

Classification of Fuzzy Logic Linguistic Terms for Accurate Load Balancing in Electric Power Distribution System.

1st Michael Robson Atim

Physics department

Mbarara University of Science and Technology

Mbarara, Uganda

mikeatim@must.ac.ug

2nd Simon Katrini Anguma

Physics department

Muni University

Arua, Uganda

s.anguma@muni.ac.ug

3rd Jimmy Wanzala Nabende

Physics department

Mbarara University of Science and Technology

Mbarara, Uganda

jwanzala@must.ac.ug

Abstract—Intelligent controls in electric power distribution system can be used to improve electric power distribution by balancing loads in a three-phase system at any time. One of such intelligent controls is fuzzy logic. In this paper we propose the use of unlimited linguistic terms for intelligent distribution management using fuzzy logic technique to relocate phase load for a balanced three phase system in electric power distribution network system. The classified numerous linguistic terms culminate into numerous clustered regions of input load and output load change variables. These variables are used in fuzzy inference rules to provide the criteria for effective load balancing in three phases. The algorithm developed using the fuzzy set rules using seventeen clustered regions was subjected to the management of 2100 kW peak load in all the three phases. The simulation results showed balanced phase load with a peak load value close or equal to 700 kW per phase as expected. The developed fuzzy set rules is flexible and can be subjected to any grid load of interest to generate its algorithm. Furthermore, the simulation results of the developed fuzzy set rules and the subsequent generated fuzzy algorithm were subjected to the same test. The fuzzy logic algorithm developed in the current study gave low final values of maximum phase difference between two phases and subsequently low values of final absolute average unbalanced per phase.

Index Terms—Fuzzy Logic, Load Balancing

I. INTRODUCTION

The foundations of fuzzy set theory was developed by L. A. Zadeh as a method of perfecting practical systems [1], [3]. Much of the decision making in the real world takes place in an environment in which the goals, the constraints, and the consequences of possible action are not precise [4], [10]. The imprecision is the nucleus of the applications of fuzzy logic which uses fuzzy sets that were proposed as a generalization of conventional set theory.

Studies have been conducted to stabilise power by reducing on the errors caused by unbalanced loads [11], [12], [9], [13]. Ukil in [9] uses few linguistic terms to reduce the error in the switching scheme; however, to achieve an accurate system control with highly minimized error, there is need to enrich the fuzzy linguistic terms which can accommodate small changes in large system controls such as balancing huge amount of electric load in a three-phase system in an electric power

TABLE I: Meaning of Typical Linguistic Terms in Fuzzy Logic

Linguistic Term	Meaning
PL	Positive Large
PM	Positive Medium
PS	Positive Small
ZE	Zero
NS	Negative Small
NM	Negative Medium
NL	Negative Large

distribution.

Fuzzy logic implements human experiences and preferences through membership function and fuzzy rules. Fuzzy membership functions can have different shapes depending on the experience and preference of the designer [6]. There are basically four categories of fuzzy rules [5]: First, extraction from expert experience and control engineering knowledge, secondly, observation of the behavior of human operators, thirdly, use of a fuzzy model of a process, and finally, learning the relationships through experience or simulation with a learning process. In this way, fuzzy logic can be utilized as a general method to compound knowledge and heuristics into controllers. The system can be made understandable to non-expert operators by use of linguistic variables and fuzzy rules. Some of the linguistic terms used are as shown in Table I, which represent the load condition of the phase from heavily over loaded to grossly under loaded.

A. Application of Fuzzy Logic in Electric Power Distribution

1) *Fuzzy Logic Toolbox*: The fuzzy logic can be obtained from a MATLAB platform. In fuzzy logic, choices of sets of rules and membership functions significantly affect the achievement of performance goals. Two well known fuzzy rule-based inference systems are the Mamdani and Tagaki-Sugeno fuzzy methods. In this paper we considered Mamdani model for intuitiveness and simplex output expression that is well suited to human reasoning as a better choice when

applying fuzzy logic technique in electric power distribution system control since the Tagaki-Sugeno inference system has difficulties in dealing with the multi-parameter synthetic evolution and assigning weight to each input and fuzzy rules [8].

