

Genetic Algorithm based Methodology for an Single-Hop Metro WDM Networks

Hyo-Sik Yang, Sung-Il Kim, Wee-Jae Shin

Division of Electrical and Electronic Engineering, Kyungnam University

Abstract

We consider the multi-objective optimization of a multi-service arrayed-waveguide grating-based single-hop metro WDM network with the two conflicting objectives of maximizing throughput while minimizing delay. We develop and evaluate a genetic algorithm based methodology for finding the optimal throughput-delay tradeoff curve, the so-called Pareto-optimal frontier. Our methodology provides the network architecture and the Medium Access Control protocol parameters that achieve the Pareto-optima in a computationally efficient manner. The numerical results obtained with our methodology provide the Pareto-optimal network planning and operation solution for a wide range of traffic scenarios. The presented methodology is applicable to other networks with a similar throughput-delay tradeoff.

I. Introduction

Optical single-hop wavelength division multiplexing (WDM) networks have the potential to provide high throughput and low delay connectivity in metropolitan and local area settings [1]. The throughput-delay performance of these single-hop WDM networks is typically very sensitive to the setting of the architecture parameters and the medium access control (MAC) protocol parameters. For good network performance, these parameters must be set properly, which is a challenge due to the large search space of possible parameter combinations and the typically computationally demanding evaluation of a particular parameter combination. The objectives to maximize the throughput while minimizing the delay are typically conflicting. With certain combinations of parameter settings, the networks achieve a small delay and moderate throughput, which is perfectly suited for delay sensitive traffic. On the other hand, certain combinations of parameter settings achieve a large throughput but introduce some moderate delays, which is perfectly suited for throughput sensitive traffic that can tolerate some delays.

In this paper, we develop a genetic algorithm based methodology for solving the multi-objective optimization problem of maximizing throughput and minimizing delay in single-hop WDM networks. We consider the Arrayed-Waveguide Grating (AWG) based

network [2] as an example throughout this paper. Our methodology finds the optimal tradeoff curve and the parameter combinations attaining the curve in a computationally efficient manner. Our work enables network planners to select the network architecture parameters that give the best performance. In addition, our methodology enables network operators of installed network hardware to optimally tune the throughput-delay performance along the optimal tradeoff curve by changing the network MAC protocol parameters. Our methodology applies analogously to networks with a similar throughput delay tradeoff.

II. AWG based Single Hop WDM Network

Fig. 1. shows the architecture of considered network. Due to the page constraints, we will not discuss detail about the network. For interesting readers, please refer [2].

The two key performance metrics of single-hop WDM networks, such as the AWG based network, are the mean throughput and the mean delay. The typical goal of the optimization of single-hop WDM networks is to maximize the throughput while minimizing the delay. For the AWG based network, the mean throughput and the mean delay have been derived in [3]. For the same reason, we will not discuss detail about the derivation of the objective functions.

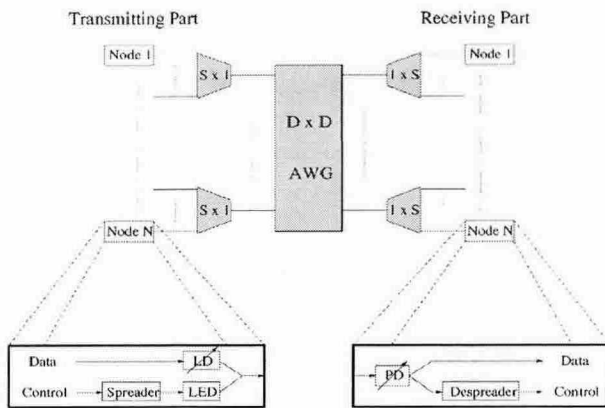


Fig. 1. Architecture of AWG based WDM network.

