Accurate Fault Location Technology for Power Lines

Final Report

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1 Introduction

1.1 Purpose of the report

This report aims to inform the project partners on the progress made in the desktop studies of accurate fault location technology using electromagnetic time reversal. The report covers a range of topics, including the modifications and improvements made to existing time reversal-based fault location methods, allowing for a thorough desktop study, a model of a rural REFCL feeder in Victoria, implementation of two fault location algorithms, and comparisons of each algorithms' performance. The report will provide an understanding of the current state of the research, recommendations for which algorithm may be best suited for specific situations, and an overview of the performance of the two algorithms for different fault cases. The report will aid in making informed decisions about the implementation of these accurate fault location techniques in Australian power networks.

1.2 Overview of the algorithms: Energy and Similarity methods

The Energy algorithm is a well-researched method that uses the principle of time reversal invariance of travelling waves in transmission lines to locate faults. This method has been tested in previous trials in China and Switzerland. This process involves measuring the voltage transients at measurement point(s) in the network, then 'back-injecting' a time reversed copy of the measured voltage in a simulated environment. In simulation, the waveforms converge at the location of the fault origin, allowing the fault to be located. The algorithm measures the current at the guessed fault location and calculates the signal energy.

The Similarity metric is a newly proposed algorithm that is currently being developed through PhD research. This method exploits other features of the time reversal theory and aims to improve the fault location performance, in particular for high impedance faults.

1.3 Enhancements of the algorithms allowing for desktop studies

A simulation model of the GSB014 Australian feeder was built using previously available LiDAR data. The simulations use Electromagnetic transients program (EMTP), with the importing of data handled by the EMTP javascript scripting capabilities. The model was automatically generated based on the data available, however some manual modifications were still required. The generated model is initially built using frequency-dependent line models, which were further modified by a script to generate constant parameter lines. This model is more computationally-efficient and allows us to carry out more extensive simulation studies.

Existing time reversal methods require significant simulation time to analyse a network, which makes detailed desktop studies difficult to perform. The traditional approach involves generating fault signals for each of N possible fault location in the network. Then, each of these fault signals is reinjected into each possible fault location, requiring approximately N^2 simulations. With an approximate 30 seconds per simulation, this method was too time-consuming to run for a significant number of fault parameters, and could cause delays for real-time fault location. As an approximation, the GSB014 network is 89 km long, hence 100 m fault separation requires $N = 890$ simulations, or $N^2 = 792{,}100$ total simulations, which must be repeated for different fault impedances, measurement points, etc. This would require nearly a year to run for a single impedance, and would still require $\sim$7 hours if we only considered a single fault measurement – which makes it infeasible as a fault location technique.

To overcome this limitation, we demonstrated that it is possible to inject an impulse into the model network and use the corresponding impulse responses to greatly speed up the simulations. This approach requires only $2N$ simulations. The signal processing steps are performed in MATLAB. MATLAB was chosen due to its ease of use, speed, and number of relevant signal processing algorithms. The reduction from $N^2 \rightarrow 2N$ simulation time reduces the overall cost of simulation such that detailed results are obtainable in a matter of days or weeks, rather than years. This modification allows for detailed desktop studies to be performed for a range of conditions.

Lastly, we investigated the possibility of using multiple measurement points, which was not considered before. The typical approach would be to inject all waveforms co-currently at the correct time, requiring each sensor to be time-synchronized, which greatly increases cost and complexity of the system. We investigated the possibility of using non-time-synchronized sensors, which each produce their own estimate of fault locations, which are then combined to produce a final result.

In our testing, we used an a priori choice of 10 possible sensor placements, with the intention that only a subset of these should be installed on the physical network. The location of these sensors is shown in Figure 1. The objective was to find the best placement of the sensors to provide the highest fault location accuracy. We also made further improvements to the simulations to allow for all measurement points to be studied simultaneously. Originally, the back-injection impulses would have required 10 simulations for each fault location, which would have been costly to evaluate during the timeframe of the project. However, by utilizing the reciprocity of the system, we are able to generate all 10 impulse responses at the same time which allows for the required results to be obtained from a single simulation. This modification greatly improves the speed of simulation, and allows for multiple measurement points to be effectively utilized.

2 Discussion of the network under test

The network under test is the GSB014 network, a 22kV distribution feeder in western Victoria, Australia (shown in Figure 1). It contains a mix of overhead and underground lines, with 248 branches and a total length of 88.7 km. The model was generated in EMTP from an excel file containing the specified connections and line types, and it was validated by importing the generated netlist file into MATLAB. The validation process included verifying the number of lines, non-looping conditions, non-repeated names, and total length, among others.

