SOLVING THE RING ARC-LOADING PROBLEM USING A HYBRID SCATTER SEARCH ALGORITHM

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Abstract: Resilient Packet Ring (RPR) is a standard that uses Ethernet switching and a dual counter-rotating ring topology to provide SONET-like network resiliency and optimised bandwidth usage, while it delivers multipoint Ethernet/IP services. An important optimisation problem arising in this context is the Weighted Ring Arc Loading Problem (WRALP). That is the design of a direct path for each request in a communication network, in such a way that high load on the arcs will be avoided, where an arc is an edge endowed with a direction. The load of an arc is defined as the total weight of those requests routed through the arc in its direction. WRALP ask for a routing scheme such that the maximum load on the arcs will be minimum. In this paper we study the loading problem without demand splitting and for solving it we propose a Hybrid Scatter Search (HSS) algorithm. Coupled with the Scatter Search algorithm we use a Tabu Search algorithm to locate the global minimum. We show that HSS is able to achieve feasible solutions to WRALP instances, improving the results obtained by previous approaches.

1 INTRODUCTION

The past two decades have witnessed tremendous research activities in optimisation methods for communication networks. Resilient Packet Ring (RPR), also known as IEEE 802.17, is a standard, designed to optimise the transport of data traffic through optical fiber ring networks (Davik et al., 2004; RPR Alliance, 2004; Yuan et al., 2004). The RPR aims to combine the appealing functionalities of Synchronous Optical Network/Synchronous Digital Hierarchy (SONET/SDH) networks with the advantages of Ethernet networks. The load balancing model for RPR differs from the SONET/SDH ring loading. Namely, SONET/SDH demands are bi-directional and the demands assigned to go clockwise compete for common span capacity with the demands assigned to go counter-clockwise. In RPR there are two distinct rings (clockwise and counter-clockwise) and the demands do not compete for common capacity. In this paper we consider the Weighted Ring Arc-Loading Problem (WRALP) which arises in engineering and planning of RPR systems. Specifically, for a given set of non-splitable and unidirectional point-to-point demands, the purpose is to find the routing for each demand so that the maximum link segment load will be minimised (Karunanithi and Carpenter, 1994; Cho et al., 2005; Kim et al., 2008; Bernardino et al., 2010a).

There are three variants to solve this problem: (i) demands can be split in two parts, and then each one is sent in a different direction; (ii) demands are allowed to be split in two parts, but restricted to be integrally split; (iii) each demand must be entirely routed in either one of the two directions, clockwise or counter-clockwise. In this paper we study the third variant, where NP-hardness can be drawn from the results in literature (Cosares and Saniee, 1994; Kubat and Smith, 2005).

Cosares and Saniee (1994) and Dell'Amico et al. (1998) studied a similar no-split loading problem on

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SONET/SDH rings. For the split problem, several approaches have been summarised by Schrijver et al. (1998) and their algorithms are compared in Myung and Kim (2004) and Wang (2005). Recently Kim et al. (2008) presented an Ant Colony Optimisation (ACO) algorithm using different strategies to solve the loading problem on SONET/SDH rings.

The non-split WRALP considered in the present paper is identical to the one described by Kubat and Smith (2005) (non-split WRALP), Cho et al. (2005) (non-split WRALP and split WRALP) and Yuan and Zhou (2004) (split WRALP), that studied the loading problem on RPR systems .

We verify that the main purpose of previous works was to build feasible solutions for the loading problems in a reduced amount of time. Our purpose is different - we want to compare the performance of our algorithm with others in the achievement of the best-known solution. Using the same principle Bernardino et al. (2008, 2009a, 2009b, 2010a, 2010b) presented several Evolutionary Algorithms (EAs) and a Tabu Search (TS) algorithm to solve the non-split loading problem on SONET/SDH rings and several EAs and Swarm Optimisation algorithms to solve the non-split WRALP.

The WRALP problem is a NP-complete combinatorial optimisation problem (Cosares and Saniee, 1994; Kubat and Smith, 2005). It means that we cannot guarantee to find the best solution in a reasonable amount of time. In practice, approximate methods are used to find a good solution to complex combinatorial optimisation problems where classical heuristics have failed to be efficient. The existing, successful methods in approximate optimisation fall into two classes: Local Search (LS) and population-based search. There are many LS and population-based optimisation algorithms.

This paper presents an application of a population-based optimisation algorithm called the Scatter Search (SS) algorithm combined with a LS technique called the Tabu Search (TS).

The SS is an EA that has recently been found to be promising to solve combinatorial optimisation problems. The SS was first introduced in 1977 by Fred Glover and extensive contributions have been made by Manuel Laguna (2002). The SS operates on a small set of solutions and makes only limited use of randomisation as a proxy for diversification when searching for an optimal solution.

Embedded in the SS algorithm we use a TS algorithm, which is used to improve the solutions' quality. The TS algorithm is a mathematical optimisation method, which belongs to the class of LS techniques.

