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Multicast Routing and Wavelength Assignment in Optical Networks with Particle Swarm Optimization

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Abstract. Large bandwidth on hand in WDM networks is the best choice for increasing traffic demand; although, routing and wavelength assignment (RWA) problems still remain a challenge. This work proposes a novel method to solve multicast-RWA problems, using multi-objective Particle Swarm Optimization (PSO), implementing four competitive approaches of state-of-the-art. Such algorithms minimize simultaneously the hop count, the number of splitting power light, the number of splitter node and the balancing of multicast tree for a given set of multicast demands. This way, a set of optimal solutions (known as Pareto set) is obtained in one run of the algorithms, without *a priori* restrictions. Simulation results prove the viability of the PSO proposal and the advantage compared on classical approaches as Multicast Open Shortest Path First routing algorithm and Least Used wavelength assignment algorithm.

1 Introduction

Wavelength Division Multiplexing (WDM) technology applied to optical networks has largely solved the problem of underemployed bandwidth for fiber optics, what is especially useful in already large deployed infrastructure. WDM divides potential bandwidth in different wavelengths avoiding electronic bottleneck [1]. The selection of paths and wavelengths for the interconnection of source-destination pairs (lightpath) is another problem related to optical networks. This problem is known as Routing and Wavelength Assignment (RWA). This work focuses on static traffic for Wide Area Networks (WANs), where changes in the reserved bandwidth only occur occasionally and there is no real time restriction; therefore, calculation may be afforded to find a good solution.

Since RWA belongs to the class of NP-Complete problems [2], the research community focuses on the development of heuristic methods [3] [5]. One of the first works dealing with this problem proposed the optimization of the number of transceivers and the end-to-end mean delay, using a Simulated Annealing (SA) metaheuristic [5]. Saha and Sengupta proposed a simple Genetic Algorithm (GA) to solve a virtual static topology design [3]. Considering a restriction on the wavelengths, they looked for an optimization of the generated traffic weighted sum, the hop count and other objective functions. In [4], Chlamtac et al. presented an evolutionary algorithm for the simultaneous optimization of the number of wavelengths and the mean delay, considering wavelengths and continuity conflicts. Varela and Sinclair proposed a single-objective Ant Colony Optimization (ACO) approach for the routing problem, while the wavelength assignment is solved by means of a greedy method [13].

This work proposes the resolution of a more challenging problem, *multicast Routing and Wavelength Assignment* (multicast-RWA). Multicast-RWA is one central problem in Optical Telecommunication due to its use in different critical applications as high definition TV (HDTV), IP routing, traffic grooming and 1+1 optical layer protection [2]. In this context, the lightpath is generalized to a light-tree, seeking to optimize simultaneously: a) the hop count, b) the number of splitting power light, c) the number of splitter node and d) the balancing of light-tree under the minimal power light at destination and the wavelength continuous constraints [2]. The most important approach that solved multicast-RWA problem, Xin and Rouskas [12], proposed a heuristic to balance multicast-tree subject to the minimal power light at destination and the wavelength continuous constraint.

For the resolution of a multicast-RWA, this work proposes to implement four competitive multi-objective PSO algorithms proposed by (1) Coello and Lechuga (CL) [7], (2) More and Chapman (MC) [8], (3) Hu and Eberhart (HE) [9] and (4) Mostaghim and Teich (MT) [10]. These PSO algorithms have been chosen due their proven success in solving different multi-objective combinatorial optimization problems [11]. In our best knowledge, the proposed approach to the problem in question has not been addressed yet.

The remainder of this work is organized as follows: section 2 presents the formal definition of a multi-objective optimization problem. The multicast-RWA problem formulation is given in section 3. The basic concept of PSO algorithm is shown in section 4, and the our approach is presented in section 5. The environment and experimental results are presented in section 6. Finally, section 7 gives the conclusions and guidelines for future research.

