Network Topology Planning Using MOEA/D with Objective-Guided Operators

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Abstract. Multiobjective evolutionary algorithms (MOEAs) have attracted growing attention recently. Problem-specific operators have been successfully used in single objective evolutionary algorithms and it is widely believed that the performance of MOEAs can be improved by using problem-specific knowledge. However, not much work have been done along this direction. Taking a network topology planning problem as an example, we study how to incorporate problem-specific knowledge into the multiobjective evolutionary algorithm based on decomposition (MOEA/D). We propose *objective-guided operators* for the network topology planning problem and use them in MOEA/D. Experiments are conducted on two test networks and the experimental results show that the MOEA/D algorithm using the proposed operators works very well. The idea in this paper can be generalized to other multiobjective optimization problems.

Keywords: Multiobjective Optimization, Evolutionary Algorithm, MOEA/D, Network Topology Planning.

1 Introduction

Multiobjective optimization problems (MOPs) present a greater challenge than single-objective optimization problems since objectives in a MOP contradict one another so that no single solution in the decision space can optimize all the objectives simultaneously. Therefore, a decision maker often wants to find an optimal tradeoff among these objectives. Pareto optimal solutions are best tradeoffs if there is no decision makers' preference information. A number of different Multiobjective evolutionary algorithms (MOEAs), such as NSGA-II [1] and MOEA/D [2][3], have been developed for approximating the Pareto optimal solution set.

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It is widely believed that problem-specific knowledge should be utilized in designing of an evolutionary algorithm in order to improve the algorithm performance. In single objective evolutionary optimization, many successful applications of problem-specific knowledge have been reported. However, not much work have been done along this direction in MOEAs. One of the major reasons is that most existing problem-specific techniques are for single objective optimization. It is not very natural to use them in Pareto dominance based MOEAs, which are most popular methods now. By decomposing a MOP into many single objective optimization subproblems, the recent MOEA/D algorithm provides a good framework for using single objective optimization techniques for multiobjective optimization. Many different variants have been proposed and applied on different MOPs [4][5]. In this paper, we take topology planning problem as an example and study how to incorporate problem-specific knowledge into MOEA/D.

Planning a network topology involves multiple objectives including minimizing the total network cost, maximizing the transport efficiency and the network reliability, etc. In transparent optical networks (TONs), more objectives should be considered, such as the security under intentional attacks [6] and energy-efficiency for a green network planning [7][8].

Network topology planning is normally formulated as bi-objective optimization problems. Kumar et al. firstly used the Pareto Converging Genetic Algorithm (PCGA) to solve the problem [9], then applied a multi-island approach with Pareto ranking method [10]. The PCGA was also used in the problem with consideration of realistic traffic models [11][12].

In this paper, we study a network topology planning problem in TONs. It is formulated as a tri-objective optimization problem. The MOEA/D algorithm with generic graph operators is firstly designed to tackle the problem. Then, we propose *objective-guided operators* and use them in the MOEA/D algorithm for this problem. The main idea is to design operators using problem-specific knowledge for all objectives, and then use them with different probabilities for each scalar subproblem in MOEA/D. Due to the decomposition approach in MOEA/D, the probabilities can be easily determined with the weight vectors associated with subproblems. The proposed algorithms are evaluated on two networks with different sizes. The experimental results demonstrate the effectiveness of the MOEA/D algorithm using the *objective-guided operators*. Our algorithm provides a new approach for using problem-specific knowledge in MOEAs.

The rest of the paper is organized as follows. The problem is formulated in Section 2. Section 3 describes the MOEA/D algorithm using generic graph operators. The MOEA/D algorithm using objective-guided operators is proposed in Section 4. The experimental results are presented in Section 5 and the paper is concluded in Section 6.

2 Problem Formulation

Topological design of a transparent optical networks (TON) for meeting the requirements of consumers is a fundamental task before its deployment. Network topology design involves determining the layout of links between nodes to satisfy the requirements of average delay, cost and reliability. In packet-switching networks, the average delay between a source and a destination can be estimated from queuing theory. Normally, the transferring delay is affected by the number of intermediate hops and the traffic load on links made of a path. However, due to the circuit-switching nature of optical networks, the average delay is mainly determined by the hops a lightpath traverses.

