CHAPTER 1 INTRODUCTION

1.1 Overview of Multi-Objective Grooming, Routing and Wavelength Assignment Problem

In Wavelength Division Multiplexing (WDM) optical networks, the optical data stream is typically encapsulated into a "lightpath". Each traffic demand (connection or commodity) needs the lightpath to transmit the information from one source to a destination. An optical fiber link can be split into multiple channels. Recent dense wavelength division multiplexing (DWDM) contains 160 wavelength channels per fiber [1]. The wavelength channels are identified by the length of the wave. In current optical technology, the data rate of a wavelength is 2.5 to 10 Gigabits per second while 40 Gigabits per second has been proposed [2] to be commercially available. Thus one channel can carry a huge bandwidth. In practice, the traffic demands are typically with a low rate (sub-wavelength) of a wavelength channel and the number of wavelength channels is limited on each logical link.

Traffic grooming is the process of combining multiple low rate traffic demands into single channel. Traffic grooming can be considered as a Grooming, Routing and Wavelength Assignment (GRWA) problem. GRWA is comprised of three sub-problems: grooming or grouping, routing and wavelength assignment. Grooming combines multiple low rate traffic flows into one channel. We denote a source-destination node pair with traffic demand as a "commodity" [3]. Routing assignment allocates the route of lightpath to each traffic flow in a given set of commodities. The incoming commodities have to occupy an available wavelength channel for transmitting and receiving information. The channel assignment procedure is called wavelength assignment.

Grooming, routing and wavelength assignment are interrelated. An effective wavelength assignment is needed to have the optimal groups of multiple low rate traffic demands. An optimal grooming solution is also needed to have the optimal routing. Typical GRWA is considered as a combination of traffic routing and wavelength assignment [1, 16-17]. The problem is to find and optimize routing and wavelength assignment with multi-commodity flows. The low rate traffic streams are multiplexed into a single lightpath to improve the bandwidth efficiency. Traffic grooming and routing are simultaneously considered in order to select which traffic flows can be multiplexed by bundling the low-rate network flows into a single lightpath.

The GRWA problem requires assigning a limited number of channels to many lightpath connections in the overlap time of connections. The network has to support multiple connections at the same time. Several design objectives can be considered in the GRWA problem. In 2002, Zhu and Mukherjee [4] considered using GRWA to improve network throughput and reduce the network cost. In 2003, Zhu and Mukherjee [5] also proposed GRWA to reduce the grooming device cost while all traffic demands must be served. In 2007, Awwad et al. [1] designed GRWA to minimize total cost of grooming and conversion equipment. Later in 2009, Shen and Tucker [6] proposed GRWA to maximize the served traffic demand and minimize the wavelength capacity. The GRWA problem has many design approaches such as design for minimizing bandwidth consumption, design for minimizing network resource or network cost, or design for maximizing network throughput (accepted commodities). In a network design problem, it could happen that multiple functions influence the decision of which option to select. Each of the functions may conflict with the other functions. For example, when a function is optimized, the other functions may get worse [7, 8].

Multi-objective Evolutionary Algorithms such as Strength Pareto Evolutionary Algorithm (SPEA2) [9] and Fast Non-dominated Sorting Genetic Algorithm (NSGA-II) [10] have previously been proposed for solving multi-objective problems. This dissertation considers a multi-objective GRWA problem by optimizing three objective functions i.e., maximizing the number of accepted commodities, minimizing the number of wavelength channels and minimizing the number of total switching ports. Maximizing accepted commodities normally requires a large number of wavelengths and switching ports. In contrast, minimizing the number of switching ports could cause a large number of commodities to be blocked or fewer commodities to be accepted. In this dissertation, we consider design objectives that are usually considered in the network design. The design objectives are to maximize throughput or profit and to minimize cost or resource consumption.

To solve this problem, we consider potential routes for a routing algorithm by using a Genetic Algorithm (GA) to combine multiple low rate traffic demands with Extended Traffic Grooming Algorithm (ETG) and assign the wavelength channel by using the Maximum Degree First Wavelength Assignment (MaxDF) algorithm. We then apply the NSGA-II to search for non-dominated solutions in terms of accepted commodities, required wavelength channels and required switching ports. The results are provided as a front or non-dominated candidates.

1.2 Research Statement

Our research aims to study and understand the concept of grooming, routing and wavelength assignment in WDM network design by considering multiple objectives and constraints. The design objectives are to maximize the number of accepted commodities, to minimize the number of wavelength channels and the number of switching ports subject to a limited number of wavelength channels available on each network link while at least a certain set of commodities (communication requests) must be accepted. Many design and optimization approaches are considered and evaluated for their effectiveness and drawbacks.

1.3 Scope of Work and Objectives

1. This study reports on backbone network equipment and the existing network topologies for grooming, routing and wavelength assignment in backbone network design and optimization. An efficient off-line traffic grooming technique is proposed and called "Genetic Algorithm for Routing, Extended Traffic Grooming and Minimum Degree First Wavelength Assignment".
2. Multiple network design objectives are considered with real-life conditions. The design objectives are to maximize throughput or profit and minimize network resources (wavelength channels and switching ports).
3. Network design and optimization approaches are discussed in terms of their main characteristics, effectiveness and drawbacks.
4. A pruning algorithm is developed for filtering the numerous solutions obtained from the multi-objective optimization algorithm.

1.4 Research Contribution

1. This study reports on grooming, routing and wavelength assignment (GRWA) in WDM optical network design and optimization.
2. Multiple design objectives are simultaneously optimized. The obtained results are compared with traditional approaches considering all design objectives, not just using one objective or one aggregated weight of multiple design objectives.
3. The GRWA design technique is investigated and various sets of communication demands are considered.
4. A practical model of GRWA design problem is proposed and solved with a new GRWA algorithm. The performance of the proposed GRWA model is compared with the results from the traditional GRWA approach.
5. The evaluation of our multi-objective optimization algorithm is conducted by comparing it with the traditional and efficient approaches (i.e. the Strength Pareto Evolutionary Algorithm, SPEA2 [10] and the Fast Non-dominated Sorting Genetic Algorithm, NSGA-II [11]).
6. Multiple grooming techniques (i.e., containment techniques, as specified in *Section 2.2*) are evaluated and compared. These techniques are considered and applied to explore various sets of non-dominated solutions.
7. The multi-objective GRWA design problem is solved and the compositions of all design objectives are provided as a front. A pruning mechanism is proposed to reduce numerous solutions from the multi-objective optimization algorithm (The final solution is selected from the non-dominated solutions in the front).

1.5 List of Publications

International Journal

- P. Leesutthipornchai, C. Charnsripinyo and N. Wattanapongsakorn, "Solving Multi-Objective Routing and Wavelength Assignment in WDM Network using Hybrid Evolutionary Computation Approach ", *Journal on Computer Communications,* 15 Dec 2010, Vol.33, No.18, pp.2246-2259.

International Conferences

- P. Leesutthipornchai, C. Charnsripinyo and N. Wattanapongsakorn, "Path Level Traffic Grooming Strategies for Multi-Objective Design in WDM Networks", *ECTI-CON 2010 Conference*, Chiang Mai, Thailand, May, 2010, pp.661-665.
- P. Leesutthipornchai, C. Charnsripinyo and N. Wattanapongsakorn, "Multi-Objective Traffic Grooming in WDM Network using NSGA-II Approach", *The 6th International Conference on Networked Computing (INC 2010)*, Gyeongju, Korea, May, 2010, pp.1-6.
- P. Leesutthipornchai, N. Wattanapongsakorn, and C. Charnsripinyo, "Multi-Objective Routing Wavelength Assignment in WDM Network using SPEA2 Approach", *The IEEE 9th international Symposium on Communication and Information Technology (ISCIT)*, Songdo-iFEZ ConvensiA, Incheon, Korea, September 28-30, 2009, pp.22-27.
- P. Leesutthipornchai, N. Wattanapongsakorn, and C. Charnsripinyo, "Multi-Objective Design for Routing Wavelength Assignment in WDM Networks", *The IEEE International Workshop on Network & Communications (NeCoM)*, Beijing, China, June 30-July 2, 2009, pp.1315-1320.
- P. Leesutthipornchai, N. Wattanapongsakorn, and C. Charnsripinyo, "Routing Wavelength Assignment in WDM Networks with Maximum Communication Demand", *The International Joint Conference on Computer Science and Software Engineering*, Phuket, Thailand, May 12-15, 2009.

National Conferences

- P. Leesutthipornchai, N. Wattanapongsakorn, and C. Charnsripinyo, "Solving Multi-Objective Routing and Wavelength Assignment in WDM Network using NSGA-II Approach", *The National Computer Science and Engineering Conference (NCSEC)*, Bangkok, Thailand, November 4-6, 2009, pp.134-139.
- P. Leesutthipornchai, N. Wattanapongsakorn, and C. Charnsripinyo, "Multi-Objective Optimization Techniques Based on Genetic Algorithm", *The National Computer Science and Engineering Conference (NCSEC)*, Bangkok, Thailand, November 4-6, 2009, pp.276-281.

1.6 Dissertation Roadmap and Outline

This report is organized in the same sequence that we did the research. First, we study the Routing and Wavelength Assignment (RWA) for WDM network design problem with a single objective because it is easy to implement and to compare with other approaches. Our problem is complicated and difficult to solve with the traditional method (e.g., Integer Linear Programming, ILP). Thus we consider meta-heuristic approaches. We decided to use the Genetic Algorithm approach (GA) because GA is a technique that is effective to solve complex problems. GA is applied to explore all possible cases of routing. In this step, we also develop our wavelength assignment algorithm and compare the result with the traditional wavelength assignment approach.

Second, the RWA with two objectives is considered. We found that the number of accepted commodities and number of wavelength channels conflict. Maximizing the accepted commodities normally requires a great number of wavelength channels. Therefore both accepted commodities and wavelength channels are considered as the design objectives. We start to solve multi-objective problem by using a simple method (i.e., Weighted-sum approach). We fixed the weight of both objectives equally (i.e., 0.5). In this step, we have to set up the set of weights before the algorithm is simulated. The obtained result depends on the set of weights.

Third, we combine the existing multi-objective algorithms (SPEA2 and NSGA-II) and our RWA algorithm together. Both SPEA2 and NSGA-II proved to be effective in searching for solutions to complex optimization problems. In this step, the obtained solutions are compared in the multi-objective context. We compare the obtained results from our multi-objective optimization algorithms with the results from the Weighted-sum approach considering various set of weights.

Fourth, we consider a complicated problem that is a traffic grooming or Grooming, Routing and Wavelength Assignment (GRWA) for WDM network design. The GRWA is more complicated than the RWA because the GRWA can combine multiple traffic demands in the same wavelength channel (i.e., the bandwidth requirement of the GRWA is less than 1 wavelength while the bandwidth requirement of the RWA is equal to 1 wavelength). In this step, the GRWA with two design objectives is considered. The obtained result from GRWA is compared with no-traffic grooming algorithm and then the results from four-containment techniques (the technique to combine multiple commodities into the same wavelength channel) are compared together. For our multi-objective comparison, performance metrics are used to indicate the quality of the obtained results.

Fifth, minimization of the number of switching ports in all-optical network environment is considered. This new objective is added to the two objective GRWA problem. In the fourth step, the number of switching port is calculated but is not considered as a design objective. A switching port is an equipment unit. The number of switching ports needed directly affects the performance of the traffic grooming algorithm and dynamically depends on the route and bandwidth requirement. In this step, the GRWA with three objectives is compared with traditional traffic grooming approaches (Maximizing Single-hop Traffic, MST and Maximizing Resource Utilization, MRU). The multi-objective performance metrics are used to indicate the quality of the obtained solutions.

Sixth, we consider solution filtering. Very often, there are many solutions obtained from a multi-objective optimization problem. It is difficult to select one or few interesting solutions. This dissertation studies and proposes a filtering technique to reduce the number of final solutions. We called the filtering technique as “Pruning mechanism”.

This dissertation is organized as follows. In the next chapter, we describe and review related work in traffic grooming, multi-objective network design and multi-objective optimization algorithms. Technical terms related to grooming, routing and wavelength assignment (GRWA) are described in *Section 2.1*. *Section 2.2* reviews various studies of GRWA problem. *Section 2.3* discusses multiple GRWA techniques. In *Section 2.4*, research in multi-objective optimization problems in recent years is discussed. In *Sections 2.5-2.6*, several multi-objective algorithms are studied and evaluated in terms of effectiveness and drawbacks.

In *Chapter 3*, we summarize our previous Routing and Wavelength Assignment (RWA) work. In *Sections 3.1-3.2*, our previous RWA work is introduced and reviewed. In *Section 3.3*, RWA design problems and their essentials are described. This section contains the formulation of the multi-objective mathematical model that optimizes multiple objectives and constraints. In *Section 3.4*, the algorithm for solving the RWA problem is presented. In *Section 3.5*, a simple pruning approach (i.e., K-means) is applied for reducing the number of solutions. *Section 3.6* displays the experimental results in RWA. *Section 3.7* concludes our previous work.

In *Chapter 4*, we present the multi-objective traffic grooming problem and its design model. A three sub-problem design approaches consisting of routing of lightpath, combining multiple low rate traffic demands and wavelength assignment will be described. In *Section 4.1*, GRWA design problems and their essentials are described. This section contains the problem statement for multi-objective GRWA design. In *Section 4.2*, we formulate a multi-objective mathematical model that optimizes multiple objectives and constraints.

In *Chapter 5*, we present the GRWA heuristic algorithm for the WDM optical network design problem. We also present the NSGA-II approach used for obtaining solutions in multi-objective GRWA problem. In *Section 5.1*, we present our traffic grooming algorithm (GA-ETG-MaxDF or GA-EMF). In *Section 5.2,* the dominant based multi-objective optimization algorithms used in this dissertation are applied to solve the multi-objective GRWA problem as described.

In *Chapter 6*, we present our filtering mechanism to reduce the number of non-dominated solutions.

In *Chapter 7*, the results of our traffic grooming algorithm and the traditional approaches are discussed. The obtained results are compared in both single and multi-objective context.

Lastly, *Chapter 8* concludes our research work and summarizes our contributions.

CHAPTER 2 RELATED WORK

2.1 Technical Terminology in Grooming, Routing and Wavelength Assignment

This dissertation considers a GRWA in both physical and logical network topology. In the GRWA problem, there are many technical terms. This section defines technical terms and their logical functions used in this research.

Edge and Vertex

Edge represents a physical link of the network. Vertex represents a physical node of the network.

Node and Link

Node represents a logical node of the network, and link represents a logical link of the network.

Connection, Traffic Flow and Commodity

Connection, Network Flow and Commodity are used in this research. They have the same meaning and are interchangeable. We denote a source-destination node pair with traffic demand as a "commodity" [3]. Each incoming commodity needs an available wavelength channel for transmitting and receiving information.

Route and Lightpath

GRWA allocates a lightpath to each traffic flow (commodity) in a given set of commodities. A lightpath means a logical route. For example, in Figure 2.3(a), the physical route of the commodity from node A to node D is A→B→D. This route has a lightpath that is A→D. Each commodity has one or more lightpath(s). For the case of connection A to E, the route is A→B→D→E while this connection is assigned to use 2 lightpaths that are A→D and D→E. Two lightpaths mean that this connection has to be set up two times (add to the lighpath A→D at node A and drop from the lightpath A→D at node D and then add to the new lightpath D→E at node D and drop from the lightpath D→E at the destination node E). The conditions for setting up a lightpath are reviewed and discussed in *Section 2.3*. Grooming is the mechanism that allows many connections, traffic flows, or commodities to be multiplexed into a lightpath.

Wavelength Channel

The (dense) wavelength-division multiplexing (DWDM or WDM) splits the available frequency spectrum into a set of independent channels. WDM separates the optical spectrum into coarser units called "wavebands" and then the wavebands are divided into wavelength channels [5]. A given fiber is split to carry the traffic demands on various wavelength channels. The wavelength channel has its unique and individual length of light wave or frequency of the light wave [41]. The wavelength channels are usually denoted by λ (lamda, where the wavelength of each lightwave which is unique) such as $\lambda_1, \lambda_2, \lambda_3$ and so on. The subscript 1, 2, 3 each represents the channel index of the wavelength channels.

Wavelength Bandwidth

An optical fiber is split into multiple wavelength channels. One wavelength channel carries an amount of bandwidth, designated as OC-1, OC-3, OC-12 or OC-48[1]. For an example, suppose an optical fiber contains 160 wavelength channels [1] and the wavelength channel capacity is OC-48 (2.48 Gigabit per second) [45]. The total data rate is 396.8 Gbps while the wavelength bandwidth is 2.48 Gbps.

Wavelength Converter

Wavelength converter is an optical device that is used to convert a wavelength channel of the lightpath from one wavelength channel to another wavelength channel. For example, in Figure 2.3(b), the connection 3 from A to E is possibly changed from wavelength channel 1 to channel 2 by the wavelength converter at node D. Note that this example is considered to explain the functionality of a wavelength converter. In practice, all connections can be assigned with the same wavelength channel. Connections 1 and 3 are groomed in lightpath A→D using wavelength channel 1 and Connections 2 and 3 are also groomed in lightpath D→E using wavelength channel 1.

[1] The bandwidth of an OC-n channel is approximately n*51.84 Megabit per second (Mbps) [4]

Transmitter, Receiver, Transponder and Transceiver

Transmitter is a device that is used to transmit information through a lightpath and receiver is a device that is used to receive the transmission data from a specified lightpath. A transponder functions as both a transmitter and a receiver. For example, in Figure 2.3(b), node A performs as a transmitter of both connections 1 and 3 while the receivers are located at nodes D and E in order to receive the transmission data from connections 1, 2 and 3. The transponder is located at node D because node D performs as both a receiver (of connections 1 and 3) and a transmitter (of connections 2 and 3). Transponder and transceiver are used interchangeably.

Switching Port

In an all-optical network, the switching unit provides an optical bypass at an intermediate node. The optical bypass provides a function for avoiding the optical-electrical conversion. The optical bypass is used to speed up transmission time. In a traditional network, the switching port drops the transmission signal to the electrical domain. The optical-electronic-optical switching (or OEO) has to operate at every node that the signal passes. OEO causes the network to have a high time delay and causes a bottle neck problem when converting the signal from optical to electrical domain, because electronic devices are slower than optical devices.

In this dissertation, switching units are categorized into two types, optical and electrical units. We called the optical unit an “optical port”, the electrical unit an “electrical port” and the both of them as “switching ports”. One optical port is required at every source and destination node. A pair of optical ports is required at each intermediate node (one for receiving and another one for transmitting). In addition, one electrical port is required at the source and destination nodes.

This dissertation studies a technique to combine multiple low rate traffic demands into one wavelength channel. The existing lightpath has to drop into the electrical domain for grooming with a new low rate traffic demand. The original lightpath splits into multiple lightpaths at the terminal node of the set of traffic demands in the combined group. The grooming procedure possibly occurs at every node. If grooming occurs, twice the number of electrical ports is required, one for dropping the signal from the optical to the electrical domain and the other one for adding the combined signal into the occupied wavelength channel.

In the traffic grooming procedure, a traffic demand can share resources (switching port and wavelength channel) with existing ones. However the traffic grooming has the disadvantage that a long network path must drop into the electrical domain many times for grooming with the other traffic demands. The long path of the grooming set will have high transmission delay compared to the no-grooming transmission time.

2.2 Traffic Grooming with Hybrid Optical-and-Electrical Switching

In 2003, Huang and Copeland [15] proposed that an all-optical network can bypass the signals in the optical domain as shown in Figure. 2.1. The all-optical network can reduce the transmission time at intermediate nodes by avoiding the OEO (Optical-Electrical-Optical) conversion. An OEO has high time delay and causes a bottle neck problem when converting the signal from the optical to the electrical domain because electronic devices are slower than optical devices. Although an all-optical network can bypass the signal at the intermediate nodes, traffic grooming requires an electrical unit at the source-destination nodes as shown in Figure 2.2.

In an all-optical network, we can set up the lightpath in various routes and multiple wavelength channels. For example, in **case 1**, no-traffic grooming, the required number of wavelength channels is equal to 2, one wavelength for one connection. The number of switching ports is 14 units (10 optical units and 4 electrical units). In **case 2**, traffic grooming, there is only one wavelength channel required and 10 switching ports (6 optical units and 4 electrical units). From nodes 2$\rightarrow$4, Commodities 1 and 2 (C1 and C2) are assigned with the same wavelength channel. The traffic grooming in **case 2** uses fewer wavelength channels and requires a lower number of switching ports than **case 1** with no-traffic grooming.

An optical port differs from an electrical port in the sense that the electrical port is required at source-destination nodes only while the optical port is required on all network nodes in the transmission path. In Figure 2.2 with traffic grooming, the number of transceivers is equal to 4 (one transmitter and one receiver of each lightpath, lightpaths 1→2 and 2→4) while summation of the number of electrical and optical switching ports is 10. Two optical ports are located at each intermediate node, one for receiving and another one for transmitting.

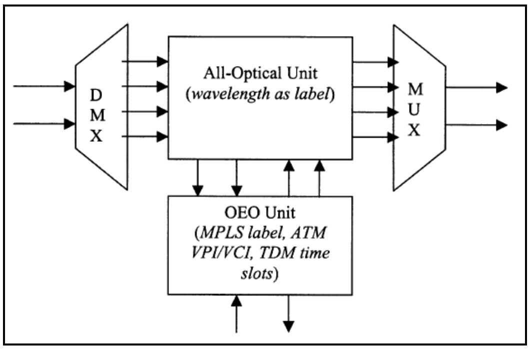


Figure 2.1 The network nodes in all-optical network [15]

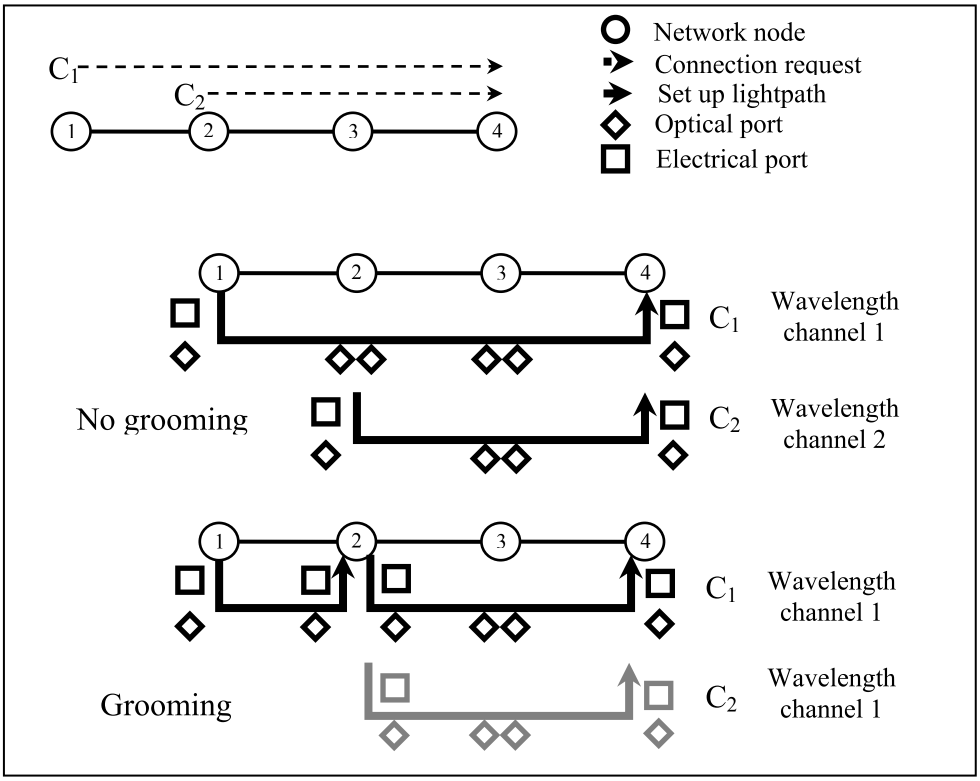
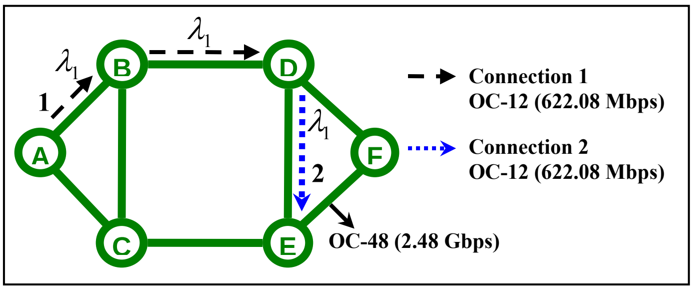
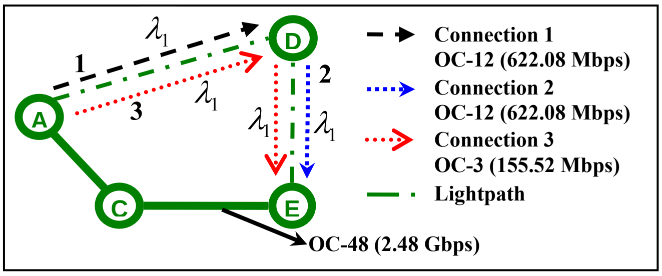


Figure 2.2 The number of switching ports used with and without traffic grooming approaches



(a) physical layer



(b) logical layer

Figure 2.3 An example of traffic grooming in WDM optical network [4]

The problem is that the number of wavelength channels and switching ports are limited on each logical link meanwhile each traffic demand typically has a low rate (sub channel). Thus it is necessary to reuse some channels in lightpath connections. One wavelength or a channel in a link can be used for only one lightpath but one lightpath can be multiplexed with many connections. Suppose we have a sample 6-node network as shown in Figure 2.3 and the three connections have to be set up in the network:

- Connection 1 from node A to node D with bandwidth requirement OC-12
- Connection 2 from node D to node E with bandwidth requirement OC-12
- Connection 3 from node A to node E with bandwidth requirement OC-3

The capacity of a wavelength channel is assumed to be OC-48[2] (2.5 Gbps approximately) [4]. Figure 2.3(a) illustrates the physical layer of a small 6-node network. In the logical network layer, two connections have already been set up. To reduce the number of wavelength channels in the network, we do not set up a connection number 3 directly from node A to node C and E. The connection number 3 has to be transmitted by using the spare capacity of the two existing connections as illustrated in Figure 2.3(b). Three connections are multiplexed into two lightpaths,

[2] The bandwidth of an OC-n channel is approximately n*51.84 Megabit per seconds (Mbps) [4]

A→D and D→E. Both lightpaths are set up to the wavelength channel 1, λ_1. The capacity of a wavelength channel is typically expressed as OC-N rate, e.g., N=48. The traffic grooming multiplexes multiple OC-M channels into one OC-N channel where M is smaller than or equal to N.

For grooming multiple connections into one lightpath, "containment techniques" are used to specify the aggregation behavior of multiple connections. The traffic aggregation strategies [14] can be categorized into four techniques (where we call "containment techniques"):

1. **Point to Point (P2P)**: This technique aggregates multiple traffic demands that have the same source and destination nodes to a single lightpath. Multiple low rate traffic demands are groomed into a single hop lightpath by using traffic grooming devices.
2. **Multi-point to Multi-point (MP2MP)**: This technique aggregates traffic demands with multiple sources and multiple destinations. This technique is efficient in term of resource sharing ability but causing lots of delay and has high switching cost (from multiple traffic grooming devices).
3. **Point to Multi-point (P2MP)**: This technique aggregates traffic demands from the same source to multiple destinations. P2MP requires higher number of de-multiplexing devices.
4. **Multi-point to Point (MP2P)**: This technique aggregates traffic demands from multiple sources to the same destination. MP2P requires higher number of multiplexing devices.

In practice, **MP2MP** technique is flexible for grooming multiple traffic demands into a lightpath. The connections can be groomed or multiplexed with the established lightpath at several source-destination nodes. MP2MP has the constraint that the groomed lightpath must not exceed the wavelength channel capacity. This technique is efficient in term of resource sharing potential and high number of accepted connections (low blocking probability) but the lightpath is assigned to pass many traffic grooming devices for multiplexing/de-multiplexing the new connection with the established lightpath. In Figure 2.4 (MP2MP), for grooming connection C_1 with the connection C_3, the lightpath must be converted into the electrical domain for combining connections C_1 and C_3.

MP2MP reduces the number of ports of traffic grooming devices but creates a high transmission delay for a long commodity. As shown in the figure, the MP2MP technique has 3 served connections and requires 8 switching ports.

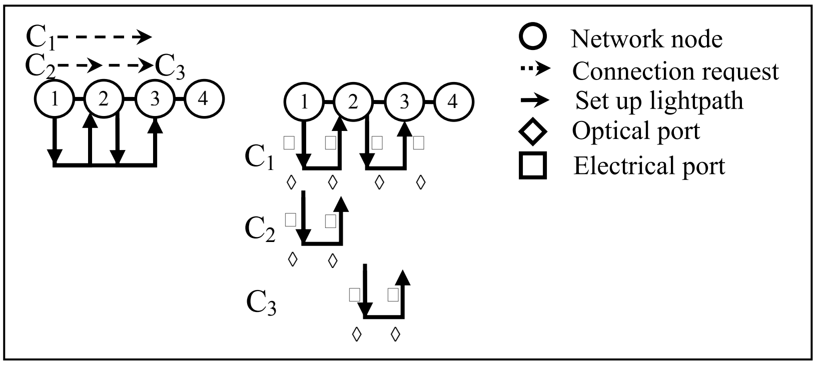


Figure 2.4 MP2MP containment technique [14]

This dissertation proposes to study traffic grooming with the MP2MP containment technique. The MP2MP technique uses fewer lightpaths and has higher wavelength utilization than the other techniques but the connections have to pass through many electrical units. Several connections can be groomed into the established lightpath at various intermediate nodes. Thus the longest connection in a lightpath has to pass through many electrical units for grooming with other connections. Multiple grooming in a lighpath leads to high number of switching ports. The large number of pass-through switching ports causes high transmission delay and transmission costs for the connections at the intermediate nodes. This dissertation considers traffic grooming, routing and wavelength assignment problem (GRWA) with multi-objective optimization design to maximize the number of accepted commodities, minimize the number of wavelength channels and minimize the number of switching ports.

2.2.1 Assumptions

1) The grooming procedure is performed only in the electrical domain.

2) This dissertation considers the grooming devices only in logical domain.

3) Only overlapped commodities are groomed together. The overlapped commodities represent two or more low rate commodities that can be assigned to use the same resource.

4) The set of traffic demands and bandwidth requirements must be available before applying the grooming technique.

2.2.2 Benefits and Drawbacks

Traffic grooming techniques are mainly used for reducing the number of switching ports because some traffic demands can share and use the same lightpath. Traffic grooming has the disadvantage that round-about or long network paths have to add and drop many times for grooming with other traffic demands.

2.2.3 Improvement from Traditional Algorithms

The conventional approaches, Maximizing Single-hop Traffic (MST) and Maximizing Resource Utilization (MRU) [4] techniques, combine multiple low-rate traffic demands according to the sequence of the requested demands. In general, two non-overlapped commodities are not integrated together. If there exists one commodity overlapping with two non-overlapped commodities while two non-overlapped commodities were previously considered in the earlier sequence, the incoming commodity can be groomed with only one of the earlier sequences. Two wavelength channels are required for the traditional cases. The sequence of traffic demands directly effects to the grooming result. We called this event as an "ordering obstruction" problem. The ordering obstruction problem means that an earlier sequence may cause the grooming criterion to require a new wavelength channel to support an incoming commodity while if the positions of them are exchanged, a new wavelength channel is not required.

In this dissertation, if a new commodity can be groomed with one or more of the previously considered commodities, they are combined together and the set of wavelength channels will be reassigned. By doing this, the number of wavelength channels and switching ports are decreased.

Our assumption is that multiple commodities are combined together, if they are overlapped. This dissertation tries to minimize the "ordering obstruction" problem. We proposed a new traffic grooming technique that potentially organizes a set of commodities into groups and then re-assigns the wavelength channel. In doing this, multiple non-overlapping commodities can be combined together using the same wavelength channels.

Traffic grooming in a ring network topology has been previously studied [2, 5]. In this dissertation, we consider grooming low-rate traffic demands in a mesh network topology [4, 17-18]. Traffic grooming in general mesh networks is difficult to solve optimally [5]. The traffic grooming techniques for solving the GRWA are reviewed and discussed. In the same source-destination of lightpath, several connection requests are either groomed or routed by the shortest path on the available wavelength channels in the virtual/logical link. If no resources are available to directly set up the lightpath between source and destination pair, the connection will avoid the direct lightpath and traverse on multiple indirect lightpaths. For example, if we are trying to save wavelength resources, the connection A to E cannot be assigned to the direct connection (i.e., A→E in Figure 2.3). The connection A→E traverses on indirect multiple lightpaths instead for saving the wavelength resource (i.e., A→D and D→E). The lightpath set up conditions (how the commodity route and set up its lightpath) are reviewed and discussed using various combining techniques as shown in *Section 2.3*.

2.3 Grooming, Routing and Wavelength Assignment Techniques

In 2002, Zhu and Mukherjee [4] proposed the grooming, routing and wavelength assignment techniques to improve the network throughput (i.e., to maximize the number of accepted commodities) subject to limited number of transmitters, receivers and available wavelength channels. The authors use the Maximizing Single-hop Traffic (MST) heuristic algorithm to assign multiple requested connections to a new lightpath. If the network has enough network resources (i.e., wavelength channel, transmitter, receiver, grooming device and wavelength converter), all requested connections can traverse on a single lightpath hop and the traffic delay will be minimized. If there are not enough network resources to support a new lightpath, the connection that is able to be established in a single hop lightpath will be selected to be set up first. Later, the connection with multiple lightpaths will be considered for establishment.

Zhu and Mukherjee [4] used the Maximizing Resource Utilization (MRU) heuristic algorithm to utilize limited network resources. The MRU approach is to set up a lightpath using available spare wavelength channels in the logical network links. In this stage, the connection requests will be assigned to multiple lightpaths. If the remaining connection requests can be groomed or multiplexed with the existing lightpath, the

MRU technique will groom those connections with the spare bandwidth in the lightpaths. The connection that is able to best utilize the network resource or use fewer established lightpaths will be selected to groom first.

In 2004, Hu and Leida [17] proposed a GRWA technique to minimize total number of transponders required in the network, subject to constraints of a limited number of wavelength channels in each fiber and each lightpath using the same wavelength channel for every link that it traverses (i.e., wavelength continuity constraint). Hu and Leida proposed that the number of transponders is twice the number of required wavelength channels (each transponder at the end of the lightpath). Thus minimizing the number of transponders is also minimizing the number of wavelengths. They solved their GRWA problem using a commercial tool called CPLEX 7.0 [17].

In 2005, Prathombutr et al. [18] proposed an algorithm for traffic grooming in WDM optical mesh networks with multiple objectives: maximizing the traffic throughput, minimizing the number of transceivers or lightpaths and minimizing the average propagation delay. They considered the GRWA problem with and without a wavelength converter. They applied the SPEA approach to search for a set of non-dominated solutions. The obtained results were compared with those from the previous algorithms, specifically MST and MRU [4].

In 2006-2007, Awwad et al. [1, 16] proposed a GRWA with sparse traffic grooming and wavelength conversion in a static traffic demand environment. They solved the GRWA in a WDM mesh network with sparse resources (i.e., some logical network nodes are able to groom while others are not). The design objective was to minimize the total equipment costs (i.e., traffic grooming and wavelength conversion equipment). The equipment in their research were 1) traffic grooming devices and 2) wavelength converters. A traffic grooming device performs both traffic grooming and wavelength conversion. The traffic grooming device functions are more complex than those of wavelength conversion device (i.e., multiplexing/de-multiplexing the connections and interchanging the wavelength channel of the lightpaths). The traffic grooming device has a higher cost than the wavelength conversion device. Both traffic grooming and wavelength conversion devices are deployed on the node based on the decision variables of the optimization based model [1]. Their GRWA implementation has no wavelength continuity constraint (i.e., multiple wavelength channels are able to use the same lightpath). Thus it significantly increases blocking probability. A Genetic Algorithm (GA) is applied to solve their GRWA problem. Their GA results are compared with those from their previous works including Most-contiguous (MC) heuristic algorithm, and Fixed Alternated Routing and First Fit Wavelength Assignment (FAR-FF) algorithm.

Table 2.1 The comparisons of GRWA researches in recent years

Previous research works	Features	Descriptions
Zhu and Mukherjee [4] (Sample 6-node network)	Problem	Maximize the network throughput
	Technique	Maximize Single-Hop Traffic (MST) and Maximize Resource Utilization (MRU)
	Benchmark	Comparing with the ILP in the small size 6 nodes network
	Discussion/Remark	Efficient and easy to implement
Hu and Leida [17] (30 nodes, 38 fiber span, 47 lightpaths and 242 traffic demands)	Problem	Minimize total number of transponders
	Technique	Integer Linear Programming (ILP)
	Benchmark	Using commercial tool CPLEX 7.0
	Discussion/Remark	Computationally intensive and cannot be solved with large-size network
Prathombutr et al. [18] (Sample 6-node network)	Problem	Maximize traffic throughput, minimize number of transceivers and minimize average propagation delay with and without wavelength converter
	Technique	Strength Pareto Evolutionary Algorithm
	Benchmark	Comparing with MST and MRU that were proposed in [4]
	Discussion/Remark	1) SPEA has a weakness that it does not have truncation operator. The solutions in the non-dominated front are randomly removed while SPEA2 removes the crowded solution first. 2) The efficiency of the alternative-based encoding string depends on the size of alternative routes.
Awwad et al. [1, 16] (16-node WDM mesh network)	Problem	Minimize the total network equipment cost (i.e., traffic grooming device and wavelength converter)
	Technique	Genetic Algorithms
	Benchmark	Comparing with previous work, Most-Contiguous (MC) heuristics and Fixed Alternate Routing and First Fit Wavelength Assignment (FAR-FF) algorithm
	Discussion/Remark	The efficiency of the algorithm depends on the alternative size of the route and enumeration matrix.
Shen and Tucker [6] (NSFNET 14-node network)	Problem	Maximize traffic demands and minimize required wavelength capacity subject to serving all traffic demands
	Technique	Virtual nodal degree ranked heuristic algorithm (the node with high traffic demands passed will be selected to place an opaque node first)
	Benchmark	Comparing with Mixed Integer Linear Programming (MILP)
	Discussion/Remark	1) Easy to scale for solving large network 2) The efficiency of the alternative-based encoding string depends on the size of alternative routes.

In 2009, Shen and Tucker [6] proposed the opaque node placement algorithm. An opaque node is a grooming device. They proposed the algorithm to select the best locations for opaque nodes. Their GRWA problem is to maximize served traffic demands (accepted connections) under a limited network capacity and minimize the required wavelength channel while all traffic demands are served.

Table 2.1 summarizes, compares and critiques the previous work in the GRWA domain.

Typically, previous research papers [1, 2, 4, 5, 17, 19] concentrated on traffic grooming with only one objective such as **improving the network throughput** or **minimizing the network resource utilization** (from wavelength channel, transmitter, receiver, traffic grooming device and wavelength converter). **The first aspect** is considered to maximize the network throughput (i.e., number of served connections, number of accepted commodities, or reduce blocking probability). In this objective, the network resources are usually insufficient to handle all traffic demands. In doing this, the solutions may have a problem with unbalanced load on the logical links. The traffic demands will crowd the shortest route and the middle located nodes. Long length or multi-hop traffic demand have a high probability to be blocked and consume a lot of bandwidth. Some logical links may be more congested and require a lot of network resources while some other logical links may not be. Corne et al. [20] specified that in the typically routing problem “the roundabout paths are lightly loaded”.

The second aspect is considered to minimize the network resources or network equipment cost (i.e., number of wavelength channels, number of transceivers, number of grooming devices, number of wavelength conversion devices, number of hop counts). In this objective, the network resources are efficiently utilized for a given traffic demand. This objective affects some traffic demands that have long length and require multiple lightpaths (i.e., require several adds and drops in multiple transmission nodes) because the resource is already used by previously served traffic demands. Transmission delay depends on hop count and grooming devices used. A high number of hops and grooming devices requires high number of OEO conversion equipments and causes high transmission delay. The multiple-lightpath (or multi-hop) connection has slow optical cross-connects (repeatedly switch from optical to electrical and electrical to optical or high OEO conversion) and requires various transmitters and receivers. The objective of traffic grooming design is to minimize network resources. This may cause some traffic demands to have high transmission delay (from multiple transmission, reception and conversion procedures). Some demands are blocked but all network equipment is equally used.

Previously, traffic grooming with multiple objectives was proposed [18] to maximize network throughput, minimize the number of transmitters and minimize the propagation delay. This dissertation improves this approach by converting from minimizing the number of transmitters to minimizing the number of switching ports. All connections require their switching ports to send and receive information. Electrical ports are required only at the source and destination nodes of the lightpath while an optical port is required at all nodes in the traversed transmission path.

This dissertation considers traffic grooming with multiple design objectives. It not only considers the number of switching ports but also considers the number of accepted commodities and wavelength channels. The number of switching ports corresponds to the transmission delay. A high number of passed switching ports requires high OEO conversion (high transmission delay). In previous traffic grooming with multiple design objectives, optical bypass switches were not considered. In this dissertation, the obtained results not only minimize the number of hybrid optical-and-electronic ports but also minimize the number of wavelength channels and maximize the number of accepted commodities.

2.4 Multi-Objective Network Design in Recent Years

The evolution of multi-objective network design starts from a network model that needs to optimize one objective function with many design constraints such as network design cost, limitation of maximum delay and network survivability requirement [21]. This approach has only one objective while the other requirements are expressed as design constraints. Researchers usually use advanced genetic algorithms to find the optimal solutions for their problems. Later, Assis et al [22] proposed a network design model that minimizes total link length and total number of hops, while maximizing link load simultaneously. This model has multiple objective functions. All objective functions are weighted into one function and then they optimize the single objective function following the design constraints. They use a mixed integer programming tool (CPLEX 10.0) to find the optimal solution. Kavian et al [23, 24] 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. Lastly, Banerjee et al [25] proposed a network design model to minimize total network cost (from nodes, links, and amplifier) and also minimize average delay. Their research also finds a set of optimal solutions using an advanced genetic algorithm but they search each solution with both objective functions simultaneously.

Moreover, some papers [26, 27] suggest that multi-objective network design can solve all objectives simultaneously by using parallel computing to find the best solution from all possible sets [26, 27]. Parallel computing distributes the possible sets into clusters and then combines the distributed results to get the best solution.

The multi-objective network design problem can be solved using an efficient optimization algorithm also. Multi-objective optimization is a technique to find the best solution from a huge number of possible solutions. Multi-objective optimization considers all objectives simultaneously. There are many multi-objective optimization approaches as described next.

2.5 Multi-Objective Optimization Techniques

Multi-objective network design which considers all objective simultaneously is very complex and requires lots of computation time but it has become important. There are many ways to optimize the network design problem such as integer linear programming [46, 47], dynamic programming [48], parallel computing [26], or meta-heuristic approaches [49-53]. Each of these approaches has its drawbacks and benefits. For solving multi-objective optimization problems, there are two basic directions, which are to solve in a single objective context and to solve in a multi-objective context as discussed in this dissertation. The multi-objective network design can be applied to design an effective computer network by considering all objective demands and all design constraints.

Multi-objective (MO) optimization is used to solve multiple objective design problems. The design problem can be expressed as many objective functions. In an actual problem it could happen that more than one function influences the decision of which option to select. These functions may conflict with each other. When a function is optimized, the other functions may become worse. In multi-objective optimizations, there are three possible requirements:

- Require to minimize all objective functions
- Require to maximize all objective functions
- Require to minimize some objectives and to maximize others.

The design problem needs to optimize multiple functions simultaneously. Commonly, the design objectives should be in the same direction such as minimizing all of them or maximizing all of them. To convert a maximum function to a minimum function, we usually multiply the function by negative one.

There are two approaches to optimize (minimize or maximize) many objective functions. Those approaches are optimizing in single objective context and optimizing in multi-objective context. Both of them are essential to find an optimal Pareto front in a combinatorial optimization problem. The popular MO techniques can be summarized as follows.

- Weight all objective functions and combine them into single fitness function (i.e., weighted-sum or aggregated function approach)
- Solve each objective individually by converting the other objectives to constraints and merge them as a union of the set (i.e., ε-constraints approach) [8]
- Search the solution space based on non-dominated solutions of all objectives (i.e., Pareto-dominance)

Comparisons of the above techniques are summarized in *Table 2.2*. These techniques are used to obtain a set of optimal solutions. The two most popular techniques are weighted-sum and Pareto dominance approaches. The weighted-sum technique is easy and straightforward to implement but it is very sensitive to the values of the weight parameters while the Pareto dominance technique is efficient to simultaneously compare the solutions that have several objectives.

Table 2.2 Comparisons of the multi-objective optimization approaches

Approaches	Advantages	Disadvantages
Weighted-sum (single objective context)	1) Easy to implement 2) Fast converge to the optimal solution	1) Weighted parameter is very sensitive. If no high level information on the significance of each objective is available, it is difficult to search for multiple trade-off solutions 2) Only one solution is obtained from one set of weights
ε-constraints (single objective context)	1) Fast converge 2) Efficient to search for the optimal solution in one objective direction	1) Difficult to merge a set of objective domains 2) The constraint thresholds are obtained from trial and error 3) The solutions trend to converge to the extreme of each objective
Pareto-dominance (multi objectives context)	1) Efficient to search for the solution in both the middle and the extreme of each objective 2) Maintain the nature of each objective function	1) Complex to implement 2) Computationally intensive

In real-life multi-objective problems, the objectives under consideration may conflict with each other. The objectives may be non-commensurable (meter, kg., piece, and etc.) and the relationships between them are not clear. Optimizing one with respect to a single objective often results in unacceptable results with respect to the other objectives. The perfect multi-objective solution that simultaneously optimizes each objective function is almost impossible.

A reasonable solution to a multi-objective problem is to investigate a set of solutions, each of which satisfies the objectives at an acceptable level without being dominated by any other solution. If the problem is analyzed in a multi-objective context, the result is shown as a set of optimal solutions (optimal Pareto front) for the different objective functions simultaneously. This dissertation considers using meta-heuristics to solve multi-objective optimization problems in a real-life multi-objective context.

In multi-objective optimization, Smith et al. [54] proposed the Dominance-Based Multi-objective Simulated Annealing approach. They define the set of possible solutions, both dominated and non-dominated solutions. When the number of possible solutions increases, it is difficult to find good solutions because the search space is huge. Coit et al. [7, 28] proposed a solution using Pareto optimal solutions to optimize all objectives simultaneously. Their approach considers only non-dominated solutions by cutting off all dominated solutions using Pareto's principle. This dissertation attempts to develop an efficient multi-objective optimization algorithm to obtain non-dominated solutions. The non-dominated solutions are expressed as a set of possible solutions, called Pareto optimal set. All of the best solutions are in the Pareto optimal set.

If all objective functions are to be minimized, a feasible solution x is said to non-dominated another feasible solution y if and only if $f_i(x) \leq f_i(y)$ for $i = 1,2,...N$ where $f_i(x)$ is the objective function i, N is the number of objective functions. In Figure 2.5, examples of non-dominated solutions are A and B whereas C is called a dominated solution.

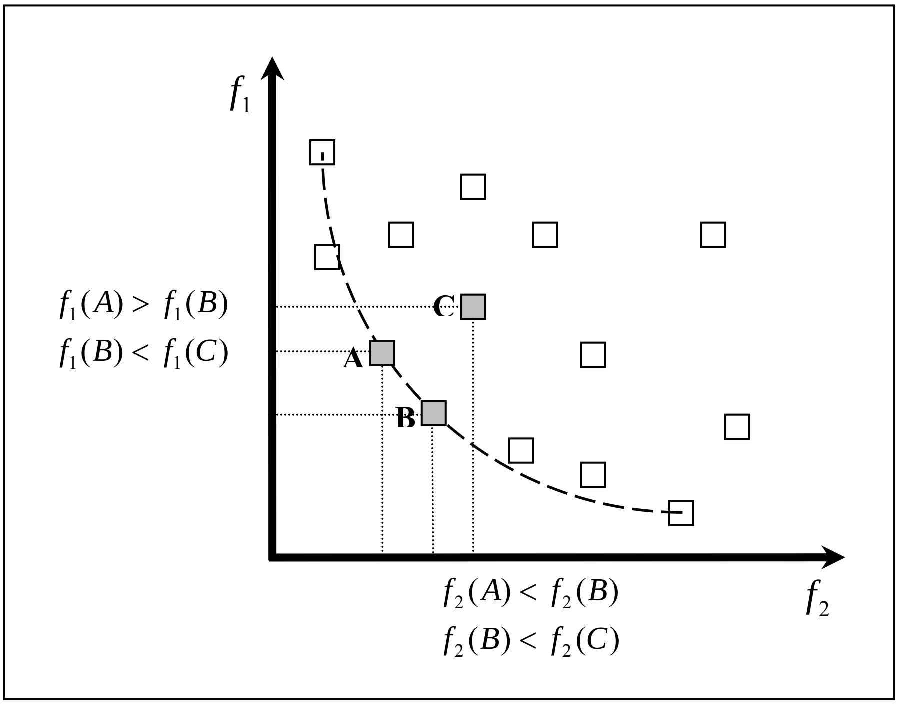


Figure 2.5 The dominated and non-dominated solution [55]

A Pareto optimal solution is the solution that is not dominated by any other solution in the solution space. A Pareto optimal solution cannot be improved with respect to any other objective. If at least one objective of all objectives is worsening, there is no Pareto optimal solution. The set of all feasible non-dominated solutions is referred as the Pareto optimal set. Pareto optimal set that corresponds to objective function values in the objective space are called the Pareto front. For many problems, the number of Pareto optimal solutions is enormous. Examples of multi-objective optimization with the Pareto optimal approach are Vector Evaluated Genetic Algorithm (VEGA) [29], Niched Pareto Genetic Algorithm (NSGA) [34], Strength Pareto Evolutionary Algorithm (SPEA) [9].

In a multi-objective design context, we find a Pareto optimal solution in **objective space**. Every decision variable in decision space is converted into the objective space. Suppose we need to minimize both objective functions f_1 and f_2. Figure 2.6 illustrates the difference between a weighted-sum approach that considers both objectives by forming into a single function, and a multi-objective approximation approach that considers both of them simultaneously. In Figure 2.6(a), a new solution obtained with weighted-sum approach must dominate the previous solution for both f_1 and f_2 since it approximates both objective functions using one linear function. Thus the better solution(s) is found along the shaded line. In general, only one solution is found with one set of weights. Figure 2.6(b) shows some set of the solutions that are not discarded when we consider both objective functions simultaneously.

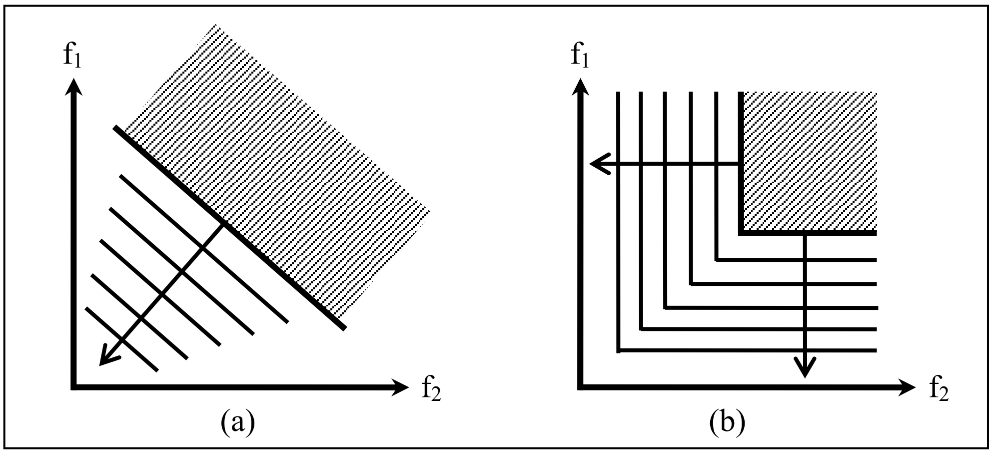


Figure 2.6 The objective space of a) single objective approximation (weighted-sum approach) and b) multi-objective approximation [56]

Since the multi-objective optimization approach tries to consider all objective functions simultaneously, the search space is very large. Multi-objective optimization algorithms are usually modified to search for the optimal solution in a very short time or with fast convergence.

Genetic Algorithms (GA) are often applied to search for optimal solutions based on Pareto-dominance technique [8]. GA has been proposed to provide fast convergence to the optimal solution [8, 28]. The efficiency of a GA depends on the following features [57].

1) The obtained solutions converge quickly to the Pareto-optimal front. The ratio of non-dominated solutions over dominated solutions (in each generation) should be as high as possible.
2) The solution should not be crowded into one area of objective space. It should be distributed across objective space.
3) The non-dominated solutions should be close to the Pareto-optimal front.

2.6 Multi-Objective Genetic Algorithms

Genetic Algorithm (GA) has 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 [28]. First, Schaffer [29] proposed Vector Evaluated Genetic Algorithm (VEGA) for solving multi-objective optimization in each objective separately and merging sub-solutions/populations of each objective together. VEGA tends to crowd solutions into particular regions of objective space rather than spreading them out. Fonseca and Fleming [30] proposed a multi-objective Genetic Algorithm (MOGA) for searching for solutions in all possible directions of objective space. Later, many GAs have been proposed to improve the searching for non-dominated solutions in all objective areas. Each of previously proposed algorithms has different efficiency/effectiveness in terms of

1) The complexity of the algorithm
2) The convergence rate (i.e., fast or slow convergence) to the Pareto-optimal front
3) The diversity of the non-dominated solutions (crowded into one area or distributed in all areas of the front)
4) The interval distance from the Pareto-optimal front (close or far from the Pareto-optimal front)

Significant sub-procedures of multi-objective GA are *Recombination* (crossover and mutation), *Fitness assignment* and *Selection procedures*. Recombination is used to explore and exploit a new and better solution in the objective space (set of all feasible solutions). Fitness assignment is used to rank the solutions in each generation. The solutions that are non-dominated by other solutions are assigned to the first order of the rank. However, the non-dominated solutions should be diverse in all areas of the front. A diversity mechanism can be used to eliminate duplicate non-dominated solutions or crowded solutions. Selection is a procedure to select the non-dominated and less-crowded solutions. This procedure determines which solutions should be preserved or discarded.

Examples of GA discussed by Konak et al. in [28] comprise of various Multi-objective Genetic Algorithms which are categorized into four groups:

1. Aggregated function of normalized objectives
   a. Weight-Based GA (WBGA) [31]
   b. Random Weighted GA (RWGA) [32]
2. No entire fitness assignment but compare using Pareto dominance approach
   a. Vector Evaluated GA (VEGA) [29]
   b. Niched Pareto GA (NPGA) [33]
3. Particular ranking approach
   a. Multi-Objective GA (MOGA) [30]
   b. Non-dominated Sorting GA (NSGA) [34] and Fast Non-dominated Sorting GA (NSGA-II) [10]
   c. Strength Pareto Evolutionary Algorithm (SPEA) [35] and the improving of SPEA (SPEA2) [9]
4. No population based approach
   a. Pareto-Archived Evolution Strategy (PAES) [36]

The first category, an aggregated function of normalized objectives, weights all objective functions and combines them into one function. The value of the aggregated function is used to determine which solution should be selected to the next generation. WBGA [31] uses different weight vectors in a generation. Multiple solutions can be simultaneously searched in each generation. RWGA [32] randomly generates weight vectors to specify multiple search directions in each replication run without additional weight parameters. This GA category is easy to implement but makes it difficult to search for a feasible solution in non-convex objective function space.

The second category compares the solutions based on Pareto dominance. The solutions with all objective values better than those of the others have high opportunity to go to the next generation. VEGA [29] divides the population into *m* subpopulations where *m* is the number of objectives. Each subpopulation is evaluated by multiple objectives and then combined together before going to the recombination process (crossover and mutation). This approach has a disadvantage that it tends to converge to the extreme solution of each objective. NPGA [33] also uses Pareto dominance comparison based on tournament selection. This approach uses a niche radius to select non-dominated solutions that are diversely located in all spaces of a non-dominated front. The drawback in this approach is that it requires additional parameters to determine the niche radius and the tournament size. The parameters are sensitive and require trial and error to determine their suitable values.

Each algorithm in the third category has its particular ranking approach and diversity mechanism. Both of them are combined into the fitness assignment algorithm. For example, MOGA [30] using Rank-based fitness assignment to assign the solutions into several fronts. The non-dominated solutions are assigned to the first front. This approach uses a niche radius to select non-dominated solutions that are diversely located in all spaces of a non-dominated front as previously mentioned. NSGA-II [10], an improvement of NSGA [34], is proposed to rapidly assign the solutions into several fronts. The fitness assignment algorithm is called "Fast non-dominated sorting approach". This NSGA-II [10] has a diversity mechanism called "Crowding distance assignment". The distance from two nearest neighbor solutions determines which solution in the same front is better than the others. The solution in the same front that has higher crowding distance (i.e. is more diverse) is preferred. SPEA2 [9] is proposed to be better than the SPEA [35] algorithm in two important ways: 1) the number of archived solutions is constant over time and 2) an algorithm called "truncation method" is proposed to protect the boundary individuals being removed. The SPEA2 [9] uses a strength value to determine which solution is dominated by the others. The non-dominated solution with high strength value usually has its raw fitness value equal to 0. The fitness assignment in this approach has a diversity mechanism based on *k*-nearest neighbor, where k is the square root of the sample size [9]. The distance from each solution to the k nearest neighbor determines which solution will be removed. In the non-dominated solution front (first front), the solution that is diverse to the extreme point is preferred.

The fourth category with no population based ranking approach is PAES [36]. This approach compares the new randomly selected solution with the old non-dominated solution based on Pareto dominance approach. If the selected solution is better than the old non-dominated solution in all objectives, it replaces the old non-dominated solution.

