DETECTION OF HIGH IMPEDANCE ARCING FAULTS USING AN ARTIFICIAL NEURAL NETWORK

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ABSTRACT

A feed–forward three–layer perceptron was trained by high impedance fault, fault–like load, and normal load current patterns, using the back–propagation training algorithm. The neural network parameters were embodied in a high impedance arcing faults detection algorithm, which uses a simple preprocessing technique to prepare the information input to the network. The algorithm was tested by traces of normal load current disturbed by currents of faults on dry and wet soil, an arc welder, computers, and fluorescent lights.

The algorithm showed good performance in identifying faults disrupted by arc noise as well as good discrimination between faults and fault–like loads. The approach is promising not only in high impedance fault detection but also for abnormal event identification and classification. An alternative neural network topology may then be essential.

Keywords : Protection, Faults, High Impedance, Downed Conductors, Neural Networks.

INTRODUCTION

High Impedance Faults present a source of threat to utilities' customers and personnel. Arcing faults result in waste of energy and can damage property. Protection against these faults comes mainly from a moral point of view, i.e. improving safety to persons.

High Impedance Faults (HIF) are difficult to detect, when the impedance at the point of fault is high enough to limit the fault current to the unprotected region of conventional overcurrent devices. Numerous detection methods have been suggested for such fault detection. However, each detection method cannot detect all electrical conditions resulting from down conductor faults. Furthermore, there are loads that imitate high impedance faults, referred to here as "high impedance fault–like loads" (HIFLL). Some detection methods could lack the security required to discriminate between faults and fault–like loads [1].

The design of a **reliable** high impedance fault detector would include a number of detection methods, to provide the required **dependability** (ability to trip when it should), as well as the proper means to ensure its **security** (ability to not trip when it shouldn't).

Previous efforts in detecting high impedance arcing faults include methods based on monitoring the power–frequency quantities, such as load and ground current levels and sequence voltages and currents, on the source side of the fault location. Others utilized the noise and harmonics produced by arcing as a fault signature [2] to [9]. The difficulty in HIF detection suggests the use of artificial intelligence methodology [10][11], and a neural network approach [12] to distinguish high impedance faults from other system events.

Quite a few of these detection methods require extensive computations in the preprocessing stage to extract the features of the input signal(s). A detection criterion is then applied to obtain the required detection parameters.

PATTERN RECOGNITION NETWORK

Network Architecture

A fully-connected three-layer (input, hidden, and output) feedforward neural network has been used to classify arcing fault currents as distinct from non-fault and fault-like load currents. The network architecture is shown in Fig. 2 . The input vector is composed of 33 elements. The first 32 elements are analog inputs, of values between "0" and "1", that represent the instantaneous values of the sampled line current per cycle, starting at the current zero crossing of the positive half cycle. The last element in the input vector holds a binary value. This element carries a value of "1" if the width of the current conduction period, defined as current samples of magnitude > 30% of the peak instantaneous current per cycle, is less than eight samples per cycle, otherwise "0".

