Genetic Algorithms for Designing Energy-Efficient Optical Transport Networks with Mixed Regenerator Placement

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***Abstract*—We design genetic algorithms (GA) to solve the mixed regenerator placement (MRP) problem of lightpaths with different lengths in optical transport networks, and investigate their performance with numerical simulations. By incorporating a theoretical model that can estimate BER changes hop-by-hop along lightpaths, the GA encodes the placements of 1R/2R/3R at intermediate regeneration sites as genes, and takes quality-of-transmission (QoT) and energy-efficiency as the fitness functions. With a relatively small population size (e.g. 30-50), the algorithms obtain multiple qualified MRP results that can satisfy both the QoT and energy requirements within 32 generations, for lightpaths with lengths up to 28 hops. Two crossover and two mutation operators are investigated within the GA. By adjusting the possibilities of the crossover and mutation intelligently, the adaptive scheme outperforms the uniform one by getting a larger percentage of fit individuals. We also propose two selection operators, and demonstrate an adjustable tradeoff between QoT and energy-efficiency.**

***Index Terms*—Genetic algorithm, Mixed regenerator placement, Translucent optical networks, Energy-efficient optical networks.**

I. Introduction

There has been an overwhelming growth of Internet traffic over the past decade. While the consequent bandwidth demands have stimulated intensive research on efficient and scalable optical transport networks, one of the major technical difficulties is still the physical layer limitation. In opaque optical networks, network operators have been relying on optical-electronic-optical (O/E/O) 3R (Reamplification, Reshaping, and Retiming) regeneration at every switching node to increase transmission reach. Nevertheless, due to the fact that O/E/O 3R are usually expensive and power-hungry, especially for data-rates at 10 Gb/s and beyond [1], operators have to mitigate their network structures from opaque to translucent, for reducing capital expenditures (CAPEX) and operational expenditures (OPEX) [2].

The objective of translucent optical network design is to minimize the number of O/E/O 3R in networking systems without compromising transmission performance. To address this issue, numbers of approaches have been proposed recently [3-10]. Most of them assume that the signal quality gets restored after a regenerator, and only place a 3R at where the signal's Q-factor or bit-error-rate (BER) is right above the performance threshold or there is a wavelength contention. However, both theoretical [11,12] and experimental results [1,13] have shown that 3R cannot restore a signal's BER without forward-error-correction (FEC). Due to the cost and energy constrictions, some 3R may not have the FEC capability. Hence, placing such a 3R at where the signal's quality is at the borderline may not satisfy the end-to-end performance requirement of a lightpath. Recently, we reported a more realistic model to estimate BER evolution along a lightpath with cascaded regenerators [12]. The model considered several imperfections of the regenerators, such as the degree of regenerative nonlinearity, bandwidth limitation, pattern dependence, timing jitter, and etc. Numerical results with this model showed a good match with the experimental results, for both all-optical 2R (Reamplification and Retiming) and O/E/O 3R [12]. Another drawback of previous works in [3-10] is that they rely solely on O/E/O 3R to solve the signal quality and wavelength contention issues. All-optical 2R can extend signal transmission reach with a more cost-effective and energy-efficient way [1,14]. Moreover, a majority of them achieve signal regeneration with an all-optical wavelength conversion, and can resolve wavelength contention simultaneously [1,14]. With these benefits in mind, we have proposed a green translucent network structure that involves mixed placement of optical amplifiers (1R), all-optical 2R, and O/E/O 3R [15,16].

It is well known that quality-of-transmission (QoT) estimation is usually time-consuming [17,18]. The mixed regenerator placement (MRP) algorithm in [16] implements an exhaustive search approach, which will become impractical when the number of candidate positions is large, or the routing and wavelength assignment (RWA) algorithm afterwards requires multiple placement candidates. Genetic algorithms are stochastic search optimization methods that mimic the process of natural evolution [19]. They have been recently used for solving topological design [20], impairment-aware RWA [21], and other complicated problems in optical networks.

