# Comparison of Different Cluttering Validity Methods in the Evaluation of Results for Finding Electrical Fault Location in Industrial MV Network Using Fuzzy Clustering Technique 

Muhammad M.A.S. Mahmoud and Emin Husinli

# Comparison of Different Cluttering Validity Methods in the Evaluation of Results for Electrical Fault Location in Industrial MV Network Using Fuzzy Clustering Technique 

Muhammad M.A.S. Mahmoud<br>Process Automation Engineering<br>Department<br>Baku Highr Oil School<br>Baku, Azerbijan<br>muhammad.salih@socar.az

Amin Husinly<br>Process Automation Engineering<br>Department<br>Baku Highr Oil School<br>Baku, Azerbijan<br>mmanar3@yahoo.com


#### Abstract

Comprehensive study is carried out to compare three different Cluttering Validity methods; Partition Coefficient, Partition Entropy and Proportional Exponent to evaluate the results of finding electrical faults in industrial MV network using fuzzy clustering technique. Different data normalization methods and different range of Alfa-cut values for defuzzification are considered in the comparison process. The result shows that using Partition Entropy with Maximum Matrix normalization and 50\% Alpha*cut gives the best effort saving of $\mathbf{9 5 , 1 5}$ in finding the fault.


Keywords- network distribution, fuzzy clustering, cluster validity, finding fault

## I. Introduction

Finding electrical fault location in oil \& gas MV Network is necessary and main issue for continuous power delivery specially in old system, harsh environment and remote where the grid experience repeated faults. Any delay in finding the faults and repair it affects considerably reduction oil productivity. Therefore, the technique to find the faults needs to be efficient, fast and accurate as much as possible. Many years, researchers have done lot of efforts based on intelligent techniques in order to create effective solution. Fuzzy Clustering, Artificial Neural network, Expert Genetic Algorithm and System are example for intelligent programming techniques [1]. PC based techniques for fault finding are become very important for the fast results. Artificial Neural Networks (ANN) and Fuzzy Logic (FL) methods have recently gained popularity and proved successful in many practical problems [2] [3] [4].

In [5], the paper studied an existing 13.8 kilovolt distribution network which, serves an oil production field spread over an area of approximately 60 kilometers square, in order to locate any fault that may occur anywhere in the network using fuzzy c-mean classification techniques [6]. Two different methods for normalizing data and selecting the optimum number of clusters in order to classify data is introduced. Functional Coefficient Index was used to validate the clustering process. Results and conclusions are given to show the feasibility for the suggested fault location method.

In this paper the research of [5] is extend to study the results in case Partition Coefficient, Partition Entropy and Proportional Exponent are used to validate the clustering and hence to find the faults [7][8][9].

In section II of this paper, description for the electrical network under discussion is provided to illustrate the complexity of the network. Section III discusses the data
collection to construct the faults-feature matrix and the methods of normalizing these data to be suitable for clustering and validation process. Then, in section IV, indices of Partition Coefficient, Partition Entropy and Proportional Exponent are discussed. Section V discusses the fault location algorithm and procedures. The result of applying the above mentioned three clustering validity indices in the process of finding the fault in the network is also illustrated in this section. Summary and conclusion of the results is give in section VI.

## II. Electrical Network Discription

An Oil Company operates two production areas; Area-1 and Area-2 . Each area provided with power distribution system. Area-1 power generation plant with 130 MVA capacity supplies power for Area 1 and send the needed power to Area-2 too. Also, Area-2 has local generation of 3.16 MVA capacity. Area 1 and Area 2 are electrically interconnected to transmit around 40 MVA from Area-1 to Area-2. At Area-2 (Fig. 1), the field oil-well loads are distributed among three wooden overhead transmission lines (OHTL). At Area-2 substation Smart relays are available to record any disturbance in the Area 2 network. The three OHTL are connected in mish configuration that add more completion to find the fault.

## III. Data Collection and Fault Feature Matrix

Load-Flow study is conducted to identify the pre-faultand post-fault active power and reactive power and hence the loss in respective power at each feeder for every short-circuit case.


