

COMPARISON BETWEEN THE PERFORMANCE OF ANN-BASED LOSS OF MAINS RELAYS USING MULTI-LAYER AND NON-LAYERED PERCEPTRON APPROACHES

S K Salman

D J King

School of Engineering, The Robert Gordon University,
Schoolhill, Aberdeen, AB10 1FR,U.K

School of Computing & Creative Technologies, University of
Abertay, Bell Street Dundee

ABSTRACT

Loss of mains is a condition whereby an embedded/distributed generator becomes islanded with part of a public load. This is usually caused by disturbances on the associated utility network which results in having an EG (embedded generation) to become “islanded” with a public load. This condition is highly undesirable and should be correctly detected in order to ensure the tripping of the generator affected by such conditions. Currently the two methods most commonly in use to detect LOM (loss of mains) utilise ROCOF (rate of change of frequency) and PDM (vector surge) techniques, either on their own, or in tandem. However, these methods have not proved to be totally reliable. This paper reports the development of a new relay for detecting LOM. It is based on the application of artificial neural network (ANN). Two ANN architectures have been considered; one based on multi-layer perceptron approach while the other based on a non-layered approach using NeuralWorks Predict features.

However, these methods have not proved to be totally reliable. Although relays based on ROCOF or PDM appear to be suitable, getting the correct settings to give sensitivity without mal-operation is very difficult [10, 11]. In fact, of the two methods mentioned above, ROCOF is prone to nuisance tripping due to large frequency changes that can occur naturally on the utility network, and the vector surge method is sometimes not sensitive to the small changes in phase angle that may result from LOM [12, 13].

This paper reports investigating the development of a new relay for detecting LOM. It is based on the application of artificial neural network (ANN). Two ANN architectures have been considered; one based on multi-layer perceptron approach [14] while the other based on a non-layered approach using NeuralWorks Predict features [15].

1. INTRODUCTION

Loss of mains is a condition whereby an embedded/distributed generator (EG/DG) becomes islanded with part of a public load as shown in Figure 1. This is caused by disturbances on the utility network which results in the line between buses 1 and 2 being disconnected, which in turn causes the EG to become “islanded” with the load connected to bus 2. This condition is highly undesirable due to (i) safety considerations and (ii) the power quality in the islanded network can not be guaranteed. It has therefore become a requirement in the UK [1] and elsewhere [2] to provide LOM protection at the interfacing point between an embedded generator and its associated network.

Several methods for detection of LOM have been reported in literature [3-9]. The two methods most commonly in use to detect LOM utilise ROCOF and PDM (or vector surge) techniques, either on their own, or in tandem.

2. INVESTIGATED SYSTEM

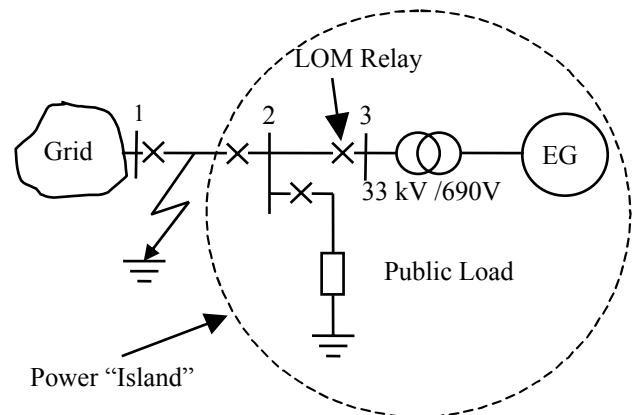


Figure 1 An Embedded Generator “Islanded” with public load.