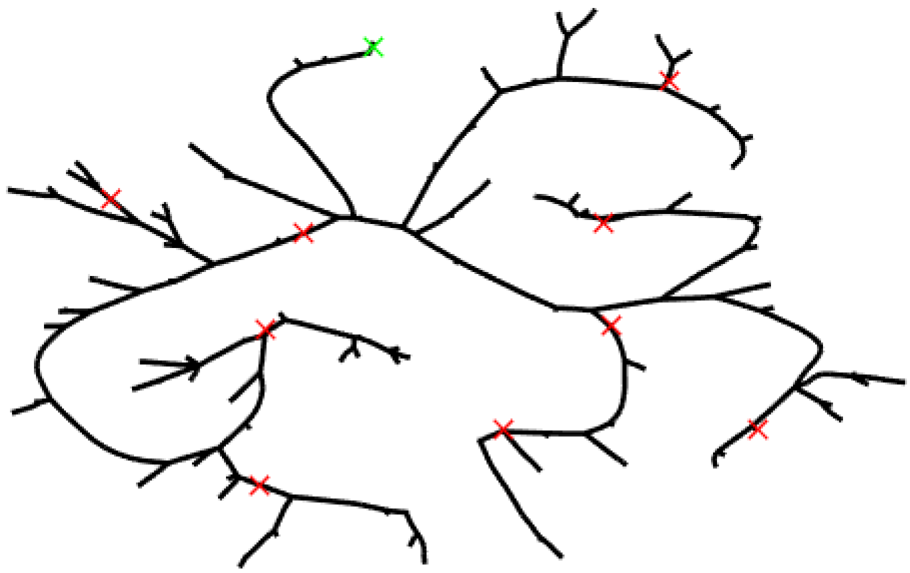

Figure 1 GSB014 Network. Sensor locations denoted by X's. Green X denotes the zone substation

Table I. Specifications of the network

Property	*Value*
Total Spans	*773*
Underground Spans	*25*
Overhead Spans	*748*
Length	*88.73 km*
Branches	*248*
Terminal Points	*130*

3 Multiple Measurement Points and Their Optimal Location

In the literature, limited investigations have been performed on how to combine the results of non-time-synchronised measurement points together. Nonetheless, preliminary investigations show that different measurement locations can produce accurate results in different sections of the network, and hence may allow for improved accuracy. While a number of different techniques were investigated, compared to a simple approach, they typically added complexity to the procedure, without showing significant improvement, if any, to the location statistics. Hence the simplest approach was selected.

It's worth noting that utilizing multiple sensors not only improves the accuracy in the region where the sensor is installed, but improves accuracy throughout the network. This is because the additional sensor may contain information that the fault is not close to itself, hence faults that are far away from itself are able to have their location narrowed down.

4 Algorithm 1: Energy Method

4.1 Description of the algorithm

The Energy algorithm is a well-researched method that uses the principle of time reversibility of waves to locate faults. The method was first described by Razzaghi et al. in [1]. Other studies have shown variations of the algorithm (e.g., [2] and [3]) with some improvements. This method has been successfully tested in field trials in China and Switzerland.

The algorithm relies on the time reversibility of waves. A single sensor is used to measure the waves at a line end – examples of which are shown in Figure 2. These are then filtered (Figure 3) and time reversed, before being back injected in the simulated environment. A number of a priori guessed fault locations are required for the back-injected signal, as the wave propagation changes for each possible fault location. When the guessed fault location is correct, we observe the current through the fault branch to be significantly higher than for the false fault locations (Figure 4), allowing us to determine which a priori guessed fault location is the true fault location. The method is robust against noise, however, it becomes less accurate for large, complex branching networks. The model on which it is being evaluated fits these criteria, hence it fails to generate accurate estimates. This was the motivation to use the Similarity algorithm.

