Application of Neural Networks in Solving Some Problems in Modern Telecommunications

Irini Reljin and Branimir Reljin

Abstract – **Modern telecommunication network is characterized by intensive growth and enormous capabilities. A huge number of users, types of services offered, and permanent trend of increasing the transfer rate make very difficult, or even impossible, to model, predict and control such a traffic. The paper describes the possible use of neural networks (NNs) in solving some problems arising in modern telecommunications. The main attention is devoted to applications of NNs in the traffic control: the scheduling in ATM node, the packet switch control, and the routing protocols, particularly for regular structure networks such as mesh topologies. The cellular neural network (CNN), according to its structure, is proposed for arbitration between the packets that are to be deflected or buffered in mesh topology networks. The parallel analog processing embedded in the CNN leads to very fast and optimal routing.**

Keywords – **Modern communication networks, scheduling, switching, routing, Manhattan Street Networks, cellular neural networks, optical neural networks**

I. INTRODUCTION

In the last few years we are witnesses of very intensive growth of different information technologies. Recall that there are little more than ten years since World Wide Web (WWW) – initially invented as a computer network – was born, in 1992. But, its phenomenal growth and enormous capabilities, changed all aspects of our lives. For instance, in January 1992 the network for transmitting audio and video over the Internet did not exist. Only three years later, it made up 20-50% of all the Internet traffic, while nowadays almost all Internet communications are accompanied by multimedia contents.

Telecommunications technology has rapidly evolved from circuit switching (as in traditional telephony, usually referred to as POTS = Plain Old Telephone Services) to packet switching, frame relay and fast packet switching; and from copper wires to optical fiber links, satellites, and mobile communications. In the near future high-speed (operating at giga or tera bits/sec – Gbps or Tbps) and broadband integrated services digital networks (B-ISDN) employing asynchronous transfer mode (ATM) cell switching, will be used to provide significant services and applications. Video teleconferencing, video-on-demand, e-business, multimedia communications, high definition television, telemedicine, and personal communications services are just a few examples of those services that will have a profound impact on all aspects of our social, political, economic, and cultural life. The typical structure of global interconnection of modern telecommunication network is depicted in Fig. 1.

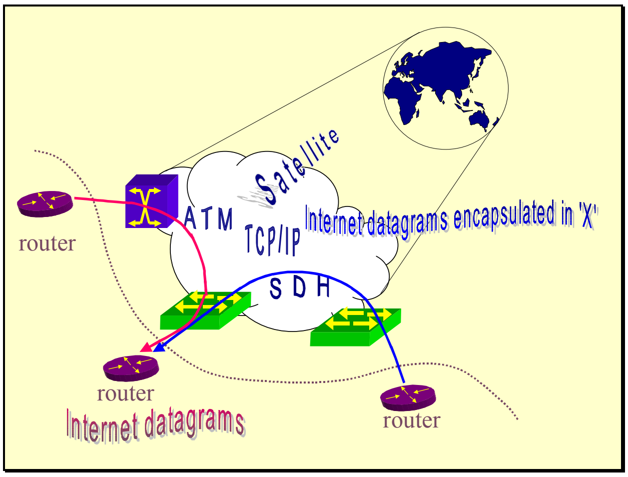

Fig. 1 Typical structure of global interconnection in modern telecommunication network.

The main characteristics of modern telecommunications are their *immensity*, *variability*, *interactivity*, and finally, *unpredictability*. Actual telecommunications network contains hundreds and thousands of nodes, to which thousands of users are connected (*immensity*), in a direct and simultaneous way (*interactivity*), or indirectly, changing and sharing messages from different sources and with different types of traffic (*variability*). Furthermore, a permanent trend of the intensive extension of the traffic is evident: as by number of users, by types of services offered, and by transfer rate speed. As a consequence, it is very difficult, or even impossible, to model and to predict such traffic (*unpredictability*). Instead of mainly static nature of POTS the new multimedia traffic exhibits high variability and significant burstiness, as shown in Fig. 2 [1]. Such complex traffic requires highly dynamic techniques for management with minimal intervention and very fast reaction times (in the order of microseconds or less), and adaptive and learning capabilities. Intensive experiments over living networks demonstrate that classical approaches in

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characterizing and modeling the traffic are not appropriate for multimedia traffic [2]-[6]. For such complex traffic it is necessary to use adaptive and intelligent systems in order to provide high network reliability, accurate traffic prediction, efficient use of channel bandwidth, and optimized network management in relation to various, dynamically changing environments. Artificial neural networks (NNs) can contribute to this emerging new telecommunication infrastructure by providing fast, flexible, adaptive, and intelligent control. No explicit model of the traffic is needed, as in traditional methods, only a good representation of the problem. The neural networks, accompanied by the fuzzy logic (based on the 'soft computing' mechanism and the expert knowledge), are able to approximate complicated input-output relations by autonomously selecting significant inputs and deriving feature parameters. In this way it is possible to control network parameters by adapting on its changing environment via learning.

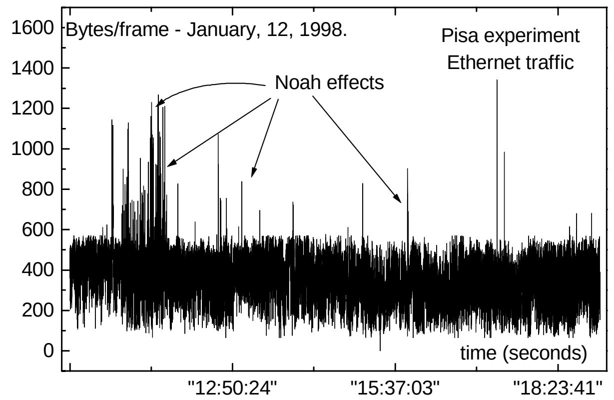


Fig. 2. Ethernet traffic (bytes/frame) measured in living network.

