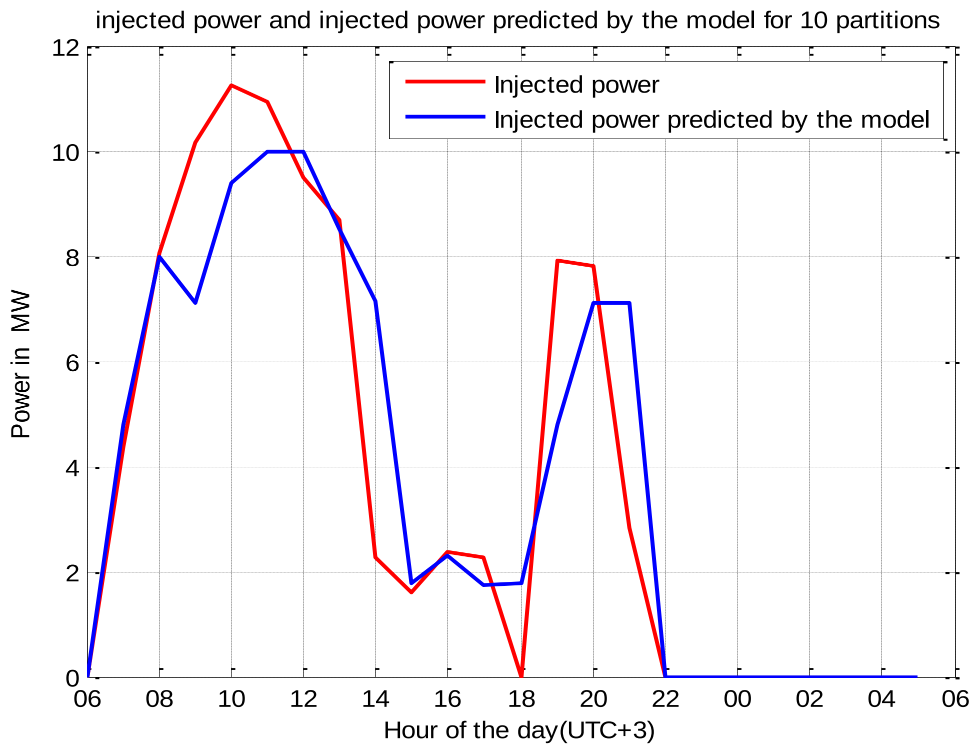

Figure 6: Modeling results for 10 partitions

b) Results of modeling with 20 partitions

➢ **Results of step 1: fuzzification with 20 partitions**

For 20 partitions, we create 20 fuzzy sets called $\overset{\frown}{A_1}$, $\overset{\frown}{A_2}$, $\overset{\frown}{A_3}$, $\overset{\frown}{A_4}$, $\overset{\frown}{A_5}$, $\overset{\frown}{A_6}$, $\overset{\frown}{A_7}$, $\overset{\frown}{A_8}$, $\overset{\frown}{A_9}$, $\overset{\frown}{A_{10}}$, $\overset{\frown}{A_{11}}$, $\overset{\frown}{A_{12}}$, $\overset{\frown}{A_{13}}$, $\overset{\frown}{A_{14}}$, $\overset{\frown}{A_{15}}$, $\overset{\frown}{A_{16}}$, $\overset{\frown}{A_{17}}$, $\overset{\frown}{A_{18}}$, $\overset{\frown}{A_{19}}$, $\overset{\frown}{A_{20}}$ .The membership functions of these fuzzy sets are shown below (Figure 7-a and 7-b)

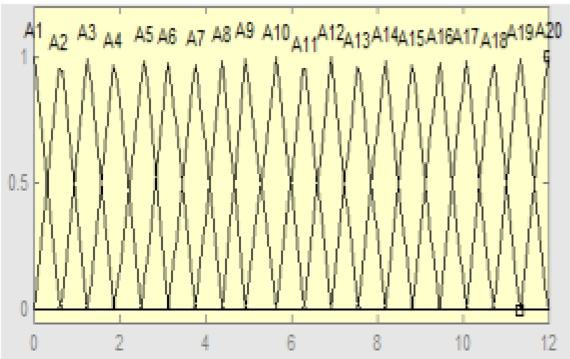

Figure 7-a: Partitioning of the discourse universe for model’s input (20 partitions)

