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An Application of Multidimensional Scaling in Fault Detection of Smart Grids

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Abstract

Monitoring smart grids and detecting faults in such huge networks has recently become an active area of research. The huge amount of data transferred from the measurement units to the control center makes it difficult to detect faults in a reasonable amount of time. Some existing methods have been investigated and tested on many IEEE models such as wavelet transform, principal component analysis (PCA) to extract the abnormal behavior of signals under monitoring [1]. However, such techniques pose difficulties in detecting different faults properly. In this paper, the multidimensional scaling (MDS) is investigated as an alternative technique for reducing the dimensionality of the data to lower dimensions, while maintaining the necessary information needed for fault detection. MDS is then used to investigate the behavior of some IEEE models under different types of faults in order to detect and locate the faulty bus bars.

Keywords: *Multidimensional scaling, MDS, fault detection, smart grid, cluster analysis.*

1. Introduction

Smart grid is a term widely used nowadays to describe a complete power system that has the capability to monitor its elements and take necessary steps to protect them throughout the whole network. The power system network can be categorized into high voltage, medium voltage, and low voltage networks, and also can be categorized into four basic categories: generation, transmission, distribution, and consumer [2]. Challenges are expected in such a huge network. One of these challenges is detecting and locating faults at early stage for prevention of the fault propagation from one area to another 2003 blackout that hits the Eastern United States and Canada is an example of cascading faults. The fault started in a small area and eventually propagated to cover such a huge area as mentioned above. Smart grids are now equipped with phase measurement units (PMUs) to form a wide area measurement system (WAMS) based on the global positioning system (GPS). WAMS is used to take the measurements of voltage, current, and phase of the components of the smart grid. These measurements are collected at a small interval of time, which produces an enormous amount of data. Therefore, it is difficult to process these data in a limited amount of time.

Recently many applications based on WAMS have emerged to deal with this issue such as instability analysis [3], fault detection [4-6], etc. In this study, a MDS is used to monitor the behavior of some of IEEE models under abnormal operations by visualizing the data in a lower dimensional space. Many researches have been published recently on fault detection on power systems using different approaches to locate the faults. Wavelet transform combined with artificial neural network (ANN) approach has been used to detect faults on transmission lines [3]. This method showed reasonable results but failed to detect some voltage sags on 230-kV transmission lines [3]. Another approach is based on a hybrid framework consisting of symmetrical component analysis, wavelet transform, principal component analysis (PCA), and support vector machine (SVM) [4]. This method has an excellent result of fault detection on IEEE 14 bus system with accuracy of 99.9%. The only drawback of this approach is the high computational complexity. As a result, applying this approach on larger systems will increase the computational complexity due to the huge input data that need to be processed. Therefore, it is critical to develop a novel technique that combines high accuracy with lower computational complexity and cost. In this paper, MDS is used to detect and locate faults in smart grids through two models, IEEE 14 and IEEE 39 Bus systems. A metric MDS has been used to observe and analyze the behavior of bus bars under abnormal operations. Symmetrical and asymmetrical faults have been applied to different bus bars to test the capability of MDS to visualize the data in two-dimensional space. Faulty bus bars tend to have a larger Euclidean distance than the others. Finally clustering analysis has been used to locate the faults.
The current study provides the background of the main multidimensional scaling approaches, presents the proposed fault detection algorithm, and illustrates the clustering analysis with case study results. Also, it can be a platform on which to build further MDS studies to provide a comprehensive picture.

2. Methodology

MDS is used widely to depict the relationships between objects in huge systems in such a way that the distance between any two objects reflects the dissimilarity between them [5-7]. A dissimilarity matrix D can be constructed in order to measure the dissimilarity between any two objects i and j, based on the mean of Euclidean distance [8]. MDS is divided into two major categories: metric-MDS and non-metric-MDS [9], [10]. In this paper metric MDS has been used since the measurement is numerical data and precise information is available. MDS has been used in many fields such as psycho physics [11], chemical engineering [12], computer network [13], etc. The following symbols that will be used in this paper as follows:

- Total number of objects is n.
- Proximity p_{ij} represents the dissimilarity between any two objects i and j.
- To measure the dissimilarity between any two objects i and j, an Euclidean distance d_{ij} between these objects is expressed as follows:

$$d_{ij} = \sqrt{\sum_a^m (x_{im} - x_{jm})^2} \tag{1}$$

where x_{im} and x_{jm} are the coordinates of the objects i and j respectively.
The following are always true: $d_{ii} = d_{jj} = 0$ and $d_{ij} = d_{ji}$.

