

All-Optical Network with Simultaneous in-node Routing and Wavelength Assignment

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Abstract — The paper describes a modified topology of an all-optical network with simultaneous in-node routing and wavelength assignment. The routing process is controlled by the Hopfield neural network. Intensive simulations demonstrate the stability and scalability of proposed algorithm and its capability for dynamic routing.

Keywords — All-optical networks, routing, wavelength conversion, optimization, Hopfield neural network.

I. INTRODUCTION

RAPID growth of modern telecommunication services, particularly, real-time multimedia with a huge amount of video material, has led to dramatic demands for bandwidth in transmission systems. A possible solution is the use of optical networks. Although the bandwidth was significantly increased in the optical network, the optical-electrical-optical conversion, which is used in classical routers, hardly degrades the network performances, particularly when it is necessary to retain the quality of service and to minimize the probability of blocking [1]. All these problems may be resolved in all-optical networks – networks containing optical amplifiers, optical/photonic switches and wavelength division multiplexers (WDM). The improvements in technology and decaying cost of optical fibers make a fiber-to-the-home solution reliable.

Routing in all-optical networks is usually performed through two steps: *route assignment* and *wavelength assignment*. The resulting procedure is known as *routing and wavelength assignment* (RWA) procedure [2]. Route assignment comprises finding the best physical path between the source and destination node (known as a lightpath). Route selection may be derived under different criteria, such as the path length, transport delay, delay in routers, link capacity, the cost, etc. Basic algorithms for route selection are: fixed routing, alternate routing, and exhaust routing.

After the route assignment, the *wavelength assignment* – a procedure of allocating available wavelengths to selected lightpaths is performed. In this procedure the main goal is to minimize the number of wavelength conversions and avoid the packet blocking in the lightpath [3].

In this paper an all-optical network with a simultaneous in-node RWA procedure is proposed. The routing process is controlled by the Hopfield neural network (HNN), adapted for finding the optimal path under given

constraints, similar to our previous work [4,5]. The final result of an algorithm is finding an optimal path between arbitrary selected source (S) and destination (D) nodes in an optical network of arbitrary topology, and under different, and possibly changeable, network and traffic conditions. The optimization procedure derived by HNN considers several network parameters, such as the cost, path length, number of hops, number of wavelength conversions in routers, link capabilities to support particular wavelengths. Simulations are realized in C++, with an appropriate user interface enabling easy and flexible managing. The paper is organized as follows. Section II briefly describes the HNN and its modifications enabling the routing control. Section III considers the suggested modifications of network topology for obtaining simultaneous in-node RWA and the neural network routing control. Simulation results and concluding remarks are given in Sections IV and V, respectively.

II. THE USE OF HOPFIELD NEURAL NETWORK IN ROUTING

A. Hopfield Neural Network Basics

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In his seminal paper [6] Hopfield introduced a discrete recurrent neural network well suited for solving content-addressable (associative) memories problems. The block scheme of the HNN is depicted in Fig. 1. Processing units (neurons) are realized according to the McCulloch-Pitts model of formal neuron [7], consisting of weighted summers and nonlinear amplifiers, g_i , $i=1,2,\dots,N$. Neuron outputs, v_i , may have unipolar values, $v_i \in \{0,1\}$, or bipolar, $v_i \in \{-1,1\}$, depending on the realization. Outputs are connected to inputs of other neurons, u_j , through synapses, T_{ij} , realized by conductances, modifying the neuron states in an iterative manner. By adding constant input signals (bias), I_i , particular cell(s) (or a global network) may be excited, as well.

It was shown [8] that recurrent networks are stable if the weight matrix $\mathbf{T}=[T_{ij}]$ is symmetric, with zeros on its main diagonal. In HNN realization [6] that means $T_{ij}=T_{ji}$ and $T_{ii}=0$ – thus synapses T_{ii} are not depicted in Fig. 1. For stable networks, after a sufficiently large number of successive iterations, outputs move toward limiting values 0 or 1, for a unipolar network (or -1 or 1, for bipolar). The Hopfield network with N neurons may have $M=2^N$ different stable states associated with an N -dimensional hypercube with vertices $v_i \in \{0,1\}$ (or $v_i \in \{-1,1\}$).

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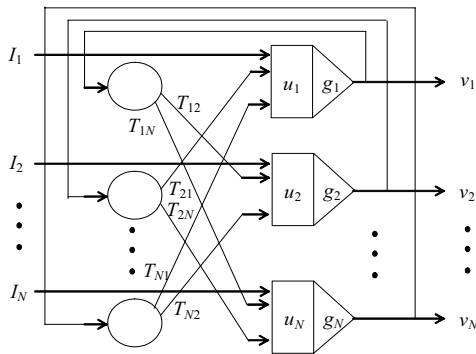


Fig. 1. Block scheme of the Hopfield neural network.