2) *Developing the Fuzzy Logic Model and Algorithm:*

The Mamdani type of inference is considered and the defuzzification method considered is centroid with one set of each input variables named Load (kW) and one set of each output variables named Change (kW). A positive value change implies an under-loading condition, and the change value is added to the input load to constitute the final load. A negative change value indicates an over-loading condition, and the change value is subtracted from the input load to constitute the final load. The implementation of the necessary addition or subtraction of the output load change value on the input load variable culminates in a perfectly balanced load condition of the system.

Therefore, the designed fuzzy system controls by relocating the phase load for a balanced three phase system in electric power distribution network system using unlimited linguistic terms.

II. METHODS

A. *Classification of Fuzzy Linguistic Terms*

1) *Definition of the Proposed Input Variables:* Linguistic terms proposed in this paper are listed in Table II. Describing input load this way can generate many clustered regions of input variable because of sufficient fuzzy logic linguistic terms. We have considered seventeen regions which are classified as indicated in the Table II. Note that this can be extended for numerous clustered regions more than the ones indicated in Table II.

It can be noted from Table II that C8UL < C7UL < ... < C1UL < PL < C1OL ... C7OL < C8OL. Linguistically, C8UL means that the system is grossly under loaded, PL means that the system is perfectly loaded and this is the desired balanced condition where no additional load balancing is required, and C8OL means that the system is heavily over loaded and load balancing is required to remove some load so that the system can attain a balanced state.

B. *Definition of Proposed Output Change Variables*

The load change variables in the fuzzy logic output are linked to the input load variables with an inverse relationship. These output load change variables are shown in Table III (Note from Table III that C8NC > C7NC > ... > C1NC and C1PC < C2PC < ... < C8PC). If the system is grossly out of balance (i.e. the input load is at an extreme), then the output load change should be at the opposite extreme. Adding C8PC kW load to C8UL kW load balances the final load at PL kW load, and subtracting C8NC kW load from C8OL kW load also balances the final load at PL kW. Therefore, the range of values of output load change variables can be from C8NC kW load to C8PC kW load for C8UL kW to C8OL kW input

TABLE II: Regions of input variables

Input Load Description	Fuzzy Logic Linguistic Term
Class 8 Under Load	C8UL
Class 7 Under Load	C7UL
Class 6 Under Load	C6UL
Class 5 Under Load	C5UL
Class 4 Under Load	C4UL
Class 3 Under Load	C3UL
Class 2 Under Load	C2UL
Class 1 Under Load	C1UL
Perfect Load	PL
Class 1 Over Load	C1OL
Class 2 Over Load	C2OL
Class 3 Over Load	C3OL
Class 4 Over Load	C4OL
Class 5 Over Load	C5OL
Class 6 Over Load	C6OL
Class 7 Over Load	C7OL
Class 8 Over Load	C8OL

TABLE III: Regions of output load change variables

Output Change Description	Fuzzy Logic Linguistic Term
Class 8 Negative Change	C8NC
Class 7 Negative Change	C7NC
Class 6 Negative Change	C6NC
Class 5 Negative Change	C5NC
Class 4 Negative Change	C4NC
Class 3 Negative Change	C3NC
Class 2 Negative Change	C2NC
Class 1 Negative Change	C1NC
Perfect Change	PC
Class 1 Positive Change	C1PC
Class 2 Positive Change	C2PC
Class 3 Positive Change	C3PC
Class 4 Positive Change	C4PC
Class 5 Positive Change	C5PC
Class 6 Positive Change	C6PC
Class 7 Positive Change	C7PC
Class 8 Positive Change	C8PC

load variable range respectively. Thus, the input load status of the system determines the output load change that is required for a balanced condition.