III. Genetic Algorithm based Methodology

1. Multi-Objective Problem

The familiar notion of an optimal solution becomes somewhat vague when a problem has more than one objective function, as is the case in our metro WDM network optimization. A solution that gives very large throughput may also give large delay and thus rate poorly on the minimize delay objective. The best we can do is to find a set of optimal tradeoff solutions, i.e., solutions that give the largest achievable throughput for a given tolerable delay, or equivalently the smallest achievable delay for a required throughput level. After a set of such optimal tradeoff solutions is found, a user can use higher level considerations to make a choice. A feasible solution to a multi-objective optimization problem is referred to as *efficient frontier* or *Pareto optimal solution* [4]. As illustrated in Fig. 2, we have two objectives, maximizing throughput and minimizing delay. The goal of multi-objective optimization is to find such a feasible efficient frontier. Classical methods for generating the Pareto-optimal solution set aggregate the objectives into a single, parameterized objective function [5].

2. Operation of Genetic Algorithm

In the genetic algorithm, we consider a population of individuals. Each individual is represented by a string of the decision variables. In the terminology of genetic algorithms the string of decision variables is referred to as *chromosome*, while each individual decision variable is referred to as *gene*. The quality of an

individual in the population with respect to the two objective functions is represented by a scalar value, called *fitness*. After generating the initial population (by randomly), each individual is assigned a fitness value. The population is evolved repeatedly, generation by generation, using the crossover operation and the mutation operation. The crossover and mutation operations produce offspring by manipulating the individuals in the current population that have good fitness values. The crossover operation swaps portions of the chromosomes. The mutation operation changes the value of a gene. Individuals with a better fitness value are more likely to survive and to participate in the crossover (mating) operation. After a number of generations, the population contains members with better fitness values. The Pareto-optimal individuals in the final population are the outcome of the genetic algorithm.

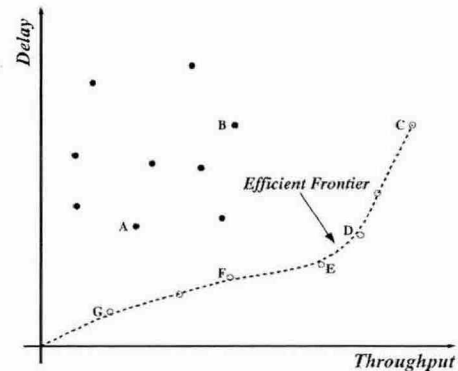


Fig. 2. Illustration of efficient frontier for maximizing throughput-minimizing delay.

1) Fitness Function

The fitness function is typically a combination of objective functions. We evaluate three commonly used types of fitness function. We generate 20 generations, each with a population size of 200 to compare the quality of the fitness functions. We set the probability of crossover to 0.9 and the probability of mutation to 0.05. We compare the genetic algorithm outputs with the true Pareto-optimal solutions which were found by conducting an exhaustive search over all possible combinations of the decision variables in limited condition. We fix mean arrival rate of 0.6 for this evaluation.

First, we evaluate the Vector Evaluated Genetic Algorithm (VEGA), which is easy to implement. The VEGA algorithm divides the population into two subpopulations according to our two objective functions. The individuals in each subpopulation are

assigned a fitness value based on the corresponding objective function. The main disadvantage of VEGA is that typically after several generations, the algorithm fails to sustain diversity among the Pareto-optimal solutions and converges near one of the individual solutions.

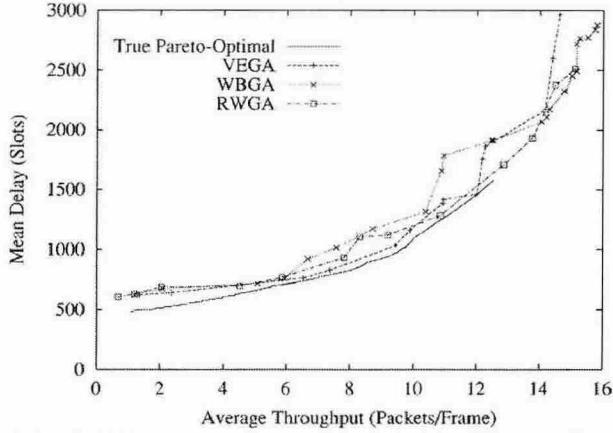


Fig. 3. Efficient frontier obtained with different fitness functions without elitism.

