Dynamic Unicast/Multicast-Capable RMSA in Elastic Optical Networks

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Abstract—Recently, optical orthogonal frequency-division multiplexing (O-OFDM) technology has attracted intensive research interests due to the reason that elastic optical networks can be constructed based on it. In this paper, we propose to solve the dynamic routing, modulation, and spectrum assignment (RMSA) problem for time-variant unicast and multicast connection requests with adaptive genetic algorithms (GAs). The proposed algorithms can be applied to network provisioning, where a network operator needs to figure out an efficient way to serve dynamic connection requests based on current network status. In the GAs, unicast requests are encoded as genes directly, while each multicast request is decomposed into several related unicast requests and then encoded as a group of genes. The GAs then apply adaptive genetic operations to optimize dynamic RMSA of the requests for efficient network provisioning. Simulations are designed with the NSFNET and US Backbone topologies. By using the Poisson traffic model, we verify that the GAs could converge within 25 - 45 generations, even for the high traffic-load scenarios. We also implement several existing dynamic unicast/multicast-capable RMSA algorithms and compared their performance with that of the GAs. The simulation results show that the proposed GAs outperform those existing ones by providing more load-balanced network provisioning solutions with lower request blocking probabilities.

Index Terms—Optical orthogonal frequency-division multiplexing (O-OFDM), Unicast/multicast traffic, Dynamic routing, modulation, and spectrum assignment (RMSA), Adaptive genetic algorithm

I. INTRODUCTION

Recent advances on optical orthogonal frequency-division multiplexing (O-OFDM) technology have demonstrated efficient and elastic bandwidth allocation in the optical layer [1]. As a multi-carrier scenario, O-OFDM achieves ultra-high speed data transmission by grooming the capacities of several narrow-band orthogonal subcarrier slots (bandwidth at a few GHz or smaller). Compared to wavelength-division multiplexing (WDM), O-OFDM provides an intrinsic finer bandwidth allocation granularity as a bandwidth-variable O-OFDM transponder can adjust subcarrier slots and assign just-enough spectral resource to each connection request [2–41]. Together with its flexibility, O-OFDM also brings challenges to future optical networks, as more sophisticated network control and management algorithms would be required for efficient and robust operations, especially in dynamic network environments with time-variant connection requests.

In WDM networks, routing and wavelength assignment (RWA) is the fundamental problem for network planning and provisioning [42–63], while the corresponding problem in O-OFDM networks is routing and spectrum assignment (RSA). In RSA, network operators have to manipulate contiguous subcarrier slots instead of discrete wavelength channels. Previous investigations have addressed the RSA algorithms for both static network planning and dynamic network provisioning [2–41]. However, all RSA/RMSA algorithms mentioned above were only designed for unicast traffic. Note that multicast is widely used to support applications such as teleconferencing, IP television, stock exchanges, and etc. Therefore, it is desired that dynamic RSA/RMSA in future elastic optical networks can also support multicast traffic.

Previously, we proposed to incorporate efficient and effective genetic algorithms (GAs) to solve network planning with static RMSA [2], and demonstrated that our algorithm could outperform existing ones. In this paper, we extend our previous works in [2] to solve RMSA in dynamic network environments with time-variant connections requests. The proposed algorithms can be applied to network provisioning, where a network operator needs to figure out an efficient way to serve dynamic connection requests based on current network status. Moreover, the proposed dynamic RMSA algorithm can support both unicast and multicast connection requests. To adapt to these requirements, we leverage the genetic encoding scheme defined in [2] for static RMSA, define new fitness function, and optimize algorithm design to improve efficiency. Specifically, when traffic load is low, the GA tries to minimize the maximum number of subcarrier slots required on any fiber link in the network; otherwise, its objective is to minimize request blocking. Also, since dynamic RMSA needs to provide real-time solutions for dynamic requests on-the-fly, we design and optimize an adaptive scheme.

