Neuron-based wavelength assignment for optical wavelength division multiplexing service systems

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Abstract

The concept of wavelength assignment (WLA) has become the key technology in optical wavelength division multiplexing (OWDM) service networks. We present an artificial neural network (ANN) scheme whose small computational complexity makes it attractive for on-line and dynamic OWDM WLA. This ANN was constructed according to the back propagation learning rule and was used to dynamically assign wavelengths for real-time traffic streams using training data. The data was derived by using the merge-split-block algorithm to assign the wavelength. To demonstrate the effectiveness of the proposed approach, a WLA including 10 nodes, four wavelengths, and 4–48 connections was performed. Our study indicates that the proposed strategy may significantly reduce the computational complexity and investment cost compared with other approaches at the expense of a small amount of training time. © 2002 Elsevier Science Ltd. All rights reserved.

Keywords: Artificial neural network; Wavelength assignment; OWDM networks

1. Introduction

To meet the increasing demand for multimedia processing and communication services, fiber optic transmission technology has been accepted as the most realistic solution for the future growth of broadband transport networks [1,2]. While the classical transmission systems used the multiplexing temporal method for transmission of 155 Mb/s, 622 Mb/s, 2.5 Gb/s, even 10 Gb/s on...
only one wavelength, a new generation system, conceived in 1990, initiated wavelength multiplexing (optical wavelength division multiplexing, OWDM) [3]. OWDM networks allow the optical bandwidth to be efficiently exploited and each fiber link to reach gigabit capacity [4]. Each link carries high-rate traffic on optical signals at many light paths, shown in Fig. 1. OWDM networks are being developed in testbeds and expected to be an integral part of personal communication networks backbone networks in the future [5].

In Fig. 1, some of the light paths pass through a node in optical form when the traffic carried is not intended for that node. The remaining light paths are terminated at the node by one or more fixed or tunable transceivers (drop/add channel) and their traffic is converted into electronic/optical form [6]. One of the key features of multiwavelength optical networks is convertibility, i.e., the ability to dynamically optimize the network for changing traffic loads [7]. Efficient wavelength assignment (WLA) can have a good impact on network costs [8].

The design of OWDM ring networks is not a well-established science or even a stable craft. Many research activities therefore currently pay considerable attention to this issue. In Ref. [9], Gerstel analyzed the network cost in terms of the transceiver cost and the number of wavelengths with respect to the maximum numbers of hops for a light path. The work in Ref. [10] considered the problem of reconfiguring single-hop networks by retuning a subset of the slowly tunable receivers for changing traffic patterns. Baldine also studied the problem of dynamic load balancing in broadcast OWDM networks by retuning a subset of transceivers in response to the changes in the overall traffic patterns [11]. Wuttisittikukij studied the performance with and without wavelength conversion capabilities on various traffic scenarios in multiwavelength all-optical ring networks [1]. These mechanisms can produce the optimal or sub-optimal status at a specified OWDM service network. However, their computational complexity is large, thus they are not suitable for dynamic and real-time environments.

Artificial neural network (ANN) are based on an analogy of the neuron structure in the human brain. Considerable progress has been made in the application of ANN to computer and communication issues [12,13]. However, ANN applications to the WLA problem are rather limited. In this study, an ANN was developed that can solve the dynamic WLA problem by learning from previously encountered patterns. Many types of neural networks and many powerful machine learning techniques exist, but the research presented here focuses on the multilayer perceptron network with the back propagation learning rule. Results from the developed ANN are rather satisfactory compared to those scheduled using the merge–split–block (MSB) algorithm. With sufficient learning, the ANN generates results very fast and incurs only tiny deviations. This ANN will assist managers in the WLA for on-line and dynamic traffic streams.

The remaining parts of this paper are organized as follows. Section 2 describes the OWDM service systems under study and the MSB algorithm. The subsequent section depicts the con-
struction of such an ANN. The results from preliminary experiments are given in Section 4. Section 5 discusses our work. Finally, some conclusions are given in Section 6.

2. Optical wavelength division multiplexing service systems

This section echoes Section 1, where we discussed how WLA is cost-effective. The OWDM network discussed here consists of $N$ nodes and $L$ links. There are $(W + 1)$ wavelengths in the network where $W \ll N$. One of the wavelengths is reserved for a control channel which is shared by all nodes. Each of the nodes is equipped with one or more fixed or tunable transceivers. One of the fixed transmitters and the fixed receivers are for the control channel. The others transmitter is for the data channel. To improve the blocking performance and the network resource utilization, a number of converters, $C$, are also provided for the service network.

The system operates as follows. When new traffic demands arrive at an OWDM network, the WLA algorithm is invoked at all nodes to assign the data channel for transmitting and receiving data packets. The source node will transmit the scheduled traffic stream on the reserved channel. The destination node receiver should tune to the source node transmission wavelength to receive the data packets. Selecting a suitable network topology and relinquishing or forging wavelengths may impact the network cost.