2 Multi-objective Optimization

A Multi-Objective Optimization Problems (MOP) generally consists of a set of n decision variables, a set of k objective functions and a set of m restrictions [7]. Objective functions and restrictions are function of the decision variables. Therefore, MOP generally optimizes:

$$z = f\left(x\right) = \left(f_1\left(x\right), f_2\left(x\right), \ldots, f_k\left(x\right)\right) \tag{1}$$

subject to

$$g\left(x\right) = \left(g_1\left(x\right), g_2\left(x\right), \ldots, g_m\left(x\right)\right) \geq 0 \tag{2}$$

where $x = (x_1, x_2, \ldots, x_n) \in X$ is a decision vector, X denotes the decision space of $f(x), z = (z_1, z_2, \ldots, z_k) \in Z$ is an objective vector while Z denotes the objective space of $f(x)$. The feasible solution set $\Omega \subset X$ is defined as a set of decision vectors x that satisfies $g(x)$. A vector $u \in \Omega$ is said to dominate $v \in \Omega$ (denoted by $u \succ v$) if u is at least as good as v in every objective function and strictly better in at least one objective function. For a given MOP, the Pareto optimal set P^* is defined as the set of non-dominated solutions of Ω. The objective space of P^*, known as Pareto Front, is denoted as PF^*, i.e. $PF^* = f(P^*)$.

Performance figures [7] used in this work aim to compare different approaches in a multi-objective context, and are presented following next:

$$\textit{Contributed Solution:} \quad CS_a = |PF_a \cap PF^*| / |PF^*| \tag{3}$$

Values of CS_a close to 1.0 indicates that many solutions from PF_a belong to PF^*, where PF_a is a Pareto Front calculated by algorithm a.

$$\textit{Extension:} \quad EX_a = \left(\sum_{i=1}^{b} max(d(p_i, q_i)) | p, q \in FP_a \right)^{1/2} \tag{4}$$

where b is the number of objectives and $d(p, q)$ is Euclidean distance between two points in the objective space. In general, an algorithm whose calculated front obtains the highest value in this EX_a metric is the best one.

$$\textit{Error:} \quad ER_a = 1 - (|PF_a \cap PF^*|) / (|PF_a|) \tag{5}$$

If all solutions of PF_a belong to PF^* then the error of PF_a is zero.

3 Problem Formulation

In the present work an optical network is modeled as a graph $G = (V, E, C)$, where V is the set of nodes, E the set of optical links between a pair of nodes and C the set of wavelengths available for each link belonging to E. Let:

$c_{ij} \in C$	maximum number of available wavelengths at link $(i, j) \in E$;
$m = (s, D)$	multicast request m with source node s and destination nodes D, where $s \in V$ and $D \subset V - s$;
M	set of multicast requests, $M = \{m_1, m_2, \ldots, m_{\vert M \vert}\}$ $\vert \cdot \vert$ denote cardinality;
l_m	light-tree connecting a node s to a set of destination nodes D with a wavelength assigned to each link;
$\lambda_{ij}^{l_m}$	wavelength λ assigned to link $(i, j) \in l_m$;
$path_{sd}(m)$	path between a source node and a destination node of request m; note that $path_{sd}(m) \subset l_m$;
L_M	multicast-RWA solution for request set M, i.e. $L_M = \{l_m \vert m \in M\}$; L_M is the decision variable x of previous section.

pt_m power of transmitted light by source node $s \in m$;
it is possible considered $pt_m = 1$ as normalized value.
$pr_m(d)$ power of received light in a destination node $d \in D_m$;
pm_m average of power light received in set of destination node D_m,
i.e. $pm_m = \frac{1}{|D_m|} \sum_{d \in D_m} pr_m(d)$.

A multicast-RWA problem can be expressed as a MOP searching for the best solution L_M which simultaneously minimize the following objective functions:

1- Hop Count:

$$y_1 = \sum_{m \in V} |l_m| \tag{6}$$

2- Number of Splitting:

$$y_2 = \sum_{i \in V; l_m \in L_M} \varphi_i^{l_m} \quad \text{where} \quad \varphi_i^{l_m} = \left\{ \begin{matrix} 1 \text{ if node } i \text{ is a bifurcation node of } l_m \\ 0 \text{ otherwise} \end{matrix} \right\} \tag{7}$$

3- Number of Splitter Node [1]:

$$y_3 = \sum_{i \in V; l_m \in L_M} \left\lceil \frac{\varphi_i^{l_m}}{|L_M|} \right\rceil \tag{8}$$

4- Balancing of light-trees:

$$y_4 = max_{m \in M} \{\sigma_m\} \quad \text{where} \quad \sigma_m = \frac{1}{|D_m|} \sum_{d \in D_m} (pr_m(d) - pm_m)^2 \tag{9}$$