- m is the total number of samples for each object.
- Y is an $n \times$ m matrix that contains the observed data.

$$Y = \begin{pmatrix} y_{11} & \cdots & y_{1m} \\ \vdots & \ddots & \vdots \\ y_{n1} & \cdots & y_{nm} \end{pmatrix} \tag{2}$$

- O is the number of dimensions in the desired space $\mathbb{R}^O$.
- X is an $n * O$ matrix representing the coordinates of the object in the desired space.
- f is a function to transform the proximity p_{ij} to the desired space $\mathbb{R}^O$ and it is written as $f(p_{ij})$. There are many functions in literature to transform proximities such as:

$$f(p_{ij}) = a + b.p_{ij} \tag{4}$$

$$f(p_{ij}) = a + b.\log(p_{ij}) \tag{5}$$

$$f(p_{ij}) = a + b.\exp(p_{ij}) \tag{6}$$

Equations (4), (5), and (6) are called Linear, Logarithmic, Exponential transformation respectively. Choosing the proper transformation depends on the characteristics of the input data [9].

The objective of MDS is to find a set of lower dimensional coordinates that represents objects such that the distance between any two objects is as close as to their proximities in the original coordinates system. In other words, in the desired space any two points are located close to each other if their similarity is high, whereas the distance between them is large and distinguished if their dissimilarity is high [14]. To achieve this goal, it is necessary to utilize a proper raw stress function $\sigma_r(x)$.

$$\sigma_r(x) = \sum_{i,,j} \left[f(p_{ij}) - d_{ij}(X)\right]^2 \tag{7}$$

When the distance between objects is high, we will end up with high raw stress function. To avert the scale dependency, a formula of (stress – I) can be used instead of $\sigma_r(x)$ [9]. The formula of (stress – I) is defined in equation (8).

$$\text{stress} - \text{I} = \sigma_1 = \sqrt{\frac{\sum_{i,,j} [f(\mathrm{p_{ij}}) - \mathrm{d_{ij}}(X)]^2}{\sum[\mathrm{d_{ij}}(X)]^2}} \quad (8)$$

The square root here is used because the value normalized raw stress is normally small in practice. Adoption of the square root leads to easiness of discriminating the goodness of fit [15]. Another formula suggested by [16] is called (stress – II), which can be adopted as an alternative.

$$\text{stress} - \text{II} = \sigma_1 = \sqrt{\frac{\sum_{i,,j} [f(\mathrm{p_{ij}}) - \mathrm{d_{ij}}(X)]^2}{\sum[\mathrm{d_{ij}}(X - d')]^2}} \quad (9)$$

where d' is the average distance of all the Euclidean distances $\mathrm{d_{ij}}$. Table 1 gives a guide line for the goodness of fit by using stress − I formula [15].

Table 1. Goodness of fit

stress − I	Goodness of fit
> 0.20	Poor
0.1	Fair
0.05	Good
0.025	Excellent
0	Perfect

In order to minimize stress − I, an optimal X in the desired space $\mathbb{R}^{\mathrm{O}}$ must be determined.. Further, the parameters of the function *f* must be defined. There are many algorithms available in the literature to achieve this task [9]. In this paper an algorithm suggested by [17] is used to minimize the raw stress in order to find the optimal X configuration. Figure 1 summarizes the algorithm used to minimize the raw stress function.

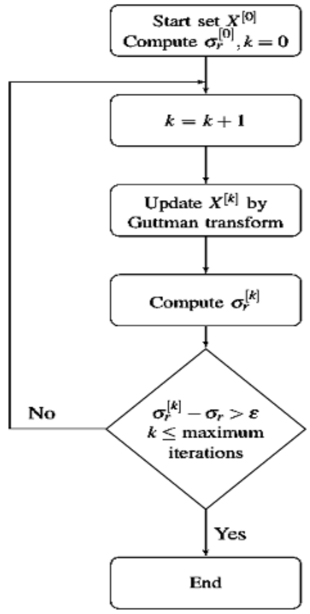

Figure 1. Minimization algorithm's flowchart.

