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The development of a neural network-based multi-function protection relay

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Abstract

The protection of DC traction circuits from fault conditions is a difficult task. The paper describes the development of a neural network to be used in a multi-function protection relay. The neural network developed can discriminate between normal train operation and short-circuit conditions on the DC traction supply. The neural network provides fault protection and location. The neural network was trained and tested using both simulated and actual data. The paper presents results showing that the neural network can discriminate between faults on a DC traction system and the normal operation of both camshaft and chopper controlled rolling stock. Conclusions are given on the advantages and disadvantages of using neural networks, along with their possible use in also locating a fault.

1 Introduction

The protection method traditionally used on dc railways was direct-acting over-current circuit breakers. As the total number of substations on a line is minimised, for economy, leading to greater inter-substation distances, and the trains draw higher accelerating currents, increasingly sophisticated protection systems are needed to provide discrimination between fault and load currents. Current practice involves the use of a mixture of direct-acting, undervoltage, rate of rise (di/dt), and timed overload trip protection in order to provide the required discrimination. However remote fault detection is still problematic.

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2 Fault Simulations

In order to develop the relay [1], it was first necessary to simulate the fault current-time profiles associated with dc railways to provide the data for the neural network. This was achieved by modelling the railway circuit and equipment, and deriving equations based on the circuit parameters to represent its behaviour under fault conditions. The neural network-based protection relay was developed to recognise faults on a section of the London Underground Central Line.

Two computer packages were used in producing the models and simulations. MathCAD, with its facility to handle complex equations, was used as a modelling tool to build up a mathematical representation of the circuits used. A spreadsheet package, Microsoft Excel, was used to reproduce the fault simulations in numerical format for use with the neural network.

For ease of analysis of the circuits, and because they cause the most problems for detection and protection, the study has been confined to remote short circuit faults.

2.1 The Circuit Models

Initially a simple theoretical circuit, comprising a single end fed track section, was modelled. Theoretical parameter values were used and the simulated fault profiles developed based on these. Following this the circuit for which the protection was to be developed was modelled. This included real data, supplied by London Underground Ltd, to produce a more realistic model. In developing the models consideration was given to the work of Brown et al [2], [4], [5], Denning [3] and Vlahakis [6].

2.1.2 The Theoretical Circuit Model The theoretical single end fed track was assumed to consist of a substation with a single six-pulse rectifier and a third rail track configuration. The complete circuit used as the test model is shown in Figure 1

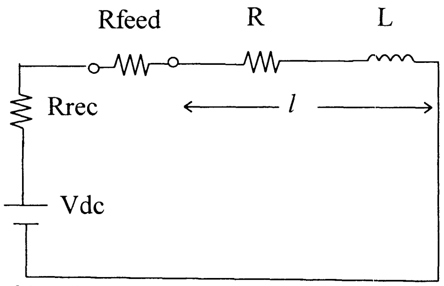

Figure 1 Circuit for a Theoretical Single End Fed Track

2.1.2 The Actual Circuit Model This circuit was modelled on a section of the London Underground Central Line between Wood Lane and Bond Street substations. This gave a circuit consisting of three substations and two sets of

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rails and feeder cable equipment connecting them, as can be seen diagramatically in Figure 2.

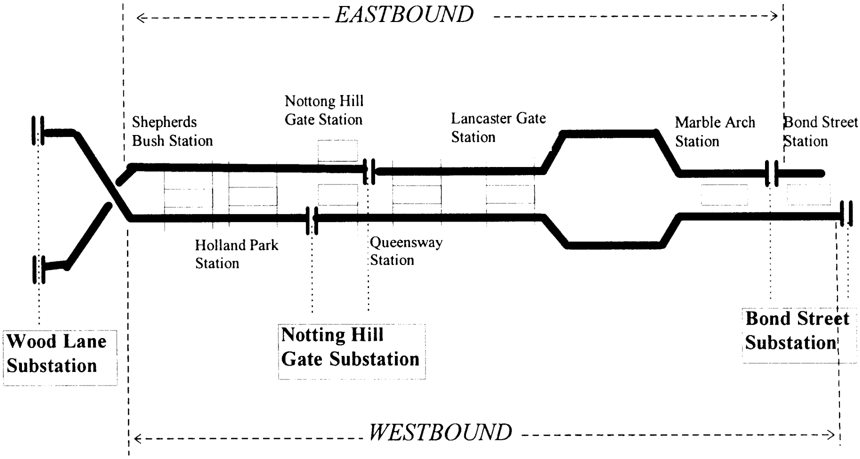

Figure 2 Schematic Diagram of Track Sections

A single line diagram for each track section was obtained from this and is shown in Figure 3.

