Diagnosing Faults on Telephone Subscriber Loops Using Neural Networks

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Montréal

September 1993

A thesis submitted to the Faculty of Graduate Studies and Research

in partial fulfillment of the requirements for the degree of

Master of Engineering

Abstract

Neural networks have recently regained significant interest in the scientific community for their ability to generalize about large samples of data. In this thesis, the feasibility of applying neural networks in the domain of telephone access network fault identification and localization is explored. Firstly, the access network and the computerized work environment of today's Repair Service Bureaus are described. A survey of past and present automated diagnosis systems used in communications follows. Neural networks are then presented and the back-propagation learning algorithm is given particular attention. Another literature review ensues where neural network based diagnosis systems from a number of domains are presented. Finally, the first components for an improved access network maintenance system are laid. Experimental results show that the opportunity exists to benefit from neural networks pattern classification ability in access network maintenance. A discussion of results and suggestions for future research work ends this thesis.

Sommaire

Les réseaux neuronaux ont récemment connu un regain d'intérêt marqué de la part de la communauté scientifique, en grande partie pour leur capacité de généraliser à partir d'exemples d'entraînement. Dans cette dissertation, la faisabilité d'appliquer les réseaux neuronaux aux problèmes d'identification et de localisation de pannes dans le réseau d'accès téléphonique est explorée. Le réseau d'accès et l'environnement de travail informatisé des centres de vérification actuels sont tout d'abord décrits. Une revue des systèmes de diagnostic automatique présents et passés utilisés dans le domaine des communications suit. Les réseaux neuronaux sont ensuite présentés et une étude particulière de l'algorithme d'apprentissage basé sur la rétro-propagation est offerte. Une seconde revue litéraire suit, couvrant cette fois les systèmes de diagnostic basés sur les réseaux neuronaux dont l'application n'est cependant pas restreinte au domaine des communications. Finalement, les premiers blocs d'un système amélioré de maintenance du réseau d'accès sont jetés. Les résultats d'expérimentation indiquent que l'opportunité pour les systèmes de maintenance du réseau d'accès de bénéficier du pouvoir de classification des réseaux neuronaux existe. Une discussion des résultats accompagnée de suggestions touchant de futurs travaux de recherche terminent cette dissertation.

Acknowledgments

I would like to thank my research advisor Dr. Alfred S. Malowany for giving me the opportunity to carry out this research. I particularly appreciated his support and guidance throughout this work. Special thanks also go to Rajiv Pancholy and Louis Barbeau of Bell-Northern Research who initiated this project with McGill University and to the members of the Testing Automation Research Project at BNR: Eugene Gulko, Abbas Taher, Christian Lefebvre, Asnat Macoosh, and Woon Tong with whom I shared many enlightening discussions. My fellow students at McRCIM also deserve my gratitude. It was reassuring to know I could always count on the "veterans". So thanks to Marco Petroni, Nick Fumai, Christian Collet, Jean Drolet, Jean-François Panisset, Gilles Fayad, and especially Kathleen Roger for helping me with this second language and for reviewing my thesis.

Je désirerais remercier mes parents et ma soeur pour leur support et leur compréhension. Je leur dois tout ce que j'ai appris. La rédaction de cette dissertation s'est faite au détriment de leur compagnie et celle de mes amis proches. Je remercie donc également Daniel Desmeules, Nathalie Brault et Lise Coulombe pour leur patience, leur compréhension et leur amitié. Finalement, c'est avec la plus grande affection que je remercie ma compagne, Chantale. L'ampleur de ce travail a inévitablement affecté le temps que je pouvais consacrer à notre vie commune et j'apprécie son support ainsi que l'extrême patience dont elle fit preuve.

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1.1 Motivation

It is now estimated that there are around 15 million telephone lines in service in Canada [71]. Because of forces like fault avoidance, cost reduction, and customer satisfaction, it is in the interest of telephone companies to enhance their network maintenance operations. Significant improvements have been achieved in the past two decades, especially with the introduction of Operational Support Systems (OSS). With these systems, Repair Service Bureaus (RSB) have become virtually paperless operations. With the ever increasing complexity and diversity of the telephone access network, the automation and improvement of many maintenance processes are now being considered.

1.2 Objectives

The scope of this research work is to investigate the applicability of neural networks to telephone access network maintenance. The access network is the portion of the network which connects the subscriber's equipment to the telephone operating company switching device. The other portion — the transport network — interconnects switching equipment. Trunks connecting switches in the transport network are designed with robustness in mind as they carry high volumes of traffic. Alternate routes are even made available in case the primary ones would fail. Such protection is unfortunately not given to the access network. It would not be economically feasible to provide every single line with all the protection given to trunks. Not surprisingly, a significant portion of the total network maintenance cost is devoted to the access network [67].

Neural networks have been chosen for their pattern classification capabilities. The prime objective of this research is to evaluate the improvements in diagnosis performance that could be brought to current network maintenance operations by using neural networks fed with data readily available in various OSS, and to determine which additional data elements would be necessary to provide wider fault coverage.

1.3 Thesis Overview

Chapter 2 gives an overview of the telephone access network maintenance environment. This sets the context in which this research work was carried out. A literature review in Chapter 3 reports advances that have been made in the past years to improve telephone access network maintenance. Chapter 4 gives an introduction to neural networks and details the learning algorithm that was used in this research work. A literature review of neural network classifiers used in diagnosis is then given. Chapter 5 presents the prototype system that was used to evaluate neural networks for performing diagnosis on telephone lines. A discussion on implementation, results and future extensions follows. Finally, chapter 6 concludes this thesis.

Chapter 2 Overview of Telephone Access Network Maintenance

This chapter describes the context in which this research work has been carried out. The first section presents the subscriber loop and its various components. The next section gives an overview of the functionality of the Centralized Automated Loop Reporting System (CALRS[1]), and the problem domain it covers. The subsequent section presents some other Operational Support Systems involved in maintenance, provisioning and billing. A discussion of the evolution of telephone network technology, services, and maintenance operations ends this chapter.

2.1 The Access Network

Figure 2.1 shows a typical subscriber loop. All subscriber loops taken together form the access network. This section describes the subscriber loop first in terms of its components and second, in terms of how it has been partitioned by the various telephone company maintenance organizations. An understanding of the subscriber loop from both these points of view is necessary to grasp why access network maintenance is carried out the way it is today. Finally, problems that may affect subscriber loops are described.

2.1.1 The Components Forming the Subscriber Loop

A subscriber loop usually designates a pair of wires called *tip* and *ring*. It also shares a third wire called *ground* (or *sleeve*) with the other loops in the cable to which it belongs. Tip and ring are denominations that date back to the days of switchboards when switching was done manually. In those days, operators connected calls using connection cords ended by switchboard jacks. The tip of the plug connected one wire while the ring, which was isolated from the tip,

1. CALRS is a trademark of Northern Telecom.

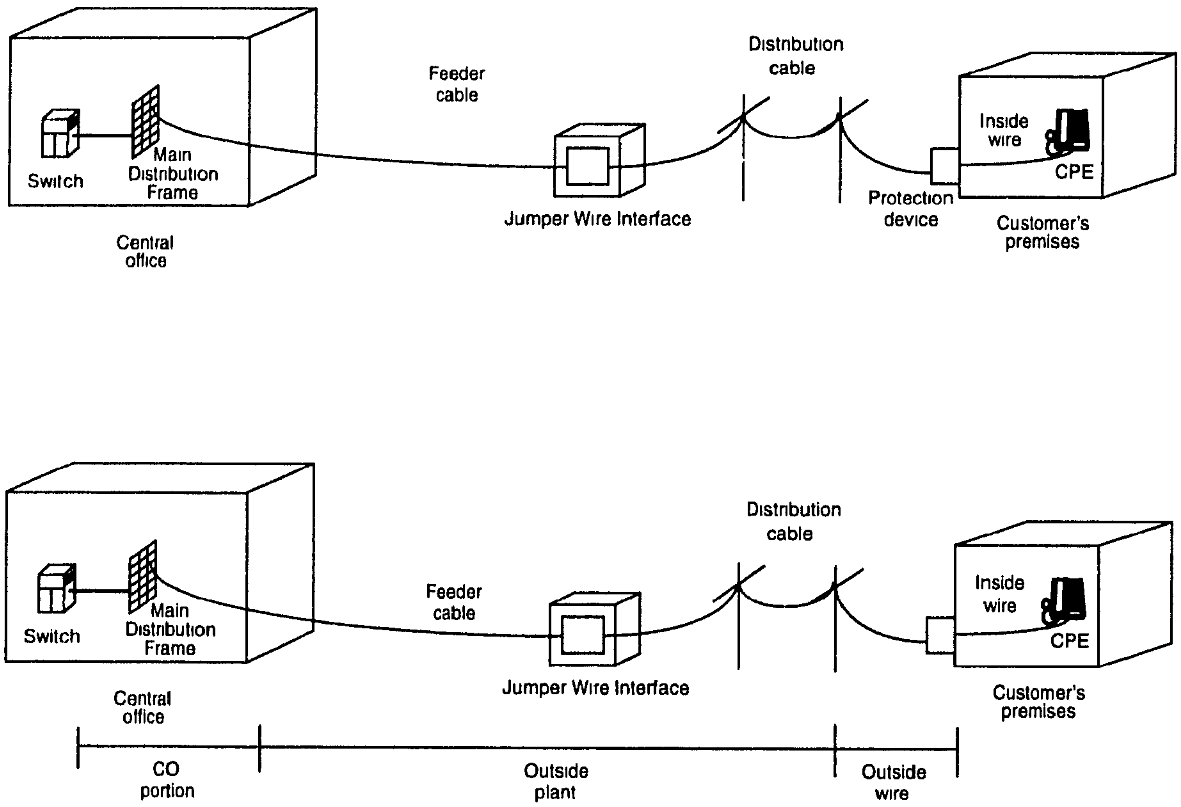

Figure 2.1: (a) The components of the subscriber loop;(b) the subscriber loop as divided by various telephone company maintenance organizations.

connected the other wire. The sleeve was composed of the body of the plug and was connected to a common ground. Figure 2.2 shows a switchboard jack. This terminology will be used when we discuss problems affecting subscriber loops. Prior to this, the components forming the subscriber loop are described.

The subscriber loop originates at the line card in the central office switch. In modern digital switching devices, the line card is the circuit responsible for the analog-to-digital and digital-to-analog conversions between the switching device and subscriber loop. The pair of wires connected to this line card goes to the main distribution frame (MDF). One can think of the main distribution frame as a matrix where any line card can be connected to any subscriber loop. The

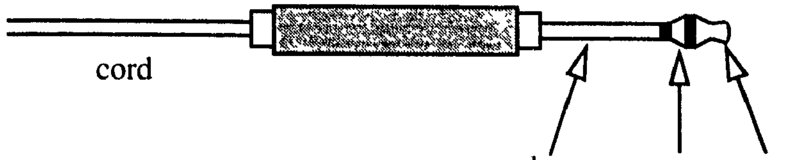

Figure 2.2: Switchboard jack.

pair of wires on the subscriber's side of the main distribution frame is called a feeder pair and is part of a feeder cable. Not too far from the subscriber's premises is the jumper wire interface (JWI) cabinet. This cabinet can be thought of as a small version of the main distribution frame. There, every pair of the feeder cable has an appearance on a connection matrix and any pair of wire connected to the subscriber's premises, i.e. any distribution pair, can be connected to any of the available feeder pairs. In a jumper wire interface, there are more distribution pairs than feeder pairs. This is normal since up to three pairs of distribution wires can run to all subscriber's premises even though only one of them is typically used. The distribution pair connects to a protection device just as it enters the subscriber's premises. This protection device is typically a set of carbon fuses that protect the inside premises loop from hazardous voltages. Finally, on the other side of the protection device, the distribution pair, then called the inside wire, runs to the customer premises equipment (CPE). Telephone sets are typically the CPEs found in subscriber premises, but modems, facsimile machines and answering machines are also common.

The description given above is that of a typical subscriber loop. However, if the loop is long, loading coils are installed at regular intervals on the loop to help reduce attenuation. In other cases, the subscriber loop may originate from a remote concentration unit. In such a situation, the feeder cable in Figure 2.1 on page 4 can be replaced by a carrier, and the jumper wire interface cabinet by a remote concentration unit. Subscriber loops are connected to the remote unit as if they were connected to a switching device in a central office. However, conversations carried on those loops are all concentrated on a carrier that goes to the central office. At the central office, the switching device processes all these conversations as if they were carried by normal loops to the main distribution frame.

2.1.2 The Subscriber Loop as Viewed by Maintenance Organizations

Telephone network maintenance organizations partition subscriber loops in a slightly different way. The length of wire that is inside the central office is known as the CO portion of the loop. The stretch going from the central office to the last pole on the way to the subscriber's premises is known as the portion belonging to the outside plant. The pair of wire going from the last pole to the protection box is called the outside wire. Finally, the last stretch of wire going from the protection box to the customer premises equipment is termed the inside wire.

The partitioning described above reflects the way maintenance is distributed among telephone company work forces. The central office maintenance people take care of the CO portion of the subscriber loop. The cable repair staff handles the maintenance of the outside plant. Finally, station repair people are responsible for inside and outside wire problems as well as telephone sets problems.

2.1.3 Problems That May Affect Subscriber Loops

Problems affecting subscriber loops are generally of two types: physical damage and transmission impairments.

Physical damage

The subscriber loop operates in a hostile environment: outside wires are ruptured by trucks, underground cables are torn apart by excavating machines, inside wires are cut or squeezed by people renovating their house, weather conditions cause wires to rust, etc.

A loop that has tip and/or ring open, or tip and ring short-circuited prevents a subscriber from placing and receiving calls. Loops damaged by rust are noisy. In the worst cases, rust may cause conductors to short circuit each other, or to crack open.

Physical damage to the loop is the main cause of all problems reported to Repair Service Bureaus [81]. It is naturally easier to fix a problem when the subscriber can visually identify the trouble since this saves repair personnel the laborious task of locating the fault. When the customer cannot visually identify the problem, maintenance people must rely on electrical measurements to identify and attempt to locate the fault. A short circuit is recognized by the low resistance value measured between tip and ring. A grounded conductor has a low resistance value between its terminal and ground. A loop that has both tip and ring cut open will show an abnormally low capacitance value between tip and ring. Finally, a pair that has either tip or ring cut will give significantly different measurements for tip-to-ground and ring-to-ground capacitances.

Transmission impairments

Transmission impairments that may be encountered during a conversation can be due to [35][93]:

- transmission loss;
- crosstalk;
- circuit noise;
- power influence;
- impulse noise;
- distortion;
- echo.

Transmission loss accounts for the attenuation that the signal suffers from going through wiring, coupling transformers, coupling capacitances, and other devices. Crosstalk is the partial replication of a signal from one channel into another channel. Crosstalk can be caused by electromagnetic coupling between physically adjacent circuits, circuit unbalance, components and circuit boards in the switching device, or excessive repeater gain. Circuit noise is the noise that appears across the two conductors of the loop. It can be due to random thermal motion of electrons, static from lightning storms, or errors caused by quantizing the signal into discrete steps. Power influence designates the type of noise resulting from longitudinal currents induced from power lines adjacent to the loop. Its effect — a steady "hum" — is more noticeable when the loop is unbalanced. Impulse noise is caused by arcing relay contacts, corroded connections, and bad wire splices. It is usually defined as a voltage increase of 12 dB or more above the background noise lasting 10 ms or less. Data communications are particularly affected by this type of noise. Distortion can be linear or non-linear. Non-linear distortion can be caused by transformers, active devices, analog-to-digital converters, etc. Linear distortion can be caused by phase and amplitude variations in some filters [35]. Finally, echo or signal reflection can happen in a circuit with badly matched impedance and becomes objectionable when there is sufficient delay, thus making conversation very difficult.

Non-Electrical Problems

Customer Action Faults form a category comprising all the faults generated by subscribers not properly using their telephone sets. A well-known fault included in this category is the receiver off-hook. Telephones left off-hook draw current from the central office battery. After a certain period of no signalling activity from the user, the switching equipment seizes the line, i.e. it removes the battery from the line to avoid wasting resources, both in terms of energy and call processing. Somebody trying to make a call on a line which has a secondary set with the receiver off-hook will not be able to signal the number desired and may go to the neighbor to call the Repair Service Bureau. These calls sometimes result in unnecessary dispatches.

This category of faults has grown in the recent years with the offering of Custom Calling Features (CCF) and Call Management Services (CMS)[1], and it is likely to grow even more with the advent of ISDN, home telecommunications, video-on-demand, etc. A new breed of problems with no relation to the loop itself, but rather to the services it carries, has appeared and

1 Also known as Custom Local Area Signaling Services (CLASS) in the U.S.

will continue to grow and stress the urgent need for a better integration of telephone companies' management information systems.

2.2 CALRS: A Centralized Automated Loop Reporting System

Northern Telecom first introduced CALRS in late 1976 to answer telephone companies' need to automate and streamline their Repair Service Bureau operations [28]. The creation and flow of trouble reports, the maintenance of customer line records and trouble reports, line testing, and, to some degree, diagnosis, were all mechanized. This led the way to a paperless Repair Service Bureau. In addition, CALRS provided tools for the analysis of trouble trends and for administrative tasks, such as the evaluation of the workforce performance.

2.2.1 Hardware Architecture

Figure 2.3 shows the original architecture of CALRS. The CALRS system was originally composed of 3 PDP-11 mini computers, each one of them handling specific tasks. The database processor handled the database disk drive, the backup magnetic tape drives, and the local and remote printers. The terminal processor provided the person machine interface to the system and performed some system administration tasks as well. The different positions are explained in the next section. Finally, the test processor performed all loop accesses and test functions using local or remote test units. Today, CALRS has been ported to the UNIX environment.