Subject to optical layer constraint:

a. Wavelength assigned: two multicast requests can not be assigned with the same wavelength λ on the same optical link (i,j):

$$\lambda_{ij}^{l_{m_a}} \neq \lambda_{ij}^{l_{m_b}} \quad \forall (i,j) \in E \tag{10}$$

b. Wavelength continuity: the same wavelength λ should be assigned on all optical link of light-tree:

$$\lambda = \lambda_{ij}^{l_m} \quad \forall (i,j) \in l_m \tag{11}$$

c. Minimal power at destination: the power light received at destination node should be bigger than the minimum power sensitivity (pr_{min}) defined by optical technology [12]:

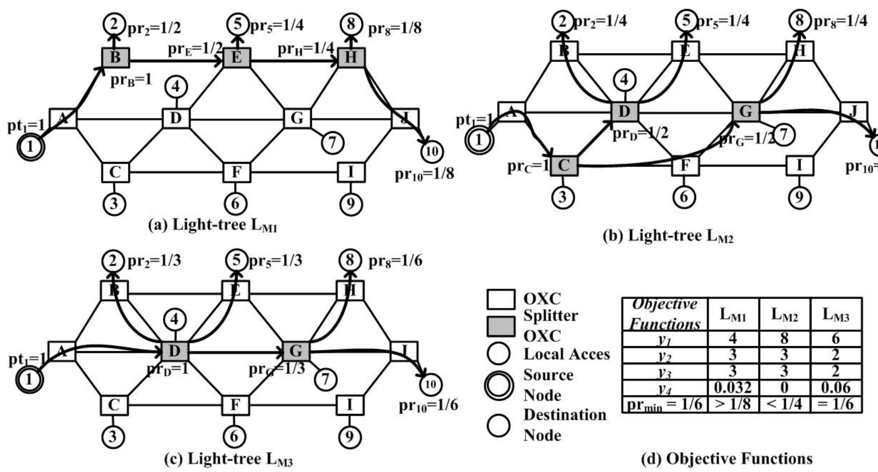
$$pr_m(d) \geq pr_{min}, \forall d \in m \wedge \forall m \in M \tag{12}$$

In general, $pr_m(d) \leq pt_m$ because the splitter nodes divide the power light according at number of exit branches. This loss of power is solved partially by power amplifier [2].

The following example is presented to clarify the problem formulation and the objective functions. Figure 1 shows a small optical network with possible

[1] $\lceil x \rceil$ is the minimum integer bigger than x.

solutions L_M for a multicast requests $M = \{m\}$, where $m = \{\{0\}, \{2, 5, 8, 10\}\}$. Table 1.d summarizes the calculations for the objective functions (equation 6 to 9). Notice that, a simple node without splitting is called OXC (Optical Cross-Connect) [2].



Objective Functions	L_{M1}	L_{M2}	L_{M3}
v_1	4	8	6
v_2	3	3	2
v_3	3	3	2
v_4	0.032	0	0.06
$pr_{min} = 1/6$	> 1/8	< 1/4	= 1/6

Fig. 1. Routing and wavelength assignment for L_M. Note that light-tree L_{M1} does not have the minimum of power light and became a unfeasible solution ($pr_8 < pr_{min}$). Light-trees L_{M2} and L_{M3} got a good power light on their destination node, additionally, their are trade-off solutions. On stage (a), the nodes B, E and H are splitter nodes and that divide the input power received where we can see from the minimum power at the nodes 8 and 10 ($pr_8 = pr_{10} = 1/8$).

4 Particle Swarm Optimization

PSO metaheuristic is a class of algorithm inspired in the foraging behavior of swarm of different animal species as fishes, birds and others [11]. PSO proved to be successful in the resolution of combinatorial optimization problems [8]-[11]. For a mono-objective optimization approach, the basic elements for an PSO algorithm at t iteration are: a population of current particles $P^t = \left\{x_1^t, x_2^t, \ldots, x_{|P|}^t\right\}$, a memory of best solutions calculated by each particle in its history $P_{lb}^t = \left\{y_1^t, y_2^t, \ldots, y_{|P|}^t\right\}$ and the global best solution s_{global}^t calculated by all particles. A particle is a position in the decision space given by coordinates whose new position is made in two steps: first, it calculates a particle velocity and next it is obtained a new particle according following equation (see [8]-[11]):

$$v_i^{t+1} = c_0 \cdot v_i^t + r_1 \cdot c_1 \cdot (y_i^t - x_i^t) + r_2 \cdot c_2 \cdot (s_{global}^t - x_i^t) \quad (13)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad \forall i \in \{1, 2, \ldots, |P|\} \tag{14}$$

v is the particle velocity, r_1 and r_2 are random numbers between (0, 1), c_0 is an inertial factor, c_1 and c_2 are learning factors. Typically, $c_0 = 1$, $c_1 = c_2 = 2$ [8].

