Computational Intelligence in Management of ATM Networks: A Survey of Current State of Research

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Abstract

Designing effective control strategies for Asynchronous Transfer Mode (ATM) networks is known to be difficult because of the complexity of the structure of networks, nature of the services supported, and variety of dynamic parameters involved. Additionally, the uncertainties involved in identification of the network parameters cause analytical modeling of ATM networks to be almost impossible.

Consequently, some researchers are looking at alternative, non-analytical control system design and modeling techniques that have the ability to cope with these difficulties to devise effective, robust ATM network management schemes in which artificial neural networks, fuzzy systems and design methods based on evolutionary computation. In this survey, the current state of ATM network management research employing these techniques as reported in the technical literature are summarized, and their salient features are reviewed.

1 Introduction

Asynchronous Transfer Mode (ATM) based networks are designed to be scalable, high-bandwidth, manageable, and have the flexibility of supporting various classes of multimedia traffic with varying bit rates and Quality of Service (QoS) requirements. Thus, they have the potential to create a unified communications infrastructure that can transport services with widely different demands on the network (such services include real-time video and voice with no tolerance to delays, but some tolerance to loss, and data with some tolerance to delay, but no tolerance to loss).

An important difficulty of exploiting the potential of ATM optimally is the management and control complexity of the scheme itself (the basic concept is simple). Since ATM simultaneously attempts to support voice, data and video applications which all have differing performance and QoS requirements, optimal utilization of the network resources requires complex, nonlinear, distributed control structures. In order to achieve its potential, ATM networks will need to accommodate several interacting control mechanisms, such as call admission control, flow and congestion control, input rate regulation, routing, bandwidth allocation, queue scheduling, and buffer management.

Due to the complex nature of the above mentioned control issues, some researchers are looking for solutions by application of Computational Intelligence (CI) techniques to design intelligent control systems to various aspects of ATM network management, often supplementing the existing control techniques. Their motivation arises from the reported success of those techniques in various previously unsolvable or difficult control problems in many diverse fields.

The focus of this paper is CI applications in ATM network control. It seeks to update, merge and (inevitably) summarize the previous reviews of the literature [14, 12, 13].

2 Computational Intelligence

Computational Intelligence (CI) [3, 4, 30] is an area of fundamental and applied research involving numerical information processing (in contrast to the symbolic information processing techniques of Artificial Intelligence (AI)). Nowadays, CI research is very active and consequently its applications are appearing in some end user products.

The definition of CI can be given indirectly by observing the exhibited properties of a system that employs CI components [4]:

> A system is *computationally intelligent* when it: deals only with numerical (low-level) data, has a pattern recognition component, and does not use knowledge in the AI sense; and additionally, when it (begins to) exhibit: computational adaptivity; computational fault tolerance; speed approaching human-like turnaround; error rates that approximate human performance.

The major building blocks of CI are artificial neural networks, fuzzy logic, and evolutionary computation.

3 Applications of CI Techniques in Management of ATM Networks

The complexity of the ATM networks and multidimensionality of the control problems dictate that traffic control in ATM networks to be structured and most likely implemented in a multilevel architecture which partitions the solution into different levels of control with varying temporal decomposition in network, call and cell levels [31, Chapter 2], [27].

In the following sections, an overview of the reported research done to date to implement control methods which employ fuzzy logic, artificial neural networks and genetic algorithms on these levels is presented.

4 Network Level Control

The main objective of network level control is to enable the completion of the maximum possible number of successful B-ISDN service calls [48]. An attempt is made to achieve this objective by implementing two main functionalities at the network level controls: fault management and resource management.

4.1 Fault Management

Fault management is concerned with the detection, isolation, and correction of acute failures that interrupt the availability of network resources. Besides acute failures, some failures may be manifested intermittently, or malfunctions may subtly degrade network performance while network resources remain available (for example, corruption of virtual path identifier (VPI)/virtual channel identifier (VCI) translation tables may cause misrouting for certain connections). It is the role of fault management to continually monitor the network facilities to detect degradations in performance caused by such conditions, and respond with appropriate actions in order to minimize the effect on offered services [9]. This responsibility is fulfilled by Operations and Management (OAM) in ATM networks.

In the area of fault management in communication networks, reported research on applications of CI is very limited in scope. Applications of AI in network management have been surveyed and reported by Smith and Fry [40].

