Dynamic RMSA in Elastic Optical Networks with an Adaptive Genetic Algorithm

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***Abstract*—We develop an adaptive and efficient genetic algorithm (GA) to solve the dynamic routing, modulation and spectrum assignments (RMSA) for elastic O-OFDM networks. The algorithm offers an efficient way of serving the dynamic lightpath requests based on the current network status at each service provision time. The GA is designed for multi-objective optimization. For low traffic cases when there is no blocking, the GA minimizes the maximum number of slots required on any fiber in the network; otherwise, it minimizes the blocking probability. The performance of the proposed GA is evaluated in dynamic RMSA simulations with the 14-node NSFNET and the 28-node US Backbone topologies, and the results show that it converges within 25 generations. The simulation results also verify that the GA-RMSA outperforms several existing algorithms by providing more load-balanced network provisioning solutions with lower blocking probabilities. Specifically, when the traffic load is same, the GA can achieve more than one order-of-magnitude reduction on blocking probability. To the best of our knowledge, this is the first attempt to solve dynamic RMSA in elastic O-OFDM networks with a GA.**

***Index Terms*—Network provisioning, Optical orthogonal frequency-division multiplexing (O-OFDM), Dynamic routing, modulation and spectrum assignments (RMSA), Elastic optical networks, Adaptive genetic algorithm**

I. Introduction

The booming of bandwidth-hungry applications has been driving the Internet traffic to grow at an annual rate of more than 30%, and this situation will not change for the short-to-mid-term future [1]. The network operators and service providers have been relying on fiber-optic technologies to scale their networks with this rising trend of bandwidth requirement. It is well-known that optical fiber has numerous bandwidth, and recent research advances have demonstrated transmission of 20 Tb/s signals on one optical fiber [2]. In order to facilitate efficient and flexible access to this almost unlimited bandwidth, researchers are still looking for methods that can expedite elastic bandwidth provisioning in the optical layer.

A. Spectrum-Sliced Elastic Optical Transport Networks

Recently, optical orthogonal frequency-division multiplexing (O-OFDM) [3,4] technology has attracted intensive research interests, due to the reason that it can achieve high bandwidth efficiency and sub-wavelength granularity [5]. Fig. 1 shows the elastic bandwidth allocation in O-OFDM networks. The resource is allocated based on contiguous subcarrier slots with bandwidths at a few GHz, and the modulation levels of the slots can be adaptive to accommodate various transmission reaches [6,7]. With this mechanism, a bandwidth-variable (BV) O-OFDM transponder [8] can assign just-enough numbers of slots to serve the lightpath requests.

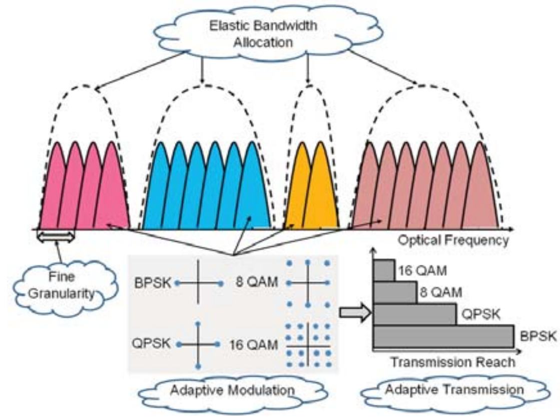

Fig. 1. Elastic frequency resource allocation in O-OFDM networks.

O-OFDM technology brings challenges to future optical transport networks. Its elastic nature has determined that more sophisticated network planning and provisioning procedures would be necessary for efficient and robust operations. Specifically, operators have to manipulate contiguous subcarrier slots instead of independent wavelength channels for Routing, Modulation, and Spectrum Assignments (RMSA). Additionally, as the spectrum converters may not be practically available in the near future [9], bandwidth fragmentation will be a concern, especially when the network operations are dynamic [10].

