

A Genetic Algorithm Approach for Solving the Routing and Wavelength Assignment Problem in WDM Networks

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Abstract—The Static RWA (Routing and Wavelength Assignment) problem in WDM optical network is a combinatorial optimization problem fit to iterative search methods. In this paper we formulate the Static RWA problem in optical network as a single objective as well as a multiobjective optimization problem and solve it in a novel way using Evolutionary Algorithms. A hybrid approach based on the k -shortest path for every source-destination pair is used to initialize the population. A special cost function based on the frequency of occurrence of an edge in different source-destination paths is used to evaluate the fitness of a chromosome. A m -point crossover is used to maintain diversity in the solution space. The wavelength assignment to lightpaths in fittest individuals is performed using a special graph-coloring technique. We compare the single objective results with those obtained by known heuristics like the First-Fit algorithm. To formalize the problem in the multiobjective optimization domain we introduce an additional objective of Average Delay of transmission of data in the entire network for a given number of source destination pairs. Thus, we try to simultaneously minimize the number of wavelengths (under a constraint of the total number of wavelengths in the network) and the Average Delay using a Multiobjective Evolutionary Algorithm to obtain the representative set of Pareto-optimal solutions which represent optimal paths for all SD pairs with respect to both the objectives. Representative empirical results show the accuracy of our GA. The Static RWA (Routing and Wavelength Assignment) problem in WDM optical network is a combinatorial optimization problem fit to iterative search methods. In this paper we formulate the Static RWA problem in optical network as a single objective as well as a multiobjective optimization problem and solve it in a novel way using Evolutionary Algorithms. A hybrid approach based on the k -shortest path for every source-destination pair is used to initialize the population. A special cost function based on the frequency of occurrence of an edge in different source-destination paths is used to evaluate the fitness of a chromosome. A m -point crossover is used to maintain diversity in the solution space. The wavelength assignment to lightpaths in fittest individuals is performed using a special graph-coloring technique. We compare the single objective results with those obtained by known heuristics like the First-Fit algorithm. To formalize the problem in the multiobjective optimization domain we introduce an additional objective of Average Delay of transmission of data in the entire network for a given number of source destination pairs. Thus, we try to simultaneously minimize the number of wavelengths (under a constraint of the total number of wavelengths in the network) and the Average Delay using a Multiobjective Evolutionary Algorithm to obtain the representative set of Pareto-optimal solutions which represent optimal paths for all SD pairs with respect to both the

objectives. Representative empirical results show the accuracy of our GA.

Keywords : RWA, Multiobjective Optimization , Genetic Algorithms , First-fit algorithm , Optical Network

I. INTRODUCTION

Wavelength division multiplexing (WDM) technology has been improving steadily in the recent years, with existing systems capable of providing huge amounts of bandwidth in a single fiber [2]. WDM wide-area networks (WANs) employ tunable lasers and filters at access nodes and optical/electronic switches at routing nodes [2][3] which increase the bandwidth considerably. An access node may transmit signals on different wavelengths, which are coupled into the fiber using wavelength multiplexers. However, the electronic switching and processing costs at the nodes can potentially be very high leading to severe performance bottlenecks and limiting the delivery of optical link bandwidth to the end users. Thus we look to assign single hop traffic (single lightpath) for most of the source-destination pairs.

A lightpath [1] is an all optical channel which may be used to carry circuit-switched traffic and it may span multiple fiber links. In the absence of wavelength converters, a lightpath would occupy the same wavelength on all fiber links through which it passes. Given a set of lightpaths, we need to route and assign a wavelength to each of them; this is called the routing and wavelength assignment (RWA) problem [8][22]. The RWA problem can be formulated as a mixed-integer linear program [2][3], in which wavelength assignment reduces to a node-coloring problem in a graph, and hence is NP-complete. Heuristics have been proposed to solve the RWA problem [2][3]. However, these when applied to large problems become computationally expensive.