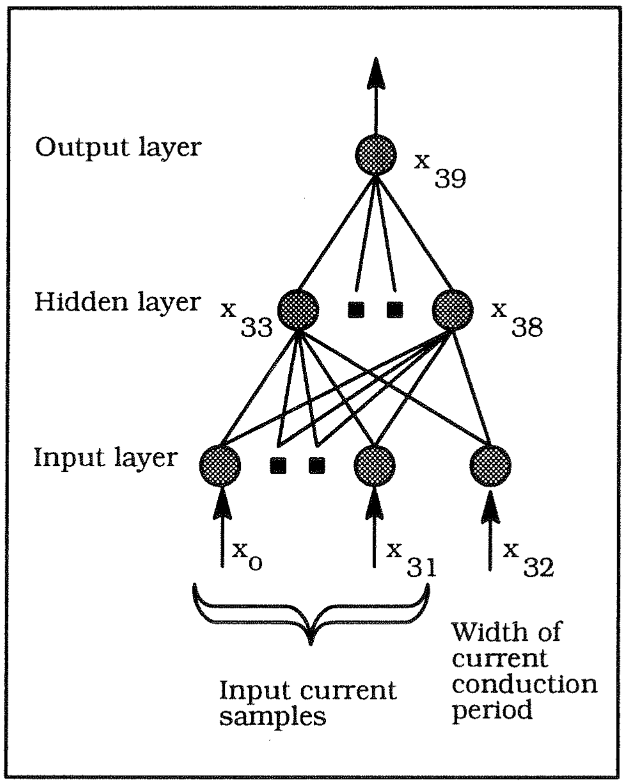

Figure 2 . Architecture of the pattern recognition network.

The hidden layer of the network is composed of six hidden neurons. This layer extracts input patterns features, i.e. undertakes the nonlinear mapping between the input and the output. Selection of the optimal number of hidden neurons to provide optimum network performance, taking into account the training patterns and network topology, is still an open issue. Nevertheless, the guidelines for determining the number of hidden neurons in a binary network [15][16] was adopted as a starting point for this hybrid input network. Further analysis using different numbers of hidden neurons showed that the best performance is achieved with six hidden neurons.

The output layer has one neuron. The target output of the network in the HIF event is "1", otherwise "0". Since the neuron output function is a sigmoid, the "network *score*" will be between these two values.

Training Patterns

The neural network was trained by a set of current patterns of arcing faults on dry and wet soil, computers, an arc welder, fluorescent lights, and sinusoidal loads. Figures 3 to 5 illustrate the patterns used to train the network.

The "high impedance fault" current behavior, Fig. 3 , is affected by the surface conditions. Faults on dry soil are characterized by unsymmetrical half cycles and short current flow interval per half cycle. This is in contrast with faults on wet soil. The degree of dryness or wetness and the surface conditions would result in a different combination of these features for a given ground material. Eighteen patterns of arcing faults, on dry and wet soil, were used in the training set.

The "computer current", Fig. 4 , shows similarity to that of the HIF on dry soil. However, the narrower, and symmetrical peaks in each half cycle are distinctive. Therefore, the width of the current conduction period above 30% of the peak instantaneous current is an easy extractable feature that discriminates the computer current from the fault current.

The "arc welding machine current", shown in Fig. 5 , is composed of two components, namely, the welding transformer magnetizing current and the arc current. The arc current level modifies the waveform of the total welder current. Short arc length is a characteristic common to both an arc welder and a HIF. Compared with a HIF on wet soil of Fig. 3 , the arc welder has a comparable current flow period per half cycle.

The "fluorescent lighting load" represents a widely used non–linear load. Waveform distortion suggests that this type of load contains harmonics used in HIF detection.

To reinforce the network experience in distinguishing faults on wet soil from normal load, a sinusoidal current pattern was supplied in the training set.

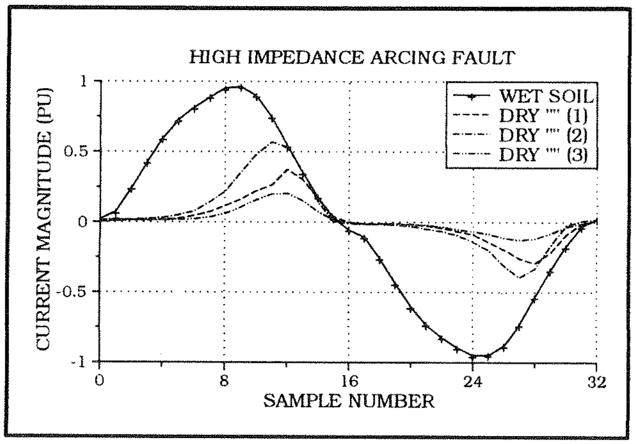

Figure 3 . High impedance arcing fault training patterns.