The data required to train and test the proposed ANN-based LOM relay was generated using the power network shown in Figure 2. It comprises of a 25 MVA, 0.69 kV embedded synchronous generator, which is connected to a

33 kV distribution network. The grid is represented by an infinite voltage source connected at 132 kV, behind the grid impedance, which has a 20/1 X/R ratio and a fault level of 3436 MVA. A load is connected close to the EG, whose rating is approximately the same as that of the EG. Other loads or generators can be connected or disconnected at bus 2 to simulate operational disturbances on the network. A parallel feeder can also be connected to determine the consequences of the loss of parallel feeder/line (LOPF). Without the parallel line, the LOM condition can be simulated by creating a three phase to ground fault halfway along overhead line 1 and then clearing it by opening the circuit breakers at busses 3 and 4. This will effectively create a power “island” involving the EG and the load at bus 4. The LOM relay is positioned at bus 5. The system was simulated using EMTP which enables the generation of data that cover wide ranging operating conditions as well as abnormal conditions.

3. ARCHITECTURES OF ANN-BASED LOM RELAY

Two architectures have been considered for the proposed ANN-based LOM relay. The first one based on the standard multi-layer architecture [14] as shown in Fig. 3, while the second one is based on non-layered architecture as shown in Fig 4. The latter is constructed using NeuralWorks Predict features approach [15]. The two architectures are similar to each other by the fact that each of them has an input layer and an output layer with one processing element (PE). However they differ in the way the hidden PEs are arranged. The other major difference between the two architectures is that the non-layered version has the processing elements of its input layer all directly connected to the processing element of its output layer which is not the case in the multi-layer version.

3.1 Multi-layer architecture

Initially, the results from EMTP simulations indicated that the voltage signal showed the most sensitivity to LOM, it was decided to use the instantaneous three phase voltages as training and testing input data for the ANN-based LOM protection relay. The chosen ANN was back propagation network consisting of an input layer, output layer and one (or more) hidden layers similar to the one shown in Fig 3. As the input data is time varying, the input data set is organised in the form of a sliding data window with a fixed length of one cycle of the fundamental waveform [16].

To generate the data the EMTP simulation was run for several different cases representing LOM, LOPF and other disturbances for various different system topologies, to try to get sufficient data to train the ANN all possible operating conditions.

Initially, two back-propagation ANNs were considered, each with 48 input nodes and one output node. The first had 5 and the second had 25 processing elements (PEs) in the hidden layer. The idea being that both networks are trained with the same data to find which one achieves the required accuracy in the lowest number of iterations, thus indicating which network is closest to the optimum. In this way the minimum number of PEs in the hidden layer can be determined. The 48 inputs correspond to 16 samples per each phase voltage per cycle and the single output corresponds to trip or non trip conditions.

After making several attempts and refinements it has been concluded that the best network is the one with 5 hidden PEs using the tanh transfer function, which has bounds of ± 1 . After having the network been trained for 15000 iterations of the training data, when tested on one run through the test data it gave a 79.77% successful classification rate.

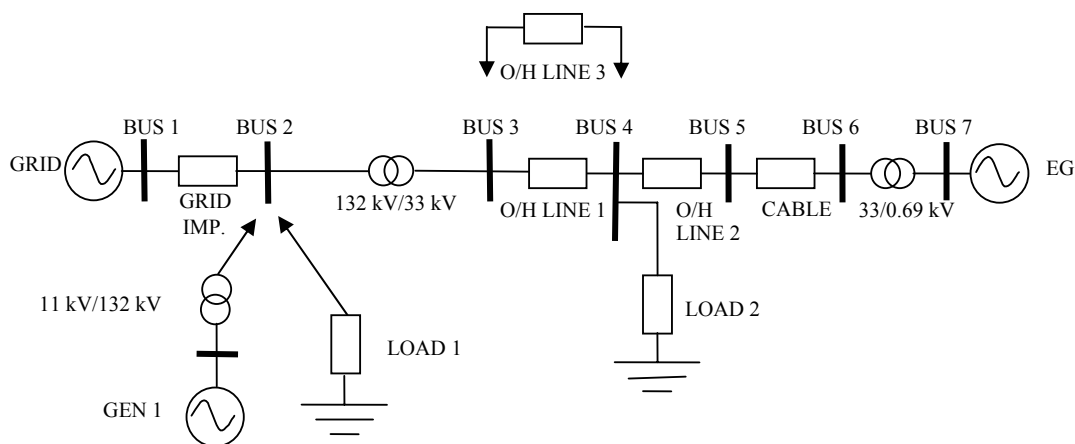


Figure 2 Single Line Drawing of Simulation Network.