C. *Fuzzy Inference Rules Based on Proposed Linguistic Terms*

Fuzzy inference rules provide the criteria for effective load balancing. They are a set of rules that describe the control action of the entire fuzzy system. The change in output load is determined by the input load value and the rules are defined by Fuzzy Inference System (FIS) as described in Table IV.

D. *Fuzzy Models*

1) *Fuzzy Logic Algorithm:* An algorithm can be generated using the defined fuzzy inference set rules described in Table IV. The algorithm that is generated depends on the range of the input load variables and output load change variables. Suppose the peak load for a three-phase network at any grid of interest is P , then the peak load per phase for a balanced system is $\frac{P}{3}$. The input load variable will then range from zero to twice the

TABLE IV: Fuzzy set rules

Rule Number	Rule Description
1	If (Load (kW) is C8UL) then (Change (kW) is C8PC)
2	If (Load (kW) is C7UL) then (Change (kW) is C7PC)
3	If (Load (kW) is C6UL) then (Change (kW) is C6PC)
4	If (Load (kW) is C5UL) then (Change (kW) is C5PC)
5	If (Load (kW) is C4UL) then (Change (kW) is C4PC)
6	If (Load (kW) is C3UL) then (Change (kW) is C3PC)
7	If (Load (kW) is C2UL) then (Change (kW) is C2PC)
8	If (Load (kW) is C1UL) then (Change (kW) is C1PC)
9	If (Load (kW) is PL) then (Change (kW) is PC)
10	If (Load (kW) is C1OL) then (Change (kW) is C1NC)
11	If (Load (kW) is C2OL) then (Change (kW) is C2NC)
12	If (Load (kW) is C3OL) then (Change (kW) is C3NC)
13	If (Load (kW) is C4OL) then (Change (kW) is C4NC)
14	If (Load (kW) is C5OL) then (Change (kW) is C5NC)
15	If (Load (kW) is C6OL) then (Change (kW) is C6NC)
16	If (Load (kW) is C7OL) then (Change (kW) is C7NC)
17	If (Load (kW) is C8OL) then (Change (kW) is C8NC)

value of the load per phase, i.e., from 0 to $\frac{2}{3}P$. The output load change in this case ranges from $-\frac{P}{3}$ to $\frac{P}{3}$. Therefore, when the value of P for a section of grid network is known, then the algorithm for that particular section of the grid network can be generated, which can then be written into the fuzzy logic controller through a micro-controller “burning process” for execution of the operation.

2) *Fuzzy Inference Rules:* The fuzzy design implemented by fuzzy inference rules in Table IV contain

rules that can generate a different fuzzy logic algorithm as long as the input variables are different. These input variables are characteristics of the grid or part of the grid in the case of a wide distribution network.

3) *Input Membership Function:* According to proposed classified linguistic terms, the input variables are programmed as input membership functions. Using the peak load value of P kW, the load per phase at peak can be determined to be approximately $\frac{P}{3}$ kW for a balanced system. For any input load fluctuations in this particular case, the range of fluctuations would be between 0 and $\frac{2P}{3}$ kW. The fuzzy logic algorithm to perform these tasks can be constructed. The performance of the algorithm is such that if the load per phase exceeds $\frac{2P}{3}$ kW, the entire system should be cut off to avoid system damage.

4) *Output Change Membership Function:* The output change variables can be programmed as output membership functions. In this membership function editor, the membership function plots range from C8NC through PC up to C8PC. This range starts from $-\frac{P}{3}$ kW to $\frac{P}{3}$ kW. The output change value is determined by the input value.

