Grounding Grid Fault Diagnosis with Emphasis on Substation Electromagnetic Interference

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ABSTRACT Grounding grid fault diagnosis is essential for the safe operation of a substation. However, the substation vicinity is highly electromagnetic. Therefore, the electromagnetic based fault diagnosis is vulnerable to electromagnetic interference (EMI). This paper presents the gradient electromagnetic method for the grounding grid fault diagnosis but unlike the previous methods, fault diagnosis here includes the breakpoints and percentage corrosion simultaneously. The diagnosis is based on comparing the calculated resistivity with the designed resistivity of the grid. The resistivity is calculated from the grid’s surface electric and magnetic fields. Furthermore, the existing literature, emphasis on EMI is negligible with the main focus on fault diagnosis only. Therefore, to cope with the EMI, we utilized the Independent Vector Analysis (IVA) to isolate the grounding grid signal from the interfered signal. The validity of IVA is examined by comparing with different known isolation algorithms considering various evaluation criteria. The mathematical reasoning, simulation results and experimental output illustrate that the gradient electromagnetic method along the IVA is feasible for grounding grid fault diagnosis under substation electromagnetic environment (EME).

INDEX TERMS Electromagnetic field, EMI, Fault Diagnosis, Grounding Grid, IVA.

I. INTRODUCTION

Grounding grids in substations are installed to ensure power systems safety and reliability. It is the sole responsibility of grounding grid to discharge hazardous currents into earth in case of lightning strokes and faults [1]–[3]. Most grounding grids are made up of copper, steel, galvanized steel, etc. The working of grounding grid under the moist conditions of soil significantly causes corrosion and even breaks. This degrades the performance of grounding grid that directly jeopardizes the safety of power system and workers. Therefore, it is important to develop effective fault diagnosis techniques to regularly monitor the status of grounding grid without excavation and power disruption.

The literature on the fault diagnosis of grounding grid is classified into three categories: electric network methods [4]–[7], electrochemical detection methods [8]–[10] and electromagnetic methods [11]–[15]. In electric network methods the grounding grid is treated as a resistive network and measures the port resistance of the vertical conductor to calculate the branch resistance. The corrosion status is determined by comparing the calculated branch resistance with the design value. The electric network methods are ineffective as they can only diagnose corrosion and no breakpoints. Furthermore, the change in grounding resistance is quite small even if the grid is fractured. Electrochemical methods work by measuring electrochemical properties between soil and grounding grid. These methods are quite effective to diagnose corrosion level but fails to detect breakpoints. Furthermore, the electrical impedance tomography (EIT) is used in [16] to image the corrosion in grounding grid. The data points in this method are low but the potential measurement at the downlead wires is a major shortcoming of this method. Since the downlead wire is not connected at each node of the grid, therefore, to get more node potentials the cycle measurement is utilized [17]. This method is also tedious as it utilizes the Tikhonov regularization to weaken the ill-posedness of the inverse problem.

Electromagnetic (EM) methods are classified as current
injection methods [11]–[13], [18] and transient electromagnetic methods [14], [15], [19]. EM methods are aimed to induce current in the grid. As a result, the magnetic field at the surface is measured and processed. I.e, Zhang et al. [11] measured the surface potential difference taking the frequency characteristics of soil and grounding conductors into account to diagnose faults in a grounding grid. In [12], the authors diagnosed faults in grounding grid using magnetic detection electric impedance tomography (MDEIT). In this method the surface magnetic flux density generated from the current injection is subjected to inversion calculations to obtain electric resistivity. The faults in the grounding grid are diagnosed from the electric resistivity distribution. The main shortcoming of this method is the enormous number of measurements. In [13], derivative method is used to diagnose breakpoints in the grounding grid. Gradient peak of magnetic flux density at conductor’s location shows normal conductor while no peak at conductor location confirms broken conductor. Derivative method fails in the presence of strong electromagnetic environment (EME) as it enhances the magnetic field of substation along with the magnetic field of grounding grid. Moreover, the authors of [18], utilized the electrical resistance tomography (ERT) to diagnose leaks from buried pipes. Electrodes were used to inject current and measure the potential drop at the earth’s surface using dipole-dipole and an updated Schlumberger array. In [14], [15], [19], transient electromagnetic method (TEM) is used to diagnose breakpoints. In this method the faults are diagnosed using equivalent resistivity distribution that is calculated from the secondary magnetic field of the grounding grid using optimization technique. This method fails as it cannot distinguish an absent conductor from the one that is broken.

Distribution substation comprises of multiple equipment such as power transformers, circuit breakers, instrument transformers, conductors, busbars, grounding grid, etc. Therefore, the substation surrounding is intensely electromagnetic. In such strong electromagnetic environment (EME), utilizing electromagnetic methods for fault diagnosis of grounding grid are subjected to electromagnetic interferences (EMI) [20]. The existing techniques concentrate only on fault detection with minimum consideration to EMI. This is why the electromagnetic method for fault diagnosis must be accompanied by methods to curb the EMI.

