Abstract—In wavelength division multiplexing (WDM) all-optical networks, the size of a request stream may be less than the maximum capacity of a lightpath. To avoid assigning an entire lightpath to a small request, many researchers have looked at adding traffic grooming to the routing and wavelength assignment (RWA) problem. In this work, we consider the RWA problem with traffic grooming (GRWA) for mesh networks. The GRWA problem is NP-Complete since it is a generalization of the RWA problem which is known to be NP-Complete. While most of the previous work in this field focuses on optical networks without grooming or with full grooming capabilities, in this work we study networks with sparse traffic grooming and wavelength conversion resources. In this paper, we propose two novel heuristics that minimize the cost of the traffic grooming and wavelength conversion equipment used in optical network without hindering the network blocking performance. The strength of the proposed heuristics stems from their simplicity, applicability to large-scale networks, and efficiency compared to other heuristics proposed in the literature. The performance of our proposed heuristics is compared to that of other efficient heuristics proposed in the literature in terms of the total cost of traffic grooming and wavelength conversion devices used and the blocking performance of the network.

Index Terms—DWDM optical networks, RWA, wavelength assignment, traffic grooming, genetic approach.

I. INTRODUCTION

The general Routing and Wavelength Assignment (RWA) problem in Dense Wavelength Division Multiplexing (DWDM) networks can be reduced to only a routing problem if all the nodes have full wavelength conversion capabilities. A side effect is the overall blocking probability is decreased. The problem is the cost of wavelength conversion equipment is expensive, and it has been shown that near-optimal performance can be achieved with sparsely located wavelength conversion equipment. However, the performance of a network with sparse wavelength conversion is very sensitive to the placement of the wavelength conversion equipment. In addition, finding a near-optimal solution to an RWA problem with sparse wavelength conversion is even more difficult than the same RWA problem with no wavelength conversion [5].

Besides the added complexity of sparse wavelength conversion, the RWA problem can be further complicated by allowing traffic grooming. Traffic grooming takes two or more incoming connections and sends them out on the same lightpath. That is, traffic grooming allows for the multiplexing and demultiplexing of connections as long as they respect the bandwidth constraint of the lightpath. We denote the RWA problem with traffic grooming as the GRWA problem.

In this paper, we study the problem of efficiently routing lightpath requests and assigning them minimum traffic grooming and wavelength conversion resources in mesh optical networks with sparse resources. Section II, defines and discusses the GRWA problem under relatively static traffic patterns. Next, in Section III we discuss the costs associated with traffic grooming and wavelength conversion in optical networks. In Section IV we introduce our most contiguous GRWA heuristic and the rationale behind the heuristic. Next, we apply the genetic algorithm to the GRWA problem in networks with sparse resources in Section V. Detailed performance comparisons are provided in Section VI. Finally, Section VII concludes this study and provides ideas for future extensions.

II. TRAFFIC GROOMING, ROUTING, AND WAVELENGTH ASSIGNMENT PROBLEM (GRWA)

The routing and wavelength assignment problem with traffic grooming for static lightpaths (GRWA) provides a method to handle connection requests with a wide range of capacities. For example, in backbone transport networks with OC-192 capacity on each wavelength, an OC-1 connection request will require a lightpath of size OC-192 in the absence of traffic grooming devices. In this case, most of the capacity of the lightpath is unused. This problem can be resolved by allowing the multiplexing (i.e., traffic grooming) of two or more connections one a single wavelength such that the total capacity after multiplexing is less than the maximum capacity that can be carried over a single wavelength. Thus, traffic grooming increases the utilization of network bandwidth.

The GRWA problem can be split into two cases. In the case of single-hop traffic grooming [1], grooming is performed at the edge of the transport optical network (i.e., grooming is performed before entering and after exiting the optical network by the source node and destination nodes respectively). If we
remove this restriction, then grooming can be performed at any node in the network; we denote the general grooming case as multi-hop traffic grooming [1]. In this paper, we present heuristic to handle the general multi-hop traffic grooming case, and allow the flexibility where one or more nodes have no grooming resources.

