Designing resilient networks using multicriteria metaheuristics

Crina Grosan · Ajith Abraham · Aboul Ella Hassainen

Abstract The paper deals with the design of resilient networks that are fault tolerant against link failures. Usually, fault tolerance is achieved by providing backup paths, which are used in case of an edge failure on a primary path. We consider this task as a multiobjective optimization problem: to provide resilience in networks while minimizing the cost subject to capacity constraint. We propose a stochastic approach, which can generate multiple Pareto solutions in a single run. The feasibility of the proposed method is illustrated by considering several network design problems using a single weighted average of objectives and a direct multiobjective optimization approach using the Pareto dominance concept.

Keywords Resilient networks · Multiobjective optimization · Metaheuristics · Pareto solutions

1 Introduction

Reliability has been a traditional goal within telecommunication network design. There has been some recent research interest in developing algorithms for problems of guaranteeing resilience against failures. Due to the fact that the assurance of continuity in traffic is a vital demand in today's networks, we have to be able to provide backup paths at the moment a failure on a edge (or in multiple edges) on the primary path occurs. For this, the backup path has to be built a priory.

There are several attempts to solve the resilience and path allocation problem in different ways. Chekuri et al. [1] deal with edge failure by building simultaneous primary and backup paths but they are only considering the case of uncapacitated networks. A hybrid genetic algorithm which deals with alternative backup paths was proposed by Chekuri et al. [1], but the problem is not considered as multiobjective. A multiobjective network design approach is proposed by Banarjee and Kumar [3] and by Yeh [11], but not directly treating resilience. Being an important and interesting research topic, in the literature, there is a h0uge amount of work related to network resilience [2, 4–10, 12, 24] are some of them. Some surveys on resilient network technology, planning and optimization can be found in [13–15].

De Vleeschouwer and Frossard [20] investigated methods for efficient packet loss recovery by retransmission, and build on explicit congestion control mechanisms to decouple the packet loss detection from the congestion feedback signals. They proposed a novel retransmission timer to deal with multiple losses of data segments and, in consequence, to allow for aggressive reset of the connection recovery timer. For different retransmission strategies that respectively rely on conventional cumulative acknowledgments or accurate loss monitoring, authors illustrated how the principles underlying the TCP retransmission mechanisms have to be adapted in order to take advantage of an explicit congestion feedback.

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Wouhaybi and Campbell [21] designed and evaluated a peer-to-peer algorithm for building resilient low-diameter peer-to-peer topologies that can resist different types of organized and targeted malicious behavior. The proposed framework leverages the strengths of some of the existing approaches without inheriting their weaknesses and is capable of building topologies of nodes that follow a power-law while being fully distributed requiring no central server, thus, eliminating the possibility of a single point of failure in the system.

Antonino et al. [22] presented the architecture of a Wavelength Division Multiplexing (WDM) optical packet network which is targeted to assess the effectiveness of optical technologies with respect to electronic ones, trying to identify an optimal mix of the two technologies. The developed architecture shows interesting resilience properties that enable the design of fast fault-recovery schemes.

The explosive growth of data generation has invoked a big challenge to design a resilient and scalable interconnection network which consolidates hundreds even thousands of storage nodes to satisfy both the bandwidth and storage capacity requirements. Deng [23] proposed a resilient interconnection network for storage cluster systems by employing multiple spare links between any two storage nodes to offer strong resilience to reduce the impact of the failures of links, switches, and storage nodes. A metric named resilience coefficient is also proposed to measure the interconnection network.

In this paper, we focus on the simultaneous allocation of primary and backup paths. We also formulate the problem as dealing with multiple criteria in the same time where several objectives can be formulated. In this research, we deal with three criteria: (1) minimize the network cost, (2) minimize the number of common links between primary and its corresponding backup path (so that in case an edge (link) failure occurs on the primary path the chances that the same edge belongs to the backup path also and makes the traffic impossible to continue is minimal) and (3) maximize the number of common links between all the backup paths (in the situation that there are several source-destination flows to be fulfilled at the same time). We also take into consideration that an edge failure can affect only one of the primary paths at one time and there is no requirement for using both backup paths as reserve in the same time. One approach to planning such networks is by simulation, where a stochastic optimization technique is applied.

We provide a detailed description of the algorithm proposed in the following section. The ways in which a solution is initialized and improved are widely described and an illustrative example is presented in Sect. 2. In Sect. 3 the proposed approach is illustrated followed by several experimental results in Sect. 4. Conclusions are provided towards the end.

2 Problem formulation

Since in today's networks, due to the demand's importance we cannot simply rely on a single network path, we have to a priori build a path, which can be used to reroute the traffic in case a failure occurs on the primary path. It is necessary to predefine a backup path (or backup sub-paths) if:

- the recovery of full capacity after failure shall be guaranteed;
- the recovery shall be almost immediate (∼50 ms), i.e. no noticeable service reduction.

Recovery by predefining backup paths is referred to as "protection". Recovery by finding back-up paths when (after) a failure has occurred is referred to as "restoration" [13, 15]. This paper focuses on the cases where it is guaranteed that no more than a fixed number of edge-failures could occur.

We then consider the problem of simultaneous primary and backup path allocation. We are given specifications of the traffic to be handled, and to make the provision for both primary as well as the backup networks. On the arrival of a pair (source, destination), the task is to find both a primary path and a backup path between them.

2.1 Network parameters

We consider the following network parameters:

- A bi-directed graph $G = (V, E)$;
  - the adjacency matrix;
- the capacity of each link: $\text{cap} : E \rightarrow R^+$;
- the cost associated to each link: $\text{co} : E \rightarrow R^+$;
- a pair source—destination $(s, d) \in V$ (or a set of pairs (s_i, d_i), $i = 1, \ldots, N$, $N, \geq 1$, in the general case) and the requirements.