The rest of the paper is organized as follows. Section II formulates the problem of dynamic RMSA for unicast/multicast request and defines the objective function. The design of the adaptive GA for dynamic unicast-capable RMSA and the corresponding performance evaluations are discussed in Section III. Section IV extends the dynamic unicast-capable RMSA using GA to support multicast requests and investigates the performance. Finally, Section V summarizes the paper.
II. PROBLEM FORMULATION

A. Network Model

We consider a physical network topology as $G(V, E)$, where $V$ is the node set and $E$ is the fiber link set. We assume the bandwidth of each subcarrier slot is the same, and each fiber link can accommodate $B$ slots at most. The capacity of one subcarrier slot is $C_{slot}$ in Gb/s, when the modulation is BPSK ($M = 1$). Here, $M$ is the modulation level in terms of bits per symbol. Hence, the capacity of one slot is $M \cdot C_{slot}$ for different modulation-levels. In this work, $M$ can be 1, 2, 3 and 4 for BPSK, QPSK, 8-QAM and 16-QAM, respectively.

B. Dynamic RMSA for Unicast Requests

For an unicast request $UR_i$ from node $s$ to $d$ ($s, d \in V$) with a requested capacity as $C_i$, the dynamic RMSA starts with determining the routing path as $R_{s,d,i}$. Here $i$ is the unique ID of the unicast request. The QoT-adaptive modulation assignment then derives the modulation level $M_i$ for $UR_i$ based on the transmission distance of $R_{s,d,i}$. Specifically, we assume that each modulation-level can support a maximum transmission distance based on the receiver sensitivities, and when the distance permits, we always assign the highest modulation level to $UR_i$ for high spectral efficiency. With $M_i$, we can obtain the number of contiguous slots as:

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

where $N_{GB}$ is the number of slots for the guard-band. Finally, we use spectrum assignment 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. Therefore, the dynamic RMSA has to satisfy the constraints from spectrum continuity, spectrum non-overlapping, and spectrum contiguousness. To reflect current network resource utilization, we define a bit-mask $b_e$ for each fiber link $e \in E$, which contains $B$ bits. When $b_e[j] = 1$, the $j$-th slot on $e$ is taken, otherwise $b_e[j] = 0$. We also define a bit-mask $a_i$ with $B$ bits to assist the spectrum assignment of $UR_i$. The bits in $a_i$ follow a similar definition as those in $b_e$. Then, the spectrum assignment of $UR_i$ becomes the problem of finding $N_i$ contiguous bits in $a_i$ to turn on based on all current $b_e$, $e \in R_{s,d,i}$. In this work, we use the First-Fit scheme for spectrum assignment to get $a_i$. The RMSA solution of $UR_i$ can be expressed as $\{R_{s,d,i}, M_i, a_i\}$. We say $UR_i$ is blocked, if we cannot find a feasible $\{R_{s,d,i}, M_i, a_i\}$ for it.

C. Dynamic RMSA for Multicast Requests

For multicast in WDM networks, three schemes have been summarized, 1) Same-wavelength scheme, where the splitting node does not change signal wavelength, 2) Same-output-wavelength scheme, where the splitting node can change signal wavelength, but the wavelengths for different multicast paths are the same, and 3) Any-wavelength scheme, where the wavelengths for different multicast paths can be different. Since we assume there is no spectrum conversion in an O-OFDM network, we only consider the same-spectrum multicast scheme in this work. A multicast request $MR_i$ is modelled with a structure that consists of a source node $s$ and a destination node set $D_m$, where $d \in D_m$ are the members in the multicast group. The dynamic multicast-capable RMSA first determines the routing paths from $s$ to each destination $d \in D_m$, and obtain a multicast path set $\{R_{s,d,i}\}, d \in D_m$. To comply with the same-spectrum scheme, the modulation level $M_i$ of $MR_i$ is the same on different multicast paths, and $M_i$ is chosen according to the longest routing path in the multicast path set $\{R_{s,d,i}\}$. Then, $N_i$ is obtained with Eqn. (1). Finally, the spectrum assignment $a_i$ is determined with the First-Fit scheme, and it is also the same for all paths in $\{R_{s,d,i}\}$. The RMSA solution of $MR_i$ can be expressed as $\{\{R_{s,d,i}, M_i, a_i\}, d \in D_m\}$. $MR_i$ is blocked, if we cannot find a feasible $\{\{R_{s,d,i}, M_i, a_i\}\}$. Note that we do not support partial provisioning of a multicast request, so $MR_i$ is blocked even if we cannot serve only one member in $D_m$.