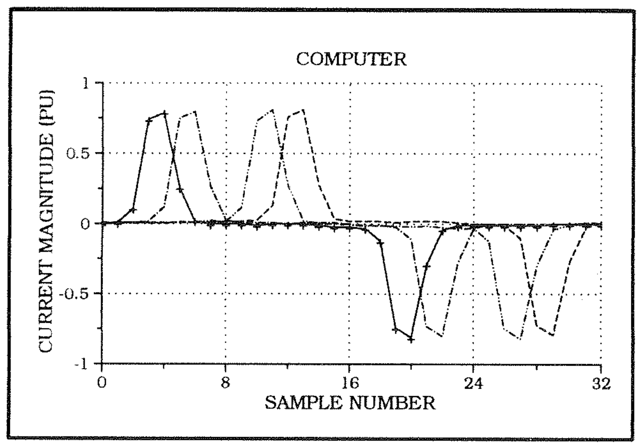

Figure 4 . Computer current training patterns.

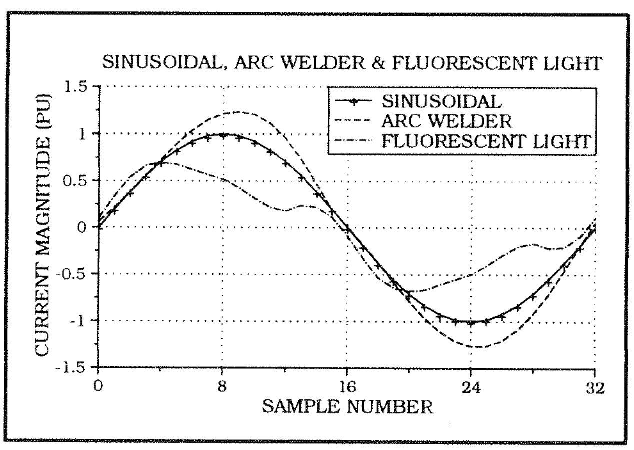

Figure 5 . Sinusoidal, Arc welder, and Fluorescent light training patterns.

Learning Algorithm

The learning rule of the network is the set of equations that modifies some of the weights of processing elements in response to input signals and values supplied by the transfer function. This allows the response of the processing elements to input signals to change over time.

The neural network was trained with the back–propagation algorithm [17]. The back–propagation algorithm is an iterative gradient algorithm that minimizes the mean square error between the actual output of a multi–layer feedforward perceptron and the desired output, see [18].

DETECTION ALGORITHM

The flow diagram of the high impedance arcing fault detection algorithm is shown in Fig. 7 . The analog line current is low–pass filtered and sampled at the rate of 32 samples–per–cycle. Filter cut–off frequency is approximately 1 kHz. The algorithm processes the data as follows :–

Startup

One cycle of the normal load current is stored in a buffer, as the reference load current pattern. Its rms value is calculated: $I_{rms_{ref}}$.

Disturbance Trigger

The algorithm compares the rms value of the following cycles to $I_{rms_{ref}}$. When the new value is sufficiently different from the reference value, the detector starts to take twenty–cycle snapshots of the input current. The excess current $i_{dif}(t)$ is calculated as the difference between the input current $i(t)$ and the reference current $i_{ref}(t)$ patterns, i.e. $i_{dif}(t) = i(t) - i_{ref}(t)$, as shown in Fig. 6 .

Preprocessing

Neural network processing requires the input pattern samples to start at the zero crossing of the positive half cycle. The search for this condition is carried out in the first snapshot. An adjustable number of cycles are skipped to escape initial high frequency oscillations of other power system events. On a cycle–to–cycle basis, the sampled values of the difference current are adjusted to analog values between "0" and "1", to suit the network input level: see Fig. 6 . In the same time the width of current conduction period above 30% of the peak current is determined. The resulting input vectors are passed one–by–one to the NN for pattern identification.