The Independent Component Analysis (ICA) is often used to isolate the sources electroencephalogram (EEG) signals in a multichannel EEG signals where they are mixed with the electrooculogram and electromyogram signals [21]. The ICA is also used to curb EMI for the inverse features identification of the grounding grid [22] but the inefficiency of ICA is reported in [23] and [24]. In literature, Canonical Correlation Analysis (CCA) is used as an alternative to ICA [25]. CCA utilizes the original signals as well as the delayed versions of the signals. It is based on the second order statistics (SOS) and extract maximally autocorrelated and mutually un-correlated signals [25]. From [26], it is known that CCA is an efficient and practically useable technique as compared to ICA. Moreover, ICA utilizes higher order statistics (HOS) to explore statistical independence while CCA is based on SOS to recover statistically un-correlated sources. It is clear from the statistical theory that un-correlatedness is a weaker condition than independence. The independent vector analysis (IVA) combines the advantages of both ICA and CCA in a single framework [27]. IVA processes the original and time delayed versions of the signals while utilizing the HOS. IVA assumes that the source signals in one data set are independent to each other and at least one source is dependent on one source of the other data set. Moreover, from [27] it is known that IVA performs well as compare to ICA and CCA.

This paper proposes gradient and independent vector analysis (IVA) techniques to diagnose faults in the grounding grid under a substation strong EME. Unlike the previous literature, the proposed gradient approach for grounding grid fault diagnosis incorporates the breakpoint and corrosion diagnosis simultaneously. This paper also, considers the substation EME that falsifies the results of electromagnetic approach. Therefore, we propose IVA to separate the source signal from the interfered signal. Furthermore, this paper is the first to introduce the IVA based technique for grounding grid fault diagnosis as well as the first to diagnose the faults accounting the EME of the substation. The IVA based technique produces more accurate signals that might help to observe some very low amplitude signals. We utilized the well known algorithm of IVA called the IVA-L for blind separation of the recorded mixed signals [28]. The proposed technique is reliable and practically applicable due to its effectiveness against EMI sources. However, the proposed method does demand the prior knowledge of the layout and depth of a grounding grid, the factors that varies both during construction and over time [12], [22], [29]. Mathematical reasoning, simulation results and experimental tests validate the feasibility of the proposed method for grounding grid fault diagnosis under substation EMI.

II. GROUNDING CONDUCTOR STATUS INVESTIGATION

A grounding conductor of infinite length stationed along y-axis is illustrated in Fig. 1. This conductor is buried at depth \( h \) in a homogeneous soil of permeability \( \mu \) and carries direct current \( I \). According to Ampère’s law the magnetic flux density at point \( P \) on the ground surface that surrounds the conductor is \( \vec{B}_\phi \). Mathematically \( \vec{B}_\phi \) is expressed as:

\[
\vec{B}_\phi = \frac{\mu I}{2\pi R} \hat{\phi} \phi 
\]

(1)

The \( \phi \) in (1) is the unit vector representing the direction of \( \vec{B}_\phi \) and \( R \) is the distance between the conductor and point \( P \). Expressing \( \vec{B}_\phi \) in terms of Cartesian coordinates is given as:

\[
\vec{B}_x + \vec{B}_z = \frac{\mu I}{2\pi R} (\cos \phi \hat{a}_x - \sin \phi \hat{a}_z) 
\]

(2)

\[
\vec{B}_x = \frac{\mu I}{2\pi} \frac{h}{x^2 + h^2} \hat{a}_x 
\]

(3)

\[
\vec{B}_z = -\frac{\mu I}{2\pi} \frac{x}{x^2 + h^2} \hat{a}_z 
\]

(4)
In x-direction the 2\textsuperscript{nd} order gradient modulus of (3) and 1\textsuperscript{st} order gradient modulus of (4) is presented as:

\[ |\vec{B}''_x| = \frac{|\mu I h|}{\pi} \times \frac{3x^2 - h^2}{(x^2 + h^2)^3} |a_x| \tag{5} \]

\[ |\vec{B}'_z| = \frac{|\mu I |}{2\pi} \times \frac{x^2 - h^2}{(x^2 + h^2)^2} |a_z| \tag{6} \]

Analyzing (5) and (6), |\vec{B}''_x| and |\vec{B}'_z| are maximum at x=0m that resembles the location of the conductor below the earth surface. The graphical representation of (5) and (6) is illustrated in Fig. 2. Main peak of |\vec{B}''_x| and |\vec{B}'_z| is positioned at x=0m that is in accordance with the mathematical result.

The presence of magnetic flux density gradient peak shows a normal conductor carrying the current. On the other hand, if the conductor is broken the flow of current is absent that will result in no peak. However, to diagnose corroded conductor or to calculate the percentage of conductor corroded, current in the conductor is calculated.