In the initial Hopfield's paper [6], the hard limiter activation function, $v_i = g(u_i)$, was used, and the neuron states changed in discrete time. Later on, Hopfield and Tank described an analog neural network [9], with a continuous activation function usually of the logistic type

$$v_i = g_i(u_i) = \frac{1}{1 + e^{-a_i u_i}}. \quad (1)$$

By changing the parameter a_i the slope of the logistic curve may be adjusted, and thus the sensitivity of the network. The dynamics of the analog HNN may be described by

$$\frac{du_i}{dt} = \sum_{j=1}^N T_{ij} v_j - \frac{u_i}{\tau} + I_i, \quad (2)$$

where τ is the circuit's time constant.

If matrix \mathbf{T} is symmetric and parameters a_i are sufficiently large (say, $a_i > 100$) – when activation functions approach to hard limiter ones, the dynamics of the neurons follow a gradient descent of the quadratic energy function

$$E = -\frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N T_{ij} v_j v_i - \sum_{i=1}^N I_i v_i. \quad (3)$$

From relations (2) and (3) it is easy to describe the dynamics of the i th neuron as

$$\frac{du_i}{dt} = -\frac{u_i}{\tau} - \frac{\partial E}{\partial v_i}, \quad (4)$$

from which it follows that the HNN is always stable, in the Liapunov sense, because, in final state (when voltages are constant, i.e., $du_i/dt=0$), relation (4) reads

$$\frac{\partial E}{\partial v_i} = -\frac{u_i}{R_i} \quad (5)$$

denoting that, irrespective of the voltage u_i (positive or negative), the product $u_i \partial v_i$ is always positive and thus the energy E decreases – the network is always stable.

B. Routing in Communications Networks by using HNN

The computational power of an analog HNN in solving constrained optimization problems was demonstrated just in the paper [9], through the well-known TSP problem (with 30 cities). Although the HNN provides only an approximate solution of the shortest path, the solution is obtained faster than would be possible with any algorithmic solution, for instance, Bellman-Ford's [10,11] or Dijkstra's [12].

By slight modifications, the HNN may be used for solving dynamic routing in telecommunication and computer networks. The nodes in a neural network may correspond to positions of routers in the communication network, and by weights T_{ij} the distances between nodes may be described. Moreover, instead of physical distances between nodes, as used for solving classical TSP problem, some other attributes, called the "cost" can be introduced describing static and/or dynamic transmission conditions between nodes; for instance, the link capacity, traffic flow, traffic density and dynamics, transit time, etc. Under these assumptions the dynamic routing can be solved using the same network as for the shortest path problem.

The use of HNN to find the shortest path between a given source-destination pair in a communication network was first suggested by Rauch and Winarske [13]. A major drawback of their approach was that the method required a fixed and a priori known number of nodes forming the shortest path. Later on, Zhang and Thomopoulos [14] introduce some extensions which made it possible to find a path with an arbitrary number of intermediate nodes. Furthermore, significant improvements are obtained in the paper of Ali and Kamoun [15]. In their work the link costs and node connectivity information are associated to bias currents I_i (linear term in energy function (3)) rather than to the weight matrix \mathbf{T} (quadratic term). In this way their algorithm becomes more flexible and attractive to work in real time, because the same neural network topology (possible hardware realization) may be used irrespective of possible changes in external communication network. In papers [4,5] further modifications are introduced in the HNN permitting the routing in all-optical networks.

III. MODIFIED TOPOLOGY OF ALL-OPTICAL NETWORK

A. Routing in All-Optical Networks

Routing in all-optical networks is based on the WDM, which is, basically, frequency division multiplexing in the optical frequency domain. Instead of frequencies, in the optical domain the wavelengths are assumed. On a single optical fiber there are multiple communication channels at different wavelengths. In real networks possible difficulties may arise if incoming packets are carried by one wavelength, say λ_i , and outgoing packets must be carried out by some other wavelength, λ_j . In this case the wavelength conversion devices in routers are needed that can shift the wavelength of an optical signal. One possible solution of such a router was reported in [16], Fig. 2.

By using such routers in an optical network, it is necessary to define which router supports the wavelength conversion, and which conversion, because routers may have different conversion combinations. For instance, in some routers conversion $\lambda_1 \rightarrow \lambda_2$ is stimulated, but not $\lambda_1 \rightarrow \lambda_3$. Also, the network scalability (regarding the number of links and routers), and arbitrary wavelength assignment have to be fulfilled. Note again that in a „standard“ RWA procedure routing is performed in two separate steps: routing assignment and wavelength assignment. Because of that, processing speed in routing is degraded.