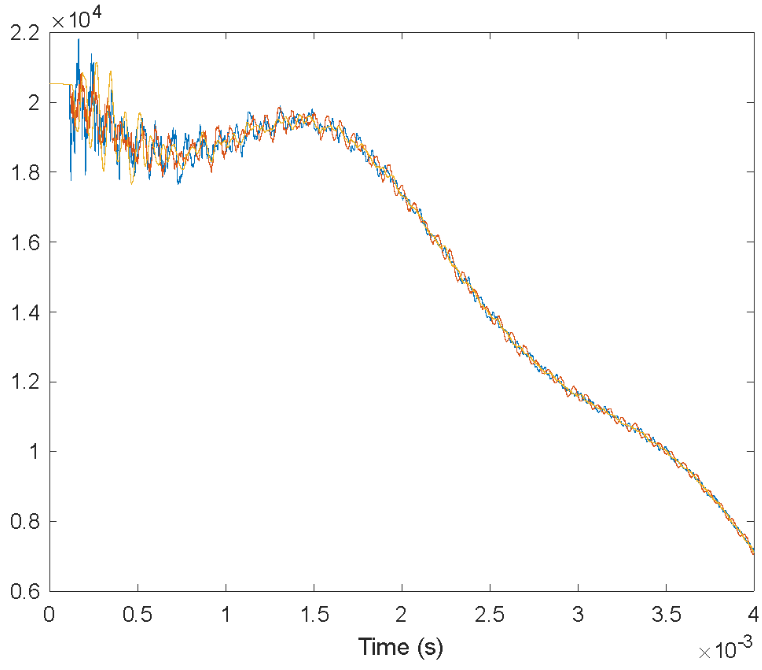

Figure 2 Example Fault Transients for 3 fault positions

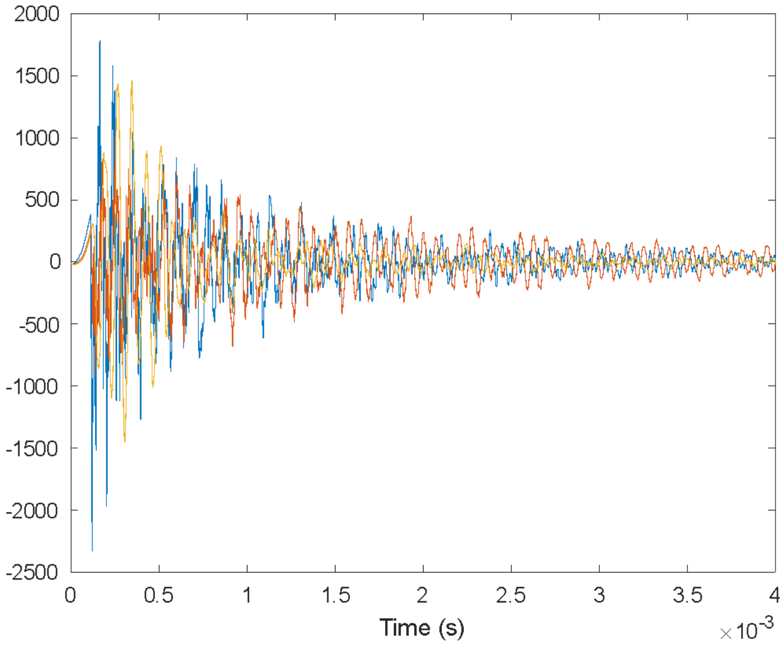

Figure 3 Example Fault Transients for 3 fault positions post filtering

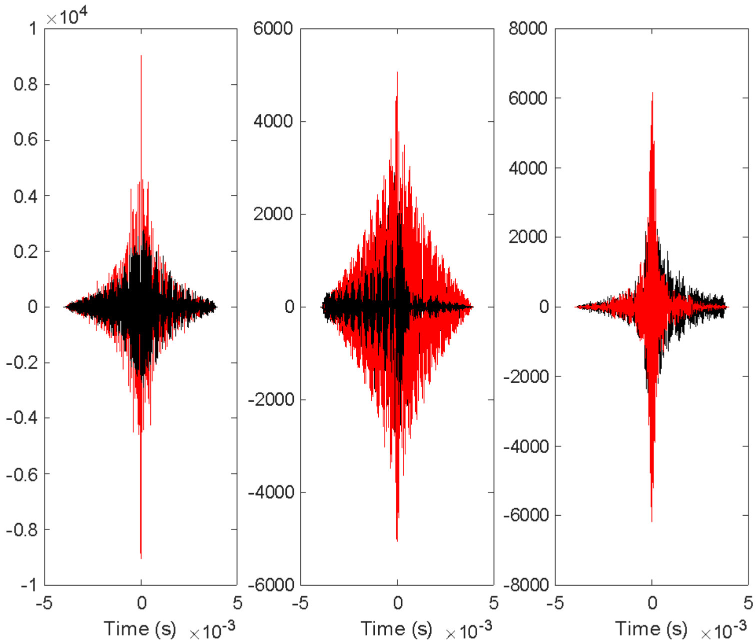

Figure 4 Fault Current for 3 sample fault locations after being back injected. Red signal corresponds to when the Guessed Fault Location matches the True Fault Location

4.2 Results of the testing

The results are shown as heatmaps, which indicate the percentage of faults located to within 2 km of the true fault location. The error tolerance of 2 km was chosen as a threshold according to comments made by industry partners. Note that the results for m measurement points are optimised over the specified fault resistance – hence a 2 measurement system may have different measurement points between 100Ω and 200Ω fault impedance. Results show the effect of fault impedance and number of measurement points. Figures 5, 6, 7 show the effect of changing sampling rate. Figures 8 and 9 show the effect with fixed measurement points (i.e., selecting the same measurement points for all fault impedance values).

