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MULTI-OBJECTIVE EVOLUTIONARY COMPUTATION HEURISTIC FOR TRAFFIC GROOMING IN WDM OPTICAL NETWORKS

Pakorn Leesutthipornchai[1], Chalermpol Charnsripinyo[2] and *Naruemon Wattanapongsakorn[3]
[1]Department of Computer Science, Faculty of Science and Technology
Thammasat University, Rangsit Campus, Pathumthani, Thailand
[2]National Electronics and Computer Technology Center, Pathumthani, Thailand
[3]Department of Computer Engineering, Faculty of Engineering
King Mongkut's University of Technology Thonburi, Bangkok, 10140, Thailand

ABSTRACT

Traffic grooming, which is the combination of traffic demands into a single wavelength channel is a well-known issue in Wavelength Division Multiplexing (WDM) optical networks. Grooming allows wavelength channels with high transmission capacity to serve many low-rate traffic demands simultaneously. In this paper, we address the traffic grooming, routing and wavelength assignment (GRWA) problem for WDM optical networks by considering multiple design objectives: maximizing the number of demands (commodities) served, minimizing the number of wavelength channels assigned, and minimizing number of transmission ports required. We use a hybrid multi-objective evolutionary computation approach consisting of Genetic Algorithm for routing allocation, Extended Traffic Grouping for traffic grooming and Maximum Degree First for wavelength assignment (GA-ETG-MaxDF). Then we apply the Fast Non-dominated Sorting Genetic Algorithm (NSGA-II) to search for the set of non-dominated candidate solutions in multi-objective space. We compare the simulation results obtained from our approach (GA-ETG-MaxDF) with the alternative approaches (MST and MRU) published in the literature. We also examine standard performance metrics for multi-objective optimization solutions such as Hyper-volume, Spread, and Inverted Generational Distance. Based on our results, we conclude that the proposed technique is effective for solving the multi-objective GRWA problem in WDM optical networks.

Keyword: Multi-Objective Genetic Algorithm, multi-objective optimization, traffic grooming, routing and wavelength assignment, WDM optical network.

INTRODUCTION

In new generation optical networks, wavelength division multiplexing (WDM) technology will be widely used. Each optical fiber link can be divided into multiple channels which are identified by the length of light waves, called "wavelength channels". Dense wavelength division multiplexing (DWDM) technology can support over a hundred wavelength channels per fiber (Awwad *et al*., 2007). The transmission speed of each channel can be several Gigabits per second (Gbps). Speeds of 2.488 Gbps (OC-48), 10 Gbps (OC-192) and 40 Gbps (OC-768) have been proposed (Dutta and Rouskas, 2002) for commercial use. Most traffic demands (connections) typically have lower data rates than the full capacity of a wavelength channel. In order to fully utilize the network resources, multiple low-speed traffic streams need to be efficiently multiplexed or "groomed" into high-speed light-paths for data transmission between sources and destinations. This procedure is known as Traffic Grooming. Traffic grooming consists of three sub-problems which are Grooming, Routing and Wavelength Assignment (GRWA). We denote a source-destination node pair with traffic demand as a "commodity" (Jaekel *et al*., 2008). Grooming combines multiple low-data-rate commodities into a higher transmission rate channel. Routing allocates a light-path to each traffic flow in a given set of commodities. Finally, a group of commodities is assigned to an available wavelength channel. Grooming, routing and wavelength assignment are interrelated. Optimal routing depends on effective grouping, and effective wavelength assignment requires optimal routing. The GRWA problem tries to find optimal solutions for routing, and wavelength assignment with multi-commodity flows. The traffic grooming or GRWA problem is an NP complete problem (Shalom *et al*., 2007).

Previous research has considered the GRWA problem with various different design objectives. Another study, Zhu and Mukherjee (2002, 2003) have considered the GRWA problem to improve network throughput and reduce the network cost and to reduce the grooming device cost while serving all traffic demands. While, Awwad *et al*. (2007) considered GRWA to minimize total cost of grooming and conversion equipment, Shen and

*Corresponding author email: naruemon@cpe.kmutt.ac.th

Tucker (2009) considered GRWA to maximize the served traffic demand and minimize the wavelength capacity. Given many different potential design objectives, the GRWA problem can be formulated as a multi-objective optimization problem. In such problems, multiple evaluation functions influence the decision of which option to select.

This paper considers the GRWA problem with three objective functions. We attempt to simultaneously maximize the number of accepted commodities, minimize the number of wavelength channels and minimize the number of switching ports. Each of these objectives can conflict with the others such that when one is optimized, the other functions may get worse (Coit and Konak, 2006). For instance, maximizing accepted commodities normally requires a large number of wavelengths and switching ports. Minimizing the number of switching ports could cause a large number of commodities to be blocked or fewer commodities to be accepted. Several Multi-objective Evolutionary Algorithms such as Strength Pareto Evolutionary Algorithm: SPEA2 (Zitzler *et al*., 2001) and Fast Non-dominated Sorting Genetic Algorithm: NSGA-II (Deb *et al*., 2002) has been previously proposed for general multi-objective optimization problems. To solve the multi-objective GRWA problem, we propose a new evolutionary computation heuristic called "GA-ETG-MaxDF" and use it with NSGA-II. We construct potential routes by using a Genetic Algorithm (GA), combine multiple low rate traffic demands by using Extended Traffic Grouping (ETG) algorithm and assign the wavelength channel by using the Maximum Degree First (MaxDF) algorithm. We then apply the NSGA-II to search for non-dominated solutions in the three dimensional space of accepted commodities, required wavelength channels and required switching ports. The results are provided as non-dominated candidates.

After implementing our approach in a simulation, we compare the results from GA-ETG-MaxDF with those from the alternative approaches (MST and MRU). We also compare the approaches in terms of indicators of multi-objective solution quality.

MATERIALS AND METHODS

Traffic Grooming, Routing and Wavelength Assignment Problem

Traffic grooming, routing and wavelength assignment (GRWA) problems have been previously studied by a number of researchers. Traffic grooming has been applied to both ring network topology (Wang *et al*., 2001; Dutta and Rouskas, 2002; Zhu and Mukherjee, 2003) and mesh network topology (Zhu and Mukherjee, 2002; Hu and Leida, 2004; Prathombutr *et al*., 2005). Traffic grooming in mesh networks is usually difficult to solve optimally (Zhu and Mukherjee, 2003). The evolution, challenges and future vision of traffic grooming and all-optical network are proposed by Saleh and Simmons (2012).

Zhu and Mukherjee (2002) proposed grooming, routing and wavelength assignment techniques to improve the network throughput subject to a limited number of transmitters, receivers and available wavelength channels. They used the Maximizing Single-hop Traffic (MST) heuristic algorithm to assign multiple requested connections to a new light path. If the network has enough network resources (i.e., wavelength channels, transmitters, receivers, grooming devices and wavelength converters), all requested connections can traverse on a single light path and the traffic delay will be minimized. If there are not enough network resources to support a new light path, the method assigns connections that can complete in a single hop light path before connections that require multiple light paths. Zhu and Mukherjee (2002) used a Maximizing Resource Utilization (MRU) heuristic algorithm to allocate limited network resources. The MRU approach sets up a light path using available spare wavelength channels in the logical network links, possibly assigning connection requests to multiple light paths, then multiplexes the remaining connection requests with the existing light paths. The connection that uses the fewest established light paths will be groomed first. Hu and Leida (2004) proposed a GRWA technique to minimize the total number of transponders required in the network, subject to a limited number of wavelength channels in each fiber and requiring that each light path use the same wavelength channel for every link that it traverses (i.e., wavelength continuity constraint). In their work, they assumed a transponder is required at each end of the light path. Thus minimizing the number of transponders also minimized the number of wavelengths. They solved their GRWA problem using a commercial tool called CPLEX 7.0. In a recent study, Awwad *et al*. (2007) proposed a GRWA in a WDM mesh network with sparse resources (i.e., some logical network nodes are able to groom while others are not). Their objective was to minimize the total costs for traffic grooming and wavelength conversion devices. The traffic grooming device has more functions and higher cost than the wavelength conversion device. Both types of devices are deployed on the nodes based on the decision variables of the optimization model. Because their GRWA implementation allows a light path to use different wavelength channels, it significantly increases blocking probability. They applied a Genetic Algorithm (GA) to solve their GRWA problem and compared the results with their previous approaches including Most-contiguous (MC) heuristic algorithm, and Fixed Alternated Routing and First Fit Wavelength Assignment (FAR-FF) algorithm.

Shen and Tucker (2009) proposed an algorithm to select the best locations for opaque nodes (a kind of grooming device). They aimed to maximize served traffic demands under a limited network capacity and minimize the required wavelength channel while all traffic demands are served. Chatterjee *et al*. (2012) proposed a priority based routing and wavelength assignment with traffic grooming mechanism (PRWATG) to reduce blocking probability. The blocking probability increases when the number of connections is increased. In their algorithm, which enforces the wavelength continuity constraint, connections with the same source and destination are combined first to avoid optical to electrical conversions. Then, the set of routes and wavelength channels are assigned to the groomed connections according to their priority. A groomed connection with a direct path had higher priority than one with an indirect path. Zhao *et al*. (2013) considered the GRWA problem with the goal of satisfying quality of transmission requirements (QoT). The QoT Guaranteed (QoT-G) algorithm accommodates a set of traffic demands with heterogeneous bandwidth requirements in order to minimize the blocking probability. Their paper used the shortest path algorithm for routing. In the grooming step, the connection requiring the most bandwidth is considered first. If multiple connections have the same bandwidth requirement, the connection with the shorter path is selected. Most studies in the literature (Dutta and Rouskas, 2002; Zhu and Mukherjee, 2003; Hu and Leida, 2004; Awwad *et al*., 2007; Chatterjee *et al*., 2012; Zhao *et al*., 2013) have concentrated on traffic grooming with a single objective function. Research work on traffic grooming with multiple objectives has been proposed (Prathombutr *et al*., 2005).

