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# Multi-objective Genetic Algorithm for Solving Routing and Spectrum Assignment Problem

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***Abstract*—Routing and spectrum assignment (RSA) problem is a crucial task in designing, planning and operating next-generation optical network based on flex-grid scheme. In practical cases, solving RSA problem involves a number of objectives which, very often, may be in conflict to each other. The need is therefore to find a pool of solutions, known as Pareto-optimal solutions, which are equally optimal. In this context, the paper focuses on the use of multi-objective genetic algorithm for finding such Pareto front in solving RSA problem with multiple objectives. Numerical results show that the algorithm could find Pareto front in an efficient time manner and indeed achieve good convergence rate.**

***Index Terms*—multi-objective genetic algorithm; fiber-optic network; routing; spectrum assignment**

## I. Introduction

The significant progress of optical technologies from both hardware and software aspects has open the door for a more efficient, flexible optical network based on *flex-grid* paradigm. Being considered as the promising architecture for next-generation optical network to meet an ever increasing Internet traffic in such an cost and energy-efficient fashion, flex-grid optical network has been receiving increasing attention from research community and standard body [1], [2]. In an analogy to the importance of routing and wavelength assignment (RWA) [3] in traditional fixed-grid wavelength-routed optical network, routing and spectrum assignment (RSA) is a crucial task for planning and operating network with elastic spectrum spacing [4], [5].

Planning a network practically involves a number of metrics, sometimes, conflicting ones [6]. Thus, minimizing only one metric possibly exhibits high penalties with respect to others. Therefore, a multi-objective optimization is an efficient technique to jointly capture objectives and/or strike a compromise among them. In [6], we proposed an approach based on weighting method where there is priori preference information among constituent objectives and thus, the multiple objective RSA could be converted into a single objective case. However, in the cases where there is no priority information among individual objectives, the goal turns out to find best set of solutions, known as Pareto front, where all solutions are equally optimal. While there are quite a number of works for multi-objective RWA, for example [7]–[11], multi-objective framework for RSA problem has not yet been adequately addressed. The added constraints on spectrum contiguity of RSA problem [12], [13] accounts for the fact that it is not straightforward to apply similar framework multi-objective genetic algorithm for RWA to RSA problems. Indeed, the complexities due to spectrum contiguity remains a challenge to be solved for multi-objective RSA.

This paper focuses on the case where all the constituent objectives are equally important and thus, the finding of all the non-dominated solutions are desired. The feature of genetic algorithm [14] which is based on the evolution of a population of solutions is well-suited for multiple objective optimization when there is no further information about the priority of each objective. In this case, there is in general no single best solution. Instead, there are set of solutions, known as Pareto-optimal solutions or non-dominated solutions. Without additional information, all these solutions are equally satisfactory. The goal of optimization in this case is to find as many of these solutions as possible.

The paper is organized as followed. The next section introduces the Pareto front and dominance concept. In section III, multi-objective framework based on controlled elitist fast non-dominated sorting genetic algorithm (NSGA-II) for solving RSA problem are presented in detail. Numerical results are shown in section IV and finally section V are left for conclusion and perspectives.

## II. Pareto front and Dominance Concept

This section provides definition on domination concept and Pareto front for solutions in multi-objective problem. Without loss of generality, we consider the minimization of two objectives ($f_1$ and $f_2$) and all are equally important.

A solution to the problem could be represented by vector $\mathbf{x}$ in the design space. The evaluation of two objective functions on $\mathbf{x}$ produces corresponding objective values $\mathbf{f(x)} = (f_1, f_2)$ in the objective space. For comparing two solutions $x_1$ and $x_2$, a dominance concept is defined. In multi-objective optimization, Pareto criteria is mostly used. It is stated as followed:

- An objective vector $\mathbf{f_1}$ is said to dominate another objective vector $\mathbf{f_2}$ if no component of $\mathbf{f_1}$ is greater than the corresponding component of $\mathbf{f_2}$ and at least one component is absolutely greater.
- The solution $\mathbf{x_1}$ dominates $\mathbf{x_2}$ if $\mathbf{f_1} = \mathbf{f}(\mathbf{x_1})$ dominates $\mathbf{f_2} = \mathbf{f}(\mathbf{x_2})$

- All non-dominated solutions are the optimal solutions of the problem, i.e., solutions which are not dominated by any others. The set of these solutions is named Pareto set while its corresponding objective values is named Pareto front.

