IMPROVEMENTS TO NEURAL NETWORK BASED RESTORATION IN OPTICAL NETWORKS

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

FETHİ TÜRK

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
ELECTRICAL AND ELECTRONICS ENGINEERING

MAY 2008

Approval of Thesis:

IMPROVEMENTS TO NEURAL NETWORK BASED RESTORATION IN OPTICAL NETWORKS

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ABSTRACT

IMPROVEMENTS TO NEURAL NETWORK BASED RESTORATION IN OPTICAL NETWORKS

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May 2008, 66 pages

Performance of neural network based restoration of optical networks is evaluated and a few possible improvements are proposed. Neural network based restoration is simulated with optical link capacities assigned by a new method. Two new improvement methods are developed to reduce the neural network size and the restoration time of severed optical connections. Cycle based restoration is suggested, which reduces the neural network structure by restoring the severed connections for each optical node, iteratively. Additionally, to reduce the restoration time, the necessary waiting time before the neuron outputs fire for the propagation delay over the network is computed and embedded in the control structure of the neural network. The improvement methods are evaluated by simulations in terms of restorability, restoration time, network redundancy and average length of restoration paths for different failure cases and different security requirements.

Keywords: Optical networks, distributed restoration, neural network based restoration.

ÖZ

OPTİK AĞLARIN YAPAY SİNİR AĞLARI KULLANILARAK ONARIMINDA İYİLEŞTİRMELER

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Mayıs 2008, 66 sayfa

Optik ağların yapay sinir ağları kullanılarak onarım performansı ve mümkün iyileştirme yöntemleri araştırıldı. Yapay sinir ağları kullanılarak onarım yönteminin yeni atanmış kapasiteler ile benzetimi yapıldı. Özgün önerideki eksikliklere göre, yapay sinir ağlarının boyutunu azaltmak ve kopan bağlantıların onarım süresini düşürmek için iki yeni iyileştirme yöntemi geliştirildi. Her optik düğümdeki kopan bağlantıların onarımı art arda yapılarak, yapay sinir ağının boyutunu azaltan döngüsel onarım yöntemi önerildi. Ayrıca onarım süresini azaltmak için yapay sinirlerin elde ettikleri sonuçları göndermelerinden önce optik ağdaki bilgi yayılımı için ne kadar beklemesi gerektiği hesaplanarak, elde edilen değerler yapay sinir ağının denetim yapısına gömüldü. Önerilen iyileştirme yöntemleri benzetim yöntemi ile değişik hata durumları ve güvenlik beklentileri için, bağlantıları onarabilme oranı, onarım süresi, ağ üzerinde gereken yedek kapasite miktarı ve ortalama onarım yolu uzunluğuna göre değerlendirildi.

Anahtar kelimeler: Optik ağlar, dağıtık onarım, yapay sinir ağı tabanlı onarım.

To My Parents

ACKNOWLEDGMENTS

I express sincere appreciation to Prof. Dr.Semih BİLGEN for his valuable guidance and encouragements throughout this study.

I also would like to express my appreciation to TÜBİTAK-UZAY and my colleagues for their understanding and support during my academic studies.

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AIS	Alarm Indication Signal
ATM	Asynchronous Transfer Mode
CAFES	Compute a Feasible Solution
DWDM	Dense Wavelength Division Multiplexing
ILP	Integer Linear Programming
IMKB	İstanbul Menkul Kıymetler Borsası (Istanbul Stock Exchange)
ISGA	Integrated Survivable Grooming Algorithm
LSR	Label Switching Router
NACK	Not Acknowledged
MCgR	Minimum Congestion Routing
O-E-O	Optical to Electrical and Electrical to Optical converter
OXC	Optical Cross Connect
PXT	Pre-cross-connected Trail
RWA	Routing and Wavelength Assignment
SDH	Synchronous Digital Hierarchy
SONET	Synchronous Optical Networking
SSGA	Separated Survivable Grooming Algorithm
TSGA	Tabu-search Survivable Grooming Algorithm

CHAPTER 1

INTRODUCTION

As the usage of Internet and other telecommunication tools increases, our dependence on the communication networks also increases. Accordingly, new technologies are developed; and the communication capacity of the networks increases. Due to their huge transmission capacity, most of the researchers' interests have shifted to optical networks, especially to the dense wavelength division multiplexing (DWDM) method. With this method many connections with different wavelengths can be multiplexed and it is practically possible to transmit more than 10 terabits of data over a single fiber in one second [1]. While the capacity and usage of networks increases the reliability of the infrastructure should also increase to guarantee the promised service quality and to maintain the critical applications.

In different communication systems, such as microwave or satellite, the communication system consist of the transmission and receiving equipments which are securely protected by the operators. In optical networks, the transmission media is, although it is coated for durability, still very sensitive because of its thin fiber structure, and it is routed thousands of kilometers through the underground or underwater. Also the receiver and transmitter equipments are much more complex in optic systems, and consequently they are less reliable. As a result, in optical network operations a failure is more probable. According to a failure survey [2], it is estimated that a one mile single fiber can operate 228 years before it fails. According to this estimation a long haul network established with thousands of miles of optical network possibly faces a fiber failure every day and in a comparatively small metropolitan network, every four days a failure can be expected.

The problem is not only those failures are frequent; but also failures can cause great economic impacts. As an example, a summary of an AT&T report on the cost of network failures is given in table 1.1. It shows the cost of a network failure in different areas according to the statistics [3].

Table 1.1 Average cost of a network failure in different areas [3]

Working Area	Business	Average cost per hour
Financial	Brokerage operation	$6.5 M
Financial	Credit card /sales authorization	$2.6 M
Media	Pay-per view television	$1.1 M
Retail	Home Shopping (TV)	$113,000
Retail	Home catalogue sales	$90,000
Transportation	Airlines reservation	$89,500

Another example can be given from Turkey, the private fiber links of the Istanbul Stock Exchange (IMKB) were cut off during a road working in 28.Nov.2007. Diagnosis and repair of the failure took more than 5 hours. The expected loss of business volume was $600M and the financial loss of only IMKB was approximately $1.5M corresponding to the commission from the exchanges [4].

Additionally, failures also cause negative social effects by breaking mass communications, some of which can be critical and priceless, such as emergency calls. According to the mentioned costs and frequency about the optical network failures, we need survivable networks against the failures. In the literature many suggestions can be found about this problem and some of them will be discussed in the next chapter.

In this thesis, new improvements are proposed about a novel restoration mechanism based on neural networks [5]. The first suggestion is related to the effective usage and scalability of neural networks; it aims at reducing and restricting the neural network size. This is achieved by using a cycle based method in the restoration procedure. Also for reducing the restoration time, which is an important evaluation criterion for the restoration mechanism, the minimum communication time over the whole network is computed for single link failure cases and obtained results are embedded to nodes of the optical network for faster restoration. Detailed simulations are done for different topologies, for different security level connections to evaluate the suggestions.

The outline of the thesis can be given as: In chapter 2, the related background concepts are given. Then earlier suggested methods about the survivable network problem are presented. In chapter 3, firstly the previously suggested method [5] for neural network based restoration is explained in detail. Secondly, the needed capacities for simulations are recomputed with a different mathematical model and compared with the previously obtained results and lastly previous simulations are repeated with new obtained capacities and the acceptability of the results is demonstrated. The insufficiencies of the previous method and possible improvement suggestions are presented in chapter 4. Also in the same chapter, new simulations are done to evaluate the improvement suggestions and to compare them with the previously obtained results. Finally, in chapter 5 the thesis is concluded by commenting on obtained results and suggesting possible further studies on the subject.

CHAPTER 2

BACKGROUND ON OPTICAL NETWORK PROTECTION AND RESTORATION

In the previous chapter, the question: “Why do we need survivable networks?” was considered. In this chapter, after reviewing the related terminology, different methods for achieving survivability will be investigated and compared.

2.1 Related Terminology

Disasters, terrorist attacks, power outages or operational mistakes can result in network failures. These failures can be generally classified as two groups: *link failures* and *node failures*. According to the statistics [34], the most common one is the link failure, and in this study complete link failure is considered, where all of the connections traversing over the failed link are broken.

Available capacity is one of the major criteria in the management of connections in an optical network both in the normal operation and in case of failures that raise the question of survivability. *Working capacity* is defined as capacity used to serve demands during normal operation. It is determined according to the primary paths of connections and expected load. *Spare capacity* can be defined as reserved capacity that will be used for the restoration of failed connections. Spare capacity can also be used for compensating sudden demand increases of the network. *Redundancy* is defined as the ratio of reserved spare capacity to working capacity. Redundancy of the network should be low for efficient resource usage.

An important problem in optical network formation is assigning the mentioned capacities. The minimum capacity should be computed and assigned for guaranteeing network requirements for both routing normal and severed connections. In general, capacity assignment and connection routing problems are solved by *Integer Linear Programming* (ILP). ILP is a set, which consists of equations and inequalities to satisfy the requirements of the problem and an objective function which should be minimized or maximized [37]. After forming this set, it should be solved by an optimizer to obtain the suitable values for variables. In most cases, due to its complexity, exact ILP solution is not feasible for large networks and sub-optimal but acceptable results can be found via *heuristic* algorithms.

Restoration time is generally defined as elapsed time between the moment that the failure occurs and the moment the severed connections start to work over the restoration path. This time equals the sum of the times needed for failure detection, establishing the protection path and switching of demand to the new path. In this study, restoration time is defined as the time between failure occurrence and establishment of the restoration paths. Restoration time is an important criterion in the evaluation of the restoration methods.

Restorability is another important measure on restoration methods. It is defined as the percentage of the restored demand to the total severed demand. One of the important aims of suggested methods is to achieve 100% restorability with a low level of redundancy.

2.2 Suggestions for Survivable Networks

As stated earlier, link failures are frequent for optical networks and where and when they will happen is indefinite. For satisfying service level agreements and for supporting critical applications (military, commercial, medical …etc) survivable networks are needed, in which, in a failure case (often fiber cut), the severed connections can be rerouted from different paths to the destination, with an acceptable delay, instead of blocking of severed demand. Different methods for achieving survivability will be discussed in this section.

The problem of network survivability has been comprehensively studied and many different solution suggestions can be found in the literature. In the early days (1970's) network failures were handled manually, but due to the necessity of fast recovery, trends have shifted towards protected networks. Ring topologies have become preferred, in which, in case of failure the severed connection is switched to the reverse direction. This method has been used in two popular networks: SONET and SDH. The expected recovery time in these topologies is comparatively low, typically 50ms or less [36]. Restoration in a ring topology is shown in figure 2.2. Connection-2 is restored over the reserved ring path in the reverse direction of the primary path.

Today due to bad resource utilization of ring topologies, most researchers' attention has shifted to the mesh topology. While the mesh topology yields better resource utilization, it makes harder to handle the network due to the graph theory related problems in optimization. Furthermore, the control mechanism for mesh networks is usually much more complex.