We compare the performance of Hybrid SS (HSS) algorithm with five algorithms: Probability Binary Particle Swarm Optimisation (PBPSO), Genetic Algorithm (GA), Hybrid Differential Evolution (HDE) algorithm, Hybrid ACO (HACO) algorithm and Discrete Differential Evolution (DDE), used in literature.

The paper is structured as follows: in Section 2 we present the problem definition; in Section 3 we describe the implemented HSS algorithm; in Section 4 we discuss the computational results obtained and in Section 5 we report about the conclusions.

2 PROBLEM DEFINITION

An optimal loading balance in RPR systems is of paramount importance as it increases system capacity and improves the overall ring performance. Considering a given set of non-split and unidirectional point-to-point requests (weights), the purpose is to find the routing for each request in such a way that the maximum arc load will be minimised (Schrijver et al., 1998).

Let R_n be a n-node bidirectional RPR ring with nodes $\{n_1, n_2, \ldots, n_n\}$ labelled clockwise. Each edge $\{e_k, e_{k+1}\}$ of R_n, $1 \leq k \leq n$, is taken as two arcs with opposite directions, in which the data streams can be transmitted in either direction:

$$a_k^+ = (e_k, e_{k+1}) \text{ or } a_k^- = (e_{k+1}, e_k).$$

A communication request on R_n is an ordered pair (s,d) of distinct nodes, where s is the source and d is the destination. We assume that data can be transmitted clockwise or counter-clockwise on the ring, without splitting. We use $P^+(s,d)$ to denote the directed (s,d) path clockwise around R_n, and $P^-(s,d)$ the directed (s,d) path counter-clockwise around R_n.

Often a request (s,d) is associated with an integer weight $w>=0$; we denote this weighted request by $(s,d;w)$. Let $Z=\{(s_1,d_1;w_1), (s_2,d_2;w_2), \ldots, (s_m,d_m;w_m)\}$ be a set of integrally weighted requests on R_n. For each request (s_i,d_i) we need to design a directed path P_i of R_n from s_i to d_i. A collection $P=\{P_i: i=1,2,\ldots,m\}$ of such directed paths is called a routing for Z.

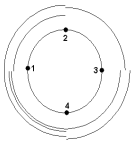
In this work, the solutions are represented using binary vectors (Table 1). If a position has the value 1 the demand flows in the clockwise direction, if it has the value 0, it flows in the other way.

We assume that weights cannot be split, that is, for some integer $L_i=1$, $1 \leq i \leq m$, the total amount of data is transmitted along $P^+(s_i,d_i)$; $L_i=0$, the

total amount of data is transmitted along $P^-(s_i, d_i)$. The vector $L = (L_1, L_2, \ldots, L_m)$ determines a routing scheme for Z.

Table 1: Representation of the solution.

Pair(s, t) Demand						
1: (1, 2) → 15	15 C					
2: (1, 3) → 3	3 CC					
3: (1, 4) → 6	6 CC					
4: (2, 3) → 15	15 C					
5: (2, 4) → 6	6 CC					
6: (3, 4) → 14	14 C					
n=numberNodes=4	C - clockwise					
m=numberPairs=6	CC - counter clockwise					
	$Pair_1$	$Pair_2$	$Pair_3$	$Pair_4$	$Pair_5$	$Pair_6$
Representation (x)	1	0	0	1	0	1



3 SCATTER SEARCH ALGORITHM

This metaheuristic technique derives from strategies proposed by Glover (1977) to combine decision rules and constraints, and was successfully applied to a large set of problems (Glover et al., 2003). The basic idea is to create a set of solutions (the reference set), that guarantees a certain level of quality and diversity. The iterative process consists in selecting a subset of the reference set, combining the corresponding solutions through a strategy, in order to create new solutions and to improve them through a LS optimisation technique. The process is repeated with the use of diversification techniques, until certain stopping criteria are met.

In SS algorithm it is built an initial set of solutions (reference set) and then the elements of specific subsets of that set are systematically combined to produce new solutions, which hopefully will improve the best-known solution (see Glover et al., 2003 for a comprehensive description of the algorithm).

The basic algorithmic scheme is composed of five steps:

1. Generation and improvement of solutions;
2. Construction of the reference set;
3. Subset selection;
4. Combination;
5. Reference set update.

The standard SS algorithm stops when the reference set cannot be updated. However, the scheme can be enhanced by adding new steps in which the reference set is regenerated. Our algorithm uses a diversification mechanism after a pre-defined number of nid iterations without improving the best solution found so far. The reinitialisation can be very useful to refocus the search on a different search space region and to avoid the early convergence of the algorithm.

The main steps of the HSS algorithm applied to the WRALP are detailed below:

```
Initialise Parameters
Generate initial set of Solutions
Evaluate Solutions
Apply Improvement Method
Generate Reference Set
WHILE TerminationCriterion()
   Select subsets
   Apply Combination Method
   Apply Improvement Method
   Update Reference Set
   IF (no new solutions) THEN
      Regenerate Reference Set
   IF (nid iterations without improve
best solution) THEN
      Apply Diversification Mechanism
```

The next subsections describe each step of the algorithm in detail.