B. Related Works and Our Contributions

To address above challenges, researchers have been developing RMSA algorithms for network planning and provisioning [10-18]. The RMSA-based network planning that serves a given set of lightpath requests by assigning routing paths, modulation levels, and frequency slots is known as non-polynomial (NP)-complete [11]. It is also considered as a static RMSA since all the lightpath requests are known a priori. In [12], Jinno *et al.* proposed a bandwidth-efficient and distance-adaptive RSMA that examined K shortest routing paths for each request and chose the one with the lowest available contiguous slots. Several integer linear programming (ILP)

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models were formulated and solved in [11], and a simulated-annealing-based optimization was proposed to reduce the computation complexity. An ILP model of static RSA was independently formulated in [13], and two heuristic algorithms, K Shortest Path Routing and Balanced-Load Spectrum Assignments (KSP-BLSA) and Shortest Path Routing and Maximum Spectrum Reuse Assignments (SPR-MSRA), were proposed to improve the computation efficiency.

The RSMA-based network provisioning considers how to serve time-variant lightpath requests in a dynamic network environment. With a dynamic Routing and Spectrum Assignment (RSA) algorithm that employed Shortest Path Routing and First-Fit Spectrum Assignment (SPR-FFSA), Shen *et al.* investigated the relationship between blocking probability and spectrum assignment granularity in [15]. In [16], Wan *et al.* proposed several dynamic RSAs based on routing algorithms such as K shortest path routing, modified Dijkstra shortest path routing, and etc. However, the authors of [15,16] have not considered the adaptiveness of modulation-level assignments. By making extensions to the GMPLS signaling, Sambo *et al.* proposed a distributed dynamic RMSA that chose the least congested routing path based on the modulation level, and performed First-Fit-based spectrum assignments [17]. A dynamic RMSA that employed a metric to quantify the consecutiveness of available slots among relevant fibers was proposed in [18]. A RMSA-based spectrum defragmentation technique was proposed in [10]. The authors of [10] proposed a slot-search algorithm based on auxiliary graphs and counted on four-wave-mixing based spectrum conversion for defragmentation.

In this paper, we develop an adaptive and efficient genetic algorithm (GA) to solve the dynamic RMSA for elastic O-OFDM networks. The algorithm can be applied to network provisioning, where a network operator needs to find an efficient way of serving dynamic lightpath requests based on current network status at each service provision time. When traffic load is low and there is no blocking, the GA tries to minimize the maximum number of slots required on any fiber in the network. Otherwise, the GA's objective is to minimize request blocking. The simulation results show that the GA converges within 25 generations even for a high traffic case (1000 Erlangs). The network topologies under consideration are mesh networks with certain complexity, such as the 14-node NSFNET (NSF) and the 28-node US Backbone (USB). Hence, it will be feasible to implement the GA for dynamic network provisioning. The simulation results also verify that the proposed GA-RMSA outperforms several existing algorithms by providing more load-balanced network provisioning solutions with lower blocking probabilities. To the best of our knowledge, this is the first attempt to solve dynamic RMSA in elastic O-OFDM networks with a GA.

The rest of the paper is organized as follows. Section II formulates the dynamic RMSA problem and explains the constraints and the fitness function. The design of the adaptive GA for dynamic RMSA is discussed in Section III. Section IV shows the simulation results for performance evaluations. Finally, Section V summarizes the paper.