Next, we evaluate the Weight Based Genetic Algorithm (WBGA) which uses the weighted sum of the objective functions as fitness function. The main difficulty in WBGA is that it is hard to choose the weight factors. We use the same weight factor of 1/2 for each objective function. The fitness function used is

$$Fitness = 0.5 \times Th - 0.5 \times Delay \quad (1)$$

Finally, we evaluate the Random Weight Genetic Algorithm (RWGA) which weighs the objective functions randomly. A new independent random set of weights is drawn each time an individual's fitness is calculated. We use the fitness function

$$Fitness = \varepsilon \times Th - (1 - \varepsilon) \times Delay \quad (2)$$

where ε is uniformly distributed in the interval (0, 1).

We observe from Fig. 3 that the RWGA efficient frontier is relatively far from the true efficient frontier in the throughput range from 8-10 pkts/frame.

We now study the concept of *elitism*. Elitism is one of the schemes used to improve the search; with elitism the good solutions in a given generation are kept for the next generation. This prevents losing the already found good solutions in the subsequent crossover operation(s), which may turn good solutions

into bad solutions. The results obtained with elitism are given in Fig. 4. We observe that the efficient frontiers are closer to the true efficient frontier of the problem. According to the observations made in this section, we use RWGA with elitism throughout the remainder of this paper.

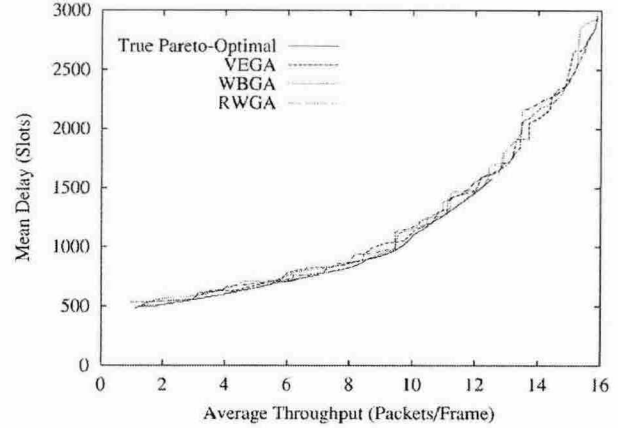


Fig. 4. Efficient frontier obtained with different fitness functions with elitism.

2) Population Size and the Number of Generation

The population size trades off the time complexity (computational effort) and the number of optimal solutions. In order to accommodate all Pareto-optimal solutions, the population should be large enough. However, as the population size grows, the time complexity for processing a generation increases. On the other hand, for a smaller population, the time complexity for the population decreases while the population may lose some Pareto-optimal solutions. As a result, the smallest population size which can accommodate all Pareto-optimal solutions is preferable. Efficient frontiers with different population size, P , and the number generations, G , are shown in Fig. 5.

IV. Numerical Results

In this section, we employ the genetic algorithm based methodology developed in the preceding section to optimize the AWG-based single-hop WDM network. We determine the settings of the network architecture parameter that give Pareto-optimal throughput-delay performance. We use the random weight genetic algorithm (RWGA) with elitism with the parameter settings found in the preceding section, a population size of 200, 40 generations, crossover probability 0.9,

and mutation probability 0.05. Data packets can have one of two lengths. A data packet is long packet with probability q , and short packet with probability $(1-q)$. To reasonably limit the search space we restrict the number of slot in a frame to be no larger than 400 slots. The number of nodes in the network is set to 200 and the transceiver tuning range is fixed at 8 wavelengths.