Two main schemes suggested for achieving survivability are *protection* and *restoration*. Although these terms may seem similar, in which both of them involve the recovery and rerouting of severed demands, there is an important difference. In protection, while a light path is provisioning for the connection also some spare capacity is reserved for the same connection to protect against failures. However, in restoration, when a failure occurs, restoration mechanism determines an appropriate route with sufficient spare capacity for restoration of the severed connection. Obviously, restoration takes much more time than protection and also in this method blocking is possible [10]. Related methods for fault managing in optical networks with protection or restoration are categorized in figure 2.1

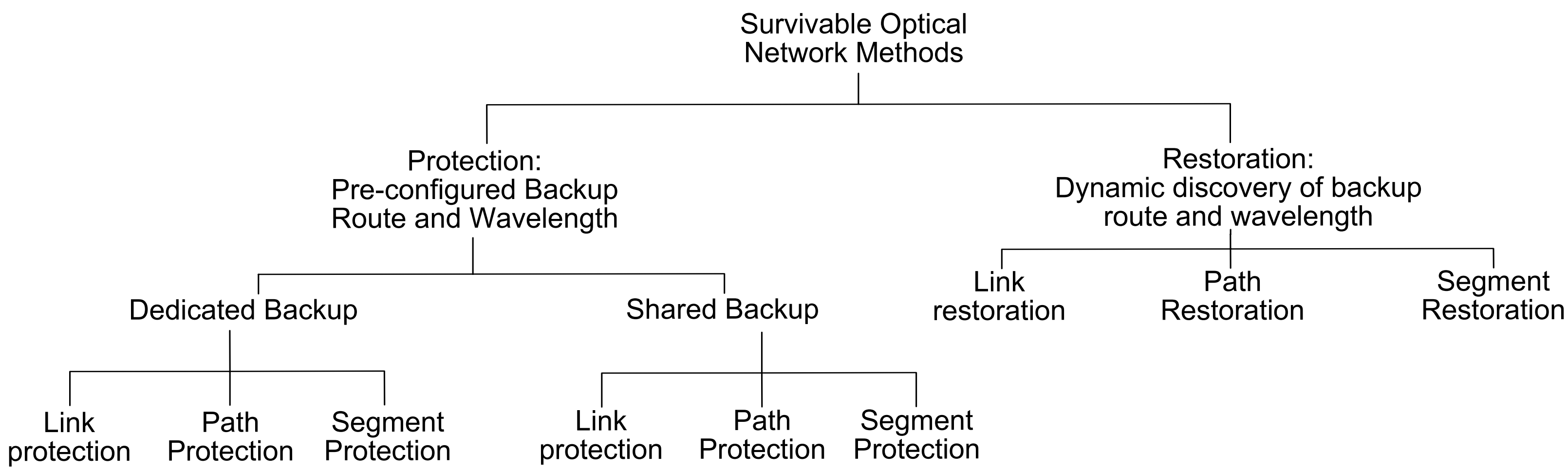

Figure 2.1: Fault- Management in Survivable Networks (Adapted from [10])

In figure 2.3 a graphical demonstration of path, link and the segment protection are given. According to figure 2.3, different approaches can be used for protection and restoration. The distinction in these approaches, as can be seen, is based on how much of the severed path will be rerouted for restoration of the severed demands. Main criteria in selection of the method are the priority of the resource utilization and restoration time. While protection time is lower for link protection, it has inefficient resource utilization and the reverse is true for path protection. Segment protection, which is a newer suggestion [28, 31 and 32] is used for adjusting the tradeoff between protection time and resource utilization. In dedicated protection schemes for each connection a unique spare capacity is reserved for backup. These protections can be referred as 1+1 or 1:1. While in 1+1 data is sent from two distinct paths to the destination and receiver considers the better signal as data, in 1:1 the reserved path is used for restoration only in case of a failure occurrence. Shared backup protection schemes can be referred as 1:N. In these schemes, connections that are routed from distinct paths to the destination share suitable links as backup, because only one of the connections suffers in a single failure. In this method, sharing of backups increases the resource utilization. The disadvantages of shared protection are: finding shared-backup routing is more complex and although it is a protection method, the restoration time is relatively high because of configuration of optical cross-connects (OXC) [10] [35][38].

While provisioning lightpaths for a requested protected connection, different algorithms can be used. For the dedicated protection scheme, in [11] different suggested algorithms are evaluated and compared by simulations. In [11], routing and wavelength assignment problem (RWA) is studied for path protected connections to obtain better utilization. According to the authors, while one step approach gives the best results, its complexity and computation time is relatively high. Also applicable two step approaches are evaluated and the most-used wavelength method is shown to yield better blocking characteristic in wavelength assignment.

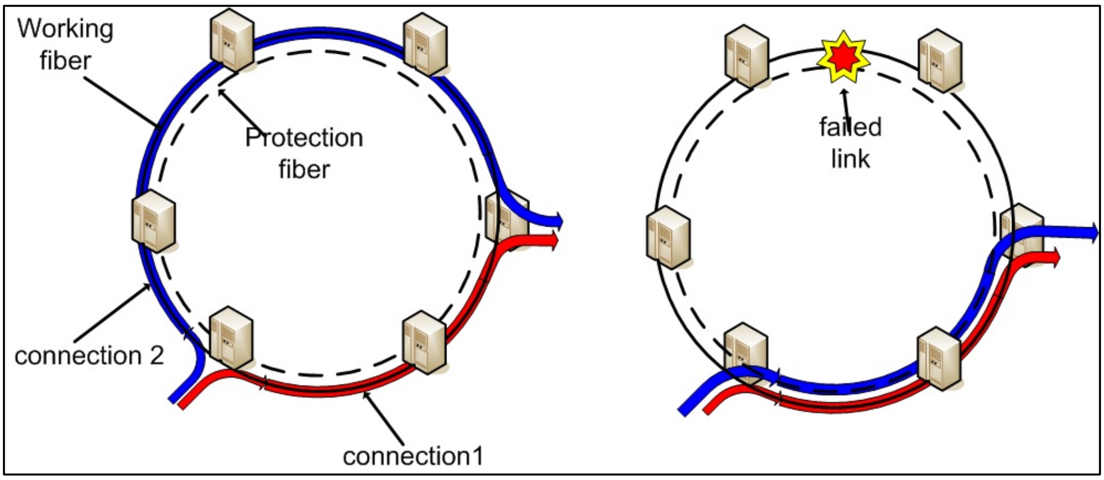

Figure 2.2: Basic ring topology restoration

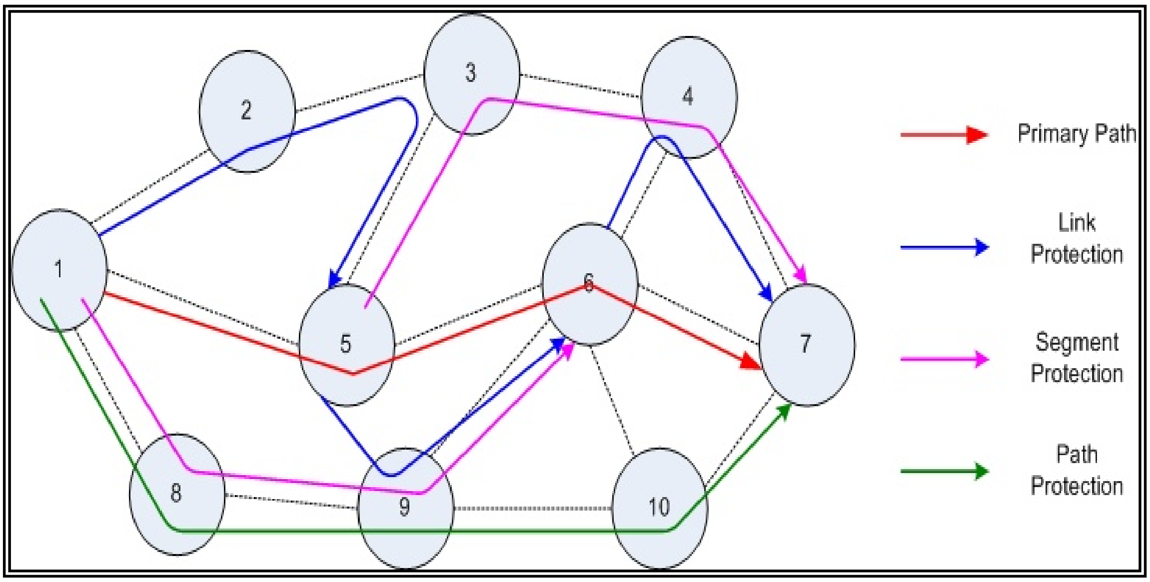

Figure 2.3: Protection Methods in Optical Networks

In [12], the authors suggest a mathematical model for failure analysis, in which they connect all resources (OXC's, conduits, amplifiers…etc) in parallel or in series depending on their relative positions in connections and obtain mathematical formulations for the relation between the failure and deployed equipment in the network. They also suggest heuristics with respect to this model to improve the resource utilization and recovery time. But in this method complete knowledge is needed about the network states and connections. An improved version of this mathematical model is given in [13]. The authors have added the usage of some primary path resources in the restoration path to their formulations, because these resources are released due to failure in primary path, which is also known as *stub release.* The authors have generalized the shared-risk group model according to this modification in resource usage. This method is shown to result in better resource utilization, but its drawback is that it becomes failure dependent.

An important issue in survivable networks is finding an optimum algorithm which computes the primary and backup paths according to the requirements. Capacity utilization and routing related algorithms are studied in [14], [15] and [16]. In the first one, three heuristics: separated survivable grooming algorithm (SSGA), integrated survivable grooming algorithm (ISGA) and tabu-search survivable grooming algorithm (TSGA), were evaluated according to the computation time and blocking probability and the best performance results were obtained in the tabu-search based algorithm. In the second study ([15]), they used two-level approach for optimization: First they use "compute a feasible solution" (CAFES) method to compute paths and wavelengths, then they optimize the obtained paths for better resource consumption. Also in their study, they add extra cost for some common paths in optimum path computations, in order to avoid blocking in the new connection requests. The added extra cost provides available capacities in the densely used links. In this suggestion both complete versus partial information and ILP versus heuristics are evaluated and efficient results are obtained with heuristics. In the third one, [16], while calculating the optimum paths, the authors have added two new parameters: ϵ is used for bandwidth consumption adjustment between the primary and backup paths, and μ is used for restricting the backup path length. Although this method can increase the quality for the backup paths, it decreases utilization and increases the solution complexity.

Dynamical provisioning and routing of survivable connections is also an important subject. Although future demand can be forecasted according to statistics, the exact future connection requests are uncertain. In dynamical solutions, less computation time is also necessary for faster provisioning. In [18] a novel solution is suggested for dynamic routing. Mobile agents are used to examine the network state and apply a genetic algorithm for optimum routing. This is referred as a hybrid solution and by this method lower blocking probability is achieved in shorter computation time. In that study, unavailability of wavelength converters is considered to generalize the method.

A different approach is suggested for resource utilization in [19]; optical equipments are also considered in the sharing of the backup paths, which form the major cost in the optical network infrastructure. In the evaluation of the suggested methods by simulations, both ILP and tabu-search based algorithms were used and high level sharing (60%) was achieved in O-E-O equipments sharing and 30% in wavelength link sharing. Also the authors studied the position of nodes, where these equipments should be placed to satisfy signal quality constrains. In [20], the author suggests generalized sharing policy which is similar to the previous one in the sense of sharing of O-E-O equipments. An extensive evaluation is done with respect to the resource utilization with five different solution algorithms: ILP-Full, Heuristic-Full, ILP-Static, Heuristic-Static and Heuristic-Static Swap. Full knowledge yields the best utilization results (but it is not possible in many situations); ILP-statics yields acceptable results and the Heuristic-Static Swap results in comparatively low efficiency. The comparisons were done with respect to dedicated solutions. The earlier mentioned resource sharing methods can be combined with this suggested method in terms of sharing of O-E-O equipments to obtain better resource utilization.

For better handling of optical networks a new method was suggested in [21]. The basic idea is very familiar: “Divide and conquer”. In the referred paper, the authors tackle the complexity problems that are mentioned above, by partitioning the networks. Consequently, the suggested methods become scalable and ILP formulations can be computed separately for each domain, in an acceptable time. Also it is possible to use local information for each domain, and this is sufficient for finding effective solutions. But in this approach one can obtain optimum solutions for sub-networks but not for the entire optical network. The main problem in this method is: how the network should be partitioned into domains.