2.1. Mathematical model

The network model and operating actions were given in the previous paragraphs. The problem we are concerned with is scheduling the wavelength as well as the corresponding devices such that the investment cost is minimum. As derived in [14,15], the overall network cost includes the cost of the transceivers and wavelength converters required at the nodes as well as the cost of the number of wavelengths. The mathematical model, a set of linear equalities and inequalities, for solving the WLA problem is described as follows:

- total network cost $= T_c = K_1 C_T + K_2 C_W + K_3 C_C + K_4$ (1)
- objective function $= \text{minimize}(T_c)$ (2)

subject to

- link capacity constraint $\sum_{m=1}^{W_{\text{scheduled}}} B_{m,i} \leq \sum_{n=1}^{W_{\text{limited}}} B_{n,i}$ for $i$th link $(i \leq L)$ (3)
- wavelength number constraint $W_{\text{scheduled}} \leq W_{\text{limited}}$ (4)
- traffic demands $\sum_{m=1}^{W_{\text{scheduled}}} B_{m,i} \geq T$ (5)

where $C_T, C_W, C_C, K_4$ are the cost of each transceiver, each wavelength, each wavelength converter and the required scheduling time, respectively. $K_1, K_2, K_3$ are the number of required
transceivers, required wavelengths, and required converters. The scheduled wavelength matrix $B = (b_{ji})$ and traffic matrix $T = (t_{ji})$ are both the $W_{\text{scheduled}} \times L$ wavelength-link incidence matrixes.

2.2. Merge–split–block algorithm

To clearly investigate the MSB algorithm for the WLA problem, a simple example follows our scenario that provides the tradeoff selection between transceiver, wavelength, and converter such that the network investment cost should be minimized. The given assumptions and criteria in the example are as follows:

I. Topology of OWDM network
   
   - uni-directional ring architecture;
   - attached node $N = 8$;
   - link $L = 8$.

II. Link capacity of the OWDM network
   
   - the number of limited wavelengths on each link $= 4$;
   - link capacity $= 4$ unit.

III. Traffic statistics between the nodes
   
   - (source, destination) = (1,3); (2,4); (3,8); (8,3); (5,6); (6,8).

Fig. 2 is the flow chart of MSB algorithm, we describe the scenarios step by step in the following.

2.2.1. Step 1: pre-process

In WLA problems, the wavelength will be dynamically reassigned while the new traffic streams are merged into the service network. To reduce the non-negligible scheduling cost, the existing schedule will be continuously utilized if the new traffic demands can be fed into the existing wavelengths. In this case, the existing traffic streams will not interfere and the network performance will not be disrupted. If not, the initial step in our approach is to produce a simple wavelength schedule according to the new traffic streams and then check the constraints (Eqs. (3) and (4)). If the constraints are met, the cost is evaluated using Eq. (1) and the process moves on to step 2. Otherwise, the scenario will go directly to step 2 and the traffic will be merged. A simple example following the above parameters is listed in Table 1. From Table 1, there are six scheduled wavelengths ($K_2 = 6$) assigned in the initial schedule, and thus the constraint equation (4) will not be met. Therefore, we will go to scenario step 2.

2.2.2. Step 2: traffic merge (MSB-M)

This step will try to reduce the number of wavelengths such that the constraints are met or the cost is minimized. The last column in Table 1 is the sum of links whose $i$th wavelength is used. The following actions are performed.

Action I: First traffic merge. Every two scheduled wavelengths $\lambda_i$ and $\lambda_j$ are summed by the XOR operation. If the new weight value is equal to the sum of weight ($\lambda_i$) and weight ($\lambda_j$), traffic merging is available. Table 2 is an example derived from Table 1. The new wavelength 1 is derived from wavelength 1 and wavelength 3 in Table 1. The new wavelength 2 is derived from wavelength
2 and wavelength 6. And the wavelength 3 is generated from wavelength 4 and wavelength 5 in Table 1. The cost of each available schedule is also evaluated using Eq. (1).

**Action II:** Second traffic merge. As a result of Action I, the minimal number of wavelengths or corresponding devices may not be obtained in a single merge action. Usually, only a few merges

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**Table 1**
The pre-process in MSB algorithm

<table>
<thead>
<tr>
<th>Wavelength</th>
<th>Link</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
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<td>1</td>
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<td>1</td>
<td>1</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
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<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>2</td>
</tr>
</tbody>
</table>

\[ K_1 = 12; K_2 = 6; K_3 = 0. \]
are needed. The operations in the second emerge action are conducted as in Action I. The purpose is to reduce the number of wavelengths or corresponding devices. Table 3 is derived from the first traffic merge action schedule. These traffic merge actions are continuous until no new schedule is generated.

