An AI method to Anticipate and Localise Faults within Telecommunication Networks

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Abstract. The application of IT technologies that make use of the telephone network is dramatically increasing. There is a growing demand to rapidly detect and repair faulty telecommunication lines. This paper identifies a method to anticipate and localise possible fault areas within the Local Access Copper Networks (LACNs). The system employs a proactive approach to identify potential faults within the network. Therefore it is possible to replace plant before an actual fault state occurs. The paper outlines a typical network topology, overview of artificial neural networks, current anticipation and localisation procedures and suggests an artificial intelligent technique for a new anticipation and localisation method. Ultimately these methods may lead to tools being developed to aid an expert and provide better guidance for field maintenance engineers to replace faulty plant.

1. Introduction

With the advent of new technologies such as ADSL (Asymmetric Digital Subscriber Line) permitting higher bandwidths over single copper pairs, there has been less emphasis on replacing old "twisted-pair" copper wires, that appear to have been around forever, with fibre.

The current copper platform between the exchange and the customer is inherently implemented as a tree and branch architecture and does not provide automatic fault detection. With increasing data services being carried by the copper platform, greater reliance is placed on the network. There is a need for proactive daily repairs to be carried out to reduce potential faults in order to improve reliability and maintain customer satisfaction.

This paper discusses an AI based approach to anticipate and locate faulty plant within a telecommunication network.

2. Network Topology

The copper access network in general conforms to the standard tree architecture shown in Figure 1, *Structure of a local access network*. This consists of a primary network that connects the serving exchange to intermediate primary connection points (PCP's) and a secondary network that further distributes capacity from the PCP to customers via intermediate distribution points (DP's). The primary network is normally pressurised with desiccated air from a serving exchange, since access to individual bearers between the PCP and the exchange is not standard practice. Potential problems can be identified within the primary cable by monitoring the airflow to the cable. In contrast, the secondary network is highly unstable and suffers from continuous interventions driven by the re-distribution of secondary capacity and service restorations. The non-pressurised secondary network prevents any proactive monitoring of the cable sheath to take place. Consequently the only way to detect sheath failures indirectly is to use the parametric data obtained from the line test systems.

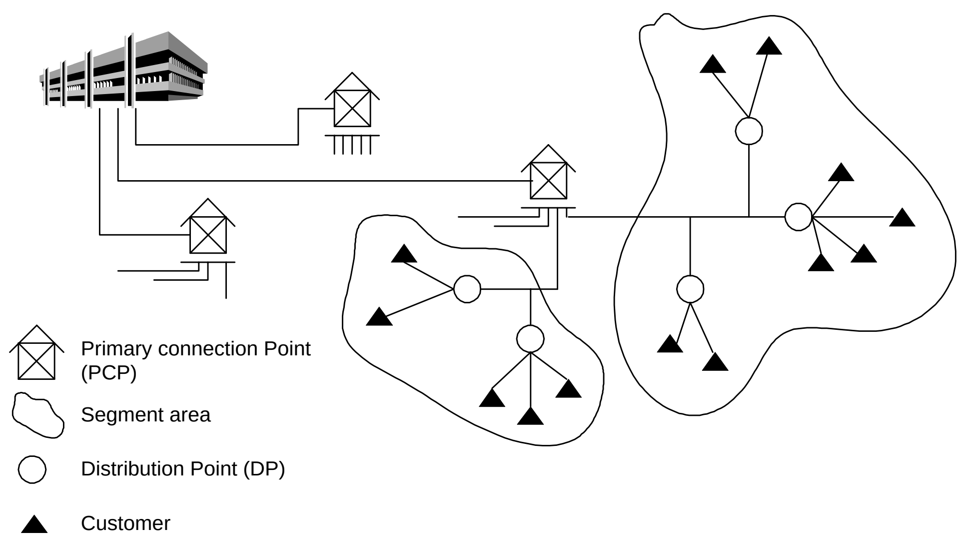


Figure 1 Structure of a local access network

The transmission performance of a network cannot be easily monitored from the line test data. The subjective nature of customer fault reporting makes it difficult to determine with any certainty the parametric values that should be used to identify an under-performing circuit.