3.1 Initialisation Parameters

The following parameters, must be defined by the user: (1) mi– number of iterations; (2) ni– number of initial solutions; (3) b1– number of best solutions in the reference set; (4) b2– number of most different feasible solutions in the reference set and (5) nid- number of iterations without improvement (used for diversification).

3.2 Generation of Solutions

The initial solutions can be randomly created or in a deterministic form based in a Shortest-Path Algorithm (SPA). The SPA is a simple traffic demand assignment rule in which the demand will traverse the smallest number of segments.

3.3 Evaluation of Solutions

To evaluate how good a potential solution is relative to other potential solutions we use a fitness function. The fitness function returns a positive value (fitness value) that reflects how optimal the solution is.

The fitness function is based on the fitness function used in (Bernardino et al., 2008, 2009a, 2009b, 2010a, 2010b):

$W_i, \ldots, w_m$ between $(s_i, d_i), \ldots, (s_m, d_m)$ (1a)
$L_i, \ldots, L_m = 0 \rightarrow P^-(s_i, d_i)$

$1 \rightarrow P^{+}(s_i, d_i)$ (1b)

Load on arcs:

$$Load(L, a_k^{+}) = \sum_{i: a_k^{+} \in P^{+}(s_i, d_i)} W_i \quad (2a)$$

$$Load(L, a_k^{-}) = \sum_{i: a_k^{-} \in P^{-}(s_i, d_i)} W_i \quad (2b)$$

$\forall k=1,\ldots,n; \quad \forall i=1,\ldots,m$

Fitness function:

$$\max \{\max Load(L, a_k^{+}), \max Load(L, a_k^{-})\} \quad (3)$$

For a given ring, between each node pair (s_i, t_i) there is a demand value >=0. Constraint sets (1) state that each positive demand value is routed in either clockwise (C) or counter-clockwise (CC) direction.

For an arc, the load is the sum of w_i for clockwise or counter-clockwise between nodes e_k and e_{k+1} (2). The purpose is to minimise the maximum load on the arcs of a ring (3).

3.4 Generation of Reference Set

The best b1 solutions in the initial set of solutions are selected to be in the reference set. The b2 feasible solutions in the initial set of solutions that are the most different when compared to the solutions already in the reference set, are also selected to be in the reference set.

As a measure of the difference between two solutions, we compute the total number of different assignments between the two solutions.

3.5 Subset Selection

In literature, several methods can be applied to generate the subsets. In our implementation, the subsets are formed by combining two solutions from the reference set:

(1,2), (1,3), (1,4),…, (1,b1+b2), (2,3),…, (b1+b2-1,b1+b2).

We adopt Type-1 (Glover et al., 2003). This method consists of $((b1+b2)^2 - (b1+b2))/2$ pair wise combinations of the solutions.

All pairs of solutions in the reference set are selected for the combination procedure (see subsection 3.6).

3.6 Combination Method

This method combines the solutions in each subset to form new solutions.

First a random node is chosen and then the pairs with that node are exchanged (see Fig. 1) between the two solutions.

Pairs	**1,2**	**1,3**	**1, 4**	**2,3**	**2, 4**	**3, 4**
Solution1	1	0	1	0	1	1
Solution2	0	1	1	0	0	0
CombinedSolution1	0	1	1	0	1	1
CombinedSolution2	1	0	1	0	0	0

Random Node: 1

Figure 1: .Combination Method – produces two combined solutions – example with n=4 (number of nodes) and m=6 (number of pairs). The node chosen was "1".

The combination method consists of the following steps:

```
node= random(n)
FOR i=1 TO m DO
IF Solution1(i) has node OR
          Solution2(i) has node THEN
  CombinedSolution1(i)= Solution2(i)
  CombinedSolution2(i)= Solution1(i)
ELSE
   CombinedSolution1(i)= Solution1(i)
   CombinedSolution2(i)= Solution2(i)
```

The combination method produces two combined solutions.

The combined solutions go through the improvement phase (see subsection 3.7).

3.7 Improvement Method

A TS algorithm is applied to each solution in the initial set of solutions in order to reduce its cost, if possible. After the combination, the TS algorithm is also applied to improve the quality of the combined solutions.

The basic concept of TS was described by Glover (1986). TS allows the search to explore solutions that decrease the objective function value only in those cases where these solutions are not forbidden. This is usually obtained by keeping track of the action used to transform one solution into the next. When an action is performed it is considered tabu for the next T iterations, where T is the tabu status length. A solution is forbidden if it is obtained

by applying a tabu action to the current solution.

In our implementation, the TS only exploits a part of the neighbourhood. The most common and simplest way to generate a neighbour is to exchange the direction of the traffic of one request. In our implementation, some positions of the solution are selected and their directions are exchanged (partial search). This method can be summarised in the following pseudo-code steps:

```
   p1 = random (m)
   p2 = random (m)
   N = neighbourhoods of ACTUAL-
SOLUTION (one neighbourhood results of
interchange the direction of p1 and/or
p2)
   SOLUTION = FindBest (N)
   If ACTUAL-SOLUTION is worst than
SOLUTION
     ACTUAL-SOLUTION = SOLUTION
```

The positions which directions are exchanged are classified as tabu attributes. A candidate can be chosen as a new current solution, if the positions which directions are exchanged are not the same as those in the tabu list. Normally in TS algorithm, if a neighbour is the best solution found so far it could be selected as a move, even when it is tabu. In our implementation, we don't explore neighbours when the two pairs chosen are in the tabu list. In aspiration, just the best neighbour not tabu with a fitness value lower than the best is selected.