Fig. 1: Area 2 distribution network

TABLE 1: Summary of the Parameters That are Selected to Build The Feature Matrix

| Feeder 1 | Feeder 2 | Feeder 3 |
| :---: | :---: | :---: |
| Set of nods fed from <br> Feeder 1 | Set of nods fed from <br> Feeder 2 | Set of nods fed from <br> Feeder 3 |
| Circuit breaker 1 <br> status | Circuit breaker 2 <br> status | Circuit breaker 3 <br> status |
| Feeder 1 Short circuit <br> Current red from <br> substation | Feeder 2 Short circuit <br> Current red from <br> substation | Feeder 2 Short circuit <br> Current red from <br> substation |
| Phase Angel A1 | Phase Angel A2 | Phase Angel A3 |
| Phase Angel B1 | Phase Angel B2 | Phase Angel B3 |
| Phase Angel C1 | Phase Angel C2 | Phase Angel C3 |
| Power dip in | Power dip in <br> Feeder 1 | Power dip in <br> Feeder 3 |
| VAR dip in | VAR dip in <br> Feeder 1 | VAR dip in <br> Feeder 2 |
| Fault distance from <br> Feeder 1 C. Breaker | Fault Distance from <br> Feeder 2 C. Breaker | Fault Distance from <br> Feeder 3 C. Breaker |

Short-circuit study is also carried out to identify the phase short circuit current and angle for each short circuit case and the expected circuit breaker trip status. The results of these two studies are used to construct the fault-feature-matrix for 144 nodes describing the faults for the network. Table 1 describes the parameter that have been selected to construct the fault feature matrix.

Because in the fault-feature-matrix there are wide range of values, normalization is necessary to make further calculation much easier during clustering and validation process. Two normalization methods are considered; Column-maximum and absolute matrix- maximum [5].

In normalization based on column, each value of matrix column is divided by the maximum values of the respective columns. So, it makes each value of data between 0 and 1 . The second method for this is matrix normalization. However, in absolute matrix- maximum normalization, all matrix is divided by absolute maximum of whole matrix.

In the next section, data for thirteen (13) faults are selected for testing the method of fault location. Other 131 data are used to create clusters to and to build the fault location algorithm.

Using technician experience in operating this network, it is possible to preliminary cluster this data. Based on Power dip and circuit breaker trip. Accordingly, initially data matrix can be classified into six different group.
a) 1st feeder power dip and circuit breaker trip
b) 1st feeder power dip and circuit breaker doesn't trip
c) 2 nd feeder power dip and circuit breaker trip
d) 2nd feeder power dip and circuit breaker doesn't trip
e) 3rd feeder power dip and circuit breaker trip
f) 3rd feeder power dip and circuit breaker doesn't trip

This technique gives advance to improve c-means clustering performance. Nearest node will be searched in one group, not whole matrix.

In this paper the advantage of operator experience is utilize with the use of absolute matrix-maximum normalization to develop the fault location algorithm as will be illustrated in Section V.

## IV. Fuzzy C-means Clustering Algorithm and CLUSTER CALIDITY

The fuzzy c-means clustering algorithm given in [6] is used to carry out the data clustering.

The quality of a clustering is indicated by how closely the data points are associated to the cluster centers and it is the membership functions, which measure the level of association or classification. If the value of one of the membership is significantly larger than the others for a particular data point, then that point is identified as being a part of the subset of the data represented by the corresponding cluster center. But, each data point has c memberships; so, it is desirable to summarize the information contained in the memberships by a single number, which indicates how well the data point is classified by the clustering.

In [7], three cluster validity technique are proposed. First one is called Partition Coefficient.

$$
\begin{equation*}
\mathrm{PC}=\frac{1}{N} \sum_{i=1}^{c} \sum_{j=1}^{N}\left(\mu_{i j}\right)^{2} \tag{1}
\end{equation*}
$$

The second method is called Partition (Classification) Entropy

$$
\begin{equation*}
\mathrm{PE}=-\frac{1}{N} \sum_{i=1}^{c} \sum_{j=1}^{N} \mu_{i j} * \log \mu_{i j} \tag{2}
\end{equation*}
$$

There is also another cluster validity index which is called Proportion Exponent.