D. Performance Metrics and Objective Function

Similar as in static RMSA [2], we define $f(\cdot)$ as the function to return the maximum index of used slot on a fiber link $e$. Then, the maximum index of used slot on any link in the network is:

$$F_e = \max(f(e)), \forall e \in E \quad (2)$$

$F_e$ is a performance metric for evaluating RMSA. A smaller $F_e$ reflects a better RMSA in terms of spectrum efficiency, as the traffic is more evenly distributed in the network. Nevertheless, $F_e$ approaches to $B$, when the traffic load is high and frequent request blocking starts to happen. This is an unique case for dynamic RMSA since we cannot adjust total spectrum resource on fiber links on-the-fly in dynamic network provisioning. To emulate service provisioning in practical network operations, we assume that instead of being served immediately upon arrival, the requests are collected and served at discrete service provision time in a periodic manner. Hence, another performance metric $F_b$ is defined as the number of blocked requests at each service provision time. By considering these two metrics together, the Objective of dynamic RMSA is to minimize fitness $F$ at any service provision time:

$$\min F = F_e + H \cdot u(F_b) + F_b \quad (3)$$

where $H > 0$ is a large punishment coefficient to discourage RMSA solutions that involve request blocking, and $u(\cdot)$ is the unit step function that $u(x) = 1$ for $x > 0$, otherwise $u(x) = 0$.

III. ADAPTIVE GENETIC ALGORITHM FOR DYNAMIC UNICAST-CAPABLE RMSA

A. Genetic Encoding

Genetic algorithm (GA) is a metaheuristic that mimics the natural evolution in biological world. Algorithm I describes the detailed procedures of the proposed adaptive GA for dynamic unicast-capable RMSA. Before provisioning, the feasible routing paths between each $s$-$d$ pair in $G(V, E)$ are pre-determined
with a link-disjoint path search (LDPS) algorithm. \( \mathcal{R}_{s,d} \) is defined as the set of feasible routing paths from \( s \) to \( d \). We use a routing path table to map each path to an unique R-Index.

For each pending request \( UR_i \) for a capacity \( C_i \) that needs to be served at current service provision time, the dynamic RMSA starts from randomly selecting a feasible routing path \( R_{s,d} \) from \( \mathcal{R}_{s,d} \) and it then determines \( M_i \), \( N_i \), and \( \alpha_i \) according to the procedures discussed in Section II.B. If a feasible RMSA solution can be found for \( UR_i \), it is encoded as a gene \( \mathfrak{G}_i = \{ R_{s,d,i}, M_i, N_i \} \); otherwise, \( UR_i \) is blocked. After repeating the above procedures for all \( L \) pending requests, we form an individual chromosome \( \mathfrak{I} \) that contains \( L \) genes. Finally, we select different routing paths for some/all of the genes to form different individuals. \( \mathfrak{I} \) represents the population, i.e. the set of individuals \( \mathfrak{I} \), and \( |\mathfrak{I}| \) is the size of the population in the GA. We will elaborate on the details of genetic operations in the next subsection.

B. Adaptive Genetic Operations

For each individual \( \mathfrak{I} \) and the corresponding network status \( \{ b_{(c)} \}, c \in E \) associated with it, we calculate the fitness \( F \) with Eqn. (3). Then, based on fitness \( F \), the GA implements typical genetic operations, such as selection, crossover, and mutation in iterations (i.e. evolution generations), to optimize the dynamic RMSA solutions.