Besides the traditional design objectives, energy and security-related issues have gained much attention in recent years. For the green sustainable communication purpose, energy consumption of telecom networks should be reduced as much as possible. Since both switching and transmission on fibers consume power, one should try to minimize the number of intermediate hops and reuse the network link which has been already "on" in routing of lightpaths. From the view of topological design, we should try to minimize both the hops and the number of links. Apparently, they are two contradictory objectives.

Random failures of nodes and links are main factors for reliability of a network. When security is demanded, intentional attacks should be emphasized in topology design. It has been shown that a scale-free complex network is robust from random failures, but fragile under intentional attacks, e.g., removing nodes by node degrees in descending order. So, in this paper, we consider the topology design problem with new objectives including energy-saving and security.

The network topology problem is formally defined below.

1) Design Parameters

- N: the total number of nodes in a network;
- *Cost*: a cost matrix in which $Cost(i, j)$ provides the cost of the link between node i and j. Normally, the cost of link between node i and j can be estimated by their physical distance and the cost factor per unit distance;

2) Objectives

- *network cost*: the sum of cost of all links;
- *average path length*: the average hops of each path. Since there may be unreachable node pairs in a network, we use the concept of network efficiency to calculate the objective value. The network efficiency is defined as the mean value of inverse values of shortest path lengths in a graph. Given a graph $G{=}(V, E)$, the average path length is measured by:

$$Lp(G) = 1 - \frac{1}{n(n-1)} \sum_{i \neq j \in V} \frac{1}{l_{i,j}} \tag{1}$$

  where $n{=}|V|$ and $l_{i,j}$ is the shortest path length from node i to node j;
- *Vulnerability under intentional attacks*: we use the robustness measure R proposed by Schneider et al. [13], which is defined as:

$$R = \frac{1}{N+1} \sum_{Q=0}^{N} s(Q) \tag{2}$$

where N is the number of nodes in a network and $s(Q)$ is the fraction of nodes in the largest connected cluster after removing Q nodes. The range of R is $[0, 0.5]$, where $R = 0$ corresponds to a network with all nodes isolated, and $R = 0.5$ corresponds to a fully connected network. The vulnerability of a network under intentional attacks is calculated by:

$$Vu(G) = 1 - 2R \tag{3}$$

The average delay is measured by the average path length, while minimizing the average path length also contributes to the saving of energy. To calculate the shortest path lengths, the Dijkstra's shortest-path algorithm is used. To calculate the robustness measure R, a greedy attacking strategy is applied. That is, each time the node with the maximal nodal degree is selected and removed from the network and the size of the largest connected cluster is calculated.

3 MOEA/D for Network Topology Planning

The original MOEA/D algorithm [2] can be directly applied to solve the network topology planning problem. We call it as *MOEA/D-direct* algorithm. Each individual in the population encodes a possible network topology. A network topology is represented by its binary adjacency matrix A where $A_{i,j} = 1$ if there is a link between node i and j. Generic graph operators are used.

Let the adjacency matrices of two parents be A and B and the adjacency matrix of offspring be C. The crossover operator produces an offspring C as follows:

$$C_{i,j} = \begin{cases} A_{i,j} & , \quad r \leq p_c \\ B_{i,j} & , \quad otherwise \end{cases} \tag{4}$$

where r is a uniformly random value in $[0, 1]$. The parameter p_c is used to control the amount of information inherited from each parent. The offspring inherits from A with a probability of p_c and from B with a probability of $(1 - p_c)$.

In the mutation operator used in this paper, the bits in the adjacency matrix are flipped with a mutation probability p_m. Since undirected networks are considered in this paper, the adjacency matrices are symmetric. Thereafter, the crossover and mutation operators are applied only for elements when $i < j$, and we always let $C_{j,i} = C_{i,j}$.

The generated network topology may not be connected. In reality, a network may not be connected at its initial construction stage due to insufficient finance. Thus, disconnected networks are considered as valid solutions to the problem in this paper so that the algorithm can be simplified.

Parents for crossover are selected using a strategy slightly different from that in the original MOEA/D algorithm, whose details can be found in [2]. To generate the i-th offspring, we select an index k randomly from the neighborhood $B(i)$, and then use the i-th individual as the first parent and the k-th individual as the second parent. After the offspring is generated, its objective values are calculated. Then, the i-th and the k-th individual are updated if the new individual is better than them.