This paper concentrates to the possible use of neural networks in solving some problems arising in modern telecommunications. The main attention will be devoted to applications of NNs in the traffic control: the scheduling in ATM node, the packet switch control, and the routing protocols, particularly for regular structure networks such as mesh topologies.

The paper is organized as follows. In Section II a brief review of the use of NNs in traffic modeling and policing is exposed. Section III considers the NN control in the ATM node, while in Section IV the use of NNs in switching control is described. The main attention is devoted to the multihop networks of mesh topology, particularly the Manhattan-street network (MSN) and the neural network control in the MSN node, in Section V. Finally, some new trends in routing policies in optical networks are shortly described in Section VI.

II. A BRIEF REVIEW OF THE USE OF NEURAL NETWORKS IN TRAFFIC MODELING AND POLICING

Although the investigations of possible neural network applications in communications started in 70's [7]-[8], first serious indication that this new technique may be very usable in this field is announced in November 1989, in IEEE Communication Magazine, Special Issue addressed to neural networks in communication [9]. Probably the best description of the significance of this issue can be found in the paper of E. Posner [10] who inferred that eight invited papers from this journal clearly traced future directions in investigation in this field.

The inherent property of neural networks is to learn from presented data and to perform some decision on that basis. Thus, the traffic characterization and prediction may be realized in this way. It is also possible to perform some statistics of traffic parameters [11]-[16]. One of the first solutions of neural network applications in communications was that for a call admission control [17]-[18]. Hiramatsu was the first one who notified the high efficiency of neurocomputing in very complex field of communication networks.

Traffic policing mechanism, based on the NNs, is proven to be more effective than algorithmic ones due to nonlinear and time-varying nature of the traffic. A policing mechanism using NNs, called neural network traffic reinforcement mechanism, is proposed in [12]. It is based on the estimation of the probability density function of the multimedia traffic via its counting process. Another approach to congestion control using the NN is presented in [14]. Results prove that the new mechanism provides the improvements in cell-loss rate (CLR) compared to the feedback congestion with static threshold values. Moreover, the transmission delay introduced by the NN controller is also smaller than in the static threshold case.

III. NEURAL NETWORK CONTROL IN ATM NODE

Traffic streams in the ATM, already adopted in the B-ISDN, exhibit burstiness with peak transmission rates much higher than their averages. With the aim of high link utilization, statistical multiplexing is used. Buffering in the intermediate nodes is expected to absorb bursts and to avoid cell losses. On the other side, large buffers may produce excess in delays that are undesired for most of the service types. In order to avoid the degradation of quality of services, and to prevent high cell losses, a proper scheduling mechanism has to be chosen.

According to [19]-[20] aggregate traffic is as bursty as individual flows are, exhibiting the self-similar nature. This is one of the reasons why it is complicate to model and predict traffic in the ATM. As a consequence, the exact method for its control, suitable under rather different conditions, is (almost) impossible.

A network node with the superposition of arrival processes is presented in Fig.3. The case with multiple-inputs (each having its own buffer) and single (non-buffered) output is considered. Inputs are the sequences of ATM cells (packets of the fixed length of 53 bytes). All buffers have the same capacities of x_b cells.

The number of cells in individual buffers (i.e., the input queue lengths) are denoted as x_i, i=1,2,...,n. Scheduling control creates a policy according to which the cells from buffers are selected and transferred to the output.

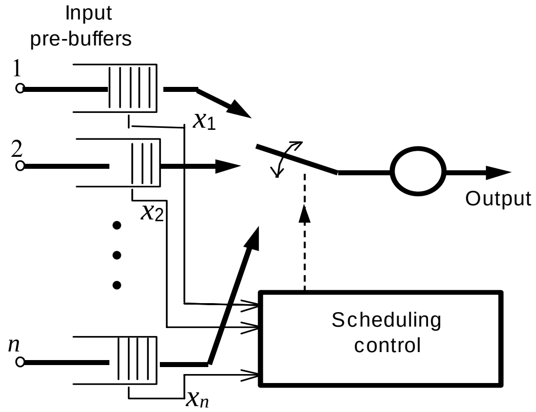


Fig. 3. ATM network node.

There are many different scheduling algorithms presented in literature. Most of them are based on the round-robin (RR) mechanism, exhaustive RR or non-exhaustive RR, as well as on the weighted fair queuing mechanisms [19]-[21]. Differences in their performances determine the cases of their applicability. The main disadvantages, these rules include, are caused by their incapability to track the instantaneous traffic parameters. Besides this, deterministic nature of the rules (exact frame interval, assignment of the fixed service time, etc.) may be the source of the unpleasant synchronization between the traffic streams.