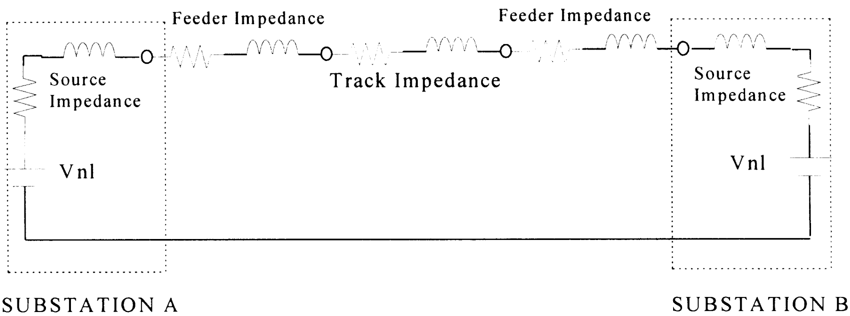

Figure 3 Single Line Diagram of a Single Track Circuit

2.2 Short Circuit Fault Current Simulation

The fault current-time profile has been simulated as an exponentially rising current waveform of the form,

$$i(t) \quad = \quad E/R(1-e^{-t/T})$$

where E = the voltage behind the fault

R = the resistance of the power feed circuit and rectifier

T = the faulted circuit time constant

Since the main aim of this project was to investigate the feasibility of using pattern recognition techniques for dc protection purposes a general approximation of the shape of the profile was considered to be sufficient.

For the Central Line circuit model a range of waveforms were simulated for short circuit faults at 10% intervals along the entire length of each track, as seen from the Notting Hill Gate substation.

3 Artificial Neural Networks

3.1 Description of an Artificial Neural Network

Conventional computing methods execute programs sequentially. Artificial neural networks are based on parallel processing and are said to "learn". This is achieved with the following basic building blocks. The artificial neuron is known as a node and is a processing element. A number of inputs are applied simultaneously and the node determines the strength of each and calculates a combined total. This is then compared with some threshold level to establish whether the output should be high or low

In order to simulate an external disturbance an extra input, known as a bias, or forcing term, can be included or, if required, a forgetting term can be introduced to cause the system to "unlearn" something.

A number of nodes may be combined to form a layer with each node assigned a different weight. Inputs can then be connected to any number of these nodes to produce a series of outputs, one per node. Layers can then be interconnected resulting in three different layer types:

i) the input layer, which buffers the input signals
ii) the output layer from which the network outputs are generated
iii) hidden layers which are internal to the network

The network may or may not be fully connected. Full connection means that all outputs from one layer are passed to every node in the next layer, Figure 4.

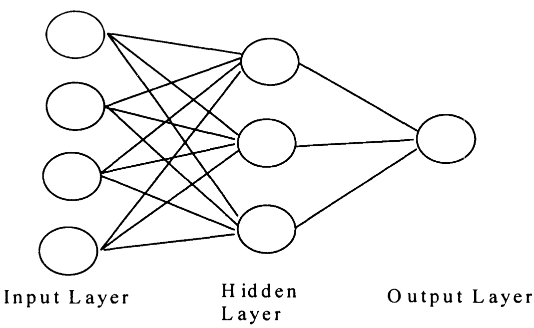

Figure 4 Example of a Fully Connected Artificial Neural Network

3.2 Applications

Artificial neural networks are considered to be well suited to several broad classes of problem, Illingworth [7]. These include constraint satisfaction

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problems, such as scheduling and search problems, dealing with incomplete, fuzzy or corrupted data and pattern/object recognition problems.

They can be used to build up a complete pattern when only partial data is available for the input. Another use is to enable the transmission of compressed data, without loss of important information, by performing vector quantisation, or clustering. A third use, and the one used in this project, is to enable identification of the class best representing an input pattern where the inputs have been corrupted by noise.

4 Development Of A Neural Network Protection Relay

For simplicity and speed of training, a feedforward network structure was used, employing the backpropagation training method. It was implemented in the Stuttgart Neural Network Simulator (SNNS). Data produced by circuit modelling and fault simulation was used to train the network. Test data was derived from measurements and the simulations.

4.1 Preparation of the Training Data

The data used in training the neural network was derived from the simulated current-time profiles. Two sets of data were developed, one to train the network to distinguish between fault and load currents, the other to train it to recognise fault locations.

The input patterns were developed for the fault waveforms by taking 20 equi-spaced values representing the first 200ms of the curve for the faults at 10% intervals along each track section. To prevent the training data from being too precise, and thus limiting the effective operation of the relay, two waveforms were generated for each fault location, one based on the no-load voltage of 670V and the other using the minimum expected voltage of approximately 630V, allowing for tolerances. In this way it was possible to specify a single output for the two fault patterns at a given location. Thus when the test data was applied, the output would apply to any waveform falling within that region, as shown by the shaded area in Figure 5.

