TELECOMMUNICATIONS AND EXPERT SYSTEMS

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Abstract: Telecommunications is one of the most rapidly growing industries worldwide. In developing countries, there is a huge market to offer both wireline and wireless telephone services. The majority of people there simply do not have the basic telephone service. Many of these countries have started to privatize their telephone industry. In the developed countries such as the Romania, the explosion of Internet usage and the growth of personal computers are forcing telecommunications companies to expand the facility to offer both data and voice services. As the deregulation of the telephone industry gradually opens up the Romania market for competition, telecommunications companies here will rely on advanced technologies for competitive leverage. One such technology is the expert system technology that enables telecommunications companies to offer improved products and services at low cost. Expert systems in this context are computer programs that emulate the behavior of telecommunications experts and automate the operation of telecommunications systems using artificial intelligence techniques.

Keywords: telecommunication, neural networks, artificial intelligence

1 INTRODUCTION

A telecommunications network is a complex aggregate of switches and a transmission medium, which together provide a multiplicity of channels over which many customers' messages and associated control signals can be transmitted. The telecommunications network provides access to different types of circuits and services that use them. Network switch software is one of the most complex software systems in the world. These networks must be managed carefully for efficient and reliable operation.

According to the Telecommunications Management Network (TMN) framework, there are four layers of functionalities in a telecommunications management model: element management layer that manages network elements, network management layer that manages telecommunications networks, service management layer that deals with customers, and business management layer that handles business decisions (see Figure 1). The information required to make a decision is passed upward toward the higher layers, whereas control messages are always directed downward the lower layers.

Specifically, in the bottom element management layer, one deals with network elements such as switches, cell sites, transmission medium, signaling system components (e.g., SS7), or customer access facilities (e.g., PBX). Each element generates alarms that need to be monitored and filtered. Hardware problems must be corrected on the spot quickly. In the next network management layer, there are (1) fault management that is concerned with the detection, isolation, and correction of anomalous network conditions, (2) performance management that evaluates the quality of network services and determines the effectiveness of communication processes, (3) configuration management that allows technicians to view and modify the network configuration, (4) security management that authorizes use of system resources and protects network management data, and (5) accounting management that addresses costs associated with the use of network resources and allocates charges for the usage. Above that, the service management layer deals with customers including service setup, quality control and response, and billing. It often needs information retrieval. Finally, at the top layer, the business management makes decisions about network planning, market analysis, finance and budget, and resource allocation. Not all telecommunications companies follow the exact same management model, but TMN does summarize telecommunications management tasks.

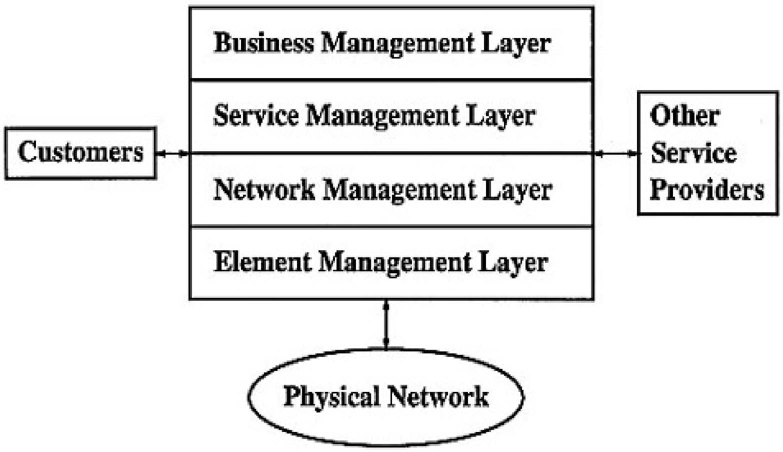

Figure I.1. The TMN framework.

Historically, expert system applications mainly focused on the network management layer (Liebowitz, 1988). Due to the complexity and diversity of telecommunications systems, telephone companies started to invest resource on artificial intelligence (AI) technology in the early 1980s to automate some of the operations. As a result, various rule-based expert systems were prototyped and fielded, especially in the areas of network repair and maintenance requiring monitoring and diagnosis. Some of them saved companies millions of dollars. Based on these initial successes, other AI techniques were also explored, including case-based reasoning, distributed AI, data mining, and machine learning. Cooperation between industries and universities on AI technology in that period was frequent. People had high expectation for AI in general.