Prathombutr *et al*. (2005) proposed an algorithm for traffic grooming in WDM optical mesh networks with the objectives of maximizing the traffic throughput, minimizing the number of transceivers and minimizing the average propagation delay. They considered the GRWA problem with and without a wavelength converter. They applied the SPEA approach to search a set of non-dominated solutions. They offered superior results than those from MST and MRU (Zhu and Mukherjee, 2002). The results from MST and MRU are also used to compare with the obtained solutions from the Multi Objective Evolutionary Algorithm (MOEA) as proposed in (De *et al*., 2008). MST and MRU algorithms are easy to follow and implement. Traffic grooming is a network design problem that the network topology affects the obtained results. MST and MRU are developed on the basis of the shortest path algorithm and well known as efficient traffic grooming algorithms.

Multi-Objective Network Design

Multi-objective network design evolved from a network model that seeks to optimize only one objective function, but with many design constraints such as network design cost, limitation of maximum delay and network survivability requirement (Hsu *et al*., 2008). Assis *et al*. (2008) proposed a true multi-objective network design model that minimizes total link length and total number of hops, while maximizing link load simultaneously. This research combined all objective functions into one function and then optimized the single objective function while maintaining the design constraints. A mixed integer programming tool (CPLEX 10.0) was used to find the optimal solution. Kavian *et al*. (2008) also proposed a network design model with multiple objective functions. Their network model minimized bandwidth consumption and end-to-end delay. They used a genetic algorithm to minimize each function individually and then combine the obtained results from both objectives. Finally, Banerjee and Kumar (2007) proposed a network design to minimize total network cost (from nodes, links, and amplifier) and also minimize average delay. Their research also found a set of optimal solutions using an advanced genetic algorithm but they evaluated each solution with both objective functions at the same time. Some papers Cahon *et al*. (2006) and Ribeiro *et al*. (2007) have suggested that multi-objective network design can solve all objectives simultaneously by using parallel computing to find the best solution from all possible sets. Parallel computing distributes the possible sets into clusters and then combines the distributed results to get the best solution. De *et al*. (2008) proposed the Multi Objective Evolutionary Algorithm (MOEA) for optimizing traffic grooming problem by considering multiple objectives, i.e., throughput, transceiver requirement and intermediate propagation delay simultaneously. The obtained results are compared with those of MST and MRU algorithms. Roa *et al*. (2009) proposed a Multi Objective Evolutionary Algorithm by considering two design objectives, i.e., minimizing blocking number and the number of wavelength converters. The results are compared with the solutions from SPEA algorithm. Lin *et al*. (2012) suggested two heuristics algorithms, Multicast Trail Grooming (MTG) and Multiple Destination Trail-based Grooming (MDTG) to minimize the network cost in terms of the number of higher layer electronic ports and number of wavelengths used. The solutions obtained by two heuristics are compared with the ILP optimal solution. In a most recent study, Chen *et al*. (2013) proposed the bi-objective ILP for maximizing the throughput and then minimizing the energy consumption for the obtained maximized throughput. The obtained results are compared with the single objective optimization. In this paper, we use a true multi-objective optimization algorithm which maintains separate objective functions for each criterion. There are many multi-objective optimization approaches as described in the next section.

Multi-Objective Genetic Algorithms

Genetic Algorithm (GA) approaches have been used to solve multi-objective optimization problems in several areas. The efficient multi-objective GA provides an encouraging approach for searching toward the true Pareto front while maintaining diversity in the population (Konak *et al*., 2006). Various Multi-Objective Genetic Algorithms have been previously discussed in (Konak *et al*., 2006; Leesutthipornchai *et al*., 2009). Examples of Multi-Objective Genetic Algorithms are Weight-Based GA: WBGA (Hajela and Lin, 2005), Random Weighted GA: RWGA (Murata and Ishibuchi, 1995), Vector Evaluated GA: VEGA (Schaffer, 1985), Niched Pareto GA: NPGA (Horn *et al*., 1994), Multi-Objective GA: MOGA (Fonseca and Fleming, 1993), Nondominated Sorting GA: NSGA (Srinivas and Deb, 1994), Fast Non-dominated Sorting GA: NSGA-II, Strength Pareto Evolutionary Algorithm: SPEA (Zitzler and Thiele, 1999), enhanced SPEA: SPEA2 (Zitzler *et al*., 2001) and Pareto-Archived Evolution Strategy: PAES (Knowles and Corne, 1999).

In our previous work (Leesutthipornchai *et al*., 2009), we evaluated NSGA-II with all optimal and non-dominated solutions (i.e., the Pareto-front) using a well-known combinatorial problem (i.e., Knapsack problem with 2 objective functions and 100 decision variables). The experiment showed that NSGA-II can provide excellent results.

Problem Definition and Model Formulation

In this section, we describe our multi-objective GRWA problem and present the GRWA model formulation.

We assume that the WDM optical networks have hybrid optical-electronic switching devices to support grooming. In an all-optical network (Huang and Copeland, 2003), the signals can pass through network nodes in the optical domain. An all-optical network reduces the transmission delay at intermediate nodes by avoiding the OEO (Optical-Electrical-Optical) conversion between the optical and the electrical domains. Each node requires one optical port for receiving and another optical port for transmitting, with electrical ports required only at the source and destination of the connection. However, electrical ports are also needed at some intermediate nodes, wherever multiple commodities are groomed into the same wavelength channel. The number of transmission ports and wavelength channels required for traffic grooming are different from the case when the traffic connections are not groomed. Wavelength channels and switching ports are network resources that must be efficiently used. Grooming makes it possible to combine multiple traffic streams in a single wavelength channel. The so-called wavelength continuity constraint states that a wavelength channel can be assigned only to one light path connection, so that the wavelength channel does not change along the light path from the source to the destination node.

In this paper, we consider the GRWA problem in WDM optical networks to serve a given set of commodities. Each commodity has many possible routings and each routing has several choices for aggregation with other connections and various choices of wavelength channel assignment. A percentage of commodities is allowed to be blocked if this is necessary to optimize wavelength channels and switching ports. A commodity that has been successfully assigned with a wavelength channel is called "accepted commodity". Our GRWA problem aims to maximize the number of accepted commodities, to minimize the number of wavelength channels and to minimize the number of switching ports. We consider these three design objectives simultaneously, while preserving the wavelength continuity constraint. The next section presents our notation for this problem formulation.

Set of Notations: **Network Topology Properties**

Let N be the set of network nodes. E denotes the set of edges or links in the network. $E(i,*)$ is the set of edges that leave from node $i \in N$. $E(*, i)$ is the set of edges that go to node $i \in N$. D is the set of network edge distances where D_e represents the length of network edge $e \in E$. Each network edge has $|K|$ wavelength channels. K is the set of available wavelength channels. G is the set of aggregated groups in which multiple commodities are merged together. Each accepted commodity must belong to a group (which might have only a single member). Q is the set of given commodities, expressed as a source-destination node pair with a bandwidth requirement. In this paper, the bandwidth is a fraction of the wavelength capacity. $P_{\max}$ is the maximum number of switching ports in the network. P_A is the required number of switching ports. Q_A is the number of accepted commodities. K_A is the number of required/assigned wavelength channels. L is the maximum acceptable path length (in kilometer). H is an upper-bound hop counts.

Let ω_g^e be the number of commodities in the group $g \in G$ on network edge $e \in E$. ω_g^e is a positive integer number. $\psi(o)_g^e$ is the number of optical ports. $\psi(e)_g^e$ is the number of electrical ports. The electrical port count is calculated as the sum of the electrical transmitting units $\varphi(s)_g^e$ and electrical receiving units $\varphi(d)_g^e$. $\varphi(s)_g^e$ is the number of electrical transmitting units of the group on the network edge. $\varphi(d)_g^e$ is the number of electrical receiving units of the group on the network edge. $\varphi(o)_g^e$ is the number of optical units of the group on the network edge. T_{acc} is the minimum threshold value representing the ratio of accepted commodities that are required over the total number of commodities, where $0 \leq T_{acc} \leq \frac{Q_A}{|Q|} \leq 1$. $|K| \leq K_{max}$ which is an upper-bound number of wavelengths. t_q is the bandwidth requirement of the commodity.

Set of Notations: **Decision Variables**

Let $\delta_{q,g}^{e,k}$ denotes the decision variable of a commodity q that decides whether to occupy a wavelength channel k on network edge e with group g, or not. Note that $\delta_{q,g}^{e,k}$ is equal to 1 if the wavelength channel on the edge is occupied by the commodity and it belongs to a group; otherwise it is equal to 0.

Given

Network topology

Set of source-destination node pairs with bandwidth requirements

Assumption

The combination of commodities can be performed in the electrical domain only.

Design Objectives

Minimize:

$$f_{obj} = \min\left(f_c, f_w, f_p\right) \tag{1}$$

$$f_c = \frac{|Q| - Q_A}{|Q|} \tag{2}$$

$$f_w = \frac{K_A}{K_{\max}} \tag{3}$$

$$f_p = \frac{P_A}{P_{\max}} \tag{4}$$

Design Constraints

Subject to:

$$\sum_{g\in G}\sum_{e\in E(*,i)}\sum_{k\in K}\delta_{q,g}^{e,k} - \sum_{g\in G}\sum_{e\in E(i,*)}\sum_{k\in K}\delta_{q,g}^{e,k} = \begin{cases} -\beta_q, i = Source_q \\ \beta_q, i = Dest_q \\ 0, otherwise \end{cases} \quad ;\forall q \in Q, i \in N \tag{5}$$

$$\sum_{q\in Q}\sum_{k\in K}\delta_{q,g}^{e,k} \cdot t_q \leq \Re_g^e \qquad ;\forall g \in G, \forall e \in E \tag{6}$$

$$\Re_g^e \leq 1 \qquad ;\forall g \in G, \forall e \in E \tag{7}$$

$$\delta_{q,g}^{e,k} \leq \gamma_q^k \qquad ;\forall q \in Q, \forall g \in G, \forall e \in E, \forall k \in K \tag{8}$$

$$\sum_{k\in K}\gamma_q^k \leq 1 \qquad ;\forall q \in Q \tag{9}$$

$$\sum_{g\in G}\sum_{k\in K}\delta_{q,g}^{e,k} \leq \beta_q \qquad ;\forall q \in Q, \forall e \in E \tag{10}$$