In this paper, we propose genetic algorithms (GA) for solving the MRP problem with fast convergence speeds. We design two selection operators, two crossover operators, and two mutation operators, and compare their performance within the GA using numerical simulations. The rest of the paper is organized as follows. Section II presents the formulation of the MRP problem. Section III discusses the designs of the GA in

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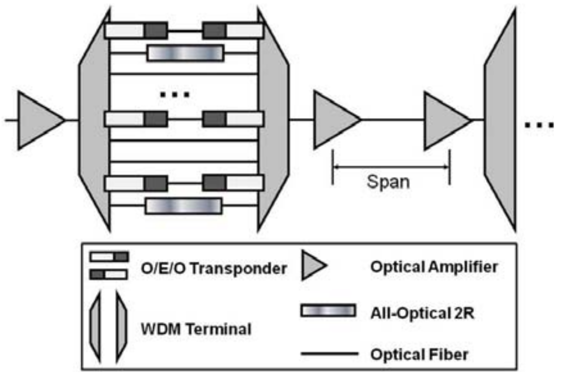

Fig. 1. Configuration of a regeneration site with mixed regenerator placement.

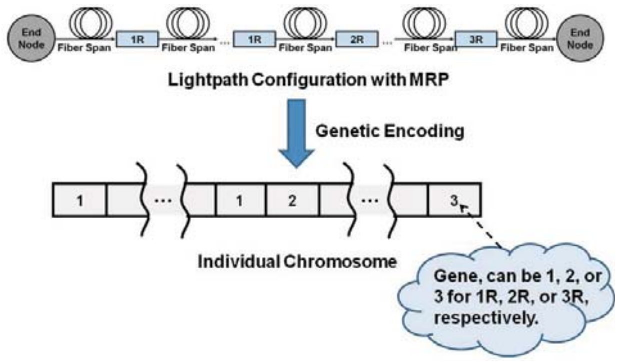

Fig. 2. Genetic encoding of the MRP problem.

detail. Section IV presents the performance evaluations of the GA. Finally, Section V summarizes this paper.

II. Problem Formulation

A. Physical Layer Model of Cascaded Regenerators

In this work, we consider a hybrid configuration of regeneration site as illustrated in Fig. 1. When there is no regenerative device between the WDM terminals, the signal is re-amplified (1R) only with optical in-line amplifiers. The optical signal is in an on-off keying (OOK) format, and we use BER as the performance indicator. For an arbitrary lightpath, the BER evolution is calculated hop-by-hop with [16]:

$$BER_n = BER_{n-1} + Err(L_{n-1,n}, R_n(\gamma, \sigma^2_{regen}, i)) \quad (1)$$

where the parameters inherit the same definitions as in [16]. To determine $L_{n-1,n}$, we use a similar model as in [22]. The model of $Err(.)$ considers timing jitter, and the imperfections of all-optical 2R, such as pattern dependence from the finite carrier recovery time of the devices [12,16].

B. Mixed Placement of 1R/2R/3R Regenerators

The network design considers a WDM network topology $G(V, E)$, where V is the node set, E is the fiber link set. Each fiber link supports wavelength set W. For a lightpath from node s to d, $s, d \in V$, we define $R_{s,d}$ as the set of nodes that the lightpath passes through in the network. The regenerator placement flag is $f^{(i,u)}_{s,d}(w), u \in R_{s,d}, w \in W$, $i = 1, 2, 3$ for 1R, 2R and 3R, respectively. Its value is 1 if input wavelength w is terminated by a regenerator in certain type at node u. The power consumption per regenerator is P_{2R} and P_{3R}, for 2R and 3R, respectively. The BER threshold is BER_t, and $BER_{s,d}$ denotes the end-to-end BER of the lightpath. With these denotations, we formulate the energy-efficient MRP optimization problem as:

Minimize:

$$\begin{aligned} P_{Regen} = P_{2R} \sum_{u \in R_{s,d}} \sum_{w \in W} f^{(2,u)}_{s,d}(w) + \\ P_{3R} \sum_{u \in R_{s,d}} \sum_{w \in W} f^{(3,u)}_{s,d}(w) \end{aligned} \quad (2)$$

Subject to:
Performance Constraint:

$$BER_{s,d} < BER_t, \forall s, d \in V \quad (3)$$

Connection Constraint:

$$\sum_{i=1}^{3} \sum_{w \in W} f^{(i,u)}_{s,d}(w) = 1, [u : u \in R_{s,d}], \forall s, d \in V \quad (4)$$

for each lightpath. Since $BER_{s,d}$ is calculated with Eqn. (1), which is a nonlinear function, MRP is a nonlinear optimization problem.