The TS ends when a maximum number of iterations is reached. Based on preliminary observations, we consider a maximum number of `10` iterations. With a higher value of iterations, the algorithm slows down. We also observed that a high number of iterations does not produce significant better results.

For the tabu list, we consider `m/20` elements. In the tests carried out with TS, it was verified that the number of elements in the tabu list does not have a significant influence on the efficiency and quality of the search. However, if the number of elements is high, the search space will be small, which may lead to a premature convergence of the algorithm. On the other hand, if the number of elements is small, the search space will be large, which may take a long time to obtain a good solution.

The improved solutions are considered for inclusion in the reference set (see subsection `3.8`).

3.8 Reference Set Update

The purpose is to maintain a good level of quality and diversity.

We adopted the dynamic reference set update (Glover et al., 2003).

A new feasible solution immediately enters in the reference set, if its quality is better than the quality of the worst solution, or if its diversity is greater than the diversity of the less different solution. Solutions that are equal to others already in the reference set are not allowed to enter under any condition.

If the reference set is not updated, then the algorithm restarts the reference set (see subsection `3.9`).

3.9 Regeneration of Reference Set

The algorithm creates another set of solutions - `Ps` (with the same size of the initial set of solutions). The new solutions go through the improvement phase (see subsection `3.7`).

A new feasible solution immediately enters in the reference set, if its quality is better than the quality of the worst solution.

The `b2` solutions with greater diversity are erased from the reference set and the `b2` feasible solutions in `Ps` that are the most different when compared to the solutions already in the reference set are selected to be in the reference set.

3.10 Diversification Mechanism

This mechanism restarts the best `b1` solutions in the reference set.

The algorithm creates another set of solutions - `Pd` (with the same size of the initial set of solutions). The new solutions go through the improvement phase (see subsection `3.7`).

The best (`b1-1`) solutions in `Pd` are selected to be in the reference set. For the following iteration, we kept the best solution.

3.11 Termination Criterion

The algorithm stops when a maximum number of iterations (`mi`) is reached.

4 RESULTS

We evaluate the utility of the algorithms using the

same instances produced by Bernardino et al. (2009a, 2009b, 2010a, 2010b). The studied examples arise by considering six different ring sizes – 5, 10, 15, 20, 25 or 30 nodes. A ring in a telecommunication network will typically contain between 5 and 20 nodes. The instances consider the 5, 10 and 15 node rings to be ordinary-sized rings and the 20, 25 and 30 node rings to be extremely large rings. The demand cases are:

- Case 1: complete set of demands between 5 and 100 with uniform distribution;
- Case 2: half of the demands in Case 1 set to zero;
- Case 3: 75% of the demands in Case 1 set to zero.
- Case 4: complete set of demand between 1 and 500 with uniform distribution. This case was only used for the 30 nodes ring.

It was generated 1 different problem instance for each case. This yields 3 instances for each ring size (4 instances for the 30 nodes ring). For convenience, they are labelled C_{ij}, where $1<i<6$ represents the ring size and $1<j<4$ represents the demand case.

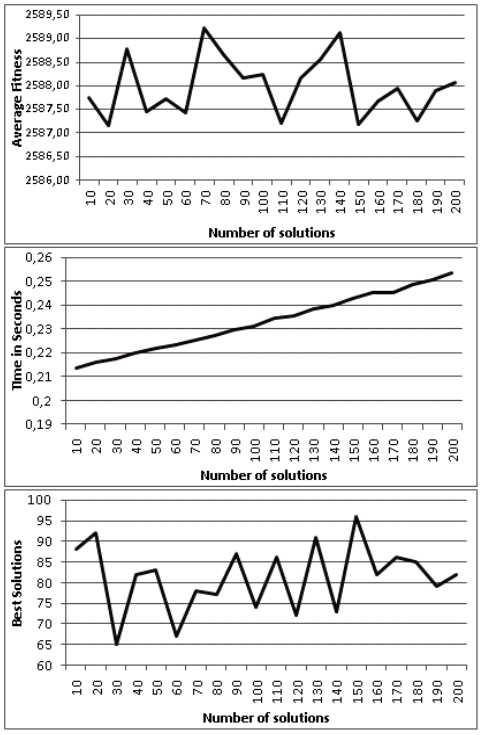


Figure 2: Number of initial solutions – Average Fitness/Execution Time/Number of Best-known Solutions - b1 =[4,8], b2=[4,8] and nid= [m/10, m/2] .