E. Method of Error Correction in Fuzzy Simulations for Electric Load Balancing

If the initial loading condition in the three phases, L_1 , L_2 , and L_3 at any time is represented by the load matrix as in

Equation 1 [9].

$$P_{initial} = \begin{bmatrix} \text{Load}_{L_1} \\ \text{Load}_{L_2} \\ \text{Load}_{L_3} \end{bmatrix} \quad (1)$$

The final load P_{final} in the three phases without performing an error correction is obtained using Equation 2, where ΔP_{fuzzy} is the fuzzy output load change configuration [9].

$$P_{final} = P_{initial} + \Delta P_{fuzzy} \quad (2)$$

The Absolute Average Unbalance Error per Phase (AAUB/Ph) is calculated according to Equation 3 [9].

$$\text{AAUB/Ph} = \frac{|L_{L_1} - L_{L_2}| + |L_{L_2} - L_{L_3}| + |L_{L_3} - L_{L_1}|}{3} \quad (3)$$

Where L stands for Load. The average correction (A_{corr}) is calculated using equation 4.

$$A_{corr} = \text{round} \left(\frac{\sum \Delta P_{fuzzy}}{3} \right) \quad (4)$$

The correction matrix can be obtained using the average correction by distributing the A_{corr} evenly among the three phases as follows:

$$\Delta P_{corr} = \begin{bmatrix} A_{corr} \\ A_{corr} \\ \sum \Delta P_{fuzzy} - 2A_{corr} \end{bmatrix} \quad (5)$$

Then the final load change configuration, ΔP can be obtained by subtracting ΔP_{error} from the uncorrected fuzzy output load ΔP_{fuzzy} [9], i.e.;

$$\Delta P = \Delta P_{fuzzy} - \Delta P_{corr} \quad (6)$$

Note that, the sum of the load change should be zero, i.e.;

$$\sum \Delta P = 0 \quad (7)$$

The final load configuration after performing error correction is calculated using Equation 8

$$P_{final} = P_{initial} + \Delta P \quad (8)$$

III. SIMULATION RESULTS

Figures 1, 2, and 3 represent the initial loading condition in the three phases L_1 , L_2 , and L_3 respectively, at a total peak load value of 2100 kW, and are represented by the load matrix shown in Equation 1.

$$P_{initial} = \begin{bmatrix} 350 \\ 800 \\ 950 \end{bmatrix} \text{ kW.}$$

The fuzzy output load change configuration obtained from the simulation results in Figures 1, 2, and 3 were:

$$\Delta P_{fuzzy} = \begin{bmatrix} 350 \\ -103 \\ -253 \end{bmatrix} \text{ kW.}$$

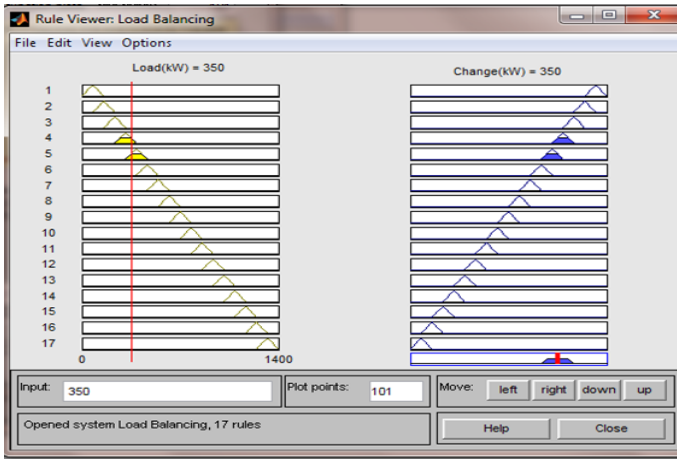


Fig. 1: Simulation result viewer at input power of 350 kW for Phase 1 (L_1)

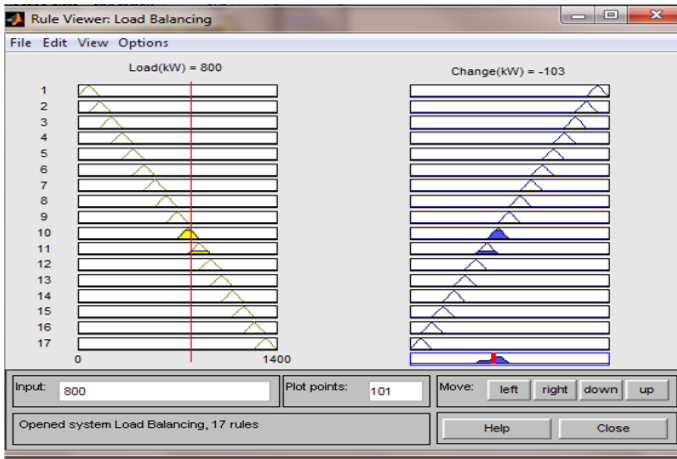


Fig. 2: Simulation result viewer at input power of 800 kW for Phase 2 (L_2)