Minimizing the raw stress may give an indication for the goodness of fit. To be more confident with the results, the Scree plot can be used to further test the goodness of fit.

In order to construct the proposed fault detection algorithm, the distance matrix D must be created as follows:

$$D = \begin{pmatrix} d_{11} & \cdots & d_{1j} \\ \vdots & \ddots & \vdots \\ d_{i1} & \cdots & d_{ij} \end{pmatrix} \quad (10)$$

The idea here is to transform the matrix D to O- dimensional space. The distance matrix is squared as follows:

$$D^2 = [d_{ij}]^2 \quad (11)$$

J matrix is defined as,

$$J = I - n^{-1}.1.1' \quad (12)$$

where I is the identity matrix, 1 is n × 1 vector with all elements as 1, $1'$ is the transpose of vector 1. Matrix B is constructed as,

$$B = -\frac{1}{2} JD.J \quad (13)$$

Now assume we need to transfer the matrix B to a matrix X such that

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1O} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nO} \end{pmatrix} \quad (14)$$

where, $X_j = (x_{j1}, \ldots\ldots., x_{jO})$ represents the location of object j in the desired space $\mathbb{R}^O$.

The goal here is to obtain X that satisfies the following relation:

$$B = -\frac{1}{2}\, JD^2.J = XX' \tag{15}$$

Using the Eigen decomposition on the term $-\frac{1}{2}\, JD^2.J$ gives $-\frac{1}{2}\, JD^2.J = Q\,\Delta\, Q'$, $B = Q\,\Delta\, Q' = XX'$, where Q is a matrix of the Eigenvectors of the matrix B, and Δ is a diagonal matrix of the Eigenvalues $\lambda_1, \lambda_2, \ldots\ldots., \lambda_n$ of the matrix B. Q' is the transpose of matrix Q. Now $B = Q\,\Delta\, Q' = (Q\Delta^{0.5})(Q\Delta^{0.5})' = XX'$, then $X = Q\Delta^{0.5}$

In the last step, the Eigenvalues $\lambda_1, \lambda_2, \ldots\ldots., \lambda_n$ are arranged such that $\lambda_1 \geq \lambda_2 \geq \ldots\ldots. \geq \lambda_n \geq 0$. Then the largest O Eigenvalues and their Eigenvectors are selected, where $Q \ll m$. As a result the coordinates of the object j in the target space $\mathbb{R}^O$ are $Xj = (x_{j1}, \ldots\ldots., x_{jO})$. Choosing the appropriate number of dimensions O requires minimizing the raw stress function to satisfy the criteria that given in Table 1.

In order to locate and define the faults, clustering analysis process is required. Clustering analysis is widely used in data processing to divide a set of data into groups that have common features. Many algorithms are available in the literature. K-means cluster is a clustering technique that is commonly used to divide a set of data into k clusters [18]. The steps of K-means cluster are given in the flowchart in Figure 2.

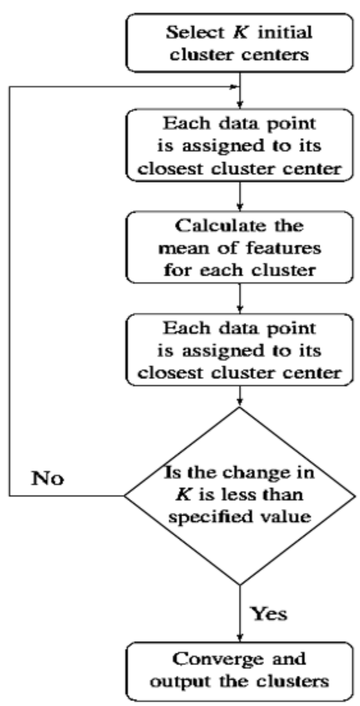

Figure 2. Flowchart of K-means cluster

3. Case Study and Results

The proposed method has been applied to IEEE 14 bus system as well as IEEE 39 bus system. The main idea is applying symmetrical and asymmetrical faults to each bus bar in the selected benchmark models. The selected models are built by using PSCAD software. Then the results were exported to Statistical Package for the Social Sciences software (SPSS) to make the required MDS analysis. Figures. 3 and 4 show the single line diagram of IEEE 14 bus system and IEEE 39 bus system respectively. Further clustering analysis was carried out to classify the faulty bus bars. The data were collected during faults at a rate of one sample per ms and a window of 250 ms was used to study the behavior of bus bars during the fault period.