2.2.2 Functional Operation

The main goal of CALRS is to ease the flow of trouble reports within the Repair Service Bureau. To this end, it electronically supports a number of different positions, each with their own functionality and privileges. Figure 2.4 shows the different positions and systems, and how

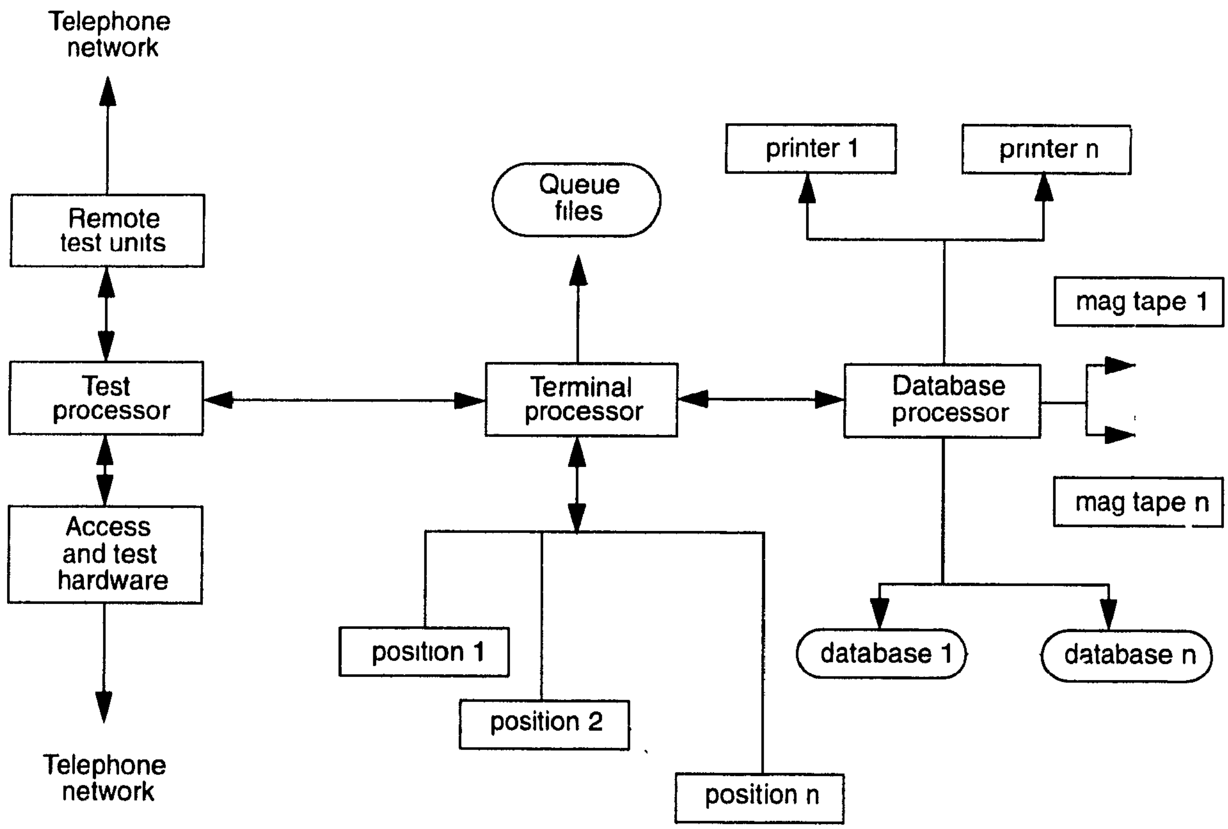

Figure 2.3: Original CALRS system architecture [28]

they interact. Even though it is not depicted explicitly, positions contained in the shaded region communicate and exchange electronic trouble tickets with one another. The roles of the different positions namely answer clerk, tester, dispatcher, analyst, records clerk, manager, and robot will now be explained [28].

Answer Clerk

The answer clerk is the contact with the customer. The function of this position is to record the description of the problem the subscriber is reporting. If the problem is a broken telephone set, the answer clerk simply directs the subscriber to the nearest phone center where the set will be

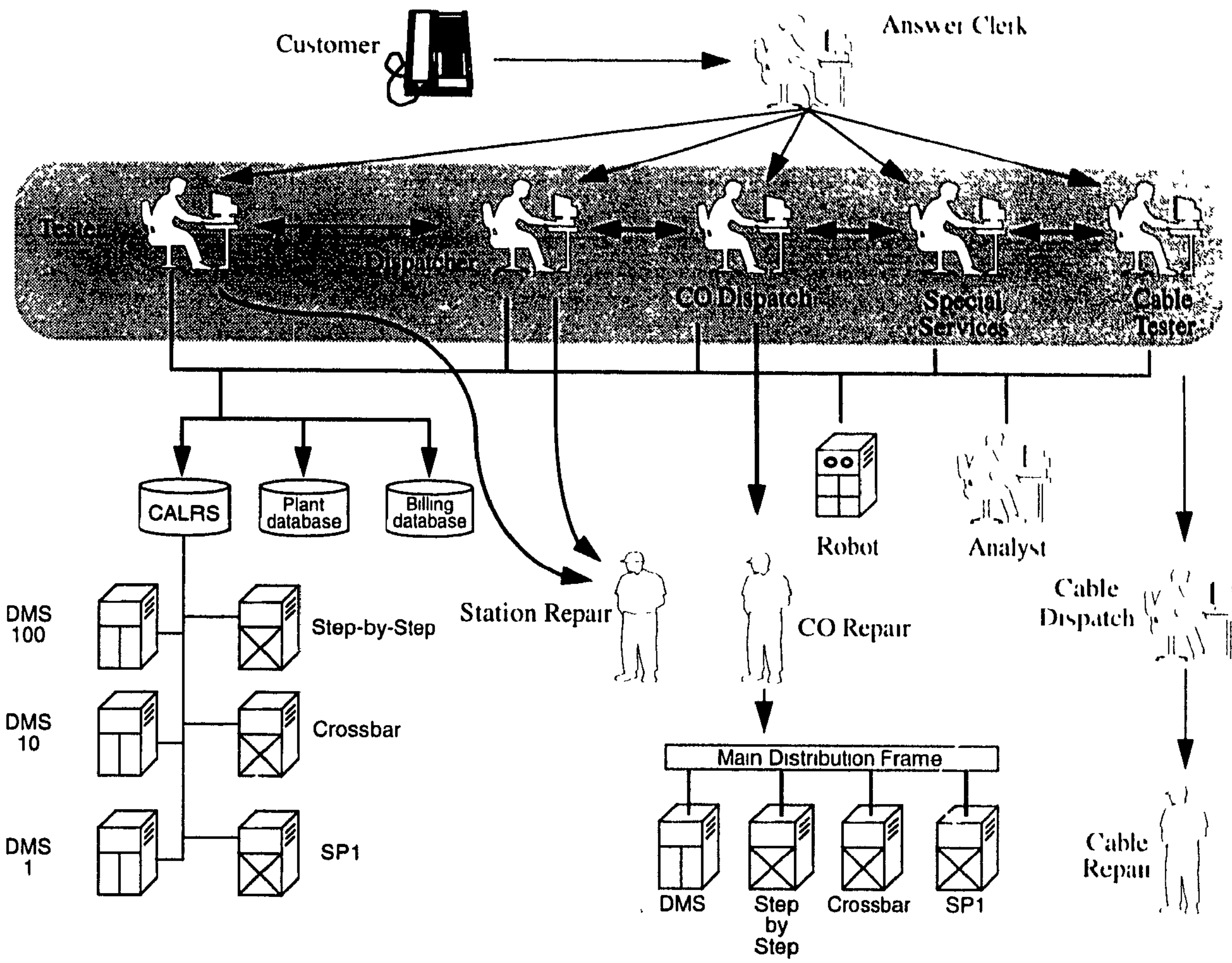

Figure 2.4: Interaction between Repair Service Bureau positions and Operational Support Systems.

replaced. If the problem lies in the misunderstanding of a feature such as call forwarding, the necessary instructions are described to the customer.

In the case of a subscriber reporting noise on a line, or being affected by metallic conditions such as open circuits, short circuits and shorts to ground, the answer clerk issues a verify command on the line in trouble provided the customer has hung up or is calling from another line. The test unit then returns electrical measurements which CALRS interprets to provide the answer clerk with a verify code. The clerk uses this code to determine if a technician needs to be sent and if so, informs the customer. If the problem is suspected to be inside the customer's premises, the answer clerk sets up an appointment with the subscriber. Finally, the clerk uses this code to route the trouble report to the appropriate position.

Tester Position

The tester picks up where the answer clerk left off for those problems requiring further investigation. In addition to the verify command available to the answer clerk, the tester has access to a suite of tests that allows for the testing of anything from the rotary dial of a subscriber's telephone to the ability of a line card to detect on/off hook conditions. The tester may also consult information about billing, switching device settings for a particular line and the physical components of the loop. Using test results and information from those databases, the tester determines what the problem is and where it is likely to be located. This information is then given to the dispatcher so that the appropriate technician gets sent out to fix the problem.

Dispatcher Position

The main responsibility of the dispatcher position is to send out field repair personnel on the trouble reports which require physical work. The size of a Repair Service Bureau may justify the further subdivision of this position into three areas. The station dispatch function dispatches all troubles on regular telephones. The cable dispatch function dispatches the cable related troubles. Finally, the central office dispatch function dispatches technicians for central office repair work. Before sending out any technician, the dispatcher verifies that the reported condition is still affecting the line. In the case where the problem has cleared up by itself, the dispatch is cancelled. In addition, the dispatcher then calls the subscriber to verify that the condition has indeed disappeared. It is common to have telephone lines affected by bad weather. The problems affecting these lines usually disappear when normal weather conditions resume.

Analyst Position

The analyst investigates related trouble reports to establish patterns in order to identify major faults that could be affecting a significant number of subscribers. The analyst must also instruct the computer system about repair activities, such as cable repair, which could affect customer service. That way, the answer clerk can readily know, when retrieving a customer record, that maintenance or repair work is already scheduled or being done on a line. Subscribers calling to report a problem are then immediately advised that work is already in progress. The analyst is also responsible for monitoring the performance of repair personnel by analyzing the trouble report history files. The performance of certain telephone lines may also be monitored by the analyst.

Records Position

The operator at the records position creates, deletes and updates entries in the customer line records database. These responsibilities are often assumed by the answer clerk, depending on Repair Service Bureau policies. Today, a portion of these modifications are carried out automatically at night when one of the business office Operational Support Systems contacts CALRS to download new information. The objective of the telephone companies is to fully automate this process in order to eliminate database discrepancies caused by manual entries done from one system to the other. Manual entry is inevitably prone to errors and introduces delays due to the sheer volume of records to process.

Management Position

The task of the manager is to supervise the operations of the Repair Service Bureau. Reporting tools supplied with the system provide the manager with statistical reports on various aspects of the maintenance operations. These reports can be either requested or generated automatically

Robot Position

The robot position provides an effective means to automatically perform follow-up tests on lines suspected of being affected by intermittent problems. In the present mode of operations, trouble reports must be explicitly sent to the robot in order to have automatic tests performed. It is presently used at night to verify trouble reports that are scheduled for dispatch the following day. The concept of having a robot launch tests on pre-defined telephone lines is important in the context of automated maintenance operations. At present, this robot must be instructed as to which line to test and at what time. Opportunities exist to make a more productive usage of this robot so that it can react to trouble reports. For instance, such a robot could be aware that a trouble report concerning a subscriber line affected by a metallic condition needs to be tested at regular intervals since the problem may disappear. As was mentioned before, a number of problems are caused by bad weather conditions and typically disappear when normal weather resumes. Having a robot consistently verifying such lines could save unnecessary dispatches and help reduce maintenance costs.

2.2.3 CALRS Benefits

A system such as CALRS radically changes Repair Service Bureau operations. First, the electronic trouble report flow provided by CALRS eliminates the requirement for the records clerks who were needed to manually retrieve and deliver trouble reports and customer line record cards to testers and dispatchers. There is still a records position in the CALRS environment, but it only serves the purpose of updating that portion of the computerized line records that cannot yet be updated electronically. This records position is normally handled by the answer clerks during their idle time.

The major advantage brought to network maintenance by a system such as CALRS is the improved quality of service to the customers, which is of prime importance to telephone companies since most of them are regulated by government agencies in their respective countries. Among the CALRS features that help improve the quality of service are [28]:

- the immediate availability of trouble reports and their current status in the system;
- the detection and identification of trouble reports in "jeopardy", i.e. those that will not be fixed by the time negotiated with the customer;
- the ability to perform loop testing while being in contact with the cus-

tomer (provided the customer is calling from a line other than the one in trouble);

- the ability for the dispatcher to re-test subscriber lines before sending out technicians,
- the elimination of delays due to lost or illegible records,
- the identification of trouble pattern and repair work activities that may affect customer service;
- better management of appointments.

In addition, CALRS helps improve the Repair Service Bureau working environment, and facilitates resource management and evaluation [28]. With the consolidation of Repair Service Bureaus made possible by CALRS, reductions in the number of answer clerks, testers, dispatchers, and managers are possible. Network maintenance operations costs can thus be significantly reduced.

2.3 Related Operational Support Systems

Many Operational Support Systems (OSS) were introduced along with CALRS in the late 70s There was a strong move towards mechanization of operations and every organization within the telephone companies developed its own system to answer specific needs without paying much attention to the opportunities for sharing information with other systems Providing and improving communication channels between Operational Support Systems is one of the telephone companies ongoing efforts [67]. Some Operational Support Systems relevant to telephone access network maintenance are described in this section.

2.3.1 Billing Information Systems

Billing information systems contain information about all the services a customer subscribes to Billing information systems are used by testers to solve problems regarding disconnected lines and services ordered but not yet installed due to delays or human errors. Since service charges are calculated based on information found in billing information systems, this system is taken as the point of reference when resolving discrepancies.

2.3.2 Plant Assignment Databases

Plant assignment databases contain information about the physical components of the access network. Feeder cable and pair numbers, distribution cable and pair numbers, jumper wire interface identifiers and locations, etc. are stored in plant assignment databases. Critical inputs to the reasoning process of a tester, such as the presence of bridge lifters, loading coils, or remote concentrator units, are also contained in plant assignment databases. Plant assignment databases are also used in cable repair. By sectioning a subscriber loop using the information contained in these databases, it becomes possible to localize a fault.

2.3.3 Switch Maintenance Interfaces

Using switch maintenance interfaces, access network maintenance personnel can query the status of a particular subscriber line. They can also verify if a line is idle, currently used, or seized by the central office equipment. The status of custom calling features, such as call forwarding, can also be verified through a switch maintenance interface. Finally, a wide variety of tests, ranging from electrical measurements to noise measurements and bit error rate tests, can also be launched from the switch maintenance interface.

2.4 Evolution in Telephone Network Technology, Services, and Operations

The telephone access network is presently going through a transition period where old equipment such as step-by-step and crossbar switching offices are gradually being replaced by more advanced equipment such as members of the DMS[1] family of digital switching devices. A variety of remote units that concentrate telephone lines in rural areas will soon be retired. These units may be replaced by AccessNodes[2] which have a fiber optics link to the central office to which they belong. In addition, each of these AccessNodes will be equipped with its own test head, which was not the case with some of the old remote units.

There are also possibilities to introduce remote isolation devices on the customer's premises side. These devices allow an operator or a system to temporarily isolate the customer's premises from the rest of the network or to place a standard termination on the customer's premises end for testing purposes. These devices would have a considerable impact on access network maintenance as they would indicate whether a fault is inside or outside the customer's premises, thus avoiding setting up unnecessary appointments with customers. In a situation such as the one which prevails in the United States where subscribers own and are responsible for the inside wiring, it would eliminate the need for the telephone company to send technicians to the customer's premises only to verify if the problem is theirs or the customer's.

The network elements that were just described are readily available. However, it will be some time before all the old equipment gets replaced by these new devices. In the meantime, maintenance organizations have to deal with the added complexity of a heterogenous network, where old technology coexists with the state-of-the-art. Testers working in these conditions must be aware of what the subscriber loop is composed of since this knowledge definitely influences their diagnosis strategy.

1. Digital Multiplex Switching (DMS) is a trademark of Northern Telecom
2. AccessNode is a trademark of Northern Telecom.

2.4.1 New Services

One of the major impacts that new network elements will have on network maintenance is the plethora of new services they make possible [89]. Revenue generating features such as call-forwarding or caller identification have also engendered a new breed of maintenance problems. When a subscriber is experiencing a problem with Plain Old Telephone Service (POTS), it is most often because of metallic conditions one can actually measure. By contrast, problems generated by new calling features are often related to the usage of those features. As features become more sophisticated, their usage becomes more difficult. Improvements in the user interface, such as going from Dual-Tone Multi-Frequency (DTMF) detection to speaker-independent speech recognition, will certainly make these features easier to use and thus reduce the number of trouble calls to Repair Service Bureaus. For the time being, testers must learn to deal with these problems and be aware of their existence. For instance, a subscriber reporting noise on a line may simply be mistaking the characteristic call-waiting signal for spurious noise. This kind of problem frequently affects Repair Service Bureaus serving regions where such features have been widely provisioned for promotional purposes.

Other services like Integrated Services Digital Network (ISDN) and wireless communication services are gaining in popularity. ISDN maintenance is very demanding in terms of testing capabilities. Wireless communication services are forcing a paradigm shift in access network maintenance since there is no concept of a subscriber loop on which one can carry out electrical measurements anymore. In addition, the actual path used may have changed quite a number of times during the conversation. Issues like keeping track of this kind of information still needs to be resolved. Finally, the move towards a fiber optics based network will undoubtedly lead to the introduction of new services, each of which will require its own testing and maintenance procedures.

2.4.2 Towards Integrated Maintenance

Traditionally, telephone company maintenance operations have always been divided into a number of separate organizations. Each of them developed its own tools and installed its own testing equipment. Today, in an effort to provide better and faster service to subscribers, telephone companies are planning to replace some Operational Support Systems by systems that will offer an end-to-end view of the network. A system that can group information from various sources to provide such a global view will considerably improve network maintenance. Maintenance personnel will have easy access to complete information about subscribers and the circuit serving their premises. It will also be possible to build automated systems whose diagnosing capabilities will be closer to that of human experts because of this end-to-end view which they will have access to.

The next chapter contains a first literature review. Articles about the research work that led telephone companies from paperless Repair Service Bureaus in the mid 70's to today's experimental and deployed systems fulfilling a more active role in diagnosis will be presented.

Chapter 3 Advances in Telephone Access Network Maintenance

Back in the 1960's the prime improvement in access network maintenance was the introduction of a conveyor to forward trouble report cards and customer line records from one desk to the other [83]. Repair Service Bureau personnel were clearly overloaded and could no longer respond to the demand. Hiring more staff to work in already overcrowded offices created more problems than it solved. The quality of the maintenance service was indubitably decreasing and there was growing evidence that telephone network maintenance operations needed major improvements.

With the advent of computers such as the IBM 370 and the PDP series, telephone companies around the world made a first effort to automate the maintenance process in Repair Service Bureaus. Researchers from various organizations were invariably striving for a common goal: the creation of a paperless Repair Service Bureau that would help telephone companies cope with the ever increasing number of subscribers. These multi-user systems annihilated the need for paper records and conveyors. All records were stored in databases and exchanged electronically between the various positions in the Repair Service Bureau. In addition, the centralization of information offered by the computer system provided an ongoing up-to-date view of all repair appointments and their status. This helped to considerably reduce the number of duplicate dispatches, resulting in savings for network maintenance organizations.

Today, telephone companies are facing a different kind of problem. On one end of the loop, subscribers are now allowed to connect whatever they like to the access network. There is a large variety of telephone sets, modems, facsimiles, and answering machines that are now available. Each of them shows different electrical characteristics. The days when a typical "500 set"[1] was expected at the subscriber's end are definitely over. What is sitting at the subscriber's end now adds an unknown variable to the problem.

All kinds of equipment are also found on the other end of the loop. Although, sophisticated digital switching offices appeared some 15 years ago, a significant number of old electro-mechanical devices, such as crossbar and step-by-step switches are still at the heart of many central offices. A knowledge of the components forming a subscriber loop is crucial in carrying out a meaningful diagnosis.

Furthermore, Plain Old Telephone Service (POTS) is no longer the only service offered. Custom Calling Features (CCF) and Call Management Services (CMS) are now available. A variety of special services including data lines, telemetry lines and alarm lines, are also installed in today's networks and more are still to come.

This wide variety of equipment at both ends of the loop coupled to the multitude of services now offered have brought subscriber loop maintenance to a high level of complexity. This chapter will focus on developments in telephone maintenance systems. The first section of the following literature review will present some of the first computerized telephone network maintenance systems that led to paperless Repair Service Bureaus. The next section will describe how artificial intelligence has been applied to telephone network maintenance. Finally, the chapter concludes by presenting the directions that new development in network maintenance is likely to follow in the decade to come.

3.1 The Paperless Repair Service Bureaus

The initial introduction of computers in network maintenance operations led to the paperless Repair Service Bureau. This section presents some of these systems and describes their functionality.