According to [29], the burial depth of the conductor for the case of \( \vec{B}_x \) and \( \vec{B}_z \) is expressed as:

\[ h \approx L_{x2} \tag{7} \]

\[ h \approx 0.5774L_{z1} \tag{8} \]

The \( L_{x2} \) and \( L_{z1} \) are the distances between the main peak and side peak of |\vec{B}''_x| and |\vec{B}'_z|. According to (5) and (6), employing the limit at x=0 results in current \( I \) that is expressed as:

\[ I = \lim_{x \to 0} |\vec{B}''_x| \times \frac{\pi h^3}{\mu} \tag{9} \]

\[ I = \lim_{x \to 0} |\vec{B}'_z| \times \frac{2\pi h^2}{\mu} \tag{10} \]

\( \%_{\text{corrosion}} = \frac{\sigma_d - \sigma_c}{\sigma_d} \times 100 \tag{13} \)

The \( \sigma_d \) is the designed conductivity of the conductor.

As the substation surrounding is highly electromagnetic (EM), the measured data is mixed signals comprising source (grounding grid) signal and surrounding EM signals. Applying the gradient approach to the raw measurement will enhance the noise (EMI). Therefore, to overcome the problem of EMI, the IVA technique is utilized to separate the source signal from the mixed recorded signal before the gradient approach is applied. The system model of IVA is discussed in Section III-A.

The surrounding of substation is highly electromagnetic due to the presence of electromagnetic equipment such as transformers, bus bars, etc. Therefore, the gradient of raw measurements to diagnose faults in grounding grid is unpractical that will result in perverted results.

The behavior of EM signal from various instruments in a substation is different but due to the IVA being a blind source separation technique, it is independent of the EMI.
Mixed Magnetic Flux Density $\vec{M}_x (T)$
Horizontal Position $X (m)$

(a)

Mixed Magnetic Flux Density $\vec{M}_z (T)$
Horizontal Position $X (m)$

(b)

Normalized Amplitude of $|\vec{M}_x''| (T/m^2)$
Horizontal Position $X (m)$

(c)

Normalized Amplitude of $|\vec{M}_z'| (T/m)$
Horizontal Position $X (m)$

(d)

FIGURE 3. Influence of EME on the magnetic flux density gradient. Fake peaks emerged compelling the identification of true peaks impossible. (a) Mixed magnetic flux density $\vec{M}_x$ is obtained by mixing $\vec{B}_x$ with the Matlab generated EME environment. (b) Mixed magnetic flux density $\vec{M}_z$ is obtained by mixing $\vec{B}_z$ with the Matlab generated EME environment. (c) Normalized 2nd order gradient modulus of $\vec{M}_x$. (d) Normalized 1st order gradient modulus of $\vec{M}_z$.

behavior. Although, the number of IVA sensors must be equal to the number of EM signals. IVA being independent of EMI behavior, the influence of EME on the gradient of grounding conductor magnetic flux density is illustrated by considering the EMI as a single electromagnetic signal (EMS) that is mixed with $\vec{B}_x$ and $\vec{B}_z$ each. This is illustrated in Fig. 3a and 3b. Afterwards, the 2nd order gradient of the mixed signal $\vec{M}_x$ and 1st order gradient of the mixed signal $\vec{M}_z$ is illustrated in Fig. 3c and 3d. The gradient results show multiple peaks. This is because the EMS is also enhanced with the grounding conductor magnetic flux density. In current state, the identification of the true peak corresponding to the grounding conductor is impossible. To combat the problem of EME, the IVA technique is utilized to separate the original signal from the mixed signal before the gradient process.

III. INDEPENDENT VECTOR ANALYSIS

Independent vector analysis is one of the Blind Source Separation techniques (BSS) that utilizes higher order statistics (HOS) to separate the source signal from the mixed signal. The conceptual model of IVA is illustrated in Fig. 4. In this figure, $x_1$ and $x_2$ represent the vectors of mixed recorded signals, $a_{11} \cdots a_{22}$ represent mixing matrix elements and $s_1$ and $s_2$ represent the transmitted signal vectors. The received

![Conceptual model of Independent Vector Analysis (IVA).](image)

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signals by the sensors contain directly transmitted and reflected signals. Therefore, the superscript \([d]\) represents the data of directly transmitted and \([d]\) represents the data set of reflected signals. The superscript \([d]\) is meant for a general data set.