Similar to the simple RWA a wide range of optimization methods have been employed to solve various other optical network optimization problems. Some use traditional optimization methods that are guaranteed to find the global optimum, such as integer linear programming, employed for instance in [24][11][13][16][37]. However, due to the complexity of the problem and the prohibitive

computational efforts required for solving them with traditional methods, novel heuristic algorithms such as Tabu-search (e.g., in [34],[30],[31]), simulated annealing(e.g. in [4],[15]) and genetic algorithms (in [21],[14][33][32]) are applied. We note that the use of Evolutionary algorithms in the design of general wide area mesh network topology that minimize the network cost is studied in [29]. Genetic algorithms are compared with simulated annealing for optimizing the topological design of a network in [26] and it is found that genetic algorithm gives better performance than simulated annealing. The existing studies employing genetic algorithm for optical network optimization typically optimize a single objective , e.g., minimize the number of amplifiers [32], minimize the network cost [6],[7], or maximize the number of connections while satisfying power constraints [21].

In this paper we formalize the RWA problem both as a single and bi-objective combinatorial optimization problem and solve it using an Evolutionary Algorithm. In this work we use a special fitness function based on the frequency of occurrence of an edge in different paths to evaluate the fitness of an individual in the population for the single objective case. A m -point crossover is used for exploring the entire decision space. A global random uniform mutation is used to cross Hamming valleys that may be inherent in the problem. The algorithm is tested on real life optical networks like the ARPANet,UKNet,NSFNet and the EON(European Optical Network). To formalize the problem in the multiobjective domain we introduce another objective of Average Delay of the entire network and try to simultaneously optimize both the criteria using a generic MOEA. It is clear that Average Delay minimization and wavelength minimization are mutually conflicting objectives. Our methodology finds the optimal trade-off curve, attaining the Pareto-optimal solution set in a computationally efficient manner. Our work enables network planners to select the optimal paths for various source-destination pairs such that the total number of wavelengths required for the network and the average delay of the network is minimized.

The next section formalizes the RWA problem as a single objective combinatorial optimization problem and introduces the new evolutionary strategy used for solving it. Section 3 extends the definition of the problem to the multiobjective scenario. Section 4 discusses the empirical results obtained for the suggested EA. Section 5 concludes the paper.

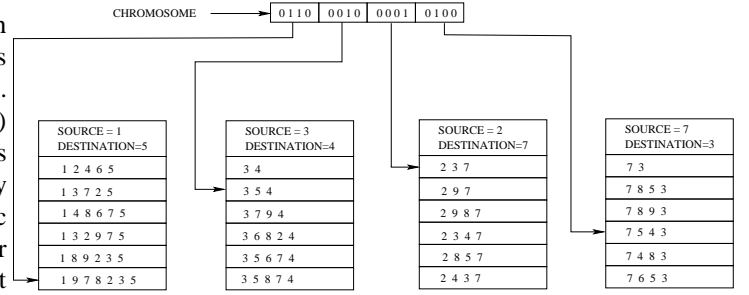
II. SINGLE OBJECTIVE RWA : DESIGN AND IMPLEMENTATION

A. Problem Definition :

Given a set of source-destination pairs the aim is to minimize the number of wavelengths needed to support the given set of lightpaths for the SD pairs.

B. Design Parameters :

The input parameters of the problem can be defined as follows :



Chromosome Encoding : Each Gene points to a path in corresponding Source–Dest. Table

Fig. 1. Example of the chromosome structure

- 1) A physical topology of an optical network which is a graph $G = (V, E)$ where V is the number of vertices of the graph and E refers to the number of edges in the network.
- 2) A set $S = \{(i,j) \mid i \text{ is a source and } j \text{ is a destination}\}$.