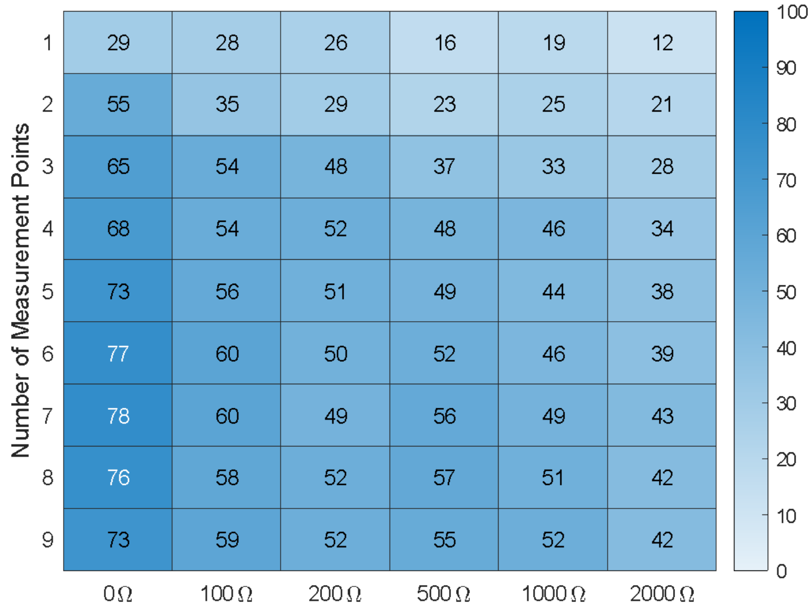

Figure 5 Percentage of faults correctly identified to within 2 km of true fault location given 20MHz sampling and 50dB SNR measurement noise

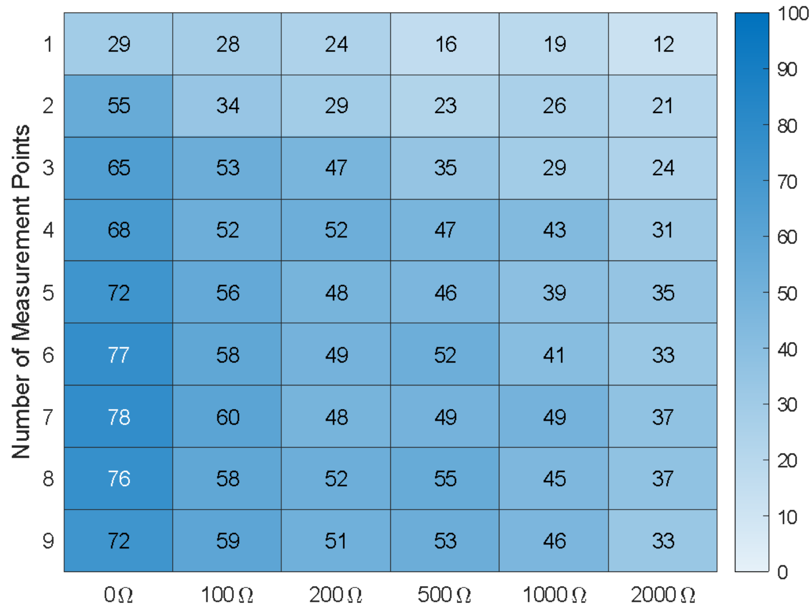

Figure 6 Percentage of faults correctly identified to within 2 km of true fault location given 1MHz sampling and 50dB SNR measurement noise