In our experiment, two multi-objective GAs (i.e., SPEA2 and NSGA-II) were evaluated in various aspects such as the complexity of the algorithm, the efficiency of the algorithm (based on the convergence rate, the diversity and interval from the Pareto-front) and computation time. Both SPEA2 and NSGA-II were evaluated with all optimal and non-dominated solutions (i.e., the Pareto-front) using a well known combinatorial problem (i.e., Knapsack problem with two objective functions and 100 decision variables). NGSA-II is effective in terms of computation time and complexity of the algorithm. However there is no information provided to compare and benchmark the accuracy of the proposed algorithm. Therefore we used the data set as same as used in SPEA2 [9]. On the other hand, the SPEA2 is efficient in searching for the optimal solutions. It has an external population to maintain the elitism and a mechanism to spread the solutions in various objective spaces (diverse solutions) [28]. Both SPEA2 and NSGA-II can provide excellent results. However, the SPEA2 requires more CPU time than the NSGA-II does with the same problem size.

This dissertation presents the details of these two efficient multi-objective Genetic Algorithms, the Strength Pareto Evolutionary Algorithm (SPEA2) [9] and the Fast Non-dominated Sorting Approach (NSGA-II) [10], in Appendices C and D.

CHAPTER 3 ROUTING AND WAVELENGTH ASSIGNMENT

This chapter presents our implemented work on the Routing and Wavelength Assignment (RWA) problem. RWA is a sub-problem of the GRWA problem. The bandwidth requirement of traffic demands in RWA is always equal to 1 wavelength channel while the bandwidth requirement in GRWA is may be less than 1 wavelength channel. In our previous study [38], we considered the RWA optimization problem with maximizing the number of accepted commodities and minimizing the number of wavelength channels. We found that these two objective functions conflict. When we optimize the number of accepted commodities, the number of wavelength channels may increase to an unacceptable level. In this dissertation, both objectives are optimized simultaneously. A model formulation for RWA problem is proposed. Many multi-objective optimization approaches are studied. The RWA optimization problem is solved by using the Weighted-sum approach, SPEA2 [9] and NSGA-II [10]. The obtained results from the Weighted-sum, SPEA2 and NSGA-II are compared and evaluated. We apply our optimization algorithm to solve the RWA problem in NSFNET [41] topology design. The details of our RWA research are discussed in this chapter.

3.1 Introduction to RWA

In Wavelength Division Multiplexing (WDM) optical networks, each optical fiber link can be divided into multiple channels which are identified by the length of the wave, called “wavelength channel”. The number of wavelength channels is limited on each optical link. The data stream of traffic demand is typically encapsulated into a “lightpath” for transmission from one source to another destination. In WDM network design, Routing and Wavelength Assignment (RWA) is a well-known issue [11, 40]. The RWA problem can be separated into two sub-problems, routing allocation and wavelength channel assignment. We denote a source-destination node pair with amount of traffic demand in bandwidth granularities as a “commodity” [3]. The routing sub-problem allocates the route of lightpath to each given commodity. The incoming commodities have to occupy an available wavelength channel along the light path for transmitting and receiving information. The channel allocation is called Wavelength assignment.

Routing and wavelength assignment are interrelated. An effective wavelength assignment is needed to have an optimal routing. The RWA problem has been previously considered for various design objectives, for instance, minimizing the number of wavelengths required on each edge while all commodities must be satisfied [11] or minimizing the number of light paths in the logical topology subject to a limited number of transmission wavelengths [3]. The RWA problem has been proved to be NP-complete [37].

In this dissertation, multi-objective RWA in WDM networks is considered by optimizing two objective functions i.e., maximizing the number of accepted commodities and minimizing the number of wavelengths on each network edge. In an actual RWA problem, it could happen that multiple functions influence the decision of which option to be selected. These functions may conflict with each other. For example, when a function is optimized, the other functions may get worse [7, 8]. Maximizing accepted commodities normally required a large number of wavelengths. In contrast, minimizing the number of wavelengths could cause a large number of commodities to be blocked or a smaller number of commodities to be accepted. To solve this problem, both objectives are considered simultaneously. We consider potential routes for routing by using a Genetic Algorithm (GA) and assign the wavelength channel by using our Minimum Degree First Wavelength Assignment (MinDF) algorithm as previously proposed in [39]. Both objectives in the solution are calculated from the set of routes and wavelength channels. Each solution consists of a specified number of accepted commodities and a number of wavelength channels. We then apply the NSGA-II to search for non-dominated solutions in terms of accepted commodities and required wavelength channels. The results are provided as a front of non-dominated solutions. Non-dominated solutions have a behavior that no one solution is better than the others. Normally, the non-dominated solutions are numerous and so it is difficult to select the best single solution. Therefore, the Pruned Pareto-optimal mechanism [58, 72] is then applied to reduce the number of non-dominated candidates and to help selecting the best solution.

The remainder of this chapter is organized as follows. In the next section, we describe the background concepts of the optimization algorithms we used, which are the weighted-sum approach, SPEA2 and NSGA-II. The literature review in multi-objective network design and multi-objective optimization algorithms were previously described in *Sections 2.4 and 2.5*. In this section, we focus on the optimization techniques that are used to solve the multi-objective RWA optimization problem. In *Section 3.3*, we present the multi-objective WDM optical network design problem and its design model. The two objective functions consisting of maximizing the number of accepted commodities and minimizing the number of required wavelength channels will be described. A multi-objective RWA optimization model will be presented. In *Section 3.4*, we present a hybrid evolutionary computation approach as a heuristic algorithm to solve the multi-objective RWA problem in WDM optical network design. The GA-MinDF and NSGA-II algorithms are presented for selecting potential route and wavelength assignment as well as to search non-dominated solutions in multi-objective RWA problem respectively. We also present the pruning mechanism to cut off the numerous solutions obtained from NSGA-II. *Section 3.5* presents our numerical results and analysis. Lastly, *Section 3.6* concludes our research work and contribution.

3.2 Previous Multi-Objective Optimization Techniques in RWA

In this section, we present the algorithms used to solve the multi-objective routing and wavelength assignment (RWA) problem. In our approach, we first consider potential routes for routing algorithm by using a Genetic Algorithm (GA) and assign the wavelength channel by using Minimum Degree First Wavelength Assignment (MinDF) algorithm. The algorithm for finding a route and assigning a wavelength channel is called “GA-MinDF”. The GA-MinDF applies a multi-objective optimization approach to search for non-dominated solutions in terms of accepted commodities and required wavelength channels. Based on our previous work, we focus on various multi-objective optimization techniques, in both single and multi-objective contexts. The multi-objective optimization techniques that are implemented to solve the RWA problem are the weighted-sum approach, SPEA2 and NSGA-II.

3.2.1 Weighted-sum Approach

In our weighted-sum approach [39], we consider the RWA by optimizing both maximum number of accepted commodities and minimum number of wavelengths. The obtained results from the Weighted-sum approach are considered with various cases of W_c and W_w. W_c is a given weight parameter value between 0.0 and 1.0 for maximizing the number of accepted commodities. W_w is a given weight parameter value between 0.0 and 1.0 for minimizing the number of required wavelengths. Both objectives are weighted with W_c and W_w respectively as shown in *Equation 3.1*. The expression $(|Q|-Q_A)/|Q|$ is a fraction of the number of accepted commodities and the expression $K_A/K_{\max}$ is the number of required wavelength channels. The description is shown in *Section 3.3*.

$$f_{obj} = W_c\left(\frac{|Q|-Q_A}{|Q|}\right) + W_w\left(\frac{K_A}{K_{\max}}\right) \tag{3.1}$$

We consider the RWA by optimizing both maximum number of accepted commodities and minimum number of wavelengths. We analyze our design problem in various cases, as follows:

- Case 1: optimize both objectives simultaneously (with W_c = 0.5 and W_w = 0.5)
- Case 2: minimize the number of wavelengths with 100% of commodities accepted
- Case 3: minimize the number of wavelengths with 80% of requested commodities to be accepted.

The results are shown in *Tables 3.1 and 3.2*. We capture the best result with 3 simulation runs. In the first column of Table 3.1, we weight both objectives with 0.5. At 150 commodities, the number of wavelength channels required in Case 2 is double of the number of wavelength channels required in Case 1. When the number of commodities increases, the number of wavelengths required in Case 1 is close to the number of wavelengths obtained from Case 2, meaning that the number of wavelengths in our multi-objective optimization algorithm efficiently gives a result near the minimal number of wavelengths required (with 80% of requested commodities accepted).

The results from *Table 3.1* are displayed in an objective space in Figure 3.1. In Figure 3.1, "+" represents the results from Case 1: optimize both objectives simultaneously. Various numbers of commodities (i.e., 10, 30, 50, 100, and 150) are considered. "□" represents the results from Case 2: minimize the number of wavelengths with 100% of requested commodities to be accepted and "O" represents the results from Case 3: minimize number of wavelengths required (with 80% of requested commodities to be accepted). We analyze the effect of weight values in our objective functions as shown in *Table 3.2*. In *Table 3.2*, the weights W_c and W_w are varied from 0 to 1. The number of accepted commodities as well as the number of wavelengths are displayed. The results show that the ratio of the weight values greatly affects the number of wavelengths required. *Table 3.2* shows a great effect on number of wavelengths for 150 commodities.

Table 3.1 The number of accepted commodities and number of required wavelength channels in three consideration cases

	No. of commodities	Accepted commodities	Wavelength required	Total CPU time (sec)
Case 1: Optimize both objectives simultaneously (W_c =0.5 & W_w =0.5)	10	10	2	3
	30	28	3	37
	50	45	5	125
	100	85	7	460
	150	124	10	1,602
Case 2: Maximize number of commodity (100 % accepted commodity)	10	10	2	3
	30	30	4	29
	50	50	6	110
	100	100	12	436
	150	150	21	1207
Case 3: Minimize number of wavelength (80 % accepted commodity)	10	9	1	3
	30	25	2	31
	50	44	4	106
	100	81	6	495
	150	121	10	1344

Table 3.2 The number of accepted commodities and number of required wavelength channels for several ratios of weight values

Weighted of maximal number of accepted commodity (W_c)	Weighted of minimal number of wavelength (W_w)	50 commodities		100 commodities		150 commodities	
		Number of accepted commodities	Number of wavelengths	Number of accepted commodities	Number of wavelengths	Number of accepted commodities	Number of wavelengths
1.0	0.0	50	6	100	12	150	21
0.9	0.1	49	6	94	10	140	17
0.8	0.2	45	5	86	8	126	11
0.7	0.3	45	5	86	8	126	11
0.6	0.4	45	5	86	7	125	11
0.5	0.5	45	5	85	7	124	10
0.4	0.6	45	4	85	7	122	10
0.3	0.7	44	4	81	6	122	10
0.2	0.8	44	4	81	6	122	10
0.1	0.9	44	4	81	6	122	10
0.0	1.0	44	4	81	6	121	10

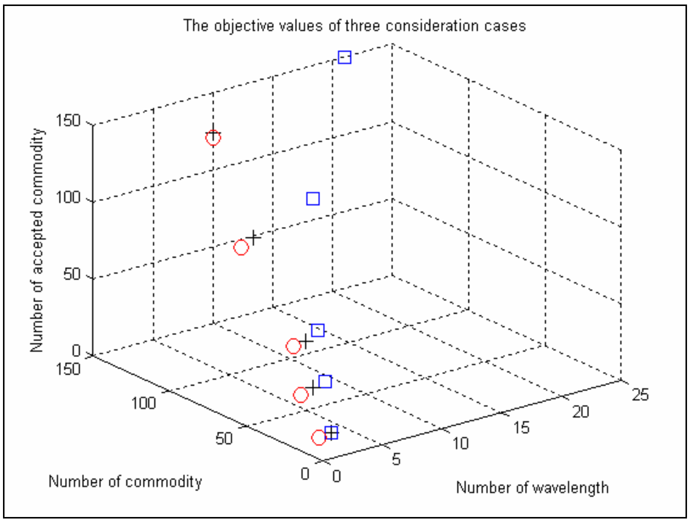


Figure 3.1 The objective values of three considered cases which are to optimize both objectives simultaneously (represented by "+"), to maximize the number of accepted commodities (100% of commodities accepted**,** represented by "□"), and to minimize the number of wavelengths required (80% of commodity accepted, represented by "O")

3.2.2 Strength Pareto Evolutionary Algorithm (SPEA2)

The Improving Strength Pareto Evolutionary Algorithm (SPEA2) is famous as an efficient technique to search for the Pareto-optimal set in general multi-objective optimization problems. SPEA2 was proposed by Zitzler et al [9]. SPEA2 is described in detail in Appendix C.

In our SPEA2 approach [76], we consider the RWA by optimizing both maximum number of accepted commodities and minimum number of wavelengths. SPEA2 is applied to search for a front or set of non-dominated solutions. Both objective functions are simultaneously considered. The expressions of simultaneous optimization are shown in *Equations 3.2-3.4*. f_c is an expression of a fraction of the number of accepted commodities and f_w is an expression of the number of required wavelength channels. The description of our RWA problem is shown in *Section 3.3*.

$$f_{obj} = \min\left(f_c, f_w\right) \tag{3.2}$$

$$f_c = \frac{|Q| - Q_A}{|Q|} \tag{3.3}$$

$$f_w = \frac{K_A}{K_{\max}} \tag{3.4}$$

The obtained results from SPEA2 are compared to the Weighted-sum approach with various cases of W_c and W_w. Both objectives are weighted with W_c and W_w respectively as shown in *Equation 3.1*.

Table 3.3 shows the obtained results with 150 total commodities by using the Weighted-sum approach, where, 11 cases of weight values (i.e., {W_c=1.0,W_w=0.0}, {W_c=0.9,W_w=0.1}, {W_c=0.8,W_w=0.2}, …, { W_c=0.0,W_w=1.0}) are considered. Those results (shown as "□" symbol) are compared with the obtained results from the SPEA2 (shown as "•" symbol) in Figure 3.2. The results are plotted as a front or sets of candidate solutions. There is no one solution better than the other solutions. Each solution is the best for a certain consideration. The best solution is determined based on the main objective function (or the most significant objective). For example, if the network is considered to have a maximum of 12 wavelength channels, then the number of accepted commodities is maximized at 145. However, if the network aims for all commodities to be accepted, then the number of wavelength channels required is 15. Note that the results of the SPEA2 algorithm are plotted for visualization of the nature of relations between the number of accepted commodities and the wavelength channels. A non-dominated solution is the individual that is on the top of the column for a certain number of wavelengths.

Figure 3.2 shows that the Weighted-sum approach has a problem, that its weight parameters are very sensitive. Different weight parameters (e.g., {W_c=0.7, W_w=0.3} and {W_c=0.6,W_w=0.4}) may give the same results.

Table 3.3 The obtained results with 150 commodities from the weighted sum approach with various cases of weighted parameters

Weighted of maximal number of accepted commodities (W_C)	Weighted of minimal number of wavelengths (W_W)	Number of accepted commodities	Number of wavelengths used
1.0	0.0	123.0	9.0
0.9	0.1	123.0	9.0
0.8	0.2	121.0	9.0
0.7	0.3	122.0	9.0
0.6	0.4	122.0	9.0
0.5	0.5	123.0	9.0
0.4	0.6	127.0	10.0
0.3	0.7	127.0	10.0
0.2	0.8	127.0	11.0
0.1	0.9	140.0	13.0
0.0	1.0	150.0	17.0

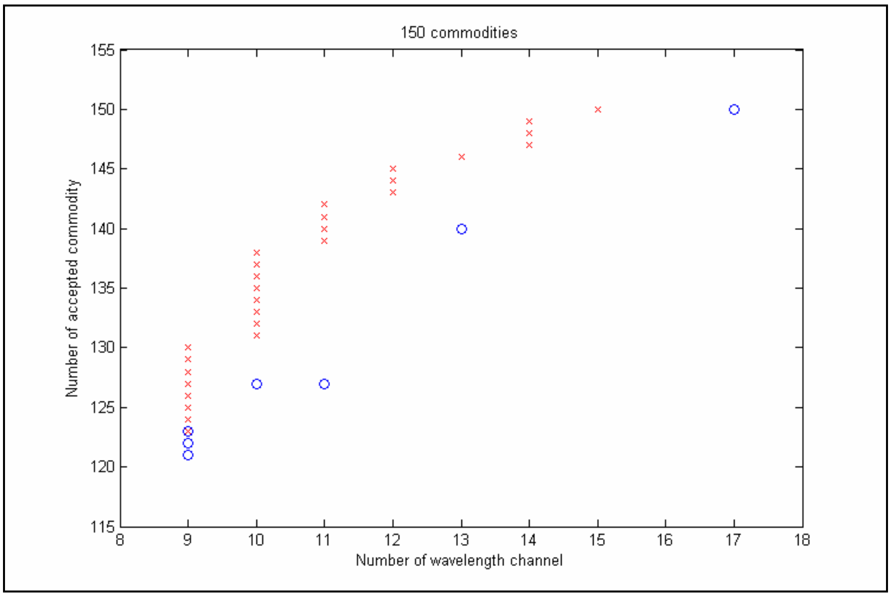


Figure 3.2 The obtained results from the weighted-sum approach with various cases of weight (represented by "o") and the SPEA2 approach ("×" symbol)

As shown in *Table 3.4*, the SPEA2 algorithm is very computationally intensive. The average CPU time of the total of 150 commodities obtained from the SPEA2 algorithm is 29,161.0 seconds while those obtained from the weighted sum approach (with 11 cases of weights) is only 349.0×11 = 3,839 seconds. In [9], it was stated that the computation complexity of the SPEA2 algorithm is $O(K \cdot 2 \cdot (\log K))$ where $K=N+N'$, N is the population size, and N' is the archive population size. Thus our SPEA2 computation time can be reduced by adjusting the size of K.

Table 3.4 Number of iterations and computation time of the weighted sum (multiple weights) and the SPEA2 approaches

	Number of total commodity	Weighted sum (multiple weights)		SPEA2	
		Iteration	CPU time (sec.)	Iteration	CPU time (sec.)
Average (per 1 replication run)	10	33.0	1.0	2,400.0	176.0
	30	39.2	9.1	2,400.0	1,216.3
	50	50.2	32.6	2,400.0	3,207.0
	100	51.0	132.2	2,400.0	12,609.7
	150	58.2	349.0	2,400.0	29,161.0
Total	10	1,090.0	33.0	7,200.0	528.0
	30	1,293.0	300.0	7,200.0	3,649.0
	50	1,656.0	1,077.0	7,200.0	9,621.0
	100	1,684.0	4,363.0	7,200.0	37,829.0
	150	1,921.0	11,518.0	7,200.0	87,483.0

3.2.3 Fast Non-dominated Sorting Approach (NSGA-II)

The Fast Non-dominated Sorting Genetic Algorithm (NSGA-II) is famous as an efficient technique to search for the Pareto-optimal set in general multi-objective optimization problems. NSGA-II is a very fast algorithm. It can rapidly converge to the Pareto-front. The NSGA-II was proposed by Deb et al [10]. The NSGA-II is described in detail and showed the efficiency of the implemented algorithm in Appendix D.

In our experiment, we found that both SPEA2 and NSGA-II are efficient to converge to the Pareto-optimal front; however, NSGA-II converged more rapidly than SPEA2. Therefore we selected NSGA-II as a multi-objective optimization algorithm. The experimental result of our Hybrid Evolutionary Computation Approach is showed in *Section 3.6*.

3.3 Problem Definition and Model Formulation

In this section, we present the multi-objective RWA design problem and its design model. We consider the RWA problem of WDM optical network design to support many commodities simultaneously (multi-commodity flow problem). Each commodity has many possible routings and each routing has several choices of wavelength channel assignment. Our network design problem is to maximize the number of accepted commodities from a given set of commodities and to minimize the number of required wavelengths. This dissertation allows some given commodities to be blocked to reduce the number of wavelength channels. A commodity that has been successfully assigned to a wavelength is called an “accepted commodity”. Our objective functions are as follows.

1) The first design objective is to maximize the number of accepted commodities. A large number of commodities certainly requires a great number of transmission channels (called wavelength channels in this dissertation). This design objective is subject to a limited number of wavelength channels on each network edge.

2) The second design objective is to minimize the number of wavelengths required on each edge while satisfying a target value of accepted commodities. We assume that each

network edge has the same number of wavelengths. This design objective is to minimize the number of wavelengths while satisfying a target value of accepted commodities.

In this dissertation, we consider both the number of accepted commodities and the number of required wavelengths simultaneously. The network design problem can be formulated as an optimization-based model. Our proposed RWA model is based on "wavelength continuity constraint" with the following set of notations.

Let N be the set of network nodes in the network and $|N|$ be the total number of nodes. E is denoted as the set of network edges or network links in the network. $E(i,*)$ is the set of edges that leave from node $i \in N$ and $E(*,i)$ is the set of edges that go to node $i \in N$. $|E|$ is the total number of edges. D is the set of network edge distances where D_e represents the edge length of network edge $e \in E$. Each network edge e has $|K|$ wavelength channels. K is the set of available wavelength channels and $|K| \leq K_{max}$ which is an upper-bound number of wavelengths. K_A is the number of required/assigned wavelengths. Let Q be the set of commodities (source-destination node pair with bandwidth granularity). In this dissertation, the bandwidth granularities of all commodities are equal to 1 wavelength. $|Q|$ is the total number of communication requests or commodities. Q_A is the number of accepted commodities. T is the minimum threshold value represented as the ratio of accepted commodities that are required over the total number of commodities, where $0 \leq T \leq Q_A / |Q| \leq 1$. L is the maximum path length (in kilometer.) and H is an upper-bound number of hop counts.

Let $\delta_q^{e,k}$ denotes the decision variable of a commodity $q \in Q$ that occupies wavelength channel $k \in K$ on edge $e \in E$ in the network. Note that $\delta_q^{e,k}$ is equal to 1 if the wavelength channel $k \in K$ on the edge $e \in E$ is occupied by the commodity $q \in Q$; otherwise it is equal to 0. β_q denotes the variable of commodity $q \in Q$ to be set up from one source to another destination. β_q is equal to 1, if the commodity $q \in Q$ is successfully set up with a wavelength channel; otherwise, it is equal to 0. ϕ_k denotes the variable of wavelength channel $k \in K$ to be used in the network. ϕ_k is equal to 1, if the wavelength k is assigned to a commodity or non-overlapped commodities $q \in Q$; otherwise, it is equal to 0. γ_q^k denotes the variable of assigning a wavelength channel $k \in K$ to a commodity $q \in Q$ if the commodity q is accepted. γ_q^k is equal to 1, if the wavelength k is assigned to the commodity $q \in Q$; otherwise, it is equal to 0. Note that a commodity can have several routes from source to destination but only one route is considered at a time and the available wavelength channel is occupied for the selected route. The network design formulation presented here is to optimize the objective function consisting of two parts: maximizing the number of accepted commodities (converted into minimization function, f_c) and minimizing the number of required wavelengths (f_w).

Given:

Network topology

Set of commodities (i.e., source-destination node pairs with bandwidth requirements)

Minimize:

$$f_{obj} = \min\left(f_c, f_w\right) \tag{3.5}$$

$$f_c = \frac{|Q| - Q_A}{|Q|} \tag{3.6}$$

$$f_w = \frac{K_A}{K_{\max}} \tag{3.7}$$

Subject to:

$$\sum_{e \in E(*,i)} \sum_{k \in K} \delta_q^{e,k} - \sum_{e \in E(i,*)} \sum_{k \in K} \delta_q^{e,k} = \begin{cases} -\beta_q, i = Source_q \\ \beta_q, i = Dest_q \\ 0, otherwise \end{cases} \quad ; \forall q \in Q, i \in N \tag{3.8}$$

$$\delta_q^{e,k} \le \gamma_q^k \qquad ; \forall q \in Q, \forall e \in E, \forall k \in K \tag{3.9}$$

$$\sum_{k \in K} \gamma_q^k \le 1 \qquad ; \forall q \in Q \tag{3.10}$$

$$\sum_{k \in K} \delta_q^{e,k} \le \beta_q \quad ; \forall q \in Q, \forall e \in E \tag{3.11}$$

$$Q_A = \sum_{q \in Q} \beta_q \tag{3.12}$$

$$\sum_{q \in Q} \delta_q^{e,k} \le \phi_k \quad ; \forall e \in E, \forall k \in K \tag{3.13}$$

$$K_A = \sum_{k \in K} \phi_k \tag{3.14}$$

$$\frac{Q_A}{|Q|} \ge T \tag{3.15}$$

$$\sum_{e \in E} \delta_q^{e,k} \leq H \qquad ;\forall q \in Q, \forall k \in K \tag{3.16}$$

$$\sum_{e \in E} (D_e \cdot \delta_q^{e,k}) \leq L \quad ;\forall q \in Q, \forall k \in K \tag{3.17}$$

$$\beta_q \in \{0,1\} \qquad ;\forall q \in Q \tag{3.18}$$

$$\phi_k \in \{0,1\} \qquad ;\forall k \in K \tag{3.19}$$

$$\gamma_q^k \in \{0,1\} \qquad ;\forall q \in Q, \forall k \in K \tag{3.20}$$

$$\delta_q^{e,k} \in \{0,1\} \qquad ;\forall q \in Q, \forall e \in E, \forall k \in K \tag{3.21}$$

Our proposed network model considers routing wavelength assignment (RWA) problem to minimize f_c which is the expression of a fraction of maximizing the number of accepted commodity (Q_A) from a given set of commodities and to minimize f_w which is the expression of minimizing the number of wavelength required (K_A) as shown in *Equations 3.5-3.7*. Both objective functions are normalized by dividing by their total range of values (or magnitudes) that are $\left(|Q| - Q_A\right)/|Q|$ and $K_A/K_{\max}$. Therefore, we can transform both maximizing the number of commodity function value and minimizing the number of wavelength function value into the same range that is [0, 1]. *Equation 3.6* converts the maximization context into a minimization context. When the Q_A is maximized to reach the total number of commodities ($|Q|$), the value of *Equation 3.6* will be minimized to 0.

The set of constraints *Equations 3.8-3.17* can be described as follows. *Equation 3.8* is the network flow constraint. The bandwidth granularities of all commodities are equal to 1 wavelength. The flow of a traffic demand $q \in Q$ that goes to and leaves from node $i \in N$ must be equal to 0 while the traffic demand q from source node is equal to $-\beta_q$ and the traffic demand at the terminated (destination) node is β_q. Note that β_q=1, if the commodity q is accepted. Otherwise, it is equal to 0. *Equation 3.8* will ensure that all accepted traffic demands have the traffic flow from the source node to its destination node.

Equations 3.9 and 3.10 are the wavelength continuity constraints. Only one wavelength channel k is used for the commodity q throughout multiple (connected) edges. Since multiple edges can be used for the commodity q with a wavelength k, in *Equation 3.9*, if the commodity q occupies a wavelength channel k on any edge $e \in E$, then $\gamma_q^k = 1$. If $\gamma_q^k = 0$, there is no assignment of wavelength channel k for the commodity q on any edge $e \in E$. *Equation 3.10* ensures that each commodity q must have the number of assigned wavelength channels less than or equal to 1. If the commodity q occupies wavelength channel k, then $\gamma_q^k = 1$. Otherwise, $\gamma_q^k = 0$. Thus, both *Equations 3.9 and 3.10* ensure the wavelength continuity constraint in the network design.

Equation 3.11 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 q with one wavelength channel. In another word, the commodity $q \in Q$ can be assigned with only one wavelength channel $k \in K$ on an edge $e \in E$ if the commodity q is accepted. Note that the decision variable $\delta_q^{e,k}$ is related to the network flow constraint in *Equation 3.8*.

In *Equation 3.12*, the number of accepted commodities (Q_A) is equal to the summation of all commodity $q \in Q$ which can be routed (on one or multiple edges $e \in E$) from its source to destination and assigned with a wavelength channel $k \in K$ throughout the route.

Equation 3.13 is the wavelength utilization constraint. Each wavelength channel $k \in K$ is selected if there is at least one commodity $q \in Q$ which occupies the wavelength channel. It also ensures that each wavelength channel k on edge e can be occupied by only one commodity $q \in Q$. However, if there are two or more commodities which are not overlapped, they can use the same wavelength channel (on different edges) subject to wavelength continuity constraint.
In *Equation 3.14*, the number of required wavelength channels (K_A) is equal to the summation of all assigned wavelength channels ($k \in K$) where each assigned wavelength channel is occupied by at least one accepted commodity $q \in Q$.

Note that each network edge $e \in E$ has n_k wavelength channels that are required simultaneously. Multiple edges require various numbers of wavelength channels. The satisfied number of wavelengths is equal to the maximum number of simultaneously required wavelengths. The occupied wavelength channels in each edge must not exceed the required number of wavelength channels (K_A). To optimize the number of required wavelength channels, only the first K_A^{th} wavelengths on each network edge $e \in E$ should be assigned. For example, in Figure 3.3, we have occupied 2 wavelengths on edge 1 (from node 2 to node 1, 2→1) and 2 (1→3) thus K_A=2. Only λ_0 and λ_1 will be used on both edges.

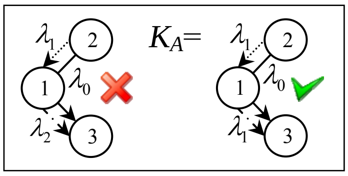


Figure 3.3 Invalid and valid wavelength channel assignments

In *Equation 3.15*, the number of accepted commodities must be greater than or equal to a threshold (i.e., T=0.8 or 80% of all commodities must be served or accepted).

In *Equation 3.16*, the hop distance of commodity q traversed on multiple edges $e \in E$ must not exceed a hop count limit.

In *Equation 3.17*, the network link distance of commodity q must not exceed the length limit (in kilometer).

Equations 3.18-3.21 define the decision variables used in the model.

The network model is formulated under the wavelength continuity constraint indicating that only one wavelength is assigned to a commodity. The commodity uses the assigned wavelength throughout the light path. The routing of commodity $q \in Q$ can be any of the possible routes that connect the specified source node to the specified destination node.

As mentioned previously, the RWA problem is NP-complete [37]. We can approximate the complexity of the RWA with the size of all possible solutions called "search space" as follows. Let S be the number of source-destination pairs. For the case of Routing, the complexity is $O(R^S)$ where R is the number of potential routes of each source-destination pair. Note that this dissertation considers the RWA in the scope of the multi-commodity flow problem. Therefore, multiple source-destination pairs select one choice of routes from R possible routes simultaneously. For the case of Wavelength Assignment, the complexity is $O(W^S)$ where W is the number of wavelength channels. Thus, the search space of RWA problem with R potential routes and W wavelength channels is $O((RW)^S)$. Note that the answer of multi-objective RWA problem considered in this dissertation is not one optimal solution but multiple optimal solutions are searched and addressed as a set. Our proposed network design model is solved by using a Hybrid Evolutionary Computation Approach as described in the next section.

3.4 A Hybrid Evolutionary Computation Approach

In this section, we present the algorithms used to solve the multi-objective routing wavelength assignment problem. The RWA problem can be classified into two sub-problems, Routing Assignment and Wavelength Assignment. Both of them are jointly dependent. In our approach, NSGA-II is used to search for non-dominated solutions in the multi-objective RWA problem. Each solution consists of a number of accepted commodities and wavelengths computed by using our GA-MinDF approach. The numerous solutions (non-dominated solutions) obtained from NSGA-II are then cut off by using the pruning mechanism.

In the multi-objective RWA problem, it could be happen that some different solutions have the same objective values (i.e., number of accepted commodities and number of wavelengths). The NSGA-II or multi-objective genetic algorithms often have diversity mechanisms to select solutions in the extreme areas first (e.g., crowding distance, niche size, or etc.). If the duplicate solutions occur in the objective space, their diversity values are equal to 0 and they are removed first. This problem can be solved if we consider the solutions with more features such as with accepted commodity, wavelength, and also with network path length. When we evaluate a solution with more features, the solutions with different properties will be considered and thus will not be removed.

3.4.1 NSGA-II Algorithm

The Fast Non-dominated Sorting Genetic Algorithm (NSGA-II) is famous as an efficient technique to search for the Pareto-optimal set in general multi-objective optimization problems. Each solution in NSGA-II is calculated a number of accepted commodities and wavelengths by using GA-MinDF. In GA-MinDF, we first consider potential routes for Routing algorithm by using a Genetic Algorithm (GA) and assign the wavelength channel by using Minimum Degree First Wavelength Assignment (MinDF) algorithm as described in Appendix A.

3.4.2 Genetic Algorithm for Routing and Minimum Degree First Wavelength Assignment (GA-MinDF)

We present a heuristic algorithm called a Genetic Algorithm for Routing with Minimum Degree First Wavelength Assignment (GA-MinDF). The GA-MinDF has two parts that are Routing with Genetic Algorithm and Wavelength Assignment with Minimum Degree First. The detail of GA-MinDF is described in Appendix A.

3.5 Pruning Mechanism

Previously, Kulturel-Konak et al. (in 2008) [58] and Taboada et al. (in 2008) [72] proposed mechanisms to reduce numerous non-dominated solutions using two approaches, which are ranking preferences and data clustering. In the first method, the decision maker has to specify a priority for each objective, and then consider it accordingly in order to find the preferred solution. In the second method, pruning by using data clustering is considered to be more suitable [72] because the decision maker does not have to know the priority of each objective. In this dissertation, the numerous solutions (non-dominated solutions) that are obtained from NSGA-II are filtered by using a well-known data clustering algorithm (i.e., *K*-means algorithm). The basic *K*-mean algorithm [73] is as follows.

Basic K-means Algorithm [73]

1. Select K points as initial centroids
2. **Repeat**
   a. Form K clusters by assigning each point to its closest centroid
   b. Recompute the centroid of each cluster
3. **Until** centroids do not change

In this dissertation, the Euclidean distance is used to measure the proximity of the solutions to the centroid. The main issue in the *K*-means algorithm is to find the suitable value of *K*. In our approach, the value of *K* is selected by considering both sum of the squared error (SSE) and the percentage of the obtained solutions. Minimum SSE typically requires a large value of *K*. Therefore, it is difficult for the decision maker to make a final decision. On the other hand, the minimum value of *K* gives high SSE which means that the selected centroid might not accurately represent the group of solutions in the clusters. The non-dominated solutions obtained from NSGA-II and the *K*-means (Pruning mechanism) for our example experiments are presented in the next section.

3.6 Experimental Settings and Simulation Results

In our experiments, we considered the multi-objective RWA network design with a given network topology and a set of commodities. A limited number of wavelength channels in each edge/link of the network was imposed and at least 80% of the commodities must be accepted. We randomly generated a set of test problems with various numbers of commodities, with a uniform distribution in each test. We implemented our algorithms in Java and ran them on a Pentium 4 PC (Core 2 Quad CPU 2.83 GHz, 3.25 GB of RAM). We adapted different example networks which are NSFNET network with 14 nodes and 42 directional edges [41], CHNNET network with 15 nodes and 54 directional edges [13] and ARPANET network with 20 nodes and 64 directional edges [13] in the experiments as shown in Figures 3.4-3.6. For each problem size, a set of communication demands was investigated with a set of wavelength channels. We assumed that all edges have the same number of wavelength channels.

We benchmarked our GA-MinDF algorithm against the Fixed-Alternate Routing and First Fit Wavelength Assignment (FAR-FF) algorithm. The simulation results are shown in Figures 3.7-3.9. GA-MinDF outperformed the FAR-FF with 5 potentially shortest routes in all three topologies of the networks. From Figures 3.7-3.9 and *Table 3.5*, the CHNNET has the highest value of average degree (i.e., 3.6). The obtained solutions from CHNNET topology are better than those from NSFNET and ARPANET. With the same number of wavelength channels, CHNNET has higher number of accepted commodities than those of NSFNET and ARPANET. For example, with 9 wavelength channels and using GA-MinDF, the number of accepted commodities for CHNNET was 129 while for NSFNET and ARPANET, the values are 123 and 120, respectively. On the other hand, with 18 wavelength channels and using FAR-FF, CHNNET accepted all 150 commodities while NSFNET and ARPANET accepted 138 and 143, respectively.

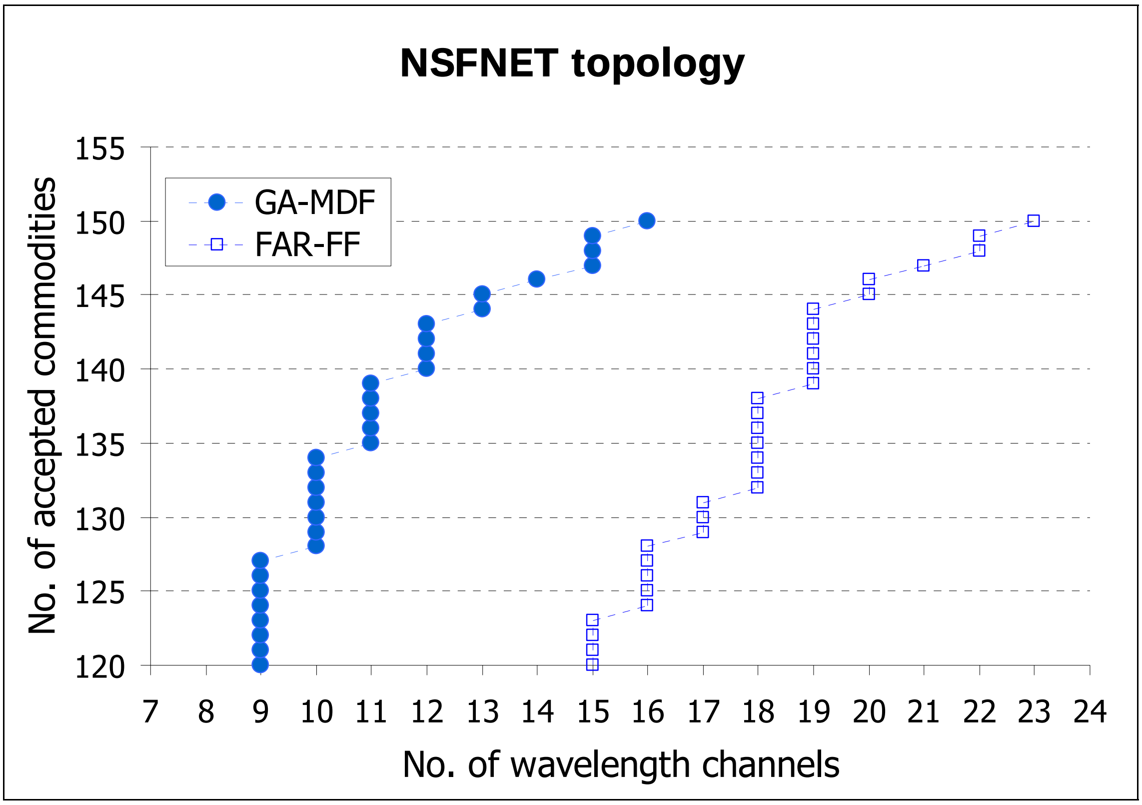


Figure 3.4 The non-dominated solutions of GA-MinDF and FAR-FF obtained from NSFNET

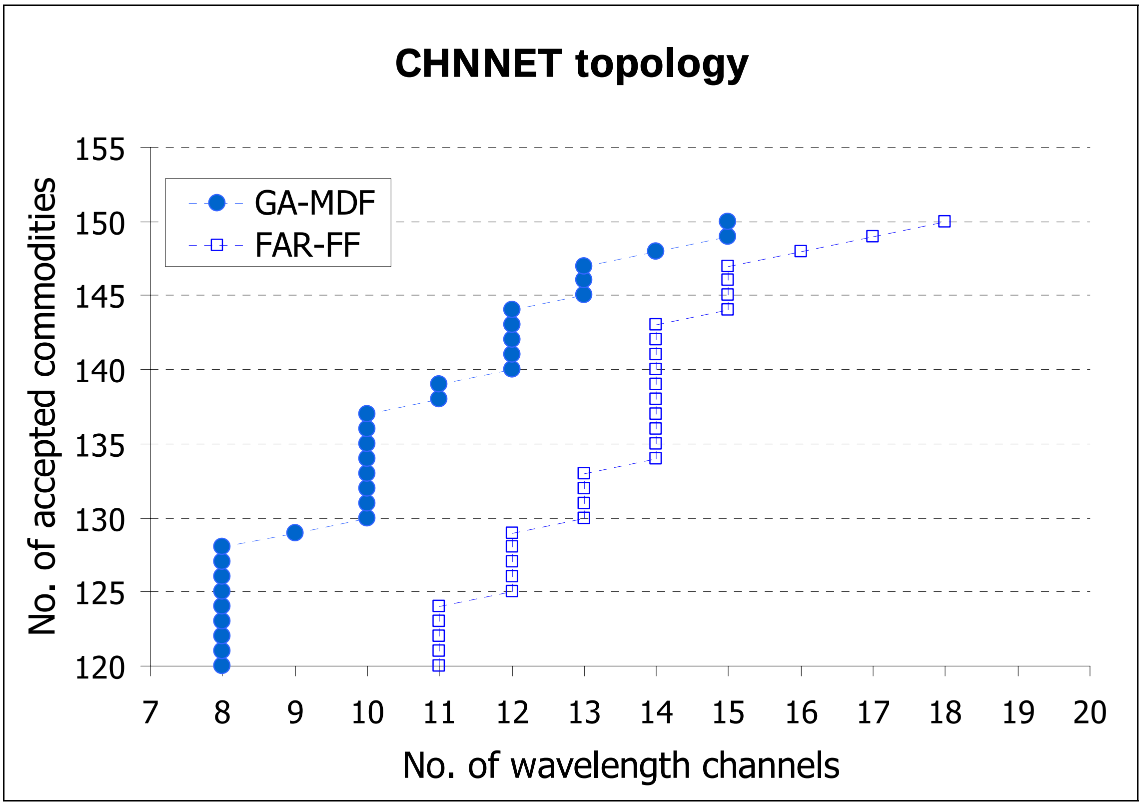


Figure 3.5 The non-dominated solutions of GA-MinDF and FAR-FF obtained from CHNNET

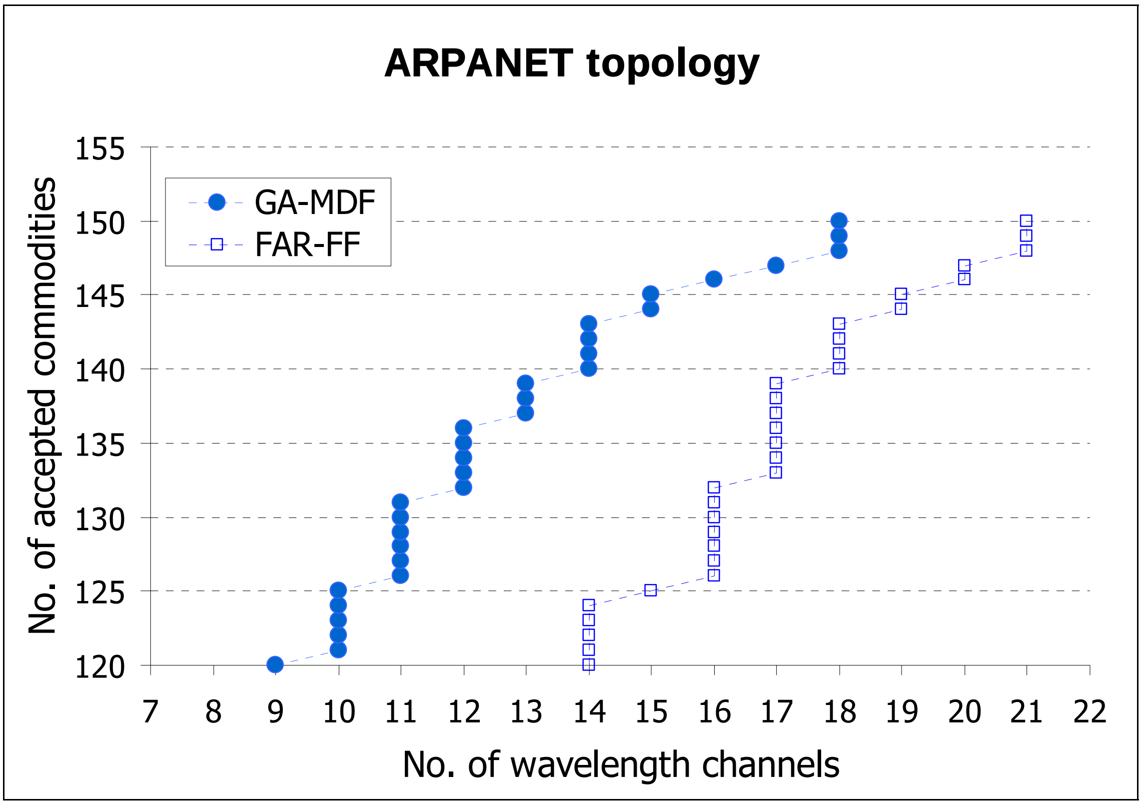


Figure 3.6 The non-dominated solutions of GA-MinDF and FAR-FF obtained from ARPANET

Table 3.5 The computation time of GA-MinDF and FAR-FF in various network topologies with 150 commodities

Network topologies	No. of (non-directional) Edges	No. of Nodes	No. of Edges/ No. of Nodes	Degree				RWA techniques	CPU Time (sec)	
				Total Deg.	Average Deg. (Total Deg./ No. of Nodes)	Min Deg.	Max Deg.		Average CPU Time (sec)	Total CPU Time (sec)
NSFNET	21	14	1.5	42	3	2	4	GA-MinDF	14,806.3	44,419.0
								FAR-FF	11,986.7	35,960.0
CHN	27	15	1.8	54	3.6	3	5	GA-MinDF	16,512.7	49,538.0
								FAR-FF	12,344.7	37,034.0
ARPANET	32	20	1.6	64	3.2	3	4	GA-MinDF	29,435.0	88,305.0
								FAR-FF	21,540.3	64,621.0

Next we compared the NSGA-II algorithm results with those obtained from the Weighted Sum approach considering various cases of weight parameters (W_c and W_w). Let W_c be a given weight parameter value between 0.0 and 1.0 for maximizing the number of accepted commodities, and W_w be a given weight parameter value between

0.0 and 1.0 for minimizing the number of required wavelength channels. Both objective values are weighted with W_c and W_w, respectively as shown in *Equation 3.22*.

$$f_{obj} = W_c \left(\frac{|Q| - Q_A}{|Q|}\right) + W_w \left(\frac{K_A}{K_{\max}}\right) \tag{3.22}$$

We simulated the network model considering various sets of total commodities from 10 to 150. *Table 3.6* shows the obtained results with 150 total commodities using the Weighted-Sum approach, where, 11 cases of weight values are considered. Those results (shown as "o" symbol) are compared with the results obtained from the NSGA-II (shown as "×" symbol) in Figure 3.7. The results are plotted as a front or sets of candidate solutions. Note that the results of the NSGA-II algorithm are plotted for visualization of the nature of relations between the number of accepted commodities and the number of wavelength channels. A non-dominated solution is the individual that is on the top of the column for a certain number of wavelength channels. Figure 3.7 shows that the Weighted Sum approach has a problem that its weight parameters are very sensitive. Different weight parameters (e.g., {W_c=0.7, W_w=0.3} and {W_c=0.6,W_w=0.4}) may give the same results.

Table 3.6 Results with 150 commodities from the weighted sum approach with various cases of weighted parameters

{W_C, W_W}	Number of accepted commodities	Number of wavelengths used	{W_C, W_W}	Number of accepted commodities	Number of wavelengths used
{1.0, 0.0}	123.0	9.0	{0.4, 0.6}	127.0	10.0
{0.9, 0.1}	123.0	9.0	{0.3, 0.7}	127.0	10.0
{0.8, 0.2}	121.0	9.0	{0.2, 0.8}	127.0	11.0
{0.7, 0.3}	122.0	9.0	{0.1, 0.9}	140.0	13.0
{0.6, 0.4}	122.0	9.0	{0.0, 1.0}	150.0	17.0
{0.5, 0.5}	123.0	9.0			

Table 3.7 Number of iterations and computation time of the weighted sum (multiple weights) and the NSGA-II approaches

	Number of total commodity	Weighted sum (multiple weights)		NSGA-II	
		Iteration	CPU time (sec.)	Iteration	CPU time (sec.)
Average (per 1 replication run)	10	33.0	1.0	2,400.0	85.0
	30	40.0	9.1	2,400.0	605.3
	50	51.0	32.6	2,400.0	1,617.7
	100	51.0	132.2	2,400.0	6,403.3
	150	59.0	349.0	2,400.0	14,806.3
Total	10	1,090.0	33.0	7,200.0	255.0
	30	1,293.0	300.0	7,200.0	1,816.0
	50	1,656.0	1,077.0	7,200.0	4,853.0
	100	1,684.0	4,363.0	7,200.0	19,210.0
	150	1,921.0	11,518.0	7,200.0	44,419.0

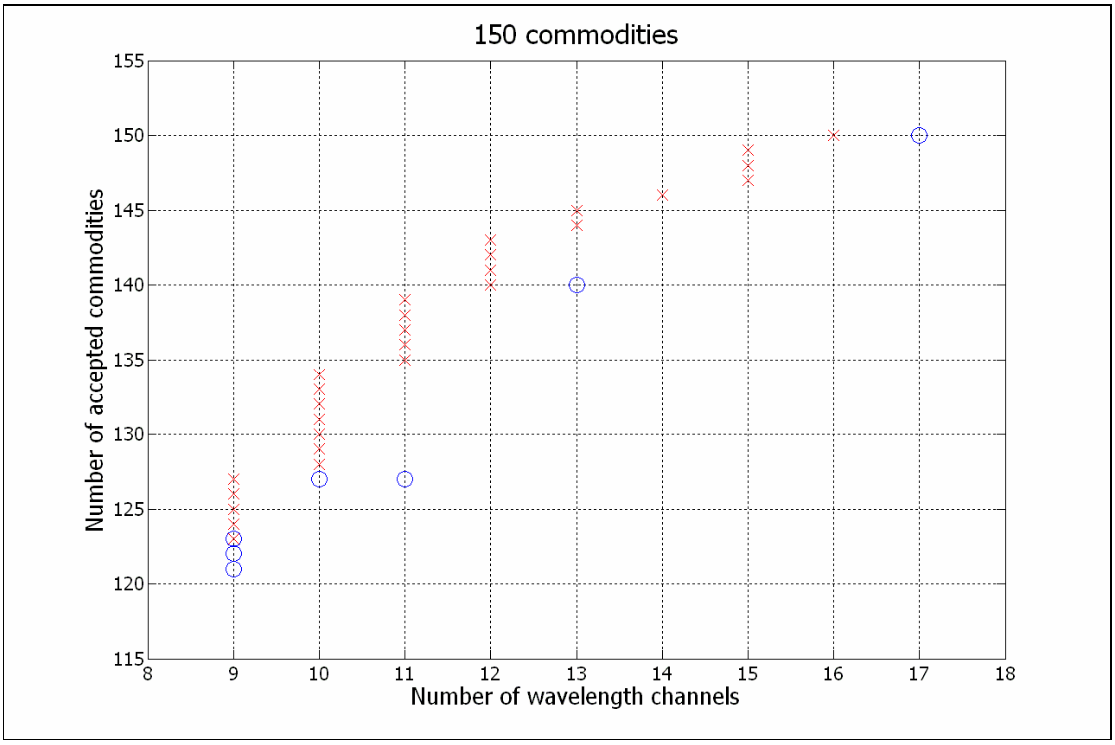
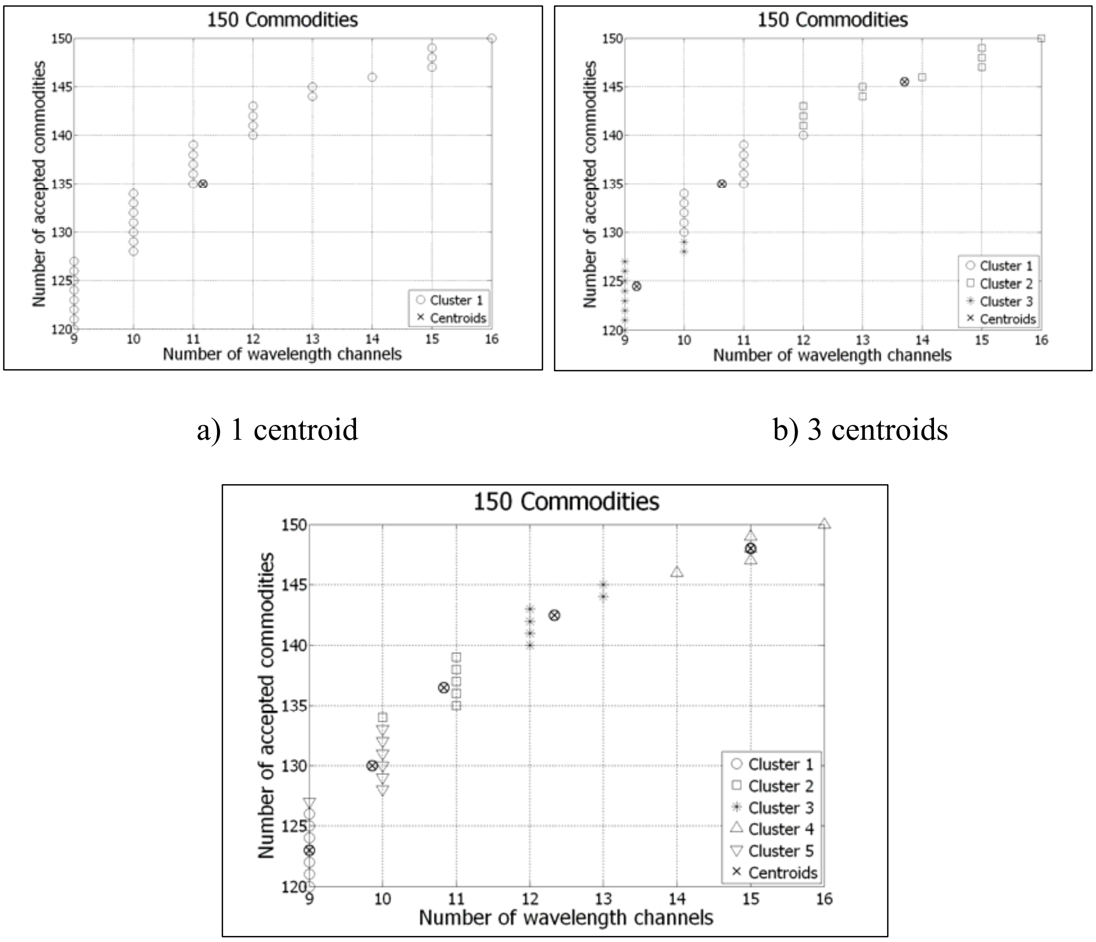


Figure 3.7 Results from the weighted-sum approach with various cases of weight (represented by "○") and the NSGA-II approach ("×" symbol)

Table 3.7 shows that the NSGA-II algorithm is computationally intensive, with an average CPU time is 14,806.3 seconds for the case of 150 commodities obtained from the NSGA-II algorithm while those obtained from the Weighted Sum approach (with 11 cases of weights) is only 349.0×11 = 3,839 seconds. Research in [10] states that the computation complexity of the NSGA-II algorithm is $O(MZ^2)$ where M is the number of objectives and Z is the population size. Thus our NSGA-II computation time can be reduced by adjusting the size of *Z*.

For the pruning mechanism, data clustering with *K*-means was selected because we do not need to prioritize the objectives in this method. The number of solutions obtained from NSGA-II in our approach is equal to 31 solutions as shown in Figure 3.7. All of them could be clustered by using the *K*-means algorithm. The solution with *K*=1 makes it easy to make a decision. It is laid in the middle of the front as shown in Figure 3.8(a). For the cases of *K*=3 and *K*=5, the centroids or representatives of all clusters are represented with the symbol ⊗. Note that the centroid is not the solution but the nearest solution to the centroid is selected. A large value of *K* can represent the obtained solutions more precisely but makes it more difficult to choose a single solution.



a) 1 centroid

b) 3 centroids

c) 5 centroids

Figure 3.8 Results from *K*-means algorithm with a) 1 centroid, b) 3 centroids and c) 5 centroids

In this dissertation, the value of K is selected by considering both sum of the squared error (SSE) and the number of the obtained solutions. The relationship between SSE and number of centroids (K values) is shown in *Table 3.8*. For example, with K=5, the average SSE is equal to 109.32 and the best solution from 3 replication runs has the SSE=107.50. Considering K=5, 16% of solutions are retained. Figure 3.9 shows that the SSE rapidly decreases when the K is changed from 1 to 3 and 5. The silhouette plot shows that the SSE marginally changes from K=7 to 31. For our multi-objective RWA problem, K=5 or 7 are optimal because these values are not too numerous to make a final selection and the SSEs are acceptable. With K=5, 16% of solutions are retained while 23% of solutions are retained for K=7.