$$\delta_{q,g}^{e,k} \leq \Lambda_{q,g} \qquad ;\forall q \in Q, \forall g \in G, \forall e \in E, \forall k \in K \tag{11}$$

$$\sum_{g\in G}\Lambda_{q,g} \leq 1 \qquad ;\forall q \in Q \tag{12}$$

$$\delta_{q,g}^{e,k} \leq y_g^k \qquad ;\forall q \in Q, \forall g \in G, \forall e \in E, \forall k \in K \tag{13}$$

$$\sum_{k\in K} y_g^k \leq 1 \qquad ;\forall g \in G \tag{14}$$

$$Q_A = \sum_{q\in Q}\beta_q \tag{15}$$

$$K_A = \sum_{k\in K}\phi_k \tag{16}$$

$$\omega_g^e \geq \sum_{q\in Q}\sum_{k\in K}\delta_{q,g}^{e,k} \qquad ;\forall g \in G, \forall e \in E \tag{17}$$

$$\varphi(s)_g^e \geq \begin{cases} \sum_{g\in G}\sum_{k\in K}\delta_{q,g}^{e,k}, e \in E(Source_q,*) \\ \sum_{g\in G}\sum_{k\in K}\delta_{q,g}^{e,k}, e \in E(*,Dest_q) \\ \sum_{g\in G}\sum_{k\in K}\delta_{q,g}^{e,k}, e \notin E(Source_q,*) \wedge e \notin E(*,Dest_q) \wedge \omega_g^{e'(*,Source_e)} \leq 1 \\ \sum_{g\in G}\sum_{k\in K}\delta_{q,g}^{e,k}, e \notin E(Source_q,*) \wedge e \notin E(*,Dest_q) \wedge \omega_g^{e'(Dest_e,*)} \leq 1 \\ 0, \quad otherwise \end{cases}$$

where $\forall q \in Q, \forall e \in E$ (18)

$$\varphi(d)_g^e \geq \begin{cases} \sum_{g\in G}\sum_{k\in K}\delta_{q,g}^{e,k}, e \in E(*,Dest_q) \\ \sum_{g\in G}\sum_{k\in K}\delta_{q,g}^{e,k}, e \in E(Source_q,*) \\ \sum_{g\in G}\sum_{k\in K}\delta_{q,g}^{e,k}, e \notin E(*,Dest_q) \wedge e \notin E(Source_q,*) \wedge \omega_g^{e'(Dest_e,*)} \leq 1 \\ \sum_{g\in G}\sum_{k\in K}\delta_{q,g}^{e,k}, e \notin E(*,Dest_q) \wedge e \notin E(Source_q,*) \wedge \omega_g^{e'(*,Source_e)} \leq 1 \\ 0, \quad otherwise \end{cases}$$

where $\forall q \in Q, \forall e \in E$ (19)

$$\psi(e)_g^e = \varphi(s)_g^e + \varphi(d)_g^e \qquad ;\forall g \in G, \forall e \in E \tag{20}$$

$$\varphi(o)_g^e \geq \sum_{g\in G}\sum_{k\in K}\delta_{q,g}^{e,k} \qquad ;\forall q \in Q, \forall e \in E \tag{21}$$

$$\psi(o)_g^e = 2 \cdot \varphi(o)_g^e \qquad ;\forall g \in G, \forall e \in E \tag{22}$$

$$P_A = \sum_{g\in G}\sum_{e\in E}\left(\psi(o)_g^e + \psi(e)_g^e\right) \tag{23}$$

$$y_g^k \leq \phi_k \qquad ;\forall g \in G, \forall k \in K \tag{24}$$

$$\frac{Q_A}{|Q|} \geq T_{acc} \tag{25}$$

$$\sum_{e\in E}\delta_{q,g}^{e,k} \leq H \qquad ;\forall q \in Q, \forall g \in G, \forall k \in K \tag{26}$$

$$\sum_{e\in E}(D_e \cdot \delta_{q,g}^{e,k}) \leq L \qquad ;\forall q \in Q, \forall g \in G, \forall k \in K \tag{27}$$

$$\beta_q \in \{0,1\} \qquad ;\forall q \in Q \tag{28}$$

$$\phi_k \in \{0,1\} \qquad ;\forall k \in K \tag{29}$$

$$\gamma_q^k \in \{0,1\} \qquad ;\forall q \in Q, \forall k \in K \tag{30}$$

$$\Lambda_{q,g} \in \{0,1\} \qquad ;\forall q \in Q, \forall g \in G \tag{31}$$

$$y_g^k \in \{0,1\} \qquad ;\forall g \in G, \forall k \in K \tag{32}$$

$$\varphi(s)_g^e \in \{0,1\} \qquad ;\forall g \in G, \forall e \in E \tag{33}$$

$$\varphi(d)_g^e \in \{0,1\} \qquad ;\forall g \in G, \forall e \in E \tag{34}$$

$$\varphi(o)_g^e \in \{0,1\} \qquad ;\forall g \in G, \forall e \in E \tag{35}$$

$$\delta_{q,g}^{e,k} \in \{0,1\} \qquad ;\forall q \in Q, \forall g \in G, \forall e \in E, \forall k \in K \tag{36}$$

Note that a commodity can have several possible routes from source to destination but only one route is considered at a time and the available wavelength channel is considered to be occupied for the selected route. Our proposed network model considers grooming, routing and wavelength assignment, attempting to maximize the number of accepted commodities (Q_A), to minimize the number of required wavelengths (K_A) and to minimize the number of required switching ports (P_A), as shown in Eq. (1)-(4). The objective function in Eq. (2) transforms the maximization of accepted commodities to a minimization function. When Q_A is maximized to reach the total number of commodities ($|Q|$), the value of Eq. (2) will be minimized to 0.

The objective functions are normalized by dividing with their total range of values (or magnitudes), so that all will have values in the interval [0,1].

The set of constraints Eq. (5)-(27) are described below.

Eq. (5) is the network flow constraint. The flow of traffic that enters and leaves from node must equal 0. The traffic demand at the source node is $-\beta_q$ and the traffic demand at the termination node is β_q. Decision variable β_q represents the existence of a network commodity. β_q=1, if the commodity has a network flow on the node. Otherwise, it is 0.

Eqs. (6) and (7) are the wavelength bandwidth constraints. The wavelength bandwidth on the network edge for all commodities in the group must be less than or equal to one unit of the wavelength channel bandwidth. Since multiple commodities can be assigned to the group on network edge, in Eq. (6), the $\Re_g^e$ is the maximum bandwidth required to support all commodities in group on the network edge. Eq. (7) ensures that each group must have a total bandwidth requirement less than or equal to 1.The bandwidth granularities of all commodities are less than or equal to 1 wavelength.

Eqs.(8) and (9) are the wavelength continuity constraints. Only one wavelength channel is used for the commodity throughout multiple (connected) edges. Since multiple edges can be used for the commodity with a wavelength, in Eq.(8), if the commodity occupies a wavelength channel on any edge, then γ_q^k = 1. If γ_q^k = 0, there is no assignment of wavelength channel for the commodity on any edge. Eq.(9) ensures that each commodity must have a number of assigned wavelength channels less than or equal to 1.

Eq.(10) is the commodity assignment constraint. The commodity variable β_q is equal to 1, if there exists one or more edge(s) occupied by the commodity with one wavelength channel.

Eqs.(11) and (12) are the single group assignment constraints. A particular commodity can be assigned to only one group. In Eq.(11), if the commodity is assigned to a group, then $\Lambda_{q,g}$ = 1. Otherwise, $\Lambda_{q,g}$ = 0. Eq.(12) ensures that each commodity must have the number of assigned groups less than or equal to 1.

Eqs.(13) and (14) are the wavelength continuity constraints for the group. Only one wavelength channel is used for the group throughout multiple (connected) edges. Since multiple edges can be used for the commodity in group with a wavelength, in Eq.(13), if the group occupies a wavelength channel on any edge, then y_g^k = 1. If y_g^k = 0, there is no assignment of wavelength channel for the group on any edge. Eq.(14) ensures that each group must have the number of assigned wavelength channels less than or equal to 1.

In Eq.(15), the number of accepted commodities (Q_A) is equal to the count of all commodities which can be routed (on one or multiple edges) from their source to destination and assigned with a wavelength channel throughout the route.

In Eq. (16), the number of required wavelength channels (K_A) is equal to the count of all assigned wavelength channels where each assigned wavelength channel is occupied by at least one accepted commodity.

Eq. (17) is the number of commodities in the group on a network edge.

Eq. (18) is the number of electrical transmitting units of the group on the network edge. If a network edge is the source of some commodity in a group, an electrical transmitting unit is required for adding the new commodity to the existing group. Note that if more than one commodity in the group has its source on the network edge, only one transmission unit is required for group on the network edge. For the group of multiple commodities, it is possible to drop the existing light path to remove a commodity from the group when the commodity reaches its destination. Therefore, in the second condition, for each network edge if there exists a commodity in the group that reaches its destination, a transmitting unit is required for adding the remaining connections after the commodity is split out of the group. In our model, it is possible to groom two commodities that do not have the same source and/or destination into the same wavelength channel. This gives rise to two additional conditions. For example in figure 1, commodities 1 and 2 are groomed into the same wavelength at edge 2→3. The network edge 2→3 is neither the source nor the destination of commodities 1 and 2. However, an electrical port is required at node 2, in order to groom commodity 2 into the light path. Furthermore, an electrical port is required at node 3, where commodity 2 leaves the common light path, to add the remaining communications after commodity 2 is split out.