### A. IVA SYSTEM MODEL

This sub-section presents the grounding grid and the EMI signals in the IVA data model. Let the number of independent source signals be \(K\) i.e., grounding grid and EMI signals. All the sources contain \(L\) number of samples for \(D\) data sets. The acquired data through sensors is represented as follows:

\[
X^d = A^d S^d \quad 1 \leq d \leq D,
\]

(14)

The \(S^d\) contains source data vectors \(s^d_1, s^d_2, \ldots, s^d_K\), each of length \(L\). Each source data vector contains real random values with zero mean data. \(A^d\) represents real valued random mixing matrices for \(D\) data sets. Here, the role of the IVA algorithm is to estimate the unknown mixing matrices for the recorded data. The source data matrices in different data sets are represented by \((S^1)^T, (S^2)^T, \ldots, (S^D)^T\). After estimating all the mixing matrices the IVA post processed data is expressed as:

\[
Y^d = W^d X^d
\]

(15)

The \(W^d\) is the un-mixing matrix estimated for \(D\) number of data sets i.e., \(d = 1, 2, \ldots, D\). The un-mixed data vectors are represented as \(y^d_1, y^d_2, \ldots, y^d_K\).

### B. IVA BASED SIGNAL PROCESSING

The grounding grid signals are recorded in the presence of strong EMI signals. The total number of signals is denoted by \(K\), each signal has data block length \(L\) with \(D\) number of data sets. The recorded mixed data contains \(D\) number of data sets \((X^1)^T, (X^2)^T, \ldots, (X^D)^T\). The task of the IVA algorithm is to estimate the source signals from the recorded mixed signals. The BSS algorithms know nothing except independence and non-Gaussianity of the source signals.

The IVA algorithm estimate the source signals as a first data set and their delayed versions as other data sets. This estimation is performed through minimization of the mutual information among the estimated source component vectors (SCVs). The cost function of IVA is demonstrated in [28] and discussed here as:

\[
Q_{IVA} = \sum_{k=1}^{K} \left( \sum_{d=1}^{D} H[y^d_k] - Q[y^d_k] \right) - \sum_{d=1}^{D} \log |W^d| - C
\]

(16)

The \(Q[y^d_k]\) represents mutual information within \(k_{th}\) SCVs, \(H\) is the entropy, \(W^d\) is the un-mixing matrix of \(d_{th}\) data set, \(C\) is a constant factor which is equivalent to \(H[X^1, X^2, \ldots, X^D]\), depending only on the recorded mixed data. The IVA algorithm minimizes the cost function in (16) and maximizes the mutual information within each SCV.

The IVA combines the advantages of CCA and ICA in a single framework. Variants algorithms of IVA exist in the literature are IVA-GGD, IVA-L and IVA-G [30] and their dominance is already proved. Motivated by this, we implemented IVA based grounding grid fault diagnosis. All these algorithms utilize the IVA cost function given in (16) to estimate the un-mixing matrices. The IVA-L utilize the HOS for un-mixing while ignoring the sample to sample dependency and SOS. Matrix gradient approach is used in the implementation of the IVA-L algorithm. Moreover, processing of the original as well as the delayed versions make the IVA algorithms more practical as compare to the ICA technique. Based on these advantages, IVA-L is used along the gradient method to diagnose faults in grounding grid considering the real substation environment.

### IV. PERFORMANCE EVALUATION OF THE GRADIENT METHOD AND RESULTS ANALYSIS

The feasibility of the gradient method for the fault diagnosis of grounding grid is shown through simulations using COMSOL Multiphysics 5.0 [31] and Matlab. Magnetic flux density and electric field from the grounding grid is acquired through COMSOL Multiphysics while the IVA is implemented using Matlab.

#### A. THE NUMERICAL MODEL

A dimensions of 6m×6m squared mesh grid with mesh size of 3m×3m illustrated in Fig. 5 is modeled under the COMSOL Multiphysics 5.0 environment. This grid is made up of copper conductors of conductivity 5.998×10^7S/m and cross sectional area 5.024×10^-5m^2. It is buried 0.3m deep in a homogeneous soil of resistivity 100Ωm and permeability \(\mu\).

Nodes are labeled from 1 to 9 and branches are represented as \(b_1\) to \(b_{12}\). To produce the surface magnetic flux density, a potential of 1V dc is applied across node 1 and 9. The flow of current in the grid is shown by arrows and value of current in each conductor is labeled.

To illustrate the performance of gradient method for the
fault diagnosis of grounding grid. Firstly, the gradient method is applied to the normal grid illustrated in Fig. 5. 2\(^{nd}\) order gradient of the horizontal component \(B_x\) and 1\(^{st}\) order gradient of the vertical component \(B_z\) is taken along the the line \(L\). The results of \(|B_x''|\) and \(|B_z''|\) are shown in Fig. 6. Fig. 6a and 6b depict three peaks at 0m, 3m and 6m along the x-axis confirming the location of branches \(b_3, b_4\) and \(b_5\). Utilizing (7) to (10) the depth of the grid and current in the branches \(b_3, b_4\) and \(b_5\) are calculated from the gradient graphs illustrated in Table 1. Analysis of the results acquired from \(B_x\) and \(B_z\) shows that \(B_x''\) delivers accurate results. The reason is the main peak width, which is the distance between two points on the main peak at which the value is 1\% of the maximum value [29]. The lower is the main peak width higher is the accuracy of it. The main peak width of \(B_x''\) from Fig. 6a is approximately 0.3m while the main peak width of \(B_z''\) from Fig. 6b is approximately 0.4m. Moreover, the main peak width also affects the distance between main peak and side peak accordingly, which is represented by \(L_{x2}\) for the \(B_x\) and \(L_{z1}\) for the \(B_z\) in Table 1. It is illustrated in the table that \(L_{x2}=0.3m\) is less than \(L_{z1}=0.38m\). Therefore, the \(B_x''\) delivers accurate results compare to the \(B_z''\).

