WAVELENGTH CONVERTERS PLACEMENT IN ALL OPTICAL NETWORKS USING DIFFERENTIAL EVOLUTION OPTIMIZATION

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Abstract: Placement of wavelength converters in an arbitrary mesh network is known to belong to the class of NP-complete problems. So far, this problem has been solved by heuristic strategies or by the application of optimization tools such as genetic algorithms. In this paper we introduce the application of differential evolution (DE) to the placement of wavelength converters problem to find the optimal solution. Many comparative studies confirm its robustness and efficiency, and in many cases DE outperforms many other well known evolutionary computational approaches in terms of convergence speed and quality of solutions. The major advantage of the DE algorithm rests in the fact that it does not need to build up a search tree or to create auxiliary graphs to find the optimal solutions. Furthermore, the method typically requires few control parameters, and the computed results show that only a small population is needed to obtain the optimal solutions of the placement of wavelength converters problem in an arbitrary network. We present an experiment that demonstrates the effectiveness and efficiency of the proposed evolutionary algorithm.

1 INTRODUCTION

Wavelength routed optical networks (WRON) promise to meet the high transmission quality and large bandwidth desired by end users for transmitting multimedia traffic. In view of this, the routing and wavelength assignment (RWA) and wavelength conversion issues are of paramount importance in reducing network blocking probability (Ramaswami and Sivarajan, 1995; Subramaniam and Barry, 1997). It is well understood that wavelength converters are presently very expensive and exhibit only a limited wavelength conversion range. Due to these reasons, a network in which selected nodes are equipped with wavelength conversion capabilities is economically more practical.

K.R. Venugopal et al. used a new heuristic approach for placement of wavelength converters to reduce blocking probabilities (Venugopal et al., 2001). Their study includes both, static and dynamic light paths establishments. C. Vijayanand et al. proposed new integer linear program (ILP) formulations for the static and dynamic RWA problems to reduce the number of conversions. In their study, a genetic algorithm (GA) was used for placing limited-range wavelength converters in an arbitrary mesh WRON (Vijayanand et al., 2000). This was the only evolutionary algorithm applied to the wavelength converters placement problem. Li et al. have proven that the optimal solution on a path could be achieved when all the segments (a path segment between two consecutive converters or between an end node and its nearest converter) on the path have equal blocking probabilities. Based on this theorem, some algorithms of linear complexity were proposed to obtain near-optimal solutions for converter placement on a path (Li et al., 1999). In short, most of the proposed techniques are either complicated, need large storage capacity, or require massive computation time. Considering these factors, C. F. Teo et al. have proposed a novel evolutionary algorithm named particle swarm optimizer (PSO) to find the optimal placement of wavelength converters to achieve minimum blocking probability (Teo C. , Foo, Chien, Low, You, and Castaño, 2005). In this paper we propose to apply for the first time according to the best of the author knowledge the DE algorithm to determine the
optimal placement of the wavelength converters in a network

The paper layout is as follows, the proposed search algorithm is discussed in Section 2. The results are then explained in Section 3. In Section 4, conclusions are addressed.

## 2 DE ALGORITHM

We assume that either only one or none full range converter is placed in the node. Our analysis is also based on the assumption of the fixed shortest path routine and random wavelength assignment. Hence, this model can be formulated as a binary programming problem. This model expresses the overall system success probability as a polynomial function of binary variables under a linear constraint (Gao et al., 2003). The traffic model can be computed as in (Teo C., Foo, Chien, Low, You, and Castañon, 2005).

We propose to apply the DE algorithm (Storn and Price, 1997) to determine the optimal placement of the wavelength converters in the network. As has been mentioned above, this algorithm uses a population of individuals. DE employs repeated cycles of recombination and selection to guide the population towards the vicinity of a global optimum. In the algorithm we apply the probability operators to the individuals population (crossing and mutation) to obtain new individuals (children) who have some properties of the ancestors of which are kept or deleted by selection, this process is done with each individual in the population to form a new population. This process is repeated for a number of iterations (called generations). DE has three crucial control parameters: the mutation constant (M), controlling the mutation strength, the recombination constant (RC) and the population size (NP). Throughout the execution process, the user define population size NP. At each generation, the target vectors are randomly chosen and mixed from the current vector population. This operation can be referred to as mutation, and the result of this as mutant individual. Then the mutant individual is mixed with the target vector by an operator called recombination. This yield to the trial vector.