3. Neural Networks

Artificial Neural Networks (ANNs) are information-processing systems inspired by models formulated from the workings of the brain. A Neural Network consists of interconnected layers of neurons or processing elements. Data is passed through the network from layer to layer via synapses/connections, each of which is characterised by a weight/strength of its own. In addition an activation function is associated to limit the amplitude of the output of a neuron and is shown in Figure 2, *A simple processing element*. To achieve the desired relationship between the input and output of a network, values must be derived for the connection weights and the activation functions. The process of this derivation is called supervised training.

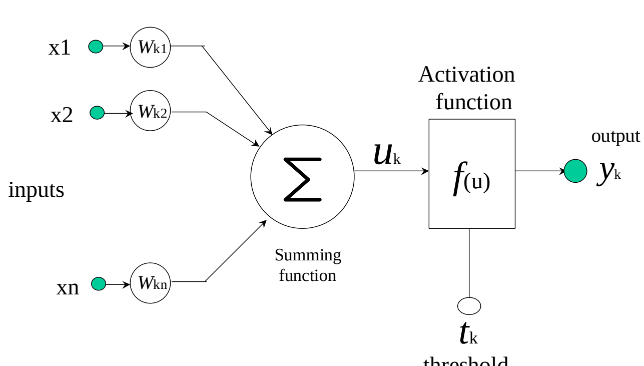


Figure 2 A simple processing element

Neural Networks offer advantages over traditional computational methods because of their parallel structures and the ability to generalise. Generalisation refers to a neural networks ability to produce reasonable outputs from inputs not encountered during the training phase. These information-processing capabilities make it possible for neural networks to solve large-scale problems not currently tractable. There is a need for neural network technology to be integrated in a systematic engineering approach since they are unable to provide a solution in isolation.

3.1 NeuroSolutions

NeuroSolutions is a GUI Windows based neural network simulation environment. Networks are constructed by placing and interconnecting components on a breadboard. Each component has a related inspector window where the user can examine and alter variables.

NeuroSolutions is a powerful working environment that facilitates code generation. The Code Generation option produces ANSI-compatible C++ source code for a breadboard. This allows a simulation prototype created within the GUI to be executed on other hardware platforms and integrated into user applications.

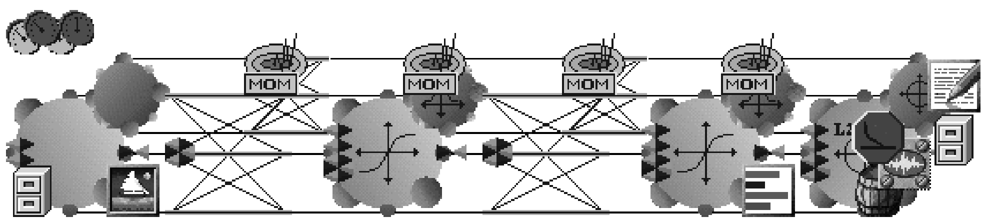


Figure 3: A typical NeuroSolutions breadboard

Shown in Figure 3, *A typical NeuroSolutions breadboard*, is a Multi-Layer Perceptron with a backpropagation plane. Input and desired data sets are read from the file system and displayed as cabinets. An extensive set of probes provides a way of visualising data at access points within the network. After a network is trained, it is possible to freeze the weights and present the network with data not previously encountered.

4. Parametric Data Gathering

The current test equipment employed is manufactured by Vanderhoff Systems. Vanderhoff LTS (Line Test System) consists of centralised computers (Master Stations) which control Remote Test Units (RTUs) located within exchanges. Each RTU connects to a customer line via the exchange Test Access Facility (TAF). Once connection is established, it is possible to perform parametric testing on the selected line.

The LTS performs a variety of DC and AC measurements on individual lines. The fixed tests consist of: -

- DC and AC Voltages A-Earth, B-Earth and B-A
- Resistance A-Earth, B-Earth, B-A, A-B, A-Battery, B-Battery
- Capacitance A-Earth, B-Earth and B-A

A typical time for a routine test is approximately 9 seconds for a Digital Exchange and 15 seconds for an Analogue Exchange. It is possible to program the RTUs to automatically line test for a given area and store the results.