1. The 500 set was a very popular telephone set manufactured by Western Electric and rented to most subscribers of the Bell System. The same set was also offered in Canada through Northern Electric which has since become Northern Telecom.

Dirilten makes two observations that were valid for the majority of Repair Service Bureaus in the early 70's [28]. First, customer records and trouble reports were kept on paper records, forcing the RSB personnel to waste considerable time just handling paper and manually copying information. Second, all testing and diagnosis activities were carried out by skilled testers, even though a significant number of the troubles were very straight forward problems that did not require such skills. Inefficiencies caused by the handling of paper records and the lack of a central memory to keep track of records and repair activities often lead to unnecessary dispatches for a significant portion of the troubles. The system he describes is a self-contained system consolidating and handling all RSB functions as a whole in an automated fashion. The result is a virtually paperless RSB where trivial problems can be handled by the answer clerks. With its ability to keep track of fault patterns and repair activities, the system saves a number of unnecessary dispatches.

Martin describes Repair Service Bureaus as having four main functions [73]. First, they handle the processing of trouble reports. Second, they perform diagnosis and testing. Third, they maintain customer and trouble records. Finally, they analyze trouble reports for patterns that are signs of major faults and that require quick repair action. He reports that during the late 60's - early 70's, it was realized that testers were spending much of their time processing simple reports, the diagnosis of which was relatively straight forward and did not require the skills of an experienced tester. Martin then reports on systems such as Line Status Verifier (LSV), Line Fault Detector (LFD), and Loop Maintenance Operations System (LMOS). LSV and LFD were the first steps toward testing automation while LMOS allowed Repair Service Bureaus to reduce the cost of record handling by mechanizing most of the administration activities.

Dale reports that Repair Service Bureaus went through three generations of Operations Support Systems up to the late 70's [24]. The first generation saw the appearance of two separate systems: LMOS which eliminated paper records and LSV, which allowed quick automated testing of subscribers' lines. Operations Support Systems of the second generation were more integrated. The Automatic Line Verification (ALV) system was capable of automatically accessing lines and made use of the data found in LMOS to determine which type of tests to run. The third generation was characterized by hardware with some imbedded intelligence. The Mechanized Line Testing (MLT) system had a more extensive test suite than the ALV and could interpret electrical measurements to provide a simple form of automated diagnosis.

The first version of the MLT system developed by Bell Laboratories did not incorporate all the features of the manual test facility known as the Local Test Desk (LTD). Dale *et al* describe the second version of the Mechanized Line Testing system [25]. Using a highly distributed processing architecture, digital signal processing techniques, and new measurement technology, this system completely replaces the LTD. In addition, the user interface was carefully designed such that Repair Service Bureau personnel with less experience than Test Desk technicians could operate it.

Morishita *et al.* report of a similar system in [80]. To improve maintenance in a telephone network serving more than forty million subscribers, a new Subscriber Line Testing System (SULTS) and a Subscriber Information Filing System (SIFS) were developed. This new system brought improvements in the following areas: flexibility in adding new information, improvement of measuring accuracy, improvements in operation through a better person-machine interface, automatic compilation of statistics for repair service management and concentration of testing operations. SULTS/SIFS is flexible enough to accommodate the introduction of new telecommunication devices in the network.

In another paper, Cartwright describes the 4TEL automated subscriber line test system which provides telephone companies with tools to offer better quality while reducing costs [19]. To accomplish this, 4TEL offers the following functions. The Daily Advisory is a managerial and repair action report based on routine tests run at night which provides input to preventive maintenance. Fault distribution is provided by the system, reducing the number of wrong or unnecessary dispatches. It also supplies means of performing accurate fault location with the help of a linesman. Finally, special diagnostic testing capabilities to handle problems such as coin phone faults and dialing problems, are also available.

Access network maintenance has always been a highly expensive and labor intensive process. Sumner reports on various Operational Support Systems that were introduced to reduce the expense in daily operations of telephone companies [99]. Such systems were introduced for planning and engineering, scheduling, keeping inventory, assigning and controlling facilities, and maintaining the access network. Sumner notices that the majority of these Operational Support Systems were designed as stand alone systems to accelerate development. Operational Support Systems have impacted the telephone companies considerably by reducing personnel requirements. However, to this date, telephone companies are still struggling with the problem of interfacing these different and most often incompatible systems.

3.2 Automating Telephone Network Maintenance

As a result of the growth and evolution of the telephone network, the need for telephone companies to improve the efficiency of their maintenance operations has arisen. Encouraged by the results of experimental diagnostic expert systems such as MYCIN [27], Prospector [30], and DART [11], a number of researchers in the communications domain have designed and studied a variety of expert maintenance systems. In this section, experimental and deployed systems that cover cable, trunk, carrier, customer trouble reports, special services, switching device, and network maintenance are described.

3.2.1 Cables, Trunks, Carriers, and Transmission Equipment

Automated Cable Expertise (ACE) [13][77][97][103] is a knowledge-based expert system that provides troubleshooting and analysis reports for telephone cable maintenance. Facts are gathered from a data base management system used to store maintenance information. Knowledge comes from the users of this database and from primers on maintenance analysis. Users of this database regularly analyze considerable volumes of data to identify cables which should receive maintenance to prevent troubles affecting a large number of customers. ACE runs at night; it looks at reports in the Cable Repair Administration System (CRAS), assesses which cables are likely to need preventive maintenance and forwards the results of its reasoning via electronic mail to users of the system who pick them up the following morning. Preventive maintenance has traditionally been an activity that was done during operators' spare time. ACE helps make preventive maintenance a regular tool of network operations.

The Interactive Repair Assistant (IRA) is an expert system that provides troubleshooting advice to field technicians who have to repair telephone circuits having noise and transmission problems. Horton *et al.* describe the goals of this system as being: improving field technicians productivity, helping field technicians to repair a broader variety of problems and equipment, and providing real-time advice in the maintenance, diagnosis, and repair of the local telephone network [47]. The system has to serve many users outside of a typical office environment. To achieve this, craftspersons are equipped with hand held display units that can communicate with the central system via a modem through regular telephone lines. This prototype system consists of 625 "screens" (plus associated help screens) and about 200 inference rules. Each screen either requests some inputs or provides information to help craftspersons during the troubleshooting process. By supplying expert advice and information, IRA increases the efficiency and productivity of field technicians.

Donaghy and Omanson describe MICE, the Metropolitan Inter-office Carrier Expert [29]. By using system integration and alarm correlation, MICE is capable of finding the cause of digital carrier failures. The information necessary to find the cause of such failures is scattered among many Operational Support Systems in the telephone operating companies which renders this task difficult to carry out. By visiting several Facility Maintenance and Administration Centers in the network, the authors were able to find a human expert who was achieving an impressive diagnosis performance by manually collecting alarm reports and other information from many Operational Support Systems. They captured this expert's knowledge into an expert system containing some 160 OPS83 production rules. By providing system integration and building an expert system capable of correlating and analyzing alarms from different network elements, they have put in place an automated system that can do the human expert's task more efficiently than the manual process normally required.

Liu *et al.* describe I-TEST, a prototype trunk testing expert system [63]. It combines procedural and declarative knowledge into a single inference mechanism to manage a complex trunk testing environment involving more than one Operational Support System. Humans used to be the interface between these various systems and data were manually copied from one system to the other, sometimes leading to errors. I-TEST eliminates the multiple terminals and different test commands required for the various Operational Support Systems by providing a common human machine interface for invoking test commands and thus improves testers' productivity. Knowledge from four domains was used to build the knowledge base. The data communication knowledge base allows I-TEST to communicate with other systems. Procedural knowledge is used to build a friendly user interface for the users. Another rule base is used to filter the necessary information from various systems. Finally, a last knowledge base controls I-TEST, manages resources, and arranges priority and testing sequences.

Khan *et al.* detail GEMS-TTA, the Generalized Expert Maintenance System - Trunk Trouble Analyzer [54][55]. The first phase of this system allows the automation of trunk trouble handling, testing and performance monitoring. Later phases of GEMS should lead to the automation of trouble sectioning and isolation, and the dispatch of the appropriate repair people. Rules are used to represent facts about the problem domain while frames are used to represent network objects. The knowledge base itself is partitioned into four segments: the initial diagnostic knowledge base, the initial action knowledge base, the extended action knowledge base, and the final diagnosis knowledge base. The implementation described by the authors offers advice to users on trunk trouble diagnosis and on test selection and monitoring strategies. Giving GEMS the capability of performing circuit tests and monitoring itself will make it a fully automated trunk maintenance system.

TOPAS-ES is a real-time distributed expert system that diagnoses transmission and signalling troubles on telephone trunks in the long-distance network [16][22]. Due to the large number of alarms generated by the electronic telephone switches, troubleshooting trunks is time-consuming and requires a rare expertise. TOPAS-ES is made of two parts: a Trouble Analyzer and a Trouble Sectionalizer. The Trouble Analyzer filters out transient problems to only deal with real trunk problems. The Trouble Sectionalizer identifies the source of the problems and communicates the information to the required technicians. TOPAS-ES is a distributed system in that a copy at one end can dialog with a copy at another end to conduct fault location.

Callahan *et al.* describe TERESA (Trouble Evaluation and Resolution by Expert System Application) [17] which is an enhanced version of TOPAS-ES [16][22]. The main function of TERESA is similar to that of TOPAS-ES, i.e. it can communicate with other TERESAs to provide end-to-end sectionalization capabilities. However, TERESA also cooperates with another system called EASA (Expert Analysis and Solution Assistant) which specializes in transport network maintenance. TERESA is specialized in DS-1 level transmission and signaling whereas EASA concentrates on DS-3 and above network elements. TERESA and EASA communicate with one another to perform correlation of events, eliminate redundancies, and localize faults.

3.2.2 Special Services

Yudkin describes ExT, an Expert Tester for troubleshooting faulty Special Service Circuits [109]. ExT makes use of model-based reasoning. By using a representation of the circuit elements and their relationships, it selects tests to run and reasons about data obtained to determine the nature of the trouble. To achieve this, ExT counts on four modules. The Building Module reads a circuit description in a database and instantiates whatever elements are found, along with the required attributes. Connectivity rules are used to build up an internal circuit diagram. The Testing Module uses the model from the Building Module to select the best test to run next

The Analyzing Module updates the dynamic model originally created by the Building Module based on the test results. Finally, the Termination Module contains rules to close trouble reports or refer problems to the required technicians.

In [110], Yudkin brings some refinements to ExT. In addition to the structural knowledge the original system handled, he now adds behavioral and functional knowledge to the model. Behavioral knowledge specifies input-to-output mappings and is used to start the diagnosis process based on observations of misbehavior. Functional knowledge characterizes the purpose of a network element and is used when no observations can be obtained from a network element. The objective of the author and his team is to design a system that makes use of rule-based reasoning for speed of execution and sophisticated model-based reasoning for enhanced problem solving.

Hautin *et al* describes Sylis, an expert system for troubleshooting specialized links [43]. According to the authors, the need for such a system stems from the limited availability of expertise in the domain. In the case of old systems, this expertise is slowly disappearing while there is almost no expertise for newer systems. Such systems allow the storage of information about extraordinary situations for which not much knowledge is available. Considering the vast amount of information that needs to be accessed, expert systems are considered an excellent means to ensure that all the relevant questions are asked to customers reporting problems and to necessary databases. The objectives of Sylis are thus to assist the human operator and secondly to improve the global performance of specialized links maintenance. Sylis accomplishes the first objective by asking questions to the user, giving explanations, and allowing easy access to databases. By helping reduce the time-to-repair, improving the trouble report process, raising technicians competence and offering training to newcomers, Sylis also reaches the second objective.

Special Services testing is done by human experts having a vast knowledge of signaling protocols, transmission parameters, transmission tests, and grade-of-service requirements. These highly paid experts are also responsible for updating various special services databases when new lines are put in service or maintenance has been carried out on existing lines. In order to improve efficiency in Special Services maintenance operations, an attempt was made at automating testing and the flow of information [1]. SARTS/AutoTest-2 contains rules grouped into three categories. The Test Strategy rules determine the best test to run with respect to the circuit configuration under examination. The Analysis Procedure interprets the results coming from the Test Strategy module. Finally, the Diagnosis module determines if the trouble is a real one or simply a side effect of another problem that is already being processed. SARTS/AutoTest-2 handles about half the problems reported to the Special Services Center and processes 80% of those without human intervention, resulting in considerable savings in maintenance operations.

3.2.3 Switching Devices

Prerau *et al.* describe COMPASS, the Central Office Maintenance Printout Analysis and Suggestion System [37][90]. COMPASS analyzes maintenance printouts from GTE's No. 2 EAX switching system and suggests maintenance actions. It achieves this by going through a multi-stage process. It starts by connecting with a Remote Monitor and Control System (RMCS) to gather monitoring data. It then formats the data and group information into clusters. Clusters are further examined and some are combined. Once its analysis stage is completed, COMPASS formulates maintenance actions, orders and merges them to finally output the ones that are most likely to provide a solution. COMPASS increases the productivity of experienced maintenance persons, improves the performance of less experienced personnel, helps provide better switch performance, and captures expertise that may not be available in the future.

Macleish *et al.* report that competition in the telecommunications industry has made it imperative that telephone operating companies improve product reliability, reduce repair costs, and increase customer satisfaction [39][65]. To this end, an expert system called NEMESYS was designed to improve central office switching maintenance systems. These systems are very complex and made of thousands of integrated circuits. Because of the complexity of these systems, switch maintenance proves to be an activity that can be performed by only a few expert craftspersons who can use their vast experience, their in-depth knowledge of the switch and "rules of thumb". NEMESYS uses more than one knowledge base. The first knowledge base describes the network using an object-oriented approach. Another knowledge base describes the types of problems that may occur while a third knowledge base contains rules capable of grouping related problems into bursts. A fourth knowledge base provides high level analysis of these bursts while the last knowledge base contains rules to suggest corrective actions. This system is a means of addressing the high cost of maintenance, the need for improved customer satisfaction and the shortage of expert knowledge in this domain.

Novik reports on an interesting addition to GTE's NEMESYS central office switch maintenance expert system [85]. This new module uses statistically based temporal reasoning to perform fault localization and determine whether a fault is located in the central office switch or outside. T1 links are all duplicated in the network. Whenever NEMESYS receives alarm messages, it tries to determine statistically if one of the twin T1s shows significant differences with respect to the other. Using this type of reasoning, NEMESYS can determine whether the fault is inside or outside the switch. More accurate localization in the outside plant will become feasible with future additions to the knowledge base and improvements to network elements.

Harrington describes CSMES, a Communication Switch Maintenance Expert System he designed to improve the maintenance of AT&T toll network [41]. The purpose of CSMES is to make expertise available to all maintenance personnel across the toll network. To accomplish this, CSMES reads and analyzes messages generated by switching equipment. The number of such messages can be significantly large. CSMES is capable of determining the severity of a message and selecting only those which have the most impact. It then translates into English the meaning of the alarm codes it received along with some recommendations for remedial action.

The TXE4A is an analog telephone exchange which includes a diagnostic subsystem that can automatically generate fault reports and alarms. In a real-life situation, literally thousands of those are generated on a daily basis making it difficult for human experts to correlate events to identify and locate faults. The Advanced Maintenance Facility (AMF) is an expert system that can either diagnose on its own or assist maintenance technicians in their tasks [101]. It handles three main types of fault indications: operational processing faults, fault printouts, and alarms. AMF will locate faults in the telephone exchange down to the faulty plug-in unit or network component by using a knowledge base with about 1550 rules. All unattended and interactive sessions are recorded for ongoing enhancements of the knowledge base. AMF greatly reduces the mean time to repair, increases the mean time between failures, and also serves as an excellent on-the-job training tool.

Baseband Distribution Subsystems (BDS) are large signal switching networks. Lafley *et al.* describes LES, the Lockheed Expert System to diagnose BDS faults [61]. LES uses three types of knowledge to carry out this task. First, factual structural knowledge about components making up the network is stored in frames. Second, diagnostic (heuristic) knowledge is stored in IF-THEN rules that are used in the main backward chaining inference process. Third, control knowledge is stored in WHEN rules which, once certain conditions are satisfied, momentarily stop the backward chaining to forward chain until some conclusion is met. At this point, backward chaining resumes where it was stopped. These WHEN rules can be used to change the priorities of the goals set in the backward chaining mode of reasoning. This allows a better modelling of human experts' way of thinking. LES performs as an advisor. It recommends which tests should be run on which devices. The user has the possibility to ask LES why it is requesting a particular test or why it has reached certain conclusions. General component-related information can also be requested through LES.

The Switching Maintenance Analysis and Repair Tool (SMART) is an advisor expert system for the maintenance of AT&T #1AESS switch [64]. SMART-I helps technicians in isolating switch faults and repairing failed components. In order to improve #1AESS maintenance to an even higher level, Loberg reports how the system went through a major upgrade to become a near real-time switch monitor expert system. Going from the advisor to the monitor paradigm forced a major rewrite of the knowledge base to allow for the understanding of messages coming from the switch, a task which was previously accomplished by technicians. Knowledge about potential solutions was also added to the knowledge base which enables the expert system to use this important information during its reasoning process.

The Bellcore Real-Time Expert System (RTES) is a prototype knowledge-based expert system that analyzes switch output messages to identify faults and offer recommendations for corrective actions to maintenance technicians [33]. RTES uses models of the switch maintenance environment and high level reasoning processes. Heuristics are stored in rules. RTES also logs historical data so that it can correlate incoming messages with past events. RTES provides its own recommendations, but also keeps a log of the recommendations and responses it was given by technicians for future improvements to the knowledge base.

Peacocke and Rabie describe MAD, an interactive expert system for helping technicians perform maintenance on the DMS-100 family of digital switches [88]. The knowledge used to build this expert system comes from the extensive Northern Telecom documentation and from troubleshooting experts in Bell Canada and NT. This version of the Maintenance ADvisor uses a "describe-recommend" cycle which allows the user to guide the system, and not the other way around. The user describes the problem by filling electronic forms. By pressing a soft key, MAD offers some recommendations. These recommendations may consist of preliminary actions to be taken which may include requests for further information from the craftsperson, or repair actions to solve the problem. Forms do not need to be complete to start the diagnosis process. Users can thus obtain recommendations from partial information or can change some information to see alternative courses of action. MAD also provides access to a switch database covering the physical composition of the switch and to a "notebook" containing locally applicable maintenance information.

Hibino and Fujimoto describe THINKING-ESS, an object-oriented troubleshooting expert system for electronic switching systems [44]. In order to tackle the increasing complexity of the telecommunication network, the authors selected a troubleshooting strategy based upon structural and behavioral models of switching systems and represented knowledge using objects. This approach allows for better fault sectionalization as it is easier to figure out which device connects to which when trying to pinpoint the faulty element on a circuit. The use of objects to represent knowledge adds flexibility to their expert system by easing the addition of new elements into the knowledge base.

In order to reduce procedural errors, shorten the mean time to repair and the training time for technicians, Berberich *et al.* have built the EWSD-XPS, an expert system for the maintenance of digital switching devices [12]. EWSD-XPS is made of six functional modules. The Alarm Analysis module handles incoming alarms. The Diag Module determines which diagnosis command should be issued while the Conf Module knows about the configuration commands that must be issued before the selected diagnosis commands can be run. The Hypothesis Module uses diagnosis results to issue some fault hypotheses weighted by certainty factors. Finally, the Replace Module figures out which components to replace while another Conf Module issues the proper configuration commands before the selected component can be replaced.