2.2 Objective functions

The goal is to find a minimal (cost wise) path between these nodes as well as to assure that the capacity of the edges is not overloaded, which is formulated in the objectives considered below.

Objective 1 Minimize the total cost of the paths (primary and backup) between source and destination:

$$\text{minimize} \sum_{i=1}^{N} \text{cost}(\text{primary path}(s_i, d_i))$$

$$+ \sum_{i=1}^{N} \text{cost}(\text{backup path}(s_i, d_i)). \tag{1}$$

Objective 2 Suppose an edge fails; in order to ensure the network survivability we have to use the backup path. But for this we have to ensure that the failed edge is not also a part of the backup path. This is formulated as a simple objective (criterion) in our model: minimize the number of common edges between primary and backup paths:

$$\text{minimize} \sum_{i=1}^{N} \text{no of common edges(primary path}(s_i, d_i),$$
$$\text{backup path}(s_i, d_i)).$$
$$(2)$$

Objective 3 This objective is used while dealing with shared backup path protection (the objective requires that the backup paths (in the situation in which we have multiple source-destination pairs) should share as many edges as possible):

$$\text{maximize} \sum_{\substack{i=1, j=1, \\ i \neq j}}^{N} \text{no of common edges(backup path}(s_i, d_i),$$
$$\text{backup path}(s_j, d_j)).$$
$$(3)$$

2.3 Constraints

Capacity is treated as a constraint. Once a solution is generated or obtained by modifying an existing one (as explained in the following sections) its validity is verified. This validity refers to the capacity restriction. If capacity is overloaded in at least one link, then the solution is not taken into consideration.

As evident, the problem involves the simultaneous optimization of multiple objectives. There are several ways to deal with a multiobjective optimization problem. Two of the standard approaches are weighted sum method—which combines the objectives and reduces the problem to a single objective optimization one- and Pareto dominance based method—which treats the problem as multiobjective and uses the standard Pareto dominance relationship.

Definition 1 (Pareto dominance) Consider a maximization problem. Let x, y be two decision vectors (solutions) from the definition domain.

Solution x *dominates* y (also written as $x \succ y$) if and only if the following conditions are fulfilled:

 (i) $fi(x) \geq fi(y); \forall i = 1, 2, \ldots, n;$
(ii) $\exists j \in \{1, 2, \ldots, n\} : fj(x) > fj(y).$

That is, a feasible vector x is Pareto optimal if no feasible vector y can increase some criterion without causing a simultaneous decrease in at least one other criterion [18, 19].

The weighted-sum method is a traditional, popular method that parametrically changes the weights among objective functions to obtain the Pareto front [16, 17].

Let us consider we have the objective functions $f_1, f_2, \ldots, f_n$. This method takes each objective function and multiplies it by a fraction of one, the "weighting coefficient" which is represented by w_i. The modified functions are then added together to obtain a single cost function, which can easily be solved using any method which can be applied for single objective optimization.

Mathematically, the new function is written as:

$$\sum_{i=1}^{n} w_i f_i \qquad (4)$$

where $0 \leq wi \leq 1$ and $\sum_{i=1}^{n} w_i = 1$.

3 Description of the proposed multiobjective optimization approach

In this section, we describe the way in which a solution is build and further improved. The model can be used by any of the approaches mentioned above (weighted sum method and Pareto dominance model). In the proposed model, a solution represents all the required paths to be designed together with their corresponding backup paths. For example, if there are 2 source nodes and 2 destination nodes, the task is to find 4 primary paths between sources and destinations as well as 4 backup paths. The developed solution represents all the 8 paths. If we have just one source node and one destination node then the solution will only consists of two paths (the primary and the backup).

In order to build a solution, we generate a set of valid paths between each source and each destination node required. From each set, the primary and backup paths are selected which will compose the solution. This selection is done on a random basis. A set of such feasible solutions is generated and maintained during the search process. Improvement techniques are used in order to assure a convergence to a better solution.

3.1 Solution design

In order to build a path, following are the steps:

Step 1. Start with the source node as current node.
Step 2. If there is a direct path (link) from the current node to the destination node, then move to destination node. Otherwise randomly chose another node from the network, which is connected to the current node and set it as new current node.

Step 3. If the current node is the desired destination node then stop. Otherwise go to Step 2.

The following constraints are taken into account:

– each node can be used at most one time in a path (for avoiding cycles);
– if a node is arrived such that further movement to another node (stuck there) is impossible (because all the connected nodes were previously used), then that solution is aborted.

3.2 Solution improvement

There are two ways to improve a solution:

By applying some improvements directly to that solution or by combining 2 (or more) solutions in order to get better ones and to obtain some diversity.

For the first case, a solution can be improved in one of the following ways:

1. Rebuild and existing path (primary or backup) from a given node.
2. Replace an existing path with another one from the set of paths generated in the beginning of the search process.

For the second case, the two solutions which are to be combined need to have a common node different from the first and second one. Both these techniques for improving solutions are considered.

3.2.1 First improvement technique

In order to improve a solution designed using the above procedure, some modifications on the existing paths are performed as follows:

– one primary path is randomly selected from the ones initially designed. One node on this path is also randomly generated. From the selected node, the path is re-built by considering another path to reach the destination different from the current one.
– one backup path is randomly selected from the ones initially generated and a procedure similar to the one used for the primary path is applied.

3.2.2 Second improvement technique

Another way in which a solution can be improved consists on exchanging a whole path with another one from the existing set (initially generated) of paths. One path (either primary or backup) between each source and destination is picked at one time and exchanged with another one. The newly obtained solution is again compared with the initial solution and the rules described above are followed. The improving procedures are applied for each of the solutions.

These improving steps are repeated for a successive number of iterations. At the end of these iterations, the non-dominated solutions among all the obtained solutions are considered.