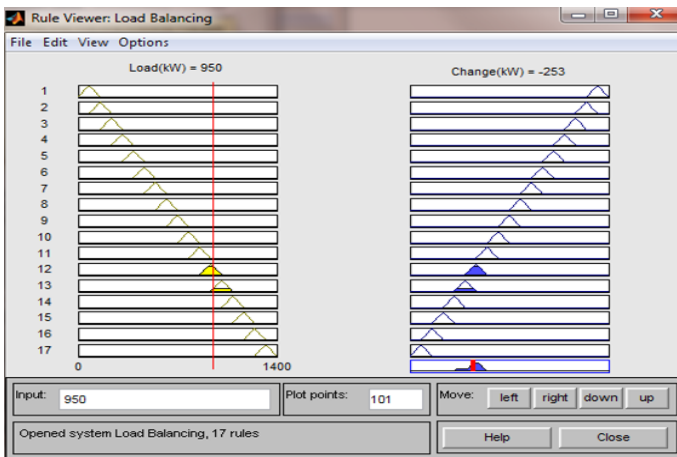


Fig. 3: Simulation result viewer at input power of 950 kW for Phase 3 (L_3)

The Initial AAUB/Ph for this case was obtained using

Equation 3:

$$\text{IAAUB/Ph} = \frac{|350 - 800| + |800 - 950| + |950 - 350|}{3} = 400 \text{ kW}$$

The error in the output load change configuration result was:

$$\sum \Delta P_{fuzzy} = 350 - 103 - 253 = -6 \text{ kW.}$$

This is the amount of load that is lost after fuzzy implementation. The final load in the three phases without performing an error correction calculated according to Equation 2 was:

$$P_{final} = \begin{bmatrix} 700 \\ 697 \\ 697 \end{bmatrix} \text{ kW.}$$

This final load was quite balanced even before performing an error correction. However, error correction was performed since the total load was expected to remain constant after fuzzy implementation.

The average correction calculated using Equation 4 was:

$$A_{corr} = -2 \text{ kW.}$$

Therefore, the correction matrix according to Equation 5 was:

$$\Delta P_{corr} = \begin{bmatrix} -2 \\ -2 \\ -2 \end{bmatrix} \text{ kW.}$$

The final load change configuration was obtained according to Equation 6 as:

$$\Delta P = \begin{bmatrix} 350 \\ -103 \\ -253 \end{bmatrix} - \begin{bmatrix} -2 \\ -2 \\ -2 \end{bmatrix} = \begin{bmatrix} 352 \\ -101 \\ -251 \end{bmatrix} \text{ kW.}$$

Thus, Equation 8 gave the final load as:

$$P_{final} = \begin{bmatrix} 350 \\ 800 \\ 950 \end{bmatrix} + \begin{bmatrix} 352 \\ -101 \\ -251 \end{bmatrix} = \begin{bmatrix} 702 \\ 699 \\ 699 \end{bmatrix} \text{ kW.}$$

After performing an error correction, the sum of the output load change, as expected according to Equation 7, was:

$$\sum \Delta P = 352 - 101 - 251 = 0.$$

Using Equation 3, the Final AAUB/Ph in this case was:

$$\text{FAAUB/Ph} = \frac{|702 - 699| + |699 - 699| + |699 - 702|}{3} = 2 \text{ kW.}$$