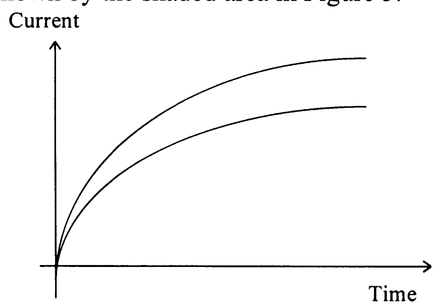

Figure 5 Pattern Range for a Single Fault

The load current waveforms were created from measured data and took account of the quoted minimum and maximum current rate of rise for each train type.

4.1.1 Protection Relay Training Data It was observed from the measured data that the di/dt relays currently in operation trip within approximately 100ms of fault inception and so it was decided that the neural network should be trained to recognise the fault waveform pattern within this time. Training was, therefore, carried out using only the first 100ms of the simulated fault profiles as training data.

In order to present the training data to the neural network inputs in a suitable format the current values had to be normalised. The circuit breaker trip setting was selected as the normalisation factor. The quoted setting was 8,000A and an extra 500A was allowed for the tolerance of the device, resulting in a normalisation factor of 8,500A.

Since the direct acting device could be expected to trip for currents of this value or greater then fault waveforms exceeding this value within the first 100ms of the profile were neglected. This meant that only the waveforms for faults at a distance from the substation of 30% of the track length and greater were used for the Bond Street track sections. For the Wood Lane sections the distance was 40% and greater. Four training patterns were produced to represent the expected limits of train operation.

4.1.2 Fault Location Detection Training Data Fault waveforms for the entire track lengths and over the full period of 200ms were used for training location detection. Normalisation was achieved by taking the value of the current at t = 200ms for the fault closest to the substation as the maximum likely value and normalising all other values based on this.

4.2 Test Data

A separate set of data was created for testing the trained network. The test data was created in the same way as the training data but calculated for faults and loads at different locations to those used for the training data.

4.2.1 Protection Relay Test Data The test data for the protection simulation network comprised a random selection of six fault waveforms and four load waveforms. These test patterns were used with the networks for each track section.

4.2.2 Location Detection Test Data Two sets of test data were prepared to test for recognition of fault location. The first was produced by only slightly varying the fault locations, to within a maximum of 2% of the training locations. The second set was obtained by varying the locations more widely with some of the test patterns falling midway between two training patterns in order to more rigorously test the operation of the networks. Again the same test data was used for each track section.

4.3 Neural Network Development

In order to simulate the protection relay operation a set of feedforward networks were created having a single output whose state should be high to represent a trip signal. Since each pattern was made up of nine values, nine input nodes were specified. A single hidden layer of five nodes was arbitrarily selected to complete the network. Full connection of the network was used so that the output from each node in one layer is fed to every node in the successive layer.

For the networks used to determine fault location the feedforward type was used. In this case the number of outputs reflected the possible number of fault locations with ten nodes being used. The number of input nodes was increased to twenty to accommodate the increased number of values per pattern. The single hidden layer was made up of fifteen nodes. As with the relay networks full connection was specified.

The learning method was chosen to be backpropagation, with a momentum term included to enhance the learning process. The initialisation function, used to set the initial weights within the network, was set to randomise the weights.

4.4 Training The Neural Networks

4.4.1 Training For The Protection Relay The training patterns were applied to the inputs of the network, in random order, for 1000 cycles. At the end of each cycle the simulator computed the error between actual and desired output and the network weights were adjusted accordingly to reduce this error. At the end of the 1000 cycles the network was tested for completeness of training by applying the training patterns individually and observing the output for correct classification.

4.4.2 Training For Fault Location Detection Training took place as for the relay network but with the training patterns being applied 5000 cycles at a time due to the increased size of the network. The training patterns were repeatedly applied until an acceptable error was achieved. This was established by testing each network's response to the application of a single training pattern, as before. If an incorrect or ambiguous classification was made then the training process was repeated. When the correct output was displayed for each of the patterns then the network was considered to be properly trained.

Following the initial testing of the network called Network 1, a further 5000 training cycles were applied to this network in order to ascertain whether performance could be improved.

4.5 Testing The Networks

In order to test for the satisfactory operation of each of the networks the appropriate test patterns were applied to their inputs. These patterns, which had not previously been presented to the network, were applied in random order. For each input pattern the state of the output(s) was noted along with the weighting on the output nodes. These results were then compared with the expected output(s).

5 Results

5.1 Network Training

Early in the training process, when the error between desired and actual output was large, learning took place very quickly. As the training data was repeatedly applied and the networks became more successful at correctly classifying the patterns the error reduced and the learning slowed down.