We design the selection operation with the tournament selection to select pairs of individuals (e.g. parents) from the current generation for crossover. The tournament selection involves running several tournaments among a fixed number of individuals that are randomly chosen from the population. The winner of each tournament, i.e. the fittest one in the group, is selected. We then take pairs randomly from the selected individuals, and let them crossover to generate their children. The crossover is a multi-point operation on the gene-level, where certain number of parents’ genes are picked out and swapped at random locations. The actual number of genes to swap is calculated with \( L \cdot p_c \), where \( L \) is the number of genes (i.e. pending requests) in the individual, and \( p_c \) is the crossover rate. From the RMSA perspective of view, crossover is to swap the routing and modulation assignments of specific pending requests between two feasible dynamic RMSA solutions for current service provision time. We keep the population size constant during evolution, and \( |\mathfrak{I}| \) fittest individuals from the chromosome pool of parents and children are chosen as the next generation. These individuals then go through the mutation phase, in which certain number of their genes are modified randomly. Similarly, the actual number of genes to mutate in each individual is calculated with \( L \cdot p_m \), where \( p_m \) is the mutation rate. Specifically, we mutate a gene \( \mathfrak{G}_i \) by modifying its routing and modulation assignments to other feasible ones randomly. After crossover and mutation, the spectrum assignment is performed again for each individual to update its fitness. To improve the efficiency of the GA, we adopt an adaptive mechanism to adjust \( p_c \) and \( p_m \) dynamically based on the individuals’ fitness.

Algorithm 1 Adaptive Genetic Algorithm for Dynamic Unicast-Capable RMSA

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>get current network status ( b_c, \forall c \in E );</td>
</tr>
<tr>
<td>2</td>
<td>( \mathfrak{I} = \emptyset );</td>
</tr>
<tr>
<td>3</td>
<td>\textbf{while} (</td>
</tr>
<tr>
<td>4</td>
<td>( b_{(c)} = b_c, \forall c \in E );</td>
</tr>
<tr>
<td>5</td>
<td>{ Construct an Individual Chromosome ( \mathfrak{I} ) };</td>
</tr>
<tr>
<td>6</td>
<td>( \mathfrak{I} = \emptyset );</td>
</tr>
<tr>
<td>7</td>
<td>\textbf{for} all pending requests ( UR_i ) \textbf{do}</td>
</tr>
<tr>
<td>8</td>
<td>select ( R_{s,d,i} ) from ( \mathcal{R}_{s,d} ) randomly;</td>
</tr>
<tr>
<td>9</td>
<td>compute ( M_i ) and ( N_i ) based on ( { R_{s,d,i}, C_i } );</td>
</tr>
<tr>
<td>10</td>
<td>construct a gene ( \mathfrak{G}<em>i = { R</em>{s,d,i}, M_i, N_i } );</td>
</tr>
<tr>
<td>11</td>
<td>insert ( \mathfrak{G}_i ) into ( \mathfrak{I} );</td>
</tr>
<tr>
<td>12</td>
<td>\textbf{end for}</td>
</tr>
<tr>
<td>13</td>
<td>\textbf{for} all genes ( { \mathfrak{G}_i } ) in ( \mathfrak{I} ) \textbf{do}</td>
</tr>
<tr>
<td>14</td>
<td>find ( \alpha_i ) based on ( { R_{s,d,i}, N_i, b_{(c)} } ) using First-Fit;</td>
</tr>
<tr>
<td>15</td>
<td>\textbf{if} a feasible ( \alpha_i ) exists \textbf{then}</td>
</tr>
<tr>
<td>16</td>
<td>update ( { b_{(c)} }, c \in E ) with ( \alpha_i );</td>
</tr>
<tr>
<td>17</td>
<td>update ( \mathfrak{G}<em>i = { R</em>{s,d,i}, M_i, \alpha_i } );</td>
</tr>
<tr>
<td>18</td>
<td>\textbf{else}</td>
</tr>
<tr>
<td>19</td>
<td>record a blocking for ( \mathfrak{G}_i ) in ( \mathfrak{I} );</td>
</tr>
<tr>
<td>20</td>
<td>update ( \mathfrak{G}<em>i = { R</em>{s,d,i}, M_i, \emptyset } );</td>
</tr>
<tr>
<td>21</td>
<td>\textbf{end for}</td>
</tr>
<tr>
<td>22</td>
<td>insert ( { \mathfrak{I}, { b_{(c)} } } ) into ( \mathfrak{I} );</td>
</tr>
<tr>
<td>23</td>
<td>\textbf{end while}</td>
</tr>
<tr>
<td>24</td>
<td>{ Phase II: Evolution }</td>
</tr>
<tr>
<td>25</td>
<td>( \mathfrak{I}_{\text{best}} = \emptyset );</td>
</tr>
<tr>
<td>26</td>
<td>\textbf{while} GA has not converged \textbf{do}</td>
</tr>
<tr>
<td>27</td>
<td>compute ( F ) for ( { \mathfrak{I}, { b_{(c)} } } ) in ( \mathfrak{I} );</td>
</tr>
<tr>
<td>28</td>
<td>\textbf{calculate} ( F_0 ) for individuals ( { \mathfrak{I}, { b_{(c)} } } ) in ( \mathfrak{I} );</td>
</tr>
<tr>
<td>29</td>
<td>( \mathfrak{I}_{\text{best}} \leftarrow ) the fittest one in ( \mathfrak{I} );</td>
</tr>
<tr>
<td>30</td>
<td>\textbf{end while}</td>
</tr>
<tr>
<td>31</td>
<td>{ Phase III: Service Provisioning }</td>
</tr>
<tr>
<td>32</td>
<td>provision all pending ( UR_i ) based on ( \mathfrak{I}_{\text{best}} );</td>
</tr>
<tr>
<td>33</td>
<td>update ( b_c ) based on ( \mathfrak{I}_{\text{best}} );</td>
</tr>
<tr>
<td>34</td>
<td>\textbf{start to collect new pending requests};</td>
</tr>
<tr>
<td>35</td>
<td>\textbf{wait for the next service provision time};</td>
</tr>
</tbody>
</table>