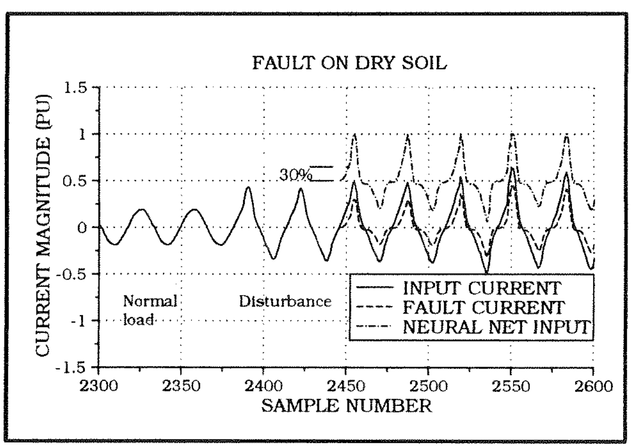

Figure 6 . Disturbance calculation and neural network preprocessed waveform.

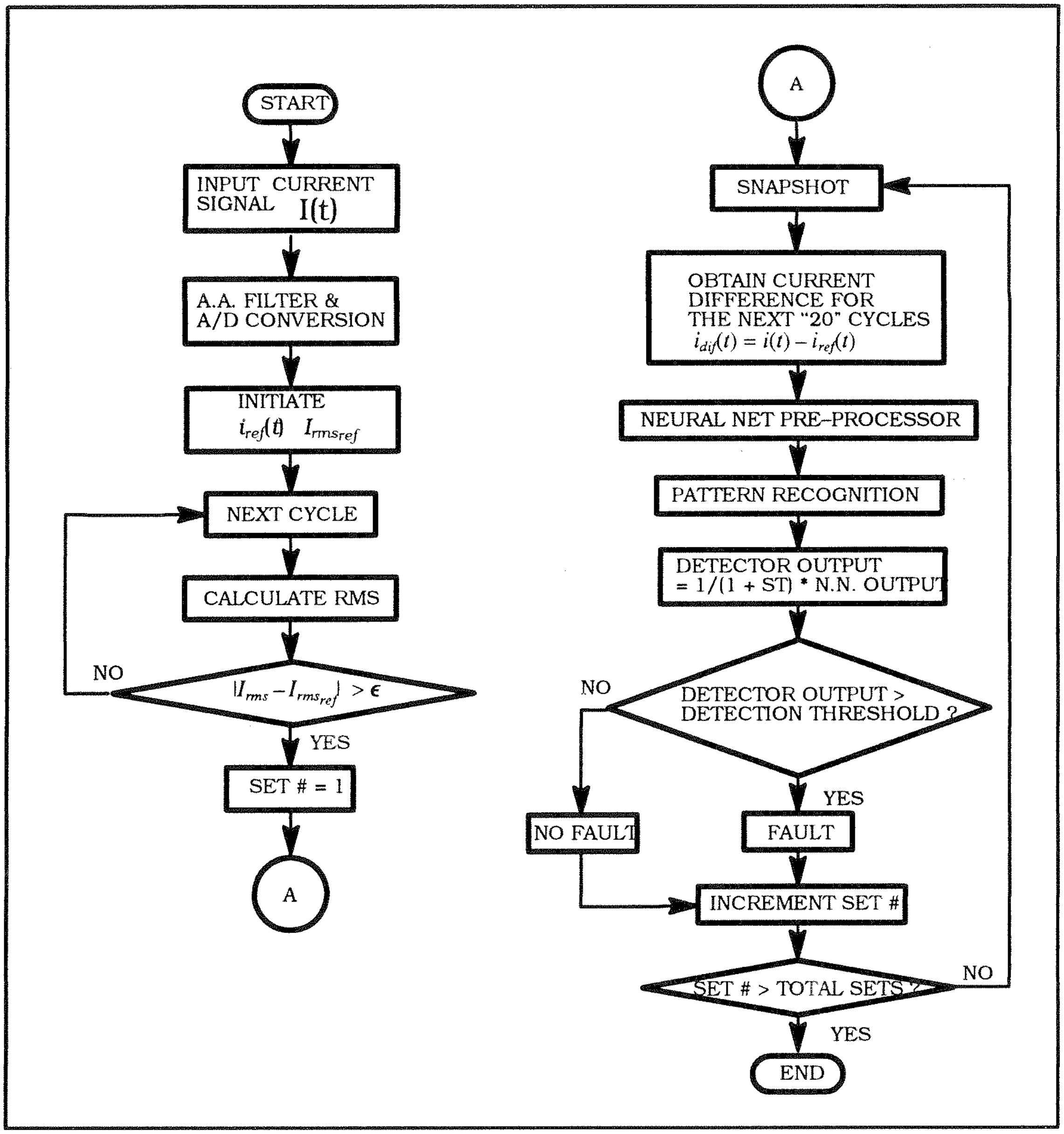

Figure 7 . Flow diagram of the arcing faults detector.

Output

The trained network maps the input to its decision region. The algorithm integrates the NN *scores* to obtain the detector output, i.e. $Output_{new} = Output_{old} + \frac{\delta t}{\tau} * (score_{new} - Output_{old})$, where δt is the integration time step (1 cycle), and τ is the integration time constant (1 second).

The detector output is compared with a detection threshold to classify whether or not the disturbance is due to an arcing fault. The process is then repeated for the next snapshots. The number of snapshots was limited by the length of test data arrays, to 10 sets.

RESULTS

The arcing fault detection algorithm was tested by four second traces of normal load current disturbed by currents of faults on dry and wet soil, an arc welder, computers, and fluorescent lights. The current was normalized to the rated values of the test apparatus. Detailed description of the test circuit, procedure, and the data acquisition methodology is given in reference [1].

Arcing Faults