Finally we came to the selection operator, according to which the trial vector is accepted for the population, and replace the target vector, only if this has a better performance in the objective function, otherwise target vector survive to the next generation, and the mutant individual it is not retained.

The following are the operators who are using DE to find the most promising region in the search space.

Now we describe the basic mutation operator using in DE optimization. Particularly, for each individual \( x^i, i = 1, ..., NP \), the mutant individual \( m^i \) is generated according to the next equation:

\[
m^i = x^{r_1} + M (x^{r_2} - x^{r_3})
\]

Where \( x^{r_1}, x^{r_2}, x^{r_3} \in \{1, ..., NP\}, x^{r_1} \neq x^{r_2} \neq x^{r_3} \neq x^i \), are three random individuals from the population, mutually different and also different from the current individual \( x^i \), and \( M \) is a scaling factor called mutation constant, and must be \( M \geq 0 \). With this parameter we control the amplification between the differences of the two individuals, which manage a trade off between exploitation and exploration on the search process. This parameter is also responsible of the convergence of the algorithm.

The recombination operator is applied to increase the diversity of the mutation process. This operator is the last step to create the trial vector too. To do this, the mutant individual, \( m^i \), is combined with the current individual of the population called target vector. Particularly, for each component \( j \), where \( j = \{1,2, ..., D\} \), of the mutant individual \( m^i \), we choose a random number \( rand \) in the interval of \([0,1]\). Next, we compare this number \( rand \) with the parameter \( RC \), which is called the recombination constant. If \( rand \leq RC \), then we select the \( j \)-th element of the mutant individual as the \( j \)-th element of the trial vector \( t^i \), in another way, we select the \( j \)-th element of the target vector as the \( j \)-th element of the trial vector. Once we have completed this process the trial vector is ready. It is important to see that a small value in \( RC \) yields to the cancelation of the mutation operator, since the target vector will become the new trial vector. This is because \( rand \leq RC \) not be met for most of cases.

Finally, the selection operator is applied, by a simple rule of elitist selection in order to optimize the objective function. This is done by comparing the fitness between the trial vector and the target vector in the objective function, by the next operator:

\[
Pop_t = \begin{cases} 
  t^i & \text{if } f(t^i) < f(x^i) \\
  x^i & \text{otherwise}
\end{cases}
\]

Where \( Pop \) is the population of the next generation, and it changes by accepting or reject new individuals.
At the end of each generation we must conserve a registry of the best individual in the population, and a record of the global best individual to keep the best result in the process of optimization.

Note that in the wavelength converter placement problem, the optimization goal is to find an assignment of the binary variables \( x_1, x_2, \ldots, x_n \). Therefore, we have applied the binary version of DE algorithm (BDE). A ‘1’ indicates a converter is needed at a particular node and a ‘0’ represents a converter is not needed at the node. With the same framework of DE, tree new operators are used to expand the continuous field of the original DE to the discrete field (Deng et al., 2009). A new mapping operator, denoted by \( f_1 \), was constructed to map the variable \( x \) in discrete domain into continuous domain. The operator can be defined as formula:

\[
f_1 = \begin{cases} 
0.5 \cdot \text{rand}, & x = 0 \\
0.5 + 0.5 \cdot \text{rand}, & x = 1 
\end{cases}
\]

Also, in DE the result in the mutation and recombination may violate the boundary constraints. Then the \( S \) operator is a Sigmoid function and can make the mutation operator results fall into the interval \([0,1]\). The \( S \) operator is defined as:

\[
f(x) = \frac{1}{1 + e^{-x}}
\]

Finally, we defined the inverse mapping operator, which make the transformation from the continuous field to the discrete field:

\[
f_2 = \begin{cases} 
0, & x \in [0,0.5) \\
1, & x \in [0.5,1] 
\end{cases}
\]

Under these considerations we can establish the pseudocode for the problem of the collocation of wavelength converters in an optical network.