Yet another novel suggestion for better resource utilization is presented in [22]. In this paper, holding time awareness is emphasized while ligthpath provisioning. In this method, according to the holding time knowledge, backup paths can be modified when a connection ends according to the computed holding time. By modifying the earlier suggested method CAFES ([15]), 10% resource overbuild is obtained in the National US network. Although this method increases resource utilization, it is hard to implement due to the need for advance knowledge of connection holding times, and increase in the control signaling of the network. Another disadvantage of this method is that it becomes less stable, because more than one backup path should be modified or established, after the starting and ending of each connection.

Another important criterion on protection schemes is the connection recovery time in case of a failure. In most cases, restoration time mostly depends on the switching taking place in the OXCs. In [23], *p-cycles* are suggested for decreasing the restoration time and making the handling of restoration easier. The main idea is establishing a dedicated ring path over mesh network for usage in the restoration, if the failed part can be restored by the preconfigured ring. In the referred study, preconfigured cycles are used for protection of links and if the network is Hamiltonian (that is, all nodes can be visited once and only once through a single non-self-overlapping path (for a thorough discussion of Hamiltonian graphs, see e.g. [46]) one *p-cycle* is sufficient for the protection of whole network. The *p-cycle* suggestion provides the speed advantage of ring protection and the resource utilization of the mesh networks. Also control of restoration mechanism becomes simpler by this method. But in this solution the backup path length cannot be guaranteed and checking whether a network is Hamiltonian, is an *NP-complete* problem. An improved version of this study can be found in [24]. In this paper *p-cycle* protection is shifted from link protection to path protection. Failure independent protection is satisfied by path protection mechanism. This solution gives comparable results with respect to the general shared mesh protection, in terms

of resource utilization but the drawback is that the ILP formulation for finding the optimum paths takes the longest time in the related simulations. To make this solution scalable, a useful heuristic with less complexity is needed. One more improvement about *p-cycles* can be found in [25] where the authors add dynamic behavior to *p-cycles*. First, they compute primary cycles, and this decreases the online computation load and when there is a connection request, first a working path is calculated, and then if there is no available *p-cycle* for protection of this connection, a new *p-cycle* is established.

The basic idea and the advantage of *p-cycle* is faster restoration by using preconfigured OXC's. With the same idea, but with a different approach, pre-cross-connected trail (PXT) is suggested in [26]. In this method, branching in the backup paths is eliminated by modifying the routing of backup paths. Branching can be briefly defined as the separation of two incoming connections in the next hop. This causes increasing of restoration time due to reconfiguration of a switch depending on a failure. Figure 2.3 depicts how branching is eliminated in a simple network. The backup path for the connection from node 1 to node 4 is modified to prevent branching in node 3.

In [27] differentiated service is added to OXC configuration. In backup paths first, higher priority connections are configured. So they do not need to wait for configuration of cross-connects in case of a failure, when there is a failure in lower priority connections, in backup path, cross-connects are configured dynamically, and after recovery of primary path of this severed connection, again the backup path's cross-connects are reconfigured according to higher priority connections.

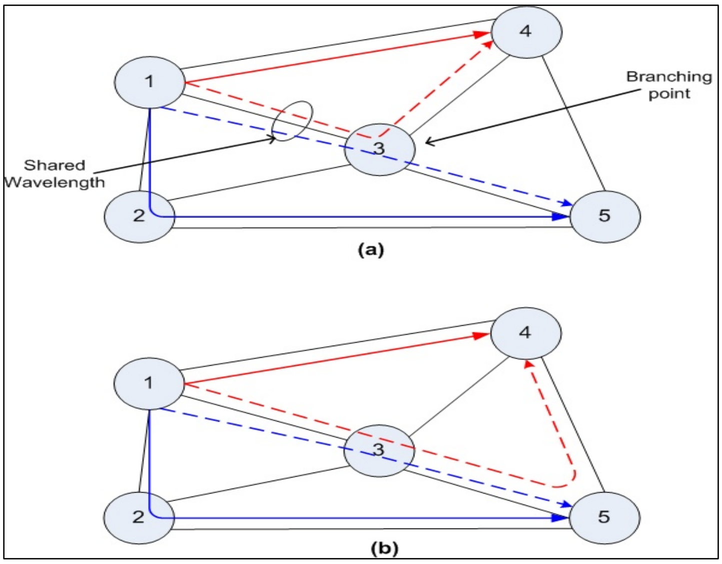

Figure 2.3: Elimination of branching at a node. [7]

In many papers, protection is categorized as path or link protection. Path protection is usually preferred because of its benefits stated earlier. In some recent papers, however, segment protection [28], [31] and [32] (Figure 2.2) has been suggested. This suggestion can be thought as a generalized version of path and link protections. According to this suggestion resource utilization and restoration time can be adjusted by modifying the segment sizes. The segment method can also be used as dedicated or shared, but both for effective resource utilization and the long structure of segments, shared protection is preferred. In [28] a heuristic is presented which restricts the hop count for protection paths and this decrease the protection switching time. A recursive solution for segment protection is suggested in [29]. With a recursive algorithm working paths are determined and then the working paths are partitioned into segments which are protected instead of whole path. Some parameters are included to limit hop count and to adjust protection time and resource utilization.

Although at the time of writing of this thesis all-optical networks are not as wide-spread as expected some years ago (see e.g. [47], [48]) protection methods have been quite extensively studied in the literature. For example in [30] a flooding based method is suggested for all-optical network protection. In that solution, first, the compute *di-graph* of the related network is computed, and then when a failure occurs, according the predetermined directions flooding starts and congestion is avoided by negatively acknowledged (NACK) signals. A heuristic is suggested for *di-graph* calculation to decrease the complexity. The disadvantage of this solution is that 1:1 protection is used which increases the redundancy; however due to the wavelength continuity constraint, converter cost is eliminated in the suggestion and RWA problem complexity decreases. Also, according to the simulation results, the restoration time is at an acceptable level (90 ms). The suggestion does not provide an efficient dynamic structure for multiple failures, in which case restorability is lower and also high computation load of finding the *di-graphs* also considered as an another drawback of this study.

In short, the main problems for protection and restoration can be summarized as: *"... tradeoffs between speed of recovery, equipment costs, protection capacity and management overheads."* [30].

2.3 Restoration with Neural Networks

An original idea has been presented by Gökışık, [6], for the restoration of optical networks. That approach will be studied in detail in the next chapter, but the fundamental idea can be summarized as the usage of a feed-forward neural network placed over the whole optical communication network for restoring the severed connections in a link failure. The related information about the failure and severed connections are fed to the neural network and restoration paths are extracted from it.

Although neural networks are used in many control applications [6], in the literature, there has not been any application as a controller for communication network restoration yet, except Gökışık's method. One neural network application for the control plane has been presented in [33] for asynchronous transfer mode (ATM) quality of service provision. In a somewhat related work [17], neural network usage has been proposed as optimizer in the capacity computation phase for network survivability instead of using the neural network in control plane. Minimum costs of the connections are found by a neural network implementing the simulated annealing algorithm.

CHAPTER 3

PERFORMANCE EVALUATION OF GÖKIŞIK'S OPTICAL NETWORK RESTORATION METHOD

In the previous chapter, some suggested methods for restoration and protection of optical networks were reviewed. In this chapter a different method is considered. This method was suggested by D. Gökışık in her PhD study [5], in which artificial neural networks are used for optical network restoration. In addition, security levels of connections were taken into account while routing them. Below, after the details of the method are given, Gökışık's simulations are repeated. At the end of this chapter some improvements for Gökışık's technique will be suggested.

3.1. Gökışık's Protection and Restoration Method

In Gökışık's technique, the control mechanism for the restoration of the failed network is based on an artificial neural network. Artificial neural networks are mathematical models which were inspired from real biological neurons [40]. They are used in many areas, such as system control and identification, pattern recognition and face identification. These networks can be in many different sizes and topologies but the most common and the one used by Gökışık is a multilayer feed-forward neural network [40]. In Figure 3.1 a simple multilayer feed-forward neural network is seen. In this topology the inputs are fed to the input neurons and each input neuron supplies the sum of its inputs to the hidden layer neurons. These neurons multiply their inputs with the adjustable weights and to the sum of these multiplied inputs, a predetermined threshold function applied and the output of this function is provided to the output neurons. The desired results can be obtained from the output of the output neurons. The different input-output relationships can be taught to neural networks by adjusting their input weights and biases by applying different learning algorithms over these neural networks.

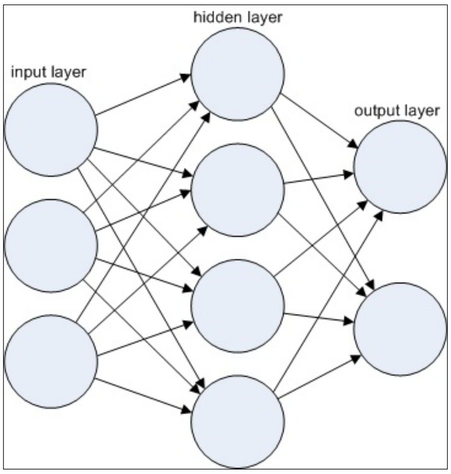

Figure 3.1 Feed-Forward Neural Network

Before deploying the neural network to the optical network, the topology and the expected load of the optical network has to be known. According to this information, first, network capacities should be assigned. In this assignment, calculation of sufficient capacities in the optical links is needed to operate in the expected connection loads. Also some redundant capacity is needed to restore the severed connections, in case of a link failure. In these assignments the protection type (path, link or unprotected), routing methods and the security level of connections were considered. Optimal design of the optical network that fits the given constraints is obtained by solving the corresponding integer linear programming (ILP) problem with an optimizer tool.

First, the routing method used in this simulation will be briefly explained. The routing method chosen in these simulations was Minimal Congestion Routing MCgR [39]. In the mentioned routing method, while choosing the routes for the connections, the main purpose is minimizing the load in each optical link instead of minimizing the total hops for each connection and this technique eliminates congestion in the densely used optical links. This method is also distributed, which can be integrated with Gökışık's technique, which does not suffer from central or single node failures.

In the mentioned routing technique, the main idea is similar to the distributed Bellman-Ford routing algorithm [41]. Each node in the network stores a routing table which shows the most preferred next node for routing to all other nodes. First every node sends its routing information to its adjacent nodes. A node that receives the routing information compares routing data with earlier stored one, if it is better than the stored one; the node replaces the earlier one with the newcomer. If a node makes a replacement according to the received data, it will broadcast this new information to the adjacent nodes except the one from which it had received the information. This information exchange can be done periodically or after every established and released connection. The received information is considered as better if it satisfies one of the conditions below [39]:

1. If the time stamp of the received information is later than the stored one,
2. Else if its time stamp is equal with the stored one but the recent one has a route that passes through links that have more available resources,
3. Else if both the time stamps and available resources are equal but the total number of hops is less in the received one than in the stored one,
4. Or lastly if all the previously mentioned routing information is equal but the total wavelength conversion on the received routing path is less than the stored path.

The main reasons for choosing MCgR method are that it results in an even distribution of connection loads to the assigned capacities to prevent blocking and also that it is a distributed method which is compatible with Gökışık's technique.

In Gökışık's technique one modification was done before usage of MCgR technique for the insecure connections: In insecure connections, neither primary nor restoration path can pass through a node that has an optical amplifier, if there is a secure connection which uses that node as primary or reserves it for restoration. So two sets of routing information is stored in each node; one for secure and the other one for insecure connections.