Training pattern sets supplied to the neural network, for faults on dry and wet soil, were obtained from fault current data shown in Fig. 8. This is the reason why the NN has high *scores* for these faults. For the fault on dry soil (Fig. 8 left) when arcing is almost off, near time 3.2 seconds, one would expect a non–fault response, and that is why the NN *score* went down.

When the soil is very wet, the fault current pattern is very close to a sinusoid. Therefore, the NN shows a relatively low *score* in the first 0.3 seconds of the fault on wet soil: Fig. 8 right. As the dissipated energy in the fault bakes the soil, it dries the surface. The fault current becomes a typical HIF, which is easily detected by the NN.

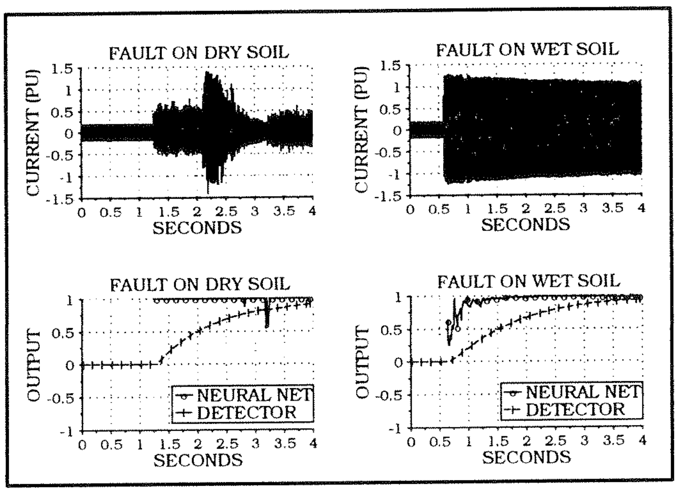

Figure 8 . Arcing faults on a dry (left), and wet soil (right). Top : Current traces. Bottom : Results.

To examine the dependability of the detection algorithm, several fallen conductor faults were staged on dry and wet grassy soil: Figures 9 and 10 respectively. The collected wave forms did contain arc generated noise. The results show an outstanding performance of the fault detector as its output indicates the probable fault presence is more than 75%, in a period of time less than 4 seconds, in all tests.