Table 3.8 The sum of the squared error (SSE) and the percentage of the obtained solutions with different number of centroids (K values)

No. of centroids	% of obtained solutions	Best case SSE	Average SSE	Normalized Average SSE
1	3.23	2612.19	2612.19	100.00
3	9.68	301.25	301.25	11.53
5	16.13	107.50	109.32	4.18
7	22.58	54.62	55.97	2.14
9	29.03	32.92	34.94	1.34
11	35.48	24.58	26.83	1.03
13	41.94	17.33	18.78	0.72
15	48.39	15.67	16.86	0.65
17	54.84	8.50	9.56	0.37
19	61.29	6.50	7.83	0.30
21	67.74	5.00	5.83	0.22
23	74.19	4.00	4.50	0.17
25	80.65	3.00	3.00	0.11
27	87.10	2.00	2.00	0.08
29	93.55	1.00	1.00	0.04
31	100.00	0.00	0.00	0.00

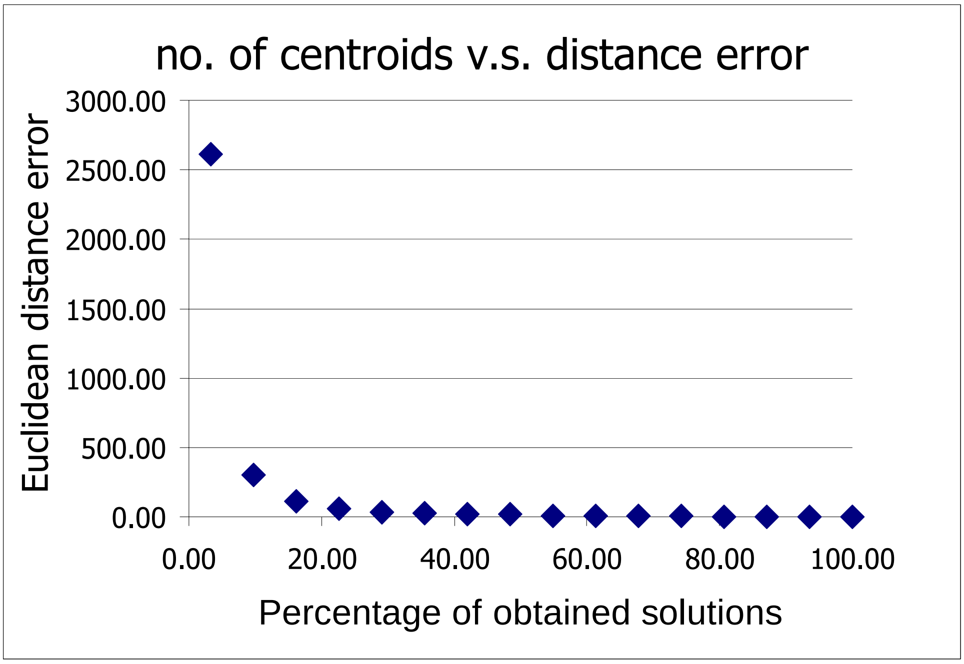


Figure 3.9 The relation between SSE and number of centroids

3.7 Conclusions for RWA

We have investigated Routing and Wavelength Assignment (RWA) in WDM optical networks with multi-objective network design approach under a wavelength continuity constraint. Each commodity uses only one assigned wavelength through the light path. Our design objectives were to maximize the number of accepted commodities and minimize the number of wavelengths required. We proposed an efficient GA-MinDF algorithm to solve the RWA problem and then applied the NSGA-II approach to search for non-dominated solutions. The obtained results were compared with those obtained from the Weighted-Sum approach for various cases of weight parameters. We found that the results from the NSGA-II are more diverse in the objective space than those of the Weighted-Sum approach. The NSGA-II approach with GA-MinDF technique is effective in solving the RWA problem with multiple design objectives. It is efficient in searching for a set of non-dominated solutions. However, the NSGA-II is computationally intensive and time-consuming. Thus, NSGA-II is suitable for network design problem with an off-line approach for static traffic demands. The obtained results from NSGA-II can be further simplified by using pruning mechanism. The data clustering with K-means algorithm is applied to reduce the number of candidates.

In this chapter, there are several research contributions that can be summarized as follows. First, the efficient GA-MinDF method is proposed for RWA problem. Second, the NSGA-II together with GA-MinDF algorithm is efficiently applied to solve multi-objective RWA network design problem. Last, the pruning mechanism is applied for filtering a large number of non-dominated solutions to help the decision maker in selecting the final solution in multi-objective RWA network optimization design problem.

CHAPTER 4 PROBLEM DEFINITION AND MATHEMATICAL MODEL OF TRAFFIC GROOMING

4.1 GRWA Design Problem

In this section, we present the multi-objective GRWA design problem and its design model. We consider the GRWA problem of WDM optical network design to support many commodities simultaneously (multi-commodity flow problem). Each commodity has many possible routings and each routing has several choices for aggregating with other connections and various choices of wavelength channel assignment. Our network design problem is to maximize the number of accepted commodities from a given set of commodities, to minimize the number of wavelength channels and to minimize the number of required switching ports. This dissertation allows some given commodities to be blocked for optimizing network resources (that are wavelength channels and switching ports). A commodity that has been successfully assigned with a wavelength channel is called "accepted commodity". The number of accepted commodities represents the network capacity, the number of wavelength channels represents the network resources and the number of switching ports represents the network cost and the grooming capability. With the same number of accepted commodities, a low number of switching ports implies high grooming capability. Our objective functions are as follows.

1) The first design objective is to maximize the number of accepted commodities. A large number of commodities certainly requires a greater number of transmission channels (called wavelength channels in this dissertation) and switching ports. This design objective is subject to a limited number of wavelength channels on each network edge.

2) The second design objective is to minimize the number of wavelengths required on each edge while satisfying a target value of accepted commodities. We assume that each network edge has the same number of wavelengths.

3) The third design objective is to minimize the number of switching ports. Each network connection requires electrical and optical ports. For optical bypass switching,

the electrical port is normally used at the source and destination of the connection. However, an electrical port is additionally used for grooming multiple commodities into the same wavelength channel at some intermediate nodes. One optical port is required at every transmission node (i.e., one port for the source, one port for the destination) and two ports (for receiving and transmitting) at the intermediate node.

4.2 GRWA Mathematical Model

In this dissertation, we consider the number of accepted commodities, the number of wavelength channels and the number of required switching ports simultaneously. The network design problem can be formulated as an optimization-based model. Our proposed GRWA model is based on "wavelength continuity constraint" with the following set of notations.

4.2.1 Set of Notations

Network Topology Properties

N is the set of network nodes in the network.

$|N|$ is the total number of nodes.

E denotes the set of network edges or network 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 $i \in N$.

$|E|$ is the total number of edges.

D is the set of network edge distances where D_e represents the edge length of network edge $e \in E$. Each network edge e has $|K|$ wavelength channel.

K is the set of available wavelength channels.

G is the set of grooming groups of multiple commodities that are groomed together. Each accepted commodity must belong to a group $g \in G$.

Q is the set of commodities (source-destination node pair with bandwidth granularity). In this dissertation, the bandwidth granularity of each commodity is a fraction of a wavelength.

$|Q|$ is the total number of communication requests or commodities.

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.

L is the maximum path length (in kilometer).

H is an upper-bound hop counts.

F_g^e is the set of commodities in the group $g \in G$ on network edge $e \in E$.

$\psi(o)_g^e$ is the number of optical ports. Two optical ports are required for every network edges that a set of grooming commodities passes.

$\psi(e)_g^e$ is the number of electrical ports. In all-optical network, the optical signal can be bypassed in the optical domain, if the signal is not required to drop into electrical domain for grooming with the other commodities or reaching the destination. The electrical port count is calculated from the summation of electrical transmitting unit $\varphi(s)_g^e$ and electrical receiving unit $\varphi(d)_g^e$.

$\varphi(s)_g^e$ is the number of electrical transmitting unit**s** (converts the signal from electrical to optical domain) of the group $g \in G$ on the network edge $e \in E$.

$\varphi(d)_g^e$ is the number of electrical receiving units (converts the signal from optical to electrical domain) of the group $g \in G$ on the network edge $e \in E$.

$\varphi(o)_g^e$ is the number of optical units of the group $g \in G$ on the network edge $e \in E$.

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 a bandwidth requirement of the commodity $q \in Q$.

Decision Variables

Let $\delta_{q,g}{}^{e,k}$ denotes the decision variable of a commodity $q \in Q$ that occupies wavelength channel $k \in K$ on edge $e \in E$ and group $g \in G$ in the network. Note that $\delta_{q,g}{}^{e,k}$ is equal to 1 if the wavelength channel $k \in K$ on the edge $e \in E$ is occupied by the commodity $q \in Q$ and it belongs to a group $g \in G$; otherwise it is equal to 0.

β_q denotes the variable of commodity $q \in Q$ to be set up from one source to another destination. β_q is equal to 1, if the commodity $q \in Q$ is successfully set up with a wavelength channel; otherwise, it is equal to 0.

ϕ_k denotes the variable of wavelength channel $k \in K$ to be used in the network. ϕ_k is equal to 1, if the wavelength $k \in K$ is assigned to a commodity or non-overlapped commodities $q \in Q$; otherwise, it is equal to 0.

γ_q^k denotes the variable of assigning a commodity $q \in Q$ to a wavelength channel $k \in K$. γ_q^k is equal to 1, if the commodity $q \in Q$ is assigned to the wavelength channel $k \in K$; otherwise, it is equal to 0.

$\Lambda_{q,g}$ denotes the variable of assigning a commodity $q \in Q$ to a group $g \in G$. $\Lambda_{q,g}$ is equal to 1, if the group $g \in G$ is assigned to the commodity $q \in Q$; otherwise, it is equal to 0.

y_g^k denotes the variable of assigning a group $g \in G$ to a wavelength channel $k \in K$. y_g^k is equal to 1, if the group $g \in G$ is assigned to the wavelength channel $k \in K$; otherwise, it is equal to 0.

$\Re_g^e$ denotes the variable of minimum bandwidth requirement of the group $g \in G$ on network edge $e \in E$. $\Re_g^e$ has a value between 0 and 1.

Note that a commodity can have several routes from source to destination but only one route is considered at a time and the available wavelength channel is occupied for the selected route. The network design formulation presented here is to optimize the objective function consisting of three parts:

1) Maximizing the number of accepted commodities (converted into minimization function, f_c),
2) Minimizing the number of required wavelength channels (f_w) and
3) Minimizing the number of required switching ports (f_p).

Given

Network topology

Set of commodities (i.e., source-destination node pairs with bandwidth requirements)

Assumption

1) The grooming procedure is considered to occur in the electrical domain only.

2) This dissertation considers the grooming device in logical function.

4.2.2 Design Objectives

Minimize:

$$f_{obj} = \min\left(f_c, f_w, f_p\right) \tag{4.1}$$

$$f_c = \frac{|Q| - Q_A}{|Q|} \tag{4.2}$$

$$f_w = \frac{K_A}{K_{\max}} \tag{4.3}$$

$$f_p = \frac{P_A}{P_{\max}} \tag{4.4}$$

4.2.3 Design Constraints

Subject to:

$$\sum_{g\in G}\sum_{e\in E(*,i)}\sum_{k\in K}\delta_{q,g}^{e,k} - \sum_{g\in G}\sum_{e\in E(i,*)}\sum_{k\in K}\delta_{q,g}^{e,k} = \begin{cases} -\beta_q, i = Source_q \\ \beta_q, i = Dest_q \\ 0, otherwise \end{cases} \quad ;\forall q \in Q, i \in N \tag{4.5}$$

$$\sum_{q\in Q}\sum_{k\in K}\delta_{q,g}^{e,k} \cdot t_q \le \Re_g^e \quad ;\forall g \in G, \forall e \in E \tag{4.6}$$

$$\Re_g^e \le 1 \quad ;\forall g \in G, \forall e \in E \tag{4.7}$$

$$\delta_{q,g}^{e,k} \le \gamma_q^k \quad ;\forall q \in Q, \forall g \in G, \forall e \in E, \forall k \in K \tag{4.8}$$

$$\sum_{k\in K}\gamma_q^k \le 1 \quad ;\forall q \in Q \tag{4.9}$$

$$\sum_{g\in G}\sum_{k\in K}\delta_{q,g}^{e,k} \le \beta_q \qquad ;\forall q\in Q, \forall e\in E \tag{4.10}$$

$$\delta_{q,g}^{e,k} \le \Lambda_{q,g} \qquad ;\forall q\in Q, \forall g\in G, \forall e\in E, \forall k\in K \tag{4.11}$$

$$\sum_{g\in G}\Lambda_{q,g} \le 1 \qquad ;\forall q\in Q \tag{4.12}$$

$$\delta_{q,g}^{e,k} \le y_g^k \qquad ;\forall q\in Q, \forall g\in G, \forall e\in E, \forall k\in K \tag{4.13}$$

$$\sum_{k\in K} y_g^k \le 1 \qquad ;\forall g\in G \tag{4.14}$$

$$Q_A = \sum_{q\in Q}\beta_q \tag{4.15}$$

$$K_A = \sum_{k\in K}\phi_k \tag{4.16}$$

$$\varphi(s)_g^e \ge \begin{cases} \sum_{k\in K}\delta_{q,g}^{e,k}, e\in E(Source_q,*) \\ 1, \left(F_g^{e'(*,Source_e)} \ne F_g^e\right)\wedge\left(F_g^e \ne \{\phi\}\right)\wedge\left(q\in F_g^{e'}\cup F_g^e\right) \\ 0, \qquad otherwise \end{cases}$$

where $\forall q\in Q, \forall e\in E, \forall g\in G$ (4.17)

$$\varphi(d)_g^e \ge \begin{cases} \sum_{k\in K}\delta_{q,g}^{e,k}, e\in E(*,Dest_q) \\ 1, \left(F_g^e \ne F_g^{e'(Dest_e,*)}\right)\wedge\left(F_g^e \ne \{\phi\}\right)\wedge\left(q\in F_g^e\cup F_g^{e'}\right) \\ 0, \qquad otherwise \end{cases}$$

where $\forall q\in Q, \forall e\in E, \forall g\in G$ (4.18)

$$\psi(e)_g^e = \varphi(s)_g^e + \varphi(d)_g^e \qquad ;\forall g\in G, \forall e\in E \tag{4.19}$$

$$\varphi(o)_g^e \ge \sum_{g\in G}\sum_{k\in K}\delta_{q,g}^{e,k} \qquad ;\forall q\in Q, \forall e\in E \tag{4.20}$$

$$\psi(o)_g^e = 2\cdot\varphi(o)_g^e \qquad ;\forall g\in G, \forall e\in E \tag{4.21}$$

$$P_A = \sum_{g\in G}\sum_{e\in E}\left(\psi(o)_g^e + \psi(e)_g^e\right) \tag{4.22}$$

$$y_g^k \le \phi_k \qquad ;\forall g\in G, \forall k\in K \tag{4.23}$$

$$\frac{Q_A}{|Q|} \geq T_{acc} \tag{4.24}$$

$$\sum_{e \in E} \delta_{q,g}^{e,k} \leq H \qquad ;\forall q \in Q, \forall g \in G, \forall k \in K \tag{4.25}$$

$$\sum_{e \in E} (D_e \cdot \delta_{q,g}^{e,k}) \leq L \qquad ;\forall q \in Q, \forall g \in G, \forall k \in K \tag{4.26}$$

$$\beta_q \in \{0,1\} \qquad ;\forall q \in Q \tag{4.27}$$

$$\phi_k \in \{0,1\} \qquad ;\forall k \in K \tag{4.28}$$

$$\gamma_q^k \in \{0,1\} \qquad ;\forall q \in Q, \forall k \in K \tag{4.29}$$

$$\Lambda_{q,g} \in \{0,1\} \qquad ;\forall q \in Q, \forall g \in G \tag{4.30}$$

$$y_g^k \in \{0,1\} \qquad ;\forall g \in G, \forall k \in K \tag{4.31}$$

$$\varphi(s)_g^e \in \{0,1\} \qquad ;\forall g \in G, \forall e \in E \tag{4.32}$$

$$\varphi(d)_g^e \in \{0,1\} \qquad ;\forall g \in G, \forall e \in E \tag{4.33}$$

$$\varphi(o)_g^e \in \{0,1\} \qquad ;\forall g \in G, \forall e \in E \tag{4.34}$$

$$\delta_{q,g}^{e,k} \in \{0,1\} \qquad ;\forall q \in Q, \forall g \in G, \forall e \in E, \forall k \in K \tag{4.35}$$

Our proposed network model considers grooming, routing and wavelength assignment (GRWA) problem to minimize f_c which is the expression of a fraction of maximizing the number of accepted commodities (Q_A) from a given set of commodities, to minimize f_w which is the expression of minimizing the number of wavelengths required (K_A) and to minimize f_p which is the expression of minimizing the number of switching ports required (P_A) as shown in *Equations 4.1-4.4*. The objective functions are normalized by dividing with their total range of values (or magnitudes) that are $\left(|Q| - Q_A\right)/|Q|$, $K_A/K_{\max}$ and $P_A/P_{\max}$.

Therefore, we can transform maximizing the number of commodities function value, minimizing the number of wavelengths function value and minimizing the number of switching ports value into the same range that is [0, 1]. *Equation 4.2* normalizes the number of accepted commodities and converts its direction. When the Q_A is maximized to reach the total number of commodities ($|Q|$), the value of *Equation 4.2* will be minimized to 0.

The set of constraints *Equations 4.5-4.26* can be described as follows.

Equation 4.5 is the network flow constraint. The bandwidth granularities of all commodities are less than or equal to 1 wavelength. The flow of a traffic demand $q \in Q$ that goes to and leaves from node $i \in N$ is equal to 0 while the traffic demand $q \in Q$ from source node is equal to -β_q and the traffic demand at the terminated (destination) node is β_q. Note that β_q=1, if the commodity $q \in Q$ is accepted. Otherwise, it is equal to 0. *Equation 4.5* will ensure that all accepted traffic demands have a traffic flow from the source node to the destination node.

Equations 4.6 and 4.7 are the wavelength bandwidth constraint. The wavelength bandwidth on the network edge $e \in E$ for all commodities in the group $g \in G$ must be less than or equal to one unit of the wavelength channel bandwidth. Since multiple commodities can be assigned to the group $g \in G$ on network edge $e \in E$, in *Equation 4.6*, the $\Re_g^e$ is the maximum bandwidth requirement for supporting all commodities in group $g \in G$ on the network edge $e \in E$. *Equation 4.7* ensures that each group $g \in G$ must have a total wavelength bandwidth less than or equal to 1. t_q is the bandwidth requirement of the commodity $q \in Q$. Both *Equations 4.6 and 4.7* are used to ensure that the bandwidth of all commodities in the group $g \in G$ traverse on edge $e \in E$ must be less than or equal to one unit of wavelength. In this dissertation, the bandwidth on the network edge $e \in E$ wavelength channel $k \in K$ is equal to 1 unit.

Equations 4.8 and 4.9 are the wavelength continuity constraints. Only one wavelength channel $k \in K$ is used for the commodity $q \in Q$ throughout multiple (connected) edges. Since multiple edges can be used for the commodity $q \in Q$ with a wavelength $k \in K$, in *Equation 4.8*, if the commodity $q \in Q$ occupies a wavelength channel $k \in K$ on any edge $e \in E$, then $\gamma_q^k = 1$. If $\gamma_q^k = 0$, there is no assignment of wavelength channel $k \in K$ for the commodity $q \in Q$ on any edge $e \in E$. *Equation 4.9* ensures that each commodity $q \in Q$ must have a number of assigned wavelength channels less than or equal to 1. If the commodity $q \in Q$ occupies wavelength channel $k \in K$, then γ_q^k = 1. Otherwise, γ_q^k = 0. Thus, both *Equations 4.8 and 4.9* ensure the wavelength continuity constraint in the network design.

Equation 4.10 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 $q \in Q$ with one wavelength channel. In another word, the commodity $q \in Q$ can be assigned with only one wavelength channel $k \in K$ on an edge $e \in E$ if the commodity $q \in Q$ is accepted. Note that the decision variable $\delta_{q,g}^{e,k}$ is related to the network flow constraint in *Equation 4.5*.

Equations 4.11 and 4.12 are the single group assignment constraints. Only one group $g \in G$ can be assigned for a particular commodity $q \in Q$. Since the commodity $q \in Q$ can be assigned to the multiple choices of groups, in *Equation 4.11*, if the commodity $q \in Q$ occupies a group $g \in G$, then $\Lambda_{q,g}$ = 1. If $\Lambda_{q,g}$ = 0, there is no assignment of group $g \in G$ for the commodity $q \in Q$. *Equation 4.12* ensures that each commodity $q \in Q$ must have the number of assigned groups less than or equal to 1. If the commodity $q \in Q$ occupies group $g \in G$, then $\Lambda_{q,g}$ = 1. Otherwise, $\Lambda_{q,g}$ = 0. Thus, both *Equations 4.11 and 4.12* ensure the single group assignment constraint in the network design.

Equations 4.13 and 4.14 are the wavelength continuity constraints for the group $g \in G$. Only one wavelength channel $k \in K$ is used for the group $g \in G$ throughout multiple (connected) edges. Since multiple edges can be used for the commodity $q \in Q$ in group $g \in G$ with a wavelength $k \in K$, in *Equation 4.13*, if the group $g \in G$ occupies a wavelength channel $k \in K$ on any edge $e \in E$, then y_g^k = 1. If y_g^k = 0, there is no assignment of wavelength channel $k \in K$ for the group $g \in G$ on any edge $e \in E$. *Equation 4.14* ensures that each group $g \in G$ must have the number of assigned wavelength channels less than or equal to 1. If the group $g \in G$ occupies wavelength channel $k \in K$, then y_g^k = 1. Otherwise, y_g^k = 0. Thus, both *Equations 4.13 and 4.14* ensure the wavelength continuity constraint for a group of commodities in the network design. Note that the group $g \in G$ is assigned to only one wavelength channel $k \in K$.

In *Equation 4.15*, the number of accepted commodities (Q_A) is equal to the summation of all commodity $q \in Q$ which can be routed (on one or multiple edge $e \in E$) from its source to destination and assigned with a wavelength channel $k \in K$ throughout the route.

In *Equation 4.16*, the number of required wavelength channels (K_A) is equal to the summation of all assigned wavelength channels ($k \in K$) where each assigned wavelength channel is occupied by at least one accepted commodity $q \in Q$.

Note that each network edge $e \in E$ has n_k wavelength channels that are required simultaneously. Multiple edges require various numbers of wavelength channels. The satisfied number of wavelengths is equal to the maximum number of simultaneously required wavelengths. The occupied number of wavelengths in each edge must not exceed the required number of wavelength channels (K_A). To optimize the number of required wavelength channels, only the first $K_A{}^{th}$ wavelengths on each network edge $e \in E$ should be assigned. For example, in *Figure 4.1*, we have occupied 2 wavelengths on edge 1 (from node 2 to node 1, 2→1) and 2 (1→3) thus K_A=2. Only λ_0 and λ_1 will be used on both edges.

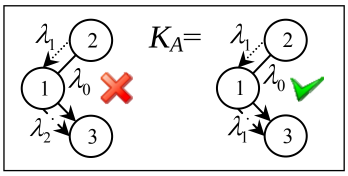


Figure 4.1 Invalid and valid wavelength channel assignments

Equation 4.17 is the number of electrical transmitting units of the group $g \in G$ on the network edge $e \in E$. If there exists a source of commodity $q \in Q$ in the group $g \in G$ on the network edge $e \in E$, an electrical transmitting unit is required for adding the new commodity to the existing group. Note that, if one or more commodities in the group $g \in G$ have their source on the network edge $e \in E$, only one transmission unit is required for group $g \in G$ on the network edge $e \in E$. For the group of multiple commodities, it is possible to drop the existing lightpath to remove a commodity from the group when the commodity $q \in Q$ reaches its destination. Therefore, in the second condition, if the set of commodities $q \in Q$ in the group $g \in G$ on network edge $e \in E$ (F_g^e) do not equal to the set of commodities $q \in Q$ in the group $g \in G$ on a previous edge $e' \in E$ which is connected to the source node of edge $e \in E$ and F_g^e is not empty set, a transmitting unit is required for adding the remaining communications after the commodity $q \in Q$ is split out of the group. In this dissertation, MP2MP is considered to groom multiple commodities into the same wavelength channel. It is possible to groom two commodities that do not have the same source and/or destination into the same wavelength channel. For example in *Figure 4.2*, commodities 1 and 2 are groomed into the same wavelength at edge 2→3. The network edge 2→3 does not contain the source or destination of either commodity 1 or 2. In the case 1, an electrical port is required at node 2, if the groomed and connected edge is reached. The case 1 is highlighted in the *Figure 4.2*. In the case 2, an electrical port is required at node 3, if the groomed and connected edge is terminated, for adding the remaining communications after the commodity $q \in Q$ is split. The case 2 is also highlighted in the *Figure 4.2*.

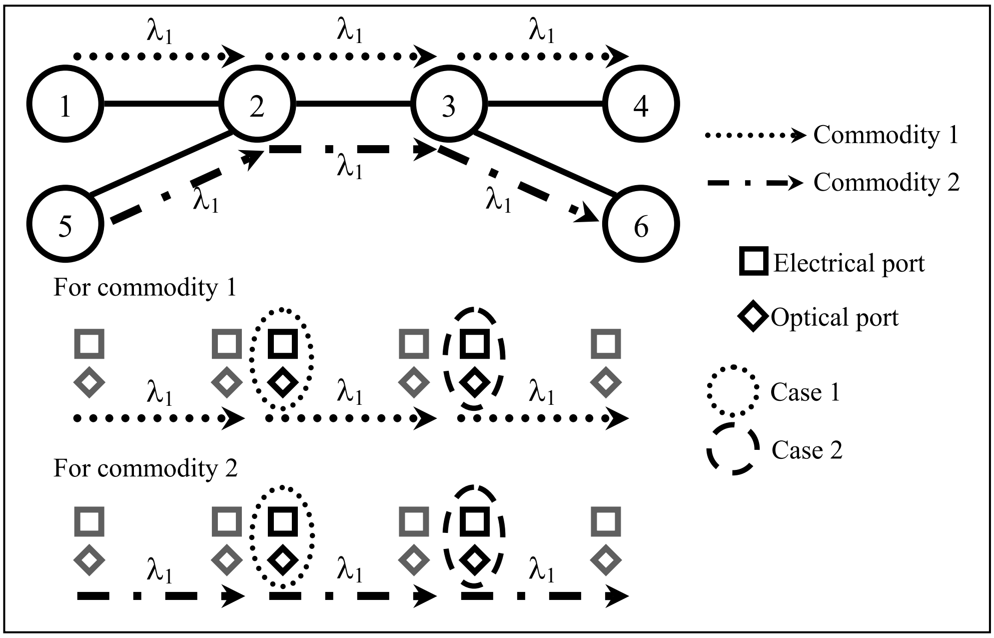


Figure 4.2 The grooming conditions in MP2MP for electrical transmitting units

Equation 4.18 is the number of electrical receiving units of the group $g \in G$ on the network edge $e \in E$**.** If there exists the destination of commodity $q \in Q$ in the group $g \in G$ on the network edge $e \in E$, an electrical receiving unit is required for dropping the commodity from the existing group. Note that, if one or more commodities in the group $g \in G$ have a destination on the network edge $e \in E$, only one transmission unit is required for group $g \in G$ on the network edge $e \in E$. For the group of multiple commodities, it is possible to drop the existing lightpath for grooming with a new incoming commodity. Therefore, in the second condition, if the set of commodities $q \in Q$ in the group $g \in G$ on network edge $e \in E$ (F_g^e) do not equal to the set of commodities $q \in Q$ in the group $g \in G$ on a next edge $e' \in E$ which is connected to the destination node of edge $e \in E$ and F_g^e is not empty set, a dropping or receiving unit is required for dropping the lightpath before the existing lightpath is groomed with the new commodity.

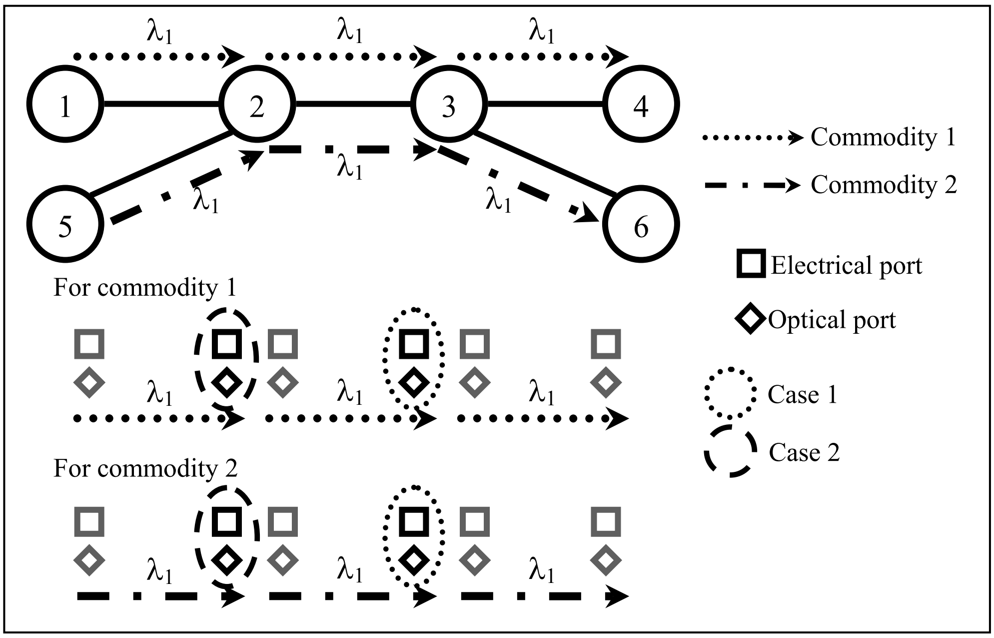


Figure 4.3 The grooming conditions in MP2MP for electrical receiving units

In this dissertation, MP2MP is considered to groom multiple commodities into the same wavelength channel. It is possible to groom two commodities that do not have the same source and/or destination into the same wavelength channel. For example in *Figure 4.3*, commodities 1 and 2 are groomed into the same wavelength at edge 2→3. The network edge 2→3 does not contain the source or destination of either commodity 1 or 2. In the case 1, an electrical port is required at node 3, if the groomed and connected edge is terminated, for dropping the commodity from the existing group. The case 1 is highlighted in the *Figure 4.3*. In the case 2, an electrical port is required at node 2, if the groomed and connected edge is reached, for dropping the lightpath before the existing lightpath is groomed with the other commodity. The case 2 is also highlighted in the *Figure 4.3*.

Equation 4.19 is the number of electrical ports for the group $g \in G$ on the network edge $e \in E$. In all-optical network, the optical signal can be bypassed in the optical domain, if the signal is not required to drop into the electrical domain for grooming with other commodities or reaching the destination. The number of electrical ports is calculated from the summation of electrical transmitting units $\varphi(s)_g^e$ and electrical receiving units $\varphi(d)_g^e$. The number of electrical ports of the group $g \in G$ on the network edge $e \in E$ may be equal to 0 at some network edge $e \in E$, if all commodities $q \in Q$ in the group $g \in G$ do not have the source or destination in the network edge $e \in E$.

Equation 4.20 is the number of optical units for the group $g \in G$ on the network edge $e \in E$. If the commodity $q \in Q$ in the group $g \in G$ traverses on the network edge $e \in E$, an optical unit is required for receiving and transmitting the optical signal. Note that, if one or more commodities in the group $g \in G$ traverses on the network edge $e \in E$, only one pair of transmission units are required for group $g \in G$ on the network edge $e \in E$.

Equation 4.21 is the number of optical ports for the group $g \in G$ on the network edge $e \in E$. Twice as many optical ports as units are required for every network edge that the set of grooming commodities passes. One optical port is used for transmitting and another one for receiving.

Equation 4.22 is the switching port calculation. The number of all switching ports is the summation of optical and electrical ports in all groups $g \in G$ where the set of commodities in the group $g \in G$ traverses on the network edge $e \in E$.

Equation 4.23 is the wavelength utilization constraint. Each wavelength channel $k \in K$ is selected if there is at least one commodity $q \in Q$ in the group $g \in G$ 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 *Equation 4.24*, the number of accepted commodities must be greater than or equal to a threshold (i.e., T_{acc}=0.8 or 80% of all commodities must be served or accepted).

In *Equation 4.25*, the hop distance of commodity $q \in Q$ traversed on multiple edges $e \in E$ must not exceed the hop count limit.

In *Equation 4.26*, the network link distance of commodity $q \in Q$ must not exceed the length limit (in kilometer).

Equations 4.27-4.35 define the decision variables used in the model.

The network model is formulated under wavelength continuity constraint indicating that the commodities cannot change their wavelength channel through the network path. Only one wavelength is assigned to each group of commodities. The commodity uses the assigned wavelength throughout the light path.

The routing of commodity $q \in Q$ can be any of the possible routes that connect the specified source node to the specified destination node. Previously, the RWA problem is shown to be NP-complete [37]. In GRWA, the problem considers not only routing and wavelength assignment but also combining multiple low rate traffic demands into the same wavelength channel. We can approximate the complexity of the GRWA with the size of all possible solutions called "search space" as follows.

Let S be the number of source-destination pairs. For the case of Routing, the complexity is $O(R^S)$ where R is the size of potential routes of each source-destination pair. Note that this dissertation considers the GRWA in the scope of the multi-commodity flow problem. Therefore, multiple source-destination pairs select one choice of routes from R possible routes simultaneously. For the case of Grooming, the complexity is $O(G^S)$ where G is the number of potential groups. The number of G is equal to the number of S if all commodities are not overlapped to each other. For the case of Wavelength Assignment, the complexity is $O(W^S)$ where W is the number of wavelength channels. The search space of GRWA problem with R potential routes, G possible groups and W wavelength channels is $O((R \cdot G \cdot W)^S)$.

Note that the answer of multi-objective GRWA problem considered in this dissertation is not one optimal solution but multiple optimal solutions that are searched and addressed as a set. Our proposed network design model is solved by using a hybrid evolutionary computation approach as described in the next chapter.

CHAPTER 5 MULTI-OBJECTIVE TRAFFIC GROOMING ALGORITHM

In this section, we present a hybrid evolutionary computation algorithm to solve the multi-objective grooming, routing and wavelength assignment (GRWA) problem in optical network design. Previously, Zhu and Mukherjee [4] proposed the Maximizing Single-Hop Traffic (MST) and Maximizing Resource Utilization (MRU) techniques to maximize the network throughput with a limited number of wavelength channels and transceivers. The proposed techniques are efficient and suitable for a single objective function but this dissertation considers a network model with multiple design objectives, where all objectives are considered simultaneously. Our multi-objective GRWA problem is that when f_c is optimized, the f_w and f_p may get worse. Our hybrid evolutionary computation approach consists of Genetic Algorithm, Extended Traffic Grooming algorithm and Maximum Degree First algorithm (GA-ETG-MaxDF or shortly called GA-EMF) applied to the Fast Non-dominated Sorting Genetic Algorithm (NSGA-II). The GA-EMF considers 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 Fast Non-dominated Sorting Genetic Algorithm (NSGA-II) is then used to search for non-dominated solutions or a set of candidate choices. The hybrid evolutionary algorithm is used as a meta-heuristic technique for obtaining good solutions with various problem sizes.

5.1 GA-EMF Heuristic Algorithm

We present a heuristic algorithm called “GA-EMF” consisting of three parts that are Routing with Genetic Algorithm, Grooming with Extended Traffic Grooming (ETG) and Wavelength Assignment with Maximum Degree First (MaxDF).

5.1.1 Genetic Algorithm for Routing

Previously, Genetic Algorithm has been used to solve a routing problem in WDM optical network [11]. Banerjee and Sharan proposed a Genetic Algorithm based on Fixed-Alternate Routing approach. Their algorithm limited the alternate routes of each commodity therefore the obtained result may not cover some feasible solutions. In traditional approaches, only potential routes are considered (e.g., K^{th} shortest routes). 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 be considered. Our proposed method and its parameter settings are described next.

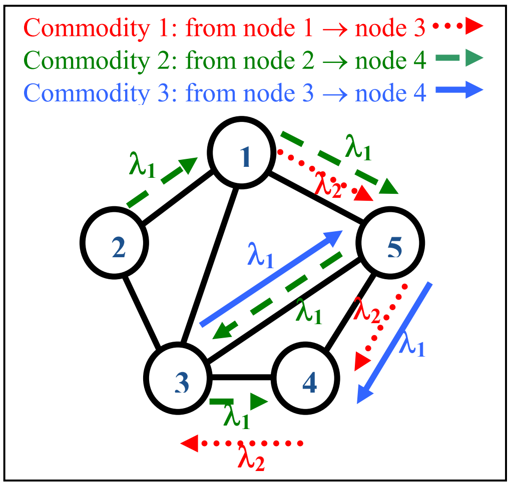


Figure 5.1 A sample 5-node network

String Encoding is a process that encodes the combinatorial problem into a set of genes or a chromosome. The string encoding, in this dissertation, is a set of integers that indicates the route of each commodity. Suppose that in the network design problem, we have 5-node network as shown in *Figure 5.1*. The corresponding string encoding is displayed in *Figure 5.2*. Each position p has the value n_p that represents the connection from n_p to n_{p+1}. The value n_p= -1, if the destination has been reached in previous connection. We can encode the string as shown *Figure 5.2*. This string encoding scheme has the benefit that all possible routes are considered.

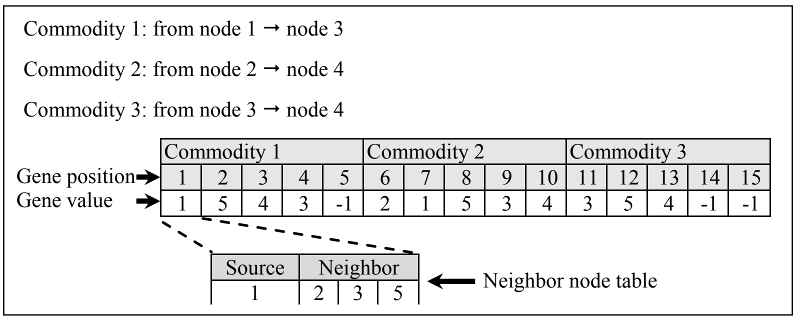


Figure 5.2 An example of string encoding

Crossover is a process that generates new solutions based on two existing solutions. An example of a crossover process is shown in *Figure 5.3*. We use one-point crossover for each commodity. 80% of the population will be crossed. In *Figure 5.3*, the crossover points are at position 2 in both Parents 1 and 2. The crossover points in Parents 1 and 2 may be different positions if they have a connection in the neighbor node table. The duplicated nodes or loops will be removed after the crossover process.

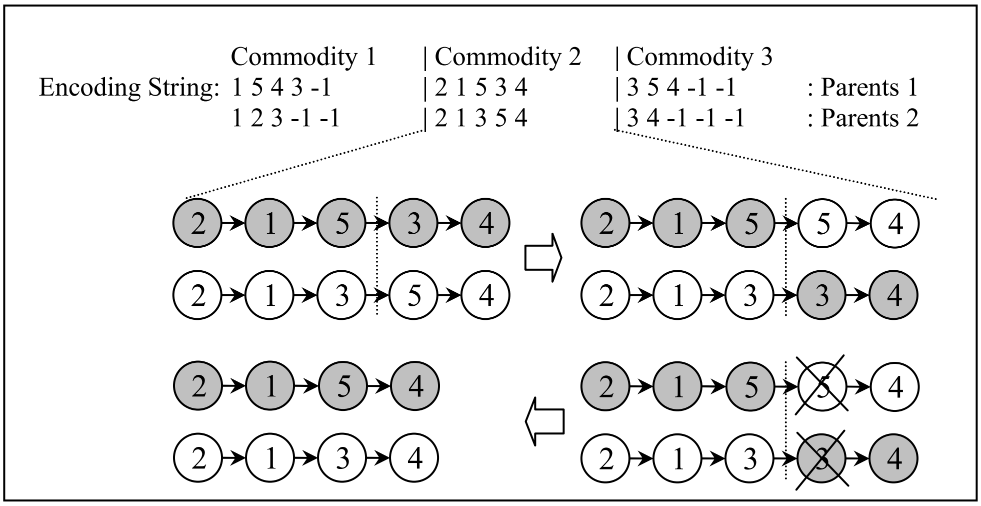


Figure 5.3 An example of crossover process

Mutation is a process that generates new solutions based on a single existing solution. An example of a mutation process is shown in *Figure 5.4*. We use one bit mutation for 25% of the population. One node is randomly selected for mutation. For the example, node 1 is selected. The mutation process removes a connection 1→3 first. Next, the shortest path between node 1→3 is calculated (i.e., 1→5→3). The new network path is 2→1→5→3→4 as shown in *Figure 5.4*. The mutation process will update the chromosome if a new shortest path is found and can be inserted in the existing path. Otherwise, the algorithm will select the pre-existing path.

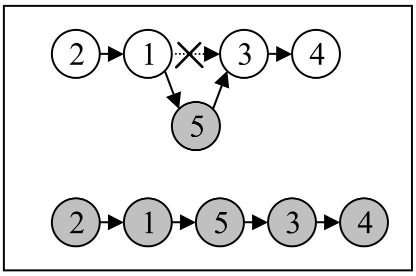


Figure 5.4 An example of mutation process

The parameter setting values of GA for routing can be summarized in *Table 5.1*. The size of population (chromosomes) is equal to 100. We preserve top ten (best) chromosomes to the next generation. The remaining 80 chromosomes are crossed and mutated for searching a new set of chromosomes. The bottom ten (worst) chromosomes are randomly generated for obtaining a new set of chromosomes.

Table 5.1 The parameter setting values of GA for routing

Encoding Technique	Genetic Algorithm for Routing
Crossover Method	Single Point Crossover
Crossover Rate	0.80
Mutation Rate	0.25
Mutation Bit Rate	0.01
Size of Population	100
Size of Preservation	10
Size of Crossover	80
Size of Alien	10
Termination Criterion	Repeat until the number of iterations is met
Maximum Iteration Count	2,400

5.1.2 Extended Traffic Grooming

In traffic grooming, the commodities that have overlapped paths and have the summation of traffic demands less than or equal to a wavelength transmission rate are groomed or combined into a group using the same wavelength channel. There are four containment techniques for traffic grooming as described in *Section 2.2*. In this dissertation, we consider multi-point to multi-point (MP2MP) containment technique to combine multiple overlapped commodities into one wavelength.

In the previous off-line traffic grooming algorithms (MST and MRU [4]), the set of commodities must be arranged before the grooming procedure starts. The traditional grooming algorithm combines multiple overlapped commodities into the same group by following the sequence. Overlapped commodities early in the sequence are first considered to be grouped together. If two commodities are not overlapped, it is determined that they cannot be groomed together. However, we notice that some non-overlapped commodities could be groomed into the same group, if there exists a commodity that is overlapped between the non-overlapped commodities as described in the following example. Suppose that we have eight commodities and the routing of each commodity is randomly generated using the GA as shown in *Table 5.2* and *Figure 5.5*. In *Figure 5.5*, C0:0.5 represents the commodity C0 with 0.5 unit of wavelength requirement. We can see that C0 and C1 do not overlap each other. They are traditionally not combined or groomed together. However, it is possible to groom C0 and C1 together when C2 is overlapped with C0 and C1. By doing this, we can reduce the number of wavelength channels required in the optical network design. Therefore, we propose an extended traffic grooming algorithm which considers both overlapping and non-overlapping commodities for traffic grooming.

Table 5.2 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

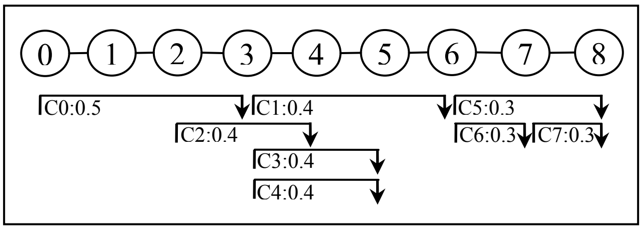


Figure 5.5 Set of commodities with bandwidth requirement in the sample network

Before we combine multiple commodities into groups, we need to create an auxiliary graph for the set of lightpaths to consider which commodities are overlapped. In the auxiliary graph as shown in *Figure 5.6*, each node represents an element in a set of commodities. The link between a pair of nodes represents their relation. If a commodity has an overlapping path with other commodities, a connection or link is created between commodity nodes in the auxiliary graph (i.e., Commodity 0 or C0 overlaps with C2 but does not overlap with C1).

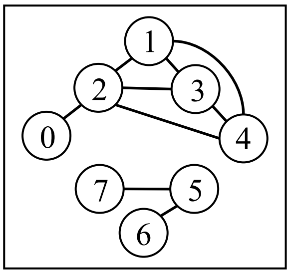


Figure 5.6 The auxiliary graph of overlapped commodities

In the traditional traffic grooming approach using MST, the commodities that are overlapped will be considered for grooming into a group. For example, in *Figure 5.6*, commodities 3 and 4 are groomed first because they have the same source and destination. After that C0 and C1 are assigned respectively. C0 and C1 cannot be groomed together because they do not overlap. C2 is groomed with C0 because high traffic demand is considered first. For grooming C2 with C0, C1 cannot use the same wavelength channel as C0 and C2 because their lightpaths overlap. Lastly, C5, C6 and C7 are groomed together in the same group.

In our extended traffic grooming approach, commodities in an existing group can be reconsidered. The extended traffic grooming will consider if there exists a commodity in the groomed group that overlaps with another commodity and whose amount of bandwidth does not exceed the wavelength bandwidth constraint.

For example, C0 and C2 are first assigned into a group and they are reconsidered to groom with the C1 because the element C2 in the group of C0 and C2 overlaps with C1 and the summation of bandwidth on link 3 to 4 does not exceed the wavelength bandwidth constraint. *Table 5.3* shows the set of commodities in each group by using MST and ETG algorithm in the example network. The MST requires four groups while ETG requires three groups for supporting all commodities.

Table 5.3 The set of commodities and link bandwidth in the groomed groups

MST			ETG		
Set of commodities	Edge	Link bandwidth	Set of commodities	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

The pseudo code of the Extended Traffic Grooming is described as followings.

Extended Traffic Grooming

```
Step 1:  Calculate the average traffic demands
Step 2:  Assign sequence order to the set of commodities
         Step 2.1: If the average traffic demand is less than the wavelength threshold,
                   Sort the set of commodities by bandwidth requirement and number of hops (in
                   descending order) respectively
         Step 2.2: Otherwise,
                   Sort by the number of hops and bandwidth requirements (in descending order)
Step 3:  Groom multiple commodities using the followings pseudo code
         Repeat
              Step 3.1: Attempt to combine with the existed group
                        Repeat
                           Repeat
                                If the amount of traffic demands in the groomed link does not exceed the
                                wavelength bandwidth and there exists an element in the group that
                                overlaps with another commodity
                                     a) Add the commodity to the set of elements of the existed group
                                     b) Update the usage bandwidth of the network link
                           Until all elements in the group are considered
                        Until all existing groups are considered
                        If the existing groups are possible to groom together (i.e., the elements in two
                        or more existing groups are overlapped and the summation of their traffic
                        demands for all links is not exceed the wavelength bandwidth)
                           Groom the existing groups together
                        End if
              Step 3.2: If a commodity is not assigned into a group,
                           a) Add the commodity to a new group
         Until all commodities are assigned to the group
```

In the ETG algorithm, the set of commodities is sorted by the number of hops (i.e., the number of hops of commodity 0 is 3) and the amount of traffic demands in descending order. In our extensive experiments, we found that when the traffic demand in each commodity is small, the sequence of commodities should be sorted by amount of traffic demands first (i.e., if two commodities have the same demand, the high number of hops is preferred). In this dissertation, we specify that if the average traffic demand is less than 0.4 wavelengths, the set of commodities are sorted by using maximum traffic demand first, otherwise, they are sorted by using longest hop first (i.e., if two commodities have the same number of hops, the commodity that has higher traffic demand is preferred).

In *Table 5.2*, the set of commodities has an average traffic demand of 0.375 which is less than 0.4 wavelengths. Therefore, the sequence of commodities is sorted in descending order by the bandwidth requirements and then the number of hops as shown in *Table 5.4*.

Table 5.4 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

Figure 5.7 shows a series of snapshots to illustrate how ETG would be applied to the sequence of commodities in *Table 5.4*. At first, commodity C0 is assigned to the group 0 and then commodity C1 to the group 1. At the snapshot 3, the commodity C2 is groomed with commodity C0 in group 0. At snapshot 4, the commodity C1 is reassigned to group 0 because C1 and C2 are overlapped and their bandwidth summation does not exceed the wavelength bandwidth. At snapshot 5, the new commodity C3 is assigned to group 1. At snapshot 6, the commodity C4 can be groomed with an existing group (i.e., group 1). At snapshot 7, the commodity C5 is assigned to a new group (i.e., group 2). At snapshots 8 and 9, commodities C6 and C7 are combined with an existing group (i.e., group 2). Finally, the ETG algorithm requires three groups for supporting the set of commodities in *Table 5.2*.

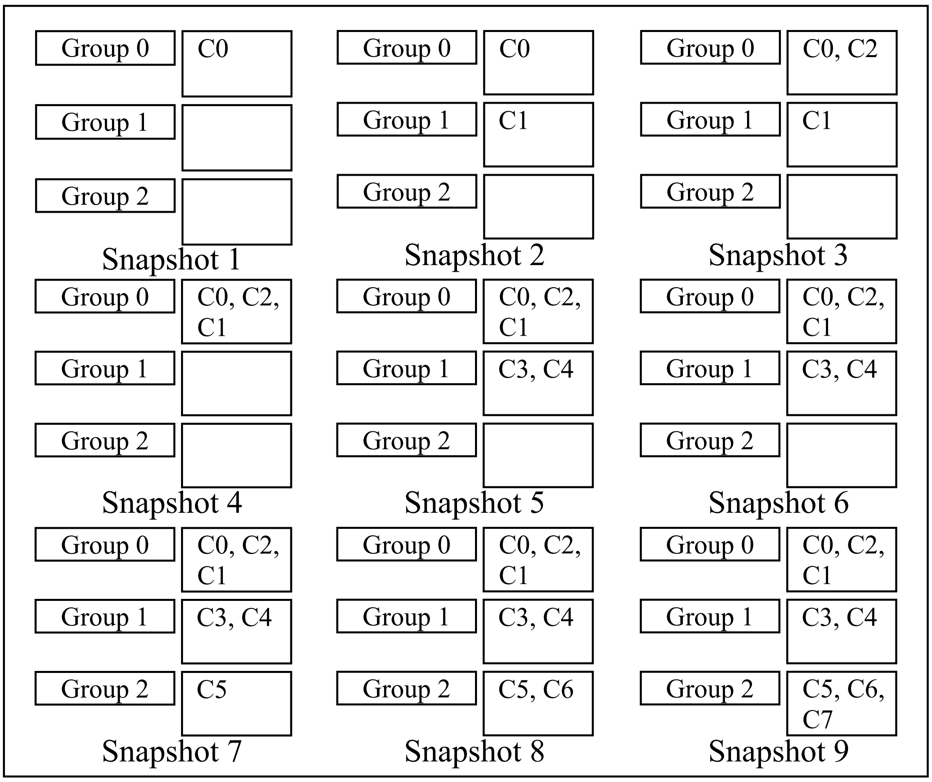


Figure 5.7 The snapshots of the ETG algorithm using commodities in *Table 5.2*

The drawback of the extended traffic grooming is that its computational complexity is increased because all commodities in the groomed group are reconsidered. However, the network design problem in this dissertation is static with offline traffic demands so that the computational time is not marginally different with or without traffic grooming.

5.1.3 Maximum Degree First (MaxDF) Wavelength Assignment

The Wavelength Assignment, Maximum Degree First (MaxDF) algorithm is proposed to assign a limited number of wavelength channels to a set of commodities. Before we assign a wavelength to a set of commodities, we need to create an auxiliary graph for the set of lightpaths. After we combine multiple low-rate traffic demands into groups in the traffic grooming phase described previously, a second auxiliary graph can be created to specify the groups of commodities that are overlapped as shown in *Figure 5.8*. A traffic group overlaps with another group if it has at least one commodity that is overlapped with the commodity members of the other group. For example, Group 0 is overlapped with Group 1 because commodity 1 in the Group 0 is overlapped with the commodity 3 and 4 in the Group 1. In the auxiliary graph, each node represents a group and the set of commodities in the group. The circle symbol represents the group and the rectangle symbol represents elements in the group. The link between a pair of nodes represents their relation. In *Figure 5.8*, for example, we have three groups. The groups 0, 1 and 2 are represented by nodes 0, 1 and 2, respectively. The groups 0 and 1 are overlapped (i.e., at network edge 3→4 and edge 4→5 in *Figure 5.5*). Therefore, a link between overlapping groups is created. Any pair of auxiliary nodes that has a link cannot be assigned to the same wavelength.

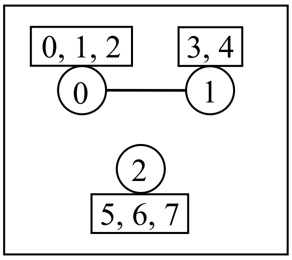


Figure 5.8 The auxiliary graph of overlapped commodities in the group

We modify the First-Fit algorithm 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. Our assumption is that the maximum degree of an auxiliary graph represents the fact that large numbers of commodities in the group are overlapped with others. Therefore, the maximum-degree commodity should be assigned first. If a low degree node in the auxiliary graph is first selected and assigned with a wavelength channel, 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 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 commodities with the other), assign the first wavelength.
3. At the next commodity, if its commodity is not overlapped with the previous commodities, assign the same wavelength channel as the previous commodity, else assign the next wavelength.
4. Repeat Step 3, until all commodities are considered.

After the MaxDF process, we have the set of commodities in the group with wavelength channel as shown in *Figure 5.9*. For instance, channel 0 is assigned to Groups 0 and 2 because none of them overlaps. The commodities in the group also have the same wavelength channel as shown in *Figure 5.10*.

Group ID.	0	1	2
Wavelength Channel	0	1	0

Figure 5.9 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

Figure 5.10 The wavelength channel of the set of commodities

In Appendix A, the performance of 1) the routing and 2) wavelength assignment algorithms are shown by comparing with the traditional routing approach called Fixed Alternate Routing (FAR) and comparing with the traditional wavelength assignment called First-Fit (FF). Our previous work showed that both routing and wavelength assignment algorithms can assign the wavelength as fast as the First-Fit algorithm but with superior results in terms of accepted community requests. The computation results are showed in Appendix A.3.

For the comparison of the traffic grooming algorithm, we have compared our GA-ETG-MaxDF algorithm with traditional approaches (GA-MST-FF and GA-MRU-FF). The experimental results are shown in *Chapter 7*.

5.2 NSGA-II Algorithm

The Fast Non-dominated Sorting Genetic Algorithm (NSGA-II) is famous as an efficient technique to search for the Pareto-optimal set in general multi-objective optimization problems. The NSGA-II was proposed by Deb et al [10] and described as follows.

NSGA-II Algorithm

Let R_t represent the total population, P_t is the preserved population, Q_t is the recombined population of the generation t. F_i is the front i where i is a positive integer. Note that the solutions in front F_1 is better than those of F_2, and so on.

1. *Combine the P_t and Q_t to R_t*
2. *Calculate the number of accepted commodities, the required wavelength channels and the switching ports, using **GA-EMF** (described in Section5.2).*
3. *Assign each population in R_t to the front (F_1, F_2, F_3, and so on) using **Fast-non-dominated-sort(R_t)** algorithm*
4. *Calculate the crowding distance in each F_i using **Crowding-distance-assignment(F_i)** algorithm*
5. ***Sort** the population R_t (sort by front order(F_i) **in ascending order** and crowding distance **in descending order**)*
6. *Select only first half of the population R_t and assign to P_{t+1}*
7. ***Recombine (crossover and mutate)** the population P_{t+1} and assign to Q_{t+1}*
8. *Increment the iteration counter ($t = t+1$)*
9. *Repeat Steps 1 to 8, until the iteration reaches with the maximum number of iterations or there is no result improvement within certain number of iterations.*

Two significant procedures of NSGA-II are Fitness assignment (*Fast-non-dominated-sort* and *Crowding-distance-assignment*) and Selection procedure. The population consists of many individuals. Each individual in a population is usually assigned a rank or order to it for the reason that the elite individuals should be maintained in the next generation. The elite individuals have higher ranks or fitness values. The ranks of the solutions are calculated from the *Fast-non-dominated-sort* first. After that, the solutions in the same front are arranged by using *Crowding-distance-assignment*. The individual that has small distance value means that it is more crowded to the others. The individual that is far away from the others will be selected first. The ranking assignment is shown in procedures 1 and 2 in *Figure 5.11*. For the selection procedure, the individual that has a lower front order is selected first. If the available space of the population in the next generation cannot support all the individuals in front F_i, an individual in the same front which has a greater crowding distance value will be selected first as shown in the procedure 3 in *Figure 5.11*. NSGA-II is described in detail in Appendix D.

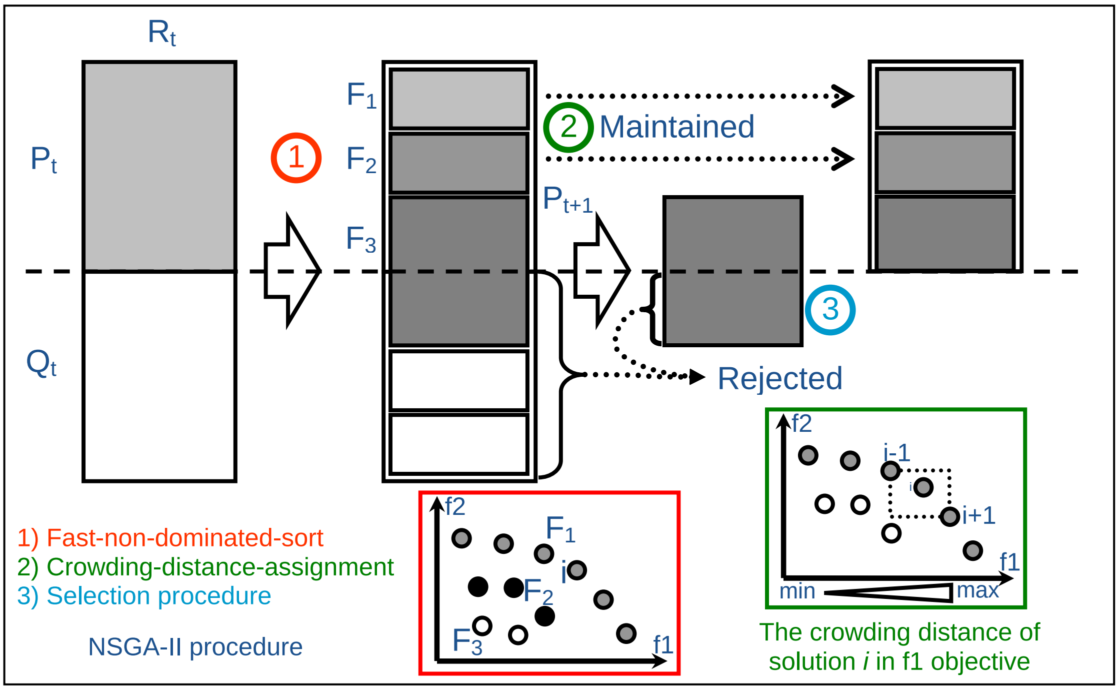


Figure 5.11 NSGA-II procedure [10]

To ensure that the NSGA-II algorithm is efficient as it was originally proposed, we applied our implemented NSGA-II algorithm to solve a combinatorial Knapsack problem using the input data and all configuration parameters as proposed in [9]. We found that our implemented NSGA-II was efficient in searching for the set of optimal individuals as shown in *Figure 5.12*. The axes represent the profit values.