II. Problem Formulation

A. Design Considerations

Consider a physical network topology as $G(V, E)$, where V is the node set and E is the fiber link set. We assume that the bandwidth of each O-OFDM frequency slot is unique as BW_{slot} GHz, and each fiber link can accommodate B slots at most. Then, the capacity of a slot is $M \cdot C_{slot}$, where M is the modulation level in terms of bits per symbol, and C_{slot} denotes the capacity of a slot when the modulation is BPSK ($M = 1$) and is a function of BW_{slot}. In this work, we assume that M can be 1, 2, 3 and 4 for BPSK, QPSK, 8-QAM and 16-QAM, respectively. For a lightpath request LR_i from node s to d, $s, d \in V$, we define the requested capacity as C_i. The RMSA starts with determining the routing path as $R_{s,d,i}$. When the transmission distance of $R_{s,d,i}$ is known, we derive the modulation level M_i from it [6]. Then, the number of contiguous slots N_i we need to assign is:

$$N_i = \lceil \frac{C_i}{M_i \cdot C_{slot}} \rceil + N_{GB} \quad (1)$$

where N_{GB} is the number of slots for the guard-band.

The last step of RMSA is to finalize the allocation of slots along the fiber links on $R_{s,d,i}$. We assume that there is no spectrum conversion in the network. For each fiber link $e \in E$, we define a bit-mask b_e that contains B bits. When $b_e[j] = 1$, the j-th slot on e is taken, otherwise $b_e[j] = 0$. For the lightpath request LR_i, we define a bit-mask a_i that also contains B bits, and the bits in a_i follow a similar definition as those in b_e. Then, the spectrum assignment of LR_i becomes the problem of finding N_i contiguous bits in a_i to turn on based on all current b_e, $e \in R_{s,d,i}$. Finally, the RMSA of LR_i is $\{R_{s,d,i}, M_i, a_i\}$. We say LR_i is blocked, if we cannot find a feasible $\{R_{s,d,i}, M_i, a_i\}$ for it.

B. Constraints and Fitness Function

Typically, a dynamic RMSA has to satisfy the constraints from traffic demand, spectrum continuity, single-path routing, spectrum non-overlapping, and spectrum contiguousness. As the first three constraints have already been taken care of in the procedures described above, we will elaborate on the last two in this section.

Spectrum Non-Overlapping Constraint:

$$sum(a_i \cap b_e) = 0, \forall e \in R_{s,d,i} \quad (2)$$

where b_e reflects the network resource usage before serving LR_i, $sum(\cdot)$ adds all bits in a bit-mask together, and $\cap$ is the bit *AND* operator.

Spectrum Contiguousness Constraint:

$$sum(a_i \cap ROR(a_i, 1)) = \{ \begin{array}{ll} N_i - 1, & N_i < B \\ B, & N_i = B \end{array} \quad (3)$$

where $ROR(\cdot)$ is the circular bit-right-shift operator.

If we define $f(\cdot)$ as the function to return the index of the last used slot on a link e, we can evaluate a dynamic RMSA with:

$$F_s = max(f(e)), \forall e \in E \quad (4)$$

when the traffic load is low and there is no blocking. Basically, a smaller F_s means that the slot usage is more evenly distributed in the network. Apparently, we also want to minimize the number of blocked requests F_b when the traffic load is high. Therefore, we define

Fitness Function:

$$F = F_s + H \cdot u(F_b) + F_b \tag{5}$$

where H is a large positive constant to punish RMSA solutions that involve request blocking, $u(\cdot)$ is the unit step function that $u(x) = 1$ for $x > 0$, otherwise $u(x) = 0$. At any service provision time, the objective of the dynamic RMSA is to minimize F.

Bandwidth fragmentation is another un-wanted factor in dynamic RMSA. To quantify it, we define the fragmentation ratio of a link e as:

$$\eta_e = \begin{cases} 1 - \frac{MaxBlock(b_e)}{B - sum(b_e)}, & sum(b_e) < B \\ 0, & sum(b_e) = B \end{cases} \tag{6}$$

where $MaxBlock(\cdot)$ returns the maximum size of available contiguous slots in b_e. At any service provision time, if we obtain more than one RMSA scenarios that the fitness function in Eqn. (5) returns the same smallest F, we choose the one that has the smallest F_η to implement, and F_η is defined as:

$$F_\eta = max(\eta_e), \forall e \in E \tag{7}$$

III. Adaptive Genetic Algorithm for Dynamic RMSA

Genetic Algorithm (GA) is a search heuristic that mimics the natural evolution in the real world [19]. GA represents each feasible solution as a group of genes, which is known as an individual chromosome. For the dynamic RMSA, we assume that the lightpath requests from customers are served at discrete *Service Provision Time* in a periodic way (as shown in Fig. 2(a)). This assumption simplifies the design of dynamic RMSA with GA, and it actually is the common case in the network control and management [20]. If the lightpath setup delay becomes an issue, we can make the service provision period adaptive.