Around the late 1980s and early 1990s, the hype of AI technology hit the wall. Meanwhile, the telecommunications industry also began to experience downsizing and focus on the bottom line. It was needed then to reaccess AI technology based on its value. Rule-based expert systems continued to serve important roles, either as independent systems or embedded within other systems. Yet, many other AI-based systems often stopped at the prototype level and did not become products. There was a gap between good concepts and hard reality. This, in some way, demonstrated the difficulty of telecommunications domains and the lack of understanding them when applying new AI techniques.

With continuing downsizing and early retirement of domain experts, AI technology was once again pushed to front in the mid 1990s. This time, deregulation spurred competition, automation is needed in all four management layers to cut cost and becomes critical to the lifehood of a company. New growth opportunities in wireless and digital services and international markets demand every company to do more with the same or less resources. In addition, many telecommunications software systems have been developed over the years. They input and output tremendous amounts of data that need to be interpreted and analyzed. This is similar to the "data overflow" of the information highway. Expert systems based on AI techniques can help to analyze this information, alleviate technicians from many routine tasks, and train them to be the experts of new technologies. More importantly, AI practitioners have learned from past lessons, and understood the potentials as well as the limitations of AI technology and what it take to develop AI-based products. Consequently, various types of expert systems have been fielded .

2 TELECOMMUNICATIONS DOMAINS AND POTENTIAL TASKS

The telecommunications domains are very diverse, ranging from wireline telephone service, wireless communication, and satellite communication, to Internet service. Each domain has its own requirements. However, they all share the following characteristics, which makes them quite different from other application domains. These characteristics present challenges and opportunities for expert system applications:

1. *Large amount of data* -- A typical network switch generates alarms on the order of a million per week and can handle millions of calls per day. Large databases are needed to store various types of data.
2. *Real time* -- Many network operations must be carried out online in real-time. Delayed reactions can result in loss of revenue and customer confidence.
3. *Mission critical* -- Hardware equipment and software systems often have redundancy built-in and expert systems must be equally reliable. Sometimes, misdiagnosis of a key transmission trunk can have a catastrophic result.
4. *Dealing with legacy systems* -- Some switch technologies have existed for decades and it is expensive to replace them right now. Communicating and integrating with them is essential for many expert systems.
5. *Embedded AI* -- Expert systems are often just a portion of a large system that uses AI techniques to accomplish special subtasks. The success of an expert system also depends on the rest of the system.
6. *Different user skills* -- Some operation support personnel are highly trained and others are not computer literate. Knowledge acquisition must be specialized accordingly.
7. *Adaptive* -- Switch version, usage pattern, telecommunications technology, and policy change frequently. Any expert systems should be adaptive to changes.

With these characteristics in mind, the following are some potential AI application tasks in each of four management layers:

1. *Element management layer* -- Alarm filtering, monitoring and correlation, and admission control.
2. *Network management layer* -- Alarm correlation, fault isolation and diagnosis; repair and maintenance; performance monitoring and tuning; traffic control and routing; configuration management and dynamic channel allocation; and workflow management that coordinates task assignments.
3. *Service management layer* -- Service order, customer helpdesk, fraud detection, churning management, Internet service offering, billing automation, international market customization, and language translation and speech recognition.
4. *Business management layer* -- Growth planning, facility design, resource scheduling, finance and contract management, and workforce training.

Some tasks are across the layers. They include data classification and interpretation, cooperation and negotiation among different systems, and data mining and trending analysis. In the next section, we discuss which AI techniques can be used for these tasks in telecommunications domains.

3. AI TECHNIQUES

Expert systems use AI techniques to emulate the behavior of experts and automate the operation of systems. Determining a right technique for a specific application is crucial for any AI-based product. There are many AI techniques that have been and can be applied to telecommunications domains. The following AI techniques have been reported extensively. The detail of each technique can be found in many AI textbooks.

4. NEURAL NETWORKS

Typical neural networks consist of several layers of nodes and links that connect the nodes between adjacent layers. They must be trained first before they can classify a pattern. Using an architecture loosely analogous to how neurons are organized in a brain, a neural network learns patterns by strengthening and weakening the

weights of link connections between nodes when given a sufficient number of training patterns. Neural networks are suitable for knowledge-poor and data-rich domains. They are adaptive and noise tolerant. Training a large-size neural network is time consuming. This limits the scope of neural network applications.
Neural networks have been applied to the task of classification and interpretation, including admission control, performance tuning, data mining, traffic control and routing, dynamic channel allocation, fraud detection, network reconfiguration, and speech recognition.