The newly obtained solution is compared to the previous solution (which was modified). In order to choose between two solutions and compare them, Pareto dominance relationship is used:

• If it dominates the previous solution then the new solution is kept;
• If it is dominated by the previous solution then the previous solution is kept;
• If the initial solution and the new obtained solution are nondominated then one of them (randomly chosen between the two) is kept.

3.2.3 Third improvement technique

Two paths from two different solutions (corresponding to the same primary or backup path) can be combined if they have a common node different from the first and last one (representing source and destination). Their combination is similar to a cutting–point procedure and consist of exchanging the sub-paths starting with the common node.

For example, if we have the paths:

```
2-7-9-4-3-8-1-5
2-8-11-9-6-5
```

It is noticed that there are 2 common nodes, 9 and 8. Then, a possible combination of the 2 paths gives the following two new paths:

```
2-7-9-6-5
2-8-11-9-4-3-8-1-5
```

A correction is then applied, which basically consists of removing all the cycles from a path. For instance, from the second path we can remove the cycle 8 11 9 4 3 and the new path will be 2 8 1 5. In the case that there are multiple cycles starting and ending in the same node, we will keep the shortest one.

The pseudo code of the proposed approach is summarized as follows:

```
Begin
For each pair source-destination
initialize a set of N possible paths.
Initialize a set of No_sol solutions.
Set t=1.
Repeat
   For k=1 to No_sol / 2 do
   Begin
      Find 2 solutions which can be
      combined using Improvement 3;
      Keep the best 2 out of the 4 ones
   End
```

```
    For i = 1 to No_sol do
    Begin
        Improvement 1 (i, j)
        If j is better than i
        Then replace i by j
        Else if i is better than j
        Then keep i
        Else keep any of i or j

        Improvement 2 (i, j)
        If j is better than i
        Then replace i by j
        Else if i is better than j
        Then keep i
        Else keep any of i or j
    End
    t = t + 1
Until t = No_of_Iterations
Print all the nondominated solutions
obtained at the final iteration.
End.
```

Remark

 (i) The *Improvements 1* and *2* procedures refer to the solution obtained by applying that specific improvement.
(ii) *No_of_iterations* is a priori known and represents the stop criterion.

4 Experiments and discussions

In order to emphasize the performance of the proposed approach we considered three examples. For the first example, the whole procedure is illustrated in detail so that the reader can easily follow all the explanations about the proposed technique in the previous section. The second example is the well known Europe network benchmark having 37 nodes and 55 connections. The third example consists of 65 nodes and 108 connections.

4.1 Experimental example 1

We consider the network given in Fig. 1. The cost associated to each pair of connected nodes is considered to be one. We have two source nodes (node 1 and node 5) and two destination nodes (node 8 and node 13). The goal is to efficiently design two primary paths and two corresponding backup paths.

Solution initialization The task is to determine 4 paths (two primary paths and two backup paths). First, a set of paths between node 1 and node 5 and a similar set of paths between node 8 and node 13 are generated and then some paths are picked randomly from these sets to construct the initial set of solutions. Then, an initialization of these sets (having 10 elements) would appear as follows:

```
1 3 11 8 9 10 12 13 6 5
1 3 4 5
1 7 3 2 9 8 10 12 13 11 6 5
1 3 11 6 5
1 3 11 12 13 6 5
1 3 2 9 8 10 12 11 6 5
1 7 3 4 5
1 2 3 11 6 5
1 7 8 11 6 5
1 7 3 2 9 12 13 6 5
8 10 12 13
8 7 1 3 4 5 6 13
8 7 3 4 6 13
8 7 11 13
8 9 12 13
8 9 11 13
8 11 13
8 10 9 11 13
8 7 3 11 13
8 7 1 3 2
```