III. Genetic Algorithms for Solving the Mixed Regenerator Placement Problem

Genetic algorithms (GA) are search strategies based on the theory of natural evolution [19]. A set of possible solutions (individual chromosomes) to the problem is first generated as the initial population S_{init}. The GA then applies a fitness function to select relatively fit individuals for the next generation. A pair of individuals may crossover to create offsprings, and individuals may mutate their genes to increase population diversity. By applying these phases iteratively, the GA modifies the population consistently, until good solutions S_{sol} that satisfy the optimization requirement of the problem have been found. *Algorithm 1* shows the logic flow of the proposed GA, and we will elaborate on the individual phases in the following subsections.

A. Encoding and Fitness Function

Fig. 2 shows the genetic encoding scheme for solving the MRP problem. For a lightpath $L_{s,d}$ with N hops, there are $N - 1$ intermediate nodes for MRP. Hence, an individual chromosome with $N - 1$ genes will be generated as an array. Each gene can be 1, 2, or 3, corresponding to a placement of 1R, 2R, or 3R at the intermediate node. The fitness function consists of two objective functions: 1) $BER_{s,d}$ from Eqn. (1) with the MRP genes, and 2) Energy cost P_{Regen} from Eqn. (2). We consider the tradeoff between these two objective functions in the MRP optimization.

B. Initial Population

An initial population is first randomly generated with an appropriate size. To improve the convergence performance of the GA, we implement an initial filtering process to kill individuals with apparently low fitness (e.g. either the $BER_{s,d}$ or the P_{Regen} is too high).

Algorithm 1 Genetic Algorithm for Solving the MRP Problem

Input: N-hop Lightpath $L_{s,d}$, Link characteristics, BER_t, Initial population size M_{init}, Desired solution set size M_{sol}, Maximal generations G_{max}, P_{2R}, P_{3R}

Output: Desired MRP solution set S_{sol}

{Phase I}
$S_{init} \leftarrow \emptyset$;
$S_{sol} \leftarrow \emptyset$;
while $|S_{init}| < M_{init}$ **do**
  generate new individuals with $N-1$ genes randomly;
  kill individuals with apparently low fitness;
  $S_{init} \leftarrow$ new individuals;
end while
{Phase II}
$Generation = 1$;
$S = S_{init}$;
while $|S_{sol}| < M_{sol}$ AND $Generation < G_{max}$ **do**
  evaluate S with the fitness function;
  $S_{sol} \leftarrow$ fit individuals;
  $S_{parents} = Select(S, SO)$;
  $S_{offsprings} = Crossover(S_{parents}, CO)$;
  $S_{temp} = S_{parents} \cup S_{offsprings}$;
  $S = Select(S_{temp}, SO)$;
  $S = Mutate(S, MO)$;
  $Generation = Generation + 1$;
end while

C. Selection

We use the selection operator (SO) for two operations: 1) to select pairs of individuals from the current generation for crossover, and 2) to select individuals for the next generation. Two SOs are proposed for different evolution directions of the population, corresponding to various balance between the two objective functions. The first is BER-preferred SO (BPSO) that sets an upper boundary on the energy cost, and uses a modified roulette method [19] to obtain individuals with the lowest $BER_{s,d}$. The second is Energy-preferred SO (EPSO) that operates similarly as the first one until the average value of the individuals' $BER_{s,d}$ is below a preset threshold (e.g. 10^{-4}). And then, it directs the evolution to obtain individuals with the lowest P_{Regen} using a modified strategy.