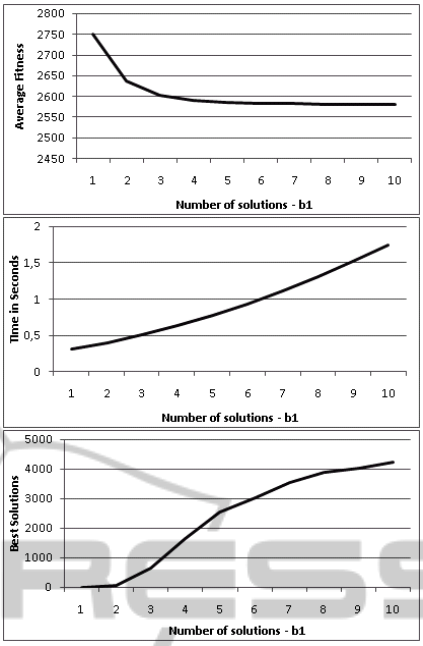


Figure 3: Number of best solutions in the reference set (parameter b1) – Average Fitness/Execution Time/ Number of Best-known Solutions – ni=10.

We perform comparisons between all parameters (using all instances) in order to establish the correct parameter setting for the HSS algorithm.

We consider the same instance – C41 (a problem with average difficulty) to show the comparisons between parameters. To compute the results we use 50 iterations.

The best results obtained with the HSS algorithm use ni between 40 and 100, b1 between 4 and 10, b2 between 4 and 10 and nid between m/10 and m/2. These parameters were experimentally considered good and robust for the problems tested.

The number of initial solutions was set to {10, 20, 30, 40, 50, 60, 70, 80, ..., 200}. We studied the impact on the execution time, the average fitness and the number of best-known solutions found. The number of solutions has a significant impact on the execution time (see Figure 2).

The best results obtained with HSS use ni between 40 and 100. With these values, the algorithm can reach, in a reasonable amount of time, a reasonable number of best-known solutions (see Figure 2). With a higher number of solutions, the algorithm is more time consuming.

The number of solutions in the reference set is typically small - 20 solutions or less (Glover et al., 2003). In our experiments the number of solutions b1 and the number of solutions b2 were set to {1,

2, 3, 4, 5, 6, 7, 8, 9, 10}. We studied the impact on the execution time, the average fitness and the number of best-known solutions found. The number of solutions in the reference set has a significant impact on the execution time (see Figure 3 and Figure 4).

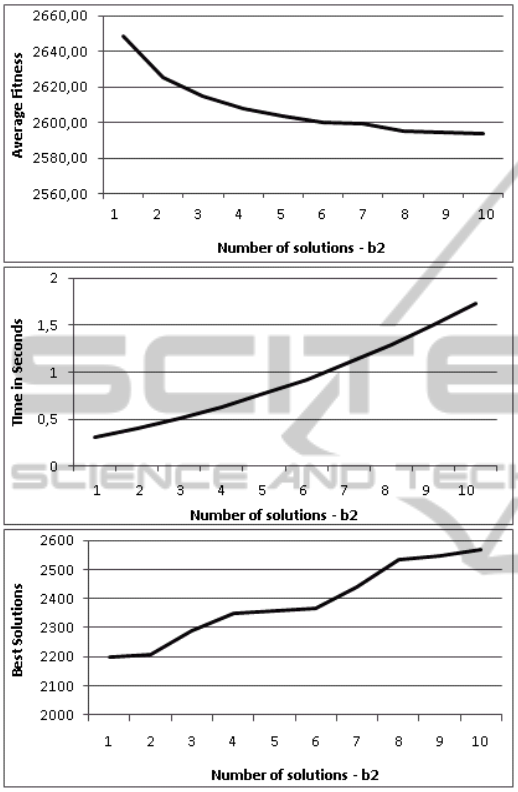


Figure 4: Number of most different feasible solutions in the Reference Set (parameter b2) – Average Fitness/Execution Time/Number of Best-known Solutions – ni=10.

The results show that the best results obtained use b1>=4 and b2>=4 (see Figure 3 and Figure 4). These parameters were experimentally found to be good and robust for the problems tested. With b1+b2>20 the algorithm can reach a better average fitness but it is more time consuming.

We observe that a small number of solutions in the reference set allows an initial faster convergence, but a worse final result, following to an increased amount of suboptimal values. This can be explained, because the quality of the initial best-located solution previous to the first restart highly depends on the reference set size: they need more diversity to avoid premature stagnation.

For parameter nid, the number of iterations used for diversification, the values between m/10 and m/2 have been shown to be experimentally more efficient.

Phenomena of stagnation and insufficient intensification have been observed for values of nid lesser than m/10 and greater than m/2.

In general, the experiments have shown that the proposed parameter setting is very robust to small modifications.

In this paper, we only compare our algorithm with: PBPSO (Bernardino et al., 2009a), GA (Bernardino et al., 2008), HDE (Bernardino et al., 2009b), HACO (Bernardino et al., 2010a) and DDE (Bernardino et al., 2010b) because the authors: (1) use the same test instances; (2) adopt the same fitness function; (3) implement the algorithms using the same language (C++) and; (4) adopt the same representation (binary).

Suggestions from literature helped us to guide our choice of parameter values for PBPSO, GA HDE, HACO and DDE (Bernardino et al., 2008, 2009a, 2009b, 2010a, 2010b).