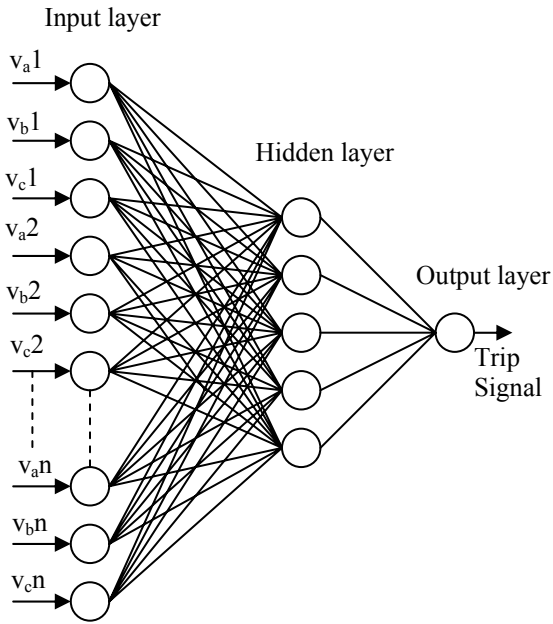


Figure 3 Multi-layer ANN-based LOM relay.

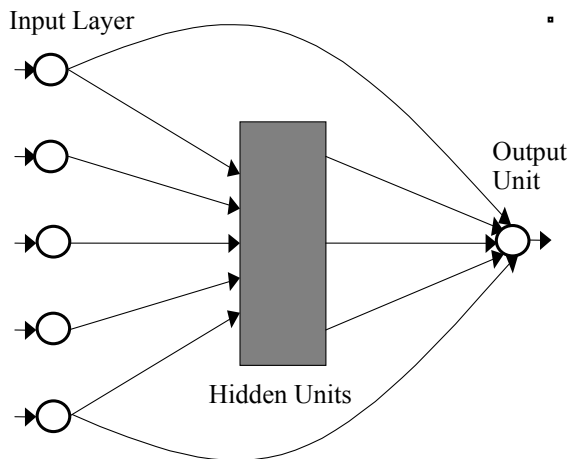


Figure 4 Non-layered ANN-based LOM relay

Further investigations were conducted by trying some other trainings for different number of hidden PEs including two and three hidden layers of PE and by slightly revised learning schedules (which allow the learning rate and momentum values to be adjusted during the training period in an attempt to achieve the minimum error more quickly), which increased the classification rate to 84.44%. It was noted that in nearly all cases the network was able to classify correctly 100% of the cases where LOM had not occurred, but it could not correctly classify LOM cases. However further investigation revealed that the majority of those

misclassified LOM cases were related to LOPF, i.e., they did not represent LOM conditions. This was confirmed when the ANN was retrained and tested while all data for those misclassified cases were removed. This resulted in a correct classification of LOM cases of 93.48%. The only erroneously classified data sets were those that occurred simultaneously with a LOM event. In all cases the ANN correctly identified all following data sets from these cases as LOM. In other words if the LOM is wrongly classified for the cycle in which the LOM occurs, then the correct decision is made for the subsequent cycle.

3.2 Non-layered architecture

The difficulties associated with data management experienced in investigating the ANN multi-layer architecture as well as its relatively poor classification rate was the main reason for considering the non-layered architecture with the help of PREDICT software tool [15]. PREDICT offers two important features. Firstly it offers efficient data management because of its integration with Microsoft Excel which makes the handling of the data much less time consuming. Secondly it can be used to determine the optimum ANN architecture, based on using the minimum number of the data inputs and the smallest possible network.