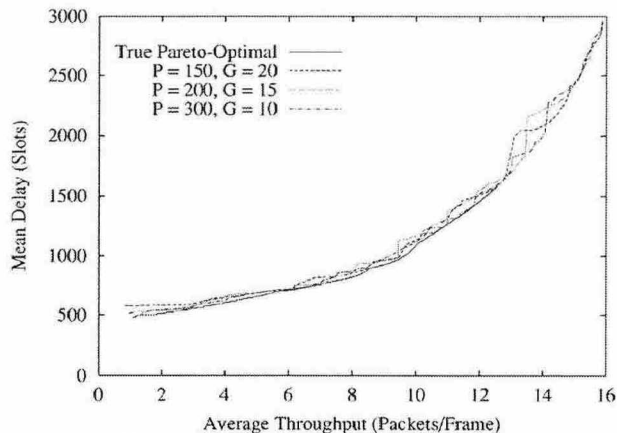


Fig. 5. Efficient frontier with different population size and the number of generations.

Efficient frontier with mean arrival rate of 0.6 is shown in Fig. 6. We also conduct an optimization where the traffic load and the fraction q of long packet traffic are free decision variables, which gives the best achievable network performance, refer to as *network frontier*. Due to the paper constraints, detailed tables of decision variables for the efficient frontier are omitted. Interested reader may refer [6].

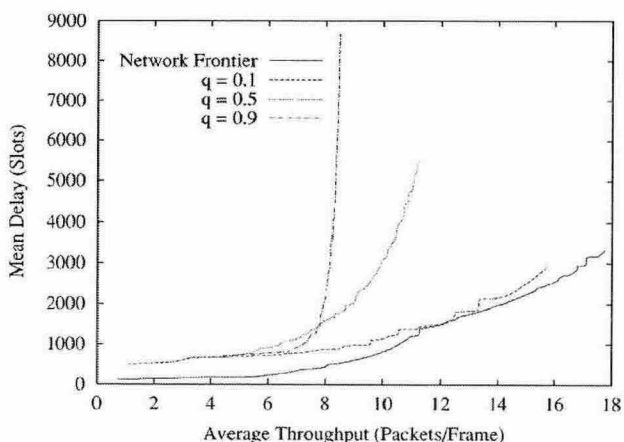


Fig. 6. Efficient frontier with mean arrival rate of 0.6 with different fraction of q of long packet traffic and network frontier.

V. Conclusion

We have developed a genetic algorithm based methodology for the multi-objective optimization problem of maximizing throughput while minimizing delay in an AWG-based metro WDM network. Our methodology finds the Pareto-optimal throughput delay trade-off curve in a computationally efficient manner. The optimal tradeoff curve can be used to optimally provide varying degrees of small delay (and moderate throughput) or large throughput (and moderate delay) packet transport services. Our methodology thus facilitates efficient multi-service convergence for increased cost-effectiveness in metropolitan and local area networks.

The developed genetic algorithm methodology can be applied in analogous fashion to networks with a similar throughput delay tradeoff. The methodology is especially useful for the multi-objective optimization of networks with complex, highly non-linear characterizations of the network throughput and delay.

References

- [1] B. Mukherjee, "WDM Optical Communication: Progress and Challenge," IEEE J. Sel. Areas on Comm. vol. 18, No. 18, pp.1810-1824, 2000.
- [2] M. Maier, M. Reisslein, and A. Wolisz "High Performance Switchless WDM Network using Multiple Free Spectral Ranges of an AWG," Proc. of SPIE Terabit Optical Networking, pp. 101-112, 2000.
- [3] M. Maier, M. Sheutzw, M. Reisslein, A. Wolisz, "Wavelength Reuse for Efficient Transport of Variable Size Packets in a Metro WDM Network," Proc. of INFOCOM, pp. 1432-1441, 2002.
- [4] K. Deb, "Multi-Objective Optimization using Evolutionary Algorithm," New York: Wiley, 2001
- [5] E. Zitzler, "Evolutionary Algorithms for Multi-Objective Optimization: Methods and Applications," Ph. D. Dissertation, Swiss Federal Institute of Technology, Zurich, 1999.
- [6] H.-S. Yang, M. Maier, M. Reisslein, and W. M. Carlyle, "A Genetic Algorithm based Methodology for Optimizing Multiservice Convergence in a Metro WDM Network", IEEE/OSA J. Lightwave Tech., Vol. 21, No. 5, 2003.