4.2 Routing and Link Capacity Assignment

In the absence of faults and malfunctions, efficient utilization of network resources is maintained by the traffic control and resource management functions which involve routing and link capacity assignment. At the network level, route selection and link capacity assignment to virtual paths are performed by using offered call traffic and tolerated call blocking probability information.

First major function at the network level control in ATM networks is route selection. In B-ISDN networks, links have to be described in terms of multiple metrics, including QoS and policy constraints, which makes routing with multiple requirements a difficult problem to solve. Second major function of network level control in ATM networks is the optimal allocation of bandwidth to virtual paths [9, 32].

Aboelela and Douligeris [1] have studied the application of fuzzy control for the route selection in ATM networks. Park and Lee [29, 28] have worked on optimized routing using recurrent ANNs.

The application of combination of evolutionary programming with fuzzy logic could be very beneficial to solve multiobjective optimization problems such as bandwidth allocation to virtual paths. Heuristics have been proposed to reach near-optimal solutions [46, 47]. In the study presented in [47] the researchers have used evolutionary-fuzzy prediction in inter-domain routing of broadband network connections with QoS requirements in the case of an integrated ATM and SDH networking infrastructure.

Early results of a study for VP bandwidth allocation using evolutionary programming techniques has been published by Pitsillides et al. [32].

5 Call Level Control

5.1 Connection Admission

Connection Admission Control (CAC) is defined as a set of actions, performed at connection set-up phase, to determine whether or not the virtual path (VP) or virtual channel (VC) requesting the connection can be accepted. The decision is based on the connection's anticipated traffic characteristics, the requested QoS, and the current state of the network. The anticipated traffic characteristics of the connection are determined by a source traffic descriptor, and the user terminal declares these source traffic descriptor values to the network when the connection set up is requested. If the request is accepted, network resources are implicitly allocated to the connection.

Application of CI techniques appears to be appropriate, and several researchers have attempted to solve the problem by using artificial neural networks and fuzzy logic control techniques.

Hiramatsu has studied ANN based ATM CAC [15] and has published his work on training techniques for ANN applications in ATM [16]. Ramalho and Scharf [35] have used a method for learning the behavior of the traffic in an ATM link. Park and Lee [29, 28] also have published their work on adaptive call admission control using feedforward ANNs. Uehara and Hirota [45] have proposed a method based on estimation of the possibility distribution of cell loss ratio (CLR).

Scheffer and Kunicki have studied the application of fuzzy logic techniques for accurate modeling of voice and video sources, and prediction of their behavior [38, 39, 36]. They have proposed a CAC scheme which uses a fuzzy logic based traffic prediction algorithm [37]. Cheng and Chang [8, 10] have devised a fuzzy control system which combines CAC and a feedback mechanism.

6 Cell Level Control

6.1 Usage Parameter Control

Usage parameter control (UPC), or in other words, traffic enforcement or policing, is a very important function in ATM networks. Its task is to ensure that traffic sources stay within the limits of the negotiated traffic parameters which are declared during the call setup phase. Traffic enforcement functions are performed by the network provider at the virtual circuit or virtual path level and corrective measures are taken if a traffic source does not stay within the declared limits. The measures could be as drastic as blocking the traffic source or could be less severe such as selectively discarding the violating cells or tagging violating cells that could be discarded in downstream nodes if necessary.

The ideal UPC mechanism should have these desirable characteristics: accurate detection of any traffic situation violating the negotiated values, and separating those connections from the ones that stay within the negotiated limits; fast response to violations; implementation simplicity and cost effectiveness. Designing a UPC mechanism encompassing these features could be a daunting task. For example, well studied mechanisms such as leaky bucket and window mechanisms cannot achieve the ideal UPC characteristics but only provide a trade-off between the above requirements.

Catania et al. [5, 6, 7] and Ascia et al. [2] have proposed a UPC mechanism based on fuzzy logic control which displays characteristics close to ideal UPC, and have also implemented the algorithm as a VLSI chip. A UPC mechanism particularly designed for policing voice sources has been proposed by Ndousse [26].