$$
\begin{equation*}
\operatorname{Pex}=\frac{1}{\mathrm{~N}} \max \left(\mu_{\mathrm{ij}}\right) \tag{3}
\end{equation*}
$$

Where:
$\mathrm{N}=$ number of data points
$\mathrm{c}=$ number of centroids(clusters)
$\mu=$ membership value
$1 \leq \mathrm{i} \leq \mathrm{c}, 1 \leq \mathrm{j} \leq \mathrm{N}$

For best clustering, the error given in (4) must be minimized

$$
\begin{equation*}
\text { Error }=1-\operatorname{abs}(\text { index }) \tag{4}
\end{equation*}
$$

At the maximum value of partition coefficient, proportional exponent and minimum value of the partition entropy, efficient number of c-clusters is achieved. Closer this index [7] to one, data is clustered more efficiently.

## V. FAULT LOCATION ALGORITHM AND PROCEDURE

In this section, fuzzy c-means clustering technique is applied based on maximum matrix normalization. Through these steps result of classification and fault finding analyzed as following:
a) First absolute maximum matrix is found. Then, all the matrix is divided by this number. Accordingly all data are normalized between 0 and 1 .
b) Based on the preliminary knowledge of electrical network, the possible fault locations are found to be as shown in the foloowing table 2 :

TABLE 2: Preliminary Clustering

| Cases Description | Possible <br> location |
| :---: | :---: |
| 1st feeder power dip and circuit breaker trip | 12 |
| 1st feeder power dip and circuit breaker doesn't trip | 6 |
| 2nd feeder power dip and circuit breaker trip | 14 |
| 2nd feeder power dip and circuit breaker doesn't trip | 6 |
| 3rd feeder power dip and circuit breaker trip | 9 |
| 3rd feeder power dip and circuit breaker doesn't trip | 7 |

c) All data is clustered based on FCM technique. Cluster validity technique is applied in order to determine the most efficient number of cluster centroid. In this case Partition Coefficient is implemented.
d) Euclidian distance is calculated between test data and the full data in the selected group is checked, based on each corresponding partition, cluster centroid for each data point is determined.
e) Alpha-cut defuzzification is selected in a range in which $100 \%$ sucessful trials (5) is achieved wherethe nearest node to the fault is located in selected cluster.
Succesfull Trials(\%) $=\frac{\text { Number of succesfull trial }}{\text { Number of testing case (13) }} * 100 \%$
f) Effort saving for each case is calculated based on the formulas (6) and (7):
Effort Savings $=\left(1-\frac{\text { Number of possible location }}{\text { all nodes(144) }}\right) * 100 \%$ (6)
Average effort savings $\%=\frac{\text { Effort Savings }}{\text { Number of testing case }(13)} * 100 \%$
Matlab program is written to implement the above six steps and the results are analyzed and summarized in the following tables, that give the saving efforts for each clustering coefficient using different Alph-cut values.

TABLE 3: Effort Saved Using Matrix Maximum Normalization (Partition Coefficient)

| Test cases | Number of Possible locations | Optimum number of clusters | Fault located in the cluster? | Saving Effort |
| :---: | :---: | :---: | :---: | :---: |
| 1 | 9 | 11 | YES | 94\% |
| 2 | 11 | 11 | YES | 92\% |
| 3 | 4 | 5 | YES | 97\% |
| 4 | 13 | 12 | YES | 91\% |
| 5 | 8 | 6 | YES | 94\% |
| 6 | 1 | 5 | YES | 99\% |
| 7 | 12 | 11 | YES | 92\% |
| 8 | 14 | 12 | YES | 90\% |
| 9 | 3 | 5 | YES | 98\% |
| 10 | 12 | 13 | YES | 92\% |
| 11 | 10 | 12 | YES | 93\% |
| 12 | 3 | 6 | YES | 98\% |
| 13 | 8 | 6 | YES | 94\% |
| Percentage of Successful trails |  | 100\% |  |  |
| Average effort savings |  | 94.15384615\% |  |  |
| Alpha cut coefficient |  | 0.6 |  |  |