Algorithm 1 describes the logic flow of our proposed GA for dynamic RMSA. Here, the variable $X^{(k)}$ shares the same definition of X, but it is for the k-th individual in the population particularly. For example, $R^{(k)}_{s,d,i}$ is the k-th individual's routing path for the i-th lightpath request LR_i that is from s to d. P is the population, or the set of individuals in the GA, $PSize$ is the size of the population, $RSet_{s,d}$ is the set of feasible routing paths from s to d, and $Gene^{(k)}_i$ is the RMSA solution of LR_i in the k-th individual. We will elaborate on the details of the GA in this section.

A. Genetic Encoding for RMSA

Fig. 2(b)-(e) illustrate the genetic encoding scheme. For each s-d pair in $G(V,E)$, the feasible routing paths are pre-determined with a Link-Disjoint Path Search (LDPS) algorithm [21]. We then use a routing path table to map each

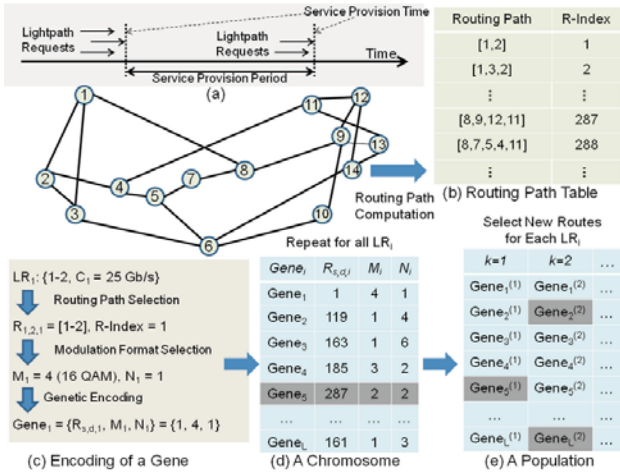

Fig. 2. Genetic encoding scheme for dynamic RMSA in an elastic O-OFDM network.

path to a unique R-Index (as in Fig. 2(b)). For each pending LR_i that needs to be served at this service provision time, the RMSA starts from randomly selecting a feasible routing path $R^{(k)}_{s,d,i}$, and then determines $M^{(k)}_i$ and $N^{(k)}_i$ based on the transmission distance of $R^{(k)}_{s,d,i}$ and the capacity of LR_i (as in Fig. 2(c)). The genetic encoding then construct a gene $Gene^{(k)}_i = \{R^{(k)}_{s,d,i}, M^{(k)}_i, N^{(k)}_i\}$.

After encoding all the genes, we perform spectrum assignment in a gene-by-gene way with a descending order based on $|R^{(k)}_{s,d,i}|$ and $N^{(k)}_i$. Specifically, the gene with longer routing path is taken care of earlier; and when the path lengths are equal, we handle the one that requests larger number of slots earlier. The assignments are done with the First-Fit scheme that is based on $R^{(k)}_{s,d,i}$, $M^{(k)}_i$, $N^{(k)}_i$, and the current network status $b^{(k)}_e$. If an $a^{(k)}_i$ that satisfies Eqn. (2) and (3) can be found, the LR_i is set up successfully; otherwise, LR_i is blocked. We then encode $Gene^{(k)}_i$ accordingly, and as shown in Fig. 2(d), a gray gene represents a lightpath request that is blocked. After repeating the above procedures for all L pending lightpath requests, we form an individual chromosome that contains L genes. Fig. 2(e) shows that if we select different routing paths for some/all of the genes, a different individual can be formed. And finally, we obtain the population by grouping different individuals together.