The purpose of multi-objective optimization genetic algorithm is to search for non-dominated solutions which is very close to real Pareto set.

## III. Multi-objective Genetic Algorithm Implementation

We present the multi-objective RSA problem and its associated genetic algorithm model. We consider the RSA problem of spectrum-sliced optical network to support many requests of different granularities simultaneously (known as multi-commodity flow problem). Each request has many possible routings and each routing has several choices of spectrum assignment. The network design problem is to minimize the spectrum width requirement to support all requests and to minimize also the overall spectrum link usage.

### *A. Genetic Encoding*

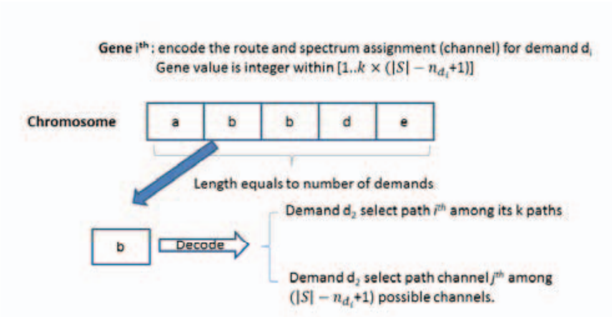


Fig. 1: Genetic Encoding for Routing and Spectrum Assignment Problem

Given the set of demands which has been numbered ($d_i$) to indicate the order of serving, each chromosome represents the serving of those demands by selecting a route and assigning a channel to each demand. Thus, the chromosome length is equal to total number of demands and the value of each gene encodes the route and spectrum assignment for the demand being represented. Figure 1 provides the illustration for the genetic encoding process. Assuming demand $d_i$ requests $n_{d_i}$ spectrum slices and there are $k$ candidate paths, the number of possible ways for routing and spectrum assignment would be: $k \times (|S| - n_{d_i} + 1)$ where $|S|$ is total number of spectrum slices on each fiber link. By assigning a positive integer value within the range $[1..k \times (|S| - n_{d_i} + 1)]$ for gene $i^{th}$, it is possible to decode that value to bring about which route and channel is selected by the demand. The decoding procedure is described in Algorithm 1. It is noticed that the serving of demand in such way satisfies the spectrum contiguity and the spectrum continuity constraint while the spectrum non-overlapping is not guaranteed. However, it is always possible to discard solutions that violates spectrum non-overlapping by assigning a very high value of objective functions to them. We opt for that option in this study.

**Algorithm 1** Chromosome Decode Procedure

**INPUT:** Chromosome, Demand set $D$, number of candidate path $k$, Spectrum set $S$
**OUTPUT:** Path and channel assignment for each demand $d \in D$

**for** $d_i \in D$ **do**
  **if** rem(chromosome(i), $|S| - n_{d_i} + 1$)==0 **then**
    path id for $d_i = \frac{chromosome(i)}{|S|-n_{d_i}+1}$ {rem: remaider after division}
    channel id for $d_i = |S| - n_{d_i} + 1$
  **else**
    path id for $d_i = \lfloor \frac{chromosome(i)}{|S|-n_{d_i}+1} \rfloor + 1$
    channel id for $d_i = rem(chromosome(i), |S| - n_{d_i} + 1$
  **end if**
**end for**

### *B. Objective function*

There are two objectives associated to each chromosome. The first objective, $f_1$, is the spectrum width indicating the maximum slice indexed used in the network and the second objective,$f_2$ is the total spectrum link usage. The pseudo-code Algorithm 2 describe the evaluation procedure. Given a chromosome, the route and channel for each demand are calculated. After serving each demand sequentially, the spectrum availability vector of each link is updated. Whenever the serving of demand violates the spectrum non-overlapping condition, the procedure returns the very high value for both objectives indicating the discard of those solution. Otherwise, all demands are served and the objectives $f_1$ and $f_2$ are evaluated by performing simple calculation on spectrum availability vector of all links $u_e$.