3.1.1 Capacity calculation and its assignment to links

One main problem in network protection is the spare capacity necessity for restoration of severed connections and deploying it effectively to minimize overall redundancy. After having sufficient information about connection demands and security restrictions of the network, primary (working) paths for the connections can be obtained with MCgR technique. Then, based on the primary paths, spare capacities on the optical links have to be calculated to obtain overall capacity needed for each link. Secure and insecure connections must be protected under three possible categories: path protection, link protection or no protection [5]. For efficiency purposes, shared backup protection was used.

Spare capacities are determined to satisfy the protection conditions while minimizing the overall capacity usage. This optimization problem is solved on the CPLEX 10 linear optimizer. The constraints given to the optimizer can be summarized as:

For every link in the network:

> For every connection in the network:
>
> > If the connection severed from the failure of given link above, the sum of all possible routing paths should be equal to the lost demand.
>
> Every link except the failed one should have equal or more spare capacity to be used in chosen restoration paths.

The obtained results for different network topologies and connections are given in Table 3.1. In the table, it can be seen that, there are some differences with the results obtained in [5]. One of the reasons of these differences is that in the present solution, CPLEX found different restoration paths for different link failures instead of a single predetermined restoration path for each connection. For example, in the 10 node network (Figure 3.7), for the connection from node 0 to node 9, the 0-1-5- 9 node sequence is used as a primary path, while 0-3-7-9 is used for restoration in case of failure of link 0-1 and the 0-2-8-9 sequence is used for restoration in case of failure of link 5-9; which decreases overall redundancy compared to assigning a single dedicated path for every connection for restoration As the complexity of the problem increases due to the integer constraints for the variables and for the large networks, the optimizer could not assess all the branches of the solution tree and could not find the optimum solution and prefers heuristic algorithms and only suboptimal solutions could be obtained.

			Gökışık's results			Present results		
Topology	Optical amp.	case	working	total	redundancy	working	total	redundancy
10nd-22lnk	-	2 secure path protected	142	180	0,27	142	180	0,27
10nd-22lnk	-	2 secure path, 2 secure link protected	284	366	0,29	284	388	0,37
10nd-22lnk	-	2 secure path protected, 2 secure unprotected	284	322	0,13	284	322	0,13
10nd-22lnk	3	2 secure path, 2 insecure path protected	286	378	0,32	286	370	0,29
10nd-22lnk	0,4,8	2 secure path, 2 insecure path protected	286	400	0,40	286	392	0,37
10nd-22lnk	3	2 secure path, 2secure link protected and 2 insecure path and 2 insecure link protected	572	778	0,36	570	826	0,45
10nd-22lnk	0,4,8	2 secure path, 2secure link protected and 2 insecure path and 2 insecure link protected	572	818	0,43	570	858	0,51
15nd-30lnk	-	2 secure path protected	456	689	0,51	442	646	0,46
	-	2 secure path, 2 secure link protected	912	1386	0,52	882	1306	0,48
	-	2 secure path protected, 2 secure unprotected	912	1140	0,25	884	1070	0,21
	0,4,8,12	2 secure path protected, 2 insecure path protected	916	1374	0,50	888	1278	0,44
7nd-10lnk	6	2 secure path, 2 insecure path, 2 secure link, 2 insecure link, 2 unprotected secure, 2 unprotected insecure	-	-	0,47	804	1062	0,32

Table 3.1 Comparison of the capacity assignment for different topologies and requested services in terms of total assigned wavelength channels

3.2 Restoration of Optical Network with a Neural Network

In this section, the details of the restoration mechanism with a neural network will be given. First the structure of the used neural network and training procedure will be explained. Then, the restoration mechanism with the neural network will be explained.

3.2.1 Neural Network Structure

The restoration mechanism of optical network is controlled with a neural network, whose neurons are deployed in the interface between the label switching routers (LSRs) and optical cross connects (OXCs). In the communication of neural network, the existing optical links are used, which reduce physical load of using neural network in the optical network. In case of a failure, the lost demand is fed to the neural network and the restoration paths and the numbers of the connections restored in determined paths are extracted from the outputs of the neural network.

A feed-forward neural network with one hidden layer is used. The number of neurons in the input layer is determined according the number of nodes of the optical network being controlled. The size of hidden layer and output layer are determined according to the both optical network size and magnitude of error after training.

Two types of information are fed to the input neurons of the neural network in every optical network node. Two input neurons are used for identifying the failed connection, and another two input neurons are used for each of the severed connections: one for the demand lost of secured connection and the other for the demand lost of insecure connection. To the dedicated input neurons on each node of the optical network, the lost demand is applied. So the number of neurons in the input layer is one more than the number of the nodes in the optical network if only the restorations of secure connections are considered and twice the number of nodes of the optical network if also insecure connections have to be restored. Normalized values are fed to the neurons of the neural network such that if the total number of nodes in the network is 8, 1 means node 8 and 0.125 means node 1.

The hidden layer has the major responsibility in processing the input data. Its size is determined according to the obtained errors in training. First with a small number of neurons in the hidden layer, the neural network is trained, and if sufficiently small error is not achieved, the number of neurons in the hidden layer will be increased until reducing the obtained error to the targeted level. Here, error is defined as the difference between the exact restoration path ids and the restored demands over these paths and; the respective outputs of the neural network with related fed inputs after training iterations.

Two types of information are expected from outputs of the neural network: restoration path ids and the number of secure and insecure connections restored over the given path id. So there has to be three output neurons for each restoration path and as a result output neuron size is increased with optical network size and load. The neural network has quantized outputs similar to its inputs. The used transfer function in neural network is sigmoid.

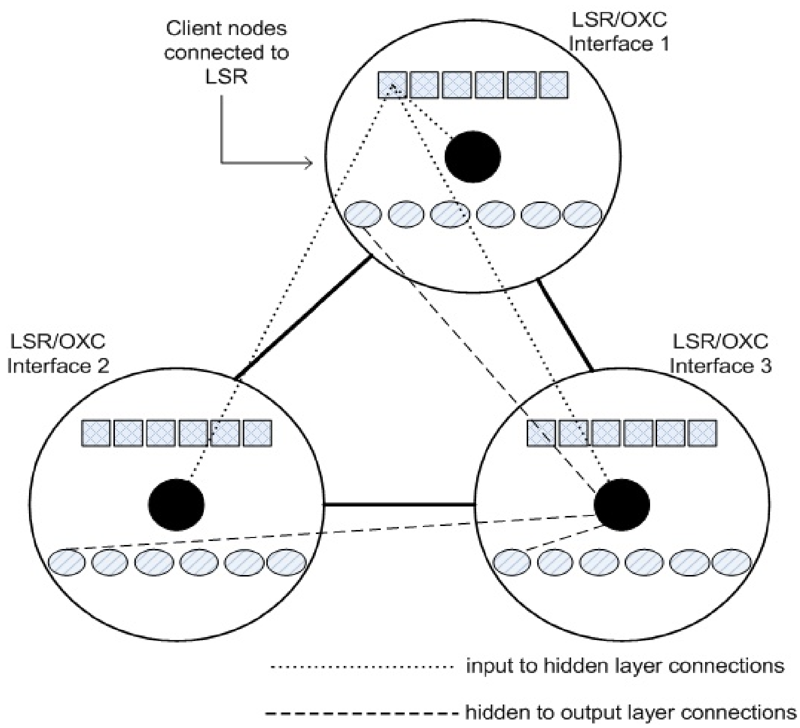

Figure 3.2 A simple neural network deployed over three nodes of optical network

In figure 3.2, a simple 3 node optical network is seen. For the sake of clarity, only the connections between first input neuron of the first node and hidden layer neurons, and the connection between the third hidden neuron and output layer neurons is shown.

3.2.2 Training the Neural Network

For training the neural network, the Levenberg-Marquardt algorithm [42] was chosen because of its quick convergence characteristics. MATLAB 7.0 neural network toolbox [43] was used for training. The neural network was trained according to the failure inputs for all different failure cases and targets are the expected outputs for restoration paths ids and number of restored connection. Negligible errors are obtained in the training of the network, after optimizing the neuron sizes in the hidden and output layers. But for large optical networks, memory restrictions of the program did not permit training, and as a result, analytically obtained results about the neural network have been considered in the simulation of the method in the next section.

3.2.3 Restoration Mechanism

After deciding on the right neural network structure and training it, it can be used in optical network restoration. The restoration mechanism is triggered by the Alarm Indication Signal (AIS) which is generated by the optical layer controllers in case of light losses in a link. AIS signal floods in the network and according to this signal the nodes along severed connections apply their lost demands to all related input neurons in all nodes. This flooding operation can take at most twice the longest propagation time which corresponds to the longest path between any pair of nodes of the network without a loop. After this time, the system assumes that all necessary inputs have been applied to the input neurons. If there is no received input from any node, at the end of this interval, to a particular input neuron, it is assumed as zero input. Then, the information accumulated at the inputs of input neurons are transmitted to the hidden layers. After the processing of inputs in the hidden layers, through the sigmoid transfer function, the output is finally transmitted to the output neurons. Lastly the restoration path ids and number of connections restored over these paths are extracted from the output neurons. According to the obtained path ids, with the help of a simple lookup table showing the node sequence according path ids, severed connections are restored. Since the system and capacity is designed for single link failure, after repairing the failed link, the restored connections will be switched back to their original paths, which enable the protection of the optical network for another failure.

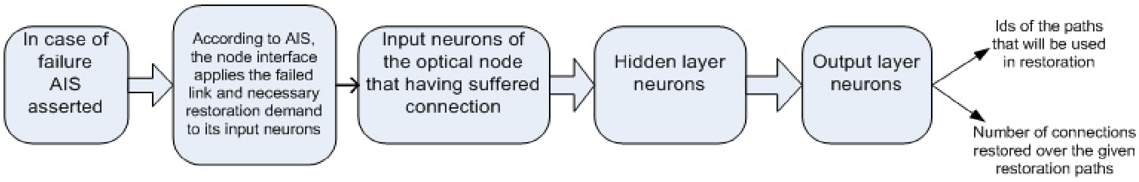

Figure 3.3 The transmission and process of control and restoration

The wide arrows show flooded propagation of the signals over the whole network

3.3 Simulation of Restoration Operation

According to the given neural network structure and Gökışık's technique described above, a C++ code was written to assess the restoration mechanism. In the simulation the connections are established and released with a Gaussian distribution that has predetermined mean. Link failures are uniformly distributed; failures arrive according to a Poisson process and repair times are exponentially distributed. When link failures are generated, the described method is applied and obtained restoration results are stored.

Restoration time is found analytically, which is equal to $3*(n-1)*(t_{prop} + t_{process})$ where n is equal to total number of nodes in the network, t_{prop} and $t_{process}$ are average propagation delay in links and processing delays on nodes respectively, assuming the worst case: routing from one node to the other can take a maximum of n-1 hops. The optical link lengths were taken as 1000 km. The average propagation delay was taken as 5.5 ms and the processing delay is taken as 250 μs. In the simulation, analytically found restoration time was directly added to delays. The major part of the restoration time is due to the propagation delay and it can be reduced if shorter routing paths can be found for the connections of neural network. The comparison of the present simulation results and Gökışık's results [5] can be seen in tables 3.2, 3.3, 3.4, 3.5 and 3.6 for different network topologies (Figure 3.7, 3.8 and 3.9) and connection types.

