Scalable Network Planning for Elastic Optical Orthogonal Frequency Division Multiplexing (OFDM) Networks

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***Abstract*—We propose to achieve scalable O-OFDM network planning with a genetic algorithm (GA) that operates in an adaptive way for high optimization efficiency. When the network topology and lightpath requests are given, the GA encodes the routing, spectrum and modulation assignments (RSMA) as genes and optimizes them iteratively. Both the crossover and mutation schemes in our proposed GA operate adaptively based on the fitness of individuals. Specifically, when the individuals are not fit yet, their genes can be modified significantly with crossover and mutation. On the other hand, for individuals that are already fit, we limit the crossover and mutation rate to avoid chromosomal disruption. The simulation results with the NSFNET topology and up to 1000 lightpath requests show that the proposed adaptive GA converges faster with better optimization performance, when comparing to a non-adaptive one. For the 1000-request case, the proposed algorithm can converge with a relatively small population size (e.g. 50) within 80 generations.**

***Index Terms*—Network planning, Optical orthogonal frequency-division multiplexing (O-OFDM), Routing, spectrum and modulation assignment (RSMA), Adaptive genetic algorithm**

I. Introduction

Due to the exponential growth of Internet traffic, more and more research works have been focused on the development of highly scalable networking technologies. With almost unlimited bandwidth [1], optical fiber has been considered as a promising media for ultra-high-capacity data transmission. While dense wavelength division multiplexing (DWDM) technology can easily achieve over 10 Tb/s throughput on a single strand of fiber [2], how to facilitate efficient and flexible access to such a numerous bandwidth is still an open question. Nowadays, optical orthogonal frequency division multiplexing (O-OFDM) [3,4] and its applications in optical networks have attracted intensive research interests. As illustrated in Fig. 1, O-OFDM systems allocate bandwidth based on contiguous subcarrier channels that are overlapped in the frequency domain. Due to the orthogonality of these subcarriers, data modulations on them can still be demodulated at the receiving end without interference [4]. Therefore, O-OFDM has a much finer bandwidth allocation granularity, compared to fixed-grid DWDM scenarios. As a bandwidth-variable (BV) OFDM transponder [5] can assign just-enough number of subcarrier frequency slots to serve a lightpath request, the concept of spectrum-sliced elastic optical network can be realized. Moreover, the modulation scheme of each subcarrier channel can be adaptive to the transmission reach or the quality of transmission (QoT) requirement [6,7]. Recently, a few practical O-OFDM systems have already been experimentally demonstrated. [5,8,9]. Shieh *et. al.* has demonstrated 107 Gb/s O-OFDM transmission over 1000 km standard single-mode fiber (SSMF) in [8]. A multi-flow, multi-rate, and multi-reach O-OFDM system for elastic spectral routing up to 400 Gb/s has been developed in [5]. The aggregation of 100 and 400 Gb/s O-OFDM lightpaths into a 1 Tb/s super channel has also been achieved [9].

Together with all these theoretical and practical benefits, O-OFDM technology also brings challenges to the planning of future optical networks. Its elastic nature has determined that more sophisticated network design procedures would be necessary. Specifically, network operators have to allocate contiguous subcarrier slots instead of wavelength channels for resource assignments. Moreover, they need to worry about choosing proper modulation scheme and make tradeoff between transmission performance and bandwidth efficiency. To address all these challenges, we have to develop effective routing, spectrum, and modulation assignment (RSMA) algorithms for scalable network planning. Given a set of lightpath requests and the network topology, the network planning with RSMA is known as non-polynomial (NP)-complete [10]. In [10], Christodoulopoulos *et. al.* formulated several integer linear programming (ILP) models for RSMA and proposed a simulated annealing (SA) based heuristics for reducing the computation complexity. Inspired by WDM network planning with mixed line rates [11], a routing and spectrum assignment (RSA) algorithm was proposed based on shortest path routing and first-fit spectrum assignment [12]. A bandwidth-efficient and distance-adaptive RSMA has been developed in [13], which examines K shortest paths for each lightpath request and picks the one with the lowest available contiguous subcarrier slots. However, most of these approaches can become time-consuming when the network topologies under consideration are large-scale mesh networks and/or the number of the lightpath requests is relatively large (e.g. 1000).