6 of the formulated solutions are given below (P and B refer to primary and backup paths respectively):

```
P ⇒ 1 3 11 8 9 10 12 13 6 5
B ⇒ 1 3 4 5
P ⇒ 8 7 1 3 4 5 6 13
B ⇒ 8 7 3 4 6 13
P ⇒ 1 3 2 9 8 10 12 11 6 5
B ⇒ 1 3 4 5
P ⇒ 8 9 12 13
B ⇒ 8 11 13
P ⇒ 1 3 11 12 13 6 5
B ⇒ 1 7 3 2 9 8 10 12 13 11 6 5
P ⇒ 8 11 13
B ⇒ 8 7 3 11 13
P ⇒ 1 3 2 9 8 10 12 11 6 5
B ⇒ 1 2 3 11 6 5
P ⇒ 8 7 1 3 4 5 6 13
B ⇒ 8 7 1 3 2 9 10 12 13
P ⇒ 1 7 8 11 6 5
B ⇒ 1 7 8 11 6 5
P ⇒ 8 11 13
B ⇒ 8 9 12 13
P ⇒ 1 7 3 2 9 12 13 6 5
B ⇒ 1 3 2 9 8 10 12 11 6 5
P ⇒ 8 10 12 13
B ⇒ 8 11 13
```
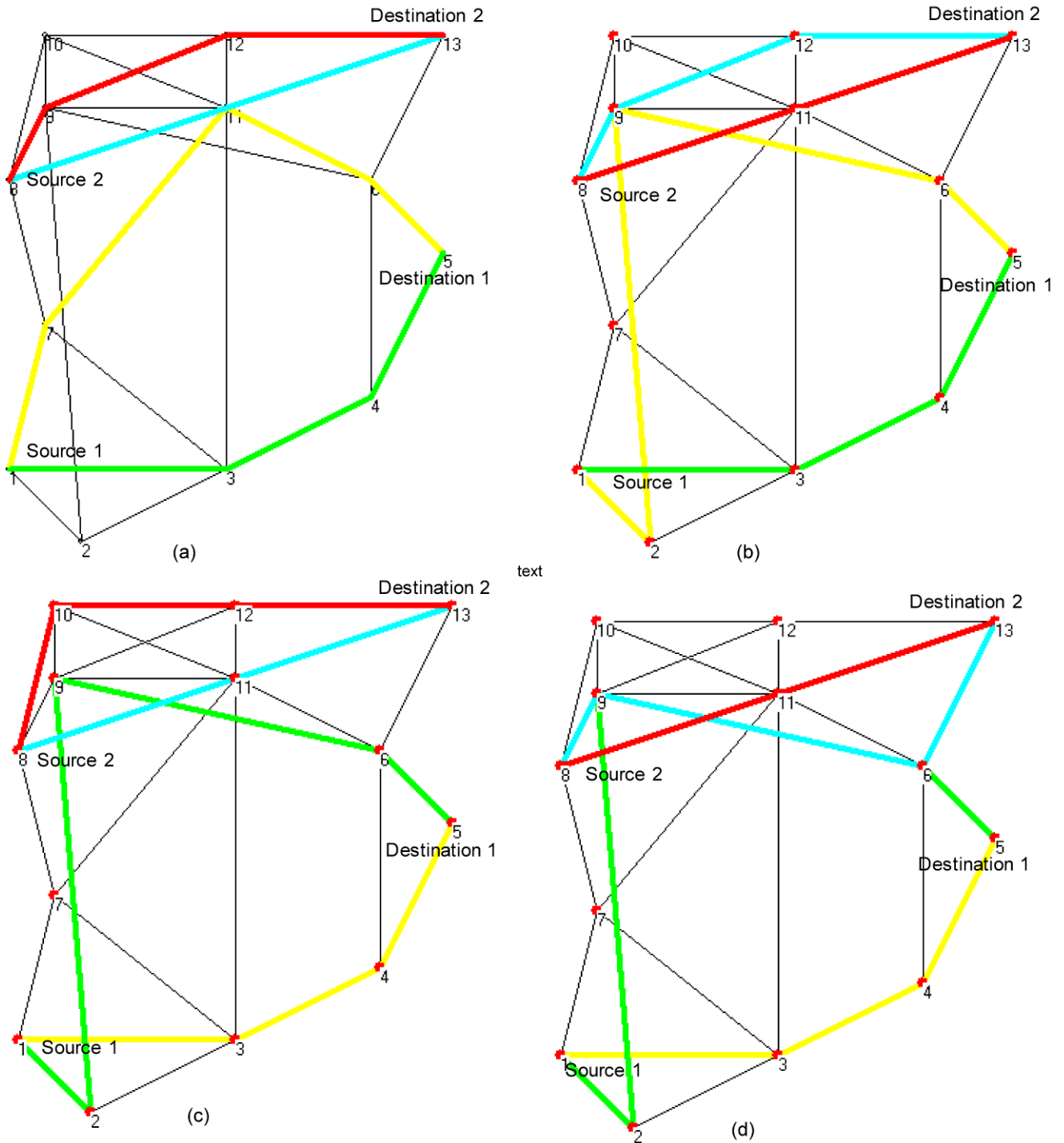
Fig. 1 Examples of Pareto solutions obtained by the proposed approach using Pareto dominance

4.1.1 Solution improvement

First improvement technique Let us consider the first solution given above.

P ⇒ 1 3 11 8 9 10 12 13 6 5
B ⇒ 1 3 4 5

P ⇒ 8 7 1 3 4 5 6 13
B ⇒ 8 7 3 4 6 13

Suppose the first and fourth paths are selected (this means, primary path between node 1 and node 5 and the backup path between node 8 and node 13). A number between 1 and the length of the primary path selected (which is 10)
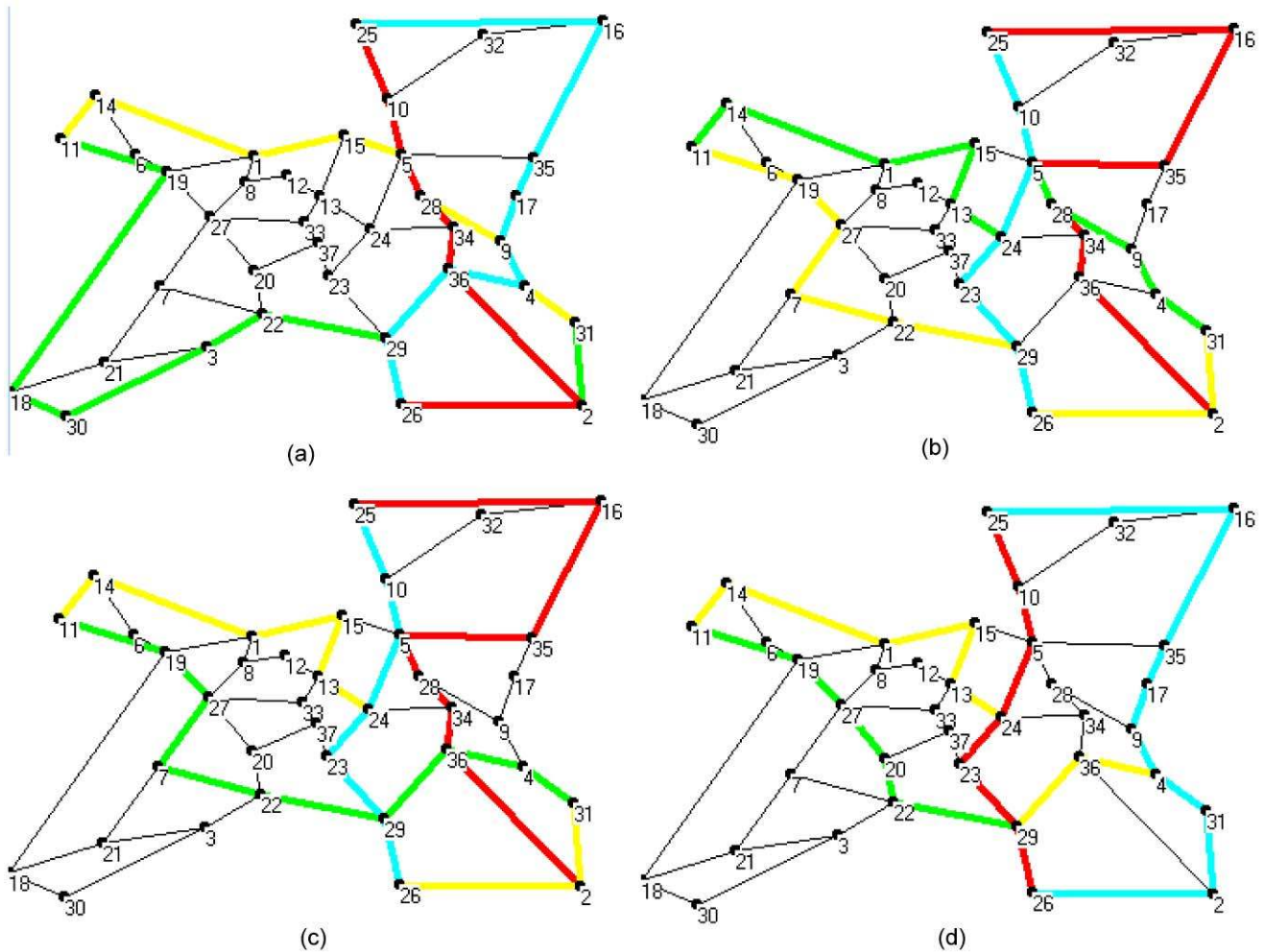
Fig. 2 Examples of solutions obtained for the Europe network benchmark. The source-destination pairs are (11, 31) and (25, 26)