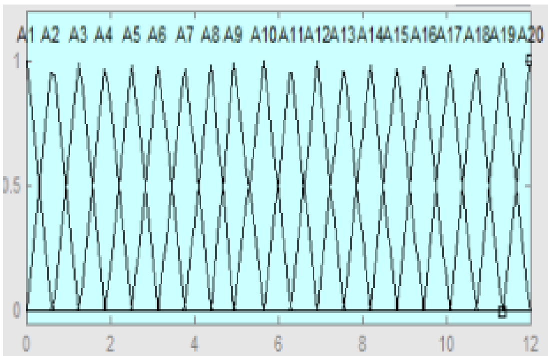

Figure 7-b: Partitioning of the discourse Universe for model’s output (20 partitions)

Table 4 summarizes the results of the fuzzification with 20 partitions.

Table 4: Results of fuzzification with 20 partitions

Schedule	Injected power(MW)	Blurred set	Schedule	Injected power(MW)	Blurred set
06h	0	$\widetilde{A_1}$	18h	0	$\widetilde{A_1}$
07h	4,37	$\widetilde{A_8}$	19h	7,92	$\widetilde{A_{14}}$
08h	8,04	$\widetilde{A_{14}}$	20h	7,92	$\widetilde{A_{15}}$
09h	10,15	$\widetilde{A_{17}}$	21h	2,81	$\widetilde{A_5}$
10h	11,26	$\widetilde{A_{18}}$	22h	0	$\widetilde{A_1}$
11h	10,92	$\widetilde{A_{16}}$	23h	0	$\widetilde{A_1}$
12h	9,48	$\widetilde{A_{14}}$	00h	0	$\widetilde{A_1}$
13h	8,7	$\widetilde{A_{14}}$	01h	0	$\widetilde{A_1}$
14h	2,26	$\widetilde{A_4}$	02h	0	$\widetilde{A_1}$
15h	1,59	$\widetilde{A_3}$	03h	0	$\widetilde{A_1}$
16h	2,37	$\widetilde{A_4}$	04h	0	$\widetilde{A_1}$
17h	2,26	$\widetilde{A_4}$	05h	0	$\widetilde{A_1}$

- **Results of step 2: The fuzzy rules used by the fuzzy inference engine**

For the case of 20 partitions, the fuzzy rules are:

Rule N°1: If "A1" then "A8"
Rule N°2: If "A8" then "A14"
Rule N°3: If "A14" then "A17"
Rule N°4: If "A17" then "A18"
Rule N°5: If "A18" then "A16"
Rule N°6: If "A16" then "A14"
Rule N°7: If "A14" then "A14"
Rule N°8: If "A14" then "A4"
Rule N°9: If "A44" then "A3"
Rule N°10: If "A3" then "A4"
Rule N°11: If "A4" then "A4"
Rule N°12: If "A4" then "A1"
Rule N°13: If "A1" then "A14"
Rule N°14: If "A14" then "A15"
Rule N°15: If "A15" then "A5"
Rule N°16: If "A1" then "A1"

- **Results of step 3: Defuzzification**

The following figures are the results of the defuzzification with 20 partitions (Figure 9) the red curve is the injected power and the blue curve is the injected power predicted by the model. In Figure 8 is an example of defuzzification.