III. OBJECTIVE FUNCTION

The static GRWA problem with sparse traffic grooming and wavelength conversion resources presented in this paper relies on the following assumptions:

1. The network is a general mesh topology with directed fiber connections. A pair of fibers links (i.e., one in each direction) are needed to connect a pair of nodes.
2. Network switches may or may not have support for traffic grooming and/or wavelength conversion.
3. Traffic grooming devices can perform wavelength conversion too but the cost a traffic grooming device is more than that of a wavelength conversion device since traffic grooming devices are capable of achieving more complex functionality (i.e., multiplexing and de-multiplexing connections).
4. Lightpaths do not contain loops. We use the K-shortest paths algorithm to enumerate the K shortest and look-free paths between two nodes.

Our objective is to minimize the total cost of required wavelength conversion and traffic grooming hardware that needs to be installed in the network without hindering the blocking performance of the network. The total routing cost is represented as:

\[ C = \sum_{i=1}^{M} D_i + \alpha G_i + \beta V_i \]  

(1)

Where:

- \( M \): Number of lightpath requests.
- \( D_i \): The number of hops for request \( i \).
- \( G_i \): The number of grooming devices used by request \( i \).
- \( V_i \): The number of wavelength conversions devices used by request \( i \).
- \( \alpha \): The cost of a single traffic grooming device
- \( \beta \): The cost of a single wavelength conversion device. It is assumed that \( \alpha > \beta \) since traffic grooming devices are capable of achieving traffic grooming as well as wavelength conversion.
- \( C \): Total cost of routing all \( M \) lightpath request though the optical network. This cost includes the cost of wavelengths used to carry the lightpath from its source to the destination node plus the cost of all wavelength conversion and traffic grooming devices used by the lightpath.

IV. MOST CONTIGUOUS WAVELENGTH ASSIGNMENT HEURISTIC

The wavelength assignment problem has been studies extensively. A summary of the research in this area can be found in [7]. A large number of wavelength assignment schemes have been proposed in the literature including random-fit, first-fit, most-used, least-used, least-loaded, min-product, max-sum, and relative capacity loss. These schemes can be classified into the following four categories [6]:

- **Balance the load among all wavelengths**: These schemes usually perform poorly when compared to other wavelength assignment schemes (e.g., random-fit, least-used).
- **Pack the wavelength usage**: These schemes are simple and perform well when the network state information is known precisely (e.g., first-fit, most-used).
- **Spread the wavelength usage**: These schemes are also simple and perform as well as the schemes that pack the wavelength usage (e.g., least-loaded).
- **Global Assignment**: These schemes are more computationally extensive compared to the other schemes but they deliver the best performance (e.g., max-sum, relative capacity loss).

However, none of these wavelength assignment schemes account for the scarcity of the traffic grooming and wavelength conversion resources in backbone transport networks. For such networks, we propose a simple GRWA heuristic that minimizes the use of traffic grooming and wavelength conversion resources as much as possible without hindering the blocking performance of the network. The rationale behind this is that the traffic grooming and wavelength conversion resources are very scarce and expensive resources in such networks and having a GRWA heuristic that conserves the usage of these resources is a critical requirement that can drastically conserve the usage of these resources without hindering the network blocking performance. Figure 2 provides a high level description of the proposed heuristic. It should be noted here that the proposed algorithm conserves the traffic grooming and wavelength conversion resources as much as possible, however, when a tie occurs between multiple wavelength assignment options, any of the simple pack/spread wavelength assignment schemes presented above can be used to break the tie. We suggest using the first-fit wavelength assignment scheme to break such ties because of the simplicity and good performance of this scheme. Also, notice that the algorithm proposed here does not guarantee that it will always find the wavelength assignment with the lowest possible number of traffic grooming and wavelength conversion devices. The algorithm strives to avoid wavelength bandwidth fragmentation in order to avoid increasing the network blocking performance. Also, the algorithm tries to keep the blocking performance as low as possible even at the expense of having more traffic grooming and/or wavelength conversion resources. A scheme that will always find the lowest number of traffic grooming and wavelength conversion resources can be
computationally extensive and the scheme proposed here provides a good balance between simplicity and the efficiency of the found solutions.