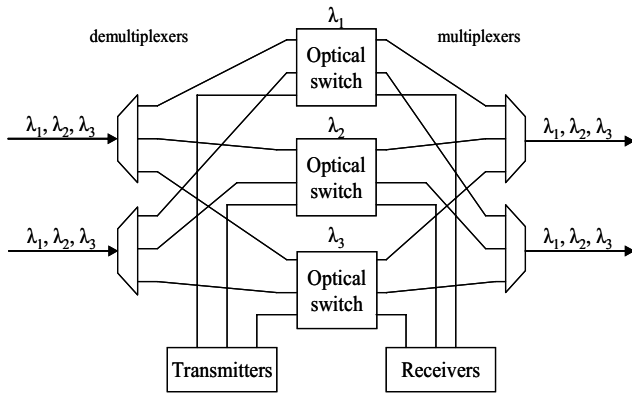


Fig. 2 Architecture of the wavelength router [16].

B. Modification of Network Topology

The goal of our research consists of two topics: (i) to derive a dynamic routing algorithm in an all-optical network and (ii) improve the processing speed, by realizing a simultaneous RWA process in router nodes. Our previous work [4,5] demonstrated the capabilities and flexibility of HNN in dynamic routing, under different and changeable network conditions. For this reason we decided to use HNN for realizing topic (i). For realizing topic (ii) it was necessary to introduce some modifications in network topology. The modifications we suggest will be illustrated by an example of optical network with $K=4$ routers and $L=3$ wavelengths, λ_1, λ_2 and λ_3 , as in Fig. 3. Routers 1 and 4 are assumed to be the source and destination nodes. As we can see, in the given example link 1-2 supports carriers with λ_1 and λ_2 , link 1-3 supports λ_2 and λ_3 , etc.

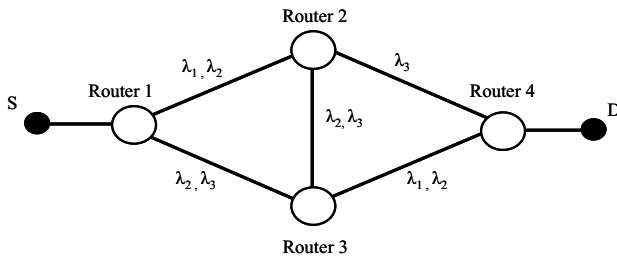


Fig. 3 Illustrative example of an all-optical network with WDM.

The core of suggested modification is illustrated in Fig. 4, representing an equivalent router node. Instead of a single router, a universal subnetwork with full-connected sub-nodes, labeled as $i=1,2,3$, drawn as shadowed rectangles in Fig. 4, is used. The number of subnodes corresponds to the number of wavelengths used in the network. These subnodes are access points for corresponding optical channels supporting wavelengths λ_1, λ_2 and λ_3 , respectively. In-node sublinks are characterized by weights W_{ij} , which describe the cost of wavelength conversions between subnodes, their disabling or stimulating. To better distinguish sub-nodes within the optical network, they will be labeled as RouterX(i), where X denotes the node in the network (in our example $X=1,2,3,4$), and index $i=1,2,3$, refers to a corresponding wavelength.

By introducing modified network nodes in optical network as in Fig. 3, an equivalent form is obtained, as depicted in Fig. 5. External channels, supporting particular

wavelengths λ_1, λ_2 and λ_3 through optical fiber links, are drawn by thin lines. Formally, network in Fig. 5 has a different topology regarding to Fig. 3, but such presentation is suitable for neural network control.

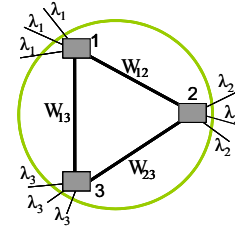


Fig. 4 Suggested subnetwork replacing network routers. Case with three wavelengths is presented.

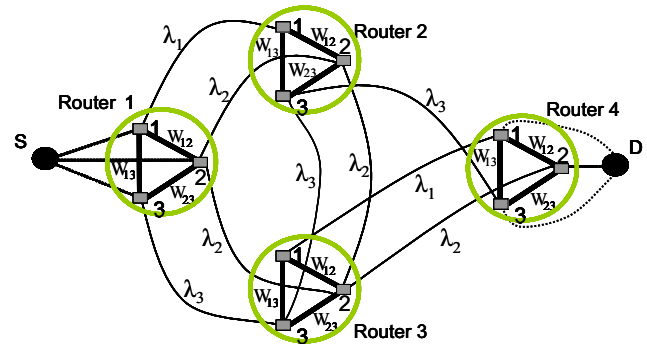


Fig. 5 Modified topology of the network in Fig. 3.