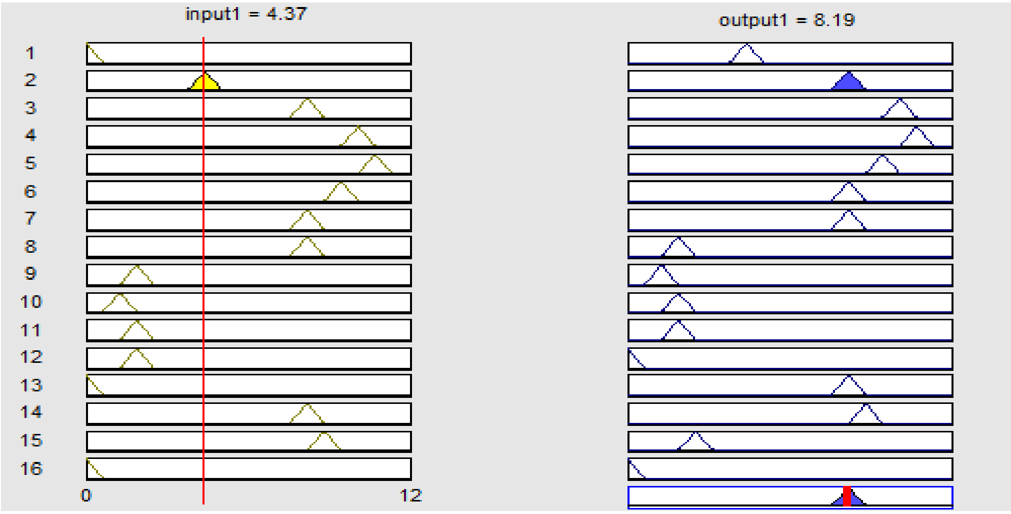

Figure 8: Example of defuzzification (20 partitions)