PBPSO was applied to populations of 40 particles and we consider the value 1.49 for the parameters C1 and C2, and for the inertia velocity (W) values in the range [0.6,0.8].

GA was applied to populations of 200 individuals; it uses "Uniform" as recombination method, "Multiple" as mutation method and "Tournament" as selection method. For GA, we consider crossover probability in the range [0.6,0.9] and mutation probability in the range [0.5,0.7].

HDE was applied to populations of 50 individuals, it uses the "Best1Bin" strategy, CR in the range [0.3,0.5] and factor F in the range [0.5,0.7].

For the HACO, we consider populations of 40 individuals, 30 modifications, Q=100, x1 in the range [0.6,0.8], x2 in the range [0.7,0.8] and q in the range [0.7,0.8].

For the DDE, we consider populations of 50 individuals, 5 perturbations, pc in the range [0.1,0.2], pp in the range [0.6,0.8] and the LS method "Exchange Direction".

Finally, the parameters of the HSS algorithm were set to ni=50, b1 between 4 and 8, b2 between 4 and 8, number of iterations of the TS =3 and nid between m/10 and m/2. The six algorithms were executed using a processor Intel Quad Core Q9450. The initial solutions of the six algorithms were created using random solutions. For the instance C64 the SPA was used to create the

Table 2: Best obtained results.

Instance	Nodes	Pairs	Best Fitness	Iterations
C11	5	10	161	25
C12	5	8	116	10
C13	5	6	116	10
C21	10	45	525	50
C22	10	23	243	25
C23	10	12	141	10
C31	15	105	1574	100
C32	15	50	941	50
C33	15	25	563	25
C41	20	190	2581	300
C42	20	93	1482	100
C43	20	40	612	50
C51	25	300	4265	500
C52	25	150	2323	400
C53	25	61	912	250
C61	30	435	5762	1500
C62	30	201	2696	1000
C63	30	92	1453	500
C64	30	435	27779	500

Table 3: WRALP results – run times and number of iterations.

Inst.	PBPSO		GA		HDE		HACO		DDE		HSS	
	Time	IT	Time	IT	Time	IT	Time	IT	Time	IT	Time	IT
C11	<0.001	2	<0.001	2	<0.001	2	<0.001	2	<0.001	2	<0.001	2
C12	<0.001	2	<0.001	2	<0.001	2	<0.001	2	<0.001	2	<0.001	2
C13	<0.001	1	<0.001	1	<0.001	1	<0.001	1	<0.001	1	<0.001	1
C21	<0.001	15	<0.001	15	<0.001	10	<0.001	20	<0.001	10	<0.001	10
C22	<0.001	3	<0.001	5	<0.001	3	<0.001	3	<0.001	3	<0.001	3
C23	<0.001	3	<0.001	3	<0.001	3	<0.001	3	<0.001	3	<0.001	3
C31	0. 1	20	0. 1	30	0. 1	15	0. 1	30	0. 1	10	0. 1	10
C32	<0.001	8	<0.001	15	<0.001	5	<0.001	10	<0.001	5	<0.001	5
C33	<0.001	5	<0.001	5	<0.001	5	<0.001	5	<0.001	3	<0.001	3
C41	0.2	50	0.1	50	0.1	30	0.15	50	0.1	25	0.1	20
C42	0.075	20	0.075	40	0.05	10	0.06	25	0.05	8	0.05	10
C43	<0.001	5	<0.001	10	<0.001	5	<0.001	5	<0.001	3	<0.001	5
C51	0.75	80	0.75	80	0.75	40	0.6	100	0.5	30	0.5	30
C52	0.1	25	0.1	40	0.1	15	0.1	30	0.1	15	0.1	15
C53	0.01	15	0.01	25	0.01	10	0.01	20	0.01	8	0.01	10
C61	2	130	1.75	130	1.75	40	1.75	150	1.5	50	1.3	40
C62	0.4	50	0.2	60	0.25	20	0.4	60	0.25	25	0.25	20
C63	0.075	15	0.075	30	0.075	10	0.075	20	0.06	10	0.05	10
C64	0.5	40	0.3	30	0.25	5	0.5	5	0.1	3	0.1	5

Table 4: WRALP results – Average Fitness / Average Time / Standard Deviation.

Inst	It	PBPSO			GA			HDE			HACO			DDE			HSS		
		AF	AT	SD	AF	AT	SD	AF	AT	SD	AF	AT	SD	AF	AT	SD	AF	AT	SD
C41	50	2594,36	0,26	7,70	2587,62	0,17	3,46	2584,31	0,27	1,15	2591,23	0,16	7,73	2582,06	0,16	1,18	2581,50	0,22	0,71
C51	75	4291,52	0,86	16,85	4273,18	0,43	2,97	4271,27	0,7	5,10	4279,49	0,76	10,10	4268,96	0,53	5,71	4265,68	0,65	1,16
C61	100	5837,58	3,10	23,19	5784,62	1,34	10,05	5783,18	1,87	7,45	5793,68	2,23	14,17	5781,52	1,39	9,78	5763,72	1,44	2,25