Private Branch Exchanges (PBX) are sophisticated switching equipments installed in large customer's sites. Daniel *et al.* describe PBXpert, an expert system that diagnoses, resolves, or offers troubleshooting advices for problems affecting AT&T's line of PBX [26]. PBXpert tracks PBX generated alarms and customer-reported problems. By rigorously following standard diagnostic procedures and making use of historical data, PBXpert can either discard and close a trouble report or make the necessary recommendations and forward these to maintenance technicians. During diagnosis, PBXpert takes into account the PBX system's characteristics to select which tests to run and correctly interprets the results. PBXpert's maintenance strategy is similar to that described in maintenance manuals, and is reviewed and updated with each new test result.

3.2.4 Networks

Covo *et al.* describe LARS/RBES, an hybrid expert system for anomaly detection, isolation, and resolution [23]. The Learning and Recognition System (LARS) uses neural network to perform status monitoring of a network. LARS is composed of two subsystems. The first one is a collection of small neural networks that evaluates elementary features known to indicate anomalies. The second subsystem performs correlation between the elementary features reported by the first stage and tries to recognize the anomaly. Using the outputs to the first subsystem, procedural actions are taken to isolate the problem. The Rule-Based Expert System (RBES) receives messages from LARS about anomalies that have occurred and uses a data driven inference mechanism to correct the anomaly by appropriately modifying routing.

Nuckolls describes an expert system which performs real-time diagnosis in a large digital radio telecommunications network [86]. This expert system utilizes the vast amount of information provided by the various devices forming the network. Some working devices may report alarms simply because they are affected by another device which has previously failed. The expert system's task is to discern truly malfunctioning equipment from all the components reporting alarms. To accomplish this, the expert system is given structural and behavioral knowledge of the network to "understand" how all the devices connect to each other. It then uses this knowledge to process information provided by the network elements and performs real-time diagnosis.

Miyazaki *et al.* report that the advent of ISDN into the commercial market has pushed for improvements towards a dynamic operation and maintenance system for switching networks [79]. This distributed system is made of five types of components: local exchanges, a centralized operation system, a database system, a diagnostics expert system, and maintenance workstations. The purpose of the expert system is to assist maintenance personnel in making optimum decisions. The hypothetical reasoning is done in four steps. First, all symptoms (alarms, messages, diagnostic results, etc.) are collected. Second, hypotheses are generated.

Third, for each symptom, the expert system selects one hypothesis and combines this information to pinpoint the faulty component. Finally, the end user verifies if the component is indeed faulty. If not, current hypotheses are discarded and the cycle starts over. The knowledge used by the expert system is stored in two knowledge bases. One contains the knowledge common to all switching system versions. The other contains the knowledge specific to each version.

Allwood *et al.* describe a prototype expert system that was developed for a large data network customer in the United Kingdom [2]. The premium objective of the expert system is to filter out simple faults from all fault reports. This allows end users to fix simple problems themselves and thus avoid having to wait for specialized technicians to come on site, most of the time only to find out some piece of equipment that had not been powered on. On the other hand, complex problems are recognized by the expert system and forwarded to a trained network engineer. The system improves the efficiency of response to customer faults while providing customers with a powerful tool to manage and control their network.

Azmoodeh describes GMS, a Generic Maintenance System for integrated broadband communication (IBC) networks [9]. To tackle the complexity of this task, a model-based approach was selected. A knowledge base of objects contains the representation of networks, network elements, services, users, etc. Objects can be in the functional or physical category A functional model of networks element details the specialization of the object based on the functions it performs. A physical model, on the other hand, describes the non-functional aspects of network elements, such as location, size, etc. Constraints control the knowledge base and force it to be only in legal states. Using this knowledge base and fault reports, the Correlation Module formulates hypotheses about faulty functional units. The Model Interpreter evaluates the consequences of these hypotheses using behavioral rules. Hypotheses and their consequences are maintained in an assumption-based truth maintenance system in the inference engine.

Azarmi describes RS, a knowledge-based Resource Scheduler for the network management layer of a Generic Maintenance System (GMS) [8]. RS is designed to handle correlation of fault reports, management of tests and supervision of repair procedures. It takes as inputs requests for repairs and tests and feedback concerning the states of ongoing repair works. RS must generate a correct and near optimal schedule of repair requests, while being capable of handling the dynamic nature of network maintenance. It accomplishes this by using three sub-modules. The Priority Scheduler uses network performance-related, service-related, and maintenance-related rules to prioritize repair requests. These prioritized repair requests are the inputs to the Predictive Scheduler which selects a set of repair actions while trying to satisfy associated constraints and resolve conflicts. Finally, the Reactive Scheduler executes and monitors these repair activities and may reschedule tasks dynamically. RS uses structural and behavioral knowledge as well as generic network knowledge. It also takes into account knowledge about available resources.

3.3 An Agenda for Telephone Network Maintenance

Telephone operating companies are presently at a turning point. In North America at least, they no longer have the monopoly on telephone services. Furthermore, competition has paved the way to a multi-vendor environment which resulted in heterogenous networks more difficult to maintain [18][66][81][98]. Similarly, on the end users' side, regulatory and marketing issues have made possible the appearance of a wide variety of customer provided equipment. Subscribers are no longer restrained to renting or buying telephone equipment solely from their telephone company. With the mostly completed modernization of the telephone network, new services have emerged and more are yet to come [98] that will require increasingly sophisticated test procedures and systems. Finally, marketing concepts such as usage sensitive pricing will put more and more pressure on maintenance operations to provide near-perfect quality of service to prevent loss of revenues due to failures [67].

The problem that maintenance operations are now facing can be in part explained by the lag of their maintenance technology and the obsolescence of their organizational hierarchy. Test hardware is limited in accuracy and does not fully qualify as measurement devices for new services such as ISDN [66]. The Operational Support Systems now in place typically have restricted domains of applications and hardly share information with other systems leading to a proliferation of terminals, printers and human-machine interfaces [81]. As new and more sophisticated network elements are introduced, these same Operational Support Systems do not get upgraded accordingly and their maintenance introduces yet more complexity in the process.

The architecture of the telephone network has also known some evolution. Some would even qualify this more a revolution than an evolution. The subscriber loop is no longer well divided among the central office, the outside plant, and the customer's premises. In reality, an increasing portion of the subscriber loop is now being shared among multiple subscribers through technological advances such as remote switches or ISDN [98].

If telephone companies are to maintain high levels of quality and survive in this new competitive environment, a number of steps must be taken. New more advanced test hardware must be introduced in the network and test access to all subscriber lines, particularly in rural areas, must be feasible through the use of distributed test systems. Operational Support Systems for maintenance must be improved or replaced. These systems should be designed to be generic enough to act as "building blocks". Whenever new services or new technologies are introduced in the network, it should be possible to easily add the necessary maintenance functionality to existing systems. Better fault identification algorithms also need to be implemented to handle new services and technologies. Enhanced automatic fault detection using all the alarm reports generated by advanced network elements will allow maintenance organizations to operate in a preventive mode. Fully automated and programmable testing must be deployed to better handle intermittent faults. Finally, new technology such as Dynamically Controlled Routing and high capacity fiber optics ring-based networks will help enhance network survivability [74].

However, new Operational Support Systems will also need to be integrated and provided with the ability to communicate with one another [74]. Furthermore, these systems will have the capability to exchange information with intelligent network elements. Work done by standard bodies on the Telecommunication Network Management (TMN) will make this possible for multi-vendor based networks [91] and will help provide an end-to-end view of the telephone network.

But the greatest challenge facing maintenance operations will probably be a shift in corporate culture. Traditionally, the telephone network has been divided into various sub-organizations, each taking care of its assigned portion. With the introduction of new technology, the topology of the network has changed and will continue to evolve. Natural boundaries that existed with the old technology are now disappearing. Work force organization and the concepts on which their regulation is based will need to be revisited. On one hand, the maintenance philosophy must shift from a reactive mode to a proactive mode. Preventive maintenance is a key to keeping high reliability and high customer satisfaction. On the other hand, automation and system integration should allow maintenance organizations to give more control to customers over services. Just like banking institutions, there is great potential there to reduce work load in maintenance operations and again increase customer satisfaction [46].

The next chapter introduces neural networks. Neural networks were explored in this research work to assess their ability to identify faults affecting subscriber loops. An introduction to neural networks is given along with the theory about the learning algorithm used. The last section of the next chapter presents a second literature review, this time on application of neural networks to diagnosis.

This chapter introduces neural networks. Following a brief historical review, a detailed description of the back-propagation algorithm is given. Finally, a literature review of neural network classifiers used in pattern recognition problems is presented.

4.1 Historical Review of Neural Networks

A brief overview of neural networks is presented here followed by a hierarchical classification of neural components.

Neural networks have not always been popular due to limitations they had when they were first studied. They are now gaining considerable credibility, especially since successful applications have been reported. A complete chronicle of the history of neural networks can be found in [68].

In 1943, McCulloch and Pitts [75] designed a model of neural networks based on their knowledge of neurology. Even though it was a rather simple model that could only deal with simple logical operations such as AND and OR, their model did introduce the concept of parallel processing using simple computing units. No computer simulation was done. Everything was carried out using pencil and paper.

Computer simulations were only produced in the mid 50's. One of the groups working on computer simulations of neuronal models was from IBM research laboratories. This group carried out the work while remaining in close contact with Donald Hebb and Peter Milner, neuroscientists at McGill University. Whatever the neuroscientists found, they shared with the IBM research group and vice versa. This led to the creation of a multidisciplinary trend that is still going on today.

In 1958, Rosenblatt [94] introduced the Perceptron. This was a three-layer neural network that could learn to associate a given input to a random output unit. The system did have some limitations, particularly in its learning method. Then, in 1960, Widrow and Hoff [107] devised the Adaline (ADAptive LINear Element) which employed a much more sophisticated learning method known as the Least-Mean-Square (LMS) learning rule or the Delta Rule.

In 1969, Minsky and Papert [78] published a book called *Perceptron* in which they proved that a single-layer Perceptron network could not even perform the XOR operation, and that it was restricted to linearly separable problems. Their publication had the sad effect of discouraging the scientific community from pursuing research in the field of neural networks. Nowadays, multi-layer networks can overcome this limitation.

Despite the massive lack of support and funding, a handful of researchers continued their work and came up with very interesting neural network architectures that now prove to be useful in many of today's applications. Among them were Grossberg [38], Anderson [5], Kohonen [60], Klopf [58], Werbos [105], Amari [4], and Fukushima [34]. It is in the early 70's that interesting results from these people were published.

Since 1986, a real resurgence of this field has been witnessed. Many conferences on neural networks are held each year around the world. A good number of journals and magazines have also appeared. A sign that the field has reached a certain maturity is the recent reports about many interesting real-world applications. A number of these applications are presented in section 4.3 of this chapter.

4.2 An Introduction to Neural Networks

This section gives a brief introduction to the theory of neural networks. Advantages of neural networks over other methods are presented and some learning algorithms are described with more attention given to the back-propagation learning algorithm.

4.2.1 What Neural Networks Are

As the name suggests, a neural network is a collection of neuron-like units often referred to as neurodes [20]. Figure 4.1 shows a typical neurode. Each neurode can have many inputs but only one output, even though this single output may serve as input to many other neurodes as will be seen later on. This output is the result of some processing done by the neurode. A typical neurode has a weight factor for each one of its input connections. Inputs are multiplied (weighted) by these factors. The result for each input are then summed. This sum is passed through an activation function which is usually non-linear sigmoidal function (such an activation function allows multi-layered back-propagation networks to form complex decision regions in multi-dimensional space). One of the inputs may be a constant bias which is sometimes compared to the ground in an electrical circuit. Some neurodes also subtract a threshold value from their summed input. This can be used for an on/off type of activation. An optional gain term may also be applied to the output of the neurode.

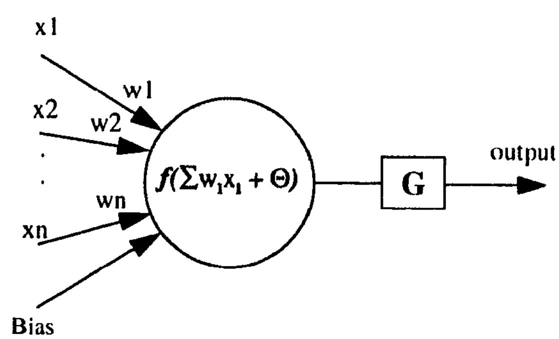

Figure 4.1: Components of a typical neurode.

Neurodes are normally organized in layers, where each layer can be seen as a different level of abstraction from the input data. Neurodes within the same layer may be interconnected or not, depending on the architecture selected.

A network is typically made of many layers and it is usual to have the outputs of one layer fully-connected to the following layer's neurodes. Full connectivity is not necessary and there exist techniques to get rid of unnecessary connections once training is accomplished and satisfies the performance requirements. Figure 4.2 shows a typical neural network with layers fully connected.

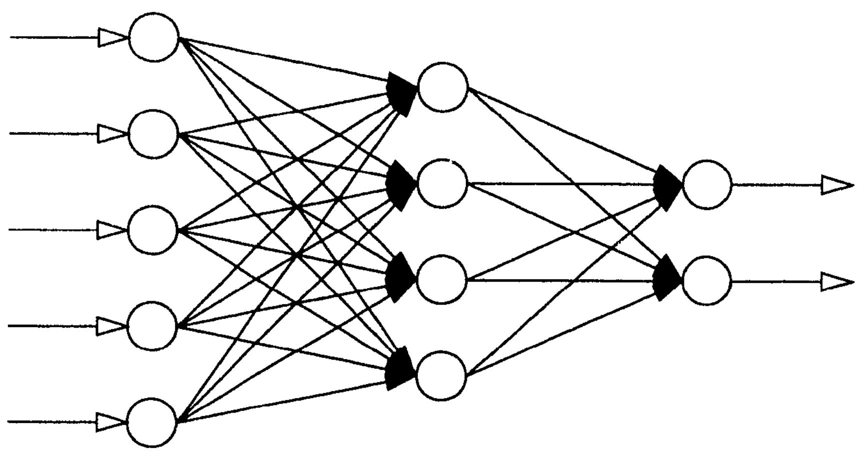

Figure 4.2: Neural network with fully connected layers.

4.2.2 The Back-Propagation Neural Network

The back-propagation neural network was initially proposed by Werbos in his PhD dissertation [105]. However, Parker [87] and Le Cun [62] — apparently independently — also published this method. Rumelhart and McClelland [95] largely contributed to the popularity of the method with their well known book, *Parallel Distributed Processing*.

Back-propagation is the most widely known neural network. Because of its relative simplicity and its long lived reputation, it has been successfully applied in many research projects. Section 4.3 describes some of them.

The Delta Rule

Back-propagation builds on the concept of the Delta Rule learning method. Also known as the Widrow/Hoff rule, it is used in neural networks made up of one set of input neurodes and one set of output neurodes. Each neurode from the input layer is connected to each neurode in the output neurode via a weighted connection.

Each connection has a strength (weight) associated with it. This weight is used to multiply the value coming from the output of an input neurode. The product is fed to the output neurode linked through that connection. At first, those weights are initialized to small random values, usually between -0.1 and 0.1. The Delta Rule is what allows the network to modify its connections and hence, learn.

One trains such a network by presenting it with both the input values and the associated desired output values. This is called training with supervision. The network uses the input values it is given and its connection weights to produce an output on its own. This output is then compared to the desired output according to the following equation:

(EQ 1)

$$\Delta w_{ji} = \alpha (D_j - O_j) I_i$$

where

D_j = *desired output pattern at the jth output neurode.*

O_j = *resulting output pattern at the jth output neurode*

I_i = *input pattern from the ith input neurode*

α = *learning constant.*

Δ_{wji} = *value to add/subtract from the connection weight going from input neurode i to output neurode j.*

The learning constant is usually small (around 0.1). Using a bigger learning constant may lead to oscillatory behavior of the network. Once a network gets trapped in oscillatory behavior, it rarely reaches completion of learning.

The Delta Rule essentially assigns credit or blame to the input neurodes. The more active is an input unit, the more responsible it should be for the good or incorrect behavior of an output neurode

The Delta Rule belongs to a class of gradient- or steepest-descent algorithms. It has been shown that the Delta Rule will cause a network to modify its connections in directions that maximize the change in an error term that sums the squares of output deltas [95].

Limitations of the Basic Delta Rule

The Delta Rule performs well for single-layered networks, i. e. networks that have only input and output neurodes. Unfortunately, the class of problems to which these networks can be applied is severely limited. As was shown in an analysis by Papert and Minsky [78], these networks cannot compute the exclusive-or (XOR) function. In fact, such networks are limited to linearly separable problems. The fact that they could not compute a logic function as simple as XOR is largely the reason why neural networks research was almost non-existent in the early 1970's.

Multi-layered networks are the solution to this problem. Multi-layered networks are networks with one or more *hidden* layers in addition to the usual input and output layers. These extra layers allow neural networks to handle problems that are non-linearly separable. However, a new learning rule is required in order to propagate the credit or blame from output neurodes back to hidden layers and input layer neurodes. This new rule is called the back-propagation learning rule or the generalized Delta Rule.

The new equation is similar to that used with the Delta Rule. The delta is now computed as follows:

(EQ 2)

$$\delta_{pj} = \alpha (D_{pj} - O_{pj}) f'_j (I_{p-1j})$$

where

α = *learning constant*

D_{pj} = *desired output of the jth output neurode*

O_{pj} = *actual output of the jth output neurode*

f'_j = *1st-order derivative of the jth neurode activation function*

I_{p-1j} = *sum of all the inputs to the jth output neurode from layer p-1*

δ_{pj} = *amount to add or subtract to connection weight going to jth output neurode*

p = *output layer*

This is similar to the Delta Rule, except for the first-order derivative. The power of back-propagation comes from its ability to propagate deltas to hidden units as well. It is this feature that allows neural network to have hidden layers that are capable of learning. The delta for hidden neurodes is computed as follows:

(EQ 3)

$$\delta_{pj} = f'(I_{pj}) \sum_k \delta_{(p+1)k} w_{kj}$$

where

I_{pj} = *sum of all the inputs of the jth hidden neurode in layer p*

f'_j = *1st-order derivative of the activation function of the jth neurode in layer p*

w_{kj} = *weight going from hidden neurode j in layer p to hidden neurode k in layer p+1 (layer p+1 may be the output layer)*

$\delta_{(p+1)k}$ = *delta computed for neurode k in layer p+1*

δ_{pj} = *delta computed for the jth hidden neurode in layer p*

The basic idea introduced by the back-propagation learning rule is the computation of weights for the hidden neurodes through propagation of deltas computed for other neurodes in previous layers, starting with the output layer and going toward the input layer. Figure 4.3 illustrates this.