D. Crossover and Mutation

In the crossover phase, the individuals are first sorted based on their fitness of $BER_{s,d}$. We then take pairs in a descending order and apply crossover operator (CO) on them. We design two types of CO: 1) uniform CO (UFCO), and 2) self-adaptive CO (SACO). For the uniform CO, we randomly generate a mask with a fixed number (M_{CO}) of crossover points. For the self-adaptive CO, the mask is also randomly generated but the M_{CO} of each mask can be changed dynamically, following:

$$M_{CO} \propto \log_{10}(BER_{s,d}) \tag{5}$$

The Mutation phase also utilizes two mutation operators (MOs): 1) fixed-rate MO (FRMO), and 2) adaptive-rate MO (ARMO). Basically, the mutation possibility of a gene can be either constant or variant (proportional to $\log_{10}(BER_{s,d})$ or P_{Regen}).

TABLE I
SIMULATION PARAMETERS

Output power per wavelength channel	$0\ dBm$
Fiber loss	$0.25\ dB/km$
PMD parameter	$0.1\ ps/\sqrt{km}$
EDFA noise figure	$6\ dB$
EDFA spacing	$80\ km$
Fiber link length between regeneration sites	$160\ km$
Total intermediate regeneration sites	8 - 27
Data rate	$40\ Gb/s$
BER_t, End-to-end BER threshold	10^{-4}
M_{init}, Initial population size	30 - 50
P_{2R}, Energy cost of an optical 2R regenerator	2×
P_{3R}, Energy cost of an O/E/O 3R regenerator	25×

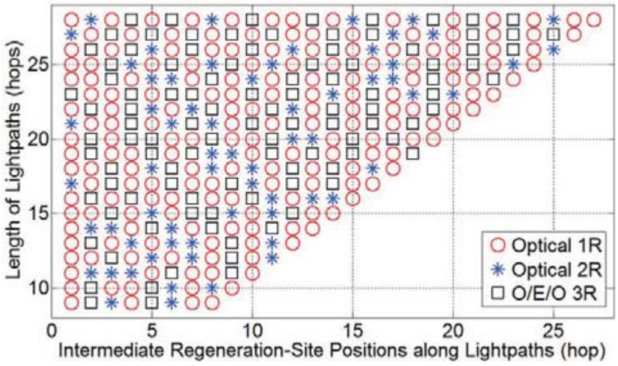

Fig. 3. MRP results for lightpahts with lengths of 9 to 28 hops.

IV. PERFORMANCE EVALUATION

Table I show the simulation parameters for the performance evaluation. Total intermediate regeneration sites means the number of regeneration sites the optical signal will experience in the lightpath before reaching the end node. For simplicity, we assume $L_{n-1,n}$ in Eqn. (1) is the same for each hop. Note that our model can also handle the situation where the link characteristic is various, as already demonstrated in [16]. We assume that the FEC functionality only exists at the end node of each lightpath, and set BER_t at 10^{-4} to accommodate the FEC threshold around 3×10^{-3} and to reserve certain performance margin. The energy costs of all-optical 2R and O/E/O 3R are determined based on the parameters in [1][23].

A. Mixed Regenerator Placements for Lightpaths

Fig. 3 shows the optimized MRP results for lightpaths with different lengths. The results are obtained by applying the GA

TABLE II
COMPARISON OF 3R-ONLY AND MRP SCHEMES

Lightpath Length (Hops)	9	13	17	21	25
No. of 3R in 3R-only Scheme	3	4	7	10	12
No. of 3R in MRP Scheme	2	2	5	7	7
No. of 3R Saved	1	2	2	3	5
Energy Cost of 3R-only Scheme (units)	75	100	175	250	300
Energy Cost of MRP Scheme (units)	54	58	129	181	185
Saving on Energy Cost (units)	21	42	46	69	115