C. Algorithm Convergence Condition

To evaluate the GA’s convergence performance, we define its degree of diversity as:

\[
D_P = \frac{2}{|\mathfrak{I}|(|\mathfrak{I}| - 1)} \sum_{k_1=1}^{[|\mathfrak{I}|]} \sum_{k_2=k_1+1}^{[|\mathfrak{I}|]} \frac{d(k_1, k_2)}{L} \tag{4}
\]

where \( d(k_1, k_2) \) returns the number of different genes between individuals \( \mathfrak{I}_{k_1} \) and \( \mathfrak{I}_{k_2} \) with \( L \) genes. We can claim that the GA has converged if \( D_P \) has been lower than a pre-set threshold for five generations or more.
D. Performance Evaluations

We evaluate the proposed dynamic unicast-capable RMSA with GA (UC-RMSA-GA) in two mesh topologies, the 14-node NSFNET and the 28-node US Backbone. The topologies are shown in Fig. 1. We set the bandwidth of a subcarrier slot as 12.5 GHz, and assume that 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. Since the total bandwidth of the C-band is around 4.475 THz, we set $B = 358$ as the number of slots on each fiber. The unicast requests are generated using the Poisson traffic model. The capacity $C_i$ of each request is randomly chosen within 10 - 100 Gb/s, and their $s$-$d$ pairs are randomly selected too. At each service provision time, the GA uses a population size $|P| = 50$.

Fig. 2 shows the convergence performance of UC-RMSA-GA when the traffic load is as high as 1000 Erlangs. We choose the threshold of $D_P$ as 0.05, according to the normal case for convergence evaluation. It can be seen that for both topologies, the algorithm has converged after around 25 generations. The corresponding computation time is within 2 seconds on a computer with 2.4 GHz Intel Core 2 CPU and 2 GB RAM. Hence, at each service provision time, the proposed UC-RMSA-GA's computation overhead is tolerable for real-time dynamic provisioning.