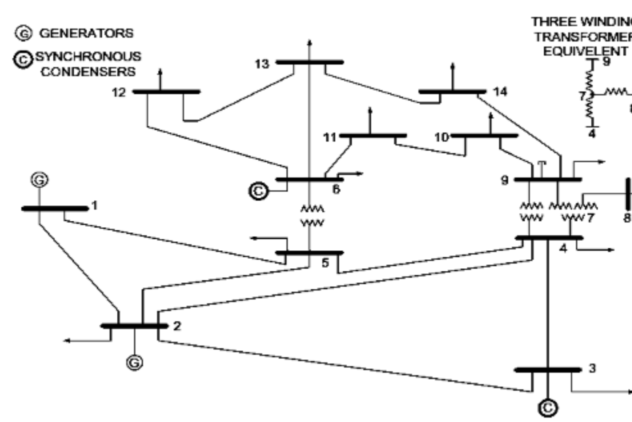

Figure 3. IEEE 14 bus system.

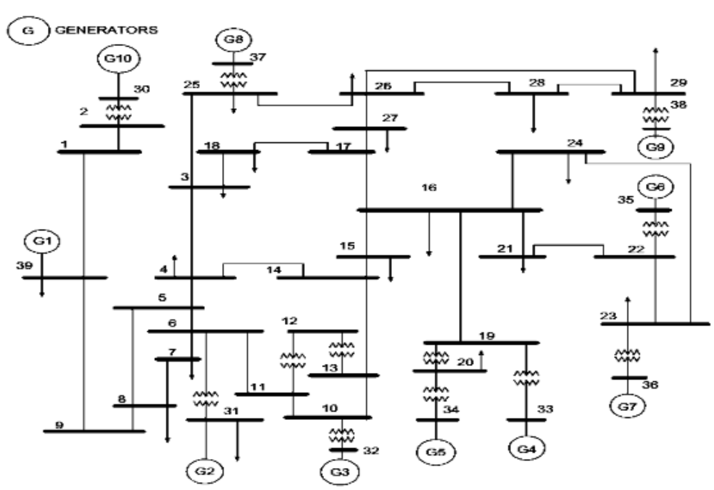

Figure 4. IEEE 39 bus system.

1.1. Symmetrical Faults

First, the symmetrical faults on both models are studied based on applying a short circuit fault to all of the three phases of the faulty bus bar. Then the data are exported to SPSS to perform MDS analysis. A Scree plot as well as the goodness of fit measurements were used to select the appropriate number of dimensions O. Figure 5 and 6 show Scree plots of the Normalized raw stress for IEEE 14 and 39 bus system.