In this paper, we propose to achieve scalable O-OFDM network planning with a genetic algorithm (GA) that operates in an adaptive way for high optimization efficiency. Both the

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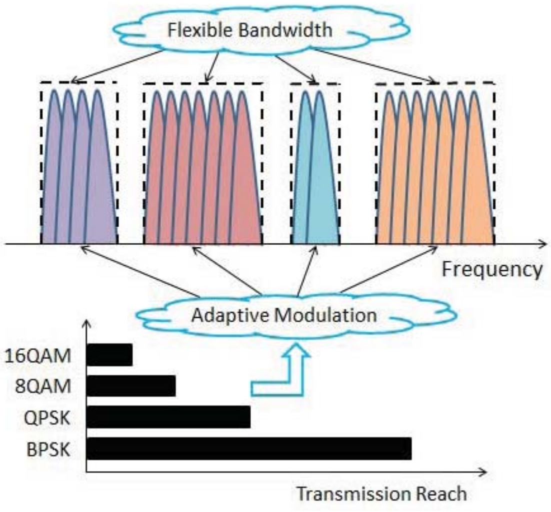

Fig. 1. Elastic bandwidth allocation in O-OFDM systems.

crossover and mutation schemes in our proposed GA operate adaptively according to the fitness of individuals. Specifically, when the individuals are not fit yet, their genes can be modified significantly with crossover and mutation. But for individuals that are already fit, we limit the crossover and mutation rate to avoid chromosomal disruption. The simulation results with the NSFNET topology and up to 1000 lightpath requests show that the proposed adaptive GA converges faster with better optimization performance, when comparing to a non-adaptive one. The rest of the paper is organized as follows. We formulate the elastic network planning with GA in Section II. The design of the GA is discussed in Section III, and Section IV shows the performance evaluation results of the proposed algorithm. Finally, Section V summarizes the paper.

II. Problem Formulation

A. Design Considerations of O-OFDM Network Planning

For the planning of O-OFDM based elastic optical networks, we assume that the lightpath requests are known a priori. The physical network topology is $G(V,E)$, where V is the node set and E is the set of fiber links. We assume the bandwidths of spectrum slots are identical as 12.5 GHz in the network, and define C as the capacity of a slot when the modulation scheme is BPSK. Therefore, for a lightpath request LR_i, if we assign a modulation level of M_i bits per symbol, the capacity of a slot is $M_i \cdot C$. Here, M_i can be 1, 2, 3, 4 for BPSK, QPSK, 8 QAM and 16 QAM modulation schemes, respectively. The choice of M_i is based on the length of the routing path for LR_i. Based on the results in literatures [6,14], we assume that the transmission reach for BPSK, QPSK, 8 QAM, and 16 QAM modulated signals are 10000 km, 5000 km, 2500 km, and 1250 km, respectively. Define the request bandwidth of LR_i as BW_i, then the number of contiguous slots we need to assign is:

$$N_i = \lceil \frac{BW_i}{M_i \cdot C} \rceil + N_g \tag{1}$$

where N_g is a constant number as the number of frequency slots for guard-band between two adjacent lightpaths. During the slot allocation, we have to make sure that both the spectrum continuity and the spectrum non-overlapping constraints have to be satisfied.

B. Genetic Encoding

In GA based optimizations, genetic encoding corresponds to the decomposition of the solution space to several dimensions. For each LR_i from s to d ($s, d \in V$), we pre-calculate the feasible routing paths with a K-shortest Link-Disjoint Search (LDPS) algorithm [15] and put them in the path set $RSet_{s,d}$. The genetic encoding represents a possible RSMA for LR_i as a gene, and combines the genes for all LR_i as an individual chromosome (i.e. feasible solution). Note that if the network planning need to accommodate M lightpath requests, each individual chromosome contains M genes. Each of these genes in individual k is a combination of routing path $R^{(k)}_{s,d,i}$, number of assigned spectrum slots $N^{(k)}_i$, and the selected modulation scheme $M^{(k)}_i$.