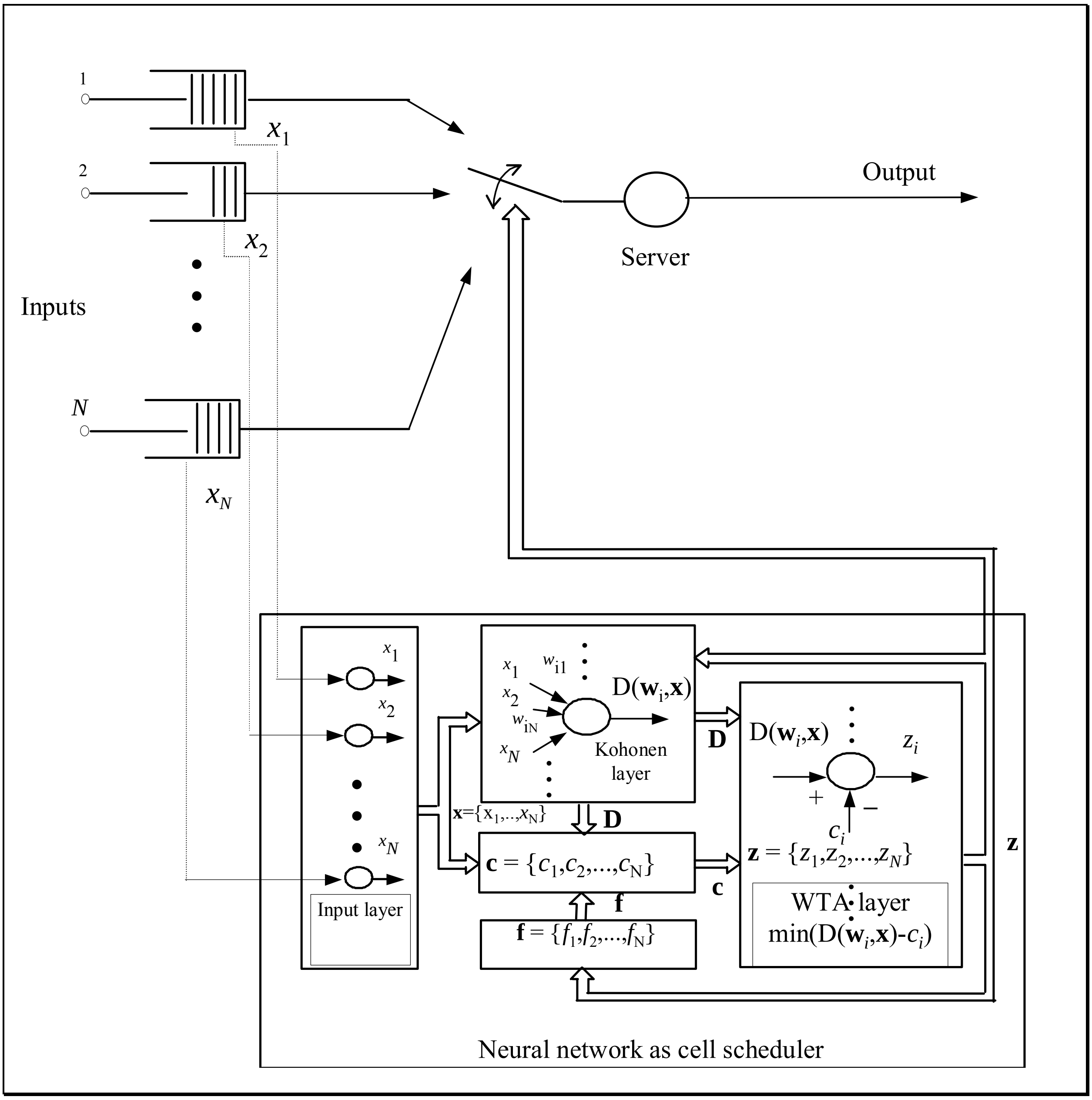


Fig. 4 Neural network control in ATM node [24].

In several papers [22]-[24] the neural network (NN) based scheduling algorithm was proposed. This new approach starts with the competitive neural network of the Kohonen's type, but with appropriate modifications leading to the adaptive network suitable for scheduling discipline in the bursty traffic case. The modification takes into account the pre-buffer capacities, number of cells in a queue, as well as the dynamic of arriving cells. In this way the significant improvements compared to the RR algorithm were achieved. The new scheduling algorithm dramatically decreases the cell loss and avoids the periodicity effect at the ATM node output. The proposed network is even realizable as hardware device. The possible structure of such network is depicted in Fig. 4.

IV. NEURAL NETWORK IN SWITCHING CONTROL

A number of different neural networks based switch control strategies are known from literature. They are based mainly on the Hopfield-Tank optimization problem [25]-[26]. Like with any optimizing problem, in the switch control action the weights of the Hopfield network are selected according to the chosen strategy, i.e., the according to the switching mechanism. By minimizing the energy function, the network states define the rule of packets scheduling from input queues towards the output, avoiding the head-of-line blocking.

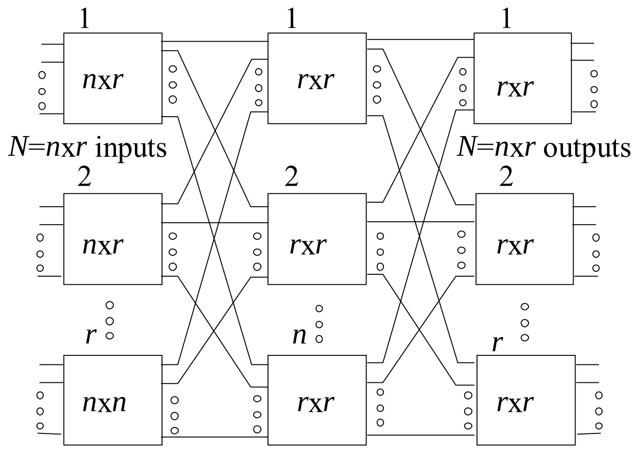


Fig. 5 Switching field considered in [27-28].

One of the first suggestions of the use of neural networks in switch control was given in [27]-[28]. Brown analyzed the commutation field containing *r* crossbar switches of *n*x*n* type. In Fig. 5 the three-level switching field is depicted. Outputs from one switching level are connected just to one of inputs of the next switching level. Switching algorithm is based on the Paull's matrix. In this matrix the number of rows corresponds to the number of input switches while the number of columns corresponds to the number of switches connected to the outputs.