TABLE 4: Effort SAvEd in Column Maximum Normalization (Partition Entropy -1)

| Test cases | Number of Possible locations | Fault located in the cluster? | Effort Savings |
| :---: | :---: | :---: | :---: |
| 1 | 27 | YES | 81\% |
| 2 | 27 | YES | 81\% |
| 3 | 11 | YES | 92\% |
| 4 | 33 | YES | 77\% |
| 5 | 9 | YES | 94\% |
| 6 | 10 | YES | 93\% |
| 7 | 6 | YES | 96\% |
| 8 | 3 | YES | 98\% |
| 9 | 11 | YES | 92\% |
| 10 | 33 | YES | 77\% |
| 11 | 33 | YES | 77\% |
| 12 | 9 | YES | 94\% |
| 13 | 6 | YES | 96\% |
| Percentage of Successful trails |  | 100\% |  |
| Average effort savings |  | 88.30769231\% |  |
| Alpha cut coefficient |  | 0.4 |  |

TABLE 5: EfFort Saved in Column Maximum Normalization (PARTITION ENTROPY-2)

| Test cases | Number of Possible locations | Is nearest node located in the cluster? | Effort Savings |
| :---: | :---: | :---: | :---: |
| 1 | 27 | YES | 81\% |
| 2 | 24 | YES | 83\% |
| 3 | 10 | YES | 93\% |
| 4 | 33 | YES | 77\% |
| 5 | 9 | YES | 94\% |
| 6 | 9 | YES | 94\% |
| 7 | 6 | YES | 96\% |
| 8 | 3 | YES | 98\% |
| 9 | 10 | YES | 93\% |
| 10 | 33 | YES | 77\% |
| 11 | 33 | YES | 77\% |
| 12 | 9 | YES | 94\% |
| 13 | 6 | YES | 96\% |
| Percentage of Successful trails |  | 100\% |  |
| Average effort savings |  | 88.69230769\% |  |
| Alpha cut coefficient |  | 0.3 |  |

TABLE 6: Effort Saved in Matrix Maximum Normalization (Partition Entropy-1)

| Test cases | Number of <br> Possible <br> locations | Optimum number of clusters | Fault located in the cluster? | Saving Effort |
| :---: | :---: | :---: | :---: | :---: |
| 1 | 6 | 9 | YES | 96\% |
| 2 | 3 | 9 | YES | 98\% |
| 3 | 3 | 6 | YES | 98\% |
| 4 | 9 | 11 | YES | 94\% |
| 5 | 7 | 7 | YES | 95\% |
| 6 | 1 | 6 | YES | 99\% |
| 7 | 10 | 9 | YES | 93\% |
| 8 | 14 | 11 | YES | 90\% |
| 9 | 3 | 6 | YES | 98\% |
| 10 | 11 | 11 | YES | 92\% |
| 11 | 11 | 11 | YES | 92\% |
| 12 | 3 | 7 | YES | 98\% |
| 13 | 8 | 8 | YES | 94\% |
| Percentage of Successful trails |  | 100\% |  |  |
| Average effort savings |  | 95.15384615\% |  |  |
| Alpha cut coefficient |  | 0.5 |  |  |

TABLE 7: Effort Saved in Matrix Maximum Normalization (PARTITION Entropy-2)

| Test cases | Number <br> of Possible <br> locations | Optimum <br> number of <br> clusters | Fault <br> located in <br> the cluster? | Saving <br> Effort |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 8 | 9 | YES | 94 |  |  |  |  |
| 2 | 11 | 9 | YES | 92 |  |  |  |  |
| 3 | 4 | 6 | YES | 97 |  |  |  |  |
| 4 | 14 | 11 | YES | 90 |  |  |  |  |
| 5 | 8 | 7 | YES | 94 |  |  |  |  |
| 6 | 1 | 6 | YES | 99 |  |  |  |  |
| 7 | 11 | 9 | YES | 92 |  |  |  |  |
| 8 | 3 | 11 | YES | 90 |  |  |  |  |
| 9 | 12 | 6 | YES | 98 |  |  |  |  |
| 10 | 10 | 11 | YES | 92 |  |  |  |  |
| 11 | 3 | 8 | YES | 93 |  |  |  |  |
| 12 | 8 | 7 | YES | 98 |  |  |  |  |
| 13 | $\mathbf{1 0 0 \%}$ | YES | 94 |  |  |  |  |  |
| Percentage of Successful trails |  |  |  |  |  |  |  |  |
| Average effort savings |  |  |  |  |  | $\mathbf{9 4 . 0 7 6 9 2 3 \%}$ |  |  |
| Alpha cut coefficient |  | $\mathbf{0 . 6}$ |  |  |  |  |  |  |