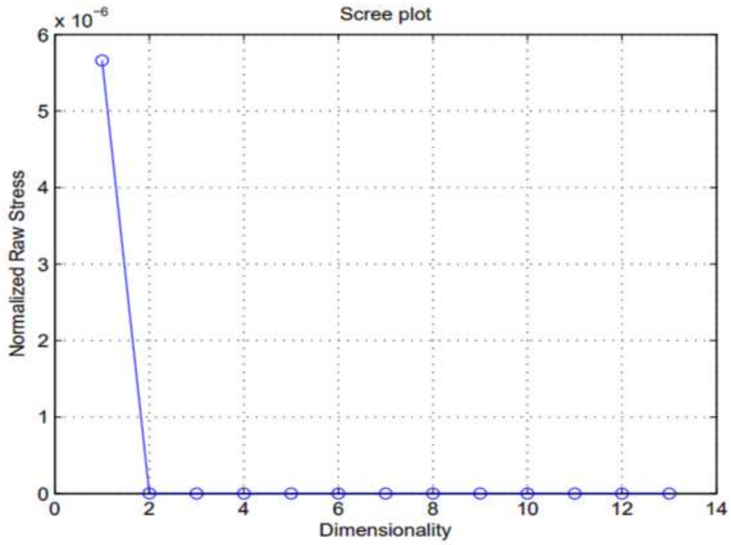

Figure 5. Scree plot of the Normalized raw stress for IEEE 14 bus system

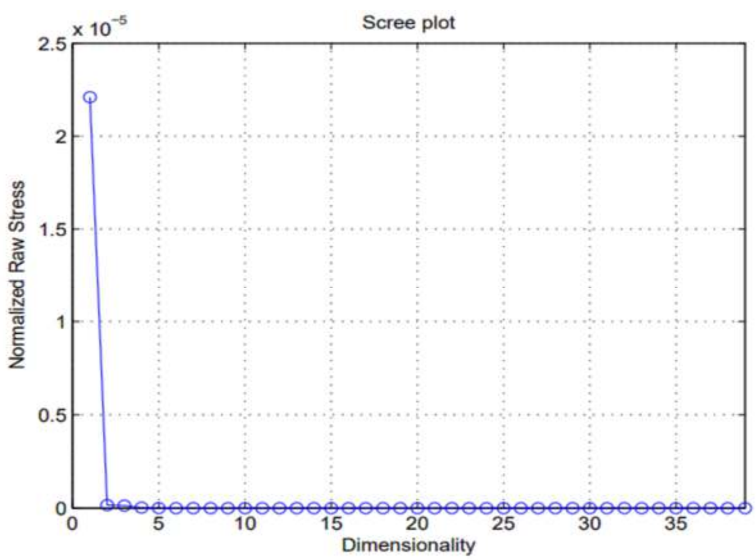

Figure 6. Scree plot of the Normalized raw stress for IEEE 39 bus system.

It can be noticed from Figures 5, and 6 that the normalized raw stress sharply decreases when moving from 1 dimension to 2 dimensions, and then it stabilizes at 0.00000. The other measurements are determined to ensure the goodness of fit for the case of symmetrical fault on the IEEE 16 bus system at a number of dimensions O = 2. The data provided in Table 2 shows excellent goodness of fit, therefore the number of dimensions is selected to be 2. The same procedures have been carried out for the collected data at each fault produced. Table 3 show the scree plot and goodness of fit measurements for the case of symmetrical fault on the IEEE 39 bus system at a number of dimensions O = 2. The results again prove that 2 dimensions are appropriate to visualize the system.

Table 2. Goodness of fit measurements at $O = 2$ on the IEEE 14 bus system.

Measurement	Value
Normalized Raw Stress	0.00000
Stress − I	0.00005
Stress − II	0.00007

Table 3. Goodness of fit measurements at O = 2 on the IEEE 39 bus system.

Measurement	Value
Normalized Raw Stress	0.00000
Stress − I	0.00004
Stress − II	0.00049

The main advantage of MDS its capability to reduce the huge amount of data in order to visualize the system in two-dimensional space. Consequently, it will be simple to monitor and cluster the system. A matrix of 39 × 250 data samples was reduced to a matrix of 39×2 that contains necessary information to detect and locate the faulty bus bars. The size of data was reduced by 125 times, which confirms the proposed approach is very effective. Figures 7 and 8 display the visualization of the IEEE 14 bus system with a fault in bus bar 5 and IEEE 39 with a fault on bus bar 16 respectively. As it can be seen from both figures that faulty bus bar and the affected bus bars tend to have larger Euclidean distances than the healthy bus bars. Moreover, the faulty bus bar has the largest Euclidean distance measured from the origin. Figure 7 shows the bus bars 4, and 5 are located away from the rest of the buses while in Figure 8 bus bars 15, 16, 17, 21, and 24 are located away from the rest of the bus bars. Based on both Figures 7, and 8 it can be noticed the faulty bus bars 5 in the first case and bus 16 in the second case have the largest Euclidean distance from the origin.