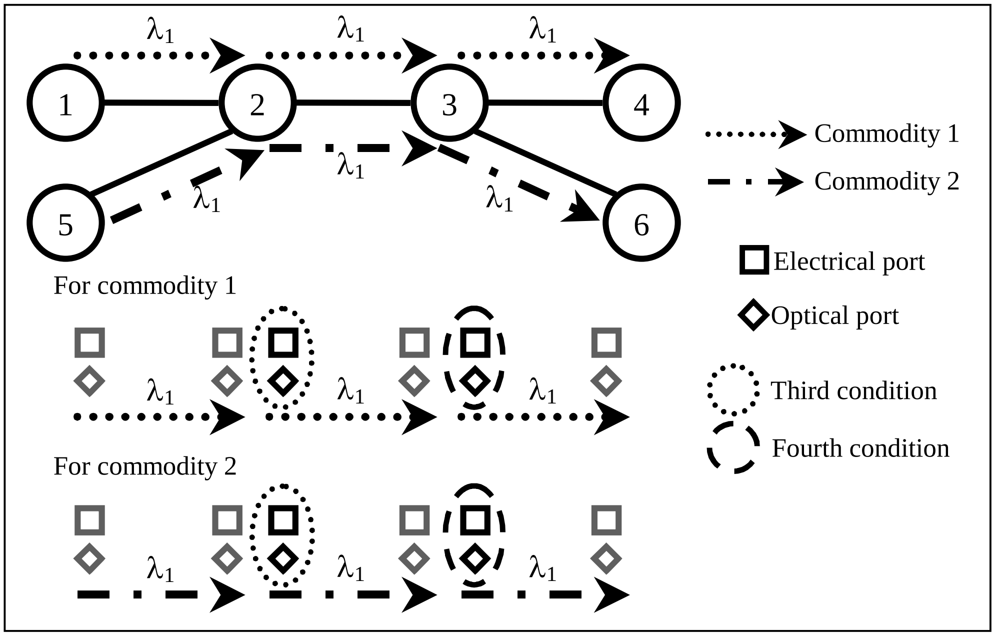

Fig. 1. The grooming condition in MP2MP for the electrical transmitting unit.

Eq. (19) is the number of electrical receiving units of the group on the network edge. As is the case with transmitting units, a unit is needed at each location where a commodity joins or leaves a path.

Eq. (20) is the number of electrical ports for a group on a network edge. The number of electrical ports is calculated as the sum of electrical transmitting units $\varphi(s)_g^e$ and electrical receiving units $\varphi(d)_g^e$. The number of electrical ports for a group on a network edge may be 0 if none of the commodities in the group have their source or destination on the network edge.

Eq. (21) is the number of optical units for the group on the network edge. If a commodity in the group traverses on the network edge, an optical unit is required for retransmitting the optical signal. Note that if more than one commodity in the group traverses on the network edge, only one transmission unit is required for group on the network edge.

Eq. (22) is the number of optical ports for the group on the network edge. Twice as many optical ports as optical units are required for every network edge. One optical port is used for transmitting and another one for receiving.

Eq. (23) is the equation for calculating the number of switching ports. The number of all switching ports is the summation of optical and electrical ports in all groups traversing one or more network edges.

Eq. (24) is the wavelength utilization constraint. Each wavelength channel is selected if there is at least one commodity in the group which is set up. If there are two or more groups which are not overlapped, they can use the same wavelength channel (on different edges) subject to wavelength continuity constraint.

In Eq. (25), the number of accepted commodities must be greater than or equal to a threshold. For example, T_{acc}=0.8 means that 80% of all commodities must be accepted.

In Eq. (26), the hop distance of commodity traversing on multiple edges must not exceed the hop count limit.

In Eq. (27), the network link distance of commodity traversing on multiple edges must not exceed the length limit (in kilometers).

Eqs. (28)-(36) define the decision variables used in the model.

The routing of a commodity can be any of the possible routes that connect the specified source node to the specified destination node. Previously, the RWA (routing and wavelength assignment) problem has been shown to be NP-complete (Chlamtac *et al*., 1992). The GRWA problem considers not only routing and wavelength assignment but also combining multiple low rate traffic demands into the same wavelength channel. Our proposed network design model is solved heuristically using a hybrid evolutionary approach described in the next section.

Multi-Objective Evolutionary Computation Heuristic

In this section, we present heuristic algorithms to solve the multi-objective grooming, routing and wavelength assignment (GRWA) problem in optical network design. Our approach considers potential routes by using a Genetic Algorithm (GA), combines multiple low rate traffic demands with the Extended Traffic Grooming (ETG) algorithm, and assigns the wavelength channel by using the Maximum Degree First Wavelength Assignment (MaxDF) algorithm. Thus, we call our method GA-ETG-

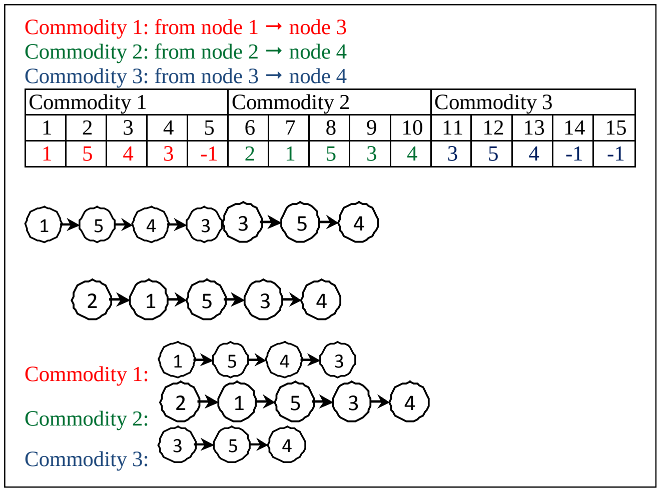

Fig. 2. An example of string encoding.

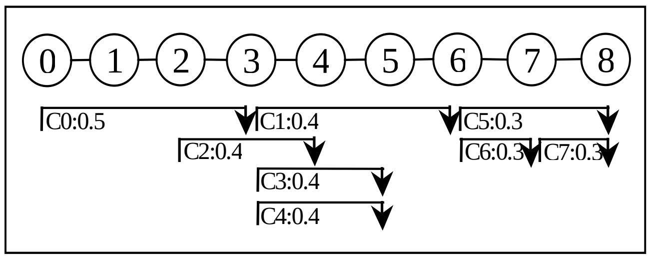

Fig. 3. Set of commodities with bandwidth requirement in an example network.

MaxDF. The Fast Non-dominated Sorting Genetic Algorithm (NSGA-II) is then applied to search for a set of non-dominated candidate solutions.

Genetic Algorithm for Routing

Banerjee and Sharan (2004) applied a Genetic Algorithm to solve a routing problem in WDM optical networks, based on a Fixed-Alternate Routing approach. Their algorithm limited the alternate routes of each commodity, considering only the K^{th} shortest routes. However, it is possible that some commodities require a longer route to avoid the congestion. In our research work, we propose a Genetic Algorithm for routing that allows most possible routes to be considered.

GA normally requires several sub-processes. The string encoding process represents each potential solution as a "chromosome" made up of genes, that is, as a vector of numeric values for each solution dimension or component. An initial set of chromosomes is generated. Then the algorithm iterates through a number of evolutionary cycles. In each cycle, the chromosomes may be modified by crossover (swapping values between chromosomes) and mutation (random modification of particular "gene" positions). A fitness function that measures solution quality is applied to the resulting chromosomes. Then the chromosomes with the highest fitness values are retained for the next iteration.

The string encoding used in this paper is a set of integers that indicates the route of each commodity. Suppose that we have a 5-node network (nodes labeled 1 through 5) and three commodities to be routed. The corresponding 15 position string encoding is displayed in figure 2. Each commodity has a separate region of the string, with a number of positions equal to the total number of nodes in the network. Each position p represents one node on a potential path for that commodity. If position p has the value n_p this represents a path segment connecting from n_p to n_{p+1}. A value of n_p= -1 indicates that the commodity's destination has been reached in previous connections. This string encoding scheme has the benefit that all possible routes can be considered.

Crossover is a process that generates new solutions from existing solutions. We pair up the chromosomes and use one-point crossover for each pair. In our work, 80% of the population will be interchanged. Each commodity pair swaps the route sections starting at the selected crossover point. Duplicated nodes or loops are detected and deleted. Mutation generates new solutions from existing solutions. We use one bit mutation for 25% of the population. One node position is randomly selected for mutation. The connection between that node and the following node is deleted, and the shortest alternative path between those nodes is calculated. If a new shortest path is found, the intervening nodes will be inserted into the chromosome. Otherwise the previous path will be retained.

As discussed earlier, a GA usually evaluates the fitness of the individuals in the current population and chooses the fittest instances to survive into the next generation. In our work, the fitness testing and selection is part of the NSGA-II process.

Extended Traffic Grooming

In traffic grooming, commodities that have overlapping paths and whose total traffic demands are less than or equal to the channel capacity can be combined into a group using the same wavelength channel.

Previously, Zhu and Mukherjee (2002) proposed Maximizing Single-Hop Traffic (MST) and Maximizing Resource Utilization (MRU) techniques for traffic grooming. These grooming algorithms sort the set of commodities assorting to some criterion and then combine multiple overlapped commodities into the same group by following the ordering. Overlapped commodities early in the sequence are considered for grouping first.

In this paper, we propose that some non-overlapped commodities can be groomed into the same group if there exists a commodity which overlaps or bridges the routes between the non-overlapped commodities. Suppose that we have eight commodities with routings generated by using the GA, as shown in table 1 and figure 3. In Fig. 3, C0:0.5 represents a commodity C0 with 0.5 unit of wavelength requirement. We can see that the routes for C0 and C1 do not overlap. However, C0 and C1 can be combined together with C2 because C2 overlaps with both C0 and C1. By doing this, we can reduce the number of wavelength channels required in the optical network design.

Table 1. The route of each commodity obtained from GA.

Commodity	Routing	Commodity	Routing
0	0→1→2→3	4	3→4→5
1	3→4→5→6	5	6→7→8
2	2→3→4	6	6→7
3	3→4→5	7	7→8

Before we combine multiple commodities into groups, we create an auxiliary graph for the set of light paths to represent which commodities overlap. In the auxiliary graph shown in figure 4, which corresponds to the routings in table 1, each node represents a commodity. If a commodity's path overlaps with another commodity a link is created between these commodity nodes in the auxiliary graph.