C. Constraints :

The RWA problem is subject to the following constraints :

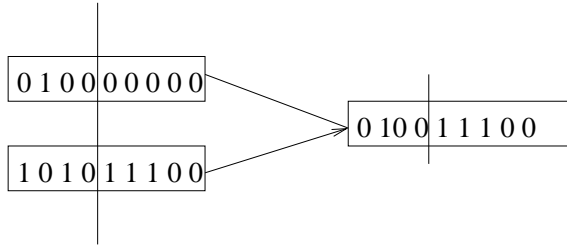
- 1) **Wavelength Continuity Constraint** : The wavelength continuity constraint implies that a particular request for a source-destination pair must follow a single lightpath [17].
- 2) **Wavelength Conflict Constraint** : The wavelength conflict constraint states that a wavelength may be used only once per fiber. Thus no two signals can traverse along the same wavelength in a particular fiber.

D. Initial Population and Encoding

A hybrid approach is used for the initialization of the population. For every source-destination pair the k -shortest paths connecting them are evaluated using Yen's algorithm as in [9][18][27]. Each gene in a chromosome represents one of the k -shortest paths selected randomly. Every gene in the chromosome has a pointer to an entry in a look up table which contains the actual path. Thus a single chromosome contains a set of plausible paths for all the source-destination pairs. The structure of the chromosome is depicted in Figure 1. Thus if there are n source destination pairs the total length of the chromosome is $\lceil \log_2 k \rceil \times n$ bits.

E. Objective Function

In the single objective formalization of the RWA problem we associate a cost with every chromosome. Let a chromosome be represented as $G = P_{ab}, \dots, P_{ij}$ where P_{ij} represents a randomly chosen path from the set of k -shortest paths between the source i and destination j . Let $E(P_{ij})$ represent the set of edges in the path P_{ij} , we define a set $K^* = \bigcup_{P_{ij} \in G} E(P_{ij})$. A cost C_k is assigned to all edges $k \in$



A m -point ($m = 2$) crossover

Fig. 2. Example of a 2-point crossover

K^* where C_k is equal to number of paths in G with k as an edge.

Cost of a chromosome $C(G) = \sum_{\forall k \in K^*} V^{C_k}$ where V is the number of nodes in the graph.

The choice of the function above needs some discussion. It is based on the idea that a chromosome having edges that appear in a number of paths in different source-destination pairs should be given a very high cost. Thus, the cost function is made to vary exponentially to the cost of each edge (which is proportional to the frequency of occurrence of the edge in the SD pairs). This cost should be greater than the maximum cost that might arise from the case where no edges appear in more than one path. This is essential because the chromosome with edges which appear in only one source-destination pair is fitter than any other chromosome and should be given the lowest cost function.

F. Genetic Algorithm

A simple single objective fitness based genetic algorithm is used for the optimization. The GA has the following salient features:

Crossover : A n -point crossover is used for a chromosome. The crossover process is illustrated in Figure 2. This mechanism is adopted so that if a path is assigned to a particular SD pair, during crossover the identity of the path is maintained in entirety. The individuals for crossover are chosen on the conventional Roulette Wheel selection scheme where the Fitness is assigned by interpolating between the best individual (whose Fitness function is least) to the worst individual (whose Fitness function is largest) according to a simple monotonic function which maps it to the Roulette wheel. After crossover an additional individual is created in the population. If the population size is ν , then the first ν individuals are selected according to their best fitness values. Thus, the individual with worst fitness is discarded.

Mutation : A random uniform mutation with a probability of $p_m = \frac{1}{k}$ is used, where k is the length of a chromosome. In mutation the created chromosome replaces itself regardless of the Fitness function . The individual with the worst Fitness

function is selected for mutation. This is done with the idea to produce a fitter individual from a bad individual in the population.

G. Wavelength Assignment

The genetic algorithm finds the individuals with the least cost function, which is found to be proportional to the number of the wavelengths used in the network. The wavelength assignment to the fittest individuals is done using Brenez heuristic [19][20].