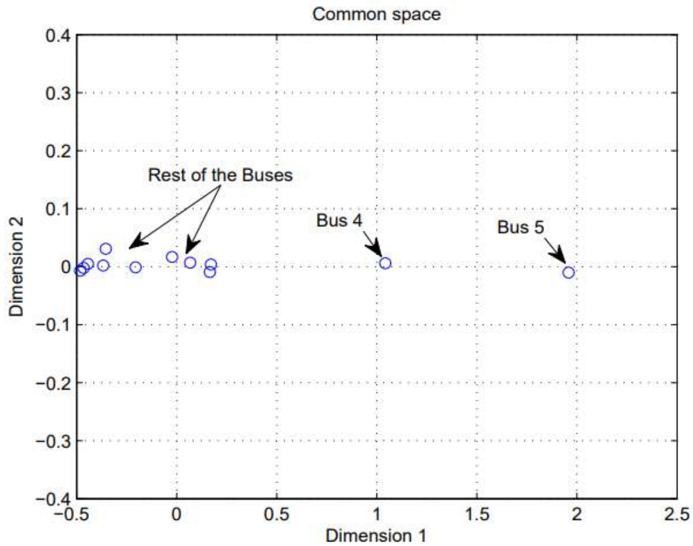

Figure 7. Visualization of IEEE 14 bus system with fault on bus 5

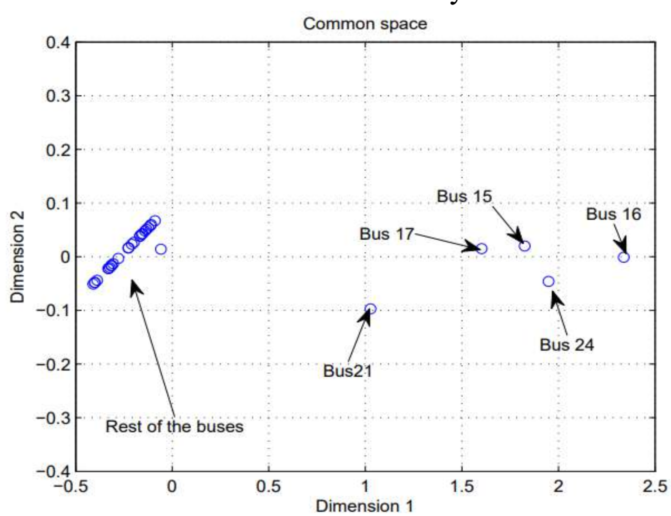

Figure 8. Visualization of IEEE 39 bus system with fault on bus 16

1.2. Asymmetrical Faults

Asymmetrical faults that include one phase to ground short circuit has been applied to all the buses on both models. Although the change in voltages across bus bars was less than the changes in the case of a symmetrical fault, the proposed method was able to distinguish the faulty bus bars as it did in the case symmetrical faults. The dimension $O = 2$ was selected again for the same reasons explained earlier. Figures 9 and 10 show the visualization of the results.

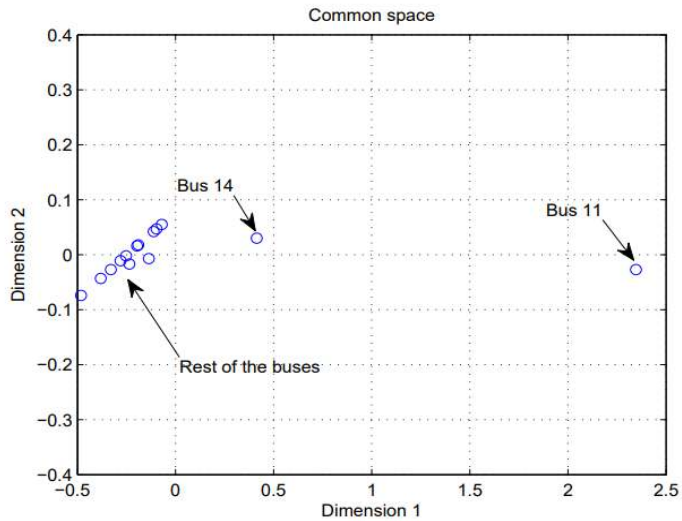

Figure 9. Visualization of IEEE 14 bus system with asymmetrical fault on bus 11.

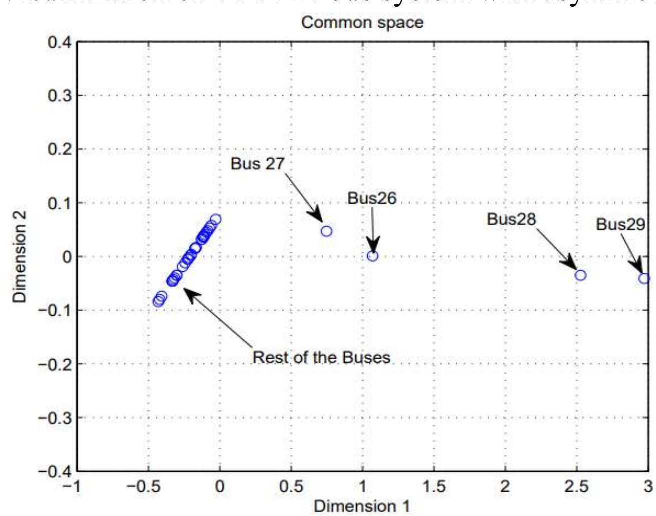

Figure 10. Visualization of IEEE 39 bus system with asymmetrical fault on bus 29.