5.1.1 Protection Relay Networks For the relay simulation network training took place very quickly with 1000 training cycles being sufficient to produce satisfactory classification of the training patterns. The error reduction curve is shown graphically in Figure 6.

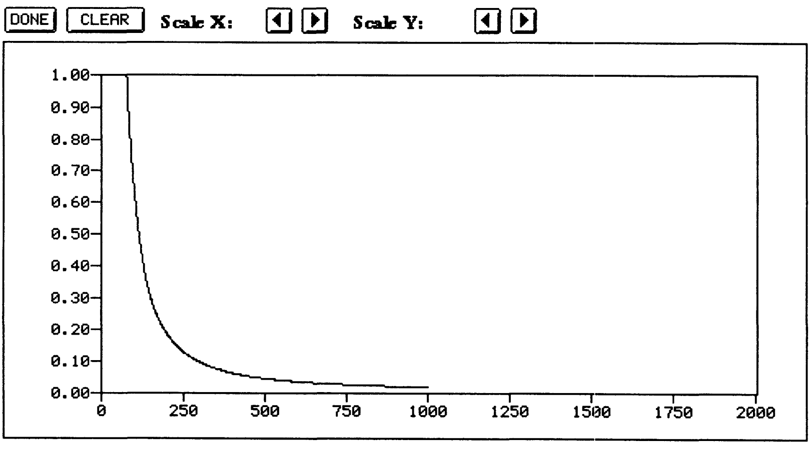

Figure 6 Error Curve for the Relay Network

5.1.2 Fault Location Detection Networks For these larger networks more training was required to obtain satisfactory classification of the input patterns. After 10,000 cycles approximately 50% of the inputs were strongly classified correctly with others being ambiguous or incorrectly classified. With further training the error was further reduced and its operation was considered to be satisfactory after 20,000 training cycles.

On completion of initial training the response of the network to the application of the individual training patterns showed that they were clearly

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classified for outputs 1 to 7 and for output 10. For outputs 8 and 9 the correct output was indicated but there was some slight ambiguity, with neighbouring outputs being indicated as possible matches also. Following the further training of Network 1 there was little variation in the results for outputs 1 to 5 or output 10, but outputs 6 to 9 were more strongly classified.

5.2 Network Testing

5.2.1 Protection Relay Application of the test data to the protection relay networks produced good results. In all cases the networks correctly distinguished between a fault pattern and that of either of the trains. The fault location detection networks resulted in a good proportion of the inputs being correctly classified.

5.2.2 Fault Detection Relay For the location detection networks it was seen that the first set of test data, where the test patterns more closely resembled the training set, produced the more accurate classifications. More ambiguity was seen when the second set of test data was applied since some of the waveforms had been deliberately calculated to fall directly between two training patterns

The classification of test input patterns following the extra 5000 training cycles for Network 1 showed only a very slight improvement in the matching of the most remote faults for the first set of test data. A slightly better response was seen for the second set of test data.

6 Conclusions

6.1 Neural Network Relay Simulation The networks which were developed were able to distinguish between the pattern of the fault waveforms and those for the chopper controlled rolling stock and cam shaft controlled trains.

However only protection against remote short circuit faults has been investigated. For this reason the networks cannot be considered to have been fully tested for complete relay operation.

6.2 Fault Location Detection It would appear to be quite feasible to expect a network of this type to be able to indicate the location of a fault, once detected, to within approximately 300m.

6.3 Advantages and Disadvantages of the Use of Neural Networks One of the advantages of neural networks is their use of associative memory. Other training information, such as patterns pertaining to fault and train locations, signalling information, etc. could also be stored, making for a more versatile device. Parallel processing enables the neural network to quickly classify new, previously unseen patterns. Its fault tolerance means that the network is still able to operate effectively with the loss of operation of a percentage of its nodes. A general disadvantage of neural networks is the painstaking trial and error involved in designing the optimum network architecture for the task.

6.4 Circuit Modelling and Fault Simulation The mathematical modelling and spreadsheet packages used in this project allow for the creation of approximate simulations of the fault waveforms associated with dc railways

6.5 Further Work

6.5.1 The Use of Neural Networks in Relaying and Fault Detection In order to establish the feasibility of using neural networks for relaying purposes the investigation should be extended to consider other types of faults, such as arcing and train borne faults. Also account should be taken of possible rectifier outages and hence reduced supply voltages or single end feeding.

Further network development should be carried out to examine the effect of varying the network structure or learning parameters. In particular it is thought that the Time Delay network may be particularly suited to the application since it is specifically designed to recognise patterns embedded in continuous data.

6.5.2 Circuit Modelling and Fault Simulation Due to the complex characteristics of the fault profiles associated with dc railways it is recommended that a more powerful, or application specific, package should be used to produce simulated profiles for practical use.

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