The total peak load was then:

$$P_{total} = 702 + 699 + 699 = 2100 \text{ kW.}$$

Therefore, the total load in the system was constant (2100 kW) as before and the IAAUB/Ph was greatly reduced from

TABLE V: Summary of simulation results at peak load of 2100 kW for WENRECo grid

Test Case	Initial Load (kW)			Final Load (kW)		
	Phases	ΔP_{ph-max}	IAAUB/Ph	Phases	ΔP_{ph-max}	FAAUB/Ph
1	350	600	400.0	700	3.0	2.0
	800			697		
	950			697		
2	500	500	333.3	699	4.0	2.7
	600			703		
	1000			703		
3	500	550	366.7	699	1.0	0.7
	550			700		
	1050			700		
4	350	550	400.0	700	1.0	0.7
	850			701		
	900			701		
5	650	100	66.7	697.8	4.4	2.9
	700			700.0		
	750			702.2		

400 kW to FAAUB/Ph of 2 kW. Furthermore, there was no significant change in the final load after the implementation of error correction.

Summary of the Simulations

Table V summarises the simulation results for 2100 kW overall grid peak load with different initial phase loading combinations of five test cases.

It can clearly be observed that the developed fuzzy logic algorithm maintained a constant power level close to or equal to 700 kW per phase at peak. However, the algorithm can be adjusted to balance any load value at any part of any grid of interest by considering the membership function range of both the input load and the output load change variables. We used practical set of data obtained by [9] with varying system loads using the current algorithm and the simulation results were obtained.

For the first test case:

$$P_{initial} = \begin{bmatrix} 245 \\ 120 \\ 82 \end{bmatrix} \text{ kW.}$$

The simulation results in Figures 4, 5, and 6 show the output load change.

$$\Delta P_{fuzzy} = \begin{bmatrix} -95.3 \\ 28.5 \\ 67.4 \end{bmatrix} \text{ kW.}$$

The results by [9] had output load change configuration given by:

$$\Delta P_{fuzzy} = \begin{bmatrix} -104 \\ 25 \\ 65 \end{bmatrix} \text{ kW.}$$

The error in this output load change configuration result was:

$$\sum \Delta P_{fuzzy} = -104 + 25 + 65 = -14 \text{ kW.}$$

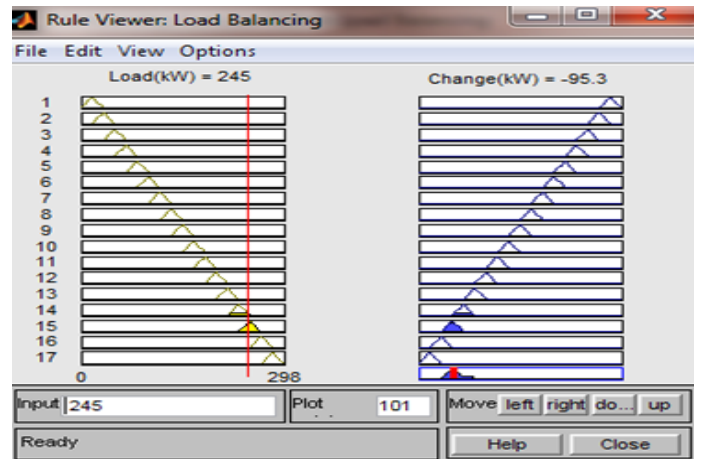


Fig. 4: Simulation result of the output load change and input load for phase 1

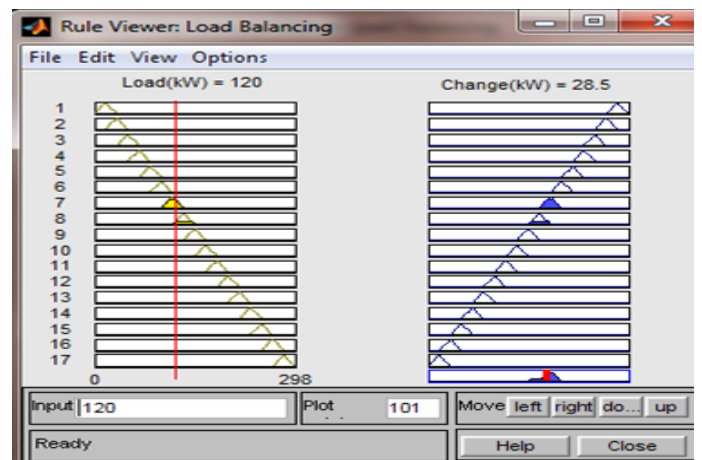


Fig. 5: Simulation result of the output load change and input load for phase 2

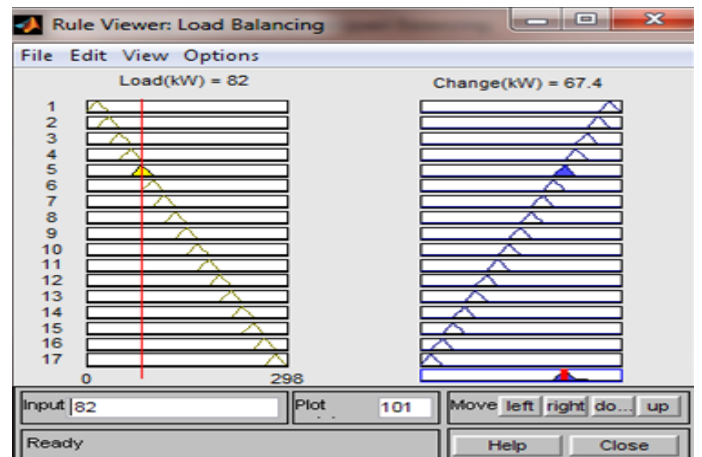


Fig. 6: Simulation result of the output load change and input load for phase 3

On performing an error correction, P_{final} became:

$$P_{final} = \begin{bmatrix} 146 \\ 150 \\ 151 \end{bmatrix} \text{ kW.}$$

In the current study, the error in the output load change configuration result was:

$$\sum \Delta P_{fuzzy} = -95.3 + 28.55 + 67.4 = -0.6 \text{ kW.}$$

This error was quite small. Therefore, the final load in the three phases without performing an error correction was:

$$P_{final} = \begin{bmatrix} 149.6 \\ 148.5 \\ 149.4 \end{bmatrix} \text{ kW.}$$

This final load was quite balanced compared to the final load in [9], even after performing an error correction. However, the error correction was performed in the current study since the total load was expected to remain constant.

Using Equation 4 without rounding, the average correction is:

$$A_{corr} = 0.2 \text{ kW.}$$

The correction matrix was obtained using Equation 5 as:

$$\Delta P_{corr} = \begin{bmatrix} 0.2 \\ 0.2 \\ 0.2 \end{bmatrix} \text{ kW.}$$

But,

$$\Delta P = \begin{bmatrix} -95.3 \\ 28.5 \\ 67.4 \end{bmatrix} - \begin{bmatrix} 0.2 \\ 0.2 \\ 0.2 \end{bmatrix} = \begin{bmatrix} -95.5 \\ 28.3 \\ 67.2 \end{bmatrix} \text{ kW.}$$

And as expected,

$$\sum \Delta P = -95.5 + 28.3 + 67.2 = 0$$

Thus,

$$P_{final} = P_{initial} + \Delta P = \begin{bmatrix} 245 \\ 120 \\ 82 \end{bmatrix} + \begin{bmatrix} -95.5 \\ 28.3 \\ 67.2 \end{bmatrix} = \begin{bmatrix} 149.5 \\ 148.3 \\ 149.2 \end{bmatrix} \text{ kW.}$$

TABLE VI: Summary of simulation results between this work and work in [9]