H. First Fit algorithm

We compare our results with the well-known First-Fit heuristic which has been used for solving the static RWA problem. Here, we underline the salient features of the algorithm:

- 1) Initially a lower bound on the number of wavelength is calculated which is given by $W = \min\{W = \lceil \frac{n}{k} \rceil\}$ over all the nodes of the graph , where n refers to the degree of a node and k refers to the number of requests originating at the node.
- 2) W copies of the network graph is made.
- 3) The first graph is taken and a path is searched for the first SD pair in the graph. Consequently the edges in the graph corresponding to the path are removed.
- 4) A path is searched for the next SD pair in the first graph . If it cannot be found then the next graph is considered and Step 3 is repeated.
- 5) Step 3 and 4 are repeated till no path can be found in any of the set of graphs.
- 6) W is incremented by 1 and the above steps are repeated till paths have been found for all the SD pairs.
- 7) Output = W = number of wavelengths.

III. MULTIOBJECTIVE RWA : FORMULATION AND IMPLEMENTATION

A. Design Inputs

- 1) Maximum number of wavelengths per fiber = M , Number of nodes = N
- 2) Physical topology P_{mn} , where $P_{mn} = P_{nm} = 1$ if and only if there exists a direct physical fiber link between nodes m and n . $P_{mn} = P_{nm} = 0$ otherwise.
- 3) Distance Matrix, i.e. , fiber distance d_{mn} from node m to node n . For simplicity on expressing packet delays, d_{mn} is expressed as a propagation delay (in time units).
- 4) Number of transmitters at node $i = T_i, (T_i \geq 1)$, Number of receivers at node $i = R_i, (R_i \geq 1)$
- 5) Traffic matrix $\lambda^{(s,d)}$ which denotes the average rate of traffic flow from node s to d , with $\lambda^{(s,s)} = 0$.
- 6) Additional assumption are : the packet interarrival durations at node s and the packet lengths are exponentially distributed, so standard $M/M/1$ queuing results can be applied to each network link (or 'hop') by employing

the independence assumption on interarrivals and packet lengths due to traffic multiplexing at intermediate hops. Also, by knowing the mean packet length, the $\lambda^{(s,d)}$, can be expressed in units of packets/second.

- 7) Capacity of each channel = C (expressed in packets/sec)

B. Design variables

- 1) Virtual Topology : The variable $b(i, j) = 1$ if there exists a lightpath from node i to node j in the virtual topology. $b(i, j) = 0$ otherwise.
- 2) Traffic Routing : The variable λ_{ij}^{sd} denotes the traffic flowing from node s to node d and employing $b(i, j)$ as an intermediate virtual link. Traffic may be bifurcated.
- 3) Physical Topology Route : The variable $P_{mn}^{ij} = 1$ if the link P_{mn} is present in the lightpath for the virtual link $b(i, j)$. $P_{mn}^{ij} = 0$ otherwise.
- 4) Wavelength color : The variable $c^k(i, j) = 1$ if the lightpath from the originating node i to terminating node j is assigned the color k , where $k = 1, 2, 3, \dots, M$; $c^k(i, j) = 0$ otherwise.

C. Objective Functions

The two objective functions that we need to minimize simultaneously for a given set of source-destination pairs are :

- 1) Delay Minimization :

$$\text{Minimize: } \sum_{ij} \left\{ \sum_{sd} \left\{ \sum_{mn} P_{mn}^{ij} * d_{mn} + \frac{1}{C - \sum_{sd} \lambda_{ij}^{sd}} \right\} \right\}$$

The 1st component inside the inner bracket is the time required for traffic to travel all the physical links present in the lightpath (i, j) .

The 2nd component is the queuing delay. If C is the capacity of a lightpath, and the total amount of traffic offered onto a lightpath from node i to j is denoted by $f_{i,j}$, the queuing delay can be computed as $\sum_{i,j} \frac{f_{i,j}}{C - f_{i,j}}$.

- 2) Total number of wavelengths for the network : The total number of wavelengths in the network is given by :

$W = \sum_{ij} W_{ij}$ where W_{ij} refers to the number of wavelengths required for a particular link under the constraint $W_{ij} \leq M_{ij}$ where M_{ij} is the maximum number of wavelengths allowed in the link of the graph.