6.2 Flow, Congestion and Rate Control

In early stages of B-ISDN development, prevailing belief among the research community was, preventive (or, in other words open-loop) type congestion control at the edge is necessary due to the large bandwidth delay product, and would be sufficient for ATM networks. But, outcomes of subsequent studies have shown that, because of the variety of the traffic to be supported in B-ISDN networks, open-loop congestion and flow control is rendered to be ineffective in ATM networks. Today, the shift is towards closed-loop congestion controls (within the network).

Tarraf, Habib and Saadawi [41, 42, 44] have investigated extensively how ANNs can be used to solve many of the problems encountered in the development of coherent traffic control strategies in ATM networks. In [44] they present congestion control schemes for ATM networks. Also, they investigate a reinforcement-learning based neural network for congestion control in ATM networks [43]. Liu and Douligeris have published the results of a comparison study on the performance of static and adaptive feedback congestion controllers which uses ANNs [23].

Huang and Yan [18] use a recurrent neural network for the dynamic control of communication systems, particularly dynamic congestion control in ATM networks. Mhrvar and Le-Ngoc [25] apply a neural network scheme for congestion control in packet switch OBP satellite systems. Pitsillides et al. [33, 34], have proposed the Fuzzy Explicit Rate Marking (FERM) algorithm, and analyzed its performance regarding fairness, responsiveness, resource utilization and cell loss in LAN and WAN environments. Douligeris and Develekos [11] have studied a FLC which is based on the short term observation of the network status to predict the near future cell discarding behavior of the switching nodes. This prediction is then fed back to traffic shapers in the sources to minimize cell losses. Jensen [22] has proposed a three-step FLC for controlling the transmission rate of sources to protect links against overload in the case of connections exceeding their negotiated traffic parameters. Hu and Petr [17] have studied an adaptive traffic controller based on Sugeno's self-tuning fuzzy control methods.

6.3 Cell Switching and Multiplexing

In an ATM network, cell queuing is required to alleviate congestion at switching nodes. Congestion occurs when multiple cells simultaneously attempt to access an output link in a switch. Cell queuing can be arranged either by placing buffers at input ports (called input queuing), or by placing cell buffers at the output ports (called output queuing). Output queuing yields better performance in terms of cell delay and throughput, but computationally more demanding to operate than input queuing. On the other hand, in input queuing, if the head-of-line blocking problem can be solved, comparable performance can be achieved. One way of solving this problem is to employ a mechanism called bypass queuing. When bypass queuing is used, a controller module schedules the cells in an optimal fashion to enhance the switch throughput. Additionally, cells can be dispatched optimally if they are assigned priorities, with higher priorities assigned to real-time traffic such as voice and video (due to rigid delay requirements) and lower priorities assigned to data traffic, by an intelligent scheduling mechanism.

Liu and Douligeris [24] have proposed a fuzzy scheduler to optimize the cell servicing sequences to reduce cell losses. In their mechanism, each traffic class in the switch has its own portion of the dedicated buffer and a fuzzy scheduling algorithm manages the server. Park and Lee [29, 28] have also worked on optimal scheduling and published their study on application of recurrent ANNs to this problem.

7 Discussion and Concluding Remarks

Research on applications of CI in telecommunication systems, particularly in ATM networks, is being pursued by an active research community, and methods are being developed simultaneously. However, unlike consumer applications, there are no commercially deployed applications as yet. The reasons could be

- the lack of comprehensive performance comparisons between the best traditional techniques and the ones involving CI applications. The comparisons performed in the research studies usually have been undertaken in simplified networking scenarios, and testing on real hardware has not been undertaken yet except for some partial implementations such as in [2]. Before the applications of CI techniques to high speed communication networks becomes accepted, it will be necessary to place a greater emphasis on rigorously demonstrating the advantages to be gained, and that is an area we strongly recommend.
- the reluctance to adopt new technologies by telecommunications companies and equipment manufacturers. This issue is closely related to the lack of comprehensive performance studies mentioned above.

As a final note, we would strongly encourage a thorough study of an integrated control structure implementing a multilevel control strategy spanning network, call and cell levels. The integration can be achieved by appropriate design of each individual strategy in a new multilevel fuzzy logic structure, and / or the integration of existing, or separately designed strategies, with their integration achieved via a fuzzy logic based supervisor, taking care of the overall "goodness" of the network and handling any interactions among the control functions, at the same or different levels.

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