The population is initialized uniformly at random. When an individual is initialized, any two nodes are connected with a probability p_r. Assume N_{pop} individuals will be generated at the initial stage, then the probability p_r for the i-th individual is set to i/N_{pop}. After an individual is generated, its objective values are calculated and all individuals in the population are updated according to their weighted objective values.

4 MOEA/D with Objective-Guided Operators

It is commonly believed that algorithms using problem-specific knowledge can achieve much better performance than a generic algorithm. Therefore, heuristic local search algorithms should be used within a MOEA or genetic operators should be designed specially for a specific application problem. However, heuristic operations often optimize only one objective at a time. For MOPs, we need to optimize multiple objectives simultaneously. Using an operator to optimize one objective has been proposed in [14] for multiobjective 0/1 knapsack problems. Using different operators for different parts of the Pareto Front (PF) in MOEA/D has been investigated in [15].

However, There is still lack of general guidelines for designing problem-specific operators in a MOEA. In this paper, we propose *objective-guided operators* to utilize problem-specific knowledge in MOEAs. Since an operator that optimizes only one objective can often be designed easily, the main idea is to design one operator for each objective and then use them alternatively.

More specifically, we design the following operators for the studied problem.

– **Operator for objective 1:** The first objective is to minimize the total network cost. Thus, the operator selects a node i_0 randomly at first. The most expensive link connected with it is then removed;
– **Operator for objective 2:** The second objective is to minimize the average path length. For this objective, we randomly select a node from the network and compare its degree with its neighboring nodes. The node with the maximal degree is called a *local hub node*. We select two local hub nodes which are not connected, then add a link between them. By connecting 'hub' nodes, the average path length can be shortened with a few new links;
– **Operator for objective 3:** The third objective is to reduce the vulnerability of the network to the maximal extent. We firstly find the node with the minimal degree in the network, then connect it to an unconnected node with the minimal cost. Since the link cost is proportional to the distance between two nodes, the node with the minimal cost will be the nearest node from it.

MOEA/D decomposes a MOP into a number of scalar optimization subproblems. Each subproblem has a weight vector which sets weights on different objectives. The weight vector represents the preference of the subproblem on different objectives. Since different subproblems have different preference on objectives, we can not apply the objective-guided operators on different subproblems in the same way. Instead, we use them based on the preference of the objectives. We design an *objective-guided mutation* operator which is illustrated as follows.

In MOEA/D, the i-th individual x^i is to find the optima of the i-th subproblem with the weight vector $\lambda^i = (\lambda^i_1, \ldots, \lambda^i_m)$ where m is the number of objectives. Normally, $\lambda^i_j \in [0, 1]$ and $\sum_{j=1}^{m} \lambda^i_j = 1$. The j-th element in the weight vector represents the preference on the j-th objective. Thus, in the *objective-guided mutation* operator, we use different operators according to the value of the weight vector. In implementation, we generate a new offspring y from the i-th individual using the following steps:

For $k = 1, \ldots, r_{num}$, **do**
  Apply the j-th operator on x^i with probability= λ^i_j;

where the j-th operator is designed for the optimization of the j-th objective. r_{num} is a control parameter which determines the number of iteration in the objective-guided mutation operator.

5 Evaluation

5.1 Experiment Setting

To demonstrate the effectiveness of the MOEA/D algorithm using objective-guided operators (called as *MOEA/D-guided*), we conduct experiments on two networks with different sizes. The parameter setting is shown in Table 1.

Table 1. Parameters of Algorithms

Variable	**Description**	**Value**
N	total number of nodes in a network	33, 340
N_{pop}	population size (also number of subproblems)	66
N_{eval}	number of function evaluations	50000
T	size of neighborhood in MOEA/D	5
p_c	probability in crossover operation	0.5
p_m	probability in mutation operation	0.05
r_{num}	iteration number in objective-guided mutation	10

The performance metrics include [2]:

– Set Coverage (C-metric): Let A and B be two approximations to the PF of a MOP. $C(A, B)$ is defined as the percentage of the solutions in B that are dominated by at least one solution in A, i.e.

$$C(A, B) = \frac{|\{u \in B | \exists v \in A : v \text{ dominates } u\}|}{|B|} \quad (5)$$

– Distance from Representatives in the PF (IGD-metric): Let P^* be a set of uniformly distributed points along the PF. Let A be an approximation to the PF, the average distance from A to P^* is defined as:

$$D(A, P^*) = \frac{\sum_{v \in P^*} d(v, A)}{|A|} \tag{6}$$

where $d(v, A)$ is the minimum Euclidean distance between v and the points in A. Here the definition is slightly different than that in [2] in order to consider the effect of size of solution set.
– Size of Solution Set: number of non-dominated solutions found.