### *C. Crossover*

For producing offsprings from parents, we use arithmetic scheme which linearly combine two parent chromosome vectors on a gene basis. By doing so, the valid range for each gene of the chromosome is preserved. Besides, in order to guarantee integer requirement for produced gene value, an upper rounding and/or lower rounding need to be performed.

$$offspring1 = \lceil \alpha * Parent1 + (1 - \alpha) * Parent2 \rceil \quad (1)$$

$$offspring2 = \lfloor (1 - \alpha) * Parent1 + \alpha * Parent2 \rfloor \quad (2)$$

### *D. Mutation*

The mutation operator is performed in this case by firstly locating the position of gene to be mutated and secondly,

**Algorithm 2** Objectives Evaluation

**INPUT:** Chromosome, Demand set $D$, Spectrum set $S$

**OUTPUT:** $f_1$ and $f_2$

**for** $d_i \in D$ **do**

  Decode *chromosome(i) into path id and channel id for demand* $d_i$

  Update the spectrum availability vector for each link $u_e$ after serving demand $d_i$

  **if** Spectrum Overlapping==True **then**

    $f_1 = Inf$

    $f_2 = Inf$

    RETURN

  **end if**

**end for**

$f_1$=maximum index of utilized slice for all links

$f_2$=arithmetic summation of spectrum availability vector of all links

generating different random value within the range of this gene to be a new value.

For a multi-objective genetic algorithm procedure, a variant of NSGA-II [15], [16], the so-called controlled elitist genetic algorithm is used. The difference between elitist version controlled elitist one lies in the fact that the former one only consider the fitness value (rank) to evaluate the solutions whereas the latter one, apart from fitness value, also take into account diversity aspect of solutions. By doing so, the diversity of population is improved, which leads to a better convergence to an optimal Pareto front. The steps of the procedure could be described as follows:

**Step 1: Initialization**

- Generate an initial population with $P_{size}$ random chromosome vectors $\mathbf{x_i}$ (i=1..$P_{size}$)
- *The initial population is sorted into categories (rank) on the basis of non-dominance. Each solution is assigned a fitness value equal to its non-dominance rank (i.e., rank 1 is the best)*

**Step 2: Update**

- A mating pool is formed by selecting the best solutions from the population based on their ranks. In case of having to choose among solutions of the same rank, the crowding distance of the solutions belonging to that front is calculated and those individuals with higher value of crowding distance are preferred so as to favor the diversity.
- Generate offspring solutions by performing crossover operation and mutation.
- Combine all the new solutions with parent solutions to form new population.
- *Sort the newly formed population into categories (rank) according to their relationship of dominance*

**Step3: Stopping Criteria**

- If the stopping criterion is reached, then stop and output the set of non-dominated solutions, otherwise, continue step 2. The stopping criteria here is based on maximum number of generations.

## IV. Numerical Results and Discussion

We perform the study on realistic European COST239 topology (11 nodes and 52 links) as in Fig. 2.

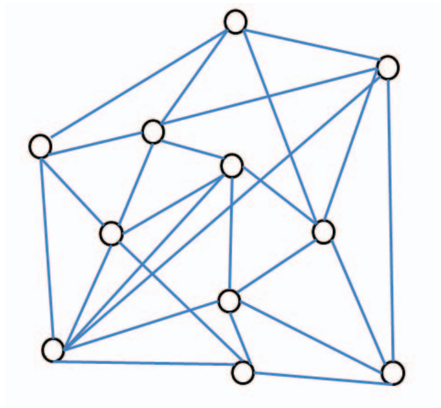

Fig. 2: European COST239 Topology

The traffic is generated randomly between node pairs and within the range $[1..10]$. Table I shows the used traffic matrix for this study. The NSGA-II algorithm is implemented by making use of available Matlab built-in function from Global Optimization toolbox with some modification [16]. Note that our proposed algorithm could work with any topology and any type of traffic.