B. Adaptive Genetic Operations

When the RMSA of each individual k is done, we evaluate its fitness with the function in Eqn. (5). The GA involves typical genetic operations, such as selection, crossover, and mutation in iterations (i.e. evolution generations), to optimize the dynamic RMSA solution. We design the selection operation based on the *Tournament Selection* [22], to select pairs of individuals (e.g. parents) from the current generation for crossover. With the selected parents, we take pairs randomly and apply the crossover operation on them to get their children.

The crossover is a multi-point operation on the gene-level, where certain number of genes are picked out and swapped at random locations of parents based on a crossover rate p_c. We then select $PSize$ fittest individuals from the chromosome pool of parents and children as the next generation, and keep the population size constant. These individuals then go through the mutation phase, in which certain number of genes are randomly changed based on a mutation rate p_m. Specifically, we mutate a gene $Gene_i^{(k)}$ by randomly changing its routing path $R_{s,d,i}^{(k)}$ to another feasible one. To update its fitness, we redo spectrum assignment for each individual in the next generation when the crossover and mutation are done.

We adopt an adaptive mechanism to dynamically adjust the crossover and mutation rates based on the individuals' fitness. We define $F_{min} = min(\{F^{(k)}, k = 1, ..., PSize\})$, $F_{mean} = mean(\{F^{(k)}, k = 1, ..., PSize\})$, and $\overline{F^{(k_1,k_2)}} = mean(F^{(k_1)}, F^{(k_2)})$. p_c and p_m are obtained by [23]:

$$p_c = \begin{cases} \alpha_c \frac{\overline{F^{(k_1,k_2)}} - F_{min}}{F_{mean} - F_{min}} + p_{c_0}, & \overline{F^{(k_1,k_2)}} \leq F_{mean}, \\ \beta_c, & Otherwise \end{cases} \tag{8}$$

$$p_m = \begin{cases} \alpha_m \frac{F^{(k)} - F_{min}}{F_{mean} - F_{min}} + p_{m_0}, & F^{(k)} \leq F_{mean}, \\ \beta_m, & Otherwise \end{cases} \tag{9}$$

where α_c, β_c, α_m, and β_m are constant coefficients $\in [0, 1]$, and p_{c_0} and p_{m_0} are the default rates for the fittest individuals.

C. Algorithm Convergence Condition

To quantify the GA's convergence performance, we define its degree of diversity as:

$$D_P = \frac{2}{PSize(PSize-1)} \sum_{k_1=1}^{PSize-1} \sum_{k_2=k_1+1}^{PSize} \frac{d(k_1, k_2)}{L} \tag{10}$$

where $d(k_1, k_2)$ returns the number of different genes between individuals k_1 and k_2, and each individual has L genes. We can claim that the GA has converged if D_P has been lower than a pre-set threshold for certain number of generations G_c [19]. Note that the thresholds of D_P and G_c are usually determined by running a large number (e.g. 100) of simulations that each has evolved the GA for hundreds of generations.

D. Lower-Bound of the Blocking Probability in Dynamic RMSA

The lower-bound of the blocking probability P_b in dynamic RMSA can be obtained by formulating Integer Linear Programming (ILP) equations based on the bit-mask definitions of a_i and b_e, and solving them at each service provision time. However, the computation time will be extremely long for a large-scale network topology and heavy traffic load. To save the computation efforts, we provide a loose lower-bound of the P_b by implementing a relaxation on the serving order of the requests. At each service provision time, we sort pending LR_i in a descending order based on their capacities, compute all feasible routing paths with a Breadth-First Path Search (BFPS) algorithm for each request, and serve it with an Exhaustive Search RMSA (ES-RMSA) approach to minimize the blocking probability. Specifically, for each request, all feasible routing paths will be tried until it can be accommodated.