5 Proposed Approach

When a multi-objective optimization problem (MOP) is considered, PSO algorithm is extended to multi-objective PSO (MOPSO) approach [8]-[11]. The main difference between PSO and MOPSO is a set of solutions PF which stores better solutions in trade-off, i.e. let be $s, s' \in FP$ then $s \not\succ s'$ and $s' \not\succ s$. Ideally, the PF set is near to Pareto Front at end of an iteration.

PSO and MOPSO are optimization approaches of general purpose. To solve a multicast-RWA problem, each particle should represent a set of light-trees or a solution L_M. In this context, it is necessary to define a structure of particle and and how to calculate a new solution L_M. This work proposes a novel approach to generate a new light-tree based in the PSO concept but in a constructive way. This mechanics is different to the classic PSO for continuous problems given in equations (13) and (14). Let be: L_M^c a current solution, L_M^l a best local solution, L_M^g a best global solution, and Y_{mij}^{φ} a binary variable. If $(i, j) \in l_m^{\varphi} ij$ then $Y_{mij}^{\varphi} = 1$ and otherwise $Y_{\varphi}^{mij} = 0$ considering $\varphi \in \{current, local, global\}$. A new light-tree L^{new}, for a set of multicast request M, is obtained according to Algorithm 1.

Basically, the *Multicast-PSO* algorithm constructs a new light-tree beginning at a source node and then adds new links up to all destination nodes. In this construction process, each link is selected according to the probability obtained by the weights assigned. The weight of a link $(k_{ij}, (i, j) \in E)$ depends on the cognitive factors (c_0, c_1, c_2) and the number of trees that the link belongs. All optical layer constraints (equations (10) to (12)) are satisfied in the process (see line 10 Algorithm 1).

Considering the above described, the following Algorithm 2 shows the performance of a generic MOPSO. In each iteration it builds a new set of solutions which replaces the old solutions (line 11). Depending on the MOPSO algorithm implemented, a solution L_M^g is selected from the set of Pareto Front FP_{known} in line 8. A new set of solution P_{new} is calculated iteratively using Multicast-PSO algorithm (line 7 to 9). After being assessed the new set of solutions, they updated the best set of solutions P_{local} and the Pareto Front PF_{known}. Finally, when the end-condition is reached, the algorithm returns a set of good solutions given for the PF_{known}. For space constraint, details on MOPSO approaches implemented (CL, MC, HE, MT) and MOSPF-LU (state-of-the-art) will be omitted (see references [7]-[10]).

6 Environment and Experimental Results

Algorithms were implemented on a personal computer with a 1.25 GHz Athlon microprocessor and 512 MB RAM. The source code was compiled using DevC++

Multicast-PSO[G, M, L^c_M, L^l_M, L^g_M, c_0, c_1, c_2, pr_{min}]

$L^{new} \leftarrow \oslash$
for all $m \in M$ **do**
  Assign to l^{new}_m a wavelength ($\lambda^{'}$) least used
  $R \leftarrow \oslash$, $R \leftarrow s_m$
  for all $(i,j) \in E$ **do**
    $k_{ij} \leftarrow 1 + c_0 \cdot Y^c_{mij} + c_1 \cdot Y^l_{mij} + c_2 \cdot Y^g_{mij}$ /* assign weights
  while $R \neq \oslash$ and $D_m \not\subset l^{new}_m$ **do**
    $n \leftarrow$ Randomly to select a node of R
    for all $i \in V$ **do**
      if $(n,j) \notin l^{new}_m$ and $(n,j)_{\lambda'}$ = free and $pr_m(j) \geq pr_{min}$ **then**
        $N_n \leftarrow N_n \cup i$
    if $N_n = \oslash$ **then**
      $R \leftarrow R - n$ /* delete node without valid neighborhood nodes
    else
      Calculate of selection probability $Pr(j \in N_n) = k_{nj}/(\sum_{g \in N_n} k_{ng})$
      Select a node $t \in N_n$ by the roulette method /* see [7]
      $l^{new}_m \leftarrow l^{new}_m \cup (n,t)$ /* building the tree
  Delete links $(i,j) \in l^{new}_m$ not used in any path ($path_{sd}(m)$)
  $L^{new} \leftarrow L^{new} \cup l^{new}_m$
return L^{new}

Algorithm 1: Pseudocode for Multicast-PSO approach proposed by this paper.