minus 1 is generated. Suppose number 2 is generated. This means, starting with the second position (which is node 3) this path is rebuild.

The new obtained path can be for example:

P ⟹ 1 3 11 6 5

Same procedure is applied for the backup selected for improvement. Let the newly obtained path is:

B ⟹ 8 7 3 11 12 13

Then, the newly obtained solution is:

P ⟹ 1 3 11 6 5
B ⟹ 1 3 4 5
P ⟹ 8 7 1 3 4 5 6 13
B ⟹ 8 7 3 11 12 13

Third improvement Consider that third and forth solutions are considered to be combined following the description of the third improvement technique. Also, consider that first

backup paths are the ones which will be combined and the cutting point is at the node 3:

B ⟹ 1 7 3 2 9 8 10 12 13 11 6 5
B ⟹ 1 2 3 11 6 5

The obtained paths are:

B ⟹ 1 7 3 11 6 5
B ⟹ 1 2 3 2 9 8 10 12 13 11 6 5

After refining and correcting the solutions, the final paths are:

B ⟹ 1 7 3 11 6 5
B ⟹ 1 2 9 8 10 12 13 11 6 5

Some nondominated solutions obtained by considering the Pareto dominance relationship are depicted in Fig. 1. For the weighted sum method we considered all the objectives to have the same weights. In this situation, we obtain only

Fig. 3 Experimental network model with 65 nodes and 108 connections
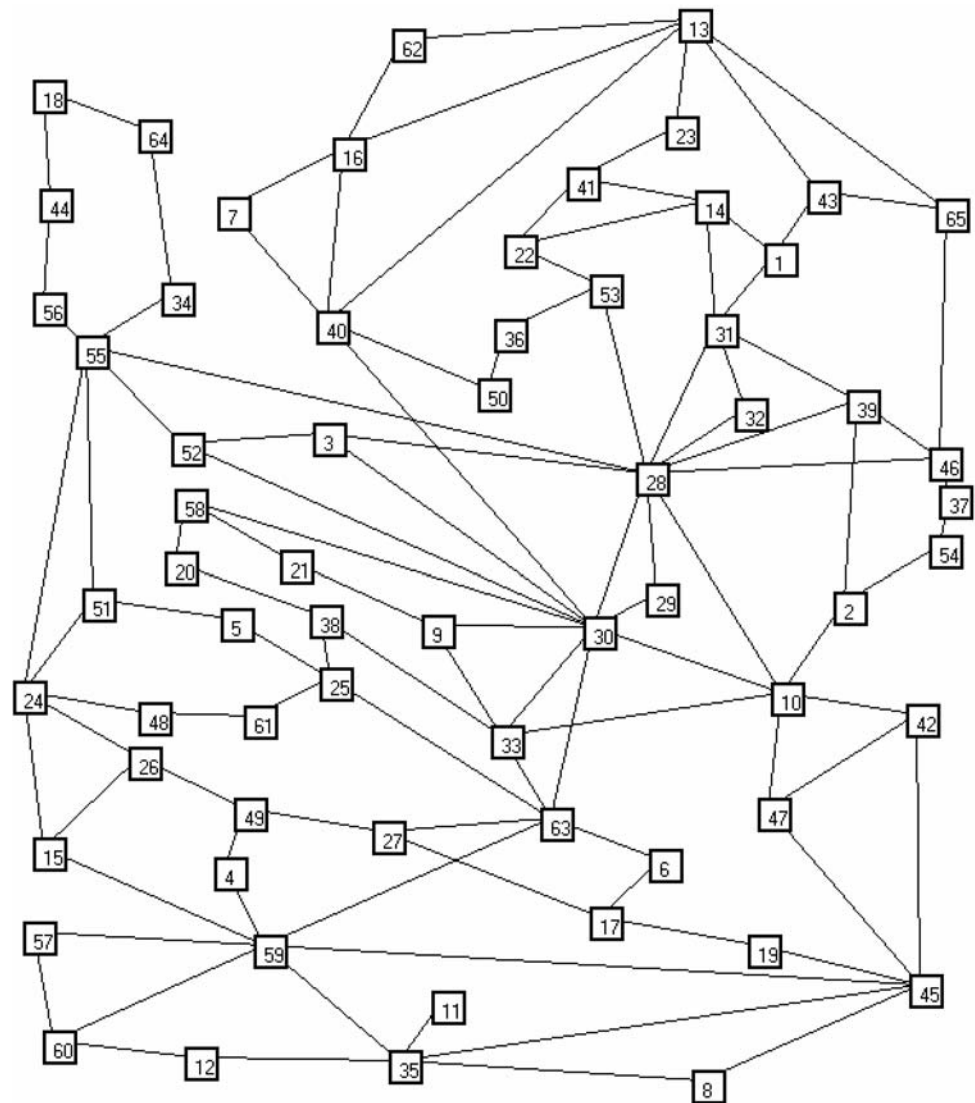
one solution. Multiple solutions may be obtained by varying the weights.