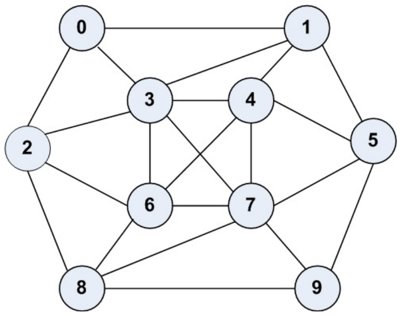

Figure 3.7 10 node network topology

Table 3.2 Comparison of obtained simulation results with Gökışık's one for 10 node network with only secure Sessions

	Gökışık's results	Present results
Session interarrival time at a node	200 s	200 s
Restorability	100%	100%
Restoration path finding	6.88ms	6.88ms
Physical network redundancy	0.27	0.27
Average restoration path length for protected traffic	3.66 hops	3,66
Neural Network Configuration:		
Input neuron number per node	11	11
Hidden layer neuron number per node	1	1
Output neuron number per node	12	12

Table 3.3 Comparison of obtained simulation results with Gökışık's one for 10 node network with secure and insecure Sessions

	Gökışık's results	Present results
Session interarrival time at a node	200s	200 a
Nodes equipped with optical amplifiers	0,4,8	0,4,8
Restorability	100%	100%
Restoration path finding	96,66 ms	96,66 ms
Physical network redundancy	0.4	0.37
Average restoration path length for secure protected traffic	3.66 hops	3,72
Average restoration path length for insecure protected traffic	4.22 hops	4,37
Neural Network Configuration:		
Input neuron number per node	20	20
Hidden layer neuron number per node	2	2
Output neuron number per node	36	36

Table 3.4 Comparison of obtained simulation results with Gökışık's one for 10 node network with secure and insecure sessions with different protection types

	Gökışık's results	Present results
Session interarrival time at a node	200 s	200 s
Nodes equipped with optical amplifiers	0,4,8	0,4,8
Restorability	100%	100%
Restoration path finding	96,66 ms	96,66 ms
Physical network redundancy	0.43	0.51
Average restoration path length for secure protected traffic	3.55 hops	3,54
Average restoration path length for insecure protected traffic	4.33 hops	4,33
Neural Network Configuration:		
Input neuron number per node	20	20
Hidden layer neuron number per node	2	2
Output neuron number per node	36	36

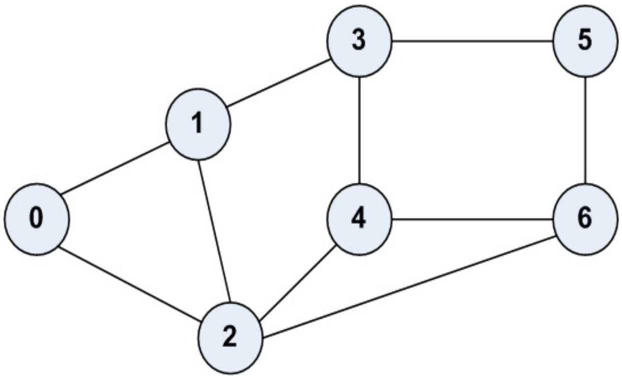

Figure 3.8 7 node network topology

Table 3.5 Comparison of obtained simulation results with Gökışık's one for 7 node network with secure and insecure sessions with different protection types

	Gökışık's results	Present results
Session interarrival time at a node	200 s	200 s
Node equipped with optical amplifiers	6	6
Restorability	100%	100% / 96%
Restoration path finding	60.3 ms	60.3 ms
Physical network redundancy	0.47	0.32
Average restoration path length for secure protected traffic	3.16 hops	3,16
Average restoration path length for insecure protected traffic	3.5 hops	3,55
Neural Network Configuration:		
Input neuron number per node	14	14
Hidden layer neuron number per node	1	1
Output neuron number per node	30	30

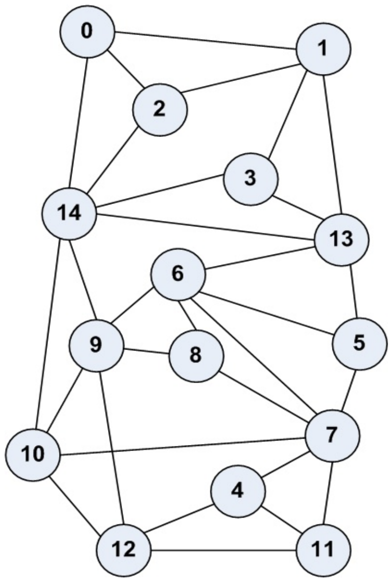

Figure 3.9 15 node network topology

Table 3.6 Comparison of obtained simulation results with Gökışık's one for 15 node network with secure and insecure sessions with path protection

	Gökışık's results	Present results
Session interarrival time at a node	200 s	200 s
Node equipped with optical amplifiers	0,4,8,12	0,4,8,12
Restorability	100%	100% / 98%
Restoration path finding	140.7 ms	140.7 ms
Physical network redundancy	0.5	0.44
Average restoration path length for secure protected traffic	4.27 hops	4,35
Average restoration path length for insecure protected traffic	4.66 hops	4,7
Neural Network Configuration:		
Input neuron number per node	30	30
Hidden layer neuron number per node	2	2
Output neuron number per node	99	99

In the tables, it is seen that in some cases, severed disconnections can be restored with less redundancy than the assigned capacity in [5].

Although 100% restoration was achieved for secure connections in simulations, in some cases due to the topology of the network and the distribution of the optical amplifiers in the networks, the restoration of the insecure traffic is impossible due to security limitations. For example, for the failure of the link between the node 7 and node 11 in figure 3.9 and between the node 3 and node 5 in figure 3.8, the insecure connections to the node 11 and node 5 cannot be routed respectively, so while designing the network topology and the placing the optical amplifiers to the nodes the security limitation should also be considered.

3.4 Improvement Suggestions

From the results obtained in the simulations and shown in the tables, it is seen that neural networks can be used effectively in optical network restoration, achieving 100% restorability for secure connections. Still, some improvements and solution of some problems about the mentioned technique can be suggested to increase its practical value:

- Finding the right neural network structure with minimum number of neurons to decrease the system complexity and to make training easier. Furthermore, using minimal structure would improve the scalability of the mentioned. For reducing neural network size, some assumptions can be made. For example while routing the severed connections; some predetermined routes can be used, which can reduce the total number of restoration paths and number of neurons used in the output layer.

- Restoration time should be decreased, which becomes high, due to the propagation delay of the complete network. For restoration, a propagation delay of $3\times(n-1)$ has to be severed. In the simulations the average optical link length was taken as 1000 km. If the links are shorter, restoration time can be below that in the ring topology networks (in SDH, it is approximately 50ms [43]). But since the restoration time varies linearly with the number of nodes, it will still be unacceptably large for large and time critical networks.

In the next chapter, these two improvement proposals will be evaluated, via simulation, in terms of the success as well as speed of restoration: First, a cycle-based restoration technique that will simplify the neural network structure will be considered. Secondly, reducing the waiting time for decision in respective stages of the neural network, by optimally routing the failure signals instead of flooding will be discussed. Other possible improvements will be considered in chapter 5 as suggestions for future work.

CHAPTER 4

IMPROVEMENT SUGGESTIONS

FOR

NEURAL NETWORK BASED RESTORATION

In the previous chapter, the restoration mechanism suggested in [5] was evaluated with new simulations and compared with the earlier obtained results. Although the suggested method can be used as suggested by Gökışık, as stated at the end of previous chapter, some improvements are possible. In this chapter two different methods for improvement of the restoration mechanism will be discussed. The aim of the first improvement suggestion is reducing the size and complexity of the neural network used in restoration. The second suggestion aims to reduce the restoration time. Both of the methods will be discussed in detail and then these improvements will be combined. Simulation will be used to illustrate the advantages of the improvement suggestions for different network topologies, security levels and failure situations.

4.1 Decreasing the neural network size

For large networks the needed number of neurons increases dramatically, and as a result handling and training of neural network becomes harder and also flooding of each neuron's output causes dense restoration traffic load over the optical network. For eliminating these problems, which is basically related with the size of the neural network, a new method is suggested. The suggestion uses cycle based restoration to reduce the number of neurons per optical node and consequently, overall size of the neural network established over the optical network is reduced.

The basic idea in cycle based restoration is dividing restoration load of severed connections, in terms of fed inputs and expected restoration outputs, into the restoration cycles. In case of a link failure, in each cycle, each optical node feeds only one of the severed connections generated by itself, to the input neurons along that connection. This method reduces the number of neurons in the input and output layers by using less input data and expecting less output data. Accordingly, the number of neurons necessary in the hidden layer also reduces.

In figure 4.1 the feeding time of the lost demands and when the path ids will be available is shown. According to the proposed method first restoration path id is obtained at the end of the 3^{rd} cycle, the second path is obtained in the 4^{th} cycle and the n^{th} restoration path id is obtained in the $(n+2)^{th}$ cycle. In the cycle time, propagation time is considered as: Maximum hop distance without loops × (propagation delay in one hop + queuing delay between two adjacent hops at a node).

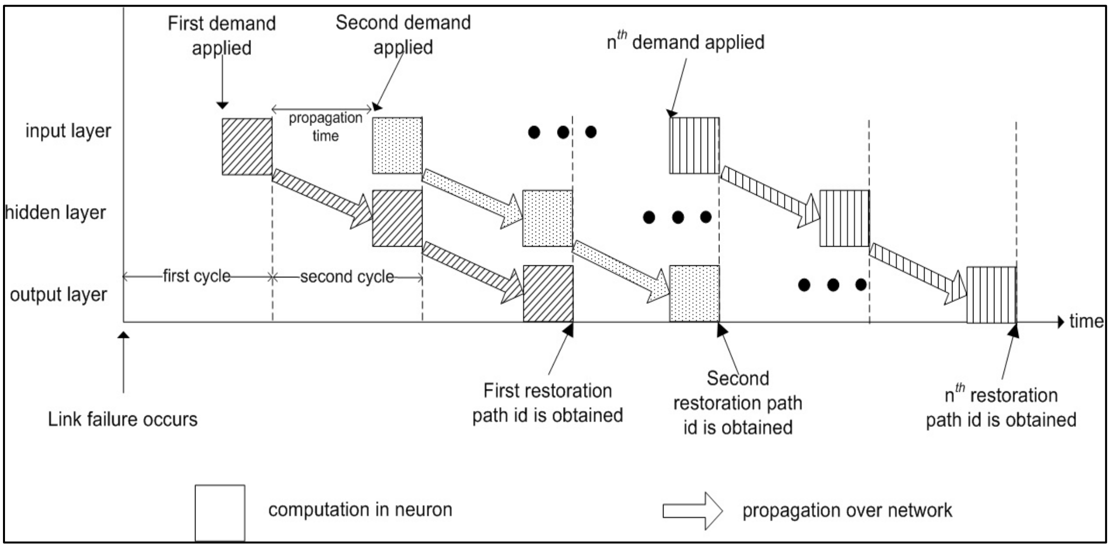

Figure 4.1 Timing diagram for input and outputs of neural network in cycle based restoration

In this new proposed method, layers of the neural network work as pipelined. In each cycle the layers are used for computation of different restoration paths. The overlapping of restoration cycles for different severed connections reduces the negative effect of cycle based restoration method on the restoration time, while also increasing utilization of neurons and capacity reserved for restoration signaling.

The basic advantages of this method are reduced training iteration time, increased number of total teachable restoration path ids and increased scalability. If an optical node does not have a severed connection or it has been restored in the previous cycles, it feeds zero to its neural network inputs and the neural network outputs of this node are simply neglected. Also, while training, when the inputs of a neuron are zero, the outputs of the related neurons are not considered and this makes training easier.