First, all the training/test data is converted into an Excel document. Then the data is analysed and all the possible data transforms that can be performed on the data for each individual variable are calculated. A genetic algorithm is then used to run through a loop to determine the optimum ANN architecture, based on using the minimum number of the data inputs and the smallest possible network. The procedure is to start with the simplest possible network, which is done by initially connecting the inputs directly to the output layer and determining its accuracy, then a new hidden node or processing element is added at each iteration, and tested for all possibilities, until there is no further improvement. Once the optimum network is found it can be tested and validated against another set of data that it has not seen before. If the results are not acceptable, then the learning parameters can be altered and the training re-started. If the results are still not satisfactory, and all the possible changes in the learning algorithms have not produced any significant improvement then different data is required. Either the data could be presented in a different way, e.g. instead of showing the network individual samples, all the samples for a single cycle could be shown which are 10 samples per cycle for the case under consideration, increasing the number of sets of input data. Or more variables can be added to the input data to provide more potential inputs to chose from.

In the process of constructing an optimum non-layered ANN optimum network architecture, various interconnections of the hidden elements to each other, as well as to the input and output layers are tried and tested. The resultant structure of the final networks produced looks similar to Figure 4. In this architecture there are no hidden layers as such, as the hidden processing units can be interconnected in a variety of patterns. Therefore the hidden units are depicted as a block. In general all the input units are connected to all the outputs (In this case only one output unit is needed.). The input units are also fully connected to all the hidden units, as are the hidden units to the output units. Therefore the main differences between any two ANN architectures produced using this approach would be the number of hidden units chosen, their interconnections and the weight values on each network connection.

After several simulations (17), it has been concluded that the most successful architecture using PREDICT requires sampled instantaneous three phase voltage and current signals which are taken immediately after the occurrence of a disturbance. This data was assembled into ten sample groups, which represented data for a complete cycle. Figure 5 shows how the data was arranged in discreet, one-cycle groups (Note that this is not a moving window). Using this architecture it was possible to achieve correct classification rate which falls between 98-99%. This is obviously a marked improvement compared to that achieved using layered ANN architecture.

4. CONCLUSION

Two ANN-based LOM relay have been considered in this investigation. The first one uses the well known multi-layer architecture network whereby the hidden processing elements are organised in one or more layers. The best ANN-based LOM using this architecture is found to consist of an input layer with 48 inputs, a hidden layer with 5 PEs and an output layer with a single PE which represents the

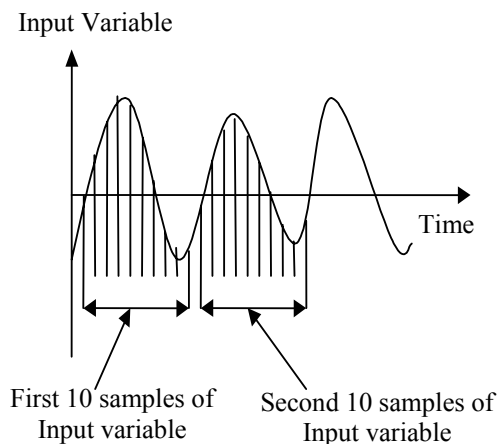


Figure 5 Data sampling from EMTP simulation

trip/non trip signal. The classification rate achieved with this network is 84.44%, which requires 16 samples of each of the three phase voltages.

The second ANN-based LOM relay investigated in this work is based on non-layered architecture where the hidden processing elements between the input and output layers are not organised in layers. Each of them is connected to each other as well as to input and output units. The inputs are also connected to the PEs of the output layer. The optimum structure ANN-based LOM using this architecture is found to consist of an input layer with 14 elements, a block of hidden elements with 10 PEs and an output layer with a single PE which represents the trip/non trip signal similar to first ANN architecture. The classification rate achieved with this network is 98-99%, which requires sampled inputs from instantaneous three phase voltages and currents.

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