TABLE I: TRAFFIC MATRIX

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 9 | 0 | 0 | 2 | 2 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 3 | 9 | 9 | 10 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 3 | 0 |
| 4 | 2 | 0 | 5 | 0 | 8 | 1 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 0 | 9 | 6 |
| 7 | 0 | 0 | 0 | 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 0 | 5 | 0 | 0 | 0 | 0 | 9 | 0 | 0 | 0 | 0 |
| 9 | 7 | 4 | 3 | 0 | 7 | 6 | 0 | 7 | 0 | 3 | 0 |
| 10 | 0 | 0 | 8 | 7 | 0 | 3 | 9 | 0 | 0 | 0 | 2 |
| 11 | 0 | 10 | 0 | 1 | 1 | 0 | 3 | 0 | 0 | 0 | 0 |

Figure 3 shows the best front found over different generations. In this experiment, it is found that after around 200 generation, the best found front does not show much of an improvement. Therefore, it could be implied that the front at 200 generation is converged to optimal one (Pareto-front). There are two different optimal points on the Pareto front clearly demonstrating the trade-off between two objectives.

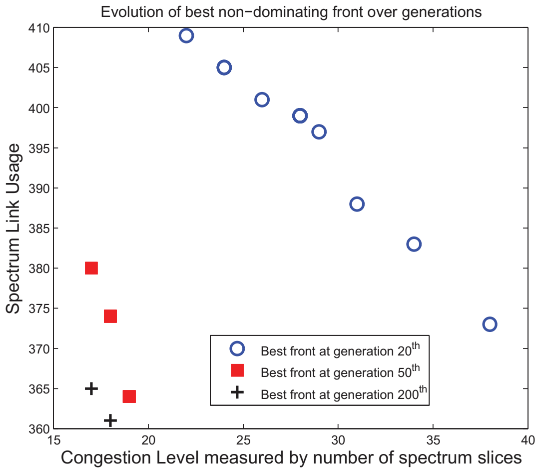


Fig. 3: Best found non-dominated front

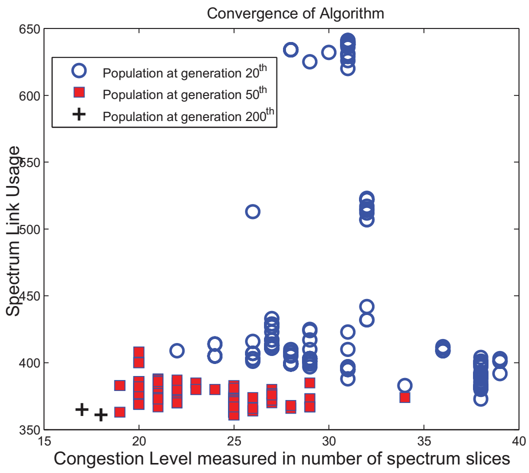


Fig. 4: Population Evolution

Figure 4 presents the evolution of population at different generations. It is shown that set of solutions are quite diversely distributed at low evolution generation. As the generation increases, the population demonstrate a good convergence as it moves to better value for both objectives. At generation of 200, the whole population is converged to the Pareto-front, which consists of two different points as shown in the Fig. 4.

## V. Conclusion

We have presented our works on the use of multi-objective genetic algorithm for solving routing and spectrum assignment problem in multi-objective context where all the constituent objectives are equally important. We have performed numerical studies on realistic topologies and traffic to demonstrate the efficiency of our algorithms in finding the Pareto front. The paper is our first attempt in this topic and we plan to extend this work into some promising directions. One of them is envisioned to exploit the high-performance and parallel computing nature of genetic algorithm for performance improvement.

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