Algorithm 1 Genetic Algorithm for Dynamic RMSA

get current network status $b_e, \forall e \in E$;
$P \leftarrow \emptyset$, $k = 1$;
{Phase I: Construct Initial Populations}
while $k \leq PSize$ **do**
    $b_e^{(k)} = b_e, \forall e \in E$;
    {Construct an Individual Chromosome k}
    for all pending lightpath requests LR_i **do**
        select $R_{s,d,i}^{(k)}$ from $RSet_{s,d}$;
        compute $M_i^{(k)}$ and $N_i^{(k)}$ with $\{R_{s,d,i}^{(k)}, LR_i\}$;
        construct $Gene_i^{(k)} = \{R_{s,d,i}^{(k)}, M_i^{(k)}, N_i^{(k)}\}$;
        $Individual[k] \leftarrow Gene_i^{(k)}$;
    end for
    sort genes in $Individual[k]$ in a descending order based on $|R_{s,d,i}^{(k)}|$ firstly and $N_i^{(k)}$ secondly;
    for all genes in $Individual[k]$ **do**
        compute $a_i^{(k)}$ with $\{R_{s,d,i}^{(k)}, M_i^{(k)}, N_i^{(k)}, b_e^{(k)}\}$;
        if a feasible $a_i^{(k)}$ exists **then**
            update $b_e^{(k)}$ with $a_i^{(k)}$;
        else
            record a blocking for $Individual[k]$;
        end if
    end for
    $P \leftarrow Individual[k]$;
    $k = k + 1$;
end while
{Phase II: Evolution}
$S_{best} \leftarrow \emptyset$;
while GA has not converged **do**
    evaluate individuals in P with F in Eqn. (5);
    evaluate individuals in P with F_η in Eqn. (7);
    $S_{best} \leftarrow$ the fittest one in P;
    evolve P for one generation with adaptive crossover and mutation schemes;
    evaluate the degree of diversity D_P for P;
end while
{Phase III: Service Provisioning}
implement service provisioning for all pending LR_i based on S_{best};
update b_e based on S_{best};
start to collect new pending lightpath requests;
wait for the next service provision time;

IV. Performance Evaluations

We utilize the proposed GA to perform dynamic RMSA in two mesh topologies, the 14-node NSFNET and the 28-node US Backbone (USB). We assume that a frequency slot is 12.5 GHz, and set the transmission reach for BPSK, QPSK, 8-QAM, and 16-QAM signals in it as 10000 km, 5000 km, 2500 km, and 1250 km, respectively, based on the experimental

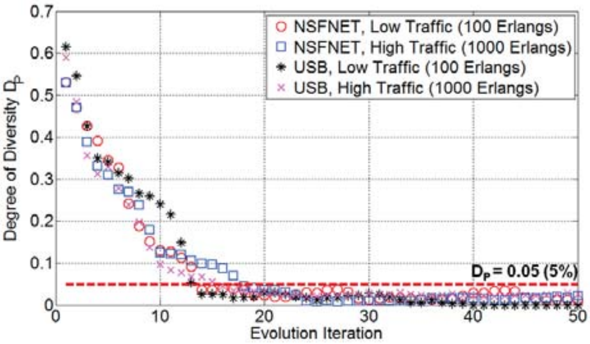

Fig. 3. Convergence performance of the GA-RMSA for two network topologies.

results in [6]. We also assume that the O-OFDM system is deployed in the C-band on each fiber link, and hence the total bandwidth for spectrum allocation is ~ 4.75 THz per fiber that can accommodate 358 frequency slots. The lightpath requests' bandwidth is randomly distributed within 10 - 100 Gb/s, and their s-d pairs are randomly chosen. The requests are generated according to a Poisson process with a rate of λ requests per service provision period, and the duration of a request follows an exponential distribution with an average value of μ service provision periods. Hence, the traffic load can be quantified with $\lambda \cdot \mu$ in Erlangs. The GA uses a population size of 50.