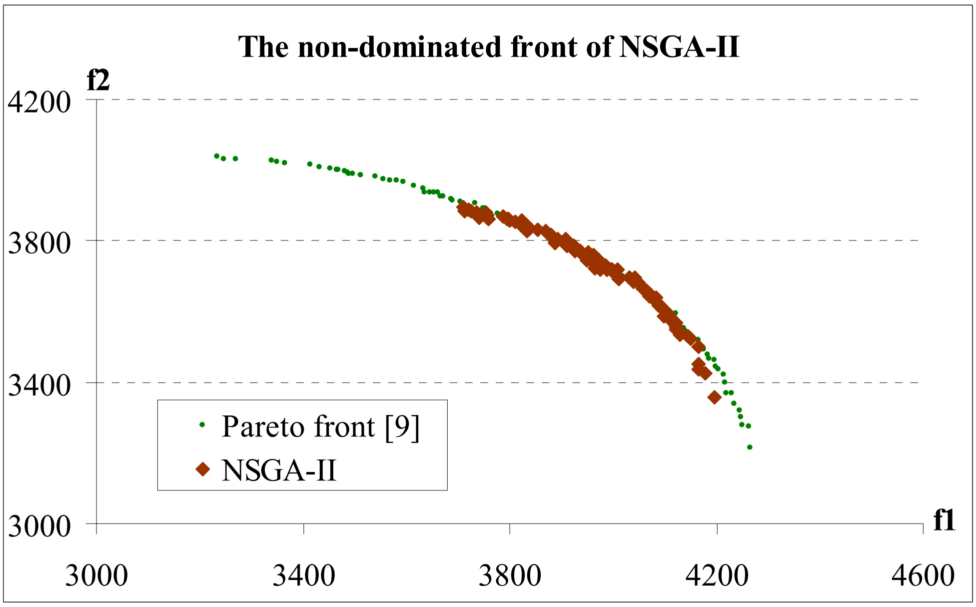


Figure 5.12 The comparison of Pareto-front and non-dominated individuals obtained from our implemented NSGA-II on the knapsack benchmark

The NSGA-II is an existing multi-objective optimization algorithm. In this dissertation, we modify the NSGA-II for solving the GRWA problem. The modified NSGA-II procedure is shown in *Figure 5.13*. It consists of eight main procedures. The algorithm starts from population initialization. Five shortest paths for each requested traffic demand or community are the top-five population and the remaining are randomly generated. After the initial state, we obtain several sets of routes equal to the size of population. One set of routes represent possible routing solutions for the given set of traffic demands and bandwidth requirements.

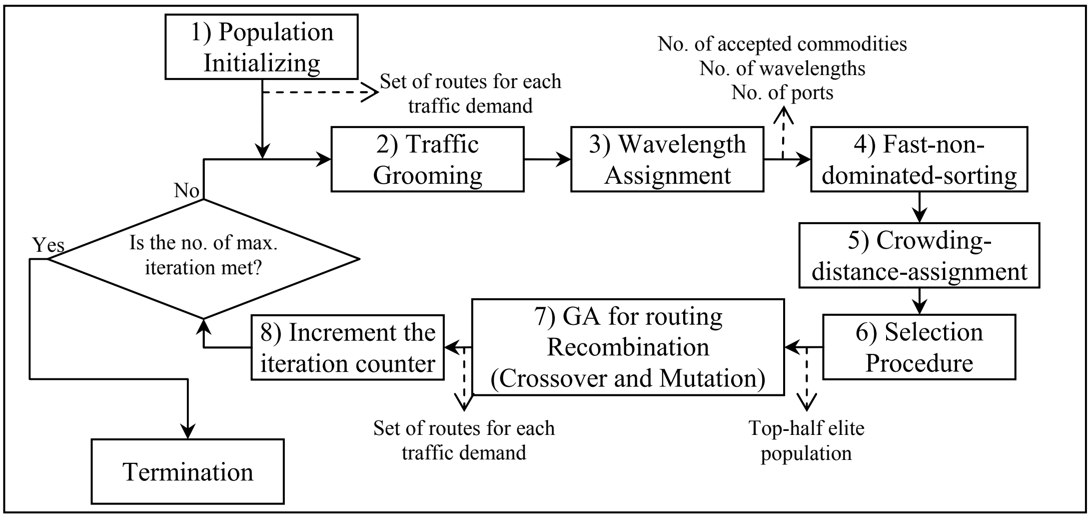


Figure 5.13 The modified NSGA-II procedure

In the second procedure which is traffic grooming, the set of routes is assigned to multiple groups for using the same network resource. Multiple low rate traffic demands are assigned to the same group for saving the wavelength and switching ports. We tried three traffic grooming procedures: Extended Traffic Grooming (ETG), Maximizing Resource Utilization (MRU) and Maximizing Single-hop Traffic (MST).

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

In the fourth, fifth and sixth procedures, the solutions are sorted and the top-half elite solutions are selected for the next generation.

In the seventh procedure, multiple set of routes are exchanged and mutated in order to obtain a new feasible route that does not exist in the current population. After the recombination procedure, the set of routes for each traffic demand is obtained. In the eighth procedure, the iteration counter is incremented. Lastly, the algorithm is checked for the termination condition. In this dissertation, the algorithm is terminated when the maximum number of iterations is reached.

In multi-objective GRWA problem, it could happen that some different solutions have the same objective values (i.e., number of accepted commodities, wavelengths and switching ports). The NSGA-II or multi-objective genetic algorithms have diversity mechanisms to select the solutions in the extreme areas first (e.g., crowding distance, niche size, or etc.). If duplicate solutions occur in the objective space, their diversity values equal zero and they are removed first. This problem can also be solved when we consider the solutions with more objectives and constraints such as with number of accepted commodities, wavelengths, switching ports and network path length.

The obtained solutions from multi-objective algorithm are non-dominated and provided as a set or front. The obtained result from the multi-objective algorithm usually involves numerous solutions. It is difficult to choose a single solution. The decision maker has trouble knowing which solution is the best because one solution is better in one or few objective(s) while the other objectives may be worsening. The comparison in all objective values is complicated for a human to interpret. In the next chapter, we present a new pruning mechanism to reduce the number of non-dominated solutions.

CHAPTER 6 PRUNING MECHANISM

The pruning mechanism is a multi-objective filtering procedure. Since the multi-objective optimization procedure produces numerous solutions, it is difficult to make a final decision. The pruning mechanism reduces the numerous solutions to a small number. In this dissertation, we separate the description of pruning mechanism into a new chapter because the pruning mechanism represents new multi-objective knowledge and there are many related works. In this dissertation, we propose a new reason to prune that removes unlikely solutions. The new pruning mechanism is called the "Adaptive Angle Based Algorithm (ADA)". *Section 6.1* introduces the pruning mechanism concept. *Section 6.2* reviews related literature. *Section 6.3* proposes our pruning mechanism called "Adaptive Angle Based algorithm". *Section 6.4* describes the multi-objective performance metrics that are used to indicate the performance of the obtained solutions. *Section 6.5* shows the experimental results of our pruning mechanism compared with the traditional approaches. *Section 6.6* concludes our research contribution on the pruning mechanism.

6.1 Introduction to Pruning Mechanisms

Several multi-objective optimization algorithms (e.g., NPGA [33], SPEA2 [9] or NSGA-II [10]) have been proposed in the previous two decades. A new and efficient technique to determine a promising set of Pareto solutions or to prune large sets of solutions for multi-objective problems is proposed in this dissertation and compared with traditional approaches. Several quality indicators have been used to provide indications or assurances that an algorithm is better than the other algorithms. Some of the traditional metrics are Inverted Generational Distance (IGD) [42], Spread [42], Hyper-volume (HV) [42] and the convergence speed (i.e., the relation between the benchmark value and the number of generations, or converged graph) [35, 9]. For all multi-objective optimization algorithms, the results obtained are numerous. Thus, it becomes difficult to make a final decision about the best approach for some specific problem [58, 59].

In this chapter, we propose a new mechanism to cut-off or prune the numerous non-dominated solutions and identify a very promising subset of representative solutions.

The cut-off mechanism is called a "pruning mechanism" as in previously studied research [58].

There are different reasons for pruning Pareto sets including 1) to reduce the number of Pareto solutions while still maintaining diversity (i.e., *K*-means algorithm [59, 73]), or 2) to reduce the subset to keep solutions that reflect objective preferences (e.g., guidance in evolutionary algorithm [64], preference algorithm [60-63]). In this dissertation, we propose a new pruning method with a different purpose which is to remove unlikely or less desirable solutions. The objective is to eliminate solutions that offer very little improvement for one objective yet are clearly less desirable for others. The new pruning mechanism is called "Adaptive Angle Based Algorithm (ADA)". With a new pruning rationale, the ADA reduces the Pareto solutions to the subset of the most likely solutions. The ADA reduces the numerous Pareto solutions based on an extension of the dominated-area from the traditional definition of the dominated area. This dissertation proposes a new performance metric to indicate the quality of the non-dominated solutions after the pruning because the general quality indicators [42] or performance metrics [43] are not always particularly informative in comparing the quality of the obtained solutions with those of the other algorithms.

Figure 6.1 shows the Pareto solutions after pruning for several examples. *K*-means can maintain the diversity of the whole solution set although some solutions are crowded in some areas while the guided multi-objective algorithm provides the set of solutions that reflect objective preferences. In this dissertation, we consider the new reason to prune which is to remove only unlikely solutions. The solutions from ADA remain only convex sets that maintain the true Pareto front.

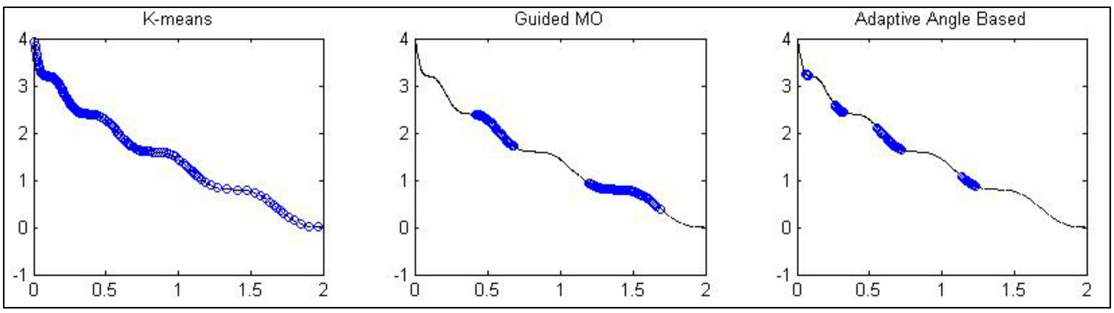


Figure 6.1 The Pareto solutions from three reasons to prune (WFG1 with two objectives [20, 21])

The remainder of this chapter is organized as follows. In the next section, we describe and review previous pruning algorithms. In *Section 6.3*, we present our pruning mechanism (ADA) with the extension of the dominated area concept. *Section 6.4* presents general performance metrics that are usually applied to compare the performance of multiple sets of non-dominated solutions. The experimental results from these general performance metrics are shown in this section. Various problems are used to benchmark the performance of the algorithms. *Section 6.5* presents a new metric for benchmarking the obtained results after the pruning algorithm. Numerical results are shown and analyzed. Lastly, *Section 6.6* concludes our research work and contribution.

6.2 Literature Reviews

Results from multi-objective optimization algorithms are numerous and there are many advantages and disadvantages for the particular algorithms so it becomes difficult for a decision-maker to make a final decision. Previously, Konak et al. [58] and Taboada et al. [72] proposed two approaches which are data clustering algorithm and ranking preference. Pruning mechanisms have considered two primary reasons. The first reason is to reduce the number of Pareto solutions while still maintaining diversity (i.e., *K*-means algorithm [59, 73]). The second reason is to reduce the solution set to a subset that reflects decision-maker preferences (Guidance in evolutionary algorithm [64], Preference algorithm [60-63]).

6.2.1 Reduce the Number of Pareto Solutions and Maintain Diversity

To prune using data clustering, the decision-maker does not have to know the priority of each objective. Data clustering is applied to filter the numerous solutions without prioritizing the objectives. The solutions after the Pruning can maintain the diversity of the Pareto front, because the obtained solutions are spread into all areas of the front.

The numerous solutions (Pareto solutions) are cut-off by using a well-known data clustering algorithm (i.e., *K*-means algorithm). Before the *K*-means pruning process, it is necessary to specify the number of centroids. The centroids are randomly selected and possibly change their positions in every iteration. The centroids are repeatedly calculated until the error is less than a defined threshold or the distance between each solution to the nearest centroid is minimized. The basic *K*-means algorithm [73] is shown as follows.

Basic K-means Algorithm [73]

1. Select K points as initial centroids
2. Repeat
   a. Form K clusters by assigning each point to its closest centroid
   b. Recompute the centroid of each cluster
3. Until centroids do not change or the termination criterion is met

In this dissertation, the Euclidean distance is used to represent the proximity of the solutions to their centroids.

The main issue in the *K*-means algorithm is to find the suitable value of *K*. The value of *K* can be selected by considering both sum of the squared error (SSE) and the percentage of the obtained solutions retained after pruning. Minimum SSE typically requires a large value of *K*. Therefore, it is difficult for the decision-maker to make final decision. On the other hand, the minimum value of *K* gives high SSE which means that the selected centroid might not accurately represent the group of solutions in the cluster.

Specific features of the *K*-means [59, 73] algorithm are:

1) Maintain the diversity of Pareto solutions.
2) The number of remaining solutions is directly specified by the decision-maker.
3) Necessary to specify the number of centroids before the algorithm processes.
4) Requires significant computational time.

6.2.2 Reduce to the Subset that Reflects Preferences

In the second approach to prune, the decision-maker has to define the priority of each objective. The preference relation established means that the objectives are not equally important. The subset that reflects preferences may be biased to one or few objectives.

In 1999, Cvetkovic and Parmee [60-63] proposed the "Preference algorithm" to convert a qualitative relation of all objectives to quantitative weighted sets. The decision-maker has to specify the relation between each objective such that objective 1 is less important than objective 2, and objective 2 is less important than objective 3 ($f_1 < f_2 < f_3$). The preference relations are specified with a constant value in the relation matrix and derived into the set of weight parameters for all objectives. For the dominated comparison, the decision-maker has to specify the dominance threshold. The dominance threshold is equal to one according to the traditional or regular dominance definition, and less than one in the special dominance case.

Specific features of the Preference algorithm [60-63] are:

1) Easy for decision-maker to specify the filtering condition (cut-off numerous non-dominated solutions to a few final solutions)
2) Suitable for a problem that has a large number of objective functions (e.g., 13 objective functions in [63])
3) Decision-maker has to possess the background knowledge or information that specifies which objective function is related to which other or which one is more important.
4) This mechanism has to express qualitative data as quantitative values. For example, it approximates the most important relation with an objective weight of 0.95.
5) The preference relations are converted into a set of weights. The objective functions that have a small weight are discarded in the comparison. This biases the obtained solution toward the objectives that have a large weight.

In 2001, Branke et al. [64] proposed the "Guided multi-objective algorithm" to guide or specify the approximate boundary in the objective space. The concept of guidance is to increase the dominated area compared to the traditional regular dominance interpretation or definition. The regular dominance is shown in *Figure 6.2*. Branke et al. proposed a technique to expand the dominated area from regular dominance by using minimum and maximum weights. For example, in minimizing both objectives 1 and 2, the solutions A and B are non-dominated in the regular dominance space as shown in *Figure 6.3a* because solution A has f_1 better than solution B but f_2 is worse. The set of non-dominated solutions is A, B, C and D. In the guidance method, the minimum and maximum slopes are specified to increase the dominated area as shown in *Figure 6.3b*. Thus, solution A is dominated by solution B. The set of non-dominated solutions is now only B, C and D.

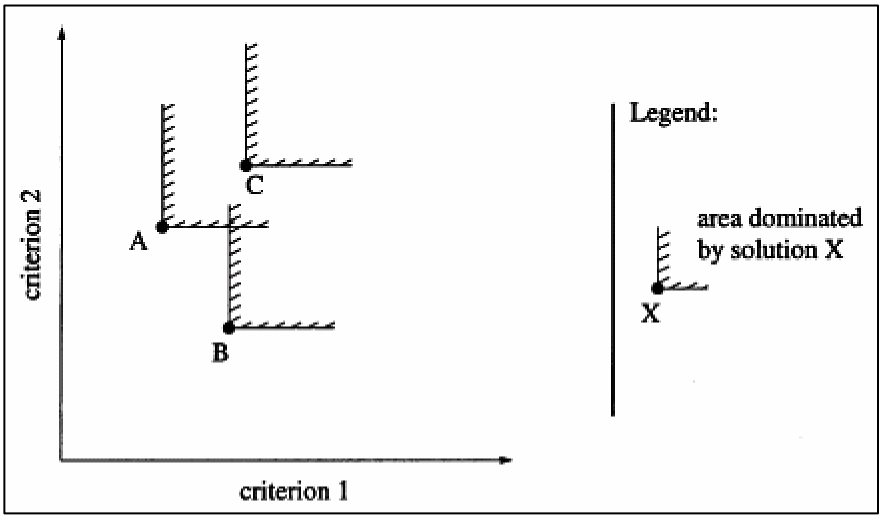
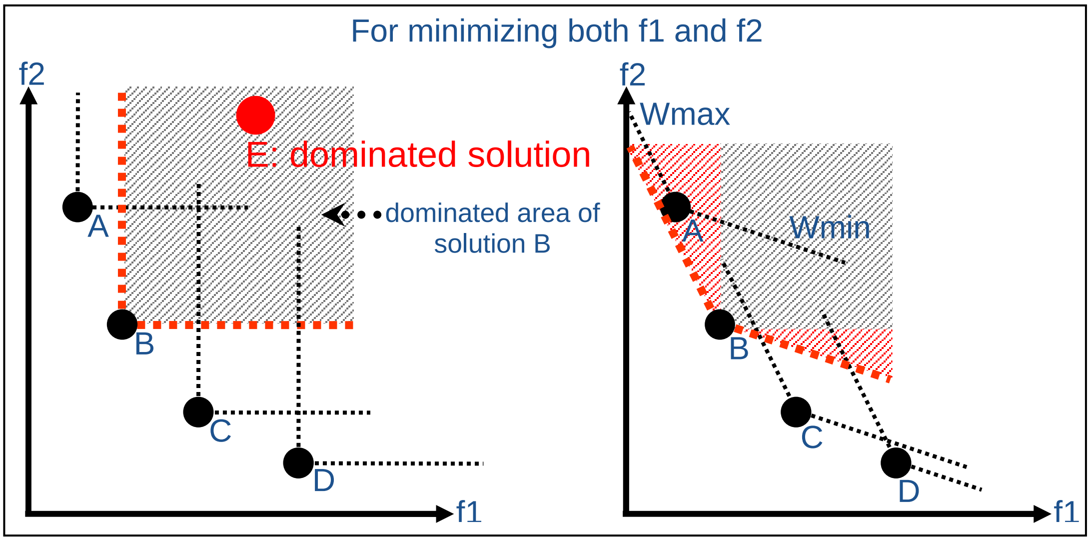


Figure 6.2 Traditional or regular dominance [64]



3a) regular dominance 3b) extended dominance

Figure 6.3 Different dominance schemes in G-MOEA [64]

Specific features of the Guided MO [64] are:

1) Efficient for filtering the non-dominated solutions by using an incremental dominated area.
2) The algorithm can guide the solutions into the specified objective area.
3) Decision-maker does not have to know or specify the relations between design objectives.
4) The maximum and minimum weights are sensitive and difficult to define as a filtering condition.
5) The obtained solutions are crowded into the guided area.

6) This algorithm is suitable for linear trade-off functions (i.e., two objective functions).

In 2004, Branke et al. [65] proposed the "Knee points concept". They considered that the Pareto-optimal front has a knee as shown in *Figure 6.4*. Branke et al. [65] suggested that the knee [65] offers a particularly attractive choice of optimal solutions. Intuitively, the solutions in the knee area are generally outstanding or preferable compared to other solutions. The obtained solutions from this approach are the solutions that are located at the converting (convex) point as shown in *Figure 6.5*. The knee point is also suitable for the multi-modal optimization problem that has multiple peaks as shown in *Figure 6.5*.

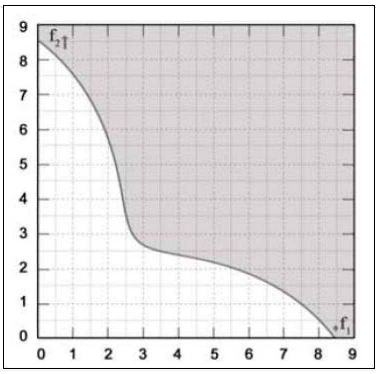


Figure 6.4 Simple Pareto-optimal front with a knee [65]

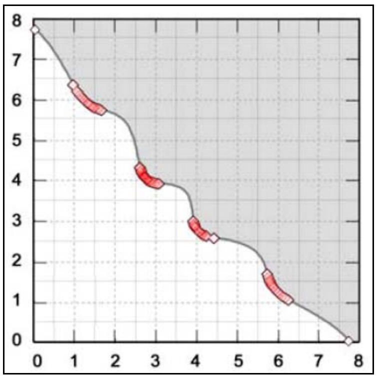


Figure 6.5 Several knees obtained from angle based focus [65]

Specific features of the Knee point [65] selection are:

1) Easy to filter the outstanding solutions. Solutions in the converting point or in the peak of curve (convex subsets [70]) are selected.
2) Filtering the non-dominated solutions can be done by comparing with the neighbor solutions.
3) Suitable for multi-modal problem (solutions that are mixed with convex and

concave subsets)

4) The obtained results are located in all converting points in the convex subsets.
5) The obtained solution is a local optimum. If there exist one or more solutions that are better than the two to four nearest neighbor solutions, those solutions are then selected. That solution may be worse when compared with the other solutions.

In 2005, Deb and Gupta [66] proposed an algorithm to select the non-dominated solutions that is called "Robust Pareto-optimal solutions." In *Figure 6.6a*, in the minimizing context, the obtained solutions are represented by the dashed line. The optimal front in area B in the figure is very sensitive and often cannot be recommended (high objective value). The dashed line at area A has better value than those of solution B because it has high possibility to actually achieve the desired solution given some uncertainty. They proposed that the robust solutions have small variation while the non-robust solutions are quite sensitive and change significantly in the objective from small perturbations in its decision variables as shown in *Figure 6.6b*. Solution A is more robust than solution B.

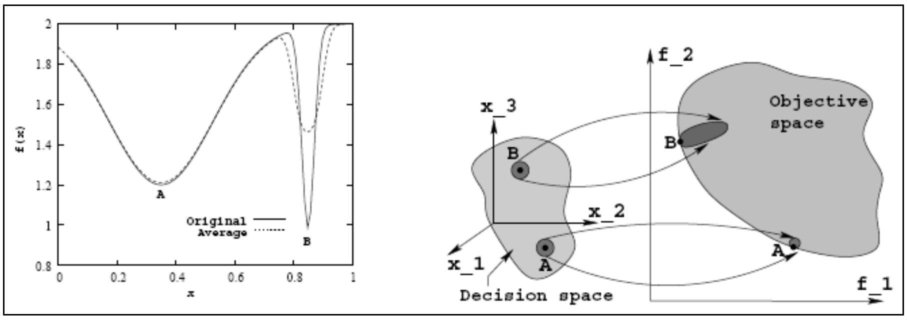


Figure 6.6 Robust solution in a) single objective and b) multi-objective optimization problem [66]

Specific features of searching for robust Pareto-optimal solutions [66] are:

1) Selects solutions in the area that is marginally different in objective values.
2) The area that has the large differences in the objective values is cut-off because that area is considered to be a non-robust area.
3) Suitable for continuous problem domains.

In this dissertation, we proposed a new pruning mechanism (Adaptive Angle Based algorithm, ADA) with a new reason or rationale for pruning, that is, removing unlikely solutions. The detail of ADA is described in the next section. The ADA reduces the whole Pareto solution set to the subset of the most likely or promising solutions. Our ADA features are as follows:

1) The obtained solutions are the subset of solutions from Guided MO with the set of weighted slopes in two objectives but this mechanism applies the angle to specify the dominance-relation. It can be applied to problems that have three or more objectives with a non-linear trade-off relation.
2) This mechanism can estimate the number of final solutions by adjusting the size of the angle.
3) Easy to apply with existing multi-objective algorithms.
4) Effective when scaling or increasing the number of objective functions.
5) The statistical value (i.e., inter-quartile range) that is obtained from the set of non-dominated solutions is applied to filter the final solutions.
6) The obtained solutions are the remaining solutions after the dominated area is expanded. The obtained results are located in the convex area. The obtained results are a subset of the most likely solutions.
7) The ADA is proposed in both parametric and non-parametric approaches. When using a parametric approach, the set of adaptive matrices has to be previously calculated before the filtering algorithm is processed. The parametric approach is used when the distribution of Pareto solutions can be predicted. In this case, the parametric approach is represented with the adjusted threshold angle. The non-parametric approach is used when the distribution of Pareto solutions cannot be approximated. This non-parametric approach is proposed with a fixed threshold angle.

6.3 Adaptive Angle Based Algorithm

Effective pruning mechanisms have been previously proposed in many past research efforts [58-66]. Our approach is to propose a pruning mechanism based on the concepts and technique from Branke et al [64]. The guidance technique [64] is simple and efficient to filter or guide the obtained non-dominated solutions into one objective area but the minimum and maximum weights are sensitive and difficult to apply for three or more objective functions because the weight affects the aggregated function of all objectives. We propose a pruning mechanism technique that is called "Angle based technique." The angle based technique is based on the following assumptions.

1) The decision-maker does not prioritize the multiple objective functions.
2) This algorithm emphasizes the final solutions that are balanced in all objective values, without applying bias into only one or few objective values. However, the extreme solutions can be obtained by adjusting the dominated area (guiding the final solutions into the middle or extreme area).

6.3.1 Dominance and Angle Relations

In general, in multi-objective optimization problem, solution A is determined to be better than solution B if and only if solution A has all objective values (i.e., f_1 and f_2) less than (in minimizing context) solution B as shown in *Figure 6.7*. If one or more solutions exist in the shading area, those solutions are dominated by (worse than) solution A. The shaded area is called the "dominated area". If solution A is not in the dominated areas of any other solution, then solution A is called a "non-dominated solution."

For two objectives, regular dominance is represented in the *Figure 6.7*. The dominated area has the boundary line with the right angle (90 degree). Considering multiple objectives with regular dominance, solution A is better than another if solution A has both f_1 and f_2 better than the other. For regular dominance, the solution has a 90 degree dominated area (shaded area). When there are more than two objectives, there is an analogous interpretation.

In this dissertation, we present an extended dominated area with an adjustable angle defining the dominance boundary. Regular dominance has 0 degree extended angle. When the dominated area is expanded, the size of angle is extended from 0 degree to higher angle values. A larger angle size indicates that the dominated area has been extended while the 'regular dominance' has a 0 degree angle size.

The dominated relation of two solutions and the angle are related and can be interchanged. The wording 'angle' is used in different meanings and purposes in this chapter. There are three types of angle which are 1) Geometric Angles, 2) Fixed

Threshold Angles, and 3) Adjusted Threshold Angles. All of them are described in *Sections 6.3.3 and 6.3.4*.

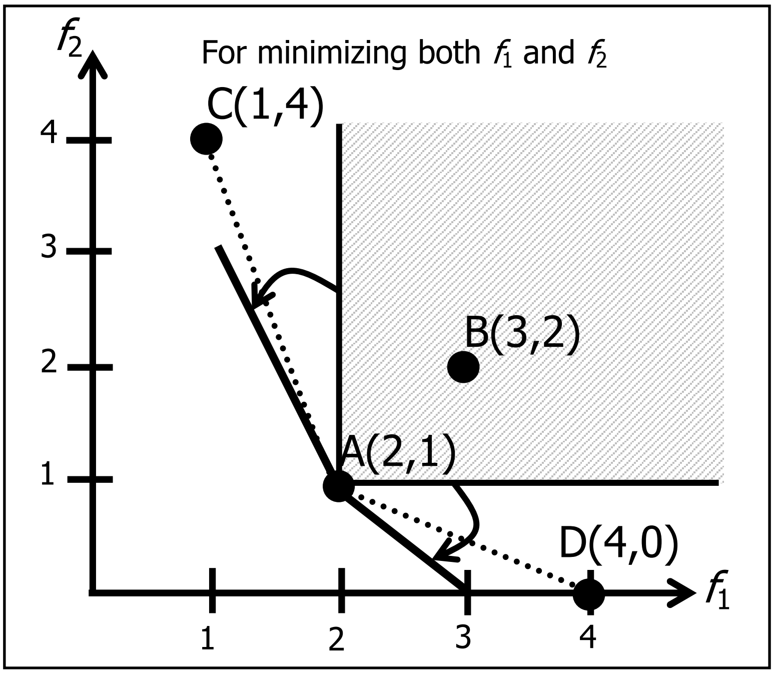


Figure 6.7 Regular and extended dominated area

6.3.2 Dominated Area and Extended Dominated Area

The regular multi-objective comparison has a rectangular dominated area (with zero extended area). One solution is worse than or dominated by the other if it is located in the other's dominated area (e.g., solution B is dominated by solution A in *Figure 6.7*). In practice, the non-dominated solutions that are obtained from multi-objective optimization algorithms can be very numerous.

In this dissertation, we increase or expand the dominated area for the purpose of removing a solution that only marginally improves the solution in some objective, while being notably worse in another objective. The extended dominance has an obtuse angle. The extra angles are expanded from the rectangular dominated area. In doing this, one or more solutions are dominated by the other(s) as shown in *Figure 6.7*. In regular dominated area, solutions A and C are non-dominated. When the dominated area is extended, solution C is dominated by solution A. The expanded area means some solutions that have marginal improvement are discarded. Only significantly improved solutions are selected to be the non-dominated set. The objective is to select a sub-set of only the most promising solutions.

6.3.3 Geometric Angles for Pareto Optimal Solutions

We calculate the angle between a pair of solutions by using a simple geometric function that is inverse tangent function. The angle between two non-dominated solutions is calculated by using *Equation 6.1*. The geometric angle is denoted by θ_n where n is the n^{th} objective. The dominated area is extended using *Equation 6.1*. For the minimizing objectives context, θ_n is given by,

$$\theta_n = \tan^{-1}\left(\frac{\sqrt{\sum_{m=1,m\neq n}^{N}(\Delta f_m)^2}}{\Delta f_n}\right) \tag{6.1}$$

where N is the number of objective functions.

n is the n^{th} objective function.

Δf_n is the difference of the n^{th} objective value between two non-dominated solutions.

For example, consider the multi-objective optimization with two objective functions, f_1 and f_2. The angles (θ_1 and θ_2) of the extended dominated-area are shown in *Figure 6.8*.

$$\theta_1 = \tan^{-1}\left(\frac{\sqrt{\left(\Delta f_2^{AD}\right)^2}}{\Delta f_1^{AD}}\right) = \tan^{-1}\left(\frac{\Delta f_2^{AD}}{\Delta f_1^{AD}}\right)$$

$$\theta_2 = \tan^{-1}\left(\frac{\Delta f_1^{AC}}{\Delta f_2^{AC}}\right)$$

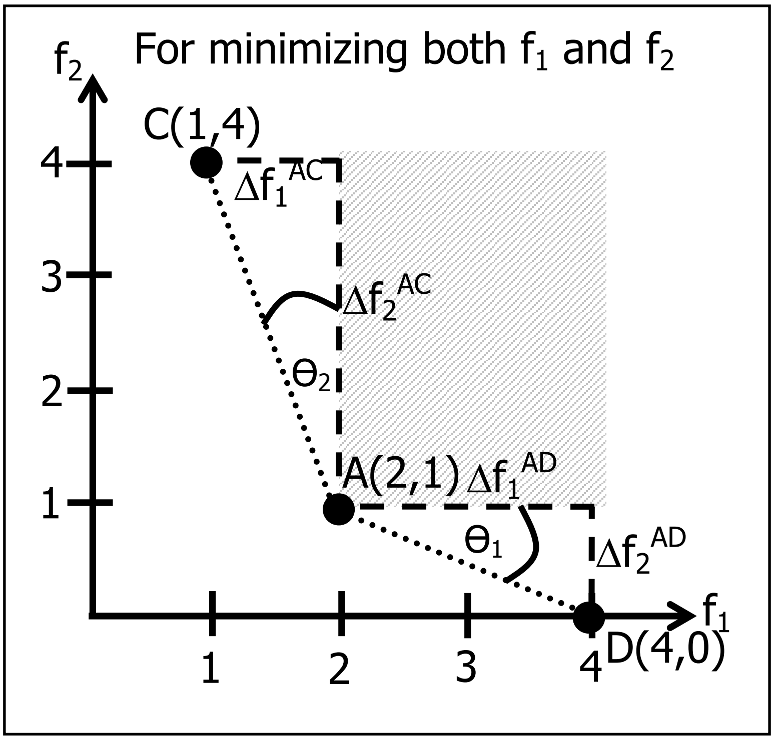


Figure 6.8 Example of angle calculation with two objective functions

Considering two objectives, the tangent of geometric angle (θ_2) is equal to the distance from solution A to solution C for the f_1 value divided by the distance from A to C for the f_2 value.

$$\tan(\theta_2) = \frac{\Delta f_1^{AC}}{\Delta f_2^{AC}}$$

Considering a three-objective optimization problem, we then have

$$\theta_1 = \tan^{-1}\left(\frac{\sqrt{(\Delta f_2)^2 + (\Delta f_3)^2}}{\Delta f_1}\right)$$

$$\theta_2 = \tan^{-1}\left(\frac{\sqrt{(\Delta f_1)^2 + (\Delta f_3)^2}}{\Delta f_2}\right)$$

$$\theta_3 = \tan^{-1}\left(\frac{\sqrt{(\Delta f_1)^2 + (\Delta f_2)^2}}{\Delta f_3}\right)$$

For three objectives, the tangent of geometric angle (θ_2) is equal to the Euclidean distance from A to C in the f_1 and f_3 plane divided by the distance from A to C for the f_2

value as shown in *Figure 6.9*. For the case with more than three objectives, the θ_n is derived correspondingly. *n* extended angle (dominated-area) for *n* objectives.

$$\tan(\theta_2) = \frac{\sqrt{(\Delta f_1)^2 + (\Delta f_3)^2}}{\Delta f_2}$$

$$\tan(\theta_2) = \frac{\sqrt{(\Delta f_1^{AC})^2 + (\Delta f_3^{AC})^2}}{\Delta f_2^{AC}}$$

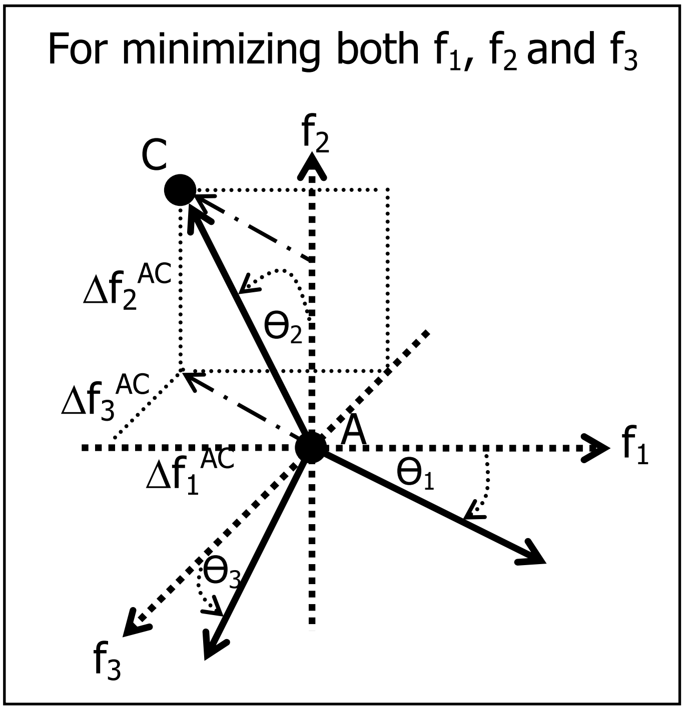


Figure 6.9 Example of angle calculation with three objective functions

6.3.4 Fixed Threshold Angles and Adjusted Threshold Angles

For establishing dominance, a threshold angle is specified. The solution that has a geometric angle (θ_n) less than the threshold angle is considered to be a dominated solution for the extended interpretation of dominance. The threshold angle is denoted by δ_n^f or δ_n^a for a fixed or adjustable threshold angle. In traditional or regular dominance, δ_n^f is 0 degrees, and there is no additional/extra dominated area required. The threshold can be a pre-defined fixed angle or it can be specified using the inter-quartile value. This dissertation estimates the threshold values using inter-quartile for each objective, i.e., the difference between the objective function of the first and third quartile considering all solutions. The estimated threshold can also be derived using the standard deviation, if the solutions are normally distributed.

We specify the adjustable threshold angle (δ_n^a) using *Equation 6.2*. δ_n^{ap} is the adjustable angle prior to the a_n and b_n adjustments.

$$\tan(\delta_n^{ap}) = \left(\frac{IQE_n}{IQ_n}\right)$$

$$\delta_n^{ap} = \tan^{-1}\left(\frac{IQE_n}{IQ_n}\right)$$

$$\delta_n^{a} = a_n \times b_n \times \tan^{-1}\left(\frac{IQE_n}{IQ_n}\right) \tag{6.2}$$

where IQ is the inter-quartile range of the data divided by 2, $(Q_3 - Q_1)/2$.

IQE_n is the inter-quartile range of the Euclidean distance from all objectives, except the n^{th} objective. A set of Euclidean distances of all objectives (not including the n^{th} objective) is first calculated and then the inter-quartile range is computed.

IQ_n is the distance of the n^{th} objective value between two non-dominated solutions, considered in terms of the inter-quartile range. There is only one IQ_n for the n^{th} objective.

a_n is the scaling factor. The scaling factor is adjusted in the experiment for the purpose of increasing or decreasing the number of remaining solutions. The scaling factor is between 0 and 1.

b_n is the crowding factor. The crowding factor is a measure of the solution density estimated by an empirical histogram of objective values or an estimated probability density function (pdf). The average of b_n from all non-dominated solution i in each objective is equal to 1. For the fixed threshold angle (δ_n^f), all solutions have $b_n = 1$.

Each threshold angle has an assigned a_n value. The a_n value is between 0 and 1. The a_n is adjusted to estimate the number of remaining solutions after pruning. Low a_n

value means the threshold angle is narrow and more solutions will be accepted for that objective. The obtained solutions are guided into low a_n objective. For that objective, it is difficult for non-dominated solutions to dominate others because of the low threshold (i.e., small dominated area).

In practice, the solutions are generally distributed unequally in the objective space. Some areas are crowded while the other may have few solutions. This dissertation proposes a variable crowding factor (b_n) of the threshold angle, which is a unique and desirable aspect of this new pruning method. The adjusted threshold angle (δ_n^a) is set to a small value in uncrowded areas and to large value in crowded areas. A crowded area has a high number of solutions in the same amount of area. The crowding factor (b_n) of each solution is altered by using the probability density function for each objective. The solutions with high probability value indicate that multiple solutions are located in one small area. The crowded solutions with high probability are assigned to a high threshold angle. By doing this, multiple solutions are dominated by others in crowded areas while few solutions are dominated by the other in the uncrowded area. Only outstanding solutions (most likely or promising solutions) survive all of the comparisons.

An empirical histogram of the solution is used to approximate the probability of solutions in a particular objective area. For plotting a histogram, two parameters are required, the size of bins and the number of bins. In this dissertation, we decided to calculate the size of bins from the "Freedman-Diaconis Rule [67]" as shown in *Equation 6.3*. *Equation 6.3* is based on the inter-quartile range.

$$BinSize = 2(IQR)n^{-1/3} \tag{6.3}$$

where IQR is the inter-quartile range of the data, $Q_3 - Q_1$

n is the number of non-dominated solutions

The number of bins can be approximated by the upper bound of the expression as shown in *Equation 6.4*.

$$\text{The number of bins } = \left\lceil \frac{\max(x) - \min(x)}{BinSize} \right\rceil \tag{6.4}$$

where $\max(x) - \min(x)$ is the range of the data

BinSize is the size of bins

The histogram is first calculated and used to approximate the probability density function, with one distribution function for each objective. For the Knapsack solutions (the Pareto front of two objectives with 100 decision variables) [35, 9], the histogram was plotted by using parameter settings in *Equations 6.3 and 6.4.* The numbers of bins were seven for both the first and second objectives, respectively. We used MATLAB's distribution fitting tool to fit the histogram with a general distribution function. For the Knapsack solutions, the Weibull distribution with α=3993.49 and β=18.1237 (α is the Weibull scale parameter, β is the Weibull shape parameter) was obtained for the first objective (f_1) and the Weibull distribution with α=3844.45 and β=23.3533 was obtained for the second objective (f_2). Both distribution functions are illustrated in *Figures 6.10 and 6.11*. The obtained distribution functions were used to calculate the probability density for each objective value. The obtained probability density was normalized into the range [0, 1].

For example, the first solution has f_1 = 3235 and f_2 = 4037. The probabilities density of f_1 and f_2 are 0.000908 and 0.004444 respectively. To determine the b_n factor, the histogram values were normalized to have an average equal to 1. The probabilities density of f_1 and f_2 were normalized to 0.109868 and 0.537724 respectively to define b_n. The average of density of all solutions (for each objective) is always equal to 1.

Note that density is an adaptive parameter; high density is associated with a large dominated area (large threshold angle). Each non-dominated solution has one dominated area. Multiple solutions have various dominated areas. A solution that has large dominated area is dominated by multiple other solutions.

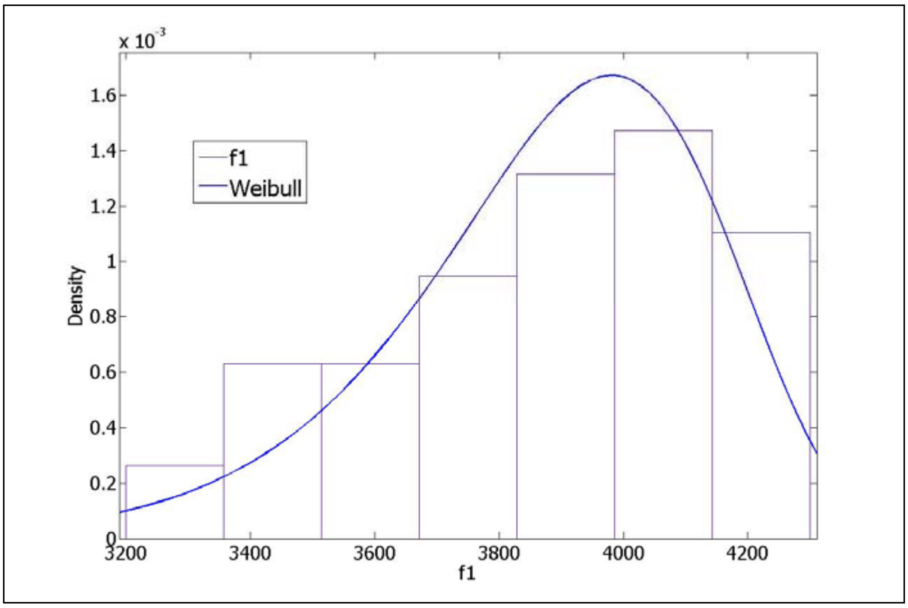


Figure 6.10 Weibull probability density function for f_1 (with α=3993.49 and β=18.12)

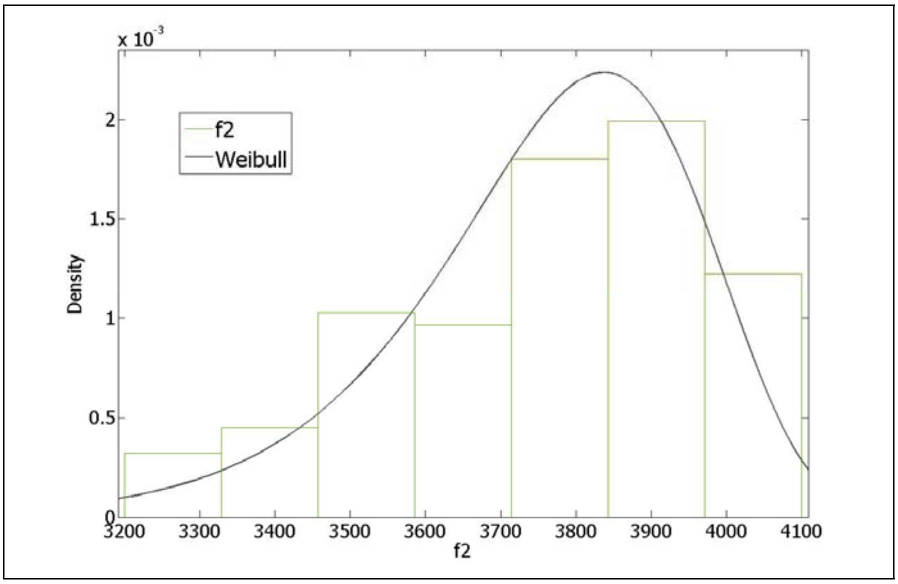


Figure 6.11 Weibull probability density function for f_2 (with α=3844.45 and β=23.35)

6.3.5 Adaptive Angle Based Pruning Algorithm

6.3.5.1 Extended Dominance

In this dissertation, multiple non-dominated solutions are compared using multi-objective optimization criteria with extended dominated area. The multi-objective comparison criterion is as follows.

For the minimization context, solution i dominates (better than) solution j represented by $i \prec j$.

$$i \prec j \Leftrightarrow \sum_{n=1}^{N} I\left(\left[\ f_n(i) \le f_n(j)\ \right] \wedge \left[\ |\theta_n(i,j)| \le |\delta_n|\ \right]\right) > 0 \tag{6.5}$$

where $I(\text{true}) = 1, I(\text{false}) = 0$

For instance, two-objective optimization has a multi-objective optimization criteria such that

$$\begin{aligned} i \prec j \quad \Leftrightarrow \quad & I\left(\left[\ f_1(i) \le f_1(j)\ \right] \wedge \left[\ |\theta_1(i,j)| \le |\delta_1|\ \right]\right) + \\ & I\left(\left[\ f_2(i) \le f_2(j)\ \right] \wedge \left[\ |\theta_2(i,j)| \le |\delta_2|\ \right]\right) > 0 \end{aligned}$$

Solution i is better than solution j if and only if there exists at least one function $I(\cdot)$ that is true. The dominated solution is usually located in only one side of the extended areas (extension from f_1 geometric angle or f_2 geometric angle).

6.3.5.2 Adaptive Angle Based (ADA) Mechanism

The overall pruning mechanism is implemented by the following procedure.

Adaptive Angle Based (ADA) procedure

Step 1 : Specify the scaling factors a_n for each threshold (n thresholds for n objectives)

Step 2 : Obtain non-dominated solutions using any MOGA (or alternative)

- **Step 2.1**: Normalize all solutions with the same range in each objective
- **Step 2.2**: Convert all objectives into minimization context (maximization can be converted minimization by multiplying by -1)

Step 3 : For each design objective

- **Step 3.1**: For the fixed threshold angle δ_n^f, go to Step 4.

  Otherwise, for the adjusted threshold angle δ_n^a, go to Step 3.2.
- **Step 3.2**: Find the histogram by using *Equations 6.3 and 6.4* to approximate the bin size and the number of bins
- **Step 3.3**: Fit general distribution functions (e.g., normal, lognormal, or Weibull) and select the most suitable (best fit)
- **Step 3.4**: Calculate the density for each non-dominated solution
- **Step 3.5**: Scale all density values to have an average of 1

Step 4 : For each non-dominated solution

- **Step 4.1**: Calculate the crowding factors b_n
  - **Step 4.1.1**: For the fixed threshold angle δ_n^f, assign the crowding factors b_n=1
  - **Step 4.1.2**: For the adjusted threshold angle δ_n^a, assign the density values to the crowding factors b_n
- **Step 4.2**: Calculate the threshold angle by using *Equation 6.2*
- **Step 4.3**: Compare with the other solutions using **Angle based** (multi-objective) **comparison** as shown in *Equation 6.5*
- **Step 4.4**: Select only the solutions that are not dominated by other solutions.

An example of Adaptive Angle Based Mechanism (ADA) with the adjusted threshold angle δ_n^a is described below. We use the non-dominated solutions in the Pareto front from the Zitzler et al. example [9], which are numerous and difficult to evaluate.

Step 1 - We set the scaling factors a_1 and a_2 to 0.604 and 0.604. For this configuration, the threshold angles are balanced.

Step 2 - The non-dominated solutions are normalized and converted into minimization context. In [35, 9], the knapsack problem is considered to maximize both f_1 and f_2. The maximum f_1 and f_2 values are converted into the minimum values.

Step 3 - The non-dominated solutions are calculated to find their density values.

Step 3.1 - Since this example is adjusted threshold angle, the crowding factor calculation is required.

Step 3.2 - Find the histogram by using *Equations 6.3 and 6.4*

Step 3.3 - Since this example estimates the density with the histogram, the probability density function is not calculated.

Step 3.4 - Calculate the density for each non-dominated solution

Step 3.5 - Scale all density values to have an average of 1

Step 4 - Calculating the crowding factors b_n

Step 4.1.2 - Assign the density values to the crowding factors b_n

Step 4.2 – Assign the adjusted threshold angles δ_n^a of all solutions as shown in *Table 6.1*. Solutions 1, 2 and 3 have the same threshold angle because their density values are equal. They have the same histogram values.

Table 6.1 Densities and adjusted threshold angles of non-dominated solutions with two objectives

Solution	f_1	f_2	Density of f_1	Density of f_2	δ_1^a	δ_2^a
1	3235	4037	0.2917	1.3399	7.8029	36.9949
2	3246	4031	0.2917	1.3399	7.8029	36.9949
3	3271	4029	0.2917	1.3399	7.8029	36.9949
			…			
Average of all solutions			1.0000	1.0000		

Step 4.3 - Compare non-dominated solutions with each other using **Angle based** (multi-objective) **comparison**. From *Equation 6.5*, solution 3 dominates (is better than) solution 2, if and only if, solution 3 is better than solution 2 and the dominated area of solution 3 covers solution 2 as shown in the *Figure 6.12*. In *Figure 6.12*, solution 3 has a better f_1 value than solution 2 and the dominated area of solution 3 covers solution 2. In this case, solution 3 dominates solution 2.

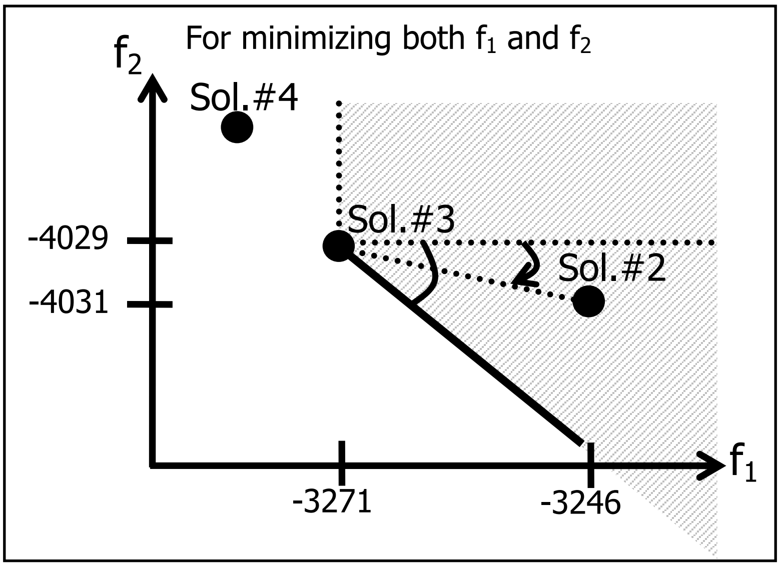


Figure 6.12 Example of dominated condition

For traditional or regular dominance (i.e., comparing solution 3 with solution 2 f_1 value), the value f_1 of solution 3 is better than solution 2 because we have to maximize both f_1 and f_2 (those are converted into minimization context for using the *Equation 6.5* comparison). Therefore, solution 2 is in the dominated area of solution 3 when considering only the f_1 domain. However when we consider both f_1 and f_2 simultaneously, solutions 2 and 3 are non-dominated.

In this dissertation, we are interested in the case where one objective is optimized, while the other is not getting worse than a threshold as shown by the line marked with an asterisk (*) of *Table 6.2*. In *Figure 6.12*, solution 3 has a large improvement compared to solution 2 in f_1 while there is a marginal drop in f_2. After the three non-dominated solutions are compared, the number of non-dominated solutions is decreased from three solutions to two solutions.

Table 6.2 Examples of the Adaptive Angle Based (multi-objective) comparisons

	Objective values		Extended dominated areas		Dominates the other solution	Non-dominated solution
	Comparing with	Better than the other	Geometric angle θ_n	Covers the other		
Solution 1	Solution 2, f_1	No	34.3776	No	No	**Yes**
	Solution 2, f_2	**Yes**	55.6224	No		
	Solution 3, f_1	No	15.5744	No	No	
	Solution 3, f_2	**Yes**	74.4256	No		
	…					
Solution 2	Solution 1, f_1	**Yes**	34.3776	No	No	No
	Solution 1, f_2	No	55.6224	No		
	Solution 3, f_1	No	5.7299	**Yes**	No	
	Solution 3, f_2	**Yes**	84.2701	No		
	…					
Solution 3	Solution 1, f_1	**Yes**	15.5744	No	No	**Yes**
	Solution 1, f_2	No	74.4256	No		
	*Solution 2, f_1	**Yes**	5.7299	**Yes**	Yes, dominates solution 2	
	Solution 2, f_2	No	84.2701	No		
	…					
…						

Note: all solutions do not need to be compared, if one solution is dominated by another, it can be removed from the comparison sets.

Step 4.4 - In the previously described example, the non-dominated solutions are reduced from 121 non-dominated solutions to only 21 non-dominated solutions. In Sections 6.4 and 6.5, we analyze solutions of several multi-objective optimization problems using the ADA algorithm. Several pruning algorithms are compared and benchmarked for both two and three objectives.

6.4 Performance Metrics

In multi-objective optimization, performance metrics are used for benchmarking to determine which set of non-dominated solutions is better. The existing quality indicators are background knowledge of decision-maker, complexity of the algorithm, Hyper-volume (HV), Spread, Generational Distance (GD) and the Inverted Generational Distance (IGD) [42], etc [43, 44]. The IGD is equal to 0 in this dissertation because the input solutions are all Pareto optimal solutions as a starting point. This dissertation considers filtering algorithms to reduce the number of solutions from Pareto optimal sets. To eliminate the impact of large objective values, the (non-dominated) solutions are normalized with the same range (i.e., [0 1]) for all objective values. The minimum objective value is assigned to 0 and the maximum objective value is assigned to 1.

6.4.1 Existing Performance Metrics

6.4.1.1 Background Knowledge of Decision Maker

Some pruning algorithms are easy to apply and require low background knowledge while others are difficult to understand and have many required factors to be defined or selected. The decision-maker may have *a priori* knowledge in the background concept of multi-objective optimization.

6.4.1.2 Complexity of the Algorithm

The complexity of the algorithm indicates how efficient an algorithm is, compared to other alternatives. In multi-objective optimization, the process to establish dominance is required to determine the non-dominated solutions from the feasible set. The number of (multi-objective) comparisons must be considered. A high number of comparisons requires more execution time. A low complexity algorithm is preferred if solutions from two algorithms are not distinguished.

6.4.1.3 Hyper-volume (HV)

The HV is an indicator to compare the efficiency of the Pareto front. High HV indicates the obtained solutions are effective and desirable. HV is the area under the front in two objectives or the volume of the front in three objectives. For example, the non-dominated solutions are A, B, C, D and E as shown in *Figure 6.13*, the shaded area is the HV of this Pareto front. For calculating HV, the reference point W is first calculated from the minimum value in each objective. For each solution, the area between the reference point and the solution, as well as the diagonal corners is calculated. The union of all sub-areas is the HV [42].

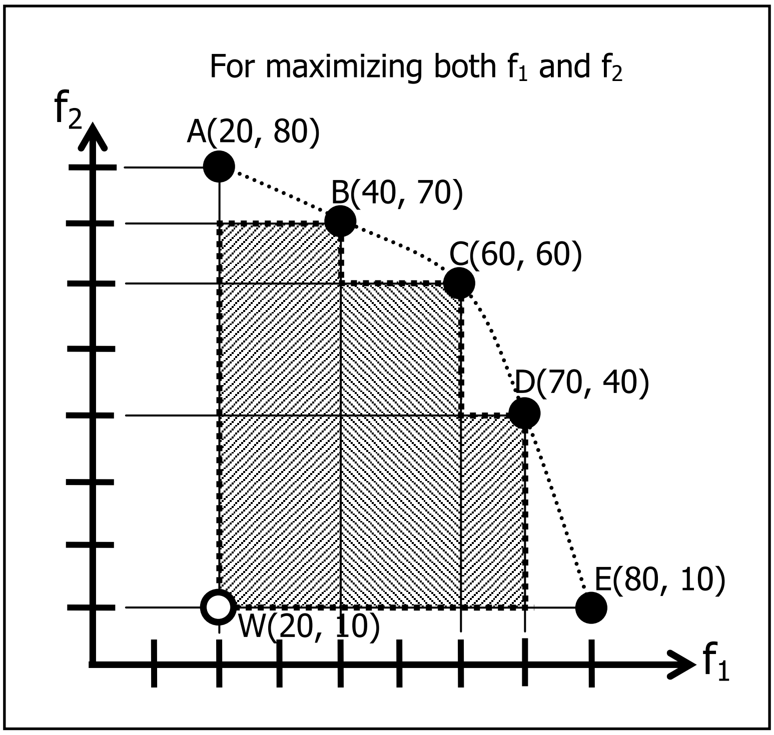


Figure 6.13 HV of non-dominated solutions with two objectives

In *Figure 6.14*, for the maximization context, the set of solutions in the left hand side has higher HV value than the set of solutions in the right hand side.