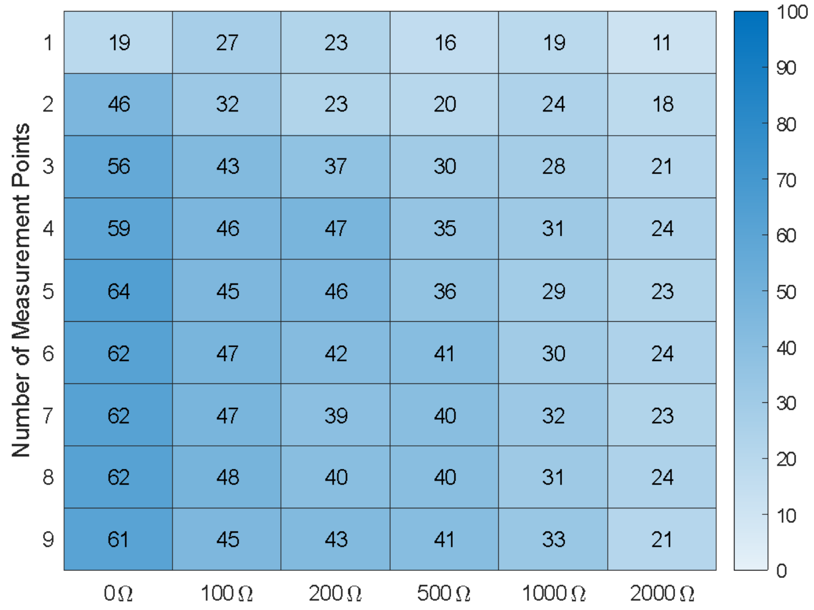

Figure 7 Percentage of faults correctly identified to within 2 km of true fault location given 100kHz sampling and 50dB SNR measurement noise

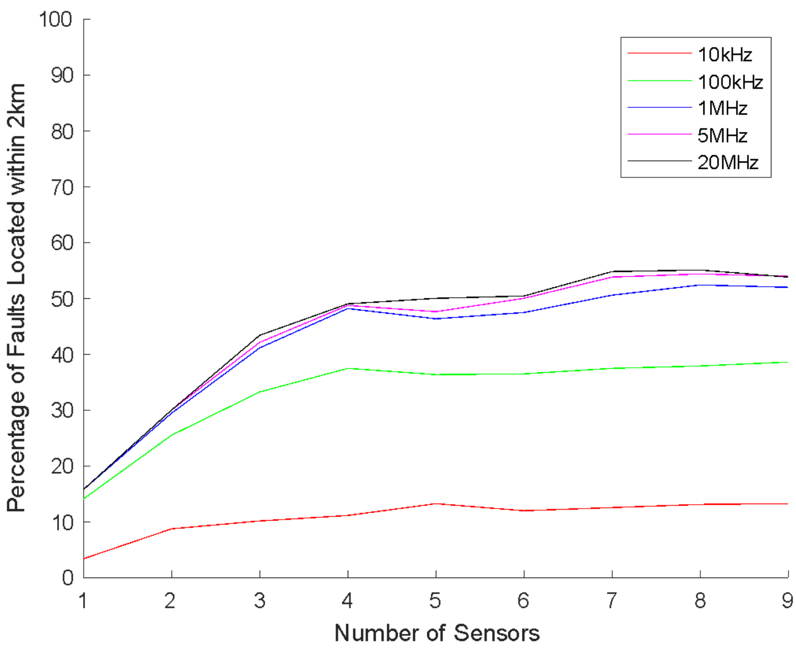

Figure 8 Percentage of faults located within 2 km using Varying Sensors. Sensors are optimized over all fault impedances simultaneously with 50dB SNR

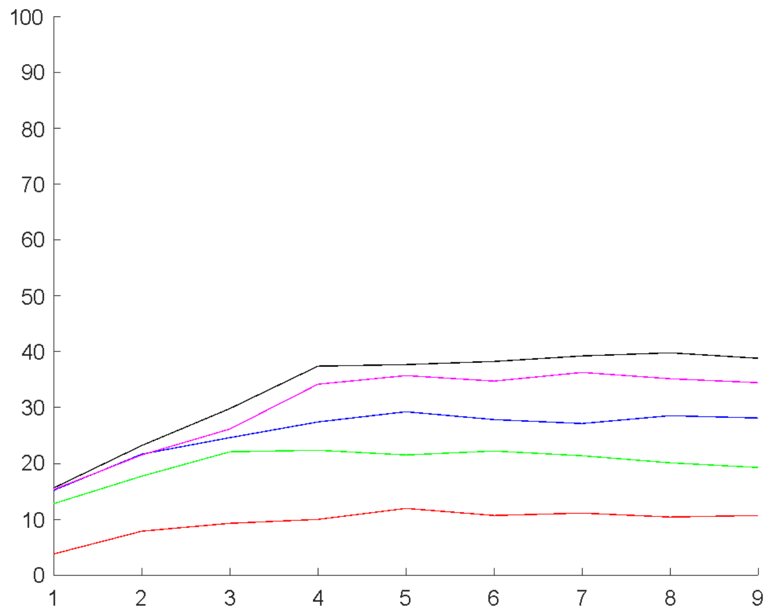

Figure 9 Percentage of Faults Located within 2 km using Varying Sensors. Sensors are optimized over all fault impedances simultaneously with 30dB SNR