MOPSO[G, M, c_0, c_1, c_2, pr_{min}]

Initialize randomly $P_{current}$
Update P_{local} with particles of $P_{current}$
$FP_{known} \leftarrow \oslash$
Update FP_{known} with $P_{current}$
while end-condition = false **do**
  $P_{new} \leftarrow \oslash$
  for all $i \in \{1, 2, \ldots, |P|\}$ **do**
    Select a solution L^g_M of FP_{known}
    Build $P_{new}(i)$ according to $P_{current}(i)$, $P_{local}(i)$ and L^g_M {Multicast-PSO}
  Evaluate $y = (y_1, y_2, y_3, y_4)$ of the P_{new}
  Update P_{local} with particles of P_{new}
  Update FP_{known} with particles of P_{new}
  $P_{current} \leftarrow P_{new}$
return FP_{known}

Algorithm 2: Pseudocode for a generic MOPSO approach.

compiler v4.9.9.2. The MOPSO algorithms implemented are: (1) Coello and Lechuga (CL) [7], (2) More and Chapman (MC) [8], (3) Hu and Eberhart (HE) [9] and (4) Mostaghim and Teich (MT) [10]. Furthermore, in order to verify the effectiveness of the implemented algorithms, classical algorithms reported in the literature were also implemented: the Multicast Open Shortest Path First (MOSPF) routing algorithm and Least Used (LU) wavelength assignment algorithm [5].

For simulations, we considered three sets of multicast demands M for low, half and high load and five classical networks topologies [14]: (a) GINAnet (15 nodes and 44 links), (b) NSFnet (14 nodes and 42 links), (c) EUROFRANCEnet (43 nodes and 75 links), (d) ARPANET (21 nodes and 25 links) and (e) NTTnet (55 nodes and 69 links). This is a total 15 different instances. In each network topology was considered 10 wavelength per fiber ($c_{ij} = 10 \quad \forall (i,j) \in E$). The following default parameters were used: $|P| = 20$ particles and $c_0 = c_1 = c_2 = 1$ adopted experimentally. For all algorithms the stop criterion was 100 iterations.

A set of near optimal solutions (FP_{known}) was found for each multicast set M by means of the following procedure:

1. each algorithm was run 5 times;
2. each solution of those 5 runs was saved in a set;
3. all dominated solutions were deleted from this set, creating a set FP_{known} that may be considered as a good approximation of FP^* (*Pareto Front true*).

In order to measure the quality of the solutions calculated by algorithms in 5 runs, each solution set M from each run was compared against FP_{known}. Note that, all experimental test consist of 375 runs in total (3 loads, 5 topologies, 5 algorithms and 5 runs).

The experimental results to small network topologies are shown in Table 1 while the Table 2 presents the results for large network topologies. Average results for all experimental are exposed in Table 3. The best value corresponds to one in all result tables (normalized values). Destination nodes blocked correspond to column DB. Other columns indicate figures performances (ER, EX, CS) that were presented in Section 2.

Overall, the results indicate that MOPSO approaches are promising to get better results than MOSPF-LU in all instances problems (see Tables 1 and 2). Moreover, it is not clear which MOPSO algorithm is better considering all instances. In this context, the Table 3 presents the average of all tests. Notice that the MU algorithm obtained the better average in blocking (DB) and error (ER) than other algorithms, but, the MC algorithm is very good to blocking (DB), extension (EX) and contributed solutions (CS). With the aim of defining a unique performance for MOPSO algorithms, the column Ranking (Table 3) presents the average for the all multi-objective performance figures and destinations blocked. The ranking of algorithms indicated similar averages obtained by MOPSO approaches. However, the MC algorithm is better with 0.83, which has reached a difference of 0.06 with respect to CL and MT approaches. Considering the Table 3 we suggest that no MOPSO algorithm is significantly superior to the problem in question.