**TABLE 1.** Comparison between designed based and gradient method based characteristics of normal (faultless) grounding grid.

| Function | \(L_{x2}\) | \(L_{z1}\) | Characteristic | Designed Based | Gradient Method Based |
|----------|------------|------------|----------------|----------------|----------------------|
| \(B_x\) 0.3m Nil | \(b_3\) location (m) | 0 | 0 | \(b_4\) location (m) | 3 | 3 | \(b_5\) location (m) | 6 | 6 |
| depth (m) | 0.3 | 0.3 | depth (m) | 210 | 209.25 | depth (m) | 99 | 97.87 |
| \(b_5\) current (A) | 111 | 109 |
| \(B_z\) Nil 0.38m | \(b_3\) location (m) | 0 | 0 | \(b_4\) location (m) | 3 | 3 | \(b_5\) location (m) | 6 | 6 |
| depth (m) | 0.3 | 0.22 | depth (m) | 210 | 79 | depth (m) | 99 | 41 |
| \(b_5\) current (A) | 111 | 43 |

To illustrate the fault diagnosis with the gradient method, let the branch \(b_3\) be corroded such that its conductivity drops to 4.998 \times 10^7 S/m. Branch \(b_4\) be broken and the conductivity of \(b_5\) be dropped to 3.998 \times 10^7 S/m. Applying the same potential of 1V across node 1 and 9 and taking the gradient of the surface magnetic flux density on line \(L\). The result is given in Fig. 7 that illustrates the absence of magnetic flux density gradient peak at 3m along the x-axis confirming the branch \(b_4\) as broken. Contrarily, \(b_3\) and \(b_5\) are carrying the current evidenced by the presence of gradient peaks at 0m and 6m. However, to diagnose the corrosion in \(b_3\) and \(b_5\), (7) to (13) are utilized. To calculate the voltage drop across \(b_3\) and \(b_5\), electric field intensity is measured on line \(L\). This is shown in Fig. 7. Table 2 lists the percentage corrosion in \(b_3\) and \(b_5\). In spite of the fact that FEM based software is open to noise due to their meshing property and the values are approximated, the conductivity calculated \(\sigma_c\) from the gradient method is in close approximation with the theoretical conductivity \(\sigma_t\).

**B. EXAMINING IVA FOR EMI SUPPRESSION**

The presence of a variety of electrical and electronic equipment, switching operations and lightning strikes in the substation sends its vicinity highly electromagnetic. These EM fields intermingle with the grounding grid signal at the receiving end acting as EM noise [33], [34]. EM noise comprises of the impulsive and continuous noise. The former includes noise due to switching and lightning while the latter include noise from the transformers, transmission lines, etc. This section illustrates the IVA performance considering the substation EM noise as a single unwanted signal. Single EM noise is considered for the sake that the IVA algorithm is independent of the character of noise as well as the number of noise (EM) signals. Therefore, increasing the EM signals does not affect the isolation performance of the IVA, rather the number of IVA sensors must be made equal to the number of EM signals.

Performance of the IVA-L algorithm of IVA is evaluated for the EMI suppression in the substation vicinity. SNRs ranging from 0 to 20dB are considered for the evaluation of IVA-L and results are compiled using Monte Carlo simulations. Furthermore, the number of source signals are \(K=2\), the number of data sets are \(D=4\), and various lengths \(L\) of the processing data blocks are considered in each data. Performance evaluation criteria considered are given below:

- Corresponding root mean square error (CRMSE) [35]:

\[
CRMSE = \frac{RMS(s^d_GG - y^d_GG)}{RMS(s^d_GG)}
\]

The \(s^d_GG\) and \(y^d_GG\) represent the source grounding grid and the reconstructed grounding grid signals simultaneously at data set \(d\).