To illustrate our most contiguous GRWA heuristic presented in Fig. 2, let us assume that the following three lightpath requests need to be established on the network shown in Fig. 1:

- **Lightpath 1**: OC-3 from node 3 to node 4
- **Lightpath 2**: OC-3 from node 1 to node 5.
- **Lightpath 3**: OC-12 from node 2 to node 4.

Assuming that the maximum capacity of a single wavelength is OC-12, our proposed algorithm will use a traffic grooming device on node 3 to multiplex lightpaths 1 and 2 on one wavelength while lightpath 3 will be carried over a separate wavelength since wavelength 1 does not have enough bandwidth to carry that lightpath as illustrated in Fig. 1a. If the first fit wavelength assignment heuristic is used, lightpaths 1 and 2 will be groomed on wavelength 1 using a grooming device on node 3 as before but lightpath 3 will use wavelength 1 on the WDM link from node 2 to node 3 and wavelength 2 on the WDM link from node 3 to node 4 using a wavelength conversion device on node 3 as illustrated in Fig 3b.

Definitions:

- **W**: Max Number of wavelengths that can be carried over a single fiber link.
- **R**: Number of requests between all source-destination pairs.
- **AvailWaves**: Vector to save available wavelengths from start hop to current hop.
- **HopsWave**: Vector to save selected wavelength for each hop on the path.
- **SelectedPath**: Lowest cost path that will carry the lightpath request.
- **EndCounter**: Counter to catch if there is no wavelength available at the end hop.
- **saveAvailableWaves**: function that saves available wavelengths from start hop to current hop. It returns true if there is an available wavelength, otherwise it returns false.

**Step 1: Pre Processing**

1.1 Generate uniform source-destination requests
1.2 Find K-Shortest Paths for very source-destination pair.
1.3 Save Number of hops for each path into a HopSD vector.