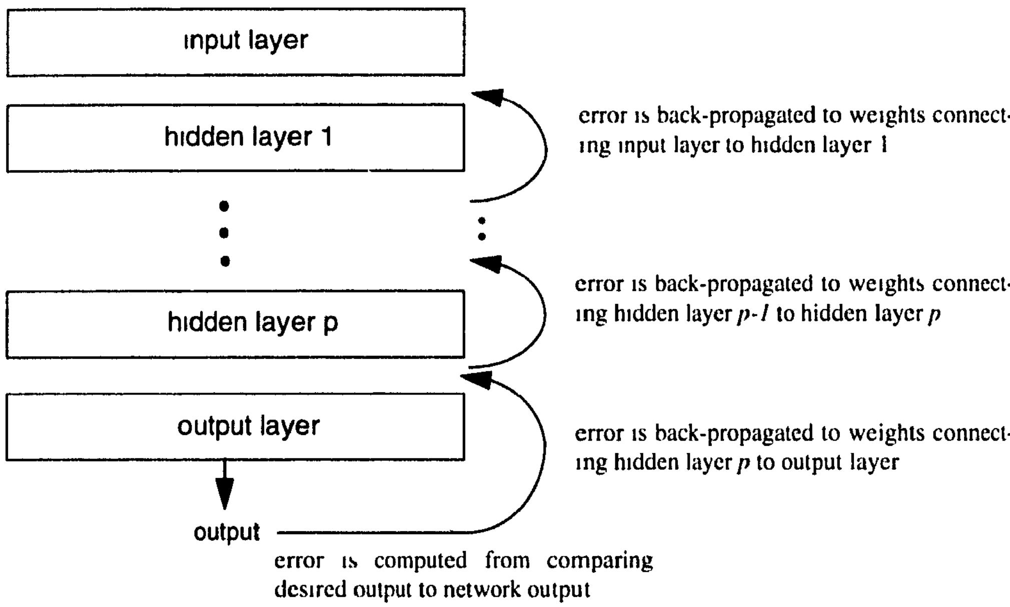

Figure 4.3: Back-propagating errors from layer to layer.

Using this rule, a network designer presents input data to the network along with the desired output until the network achieves the required level of performance. This level of performance is usually defined by setting a maximum on the magnitude of the error vector. The error vector is computed by subtracting the actual output from the desired output. The magnitude of this error vector is then compared to some threshold set by the network designer. When the network reaches this threshold, it is said to have completed its training phase. The network designer then presents the network with patterns it has not *seen* before and verifies the correctness of the given outputs. If the test phase is satisfactory, the network then goes through validation. Validation involves training and testing with different training and testing data sets. Once validation is successfully completed, the network can be deployed and applied to real-world situations for further performance assessment.

Local minima

During the learning process, the error vector can be thought of as moving along a multi-dimensional error surface. The learning is normally complete when the error vector reaches a minimum of this error surface. This minimum may be the global minimum or one of many local minima. The back-propagation learning algorithm does not guarantee the network will reach the global minimum.

A neural network gets stuck in a local minimum because the steepest-descent algorithm cannot further descend. This is an undesirable situation and one way to avoid it is to add a momentum term to the back-propagation learning rule. Equation (2) with the additional momentum term is:

(EQ 4)

$$\delta_{pj} = \alpha (D_{pj} - O_{pj}) f'_j (I_{pj}) + \beta \delta_{(pj)'}$$

where

β = *momentum multiplying constant*

$\delta_{(pj)'}$ = *previous weight delta for the same connection (calculated at time t-1)*

The other parameters are the same as in Equation (2).

The addition of this momentum term allows the neural network to escape from local minima. Let us consider skiers going down a hill. If the skiers encounter small bumps on the way, their forward motion will not be blocked because they have enough momentum to go over small hillocks. The momentum term in the back-propagation rule allows the neural network to go over most of the local minima.

Back-propagation is of interest because it is widely known and well understood. Furthermore, it has been successfully applied in many research projects, some of which are described in section 4.3. Results obtained using this method are presented and discussed in chapter 5.

4.2.3 Advantages and Disadvantages of Neural Networks Over Other Methods

The problem of fault diagnosis that we are concerned with here is mainly one of pattern recognition. Neural networks are one of many methods trying to solve this problem. This section presents some other techniques that could be used and compares them to neural networks.

Procedural Approaches

Using the traditional procedural approach, a designer is constrained to use logical comparisons (e.g. >, <, >= ...) to set boundaries in a multi-dimensional space against which input data will be checked. These boundaries are typically fixed and act as sharp delimiters of decision regions, i.e. a data sample either belongs or does not belong to a region in the multi-dimensional space. This works for well-defined cases, but data from real-world situations is often noisy and poorly distributed. One is then faced with the task of redefining previously set boundaries and adding new ones. If such a system has been built using *if-then-else* statements or a similar procedural approach, bringing those changes usually represent considerable work or simply starting from scratch.

Neural networks are known for their ability to interpolate, i.e. to generalize about data they are presented. For instance, an input vector that is very representative of the class to which it belongs will certainly yield the neural network to output a high value at the corresponding output neurode, say 0.95 out of 1. On the other hand, a vector with less similarity to that same class would result in a weaker output, say 0.65. In a pattern classification task, such results still carry enough meaning on which decisions can be made. This is similar to the concept of membership degrees found in fuzzy logic [111]. Ultimately, when significant changes occur in the problem domain, one can re-train a neural network or use a neural architecture which provides continuous learning.

Statistics

Classifiers based on statistical methods are close to neural networks. They differ in one important aspect. Statistics based systems rely on some assumptions about the input distribution. These assumptions take the form of parameters whose value must be tuned for best performance. Neural networks need no assumption about the input distribution. One may argue that neural networks do have some parameters like weights, gain factors, and thresholds. However, these parameters are not tied to the input distribution. They are initially given random values which are later refined during the learning phase.

In statistics based systems, one is often tempted to simplify the statistical model when dimensionality becomes a concern. This is because a model must be defined a priori, i.e before training. Neural networks build their own model of the input data and dimensionality is not a concern, at least not in the same sense as with statistics based systems. Dimensionality may cause a problem with neural networks if it results in the design of a huge network with very demanding computations.

Statistics are nevertheless an important tool in the design of neural networks. It is typically claimed that one does not need to be an expert in the domain of the application to use neural networks. This is not entirely true. Unlike expert systems, neural networks do not require the knowledge of a human expert to be translated into rules. However, neural network designers are expected to possess or gain some knowledge about the domain of application A data set that truly covers the problem domain of an application can otherwise hardly be built. Statistics, among other tools and sources of information, are thus often used in that perspective.

Expert Systems

As was mentioned above, expert systems rely on rules extracted from human expert knowledge. Neural networks also require expertise but only to give the designer a proper understanding of the problem domain. This knowledge may be acquired from human experts or simply from written material about the problem domain. Neural network designers do not need knowledge as much as they need a large sample data set that fairly represents the complete problem space. Expert systems do have the advantage of being more user friendly. Rules are written in plain English and can be easily understood, even by a non-programmer. In addition, expert systems can provide an explanation about how they have reached a particular conclusion. This increases the confidence of a human user who may be assisted by an expert system.

4.3 Related Research in the Domain of Neural Networks for Diagnosis

It is only recently that neural networks have gained considerable credibility and popularity. For that reason, the majority of published articles relate theoretical ground work about neural networks. The scientific community is now witnessing a growth of neural network models and associated learning methods. Very few applications have been reported. However, applications based on neural networks which have been reported to this date are typically encouraging and represent a promise of yet more interesting results to come.

In this second literature review, an overview of various neural network based diagnosis applications is given. This section is divided according to five domains of applications where neural networks have been applied to perform diagnosis.

4.3.1 Electronic Circuits Diagnosis

Jakubowicz and Ramanujam describe a neural-network based diagnostic system that directs technicians in diagnosing faults in electronic equipment [50]. The first stage of the neural network is a self-organizing feature map that learns faulty state patterns and creates feature maps corresponding to each input pattern being presented. These feature maps are then passed to a feed-forward network. In this second stage, the network uses the structural description of the system to determine which components might be responsible for the observed symptom-state. This method was successfully applied to the diagnosis of a 4-bit binary-full adder.

Kagle *et al.* describe a neural-network based system trained to identify and locate electrical faults in electronic circuit boards and perform automatic knowledge acquisition [52]. The authors used a back-propagation network trained with single event failure characteristics. Their results show that a network trained with single event failure characteristics can also identify simultaneous multiple event failures. Results also indicate that, for this problem at least, neural network performance is closely tied to the number of neurodes in the input layers. Diagnosis performance decreases when the number of input neurodes used is diminished. They also observed that the number of hidden layer neurodes needed to be adjusted so that the network could generalize its conclusions.

Tan *et al.* describe INSIDE, a neural-network-based system to troubleshoot the Inertial Navigation System, an avionic line replaceable unit [100]. Training examples were obtained from equipment failure history. Whenever the trained neural network fails to identify a failure, the system falls back on a flow chart module that technicians typically use when troubleshooting these pieces of equipment. When the problem is found using the flow chart module, the new equipment failure case is added to the set of training examples. The neural network is retrained using the improved training set and its performance and fault coverage are thus increased.

Totton and Limb have evaluated the performance of back-propagation neural networks for the diagnosis of analog/digital interface line cards for digital exchanges [102]. With only a restricted number of samples (295), they trained a neural network to recognize correct failure modes with more than 90% of accuracy. The advantage of neural networks over their previous expert system solution [53] is the considerably reduced time needed to train and test a neural network compared to the time required to write and validate rules for an expert system. However, the authors estimate that a hybrid system made of neural networks and expert systems would provide a better solution, for it would have the ability to learn from data and could provide an explanation facility.

Meador *et al.* have applied back-propagation neural networks to the problem of high-volume diagnosis of integrated circuits [76]. They compare results obtained using traditional

Gaussian Maximum Likelihood (GML) and K-Nearest Neighbor (KNN) classifiers. According to their results, classification performance of the back-propagation neural network is consistently superior or equal to that of either the GML or KNN classifier. An interesting advantage of neural networks in this application is the significantly reduced number of floating-point operations (FLOPs) needed to perform diagnosis compared to what is required with either KNN or GML. The trade-off is a greater number of FLOPs is required during training of the neural network.

4.3.2 Medical Diagnosis

Schreinemakers and Touretzky describe ELSIE, a system to detect clinical and subclinical udder infection in dairy cows [96]. The system consists of a production system module, a neural network simulation module, and a knowledge acquisition module. The diagnosis decision is performed by a neural network using measurements of milk production and leucocyte counts as inputs. Another subsystem, the Knowledge Manager (KM) operates as an intelligent rule-based dispatcher. One of the tasks of the KM is to present wrongly classified samples to a human expert for correction. New examples thus obtained are then submitted to the neural network to refine its training set. The initial diagnosis performance of the neural network is 87% compared to that of their expert veterinarian informant. While analyzing the classification errors, the authors noticed that the network had detected some inconsistencies in the training data that had been caused during the initial building of the training set by veterinarians. With the corrected training set, the network performance was raised to 98% accuracy.

Apolloni *et al.* investigated the possibility of diagnosing epilepsy using multi-layer perceptrons trained with the back-propagation algorithm [6]. Using a questionnaire designed by the International League Against Epilepsy (ILAE), the authors have built a neural network with 724 inputs and 31 outputs (the ILEA considers 31 possible diagnoses). The trained neural network offered a performance of 87% accuracy on cases it had never seen. A study of the trained network revealed that some of the inputs are not used at all (i.e. their weights are equal or very close to zero). After removing these unused inputs and retraining the network, the authors were left with only 74 inputs for their neural network, i.e. about 10% of what they originally had, and an increased accuracy of 95%. According to experts, the unused inputs point to questions in the ILAE questionnaire that are not considered particularly relevant to this problem.

Dytch *et al.* have used different types of neural networks as tools for the evaluation of DNA ploidy spectra for the objective evaluation of stratified epithelia using high-resolution karyometry [31]. The classification rates they obtained in preliminary studies are even better than what they obtained using more traditional techniques. A careful examination of the synaptic weights of their trained network revealed that the internal representation of the network corresponds to known heuristic rules for the interpretation of DNA ploidy spectra.

Boone *et al.* have evaluated how neural networks can be applied to computer aided radiologic diagnosis [14]. In their first experiment, the performance of a feedforward neural network trained with a variant of the generalized delta rule favorably compared with that of human radiologists in a basic visual perception task. An interesting aspect of this experiment is that they first had to train the network with images having a high signal-to-noise ratio. Only then were they able to use reduced signal-to-noise ratio images to further train the network. This is similar to the way humans learn. The easy concepts are learned first and the more advanced concepts are then added as refinements to the basic knowledge. Whereas the goal of their first experiment was to show the ability of neural networks to perform pattern recognition tasks, the objective of their second experiment was to assess the feasibility of applying neural networks to cognitive tasks. With 50 possible findings as inputs and 12 possible diagnoses as outputs, the two-layer feedforward network correctly identified 79% of the positive diagnoses and 99% of the negative ones.

Maricic *et al.* describe a prototype automated system for preliminary heart anomaly detection based on neural networks [69]. The first stage of the system performs image processing on chest radiographs to extract some 30 heart shape parameters. Of these, only 9 can be shown, through statistics, to be of value for this classification task. The authors used a back-propagation neural network with 3 outputs, one per possible diagnosis. The results of their experiments are encouraging, but clearly show that the heart shape parameters used as inputs do not carry the information necessary to properly classify heart anomalies with a high degree of success.

Egbert *et al.* have compared back-propagation neural networks to conventional classifiers for the task of diagnosing neck and back injuries from thermographic images [32]. These images were first preprocessed to extract feature vectors which are fed as inputs to the back-propagation neural network. Two different implementations of the back-propagation neural network were tried and yielded 90% and 80% accuracy respectively. Using the same feature vectors, conventional methods such as nearest neighbor classifiers and gaussian maximum likelihood classifiers could at best yield 45% accuracy.

Harrison *et al.* trained a multi-layered perceptron to diagnose the presence of chest pain [42]. They evaluated two neural networks, one using the mean-square-error and the other, a log-likelihood function. Both offered similar performance except that the latter completed training in less time than the former. Both networks presented a better accuracy than that of an experienced physician asked to produce diagnoses using the same data. A sensitivity analysis also revealed that both networks and physicians gave more weight to the same six most important positive contributors and the same most important four negative contributors.

4.3.3 Chemical Plant Diagnosis

Yamamoto and Venkatasubramanian describe an interesting neural network architecture to carry the diagnosis of a chemical plant [108]. The authors combine a qualitative neural network (QLN) with a quantitative one (QTN) and obtain more reliable diagnoses than with a quantitative neural network alone. The same information is fed to both the QLN and QTN networks. Inputs for the QLN is first preprocessed to make it qualitative. Both the qualitative and quantitative neural networks have the same set of possible outputs. If both types of network agree on the output, the results of the QLN network are passed to an inverse qualitative network (IQLN). The set of possible outputs of this network is identical to the set of possible inputs to the QLN network. If outputs from the IQLN network and inputs to the QLN network are similar, then it is assumed that a diagnosis has been reached. The authors use multiple copies of QLN and QTN. Since these networks are started with different random sets of weights, that provides a means of validating the networks results against each other. This architecture takes advantage of both the accurate information carried by quantitative values and the robustness to noise of qualitative information. A detailed explanation of the QLN, QTN, and IQLN architectures can be found in [108].

Hoskins *et al.* report about their experience with neural network for fault diagnosis in chemical plant processes [48]. They report that neural networks can fulfill several functions in fault diagnosis. First, they are capable of classifying labeled data inputs during training so that a clearly delimited fault partitioning is obtained. Second, they can self-organize using non-labeled training data. Third, they can form associative memories, thus making possible the retrieval of fault patterns using only partial or corrupted inputs. Fourth, using high speed parallel processing, they can handle sensor data in real-time. And fifth, they provide a non-linear mapping of inputs to outputs.

Jokinen compares Dynamically Capacity Allocating (DCA) network models to conventional neural networks in the task of fault detection and diagnosis of an industrial process [51]. The author states that it can be difficult to gather all the possible fault conditions to construct a fault detection system. A network that is capable of continuous learning is then clearly an advantage. Jokinen led an experiment identical to the one reported in [108] but used a DCA network instead. The probabilities of "correct" observed faults as a function of the underlying "actual" process faults using the DCA network were much higher that those obtained using the back-propagation algorithm. Only one type of fault was consistently misclassified. The author suggests such results most probably indicated that not enough input information was collected for that type of fault.

Arai *et al.* have evaluated a neural network for the diagnosis of problems with compressor valves using valve plate sound [7]. They found that preprocessing the raw data allowed them to obtain a network offering 100% accuracy with a significantly smaller number of neurodes. They used a conventional back-propagation neural network with inputs coming from four different types of preprocessing. Their experiment revealed that training a network with preprocessed data from one normal valve plate enabled the network to correctly recognize other normal valve plates, whereas training the network with raw data from a normal valve plate did not make this type of generalization possible. The authors thus suggest that preprocessing raw data for only one normal valve plate extracts the features invariant to all normal valve plates.

4.3.4 Engine Diagnosis

Marko *et al.* report about their experience with an attempt to develop a neural network to diagnose faults in computer controlled electro-mechanical systems in vehicles [70]. Using a mixture of digital and analog signals from the inputs and outputs of an engine control computer (ECC), they trained a back-propagation neural network to recognize 26 different faults. They attained 100% accuracy on their testing set and similar results were also obtained when using other neural network architectures such as counter-propagation. The authors conclude that validation is an issue to which attention must be paid since one cannot deduce from a trained network if the problem space — which is usually multidimensional — is adequately covered.

In another paper by Marko *et al.*, an analysis was done over a number of trainable classifiers to detect and identify faults in vehicle powertrain systems [71]. They stress the importance of assembling proper training sets and designing relevant tests for trained classifiers. Good training sets are those that adequately cover the multidimensional space such that generalization can be attained. Thorough testing is accomplished by using methods such as *leave-k-*

out. The classifiers they selected to evaluate are the nearest neighbor classifier, the Restricted Coulomb Energy (RCE) networks, the back-propagation network, and two variants of the binary tree. Even though the back-propagation neural network classifier showed one of the best performances, the authors raise the problem of training and testing time for such classifiers. For problems requiring large neural networks, back-propagation may prove to be impractical with traditional computing means.

Guo and Nurre have investigated the feasibility of using multilayer feedforward neural networks to identify sensor failures in the Space Shuttle main engine [40]. A first neural network was trained to identify, among a number of sensors, which one has an output different than the others. A second neural network was also trained to provide an estimate value for the failed sensors. They obtained 95% accuracy on their test cases, using a neural network that was easier to design and tune than conventional methods which depend on complex models of the system under diagnosis.

4.3.5 Power Systems Diagnosis

In [56], Khaparde and Mehta have evaluated the feasibility of using neural a network for detecting the presence of bad data in power systems. Their study shows that the training time is affected by parameters such as gain factor, momentum factor, and network architecture (i.e. the number of hidden neurodes). The back-propagation neural network they used is able to classify good and bad data with 95% to 100% accuracy on data it has not seen during training. The authors conclude that neural networks offer a simple and straightforward solution to a problem which typically requires elaborate algorithms.

Nishimura and Arai have evaluated both a back-propagation neural network and a structured neural network for the purpose of detecting power system states [84]. The back-propagation neural network performed successfully but did not provide acceptable results when responding to unknown patterns. This motivated the authors to develop a structured neural network which makes use of a feedback mechanism from logical knowledge to recognition. This network showed a greater ability to deal with unknown input values.

4.3.6 Applications of Neural Networks in Communications

Neural networks have also been applied in a number of areas in communications such as network control and management [92][45], network switching [72], data routing [57], data interpolation [3], adaptive filters [106], quadrature amplitude modulation [59] and local and wide area networks [10].

4.4 Summary

An historical overview of the field of neural networks was given and a detailed description of the back-propagation algorithm was presented. A number of diagnosis application taken from the scientific literature were also reviewed. The next chapter will describe the actual steps that were taken to gather data, define tests, and evaluate neural networks with respect to their applicability to the problem of identifying and locating faults in the telephone access network.