- Common inter-symbol-interference (ISI\(_{com}\)) [28]:

\[
ISI_{com} = \frac{1}{2(K-1)} \left[ \psi' + \psi'' \right]
\]

where

\[
\psi' = \sum_{n=1}^{K} \left( \sum_{m=1}^{K} \frac{g_{m,n}}{max gp_{n,m}} - 1 \right)
\]

\[
\psi'' = \sum_{m=1}^{K} \left( \sum_{n=1}^{K} \frac{g_{m,n}}{max gp_{n,m}} - 1 \right)
\]

and

\[
g_{m,n} = \sum_{d=1}^{D} |g^d_{m,n}|
\]

\[
C^d = W^d A^d
\]

The \(ISI_{com}\) is normalized so that its maximum value is one and minimum value is zero. The zero value corresponds to ideal separation performance.
Initially, the effectiveness of the IVA algorithm in comparison with the ICA and CCA techniques is demonstrated. Results of all the three techniques are illustrated in Fig. 9, taking into account the Fast-ICA algorithm [36] of ICA, the GMCA algorithm [37] of CCA and the IVA-L algorithm of the IVA. For $\text{CRMSE}$, SNR of 10dB is allowed. In case of ICA algorithm the value of data set is one. Performance evaluation is carried out for different values of $L$ ranging from 50 to 2000 samples in a single data set. The simulation results clearly show that the IVA outperforms the ICA and CCA algorithms. The results also verify that the IVA algorithm is less sensitive to the processing data block lengths. The performance improvement of IVA at $L = 100$ is approximately 83% and CCA is 16% as compared to ICA.

$$\text{TABLE 3. } ISI_{\text{com}} \text{ of the IVA-L, FastICA and CCA for the } L \text{ ranging from 50 to 2000 and SNR 20dB}$$

| $L$  | IVA-L | FastICA | CCA  |
|------|-------|---------|------|
| 50   | 0.10  | 0.60    | 0.47 |
| 100  | 0.057 | 0.12    | 0.09 |
| 500  | 0.053 | 0.08    | 0.071|
| 1000 | 0.05  | 0.07    | 0.063|
| 2000 | 0.05  | 0.06    | 0.055|

Performance of the IVA-L algorithm is also investigated for various data block lengths. The $ISI_{\text{com}}$ performance criteria is considered and the results are illustrated in Table
V. EXPERIMENTAL AUTHENTICATION

The proposed method is authenticated via experimental testing. The grounding grid illustrated in Fig. 10a is constructed in lab that has dimensions of 36 cm $\times$ 36 cm and mesh size 9 cm. DC current of 9.2 A is injected at the terminal $E$, and the node $G$ is grounded. Branch $R_2$ is considered as broken. Moreover, magnetic flux density is measured at a height of 1 cm on line $L_E$. A total of 127 points are taken on $L_E$ with adjacent points 0.3 cm apart. Fig. 10b illustrates the test equipment where the probe of F. W. BELL 7010 Gauss meter is moved via a controller in three dimensions with an accuracy of 0.01 mm [32].

The outcome of the gradient approach applied to the measurement on $L_E$ is illustrated in Fig. 11. Here, peak at 0.006 m, 0.183 m, 0.273 m and 0.36 m corresponds to the branches $R_1$, $R_3$, $R_4$ and $R_5$. The peak corresponding to $R_2$ is absent, confirming $R_2$ as broken. The Fig. 11 depicts two cases, normal grounding grid and the branch $R_1$ corroded. This is shown by the blue and the red graph respectively. The depth of the grid and the current in $R_1$ is calculated using (8)-(10). The distance between main peak and side peak of $R_1$ is 0.015 m in each case, therefore, the depth calculated is 9 mm while the current in $R_1$ is 4 A approximately when the grid is normal. When $R_1$ is corroded the figure shows that the magnitude of the gradient magnetic flux density is reduced from 0.007 T/m to 0.005 T/m that equates the current in $R_1$ as 2.5 A. Since, the current follows a low resistive path therefore, current has increased in the branch $R_3$, $R_4$ and $R_5$. This is illustrated by the increase in the magnetic flux density at the location of respective branches.

VI. CONCLUSION

Corroded grounding grid is an invisible danger to the safety of substation equipment and operators. In this paper, we have developed a new electromagnetic method to diagnose faults in grounding grid. In this method the status of the grounding conductors is determined by comparing the calculated resistivity with the designed resistivity. The resistivity is calculated using ohm’s law. Therefore, the current in grounding conductor is determined from the surface magnetic flux density of the corresponding conductor while the voltage drop across it, is calculated from the surface electric field.

Due to the presence of electromagnetic equipment in the substation, the electromagnetic methods for grounding grid fault diagnosis are open to electromagnetic interference. To isolate the grounding grid signal from the interfered signal, we utilized the IVA. To investigate the viability of the IVA, the performance criterion such as CRMSE and $ISL_{com}$ are taken into account. The CRMSE of IVA for $L=50$ illustrated in Fig. 9 is approximately 84% low as compare to ICA and 81% as compare to CCA. This performance is almost independent of the data block length. Furthermore, the $ISL_{com}$ of IVA for $L=50$ illustrated in Table 3 is 83% low than the ICA. The results illustrate that the proposed electromagnetic method along the IVA is feasible to diagnose grounding grid faults under the EME of the substation.

As a future direction, we will test the performance of the proposed approach in the real substation.