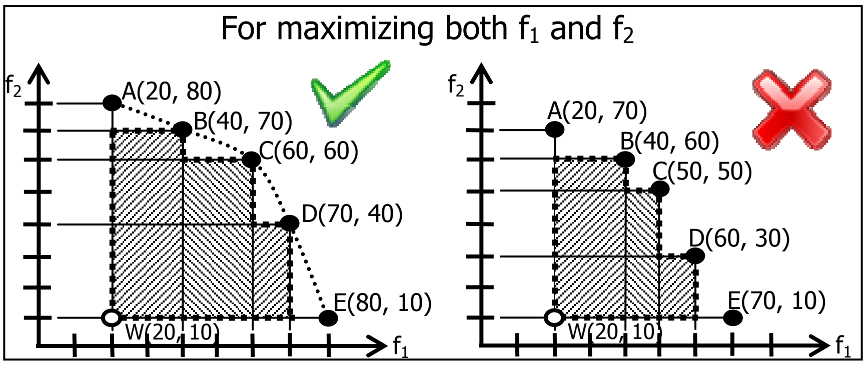


Figure 6.14 The example of preferable set of solutions in term of HV metric

6.4.1.4 Spread

The Spread is a diversity measurement. Low Spread indicates that the solution distributes into all objective areas equally (not crowding into one small objective area). Low Spread value is preferred. The Spread is defined by *Equation 6.6*.

$$\Delta = \frac{d_f + d_l + \sum_{i=1}^{N-1} \left| d_i - \bar{d} \right|}{d_f + d_l + (N-1)\bar{d}} \tag{6.6}$$

where d_i is the Euclidean distance between two consecutive solutions (except boundary solutions). d_f and d_l are the distances to the first and last (or boundary) solutions respectively. $\bar{d}$ is the average of all consecutive distances. N is the number of non-dominated solutions (except boundary solutions) with N - 1 consecutive distances. The description of Spread is illustrated by Deb et al [10].

In *Figure 6.15*, for the maximization context, the set of solutions in the left hand side has lower Spread value than the set of solutions in the right hand side. The distances between two consecutive neighbors of the set of solutions in the left hand side are equally.

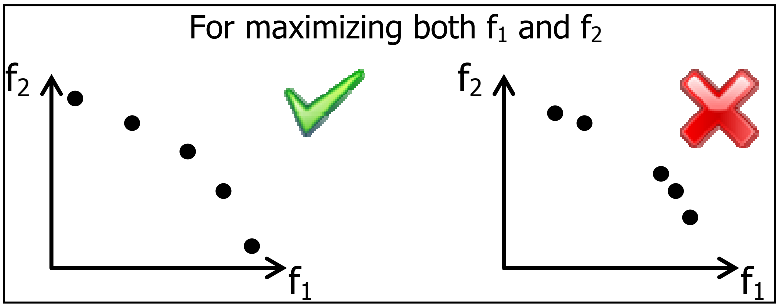


Figure 6.15 The example of preferable set of solutions in term of Spread metric

6.4.1.5 Inverted Generational Distance (IGD)

This indicator is measured as the distance from the obtained elements to the Pareto optimal set. A low IGD is preferred and it is 0 when all elements are in the Pareto optimal set. The IGD is expressed as *Equation 6.7*.

$$IGD = \frac{\sqrt{\sum_{i=1}^{n} d_i^2}}{n} \tag{6.7}$$

where n is the number of elements in the Pareto optimal set.

d_i is the Euclidean distance (in the objective space) from the obtained solution to the nearest elements in the Pareto set.

If the value of IGD is equal to 0, that means that all obtained solutions are in the Pareto set and optimal. The description of IGD is described by Nebro et al [42].

In *Figure 6.16*, for the maximization context, the set of solutions in the left hand side has lower IGD value than the set of solutions in the right hand side. The distance of the obtained solution to the nearest Pareto optimal solution in the left hand side is less than the IGD distance in the right hand side.

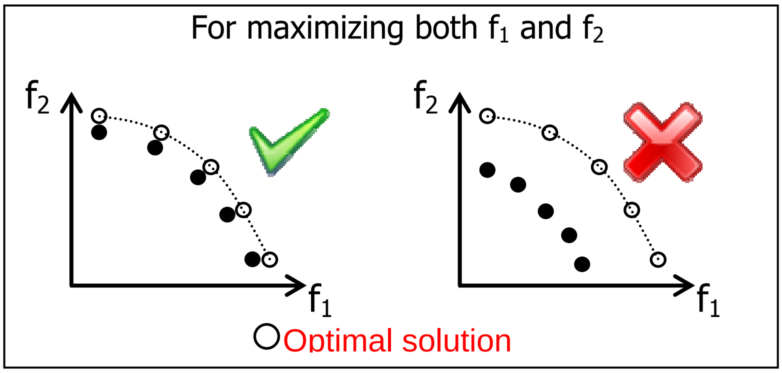


Figure 6.16 The example of preferable set of solutions in term of IGD metric

6.4.1.6 Other Performance Metrics

Since the pruning mechanism in this dissertation is a filtering criterion, the same original solutions are used in every replication run, and comparisons made based on the pruned set of solutions. The filtering criterion has the purpose of reducing the numerous Pareto optimal solutions to a smaller set as previously described in *Sections 6.2 and 6.3*. Therefore it may not be possible to apply some existing performance metrics that have a performance factor/parameter based on the capturing value (in each iteration) to benchmark the efficiency of the algorithm for our purpose. Other performance metrics have been proposed by Tan et al. [43] such as Algorithm Effort (AE), Ratio of non-dominated individuals (RNI), Size of space covered (SSC), Uniform distribution (UD) and Coverage of two set (C). Some of them are described with more detail in Zitzler's dissertation report [44]. These metrics are used to indicate the quality of the obtained results in each iteration comparing with the previous iteration. In this dissertation, we consider the quality of final obtained results. The metrics in this dissertation are HV, Spread and IGD.

6.4.2 Experimental Results for Existing Performance Metrics

In our experiments, we consider the filtering mechanism (Adaptive Angle Based mechanism) with a given set of non-dominated solutions. The set of non-dominated solutions for one optimization problem is called the “front”. The optimal set of non-dominated solutions is called the “Pareto front”. We use several fronts to benchmark the Adaptive Angle Based (ADA) mechanism against other algorithms.

Previously, Konak et al [58] and Taboada et al [59] proposed mechanisms to cut-off or prune numerous non-dominated solutions in two approaches which are ranking preference and data clustering algorithm. In this dissertation, the obtained solutions are compared with three significant and efficient traditional approaches that are Preference algorithm, Guidance in multi-objective optimization and K-means algorithm. For two objectives, the obtained solution from Preference algorithm is only one solution (with the case of threshold<1). For three objectives, it is difficult to approximate the weighted sets for Guided MO because the relation between three objectives may have a non-linear trade-off [64]. Therefore this dissertation benchmarks Guided MO, *K*-means and ADA for two objectives and Preference algorithm, *K*-means and ADA for three objectives.

We implemented our algorithms in Java and ran them on a Pentium 4 PC (Core 2 Quad CPU 2.83 GHz, 3.25 GB of RAM). Five existing quality indicators (performance metrics) were used to benchmark our algorithm (ADA) against the traditional approaches. To eliminate the impact of an unbalanced objective value, the (non-dominated) solutions were normalized with the same range (i.e., [0 1]) for all objective values. The minimum objective value was assigned to 0 and the maximum objective value was assigned to 1, and all other solutions scaled accordingly.

6.4.2.1 Test Problems

Various optimization problems were used to test the performance of pruning algorithms. Nebro et al. [42] have collected many optimization problems (see http://jmetal.sourceforge.net). This dissertation selects some diverse and representative examples of Pareto fronts from Nebro et al. [42] as indicated in *Table 6.3*.

Table 6.3 Test problems with various geometric fronts

Problem	Decision variables	Optimization Type	Variable bounds	Comments [70]
KP-m [9] 245 solutions (for two objectives) 1,472 solutions (three objectives)	750	max.	$\{0,1\}^n$	Combinatorial (Knapsack) problem
SPH-m [9] 118 solutions (two objectives) 112 solutions (three objectives)	100	min.	$[-10^3,10^3]^n$	Continuous Problem
ZDT1-2 [9] 1,001 solutions	30	min.	[0,1]	Convex
ZDT3-2 [9] 269 solutions	30	min.	[0,1]	Disconnected front
DTLZ7-m [68-70] 480 solutions (two objectives) 676 solutions (three objectives)	21	min.	[0,1]	Disconnected front
*WFG1-m [70, 71] 883 solutions (two objectives) 2,000 solutions (three objectives)	N/A	min.	[0,1]	Mixed convex and concave subset
*WFG2-m [70, 71] 111 solutions (two objectives) 2,801 solutions (three objectives)	N/A	min.	[0,1]	Convex Disconnected front

*Multiple parameter settings to approximate the obtained front

6.4.2.2 Background Knowledge of Decision Maker

For filtering numerous solutions, the preference algorithm requires background knowledge of the decision-maker in order to prioritize the importance of all objectives and specify the relation between a pair of design objectives. In the *K*-means algorithm, the decision-maker does not have to prioritize or specify the preference relationship. The comparisons of background knowledge of the decision-maker of the Pruning mechanisms are shown in *Table 6.4*.

Table 6.4 Comparisons of background knowledge of decision-maker of the Pruning mechanisms

Pruning mechanisms	Background knowledge
Preference algorithm	High
Guided algorithm	Medium
K-means algorithm	Low
Adaptive Angle Based algorithm	Medium

6.4.2.3 Complexity of the Algorithm

This dissertation approximates the complexity of the algorithm by using the number of (multi-objective) comparisons.

For n solutions and m objectives, the preference algorithm has no more than nm comparisons. The solution requires m comparisons for m objectives. All objectives are weighted with their preference weights. Preference weights are obtained from the preference relation. If one solution is better than the other, its weight is added to the summation. The solution is determined to be better than the other when the summation of all preference weights is more than a defined threshold (e.g., 0.7). Therefore, in the worse case, n^2m comparisons are required. The complexity of the algorithm is $mn \log_2(n)$ because all solutions do not need to be compared with each other. If one solution is dominated by the other, it is removed from the comparison sets.

Guidance in multi-objective optimization requires up to nm comparisons. Guidance is suitable for two objectives and linear trade-offs specified by a decision-maker. The solution has to compare minimum and maximum weights. A solution is considered to be better than the other, if its minimum and maximum weights are less than the other. In the worse case, n^2m comparisons are required. The complexity of this algorithm is $mn \log_2(n)$.

K-means is a data clustering algorithm. The decision-maker has to specify the number of final solutions (e.g., K=5). In this approach, the solution is selected from among the centroids from K choices and the Euclidean distance between the solution and nearest centroid in all objective values is calculated. The centroid of each cluster is recomputed in multiple iterations until the centroids do not change. Therefore K-means is required Kn comparisons for one iteration. The number of total comparisons is equal to KnL where L is the number of iterations.

In our new ADA approach, two conditions for each solution are to be compared with the other solutions. The two conditions are 1) determine whether it is worse than the other, and 2) determine whether its dominated area covers the other. For m objectives, the number of comparison is $2m$. Therefore, in the worst case, the number of comparisons is equal to $2n^2m$. The complexity of this algorithm is $2mn \log_2(n)$. The complexities of all filtering algorithms considered, as measured by the number of comparisons, are showed in *Table 6.5*.

Table 6.5 Number of comparisons of the Pruning mechanisms

Pruning mechanisms	Number of comparisons
Preference algorithm	mn $\log_2$ n
Guided algorithm	mn $\log_2$ n
K-means algorithm	KnL
Adaptive Angle Based algorithm	2mn $\log_2$ n

m is the number of objectives, *n* is the number of solutions, *K* is the number of centroids and *L* is the number of iterations

6.4.2.4 HV, Spread and IGD

We tested our proposed algorithm ADA considering both types of threshold (fixed threshold angle δ_n^f and adjusted threshold angle δ_n^a). For the fixed threshold angle δ_n^f, the threshold angles of all solutions are the same. For the adaptive/adjusted threshold angle δ_n^a, the angle (or dominated area) of each solution is varied as previously described in *Section 6.3*.

We calculated and compared the HV, Spread and IGD of Preference algorithm, Guided algorithm, *K*-means and Adaptive Angle Based algorithm with the same number of remaining solutions. All of them used the same input (same set of non-dominated solutions). Various optimization problems were tested. The obtained results are shown in *Tables 6.6 and 6.7*. Note that high HV, low Spread and low IGD are preferable. In the tables, all IGD values are 0 because the remaining solutions are all in the Pareto set.

With the same number of remaining solutions, the solution from K-means has highest HV value from all pruning mechanisms for both two and three objective functions. Most of solutions from K-means have a lower Spread value than those from other pruning mechanisms for both two objective and three objective functions.

Table 6.6 HV, Spread and IGD of Pruning mechanisms with the same number of remaining solutions (two objective functions)

Two Objectives					
Problem	Performance metric	Guided MO	*K*-means	ADA	
				δ_n^f	δ_n^a
KP max. 49 sol.	HV ↑	0.6650	**0.6958**	0.6651	0.6600
	Spread ↓	0.7765	**0.2946**	0.7689	0.7892
	IGD ↓	0.0000	0.0000	0.0000	0.0000
	CPU time (sec.) ↓	1	1	1	1
SPH min. 24 sol.	HV ↑	0.7253	**0.8137**	0.7285	0.7106
	Spread ↓	0.8743	**0.1956**	0.7952	0.8391
	IGD ↓	0.0000	0.0000	0.0000	0.0000
	CPU time (sec.) ↓	1	1	1	1
ZDT1 min. 201 sol.	HV ↑	0.4872	**0.6643**	0.4649	0.4774
	Spread ↓	0.8183	**0.2125**	0.8322	0.8297
	IGD ↓	0.0000	0.0000	0.0000	0.0000
	CPU time (sec.) ↓	1	81	1	1
ZDT3 min. 54 sol.	HV ↑	0.4774	**0.5134**	0.4913	0.4916
	Spread ↓	1.2834	**0.7274**	1.6321	1.4136
	IGD ↓	0.0000	0.0000	0.0000	0.0000
	CPU time (sec.) ↓	1	1	1	1
DTLZ7 min. 96 sol.	HV ↑	0.1445	**0.3341**	0.2235	0.2186
	Spread ↓	1.5684	**0.6494**	1.7227	1.7191
	IGD ↓	0.0000	0.0000	0.0000	0.0000
	CPU time (sec.) ↓	1	3	1	1
WFG1 min. 177 sol.	HV ↑	0.5475	**0.6309**	0.5761	0.5667
	Spread ↓	1.0269	**0.7267**	1.2739	1.1768
	IGD ↓	0.0000	0.0000	0.0000	0.0000
	CPU time (sec.) ↓	1	1	1	1
WFG2 min. 23 sol.	HV ↑	0.4816	**0.5506**	0.5482	0.5480
	Spread ↓	1.1861	**0.6909**	1.4118	1.2584
	IGD ↓	0.0000	0.0000	0.0000	0.0000
	CPU time (sec.) ↓	1	1	1	1

Table 6.7 HV, Spread and IGD of Pruning mechanisms with the same number of remaining solutions (three objective functions)

Three Objectives					
Problem	Performance metric	Preference	K-means	ADA	
				δ_n^f	δ_n^a
KP max. 221 sol.	HV ↑ Spread ↓ IGD ↓ CPU time (sec.) ↓	0.4654 0.4731 0.0000 1	**0.5209** **0.2879** 0.0000 10	0.5042 0.4903 0.0000 1	0.5121 0.5091 0.0000 1
SPH min. 99 sol.	HV ↑ Spread ↓ IGD ↓ CPU time (sec.) ↓	0.6537 0.4932 0.0000 1	0.6526 **0.4294** 0.0000 1	0.6543 0.5149 0.0000 1	0.6539 0.4845 0.0000 1
DTLZ7 min. 172 sol.	HV ↑ Spread ↓ IGD ↓ CPU time (sec.) ↓	0.2364 0.1590 0.0000 1	**0.3160** 0.2143 0.0000 22	0.2340 0.4182 0.0000 1	0.2754 0.3419 0.0000 1
WFG1 min. 458 sol.	HV ↑ Spread ↓ IGD ↓ CPU time (sec.) ↓	0.6844 0.8410 0.0000 2	**0.9421** **0.4119** 0.0000 34	0.9150 0.7868 0.0000 2	0.8972 0.7101 0.0000 2
WFG2 min. 158 sol.	HV ↑ Spread ↓ IGD ↓ CPU time (sec.) ↓	0.8835 0.5108 0.0000 4	**0.9141** 0.9016 0.0000 17	0.8564 0.6995 0.0000 2	0.8427 0.6665 0.0000 3

6.5 Experimental Results

6.5.1 New Performance Metrics

For general performance metrics, when you prune the solutions, these metrics indicate that the performance deteriorates. *K*-means is the best pruning algorithm based on these metrics. The general performance metrics are HV, Spread, and IGD as previously showed. Our method removes unlikely solutions and filter only the subset of the most likely or promising solutions. Since we are interesting in an extended dominated area compared to the regular or traditional dominance definition, this dissertation proposes a new metric that is based on the extended dominance concept. The details of the new metric are described in the following.

Zitzler proposed many performance measures in his dissertation [44]. A very interesting and informative one is “Coverage difference of two sets.” In this dissertation, we modify the original proposed metric to derive a new metric. The original performance metric considers the difference of the coverage area of two fronts. If two fronts are overlapped, the front that has a higher coverage area is preferred.

Let A, $B \subseteq X$ be two non-dominated solutions of decision variables. The non-dominated set A is represented by using “front 1” and non-dominated set B is represented by using “front 2”. The coverage area of front 1 is $\alpha + \gamma$ and front 2 covers the area $\beta + \gamma$. The coverage area of fronts 1 and 2 are shown in *Equations 8 - 10*.

$$C(A) \quad = \alpha + \gamma. \tag{6.8}$$

$$C(B) \quad = \beta + \gamma. \tag{6.9}$$

$$C(A \cup B) = \alpha + \beta + \gamma. \tag{6.10}$$

where $C(A)$ and $C(B)$ are the coverage area of fronts 1 and 2, respectively. $C(A \cup B)$is the coverage area of front 1 and front 2 together (i.e., the union).

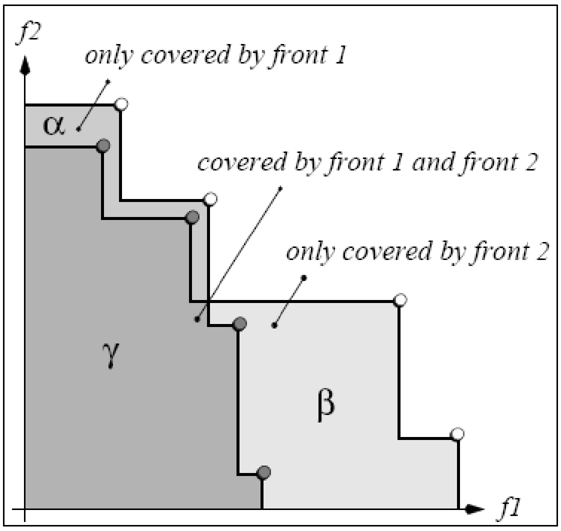


Figure 6.17 The coverage areas of fronts 1 and 2 [44]

In *Figure 6.17*, the coverage difference of two sets is specified as $D(A,B)$. $D(A,B)$ means the area that is covered by set A and not covered by set B (i.e., α). $D(B,A)$ is the area that is covered by set B, but not covered by set A (i.e., β). From *Figure 6.17*, we get the performance metric that is $D(B,A) > D(A,B)$. Thus set B or front 2 is preferred.

With this new metric, we can benchmark or compare Pareto sets based on the extra dominated-area. The extra dominated area is extended from the regular dominance as previously described in *Section 6.3*. This metric measures the performance of selected solutions by the number of superior solutions. If there exists one or more solution(s) in front 2 that are dominated by the solution in front 1, the metric D is incremented. The expressions of $D_{\tilde{\delta}}(A,B)$ and $D_{\tilde{\delta}}(B,A)$ are shown in *Equations 11 - 12*. $D_{\tilde{\delta}}(A,B)$ represents the total number of solutions in B that are dominated by solutions in A when the threshold angle is extended to $\tilde{\delta}$.

$$\varphi_{A,B}(i) = \{ j \in N(B); I(i \lhd j) = 1 \} \qquad \forall i \in N(A)$$

$$\varphi_{B,A}(j) = \{ i \in N(A); I(j \lhd i) = 1 \} \qquad \forall j \in N(B)$$

$$D_{\tilde{\delta}}(A,B) = \left| \bigcup_{i \in N(A)} \varphi_{A,B}(i) \right| \tag{6.11}$$

$$D_{\tilde{\delta}}(B,A) = \left| \bigcup_{j \in N(B)} \varphi_{B,A}(j) \right| \tag{6.12}$$

where $I(true) = 1, I(false) = 0$

where $\lhd$ represents the extended dominance. $i \lhd j$ means solution i is better than or dominates solution j. The relation $\lhd$ is not regular or traditional dominance, but instead solution i is compared with the solution j using the extended dominated-area as shown in *Section 6.3*. The minimum and maximum values of metric $D_{\tilde{\delta}}$ are 0 and $\max\{N(A),N(B)\}$ respectively. In our ADA mechanism, the extended dominance can be calculated with two approaches; the fixed threshold angle δ_n^f and adjusted threshold angle δ_n^a. For the fixed threshold angle, the extended dominance threshold angle is fixed for all non-dominated solutions while for the adjusted threshold angle, the extended dominance threshold angles are varied for the set of non-dominated solutions, such that every solution has different extended dominance angles.

For benchmarking the obtained solutions from multiple sets of solutions, the fixed extended dominance δ_n^f is specified. The value of metric $D_{\tilde{\delta}}$ is different if the fixed extended dominance is altered. In this dissertation, the fixed extended dominance δ_n^f is considered in various cases such as the minimum, maximum, average and some extended dominances. All of them are considered to benchmark the performance of the obtained solutions.

6.5.2 Fixed Threshold Angles

The performance metric $D_{\tilde{\delta}}$ is shown in *Tables 6.8 and 6.9* for the fixed threshold angle δ_n^f. In *Table 6.8*, the fixed threshold angle (FA) provides superior $D_{\tilde{\delta}}$ than *K*-means and Guided MO considering two objectives. Two solutions from *K*-means and Guided MO are dominated by FA when the dominated area is extended to the set of angles [26.3361, 28.6539]. In the ZDT1 problem, 156 solutions from 201 solutions of Guided MO are dominated by the obtained solutions from our approach. Also with three objectives, in WFG1 problem of *Table 6.9*, eight solutions from *K*-means and four solutions from Preference algorithm are dominated by the obtained results from our approach while no solutions from our approach is dominated by the other.

Table 6.8 $D_{\tilde{\delta}}$ metrics for two objective optimization: 1) FA vs. K-means and 2) FA vs. Guided MO

Two-Objective Optimization						
Problem	Extended dominance $\delta_n^f = [\,\delta_1^f \quad \delta_2^f\,]$	*K*-means*		Guided MO**		
		$D_{\tilde{\delta}}(A,B)$	$D_{\tilde{\delta}}(B,A)$	$D_{\tilde{\delta}}(A,B)$	$D_{\tilde{\delta}}(B,A)$
KP max. 49 sol.	[26.3361 28.6539]	**2**	0	**2**	0
SPH min. 24 sol.	[26.9370 27.0630]	**1**	0	**2**	0
ZDT1 min. 201 sol.	[50.1682 33.7478]	**1**	0	**156**	0
ZDT3 min. 54 sol.	[30.0172 30.2828]	**9**	0	**2**	0
DTLZ7 min. 96 sol.	[41.5339 31.5011]	**1**	0	**1**	0
WFG1 min. 177 sol.	[26.2254 34.3446]	**3**	0	**4**	0
WFG2 min. 23 sol.	[18.2160 26.7840]	**3**	0	**2**	0

* 'A' represents FA and 'B' represents *K*-means
** 'A' represents FA and 'B' represents Guided MO

Table 6.9 $D_{\tilde{\delta}}$ metrics of three objective optimization: 1) FA vs. K-means and 2) FA vs. Preference

Three-Objective Optimization					
Problem	Extended dominance $\delta_n^f = [\delta_1^f \;\; \delta_2^f \;\; \delta_3^f]$	K-means*		Preference**	
		$D_{\tilde{\delta}}(A,B)$	$D_{\tilde{\delta}}(B,A)$	$D_{\tilde{\delta}}(A,B)$	$D_{\tilde{\delta}}(B,A)$
KP max. 221 sol.	[0.0916 0.0872 0.0876]	**1**	0	**1**	0
SPH min. 99 sol.	[0.0797 0.0509 0.0832]	**3**	0	**3**	0
DTLZ7 min. 172 sol.	[1.1927 1.1927 0.4623]	**1**	0	**3**	0
WFG1 min. 458 sol.	[0.0357 0.0365 0.0309]	**8**	0	**4**	0
WFG2 min. 158 sol.	[0.0417 0.0420 0.1662]	**1**	0	**1**	0

* 'A' represents FA and 'B' represents *K*-means
** 'A' represents FA and 'B' represents Preference

6.5.3 Adjusted/ Adaptive Threshold Angles

The performance metric $D_{\tilde{\delta}}$ is shown in *Tables 6.10 and 6.11* for the adjusted threshold angle δ_n^a. In *Table 6.10*, the extended dominance is considered in various cases. This dissertation considers the extended dominance for each objective separately. In the table for each objective, the minimum and maximum angles from all solutions are presented and represented in the first and the fifth entries for each optimization problem. The third entry is the average angle of all solutions for each objective considered. The average of the minimum and the average are the second entry presented, and the average of the average and the maximum is the fourth entry.

In several cases of the extended dominance, our new approach (ADA) provides a superior result than *K*-means and Guided MO. At the maximum angle size for the SPH problem [31.8004, 32.1559], three solutions from *K*-means and seven solutions from Guided MO are dominated by the solutions from ADA while no solution from ADA is dominated by others; however, at the maximum angle size [48.1127, 36.4257] for the ZDT1 problem, 18 solutions from ADA are dominated by the solutions from *K*-means because ADA does not use the same angle size for all solutions. Some solutions have a narrow angle size but some solutions have a large angle size. The angle size is calculated based on the crowding factor, b_n. A high crowding factor value or high density provides a high angle size for removing the crowded solutions in one area.

When the size of angle is fixed for benchmarking, it is possible to have some solutions from ADA that are dominated by the other. At the same line, 137 solutions from Guided MO are dominated by the solutions from ADA. Note that the comparison is calculated from the extended dominance, and it is not a regular dominated area as previously described in *Section 6.3*.

Table 6.10 $D_{\tilde{\delta}}$ metrics for two objective optimization: 1) ADA vs. *K*-means and 2) ADA vs. Guided MO

Two-Objective Optimization					
Problem	Extended dominance	*K*-means*		Guided MO**	
	$\delta_n^a = [\,\delta_1^a \;\; \delta_2^a\,]$	$D_{\tilde{\delta}}(A,B)$	$D_{\tilde{\delta}}(B,A)$	$D_{\tilde{\delta}}(A,B)$	$D_{\tilde{\delta}}(B,A)$
KP max. 49 sol.	[13.1817 19.7514]	**1**	0	**1**	0
	[17.8702 23.4687]	**1**	0	**1**	0
	[22.5588 27.1861]	**2**	0	**2**	0
	[25.7165 29.3210]	**2**	0	**2**	0
	[28.8742 31.4559]	**2**	0	**2**	0
SPH min. 24 sol.	[11.3068 11.4332]	**1**	0	**2**	0
	[14.5457 14.7084]	**3**	0	**2**	0
	[17.7847 17.9835]	**3**	0	**4**	0
	[24.7925 25.0697]	**3**	0	**7**	0
	[31.8004 32.1559]	**3**	0	**7**	0
ZDT1 min. 201 sol.	[48.1127 26.2129]	**2**	0	**137**	0
	[48.1127 28.6179]	**2**	0	**137**	0
	[48.1127 31.0229]	**2**	0	**137**	0
	[48.1127 33.7243]	**3**	0	**137**	0
	[48.1127 36.4257]	3	**18**	**137**	0
ZDT3 min. 54 sol.	[7.4213 14.8950]	0	**0**	0	**0**
	[12.4129 17.7493]	0	**2**	0	**1**
	[17.4046 20.6036]	1	**2**	0	**1**
	[30.9661 31.3491]	**7**	6	2	**3**
	[44.5276 42.0947]	**10**	7	3	**4**
DTLZ7 min. 96 sol.	[30.3799 23.1240]	**0**	0	0	**0**
	[32.8588 28.6847]	**1**	0	0	**0**
	[35.3377 34.2454]	**2**	0	1	**0**
	[37.9221 36.1577]	**2**	2	1	**2**
	[40.5065 38.0700]	**2**	2	1	**2**
WFG1 min. 177 sol.	[2.2700 5.8956]	**0**	0	**0**	0
	[8.3319 12.8725]	**3**	0	**3**	0
	[14.3938 19.8494]	**4**	0	**8**	0
	[19.2090 29.3123]	**4**	0	**8**	0
	[24.0242 38.7751]	**6**	0	**9**	0
WFG2 min. 23 sol.	[8.1851 12.5711]	**2**	0	**1**	0
	[10.6508 15.0097]	**2**	0	**1**	0
	[13.1165 17.4482]	**2**	0	**1**	0
	[21.4668 19.3612]	**3**	0	**2**	0
	[29.8171 21.2742]	**3**	0	**3**	0

* ‘A’ represents ADA and ‘B’ represents *K*-means
** ‘A’ represents ADA and ‘B’ represents Guided MO

For three objectives, *Table 6.11* shows that ADA provides superior results than *K*-means and Preference algorithm in all problems. In some cases (e.g., WFG1 with the maximum angle size [0.0486, 0.0514, 0.0436]), There are some solutions from ADA that are dominated by others; however, those numbers are always less than the number of solutions are dominated by ADA.

Table 6.11 $D_{\tilde{\delta}}$ metrics for three objective optimization: 1) ADA vs. *K*-means and 2) ADA vs. Preference

Three-Objective Optimization					
Problem	Extended dominance $\delta_n^a = [\,\delta_1^a \;\; \delta_2^a \;\; \delta_3^a\,]$	*K*-means*		Preference**	
		$D_{\tilde{\delta}}(A,B)$	$D_{\tilde{\delta}}(B,A)$	$D_{\tilde{\delta}}(A,B)$	$D_{\tilde{\delta}}(B,A)$
KP max. 221 sol.	[0.0119 0.0031 0.0030]	**0**	0	**0**	0
	[0.0462 0.0407 0.0404]	**0**	0	**0**	0
	[0.0805 0.0783 0.0778]	**1**	0	**1**	0
	[0.1048 0.0935 0.0914]	**1**	0	**1**	0
	[0.1290 0.1086 0.1050]	**1**	0	**1**	0
SPH min. 99 sol.	[0.0004 0.0002 0.0003]	**0**	0	**0**	0
	[0.0319 0.0212 0.0326]	**2**	0	**2**	0
	[0.0635 0.0423 0.0649]	**2**	0	**2**	0
	[0.0736 0.0504 0.0838]	**2**	0	**2**	0
	[0.0838 0.0585 0.1028]	**3**	0	**3**	0
DTLZ7 min. 172 sol.	[0.8612 0.8612 0.1102]	**1**	0	**2**	0
	[0.9864 0.9864 0.1969]	**1**	0	**2**	0
	[1.1115 1.1115 0.2835]	**1**	0	**2**	0
	[1.1586 1.1586 0.4232]	**1**	0	**3**	0
	[1.2057 1.2057 0.5628]	**1**	0	**4**	0
WFG1 min. 458 sol.	[0.0038 0.0036 0.0049]	**1**	0	**1**	0
	[0.0131 0.0069 0.0095]	**1**	0	**1**	0
	[0.0224 0.0103 0.0141]	**1**	0	**1**	0
	[0.0355 0.0308 0.0288]	**7**	3	**5**	0
	[0.0486 0.0514 0.0436]	**13**	7	**10**	1
WFG2 min. 158 sol.	[0.0049 0.0007 0.0001]	**0**	0	**0**	0
	[0.0167 0.0144 0.4314]	**0**	0	**0**	0
	[0.0284 0.0280 0.8627]	**0**	0	**0**	0
	[0.0461 0.0461 1.0240]	**0**	0	**0**	0
	[0.0638 0.0641 1.1853]	**2**	0	**2**	0
* 'A' represents ADA and 'B' represents *K*-means ** 'A' represents ADA and 'B' represents Preference					

This dissertation proposes a pruning mechanism to remove the unlikely solutions so that only the most promising solutions remain. Existing performance metrics are not always appropriate or sufficient to benchmark the quality of the obtained solutions considering the extended dominance concept. The coverage of two sets is proposed as a measurement; however, it is not an exact performance metric for our pruning rationale (reduce the whole Pareto solutions to subset of the most likely solutions). The obtained solutions are illustrated in the *Figures 6.18 to 6.29* for the problem results summarized in *Tables 6.10 and 6.11*. In *Figure 6.21*, we can see that the obtained solutions from ADA are spread to all areas of the Pareto front. The ADA removes unlikely solutions that only have a marginal improvement. With the near f_1 value in x-axis, the marked solutions have high f_2 (in y-axis) improvement compared to the near solutions in the connected sub-front. The most likely solutions are also obtained in DTLZ7, WFG1 and WFG2 problem as shown in *Figures 6.22 – 6.24*. With three objectives, in *Figure 6.29*, the original Pareto front has several outstanding bars. Our proposed algorithm can preserve the strips of the 3-dimension front. The remaining solutions maintain the original shape of the front.

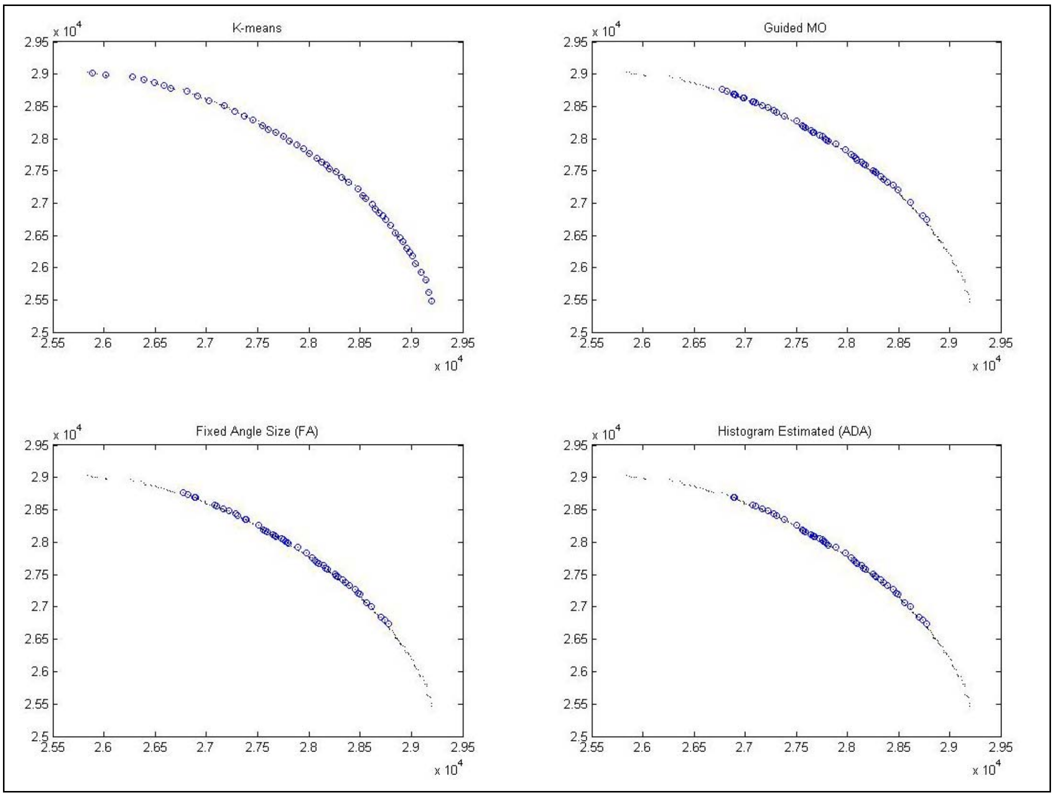


Figure 6.18 The obtained KP solutions from K-means, Guided MO, FA and ADA (two objectives)

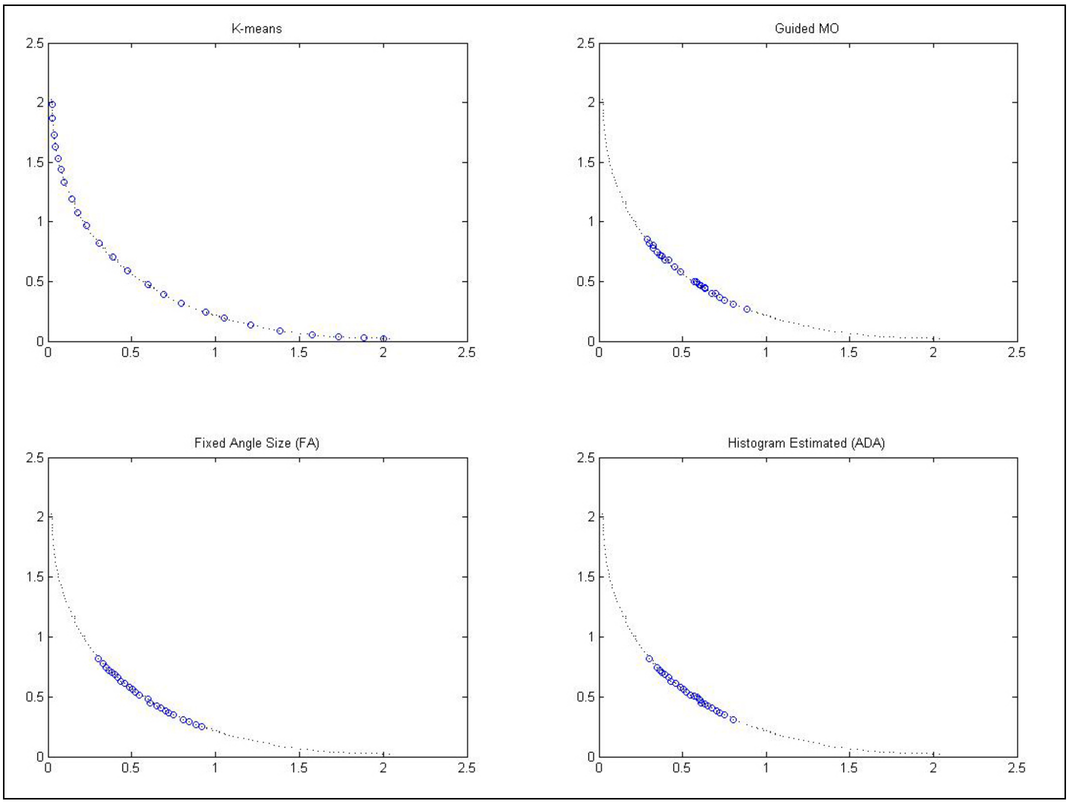


Figure 6.19 The obtained SPH solutions from K-means, Guided MO, FA and ADA (two objectives)

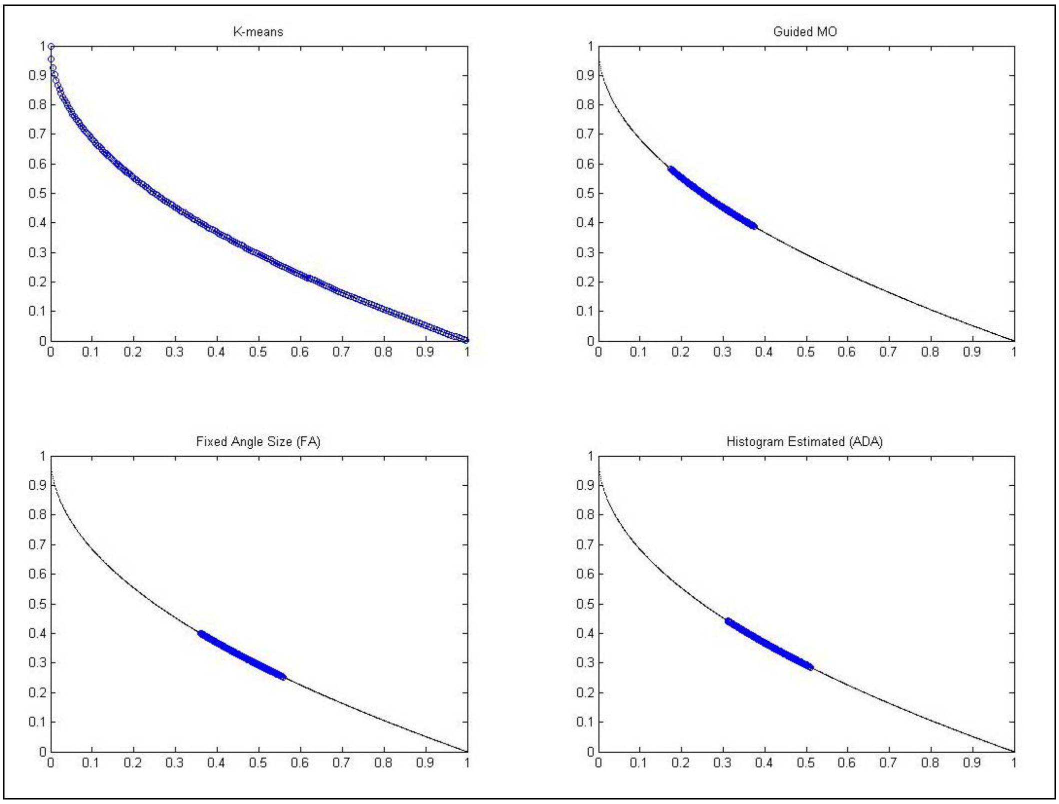


Figure 6.20 The obtained ZDT1 solutions from K-means, Guided MO, FA and ADA (two objectives)

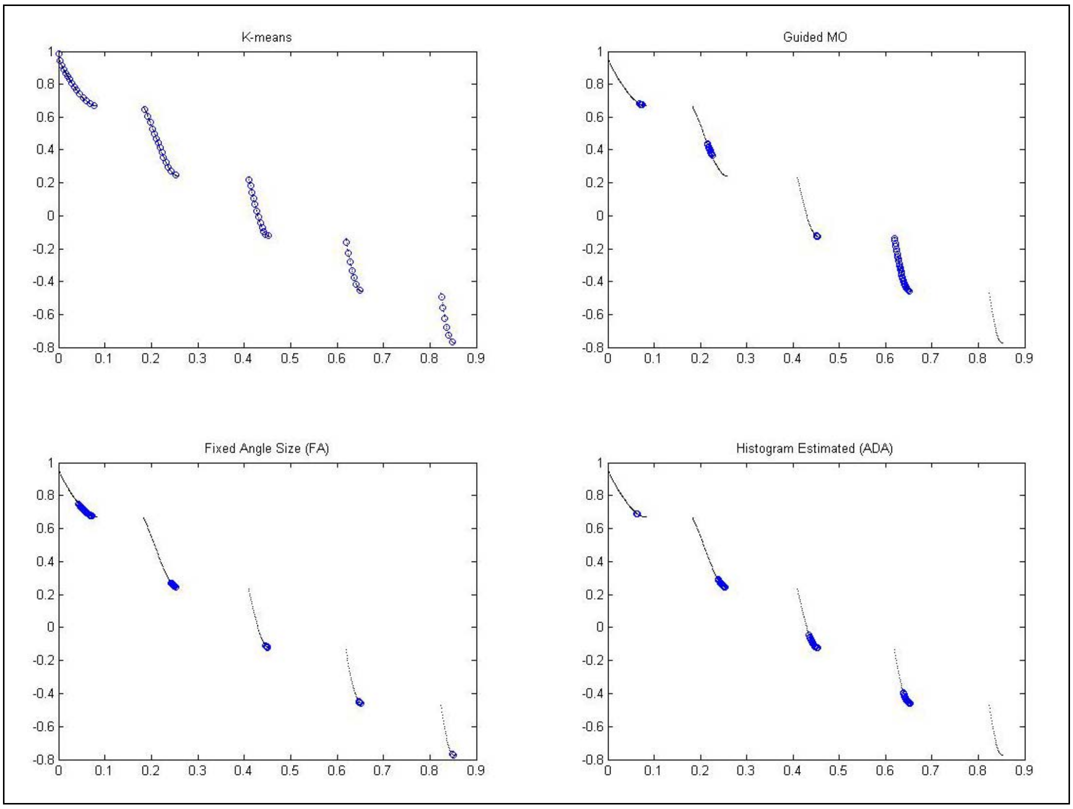


Figure 6.21 The obtained ZDT3 solutions from K-means, Guided MO, FA and ADA (two objectives)

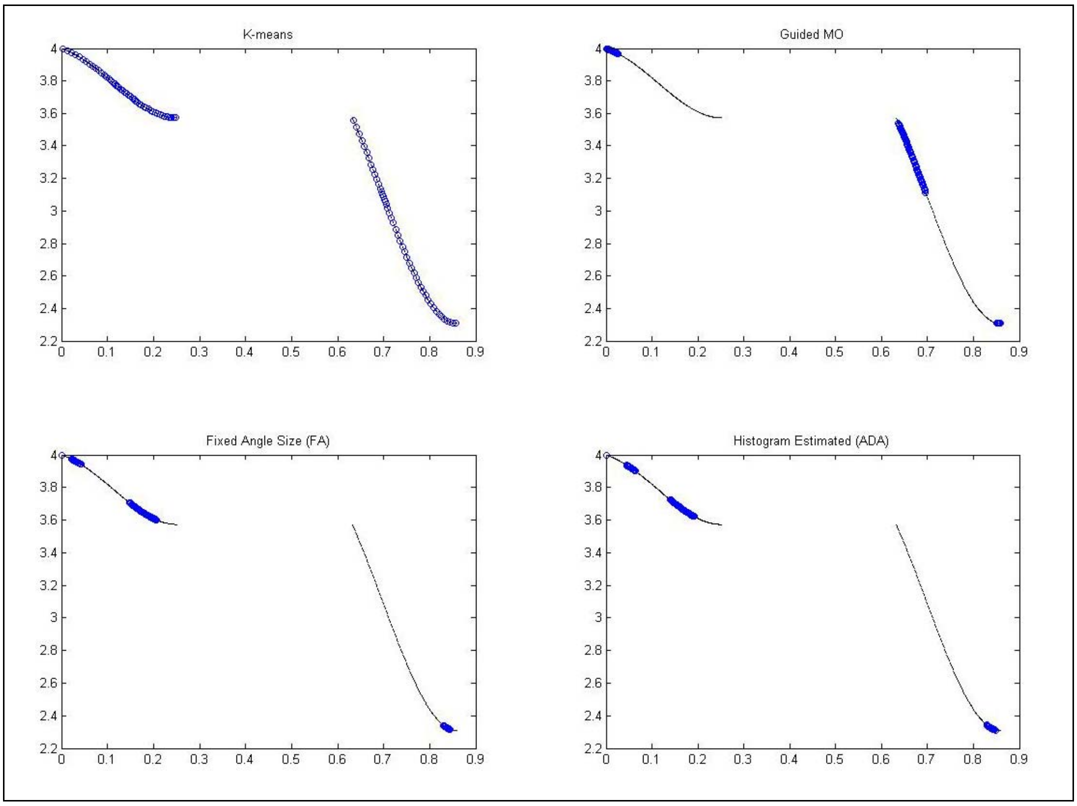


Figure 6.22 The obtained DTLZ7 solutions from K-means, Guided MO, FA and ADA (two objectives)

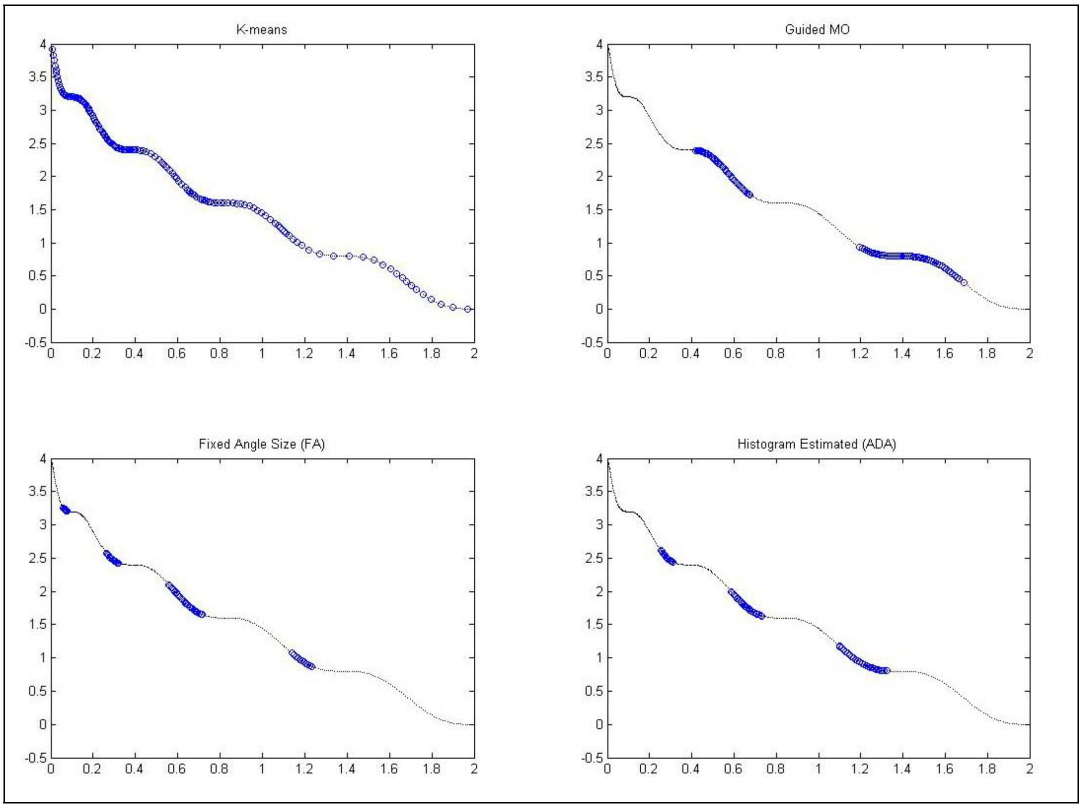


Figure 6.23 The obtained WFG1 solutions from K-means, Guided MO, FA and ADA (two objectives)

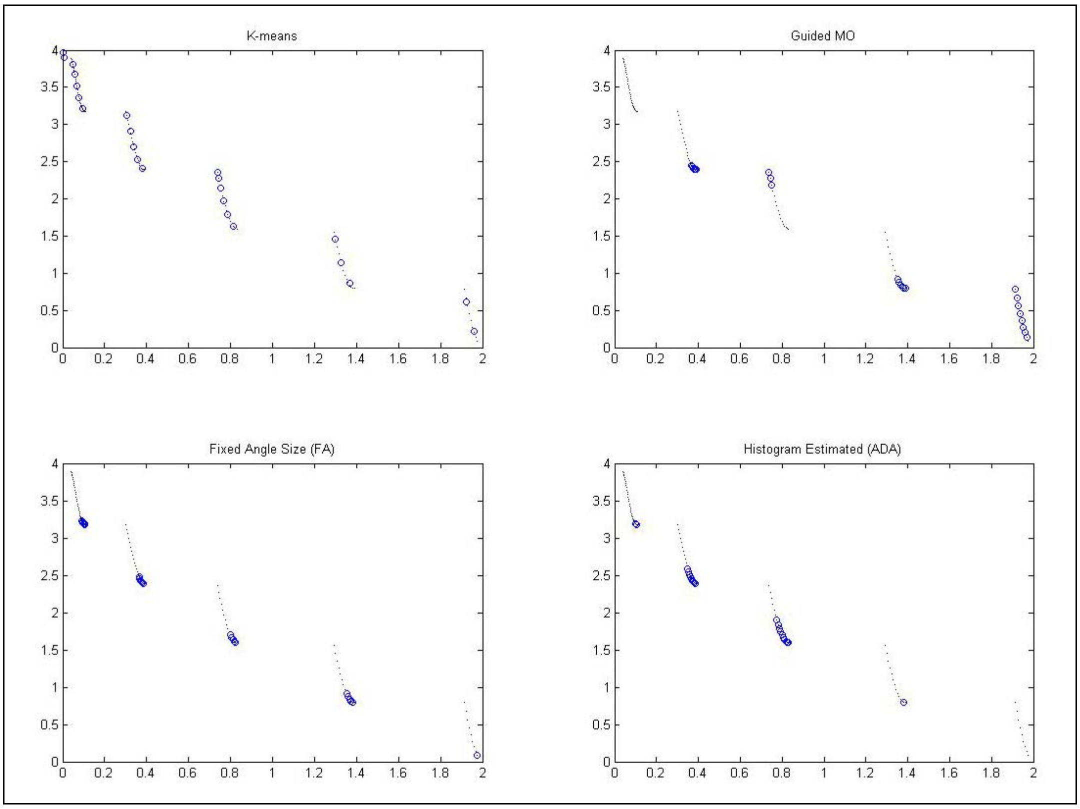
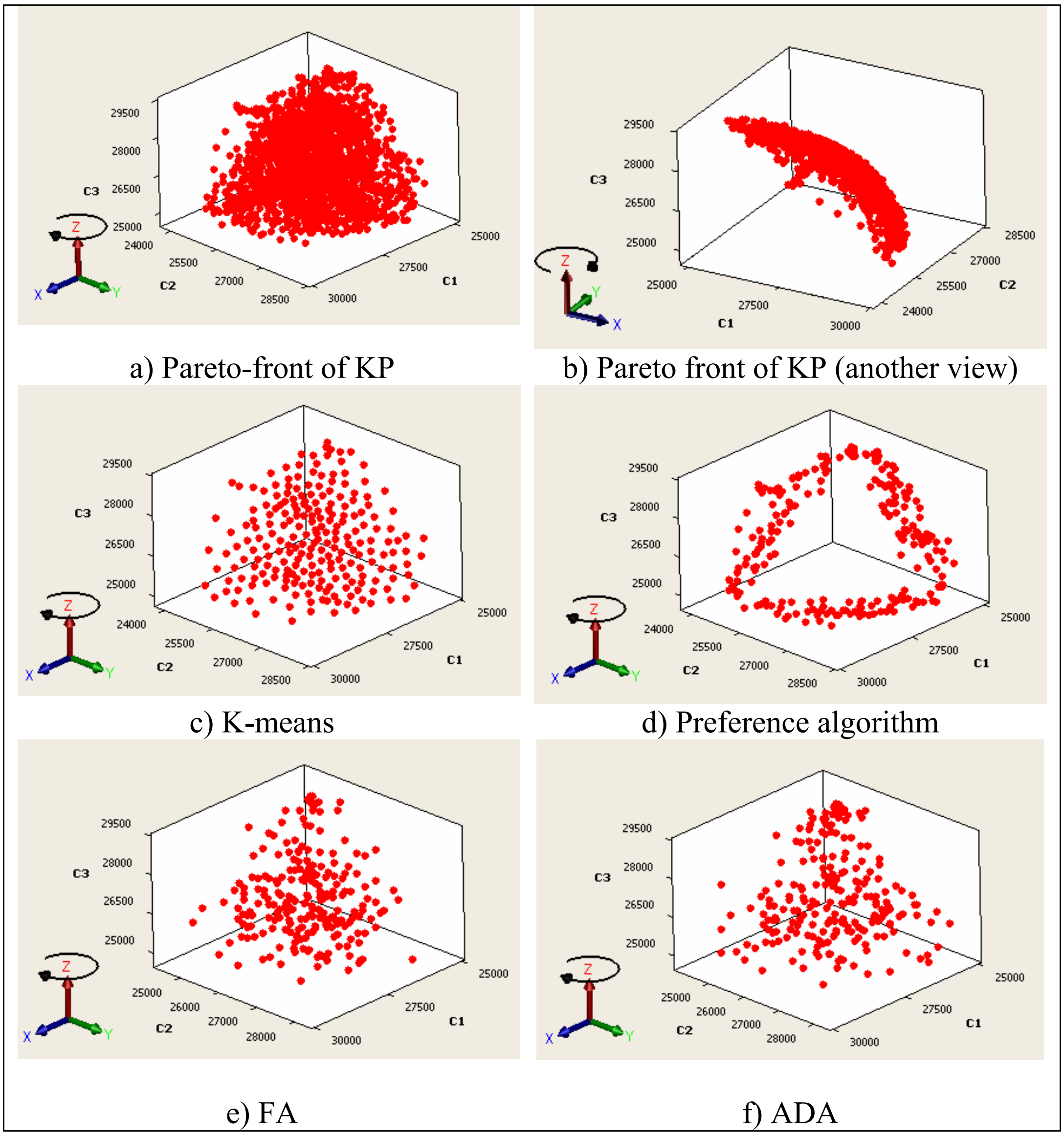


Figure 6.24 The obtained WFG2 solutions from K-means, Guided MO, FA and ADA (two objectives)



a) Pareto-front of KP

b) Pareto front of KP (another view)

c) K-means

d) Preference algorithm

e) FA

f) ADA

Figure 6.25 The obtained KP solutions from K-means, Preference algorithm, FA and ADA (three objectives)