If two incoming calls exist at the same location, the Paull's algorithm performs the rearrangement of calls. Brown suggested the Hopfield-like neural network with the topology as a replica of switching field. By using two neurons at each network node and an inhibitory logic, as in Fig. 6, the congestion of calls is avoided. If the calls from different inputs are addressed to the same output the NN produces the re-arrangement of incoming calls.

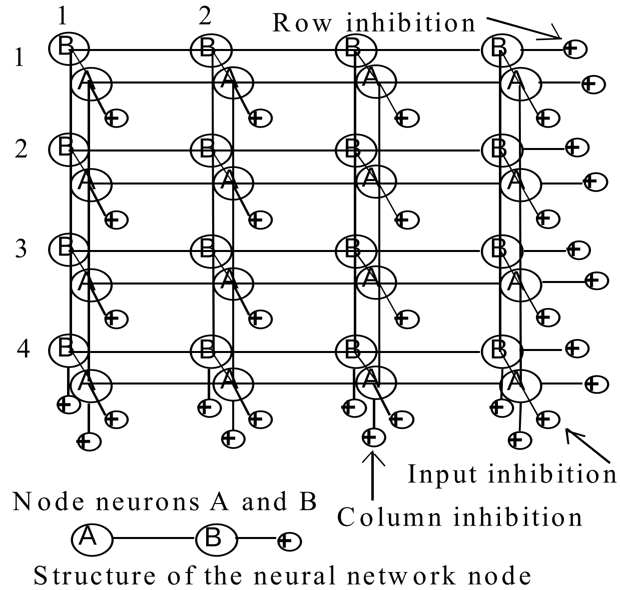


Fig. 6 Neural network for switching control [27-28].

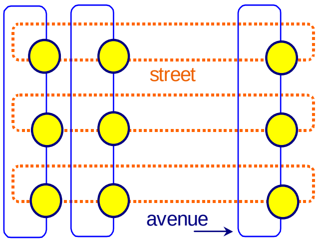
V. MULTIHOP NETWORKS OF MESH TOPOLOGY

Extremely fast networks are currently being developed for supporting multi-Gbps interconnections, with almost no latency. Options that are being considered widely are based on self-routing algorithms using fixed-length packets composed of pico-second optical pulses. Packet headers are processed on the fly, using the very fast photonic or, when possible, electronic switching [29]-[30].

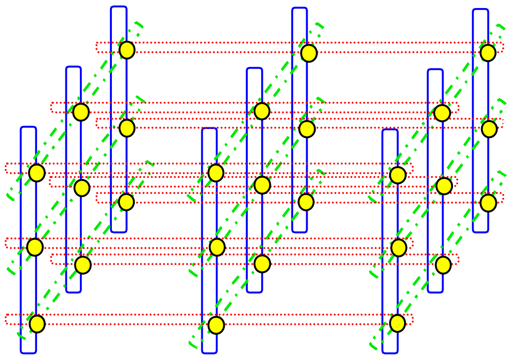
Most of the communication networks, local or metropolitan area, are based on the linear topologies. Bus and ring topologies need no routing. Their attachment units are economical, primary because of the lack of transit buffering. Unfortunately, maximum throughput of linear rings and buses is restricted by the data rate. Mesh topologies (two-dimensional, 2D, structure) overcome this problem [31]-[32]. They provide multiple paths between sources and destinations. In this way, by applying a suitable routing strategy, end-to-end reliability may be increased, as well as the overall throughput.

One of the simplest mesh structures is a regular rectangular network, Fig. 7-a, which topology resembles to Manhattan streets (rows) and avenues (columns) [31]-[32]. The nodes (network terminals) are placed at the intersections (crosses) each with two incoming and two outgoing links: in horizontal and vertical directions. No node buffers are needed, except the input and output buffers of the terminal node itself. The MSN exhibits very good feature of having identical nodes (without any boundary constraints), resulting in easier fabrication and routing algorithm. This type of network consists of unidirectional rings meaning that through one ring packets are transmitted in one direction (like in one-way streets). The routing strategy in the MSN is very simple but effective [31]: it is mainly based on the shortest-path (SP) algorithm, while the routing rules are distributed to all nodes.

Each incoming packet can be addressed to one of two possible directions: to the street (horizontally) or to the avenue (vertically), as shown in Fig. 8a – hence, this structure has the degree of freedom equals to 2. Alternating vertical and horizontal connections are made between nodes permitting the connection between each pair of nodes. When two incoming packets from different inputs have the same destination address, and according to the SP algorithm have to be destined to the same outgoing link, one of these packets is forced to take another output link, since no node buffer exists. In this way packets do not always find the shortest path but they are never lost. Due to the increased connectivity, mesh topology can achieve higher throughputs and support more source-destination pairs than other networks. Moreover, the MSN is highly modular and easily expandable.



(a)



(b)

Fig. 7. Mesh topologies: (a) 2-dimensional (2D) MSN network; (b) 3-dimensional (3D) MSN topology.

A very important extension of the MSN is a K-grid topology, meaning that its planar structure replicates in a space of *K* dimensions. As a consequence, the *K*-dimensional unidirectional MSN has the degree of freedom equals to *K*. A 27-node 3-dimensional (3D) MSN, as shown in Fig. 7b, is reported in literature [33]-[35].

The MSNs have been proposed primary for MAN (Metropolitan Area Networks). Later on, these networks founded many different applications, both in general optical networks and in multicomputer architectures [36].

The original unidirectional 2D MSN, as in Fig. 7a, can be modified to a bi-directional MSN (BMSN), first suggested by Borgonovo and Cadorin [37]-[38], where all interconnection links are full-duplex. The network node of 2D bi-directional MSN is depicted in Fig. 8b while its functional block scheme is shown in Fig. 9. Since the degree of freedom now is 4, the 2D BMSN increases the throughput in the whole network. Note that 3-dimensional unidirectional MSN can be, also, extended to bi-directional structure, exhibiting the degree of freedom equals to 6.