5. DISTRIBUTED ARTIFICIAL INTELLIGENCE

Distributed Artificial Intelligence (DAI) addresses cooperative and distributed problem-solving. Its paradigms include contracting, blackboard systems, distributed search, speech-act communication, and agent-based belief systems. DAI's goal is to find a globally acceptable solution from distributed and often limited local systems through their communication and coordination. Research in DAI involves studying the emerging behavior and convergence property of distributed agents. It also investigates the trade-off between problem solving and communication. DAI adds distribution to the complexity of AI technology.

Telecommunications domains are often distributed along spatial, functional, and organizational dimensions. In the past, special-purpose expert systems were developed independently. Recently, there is a trend to push toward the convergence and integration of these systems. For example, cooperation of management tasks is needed not only within the same management layer but also across all four layers. Public and private networks should be managed from both a logical network perspective and a physical network perspective. DAI techniques can be used to glue different expert systems (Velthuijsen, 1996). They have been tried in fault isolation, network design and management, dynamic channel allocation, resource scheduling, traffic control and routing, service order, and workflow management.

6. HYBRID SYSTEMS

Each of above AI techniques has certain strengths and weaknesses. In practice, two or more of them are often used together to complement each other. Examples include combining rule-based systems and neural networks (Tan, 1996), rule-based and model-based systems (Worrest, 1996), search and DAI (Low, 1995), model-based systems and approximate reasoning (Chen, 1996), and case-based reasoning and decision trees (Masand, 1996). They can be loosely coupled (e.g., one's output is other's input), tightly coupled (e.g., blackboard paradigm allows different AI techniques to communicate with each other during problem-solving), or fully integrated (e.g., fuzzy rule-based systems). Keep in mind that no one AI technique is effective in all domains. Every AI technique has its respective domains where it is effective. Again, the key is to find a good match between AI techniques and a specific domain.

7. APPLICATIONS

Today, telecommunications networks are highly advanced, rapidly evolving systems of complex, interdependent technologies. As telecommunications networks fuse with the Internet, and as the underlying technologies continue their rapid evolution, these networks will become increasingly difficult to manage. AI is playing a large and growing role in various telecommunications management tasks. This section describes some of fielded AI applications in wireline and wireless communications.

7.1.Eline Communication

There are many existing automated network management systems containing AI modules for diagnosis, repair, and service dispatching. AT&T's ACE maintenance expert system was developed in the early 1980s (Liebowitz, 1988). Today, ACE has been sold and installed in more than 100 sites. ACE is a rule-based system that assists telephone engineers in maintaining the local loop. The local loop is the part of the telephone network that connects residential or business telephones with a local switching center. ACE is a background data analyzer that does its analysis by querying the database of daily test results stored in the Cable Repair Administration System (CRAS) and looks for patterns in the data that indicate where trouble may exist in the local loop. Each output of ACE is a classification or diagnosis of the problem, along with detailed support evidence from the CRAS system. ACE uses a forward-chaining rules strategy that breaks the overall problem into independent subproblems. Each subproblem can therefore be solved independently and the results assembled into a complete solution.

In contrast, NYNEX's MAX, developed in the late 1980s, is a telephone trouble screening expert that takes customer reports as input to initiate a local loop diagnosis (Rabinowitz, 1991). MAX works on one trouble at a time and communicates with the Loop Maintenance Operation System (LMOS), just like a human user sitting at an LMOS terminal. It uses forward-chaining rules to perform its diagnosis based on electrical measurements, customer's service class, weather, and network topology information, and enters the recommended dispatch instructions on the original LMOS screen. A goal of MAX is to reduce the number of double and false dispatches. MAX's rules can be customized to local conditions by a set of parameters. MAX is running in every residence-oriented maintenance center of NYNEX.