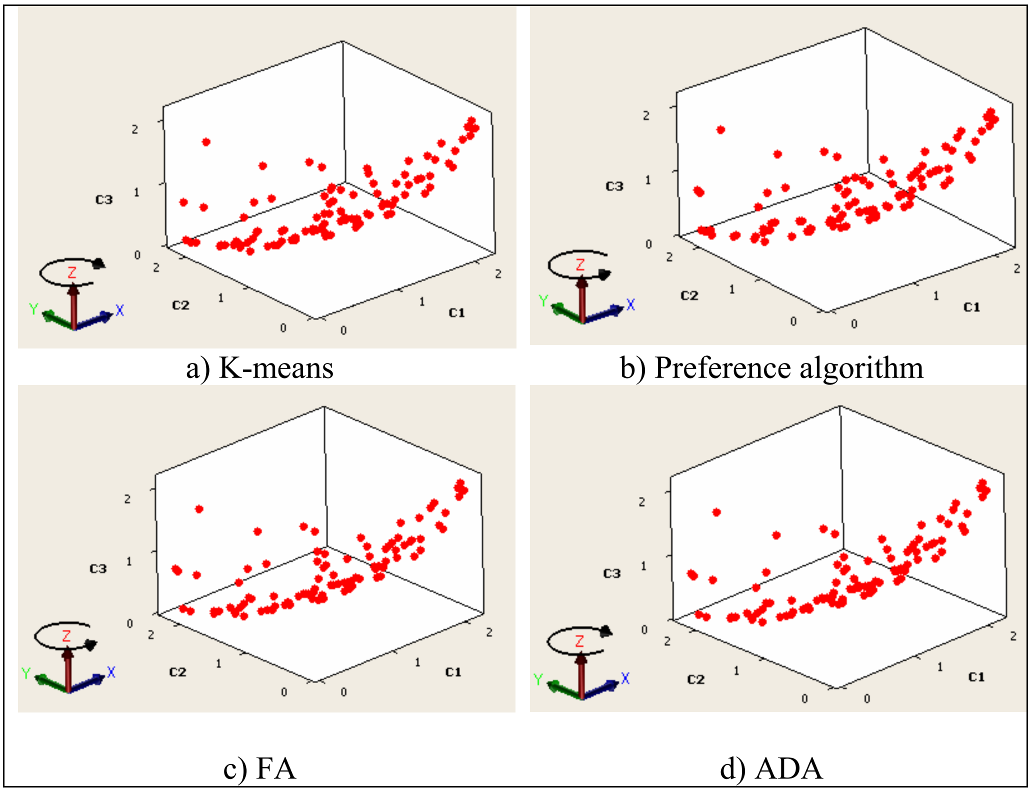
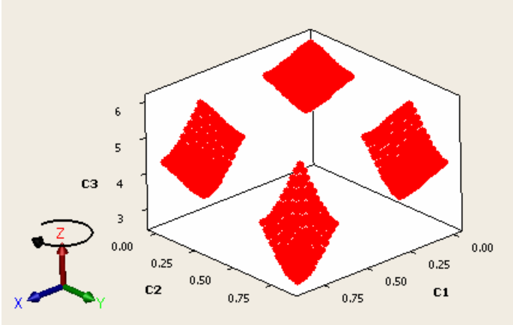
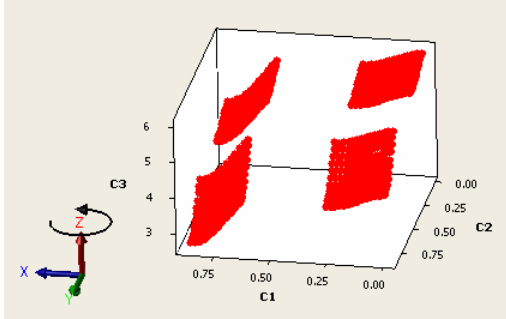


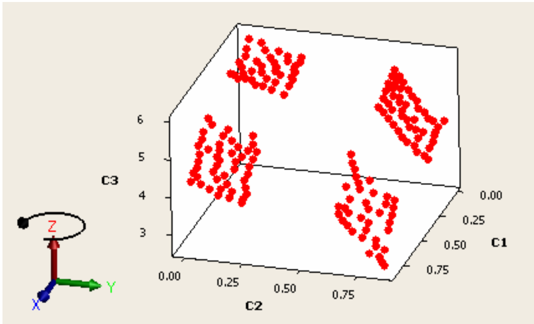
Figure 6.26 The obtained SPH solutions from K-means, Preference algorithm, FA and ADA (three objectives)



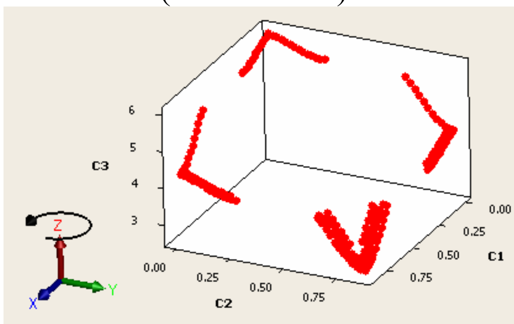
a) Pareto-front of DTLZ7



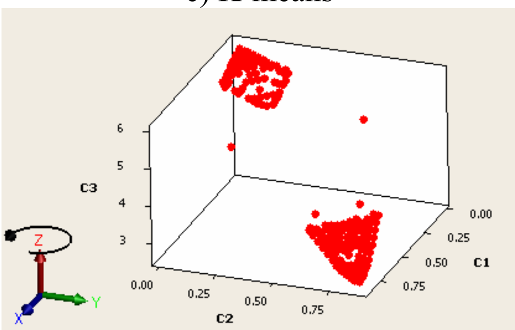
b) Pareto front of DTLZ7 (another view)



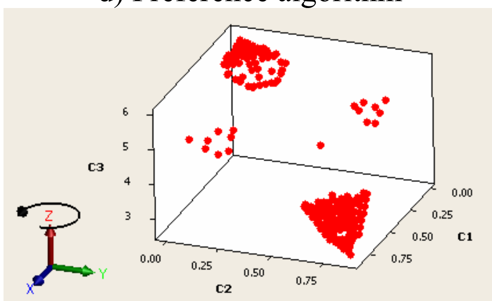
c) K-means



d) Preference algorithm



e) FA



f) ADA

Figure 6.27 The obtained DTLZ7 solutions from K-means, Preference algorithm, FA and ADA (three objectives)

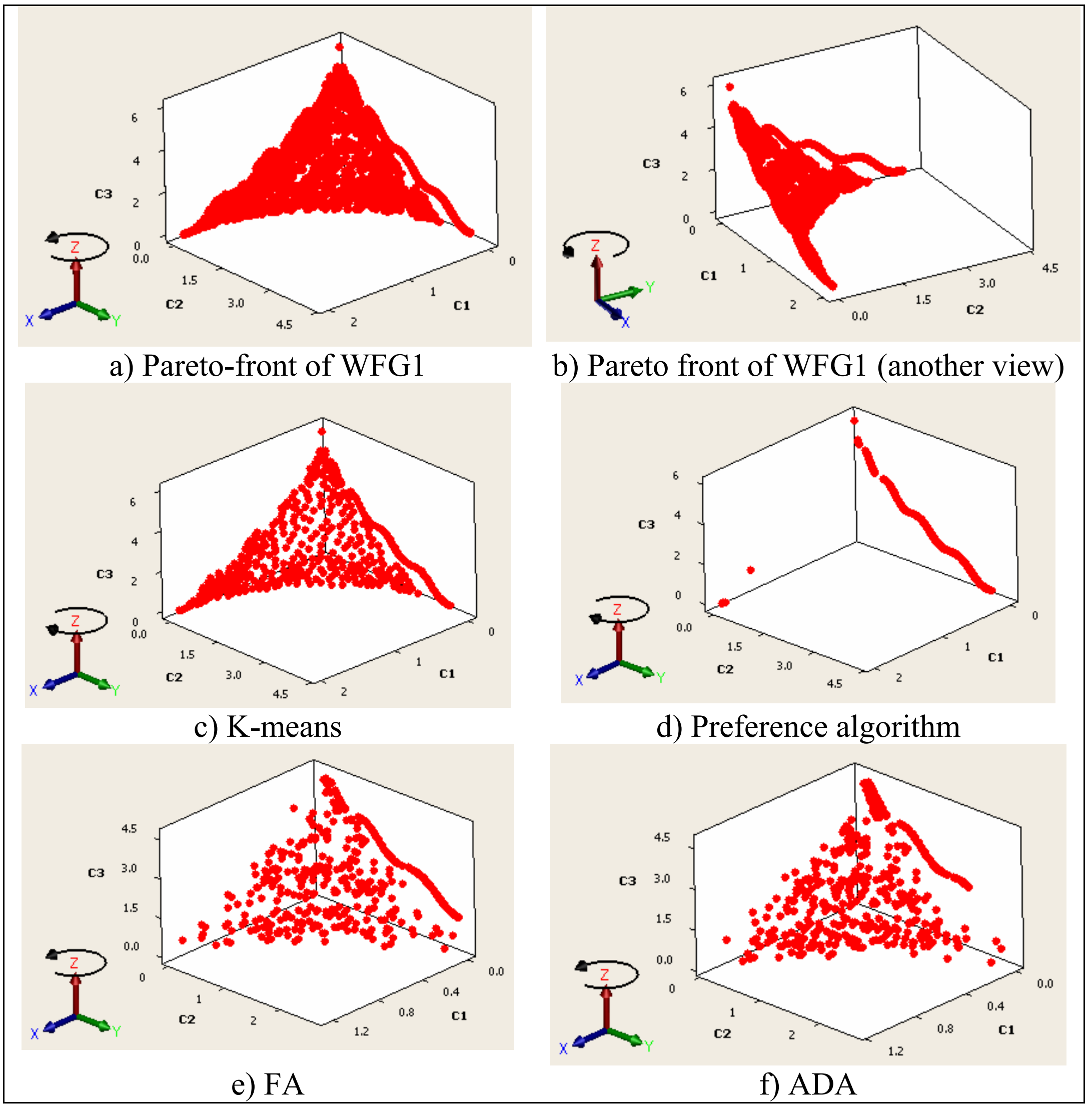


Figure 6.28 The obtained WFG1 solutions from K-means, Preference algorithm, FA and ADA (three objectives)

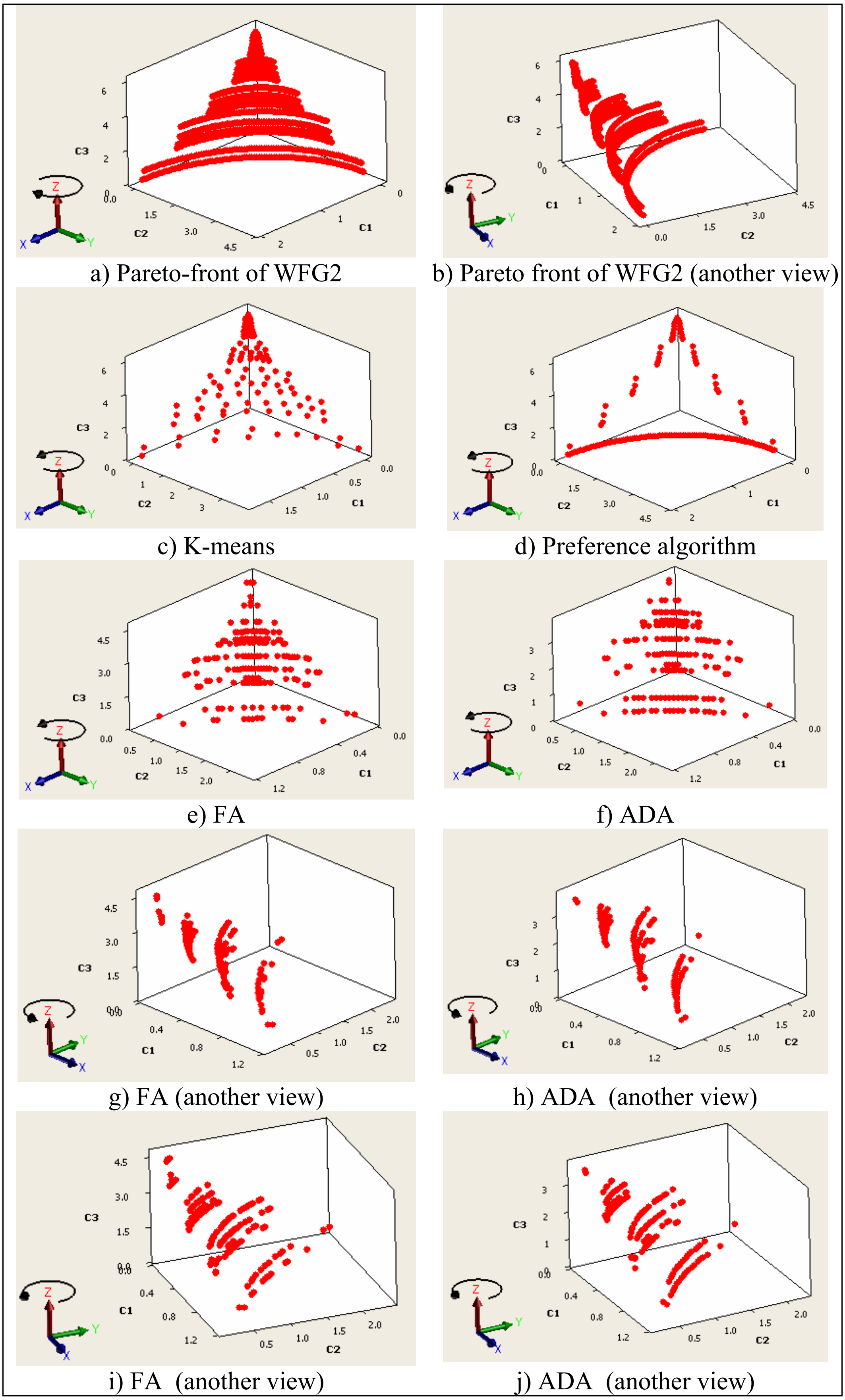


Figure 6.29 The obtained WFG2 solutions from K-means, Preference algorithm, FA and ADA (three objectives)

6.6 Conclusions Regarding Pruning Mechanism

This dissertation presents a pruning mechanism called Adaptive Angle Based algorithm or ADA to reduce less desirable solutions from larger Pareto solution sets. There have previously been two primary reasons to prune solutions from large Pareto sets. The first one is to reduce the number of Pareto solutions while maintaining diversity (e.g., *K*-means). The second one is to reduce the whole set of Pareto solutions to a subset that reflects preferences (e.g., Guided MO and Preference algorithm). This dissertation proposes another pruning rationale. Our pruning mechanism removes unlikely solutions or reduces the whole set of Pareto solutions to the subset of the most likely or promising solutions. For our pruning rationale, the existing performance metrics (e.g., Hyper-volume (HV), Spread or etc.) cannot be effectively used to benchmark because the solutions from our approach are obtained from the extended dominance concept. Extended dominance is an extension of the dominated relation from the regular dominance definition. A new performance metric (i.e., metric $D_{\tilde{\delta}}$) is proposed to make comparisons for the extended dominance. The metric $D_{\tilde{\delta}}$ compares two sets of solutions with the extra dominated-area from the regular multi-objective comparison. The obtained results show that our approach (ADA) provides superior solutions in various shapes of Pareto fronts. ADA can be scaled to solve an optimization problem when the number of objectives is increasing.

CHAPTER 7 EXPERIMENTAL RESULTS

In our experiments, we considered the multi-objective GRWA network design with a given network topology, a set of commodities and a set of bandwidth granularities (bandwidth requirement). A limited number of wavelength channels in each edge/link of the network was imposed and at least 80% of the requested commodities must be accepted. We generated a set of test problems with various numbers of commodities and bandwidth requirements, which were randomly generated with a uniform distribution.

We implemented our algorithms in Java and ran them on a Pentium 4 PC (Core 2 Quad CPU 2.83 GHz, 3.25 GB of RAM). We adapted three different example networks which are National Science Foundation Network (NSFNET) with 14 nodes and 42 directional edges [41], Chinese National Network (CHNNET) with 15 nodes and 54 directional edges [13] and Advanced Research Projects Agency Network (ARPANET) with 20 nodes and 64 directional edges [13] in our experiments as shown in *Figures 7.1-7.3*. For each problem, we specified a set of communication demands as a set of wavelength channels and switching ports. We assumed that all edges have the same wavelength capacity. Features of the considered networks are shown in *Table 7.1*, where the CHNNET has the highest value of average degree (i.e., 3.6).

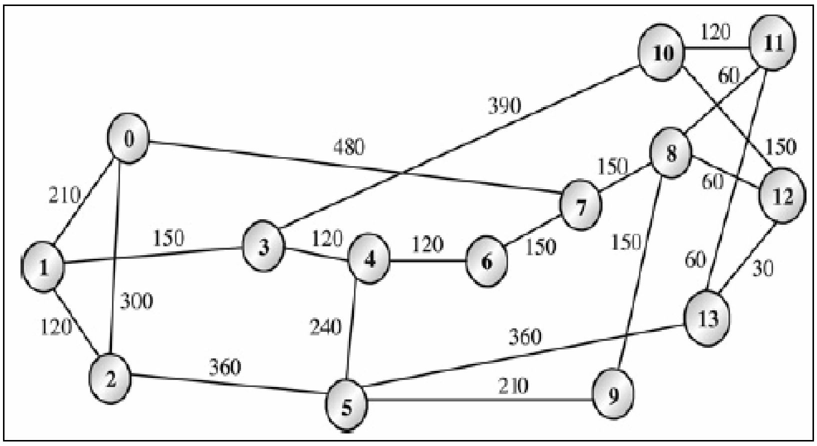


Figure 7.1 National Science Foundation Network (NSFNET) with 14 nodes and 42 directional edges [41]

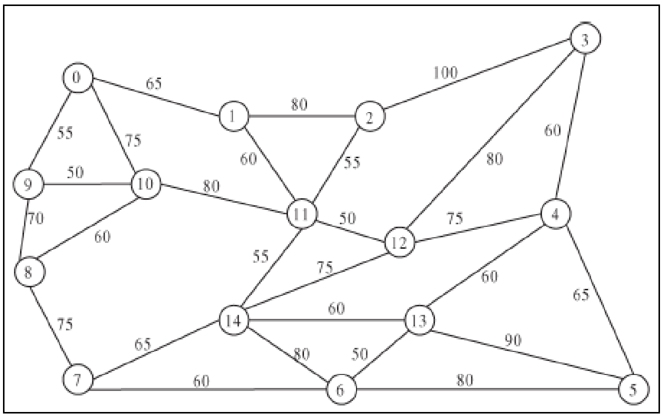


Figure 7.2 Chinese National Network (CHNNET) with 15 nodes and 54 directional edges [13]

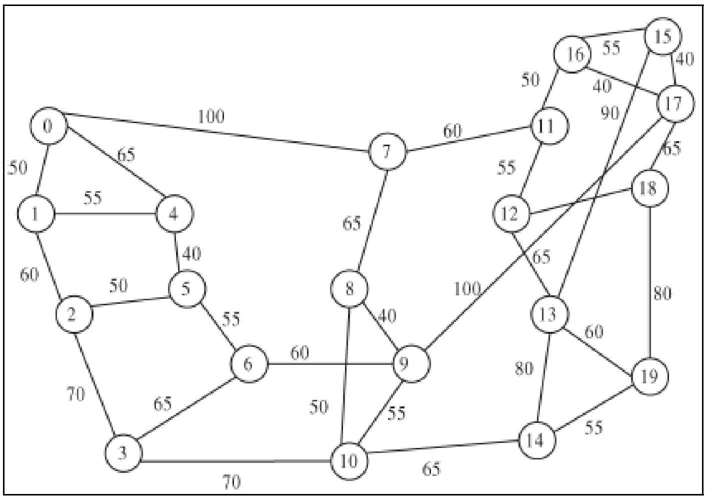


Figure 7.3 Advanced Research Projects Agency Network (ARPANET) with 20 nodes and 64 directional edges [13]

Table 7.1 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

For the GRWA problem, routing of the traffic demands is considered first. The mechanism to find an optimal route of each traffic demand is called "Routing Algorithm". In this dissertation, we use "Genetic Algorithm (GA) for routing" to generate the set of all possible routes. New routes that are not in the alternative set (obtained from Fixed Alternate Routing approach, FAR) can be explored and searched by using GA. The comparison of GA for routing and FAR is summarized in Appendix A.3.

In the second step, the set of commodities with the routes are assigned into many groups. The routes that have the same path can be grouped together. The grouping mechanism is called "Grooming algorithm". In this dissertation, we have three traffic grooming algorithms which are Maximizing Resource Utilization (MRU), Maximizing Single-hop Traffic Demands (MST) and Extended Traffic Grooming (ETG). MRU and MST are the traditional traffic grooming approaches. ETG is our proposed traffic grooming algorithm. MRU and MST are summarized in *Section 2.3*.

In conventional grooming approaches, MST and MRU techniques combine multiple low-rate traffic demands according to the sequence of the requested demands. In general, the two non-overlapped commodities are not integrated together. If there exists one commodity overlapping with two non-overlapped commodities (that were previously considered), the incoming commodity can be groomed with only one of the earlier sequences. We called this event as an "ordering obstruction" problem. Two wavelength channels are required for the traditional cases. In this dissertation, if a new commodity can be groomed with one or more of the previously considered commodities, they are combined together and the set of wavelength channels will be reassigned. By doing this, the number of wavelength channels and switching ports are decreased.

Our assumption is that multiple commodities are combined together, if they are overlapped. We proposed a new traffic grooming technique that potentially organizes a set of commodities into groups and possibly re-assigns the wavelength channels.

In the third step, the set of commodities with the routes and occupied groups are assigned to the set of available wavelength channels. The channel assignment is called "Wavelength Assignment". In this dissertation, we have three wavelength assignment methods which are First Fit (FF), Minimum Degree First (MinDF) and Maximum Degree First (MaxDF). The FF is a traditional wavelength assignment method while the MinDF and the MaxDF are our wavelength assignment methods. The descriptions of MinDF and MaxDF are summarized in *Appendix A.2 and B.3* respectively.

In summary, in *Section 7.1*, we consider 9 different approaches for grooming algorithms and wavelength assignments: MRU-FF, MST-FF, ETG-FF, MRU-MinDF, MST-MinDF, ETG-MinDF, MRU-MaxDF, MST-MaxDF and ETG-MaxDF). In *Section 7.1.1*, the wavelength channel is limited and fixed. The number of accepted commodities of the grooming algorithms and wavelength assignments are compared given the same number of wavelength channels. In *Section 7.1.2*, we consider the number of required wavelength channels that satisfies all traffic demands (all commodities are accepted). In *Section 7.2*, the obtained results are compared in a multi-objective environment. The multi-objective performance metrics are used to indicate the efficiency of the obtained results. In *Section 7.2.1*, the obtained solutions from traffic grooming are compared with the solutions from non-traffic grooming. *Section 7.2.2* compares the obtained results from four containment techniques. In *Section 7.2.3*, the traditional traffic grooming algorithms and wavelength assignment methods, MRU-FF and MST-FF, are compared with the new traffic grooming and wavelength assignment technique, that is, ETG-MaxDF. In this section, the number of accepted commodities, required wavelength channels and switching ports are considered as a three-objective GRWA optimization problem. *Section 7.2.4* shows the simulation results after the pruning mechanism discussed in Chapter 6 is applied to non-dominated solutions. *Section 7.3* shows an example of graphical user interface of the network design tool.

In our experiments, we used the same set of network configurations and workloads for all traffic grooming algorithms that we considered.

7.1 Traffic Grooming Comparison in Single Objective Optimization

In this section, one objective function from the three-objective GRWA (as proposed in *Chapter 4*) is fixed and limited. We observe the other objective values. In *Section 7.1.1*, we fix the number of available wavelength channels on the directional edge. The number of commodities with a limited wavelength is observed and compared. In *Section 7.1.2*, we consider the number of required wavelength channels to satisfy all incoming commodities. The input workload or the set of commodities were fed to the algorithms. Then we observed the objective value (i.e., accepted commodity or wavelength channel).

7.1.1 Comparing by Using Accepted Commodities

This simulation compares the performance of nine traffic grooming algorithms (MRU-FF, MST-FF, ETG-FF, MRU-MinDF, MST-MinDF, ETG-MinDF, MRU-MaxDF, MST-MaxDF and ETG-MaxDF) as shown in *Table 7.2*. In this experiment, we limited the number of wavelength channels in the network edge. All of them used the same set of commodities with bandwidth requirements. The number of accepted commodities was captured to benchmark the algorithm. A high number of accepted commodities is preferred. *Table 7.2* shows the number of accepted commodities of ETG-MaxDF was greater than those of the other traffic grooming algorithms with the same number of wavelength channels.

Table 7.2 Number of accepted commodities with a limited number of wavelength channels

No. of total commodities	No. of λ	First Fit (FF)						Minimum Degree First (MinDF)						Maximum Degree First (MaxDF)					
		MRU		MST		ETG		MRU		MST		ETG		MRU		MST		ETG	
		#acc	#ports	#acc	#ports	#acc	#ports	#acc	#ports	#acc	#ports	#acc	#ports	#acc	#ports	#acc	#ports	#acc	#ports
10	1	9	62	8	58	10	62	9	62	8	58	10	62	9	62	8	58	10	62
10	2	10	68	10	66	10	62	10	68	10	66	10	62	10	68	10	66	10	62
10	3	10	68	10	66	10	62	10	68	10	66	10	62	10	68	10	66	10	62
30	1	18	100	23	140	23	136	20	122	23	140	19	108	17	98	18	104	23	136
30	2	27	166	29	178	29	172	24	148	28	170	29	172	27	166	29	178	29	172
30	3	30	186	30	182	30	176	30	186	30	182	30	176	30	186	30	182	30	176
50	2	35	204	36	212	40	214	26	160	29	172	35	180	32	180	37	208	40	214
50	3	41	250	42	256	50	270	35	220	36	210	43	222	40	238	43	258	50	270
50	4	46	288	48	294	50	270	43	274	40	242	50	270	45	282	47	288	50	270
100	4	69	356	82	466	83	466	62	326	75	426	77	424	65	338	89	514	83	466
100	5	84	422	93	534	99	538	75	394	90	512	85	456	78	426	95	550	99	538
100	6	94	494	98	566	100	542	85	464	95	544	94	498	87	486	100	578	100	542
150	7	125	586	126	712	146	744	126	636	120	646	131	624	131	634	133	768	150	756
150	8	140	666	140	792	150	756	135	682	125	676	137	664	141	710	145	832	150	756
150	9	147	716	145	824	150	756	145	728	130	708	143	706	145	734	150	856	150	756
200	8	147	672	164	918	164	878	150	700	155	848	155	714	157	840	167	950	171	918
200	9	162	756	174	984	180	956	165	796	165	910	162	762	173	910	180	1014	183	958
200	10	172	824	185	1062	193	1008	180	896	180	1000	176	856	182	958	188	1064	200	1032
250	11	216	976	222	1226	235	1252	215	970	215	1152	206	966	228	1144	224	1250	239	1272
250	12	225	1042	235	1302	240	1280	225	1038	225	1224	213	1034	238	1188	241	1338	250	1320
250	13	235	1104	240	1332	247	1304	230	1076	230	1256	220	1090	248	1216	248	1380	250	1320
300	12	249	1050	257	1366	287	1346	260	1142	241	1244	276	1224	264	1266	242	1324	293	1370
300	13	257	1106	271	1444	300	1394	275	1224	251	1310	283	1272	283	1344	261	1424	300	1394
300	14	272	1192	285	1536	300	1394	285	1296	265	1396	291	1330	298	1402	279	1520	300	1394
350	14	319	1412	317	1558	339	1574	306	1338	301	1472	327	1448	318	1528	308	1542	341	1590
350	15	329	1488	327	1620	350	1622	316	1416	311	1536	334	1496	338	1604	327	1654	347	1606
350	16	336	1538	337	1692	350	1622	326	1474	326	1620	341	1540	350	1660	332	1686	350	1622
400	15	344	1444	334	1590	368	1686	337	1386	320	1506	362	1516	348	1644	328	1620	382	1714
400	16	354	1518	342	1642	382	1734	352	1492	330	1576	370	1568	373	1744	350	1736	389	1750
400	17	364	1600	352	1700	400	1790	360	1560	345	1666	376	1618	388	1814	365	1802	400	1790

Figure 7.4 shows the number of accepted commodities from 200 commodities with 10 wavelength channels. *Figure 7.5* shows the number of accepted commodities from 400 commodities with 17 wavelength channels. ETG-MaxDF has higher number of accepted commodities than other approaches with the same number of wavelength channels.

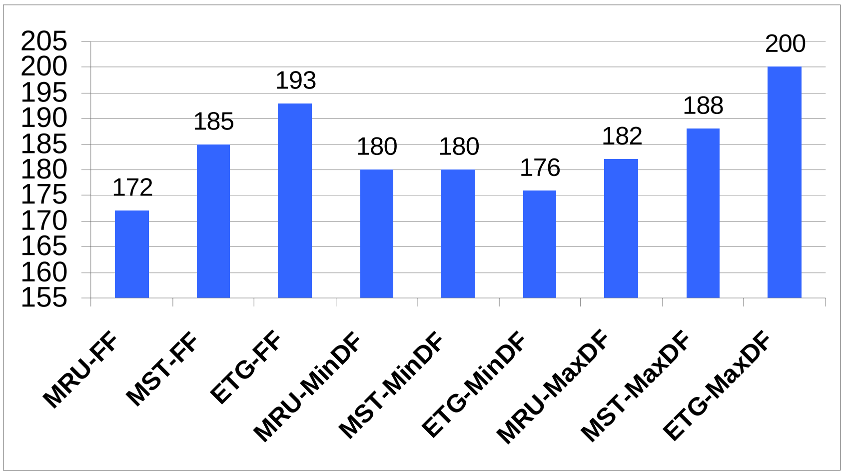


Figure 7.4 The number of accepted commodities from 200 commodities with 10 wavelength channels

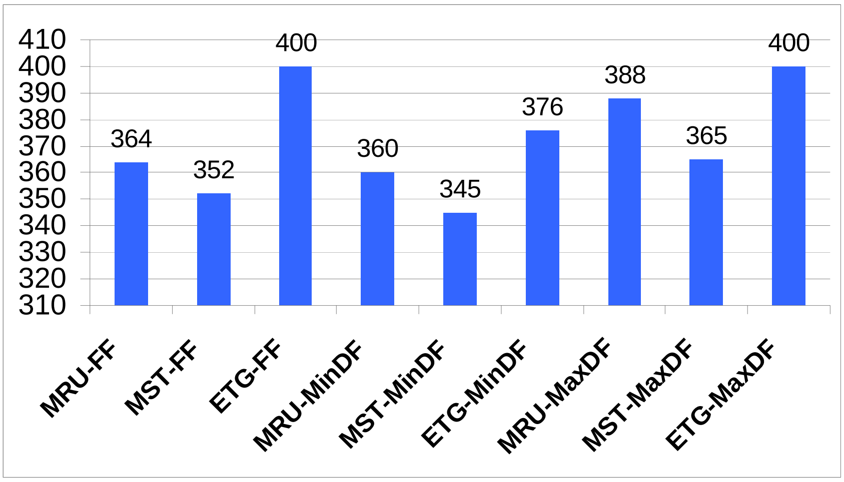


Figure 7.5 The number of accepted commodities from 400 commodities with 17 wavelength channels

7.1.2 Comparing by Using Wavelength Channels

Typically, in the RWA problem, the number of required wavelength channels for a certain set of requested commodities is used to evaluate performance of the algorithms. Thus, in these experiments, we compared the number of wavelength channels that were needed to serve all incoming commodities or 100% accepted commodities. We compared the performance of nine traffic grooming algorithms which are MRU-FF, MST-FF, ETG-FF, MRU-MinDF, MST-MinDF, ETG-MinDF, MRU-MaxDF, MST-MaxDF and ETG-MaxDF as shown in *Table 7.3*. All of them used the same set of commodities with bandwidth requirements. The number of obtained wavelength channels was captured to evaluate the algorithms. A low number of wavelength channels is preferred. *Table 7.3* shows that the number of wavelength channels obtained from the ETG-MaxDF algorithm is better than those obtained from the other traffic grooming algorithms. To satisfy all the requested commodities, the ETG-MaxDF requires fewer number of wavelength channels.

Table 7.3 Number of groups, wavelength channels and switching ports to serve all accepted commodities

No. of accepted commodities	First Fit Wavelength Assignment (FF)								
	MRU			MST			ETG		
	#groups	#λ	#ports	#groups	#λ	#ports	#groups	#λ	#ports
10	7	2	68	7	2	66	6	1	62
30	16	3	186	13	3	182	12	3	176
50	20	5	312	20	5	306	17	3	270
100	30	7	542	31	7	578	28	6	542
150	38	10	758	43	10	856	37	8	756
200	45	14	1048	51	12	1150	44	11	1032
250	53	16	1228	61	15	1394	54	14	1320
300	63	18	1414	73	17	1628	57	13	1394
350	73	19	1660	79	19	1782	69	15	1622
400	83	24	1858	90	22	1998	74	17	1790

No. of accepted commodities	Minimum Degree First (MinDF)								
	MRU			MST			ETG		
	#groups	#λ	#ports	#groups	#λ	#ports	#groups	#λ	#ports
10	7	2	68	7	2	66	6	1	62
30	16	3	186	13	3	182	12	3	176
50	20	6	312	20	6	306	17	4	270
100	30	8	542	31	7	578	28	7	542
150	38	10	758	43	12	856	37	10	756
200	45	13	1048	51	13	1150	44	13	1032
250	53	16	1228	61	17	1394	54	17	1320
300	63	16	1414	73	18	1628	57	15	1394
350	73	20	1660	79	20	1782	69	17	1622
400	83	23	1858	90	25	1998	74	20	1790

No. of accepted commodities	Maximum Degree First (MaxDF)								
	MRU			MST			ETG		
	#groups	#λ	#ports	#groups	#λ	#ports	#groups	#λ	#ports
10	7	2	68	7	2	66	6	1	62
30	16	3	186	13	3	182	12	3	176
50	20	5	312	20	6	306	17	3	270
100	30	7	542	31	6	578	28	6	542
150	38	10	758	43	9	856	37	7	756
200	45	12	1048	51	11	1150	44	10	1032
250	53	14	1228	61	14	1394	54	12	1320
300	63	15	1414	73	17	1628	57	13	1394
350	73	16	1660	79	19	1782	69	16	1622
400	83	18	1858	90	21	1998	74	17	1790

Remark: the number of switching ports with the same traffic grooming algorithm in all wavelength assignments are equal because the grooming algorithms (MRU, MST and ETG) are considered before the wavelength assignment is processed.

Figures 7.6 and 7.7 shows the number of wavelength channels and switching ports required to serve 200 commodities. *Figures 7.8 and 7.9* shows the number of wavelength channels and switching ports required to serve 400 commodities. ETG-MaxDF requires lower number of wavelength channels and switching ports than other approaches for serving the same number of accepted commodities.

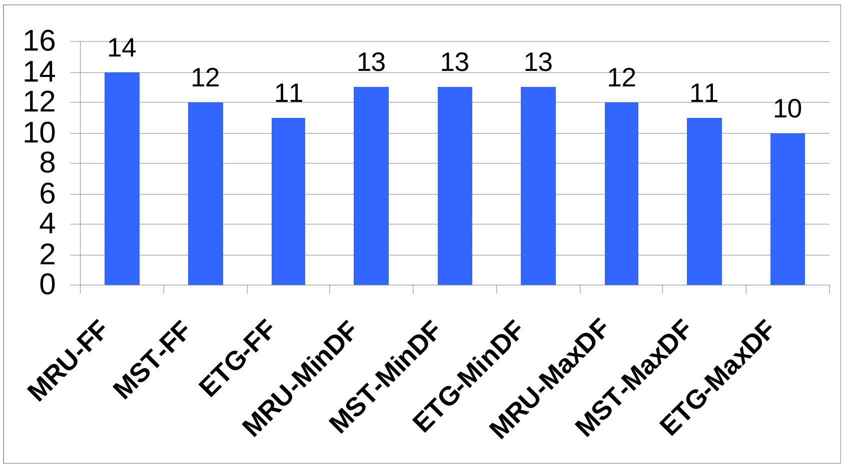


Figure 7.6 The number of wavelength channels to serve 200 commodities

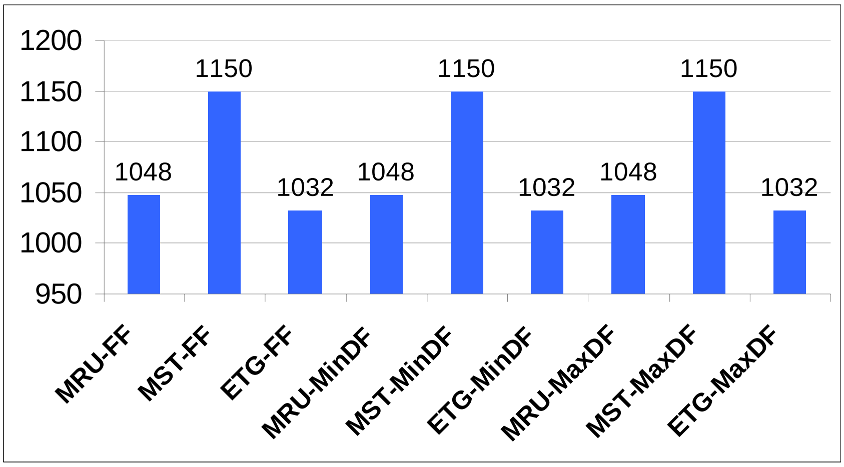


Figure 7.7 The number of switching ports to serve 200 commodities

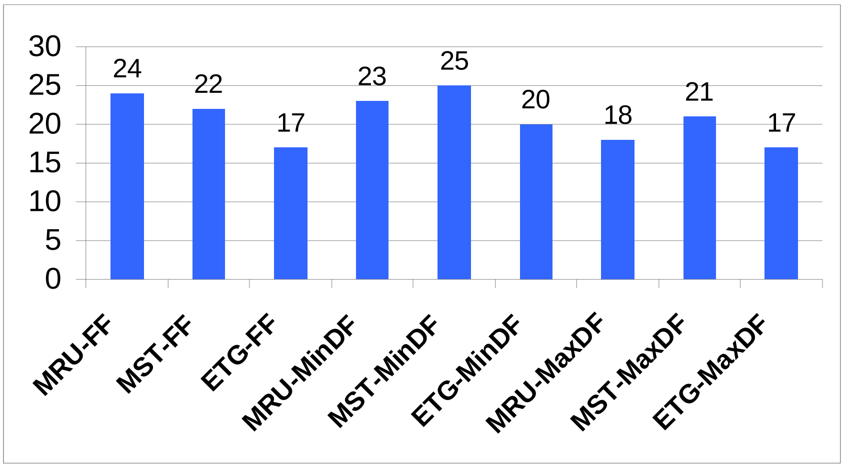


Figure 7.8 The number of wavelength channels to serve 400 commodities

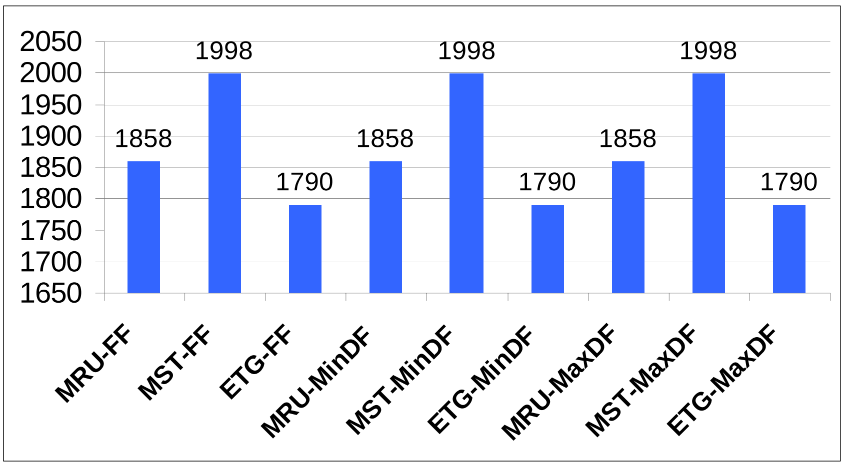


Figure 7.9 The number of switching ports to serve 400 commodities

7.2 Traffic Grooming Comparison with Multiple Objectives

This experiment investigated multiple objective cases. Since the obtained results in the multi-objective context consist of multiple solutions, the obtained results are provided as a set of candidate solutions. Performance metrics are used to indicate which the set of solutions is better. The performance metrics are described in *Section 6.4*. In this section, the GA for routing, ETG for grooming and MaxDF for wavelength assignment were sequentially applied to solve the GRWA optimization problem. The GA-ETG-MaxDF combination will be referred to as "GA-EMF".

7.2.1 Comparing with No Traffic Grooming

In our experiments, we considered the network design with a given network topology and a set of commodities. A limited number of wavelength channels in each edge/link of the network was imposed and at least 80% of commodities were required to be accepted. We simulated the network model considering various sets of total commodities from 10 to 150 commodities. They were randomly generated with a uniform distribution. For each problem size, a set of communication demands was investigated with a set of wavelength channels. We assumed that all edges had the same wavelength capacity. An ARPANET network [13] with 20 nodes and 64 directional edges was considered as a simulation network as shown in *Figure 7.3*.

We considered the GRWA by maximizing the number of accepted commodities and minimizing the number of wavelengths. The NSGA-II algorithm was applied to search for a set of non-dominated solutions. *Table 7.4* shows the computation time obtained from traffic grooming algorithm (GA-EMF), non-traffic grooming algorithm (GA-MinDF) and the traditional non-traffic grooming algorithm (FAR-FF). Three algorithms are applied with NSGA-II. The obtained results are compared in *Figure 7.10*.

In multi-objective optimization, the results are plotted as a front or sets of candidate solutions. There is no one solution better than the other solutions. Each solution is the best for a certain consideration. These solutions are called non-dominated solutions. However, the best solution can be determined based on the importance or priority of objective functions. From *Figure 7.10*, if the network is considered to have a maximum of 15 wavelength channels, then the number of accepted commodities of GA-EMF, GA-MinDF and FAR-FF can be maximized at 150, 145 and 125, respectively. With the same number of wavelengths, GA-EMF provides higher number of accepted commodities. However, if the network requires all 150 commodities to be accepted, then the number of required wavelength channels obtained from the GA-EMF, GA-MinDF and FAR-FF are 14, 18 and 21, respectively. To serve all commodities, the GA-EMF requires a lower number of wavelengths comparing with the other algorithms.

Table 7.4 shows that the NSGA-II algorithm is computationally intensive, with an average CPU time of the total of 150 commodities obtained from GA-EMF, GA-MinDF and FAR-FF are 21,540.3, 29,435.0 and 29,921.0 seconds, respectively. The traffic grooming algorithm (GA-EMF) requires higher amount of time but gives cost-effective results in term of wavelength channels required. From [10], it was stated that the computation complexity of the NSGA-II algorithm is $O(MN^2)$ where M is the number of objectives and N is the population size. Thus our NSGA-II computation time can be reduced by adjusting the size of N.

Table 7.4 Computation time of GA-EMF, GA-MinDF and FAR-FF using NSGA-II approaches with 2,400 iterations

	Number of total commodities	CPU Time (sec.)		
		FAR-FF	GA-MinDF	GA-EMF
Average (per 1 replication run)	10	102.0	173.7	179.7
	30	838.0	1,263.3	1,281.3
	50	2,295.0	3,350.7	3,414.7
	100	9,214.7	13,134.7	13,173.3
	150	21,540.3	29,435.0	29,921.0
Total	10	306.0	521.0	539.0
	30	2,514.0	3,790.0	3,844.0
	50	6,885.0	10,052.0	10,244.0
	100	27,644.0	39,404.0	39,520.0
	150	64,621.0	88,305.0	89,763.0

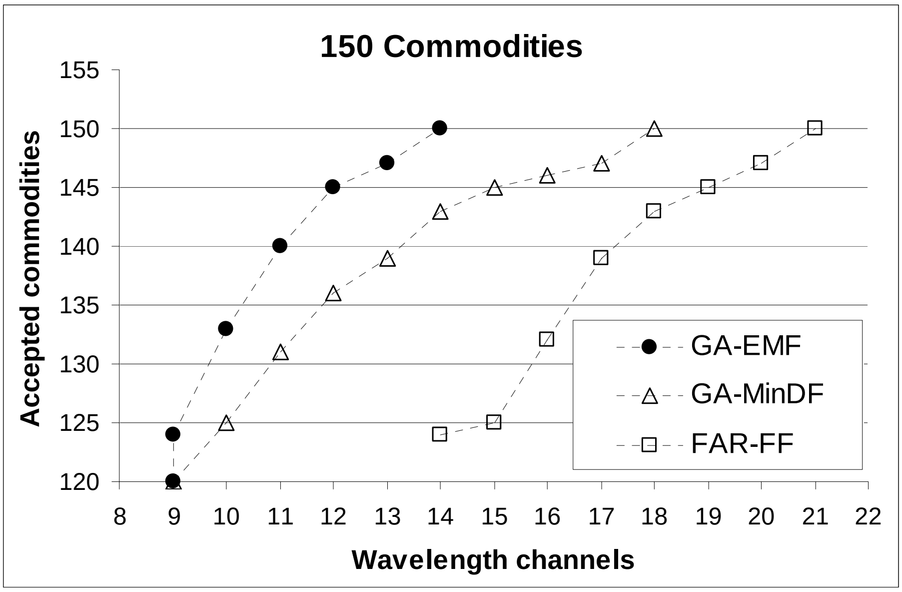


Figure 7.10 The non-dominated solutions of GA-EMF, GA-MinDF and FAR-FF obtained from ARPANET

In multi-objective optimization, the performance of the obtained results can be evaluated by performance metrics or quality indicators [42-44]. The performance metrics that are Hyper Volume (HV), Spread and Inverted Generational Distance (IGD) are used in this dissertation. HV represents the volume that the obtained results cover. High HV is preferred. Low Spread indicates that the solution distributes into all objective areas equally (not crowding into one small objective area). IGD is measured the distance from the obtained elements to the Pareto optimal set. The low IGD is preferred and it is 0 when all elements are in the Pareto optimal set. Note that high HV, low Spread and IGD indicate a superior result.

Table 7.5 shows the multi-objective performance metrics (HV, Spread and IGD) calculated for the obtained solutions from FAR-FF, GA-MinDF and GA-EMF algorithms. The performance metrics are described in *Section 6.4*. The obtained HV from the traffic grooming algorithm (GA-EMF) is greater than the HV from non-traffic grooming algorithms. This means that the obtained results from the GA-EMF traffic grooming algorithm are diverse and cover the objective spaces than those from the non-traffic grooming algorithms (GA-MinDF and FAR-FF). *Figure 7.10* shows that the obtained solutions from the GA-EMF traffic-grooming algorithm are optimized in both terms of accepted commodity and required wavelength channel when they are compared with the non-traffic grooming algorithms (GA-MinDF and FAR-FF). The obtained IGD from GA-EMF is equal to 0. This means the algorithm has the interval distance from the non-dominated solutions to the Pareto solutions equal to 0. In other words, all obtained solutions from the GA-EMF are the Pareto optimal solutions.

Table 7.5 Multi-objective performance metrics of GA-EMF, GA-MinDF and FAR-FF in ARPANET network topologies with 150 commodities

Type	Technique	HV.	Spread	IGD.	CPU Time (sec.)	
					Average*	Total
Non-traffic grooming	FAR-FF	$HV_{FAR\text{-}FF} = 0.3194$	0.6623	0.0927	21,540.3	64,621.0
	GA-MinDF	$HV = 0.6722 = 2.10*HV_{FAR\text{-}FF}$	0.5038	0.0307	29,435.0	88,305.0
Traffic Grooming	GA-EMF	$HV = 0.8306 = 2.60*HV_{FAR\text{-}FF}$	0.6504	0.0000	29,921.0	89,763.0

* per one replication run

7.2.2 Comparing Four Containment Techniques

In our experiments, we considered a network design with a given network topology and a set of commodities. A limited number of wavelength channels in each edge/link of the network was imposed and at least 80% of commodities had to be accepted. We simulated the network model considering various sets of total commodities from 10 to 150 commodities, which were randomly generated with a uniform distribution. For each problem size, a set of communication demands was investigated with a set of wavelength channels. We assumed that all edges had the same wavelength capacity. An ARPANET network [13] with 20 nodes and 64 directional edges was considered as a simulation network as shown in *Figure 7.3*.

We considered the GRWA by maximizing number of accepted commodities and minimizing the number of wavelengths. The NSGA-II algorithm was applied to search for a set of non-dominated solutions with four grooming criteria. The descriptions of four grooming criteria are provided in *Section 2.2*. *Table 7.6* shows the computation time obtained from traffic grooming algorithm (GA-EMF) with four grooming criteria. All four criteria were applied with NSGA-II. The obtained results are compared and evaluated in *Figure 7.11*.

In multi-objective optimization context, the results are plotted as a front or sets of non-dominated solutions. *Figure 7.11* shows that if the network is considered to have a maximum of 15 wavelength channels, then the number of accepted commodities of P2P, P2MP, MP2P and MP2MP are maximized to 139, 150, 150 and 150, respectively. With the same number of wavelengths, multiple sources/destinations criteria provide the highest number of accepted commodities. However, if the network requires 150 commodities to be accepted, then the number of wavelength channels required from the P2P, P2MP, MP2P and MP2MP are 19, 15, 15 and 13, respectively. To serve all commodities, the MP2MP requires a lower number of wavelengths compared to the other three grooming techniques.

Table 7.6 Computation time of P2P, P2MP, MP2P and MP2MP using NSGA-II approaches with 2,400 iterations

	No. of total commodities	CPU Time (sec.)			
		P2P	P2MP	MP2P	MP2MP
Average (per 1 replication run)	10	180.3	179.7	181.0	177.3
	30	1,314.7	1,300.0	1,306.0	1,305.7
	50	3,470.7	3,435.0	3,437.0	3,406.0
	100	13,699.3	13,410.7	13,322.0	13,181.3
	150	31,841.0	30,509.0	30,452.0	29,928.0
Total	10	541.0	539.0	543.0	532.0
	30	3,944.0	3,900.0	3,918.0	3,917.0
	50	10,412.0	10,305.0	10,311.0	10,218.0
	100	41,098.0	40,232.0	39,966.0	39,544.0
	150	95,523.0	91,527.0	91,356.0	89,784.0

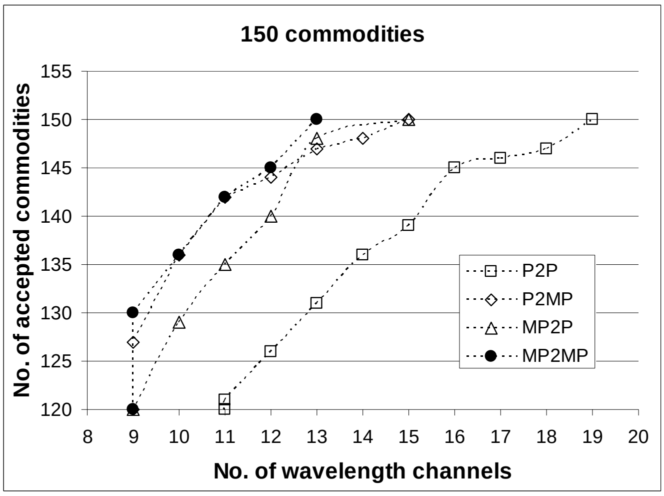


Figure 7.11 The non-dominated solutions of P2P, P2MP, MP2P and MP2MP obtained from ARPANET

Table 7.6 once again shows that the NSGA-II algorithm is computationally intensive, with an average CPU time of the total of 150 commodities obtained from P2P, P2MP, MP2P and MP2MP are 31841.0, 30509.0, 30452.0 and 29,928.0 seconds, respectively.

All four types of traffic grooming algorithm require high amount of computation time but multiple sources/destinations grooming (P2MP, MP2P and MP2MP) gives more cost-effective results in term of wavelength channels required. As shown in *Figure 7.11*, the solutions obtained from the P2MP technique are closed to the obtained solutions from MP2MP technique. This result means the obtained solutions are efficient when multiple commodities with the same source are groomed. Meanwhile computation for the P2MP grooming criterion is less complex than for the MP2MP technique.

Table 7.7 shows the multi-objective performance metrics (HV, Spread and IGD) calculated for the obtained solutions from the four containment techniques. The obtained HV from the MP2MP technique is greater than the HV from the other techniques, meaning that the obtained results from the MP2MP are more diverse. They cover the objective spaces more broadly than the other techniques. *Figure 7.11* shows that the obtained solutions from the MP2MP are optimized both in terms of accepted commodity and required wavelength channel when they are compared with the other techniques (P2P, P2MP and MP2P). The obtained IGD from the MP2MP is equal to 0. This means the algorithm has the interval distance from the non-dominated solutions to the Pareto solutions equal to zero. In other words, all obtained solutions from the MP2MP are the Pareto optimal solutions.

Table 7.7 Multi-objective performance metrics of four containment techniques in ARPANET network topologies with 150 commodities

Containment technique	HV.	Spread	IGD.	CPU Time (sec.)	
				Average*	Total
P2P	$HV_{P2P} = 0.4367$	0.5755	0.0747	31,841.0	95,523.0
P2MP	$HV = 0.8133 = 1.86*HV_{P2P}$	0.5650	0.0133	30,509.0	91,527.0
MP2P	$HV = 0.7333 = 1.68*HV_{P2P}$	0.5673	0.0222	30,452.0	91,356.0
MP2MP	$HV = 0.8433 = 1.93*HV_{P2P}$	0.6112	0.0000	29,928.0	89,784.0

* per one replication run

7.2.3 Comparing with Traditional Traffic Grooming

In our experiments, we considered the network design with a given network topology and a set of commodities. A limited number of wavelength channels in each edge/link of the network was imposed and at least 80% of commodities had to be accepted/ served. We considered various test problems with a number of commodities. We simulated the network model considering various sets of total commodities from 10 to

150 commodities. They were randomly generated with a uniform distribution. For each problem size, a set of communication demands was investigated with a set of wavelength channels. We assumed that all edges have the same number of wavelength capacity. Three network topologies (as shown in *Figures 7.1-7.3*) were considered as a simulation network.

We considered the GRWA with three design objectives that are maximizing number of accepted commodities, minimizing the number of wavelength channels and minimizing the number of switching ports. The NSGA-II algorithm was applied to search for a set of non-dominated solutions. The obtained results are compared in all three objective values shown in three-dimensional space. The obtained results were compared to each other as shown in *Figures 7.12-7.21*. In multi-objective optimization, the results are plotted as a front or sets of non-dominated solutions. In this dissertation, we used performance metrics to specify the performance of the obtained sets from multiple algorithms. *Table 7.8* shows the multi-objective performance metrics and computation time obtained from our and traditional approaches with various network topologies.

The obtained results from our GRWA algorithm as called "GA-ETG-MaxDF" (GA for routing, ETG for grooming and MaxDF for wavelength assignment) are compared with the obtained results from the traditional algorithms 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). Note that the GA for routing has a benefit that all possible network routes are considered. A new route that is not in the alternate set (e.g., from Fixed Alternate Routing approach, FAR) can be explored and searched by using the GA. A comparison of GA for routing and FAR is presented in *Appendix A.3*. The original traffic grooming and wavelength assignment proposed by Zhu and Mukherjee [4] in 2002 are MRU-FF and MST-FF. Therefore this section compares the obtained solutions from GA-ETG-MaxDF with those from the existing approaches which are GA-MRU-FF and GA-MST-FF.

Figure 7.12 shows 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. In the NSFNET topology, the solutions from the GA-ETG-MaxDF requires 626-860 switching ports while the solutions from the GA-MRU-

FF and the GA-MST-FF requires 632-886 and 680-962 ports, respectively. *Figures 7.12-7.13* shows that the GA-ETG-MaxDF can support 150 commodities within 860 ports. With the same number of ports, the GA-MRU-FF can support 145 commodities and the GA-MST-FF can support 140 commodities. On the other hand, the GA-ETG-MaxDF requires a fewer switching ports compared with the GA-MRU-FF and the GA-MST-FF for satisfying all commodities. *Figure 7.14* shows that the GA-ETG-MaxDF can support a larger number of accepted commodities than those of 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 wavelengths than the GA-MRU-FF and the GA-MST-FF.