REFERENCES

[1] Z. Fu, X. Wang, Q. Wang, X. Xu, N. Fu, and S. Qin, “Advances and challenges of corrosion and topology detection of grounding grid,” Applied Sciences, vol. 9, no. 11, p. 2290, 2019.
[2] “Ieee guide for safety in ac substation grounding - redline,” IEEE Std 80-2013 (Revision of IEEE Std 80-2000/ Incorporates IEEE Std 80-2013/Cor 1-2015) - Redline, pp. 1–426, 2015.
[3] R. Alipio, M. A. O. Schroeder, and M. M. Afonso, “Voltage distribution along earth grounding grids subjected to lightning currents,” IEEE Transactions on Industry Applications, vol. 51, no. 6, pp. 4912–4916, 2015.
[4] Y. He, X. Shao, J. Hu, Y. Liu, C. Jin, and J. Pan, “Corrosion condition detect of entire grounding system in a 500kv converting station using electrical impedance imaging method,” in 2018 IEEE International Conference on High Voltage Engineering and Application (ICHVE). IEEE, 2018, pp. 1–4.
[5] X. Li, F. Yang, J. Ming, A. Jadoon, and S. Han, “Imaging the corrosion in grounding grid branch with inner-source electrical impedance tomography,” Energies, vol. 11, no. 7, p. 1739, 2018.
[6] K. Liu, F. Yang, X. Wang, B. Gao, X. Kou, M. Dong, and A. Jadoon, “A novel resistance network node potential measurement method and application in grounding grids corrosion diagnosis,” Progress In Electromagnetics Research M, vol. 52, pp. 9–20, 2016.
FIGURE 10. Lab testing grounding grid model and experimental setup [32]. (a) 36cm × 36cm grounding grid with mesh size 9cm. 9.2A dc is injected at T and G is grounded. L is the line of measurement and R2 is the broken branch. (b) Experimental setup.

FIGURE 11. Gradient modulus of magnetic flux density on L. The absence of peak at 0.096m confirms R2 as broken. The blue graph illustrates the magnetic flux density of the normal grounding grid while the red graph shows the magnetic flux density when R2 is corroded.

[7] F. Yang, Y. Wang, M. Dong, X. Kou, D. Yao, X. Li, B. Gao, and J. Ullah, “A cycle voltage measurement method and application in grounding grids fault location,” Energies, vol. 10, no. 11, p. 1929, 2017.

[8] Y. Shao, M. Mu, B. Zhang, K. Nie, and Q. Liao, “Corrosion behavior of copper-clad steel bars with unclad two-end faces for grounding grids in the red clay soil,” Journal of Materials Engineering and Performance, vol. 26, no. 4, pp. 1751–1757, 2017.

[9] J. Li, H. Su, F. Chai, D.-m. Xue, L. Li, X.-y. Li, and H.-m. Meng, “Corrosion behavior of low-carbon cr micro-alloyed steel for grounding grids in simulated acidic soil,” Journal of Iron and Steel Research International, vol. 25, no. 7, pp. 755–766, 2018.

[10] X.-L. Zhang, X.-H. Zhao, Y.-G. Wang, and N. Mo, “Development of an electrochemical in situ detection sensor for grounding grid corrosion,” Corrosion, vol. 66, no. 7, pp. 076.001–076.001, 2010.

[11] P.-H. Zhang, J.-J. He, D.-D. Zhang, and L.-M. Wu, “A fault diagnosis method for substation grounding grid based on the square-wave frequency domain model,” Metrology and Measurement Systems, pp. 63–72, 2012.

[12] L. Kai, Y. Fan, Z. Songyang, Z. Liwei, H. Jiayuan, W. Xiaoyu, and I. Ullah, “Research on grounding grids imaging reconstruction based on magnetic detection electrical impedance tomography,” IEEE Transactions on Magnetics, vol. 54, no. 3, pp. 1–4, 2018.

[13] A. Qamar, N. Shah, Z. Kaleem, Z. Uddin, and F. A. Orakzai, “Breakpoint diagnosis of substation grounding grid using derivative method,” Prog. Electromagn. Res. M, vol. 57, pp. 73–80, 2017.

[14] S. Qin, Y. Wang, Z. Xu, X. Liao, L. Liu, and Z. Fu, “Fast resistivity imaging of transient electromagnetic using ann,” IEEE Geoscience and Remote Sensing Letters, 2019.

[15] C. Yu, Z. Fu, Q. Wang, H.-M. Tai, and S. Qin, “A novel method for fault diagnosis of grounding grids,” IEEE Transactions on Industry Applications, vol. 51, no. 6, pp. 5182–5188, 2015.

[16] X. Li, F. Yang, J. Ming, A. Jadoon, and S. Han, “Imaging the corrosion in grounding grid branch with inner-source electrical impedance tomography,” Energies, vol. 11, no. 7, p. 1739, 2018.

