

An EC-Memory based Method for the Multi-Objective TSP

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ABSTRACT

In this paper we present a new method for the multi-objective TSP. This method is a modified version of an earlier multi-objective evolutionary algorithm, which uses an explicit collective memory (EC-memory) method, named EVL. We adapted and improved the algorithm and the EVL for the multi-objective TSP and developed a new evolutionary algorithm.

Categories and Subject Descriptors

12.8 [Artificial Intelligence]: Problem Solving, Control Methods and Search – heuristic methods

General Terms

Algorithms.

Keywords

TSP, EC-memory, multi-objective optimization.

1. INTRODUCTION

In this paper we show a new evolutionary algorithm (EA) for the multi-objective TSP (MOTSP). Our algorithm is based on a multi-objective algorithm for the bi-objective quadratic assignment problem from [1]. This algorithm uses an extended version of an explicit collective memory method, named virtual loser. The extended virtual loser (EVL) enables to handle more discrete values and the values of the variables can be e.g. values of permutations too. We adapted this algorithm and the EVL method for the MOTSP.

With the new algorithm (named MOSCA2b) we want to show that: we can use successfully the framework of the earlier algorithm with the EVL technique for other combinatorial problems, and based on the EVL technique, we can solve the MOTSP without sophisticated selection and recombination operators.

2. THE NEW ALGORITHM

Our algorithm has some special, new attributes that are different from the earlier algorithm ([1]):

- We adapted the EVL for the TSP,
- We improved the EVL technique with a restart strategy,

- We used two special versions of the truncation selection,
- Our algorithm uses a special stochastic 2-opt local search.

3. EXPERIMENTAL RESULTS

Following [2], we use some MOTSP instances based on the TSPLIB library. As reference solutions to these instances we used the solutions of [2]. These are available in the Internet at <http://www.idss.cs.put.poznan.pl/~jaszkiewicz/motsp/>.

To compare the results of the *MOSCA2b* we chose the *MOGLS* algorithm of [2]. As performance measure we used the binary ε -indicator (see e.g. in [1]). In the table 1 we can see some results (we give the number of objectives (*no*), the name of the instances (*instance*), ε_1 gives $I_\varepsilon(B,A)$, ε_2 gives $I_\varepsilon(A,B)$ (where *A* is the outcomes of *MOSCA2b* and *B* is the outcomes of *MOGLS*) and *ndn* is the number of non-dominated solutions). We can conclude: the quality of *MOSCA2b*' result is similar to the results of one of the state-of-art-methods (*MOGLS*).

Table 1. The best non-dominated results of *MOSCA2b*

no	instance	ε_1	ε_2	ndn
2	kroAB50	1.082	1	253
	kroAD50	1.002	0.999	213
	kroAB100	0.991	1.019	319
	kroAD100	0.974	0.997	312
3	kroABC100	0.979	1.025	2565
	kroABD100	0.977	0.998	2515

4. ACKNOWLEDGEMENTS

The Hungarian Research Foundation OTKA T 042448 supported the study

5. REFERENCES

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