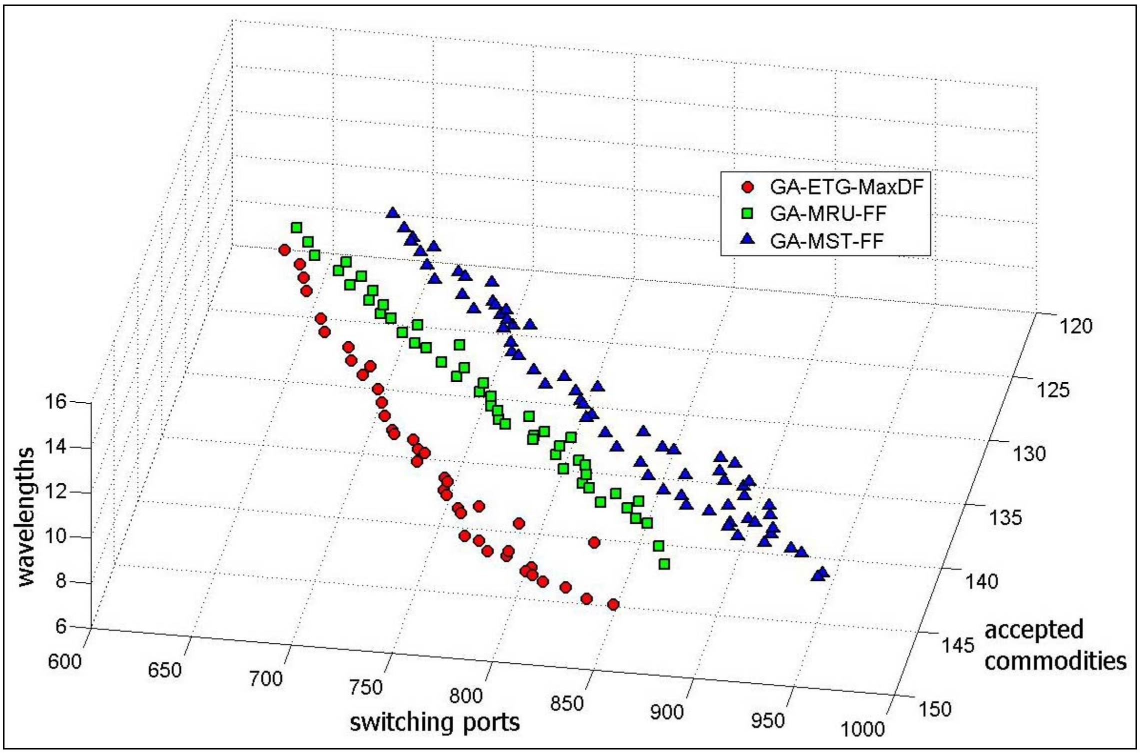


Figure 7.12 The non-dominated solutions of GA-ETG-MaxDF, GA-MST-FF and GA-MRU-FF obtained from NSFNET

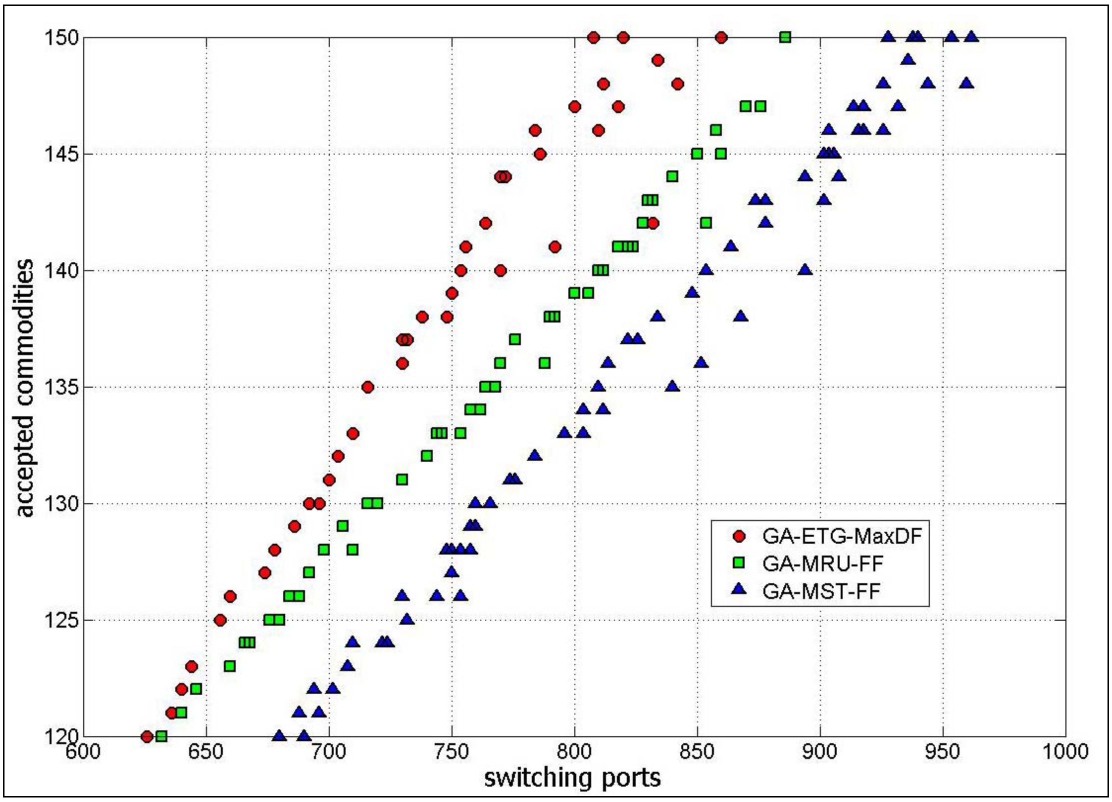


Figure 7.13 The relation between accepted commodity and switching port of GA-ETG-MaxDF, GA-MST-FF and GA-MRU-FF obtained from NSFNET

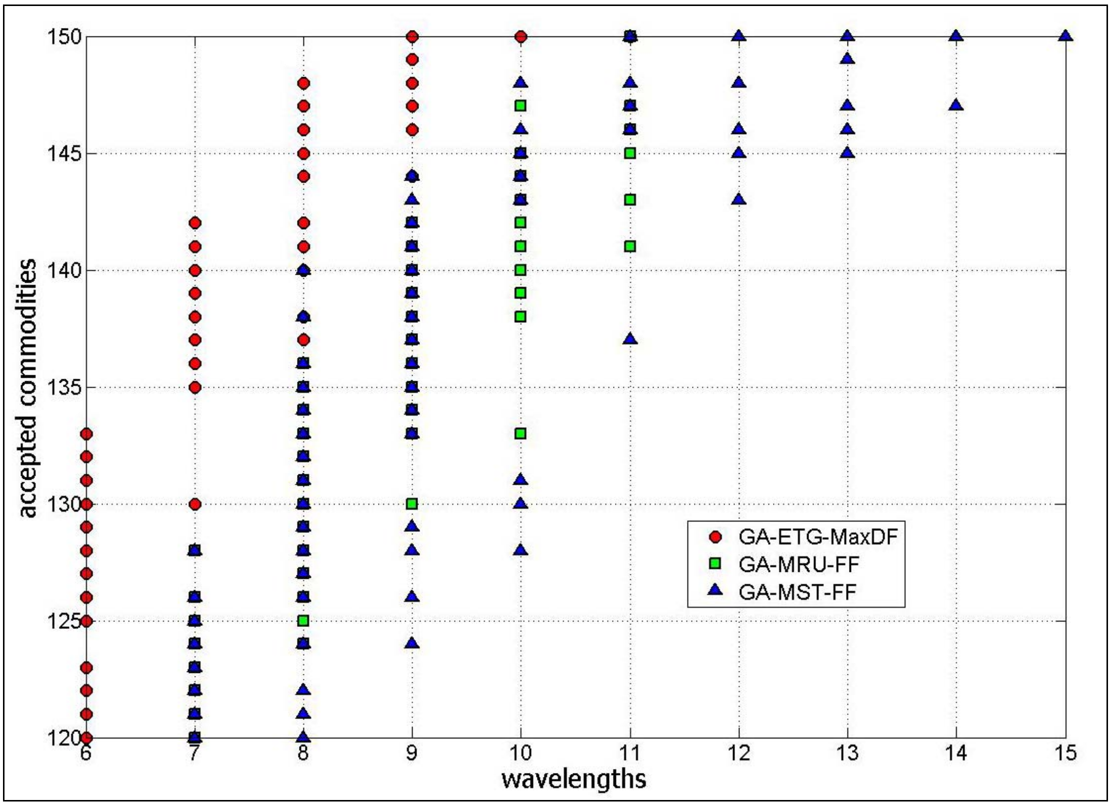


Figure 7.14 The relation between accepted commodity and wavelength of GA-ETG-MaxDF, GA-MST-FF and GA-MRU-FF obtained from NSFNET

Figure 7.15 shows that the set of solutions from the GA-ETG-MaxDF is located in the area of high number of accepted commodities, with fewer switching ports and fewer wavelengths when compared with the other algorithms. In the CHNNET topology, the solutions from the GA-ETG-MaxDF require 604-948 switching ports while the solutions from the GA-MRU-FF and the GA-MST-FF require 600-926 and 654-1026 ports, respectively. *Figures 7.15-7.16* shows that the GA-ETG-MaxDF can support 150 commodities using at most 840 ports. With the same number of ports, the GA-MRU-FF can support 146 commodities and the GA-MST-FF can support 144 commodities. On the other hand, the GA-ETG-MaxDF requires fewer switching ports compared with the GA-MRU-FF and the GA-MST-FF to satisfy all commodities. *Figure 7.17* shows that with a certain amount of wavelength usage, the GA-ETG-MaxDF can support a larger number of accepted commodities than the GA-MRU-FF and the GA-MST-FF can support. For satisfying all commodities, the GA-ETG-MaxDF requires fewer wavelengths than the GA-MRU-FF and the GA-MST-FF do.

Figure 7.18 shows the solution with 150 accepted commodities or 100% accepted commodities. We can see the marginal conflict relation between switching port and wavelength. With a few switching ports provided, a large number of wavelengths is required for the network design. On the other hand, providing a larger number of switching ports causes the network design to require fewer wavelengths. At 10 wavelengths, the GA-ETG-MaxDF requires 866 ports while the GA-MRU-FF and the GA-MST-FF require 926 and 972 ports, respectively.

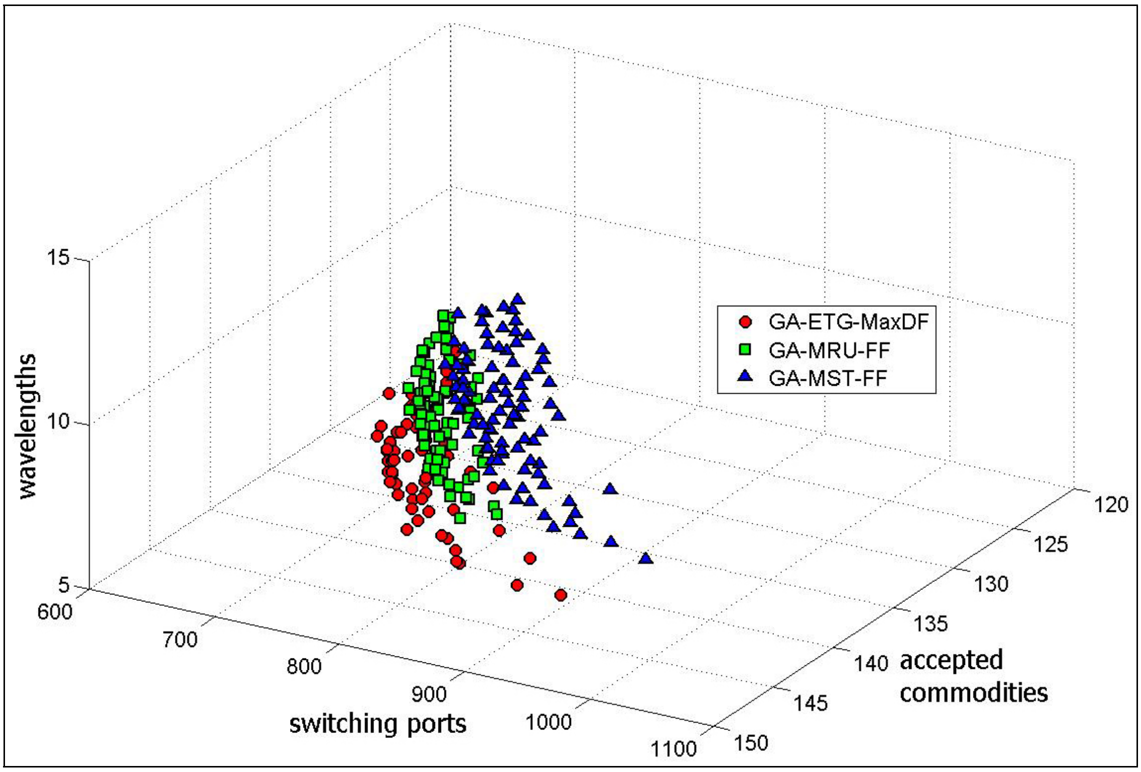


Figure 7.15 The non-dominated solutions of GA-ETG-MaxDF, GA-MST-FF and GA-MRU-FF obtained from CHNNET

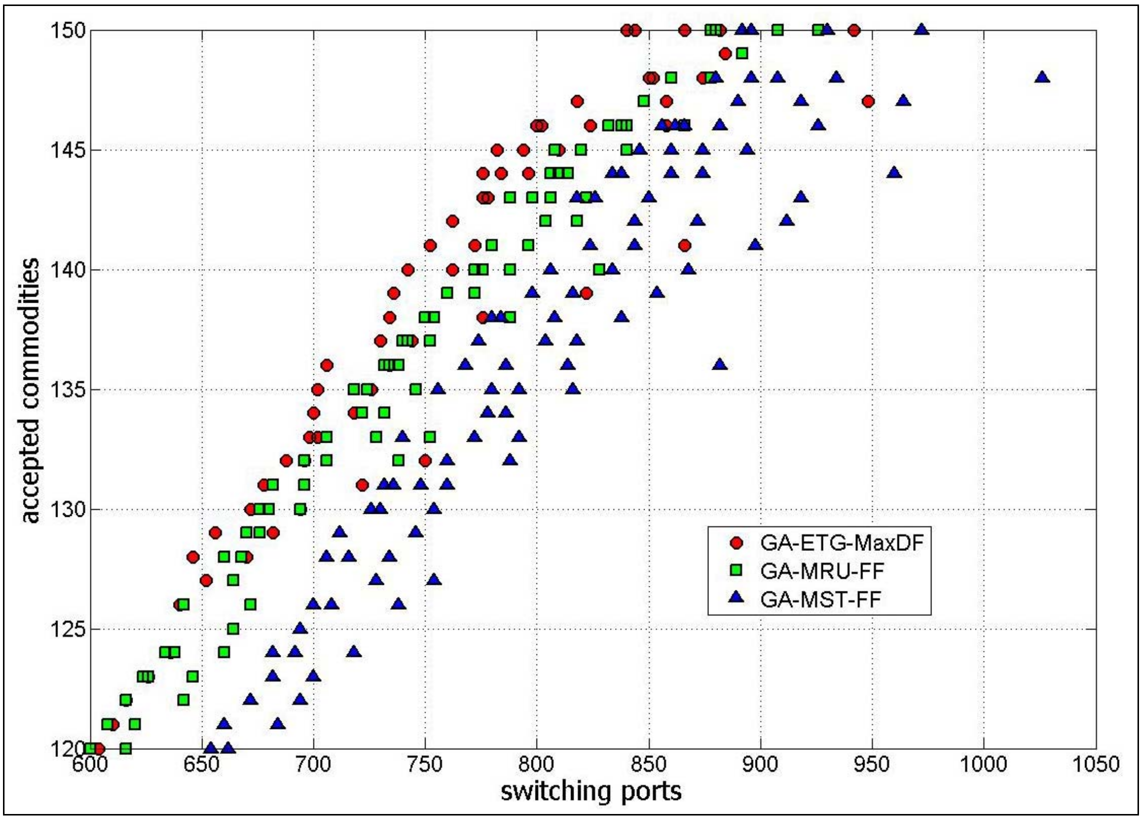


Figure 7.16 The relation between accepted commodity and switching port of GA-ETG-MaxDF, GA-MST-FF and GA-MRU-FF obtained from CHNNET

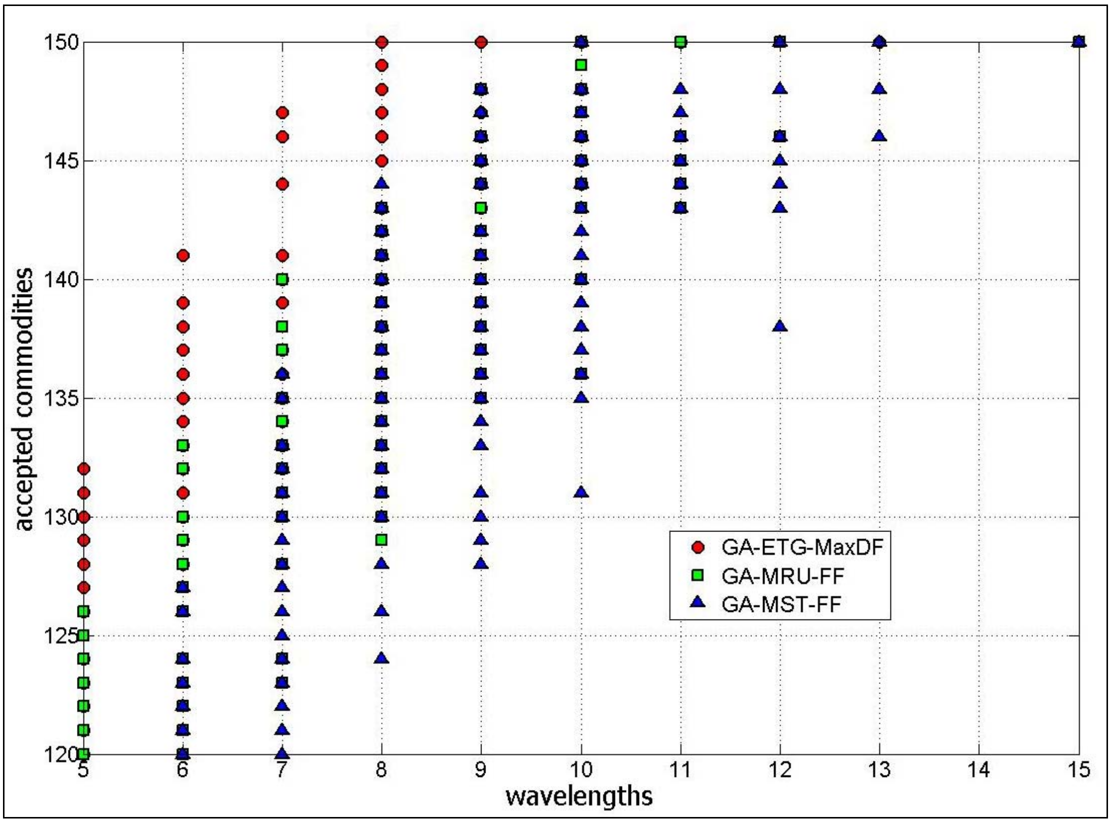


Figure 7.17 The relation between accepted commodity and wavelength of GA-ETG-MaxDF, GA-MST-FF and GA-MRU-FF obtained from CHNNET

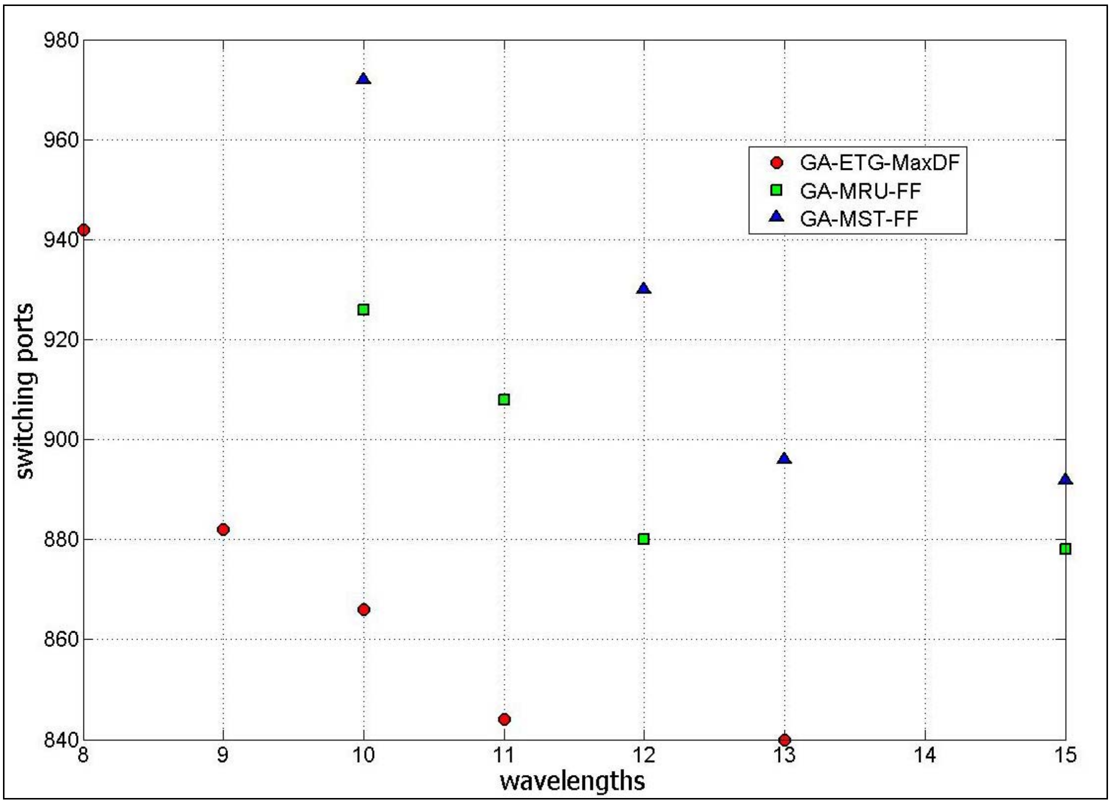


Figure 7.18 The relation between switching port and wavelength of GA-ETG-MaxDF, GA-MST-FF and GA-MRU-FF obtained from CHNNET

Figure 7.19 shows that the set of solutions from the GA-ETG-MaxDF is located in the area of high number of accepted commodities, with fewer switching ports and fewer wavelengths when compared with the other algorithms. In the ARPANET topology, the solutions from the GA-ETG-MaxDF require 796-1156 switching ports while the solutions from the GA-MRU-FF and the GA-MST-FF require 776-1232 and 832-1270 ports, respectively. *Figures 7.19-7.20* illustrates that the GA-ETG-MaxDF can support 150 commodities with 1030 ports. With the same number of ports, the GA-MRU-FF can support 143 commodities and the GA-MST-FF can support 141 commodities. At the same time, the GA-ETG-MaxDF requires fewer switching ports compared with the GA-MRU-FF and the GA-MST-FF when satisfying all requested commodities. *Figure 7.21* makes it clear that the GA-ETG-MaxDF can support a larger number of accepted commodities than the GA-MRU-FF and the GA-MST-FF do with the same number of wavelengths. For satisfying all commodities, the GA-ETG-MaxDF requires fewer wavelengths than the GA-MRU-FF and the GA-MST-FF.

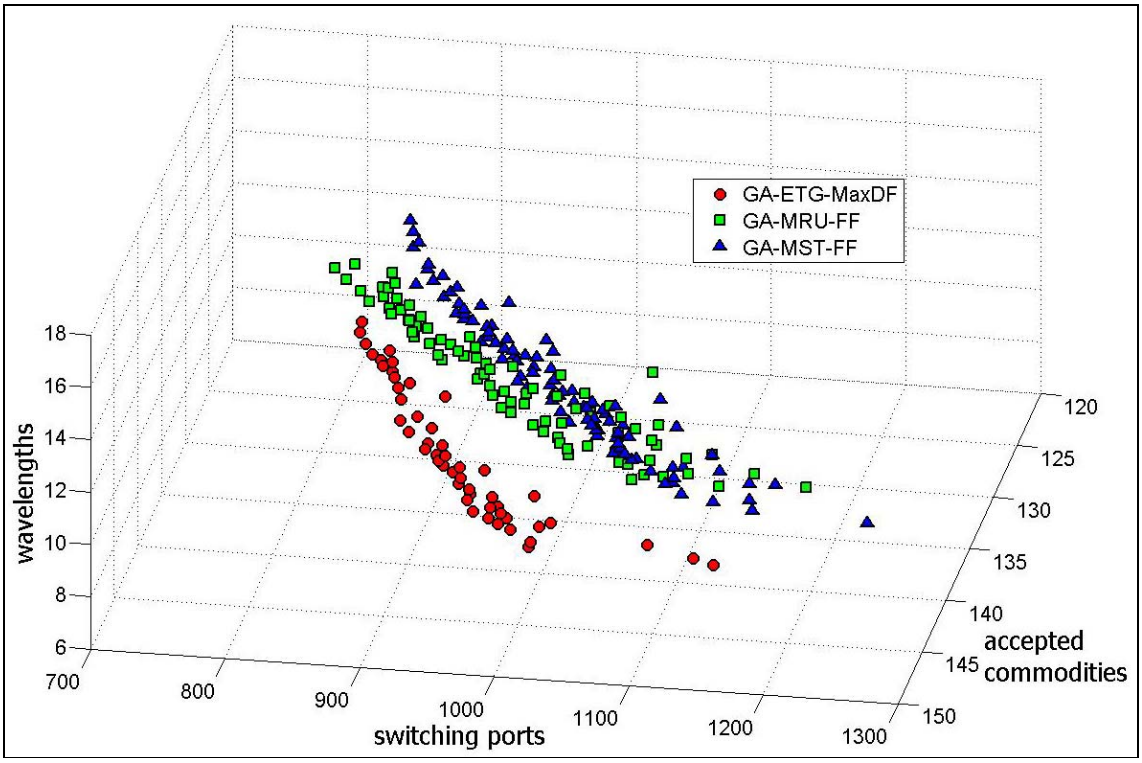


Figure 7.19 The non-dominated solutions of GA-ETG-MaxDF, GA-MST-FF and GA-MRU-FF obtained from ARPANET

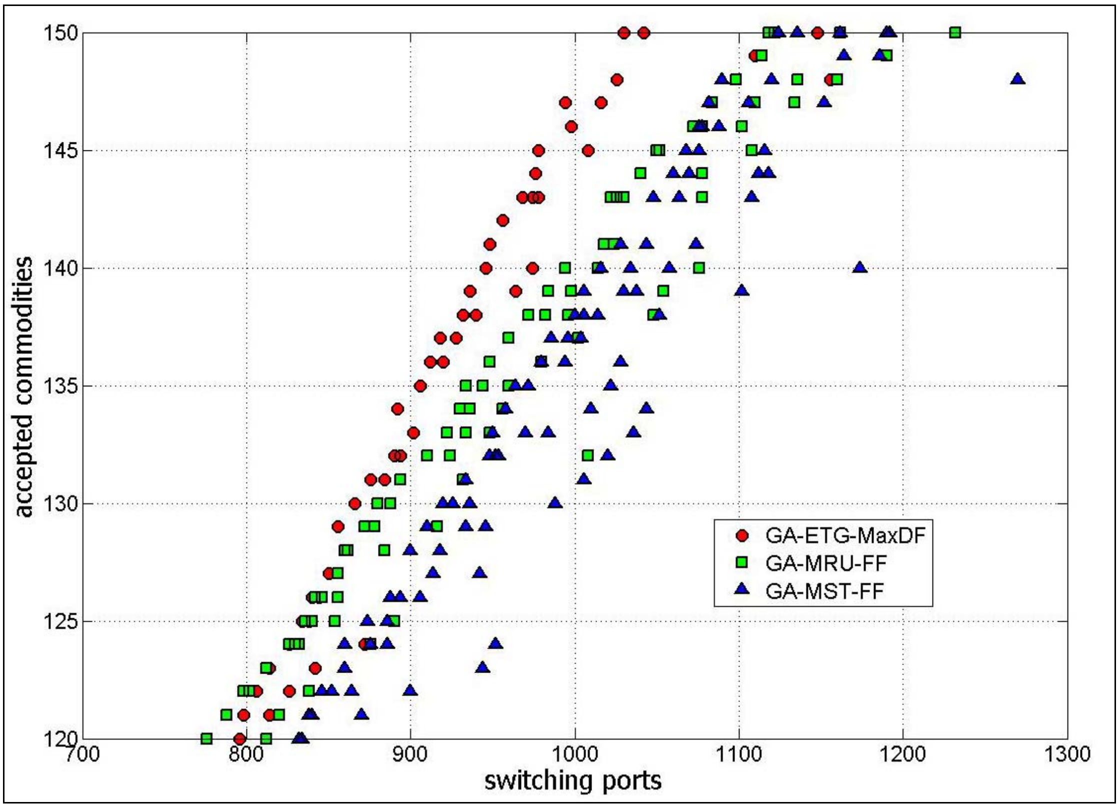


Figure 7.20 The relation between accepted commodity and switching port of GA-ETG-MaxDF, GA-MST-FF and GA-MRU-FF obtained from ARPANET

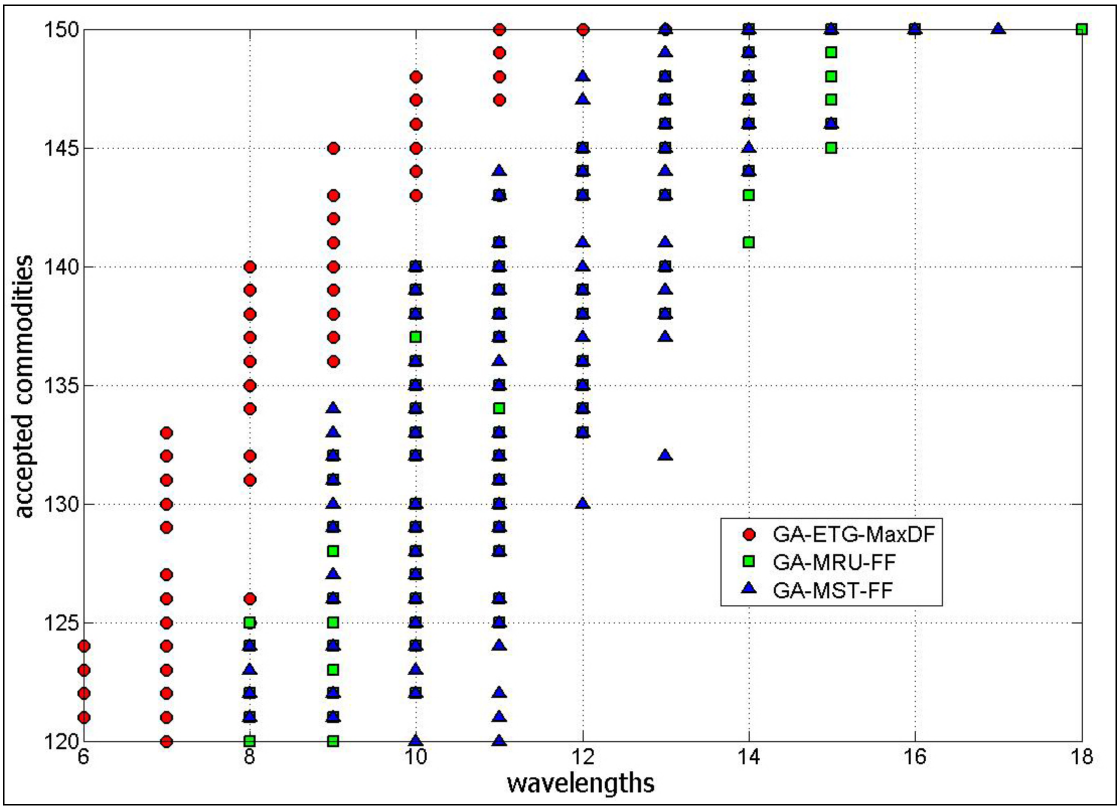


Figure 7.21 The relation between accepted commodity and wavelength of GA-ETG-MaxDF, GA-MST-FF and GA-MRU-FF obtained from ARPANET

In summary, the simulation results shown in *Figures 7.12-7.21* demonstrate that the GA-ETG-MaxDF outperforms both the GA-MST-FF and the GA-MRU-FF in all three network topologies.

Table 7.8 shows the obtained performance metrics of GA-ETG-MaxDF compared to GA-MST-FF and GA-MRU-FF. 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. High HV value means that the coverage area of solutions from GA-ETG-MaxDF is larger than the coverage area of solutions from the other algorithms. The large coverage area means that the solutions are spread into all three dimensions of the objective area. For an example with 150 requested commodities in the NSFNET topology, the GA-ETG-MaxDF give results with HV = 0.5064 while the HVs of GA-MST-FF and GA-MRU-FF are 0.1522 and 0.2704 respectively.

Table 7.8 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

In term of Hyper-volume (HV), high HV value is preferred. High HV represents the non-dominated solutions cover the objective spaces more broadly. *Table 7.9* and *Figure 7.22* show that the obtained results from our GA-ETG-MaxDF approach have higher HV value than traditional approaches (GA-MRU-FF and GA-MST-FF) in all size of traffic demands and all network topologies.

Table 7.9 Hyper-volume of three traffic grooming algorithms in three network topologies

Network Topologies	Traffic Grooming Algorithms	Set of Traffic Demands		
		50	100	150
NSFNET	GA-ETG-MaxDF	0.4701	0.5085	0.5064
	GA-MRU-FF	0.3333	0.3181	0.2704
	GA-MST-FF	0.2684	0.1738	0.1522
CHNNET	GA-ETG-MaxDF	0.3677	0.5826	0.5884
	GA-MRU-FF	0.0839	0.5154	0.4955
	GA-MST-FF	0.0129	0.4142	0.3420
ARPANET	GA-ETG-MaxDF	0.3825	0.4875	0.4859
	GA-MRU-FF	0.2497	0.3230	0.2558
	GA-MST-FF	0.2235	0.2120	0.2106

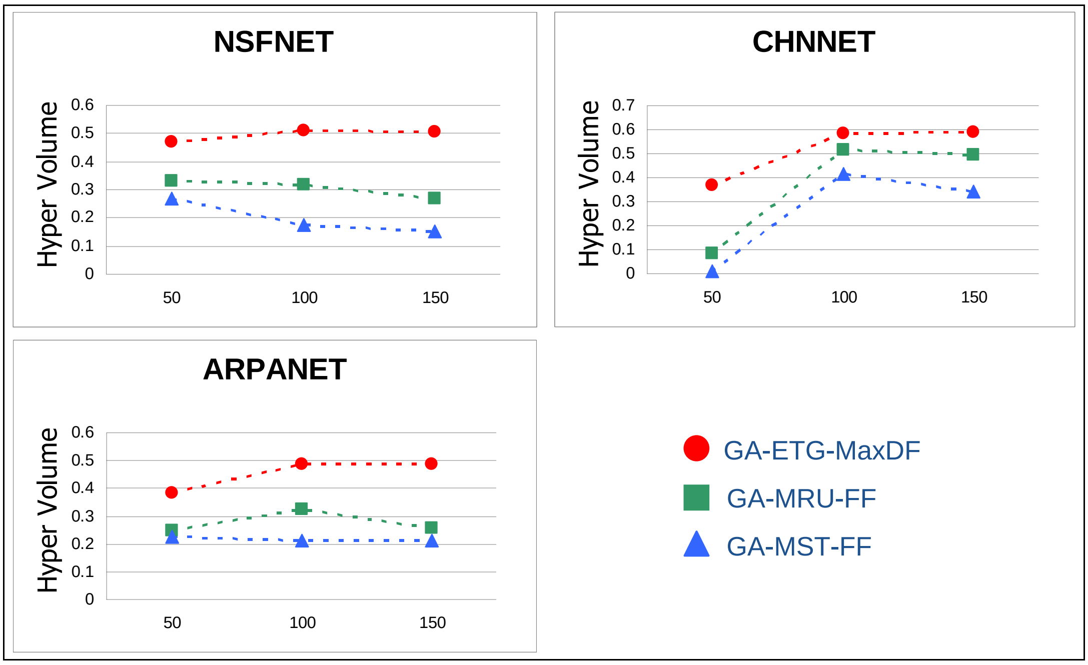


Figure 7.22 Hyper-volume of three traffic grooming algorithms in three network topologies

In term of Spread, low Spread value is preferred. Low Spread indicates that the solution distributes into all objective areas equally (not crowding into one small objective area). In our experimental result, the obtained results from our GA-ETG-MaxDF approach have less Spread value than traditional approaches (GA-MRU-FF and GA-MST-FF) for all size of traffic demands only for ARPNET topology as shown in *Table 7.10* and *Figure 7.23*.

Table 7.10 Spread of three traffic grooming algorithms in three network topologies

Network Topologies	Traffic Grooming Algorithms	Set of Traffic Demands		
		50	100	150
NSFNET	GA-ETG-MaxDF	0.4262	0.4084	0.5124
	GA-MRU-FF	0.3555	0.5411	0.4818
	GA-MST-FF	0.4000	0.5213	0.5412
CHNNET	GA-ETG-MaxDF	0.0692	0.4244	0.4832
	GA-MRU-FF	0.6010	0.3482	0.4894
	GA-MST-FF	0.8172	0.3532	0.4709
ARPANET	GA-ETG-MaxDF	0.2685	0.4170	0.4830
	GA-MRU-FF	0.4619	0.4238	0.4972
	GA-MST-FF	0.4654	0.4557	0.4953

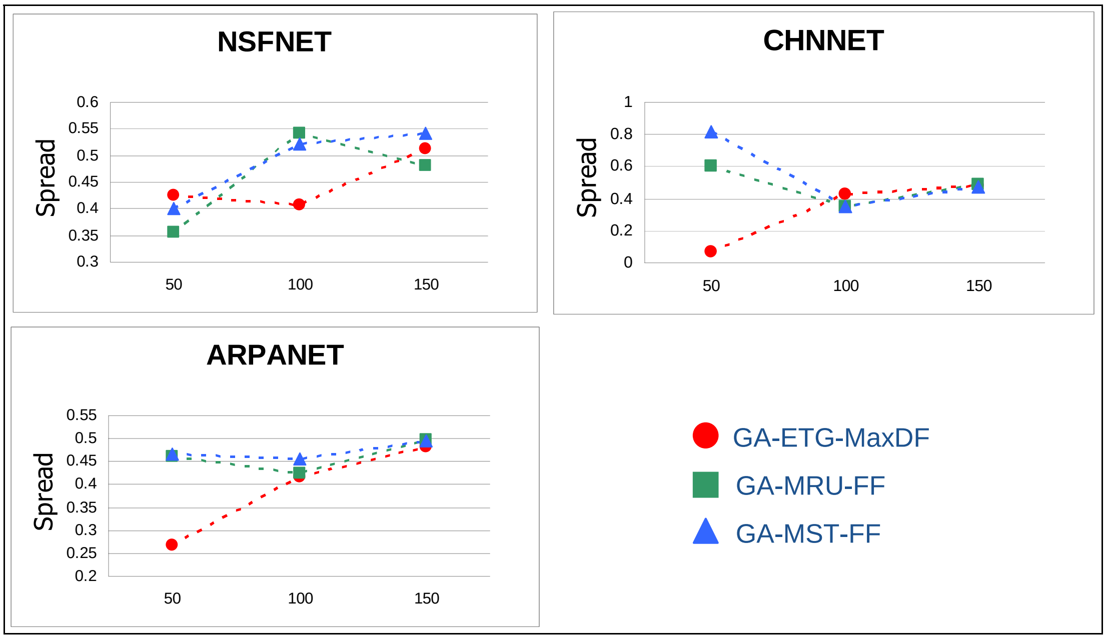


Figure 7.23 Spread of three traffic grooming algorithms in three network topologies

In term of Inverted Generational Distance (IGD), low IGD value is preferred. IGD is the distance from the obtained elements to the Pareto optimal set. IGD is equal to zero when all elements are in the Pareto optimal set. *Table 7.11* and *Figure 7.24* show that the obtained results from our GA-ETG-MaxDF approach have lower IGD value than traditional approaches (GA-MRU-FF and GA-MST-FF) in all size of traffic demands and all network topologies. In some cases, such as for NSFNET topology and 150 commodities, the IGD value from GA-ETG-MaxDF is equal to zero as shown in *Table 7.11*. This means that all obtained solutions from GA-ETG-MaxDF are in the Pareto optimal set.

Table 7.11 IGD of three traffic grooming algorithms in three network topologies

Network Topologies	Traffic Grooming Algorithms	Set of Traffic Demands		
		50	100	150
NSFNET	GA-ETG-MaxDF	0.0000	0.0062	0.0000
	GA-MRU-FF	0.0317	0.0330	0.0369
	GA-MST-FF	0.0556	0.0525	0.0502
CHNNET	GA-ETG-MaxDF	0.0000	0.0051	0.0051
	GA-MRU-FF	0.2308	0.0130	0.0127
	GA-MST-FF	0.2411	0.0195	0.0245
ARPANET	GA-ETG-MaxDF	0.0000	0.0000	0.0098
	GA-MRU-FF	0.0487	0.0270	0.0288
	GA-MST-FF	0.0494	0.0384	0.0346

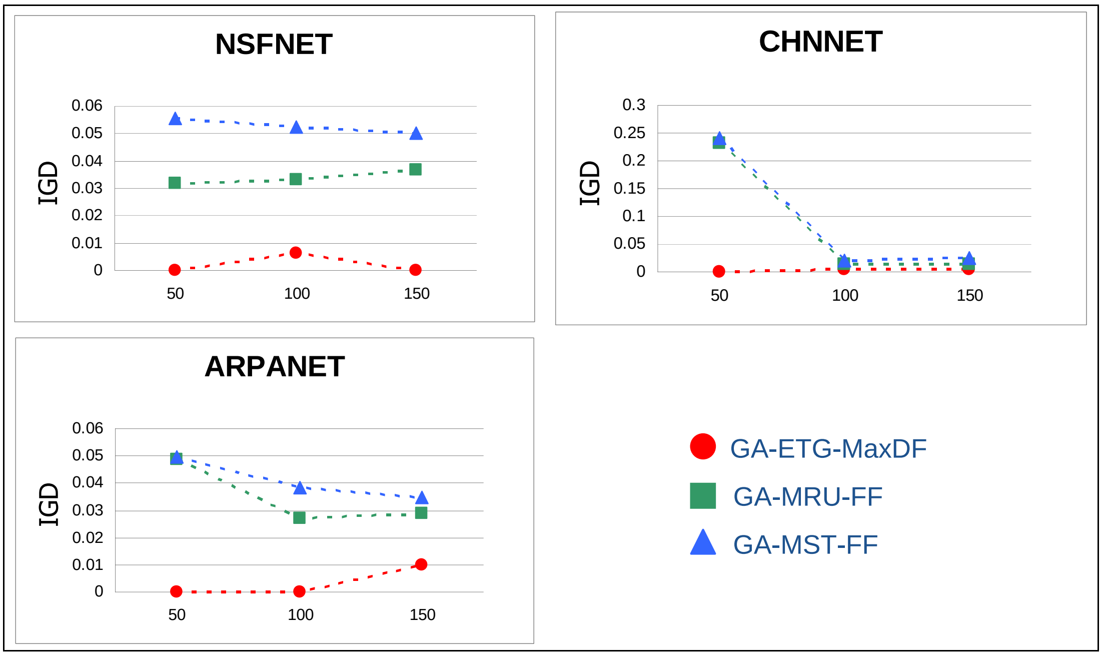


Figure 7.24 IGD of three traffic grooming algorithms in three network topologies

In term of CPU time, low computational time is preferred. *Table 7.12* and *Figure 7.25* show the average CPU time of three traffic grooming algorithms in three network topologies. *Table 7.13* and *Figure 7.26* show the total CPU time of three traffic grooming algorithms in three network topologies. The obtained results in the *Tables 7.12 and 7.13* show that the average and total CPU time of three traffic grooming algorithms show the same patterns for all three network topologies and for all algorithms.

Table 7.12 Average CPU time of three traffic grooming algorithms in three network topologies

Network Topologies	Traffic Grooming Algorithms	Set of Traffic Demands		
		50	100	150
NSFNET	GA-ETG-MaxDF	2,352.7	8,606.3	19,265.3
	GA-MRU-FF	2,300.3	8,594.0	19,269.0
	GA-MST-FF	2,320.0	8,591.3	19,249.7
CHNNET	GA-ETG-MaxDF	2,613.7	9,713.7	21,544.0
	GA-MRU-FF	2,548.0	9,584.0	21,254.3
	GA-MST-FF	2,561.0	9,602.7	21,400.0
ARPANET	GA-ETG-MaxDF	4,511.3	16,860.3	37,212.7
	GA-MRU-FF	4,428.3	16,729.0	37,187.7
	GA-MST-FF	4,433.0	16,728.3	37,218.7

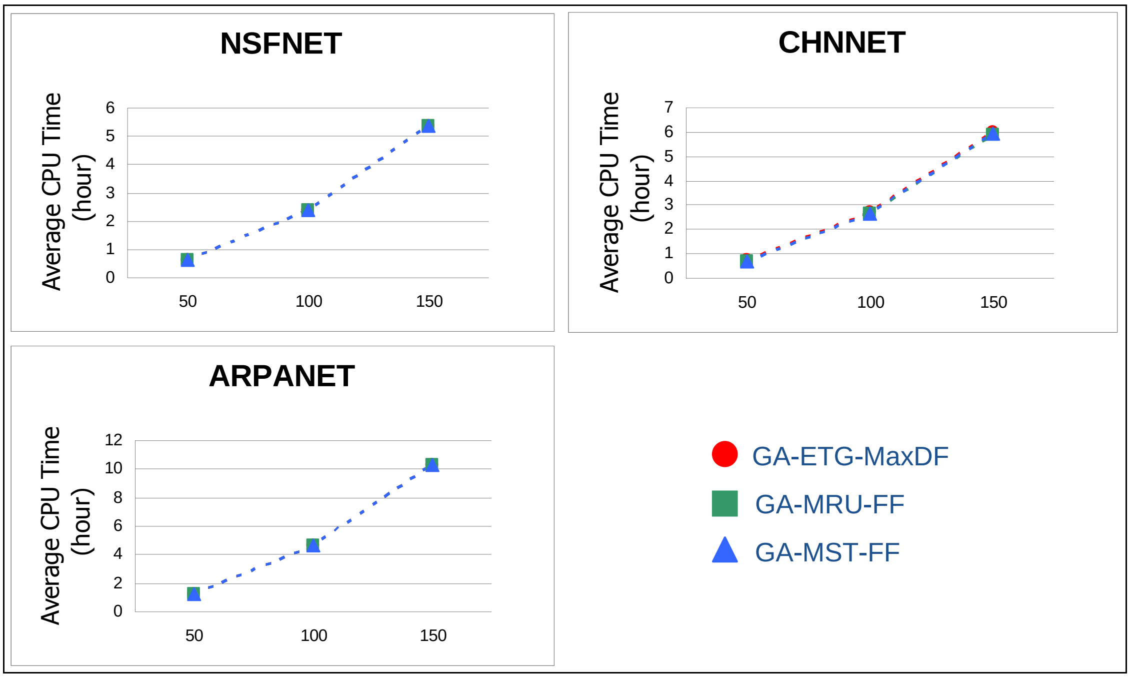


Figure 7.25 Average CPU time of three traffic grooming algorithms in three network topologies

Table 7.13 Total CPU time of three traffic grooming algorithms in three network topologies

Network Topologies	Traffic Grooming Algorithms	Set of Traffic Demands		
		50	100	150
NSFNET	GA-ETG-MaxDF	7,058	25,819	57,796
	GA-MRU-FF	6,901	25,782	57,807
	GA-MST-FF	6,960	25,774	57,749
CHNNET	GA-ETG-MaxDF	7,841	29,141	64,632
	GA-MRU-FF	7,644	28,752	63,763
	GA-MST-FF	7,683	28,808	64,200
ARPANET	GA-ETG-MaxDF	13,534	50,581	111,638
	GA-MRU-FF	13,285	50,187	111,563
	GA-MST-FF	13,299	50,185	111,656

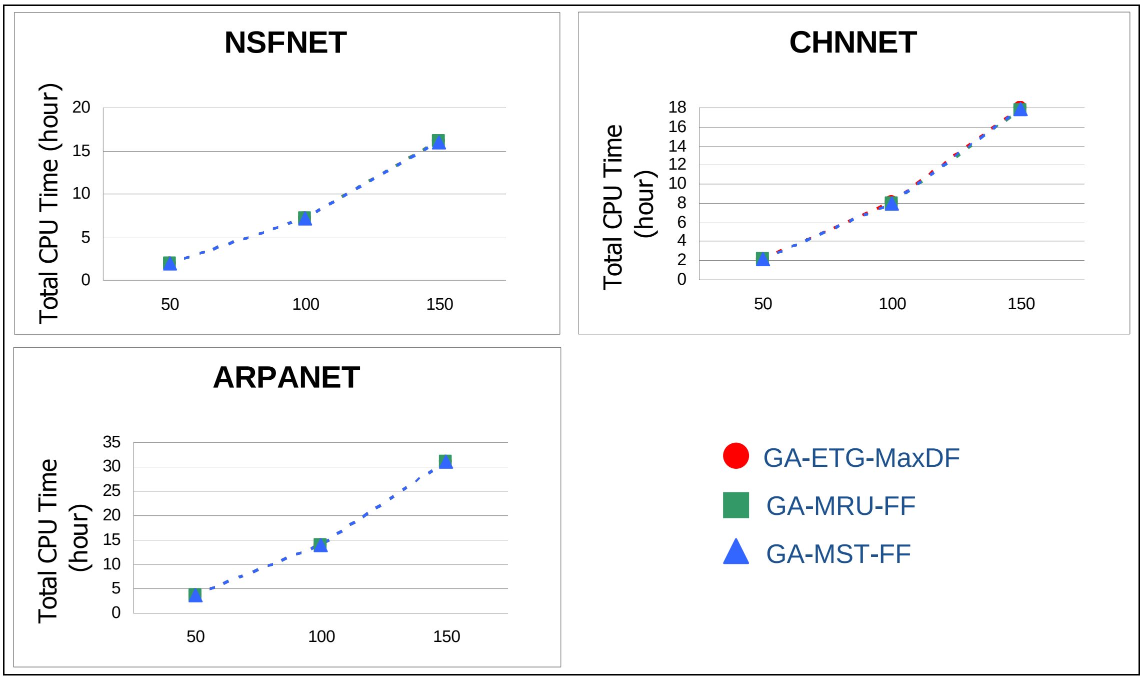


Figure 7.26 Total CPU time of three traffic grooming algorithms in three network topologies

7.3 Simulation Results after Pruning

The pruning mechanism was applied in order to reduce the number of final solutions. *Tables 7.14-7.16* show examples of the final solutions from GA-ETG-MaxDF solutions after applying our pruning mechanism, Adaptive Angle Based algorithm (ADA). The ADA is explained in *Section 6.3*. In this example, we fixed the number of final solution to five solutions. The previous obtained solutions as shown in *Figures 7.12-7.21* are pruned by using ADA. The obtained results are the non-dominated solutions obtained when three objectives are considered simultaneously. The pruning mechanism reduces the number of solutions from more than twenty solutions to only five solutions. By doing this, the pruning mechanism can help the decision maker to make a final selection.

Table 7.14 The pruned solutions for ARPANET network topology with 150 commodities where 5 out of 55 of the obtained results are chosen

Solution	No. of Accepted Commodities	No. of switching ports	No. of wavelength channels
1	129	856	7
2	130	866	7
3	133	902	7
4	137	928	8
5	138	940	8

Table 7.15 The pruned solutions for CHNNET network topology with 150 commodities where 5 out of 66 of the obtained results are chosen

Solution	No. of Accepted Commodities	No. of switching ports	No. of wavelength channels
1	126	640	5
2	127	652	5
3	144	796	7
4	146	824	8
5	149	884	8

Table 7.16 The pruned solutions for NSFNET network topology with 150 commodities where 5 out of 40 of the obtained results are chosen

Solution	No. of Accepted Commodities	No. of switching ports	No. of wavelength channels
1	132	704	6
2	133	710	6
3	137	732	7
4	139	750	7
5	144	772	8

7.4 Summary

This chaper has presented the simulation results of our traffic grooming algorithm compared with the traditional approaches. The obtained results are compared in both single and multi-objective contexts. For single objective comparison, we fixed the other objectives as constraints and compared with traditional appraches. For multi-objective comparison, the performance metrics are used to indicate the quality of the obtained set of solutions. The GA-EMF or GA-ETG-MaxDF was compared with the no traffic grooming algorithms and then the four containment techniques were evaluated. Then, the GA-ETG-MaxDF was compared with the traditional traffic grooming approaches. The obtained performance metrics show that the GA-ETG-MaxDF is superior to the traditional approaches in terms of HV and IGD. Finally, we applied the ADA pruning mechanism to help a decision maker to make a final selection.

CHAPTER 8 CONCLUSIONS

Traffic Grooming, Routing and Wavelength Assignment (GRWA) in WDM optical network is addressed with a multi-objective network design approach under a wavelength continuity constraint. Multiple commodities are grouped or groomed as a single channel for bandwidth efficiency. Each groomed commodity uses only one assigned wavelength through the light path. Our design objectives are to maximize the number of accepted commodities, minimize the number of required wavelengths and minimize the number of switching ports. We proposed an efficient GA-ETG-MaxDF algorithm to solve the off-line GRWA problem and then applied the NSGA-II approach to search for non-dominated solutions. Our GA-ETG-MaxDF algorithm grooms multiple non-overlapped commodities into the same channel. The obtained results were compared with those obtained from previous traffic grooming algorithms. We simulated our traffic grooming algorithms using various network topologies. The performance of the obtained results was measured by using multi-objective performance metrics, based on Hyper-volume (HV), Spread and Inverted Generational Distance (IGD). For the metrics, we find that the results from the GA-ETG-MaxDF were superior to those from the existing traffic grooming approaches. The NSGA-II approach with GA-ETG-MaxDF technique is effective in solving the GRWA problem with multiple design objectives. It is efficient in searching for a set of non-dominated solutions. However, the NSGA-II is computationally intensive. Thus, the NSGA-II is suitable for network design problem with an off-line approach for static traffic demands.

In this dissertation, we found that the number of solutions obtained from multi-objective design problem is usually numerous, and it is difficult to make a final decision for result selection. Therefore, we presented a pruning mechanism to reduce the number of non-dominated solutions. The pruning mechanism is called the Adaptive Angle Based mechanism (ADA). The ADA was proposed to reduce the whole Pareto solutions to a subset of most likely or promising solutions. The ADA was applied in our GRWA algorithm to help the decision maker to make a final selection.

Our research work has several contributions as follows. 1) The efficient traffic grooming, routing and wavelength assignment (GA-ETG-MaxDF) method is proposed for solving the GRWA problem. 2) NSGA-II together with GA-ETG-MaxDF algorithm is efficiently applied to solve multi-objective GRWA network design problem. 3) A pruning mechanism with a new reason to prune is proposed. 4) A new performance metric to benchmark the quality of the non-dominated solutions after the pruning is proposed. We summarize the research works as bullets in the next section.

8.1 The Conclusion of Preliminary Work

We conclude our preliminary works and research findings with related publication as follows:

- Journal on Computer Communications [38]
- ECTI-CON2010 [78]
- INC2010 [77]
- NCSEC2009_1 [74]
- NCSEC2009_2 [12]
- ISCIT2009 [76]
- NeCOM2009 [39]
- JCSSE2009 [75]

Detail information of research work presented in each paper publication is shown in *Table 8.1*.

Table 8.1 Paper publication

Research paper	Main research scope
Journal on Computer Communications	• Appling the GA-MinDF algorithm to the multi-objective optimization algorithm • Solving the RWA problem by using "Hybrid Evolutionary Computation Approach" • Study and apply a pruning mechanism to reduce the numerous solutions that are obtained from multi-objective algorithm
ECTI-CON2010	• Solving the GRWA problem in multi-objective context using NSGA-II • Comparing four containment techniques of the traffic grooming solutions in multi-objective context
INC2010	• Solving the GRWA problem in multi-objective context using NSGA-II • Comparing the grooming solutions with no-traffic grooming solutions in multi-objective context
NCSEC2009_1	• Solving the RWA problem in multi-objective context using NSGA-II approach
NCSEC2009_2	• Review and criticize various multi-objective optimization algorithms • Select two popular approaches that are SPEA2 and NSGA-II for benchmarking in multiple aspects
ISCIT2009	• Solving the RWA problem in multi-objective context using SPEA2 approach
NeCOM2009	• Solving the RWA problem in multi-objective context using Weighted-Sum approach
JCSSE2009	• Study Routing and Wavelength Assignment (RWA) problem • Implement using a new heuristic (GA-MinDF) approach in single objective

International Journal

- "Solving Multi-Objective Routing and Wavelength Assignment in WDM Network using Hybrid Evolutionary Computation Approach ", *Journal on Computer Communications,* 15 Dec 2010, Vol.33, No.18 [38]

International Conferences

- "Path Level Traffic Grooming Strategies for Multi-Objective Design in WDM Networks", *ECTI-CON 2010 Conference* [78]
- "Multi-Objective Traffic Grooming in WDM Network using NSGA-II Approach", *The 6th International Conference on Networked Computing (INC 2010)*, Korea [77]
- "Multi-Objective Routing Wavelength Assignment in WDM Network using SPEA2 Approach", *The IEEE 9th international Symposium on Communication and Information Technology (ISCIT)*, Korea [76]

- “Multi-Objective Design for Routing Wavelength Assignment in WDM Networks”, *The IEEE International Workshop on Network & Communications (NeCoM)*, China [39]
- “Routing Wavelength Assignment in WDM Networks with Maximum Communication Demand”, *The International Joint Conference on Computer Science and Software Engineering* [75]

National Conferences

- “Solving Multi-Objective Routing and Wavelength Assignment in WDM Network using NSGA-II Approach", *The National Computer Science and Engineering Conference (NCSEC)* [74]
- “Multi-Objective Optimization Techniques Based on Genetic Algorithm", *The National Computer Science and Engineering Conference (NCSEC)* [12]

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APPENDIX A

GENETIC ALGORITHM FOR ROUTING AND MINIMUM DEGREE FIRST WAVELENGTH ASSIGNMENT (GA-MinDF)

We present a heuristic algorithm called a Genetic Algorithm for Routing with Minimum Degree First Wavelength Assignment (GA-MinDF). The GA-MinDF has two parts that are Routing with Genetic Algorithm and Wavelength Assignment with Minimum Degree First.

A.1 Genetic Algorithm for Routing

Genetic Algorithm (GA) is a stochastic optimization technique that uses the biological paradigm of evolution. It has a concept where a good chromosome has a better potential of being carried to the next generation than a bad chromosome. It uses mathematical principles to indicate which chromosome is better or worse.

First, to use GA we must encode the solution of problem into a string called "chromosome". Each string has its unique characteristic indicated by "genes". Each chromosome is evaluated by a fitness function to indicate its potentiality toward the final solutions. The desirable fitness function value depends on the problem (maximization/ minimization).

After that we must generate an initial population (a set of chromosomes), and use the three main operators to find the best solution, as described next.

Step 1: Selection Operator: The process of selecting potentially good chromosomes from the current population generation to the next generation.