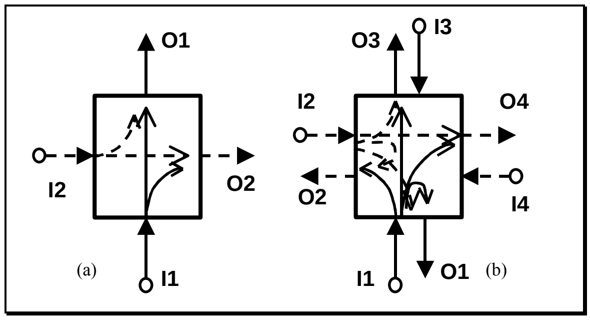


Fig. 8. The 2D MSN network node: (a) unidirectional, and (b) bi-directional.

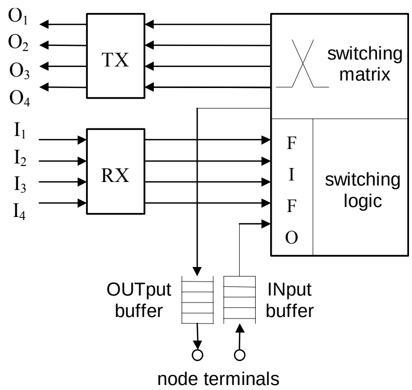


Fig. 9. The functional block scheme of the 2D BMSN node [38].

Recently, a novel algorithm for routing in the BMSN networks, based not only on the standard shortest-path (SP) strategy but, also, taking into account the traffic density (TD): the actual buffer occupancy in the network nodes, is suggested [39]. By spatially distributing packets over the network, as uniformly as possible, routing is done in such a way that it prevents collisions, congestions, and the packet loss. Namely, the routing strategy based only on the SP algorithm, even in the BMSN networks, exhibiting at least two drawbacks. First, if at the same time the node is affected by several (two, three or four) incoming traveling packets, having the same destination address, packets are redirected to the non-optimal paths and can circulate around their destination increasing the overall message delivery time. Second, if the node, having long input queue, is frequently affected with all four inputs at the same clock cycle, its input queue will be blocked and its input buffer can be overloaded producing the cell loss.

The TD-SP algorithm counts the actual input buffer occupancy as well as the distance of the actual position of the traveling packet to its destination. Then the new TD-SP routing algorithm forces the packet(s) to bypass a node(s) having long input queue(s) (the dense traffic). That means that packets circulate through network for finding their destinations, possibly by using the shortest path, but with the intention of avoiding nodes having long input queues. In this way the average message delivery time decreases while the overall throughput increases compared to the SP routing under the same conditions. The new routing strategy was refined in [40]-[41]. Performance improvements rise with a traffic density, so in heavy-traffic conditions the throughput is increased more than 53% and the message delivery time is decreased about 23% [39]. The proposed routing strategies are realized by using the Cellular Neural Network (CNN) – a relatively new class of nonlinear analog networks [42] capable for solving different tasks in parallel processing manner.

The CNN is a massive parallel multi-dimensional array of locally interconnected analog processing elements (cells) operating in real-time. Although different CNN topologies are possible, most commonly used is the two-dimensional (2D) rectangular structure, as in Fig. 10a. Each cell communicates to its neighbors sharing memorized states. In Fig. 10b the electric model of the CNN cell is depicted, which can be realized by using standard electronic components: amplifiers, resistors, and a capacitor [42]. One possible realization of CNN cell using only one operational amplifier [43]-[44] is depicted in Fig. 4c. Simple cell structures and their strong local connectivity make this structure very suitable for efficient VLSI implementation.

By appropriate choice the network components: the conductances (synapses) *A* and *B* between cells, and the bias source *I*, different complex problems can be resolved in a similar way as with the Hopfield network. Due to massive parallel processing each problem can be solved very fast – after few time-constants, irrespective of the problem complexity. Moreover, due to its planar structure, the CNN is very attractive for VLSI realizations. As an example, in Fig. 11 the layout of the CMOS realization of the CNN cell [44] is depicted.

Since the topology of the CNN is quite similar to the 2D MSN structure the realization of the TD-SP algorithm by using CNN was derived [39]-[41]. The CNN was used to model the traffic density in the vicinity of each MSN node. The in-node switching logic is performed with the 4x4 Winner-Take-All (WTA) network and additional analog circuitry, permitting the optimal routing. The rows and columns of the WTA correspond to the node input and output terminals, respectively) dictating the connection between the particular input (I_1 to I_4) and the output (O_1 to O_4) – see Figs 9 and 12. In Fig. 12 each WTA layer and the switching fabric correspond to only one node of the whole MSN network.

The developed CNN based Fast-Optimal-Packet-Routing (FOPR) network, due to its simple and spatial invariant structure, is perfectly suited for efficient VLSI implementation. Note that it is possible to extend the original FOPR-CNN of rectangular topology, as in Fig. 10, to cases when the corresponding network or node structure is different from the originally considered 4-connected MSN-like topology. For instance, similar solution can be implemented in re-addressing the calls in mobile telephony. In Fig. 13 the typical mobile telephony network is depicted. If the CNN cells (denoted as dots in Fig. 13) correspond to the intersection points of zones covered by base stations (circles labeled as ‘Mobile network cells’ in Fig. 13) then CNN can be used as call routing device.