TABLE 8: EfFort Saved in Matrix Maximum Nnormalization (Partition Entropy-1)

| Test cases | Number of <br> Possible <br> locations | Fault located in <br> the cluster? | Effort Savings |
| :---: | :---: | :---: | :---: |
| 1 | 27 | YES | $81 \%$ |
| 2 | 27 | YES | $81 \%$ |
| 3 | 11 | YES | $92 \%$ |
| 4 | 33 | YES | $77 \%$ |
| 5 | 9 | YES | $94 \%$ |
| 6 | 9 | YES | $94 \%$ |
| 7 | 6 | YES | $96 \%$ |
| 8 | 3 | YES | $98 \%$ |
| 9 | 10 | YES | $93 \%$ |
| 10 | 33 | YES | $77 \%$ |
| 11 | 33 | YES | $77 \%$ |
| 12 | 9 | YES | $94 \%$ |
| 13 | 6 | YES | $96 \%$ |
| Percentage of Successful trails | $\mathbf{1 0 0 \%}$ |  |  |
| Average effort savings |  |  |  |
| Alpha cut coefficient |  |  |  |

TABLE 9: Effort Saved in Column Maximum Normalization (Proportional Exponent-2)

| Test cases | Number of Possible locations | Fault located in the cluster? | Effort Savings |
| :---: | :---: | :---: | :---: |
| 1 | 27 | YES | 81\% |
| 2 | 22 | YES | 85\% |
| 3 | 9 | YES | 94\% |
| 4 | 28 | YES | 81\% |
| 5 | 9 | YES | 94\% |
| 6 | 9 | YES | 94\% |
| 7 | 6 | YES | 96\% |
| 8 | 3 | YES | 98\% |
| 9 | 10 | YES | 93\% |
| 10 | 32 | YES | 78\% |
| 11 | 20 | YES | 86\% |
| 12 | 9 | YES | 94\% |
| 13 | 6 | YES | 96\% |
| Percentage of Successful trails |  | 100\% |  |
| Average effort savings |  | 90\% |  |
| Alpha cut coefficient |  | 0.3 |  |

TABLE 10: Effort Saved in Matrix Maximum Normalization (PROPORTIONAL EXPONENT)

| Test cases | Number of Possible locations | Optimum number of clusters | Nearest node exist in fault locations | Saving Effort |
| :---: | :---: | :---: | :---: | :---: |
| 1 | 5 | 10 | YES | 97\% |
| 2 | 11 | 10 | YES | 92\% |
| 3 | 4 | 5 | YES | 97\% |
| 4 | 13 | 11 | YES | 91\% |
| 5 | 8 | 6 | YES | 94\% |
| 6 | 1 | 4 | YES | 99\% |
| 7 | 11 | 10 | YES | 92\% |
| 8 | 14 | 11 | YES | 90\% |
| 9 | 3 | 5 | YES | 98\% |
| 10 | 12 | 11 | YES | 92\% |
| 11 | 10 | 11 | YES | 93\% |
| 12 | 3 | 6 | YES | 98\% |
| 13 | 8 | 6 | YES | 94\% |
| Percentage of Successful trails |  | 100\% |  |  |
| Average effort savings |  | 94.38461538\% |  |  |
| Alpha cut coefficient |  | 0.6\% |  |  |