Chapter 5 Subscriber Loop Fault Diagnosis with Neural Networks

This chapter describes the experimentation that was carried out to evaluate the feasibility of employing neural networks in the telephone access network fault diagnosis process. The input data available and the output goals desired from an automated diagnosis system are first presented. The actual neural network implementation, training and testing are then described. A discussion of results and future extensions ends this chapter.

5.1 Output Goals

Telephone access network maintenance is concerned with the two following objectives: identifying faults and localizing them. Faults can be categorized by the following:

- metallic problems (damaged wires, short-circuits, open-circuits, resistive leakages, etc.)
- profile problems (erroneous database entries)
- user problems (users having difficulties using calling features such as call hold, call forwarding, etc.)

A fault may sometimes be identified simply by talking with the customer. If the customer calls to report a wire that was accidentally damaged, the fault is identified right away. Similarly, customers calling to request help do not involve further investigation from Repair Service Bureau personnel.

Less straightforward are problems for which the customer can only describe the symptoms of the fault. For instance, a customer may call to report an inability to receive calls. The cause could be that another phone stayed off hook or that rust has finally deteriorated the inside wire to such a degree that it is now cut open. But it could also be the result of a number of other failures. The repair process can only start once the fault has been identified. As it is costly for telephone companies (or for subscribers, if it is shown that they are responsible) to have a technician examine the equipment and installation at the subscriber's premises, it is desirable to obtain the best indication possible of what fault occurred and its location before any dispatch decision can be made. Fault identification and localization is the prime aspect of telephone access network maintenance. The rapidity with which a problem is fixed depends largely on the quality of this process. Telephone companies have regulated deadlines to meet regarding repair work and customer satisfaction increases when problems are resolved faster.

Another factor to consider is the organizational division of the repair work force. Repair personnel are typically organized into outside plant group, central office group, and customer premises group. Since the performance of each of these organizations is normally evaluated according to the number of troubles received, how many that were solved, etc., it is important to know the exact location of the fault in order to route the problem to the proper group.

The objective of this research work was to assess the feasibility of using neural networks to carry out telephone access network fault identification and localization tasks. The following section presents what type of data was available to that end.

5.2 Input Data Available

The information available for subscriber loop fault diagnosis currently stems from five sources: the customer, the trouble report files and line records, billing information, network elements and test heads.

5.2.1 The Customer

In the present mode of operation, known as the reactive mode, the customer triggers the maintenance process by calling the Repair Service Bureau to report a problem. The answer clerk, who greets the customer, is responsible for getting the customer's phone number, verifying the coordinates, and registering the reported problem. Subscribers typically report problems such as "I cannot call", "I cannot receive calls", "I keep on reaching the wrong number", "I hear noise on the line", "The wire outside was accidentally ruptured by a truck", etc. With this kind of information as a starting point, an experienced human tester can then initiate the diagnosis process and request more information from the subscriber if need be.

The information provided by the subscriber is of significant importance since it is currently the only means of probing what is happening at the far end of the loop.

5.2.2 Customer Line Records and Trouble Report Files

Each customer has a line record. This record indicates when the installation was done, which equipment in the central office serves the line, and identifies the components (cables, junction boxes, protection devices, etc.) that make up the loop.

If a customer has called the Repair Service Bureau in the past to report a problem, the type of trouble reported, the problem found, and the solution used to fix it are stored in the trouble report history file. This can be used to correlate new troubles with repair or installation work done in the past. Similarly, active trouble report files can be used to correlate problems that have a common source and thus need only a single dispatch [15][21][73].

5.2.3 Billing Information

Billing records often serve as a point of reference when trying to solve a problem. Customers may call the Repair Service Bureau to report a complete service outage or the absence of a calling feature they have ordered. In some instances, after it has been verified that service from a line has indeed been purposely removed or that the switch has not been provisioned for a particular calling feature, the tester will consult the subscriber's billing record. The billing record can show whether service was removed because of non-payment or upon customer request, and if there is a subscription to one or more calling features.

5.2.4 Network Elements

Network elements now have a more active role in access network maintenance. Even though a separate test card is often used to collect electrical measurements from the loop, today's switching devices can now carry out their own tests on subscriber loops. They can also provide information about the current state of a subscriber loop and its provisioned features. As network elements are becoming increasingly "intelligent", more and more consideration is given to their potential for access network maintenance.

5.2.5 Test Heads

Test heads are stand-alone devices that can receive commands from Operational Support Systems and perform the functions requested. The most commonly found test head in the Repair Service Bureau environment is the type that can perform electrical measurements on subscriber loops. These test heads can measure AC and DC voltages, resistances, and capacitances. They are also capable of a number of other functions, such as [19][24][25][28][36][49]:

- connection/disconnection commands;
- monitor or talk on line under test;
- look in toward central office, look out toward subscriber, or bridge across line under test;
- transfer test connection to another operator;
- breakdown test, i.e. application of high voltages to dry out wet pairs;
- release lines that have a permanent signal condition, i.e. that have been seized by the switching equipment;
- ring subscriber;
- verify subscriber equipment capability to produce acceptable Dual-Tone Multi-Frequency (DTMF) tones;
- test rotary dials;
- apply howler tone to notify subscriber of a phone that is off hook;
- apply sounder tone for cable localizing;

- set loop current to test coin telephone operation;
- apply transmitter current to measure current through transmitter in subscriber telephone;
- reverse tip and ring;
- test ability of subscriber line to obtain dial tone from central office with option to insert additional impedance on the line;
- dial on a subscriber line;
- send on hook signal toward central office on subscriber line;
- check subscriber line card in central office;
- verify office equipment to find if line is a tip or ring party, or PBX hunting group;
- verify ringer presence;
- detect voice.

With the increased power of digital switching systems, the functionality provided by traditional test heads can be replicated by the switch hardware and associated software. With these capabilities, one can look forward to a preponderant role of intelligent network elements, such as modern digital switching systems, in future access network maintenance systems.

5.3 A Neural Network for Fault Identification and Localization

5.3.1 Selection of Data for the Neural Network

Out of the five sources of information mentioned earlier, only one was used: the trouble report This choice is not as restrictive as it appears since much information coming from other sources is transcribed into the trouble report. The problem reported by the customer is entered as codes in the trouble reports and some free-format information is also stored in remark fields. Information about subscriptions to different services is taken from the billing system and copied onto the customer line record, even though it is sometimes outdated. Results returned by test heads are appended to trouble reports and available for future reference. Finally, network elements can carry out some tests of their own and provide a snapshot of the calling features of a particular telephone line. Unfortunately, this information is not currently integrated to the customer line record.

Human testers seem to base their decision on a few data fields only. They typically consider the following [18][19][24][25][49][66][73][80][81]:

- the description of the problem entered by the answer clerk;
- the additional remark the answer clerk may have entered;
- the 12 electrical measurements returned by the test head;
- the verify code which is a machine interpretation of the electrical measurements.

Other fields may be exceptionally considered. As the first two items have free formats on the trouble report and are of a subjective nature, they were not considered in the experimentation. The verify code is in fact one of the items this research work is looking to improve and will serve as a measure of comparison. Finally, the electrical measurements returned by the test heads are without a doubt the most objective information available. These measurements consist of four groups of three measurements taken between tip and ring, tip and ground, and ring and ground. The four groups are AC voltages, DC voltages, resistances, and capacitances.

5.3.2 Preprocessing the Data

A selection of 5,335 trouble reports was available for experimentation. Out of these, 891 were hand-picked and labelled. The machine-generated verify code indicates if the problem was diagnosed as a short, an open, etc. However, the exact nature of the problem is contained in the last remark field where the dispatcher enters the cause of the fault, along with the solution used to fix it, before closing the report. This remark field had to be read for each trouble report and encoded into a form acceptable to a neural network. The categories of problems for the data samples used were:

- good lines;
- open circuits;
- lines affected by a dead left-in wire. Such lines appear to be short-circuited;
- lines affected by noise. Such lines are typically affected by rust. The resistance measurement taken between tip and ring typically shows a value around 5 MΩ instead of the normal 9.999 MΩ. Conversation is still possible under these conditions;
- lines affected by rust. Such lines are affected by rust to a higher degree where drawing dial tone and conversation are no longer possible;
- short-circuits. This category includes short-circuited lines where drawing dial tone and conversation are not possible but for which no cause was provided in the trouble report;

Values of resistance measurements ranged from 0 Ω to 9.999 MΩ whereas the other measurements covered only 2 or 3 orders of magnitude. In order to resolve this disparity, the logarithm of these resistance measurements were taken and fed to the neural network. Finally, capacitances were sometimes not measured because of the presence of high voltage that could have damaged the test equipment. Capacitance measurements were thus preprocessed to replace missing values with -1 entries (valid values being positive).

All the data samples were divided among three equal subsets, each one containing an equal number of samples from a particular category. Three different training/testing pairs of data sets were then formed by taking two subsets to form the training set, leaving one out for the test set and performing permutations.

5.3.3 Dividing the Fault Identification Task into Smaller Problems

A first attempt was made at building a neural network to handle the six categories listed above with the result that the network never completed the learning stage successfully. The problem with this approach is that the six fault categories described above were not equally represented in the sample data set. There were 15 "lines affected by noise", 36 "lines affected by a dead left-in wire", 128 "lines affected by rust", 150 "open circuits", 263 "good lines", and 303 "short circuits". For a single network to handle all cases, duplication of samples or production of samples using common sense would have been necessary to make up for the small number of samples of certain fault categories. Instead of doing this, it seemed more appropriate to approach the problem the same way human testers do, i.e. by proceeding step by step and first trying to eliminate the obvious cases.

The task was thus divided into smaller problems, each one handled by a specific neural network. Figure 5.1 shows the architecture of neural networks used to identify faults. A first neural network classifies incoming patterns into two categories: that of lines affected by open circuits and that of lines not affected by open circuits. If a line is tagged as affected by an open circuit, the fault is found and the process stops there. Otherwise, the 12 measurements are submitted to another neural network that discriminates between good lines and lines affected by problems other than open circuits. If the line is tagged as being a good line, no fault is found and the process stops. Otherwise, the 12 measurements are passed to a last network that classifies lines into 4 categories: those affected by short circuits, by noise, by rust, and by dead left-in wires

5.3.4 Training the Neural Networks

The package used to carry out the experiments is NeuralWorks developed by NeuralWare [82]. This software allows one to set up learning schedules. Using these, one can specify how the various back-propagation parameters are to behave as training progresses.

NeuralWorks allows the specification of a back-propagation neural network with up to 3 hidden layers. Neural networks with one and two hidden layers were investigated in this research and Tables 5.8 and 5.9 show the results. The number of neurodes in the input layer was set to 12 in every case since all electrical measurements were used as inputs in each problem. Even though some measurements are known to be irrelevant to identify some faults, they were nevertheless left in to study how the neural networks would react to inputs that do not carry use-

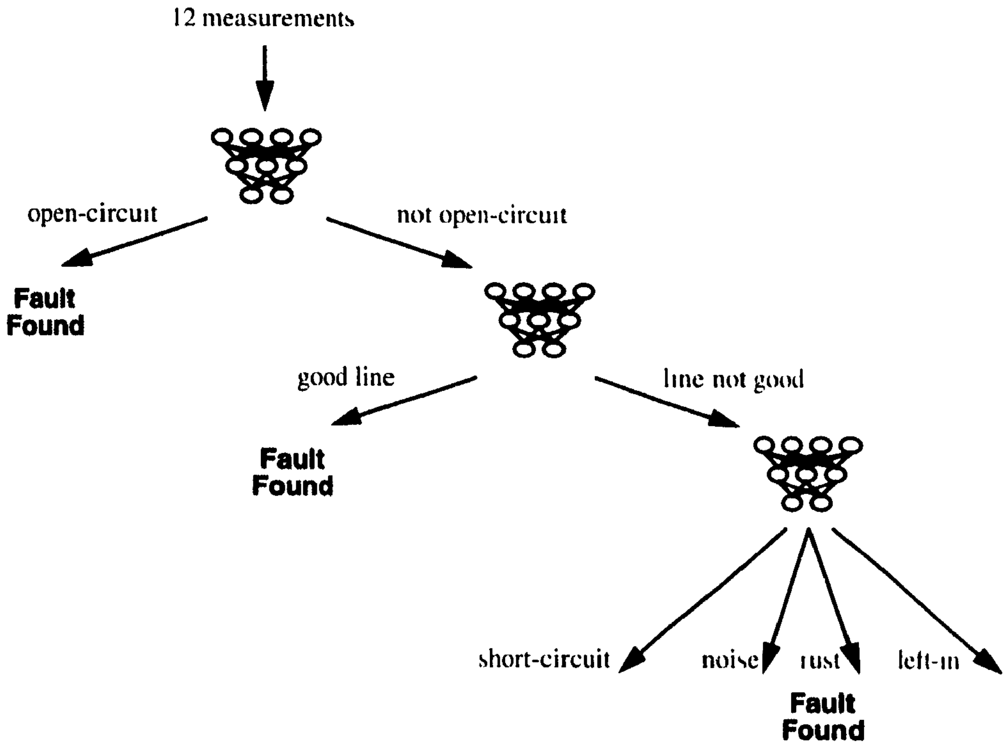

Figure 5.1: Neural network architecture for identifying faults.

ful information. The number of neurodes in the hidden layer was set to 4, 8, and 12. Tables 5.6 and 5.7 detail how the number of neurodes in the hidden layer affects the ability of the neural network to generalize. The number of neurodes in the output layer was set according to the number of categories expected for each problem.

Each one of the hidden layers and the output layer can have their own learning coefficient. The learning coefficient controls the speed of learning of a neurode. The bigger this coefficient is, the faster a neurode learns. However, a large learning coefficient may lead to oscillatory behavior. Learning coefficients are typically set to 0.1 and are decreased over time during learning. Experimentation has shown that starting with a low learning coefficient for the output layer, e.g. 0.1, and slightly smaller ones for the following hidden layers gave best results. The momentum term was set to 0.4 and the first transition point to 10,000. After 10,000 training passes, NeuralWorks switches to the next stage in the learning schedule, i.e. it multiplies the learning coefficient of each layer and the momentum term by the learning coefficient ratio, which was set to 0.5. This allows the neural network to refine its learning as time progresses.

The learning rule used was the normalized cumulative delta rule which is a derivative of the cumulative delta rule. The cumulative delta rule accumulates the weight changes over a certain number of training passes called an epoch and then make the application all at once. The problem with this approach is that changing the epoch affects the learning coefficients. The normalized cumulative delta rule takes care of this by automatically dividing the learning coefficients by the square root of the epoch. Epoch sizes of 1, 4, 8, 16, 32, and 64 were investigated. Table 5.10 shows the results. The transfer function that was selected is the hyperbolic tangent, which is more suited to input values with a range of -1 to +1.

Figure 5.2 shows the "BackProp Builder" dialog box which pops up when creating a back-propagation neural network. It is interesting to go over each of the parameters of this dialog box. A number of check boxes allows the user to specify various configurations and the inclusion of certain tools. The **Connect Bias** check box connects an input bias to each neurode in the neural network. This is similar to providing a ground path in an electrical circuit. The **Connect Prior** check box fully connects the input layer to each neurode in all other layers. Leaving this check box blank defaults to the configuration where the input layer is fully connected to the first hidden layer only. NeuralWorks allows the user to add or remove any single connection in any layer. Checking the **Functional Links** box creates another layer in parallel with the input layer to compute second order iterations. This second layer acts as a second set of inputs for the rest of the network. The **Auto-Associative** box when checked sets the number of output neurodes equal to the number of input neurodes and forces the neural network to use input data as desired output during training. As the problems under investigation all fall under the hetero-associative class (i.e. input patterns are mapped to categories), this feature was not used. The **Linear Output** check box allows the user to override the selected transfer function and forces the network to use a simple linear transfer function for the output layer. The **Gaussian Noise** check box toggles between Gaussian noise when turned on to uniform noise when turned off. The **Tolerant Error** check box forces the network to consider a parameter found in the Learning/Recall Schedule dialog box as an error value to be considered as 0. When this value is reached, learning stops. Learning can also be stopped by setting appropriate convergence criterions in tools such as the RMS Error Graph.

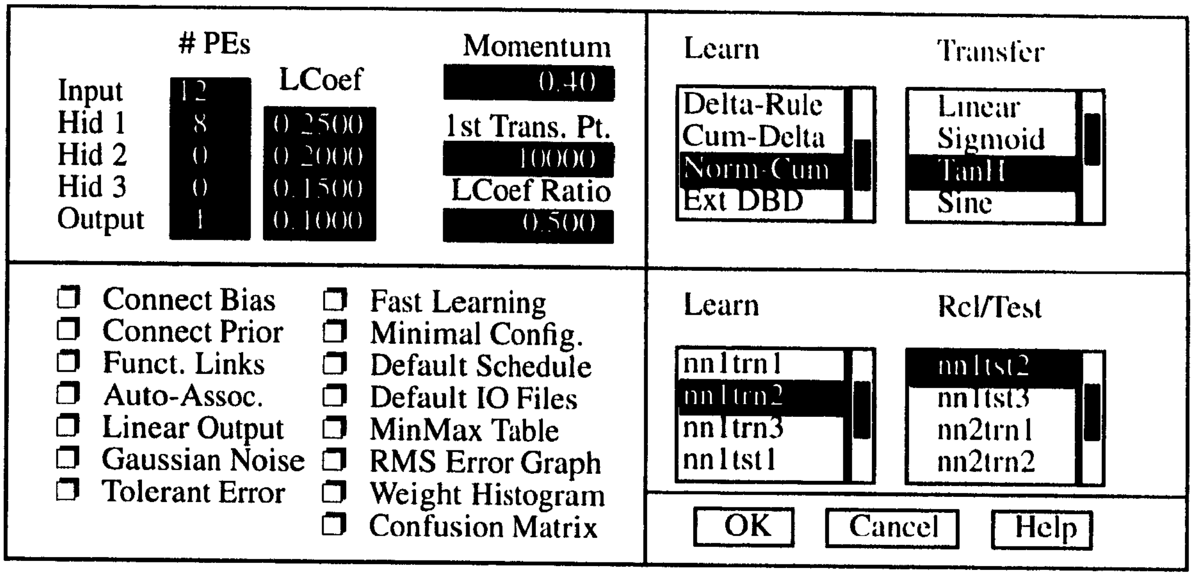

Figure 5.2: BackProp Builder dialog box.

The **Fast Learning** check box permits the user to switch to a faster variant of the back-propagation learning algorithm. The **Minimal Configuration** check box tells NeuralWorks to eliminate less critical parameters such as the momentum term when computer memory is limited. Checking the **Default Schedule** box instructs the software to use a default learning schedule for all layers whereas leaving it blank lets the neural network designer use its own schedule. The **Default I/O Files** check box allows one to direct NeuralWorks to use default file names instead of the ones specified under **Learn** and **Recall/Test**. Checking the **MinMax Table** box permits the user to get a *minmax* table automatically created while training data is being read in This must be used if one wants to take advantage of the automatic linear normalization feature provided by NeuralWorks.

The last three check boxes allows the user to specify which standard instruments are to be used during the simulation. The **RMS Error Graph** instrument shows a graph of the RMS error at the output of the neural network with respect to the number of training passes. The **Weight Histogram** instrument displays a normalized histogram of all variable weights in the neural network. Finally, the **Confusion Matrix** instrument creates a confusion matrix for each output neurode Figure 5.3 shows a confusion matrix. Desired outputs are mapped onto the x axis while actual outputs are mapped on the y axis. Each axis is divided into bins. A network that has successfully learned will have bins fully or partially filled on the lower left/upper right diagonal.