Test Case	Initial Load (kW)		Final Load (kW)			
	Phases	ΔP_{ph-max}	Current work		Work from [9]	
			Phases	ΔP_{ph-max}	Phases	ΔP_{ph-max}
1	245	163	149.70	1.20	146	5
	120		148.50		150	
	82		149.40		151	
2	157	37	136.40	1.30	139	6
	134		137.64		133	
	120		137.70		139	
3	140	16	147.20	0.32	145	6
	145		147.52		145	
	156		147.20		151	
4	205	43	178.70	0.82	181	4
	170		179.52		177	
	162		178.70		179	
5	170	87	115.40	0.40	115	9
	95		115.70		121	
	83		115.80		112	
6	117	75	77.80	0.23	72	9
	74		77.77		80	
	42		78.00		81	

After performing an error correction, there was no significant change in the final load in the current study. Table VI

presents simulation results of six test cases with different initial phase loading condition using the same data by [9] without performing the error correction in the current study.

Therefore, the fuzzy logic algorithm gives low FAAUB/Ph without performing error correction as calculated according to Equation 3 an can be checked against a low threshold hold value of FAAUB/Ph. This low threshold value can results into a more perfectly balanced load condition in the three phases.

IV. CONCLUSION

The study depicts that using more fuzzy linguistics terms yields more accurate phase load balancing. The proposed fuzzy linguistic terms pattern can be used for numerous clusterisation of regions of input load and output load change variables. This results into a highly perfect load balance during intelligent distribution management of electricity giving better scores of error reduction.

The simulation results of 2100 kW peak load considered in this study showed balanced phase load value close to 700 kW per phase in all the test cases as expected. The algorithm developed from the fuzzy set rules using any intended clustered regions can be subjected to the management of any peak load of interest. So, every peak load considered from any part of the grid has a unique algorithm because the algorithm developed depends on the peak load. Hence, the fuzzy logic algorithm developed in the current study in comparison to the study done in [9], resulted into a desired low final values of ΔP_{ph-max} and subsequently low values of FAAUB/Ph.

REFERENCES

- [1] G. Petros, "Critique of Zadeh's fuzzy set theory," 2016.
- [2] E. Cox, "The Fuzzy System Handbook," Academic Press, 1994.
- [3] L. A. Zadeh, "Fuzzy Sets in Information and Control," New York, Academic Press, vol. 8, pp. 338-353, 1965.
- [4] R. E. Bellman and L. A. Zadeh, "Decision Making in a Fuzzy Environment," Management Science, vol. 17, pp. 141-164, 1970.
- [5] M. Y. Chow, "Design Methodology of an Intelligent Controller Using Artificial Neural Networks," IECON, vol. 93, 1993.
- [6] K. Tomsovic and M. Y. Chow, "Tutorial on Fuzzy Logic Application in Power Systems," IEEE-PES Winter Meeting in Singapore, 2000.
- [7] A. Ukil, "Intelligent System and Signal Processing in Power Engineering," Book on Power Systems - Springer, 2007.
- [8] I. Elamvazuthi, P. Vasant and J. Webb, "The Application of Mamdani Fuzzy Model for Auto Zoom Function of a Digital Camera," International Journal of Computer Science and Information Security, vol. 6, 2009.
- [9] A. Ukil, and W. Siti, "Feeder Load Balancing using Fuzzy Logic and Combinatorial Optimisation-Based Implementation," Electric Power Systems Research, vol. 78, pp. 1992-1932, 2008.
- [10] W. Sehrish and Z. Ahmad, "APPLICATION OF FUZZY LOGIC IN ACADEMIC SETUP," 2011.
- [11] A. Khalid, A.M. Farhoud, and J.K. Hurtig, "Power System Stabilizers with Fuzzy Logic Switching," pp. 2152-2157, 2006
- [12] T. Hiyama, T. D. Ueno, S. Yamashiro, M. Yamagishi, and M. Shimizu, "Experimental evaluation on fuzzy logic switching control of electrical double-layer energy capacitor system for stability enhancement," vol. 3, pp. 997-1002, 2001
- [13] L. Jun, L. Wee and L. Choo, "A simplified fuzzy logic power system stabilizer". pp. 996-1000. July 2015.