Table 1. Experimental results for different traffic loads and small networks.

Load		*Algorithm*	GINA				NSF				ARPANET			
			DB	ER	EX	CS	DB	ER	EX	CS	DB	ER	EX	CS
Low	MOPSO	*CL*	1	0.14	1	1	1	0.02	0.79	0.71	0.96	0.41	0.66	0.41
		MC	1	0.12	0.97	0.89	1	0	1	0.63	1	0.33	0.30	0.33
		HE	1	0.12	0.82	0.84	1	0.03	0.81	0.75	1	0.98	0.89	0.98
		MT	1	1	0	0	1	1	0	0	1	1	1	1
	MOSPF-LU		0	0	0	0	1	0.08	0	1	0	0	0	0
Half	MOPSO	*CL*	1	0.43	0.61	1	1	0.15	0.81	1	0.92	1	0.31	1
		MC	1	0.32	1	0.73	1	0.13	1	0.91	0.92	0	0.38	0
		HE	1	0.27	0.51	0.63	1	0.14	0.73	0.93	0.84	0	0.69	0
		MT	1	1	0	0	1	1	0	0	1	0	1	0
	MOSPF-LU		0	0	0.53	0	0	0	0.32	0	0	0	0.22	0
High	MOPSO	*CL*	0.35	0	0.49	0	0.86	0	0.08	0	1	1	0.68	1
		MC	0.95	0.10	1	1	0.96	0.10	1	1	0.96	0	0	0
		HE	0.72	0	0.10	0	0.87	0	0.32	0	0.95	0	0.42	0
		MT	1	1	0	0	1	1	0	0	0.93	0	0.39	0
	MOSPF-LU		0	0	0	0	0	0	0.44	0	0	0	1	0

Table 2. Experimental results for different traffic loads and large networks.

Load		*Algorithm*	NTT				EUROFRANCE			
			DB	ER	EX	CS	DB	ER	EX	CS
Low	MOPSO	*CL*	0.99	0	0.11	0	0.99	0	1	0
		MC	0.99	0	1	0	0.98	0	0.82	0
		HE	1	0	0.07	0	1	1	0	1
		MT	1	1	0.11	1	0.98	0	0.62	0
	MOSPF-LU		0	0	0	0	0	0	0	0
Half	MOPSO	*CL*	0.98	0	0.38	0	0.99	0	0.05	0
		MC	1	1	0.21	1	1	1	0	1
		HE	0.98	0	0.25	0	0.98	0	0.07	0
		MT	1	0	1	0	0.98	0	1	0
	MOSPF-LU		0	0	0.09	0	0	0	0.02	0
High	MOPSO	*CL*	1	0	1	0	0.96	0	0.60	0
		MC	0.99	0	0.30	0	0.97	0	0	0
		HE	1	0	0.06	0	1	1	0	1
		MT	1	1	0	1	0.96	0	1	0
	MOSPF-LU		0	0	0	0	0	0	0	0

Table 3. Average of all experimental.

Algorithm	DB	ER	EX	CS	Ranking
CL	0.94	0.35	0.96	0.82	0.77
MC	0.99	0.34	1	1	0.83
HE	0.97	0.39	0.64	0.82	0.70
MT	1	1	0.68	0.40	0.77
MU	0.07	0.01	0.31	0.13	0.13

7 Conclusions and Future Work

This work presents a new approach based on PSO to solve the multicast-RWA problem in optical networks, considering WDM technology and optical layer constraints. MOPSOs were successfully adapted to solve this problem simultaneously optimizing four objective functions: (1) the hop count, (2) the number of splitting, (3) the number of splitter node and (4) the balancing of light-tree. To solve the multicast-RWA problem, a new constructive approach to calculate a light-tree was provided. Simulations were performed over five well known topologies showing that MOPSO approaches clearly outperforms MOSPF-LU in all tested cases. In particular, no MOPSO algorithm is superior when the all multi-objective performance figures are considered.

Even though the feasibility of using PSO based algorithms was clearly established for the multicast-RWA problem, a lot of work remains to be done for other topologies and different traffic demands. Also, comparisons of the proposed methods to other metaheuristics and integer linear programming could be done. Furthermore, other objective functions as the quantity of transceivers may also be easily optimized with the proposed approach.

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