5. Current Methods

5.1 Reactive

Faults are only acted upon when a customer reports a line problem to an operator. The operator will perform a demand test on a customer's line to identify any possible problems. After a problem has been identified, an electronic fault report is generated and stored in an electronic queuing system. Once the report makes its way to the head of the queue, it is then transferred to a maintenance engineer through their Works Manager. A Works Manager is a portable electronic device that connects to the Public Switched Telephone Network (PSTN) and allows an engineer to download information regarding their following job. The information collected by the fault operator is then available to the engineer who will finally locate and rectify any problems.

5.2 Proactive

Currents proactive methods employ a DP scoring algorithm (Health Score). To obtain a Health Score, parametric values are required from the LTS data. A Health Score is calculated for each DP within a given Exchange area.

The highest DP Health Scores are analysed by an expert in the field to attempt to locate potential faulty areas. The analysis process consists of retrieving secondary network maps and identifying possible access sites for an engineer to investigate. After the expert is satisfied with the analysis and has located an access point for an engineer to investigate, a report is compiled and placed on a queuing system similar to that described above in section 5.1. A proactive engineer will then download the information to their Works Manager device and attempt to rectify the problem.

6. AI Based System

The system under development utilises current and historical LTS data collected from RTU’s housed within test exchanges.

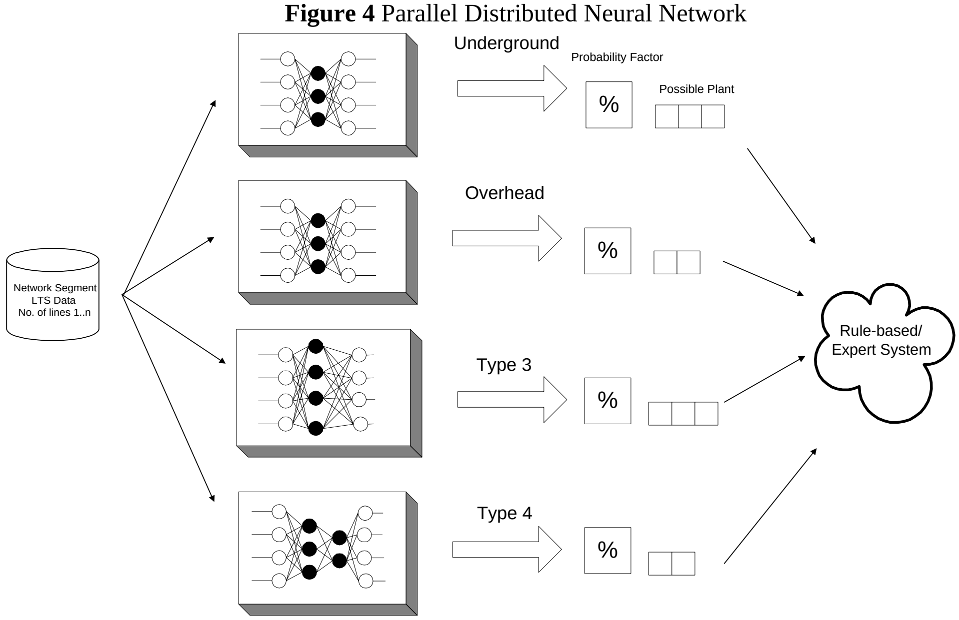
The use of object orientated programming techniques for the AI system employs a structured architecture based on the network model. An effective model is necessary so the application of AI can be utilised to analyse the data in order to derive the information and knowledge necessary for a functional system. The model hierarchy is structured in the following manner: -

- Exchange
- PCP
- Segment
- Distribution Point
- Telephone Number
- LTS

A single exchange can accommodate tens of thousands of lines. Therefore the overall formulation of the model has a major significance on the operating speed of the system. Line monitoring on a regular basis is essential to increase the system efficiency.

A two-stage process is incorporated; the first stage utilises the model and a Parallel Distributed ANN. This is used to anticipate and locate possible faults at the segment level, consequently reducing the search space and travelling time for engineers. The second stage employs a rule/expert-based system that uses deterministic methods to improve the detection of faulty plant at the geographical level. The ANN structure is shown in Figure 4, *Parallel Distributed Neural Network.*

Figure 4 Parallel Distributed Neural Network



6.1 ANN Training

The ANN system must be trained with proven historical LTS data before it can be made operational in the field. Training the ANN system is a critical procedure, therefore expert knowledge is required when generating the training set.