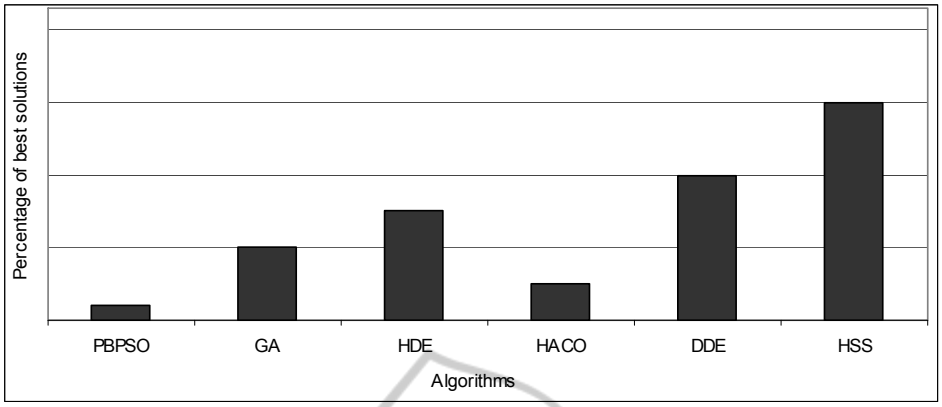


Figure 5: Percentage of best-known solutions obtained by the six algorithms – instance C41 (50 iterations).

initial populations. Table 2 presents the best obtained results. The first column represents the instance number (`Instance`), the second and third columns show the nodes' number (`Nodes`) and the pairs' number (`Pairs`), the fourth column demonstrates the minimum fitness values obtained and the fifth column demonstrates the number of iterations used to test each instance. The number of iterations was selected based upon preliminary observations.

Table 3 presents the best WRALP results obtained with the six implemented algorithms. The first column represents the instance number (`Inst.`) and the remaining columns demonstrate the obtained results (`Time` – Run Times, `IT` – Iterations) by the six algorithms. The presented values have been computed based on `100` different executions for each test instance, using the best combination of parameters found and different seeds. Table 4 only considers the `30` best executions. The six algorithms reach feasible solutions for all test instances and all the algorithms reach the best-known solutions before the run times and the number of iterations presented.

In comparison, the HSS algorithm produces a higher number of best-known solutions using the same number of iterations (Figure 5). The DDE algorithm obtains a reasonable number of best-known solutions and a good average fitness in a better running time (Figure 5, Table 4). The PBPSO is the slowest algorithm and it obtains a smaller number of best-known solutions comparing with the other algorithms (Figure 5).

When using the SPA to create the initial solutions, the times and number of iterations decrease – instance `C64`. This instance is computationally harder than the `C61` however the best-known solution is obtained faster. Based on preliminary observations we consider more efficient to initially apply a SPA and after, a metaheuristic to improve the solutions.

Table 4 presents the WRALP average fitness and the WRALP average time obtained with PBPSO, GA, HDE, HACO and DDE using a limited number of iterations for the instances `C41`, `C51` and `C61` (harder instances). The first column represents the instance number (`Instance`), the second column demonstrates the number of iterations used to test each instance and the remaining columns show the obtained results (`AF` – Average Fitness, `AT` – Average Time, `ST` – Standard Deviation) by the six algorithms. The results have been computed based on `100` different executions for each test instance using the best combination of parameters found and different seeds.

As it can be seen, the average fitness and standard deviations for the HSS are smaller. It means that the HSS is more robust than the other algorithms. DDE also presents a good average fitness and a good standard deviation.

5 CONCLUSIONS

In this paper we present a Hybrid Scatter Search algorithm to solve the WRALP. The Hybrid Scatter Search Algorithm is an evolutionary optimisation technique, able to perform simultaneous local and global search.

The performance of' Hybrid Scatter Search algorithm is compared with five algorithms from literature, namely: PBPSO, GA, HDE, HACO and DDE.

Relatively to the problem studied, the Hybrid Scatter Search algorithm presents better results. The computational results show that it had a stronger performance, improving the results obtained by previous approaches. Moreover, in terms of standard

deviation, the algorithm also proved to be more stable and robust than the other algorithms.

Experimental results demonstrate that the proposed algorithm is an effective and competitive approach in composing satisfactory results with respect to solution quality and execution time for the WRALP.

In literature the application of Scatter Search algorithm for this problem is nonexistent. For that reason, this article shows its enforceability in the resolution of this problem.

The continuation of this work will be the search and implementation of new methods to speed up the optimisation process.

REFERENCES

Bernardino, A.M., Bernardino, E.M., Sánchez-Pérez, J.M., Vega-Rodríguez, M.A., Gómez-Pulido, J.A., 2008. Solving the Ring Loading Problem using Genetic Algorithms with intelligent multiple operators. In *Proceedings of International Symposium on Distributed Computing and Artificial Intelligence 2008 (DCAI 2008)*, pp. 235-244. Springer Berlin / Heidelberg.