Step 2: Crossover Operator: The process of shuffling any two randomly selected chromosomes to generate the new offspring (like breeding).

Step 3: Mutation Operator: The process that randomly selects one chromosome to change one or more genes into a random value for generating the new offspring.

Step 4: Repeat these 3 steps until the goal is reached.

Previously, Genetic Algorithm has been used to solve routing problems in WDM optical network [11]. Banerjee and Sharan proposed a Genetic Algorithm based on Fixed-Alternate Routing approach to solve a routing problem in WDM optical network [11]. Their algorithm limited the alternate routes of each commodity therefore the obtained result may not cover some feasible solutions. In traditional approaches, only potential routes are considered (e.g., K^{th} shortest routes). It is possible that some commodities require a longer route to avoid the congestion. In this dissertation, we propose a Genetic

Algorithm for Routing for the purpose of considering most possible routes. Our proposed method and its parameter settings are described next.

Individual Structure in the Population

- The population size is 100
- We preserved top 10 individuals to the next generation
- 80 individuals are subjected to crossover and mutated with single point crossover
- 10 new individuals are randomly generated

For the network design problem, Genetic Algorithm (GA) is usually applied to solve network design problem. The significant part of GA is string or chromosome encoding. There are many string encoding techniques used in the network design problem with graph based that are node-pair [79], all arcs based [79], set of alternatives based, priority-based, or previous-node-based. In this thesis, we focus on the encoding techniques that used in the routing of GRWA problem. The string encoding techniques are considered in this thesis are set of alternatives based, priority-based, or previous-node-based. Suppose we have a sample 5-node network, the string encoding can be encoded as follows.

Set of Alternatives Based Encoding

In each source-destination pair of the connection, the set of possible routes are calculated by using K^{th} shortest paths [80] or K^{th} disjointed paths algorithm. The set of possible routes are collected into the choices. This technique proposed that the string encoding is the composite of each selected routes from the set of alternatives. For instance, we have three connections to be served in the sample 5-node network as shown in *Figure A.1*. The encoding string length is equal to 3 (i.e., each for connections a, b and c). The connection has 4 choices to be selected that are choice 1, choice 2, choice 3 and choice 4. First bit chromosome is selected choice 1, choice 1 for the second chromosome bit and choice 2 for the third chromosome bit.

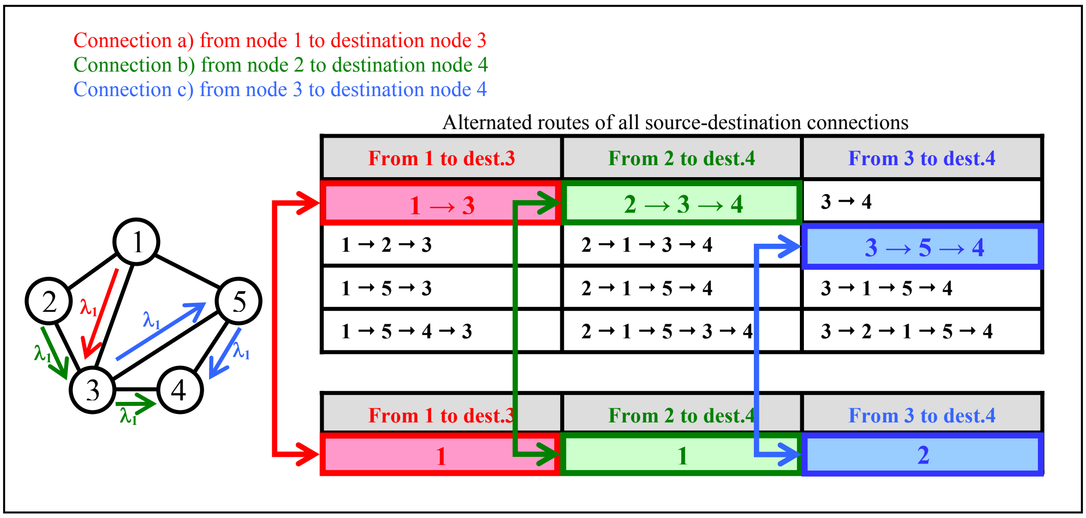

Figure A.1 An alternative based encoding

Priority-based Encoding [79]

In Priority-based encoding string, the position of a chromosome bit is represented the node identity (i.e., node1, node2, node3, node4 and node5). Each node position has a value that is represented the priority of the node to create a path. The priority must be unique. The node with highest priority value is the source node and the next node will be selected from the bigger priority value from the remaining nodes as shown in *Figure A.2*. For connection (a), the network route starts from node 1 (highest priority value) and the next node is node 3. At node 3 the destination node has reached. The communication route of connection (a) is 1→3.

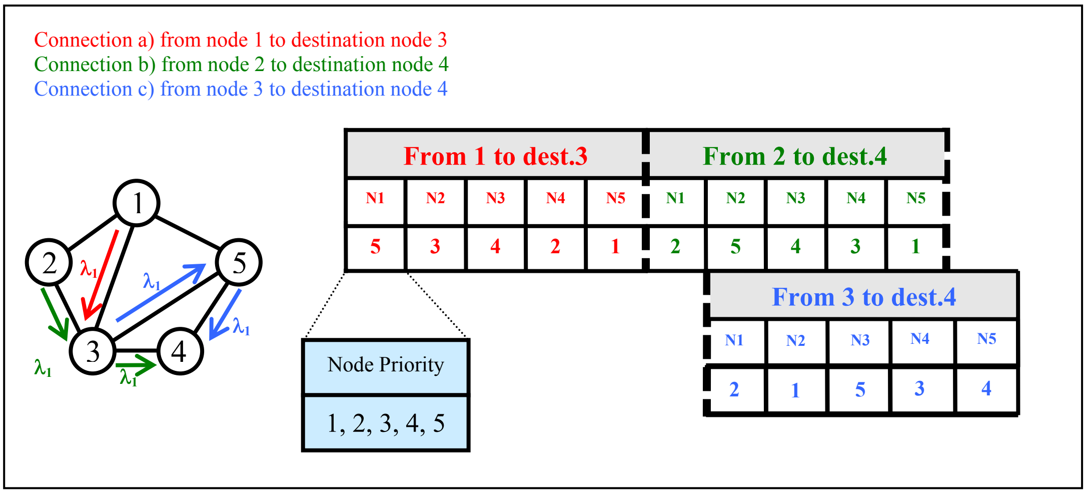

Figure A.2 Priority based encoding

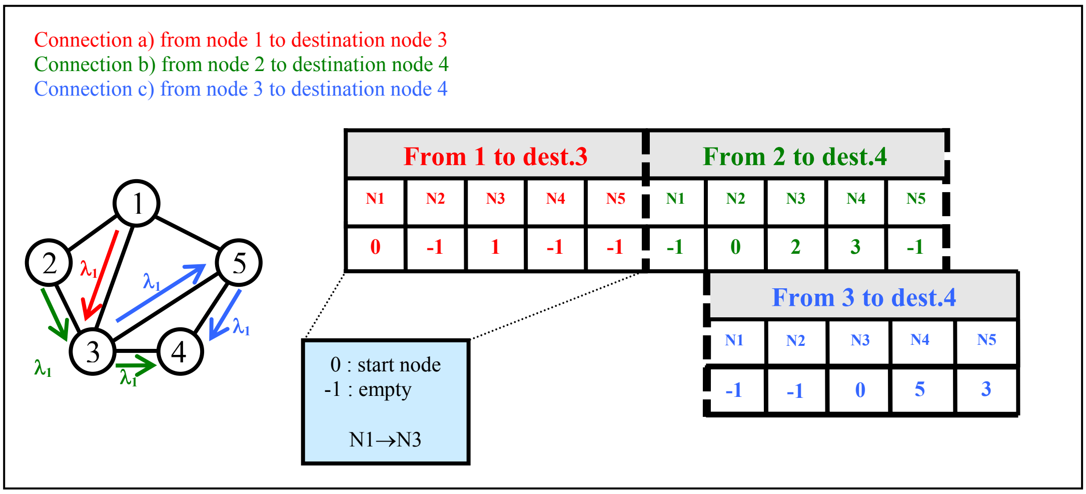

Figure A.3 Previous-node-based encoding

Previous-node-based Encoding [79]

Similar to the Priority-based encoding, Previous-node-based encoding, the position of a chromosome bit is represented the node identity (i.e., node1, node2, node3, node4 and node5). Each node position has a value that is represented the previous visited node to create a path. The node that has the value is equal to 0 is represented the source node and the next node will have the bit value equals to current node identity as shown in *Figure A.3*. For connection (a), the network route starts from node 1 (bit value=0) and the next node is node 3 because it has bit value = 1 (i.e., node 1 is visited before node 3). At node 3 the destination node has reached. The communication route of connection (a) is 1→3. The nodes that do not include in the communication path has a bit value = -1.

The advantages and disadvantages of three encoding techniques are compared in *Table A.1*. From *Table A.1*, we can see that the alternative-based encoding technique is efficient in term of computation time but the size of the candidate route affects the efficiency of the algorithm. Recent RWA and GRWA research usually applied alternative-based encoding to solve their design problem.

Table A.1 The comparisons of GRWA researches in recent years

GRWA string encoding techniques	Advantages	Disadvantages
Set of alternatives based encoding	• Easy to implement • Fast computation time • In the selection process (crossover and mutation), the exchanged chromosome is always valid.	• The efficiency of the algorithm is depending on the number of the candidate route [6]
Priority-based encoding [79]	• All possible routes are considered. • The efficiency of the algorithm is not depending on the size of candidate.	• After the selection process, the exchanged chromosome may not valid. It is required some checking procedure to check before crossover the chromosomes. • The obtained route is crowding to the long path.
Previous-node-based encoding [79]	• All possible routes are considered.	• After the selection process, the exchanged chromosome may not valid. It is required some checking procedure to check before crossover the chromosome. • Requires a lot of computation time

In this thesis, we modified a previous node based encoding technique to a straight forward routing. We modify the "Path Genetic Operator" as proposed in [20]. Our GA description and parameter setting are described in *Appendix A.1*. The significant operator that is string encoding is described next.

String Encoding, the string encoding is a process that encodes the combinatorial problem into a set of genes or chromosome. In this dissertation, the string encoding is a set of integers that indicates the route of each commodity. Suppose that in the network design problem, we have 5-node network as shown in *Figure A.4*. The corresponding string encoding is displayed. Each position p has the value n_p that represents the connection from n_p to n_{p+1}. The value n_p= -1, if the destination has been reached in previous connection. We can encode the string as shown the figure. This string encoding scheme has the benefit that all possible routes are considered.

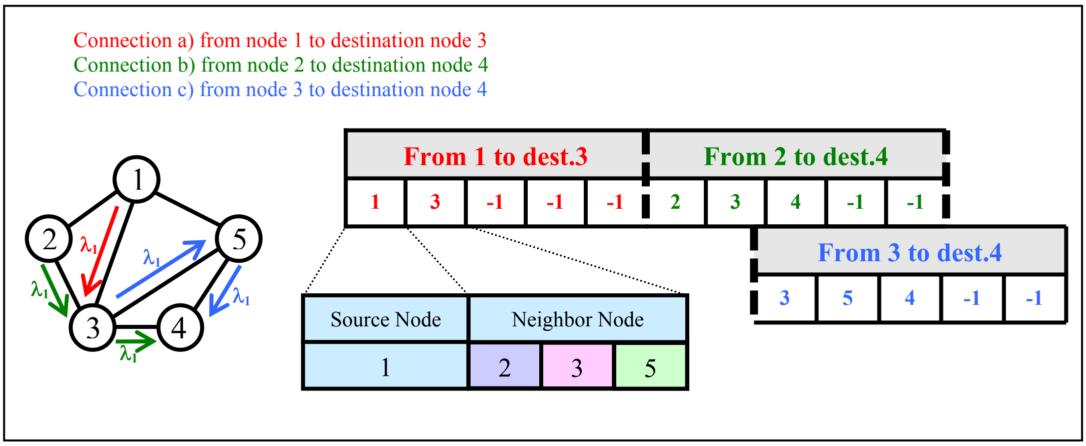

Figure A.4 The string encoding technique used in this dissertation

Initial Population

We set the initial population by randomly generating a set of chromosomes consisting of genes with uniform random number, and calculate their fitness value according to the fitness function presented in Equations 4, 5 and 6. 95% of individuals are randomly generated. The remaining 5% of individuals represent the 5 shortest paths (K^{th} first-link disjointed paths algorithm) from specified source-destination pair.

Selection

The chromosomes or population are sorted by their fitness values. The top 10 % of population with best fitness values (low total cost) are preserved to the next generation, 80 % of population are selected for the crossover process, and the remaining 10 % of population are new chromosomes which are randomly generated.

Crossover

We select a pair of chromosomes from the current population for a crossover, to produce two new offspring chromosomes. One parent chromosome comes from the top 10% and another parent chromosome can be any chromosome.

In each crossover, we exchange the chromosomes with single point crossover. Only one position of the genes is randomly selected to be the starting point for exchanging between the two parent chromosomes. If both chromosomes can be exchanged (the next gene is in the set of neighbor node table or the paths are valid), both chromosomes are exchanged, otherwise both chromosomes are rolled back to the previous values.

Mutation

The offsprings from the crossover process are mutated with a 25% mutation rate. We randomly selected the mutated position in a chromosome. At the selected position, the set of neighbor nodes are randomly selected to create a new route for the connection. The resulted chromosomes are combined and considered as the chromosomes in the current population generation.

A.2 Minimum Degree First Wavelength Assignment

In the Wavelength Assignment, Minimum Degree First (MinDF) algorithm is proposed to assign a limited wavelength channel to a set of commodities. Before we assign a wavelength to a set of commodities, we need to create an auxiliary graph for the set of lightpaths. In an auxiliary graph, each node represents the element in the set of commodities. The link between a pair of nodes represents their relation. Suppose we have commodity 1 and 2 that are represented by two nodes 1 and 2. If commodity 1 and 2 are overlapped, a link between them is created. Every pair of nodes that has a link cannot be assigned with the same wavelength. In our algorithm, we assign the wavelength from the least minimum degree of auxiliary graph first. *Figure A.6* shows the auxiliary graph of the set of commodities from *Figure A.5*.

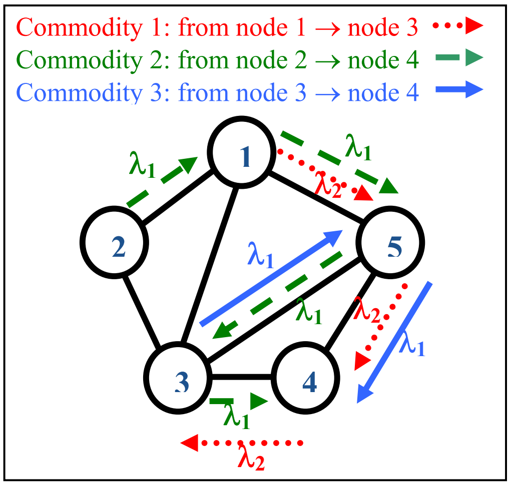

Figure A.5 A sample 5-node network

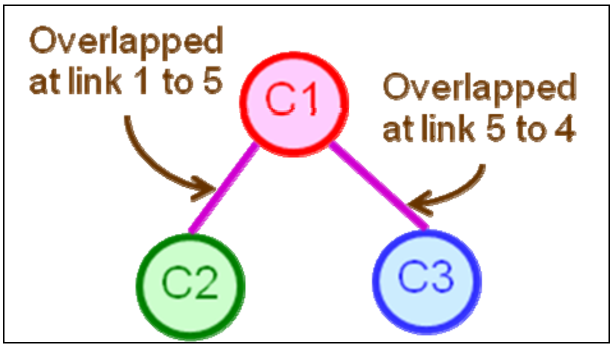

Figure A.6 The auxiliary graph of overlapped commodities

In an auxiliary graph (as shown in *Figure A.6*), each node (the circle symbol) represents the commodity. The link between a pair of nodes represents their relation. From *Figure A.6*, we have three commodities. The commodities 1, 2 and 3 are represented by nodes C1, C2 and C3 respectively. The commodities C1 and C2 are overlapped (i.e., at network edge 1→5) therefore a link between them is created. The commodities C1 and C3 are overlapped. The link between them is also created. Every pair of auxiliary nodes that have a link cannot be assigned with the same wavelength.

We modify the First-Fit algorithm that assigns the wavelength from smallest channel-index to the highest channel-index. In our MinDF algorithm, we assign the wavelength from the minimum degree of auxiliary graph first. Our assumption is that the minimum degree of an auxiliary graph has small numbers of overlapped commodities (other commodities). Therefore, the minimum-degree commodity should be assigned first. If the high degree node in the auxiliary graph is first selected and assigned with a wavelength channel, many other commodities will be blocked because the high degree node is overlapped with many others and cannot use the same wavelength channel as the overlapped commodities. The MinDF algorithm can be presented as follows.

Minimum Degree First (MinDF) Algorithm

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

The MinDF algorithm sorts the set of commodities by the degree (i.e., C2, C3 and C1).

Commodity C2: from node 2 to destination node 4 ← wavelength channel 1
Commodity C3: from node 3 to destination node 4 ← wavelength channel 1
Not overlapped with the previous communication
Commodity C1: from node 1 to destination node 3 ←wavelength channel 2
Overlapped with commodities C2 and C3

After the MinDF process, we have the set of commodities with wavelength channel as shown in *Figure A.7*. The wavelength channel 1 is assigned to Commodities C2 and C3 because both of them are not overlapped. The wavelength channel 2 is assigned to Commodity C1.

Commodity	C1	C2	C3
Wavelength channel	2	1	1

Figure A.7 The wavelength channel of the set of commodities

The performance of the GA-MinDF algorithm is shown in *Appendix A.3* by comparing with a traditional approach called Fixed Alternate Routing and First-Fit Wavelength Assignment (FAR-FF). The routing algorithm (GA) is compared with the traditional routing approach called Fixed Alternate Routing (FAR) and the wavelength assignment (MinDF) is compared with the traditional wavelength assignment called First-Fit (FF). Our previous work showed that the GA-MinDF (both 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. The computation results are showed in *Appendix A.3*.

A.3 The Efficiency of GA-MinDF Algorithm

In our experiments, we consider the network design with a given network topology and a set of commodities. We consider the RWA that maximizes the number of accepted commodities. Our design objective is subject to the limited wavelength in each edge/link of the network. We generate various test problems with a number of commodities (sets of source-destination pairs). They are randomly generated with a uniform distribution.

An NSFNET network with 14 nodes and 42 directional edges is considered as a simulation network as shown in *Figure A.8*. For each problem size, a set of communication demands (source-destination) is investigated with a set of wavelength channels. We assume that all edges have the same number of wavelength channel capacity.

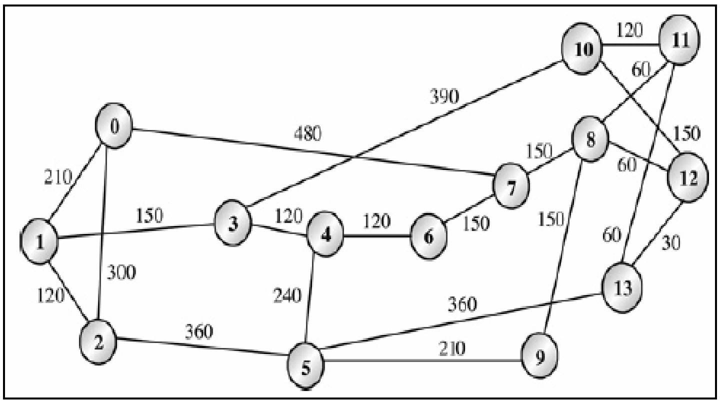

Figure A.8 NSFNET network with 14 nodes and 42 directional edges [41]

We attempt to solve small to large network problems with GA-MinDF and FAR-FF approach where the results are compared as presented in *Tables A.2, A.3 and A.4*. For benchmarking the performance of the Wavelength Assignment, we fixed the limited number of wavelengths on each edge and then manually varied them in various values. We feed the same set of commodities to both MinDF and FF. The results show that the MinDF wavelength assignment approach allows more accepted commodities than the FF wavelength assignment.

In *Table A.2*, wavelength channels on each edge are the number of limited wavelengths on each edge (i.e., 3 wavelength channels means that there are only $\lambda_1,\lambda_2,\lambda_3$ on each edge in the network). All edges in the network have the same number of wavelength channels. A higher number of allocated wavelength channels allows more commodities to be served. We see that when the number of commodities is 200, the number of wavelengths per edge is 3, accepted commodities from GA-MinDF is 68 while accepted commodities from FAR-FF is 49. Moreover, when the number of wavelengths per edge is increased to 5, the number of accepted commodities from GA-MinDF is 93 while the number of accepted commodities from FAR-FF is 74. The results shown in *Table A.2* illustrate that the MinDF can increase the number of accepted commodities at every size of limited wavelength channel, e.g. 3 or 4 or 5.

Table A.2 Number of accepted commodities at several limited wavelengths on each edge

Wavelength channel on each edge	Number of commodity	First Fit (A)	Minimum Degree First (B)	(B)-(A)
3	10	9	9	0
3	30	26	26	0
3	50	29	30	1
3	100	48	56	8
3	150	47	58	11
3	200	49	68	19
3	300	51	78	27
3	500	59	93	34
4	10	10	10	0
4	30	27	27	0
4	50	34	34	0
4	100	60	64	4
4	150	59	68	9
4	200	60	81	21
4	300	69	95	26
4	500	80	114	34
5	10	10	10	0
5	30	28	28	0
5	50	38	38	0
5	100	69	70	1
5	150	72	78	6
5	200	74	93	19
5	300	77	110	33
5	500	99	130	31

For the RWA algorithm, *Table A.3* shows the result comparisons of the GA-MinDF algorithm and the FAR-FF algorithm when the wavelength on each edge is equal to 5. We fine-tuned the parameters of our algorithm to obtain good solutions with marginally less CPU computation time. Our experimental results from *Table A.3* show that in order to maximize the number of accepted commodities when the number of wavelength channels is fixed to a single value, we should consider a large set of the total commodities. The number of accepted commodities is also increased because the set of commodities is randomly generated with uniform distribution. A large number of all requested commodities have a higher probability to get the remaining communication requests that are non-overlapped with the existed commodities. When the set of communication increases to a level that is fully supported by the limited wavelength, the blocking probability increases. The number of rejected commodities is higher than the accepted commodities.

Table A.3 Number of accepted commodities and computation time of GA-MinDF algorithm considering 5 wavelengths per edge

Number of Commodity	FAR-FF		GA-MinDF	
	Accepted Commodity	CPU Time (sec)	Accepted Commodity	CPU Time (sec)
10	10.00	2.00	10.00	3.00
30	30.00	19.67	30.00	27.00
50	47.00	128.67	47.33	99.67
100	62.33	512.67	74.00	349.33
150	66.33	1075.67	85.33	966.67

We capture the simulation results of 150 commodities with 5 wavelengths per edge. The results show that the GA-MinDF algorithm efficiently assigns wavelength to each network edge. The GA-MinDF uses fewer wavelength channels than the FAR-FF. The average number of wavelength channels used per edge is displayed in *Table A.4*. The number of wavelength channels used is the average of number of wavelength channels used divided by limited number of wavelength channels (5 wavelengths) of 42 directional edges. The RWA solution solved by the GA-MinDF supports a higher number of commodities while using fewer wavelengths than that obtained from the traditional FAR-FF approach.

Table A.4 Average number of wavelength used from GA-MinDF algorithm and FAR-FF algorithm considering 5 wavelengths per edge

Number of Commodity	FAR-FF		GA-MinDF	
	Number of Wavelength Used (C)	Edge Utilization (C/5)×100	Number of Wavelength Used (D)	Edge Utilization (D/5)×100
10	0.98	19.68	0.64	12.86
30	2.72	54.44	2.04	40.79
50	3.55	70.95	2.89	57.78
100	3.96	79.21	3.39	67.78
150	4.33	86.51	3.96	79.21

In the traditional approach, the FAR provides a set of alternative feasible routes as a choice. Every source-destination pair has its alternatives. Each commodity selects the alternate route separately. The obtained results from their FAR algorithm may not consider some feasible solutions. The First Fit (FF) approach is designed for the purpose of quickly assigning the limited wavelength channels to a set of commodities. The wavelength channel that has the lowest index will be selected first. The FF is efficient in term of computation time. Our previous work [39] showed that the GA-

MinDF can assign the wavelength as fast as the First-Fit algorithm does but with superior results in terms of accepted community requests.

The drawback of MinDF is that the algorithm has to sort the set of commodities with the overlapped degree first before the wavelength assignment procedure is processed. To ensure that the obtained result from MinDF is optimal in the small problem size, we test MinDF with a small network that has an overlapped star configuration as shown in *Figure A.9*. The overlapped relation is obtained from the set of six commodities in the NSFNET as shown in *Figure A.8*. The six commodities are

Commodity 0: has the route from node 1 to 12: 1→ 3→ 4→ 6→ 7→ 8→ 12
Commodity 1: from node 0 to 3: 0→ 1→ 3
Commodity 2: from node 3 to 5: 3→ 4→ 5
Commodity 3: from node 6 to 0: 6→ 7→ 0
Commodity 4: from node 7 to 9: 7→ 8→ 9
Commodity 5: from node 11 to 12: 11→ 8→ 12

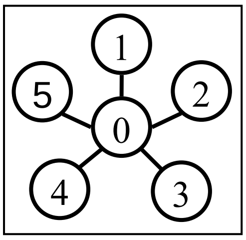

Figure A.9 An auxiliary graph for wavelength assignment algorithm

The MinDF approach assigns only two wavelength channels to the set of commodities, one channel (i.e., wavelength channel 0) for commodity 0 and another channel (i.e., wavelength channel 1) for other commodities. The First Fit (FF) approach also requires two channels (wavelength channel 0 for commodity 0 and wavelength channel 1 for other commodities). For the optimal solution, only two channels are required to support the set of commodities.

GA-MinDF algorithm is used to find the number of accepted commodity and the number of wavelength channel requires. Both of them are our objective values. Multiple commodities have several routings and wavelength channels. If the route of the commodity is changed, the objective values obtained from GA-MinDF algorithm are also changed. In *Appendixes C and D*, we apply the multi-objective optimization approaches (i.e., SPEA2 or NSGA-II) to search for non-dominated solutions in terms of accepted commodities and required wavelength channels.

APPENDIX B

GENETIC ALGORITHM FOR ROUTING, EXTENDED TRAFFIC GROOMING AND MAXIMUM DEGREE FIRST WAVELENGTH ASSIGNMENT (GA-ETG-MaxDF or GA-EMF)

We present a heuristic algorithm for solving GRWA problem. The algorithm is called a Genetic Algorithm for Routing, Extended Traffic Grooming and Minimum Degree First Wavelength Assignment (GA-ETG-MaxDF or GA-EMF). The GA-EMF has three parts that are Routing with Genetic Algorithm (GA), Grooming with Extended Traffic Grooming (ETG) and Wavelength Assignment with Maximum Degree First (MaxDF).

B.1 Genetic Algorithm for Routing

Genetic Algorithm (GA) is a stochastic optimization technique that uses the biological paradigm of evolution. It has a concept where good chromosome has a better potential of being carried to the next generation than the bad chromosome. It uses mathematical principle to indicate which chromosome is better or worse than the others. The GA for routing is previously described in *Appendix A.1*. In this Appendix, we focus on the traffic grooming technique that is described next.

B.2 Extended Traffic Grooming

In the previous off-line traffic grooming algorithms (MST and MRU [4]), the set of commodities have to be arranged before the grooming procedure starts. The traditional grooming algorithm combines multiple overlapped commodities into the same group by following the sequence. Only overlapped commodities in the early sequence are first considered to be grouped together. If two commodities are not overlapped, it is determined that they cannot groomed together. In this dissertation, we found that some non-overlapped commodities can be groomed into the same group, if there exists a commodity that overlaps both non-overlapped commodities as described in the following example (C0 and C1 can combine together by using C2). For using the extended traffic grooming algorithm, multiple non-overlapping commodities are combined together. By doing this, we will save wavelength channel capacity compared to the traditional approach.

Suppose we have 8 commodities to serve and the routing of each commodity is randomly generated using the GA as shown in *Table B.1* and *Figure B.1*. From *Figure B.1*, C0:0.5 represents the commodity C0 with 0.5 unit of wavelength requirement.

Table B.1 The routing 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

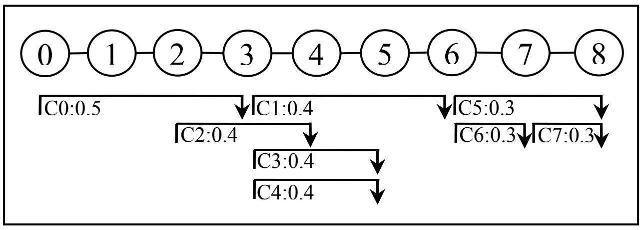

Figure B.1 Set of commodities with bandwidth requirement in the sample network

Before we combine multiple commodities into the group, we need to create an auxiliary graph for the set of lightpaths. In an auxiliary graph, each node represents the element in the set of commodities. The link between a pair of nodes represents their relation. After we have a set of routing, the auxiliary graph is created to specify which commodities are overlapped. The commodity is denoted as a circle symbol and the pair of commodities that are overlapped have a connection or link between them as shown in *Figure B.2* (i.e., commodities 0, C0 overlaps with C2 but not overlap with C1). The commodities that are overlapped can be combined into a group.

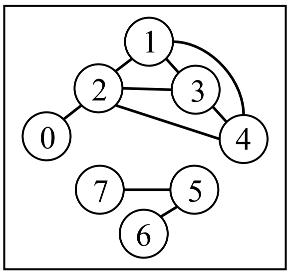

Figure B.2 The auxiliary graph of overlapped commodities

The commodities that are overlapped and have the summation of traffic demands less than or equal to a wavelength unit are groomed or combined. We groom multiple overlapped commodities into one wavelength using 'extended grooming approach'. Considering commodities in *Table B.1* with traditional grooming (i.e., MST), commodities 3 and 4 are groomed first because they have the same source and destination. After that C0 and C1 are assigned respectively. C0 and C1 cannot be groomed together because they are not overlapped. C2 is groomed with C0 because high traffic demand is considered first. For grooming C2 with C0, the C1 cannot be used the same wavelength channel with C0 and C2 because they are overlapped. The traditional approach requires 3 wavelengths for commodities C0-C5.

In this dissertation, multiple commodities in existing groups are reconsidered. The extended grooming considers whether there exists a commodity in the groomed group that overlaps with another commodity and whether the total bandwidths does not exceed the wavelength bandwidth constraint. The extended traffic grooming potentially combines the commodities into an existing group. *Table B.2* shows the set of commodities in the groomed groups from MST and ETG approaches. In traditional approach, MST requires four groups for supporting all commodities while ETG requires three groups for supporting all commodities.

In ETG approach, commodity C1 is reconsidered to combine with the existing group (C0 and C2). For example, C0 and C2 are assigned into the group and they are reconsidered to groom with the C1 because the element C2 in the group of C0 and C2 are overlapped with C1 and the summation of bandwidth on link 3 to 4 does not exceed the wavelength bandwidth constraint.

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

MST			ETG		
Set of commodities	Edge	Link bandwidth	Set of commodities	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 this dissertation, the commodities are sorted in descending order by the number of hops (i.e., the number of hops of commodity 0 is 3). If two commodities have the same number of hops, the commodity that has higher traffic demand is preferred. In our experiment, we found when the amount of traffic demands in each commodity is quite low, sorting by amount of traffic demands first (if they have the same amount of demands, the high number of hops is first considered) performs better than sorting by the number of hops and traffic demands. In this dissertation, we specified that if the average traffic demand is less than 0.4 wavelengths, the set of commodities are sorted by using maximum traffic demand first, Otherwise, they are sorted by using longest hop first.

In *Table B.1*, the set of commodities are sorted (in descending order) by the number of hops and bandwidth requirements because the average traffic demand is quite low (0.375) and less than 0.4 wavelengths. The sequence order is shown in *Table B.3*.

Table B.3 The groomed commodities

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

After the sequence order of the set of commodities is rearranged, we combine multiple commodities by using “Extended Traffic Grooming (ETG)” approach. The pseudo code of the Extended Traffic Grooming (ETG) is described as followings.

Extended Traffic Grooming

Step 1: Calculate the average traffic demands
Step 2: Assign sequence order to the set of commodities
 Step 2.1: If the average traffic demand is less than the wavelength threshold,
  Sort the set of commodities by bandwidth requirement and number of hops (in descending order) respectively
 Step 2.2: Otherwise,
  Sort by the number of hops and bandwidth requirements (in descending order)
Step 3: Groom multiple commodities using the followings pseudo code

```
Repeat
   Step 3.1: Attempt to combine with the existed group
         Repeat
            Repeat
               If the amount of traffic demands in the groomed link does not exceed the
               wavelength bandwidth and there exists an element in the group that
               overlaps with another commodity
                  a) Add the commodity to the set of elements of the existed group
                  b) Update the usage bandwidth of the network link
            Until all elements in the group are considered
         Until all existing groups are considered
         If the existing groups are possible to groom together (i.e., the elements in two
         or more existing groups are overlapped and the summation of their traffic
         demands for all links is not exceed the wavelength bandwidth)
            Groom the existing groups together
         End if
   Step 3.2: If a commodity is not assigned into a group,
            a) Add the commodity to a new group
Until all commodities are assigned to the group
```

The snapshot of the ETG procedure based on *Table B.3* is shown in *Figure B.3*. At first, commodity C0 is assigned to the group 0 and then commodity C1 to the group 1. At the snapshot 3, commodity C2 is assigned to groom with commodity C0 into the group 0. At snapshot 4, the commodity C1 is reassigned to groom with the group 0 because C1 and C2 are overlapped and the bandwidth summation of them is not exceed the wavelength bandwidth. At snapshot 5, the new commodity C3 is assigned to group 1. At snapshot 6, commodity C4 can be groomed with the existing group (i.e., group 1). At snapshot 7, the commodity C5 is assigned to the new group (i.e., group 2). At snapshots8-9, commodities C6 and C7 are combined to the existed group (i.e., group 2). ETG algorithm requires 3 groups for supporting the set of commodities in *Table B.1*.

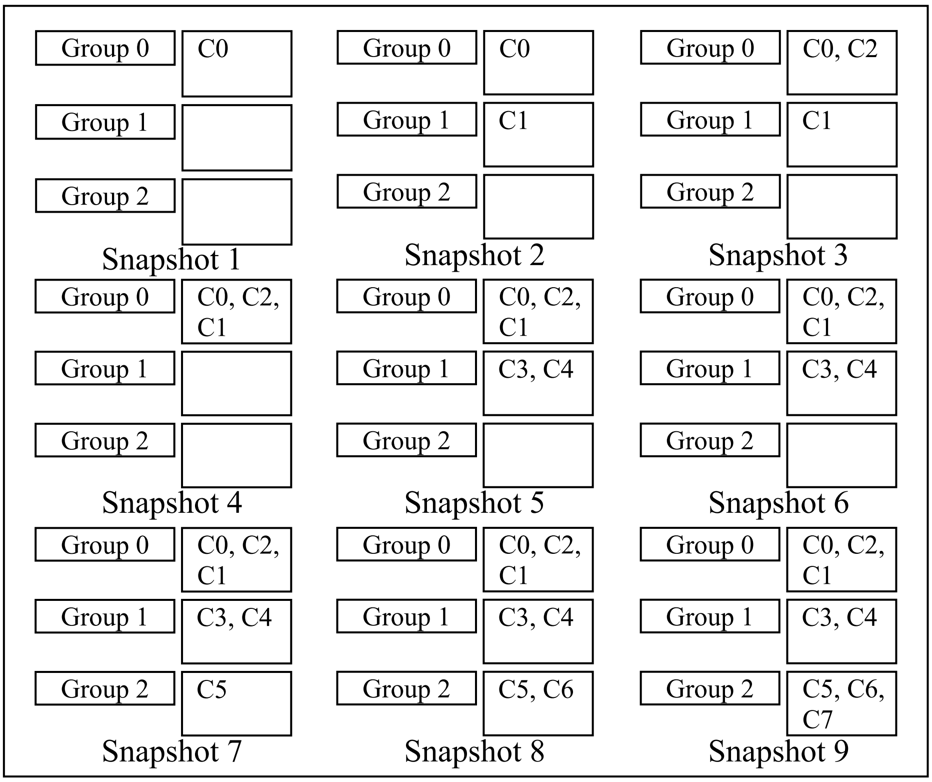

Figure B.3 The snapshots of the ETG algorithm using commodities in *Table B.1*

After we combine multiple low-rate traffic demands into a group, a second auxiliary graph is created to specify the groups of commodities that are overlapped. The group is overlapped with the other, if it has at least one commodity that is overlapped with the commodity members of the other group. The second auxiliary graph is shown in *Figure B.4*. For example, Group 0 is overlapped with Group 1 because commodities 1 and 3 in the Group 0 are overlapped with the commodity 4 in Group 1, as originally given in *Table B.1*.

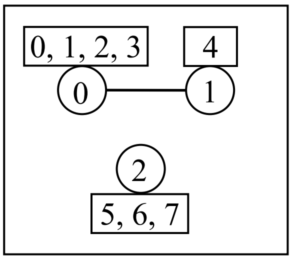

Figure B.4 The auxiliary graph of overlapped commodities in the group

The drawback of the extended traffic grooming is that its computational complexity is increased because all commodities in the groomed group are reconsidered. However, the network design problem in this dissertation is static with offline traffic demands so that the computational time is not marginally different with or without traffic grooming.

B.3 Maximum Degree First (MaxDF) Wavelength Assignment

In the Wavelength Assignment, Maximum Degree First (MaxDF) algorithm is proposed to assign a limited wavelength channel to a set of commodities. Before we assign a wavelength to a set of commodities, we need to create an auxiliary graph for the set of lightpaths. In an auxiliary graph (as shown in *Figure B.4*), each node represents the group and the set of commodities in the group. The circle symbol is represented the group and the rectangle symbol is represented elements in the group. The link between a pair of nodes represents their relation. From *Figure B.4*, we have three groups. The groups 0, 1 and 2 are represented by nodes 0, 1 and 2. The groups 0 and 1 are overlapped (i.e., at network edges 3→4 and edge 4→5 in *Figure B.1*) therefore a link between them is created. Every pair of auxiliary nodes that have a link cannot be assigned with the same wavelength.

We modify the First-Fit algorithm that assigns the wavelength from smallest channel index to the highest channel index. In our algorithm, we assign the wavelength from the maximum degree of auxiliary graph first. Our assumption is that the maximum degree of an auxiliary graph represents large amounts of commodities in the group that are overlapped with the others. Multiple commodities are groomed or combined into the group. Therefore, the maximum commodity should be assigned first. If the low degree node in the auxiliary graph is first selected and assigned with a wavelength channel, many other commodities in the group will be blocked. The MaxDF algorithm can be presented as follows.

Maximum Degree First (MaxDF) Algorithm

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

After the MaxDF process, we have the set of commodities in the group with wavelength channel as shown in *Figure B.5*. For instance, channel 0 is assigned to Groups 0 and 2 because all of them are not overlapped. The commodities in the group also have the same wavelength channel as shown in *Figure B.6*.

Group ID.	0	1	2
Wavelength Channel	0	1	0

Figure B.5 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

Figure B.6 The wavelength channel of the set of commodities

In *Appendix A*, the performance of 1) the routing and 2) wavelength assignment algorithms are compared with the traditional routing approach called Fixed Alternate Routing (FAR) and comparing with the traditional wavelength assignment called First-Fit (FF). Our previous work showed that both routing and wavelength assignment algorithms can assign the wavelength as fast as the First-Fit algorithm but with superior results in terms of accepted community requests. The computation results are showed in *Appendix A.3*.

For the comparison of the traffic grooming algorithm, we have compared our GA-ETG-MaxDF algorithm with traditional approaches (GA-MST-FF and GA-MRU-FF). The experimental results are shown in *Chapter 7*.

APPENDIX C

STRENGTH PARETO EVOLUTIONARY ALGORITHM (SPEA2)

The Improving Strength Pareto Evolutionary Algorithm (SPEA2) is famous as an efficient technique to search for the Pareto-optimal set in general multi-objective optimization problems. The SPEA2 was proposed by Zitzler et al [9] and described as following.

SPEA2 Algorithm

Let N represent the population size, $\overline{N}$ is the archive size.

1. Generate an initial population P_0 and create an empty archive $\overline{P}_0$.
2. Calculate the number of required wavelength channels and the switching ports required, using **GA-MaxDF or GA-EMF** as described in *Appendixes A and B.*
3. Calculate fitness values of individuals in P_t and $\overline{P}_t$.
4. Rank individuals by their fitness value and the *k*-nearest neighbor distance where $k = \sqrt{N + \overline{N}}$.
5. Environmental selection
   a. If size of $\overline{P}_{t+1}$ exceeds $\overline{N}$ then

      Remove the individual that has minimum *k*-nearest neighbor distance in $\overline{P}_{t+1}$ until $\overline{P}_{t+1} = \overline{N}$.

   b. If size of $\overline{P}_{t+1}$ is less than $\overline{N}$ then

      Fill $\overline{P}_{t+1}$ with dominated individuals in P_t and $\overline{P}_t$
6. Mutate and crossover individuals in P_t
7. Repeat Steps 2 to 6, until the iteration is met with the maximum number of iterations.

C.1 Fitness Assignment

The fitness value $F(i)$ is the composite of the raw fitness value, *R(i)*, and the density, *D(i)*, as expressed in Equation C.1.

$$F(i) = R(i) + D(i) \quad \text{(C.1)}$$

The raw fitness value is calculated from the strength value of each individual. Each individual *i* in the archive $\overline{P}_t$ and population P_t is calculated for the strength value $S(i)$. The strength value of an individual *i* represents the number of individuals that it dominates as expressed in Equation C.2.

$$S(i) = \left|\{ j \mid j \in P_t \cup \overline{P}_t \wedge i \succ j \}\right| \quad \text{(C.2)}$$

where $|\cdot|$ denotes the cardinality of a set, the symbol $\succ$ represents the Pareto dominance relation (i.e., $i \succ j$ represents the individual *i* that is better than *j* in all cases). The raw fitness value $R(i)$ of individual *i* is calculated by using Equation C.3.

$$R(i) = \sum_{j \in P_t \cup \overline{P}_t, j \succ i} S(j) \tag{C.3}$$

The raw fitness value of non-dominated individual *i* is equal to 0 meaning that no individual is better than the individual *i*.

$R(i)$ can fail only when individuals do not dominate each other. The density $D(i)$ is applied to expand the front of non-dominated individuals. The $D(i)$ is calculated based on the distance of *k*-nearest neighbor method, d_i^k, where $k = \sqrt{N + \overline{N}}$. The density equation is expressed in Equation C.4.

$$D(i) = \frac{1}{d_i^k + 2} \tag{C.4}$$

where distance $d_i^k \geq 0$; therefore density $D(i) < 1$. The fitness value of non-dominated individual *i* is less than 1. The minimum fitness value is assigned to the first rank.

C.2 Environmental Selection

The SPEA2 is proposed to be better than SPEA algorithm with two important characteristics that are

1) the number of archive is constant over time and
2) a removal algorithm called "truncation method" is proposed to protect the boundary individuals being removed.

In the environmental selection process, the size of non-dominated individuals in $\overline{P}_{t+1}$ can be separated into three cases.

Case 1) $|\overline{P}_{t+1}| = \overline{N}$

If the size of non-dominated individuals is the same as the archive size, the process is completed.

Case 2) $|\overline{P}_{t+1}| < \overline{N}$

If the size of the set of non-dominated individuals is less than the archive size, fill the remaining $\overline{N} - |\overline{P}_{t+1}|$ with the best dominated individuals in P_t and $\overline{P}_t$.

Case 3) $|\overline{P}_{t+1}| > \overline{N}$

If the size of non-dominated individuals exceeds the archive size, the individual *i* that has minimum distance will be selected to be removed first or the individual that is far away from others will be selected to the next iteration first. The removal process is repeated until the size of $\overline{P}_{t+1}$ is less than or equal to $\overline{N}$.

C.3 The Efficiency of SPEA2

To ensure that the SPEA2 algorithm is efficient as it was originally proposed, we applied our implemented SPEA2 algorithm to solve a combinatorial Knapsack problem using the same input data, size of archive, size of population, and all configuration parameters as proposed in [9]. Our result for the non-dominated individuals is shown in *Figure C.1*, illustrating that our implemented SPEA2 is efficient to search for the set of optimal individuals.

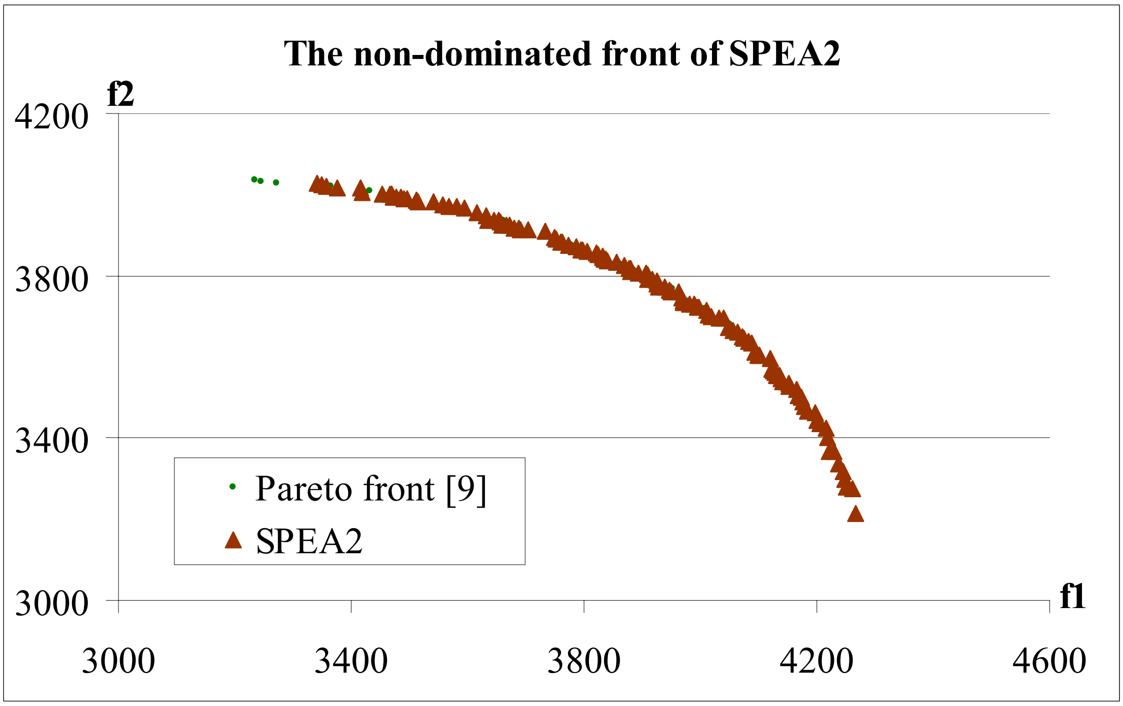

Figure C.1 The comparison of non-dominated individuals obtained from original SPEA2 and our implemented SPEA2

APPENDIX D

FAST NON-DOMINATED SORTING APPROACH (NSGA-II)

The Fast Non-dominated Sorting Genetic Algorithm (NSGA-II) is famous as an efficient technique to search for the Pareto-optimal set in general multi-objective optimization problems. NSGA-II is a very fast algorithm. It can rapidly converge to the Pareto-front. The NSGA-II was proposed by Deb et al [10] and described as following.

NSGA-II Algorithm

Let R_t represent the total population, P_t is the preserved population, Q_t is the recombined population of the generation t. F_i is the front i where i is a positive integer. Note that the solutions in front F_1 is better than those of F_2, and so on.

1. Combine the P_t and Q_t to R_t
2. Calculate the number of accepted commodities, required wavelength channels and required switching ports, using **GA-MaxDF or GA-EMF** as described in *Appendixes A and B*.
3. Assign each population in R_t to the front (F_1, F_2, F_3, and so on) using **Fast-non-dominated-sort(R_t)** algorithm
4. Calculate the crowding distance in each F_i using **Crowding-distance-assignment(F_i)** algorithm
5. **Sort** the population R_t (sort by front order(F_i) **in ascending order** and crowding distance **in descending order**)
6. Select only first half of the population R_t and assign to P_{t+1}
7. **Recombine (crossover and mutate)** the population P_{t+1} and assign to Q_{t+1}
8. increment the iteration counter (t = t+1)
9. Repeat Steps 1 to 8, until the iteration is met with the maximum number of iterations.

From the NSGA-II algorithm, the two significant procedures of NSGA-II comprise Fitness assignment (*Fast-non-dominated-sort* and *Crowding-distance-assignment*) and Selection procedure. The population consists of many individuals. Each individual in a population usually be assigned a rank or order to it for the reason that the elite individuals should be maintained to the next generation. The elite individuals have a rank lower or better than those of others. The ranks of the solutions are calculated from *Fast-non-dominated-sort* first. After that the solutions in the same front are arranged by using *Crowding-distance-assignment*. The ranking assignment is shown in procedures 1 and 2 in *Figure D.1*. The overall NSGA-II procedures are shown in *Figure D.1*.

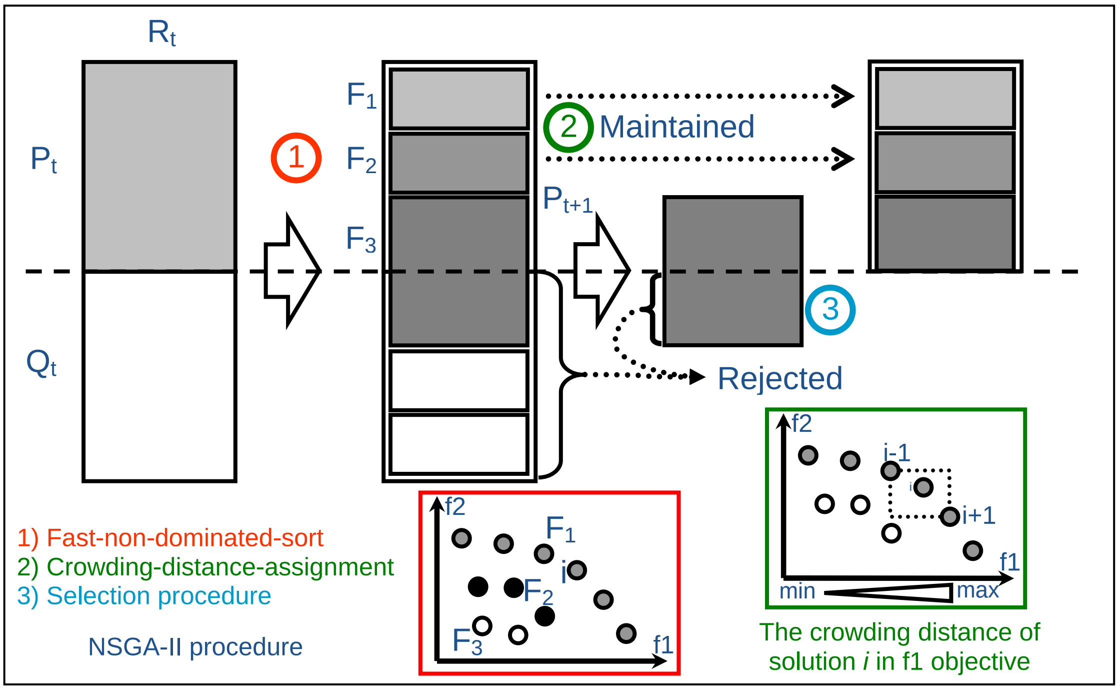

Figure D.1 NSGA-II procedure [10]

D.1 Fitness Assignment

NSGA-II ranks the individual *i* in the population using front order (F_i) and crowding distance (D_i). The front orders (F_i) are assigned using ***Fast-non-dominated-sort*** algorithm and the crowding distance is calculated using ***Crowding-distance-assignment*** algorithm.

Fast Non-dominated Sorting Approach [10]

Let F_i be the front i where i is the positive integer. Note that the individual p in F_1 is better than the individual in F_2.

1. For each individual p of the population
   a. Find the set of individuals dominated by p
   b. Find non-dominated individuals and assign to the first front F_1
2. Assign other individuals to the second front, third front, and so on, until all individuals have their front.

Using only the front order, we cannot decide which individual solution is better than others because, in the population, it could be happen that two or more individuals have the same front. Thus each individual *p* in the same front F_i is assigned the crowding distance to it before going to the selection process. For example, in the maximization of a couple objectives (f1 and f2), the crowding distance is the side length of the dashed box as shown in *Figure D.2*. The crowding distance of solutions in front F_i are calculated using Crowding-distance-assignment(F_i) as follows.

Crowding-distance Assignment [10]

Let F_i be the front i where i is the positive integer. Note that the solution i in F_1 is better than the solution in F_2. D_i be the crowding distance of solution i in the front F_i. N be the number of solution in front F_i. $f_m^{\max}$ and $f_m^{\min}$ are the maximum and minimum values of the objective m.

1. Set crowding distance of individual i (D_i) = 0, for all individuals in F_i
2. For each objective m
    a. Sort in ascending order the individual i by the objective value f_m
    b. Set the crowding distance (D_i) of individuals in the first and the last order = ∞ (i.e., $D_1 = \infty$ and $D_N = \infty$)
    c. For all other individuals (i = 2 to N-1)
        i. Calculate the crowding distance of individual i using $D_i = D_i + \frac{\left(f_m(i+1) - f_m(i-1)\right)}{\left(f_m^{\max} - f_m^{\min}\right)}$

$f_m(i+1) - f_m(i-1)$ is always positive number because individuals in front F_i are sorted in ascending order. $f_m(i+1)$ is always more than or equal to $f_m(i-1)$. The above fraction is divided by $f_m^{\max} - f_m^{\min}$ to normalize all scales in each objective *m* equivalently. Thus, no one objective *m* impacts the crowding distance (D_i) more than others.

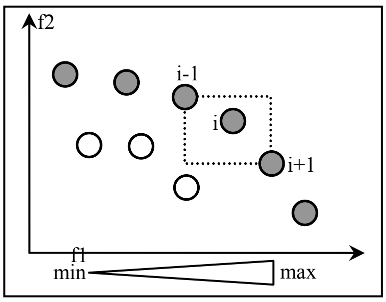

Figure D.2 The crowding distance of solution *i* in f1 objective perspective

The individual that has small distance value means that it is more crowded to others. The individual that is far away from the others will be selected first. The selection procedure is shown as follows.

D.2 Selection Procedure

The individual that has a lower front order is selected first. If the available space of the population in the next generation cannot support the entire individuals in front F_i, the individual in the same front which has greater crowding distance value will be selected first as shown in the procedure 3 in *Figure D.1*. The selection procedure is described as follows.

Selection Procedure [10]

For each individual *i*

1. Select the entire individuals that has lower front order first
2. If the entire individuals in the front F_i cannot be filled in the available space in the next generation, select the individual that has greater number of crowding distance first

D.3 The Efficiency of NSGA-II

To ensure that the NSGA-II algorithm is efficient as it was originally proposed, we apply our implemented NSGA-II algorithm to solve a combinatorial Knapsack problem using the input data and all configuration parameters as proposed in [9]. Our result for the non-dominated individuals is shown in *Figure D.3*, illustrating that our implemented NSGA-II is efficient to search for the set of optimal individuals.

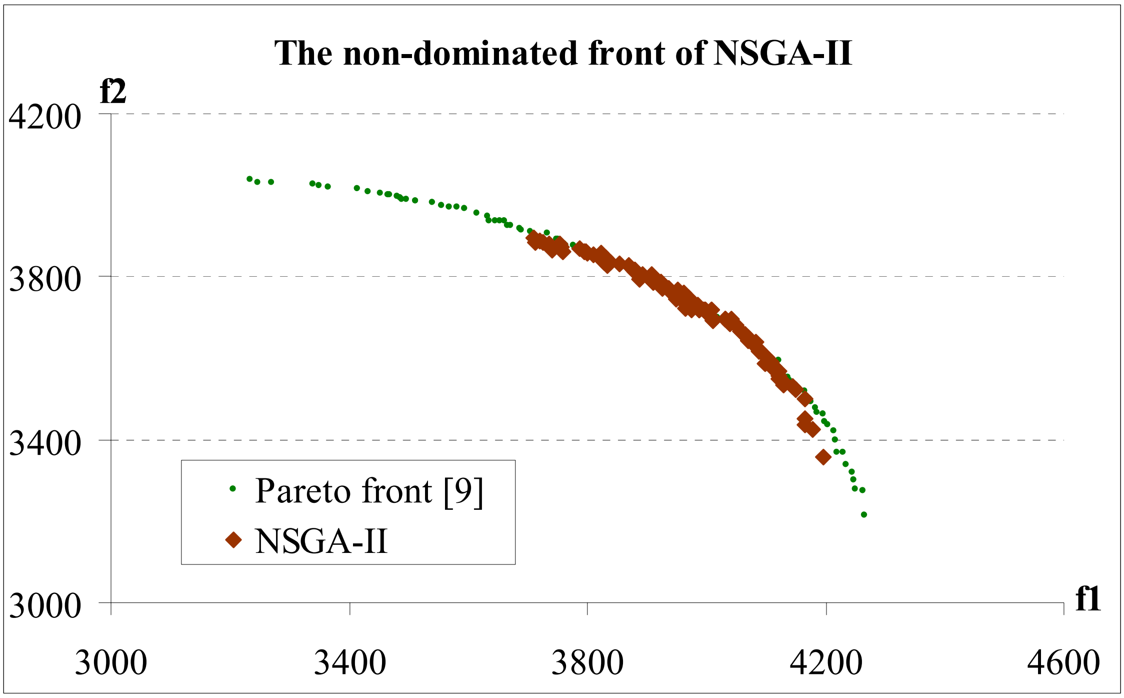

Figure D.3 The comparison of Pareto-front and non-dominated individuals obtained from our implemented NSGA-II

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