C. Spectrum Assignments and Fitness Function

For each individual k, the spectrum assignment is done with a gene-by-gene way in a descending order based on $|R^{(k)}_{s,d,i}|$ (i.e. routing path length) and then $N^{(k)}_i$. The spectrum allocation is done with the *First-Fit* scheme. When the spectrum assignment for an individual k is done, we evaluate it with a fitness function as

$$F_k = max(f(e)), \forall e \in E \tag{2}$$

where $f(\cdot)$ is the function to return the index of the last used slot on a link e in $G(V,E)$. In the GA based optimization shown in *Algorithm 1*, we try to find the RSMA that can minimize the fitness in Eqn. (2).

III. Adaptive Genetic Algorithm for O-OFDM Network Planning

When the path set $RSet_{s,d}$ are determined for each lightpath request LR_i, an initial population with a size of $PSize$ is generated as illustrated in the *Phase I* of *Algorithm 1*. The rest of the GA involves typical genetic operations, such as selection, crossover, and mutation in iterations (i.e. evolution generations). In the evolution, we adopt an adaptive mechanism to dynamically change the crossover and mutation rates according to the fitness of an individual. Basically, the fitter an individual is, the less possible it will be modified. By doing so, the individuals that are already fit are preserved with relatively low crossover and mutation rates.

A. Selection Operation

The selection operator (SO) is designed to select pairs of individuals from the current generation for crossover. We perform SO based on the *Tournament Selection* algorithm [16]. This algorithm runs several tournaments among a fixed number of individuals that are randomly chosen from the current population, based on their fitness. The winner of each tournament is selected.

Algorithm 1 Adaptive Genetic Algorithm for RSMA

Output: Optimal RSMA solution S_{opt}

{Phase I: Construct the Initial Population}

$S_{opt} \leftarrow \emptyset$;
$P \leftarrow \emptyset$;
$k = 1$;
while $k < PSize$ **do**
  $Individual[k] \leftarrow \emptyset$;
  for all lightpath requests LR_i **do**
    select $R_{s,d,i}^{(k)}$ from $RSet_{s,d}$;
    compute $M_i^{(k)}$ and $N_i^{(k)}$ based on $R_{s,d,i}^{(k)}$ and 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
  $P \leftarrow Individual[k]$;
  $k = k + 1$;
end while

{Phase II: Evolution for Optimized Solution}

$G = 1$;
while $G < G_{max}$ AND (GA hasn't converged) **do**
  evaluate individuals in P with Eqn. (2);
  $S_{opt} \leftarrow$ the fittest one in P;
  evolve P for one generation with adaptive crossover and mutation schemes;
  $G = G + 1$;
end while

B. Crossover and Mutation Operations

After the parents are selected out, we take pairs randomly and apply the crossover operation on them to get children. The crossover is done as a multi-point operation, where multiple genes are selected and swapped at random locations. We adopt an adaptive mechanism to change the crossover rate p_c (i.e. the possibility that a gene is selected for crossover) according to the parents' fitness [17]:

$$p_c = \begin{cases} a_1 \frac{F_{k_1,k_2} - min(F)}{mean(F) - min(F)}, & F_{k_1,k_2} \leq mean(F), \\ a_2, & F_{k_1,k_2} > mean(F) \end{cases} \tag{3}$$

where F is the set of the fitness F_k of selected individuals for crossover, $F_{k1,k_2} = min(F_{k1}, F_{k_2})$ is the minimum fitness of the two parents, and a_1 and a_2 are constant coefficients within [0,1]. We then select $PSize$ fittest individuals from the chromosome pool made up by parents and children, as the next generation, and keep the population size constant. The selected individuals then go through the mutation phase, in which the genes of an individual can be changed randomly based on an adaptive mutation rate [17]:

$$p_m = \begin{cases} a_3 \frac{F_k - min(F)}{mean(F) - min(F)}, & F_k \leq mean(F), \\ a_4, & F_k > mean(F) \end{cases} \tag{4}$$

where F is the set of the fitness F_k of selected individuals for mutation, F_k is the fitness of the individual for mutation, and a_3 and a_4 are constant coefficients within [0,1]. Eqn. (3) and (4) determines that p_c and p_m are zeros for all of the fittest individuals in a population. When there are more than one fittest individuals, all of them will be unmodified survivors in the next generation. This, however, may cause premature convergence. To solve this, we only preserve one of the fittest individuals and introduce a default mutation rate p_{m_0} for the rest of them to force mutation. For crossover, the same scenario will be applied to use a default non-zero crossover rate p_{c_0} for increasing genetic diversity.