Yet another advantage of this method is that different quality of service levels can be provided in the restoration, by arranging the feeding order of the severed demands. The high priority connections can be fed earlier and can be restored earlier. Also the same procedure can be applied between secure and insecure connections. Secure connections can be fed earlier or strictly restricted restoration cycles can be defined, both of them to completely separate the restoration of the two classes. Detailed performance evaluation about the improvement will be presented in section 4.3, below.

Neural network input layer size is determined according to the required input data: Two input neurons are used for defining the failed link based on its adjacent nodes, one neuron is used for defining the severed connection by giving the destination node of the connection and another input neuron is needed for specifying the demand lost in the severed connection. One more neuron is needed if both secure and insecure connections are available, to define the security level of the severed connection.

The number of neurons at the neural network output layer is also determined according to the information needed for the restoration of the severed connections. This information is a restoration path id, which provides the requirements for the restoration of severed connection and the amount of demand that will be restored over this found restoration path. So two output neurons are needed for each optical node to obtain restoration path id and demand restored over the given path. Also, only a single output neuron per node can be sufficient if a single path is sufficient for the restoration of the severed connection. In this case, the demand restored over the determined path is equal to the fed demand to the neural network. The main purpose of feeding the lost demand, is the selection of the restoration path id according to the available spare capacities in the optical network. In most cases there is a tradeoff between the restoration path length and available capacity. Usually, larger demands will be restored over longer paths.

Although one neuron is assigned for the restoration path id, if none of the available restoration paths have sufficient capacity to provide the needed demand, two distinct restoration path ids may be needed and also, the restored demand over each one of these paths should be given separately. The necessity of more than one restoration path can be solved by either increasing the neural network output layer size or applying the same severed connection to more than one cycle until obtaining sufficient capacity over separate restoration paths. Since in this suggestion, the main aim is reducing the neural network size, the second method is chosen. The necessity of using a second path for the restoration of a demand will be discussed after the simulations of suggested improvement methods.

In the computation of the restoration paths, stub release is not considered, because it increases complexity of computing possible routes according to the available capacities and it provides only a small amount of improvement in the capacity utilization [6]. But the capacity released due to the failure is used in provisioning of new connections.

The disadvantage of cycle based restoration is the increase in restoration time due to the cycle based nature of the restoration operation. Unless restoration cycles are overlapped, as mentioned earlier, the total restoration time linearly increases with the number of severed connections. If the restoration time is examined carefully, it is seen that most of the delay is due to the three way propagation of related control signals over the whole network. In the cycle based method, after feeding one of the severed demands it is not necessary to wait until obtaining restoration paths, before feeding the next demand. Instead, after waiting a sufficient time to eliminate interference between different demands and connections, each optical node feeds the next restoration demand to the related neural network inputs. When all the outputs of input neurons reach the hidden layer neurons, new restoration demands are fed to the input neurons of the neural network. As a result, after the second cycle, in each cycle a new restoration path id will be obtained until all severed connections are restored. The cycle time is determined according to this operation, and it is equal to only one way propagation delay over the whole network plus the processing time in neurons and queuing delay at the optical nodes.

Neural network training was done with MATLAB 7.0, using Levenberg-Marquardt back propagation algorithm [43]. The training set consists of possible severed demands for different link failures as input and the expected outputs are scaled restoration path ids and restored demands over these path ids. The transfer functions of the layers are “tansig[1]”, “purelin[2]” and “purelin” at the input, hidden and output layers, respectively. The expected restoration path ids used in training are obtained by a simple simulation, which generates link failures and obtains restoration routes with MCgR [39] method for nedium network load, which means the network load is less than the level which would cause congestion.

In the training, for large networks, the number of possible restoration paths and consequently the training set size increases rapidly. While forming the restoration path sets, for large optical networks, many distinct restoration paths were obtained and training with a small sized neural network became impossible. To solve this problem, the restoration paths were restricted to hop limited routes and were enforced to traverse lightly loaded links. These limitations also lead to the reduction of the blocking probability of restoration connections. For each failure a maximum of four different restoration paths per connection were considered in training.

In table 4.1 for the 10 node network (Figure 3.7), part of a simple training set input for the link failure between the node 3 and 6 is given with the expected outputs and only secure connections are considered. For insecure connections, 0 is fed to the security input and the expected outputs are the path ids that do not traverse the optical nodes that contain an optical amplifier. In the table, at the expected restoration path column, bold numbers are path ids. According to these obtained ids related paths are found from the set of all possible paths obtained earlier. Although the set of all possible restoration paths was reduced by adding some constraints, it is still large and due to practical reasons, the table that matches ids to the related paths could not be given here. A simplified version for the 7 node case is given in the Appendix B.

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[1] Tansig: Hyperbolic tangent sigmoid transfer function ($f(x) = \dfrac{2}{1+e^{-2x}} - 1$)

[2] Purelin: Linear transfer function ($f(x) = x$)

In the table for the connection between 5 and 6 only one unit of the demand can be restored over single path, so in the next cycle the same severed connection should be fed again with remaining one unit demand. In similar cases, when restoration of the whole demand over a single path is not possible, the restoration continues in the following cycles until sufficient capacity is obtained over distinct paths. In the capacity calculation sufficient spare capacity was provided to the networks according to the expected load and in the simulations the networks did not operate with full load. Unavailability of a restoration path with sufficient spare capacity is rare and it did not occur in the long period simulation time.

Table 4.1: Simple training set for a link failure (3-6)

	Fed input					Expected output	
	failed link		severed connection	security	lost demand	restoration path id	restored demand
	node1	node2					
optical node 0	3	6	6	1	1	**0** (0→1→3→2→6)	1
optical node 1	3	6	8	1	1	**8** (1→4→6→7→8)	1
optical node 3	3	6	9	1	2	**4** (3→2→6→4→7→9)	2
optical node 5	3	6	6	1	2	**9** (5→7→6)	1*
optical node 9	3	6	0	1	1	**7** (0→3→2→8→9)	1

4.2 Waiting time adjustment

Another improvement to Gökışık's method [5] is reducing the restoration time. If the restoration time is examined carefully, it is equal to sum of computation time in the neurons and the propagation of data over the network, and the propagation time part forms the major part of restoration time. To reduce the restoration time, the waiting time before the firing of the neuron outputs should be adjusted. In the original work [5], due to its simplicity, propagation delay was taken as the longest path between node pairs without a loop. This assumption results in a path with one hop less than the total number of nodes in the network. In all of the examined networks, except the ring topologies, for a single link failure case, all the related control data (i.e. AIS and neuron outputs) reached their destinations in much less time than the suggested time. In fact, this waiting time can be less than half of this suggestion if the neuron outputs and AIS are propagated by flooding.

Shortest distance between node pairs in a single link failure can be found by using Bellman-Ford algorithm [45]. By this algorithm, prior to the operation of network, all possible link failures are scanned. For each topology this algorithm computes the distance between all node pairs and additionally the longest distance is stored as a reference value. After all the link failures are scanned, the largest of the stored reference values was chosen as the maximum possible propagation delay over the network for a link failure. In the restoration procedure, when any information is flooded up to this maximum possible number of hops, flooding will be terminated. This method also reduces flooding traffic in the network. The effects of this improvement are compared with the original work in table 4.2. Especially for the large network while the original algorithm waits for propagation for a long time unnecessarily, the new suggestion reduces this time significantly.

Table 4.2: Possible restoration times after arranging of waiting time for different topologies

Network topology	According to [5]	Computed	Reduction	Possible restoration time (in ms)
7 node 10 link (Fig. 3.8)	6 hops	3 hops	50 %	31,95
10 mode 22 link (Fig. 3.7)	9 hops	3 hops	66 %	31,95
15 node 30 link (Fig. 3.9)	14 hops	5 hops	64 %	53,25
20 node 32 link ARPANET (Fig. 4.2)	21 hops	7 hops	66 %	74,55
32 node 70 link ITALIANNET (Fig. 4.3)	31 hops	7 hops	79 %	74,55

4.3 Simulation of the suggested improvements

An event driven C++ code was implemented to evaluate the improvements achieved with the proposed modification of Gökışık's method [5]. In simulation, connection requests between uniformly distributed node pairs arrive according to a Poisson process. The failures occur according to a Gaussian process. The probability of failure in all links is equal. Only single link failures are considered; that is, the occurrence of a second failure is not allowed before the previous failure is repaired.

The next failure can only occur after the switching of severed connections back to their primary paths or end (that is, repair) of these severed connections. The links are bidirectional and their lengths are taken as 1000 km, which results in 3.3 ms propagation delay between adjacent nodes. The processing and queuing delays are taken as 250 μs. Stub release is only considered in the provisioning of normal connections, it is not considered in the restoration of severed connections. In simulations both secure and insecure connections are considered. The weights obtained by Levenberg-Marquardt training algorithm in MATLAB 7.0, were embedded to the neural network before starting the optical network operation. Generalization of trained inputs and online training of neural network is not considered. In the routing of connections MCgR [39] is used. Only path restoration is considered. The assigned link capacities for the simulated networks are listed in appendix A.

The first simulation was done for the 7 node network (Fig. 3.8), which is a simple topology. The capacity is designed for a maximum of 10 secure and 10 insecure connections between the nodes. Since the necessary capacity varies linearly with the number of generated connections between the nodes, the multiples of earlier obtained results in the capacity calculations in chapter 3 (Table 3.1) are used in the simulation of network. The possible restoration paths against the link failures are given in appendix B. The details about the network, obtained results in the simulations and comparison with the Gökışık's results are presented in table 4.3

Table 4.3: Comparison of simulation results for 7 node network with Gökışık’s results

		New Results	Gökışık's Results
Session arrival time		200 s	
Node equipped with optical amplifier		6	
Restoration path finding duration (in ms)	Average	40.03 ms	60.3 ms
	Maximum	127.8 ms	
Cycle time		10.65 ms	-
Physical Network Redundancy		0.32	0.47
Average restoration path length for secure connections		2.97 hops	3.16 hops
Average restoration path length for insecure connections		3.11 hops	3.5 hops
Neural Network Structure (per optical node)	input neuron number	5	14
	hidden neuron number	1	1
	output neuron number	2	30
	transfer function	‘tansig’-‘tansig’-‘purelin’	sigmoid

The second simulation was done for a 10 node network (Fig. 3.7). The maximum number of connection between the node pairs is taken as 10. Optical amplifiers are deployed to the nodes 0, 4 and 8. The cycle time which determines the restoration time is 3 × (3.3ms + 250µs), that is 10.65ms. The obtained results and their comparison with the original work are presented in table 4.4. While the maximum restoration time is higher than Gökışık’s results, which occurs rarely, the average restoration time is comparatively low. This is due to most sessions being restored in the first cycle. Also the average restoration path length is seen to be reduced.

Table 4.4: Comparison of simulation results for 10 node network with Gökışık’s results

		New Results	Gökışık's Results
Session arrival time		200 s	
Node equipped with optical amplifier		0,4,8	
Restoration path finding duration (in ms)	Average	41.7 ms	96.66 ms
	Maximum	127.8 ms	
Cycle time		10.65 ms	-
Physical Network Redundancy		0.37	0.4
Average restoration path length for secure connections		3.46 hops	3.55 hops
Average restoration path length for insecure connections		3.77 hops	4.33 hops
Neural Network Structure (per optical node)	input neuron number	5	20
	hidden neuron number	1	2
	output neuron number	2	36
	transfer function	‘tansig’-‘tansig’-‘purelin’	sigmoid

In table 4.5 the comparison of results for the 15 node network (Fig 3.9) is given. The simulation is carried out for a maximum of 10 connections between node pairs. The cycle time for this topology increases to 17.75 ms = (5× (3.3ms + 250µs)). The average restoration time is less than half of the earlier value. It is accomplished by arrangement of the waiting time of neural network nodes. Also average restoration path lengths are reduced, but increasing network load of network increases restoration path lengths.