The DE algorithm is as follows:

Create an initial population of size \( NP \) and set the control parameters;
Evaluate the fitness of every individual;
Repeat:
For each individual \( x \in \{1, 2, \ldots, NP\} \), where \( NP \) is the number of individuals;
Generate the trial individual:
Select tree individuals from the population apply to then the following operators:
mapping operator eq. (3)
mutation operator eq. (1)
\( S \) operator eq. (4)
inverse mapping operator eq. (5)
select the better individual between the target individual and the trial individual eq.(2);
update the fitness;
update the population;
end For
Until a satisfactory solution is reached or computational limit are exceeded.

3 ILLUSTRATIVE EXAMPLE

A simple bidirectional graph (Teo C. et al., 2005) with five nodes is shown in Fig 1. It is assumed that a fiber link (\( F \)) consists of five channels, and traffic flow \( \lambda_i = 0.05 \) for any node pair \((i,j)\) where \(1 \leq i \leq N\) and \(1 \leq j \leq N\). The traffic load on each link \( \rho_i \) and the end-to-end success probability \( S(P_\text{st}) \) of any node pair \( S_i \) for \(1 \leq i \leq 5\) which is based on Eqs. (2) and (3) of (Teo C. et al., 2005).

![Figure 1: Simple 5-node bi-directional graph.](image)

According to Eq. (8) of (Teo C. et al., 2005), we can formulate the converter placement problem as a linear function of variable \( x_i \) for \(1 \leq i \leq 5\) since the number of hops \( d \) in this example is two (i.e., \( d \leq 2 \)). Note that \( \max(\ln(x)) \equiv m \ln[\ln(x)] \), when \( 0 \leq x \leq 1 \). This equation is the DE objective function and it can be written as:

\[
f(x_1, x_2, x_3, x_4, x_5) = \\
\frac{1}{20} [4gS_1 + 4(2 + x_2 + x_3)gS_2 + 2(1 + x_2)gS_3 + 4(1 - x_3)gS_4 + 2(1 - x_2)gS_5]
\]

where \( S_1 = 1-0.015, S_2 = 1-0.025, S_3 = 1-0.035, S_4=1-(1-0.97\times0.98)^7 \), and \( S_5 = 1-(1-0.98 \times 0.98)^8 \).

Based on Eq. (6), we have \( f(1,0,0,0,0) = 7.23 \times 10^6, f(0,1,0,0,0) = 6.32 \times 10^6 \) and \( f(0,0,1,0,0) = 1.90 \times 10^6 \). It means that when a wavelength converter is placed in node 3 the overall minimum blocking probability will be obtained. The capability of the applied binary DE is illustrated in Fig. 2. It can be observed that the DE algorithm finds the optimal solution in three
iterations, fewer iterations compared to five of the PSO algorithm in (Teo C. et al., 2005).

Random Initializations

<table>
<thead>
<tr>
<th>Population in next generation</th>
<th>f = 6.32 × 10^8</th>
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<tbody>
<tr>
<td>0 1 0 0 0</td>
<td></td>
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<tr>
<td>0 0 0 0 1</td>
<td></td>
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<tr>
<td>0 0 0 1 0</td>
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<td>1 0 0 0 0</td>
<td></td>
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<td>0 1 0 0 0</td>
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DE Selection according to f

Population in next generation

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Stop iterating since all individuals converge, optimal solution obtained is 00100 with 3 iterations only.

Fig.2 Illustration of DE simulation results of a 5-node network.

4 CONCLUSIONS

In this paper we introduce the application of differential evolution (DE) algorithm to find the optimal solution to the converters placement problem. We confirm the effective capabilities of the DE algorithm in terms of convergence speed and quality of solutions. The major advantage of this algorithm is that it does not need to build up a search tree or to create auxiliary graphs to find optimal solutions. Also the method typically requires few control parameters. In addition, the computed results show that only a small population is needed to search the optimal solutions of the placement of wavelength converters problem in an arbitrary network. We presented an illustrative experiment to demonstrate the effectiveness and efficiency of the proposed evolutionary algorithm. The algorithm finds the optimum value in three iterations with a population of five individuals. Further work will investigate the application of DE algorithm in larger networks of more realistic size and different topologies.

REFERENCES