1.3. Clustering Analysis

A K-means cluster technique is then applied to the result data to classify and determine the faulty bus bar and the affected ones. The data is divided into two clusters, healthy and faulty. This technique was able to classify the data properly and then the center of the healthy cluster was used to determine the exact place of the short circuit since the short-circuited bus bar will have the largest Euclidean distance measured from that center. Figure 11 and 12 show the results of applying K-means cluster on IEEE 39 symmetrical fault on bus 16, and IEEE 14 symmetrical fault on bus 5.

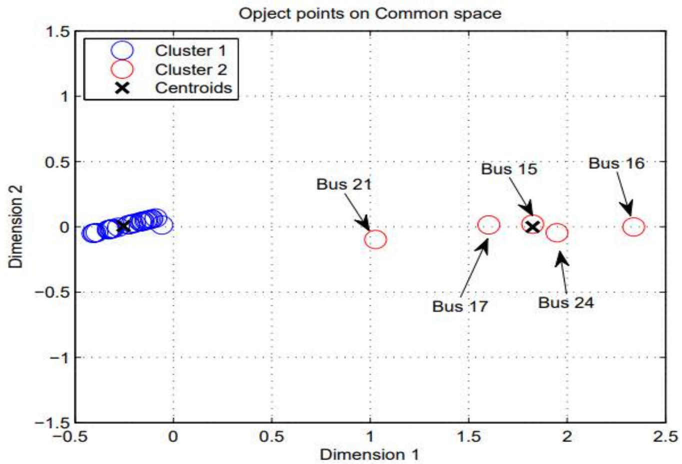

Figure 11. Clustering analysis of IEEE 39 Bus system with symmetrical fault

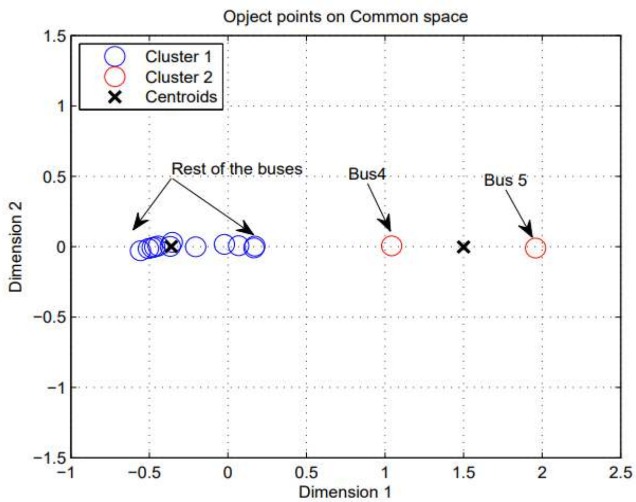

Figure 12. Clustering analysis of IEEE 14 Bus system with symmetrical fault

4. Conclusions

MDS was used in this paper to detect and locate faults in power grids by using different IEEE benchmark power systems. The current study can be a platform on which to build further MDS studies that related to the power systems. Reducing the dimensionality of the data to visualize the system and detect the faulty bus bars was the main target of this paper. Many measurements have been taken to ensure the goodness of fit. Visualization of the system in two-dimensional space showed a perfect fit with stress − I less than 0.001 in all cases studied in this paper. Scree plot was used in this paper to test the effect of increasing the number of dimensions of the desired space. The Scree plots showed that using a number of dimensions more than two will not improve the goodness of fit. Visualization of the results of the mentioned models under different symmetrical and asymmetrical faults revealed that the faulty bus bar always has a greater Euclidean distance than the others. Healthy bus bars appeared close to each other on the desired space while the affected bus bars located between the faulty bus bar and the healthy bus bars. Finally, a k-means cluster technique was used to classify each bus bar to faulty, or health cluster. The proposed cluster technique was able to detect the faulty bus bars and healthy bus bars.

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