Described modifications of network topology reflect to matrices used in optimization process (routing) derived by HNN. First, "old" terms (matrices) used for neural network control as in [4,5] now change their dimensions. Namely, without the wavelength conversion the dimension of matrices describing the cost, node connection, etc., is equal to the number of nodes, K ($K=4$ in the given example). When using the new topology with L different wavelengths ($L=3$ in our example) the dimension of these matrices becomes $D=K \times L$ ($D=12$). Furthermore, now the new terms describing the wavelengths distribution through optical links, the matrix \mathbf{WD} , the access matrix $\mathbf{SD}=\{SD_{ij}\}$ describing the connection of S and D nodes with network routers, and the weight matrices describing the costs of in-node wavelength conversion $\mathbf{W}=\{W_{ij}\}$, are introduced.

IV. SIMULATION RESULTS

The suggested algorithm was realized in C++ with appropriate GUI for easier management. Among the matrix describing network connectivity, different parameters describing, link costs, wavelength distribution over external links, cost of wavelength conversion within network nodes, and access matrix, are used. For the given example the access matrix \mathbf{SD} is sparse, having nonzero values $SD_{ij}=0.1$ only for predefined source and destination nodes (nodes 1 and 4, respectively, in our example). The new routing scheme is tested through intensive simulations under different scenarios. Several characteristic cases will be presented here, demonstrating the capabilities of the new routing algorithm.

Case 1. The same link costs (equal to 1) for all wavelengths, same weights $W_{ij}=0.5$ for all existing wavelength conversion in all nodes (other terms equal to zero). In this case neural network find an optimal lightpath **S-Router1(2)-Router3(2)-Router4(2)-D**. (Note that the number within parentheses denotes the wavelength used.)

Description: Routing from node 1 to 4 was performed with carrier λ_2 (without conversion) using a minimal possible number of hops (two): 1-3 and 3-4. Since link costs are the same for all wavelengths, there is no stimulation of any particular wavelength. Further, the same weights $W_{ij}=0.5$ for all wavelength conversions denote that there is no stimulation of any particular in-node conversion. Namely, if any conversion is made, then the path cost will be increased. Consequently, the algorithm will try to find the lightpath without wavelength conversion – in the given case such lightpath is with the wavelength λ_2 , as our routing algorithm decided.

Case 2. Assuming the same link costs (equal to 1), the low cost of in-node wavelength conversions ($W_{ij}=0.1$), and the occupancy of the link 1-3 with the wavelength λ_2 (this wavelength is suppressed in this link), our algorithm decided the optimal lightpath as **S-Router1(3)-Router3(3→1)-Router4(1)-D**.

Description: Possible lightpaths can be 1-2-3-4, i.e., in three hops but without conversion (using only wavelength λ_2), or 1-3 (with λ_3) and 3-4 (with λ_1) in two hops. Since in the given case wavelength conversions have low cost (equal to 0.1) while link costs are significantly higher (equal to 1), our algorithm decided the lightpath as above, with one wavelength conversion and two hops, rather than the lightpath in three hops without wavelength conversion.

Case 3. By using a high conversion cost, for instance $W_{ij}=3$, and all other parameters as in Case 2, our algorithm finds as optimal the three-hops lightpath **S-Router1(2)-Router2(2)-Router3(2)-Router4(2)-D**.

Description: Now the lightpath with multiple hops but without wavelength conversion is decided as an optimal solution, because the overall cost is minimal.

Case 4. Using low link costs for the wavelength λ_1 (0.1), the high link costs for other wavelengths (equal to 1), and medium cost for wavelength conversions, $W_{ij}=0.4$, the lightpath, determined by our algorithm, is **S-Router1(1)-Router2(1→2)-Router3(2→1)-Router4(1)-D**.

Description: In this case the use of particular wavelength (λ_1) is stimulated. Since the link cost for this wavelength is significantly smaller than the wavelength conversion, an algorithm will try to find all possible paths with λ_1 and with as small as possible conversions.

From given examples, the capabilities of suggested algorithm are demonstrated. Since our algorithm takes into account both physical connections and decision logic, by changing/loading appropriate parameters the actual network conditions may be implemented permitting the dynamic routing. Parameters describing the state of an optical network, that control the neural network, are associated to bias currents I_i in HNN, similar to the solution suggested by Ali and Kamoun [15], permitting possible hardware realization for real-time routing.

V. CONCLUSIONS

A new routing algorithm in all-optical networks, with HNN control, is suggested. Optical network topology and the HNN are modified appropriately enabling simultaneous in-node routing and wavelength assignments. Although the new routing algorithm is more complex than in “classical” neural network control [4,5], because the dimensions of matrices controlling the neural network are increased L times (where L is the number of wavelength used), the simultaneous in-node RWA process and computational power of HNN enable efficient routing under different network conditions. Intensive simulations demonstrate the stability and scalability of proposed algorithm. Further research will be addressed to the possibility of making router clustering and centralized control for improving the processing speed.

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