Using a Parallel Distributed ANN system enables the independent training of each ANN sub system. Different training algorithms can be selected which are most appropriate for the various fault categories. For example a standard Multi-Layer Perceptron (MLP) typically trained with static backpropagation can be implemented for small/medium data sets. As data sets increase (medium/large) Principal Component Analysis can be employed within the MLP to efficiently reduce the input space and consequently decrease training times.

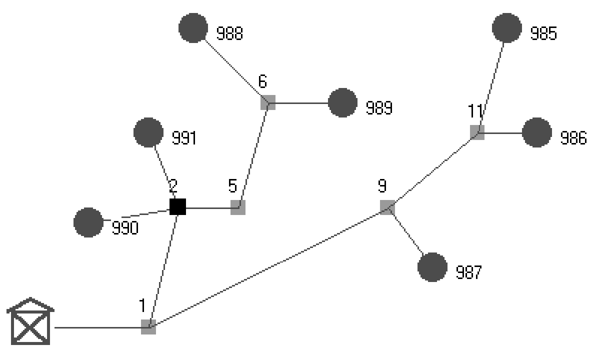
6.2 First Stage Process

After a PCP area has been selected for analysis, each segment is tested for possible faults. Past and current LTS data is automatically gathered for the relevant telecom lines and normalised for input to the ANN system. The data is presented to the system and the outputs represent the type of possible/current fault on each line. Each potential fault output is rated by a probability factor, with higher probabilities indicating a greater fault severity. Potential faults are grouped because it gives a better indication of the locality and it is more cost effective to rectify a group of faults.

6.3 Second Stage Process

For a two-stage system to be effective, DP and joint access information at a geographical level need to be captured electronically and incorporated within the model. This information is currently unavailable, but with the possibility of 80% of joint information being held electronically through the introduction of EPR (External Plant Records) within the forthcoming years, this may become a reality.

The second stage incorporated within the system applies deterministic methods to locate faulty plant effectively at the segment level. Figure 5, *A virtual map of a segment area*, shows the typical output from the system.



Node	Factor
2	38
5	29
6	29
1	27
9	3
11	0

Figure 5 A virtual map of a segment area.

A node factor is calculated from the ANN results. The highest factor (38) in the table indicates the first node (2) to be investigated. From the above output, the network shows a tree with two main branches and clearly identifies a problem in the first branch.

7. Test results

Preliminary tests have been carried out on a sub system of the parallel ANN. The network was trained on underground faults with a relatively small training set of fifty theoretical samples, each with five LTS readings. The type of neural network implemented in the tests was a generalised feed forward network with an input, single hidden and output layer with also a direct connection between the input and output layers. The supervised training algorithm employed was backpropagation.

The time taken to train the network with a mean squared error (MSE) less than 0.001 is below one minute on a 166 MHz Pentium machine. A local minimum has so far never been encountered due to the inclusion of a momentum term within the training algorithm but on some occasions it was found that the network was over training, see Table 7.1, *Classification comparison with different MSE goals*.

MSE Goal	Epochs	Classification
0.1	10	35%
0.05	19	42%
0.01	470	75%
0.001	1650	84%
0.0001	5420	79%

Table 1 Classification comparison with different MSE goals

Tests have also been carried out on the training phase using a cross validation set, around 10% of the training set was used in the experiments. Using a cross validation set ensured the network did not over train and was verified in the test stage. Numerous network simulations have been run with real data and early indications show generalisation to be quite good. The ANN recall time for a segment area to be examined is less than a second.

8. Conclusion

Since there is an ever-demanding need for efficient methods to minimise faults occurring on Telecommunication Networks, advanced AI methods need to be investigated for their effectiveness. The feasibility of such a system incorporating a Parallel-Distributed ANN has been outlined in the paper.

As machine learning is employed by the use of ANNs, there is a need for an on going training process to compensate for the daily changes that take place within the network. The ANN will ultimately learn the relationships between LTS information and the fault types that occur. Output from the ANN will give an indication of the failure that may occur, allowing an expert to better direct an engineer to inspect possible faulty plant.

Current research is underway to optimise the training process, therefore reducing the need to manually change variables that can affect the performance of the training algorithms.

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