2.2.3. Step 3: traffic split (MSB-S)

To achieve a better network performance, one traffic stream is split into two or more sub-streams. These sub-streams can be transmitted through different wavelengths but arrive at the same destination. In our approach, the wavelength whose weight value is the least will be split first and then embedded into two or more wavelengths. Table 4 is an example derived from splitting wavelength 2 in Table 1. This traffic splitting action may reduce the number of scheduled wavelengths, but wavelength converters or transceivers are required.

2.2.4. Step 4: traffic block (MSB-B)

While the network load is heavy, the WLA problem is somewhat more complicated. Situations in which no schedule meets the constraints may occur. Under these circumstances, any number of

Table 2
The first traffic merging

<table>
<thead>
<tr>
<th>Wavelength</th>
<th>Link</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>Weight</th>
</tr>
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<td>1</td>
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<tr>
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<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>3</td>
<td></td>
</tr>
</tbody>
</table>

$K_1 = 10; K_2 = 3; K_3 = 0.$

Table 3
The second traffic merging

<table>
<thead>
<tr>
<th>Wavelength</th>
<th>Link</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
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<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>6</td>
<td></td>
</tr>
</tbody>
</table>

$K_1 = 9; K_2 = 3; K_3 = 0.$

Table 4
The traffic splitting

<table>
<thead>
<tr>
<th>Wavelength</th>
<th>Link</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
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<th>Weight</th>
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<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>6</td>
<td></td>
</tr>
</tbody>
</table>

$K_1 = 9; K_2 = 3; K_3 = 1.$
the new traffic streams will be blocked, requiring the scheduling to be reprocessed. The selection of
blocked traffic is independent of the blocking probability. In our approach, the traffic stream
whose weight value is the largest will be blocked first because it requires greater resources. This
strategy will reduce the network blocking probability. Table 5 shows an example of blocking
traffic. Three new traffic streams (1,8), (7,3), and (3,6) are added in Table 1. The stream (1,8) is
blocked. The blocking performance is a penalty factor, thus the blocking performance of the
generated schedule must be reduced to a reasonable level.

2.2.5. Step 5: generate schedule

As traffic varies, the traffic matrix \( T \) is updated to reflect the changes in the traffic demands.
Through steps 1–4, many schedules may be sought to satisfy some criteria and their costs are
extensively evaluated. Therefore, the schedule that requires the minimum investment cost (Eq. (2))
will be referred to as the new schedule.

The MSB algorithm can produce the optimal solution that meets the problem-solving rules at
the expense of extensive computational complexity. However, this high computational complexity
is not acceptable for real-time and dynamic processing. Based on the MSB algorithm, we de-
developed an ANN architecture for solving this deficiency such that dynamic WLA is achieved.

3. Main design principles

Of central importance in designing an ANN is the paradigm and learning rule for determining
when various application domains and processes should be executed. Many types of ANNs exist,
but the research described here focuses on a three-layered feedforward network with a back
propagation learning rule.

3.1. Three-layer feedforward network

ANN operation consists of the presentation of a set of inputs and subsequent propagation of
these inputs through the network. The feedforward three-layer network was selected in our work
and is shown in Fig. 3. The network contains 50 nodes in the input layer, 32 nodes in the hidden layer, and 13 nodes in the output layer. In addition, the ANN is presented as a series of input patterns (e.g. network status and new traffic stream) and a corresponding set of correct output patterns (e.g. WLA for new traffic stream). Once the ANN has been trained, it can be used to simulate the WLA. For any set of inputs, it can produce a set of outputs similar to those produced from the results using the MSB algorithm.

### 3.2. Back propagation learning rule

The back propagation learning rule is an iterative gradient algorithm designed to minimize the mean square error between the actual output of a multilayer perceptron network and the desired output. An essential component of this algorithm is the iterative method that propagates error terms required to adapt weights back from nodes in the output layer to nodes in lower layers.