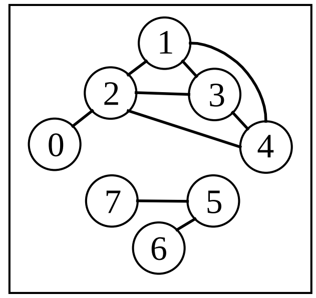

Fig. 4. The auxiliary graph of overlapped commodities.

In the traditional traffic grooming approach using MST, the commodities that overlap will be considered for grooming into a group. For example, in figure 4, commodities 3 and 4 are groomed first because they have the same source and destination. After that C0 and C1 are considered. C0 and C1 cannot be groomed together because they are not overlapped. C2 is groomed with C0 because high traffic demand is considered first. C1 cannot be groomed with C0 and C2 because their light paths overlap. Lastly, C5, C6 and C7 are groomed together in the same group.

In our extended traffic grooming (ETG) approach, we reexamine commodities in existing groups after this first phase. ETG will try to combine groups by searching for commodities in one group that overlap with commodities in another group, where the total bandwidth of the combined groups will not exceed the wavelength bandwidth constraint.

For example, C0 and C2 are first assigned into a group. C1 forms a second group on its own. We can add C1 to the group including C0 and C2 because C2 also overlaps with C1 and the summation of bandwidth on the path from 3 to 4 does not exceed the wavelength bandwidth constraint. Table 2 compares the set of commodities groomed in each group by using MST and ETG algorithms, for this example. The MST requires four groups while ETG requires only three.

The ETG algorithm sorts the commodities in descending order by the number of hops in their routes and their bandwidth requirements (traffic demand). Our experiments during algorithm development showed that when the bandwidth required by each commodity is small, the sequence of commodities should be sorted by bandwidth requirements first, and then by number of hops. In this paper, if the average bandwidth required is less than 0.4 wavelengths, we sort by bandwidth first, and then by number of hops. Otherwise we sort by number of hops first.

Table 2. The set of commodities and link bandwidth in the groomed groups.

MST			ETG		
Set of commodities	Joint edge	Link bandwidth	Set of commodities	Joint edge	Link bandwidth
C3 and C4	3→4	0.8	C0, C1 and C2	2→3	0.9
	4→5	0.8		3→4	0.8
C0 and C2	2→3	0.9	C3 and C4	3→4	0.8
C1		0.4		4→5	0.8
C5, C6 and C7	6→7	0.6	C5, C6 and C7	6→7	0.6
	7→8	0.6		7→8	0.6

In table 1, the set of commodities has the average traffic demand of 0.375 which is less than 0.4 wavelengths. Therefore, the sequence of commodities is sorted in descending order first by the bandwidth requirements and then by the hop count as shown in table 3.

Table 3. The groomed commodities.

Commodity	Traffic demand	Number of hops	Group ID.
0	0.5	3	0
1	0.4	3	0
2	0.4	2	0
3	0.4	2	1
4	0.4	2	1
5	0.3	2	2
6	0.3	1	2
7	0.3	1	2

Maximum Degree First (MaxDF) Wavelength Assignment

We propose the Maximum Degree First (MaxDF) algorithm to assign a limited number of wavelength channels to a set of commodities. After we combine multiple low-rate traffic demands into groups in the traffic grooming phase described previously, we create a second auxiliary graph to specify which groups of commodities overlap, as shown in figure 5. A traffic group overlaps with another group if it has at least one commodity whose route overlaps with a member of the other group. For example, Group 0 overlaps with Group 1 because commodity1 in the Group 0 overlaps with commodities 3and 4 in the Group 1. In the auxiliary graph, the circle symbol represents a group, while the rectangle shows members in the group. The link between a pair of nodes represents the existence of an overlap. In figure 5, for example, we have three groups. Groups 0 and 1 overlap (i.e., at network edge 3→4 and edge 4→5 in Fig. 3). Therefore, a link between overlapping groups is created. Any pair of auxiliary nodes that has a link cannot be assigned to the same wavelength.

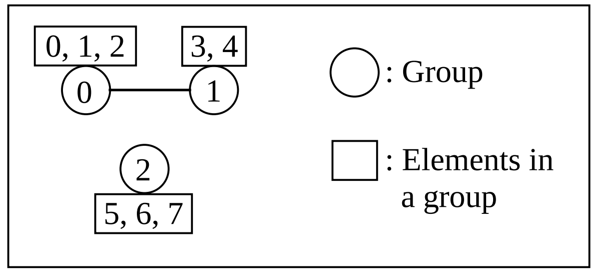

Fig. 5. The auxiliary graph of overlapped commodities in the group.

We modify the traditional First-Fit algorithm (Banerjee and Sharan, 2004) that assigns the wavelength from smallest channel index to the highest channel index. In our algorithm, we assign the wavelength according to the auxiliary graph. A node in the auxiliary graph that has a high degree represents a group that overlaps with others. Therefore, the maximum-degree node (group of commodities) in the auxiliary graph should be assigned first. If low degree nodes in the auxiliary graph are selected and assigned first, many other commodities in the group will be blocked. The MaxDF algorithm can be presented as follows.

Maximum Degree First (MaxDF) Algorithm

1. Sort all nodes (groups of commodities) by the number of degrees from the largest degree to the smallest degree.
2. At the first rank (largest number of degree, or highest overlapped group of commodities with the other), assign the first wavelength.
3. At the next group of commodities, if its commodity is not overlapped with the previous groups of commodities, assign the same wavelength channel as the previous group of commodities, else assign the next wavelength.
4. Repeat Step 3, until all groups of commodities are considered.

After the MaxDF process, we have the set of commodities in the group with wavelength channels as shown in figure 6. For instance, channel 0 is assigned to Groups 0 and 2 because none of the commodities in these groups overlap. The commodities in the group also have the same wavelength channel as shown in figure 7.

Group ID	0	1	2
Wavelength Channel	0	1	0

Fig. 6. The wavelength channel of the set of groups.

Commodity	0	1	2	3	4	5	6	7
Wavelength channel	0	0	0	1	1	0	0	0

Fig. 7. The wavelength channel of the set of commodities.

Our previous work (Leesutthipornchai *et al*., 2009) compared the performance of our routing algorithm with the traditional routing approach called Fixed Alternate Routing (FAR) and our wavelength assignment algorithm with the traditional wavelength assignment called First-Fit (FF). That study showed that our combined routing and wavelength assignment algorithms can assign the wavelength as fast as the First-Fit algorithm but with superior results in terms of accepted commodity requests.

NSGA-II Algorithm

Our GA-ETG-MaxDF algorithm generates many possible solutions, which tradeoff between our multiple objectives. We need to identify the best solution candidates in this large solution set. To do this, we employ the NSGA-II algorithm.

The Fast Non-dominated Sorting Genetic Algorithm (NSGA-II) proposed by Deb *et al*. (2002) is well-known as an efficient technique to search for the Pareto-optimal set in general multi-objective optimization problems. NSGA-II is a very fast algorithm that can rapidly converge to the Pareto-front. In this paper, we adapt the NSGA-II for the multi-objective grooming, routing and wavelength assignment (GRWA) problem as shown in figure 8.

The algorithm starts with population initialization. The five shortest paths for each commodity are created as a starting point. More possible paths are randomly generated, up to the specified population size, which was 200 in this study. The initialization stage produces multiple sets of routes, each of which represents a possible routing solution for the given set of commodities and bandwidth requirements.

In the next stage, which is used for traffic grooming, multiple low rate traffic demands are assigned to the same group to conserve wavelength channels and reduce the number of switching ports. We consider three traffic grooming algorithms which are Extended Traffic Grooming (ETG), Maximizing Resource Utilization (MRU) and Maximizing Single-hop Traffic (MST).

In the third stage which is used for wavelength assignment, non-overlapped groups are assigned to the same wavelength channel. After this wavelength assignment procedure, the number of accepted commodities, wavelength channels and switching ports are calculated. The number of required switching ports and wavelengths depend on whether a commodity is accepted or not. We consider three wavelength assignment methods which are First Fit (FF), Minimum Degree First (MinDF) and Maximum Degree First (MaxDF).

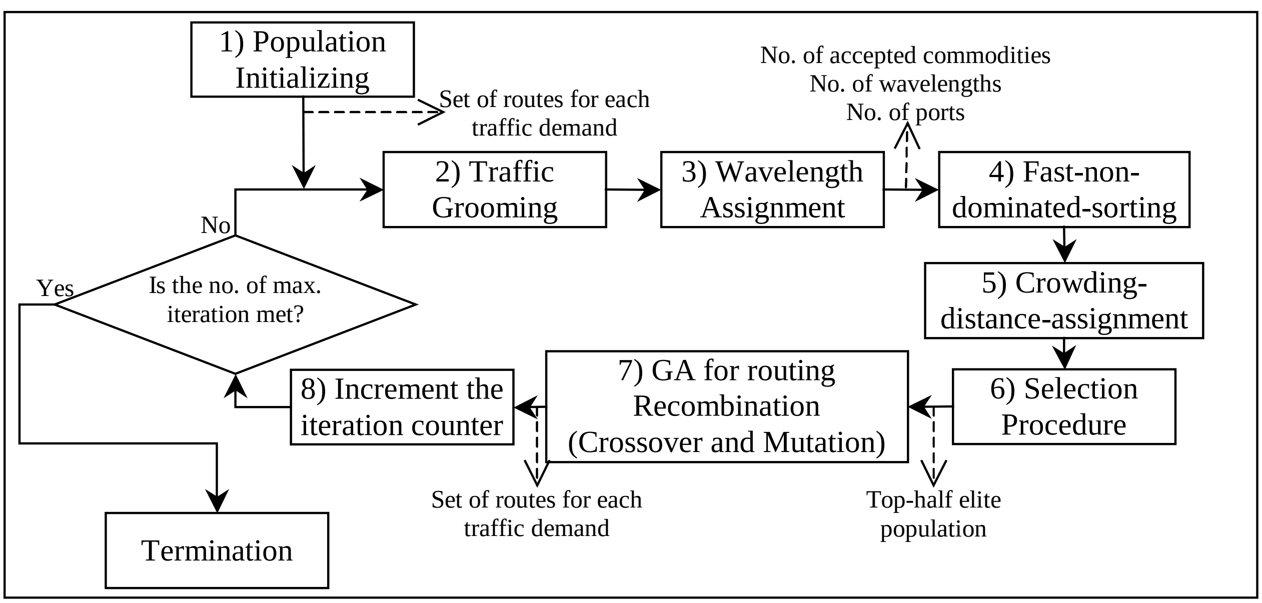

Fig. 8. The modified NSGA-II procedure.