**Step 2: Routing and Wavelength Assignment**

```
MC_Processor()
{
  2.1 For (r=1; r<=R; r++)
  2.2    startPath = getStartKPathsPtr(r)
  2.3    endPath = getEndKPathsPtr(r)
  2.4    For (k =startPath; k <= endPath; k++)
  2.5        if (AssignWave(k, r, HopsWave))
  2.6            saveRouteWaveAssignment (k,HopsWave)
  2.7    SelectedPath = selectSmallestPathCost()
  2.8    reserveResources(selectedPath ,r)
}
```

```
AssignWave(k, r, HopsWave)
2.9  NumOfHops = HopSD[k]
2.10  StartHop = 1
2.11  CurrentHop = 1
2.12  EndCounter = 0
2.13  While (CurrentHop <= NumOfHops &&
            EndCounter <=W)
  2.14    If (EndCounter=W)
            return false
  2.15    If (saveAvailableWaves(StartHop, CurrentHop, AvailWaves))
  2.16        SelectedW=getWavelength(AvailWaves)
  2.17        StartHop=CurrentHop
  2.18        CurrentHop=CurrentHop+1
  2.19        EndCounter=0;
  2.20    Else
  2.21    SelectedW=-1
  2.22    EndCounter=EndCounter+1
  2.23    For(hop=StartHop ;hop<=CurrentHop;hop++)
            if(HopsWave[hop]=SelectedW)
            return true;

Fig. 2: Most Contiguous Heuristic
A. Chromosome Encoding

A chromosome is a vector of pointers to entries in the routing and wavelength assignment enumeration table. The routing and wavelength assignment enumeration table enumerates all possible routing and wavelength assignment options for all given source-destination pairs. This table is generated by combining the K-Shortest routes for each source-destination pair with all the possible wavelength assignments for that route. Each unique wavelength assignment on a route is considered as a unique lightpath. Each gene on a chromosome represents one of those unique lightpaths for the given source-destination pair. The total length of the chromosome is equal to the number of lightpath requests presented to the networks.

To help understand our chromosome encoding technique, consider the example depicted in Fig. 3 which represents a simple three node network. The figure shows an example of a two-gene chromosome that encodes two lightpaths. The first gene points to the 5th entry of the routing and wavelength assignment enumeration table while the second gene points to the 2nd entry of that table. Notice that the entries of the enumeration table have full routing and wavelength assignment information for the lightpath. For example, the enumeration table indicates that the 2nd entry uses wavelength 1 on the WDM link from node 1 to node 2 and wavelength 2 on the WDM link from node 2 to node 3. Also, the 5th entry of that table indicates that the lightpath that uses that entry will reserve wavelength 1 on the link from node 2 to node 3.

![Chromosome Encoding Example](image)

Fig.3: Chromosome encoding example using enumeration matrix.

B. Initial Population

The first generation is formed from a combination of First-Fit, Most-Contiguous, and completely random chromosomes. In our model, the size of the initial population is 150 chromosomes (i.e., 50 chromosomes based on each of the three GRWA heuristics mentioned above).

C. Fitness Function

The fitness function of our GA model $F$ includes a penalty component $P$ as well as a cost component $C$. A high value of $\gamma$ is added to the value of the penalty component each time the selected route violates the number of traffic grooming resources, wavelength conversion resources, or the wavelength capacity constraints. In our formulation, we make the assumption that $\gamma \gg (\alpha, \beta)$, where $\alpha$ and $\beta$ represent the costs of single traffic grooming and wavelength conversion resources respectively.

The fitness function used in our model is defined as follows:

$$F = C + P$$  \hspace{1cm} (2)

$$P = \gamma \sum_{i=1}^{M} R_i$$  \hspace{1cm} (3)

$$R_i = \sum_{j=1}^{n} \sigma I_j$$  \hspace{1cm} (4)

$$\sigma = \begin{cases} 1 & \text{if Link } L_i \text{ violates the capacity or the resources} \\ 0 & \text{otherwise} \end{cases}$$  \hspace{1cm} (5)

Where:

- $M$: Number of lightpath requests (chromosome length).
- $L_i$: The WDM links that the $i$th lightpath request traverses.

D. Crossover

In our model, crossover is performed between two parent chromosomes to produce two descendents using the two-point crossover technique. We chose the two-point crossover technique in our model in order to diversify the search within the large problem space.

E. Mutation

In our GA model, mutation is performed by walking through the genes that makeup the chromosome and modifying their value with a low probability (typically 0.1%). The resulting chromosomes need to be valid after mutation. If there is a chromosome that violates the routing constrains of a source-destination pair, we repair that chromosome by replacing the bad genes with valid ones in order to make a valid chromosome. The bad genes will be replaced by ones chosen from the list of valid genes based on a uniformly distributed selection process. This repair strategy guarantees that the gene will be selected from the range of enumerated lightpaths that belong to the given source-destination pair.

F. Selection

The chromosomes for crossover are chosen using the best selection method. This selection method picks the best chromosome among the $n$ chromosomes in a population in direct proportion to their absolute fitness. After crossover and mutation, new offsprings are reproduced then the best of those offsprings will be selected for the next generation. The offsprings with the worst fitness are discarded. The best selection method guarantees that the better chromosomes have a better chance to survive for the next generations. Fig. 4 illustrates an example of our GA model when applied to Fig. 3.
In this figure, the chromosomes encode three lightpath requests as follows:
- **Lightpath 1**: From node 2 to node 3.
- **Lightpath 2**: From node 1 to node 3.
- **Lightpath 3**: From node 1 to node 3.

In this example, after crossover, mutation, and applying the best selection method, we get a new chromosome for the same source-destination pairs, but without using any traffic grooming or wavelength conversion resources as can be seen from the routing and wavelength assignment enumeration matrix illustrated in Fig. 3.

![Illustration of chromosome](image)

Fig. 4: Illustration of the GA crossover, mutation and selection process used in our model.

VI. PERFORMANCE RESULTS

The performance of our proposed Most-Contiguous and Genetic based heuristics has been compared with that of the first fit GRWA approach in networks with sparse traffic grooming and wavelength conversion capabilities. The lightpath requests presented to our model are generated between all possible source-destination pairs with equal probabilities. This means that the source and destination nodes of all lightpath requests are chosen with uniform probabilities. The capacity of the generated lightpath requests also follows a uniform distribution between $\theta$ and the maximum capacity of a single wavelength. The generated lightpath requests are assumed to be relatively static in our model. This means that the connection requests are known ahead of time. Our simulation tool generates $n$ lightpath requests to determine the blocking probability of the network and the total cost of the traffic grooming and wavelength conversion devices used by the offered lightpath requests.

The proposed heuristics were compared in terms of their blocking probability and total path cost in terms of used traffic grooming and wavelength conversion resources. We chose to compare our proposed heuristics with the first fit heuristic because of the simplicity of this heuristic. Further, it was demonstrated in the literature that the first fit heuristic produces low blocking probabilities [6].

We performed our performance evaluation study on a reasonably complex 16-node WDM mesh network [6]. The performance of our proposed genetic based GRWA heuristic is evaluated for a population size of 150 chromosomes, crossover rate of $l$, and mutation rate of 0.01% for a total of 150 epochs. Figures 5 though 7 plot the blocking probability versus the number of traffic grooming and wavelength conversion resources installed in the network for 70, 100, and 300 static lightpath requests, respectively. Those figures demonstrate that our genetic based GRWA approach achieves the best blocking probability performance under the different traffic loads compared the most contiguous and first fit heuristics. The blocking performance of our most contiguous heuristic is better than that of the first fit heuristic. Fig. 7 shows that our simple most contiguous heuristic can perform better than our genetic based GRWA approach under high traffic demands and low number of traffic grooming and wavelength conversion resources. Notice that Figures 5 through 7 show that the difference between the three heuristics is higher under low traffic demands and low number of traffic grooming and wavelength conversion resources.

Fig. 8 compares the total cost of traffic grooming and wavelength conversion resources used by the three GRWA heuristics in networks with various degrees of traffic grooming and wavelength conversion capabilities. The study shown in Fig. 8 was conducted under the same blocking probability to make our comparison study fare and accurate. Again, we used the 16-node topology shown in [6] to conduct this study. The maximum connection size is $OC-48$ and each WDM link has four wavelengths. This study shows that the total cost of the traffic grooming and wavelength conversion resources used in our proposed most-contiguous and genetic based GRWA heuristics is much better than that of the first fit heuristic. It should be emphasized here that our heuristics achieved lower costs without hindering the blocking performance of the network. Notice that the gap between our heuristics and the first fit heuristic is higher in networks with sparse traffic grooming and wavelength conversion resources.

![Blocking probability vs. Number of traffic grooming and wavelength conversion Resources](image)

Fig. 5: Blocking probability vs. Number of traffic grooming and wavelength conversion resources using 70 lightpath requests.
VII. CONCLUSIONS AND FUTURE WORK

In this paper, we propose two novel heuristics that minimize the total cost of traffic grooming and wavelength conversion equipment used in WDM networks with sparse traffic grooming and wavelength conversion resource without hindering the network blocking performance. Our first heuristic, strives to avoid wavelength conversion and wavelength bandwidth fragmentation by using paths with the most contiguous wavelength resources first. The second heuristic is an adaptation of the genetic algorithm to solve the GRWA problem in networks with sparse traffic grooming and wavelength conversion resources. The strength of the proposed heuristics stem from their simplicity, applicability to large-scale networks, and their efficiency compared to other heuristics proposed in the literature. Our results demonstrate that our proposed heuristics reduce the total number of traffic grooming and wavelength conversion resources without hindering the blocking performance of the network.

In the future, we will study the performance of our GRWA heuristics under dynamic lightpath requests with exponentially distributed inter-arrival and lightpath holding times and compare the results with the results presented in this paper.

REFERENCES