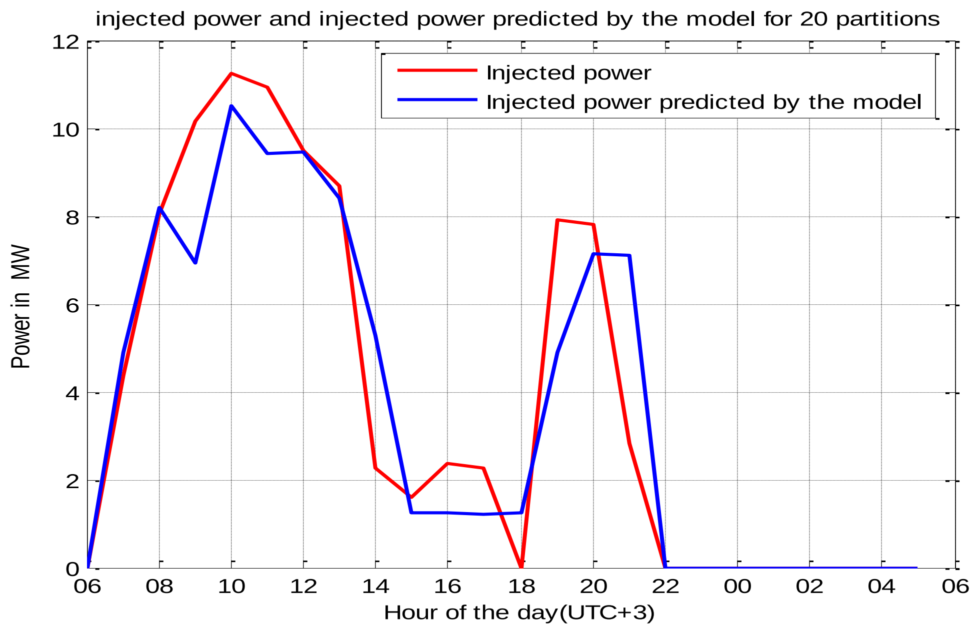

Figure 9: Modeling results for 20 partitions

c) Modeling results with 30 partitions

- **Results of step 1: fuzzification with 30 partitions**

For 30 partitions, 30 fuzzy sets with them discourse universe are created called: $\overset{\frown}{A}_{1}$, $\overset{\frown}{A}_{2}$, $\overset{\frown}{A}_{3}$, $\overset{\frown}{A}_{4}$, $\overset{\frown}{A}_{5}$, $\overset{\frown}{A}_{6}$, $\overset{\frown}{A}_{7}$, $\overset{\frown}{A}_{8}$, $\overset{\frown}{A}_{9}$, $\overset{\frown}{A}_{10}$, $\overset{\frown}{A}_{11}$, $\overset{\frown}{A}_{12}$, $\overset{\frown}{A}_{13}$, $\overset{\frown}{A}_{14}$, $\overset{\frown}{A}_{15}$, $\overset{\frown}{A}_{16}$, $\overset{\frown}{A}_{17}$, $\overset{\frown}{A}_{18}$, $\overset{\frown}{A}_{19}$, $\overset{\frown}{A}_{20}$ $\overset{\frown}{A}_{21}$, $\overset{\frown}{A}_{22}$, $\overset{\frown}{A}_{23}$, $\overset{\frown}{A}_{24}$, $\overset{\frown}{A}_{25}$, $\overset{\frown}{A}_{26}$, $\overset{\frown}{A}_{27}$, $\overset{\frown}{A}_{28}$, $\overset{\frown}{A}_{29}$, $\overset{\frown}{A}_{30}$ (Figures 10-a and 10-b).

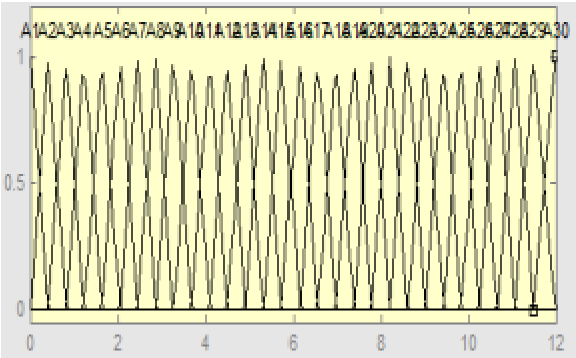

Figure 10-a: Partitioning of the discourse universe for model's input (30 partitions)

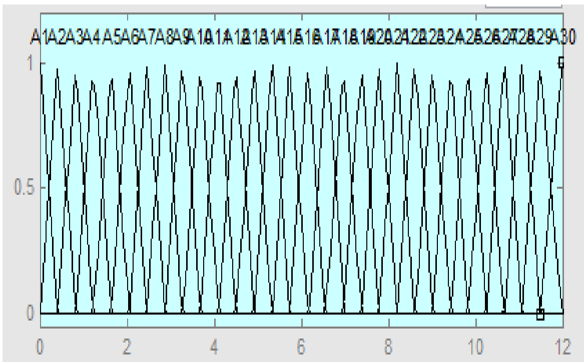

Figure 10-b: Partitioning discourse universe for model's output (30 partitions)

Table 5 summarized the results of the fuzzification with 30 partitions.

Table 5: Results of fuzzification with 30 partitions

Schedule	Injected power(MW)	Blurred set
06h	0	$\widetilde{A_1}$
07h	4,37	$\widetilde{A_{11}}$
08h	8,04	$\widetilde{A_{20}}$
09h	10,15	$\widetilde{A_{26}}$
10h	11,26	$\widetilde{A_{28}}$
11h	10,92	$\widetilde{A_{27}}$
12h	9,48	$\widetilde{A_{25}}$
13h	8,7	$\widetilde{A_{22}}$
14h	2,26	$\widetilde{A_7}$
15h	1,59	$\widetilde{A_5}$
16h	2,37	$\widetilde{A_7}$
17h	2,26	$\widetilde{A_7}$

Schedule	Injected power(MW)	Blurred set
18h	0	$\widetilde{A_1}$
19h	7,92	$\widetilde{A_{20}}$
20h	7,92	$\widetilde{A_{20}}$
21h	2,81	$\widetilde{A_8}$
22h	0	$\widetilde{A_1}$
23h	0	$\widetilde{A_1}$
00h	0	$\widetilde{A_1}$
01h	0	$\widetilde{A_1}$
02h	0	$\widetilde{A_1}$
03h	0	$\widetilde{A_1}$
04h	0	$\widetilde{A_1}$
05h	0	$\widetilde{A_1}$

➢ **Results of step 2: The fuzzy rules used by the fuzzy inference engine (case of 30 partitions)**