IV. Performance Evaluation

We evaluate the proposed adaptive GA with simulations using a 14-node, 22-link NSFNET topology. Both the s-d pair and the bandwidth of a lightpath request are randomly selected. Table I shows the simulation parameters. Fig. 2 shows the comparisons of evolutions of the adaptive and non-adaptive GA for 800- and 1000-request cases. It can be seen that in both cases, the adaptive GA achieves a better optimization results (i.e. smaller best fitness) and converges faster. For both cases, the adaptive GA converges within 80 generations, but the non-adaptive one may need more than 90 generations to converge. Fig. 3 shows the best fitness we can get from the adaptive GA for 100, 300, 500, 800 and 1000-request cases. Table II shows the comparisons of the optimization performance for adaptive and non-adaptive GA, in terms of maximum, minimum, and average values of the achievable best fitness. For each of the request case, 10 simulates are executed. It can be seen that except for the 100-request case, the adaptive GA always achieves a smaller minimum and average values of the best fitness, when comparing to the non-adaptive one.

V. Conclusion

We achieved scalable O-OFDM network planning with a genetic algorithm (GA) that operates in an adaptive way. When the network topology and requests were given, we encoded the routing, spectrum and modulation assignments (RSMA) as genes and optimized them with the GA in iterations. Both the crossover and mutation schemes in our proposed GA operated adaptively based on the fitness of individuals. The simulation results with the NSFNET topology and up to 1000 lightpath requests showed that the proposed adaptive GA converged faster with better optimization performance, when comparing to a non-adaptive one. For the 1000-request case, the proposed algorithm could converge with a relatively small population size (e.g. 50) within 80 generations.

Acknowledgments

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References

[1] R. Ramaswami, and et al., *Optical Networks A Practical Perspective (Second Edition):* San Diego, CA: Academic Press, 2002.

[2] K. Fukuchi, and et al., "10.92-Tb/s (273*40-Gb/s) triple-band/ultra-dense WDM optical repeatered transmission experiment," *in Proc. of OFC 2001*, paper PD24, Mar. 2001.

TABLE I
SIMULATION PARAMETERS

Bandwidth of a spectrum slot	12.5 GHz
Modulation formats	BPSK, QPSK, 8QAM, 16QAM
Range of lightpath requests' bit-rates	10$\sim$100 Gb/s
Number of lightpath requests	100, 300, 500, 800, 1000
Size of population	50
Maximum evolution generations	100

TABLE II
PERFORMANCE COMPARISONS OF ADAPTIVE (ADGA) AND NON-ADAPTIVE (NAGA) GENETIC ALGORITHMS

		100-Request		300-Request		500-Request		800-Request		1000-Request	
		ADGA	NAGA	ADGA	NAGA	ADGA	NAGA	ADGA	NAGA	ADGA	NAGA
Best Fitness	Max	37	36	94	94	162	165	261	262	307	315
	Min	34	34	89	90	156	158	247	251	294	301
	Average	35.5	34.8	91.3	92.5	158.7	161.3	251.4	255.4	298.1	309.5

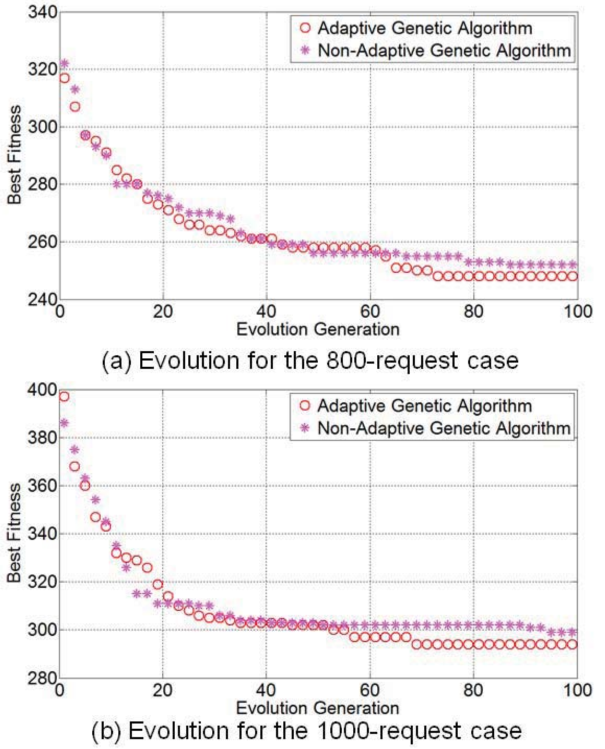

Fig. 2. Evolutions of genetic algorithms for (a) 800-request case, and (b) 1000-request case.