4.3 Analysis of the results

The analysis of the results of the Energy method shows that the method has limitations in accurately locating faults. The results highlight that, while the algorithm performs reasonably well for low impedances, it fails to do so for higher fault impedances. This is likely due to the complexity and size of the network under test. Even when provided with a significant number of sensors, the accuracy of the algorithm is limited to around 40-60%.

Additionally, the results suggest the algorithm is able to perform reasonably with low/moderate sampling rates (100kHz), with an approximate 10% decrease in accuracy. A higher sampling rate (up to 20MHz) is recommended, as it provides more room for error and ensures accurate results.

In conclusion, the Energy algorithm has limitations and is not suitable for complex networks and high impedance faults. It is best used for low impedance faults and networks with limited complexity.

5 Algorithm 2: Similarity Metric

5.1 Description of the algorithm

The Similarity algorithm has been devised and developed during the PhD research funded by a Monash University scholarship. Similar to the Energy method, it relies on simulating a number of a priori guessed locations and comparing characteristics of the simulated results to characteristics of the observed signal.

5.2 Results of the testing

The results are shown as heatmaps, which indicate the percentage of faults located to within 2 km of the true fault location. The error tolerance of 2 km was chosen as a threshold according to comments made by industry partners. Note that the results for m measurement points are optimised over the specified fault resistance – hence a 2 measurement system may have different measurement points between 100Ω and 200Ω fault impedance. Results show the effect of fault impedance and number of measurement points. Figures 10, 11, 12 show the effect of changing sampling rate. Figures 13 and 14 show the effect with fixed measurement points (i.e., forcing all fault impedances to select the same measurement nodes).

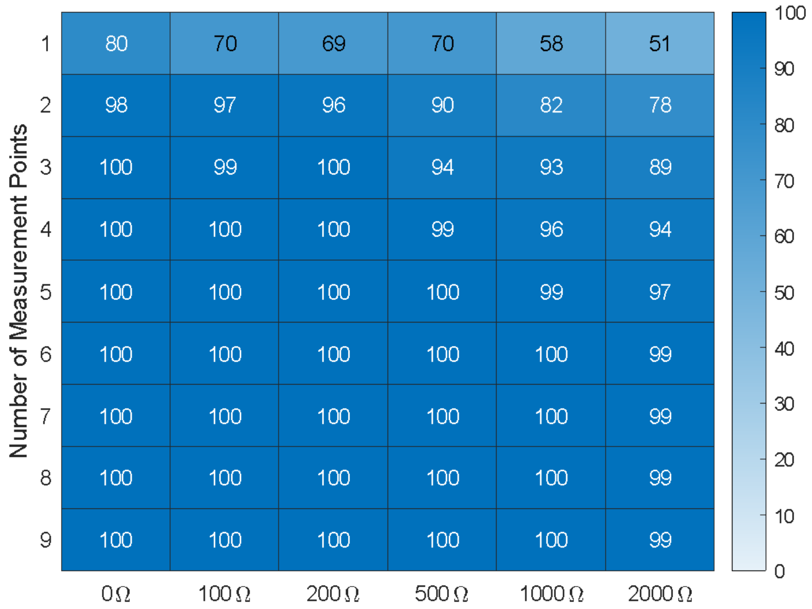

Figure 10 Percentage of faults correctly identified to within 2 km of true fault location given 20MHz sampling and 50dB SNR measurement noise