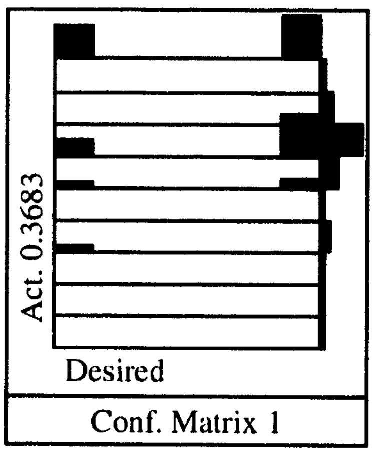

Figure 5.3: Confusion matrix.

5.3.5 Testing and Evaluation

For investigation purposes, a certain class of problems was selected. In this section, the experimental results are described. A brief overview of the method used to validate the results is given first.

Validation and Qualification of Results

In order to validate the results obtained during the experimentation, the *leave-k-out* method was applied [104]. Using this method, one takes k samples out of a total set of N samples for testing (*N-k*) samples are thus available for training. One then repeats this procedure N/k times, each time taking out a different set of k samples for testing All such sets of k samples must be mutually exclusive. When dealing with a very limited number of samples, one typically sets the value of k to 1. The size of the set of samples used for this research made a ratio of N/k equal to 3 (N/k = 891/297) seem reasonable. Three groups of 297 samples were formed and 3 "runs" were performed for each type of neural network. In each run, one group of 297 samples was left out for testing and the other two groups were used for training the network. This procedure was repeated three times per network, each time leaving a different group of 297 samples out for testing and using the other two for training.

Results were qualified according to three factors:

- ***False recognition rate***: the ratio of incorrect diagnoses to the total number of cases.
- ***Rejection rate***: the ratio of diagnoses where none of the network output neurodes could provide a value greater than 0 (in a range of -1 to +1).
- ***Recognition rate***: the ratio of correct diagnoses to the total number of cases It is equal to (1 - (*false recognition rate* + *rejection rate*)).

5.4 Experimentation Results

5.4.1 Performance of the Proposed Neural Networks

Neural networks were designed to handle the following problems:

- open-circuit vs. not open-circuit (results are in Table 5.1),
- good line vs. short-circuit (Table 5.2);
- Type of short-circuit: dead left-in, noisy, rust, short-circuit (Table 5.3),
- Type of short-circuit: dead left-in, rust, short-circuit (Table 5.4);

• Type of short-circuit: rust and short-circuit (Table 5.5).

Some verify codes in the trouble reports cover open-circuit and short-circuit problems. However, there are no codes to differentiate between types of short-circuits. The last column in Tables 5.1 and 5.2 show the performance of verify codes for the same problem diagnosed using neural networks. Neural network performance when diagnosing open-circuits (98.3%) is similar to that of verify codes (98.5%). However, there is a significant difference in performance when short circuits are considered. Neural networks offer a 96.8% performance in correct classification compared to 67.3% for verify code — an increase of nearly 30%.

Tables 5.3, 5.4, and 5.5 show the result of neural networks when trying to categorize short-circuit type of problems into subcategories. Results will not be compared with the present system as there do not exist verify codes to differentiate among categories of short-circuits. The first of these neural networks had to classify problems into 4 categories and offered an average performance of 60.8%. The "noise" category was then removed due to its very small number of samples (15). A second neural network was then trained on the 3 remaining categories and performance rose to 63.0%. Another class with a small number of samples — "dead left-in" with 36 samples — was then removed to leave only 2 categories: "rust" with 126 samples and "other short-circuits" with 303 samples. Performance for this two-category neural network was 69.2%. Results from these three neural networks are encouraging but a more rigorous study would need to be carried out using trouble reports filled following strict rules. To achieve this, technicians would be instructed to carefully identify the type of problem found and where it was located

Parameters	1st Run	2nd Run	3rd Run	Average	Verify Code Performance
# of input neurodes	12	12	12		
# of hidden neurodes	8	8	8		
# of output neurodes	1	1	1		
False recognition rate	2.4%	0.3%	2.4%	1.7%	1.5%
Rejection rate	0.0%	0.0%	0.0%	0.0%	0.0%
Recognition rate	97.6%	99.7%	97.6%	98.3%	98.5%

Table 5.1: Results for the identification of lines affected by open circuit conditions

Parameters	1st Run	2nd Run	3rd Run	Average	Verify Code Performance
# of input neurodes	12	12	12		
# of hidden neurodes	8	8	8		
# of output neurodes	1	1	1		
False recognition rate	1.6%	2.4%	5.7%	3.2%	32.7%
Rejection rate	0.0%	0.0%	0.0%	0.0%	0.0%
Recognition rate	98.4%	97.6%	94.3%	96.8%	67.3%

Table 5.2: Results for the identification of lines affected by short-circuit type of problems.

Parameters	1st Run	2nd Run	3rd Run	Average
# of input neurodes	12	12	12	
# of hidden neurodes	8	8	8	
# of output neurodes	4	4	4	
False recognition rate	36.9%	41.9%	38.1%	39.0%
Rejection rate	0.0%	0.6%	0.0%	0.2%
Recognition rate	63.1%	57.5%	61.9%	60.8%

Table 5.3: Results for the identification of lines affected by various short-circuit conditions.

Parameters	1st Run	2nd Run	3rd Run	Average
# of input neurodes	12	12	12	
# of hidden neurodes	8	8	8	
# of output neurodes	3	3	3	
False recognition rate	34.8%	39.4%	36.1%	36.8%
Rejection rate	0.6%	0.0%	0.0%	0.2%
Recognition rate	64.5%	60.6%	63.9%	63.0%

Table 5.4: Results for the identification of lines affected by the following short circuit conditions: dead left-in, rust, and short-circuit.

Parameters	1st Run	2nd Run	3rd Run	Average
# of input neurodes	12	12	12	
# of hidden neurodes	8	8	8	
# of output neurodes	2	2	2	
False recognition rate	30.0%	32.9%	29.4%	30 8%
Rejection rate	0.0%	0.0%	0.0%	0.0%
Recognition rate	70.0%	67.1%	70.6%	69.2%

Table 5.5: Results for the identification of lines affected by the following short circuit conditions: rust and short-circuit.

5.4.2 Effect of Certain Parameters on Performance

Some parameters were varied to observe how they affect diagnosis performance.Tables 5.6 and 5.7 show the effect of the number of hidden layer neurodes on performance. The "open-circuit/ not open-circuit" and "type of short-circuit" problems were studied. The performance on recall is the performance obtained on the training set once the network has successfully completed training. The performance on test is the performance on the testing set once the network has successfully completed training. As results show, the number of hidden layer neurodes does not seem to affect the classification performance. Selecting the appropriate number of hidden layer neurodes is a subject of research of its own. Rules of thumb are given by the various neural network package vendors but they are not universally applicable. In general, a network with too few hidden layer neurodes will not satisfactorily extract the features from a set of samples. On the other hand, a network with too many hidden layer neurodes will simply memorize all the cases it is presented instead of extracting common features.

Tables 5.8 and 5.9 show the effect of the number of hidden layers on performance. Varying the number of hidden layers and the number of neurodes that populate these layers do not seem to affect the performance for the "open-circuit/not open-circuit" problem. However, the performance for the "type of short-circuit" problem varies slightly according to the configuration used. The partitioning of the initial problem into sub-problems resulted in neural networks easier to train because of the reduced problem complexity. This is why adding hidden layers does not significantly impact the performance of the neural network. Adding hidden layers to a neural network is like adding levels of abstraction. Complex problems may benefit from multiple hidden layers but it does not necessarily bring more value for smaller problems

Finally, Table 5.10 shows the effect of the epoch size on performance. This parameter does not seem to have any effect on the performance for the "open-circuit/not open-circuit" problem except when the epoch size is 64, in which case, the neural network does not reach satisfactory learning. This parameter, along with others like the learning constant and the momentum term, does not typically affect the performance of the network on recall and test. However, it may have an impact on the learning time of the neural network.

	1^{st} configuration	2^{nd} configuration	3^{rd} configuration
Input layer neurodes	12	12	12
Hidden layer neurodes	12	8	4
Output layer neurodes	1	1	1
Performance on Recall	99.1%	99.3%	99.1%
Performance on Test	97.6%	97.6%	97.6%

Table 5.6: Effect of the number of hidden layer neurodes on the "open-circuit/not open-circuit" problem.

	1^{st} configuration	2^{nd} configuration	3^{rd} configuration
Input layer neurodes	12	12	12
Hidden layer neurodes	12	8	4
Output layer neurodes	4	4	4
Performance on Recall	62.8%	63.1%	63.1%
Performance on Test	62.5%	63.1%	63.1%

Table 5.7: Effect of the number of hidden layer neurodes on the "type of short-circuit" problem.

	1^{st} configuration	2^{nd} configuration	3^{rd} configuration
Input layer neurodes	12	12	12
1^{st} hidden layer neurodes	12	8	8
2^{nd} hidden layer neurodes	4	8	4
Output layer neurodes	1	1	1
Performance on Recall	99.7%	99.7%	99.3%
Performance on Test	97.6%	97.6%	97.6%

Table 5.8: Effect of the number of hidden layers and hidden layer neurodes on the "open-circuit/ not open-circuit" problem.

	1st configuration	2nd configuration	3rd configuration
Input layer neurodes	12	12	12
1st hidden layer neurodes	12	8	8
2nd hidden layer neurodes	4	8	4
Output layer neurodes	4	4	4
Performance on Recall	57.8%	60.6%	62.5%
Performance on Test	56.2%	64.3%	62.5%

Table 5.9: Effect of the number of hidden layers and hidden layer neurodes on the "type of short-circuit" problem.

	1st conf.	2nd conf.	3rd conf.	4th conf.	5th conf.	6th conf
Epoch Size	1	4	8	16	32	64
Performance on Recall	97.4%	99.7%	99.5%	99.3%	99.7%	N/A*
Performance on Test	96.0%	97.6%	97.6%	97.6%	98.0%	N/A*

Table 5.10: Effect of epoch size on the "open-circuit/not open-circuit" problem.

*. Neural network did not learn satisfactorily.

5.5 Discussion and Future Extensions

Neural networks offer a performance similar if not superior to what is currently achieved by humans assisted by traditional Operational Support Systems. One may question the complexity of the decisions arrived at by neural networks in this research. However, in the context of telephone access network maintenance, due to the high volume of trouble reports processed, decisions that can be made without human assistance eventually add up to considerable savings.

Expectations were high when this research project was initiated. With time, it became clear that data to perform more advanced fault identification was insufficient and that information needed to perform fault localization was simply not being stored by conventional Operational Support Systems. One can expect from neural networks a diagnosis performance only as good as the data available to train them.

An avenue certainly worth exploring for the continuation of this research consists in gathering new data that has simply not been collected up to now. Two sources of data are readily identifiable. First, a neural network based system should take advantage of the information exchanged during the interaction between the customer and the answer clerk. Currently, only the result of this interaction — a description code and a succinct remark — is kept in the trouble report. Projects are underway in telephone companies to replace the answer clerk position by an interactive voice response system. Such a system would allow the customer to enter a description of the problem affecting his or her line by going through a set of dialogues. Data collected in that manner would certainly provide opportunities to improve the access network maintenance process.

A second source of information resides in the many Operational Support Systems deployed in telephone companies. For instance, it is known that some provisioning systems have a record of the computed length (in capacitance) of the pair of wires composing the subscriber loop when it was originally installed. Such systems also store information regarding the specifications of the subscriber loop, such as wire gauge, etc. This type of information would definitely help in creating better automated fault localization systems. However, as the result of the last twenty years of loose mechanization that took place in telephone company operations, all these Operational Support Systems are not yet integrated. Telephone companies are becoming more concerned about obtaining an end-to-end view of their network and so are their customers. An integration of these systems and the benefits of information sharing are thus foreseeable.

Parameters, such as temperature and the occurrence of rain fall and snow storms, play a considerable role in today's mode of maintenance operations. A field trial of an interactive voice response system such as the one described above could provide the opportunity to collect such data. Current automated maintenance systems could also be programmed to test subscriber loops at night to gather a set of measurements describing each subscriber loop when they are in good condition. Data collected that way would open up interesting new possibilities for automated diagnosis based on neural networks.

Other neural network architectures are also certainly worth investigating. Self-organizing neural networks could serve as tools to study potential clusters of patterns. Probabilistic neural networks could also be used to take advantage of the various statistics collected on failures over the years. Temporal neural networks could perhaps be utilized to detect certain types of noise, such as impulse noise on telephone lines. Hardware advances in parallel processing should also open the door to other interesting applications of neural networks in the domain of maintenance diagnosis.

The coming of new telecommunications equipment will also change the way maintenance has traditionally been done. Intelligent customer provided equipment will become capable of performing maintenance on the customer's end of the subscriber loop thus helping maintenance systems at the other end, such as providing additional data for a neural network based diagnosis systems for instance. Remote Isolation Devices (RID) are quickly becoming a reality. By listening to high-voltage pulses on the subscriber loop on which they are installed, these devices can perform interesting functions, such as disconnecting the customer's premises from the loop and providing a standard "quiet termination" for testing purposes. Such devices will reduce the complexity of the fault localization problem.

However, just as one should not consider network maintenance only at the access network level but rather with a perspective of the network as a whole, one should also view neural networks as one of a number of tools for network maintenance. Interesting investigation needs to be done in the domain of hybrid systems. Automated decision-making systems based on a mixture of neural networks, fuzzy logic, and expert systems seem to be the most promising for sophisticated maintenance diagnosis applications.

Chapter 6 Conclusion

In this thesis manuscript, the feasibility of employing neural networks in the domain of fault identification and localization in the telephone access network was investigated. The access network itself and the present maintenance environment were first described. A first literature review covering experimental and deployed automated maintenance systems based for the majority on expert systems followed. Neural networks were then introduced and the back-propagation learning algorithm was detailed. A second literature review presented diagnosis systems based on neural networks. The approach used to evaluated neural networks for the task of identifying and localizing faults was then covered. A discussion of the experimentation results and possibilities for future extensions to this work concluded this thesis. The installation of a field-trial automated maintenance system will provide the opportunity to collect the data needed to investigate more advanced automated fault location and identification using neural networks

References

[1] J. M. Ackroff, "Automating the special service work flow," *Proceedings of the IEEE Global Telecommunications Conference (GLOBECOM'89)*, (Dallas, TX), pp. 492-495, IEEE, November 1989.

[2] R. J. Allwood, C. N. Cooper, and A. Taylor, "Diagnosing faults in a telecommunications network by an expert system," *IEE Proceedings*, vol. 137, no. 5, pp. 273-280, October 1990.

[3] M. D. Alston and P. M. Chau, "A decoder for block-coded forward error correcting systems," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'90 Wash DC)*, (Washington, DC), pp. 302-305, 1990.

[4] S. Amari, "A theory of adaptive pattern classifiers," *IEEE Transaction on Electronic Computers*, EC-16, pp. 297-307, 1967.

[5] J. A. Anderson, "A simple neural network generating interactive memory," *Mathematical Biosciences*, vol. 14, pp. 197-220, 1972.

[6] B. Apolloni, G. Avanzini, N. Cesa-Bianchi, and G. Ronchini, "Diagnosis of epilepsy via backpropagation," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'90 Wash DC)*, (Washington, DC), pp. 571-574, 1990.

[7] K. Arai, H. Shimodaira, Y. Sakaguchi, and K. Nakano, " Application of neural computation to sound analysis for valve diagnosis," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'91 Seattle)*, (Seattle, WA), pp. 177-182, 1991.

[8] N. Azarmi, "A knowledge based resource scheduler for network maintenance," *BT Technology Journal*, vol. 9, no. 3, pp. 80-87, July 1991.

[9] M. Azmoodeh, "Representation of generic structure and behaviour of networks for model based diagnostic applications," *BT Technology Journal*, vol. 9, no. 3, pp. 52-60, July 1991.

[10] R. S. Barga and R. B. Melton, "Framework for distributed artificial neural system simulation," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'90 Wash DC)*, (Washington, DC), pp. II-94 - II-97, 1990.

[11] A. Basden and B. A. Kelly, "DART: an expert system for computer fault analysis," in *Proceedings of the 7^{th} International Joint Conference on Artificial Intelligence (IJCAI'81)*, (Vancouver, B. C., Canada), pp. 843-845, 1981.

[12] M. Berberich, E. Feicht, E. Kwee-Christoph, T. Lauer, A. Lehmann, and T. Sturner, "An expert system approach for maintenance support of EWSD switches," in *Proceedings of the International Conference on Communications (ICC'89)*, (Boston, MA), pp. 1433-1437, IEEE, June 1989.

[13] L. Bernstein and C. M. Yuhas, "Expert systems in network management — the second revolution," *IEEE Journal on Selected Areas in Communications*, vol. 6, no. 5, pp. 784-787, June 1988.

[14] J. M. Boone, G. W. Gross, and G. S. Shaber, "Computer aided radiologic diagnosis using neural networks," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'90 Wash DC)*, (Washington, DC), pp. 98-101, 1990.

[15] K. J. Boot-Handford, H. T. Griffith, and R. I. Kimpton, "Towards the paperless international telecommunications service centre — the Keybridge engineering record system," *British Telecommunications Engineering*, vol. 5, pp. 26-32, April 1986.

[16] P. H. Callahan, "Expert systems for AT&T switched network maintenance," *AT&T Technical Journal*, vol. 67, no. 1, pp.93-103, January-February 1988.

[17] P. H. Callahan, G. J. Dome, T. J. Miller, R. U. Telson, and J. L. Thien, "On-line expert systems in network operations: the big bang theory proves true! (for the buck, that is)," in *Proceedings of the IEEE Global Telecommunications Conference (GLOBECOM'90)*, (San Diego, CA), pp. 171-176, IEEE, December 1990.

[18] W. H. Cameron, C. LaCerte, and J. F. Noyes, "Integrated network operations architecture and its application to network maintenance," in *Proceedings of the International Symposium on Subscriber Loops and Services (ISSLS'86)*, (Tokyo, Japan), pp. 261-266, IEEE, September-October 1986.

[19] R. H. T. Cartwright, "4TEL automated subscriber line test system," in *Proceedings of the International Symposium on Subscriber Loops and Services (ISSLS'82)*, (Toronto, Canada), pp. 152-155, IEEE, September 1982.

[20] M. Caudill and C. Butler, *Naturally Intelligent Systems*, Cambridge, MA: MIT Press, 1990.

[21] C. R. Clos, "LMOS/ARSB implementation and impact," in *Proceedings of the International Symposium on Subscriber Loops and Services*, (Atlanta, Georgia), pp. 80-84, IEEE, March 1978.

[22] P. A. Corn, R. Dube, A. F. McMichael, and J. L. Tsay, "An autonomous distributed expert system for switched network maintenance," in *Proceedings of the IEEE Global Telecommunications Conference (GLOBECOM'88)*, (Hollywood, FL), pp 1530-1537, IEEE, November-December 1988.

[23] A. A. Covo, T. M. Moruzzi, and E. D. Peterson, "AI-assisted telecommunications network management," in *Proceedings of the IEEE Global Telecommunications Conference (GLOBECOM'89)*, (Dallas, TX), pp. 487-491, IEEE, November 1989.