Table 4. The features of various network topologies.

Network topologies	No. of (non-directional) edges	No. of nodes	No. of edges/ No. of nodes	Degree			
				Total deg.	Average deg. (Total Deg./ No. of nodes)	Min deg.	Max deg.
NSFNET	21	14	1.5	42	3	2	4
CHNNET	27	15	1.8	54	3.6	3	5
ARPANET	32	20	1.6	64	3.2	3	4

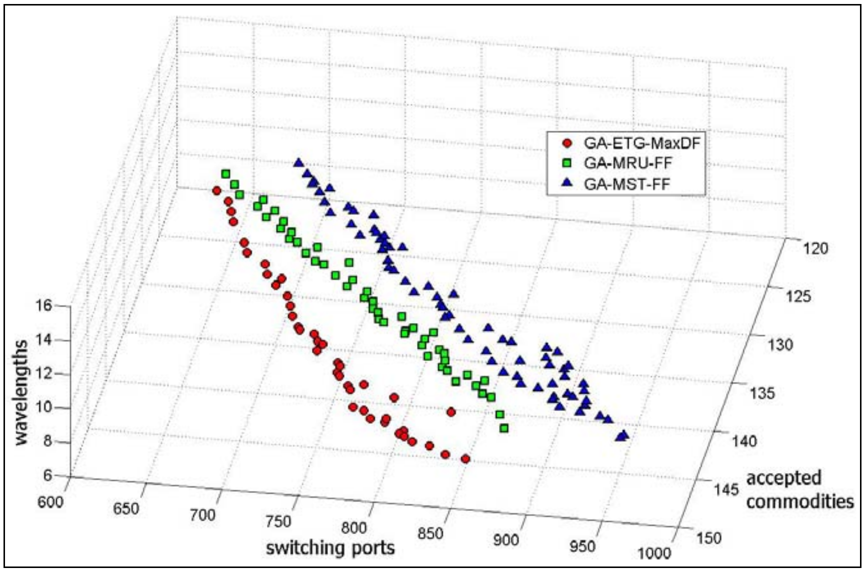

Fig. 9. The non-dominated solutions obtained from NSFNET.

Next, the potential solutions are sorted by solution quality and the best 50% are preserved for the next generation.

After sorting and selection, multiple sets of routes are exchanged and mutated in order to obtain new feasible routes that do not exist in the current population. Then the iteration counter is incremented. Lastly, the algorithm checks for the termination condition. In this paper, the algorithm is terminated when the maximum number of iterations is met, which in this case was 2,400.

RESULTS AND DISCUSSION

In our experiments, we considered the multi-objective GRWA problem with given network topologies, set of commodities and set of bandwidth requirements. We used a uniform distribution to randomly generate a set of test problems with various numbers of commodities and bandwidth requirements. We assumed that all edges have the same wavelength capacity. We limited the number of wavelength channels in each edge/link of the network and required at least 80% of the requested commodities must be accepted.

For our test network topologies, we adapted three different example networks which are National Science Foundation Network (NSFNET) with 14 nodes and 42 directional edges (Adhya and Datta, 2009), Chinese National Network (CHNNET) with 15 nodes and 54 directional edges (Guo *et al*., 2006) and Advanced Research Projects Agency Network (ARPANET) with 20 nodes and 64 directional edges. Table 4 summarizes the characteristics of these networks. CHNNET has the highest value of average degree (i.e., 3.6).

We implemented our algorithms with new own code in Java and ran our tests on a Pentium 4 PC (Core 2 Quad CPU 2.83 GHz, 3.25 GB of RAM).We compared our proposed GA-ETG-MaxDF heuristic with traditional traffic grooming algorithms and wavelength assignments methods which are 1) GA-MRU-FF (GA for routing, MRU for grooming and FF for wavelength assignment) and 2) GA-MST-FF (GA for routing, MST for grooming and FF for wavelength assignment). We used the same set of network configurations and traffic parameters for all traffic grooming algorithms. The obtained results were compared to each other as shown in figure 9-14.

In multi-objective optimization, the results are plotted as a front or set of non-dominated solutions. Table 5 also shows the multi-objective performance metrics and computation time obtained from each approach for various network configurations.

Our results show that the set of solutions from the GA-ETG-MaxDF is located in the area of high accepted commodities, few switching ports and few wavelengths, when compared with other algorithms. This is true for all network topologies as shown in figures 9-14. For the NSFNET topology, as shown in figures 9-11, the solutions from the GA-ETG-MaxDF require 626-860 switching ports while the solutions from the GA-MRU-FF and the GA-MST-FF require 632-886 and 680-962 ports, respectively. Figure 10 show that the GA-ETG-MaxDF technique can support 150 commodities within 860 ports. With the same number of ports, the GA-MRU-FF technique can support 145 commodities and the GA-MST-FF can support only 140 commodities. In other words, the GA-ETG-MaxDF requires a fewer number of switching ports compared with the GA-MRU-FF and the GA-MST-FF for satisfying all commodities.

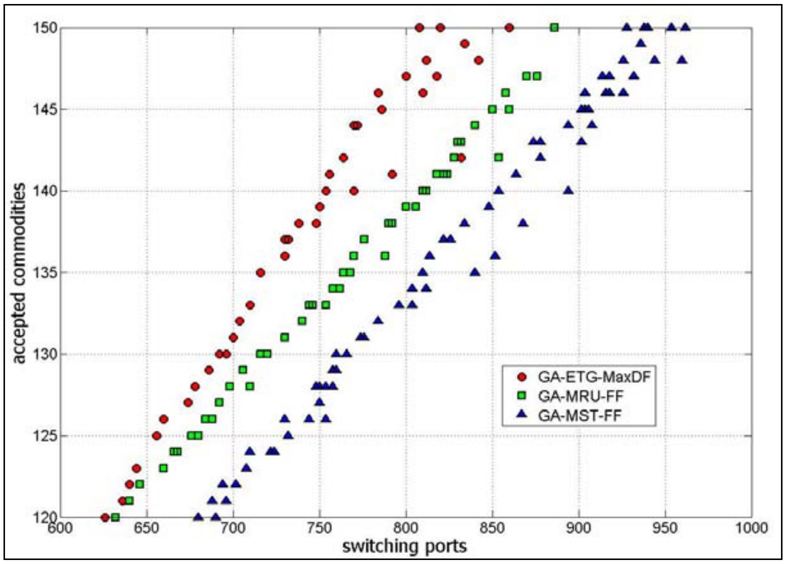

Fig. 10. The relation between accepted commodity and switching port obtained from NSFNET (with the number of wavelengths in the range of 6 to 15).

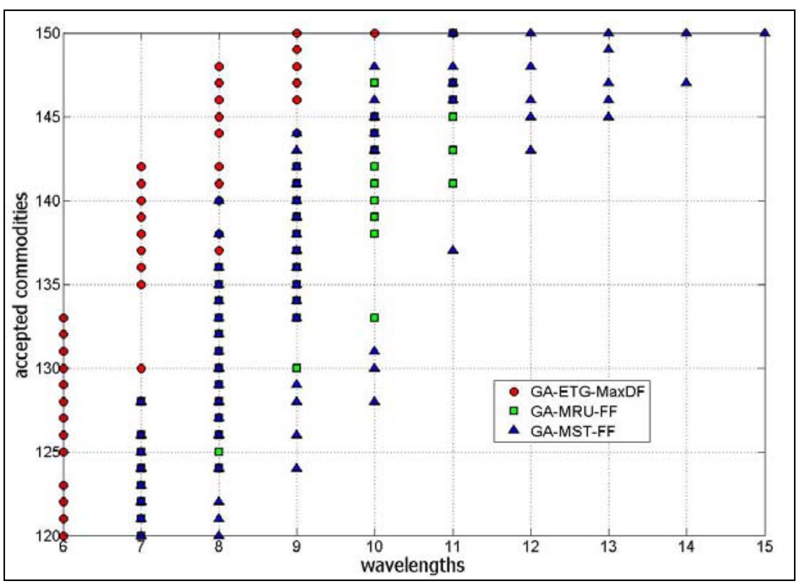

Fig. 11. The relation between accepted commodity and wavelength obtained from NSFNET (with the number of switching ports in the range of 626 to 962).

Figure 11 shows that the GA-ETG-MaxDF can support a larger number of accepted commodities than the GA-MRU-FF and the GA-MST-FF with the same number of wavelengths. To satisfy all commodities, the GA-ETG-MaxDF requires fewer wavelength channels than the GA-MRU-FF and the GA-MST-FF.

Similar patterns of results are obtained for the CHNNET topology as shown in figures 12 and 13, and the ARPANET topology as shown in figure 14.

In addition to the results shown in figures 9-14, we compared values of various multi-objective performance metrics (Zitzler, 1999; Tan *et al*., 2001; Nebro *et al*., 2009), namely Hyper-volume (HV), Spread, and Inverted Generational Distance (IGD). These metrics have been proposed to measure the "goodness" of a Pareto solution set, independent of the decision criteria functions.

Table 5 together with figures 15-17 show the obtained performance metrics of GA-ETG-MaxDF compared to GA-MST-FF and GA-MRU-FF.