Table 4.5: Comparison of simulation results for 15 node network with Gökışık’s results

		New Results	Gökışık's Results
Session arrival time		200 s	
Node equipped with optical amplifier		0,4,8,12	
Restoration path finding duration (in ms)	Average	62.153 ms	140.7 ms
	Maximum	266.25 ms	
Cycle time		17.75 ms	-
Physical Network Redundancy		0.44	0.5
Average restoration path length for secure connections		3.39 hops	4.27 hops
Average restoration path length for insecure connections		4 hops	4.66 hops
Neural Network Structure (per optical node)	input neuron number	5	20
	hidden neuron number	1	2
	output neuron number	2	36
	transfer function	‘tansig’-‘tansig’-‘purelin’	sigmoid

The next simulation is done for ARPANET topology (Fig. 4.2), with 20 nodes and 32 links. The implementation of neural network structure for this topology with the previous method is not practical due to its load to data network and due to serious training problems, so for this topology only, the obtained results are given and are not compared with the original method. The obtained results for this topology are given in table 4.5. In this case, the necessary number of neurons increases to two neurons in the hidden layer for training but it does not make considerable change in the scalability of the method. Due to the reduced connectivity of the network (nodal degree (d) =3.2 link/node) the path lengths and consequently the restoration paths become longer. In this topology, for the insecure connections, the lengths of restoration paths are determined according to the position of the nodes equipped with optical amplifiers. If they are deployed to the nodes connecting two distant nodes, the average insecure restoration path increases (i.e. deploying to nodes 7, 9 and 10).

The largest hop distance in a single failure for this topology is found as 7 hops. Accordingly, for this case computed cycle time is equal to 24.85 ms = (7× (3.3ms + 250μs)).

The average restoration time is 81.63 ms which is an acceptable time and the maximum restoration time is found as 223.65 ms which corresponds to 9 restoration cycles.

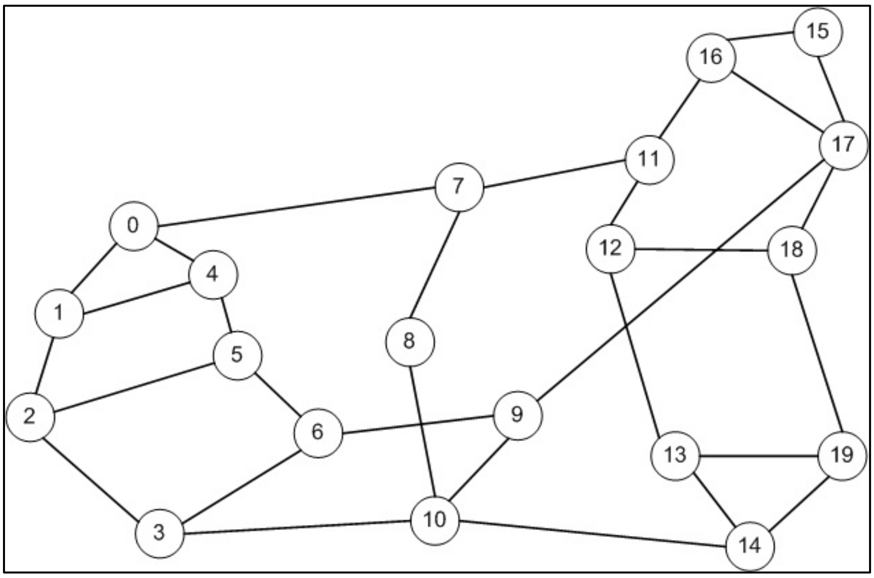

Figure 4.2: ARPANET topology

Table 4.6: Simulation results for ARPANET topology

<table>
<tr><td colspan="2"></td><td>Simulation configuration/results</td></tr>
<tr><td colspan="2">Session arrival time</td><td>200 s</td></tr>
<tr><td colspan="2">Node equipped with optical amplifier</td><td>2,9,12</td></tr>
<tr><td rowspan="2">Restoration path finding duration (in ms)</td><td>Average</td><td>81.63 ms</td></tr>
<tr><td>Maximum</td><td>223.65 ms</td></tr>
<tr><td colspan="2">Cycle time</td><td>24.85 ms</td></tr>
<tr><td colspan="2">Physical Network Redundancy</td><td>0.46</td></tr>
<tr><td colspan="2">Average restoration path length for secure connections</td><td>4.66 hops</td></tr>
<tr><td colspan="2">Average restoration path length for insecure connections</td><td>4.82 hops</td></tr>
<tr><td rowspan="4">Neural Network Structure (per optical node)</td><td>input neuron number</td><td>5</td></tr>
<tr><td>hidden neuron number</td><td>2</td></tr>
<tr><td>output neuron number</td><td>2</td></tr>
<tr><td>transfer function</td><td>‘tansig’-‘tansig’-‘purelin’</td></tr>
</table>

For the last simulation a large network is chosen. The ITALIANNET, which has 32 nodes and 70 links, is used in simulation. In figure 4.3 this topology is given. The optical amplifiers are deployed to the nodes: 3, 9, 14, 17 and 24. The capacity is assigned for maximum 10 connections between the each node pair. The cycle time is equal to 24.85ms. Due to the size and connectivity of the network, the average restoration path is longer than the previous networks. The difference between the length of secure and insecure connections is comparatively low, because the alternative paths that do not traverse the nodes that have optical amplifiers are comparatively numerous and finding shorter paths that provide the security conditions is possible.

In this case, as the previous one, two neurons are needed in the hidden layer for each optical node. For the other layers, the number of neurons per node is constant and it is independent of the neural network. The detailed information about the simulation is given in table 4.7. According to the results, it can be stated that the improved method is highly scalable.

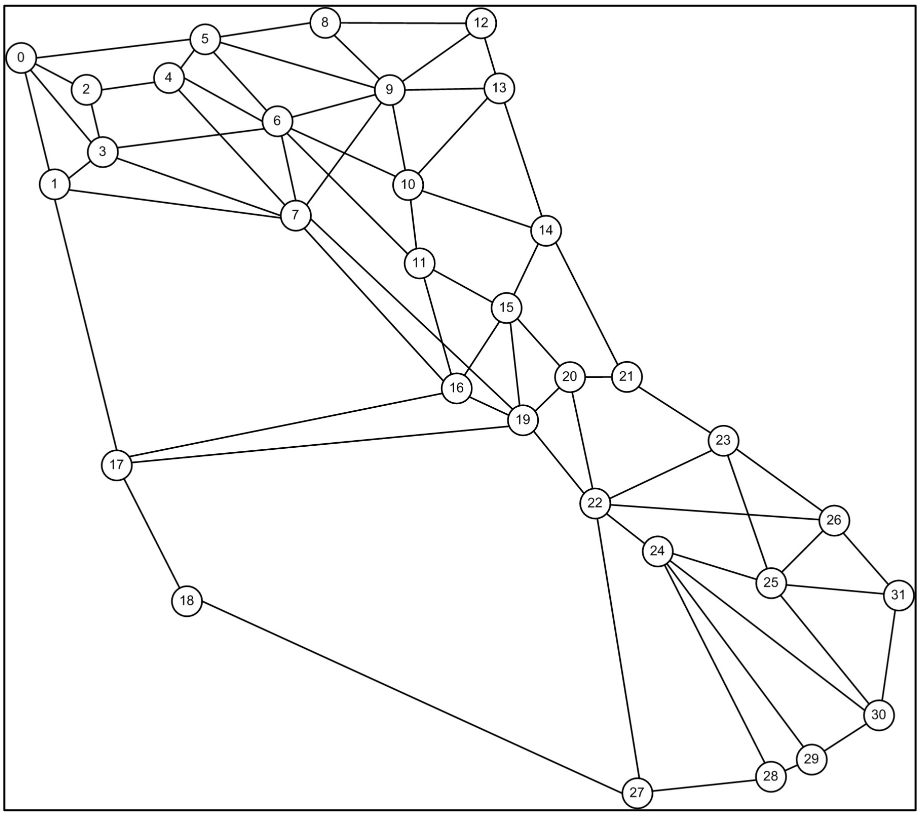

Figure 4.3: ITALIANNET topology

Table 4.7: Simulation results for ITALIANNET topology

		Simulation configuration/results
Session arrival time		200 s
Node equipped with optical amplifier		3,9,14,17,24
Restoration path finding duration (in ms)	Average	79 ms
	Maximum	223.65 ms
Cycle time		24.85 ms
Physical Network Redundancy		0.41
Average restoration path length for secure connections		5.28 hops
Average restoration path length for insecure connections		5.52 hops
Neural Network Structure (per optical node)	input neuron number	5
	hidden neuron number	2
	output neuron number	2
	transfer function	‘tansig’-‘tansig’-‘purelin’

4.4. Evaluation of the simulation results

The main aim of this study is reducing the size of the neural network structure and limiting the number of neurons to improve scalability. According to the obtained results, the modified neural network based restoration can be used for the restoration of connections in single link failure cases with an acceptable size neural network structure. While the restoration time depends on topology, network load and connection priority, it is bounded and can be formulated as:

$$t_{max} = 3 \times t_{cycle} \times (C_{link} + 2) \quad (4.1)$$

Where t_{cycle} is cycle time for the network and C_{link} is the maximum connection capacity or wavelength capacity of the failed link.

In medium or large size networks with evenly distributed connection requests, usually no or single severed connection occurs per node and most of the restoration paths can be found at the end of third cycle.

While defining the neural network structure, it was stated that in some cases one may need more than one path for restoration of a connection, if its demand is high to route with a single path. In the simulation this did not occur due to sufficient capacity assignment and even distribution of connections. But if this case occurs it would only slightly increase the average restoration time.

Since in the training phase, only limited number of paths that have fewer hops are considered, in this method average length of restoration paths is reduced. The reason for this reduction is the usage of simpler training sets. So the neural network can be trained with the larger path sets, increasing the chances of choosing shorter paths in case of failures. By the proposed modifications, compression level of data about the restoration paths in the neural network weights increases.

The restoration of a link failure, even together with the node failures would be possible because of the distributed nature of the method, as the failure of an irrelevant node mostly would not affect the restoration mechanism.

Although in the cycle based restoration, the total restoration time increases linearly with the number of severed connections, the overlapping (pipelining) of restoration cycles reduces this time. Furthermore, reduction of the waiting time reduces the average restoration time below the one obtained in Gökışık's work.

In the simulations, link lengths and queuing times were taken as 1000km and 250µs, respectively. In practice these may be shorter, leading to even lower actual restoration times than those reported in this study.

CHAPTER 5

CONCLUSION

Survivability of optical networks is a critical issue, because failures are frequent in these networks and their cost can be significant due to the loss of high volumes of data. So while provisioning the connections either dedicated capacities should be reserved over predetermined protection paths or a mechanism should be implemented for the network, which dynamically finds restoration paths and restores the severed connections over it. In planning and assigning of network capacities for future demand expectations failures should be considered. While determining the survivability method; restoration time, redundancy, restorability should also be considered.