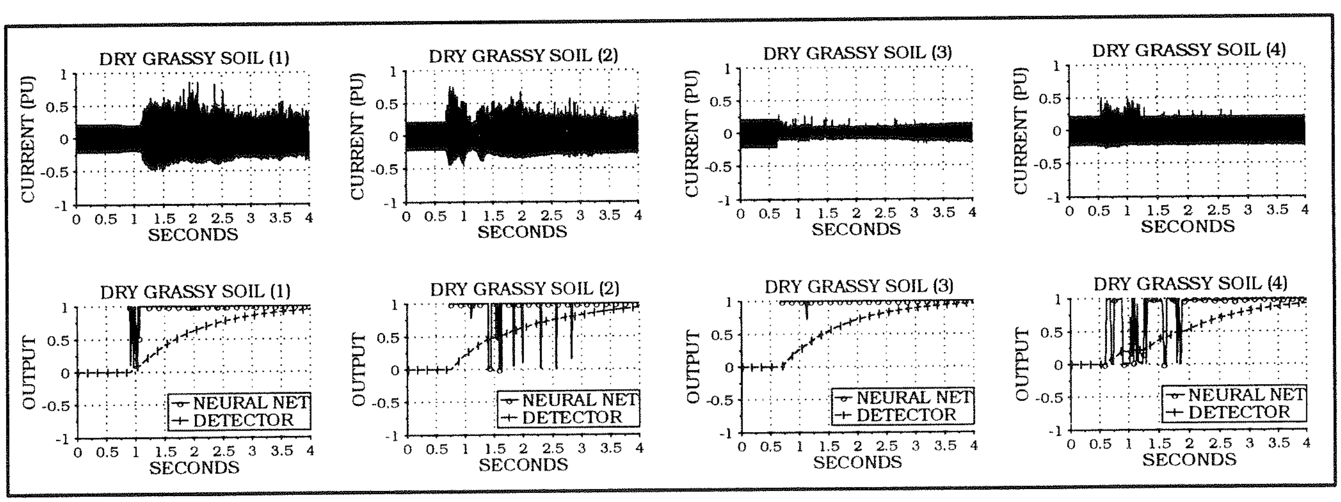

Figure 9 . Tests of arcing faults on dry grassy soil. Top : current traces. Bottom : test results.

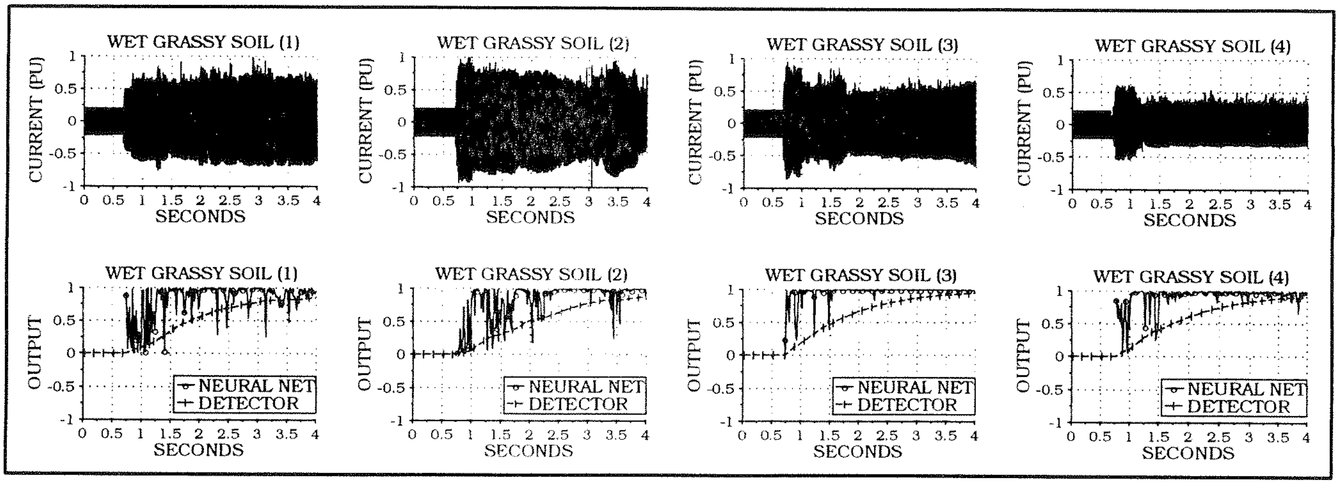

Figure 10 . Tests of arcing faults on wet grassy soil. Top : current traces. Bottom : test results.