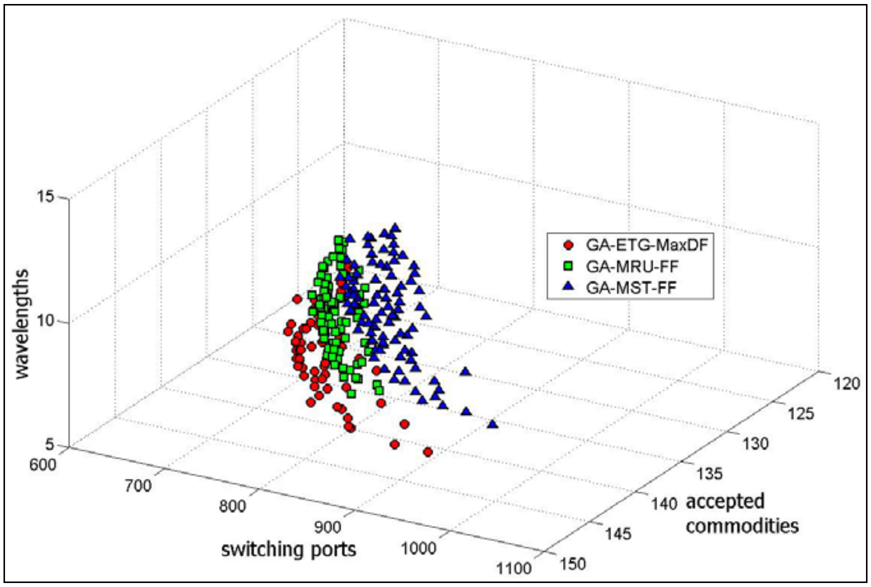

Fig. 12. The non-dominated solutions obtained from CHNNET.

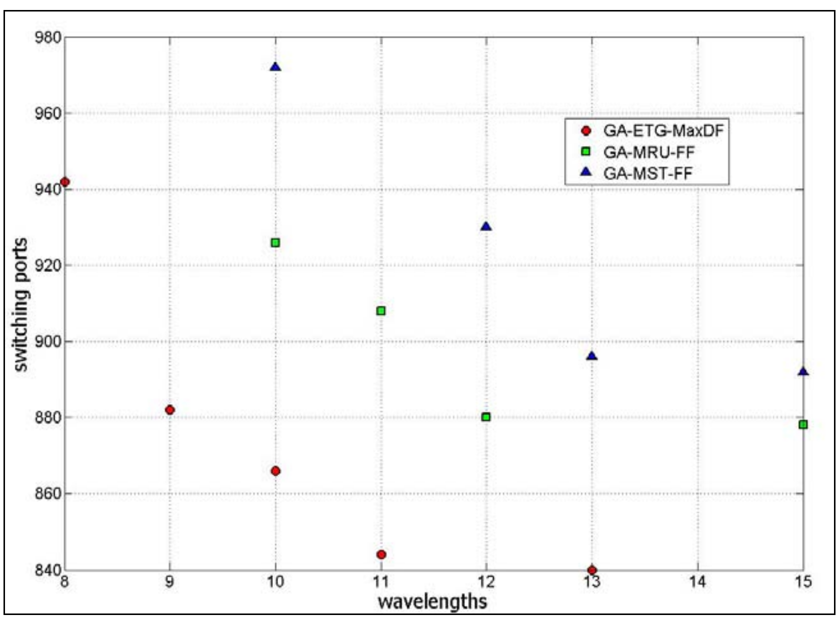

Fig. 13. The relation between switching port and wavelength obtained from CHNNET.

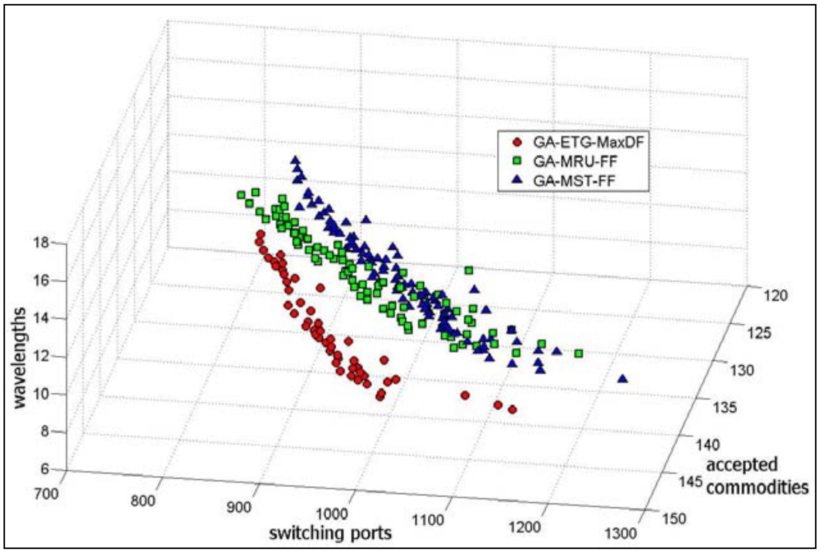

Fig. 14. The non-dominated solutions obtained from ARPANET.

Table 5. Multi-objective performance metrics of GA-ETG-MaxDF, GA-MST-FF and GA-MRU-FF in various network topologies.

Traffic demands (No. of source-destination pairs)	Network topologies	GRWA techniques	HV.	Spread	IGD.	CPU time (sec.)	
						Average*	Total
50	NSFNET	GA-ETG-MaxDF	**0.4701**	0.4262	**0.0000**	2,352.67	7,058.00
		GA-MST-FF	0.2684	0.4000	0.0556	2,320.00	6,960.00
		GA-MRU-FF	0.3333	0.3555	0.0317	2,300.33	6,901.00
	CHNNET	GA-ETG-MaxDF	**0.3677**	0.0692	**0.0000**	2,613.67	7,841.00
		GA-MST-FF	0.0129	0.8172	0.2411	2,561.00	7,683.00
		GA-MRU-FF	0.0839	0.6010	0.2308	2,548.00	7,644.00
	ARPANET	GA-ETG-MaxDF	**0.3825**	0.2685	**0.0000**	4,511.33	13,534.00
		GA-MST-FF	0.2235	0.4654	0.0494	4,433.00	13,299.00
		GA-MRU-FF	0.2497	0.4619	0.0487	4,428.33	13,285.00
100	NSFNET	GA-ETG-MaxDF	**0.5085**	0.4084	**0.0062**	8,606.33	25,819.00
		GA-MST-FF	0.1738	0.5213	0.0525	8,591.33	25,774.00
		GA-MRU-FF	0.3181	0.5411	0.0330	8,594.00	25,782.00
	CHNNET	GA-ETG-MaxDF	**0.5826**	0.4244	**0.0051**	9,713.67	29,141.00
		GA-MST-FF	0.4142	0.3532	0.0195	9,602.67	28,808.00
		GA-MRU-FF	0.5154	0.3482	0.0130	9,584.00	28,752.00
	ARPANET	GA-ETG-MaxDF	**0.4875**	0.4170	**0.0000**	16,860.33	50,581.00
		GA-MST-FF	0.2120	0.4557	0.0384	16,728.33	50,185.00
		GA-MRU-FF	0.3230	0.4238	0.0270	16,729.00	50,187.00
150	NSFNET	GA-ETG-MaxDF	**0.5064**	0.5124	**0.0000**	19,265.33	57,796.00
		GA-MST-FF	0.1522	0.5412	0.0502	19,249.67	57,749.00
		GA-MRU-FF	0.2704	0.4818	0.0369	19,269.00	57,807.00
	CHNNET	GA-ETG-MaxDF	**0.5884**	0.4832	**0.0051**	21,544.00	64,632.00
		GA-MST-FF	0.3420	0.4709	0.0245	21,400.00	64,200.00
		GA-MRU-FF	0.4955	0.4894	0.0127	21,254.33	63,763.00
	ARPANET	GA-ETG-MaxDF	**0.4859**	0.4830	**0.0098**	37,212.67	111,638.00
		GA-MST-FF	0.2106	0.4953	0.0346	37,218.67	111,656.00
		GA-MRU-FF	0.2558	0.4972	0.0288	37,187.67	111,563.00

*per 1 replication run

Hyper-Volume (HV) measures the coverage area of solutions. A high HV value is preferred, since this indicates that the non-dominated solutions cover the objective space more broadly. Table 5 and figure 15 show that the solutions from the GA-ETG-MaxDF give a higher HV value than those of GA-MRU-FF and GA-MST-FF in all network topologies and all cases of traffic demands.

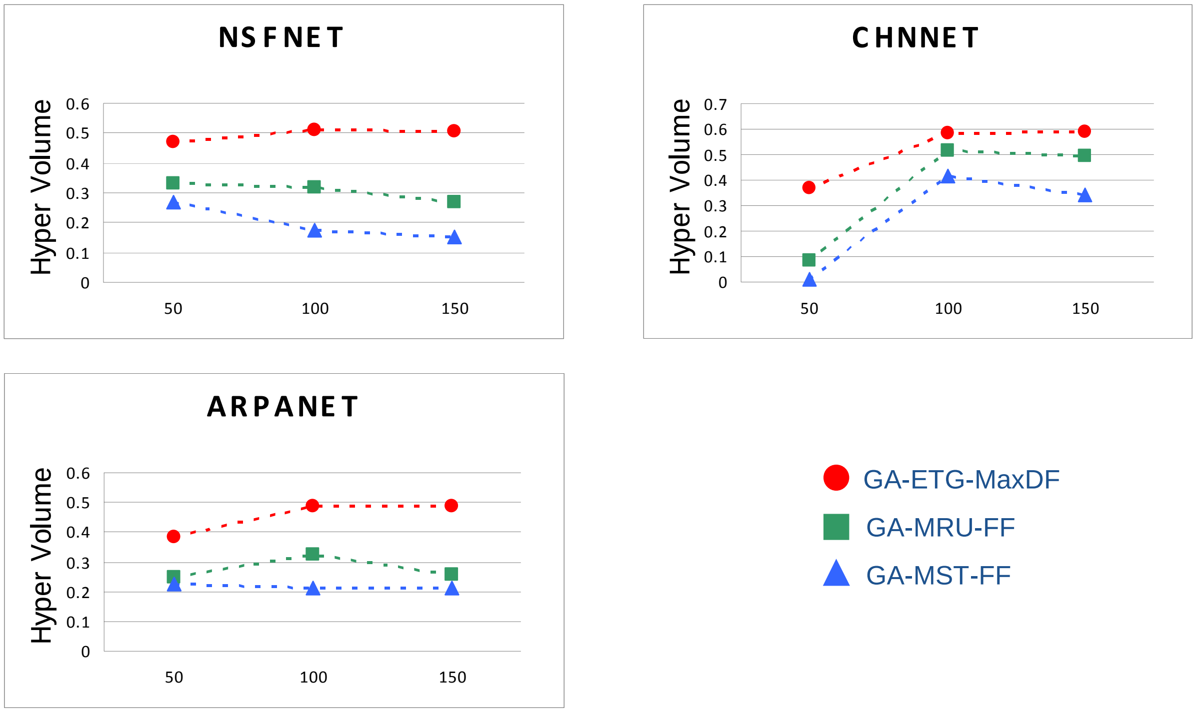

Fig. 15. Hyper-volume of traffic grooming algorithms with 50, 100 and 150 commodities for three network topologies.