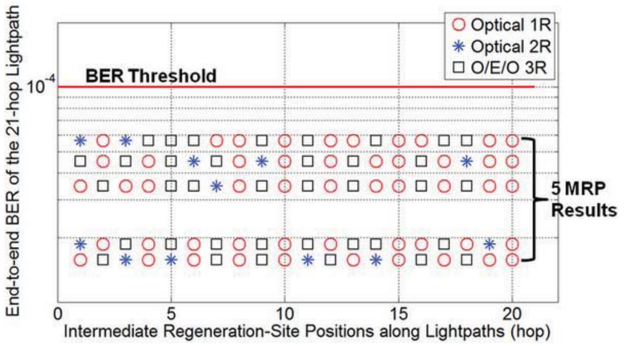

Fig. 4. MRP results for a 21-hop lightpath obtained by the GA.

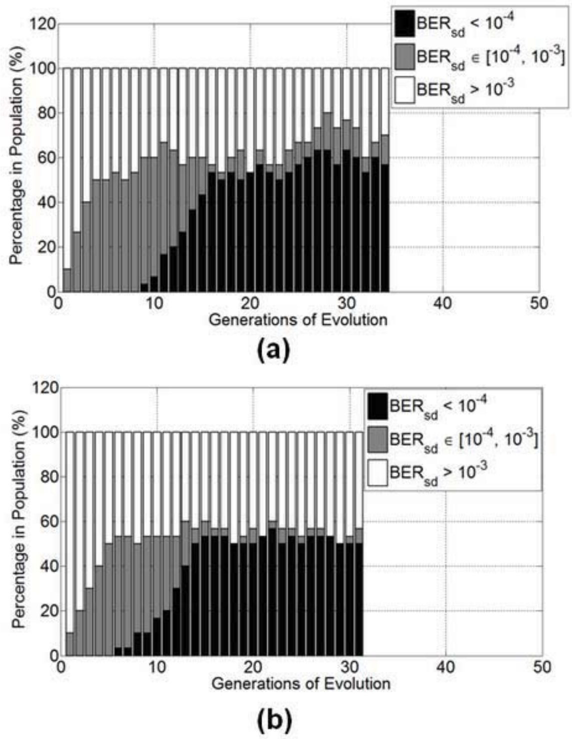

Fig. 5. $BER_{s,d}$ histograms of MRP results for a 26-hop lightpath, from GAs using (a) Adaptive scheme (GA-BPSO-SACO-ARMO), and (b) Uniform scheme (GA-BPSO-UFCO-FRMO).

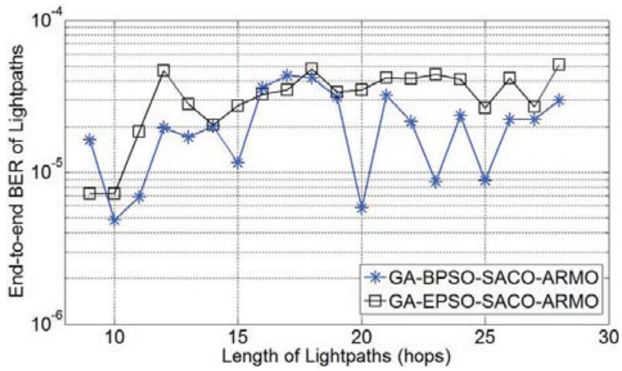

Fig. 6. Comparison of $BER_{s,d}$ of MRP results obtained by GAs using BPSO and EPSO.

algorithm that uses the combination of EPSO, SACO, and ARMO. For the longest lightpath with 28 hops, the GA gets the optimized results within 32 generations. Table II shows the comparison of the 3R-only scheme where there is no all-optical 2R being involved, and the MRP scheme. Effective saving on both the number of O/E/O 3R and the total energy cost can be achieved with the MRP scheme. Moreover, the saving increases with the length of the lightpath, which makes MRP more attractive for long distance transmissions. Even though we only plot one best result, in terms of P_{Regen}, for each lightpath in Fig. 3, the GA can actually obtain multiple MRP candidates that satisfy both the BER and energy requirements simultaneously. This provides more flexibility for the network design afterwards (e.g. routing and wavelength assignments (RWA)). If we set the upper boundary of the energy cost as 210 units for a 21-hop lightpath, Fig. 4 plots five qualified MRP results and their corresponding $BER_{s,d}$. The GA obtains these MRP results within 20 generations.