We first evaluate the convergence performance of the GA with the D_P defined in Eqn. (10). We simulate both the low (100 Erlangs) and high (1000 Erlangs) traffic cases. Fig. 3 shows the evolutions of D_P at a service provision time. If we set the threshold of the D_P at 0.05 (5 %) and $G_c = 5$, we can see the GA has converged for all cases after ~ 25 generations. The computation time is within 2 seconds on a personal computer with 2.4 GHz Intel Core 2 CPU and 2 GB RAM. Fig. 4 and 5 illustrate the performance comparisons of the GA-RMSA to two existing algorithms, the Shortest Path and First Fit Spectrum Assignment (SP-FFSA) [11], and the K-Shortest Paths and Balanced Load Spectrum Assignment (KSP-BLSA) [13]. Note that the KSP-BLSA in [13] did not consider the modulation-level assignment, we modify it to a real RMSA algorithm with $K = 4$. The network topology for simulation is the NSFNET. Fig. 4 plots F_s in Eqn. (4) at each service provision time from different dynamic RMSA algorithms. For the low traffic case (100 Erlangs) in Fig. 4(a), the F_s from the GA-RMSA is the smallest throughout the simulations, and compared to SP-FFSA and KSP-BLSA, GA-RMSA can reduce F_s by ~ 20 % on average. For the high traffic case (800 Erlangs) in Fig. 4(b), the network with the GA-RMSA goes to the saturation state with the slowest speed. Similar trend can be observed in Fig. 5 for the comparisons of F_η in Eqn. (7), the maximum bandwidth fragmentation ratio in the network. Therefore, the proposed GA-RMSA reduces bandwidth fragmentation when allocating frequency resources.

Fig. 6 shows the comparisons of the blocking probabilities from different dynamic RMSA algorithms. Compared to SP-FFSA and KSP-BLSA, GA-RMSA provides the smallest blocking probabilities for both topologies. For the NSFNET topology, the blocking probabilities from the GA is almost match with the relaxed lower-bound from the Exhaustive Search RMSA (ES-RMSA). For the US Backbone topology, there is noticeable difference between the results from GA-RMSA and ES-RMSA when the traffic load is smaller than 400 Erlangs. This is due to the reason that the US Backbone topology is much more connected than the NSFNET. Specifically, for a s-d pair in the US Backbone topology, the LDPS routing algorithm returns much less feasible routing paths than the BFPS one, and therefore the GA's search space is limited. This can be improved by designing the genetic encoding with a routing algorithm that can return more feasible routing paths for s-d pairs.

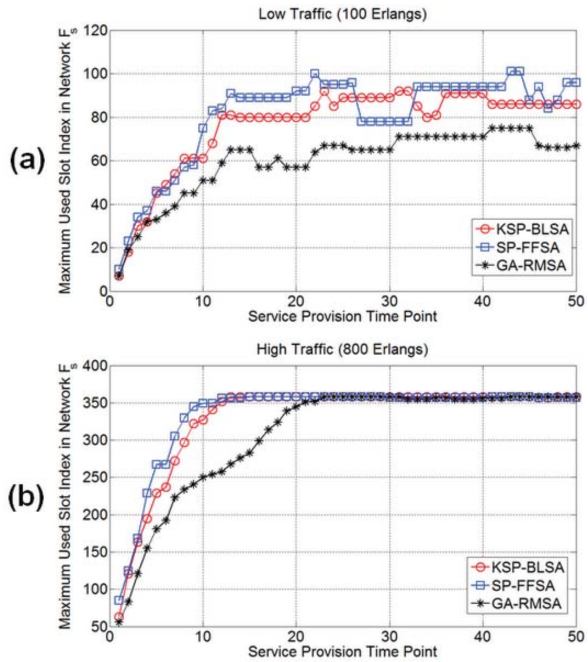

Fig. 4. Evolutions of F_s from three different RMSA algorithms, (a) Low traffic case (100 Erlangs) and (b) High traffic case (800 Erlangs).