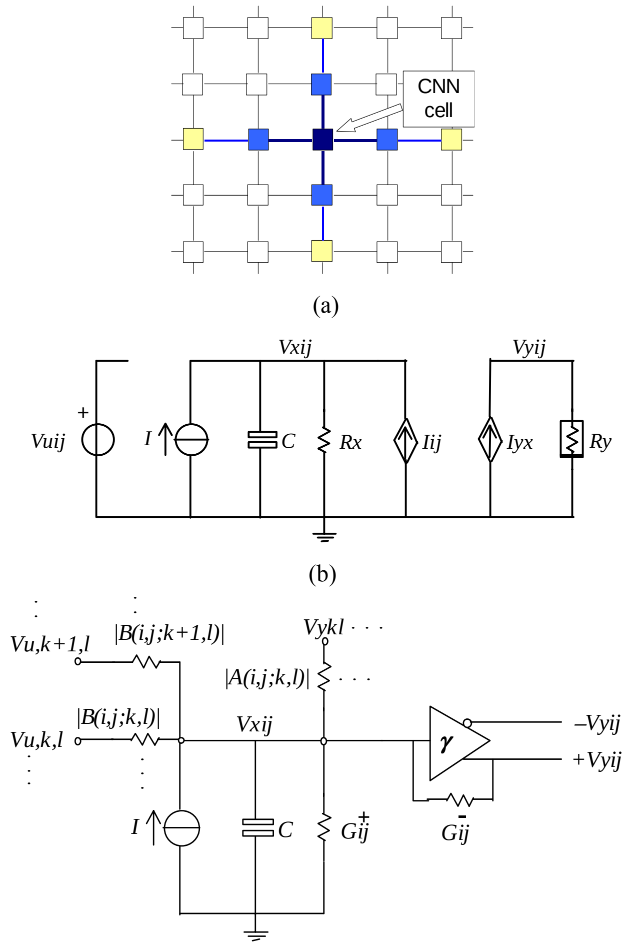


Fig. 10 (a) The 2-D CNN with 4-connected cells, (b) the model of the CNN cell [42], and (c) one possible single-amplifier realization [43]-[44].

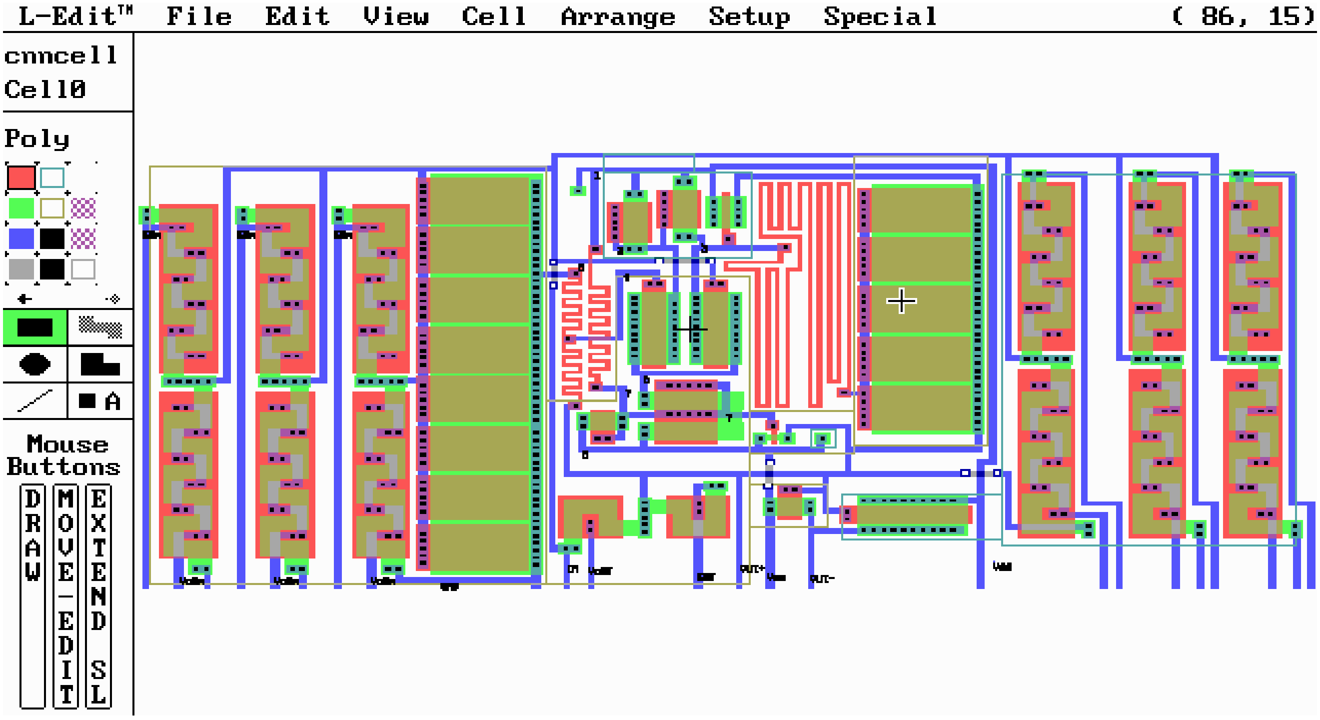


Fig. 11. The layout of the single-amplifier CNN cell, including synapses, designed in CMOS technology [44].