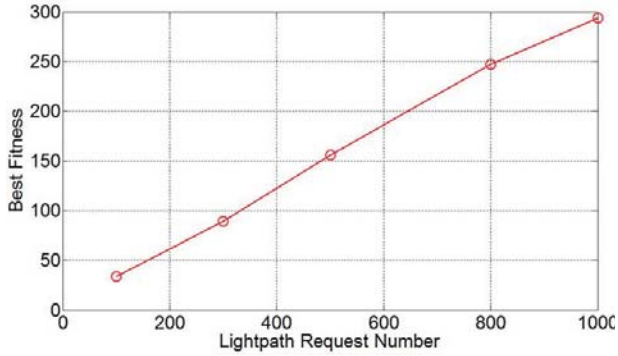

Fig. 3. Best fitness from the adaptive genetic algorithm for 100, 300, 500, 800, and 1000-request cases.

[3] W. Shieh, and et al., "Transmission experiment of multi-gigabit coherent optical OFDM systems over 1000 km SSMF fiber," *IEE Electron. Lett.*, vol. 43, pp. 183-185, 2007.
[4] J. Armstrong, "OFDM for optical communications," *J. Lightwave Technol.*, vol. 27, pp. 189-204, Feb. 2009.
[5] H. Takara, and et al., "Experimental demonstration of 400 Gb/s multi-flow, multi-rate, multi-reach optical transmitter for efficient elastic spectral routing," *in Proc. of ECOC 2011*, paper Tu.5.A.4, Sept. 2011.
[6] A. Bocoi, and et al., "Research-dependent capacity in optical networks enabled by OFDM," *in Proc. of OFC 2009*, paper OMQ4, Mar. 2009.
[7] B. Kozicki, and et al., "Distance-adaptive spectrum allocation in elastic optical path network (SLICE) with bit per symbol adjustment," *in Proc. of OFC 2010*, paper OMU3, Mar. 2010.
[8] W. Shieh, and et al., "107 Gb/s coherent optical OFDM transmission over 1000-km SSMF fiber using orthogonal band multiplexing," *Opt. Exp.*, vol. 16, pp. 6378-6386, 2008.
[9] B. Kozicki, and et al., "Optical path aggregation for 1-Tb/s transmission in spectrum-sliced elastic optical path network," *IEEE Photon. Technol. Lett.*, vol. 22, pp. 1315-1317, Sept. 2010.
[10] K. Christodoulopoulos, and et al., "Elastic bandwidth allocation in flexible OFDM-based optical networks," *J. Lightwave Technol.*, vol. 29, pp. 1354-1366, May 2011.
[11] A. Nag, and et al., "Optical network design with mixed line rates and multiple modulation formats," *J. Lightwave Technol.*, vol. 28, pp. 466-475, Feb. 2010.
[12] W. Zheng, and et al., "On the spectrum-efficiency of bandwidth-variable optical OFDM transport networks," *in Proc. of OFC 2010*, paper OWR5, Mar. 2010.
[13] M. Jinno, and et al., "Distance-adaptive spectrum resource allocation in spectrum-sliced elastic optical path network," *IEEE Commun. Mag.*, vol. 48, pp. 138-145, Aug. 2010.
[14] O. Rival, and et al., "Impact of inter-channel nonlinearities on the planning of 25-100 Gb/s elastic optical networks," J. Lightwave Technol., vol. 29, pp. 1326-1334, May 2011.
[15] W. Hoffman, and et al., "A method for the solution of the N-th best path problem," *J. ACM*, vol. 6, pp. 506-514, 1959.
[16] B. Miller, and et al., "Genetic algorithms, tournament selection, and effects of noise," *Complex Syst.*, vol. 9, pp. 193-212, Jul. 1995.
[17] M. Srinivas, and et al., "Adaptive probabilities of crossover and mutation in genetic algorithms", *IEEE Trans. Syst. Man Cyber.*, vo. 24, pp. 656-667, Apr. 1994.