For the case of 30 partitions, the fuzzy rules are:

Rule N ° 1: If "A1" then "A11"
Rule N ° 2: If "A11" then "A20"
Rule N ° 3: If "A20" then "A26"
Rule N ° 4: If "A26" then "A28"
Rule N ° 5: If "A28" then "A27"
Rule N ° 6: If "A27" then "A25"
Rule N ° 7: If "A25" then "A22"
Rule N ° 8: If "A22" then "A7"
Rule N ° 9: If "A7" then "A5"
Rule N ° 10: If "A5" then "A7"
Rule N ° 11: If "A7" then "A7"

Rule N ° 12: If "A7" then "A1"
Rule N ° 13: If "A1" then "A20"
Rule N ° 14: If "A20" then "A20"
Rule N ° 15: If "A20" then "A8"
Rule N ° 16: If "A1" then "A1"

- **Results of step 3: Defuzzification (30 partitions)**

The following figures are the results of the defuzzification with 30 partitions (Figure 12) the red curve is the injected power and the blue curve is the injected power predicted by the model. In Figure 11 is an example of defuzzification.

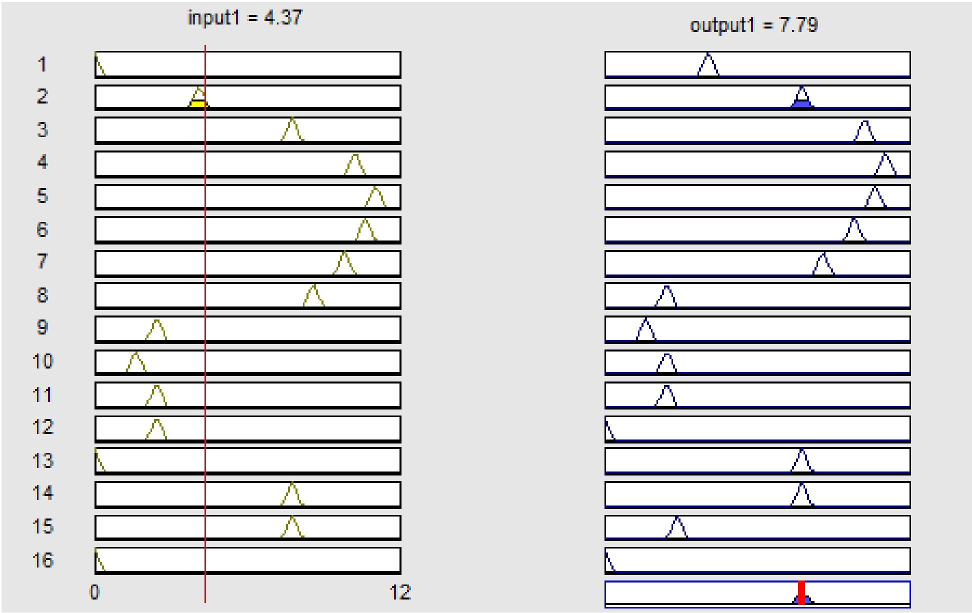

Figure 11: Example of defuzzification by Barycenter method (30 partitions)