The quality of two solution sets with respect to Pareto dominance can be compared using the C-metric. The D-metric could measure both the diversity and convergence of a solution set in a sense. Since the actual Pareto fronts of the test networks are not known, we use an approximation of the PF as P^*. The approximation of PF is obtained from all non-dominated solutions found in all the runs of the two algorithms. The size of solution set reveals the ability of algorithm to find non-dominated solutions.

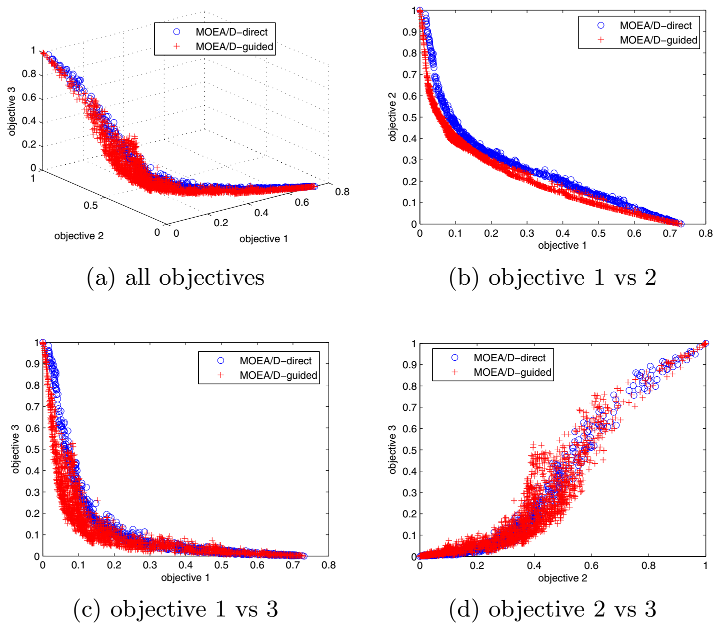
5.2 Experiment Results

Figure 1 shows the distribution of solution set found in one run on a network with 33 nodes. It can be seen that the MOEA/D-guided algorithm has obtained better distributed solutions and most solutions obtained by the MOEA/D-direct algorithm are dominated by those by the MOEA/D-guided algorithm.

On a network with 340 nodes, the results are quite different. As shown in Figure 2, the solutions of the two algorithms have very different distributions. The MOEA/D-direct algorithm has produced very few solutions with low values of objective 1 (network cost). The MOEA/D-guided algorithm has generated a lot of solutions distributed in the objective space with low values of objective 1 and relatively large values of objective 2 and 3. Thus, we can still conclude that the MOEA/D-guided algorithm has better exploration ability than the MOEA/D-direct algorithm on this test instance.

The performance metrics are averaged over 10 independent runs. The results are shown in Figure 3. With the increase of the function evaluation number, the C-metric of MOEA/D-guided vs MOEA/D-direct increases too. It implies that more solutions of MOEA/D-direct are dominated by solutions of MOEA/D-guided if more computational efforts are made. In the case of network with 33 nodes, the C-metric of MOEA/D-direct versus MOEA/D-guided is zero and not shown in Figure 3a.