In this thesis, neural network based restoration and two possible improvements for this restoration method were studied. Neural network based restoration can be defined as the control of restoration of failed connections by a neural network distributed over the optical network. In this work, firstly a new capacity assignment procedure is applied and new link capacities are obtained for different topologies. Then the original approach for neural network based restoration of optical networks [5] was evaluated with new capacities and satisfying results were obtained. The basic shortcomings of that approach were identified as the rapid increase of the number of neurons with optical network size and the fact that a training set of restoration paths cannot be generalized for restoration in different failure cases. In this study, the solution of the first problem was considered. For solving the scalability problem, cycle based restoration was suggested in which, the severed connections are restored by turns. In this way, the neural network size is reduced significantly, but at the same time the restoration time increases. To compensate for the increase in restoration time, the exact waiting time for propagation delay is computed for different failures and the mechanism was modified according to the obtained waiting times. In all of the restoration cases, the security requirements of connections with respect to the traversed nodes were also considered.

By these two improvement suggestions the following results were obtained:

- An appropriate neural network structure is obtained with reduced number of neurons per node regardless of optical network size.
- The training of neural network has become easier and neural network can be trained with larger sets and better restoration paths can be obtained for severed demands.
- The average restoration time is reduced.
- In the restoration procedure, different quality of service levels can be provided to the connections, in terms of restoration time.
- Flooding traffic used for the control signals is reduced by limiting the number of hops per restoration path.

Although with the suggested modifications significant improvements are achieved, some drawbacks must also be noted. These can be listed as:

- The restoration time of the connections varies depending on connection priority, network load and the distribution of connection pairs traversing over the failed link. The topology of the network determines the cycle time and this time has an inverse relation with the connectivity and size of the network. The total number of restoration cycles is related with the load of the network. The priority for each connection determines in which cycle the failed connection will be restored.
- Due to the usage of cycle based restoration, a precise synchronization is needed between the optical nodes to eliminate the interferences between the different restoration signals.

Further study about neural network based restoration of optical networks can be suggested as follows:

- In this study the restoration paths are computed according to the predetermined primary paths, improving of the method for dynamically restoration of different primary paths can be investigated
- Improving the neural network control by means of training it online instead of offline. If the neural network can be trained online, the following improvements can be obtained :
    - The smaller training set, which depends on current working connections, is sufficient for training the network, instead of trying to teach all possible input cases to the neural network.
    - The severed connections need not be restored back to earlier path after repairing failed link.
    - Restoration of multiple link failures collectively.
- Generalization of trained set by the neural network to survive from all different failure cases can be investigated.
- Survivability in multi-failure cases can be addressed.
- Survivability in cases of limited numbers or total absences of wavelength converters also deserves to be considered.
- Different training methods can be investigated and compared to find better training performance with respect to error level and size of trainable set.

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APPENDIX A

CAPACITY ASSIGMENT FOR PATH PROTECTED NETWORKS

A.1. ILP formulation for spare capacities

Objective function:

Minimize assigned total spare capacity for the links:

$$\min\left\{\sum_{l\in L} Sp_l\right\} \tag{A.1}$$

Constraints:

The demand constraint for secure connections:

$$\forall l \in L, \forall c \in C, \sum_{k} rs_{c,l}^{k} = \beta s_{c,l} \tag{A.2}$$

The demand constraint for insecure connections:

$$\forall l \in L, \forall c \in C, \sum_{k} (ri_{c,l}^{k} \times Amp_{c,k}) = \beta i_{c,l} \tag{A.3}$$

None of the restoration paths can pass through the failed link:

$$\forall l \in L, \forall c \in C, \zeta_{c,k}^{l} \times rs_{c,l}^{k} = 0, \zeta_{c,k}^{l} \times ri_{c,l}^{k} = 0 \quad \text{(A.4)}$$

For all the links l_1 and l_2, the minimum spare capacity per link l_2 should be equal to or larger than the needed capacity for the restoration paths for a single link failure l_1:

$$\forall l_1 \in L, \forall l_2 \in L, \sum_{k} \sum_{c \in C} \zeta_{c,k}^{l_2} \times (rs_{c,l_1}^{k} + ri_{c,l_1}^{k}) \leq Sp_{l_2} \quad \text{(A.5)}$$

Sp_l	: Assigned spare capacity for link l.
L	: Set of links for the optical network
C	: Set of connections between the node pairs
$rs_{c,l}^{k}$	: The restored secure demand over kth route for the connection pair c for the link failure l.
$ri_{c,l}^{k}$	: The restored insecure demand over kth route for the connection pair c for the link failure l.
$Amp_{c,k}$	: 0 if kth route for the connection pair c traverses a node that has an optical amplifier, else 1
$\beta s_{c,l}$	: The lost secure demand for connection pair c for the link failure l.
$\beta i_{c,l}$	: The lost insecure demand for connection pair c for the link failure l.
$\zeta_{c,k}^{l}$	: 1 if the kth route for the connection pair c, traverses link l, else 0.

A.2. Overall capacities per link obtained for the path protection case for the simulated networks for the load of 10 connections per node pair

Table A.1. Assigned capacity for the 7 node 10 link network

link		Assigned capacity
first node	second node	
0	1	**45**
0	2	**45**
1	2	**60**
1	3	**75**
2	4	**45**
2	6	**60**
3	4	**45**
3	5	**60**
4	6	**30**
5	6	**30**

Table A.2. Assigned capacity for the 10 node 22 link network

link		Assigned capacity
first node	second node	
0	1	**85**
0	2	**75**
0	3	**25**
1	3	**50**
1	4	**25**
1	5	**75**
2	3	**50**
2	6	**25**
2	8	**65**
3	4	**25**
3	6	**25**
3	7	**65**
4	5	**40**
4	6	**40**
4	7	**15**
5	7	**25**
5	9	**50**
6	7	**25**
6	8	**25**
7	8	**25**
7	9	**40**
8	9	**25**

Table A.3. Assigned capacity for the 15 node 30 link network

link		Assigned capacity	link		Assigned capacity
first node	second node		first node	second node	
0	1	**90**	6	7	**105**
0	2	**15**	6	8	**90**
0	14	**160**	6	9	**160**
1	2	**60**	6	12	**105**
1	3	**45**	6	13	**160**
1	13	**190**	7	8	**60**
2	14	**135**	7	10	**210**
3	13	**120**	7	11	**170**
3	14	**45**	8	9	**60**
4	7	**190**	9	10	**15**
4	11	**15**	9	14	**145**
4	12	**30**	10	12	**60**
5	6	**60**	10	14	**265**
5	7	**190**	11	12	**15**
5	13	**220**	13	14	**45**

Table A.4. Assigned capacity for ARPANET

link		Assigned capacity	link		Assigned capacity
first node	second node		first node	second node	
0	1	**220**	9	10	**120**
0	4	**220**	9	17	**435**
0	7	**540**	10	14	**465**
1	2	**280**	11	12	**350**
1	4	**75**	11	16	**205**
2	3	**395**	12	13	**250**
2	5	**105**	12	18	**145**
3	6	**235**	13	14	**250**
3	10	**410**	13	15	**160**
4	5	**135**	13	19	**120**
5	6	**160**	14	19	**145**
6	9	**380**	15	16	**135**
7	8	**305**	15	17	**105**
7	11	**570**	16	17	**120**
8	9	**190**	17	18	**205**
8	10	**190**	18	19	**45**

Table A.5. Assigned capacity for ITALIANNET

link		Assigned capacity	link		Assigned capacity
first node	second node		first node	second node	
0	1	**380**	13	14	**120**
0	4	**145**	13	15	**235**
0	9	**410**	14	15	**120**
0	10	**45**	14	17	**145**
1	2	**220**	14	20	**190**
1	5	**235**	15	16	**280**
1	6	**175**	15	17	**220**
1	7	**205**	15	18	**135**
2	3	**145**	16	19	**640**
2	7	**205**	17	18	**235**
3	7	**280**	17	20	**205**
3	8	**175**	17	22	**2165**
4	5	**305**	18	19	**190**
4	10	**30**	18	22	**190**
5	6	**175**	19	23	**525**
5	11	**580**	20	21	**480**
6	7	**135**	21	28	**320**
6	10	**190**	22	23	**395**
6	11	**250**	22	24	**625**
6	12	**335**	22	25	**1320**
6	13	**280**	22	28	**380**
7	8	**435**	23	24	**145**
7	11	**785**	23	26	**435**
7	12	**45**	24	26	**30**
8	12	**30**	24	27	**380**
8	16	**450**	25	26	**75**
9	10	**120**	25	29	**365**
9	11	**610**	25	30	**380**
9	20	**450**	25	31	**320**
10	11	**190**	26	27	**45**
11	13	**175**	26	31	**105**
11	14	**175**	27	31	**30**
11	17	**1930**	28	29	**105**
12	13	**175**	29	30	**45**
12	16	**305**	30	31	**30**

APPENDIX B

COMPUTED RESTORATION PATHS FOR THE 7 NODE NETWORK

Table B.1 Simple restoration path sets for the 7 node network and their ids

Paths between 0 and 1		Paths between 1 and 3	
0→1	0	1→0→2→4→3	0
0→2→1	1	1→2→4→3	1
0→2→4→3→1	2	1→2→6→4→3	2
0→2→6→5→3→1	3	1→3	3
Paths between 0 and 2		Paths between 1 and 4	
0→1→2	0	1→0→2→4	0
0→1→3→4→2	1	1→2→4	1
0→2	2	1→2→6→4	2
Paths between 0 and 3		1→3→4	3
0→1→2→4→3	0	1→3→5→6→2→4	4
0→1→3	1	Paths between 1 and 5	
0→2→1→3	2	1→0→2→4→3→5	0
0→2→4→3	3	1→2→4→6→5	1
0→2→6→4→3	4	1→2→6→5	2
Paths between 0 and 4		1→3→4→6→5	3
0→1→2→4	0	1→3→5	4
0→1→3→4	1	Paths between 1 and 6	
0→2→1→3→4	2	1→0→2→4→3→5→6	0
0→2→4	3	1→2→4→6	1
0→2→6→4	4	1→2→6	2
Paths between 0 and 5		1→3→4→6	3
0→1→2→4→3→5	0	1→3→5→6	4
0→1→3→5	1	Paths between 0 and 6	
0→2→1→3→5	2	0→1→2→4→3→5→6	0
0→2→4→6→5	3	0→2→4→6	1
0→2→6→5	4	0→2→6	2
Paths between 1 and 2		Paths between 2 and 3	
1→0→2	0	2→0→1→3	0
1→2	1	2→1→3	1
1→3→4→2	2	2→4→3	2
1→3→5→6→2	3	2→4→6→5→3	3
		2→6→4→3	4
		2→6→5→3	5

Table B.1 (continued)

Paths between 2 and 4		Paths between 3 and 6	
2→0→1→3→4	0	3→1→0→2→4→6	0
2→1→3→4	1	3→1→2→6	1
2→4	2	3→4→2→6	2
2→6→4	3	3→4→6	3
2→6→5→3→4	4	3→5→6	4
Paths between 2 and 5		Paths between 4 and 5	
2→0→1→3→4→6→5	0	4→2→0→1→3→5	0
2→1→3→5	1	4→2→6→5	1
2→4→3→5	2	4→3→1→2→6→5	2
2→4→6→5	3	4→3→5	3
2→6→5	4	4→6→5	4
Paths between 2 and 6		Paths between 4 and 6	
2→0→1→3→4→6	0	4→2→0→1→3→5→6	0
2→1→3→5→6	1	4→2→6	1
2→4→3→5→6	2	4→3→1→2→6	2
2→4→6	3	4→3→5→6	3
2→6	4	4→6	4
Paths between 3 and 4		Paths between 5 and 6	
3→1→0→2→4	0	5→3→1→0→2→4→6	0
3→1→2→4	1	5→3→4→6	1
3→4	2	5→6	2
3→5→6→2→4	3		
Paths between 3 and 5			
3→1→0→2→4→6→5	0		
3→1→2→6→5	1		
3→4→2→6→5	2		
3→4→6→5	3		
3→5	4		