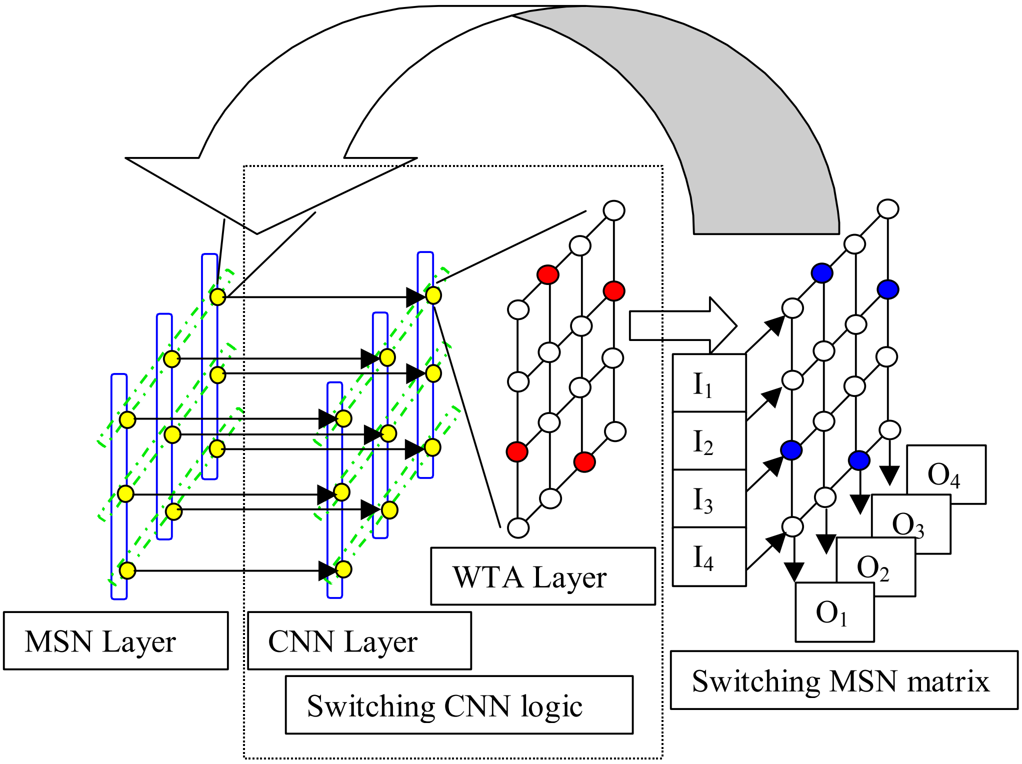


Fig. 12 The block scheme of the CNN-assisted routing in the 2D BMSN network [39]-[41].

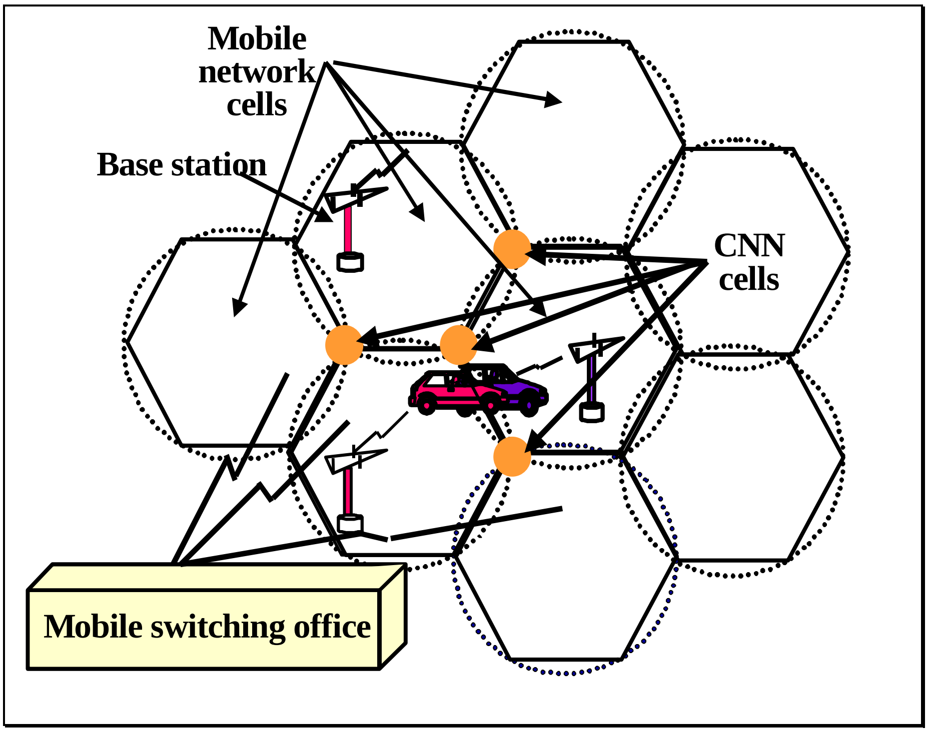


Fig. 13 Possible use of CNN routing strategy in mobile telephony.

VI. NEW TRENDS IN ROUTING POLICIES

Existing routing schemes usually employ distance vector and link state routing algorithms. As network increase in size, the memory requirements for the routing tables and the time taken to search the tables increase accordingly. Further, as the popularity of computer networks increases, the size of the address space can become a limiting factor: table search times can degenerate to O(n) and O(log(n)) (where n is the number of entries in the routing table) for unordered and ordered tables, respectively. Consequently, routers become the bottleneck in high-speed optical networks since packets must be converted from the network's media (optical signal) to the router's media (electrical signal).Several methods recently are proposed to overcome this problem. One of them is so-called Cartesian Routing [45]-[46]; a routing methodology in which a packet's route is determined only by the position of the router relative to that of the destination. Since there are no routing tables the routing decisions can be made in O(1) time, without the need of the specialized hardware.