[17] F. Yang, Y. Wang, M. Dong, X. Kou, D. Yao, X. Li, B. Gao, and I. Ullah, “A cycle voltage measurement method and application in grounding grids fault location,” Energies, vol. 10, no. 11, p. 1929, 2017.

[18] J. Jordana, M. Gasulla, and R. Pallás-Areny, “Electrical resistance tomography to detect leaks from buried pipes,” Measurement Science and Technology, vol. 12, no. 8, p. 1061, 2001.

[19] X. Wang, Z. Fu, Y. Wang, R. Liu, and L. Chen, “A non-destructive testing method for fault detection of substation grounding grids,” Sensors, vol. 19, no. 9, p. 2046, 2019.

[20] B. Z. Jinliang He, Rong Zeng, Methodology and Technology for Power System Grounding. John Wiley & Sons Singapore, 2013.

[21] A. K. Madhira and R. A. Shaik, “Separation of sources from single-channel eeg signals using independent component analysis,” IEEE Transactions on Instrumentation and measurement, vol. 67, no. 2, pp. 382–393, 2017.

[22] A. Qamar, Z. Uddin, and F. Yang, “Inverse features extraction for substation grounding grid: derivative and ica combinatorial approach,” IET Generation, Transmission & Distribution, vol. 13, no. 24, pp. 5457–5466, 2019.

[23] E. Urrestarazu, J. Iriarte, M. Alegre, M. Valencia, C. Viteri, and J. Artieda, “Independent component analysis removing artifacts in ictal recordings,” Epilepsia, vol. 45, no. 9, pp. 1071–1078, 2004.

[24] A. J. Shackman, B. W. McMenamin, H. A. Slagter, J. S. Maxwell, L. L. Greischar, and R. J. Davidson, “Electromyogenic artifacts and electroencephalographic inferences,” Brain topography, vol. 22, no. 1, pp. 7–12, 2009.

[25] W. De Clercq, A. Vergult, B. Vanrumste, W. Van Paesschen, and S. Van Huffel, “Canonical correlation analysis applied to remove muscle artifacts from the electroencephalogram,” IEEE transactions on Biomedical Engineering, vol. 53, no. 12, pp. 2583–2587, 2006.

[26] M. R. Mowl, S.-C. Ng, M. S. Zilany, and R. Paramesran, “Artifacts-matched blind source separation and wavelet transform for multichannel eeg denoising,” Biomedical Signal Processing and Control, vol. 22, pp. 111–118, 2015.

[27] M. Anderson, G.-S. Fu, R. Phlypo, and T. Adali, “Independent vector analysis: Identification conditions and performance bounds,” IEEE Transactions on Signal Processing, vol. 62, no. 17, pp. 4399–4410, 2014.

[28] M. Anderson, T. Adali, and X.-L. Li, “Joint blind source separation with multivariate gaussian model: Algorithms and performance analysis,” IEEE Transactions on Signal Processing, vol. 60, no. 4, pp. 1672–1683, 2011.

[29] Y. Fan, L. Kai, Z. Liwei, Z. Songyang, H. Jiayuan, W. Xiaoyu, and G. Bin, “A derivative-based method for buried depth detection of metal conductors,” IEEE Transactions on Magnetics, vol. 54, no. 4, pp. 1–9, 2018.

[30] T. Kim, H. T. Attias, S.-Y. Lee, and T.-W. Lee, “Blind source separation...
exploiting higher-order frequency dependencies,” IEEE transactions on audio, speech, and language processing, vol. 15, no. 1, pp. 70–79, 2006.

[31] AC/DC Module User’s Guide, version 5.0”, COMSOL, Inc, http://www.comsol.com.

[32] A. Qamar, F. Yang, W. He, A. Jadoon, M. Z. Khan, and N. Xu, “Topology measurement of substation’s grounding grid by using electromagnetic and derivative method,” Progress In Electromagnetics Research, vol. 67, pp. 71–90, 2016.

[33] M. Au, F. Gagnon, and B. Agba, “An experimental characterization of substation impulsive noise for a rf channel model,” in PIERS Proceedings, 2013.

[34] X. Chen, H. Peng, F. Yu, and K. Wang, “Independent vector analysis applied to remove muscle artifacts in eeg data,” IEEE Transactions on Instrumentation and Measurement, vol. 66, no. 7, pp. 1770–1779, 2017.

[35] Z. Uddin, A. Ayaz, and I. Muhammad, “Ica based mimo transceiver for time varying wireless channels utilizing smaller data blocks lengths,” Wireless Personal Communications, vol. 94, no. 4, pp. 3147–3161, 2017.

[36] Y.-O. Li, T. Adali, W. Wang, and V. D. Calhoun, “Joint blind source separation by multiset canonical correlation analysis,” IEEE Transactions on Signal Processing, vol. 57, no. 10, pp. 3918–3929, 2009.

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