V. Conclusion

We developed an adaptive and efficient genetic algorithm (GA) to solve the dynamic RMSA for elastic O-OFDM networks. The algorithm offered an efficient way of serving the dynamic lightpath requests based on the current network status at each service provision time. When the traffic load was low and there was no blocking, the GA minimized the maximum number of slots required on any fiber in the network; otherwise, it minimized the blocking probability. The results from the simulations of dynamic RMSA in the 14-node NSFNET and the 28-node US Backbone topologies showed that the GA could converge within 25 generations even for a high traffic case (1000 Erlangs). Hence, it would be feasible

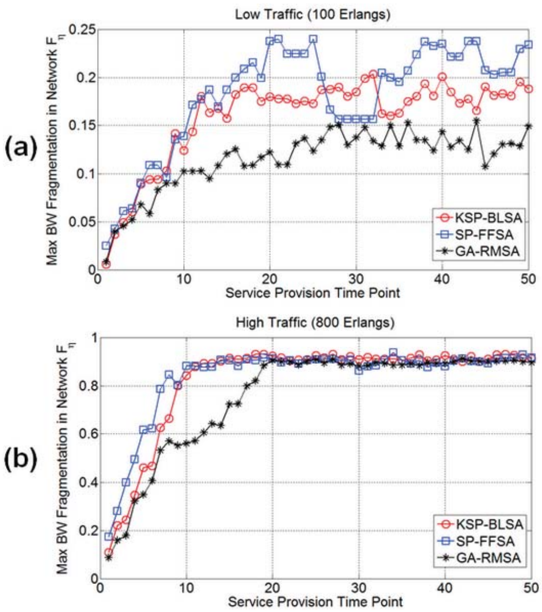

Fig. 5. Evolutions of F_η from three different RMSA algorithms, (a) Low traffic case (100 Erlangs) and (b) High traffic case (800 Erlangs).

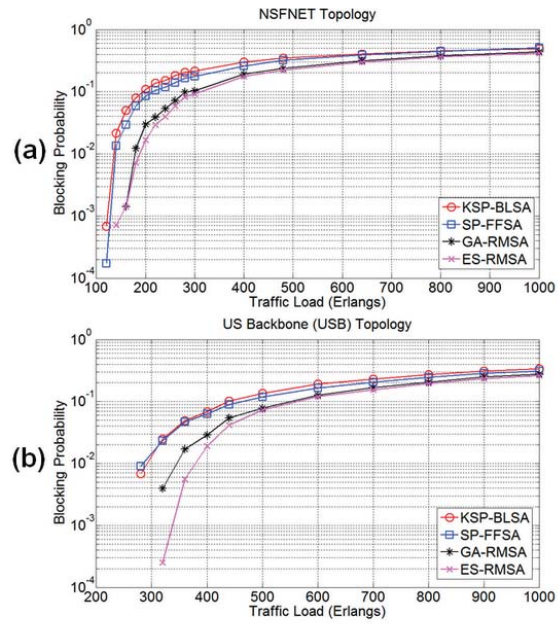

Fig. 6. Blocking probability comparisons for (a) NSFNET topology and (b) US Backbone (USB) Topology.

to implement the GA for dynamic network provisioning. The simulation results also verified that the proposed GA-RMSA had outperformed several existing algorithms by providing more load-balanced network provisioning solutions with lower blocking probabilities. Specifically, for the same traffic load, the GA decreased the maximum number of slots required on any fiber in the network by ~ 20 % on average, and could achieve more than one order-of-magnitude reduction on blocking probability.

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