Bernardino, A.M., Bernardino, E.M., Sánchez-Pérez, J.M., Vega-Rodríguez, M.A., Gómez-Pulido, J.A., 2009a. Solving the non-split weighted ring arc-loading problem in a Resilient Packet Ring using Particle Swarm Optimisation. In *Proceedings of the International Joint Conference on Computational Intelligence*, pp. 144-151. INSTICC Press.

Bernardino, A.M., Bernardino, E.M., Sánchez-Pérez, J.M., Vega-Rodríguez, M.A., Gómez-Pulido, J.A., 2009b. Solving the weighted ring edge-loading problem without demand splitting using a Hybrid Differential Evolution Algorithm. In *The 34th IEEE Conference on Local Computer Networks,* pp. 562-568. IEEE Press.

Bernardino, A.M., Bernardino, E.M., Sánchez-Pérez, J.M., Vega-Rodríguez, M.A., Gómez-Pulido, J.A., 2010a. A Hybrid Ant Colony Optimization Algorithm for Solving the Ring Arc-Loading Problem. In A*rtificial Intelligence: Theories, Models and Applications, 6th Hellenic Conference on AI, SETN 2010*, 2010, pp. 49-59. Springer Berlin / Heidelberg.

Bernardino, A.M., Bernardino, E.M., Sánchez-Pérez, J.M., Vega-Rodríguez, M.A., Gómez-Pulido, J.A., 2010b. A Discrete Differential Evolution Algorithm for solving the Weighted Ring Arc Loading Problem. In *The 23rd International Conference on Industrial, Engineering & Other Applications of Applied Intelligent Systems Applications of Evolutionary Computation*, pp. 61-70, Springer Berlin / Heidelberg.

Cho, K.S., Joo, U.G., Lee, H.S., Kim, B.T., Lee, W.D., 2005. Efficient Load Balancing Algorithms for a Resilient Packet Ring. *ETRI Journal*, vol.27, no.1, pp. 110-113.

Cosares, S., Saniee, I., 1994. An optimization problem related to balancing loads on SONET rings. *Telecommunication Systems*, vol. 3, no. 2, pp. 165-181. Springer Netherlands.

Davik, F., Yilmaz, M., Gjessing, S., Uzun, N., 2004. IEEE 802.17 Resilient Packet Ring Tutorial, *IEEE Communications Magazine*, vol.42, no.3, pp. 112–118.

Dell'Amico, M., Labbé, M., Maffioli, F., 1999. Exact solution of the SONET Ring Loading Problem. *Operations Research Letters*. vol.25, no.3, pp. 119-129.

Glover, F., 1977. Heuristics for integer programming using surrogate constraints. *Decision Sciences*, vol.8, pp. 156–166.

Glover, F., 1986. Future paths for Integer Programming and Links to Artificial Intelligence. *Computers and Operations Research*, vol. 13, no. 5, pp. 533–549.

Glover, F., Laguna, M., 1997. *Tabu Search*. Kluwer Academic Publishers.

Glover, F., Laguna, M., Marti, R., 2003. Scatter Search and Path Relinking: Advances and Applications. In *Handbook of Metaheuristics*, vol. 57, pp. 1–35. Springer.

Karunanithi, N., Carpenter, T., 1994. A Ring Loading Application of Genetic Algorithms. In *Proceedings of the ACM Symposium on Applied Computing,* pp. 227-231.

Kim, S.-S., Kim, I.-H., Mani, V., Kim, H.J., 2008. Ant Colony Optimization for SONET Ring Loading Problem. *International Journal of Innovative Computing, Information and Control*, vol.4, no.7, pp. 1617-1626.

Kubat, P., Smith, J.M., 2005. Balancing traffic flows in resilient packet rings. *Girard, André (ed.) et al., Performance evaluation and planning methods for the next generation internet.* GERAD 25th Anniversary, Series 6, pp. 125-140. Springer.

Laguna, M., 2002. Scatter search. In *Handbook of Applied Optimization*, P. M. Pardalos and M. G. C. Resende, editors, pp. 183–193.

Myung, Y.S., Kim, H.G., 2004. On the ring loading problem with demand splitting. *Operations Research Letters*, vol. 32, no. 2, pp. 167-173.

RPR Alliance, 2004. A Summary and Overview of the IEEE 802.17 Resilient Packet Ring Standard.

Schrijver, A., Seymour, P., Winkler, P., 1998. The ring loading problem. *SIAM Journal of Discrete Mathematics*, vol. 11, pp. 1–14.

Wang, B.F., 2005. Linear time algorithms for the ring loading problem with demand splitting. *Journal of Algorithms*, vol. 54, no. 1, pp. 45-57.

Yuan J., Zhou S., 2004. Polynomial Time Solvability Of The Weighted Ring Arc-Loading Problem With Integer Splitting. *Journal of Interconnection Networks*, vol. 5, no.2 , pp. 193-200.

Yuan, P., Gambiroza, V., Knightly, E., 2004 The IEEE 802.17 Media Access Protocol for High-Speed Metropolitan-Area Resilient Packet Rings, *IEEE Network*, vol.18, no.3, pp. 8–15.