B. Convergence Performance of the Genetic Algorithms

Fig. 5 shows the convergence performance of the adaptive and uniform schemes for crossover and mutation. The simulations are done for a 26-hop lightpath with BPSO. Both schemes start to converge within 15 generations in total, and within 10 generations from when the first fit individual ($BER_{s,d} < 10^{-4}$) appears. Since the adaptive scheme adjusts the possibilities of the crossover and mutation intelligently based on the fitness of the individuals, it can obtain larger percentage of good individuals ($\sim 60\%$), while the percentage from the uniform case saturates at $\sim 50\%$.

C. Trade-off between Energy Consumption and Transmission Performance

To investigate the tradeoff between energy consumption and transmission performance, we plot the $BER_{s,d}$ and P_{Regen} of the optimized MRP results obtained by the two selection operators (SOs), BER-preferred SO (BPSO) and Energy-preferred SO (EPSO), in Fig. 6 and 7. The GAs we used to get these results are the combinations of BPSO, SACO, and ARMO (GA-BPSO-SACO-ARMO), and EPSO, SACO, and ARMO (GA-EPSO-SACO-ARMO), respectively. The results are obtained within 20 generations, and lightpath lengths from

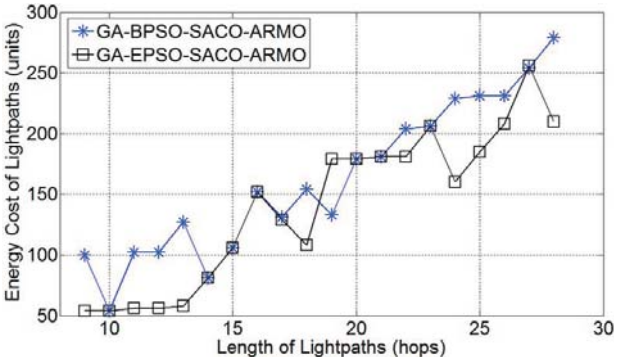

Fig. 7. Comparison of P_{Regen} of MRP results obtained by GAs using BPSO and EPSO.

9 to 28 hops are covered. As shown in Fig. 6 and 7, the two SOs direct the evolution directions of the GA algorithms to either BER-preferred or Energy-preferred successfully for most of the lightpath lengths. Note that both the size of the initial population and the number of generations can limit the effectiveness of the SOs. This is the reason why several results, such as $BER_{s,d}$ of 9, 16, and 17 hops in Fig. 6, and P_{Regen} of 19 hops in Fig. 7 are not as expected.

V. Conclusion

We proposed genetic algorithms (GA) with fast convergence speeds to solve the mixed regenerator placement (MRP) problem of lightpaths with different lengths. By incorporating a theoretical model that could estimate BER changes hop-by-hop along lightpaths, the GA encoded the placements of 1R/2R/3R at intermediate regeneration sites as genes, and used end-to-end BER and energy cost as the fitness functions. With a relatively small population size (e.g. 30-50), the GA obtained multiple qualified MRP results that could satisfy both the BER and energy requirements within 32 generations, for lightpaths with lengths up to 28 hops. Compared to the traditional scheme where there was no all-optical 2R, the MRP results demonstrated effective savings on total regeneration energy cost. Therefore, energy-efficient optical transport network design was achieved. The convergence performance of the GA was then investigated by using two crossover and two mutation operators. Both schemes started to converge at the 15-th generation, and the adaptive scheme outperformed the uniform one by getting a larger percentage of fit individuals. To achieve an adjustable tradeoff between BER and energy in the GA optimizations, we proposed two selection operators (SO), BER-preferred SO and energy-preferred SO. The simulation results showed that the two SOs guided the evolutions of the GA algorithms to the expected directions successfully.

Acknowledgments

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