4.2 Second example: Europe network

We consider the Europe network benchmark, which consists of 37 nodes. The problem is to find primary and backup paths between the pairs (11, 31) and (25, 26). The cost of each existing link is set to be one.

The parameters used by the proposed method are the same as the ones used for the first example. A set of 8 feasible solutions is obtained at the end of the search process. Four of the developed solutions are depicted in Fig. 2. The value of the second objective is 0 for the obtained solutions, which means there are no common edges between a primary path and its corresponding backup.

4.3 Third example

Consider the network having 65 nodes and 108 connections as depicted in Fig. 3. We applied the techniques considering the following 2 cases:

– 3 sources and 3 destinations: (24, 45), (28, 35), (7, 46);
– 4 sources and 4 destinations: (24, 45), (28, 35), (7, 46), (18, 42).

Some nondominated solutions obtained by the multiobjective approach are depicted in Figs. 4 and 5. Four nondominated solutions for the first case and 2 solutions for the second case are presented. The solutions were picked from the whole set of nondominated solutions obtained in 30 independent runs. For a set of 10 initial solutions and 15 iterations we obtained between 1 and 5 nondominated solutions in one run. The improvement of cost objective (fitness) is depicted in Fig. 6 and the perfor-
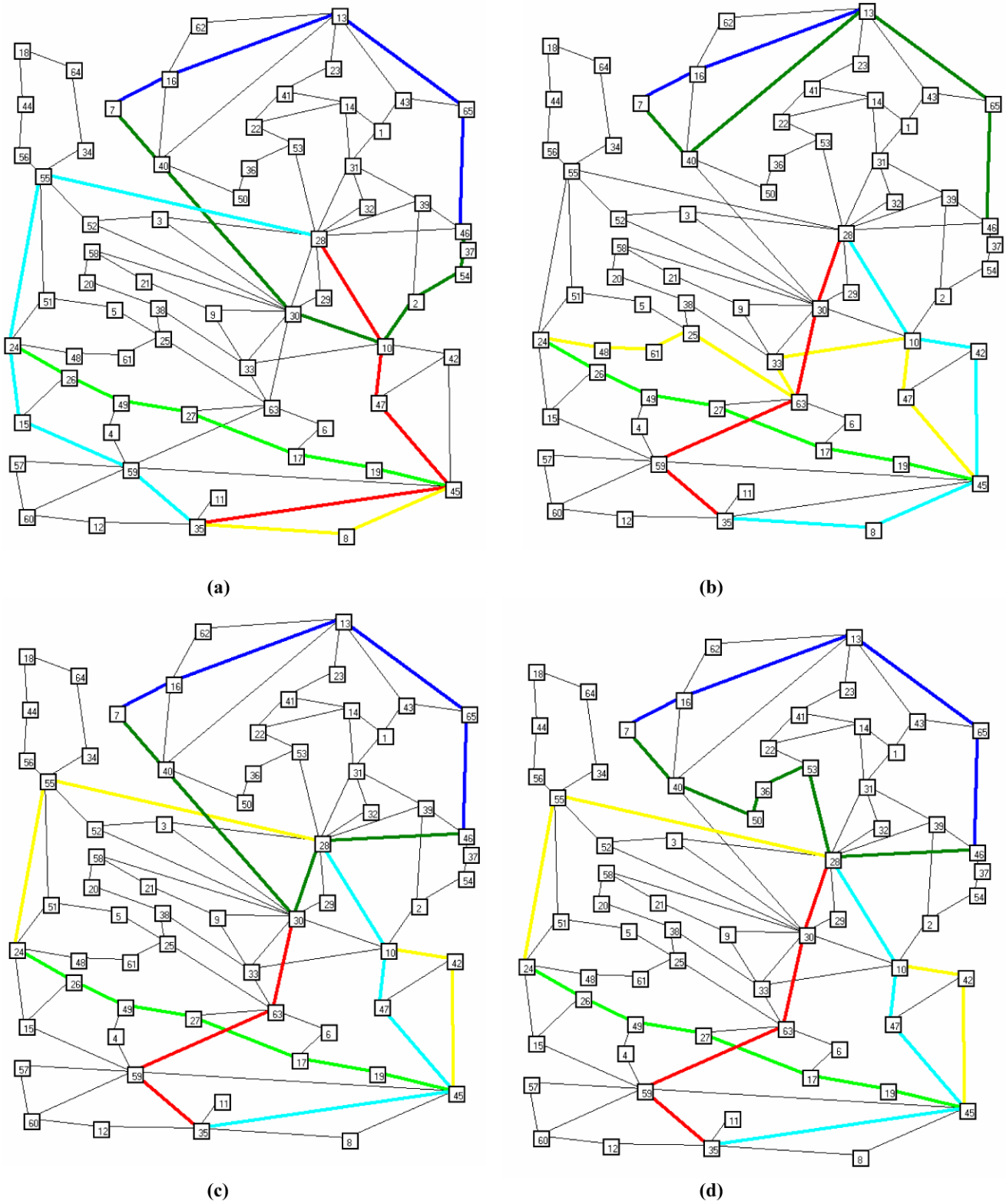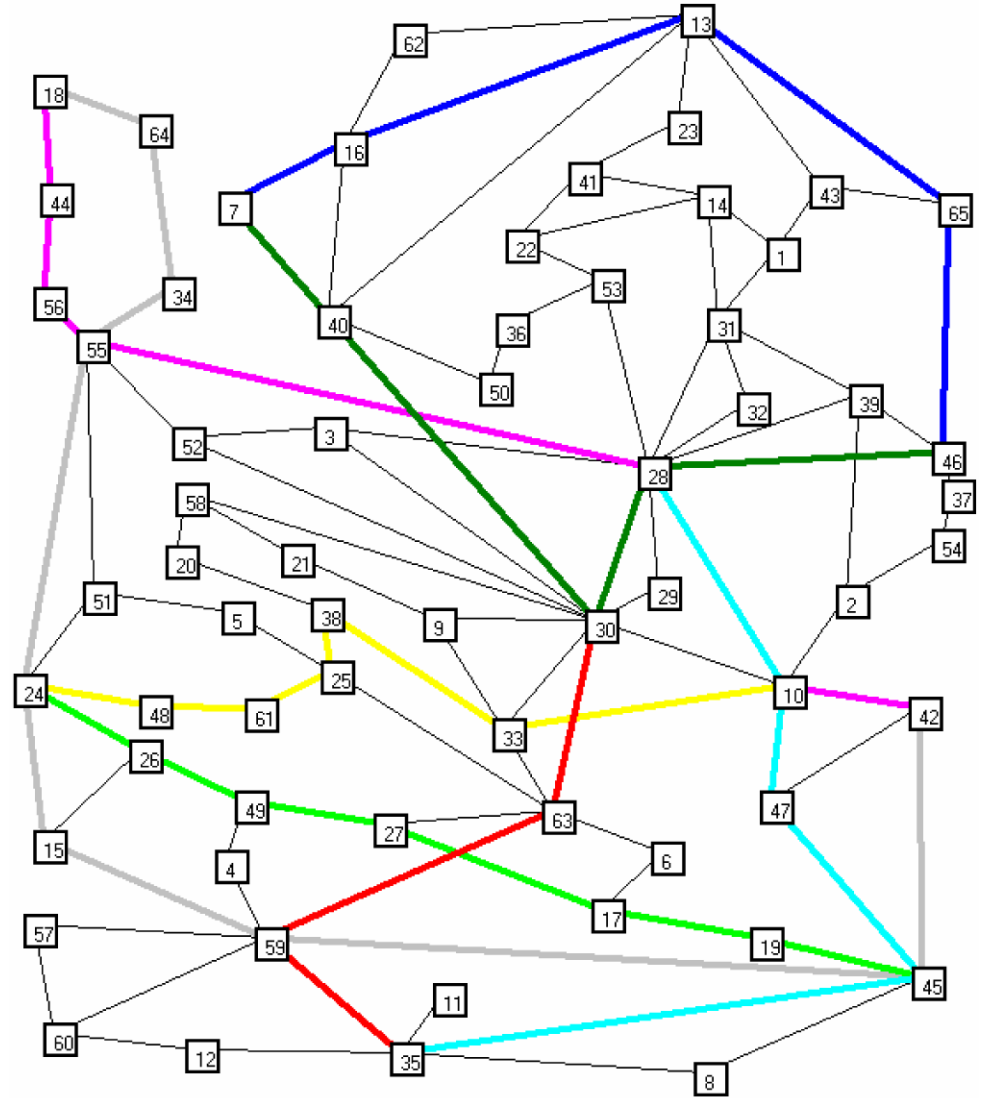
Fig. 4 (**a–d**) Four nondominated solutions obtained by considering Pareto dominance relationship for the third example having 3 source nodes and 3 destination nodes given by the pairs: (24, 45), (28, 35), (7, 46)

Fig. 5 (**a–b**) Two nondominated solutions obtained by considering Pareto dominance relationship for the third example having 4 source nodes and 4 destination nodes given by the pairs: (24, 45), (28, 35), (7, 46), (18, 42)

(a)

mance of the objective giving the number of common edges between primary and backup paths is depicted in Fig. 7.

The evolution of the criteria considered for the single objective approach is depicted in Fig. 8. For the weighted approach, the objective weights were set to have the same value.

5 Conclusions

The paper proposes an algorithm dealing with multiobjectivity in resilience network. The Pareto Resilience Model (PRM) proposed herein focuses on simultaneous allocation of both primary and backup paths. Several criteria to be optimized at one time can be considered but we used only 3

objectives. Capacitated networks are considered while capacity is treated as a constrained. The performance of the proposed approach is tested for three different networks and the approach is able to detect multiple feasible solutions in a very short time (less than a second). Since the proposed model uses only few ways to improve a solution and no modality to combine two existing solutions, we propose as future work the introduction of multiple ways to generate and obtain new solutions from the existing ones, which can increases the diversity of the results at the end of the search process. It is worth to mention that an advantage of this technique is the computational time which is very less for all the considered experiments for both Pareto dominance based approach and weighted sum method (less than one second).