D. Constraints

The constraints involved with the design are stated below formally :

On virtual topology connection matrix : $b(i, j)$:

- 1) $\forall i, \sum_j b(i, j) \leq T_i$, i.e., the number of lightpaths emanating out of node i is at most equal to the number of transmitters at i .
- 2) $\forall j, \sum_i b(i, j) \leq R_j$, i.e., the number of lightpaths terminating at node j is at most equal to the number of receivers at j .

The above constraints ensure that the number of lightpaths are equal to the nodes' in-degree and out-degree.

On physical topology route variables : P_{mn}^{ij} :

- 1) $P_{mn}^{ij} \leq P_{mn}$, thus physical link P_{mn} present in lightpath (i, j) is possible only if there exists a physical link P_{mn}
- 2) $P_{mn}^{ij} \leq b(i, j)$, therefore the physical link P_{mn} present in lightpath (i, j) is possible only if there exists a virtual link $b(i, j)$.
- 3) $\sum_m P_{mk}^{ij} = \sum_n P_{kn}^{ij}$ if $k \neq i, j$. The constraint implies that if there is a physical link (present in the lightpath (i, j)) between (m_1, k) there should be another physical link (k, n_1) in lightpath (i, j) .
- 4) $\sum_n P_{in}^{ij} = b(i, j)$, thus there cannot be more that one physical link from node i present in the lightpath (i, j) .
- 5) $\sum_m P_{mj}^{ij} = b(i, j)$, there cannot be more than one physical link to node j present in the lightpath (i, j) .

On the virtual topology traffic variables λ_{ij}^{sd}

- 1) $\lambda_{ij}^{sd} \geq 0$
- 2) $\sum_j \lambda_{sj}^{sd} = \lambda_{sd}$, thus the traffic flowing from the node s to node d through the lightpaths $(s, j_1), (s, j_2), \dots, (s, j_n)$ is equal to the total traffic flow from s to d .
- 3) $\sum_i \lambda_{id}^{sd} = \lambda_{sd}$, hence the traffic flowing from node s to node d through all lightpaths $(i_1, d), (i_2, d), \dots, (i_n, d)$ is equal to the total traffic from s to d .
- 4) $\sum_i \lambda_{ik}^{sd} = \sum_j \lambda_{kj}^{sd}$ if $k \neq s, d$. The constraint implies that the traffic flowing in to a node k through lightpaths $(i_1, k), (i_2, k), \dots, (i_n, k)$ from a source s is equal to the traffic flowing out of node k through the lightpaths $(k, j_1), (k, j_2), \dots, (k, j_n)$ to the destination d .
- 5) $\sum_{s,d} \lambda_{ij}^{sd} \leq b(i, j) * C$, therefore, the traffic flowing from all source to all destination through lightpath (i, j) cannot increase the capacity of the virtual link (i, j)

On coloring of lightpaths $c^k(i, j)$

- 1) $\sum_k c^k(i, j) = b(i, j)$, hence, the color of lightpath (i, j) is the same (wavelength continuity constraint) and equal to the color of the virtual link (i, j) .
- 2) $\sum_{ij} P_{mn}^{ij} * c^k(i, j) \leq 1, \forall m, n, k$, therefore no two lightpaths (i, j) having the same color k can pass through the same physical link (m, n) .

E. Multiobjective Optimizer

We use a steady state generic MOEA (Multi-objective Evolutionary Algorithm) to solve the multi-objective formulation of the RWA problem. Most of the MOEAs available in the literature, like the MOGA[10], NSGA[23], SPEA[28] and PEAS [25], achieve diversity and equivalent solutions through some diversity preserving mechanism. However, they do not talk about convergence. Any explicit diversity preserving method needs prior knowledge of many parameters and the efficacy of such a mechanism depends on successful fine tuning of these parameter. In a recent study, Purshouse and Fleming [36] extensively studied the effect of sharing, along with elitism and ranking, and concluded that

while sharing can be helpful, it can also prove surprisingly *ineffective* if the parameters are not carefully tuned.