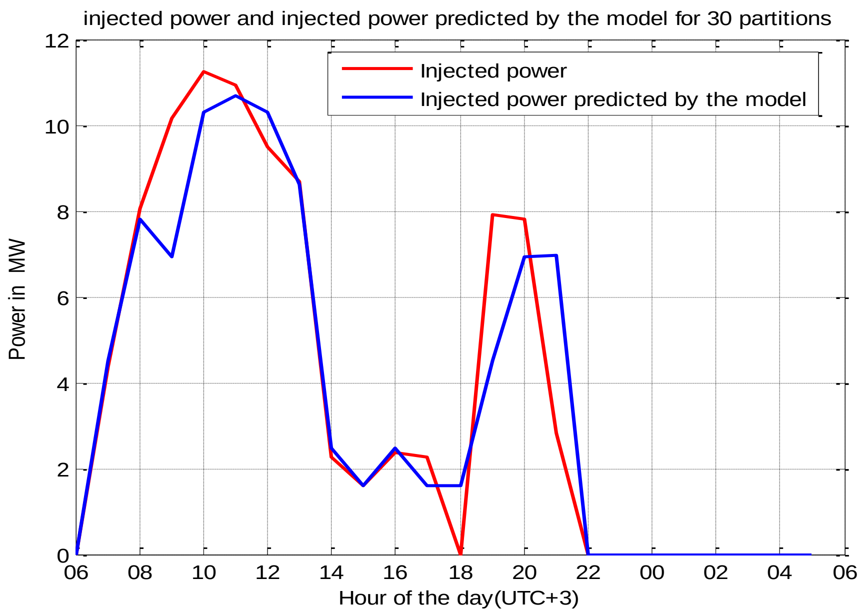

Figure 12: Modeling results for 30 partitions

- **3.3 Results of the evaluation of candidate models**

Each partition number value corresponds to a model. For this case, three models are used with 10, 20 and 30 partitions. The difference between forecast and observation is assessed applying the MAE metric. If the difference is small, the model is reliable.

Table 6 summarizes the MAE values for each partition number. We can conclude that among our proposed models, the model with 30 partitions is the best. The reliability of the model increases with the number of partitions.

Table 6: MAE according to the number of partitions

Number of Partitions	10	20	30
MAE (Mean Absolute Error) in MW	0,94	0,88	0,69

IV. Discussions

Several researchers from various fields use the fuzzy inference system for modeling. In general, and in our case, both the number of inputs to the model and the number of parameters taken into consideration are equal. In this study, the injected power is modelized from its own data by the fuzzy inference system. Several research on fuzzy inference system modeling use different membership functions for partitioning the input and output of the model. We have taken on the same membership functions for both input and output. The fuzzy rules employed in fuzzy inference systems are obtained from elucidating experts. The approach applied Chen's method in fuzzy time series to have fuzzy inference rules. The evaluation of the models is systematic at the end of the modeling. It consists of assessing the differences between the real data and the simulated data. We used the MAE (Mean Absolute Error) metric to evaluate the model. Other metrics are also relevant such as RMSE (Root Mean Square Error), MAPE (Mean Absolute Percentage Error) etc.

V. Conclusion

In conclusion, this work consists in modeling the injected power data to reinforce the under voltage of Ambodivona Antananarivo. The model that we are applying is the fuzzy both one input and output inference system. The input corresponds to the injected power at time t and the output is the injected power predicted for at time t+1 hour. The model parameter is the number of partitions: they are 10, 20 and 30 and for each partition number corresponds with a model. After evaluating the candidate models by the MAE metric, the model with 30 partitions is the best. The highest number of partitions gives the most reliable model.

The originality of our approach, regardless in the application of the Chen’s method in fuzzy time series to the fuzzy inference system is to generate the fuzzy inference rules.

VI. References

1. https://www.madagascar-tribune.com/Jirama-retour-en-force-du-delestage.html
2. Zadeh, L.A. 1965, Fuzzy sets, Information and Control, pages 500p.
3. Kikuchi, S., & Chakroborty, P. (1992). Car-following model based on fuzzy inference system. Transportation Research Record, 82-82.
4. H.A.RAJAONARISOA et al, (2020), Annual precipitation in Southern of Madagascar : Modelling using high order fuzzy time series. International Journal of Fuzzy Logic Systems (IJFLS) Vol.10, No.3/4).
5. Pourjavad, E., & Mayorga, R. V. (2019). A comparative study and measuring performance of manufacturing systems with Mamdani fuzzy inference system. Journal of Intelligent Manufacturing, *30*(3), 1085-1097
6. Chen, S. M., & Hsu, C. C. (2004). A new method to forecast enrollments using fuzzy time series. International Journal of Applied Science and Engineering, *2*(3), 234-244.
7. http://www8.umoncton.ca/umcmcormier_gabriel/Asservissements/GELE5313_Notes11.pd.