An even more proactive approach was used by TCAF (Silver, 1995), a rule-based expert system that performs 24-hour monitoring and surveillance of the local loop in GTE's telephone network. The aim of TCAF is to identify and fix developing faults before the customer detects any problem. At the same time, TCAF is designed to be quickly reactive to such problems that cannot be foreseen. Like MAX, TCAF diagnoses faults using several sources of information, including electrical measurements, customer's service class, and network topology (no weather information). Unlike MAX relying on customer reports, TCAF combines interrupt-driven events (switch alarms) that trigger measurements, and an intelligent polling algorithm (based on prior test results, customer fault history, and loop topology) to schedule measurements, for fault discovery. There is no human input to the whole process of trouble detection. TCAF can correctly detect cable cuts and coin faults over 90% of time. It is monitoring over 8 million GTE telephone lines (out of total 18 million).

Recently, Pacific Bell adopted a different approach for the same local loop problem. The Trouble Localization (TL) system (Chen, 1996) utilizes probabilistic reasoning techniques and logical operators to determine which component has the highest failure probability. This is achieved by building a topology of the local cable network and constructing a causal (Bayesian) network model. The model contains belief of failure for each component, given their current status, history data, cable pair distribution, and connectivity to other components. The resulting system can handle the poor quality of information in databases, perform nonmonotonic reasoning, and generate a ranked list of faulty components. The TL system is a crucial part of Outside Plant Analysis System that has been deployed statewide in California.

SSCFI (Special Service Circuit Fault Isolation) is a rule-based expert system that is in operation at all GTE's U.S. sites (Worrest, 1996). Special circuits are the telephone circuits other than the regular ones in the local loop (e.g., bank ATM, or any high-capacity, hard-wired, customized circuits). They are considered more complex than regular circuits. SSCFI diagnoses problems by recursively partitioning the circuit until the responsible fault is isolated. SSCFI reads and interprets trouble reports based on the design of special service circuits, conducts analog and digital tests via remotely activated test equipment, and routes the report to the appropriate repair group with the results of its analysis. This rule-based system also has a model-based component. SSCFI reads the target circuit's design to generate an internal circuit model to select tests that maximize diagnosis quality and minimize test time.

A telecommunications network can also be thought of as having two parts: the local loop and the interoffice facilities (IOF) network. The IOF network connects the local switching centers to one another. NYNEX has developed an expert system called Arachne for planning the IOF network (Alesi, 1996). Arachne's task is to ensure that NYNEX's investment in the IOF portion of its network satisfies the forecasted demand between switching centers, while achieving the maximum benefit per dollar invested. Arachne views the IOF network in terms of four layers of multiplexed signals: DS0, DS1, DS3, and Optical. It decomposes the planning task into two types of subtasks: (1) subtasks (in DS0 and DS1 levels) in which the size of the data is large, the variation in planning styles is great, and the equipment cost of decisions is small, and (2) subtasks (in DS3 and Optical levels) in which the data size is small and the equipment cost of decisions is high. Efficient heuristics are used to

make the routing decisions in the former, while optimization techniques (dynamic programming) are used to optimize the routing decisions over the entire network for the latter. This cost-effective approach of combining heuristics and optimization techniques saves the company millions of dollars in IOF planning.
Telephone companies deal with customers on a daily basis. SAR, developed by Telesoft, is an expert system that supports salespeople in selling Intelligent Network services (Liebowitz, 1995). Intelligent Network services are a class of complex and flexible telecommunication services, whose configuration can be significantly personalized by salespeople in order to fit customer needs (using special circuits). Salespeople use SAR while they interact with customers to define all the information needed to set up a service configuration. SAR is a helpdesk application that provides congruency check, completeness check, cost estimation, and checking available resources for each service order. SAR uses forward-chaining rules and interacts with databases based on standard SQL queries. SAR has been fielded since 1993.

Telecommunications databases contain hundreds of millions of customer records. Controlling uncollectables falls into the larger risk management process. Predicting or modeling uncollectables is inherently probabilistic. Therefore, AT&T's APRI system (Ezawa, 1996) uses a special type of Bayesian network model for classifying uncollectible calls, which can be constructed efficiently from extremely large databases (reading a database just five times). APRI automatically constructs graphical probability models using the entropy-based concept of mutual information to select nodes and links of the Baysian networks. Given 800 million bytes of test data, the resulting models correctly classified 37% of the uncollectable calls, compared with only 10% by other approaches.