However, Kumar and Rockett[35] proposed the use of Rank-histograms for monitoring convergence of Pareto-front while maintaining diversity without any explicit diversity preserving mechanism in their algorithm. Their algorithm is proposed to work on hard problems of *unknown* nature where the Pareto-optimal front is not known apriori(as in RWA).

In this work we use their Pareto Converging Genetic Algorithm (PCGA) [35] which has been demonstrated to work effectively across complex problems and achieves diversity without needing *a priori* knowledge of the solution space. PCGA allows a natural selection process to maintain diversity. Thus, multiple equally good solutions to the problem are available. We use the same encoding scheme for the initial population in PCGA as in the single objective case. We give a brief outline of the salient features of PCGA in the next subsection.

F. Pareto Converging Genetic Algorithm

PCGA is a steady-state algorithm and can be seen as an example of $(\nu + 2)$ -ES in terms of its selection mechanism. The basic concept of PCGA is that the individuals are compared against the total population set according to tied Pareto-ranking and the population is selectively moved towards convergence by discarding the two lowest ranked individuals in each evolution. In doing so, we require no parameters such as the size of subpopulation in tournament selection or sharing/mating parameters. Additionally, we remove all subjective decision(s) about prioritizing the objectives

Selection : Initially, the whole population of size N is ranked using Fonseca and Fleming's ranking [10] algorithm. In this algorithm, ranking with ties is employed; the rank of an individual is equal to the number of individuals by which it is dominated, and all nondominated individuals are given the same rank. If two individuals have the same objective vector, we lower the rank of one of the pair by one; this way, we are able to remove the duplicates from a set of nondominated solutions without loss of generality. For a meaningful comparison of two real numbers in ranking, we restrict the floating-point precision of the objective values to a few units of precision. Fitness is assigned by interpolating from the best individual (rank = 1) to the worst (rank = N) according to a simple monotonic function to map the individuals onto a conventional roulette wheel for mating selection. In this work, we have taken fitness as a linear function of tied Pareto ranks. A pair of mates is randomly chosen biased in the sizes of the roulette wheel segments and crossed over and/or mutated to produce offspring. The offspring are inserted into the population set according to their ranks against the whole population. At this stage, the population set also includes the parents, and the population consists of $(N + 2)$ members, so the two lowest ranked individuals of the population are eliminated, and the size restored to N . In case of a tie, i.e., there are more than two solutions of lowest rank, we resolve this by random selection. The process is iterated until a convergence criterion is satisfied.