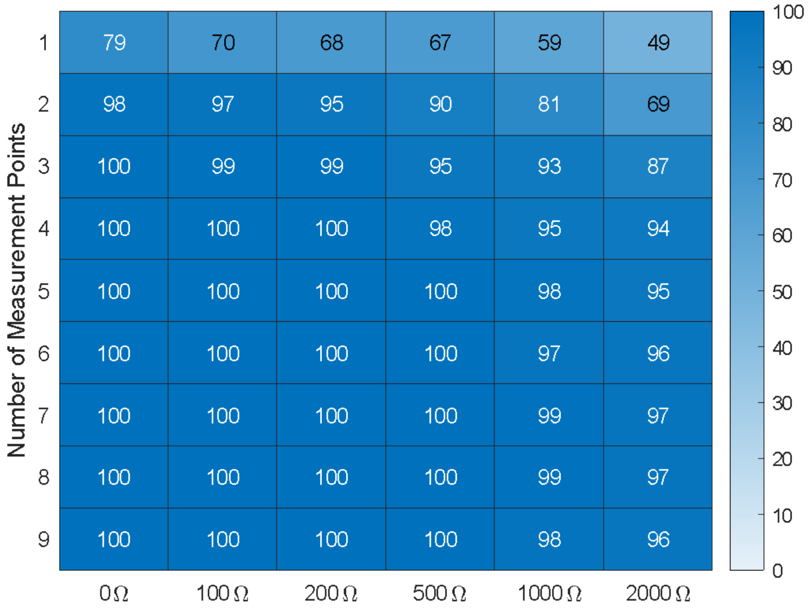

Figure 11 Percentage of faults correctly identified to within 2 km of true fault location given 1MHz sampling and 50dB SNR measurement noise

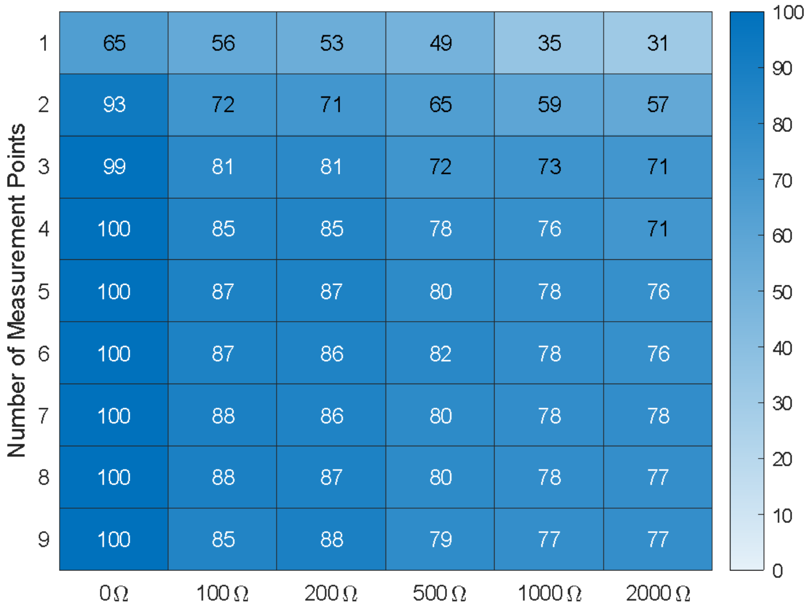

Figure 12 Percentage of faults correctly identified to within 2 km of true fault location given 100kHz sampling and 50dB SNR measurement noise

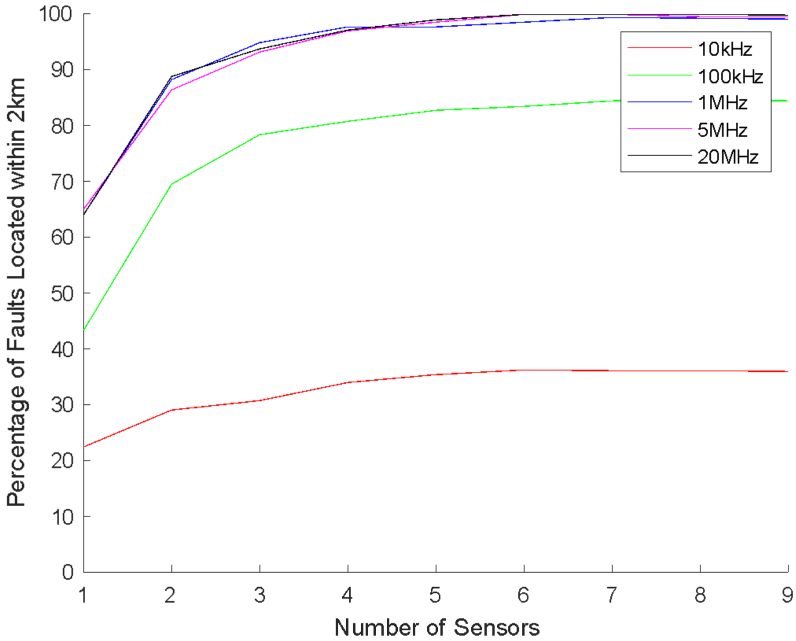

Figure 13 Percentage of Faults Located within 2 km using Varying Sensors. Sensors are optimized over all fault impedances simultaneously with 50dB SNR