We implement two existing algorithms, the shortest path and First-Fit spectrum assignment (SP-FFSA), and the K-shortest paths and balanced-load spectrum assignment (KSP-BLSA), as the benchmark algorithms. Note that both algorithms were proposed as RSA that did not consider modulation assignment, we modify them to RMSA algorithms. Fig. 3 shows the comparisons on request blocking probability. Among the three dynamic RMSA algorithms, UC-RMSA-GA achieves the lowest request blocking probabilities in both topologies.
IV. ADAPTIVE GENETIC ALGORITHM FOR DYNAMIC MULTICAST-CAPABLE RMSA

A. Genetic Encoding and Operations

To extend UC-RMSA-GA to support multicast, we take a multicast request $MR_i = \{s, D_m, C_i\}$ and decompose into a related unicast request set $\{\{s, d, C_i\}, d \in D_m\}$. Then, we encode each unicast request in the set as a gene with the same procedures discussed in Section III.A. Note that to comply with the same-spectrum multicast scheme, the assignment of modulation level $M_i$ is kept the same for all related unicast requests in the set, according to the longest routing path in the multicast path set $\{R_{s,d}\}, d \in D_m$. We use $\{R_{s,d}\}$ to construct a multicast-tree for $MR_i$. Finally, the spectrum assignment $a_i$ is determined for each related unicast request (i.e. gene) with the First-Fit scheme based on the multicast-tree. $a_i$ is the same for all related unicast requests derived from the same multicast request, their modulation and spectrum assignments are always the same throughout the optimization. For example, if crossover or mutation causes a change on the distance of the longest routing path in $\{R_{s,d}\}, d \in D_m$ and $M_i$ needs to be updated, the genes of all related unicast requests are updated accordingly. Same thing applies to the spectrum assignment $a_i$. The dynamic RMSA solutions are still evaluated with the fitness in Eqn. (3).

B. Performance Evaluations

The topologies used for simulations are still the NSFNET and US Backbone as shown in Fig. 1. The simulation parameters are similar to those for the unicast scenario in Section III.D. To setup a multicast group, we first select $s$ randomly and then determine $D_m$ based on a multicast-join probability $p_j$. Specifically, for all nodes ($v \in V, v \neq s$), they are selected to join the multicast group with a probability of $p_j$. Hence, the size of $D_m$ is variable in simulations. At each service provision time, the GA uses a population size $|\mathcal{P}| = 100$. The multicast requests are also generated using the Poisson traffic model. Note that since one multicast request associates with multiple related unicast ones, the multicast simulations handle more RMSA at each service provision time than the unicast ones, under the same traffic load in Erlangs.

We then implement two multicast-capable RMSA algorithms, based on the shortest path tree (MC-RMSA-SPT) and the minimal spanning tree (MC-RMSA-MST), as the benchmark algorithms. Specifically, we modify the MC-RSA algorithms proposed in [5] to consider modulation assignment and implement them as MC-RMSA algorithms. Fig. 4 and 5 shows the comparisons on request blocking probability, and we test two multicast-join probabilities as $p_j = 0.2$ and $p_j = 0.3$. The results show that MC-RMSA-GA offers the lowest request blocking probabilities, among the three MC-RMSA algorithms.

V. CONCLUSION

We put forward adaptive genetic algorithms (GAs) to address dynamic unicast/multicast-capable RMSA in elastic optical networks that have time-variant connection requests. The proposed algorithms offered efficient ways of serving the dynamic multicast/unicast requests based on the current network status at each service provision time. Simulations were designed with the 14-node NSFNET and the 28-node US Backbone topologies. By using the Poisson traffic model, we verified that the GAs could converge within 25 - 45 generations, even for high traffic-load scenarios. The computation time for each provisioning is well controlled within 9 seconds on a normal personal computer with 2.4 GHz Intel Core 2 CPU and 2 GB RAM. Hence, the computation overhead from the GAs was not significant, and it is feasible to implement the GAs for real-time network provisioning.
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