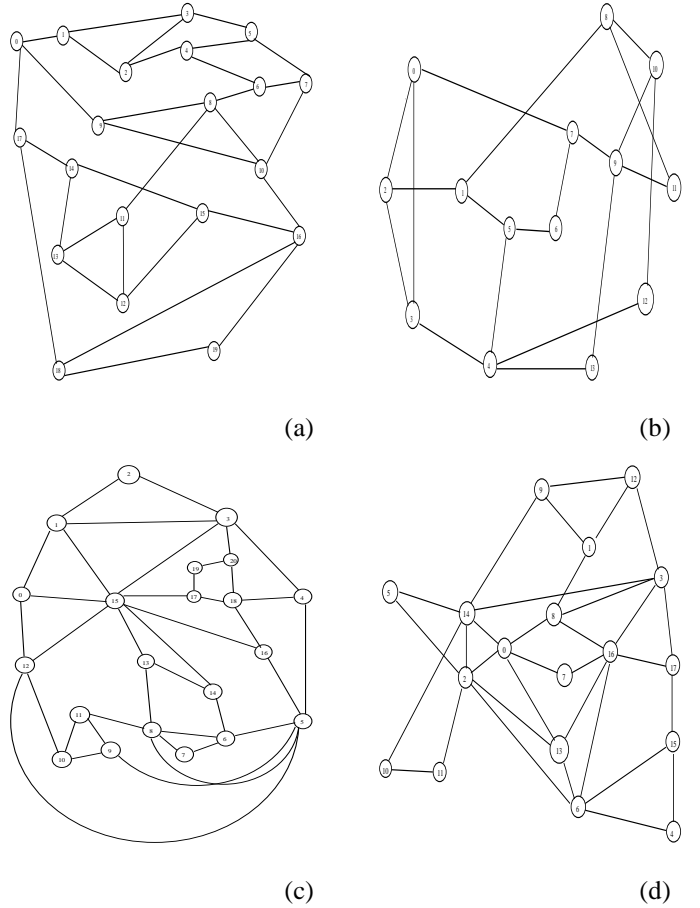


Fig. 3. a. 20 nodes ARPA Network b. 14 node NSF Network c. 21 node UK Network d. 18 node European Optical Network

IV. SIMULATION RESULTS

We evaluate the effectiveness of the proposed algorithm by extensive simulation. The simulation networks considered are real life existing networks like the 20 node ARPA network, 18 node European optical network, 22 node UK network and 14 node NSF network. The physical topologies of the networks are shown in Figure 3. The simulation results are presented for both the single objective and the multiobjective formalization of the problem for the above networks.

A. SingleObjective case:

In the single objective case the results are shown in table 1. We ran the simulation on the given networks for large and small number of Source destination pairs. We present results of 20, 40, 60 and 100 source-destination pairs for all the networks. The EA was run with the following parameters.

- 1) Population size : 200
- 2) Crossover probability : 0.01
- 3) Mutation probability : $\frac{1}{n}$ where n stands for the number of bits in the chromosome
- 4) Number of iterations : 100

The results of the different networks are almost comparable. The EA found optimal paths for different

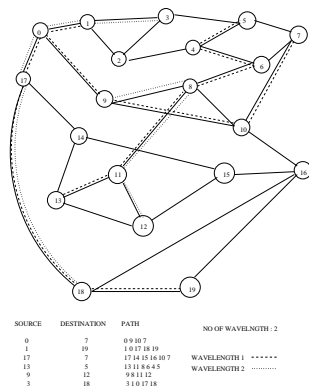


Fig. 4. Resultant Paths given by the GA for 6 SD pairs in the ARPAnet

source destination pairs and reduced the number of required wavelengths to less than 10 in most of the cases. In case of NSF however, the number of wavelength required is more since NSF network is a small and sparse graph and the likelihood of there being common edges in different source-destination pair paths is more. The same reason holds for the ARPA network requiring more wavelengths than the EON for the same number of SD pairs. In figure 2 we show the various paths found by the GA for the ARPA network for a small number of SD pairs (if fact 6). It is clear from the network that the single hops between various source-destination pairs is not possible with less than 2 wavelengths. Moreover, the paths show that the GA has produced one of the optimal sets of paths between every SD pair since it looks for paths which have edges common to least number of paths. Figure 2 shows that for a given topology the algorithm is able to find out the best possible paths between every SD pair.

The comparison with the first-fit algorithm (Table 1) depicts that the results are comparable to the GA when the number of SD pairs is few. When the number of source-destination pairs are increased to 80 or 100 the GA gives better results than the first-fit. For e.g. in the ARPA network for 100 SD pairs the number of wavelengths required is 27 for the first-fit and 22 for the GA. Hence, it can be said that the GA outperforms other known heuristics when the problem size is increased. This is one of the major advantages of using genetic algorithms for solving such hard problems when the input size is large.

B. Multi-Objective case:

For the multiobjective case we tested our MOEA on the same networks as in the single objective case. Synthetic *TRAFFIC* and *DISTANCE* matrices were generated considering Poisson's distribution of arrival of packets for the traffic. The distance matrices were formulated using the real distances between the cities in the network. Both the matrices are symmetric matrices.