The results show good promise of applying the neural networks approach in recognizing high impedance fault current patterns. The algorithm needs to be tested for faults on different ground materials. This may require additional training patterns, and could require different NN architecture or even another network model. Certainly, on-line testing of the algorithm is required. The combination of different test results, and detector hardware would determine the optimum size, number of snapshots, detection threshold level, and the decision time required to determine whether the existing disturbance is a permanent or a temporary HIF.

Fault-like Loads

Arcing loads, such as arc welders and arc furnaces, are loads likely to be confused with high impedance arcing faults. Testing the algorithm with an arc welder load, top of Fig. 11, shows how far the above possibility is a problem for the detection algorithm. The detector estimation for this event as a fault was less than 20%. The results of testing the computer and the fluorescent light loads, middle and bottom of Fig. 11, indicate that the algorithm will also be secure in these events.

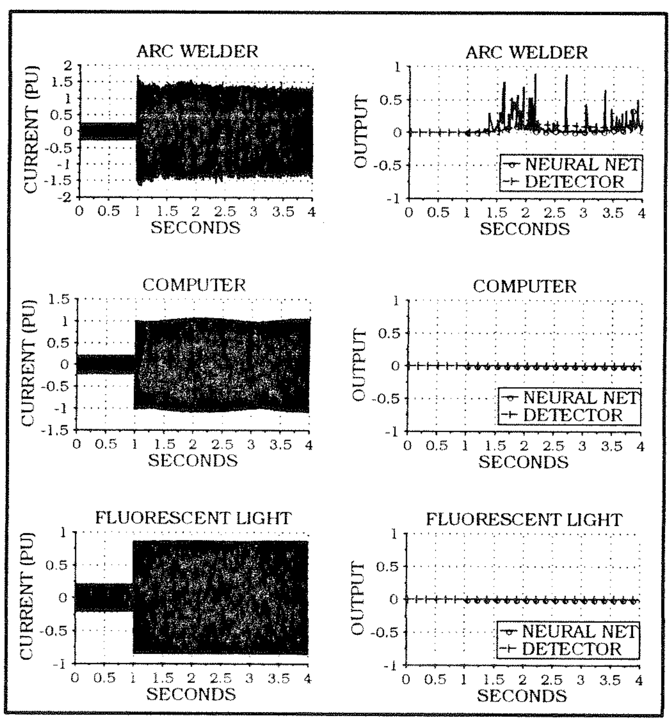

Figure 11 . Fault-like loads. Top : Arc welder. Middle : Computer. Bottom : Fluorescent light.

Training the NN with more patterns of non–linear loads that mimic fault conditions would add to the detector reliability.

CONCLUSIONS

A high impedance arcing faults detection algorithm was designed. The algorithm implemented an artificial neural network for fault current recognition. The algorithm was tested by traces of normal load current disturbed by currents of faults on dry and wet grassy soil, an arc welder, computers, and fluorescent lights.

The detector was able to identify fault events distorted by arcing noise. It was also able to identify the fault–like load conditions. The outcomes of this study indicated that the neural network was able to reach a general solution of the problem, for the available training patterns.

More training examples, that include patterns of faults on different ground materials and fault–like loads, could enhance the network performance. The approach is not only promising in high impedance fault detection but also suggests its use for abnormal event identification and classification. In both cases a different neural network model may be required.

On–line testing is the next step to confirm algorithm reliability.

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BIOGRAPHIES

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