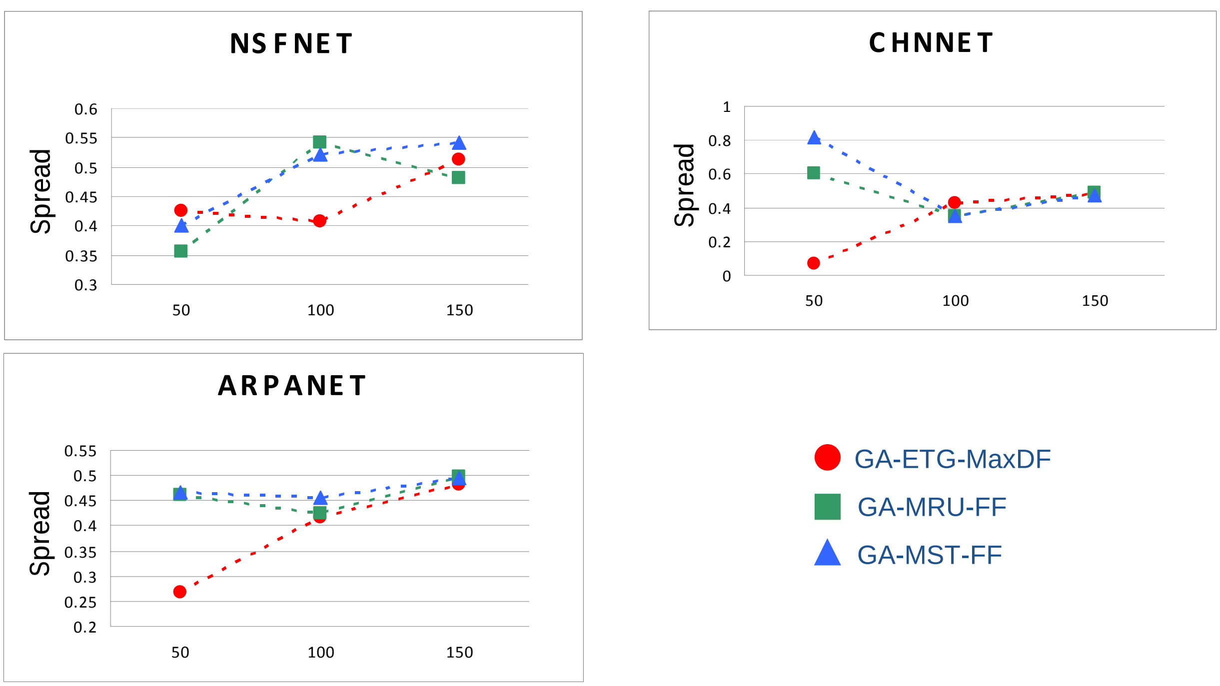

Fig. 16. Spread of traffic grooming algorithms with 50, 100 and 150 commodities for three different network topologies.

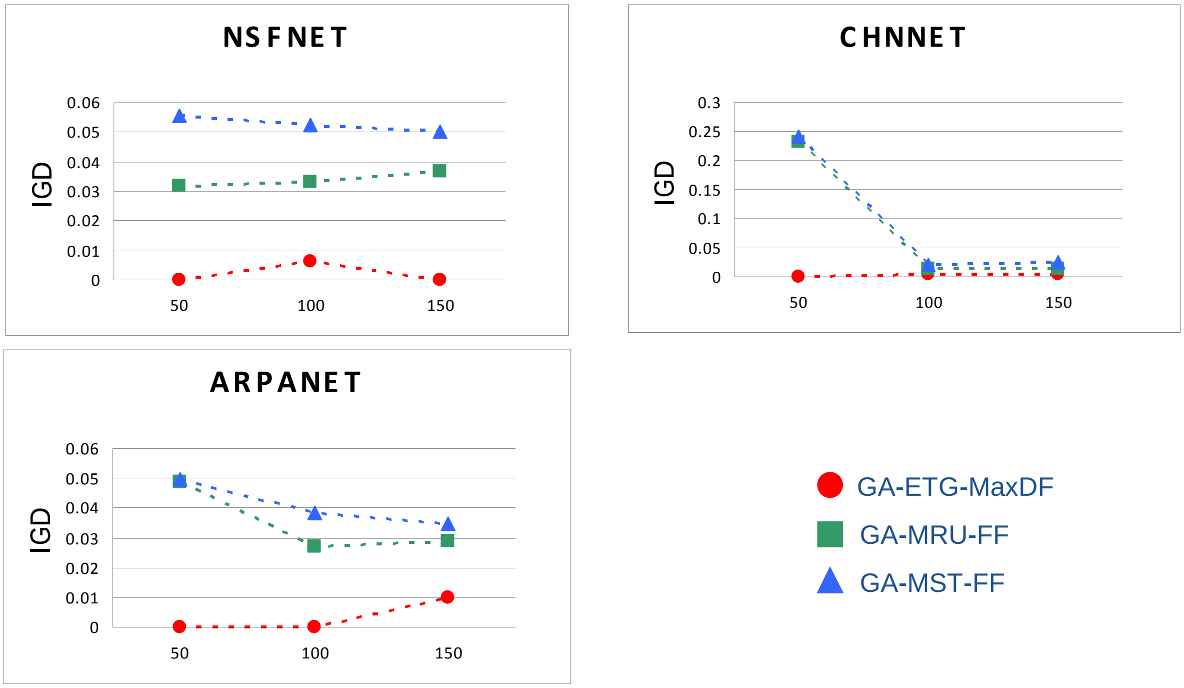

Fig. 17. IGD of traffic grooming algorithms with 50, 100 and 150 commodities for three different network topologies.

For the Spread metric, a low value is preferred. Low Spread values indicates that the solutions distribute into all objective areas equally (not crowding into one small objective area). In our experimental results, the Spread values from the three traffic grooming algorithms do not show any consistent patterns for NSFNET or CHNNET. However, for the ARPANET topology, the obtained results from our GA-ETG-MaxDF approach have lower Spread values than alternative approaches for all sizes of traffic demand as shown in figure 16.

Inverted Generational Distance (IGD is the distance from the obtained solutions to the Pareto optimal set. Lower IGD values indicate better solution quality. IGD is equal to zero when all elements are in the Pareto optimal set. Table 5 and figure 17 show that the results from our GA-ETG-MaxDF approach have lower IGD values than alternative approaches for all sizes of traffic demands and all network topologies. In some cases, such as for NSFNET topology with 150 commodities, the IGD value from GA-ETG-MaxDF is equal to 0. This means that all obtained solutions from GA-ETG-MaxDF are in the Pareto optimal set.

Finally, table 5 also shows the average and total CPU time of the three traffic grooming algorithms used to find solutions indifferent network topologies and traffic demands. The average and total CPU time of the three traffic grooming algorithms do not differ in any consistent way. These times are acceptable for offline computation.

In summary, the experimental results demonstrate that the GA-ETG-MaxDF heuristic outperforms both the GA-MST-FF and the GA-MRU-FF for solving the GRWA problem with a variety of network topologies and levels of demand. The solution sets produced by the algorithm also tend to score higher on measures of Pareto optimality.

CONCLUSION

In this paper, the Traffic Grooming, Routing and Wavelength Assignment (GRWA) problem in WDM optical network is addressed with a multi-objective network optimization approach. Our network design objectives are to maximize the number of accepted commodities, minimize the number of required wavelengths and minimize the number of switching ports. We propose a heuristic multi-objective solution procedure which combines GA-ETG-MaxDF and NSGA-II algorithms to solve the GRWA problem and search for a set of non-dominated solutions. The GA-ETG-MaxDF considers all potential routes by using Genetic Algorithm (GA), combines multiple low rate traffic demands with Extended Traffic Grooming (ETG) algorithm, and assigns the wavelength channel by using Maximum Degree First Wavelength Assignment (MaxDF) algorithm. The GA-ETG-MaxDF heuristic allows multiple non-overlapped commodities to be groomed into the same group which results in better utilization of network resources. We compared the performance of our proposed GA-ETG-

MaxDF approach with previously published traffic grooming algorithms, MST-FF and MRU-FF. All traffic grooming approaches used the same GA process for route generation and NSGA-II for searching non-dominated solutions. The results showed that the proposed GA-ETG-MaxDF heuristic together with NSGA-II algorithm outperforms the other two traffic grooming algorithms by providing a set of non-dominated solutions with a higher number of accepted commodities, fewer switching ports and fewer wavelength channels. We also compared all three traffic grooming algorithms by using the multi-objective performance metrics of Hyper-volume (HV), Spread and Inverted Generational Distance (IGD). We found that the results from the GA-ETG-MaxDF were generally superior to those from the existing traffic grooming approaches. Therefore, we are confident that the GA-ETG-MaxDF technique with NSGA-II algorithm is effective for solving the GRWA problem with multiple design objectives. Our research work makes several contributions as follows. 1) We have formulated the traffic grooming, routing and wavelength assignment (GRWA) problem in WDM optical networks as a multi-objective optimization model. 2) We have developed an effective technique called "GA-ETG-MaxDF" for solving the GRWA problem. 3) We have applied the state-of-the-art NSGA-II approach together with the GA-ETG-MaxDF technique as a multi-objective evolutionary computation heuristic to solve the multi-objective GRWA network design problem.

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