The Cartesian routing is mainly intended for local or metropolitan communications; for instance, communications within a limited area such as a building or small town. A Cartesian topology is composed of two or more horizontal subnetworks, called collectors, consisting of routers connected horizontally and sharing a common horizontal identifier. Collectors are interconnected with one or more vertical subnetworks, called arterials, consisting of routers connected vertically; arterials need not share a common vertical identifier. Collector router has two horizontal ports, while an arterial router has two horizontal ports and, typically, a minimum of two vertical ports, as depicted in Fig. 14 – see Network A, for instance. Horizontal connections (collectors) can correspond to the offices on the floor, while vertical connections can correspond to floors in a building. Several such networks can be connected to a multiple layer Cartesian network, Fig. 14.

Since the topology of the Cartesian network is restricted to horizontal and vertical links, minimal state is required for routing. Packets are kept, forwarded or discarded as each router compares its address with the packet's destination address; as a result, the algorithm eliminates the need for routing tables. At present, the authors [45]-[46] are implementing a visual representation of the Cartesian routing algorithms and expect a possible hardware design. Although the Cartesian routing decisions can be made in O(1) time being thus very fast in electrical hardware technology, authors expected that new optical hardware would further reduce packet transmission times.

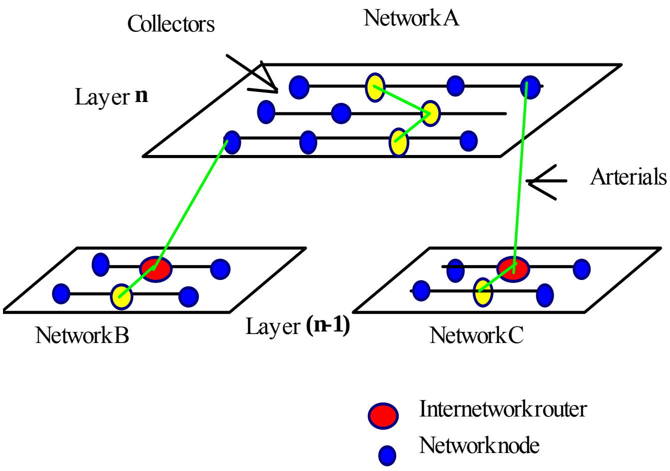


Fig. 14 Multiple-layer Cartesian network [46].

In order to provide fast processing in network nodes, few research teams from different companies have independently proposed optical neural network as packet scheduler. The point is that these networks have been realized and tested in laboratory environment as pure optical neural networks [47]-[48]. Huge amount of communication between the neurons is obtained connecting all elements in a given row and column. Similarly to a high-connected network, for example the CNN, a two-dimensional array of optoelectronic elements is getting the information from the incoming packets. The same principle of packet header is assumed. A winner-take-all neural network layer, consisting of vertical-cavity surface-emitting laser (VCSEL) is implemented. Each neuron upon a request from the packet, broadcasts a beam from VCSEL to all other neurons in its row and column. The more incident light falls on a neuron, the less it is able to fire itself. The consequence is that only the non-blocking routes survive. This is just the same principle as classical (electrical) neural network works. It should be noted that his procedure incorporates the space division multiplex.

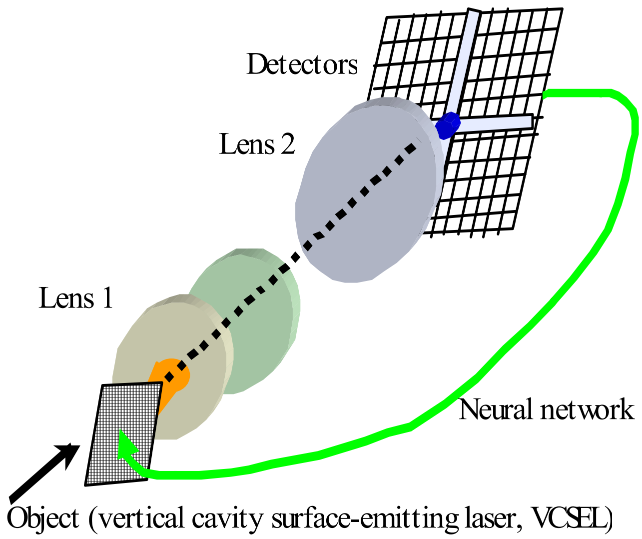


Fig. 15. The optical neural network packet scheduler [48].

Fig. 15 represents a neural network scheduler described above [48]. Many problems have to be solved before its implementation in real environment: immaturity of the existing optoelectronic components, precise displacement of optical components that are rather sensitive to bad alignments (components are free spaced now), power that is not converted into the optical domain is dissipated as heat. But, the pure optical neural network can be realized. A number of very serious experimental results exist [49]. Note that optical neural network controller using VCSEL (Vertical Cavity Surface-Emitting Laser) is used recently [50] in packet switch scheduling.

VII. Conclusions

In this paper some applications of neural networks in modern communication is briefly described. Among others, special attention is devoted to different routing procedures in high-speed optical networks of the regular structures. The mesh topologies are mainly considered since they provide multiple paths between sources and destinations increasing thus the whole throughput and decreasing the cell loss. A novel cellular neural network (CNN) structure is very useful for fast in-node packet switching in Manhattan Street type of networks. The new routing policies based on the TD-SP (Traffic-Density Shortest-Path) routing algorithm, can be embedded in the appropriate CNN hardware. In such a way, the in-node routing decision is performed in only few time constants (less than 1µs). The described CNN-based routing method exhibits simple and spatial invariant structure, being thus perfectly suited for the VLSI implementation.

Although integrated optics exists a very serious job has to be finished before the first optoelectronic scheduler comes to reality. It is expected that a cheap, smart-pixel, fabricated as small footprint and with considerable improved performances component would be obtained. Thus, high speed of transmission, obtained in all-optical systems, will be accompanied with parallel (thus, very fast) processing offered by neural networks. Modern optical communication networks are expected to work in this way in the very near future.

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