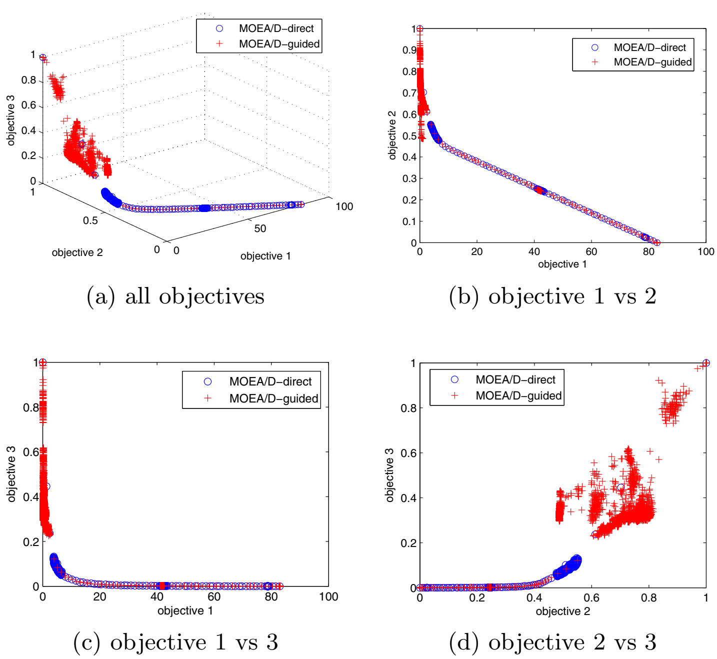
The D-metric values of MOEA/D-guided are lower than those of MOEA/D-direct in the case of 33 nodes. It means that the solution set of MOEA/D-guided is more close to the approximated Pareto front. The D-metric values of MOEA/D-guided are higher than those of MOEA/D-direct in the case of 340 nodes. However, the values are getting closer with the increase of function evaluation number. Obviously, the complexity of the problem has increased when the



(a) all objectives (b) objective 1 vs 2

(c) objective 1 vs 3 (d) objective 2 vs 3

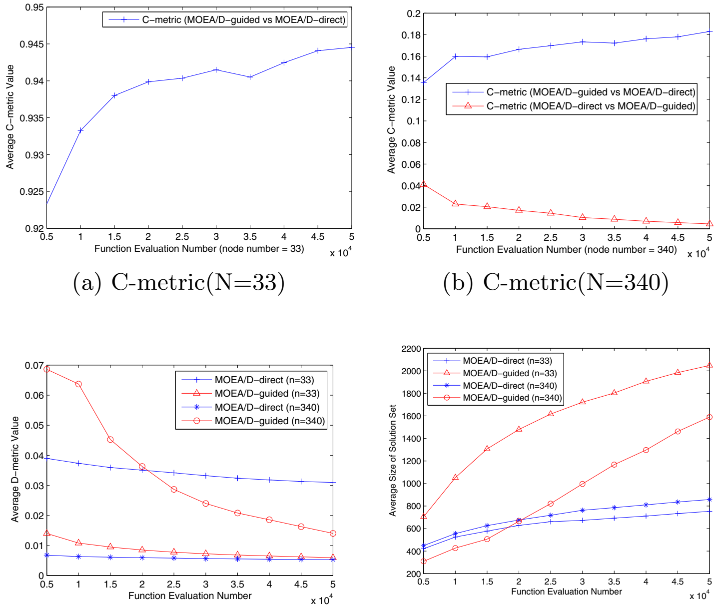
Fig. 1. Results on network with 33 nodes



(a) all objectives (b) objective 1 vs 2

(c) objective 1 vs 3 (d) objective 2 vs 3

Fig. 2. Results on network with 340 nodes



(a) C-metric(N=33) (b) C-metric(N=340)

(c) D-metric (d) solution set size

Fig. 3. C-metric, D-metric and Size of Solution Set

network scale increases. The higher D-metric values in MOEA/D-guided may be explained by the solution set size. AS shown in Figure 3d, the final solution sets of MOEA/D-guided in both cases are larger than those of MOEA/D-direct. With solutions distributed more widely, the distance from one solution to the approximated Pareto front is more likely large. The larger solution set of MOEA/D-guided also demonstrates its stronger exploration ability.

6 Conclusion

In this paper, we have investigated how to utilize problem-specific knowledge in multi-objective evolutionary algorithms. Specifically, we have studied the network topology planning problem using the MOEA/D algorithm. The algorithm was firstly applied on the problem using generic graph operators. Then the objective-guided operators were proposed and a way to use them in MOEA/D was proposed. The main idea is to design one operator for each objective and use the operators based on the weight vectors of subproblems in MOEA/D. Experimental results on networks of different scale have shown the superiority of the MOEA/D-guided algorithm which uses objective-guided operators.

Future work includes further improvement of the algorithm on large-scale problem instances. Other problem-specific operators may be incorporated and other approaches to exploit problem-specific knowledge can be investigated.

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