7.2.Wireless Or Satellite Communication

A cellular network is a telecommunications network with some distinct features. It consists of a mobile switch center and a number of radio base stations, each responsible for covering a geographical service area called a cell. A mobile unit (portable or handheld) communicates with the base station via a voice channel. All base stations are linked by some transmission facilities to the switch center, which coordinates the operation for the entire system and serves as a connection point to the public switched telephone network. For satellite communication, each satellite can be treated as a big cell in this context. The cellular industry has been experiencing tremendous growth in recent years and needs AI technology to assist the operation and management of cellular networks.

AutoCell is a distributed client/server expert system operated by Singapore Telecom (Low, 1995). AutoCell periodically acquires cellular network status and traffic data. Based on these, it generates traffic forecasts for all cells, and performs automatic frequency reassignments to make more channels available at cells that are congested due to unexpected high demands or faulty channels. AutoCell also provides a performance reporting facility. AutoCell is implemented based on a multi-agent architecture where each agent is assigned a specific function, and agents communicate via the exchange of messages. It uses a heuristic search approach that combines hill climbing and branch-and-bound pruning to perform dynamic channel assignment. The revenue generated by improved traffic capacity due to AutoCell is estimated at over 1 million Singapore dollars in the first year (1994) alone.

PERFEX is a performance analysis and tuning expert system for cellular networks developed at GTE (Tan, 1996). Like AutoCell, it collects and displays the network status and traffic data. Based on performance and configuration data, PERFEX uses a neural network to discover generic performance problems in the network, and then uses rules to generate expert advice on how to fine-tune the system parameters to improve performance before resorting to adding or reassigning channels. These parameters include handoff thresholds, reassignment of handoff neighbors, configuration errors, and dynamic power control parameters. PERFEX provides a set of cellular tools to examine the network in finer detail and tightly integrates its different information presentation forms such as the map, tools, graphs, reports, and templates. PERFEX is in daily use at most GTE mobile switch centers.

InCharge is a system developed by SMARTS for real-time isolation and handling of network system problems (Kliger, 1996). InCharge employs a coding approach that reduces the event correlation time significantly by replacing a causal graph with simple codebooks. In a codebook, each problem is associated with a collapsed set

of symptoms. At runtime, the actual symptoms are compared with the ones in the codebook by calculating the Hamming distance. The stored problem with the smallest Hamming distance is selected as the actual problem. InCharge has been adopted by Motorola Satellite Communications, which is using InCharge's codebook event correlation for their IRIDIUM project. The IRIDIUM project is a worldwide satellite-based communications system that will receive thousands of problems or symptoms at very high rate in real-time.
CHAMP is a churn analysis, modeling, and prediction system developed for GTE Mobilnet (Masand, 1996). Churn, a term for customer disconnecting the cellular service, is a very serious problem for the cellular industry, with churn rates ranging between 20 and 30% a year in most markets. CHAMP tries to identify those customers most likely to churn, which can be contacted for proactive churn prevention. CHAMP analyzes billing data using neural networks, decision trees, case-based reasoning, or a combination of the three methods. Its training and test data are preprocessed by eliminating irrelevant data fields, pruning unrelated subscribers, merging data from different months, sampling data, and selecting best fields using decision trees. The CHAMP system is able to identify a large part of predictable churn, with prediction rates (lift) usually 5 to 6 times better than random.

8. CONCLUSIONS

Artificial Intelligence (AI) technology is filling an essential need in telecommunications management tasks as networks grow in size, complexity, and importance. When conventional software approaches become severely stressed in certain areas, expert systems using AI technology have been demonstrated as viable alternative solutions. This chapter first lays out the overall picture of telecommunications management tasks, and then identifies those tasks where expert systems have made significant contributions. To benefit future expert system developers, it characterizes telecommunications domains and provides a list of commonly used AI techniques, where each of the techniques is described in terms of its main strength and weakness, plus its possible application tasks. In addition, this chapter describes some recent fielded expert systems in both wireline and wireless communication domains and sheds some light on the current state-of-the-art. Finally, it discusses development methodology, lists common development pitfalls found in telecommunications domains, and addresses research issues by challenging AI techniques for some currently needed tasks.
In the future, intelligent networks will self-diagnose, engage in distributed cooperative problem-solving, and perform proactive network management. People will have instant access to the information highway through intelligent agents that can navigate heterogeneous data sources, finding and presenting the information they need. Office and home computers will behave as smart telephones loaded with capabilities such as speech recognition, natural language translators and schedulers, and handle voice, fax, data, and video seamlessly. Clearly, AI will play an important enabling role in the communications network of the future.

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