For each of the network we ran the Genetic algorithm with varying probability of crossover and varying initial population. At the end of each epoch the set of non-dominated individuals

Graph	Nodes	Edges	SD Pairs	Wavelengths	FirstFit
ARPA	20	31	20	4	5
	20	31	40	9	11
	20	31	60	14	17
	20	31	80	19	24
	20	31	100	22	27
NSF	14	20	20	5	6
	14	20	40	9	11
	14	20	60	14	21
	14	20	80	23	31
	14	20	100	23	41
UK	22	38	40	9	10
	22	38	20	7	8
EON	18	33	20	4	5
	18	33	40	6	9
	18	33	60	10	13
	18	33	80	11	15
	18	33	100	11	18

TABLE I

THE RESULTS OF THE 20,40,60,80 AND 100 SOURCE-DESTINATION PAIRS FOR THE FOUR NETWORKS

were collected and stored. The GA was run for an average of 300 epochs, after which the front did not show much of an improvement. The representative results for the ARPAnet for 40 source-destination pairs for an initial population of 100 individuals is shown in Figure 5, 6 and 7. Figure 5 shows the improvement of the initial hybrid population to the converged population after 200 epochs. It can be seen from the plot that the initial population is random inspite of of the hybrid approach used to initialise the population. It is also clear that the GA is able to minimise both criterions considerably. After the 230th epoch however, the improvement was seen to be very less. Therefore, it implied that the population had nearly converged to the optimal solution by the 230th epoch. Since, we used random uniform mutation it was very unlikely that the solution could get trapped in a local optimum. Figure 6 shows the entire set of dominated and nondominated individuals for the 150th epoch. This figure has been included to depict the diversity of the solution. It can be seen that the algorithm is able to maintain a very high diversity in its solutions while moving towards the optimum. Figure 7 depicts the final Pareto-optimal front for the problem. It can be seen that the distribution of the points is very uniform depicting the high quality of the solution obtained. The number of wavelengths found by using the Brelaz algorithm on the end point of the front was found to be the same as that found in the single objective case. This is obvious , since, the solution optimal with respect to one objective is definitely an optimal solution for the multiobjective case. This shows that the solutions obtained by the MOEA are correct.

V. CONCLUSIONS AND DISCUSSION

In this paper we discussed a single and multiobjective formalization of the Static RWA problem in WDM networks and solved it using Evolutionary algorithms. The results in the single objective show that they are comparable to solutions obtained by existing heuristics like the first-fit algorithm. In fact, the solutions obtained are superior when the size of the

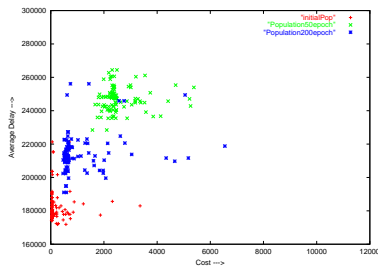


Fig. 5. Initial Population and Converging populations after 50 and 200 epochs

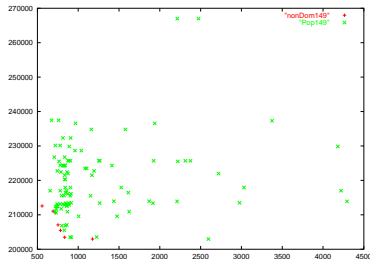


Fig. 6. Dominated and Non-dominated points after 149 epochs

input is increased. The multiobjective formalization is new where the Average Delay and the number of wavelengths are simultaneously minimized to obtain optimal paths between various SD pairs. The two objectives to be optimized have not been combined into one and hence the general nature of the solution is maintained. In most multiobjective optimisation problems it is crucial that the obtained solution is diverse. In this work we find from Figure 6 and 7 that our GA obtains a good diversity. Thus a virtual topology designer having a range of wavelengths and delays in mind, can examine several topologies and can choose the one that best matches his requirement and other engineering considerations. This is the main advantage of using EAs for such a NP-hard problem.

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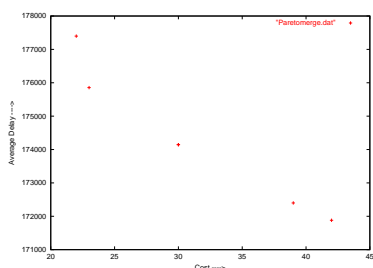


Fig. 7. Non-Dominated points after 230 epochs

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