[24] O. B. Dale, "The evolution of the automated RSB with respect to loop testing," in *Proceedings of the International Symposium on Subscriber Loops and Services (ISSLS'78)*, (Atlanta, Georgia), pp. 64-68, IEEE, March 1978.

[25] O. B. Dale, H. Rubin, and R. W. Vetter, "A highly distributed mechanical loop testing system," in *Proceedings of the International Symposium on Subscriber Loops and Services (ISSLS'82)*, (Toronto, Canada), pp. 146-151, IEEE, September 1982.

[26] W. F. Daniel, K. C. Loeb, and C. S. Roush, "Quality of maintenance advanced by PBX-pert," *AT&T Technology*, vol. 5, no. 3, pp. 16-21, 1990.

[27] R. Davis, B. Buchanan, and E. Shortliffe, "Production rules as a representation for knowledge-based consultation programs," *Artificial Intelligence*, vol. 8, no. 1, pp. 15-45, February 1977.

[28] H. Dirilten, "CALRS: a multiprocessor centralized automated loop reporting system," in *Proceedings of the International Symposium on Subscriber Loops and Services (ISSLS'78)*, (Atlanta, Georgia), pp. 59-63, IEEE, March 1978.

[29] J. P. Donaghy and R. C. Omanson, "MICE: a facility maintenance expert system," in *Proceedings of the International Conference on Communications (ICC'89)*, (Boston, MA), pp 1418-1422, IEEE, 1989.

[30] R. O. Duda, J. Gaschnig, and P. Hart, "Model design in the Prospector consultant system for mineral exploration," in *Expert Systems in the Microelectronic Age* (D. Michie, Ed.), pp. 153-167, Edinburgh: Edinburgh University Press, 1979.

[31] H. E. Dytch, G. L. Wield, and M. Bibbo, "Artificial neural networks as tools for expert systems in objective histopathology," in *Proceedings of the 10th Annual International Conference of the Engineering in Medicine and Biology Society*, pp. 1375-1376, 1988.

[32] D. D. Egbert and P. H. Goodman, "Neural network discrimination of subtle image patterns," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'90 San Diego)*, (San Diego, CA), pp. 517-524, 1990.

[33] J. R. Fox and G. M. Slawsky, "The role of expert systems in switch maintenance operations and the generation of switch analysis requirements," *IEEE Journal on Selected Areas in Communications*, vol. 6, no. 4, pp. 706-714, IEEE, May 1988.

[34] K. Fukushima, S. Miyake, and T. Ito, "Neocognitron: a neural network model for a mechanism of visual pattern recognition," *IEEE Transactions on Systems, Man, and Cybernetics*, SMC-13, pp. 826-834, 1975.

[35] W. D. Gayler, *Telephone Voice Transmission: Standards and Measurements*, Englewood Cliffs, New Jersey: Prentice Hall, 1989.

[36] J. P. Gervois and B. Prunel, "L'Essais à distance des lignes d'abonnés," in *Proceedings of the International Symposium on Subscriber Loops and Services (ISSLS'74)*, pp. 2.1.1-2.1.6

[37] S. K. Goyal, D. S. Prerau, A. V. Lemmon, A. S. Gunderson, and R. E. Reinke, "COMPASS: an expert system for telephone switch maintenance," *Expert Systems in Government Symposium*, (McLean, VA), pp.112-122, IEEE, October 1985.

[38] S. Grossberg, "Adaptive pattern classification and universal recoding: II. feedback, expectation, olfaction, illusions," *Bio. Cybernetics*, vol. 23, pp. 187-202, 1976.

[39] S. Guattery and F. J. Villarreal, "NEMESYS: an expert system for fighting congestion in the long distance network," *Expert Systems in Government Symposium*, (McLean, VA), pp. 123-126, IEEE, October 1985.

[40] T. H. Guo and J. Nurre, "Sensor failure detection and recovery by neural networks," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'91 Seattle)*, (Seattle, WA), pp. 221-226, 1991.

[41] P. V. Harrington, "Communication switch maintenance expert system," in *Proceedings of the IEEE Global Telecommunications Conference (GLOBECOM'86)*, (Houston, TX), pp 229-233, IEEE, December 1986.

[42] R. F. Harrison, S. J. Marshall, and R. L. Kennedy, "The early diagnosis of heart attacks: a neurocomputational approach," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'91 Seattle)*, (Seattle, WA), pp. 1-5, 1991.

[43] F. Hautin, J.-F. Cudelou, and F. Alizon, "L'introduction des systèmes experts dans les télécommunications françaises," *Annales des Télécommunications*, vol. 44, nos. 5-6, pp. 324-330, Mai-Juin 1989.

[44] Y. Hibino and K. Fujimoto, "An object-oriented troubleshooting expert system for electronic switching systems," in *Proceedings of the IEEE Global Telecommunications Conference (GLOBECOM'89)*, (Dallas, TX), pp. 475-491, IEEE, November 1989.

[45] A. Hiramatsu, "ATM communications network control by neural network," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'89)*, (Washington, DC), pp. 259-266, 1989.

[46] W. M. Hladik, T. R. Schiller, and H. T. Stump, "Mechanizing the customer access to network trouble reporting operations," in *Proceedings of the International Symposium on Subscriber Loops and Services (ISSLS'88)*, (Boston, MA), pp. 262-266, IEEE, September 1988.

[47] E. M. Horton, J. Hsiao, and J. E. Zielinski, "Interactive Repair Assistant a knowledge-based system for providing advice to field technicians," *IEEE Communications*, vol. 26, no. 3, pp. 21-24, March 1988.

[48] J. C. Hoskins, K. M. Kaliyur, and D. M. Himmelblau, "Insipient fault detection and diagnosis using artificial neural networks," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'90 San Diego)*, (San Diego, CA), pp. 81-86, 1990.

[49] P. E. Inshaw and T. J. Bowlin, "A fresh approach to loop maintenance," in *Proceedings of the International Symposium on Subscriber Loops and Services (ISSLS'76)*, pp. 44-46, IEEE, May 1976.

[50] O. Jakubowicz and S. Ramanujam, "A neural network model for fault-diagnosis of digital circuits," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'90 Wash DC)*, (Washingon, DC), pp. 611-614, 1990

[51] P. A. Jokinen, "Comparison of neural network models for process fault detection and diagnosis problems," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'91 Seattle)*, (Seattle, WA), pp. 239-244, 1991.

[52] B. J. Kagle, J. H. Murphy, L. J. Koos, and J. R. Reeder, "Multi-fault diagnosis of electronic circuit boards using neural networks," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'90 San Diego)*, (San Diego, CA), pp 197-202, 1990.

[53] D. Kennett and K. A. E. Totton, "Experience with an expert diagnostic system shell," in *Proceedings IFIP International Workshop on Knowledge Based Systems for Test and Diagnosis* (G. Saucier, A. Ambler, and M. A. Breuer Eds.), North-Holland, 1989

[54] N. A. Khan and R. Dube, "The GEMS trunk trouble analyzer: a knowledge-based expert system for trunk maintenance," in *Proceedings of the IEEE INFOCOM (INFOCOM'87)*, (San Francisco, CA), pp. 459-465, IEEE, 1987.

[55] N. A. Khan, P. H. Callahan, R. Dube, J. L. Tsay, and W. Van Dusen, "An engineering approach to model-based troubleshooting in communication networks," *IEEE Journal on Selected Areas in Communications*, vol. 6, no. 5, pp. 792-798, IEEE, June 1988.

[56] S. A. Khaparde and R. Mehta, "Feasibility of use of a neural network for bad data detection in power systems," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'90 Wash DC)*, (Washington, DC), pp. 615-618, 1990.

[57] K. Kitamaya and F. Ito, "Multiple fiber coupler associative memory with bit significance retrieval," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'89)*, (Washington, DC), pp. 633, 1989.

[58] A. Klopf, *Brain function and adaptive systems: a heterostatic theory*, Air Force Research Labo Tech Report, AFCRL-72-0164, 1972.

[59] T. Kohonen, K. Raivio, O. Venta, and J. Henriksson, "An adaptive discrete-signal detector based on self-organizing maps," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'90 Wash DC)*, (Washington, DC), pp. II-249 - II-252, 1990.

[60] T. Kohonen, "Self-organized formation of topologically correct feature maps," *Bio. Cybernetics*, vol. 43, pp. 59-60, 1972.

[61] T. J. Laffey, W. A. Perkins, and T. A. Nguyen, "Reasoning about fault diagnosis with LES," *IEEE Expert*, vol. 1, no. 1, pp. 13-20, IEEE, Spring 1986.

[62] Y. LeCun, "Learning processes in an asymmetric threshold network," *Disordered Systems and Biological Organization* (E. Beinenstock, F. Souli, and G. Weisbuch Eds.), Berlin: Springer, 1986.

[63] D.-M. D. Liu and D. A. Pelz, "I-TEST: integrated testing expert system for trunks," *IEEE Journal on Selected Areas in Communications*, vol. 6, no. 5, pp. 800-804, June 1988.

[64] G. Loberg, "SMART II: knowledge requirements for expert systems," in *Proceedings of the International Conference on Communications (ICC'88)*, (Philadelphia, PA), pp. 537-541, IEEE, June 1988.

[65] K. J. Macleish, S. Thiedke, and D. Vennergrund, "Expert systems in central office switch maintenance," *IEEE Communications*, vol. 24, no. 9, pp. 26-33, IEEE, September 1986.

[66] R. P. Manning, W. F. Sewell, "Distributed line testing — advantages and implementation options," in *Proceedings of the International Symposium on Subscriber Loops and Services (ISSLS'82)*, (Toronto, Canada), pp. 156-160, IEEE, September 1982.

[67] R. P. Manning, S. Homayoon, and J. F. Noyes, "Evolution of access network maintenance in Bell Canada," in *Proceedings of the International Symposium on Subscriber Loops and Services (ISSLS'84)*, (Nice, France), pp.233-237, IEEE, October 1984.

[68] A. Maren, C. Harston, and R. Pap, *Handbook of Neural Computing Applications*, San Diego, CA: Academic Press, 1990.

[69] B. Maricic, D. Beocanin, B. Modric, and J. Buljan, "Detection of heart malformation using error back-propagation network," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'90 Wash DC)*, (Washington, DC), pp. 655-658, 1990.

[70] K. A. Marko, J. James, J. Dosdall, and J. Murphy, "Automotive control system diagnostics using neural nets for rapid pattern classification of large data sets," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'89)*, (Washington, DC), pp. 13-16, 1989.

[71] K. A. Marko, L. A. Fedkamp, and G. V. Puskorius, "Automotive diagnostics using trainable classifiers: statistical testing and paradigm selection," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'90 San Diego)*, (San Diego, CA), pp. 33-38, 1990.

[72] A. Marrakchi and T. Troudet, "A neural network arbitrator for large crossbar packet switches," *IEEE Transactions on Circuits and Systems*, vol. 36, no. 7, pp. 1039-1041, July 1989

[73] R L. Martin, "Automation of repair service bureaus," in *Proceedings of the International Symposium on Subscriber Loops and Services (ISSLS'76)*, pp. 39-43, IEEE, May 1976.

[74] O. W. McAleer, "Meeting Canadian customer needs through advanced switching technology," in *Proceedings of the International Switching Symposium (ISS'92)*, session 23-11, 1992.

[75] W. S. McCulloch, and W. Pitts, "A logical calculus of the ideas immanent in nervous activity," *Bulletin of Mathematical Biophysics*, vol. 5, pp. 115-133, 1943.

[76] J. Meador, A. Wu, C. T. Tseng, and T. S. Lin, "Diagnosis of integrated circuit faults using feedforward neural networks," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'91 Seattle)*, (Seattle, WA), pp. 269-273, 1991.

[77] F. D. Miller, G. V. E. Otto, E. M. Siegfried, and P. E. Zeldin, "ACE: a knowledge based maintenance analyzer," in *Proceedings of the International Automatic Testing Conference, (AUTOTESTCON'85)*, (Uniondale, NY), pp. 148-152, IEEE, 1985.

[78] M. L. Minsky and S. Papert, *Perceptrons*, Cambridge, MA: MIT Press, 1969, 1987 and reprinted in *Neurocomputing* (J. Anderson and E. Rosenfeld Eds.), Cambridge, MA: MIT Press, pp. 161-170, 1988.

[79] T. Miyazaki, M. W. Kim, and M. Wakamoto, "Dynamic operation and maintenance systems for switching networks," *IEEE Communications*, vol. 28, no. 9, pp. 34-39, IEEE, September 1990.

[80] S. Morishita, K. Okamoto, and A. Tomita, "New subscriber line testing system with subscriber information filing system," in *Proceedings of the International Conference on Communications (ICC'82)*, (Philadelphia, PA), pp. 1D.5.1 - 1D.5.5, IEEE, June 1982.

[81] G. A. Morrison, P. R. Petzold, R. F. Girard, and A. N. Schmidt, "Strategies and system solutions for future loop maintenance operations," in *Proceedings of the International*

Symposium on Subscriber Loops and Services (ISSLS'80), (Munich, FRG), pp. 155-161, IEEE, September 1980.

[82] NeuralWare Inc., *Reference Guide: NeuralWorks Professional II/Plus and NeuralWorks Explorer*, Pittsburgh, PA, 1991.

[83] New York Telephone, Repair Service Bureau Operations Survey: Special Task Force Report, New York Telephone, 1965.

[84] K. Nishimura and M. Arai, "Power system state evaluation by structured neural network," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'90 San Diego)*, (San Diego, CA), pp. 271-277, 1990.

[85] E. Novik, "An application of statistically based temporal reasoning to an expert system performing central office hardware fault diagnosis and isolation," in *Proceedings of the International Conference on Communications (ICC'89)*, (Boston, MA), pp. 1423-1427, IEEE, June 1989.

[86] V. Nuckolls, "Telecommunications diagnostic expert system," in *Proceedings of the IEEE Global Telecommunications Conference (GLOBECOM'89)*, (Dallas, TX), pp. 507-511, IEEE. November 1989.

[87] D. Parker, *Learning Logic*, Technical Report TR-87, Center for Computational Research in Economics and Management Science, Cambridge, MA: MIT Press, 1985.

[88] D. Peacocke and S. Rabie, "Knowledge-based maintenance in networks," *IEEE Journal on Selected Areas in Communications*, vol. 6, no. 5, pp. 813-818, IEEE, June 1988.

[89] T. S. Perry, "Telephone challenges: a plethora of services," *IEEE Spectrum*, vol 27, no 7, pp. 25-28, July 1990.

[90] D. S. Prerau, A. S. Gunderson, R. E. Reinke, and S. K. Goyal, "COMPASS expert system: verification, technology transfer, and expansion," in *Proceedings of the 2nd Conference on Artificial Intelligence Applications*, (Miami, FL), pp. 597-602, IEEE, December 1985.

[91] D. Proudfoot, S. Aidarous, and M. Kelly, "Network management and TMN in an evolving network," in *Proceedings of the International Switching Symposium (ISS'92)*, session 23-10, 1992.

[92] H. E. Rauch and T. Winarske, "Neural networks for routing communications traffic," *IEEE Control Systems Magazine*, pp. 26-31, April 1988.

[93] W. D. Reeve, *Subscriber Loop Signaling and Transmission Handbook*, New York, New York: IEEE Press, 1992.

[94] F. Rosenblatt, "The Perceptron: a probabilistic model for information storage and organization in the brain," *Psych. review*, vol. 65, pp. 386-408, 1958, and reprinted in *Neurocomputing* (J. Anderson and E. Rosenfeld, Eds.), Cambridge, MA: MIT Press, pp. 92-114, 1988.

[95] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning internal representations by error propagation," *Parallel Distributed Processing* (D. E. Rumelhart and J. L. McClelland Eds.), chapter 8, pp. 318-364, 1986.

[96] J. F. Schreinemakers and D. S. Touretzky, "Interfacing a neural network with a rule-based reasoner for diagnosing mastitis," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'90 Wash DC)*, (Washington, DC), pp. 487-490, 1990.

[97] E. M. Siegfried and J. R. Wright, "ACE: taking an expert system from prototype to product," in *Expert Systems and Knowledge Engineering* (T. Bernold, Ed.), pp. 121-130, Amsterdam, The Netherlands: Elsever Science Publishers, 1986.

[98] H. T. Stump, "Surveillance-based maintenance: a strategy for future network operations," in *Proceedings of the International Symposium on Subscriber Loops and Services (ISSLS'86)*, (Tokyo, Japan), pp. 271-276, September-October 1986.

[99] E. E. Sumner, "Loop operations systems," in *Proceedings of the International Symposium on Subscriber Loops and Services (ISSLS'76)*, pp. 1-4, IEEE, May 1976.

[100] A. H. Tan, Q. Pan, H. C. Lui, and H. H. Teh, "INSIDE: a neuronet based hardware fault diagnostic system," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'90 San Diego)*, (San Diego, CA), pp. 63-68, 1990.

[101] M. Thandasseri, "Expert systems application for TXE4A exchanges," *Electrical Communication*, vol. 60, no. 2, pp. 154-161, September 1986.

[102] K. A. E. Totton and P. R. Limb, "Electronic diagnosis using a multilayer perceptron," *BT Technology Journal*, vol. 10, no. 3, pp. 97-102, July 1992.

[103] G. T. Vesonder, S. J. Stolfo, J. E. Zielinski, F. D. Miller, and D. H. Copp, "ACE: an expert system for telephone cable maintenance," in *Proceedings of the 8th International Joint Conference on Artificial Intelligence (IJCAI'83)*, (Karlsruhe, West Germany), pp. 116-121, August 1983.

[104] S. M. Weiss and C. A. Kulikowski, *Computer Systems That Learn: Classification and Prediction Methods from Statistics, Neural Nets, Machine Learning, and Expert Systems*, San Mateo, CA: Morgan Kaufmann Publishers, 1991.

[105] P. Werbos, *Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences*, Ph.D. dissertation, Harvard University, Cambridge, MA, 1974.

[106] B. Widrow, J. R. Glover, J. McCool, J. Kaunitz, C. S. Williams, R. H. Hearn, J. R. Zeidler, E. Dongle, and R. C. Goodlin, " Adaptive noise canceling: principles and applications," *Proceedings of the IEEE*, vol. 63, no. 12, pp. 1692-1716, December 1975.

[107] B. Widrow, and M. E. Hoff, "Adaptive switching circuits," *Institute of Radio Engineers, Western Electronic Show and Convention, Convention Record - Part 4*, pp. 96-104, 1960 and reprinted in *Neurocomputing* (J. Anderson and E. Rosenfeld Eds.), Cambridge, MA: MIT Press, pp. 126-134, 1988.

[108] Y. Yamamoto and V. Venkatasubramanian, "Integrated approach using neural networks for fault detection and diagnosis," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN'90 San Diego)*, (San Diego, CA), pp. 317-326, 1990.

[109] R. O. Yudkin, "EXT: an expert tester," in *Proceedings of the IEEE INFOCOM (INFOCOM'87)*, (San Francisco, CA), pp. 452-458, IEEE, March-April 1987.

[110] R. O. Yudkin, "On testing communication networks," *IEEE Journal on Selected Areas in Communications*, vol. 6, no. 5, pp. 805-812, IEEE, June 1988.

[111] L. A. Zadeh, "Fuzzy Sets," *Information and Control*, vol. 8, pp. 338-353, 1965.