Fig. 5 (Continued)

(b)

Fig. 6 Performance for the third example while considering the problem as multiobjective and using Pareto dominance
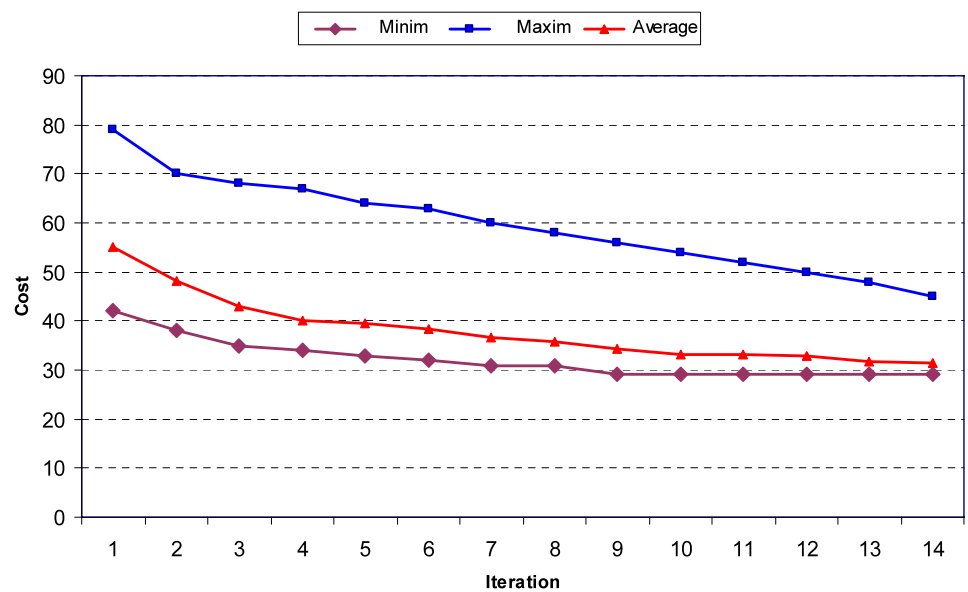
Fig. 7 Performance of the objectives cost and number of common edges for the third example while considering the problem as multiobjective and using Pareto dominance
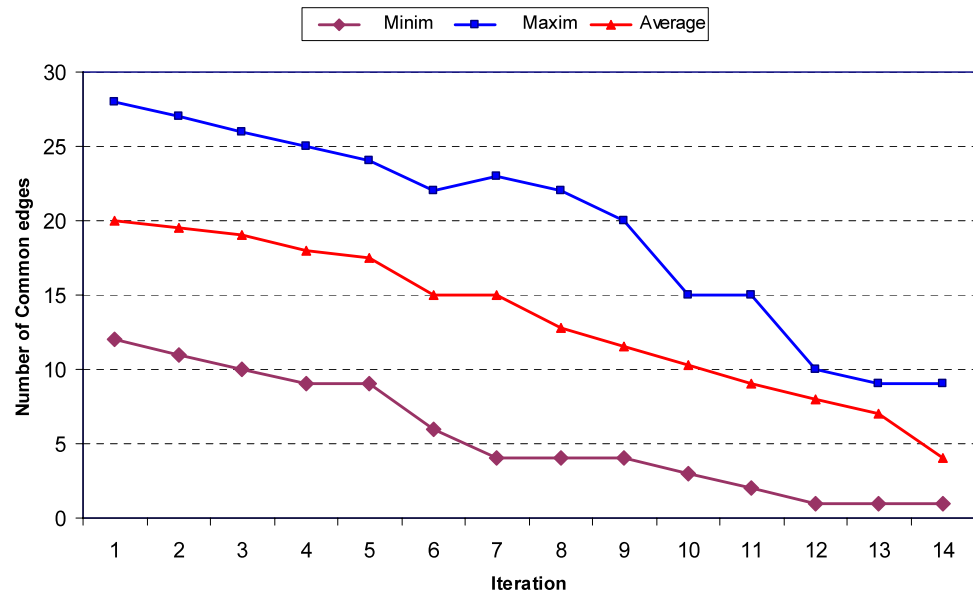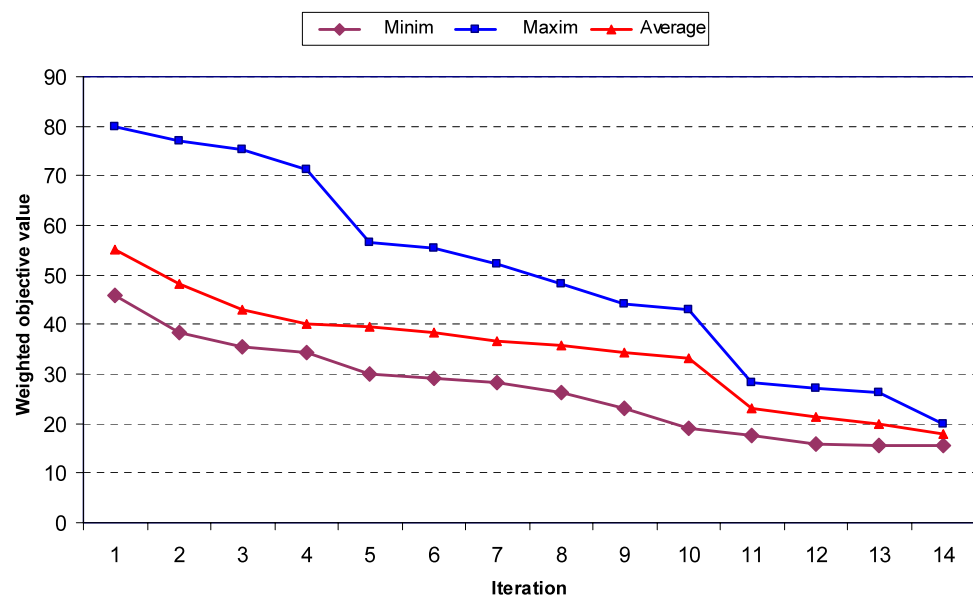

Fig. 8 Performance using the weighted sum of the objectives for the third example (considering the problem as single objective)

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