<table>
<thead>
<tr>
<th>Input pattern</th>
<th>Output pattern</th>
<th>Note</th>
</tr>
</thead>
<tbody>
<tr>
<td>1100000001</td>
<td>1101111111</td>
<td>Node = 10, wavelength = 4 New traffic: (10,3)</td>
</tr>
<tr>
<td>0101111111</td>
<td>1111100001</td>
<td>No 10, wavelength = 4 New traffic: (10,3)</td>
</tr>
<tr>
<td>0011100000</td>
<td>0000000000</td>
<td>Node = 10, wavelength = 4 New traffic: (10,3)</td>
</tr>
<tr>
<td>0110000000</td>
<td>1111111111</td>
<td>Node = 10, wavelength = 4 New traffic: (10,3)</td>
</tr>
<tr>
<td>0011100111</td>
<td>0110011111</td>
<td>Node = 10, wavelength = 4 New traffic: (10,3)</td>
</tr>
<tr>
<td>0111111111</td>
<td>011</td>
<td>Node = 10, wavelength = 4 New traffic: (10,3)</td>
</tr>
<tr>
<td>0001110000</td>
<td>1001111000</td>
<td>Node = 10, wavelength = 4 New traffic: (10,3)</td>
</tr>
<tr>
<td>1011111111</td>
<td>0000000000</td>
<td>Node = 10, wavelength = 4 New traffic: (10,3)</td>
</tr>
<tr>
<td>0001111100</td>
<td>0011110000</td>
<td>Node = 10, wavelength = 4 New traffic: (10,3)</td>
</tr>
<tr>
<td>0000011000</td>
<td>1111111110</td>
<td>Node = 10, wavelength = 4 New traffic: (10,3)</td>
</tr>
<tr>
<td>0011100111</td>
<td>0101111111</td>
<td>Node = 10, wavelength = 4 New traffic: (10,3)</td>
</tr>
<tr>
<td>0111111111</td>
<td>0111111111</td>
<td>Node = 10, wavelength = 4 New traffic: (10,3)</td>
</tr>
</tbody>
</table>
At the beginning, all weights and node offsets are set to small values \( \pm 0.3 \). The input values are presented and desired outputs are specified. The sampled patterns are shown in Table 6. Then, the ANN is used to calculate actual outputs. A recursive algorithm, starting at the output nodes and working back to the hidden layer, adjusts weights until the ANN has been trained to a satisfactory level of performance (error less than 0.00001). The training process is repeated by presenting different sets of input data to the ANN.

### 3.3. Overall architecture

The specified ANN architecture, using the predicates of the artificial intelligence language, is listed in Table 7.

### 4. Implementation status

An ANN was developed based on the architecture described in the previous section to manage OWDM service network WLA problems. Using the OWDM network data, including the 10 service nodes, four wavelengths, and numerous traffic streams, we designed the following cases to study the applicability of this ANN approach:

- **Case 1**: the MSB algorithm and genetic algorithm (GA) [16] achieve the WLAs,
- **Case 2**: the proposed ANN achieves the WLAs. The number of learning sets is 3,000,000.

The deviations between the investment cost scheduled by the proposed approach and those using the MSB algorithm and GA are illustrated in Fig. 4. The computational complexity of the proposed ANN is shown in Fig. 5.
5. Discussion

From the application and architecture presented so far, several observations are in order:

1. As can be observed from the simulation results, the proposed ANN is free from diverging problems using the previous learning procedure. Thus, the operating time for the WLA is also reduced.

2. From Figs. 4 and 5, the deviations of the values scheduled using Case 1 and Case 2 are below 1% (MSB algorithm, 48 connections) and beyond 250% (GA, 48 connections), respectively. Hence, accurate and speedy scheduling are produced using the developed ANN.

3. The final schedules from the proposed ANN are based on minimum investment cost. Hence, the cost of Case 2 is approximately minimum. However, the blocking performance is also a critical index from the user's point of view. The average blocking performance is estimated and shown in Fig. 6. It was found that the blocking performance derived from the ANN approach is between that of the MSB algorithm and GA.

4. In the study, the higher the learning frequency, the fewer the deviations in value between Case 1 (MSB algorithm) and Case 2.
(5) Because of the effect of the external environment, noise and failure cannot be avoided for all ANN processing elements. However, this problem is very serious in on-line and dynamic WLA. For enhancing the fault tolerance capacity of the ANN, a counter propagation neural network will be structured in our forthcoming research.

6. Conclusions

An ANN approach was presented in this paper for solving WLA problems. This network, a three-layer feedforward network with back propagation learning rule, was described and constructed. This network contains 50 nodes in the input layer, 32 nodes in the hidden layer, and 13 nodes in the output layer. The proposed neural network approach was applied to 10 nodes, four wavelengths, and 4-48 connections. The wavelengths of each connection were scheduled. The results were satisfactory and demonstrate well the capability of the developed neural network. In view of the effectiveness and efficiency of the proposed approach, this developed ANN will be a valuable tool for assisting OWDM managers in on-line and dynamic WLAs.

References


Tak-Goa Tsuei received his B.S. degree from National Taiwan Normal University, Taiwan, ROC in 1977 and M.S. and Ph.D. degrees in Electrical Engineering from Clarkson University, New York in 1985 and 1989 respectively. He worked in industry as software engineer and consultant for a few years. From 1989 to 1994, he served as Assistant Professor in Electrical Engineering Department of Merrimack College in Massachusetts. Currently he is an Associate Professor in Electronic Engineering Department of Ta Hwa Institute of Technology in Hsin-Chu, Taiwan, ROC. His major research interests are in the area of signal processing and network communications.

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