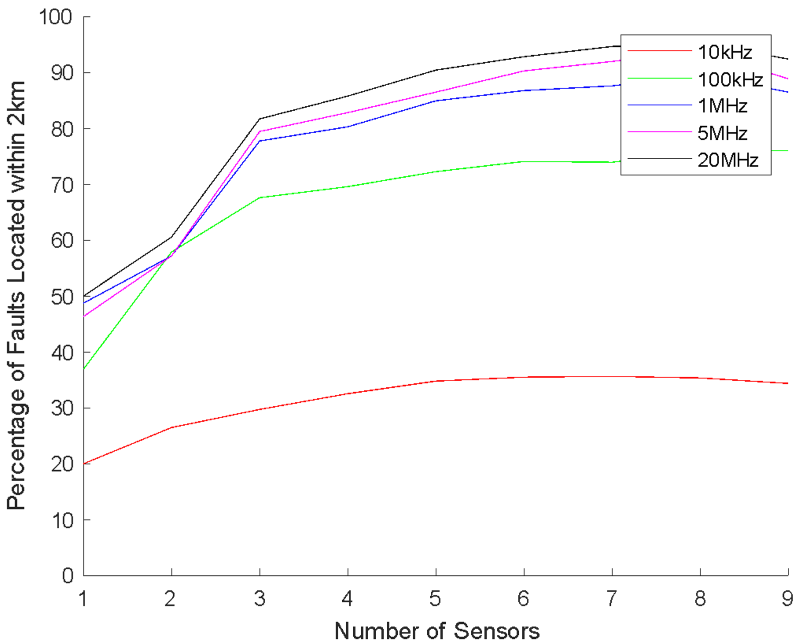

Figure 14 Percentage of Faults Located within 2 km using Varying Sensors. Sensors are optimized over all fault impedances simultaneously with 30dB SNR

5.3 Analysis of the results

The Similarity algorithm was successful in most of the tests conducted. It was able to accurately determine the location of the fault to within 2 km. With only one sensor at the substation, it achieved between 63-65% accuracy over a range of fault impedances with SNR of 50dB for the measurement noise. By increasing the number of measurement points to 2 or 3, the fault location accuracy increased to nearly 90% and 95% respectively. The results also indicated that the sampling rate of the data had little effect on the accuracy of the algorithm, with similar results observed at sampling rates between 1-20MHz. Higher sampling rates are preferred to allow for a larger margin of error.

6 Comparison of the Algorithms

6.1 Comparison of the results

The Energy algorithm has limitations in accurately locating faults in complex networks. It performs reasonably well for low impedance faults, but accuracy decreases with higher impedance faults. The algorithm performs similarly with moderate/high sampling rates, but a higher sampling rate is recommended. On the other hand, the Similarity algorithm was successful in most tests and exhibited significant accuracy improvement. Sampling rate had little effect on accuracy but a threshold still exists for low sampling rates. The most benefit would be in installing 2-3 sensors, which would provide an estimated 85-95% coverage for the Similarity algorithm, and 30-45% coverage for the Energy algorithm.

Based on the results of the tests, it is recommended to implement both the Energy and Similarity algorithms. Given that both algorithms can be utilised with the same hardware, there is little downside to implementing both. This approach will provide a more robust and reliable solution for fault location, and allows for further analysis and improvement in the future.

7 Conclusion

The key findings from testing the Energy and Similarity methods on the GSB014 network:

- The Energy algorithm has limited accuracy for higher impedance faults and complex networks. (30-45% success rate)
- The Similarity algorithm is more effective in locating faults. (85-95% success rate)
- The Similarity and Energy algorithms both benefit from more sensors at different locations of the network.
- For the GSB014, the optimal number of measurement points is 3 to achieve >90% fault location accuracy.
- It is recommended to implement both algorithms for a comprehensive solution, with cross-verification and increased accuracy.

The comparison of the Energy algorithm and Similarity algorithms has provided insights into their strengths and limitations in determining fault location in power systems. Through comprehensive simulation studies for various types of faults, fault locations, fault impedance values, number/location of measurement points, the feasibility of using the Time Reversal technique to locate faults in REFCL networks has been shown.

It is important to note that the results obtained in this study were based on simulated scenarios and further validation is necessary through real-world testing and field trials. These field tests will help to identify further research questions to improve the algorithm and develop a commercial technology.

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8 References

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