From above Tables (3-10) and [5] the results can be summarize in Table 11

TABLE 11: SUMMARY OF THE RESULTS

| Index | Normalization | Alpha-cut <br> coefficient | Average <br> effort <br> saving |
| :---: | :---: | :---: | :---: |
| Partition Coefficient [5] | Column | $60 \%$ | $75 \%$ |
| Partition Coefficient [5] | Matrix | $100 \%$ | $87 \%$ |
| Partition Coefficient | Matrix | $60 \%$ | $94.15 \%$ |
| Partition Entropy | Column | $40 \%$ | $88.31 \%$ |
| Partition Entropy | Column | $30 \%$ | $88.7 \%$ |
| Partition Entropy | Matrix | $60 \%$ | $94.07 \%$ |
| Partition Entropy | Matrix | $\mathbf{5 0 \%}$ | $\mathbf{9 5 . 1 5 \%}$ |
| Proportional Exponent | Column | $40 \%$ | $88.46 \%$ |
| Proportional Exponent | Column | $30 \%$ | $90 \%$ |
| Proportional Exponent | Matrix | $60 \%$ | $94.38 \%$ |

From above Table 11, it shows that the best result obtained from the case of "Partial Entropy" with matrix maximum normalization and 50\% Alfa-cut.

## VI. RESULT ANALYSIS AND CONCLUSION

The main purpose of this paper is to compare the results of the method that was discussed in [5] using only Partition Coefficient cluster validation with another cluster validation indices in order to find efficient way to detect the fault location in oil field area. In this paper 3 different cluster validity indices are compared; Partition Coefficient, Partition Entropy and Proportional Exponent with the result obtained from [5]. In line with [5], two different normalization method are implemented. Operator experience are used to improve the clustering process. Fault distances measured from the feeders circuit breakers are used in the clustering process as additional input to the feature matrix. Alpha-cut defuzzification technique is used and the value is selected in a range in which $100 \%$ successful trials is achieved. The results for all cases are
coppered including the result obtained in [5]. It shows that that best result is obtained by the new procedure if "Partial Entropy" with matrix maximum normalization and 50\% Alfacut are used.

## Acknowledgment

I would like to present this paper to Baku Higher Oil school, my second family.

## References

[1] Muhammad M.A.S. Mahmoud, Zafar Qurbanov, "Review of fuzzy and ANN fault location methods for distribution power system in oil and gas sectors", International Federation of Automatic Control (IFAC 21018), ELSEVER
[2] Muhammad M.A.S. Mahmoud, "Detection of singl line-to-ground faults through Impedence in Mesh distripution Network", Modern Electrical Power System MEPS15-IEEE, Wroclw, July 2015.
[3] Meshal A Al-Shaher, Manar M. sabry, Ahmad s saleh, Fault location in multi-ring distribution network using artificial neural network. Electrical Power System Research.vol. 64 CRL, pp 47-53, 2006.
[4] Muhammad M.A.S. Mahmoud, "New area in fuzzy applications" Fuzzy controls recent advanced in theoory and application (Book) Chaper 17, ISBN 978-953-51- 0759-0, PP 385 - 440. INTECH, 2012.
[5] Muhammad M.A.S. Mahmoud, "3-Phase fault finding in oil field MV distribution network using fuzzy clustering technique ", Journal of Energy and Power Engineering vol.7, pp. 155-161 2013.
[6] L.X. Wang, A Course in Fuzzy Systems and Control, Prentice-Hall International, Inc., USA, 1997
[7] M.P. Windham, Cluster validity for the fuzzy c-means clustering algorithm, IEEE Trans. Pattern Anal Machine Intell. PAMI-4 (4) (1982) 357-363.
[8] J.C. Bezdek, S.K. Pal, Fuzzy Models For Pattern Recognition, The Institution of Electrical and Electronics Engineering, Inc., USA, 1992.
[9] A New Cluster Validity Index for Fuzzy Clustering Sreeram Joopudi, Suraj S. Rathi, S. Narasimhana and Raghunathan Rengaswamy


Muhammad M.A.S. Mahmoud, Egyptian, born in Kuwait 1963. Received the B.S. degree in Electrical Engineering from Cairo University and the M.Sc. degree from Kuwait University. First Ph.D. degree from Transilvania University of Brasov, Romania in IT and Computer. Second Ph.D. Degree in Electrical Power system and Machine, Cairo Univ. Egypt.

He is currently professor working with Baku Higher Oil School in Azerbaijan. His current research interest is in Fuzzy and Artificial Neural Network Techniques application include power delivery, protection reliability, control and safety. Prof. Dr. Muhammad is of IEEE Member in 1999 and Senior Member (SM) since 2001.

