A Hybrid Evolutionary Simulated Annealing Algorithm with Incorporation of Preferences

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ABSTRACT
This paper presents a hybrid evolutionary simulated annealing approach devoted to multi-objective models, in which preferences are elicited and exploited using the principles of the outranking-based ELECTRE TRI method. Preferences are used to guide the search process including deciding about the exploitation of new neighbor solutions. The overall approach has been used in a case study to provide decision support in identifying suitable load control actions in electrical networks.

Categories and Subject Descriptors
I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search – *heuristic methods*.

General Terms
Algorithms.

Keywords
Evolutionary Algorithms, Simulated Annealing, Hybrid Algorithms, Incorporation of Preferences, ELECTRE TRI.

1. INTRODUCTION
The characterization of the whole set of (potential) non-dominated solutions in real-world multi-objective optimization problems (MOOP) is not, in general, worthwhile namely having in mind the practical exploitation of results. Meaningful incorporation of the Decision Maker's (DM's) preferences may be carried out to improve both the efficiency (by reducing the computational effort) and efficacy (by finding solutions more in accordance with those preferences) of the algorithm. In this way the computational effort is progressively directed to the regions of the non-dominated frontier offering the DM more suitable trade-offs between the multiple, conflicting and incommensurate objective functions [1].

Despite the success of meta-heuristics in the resolution of MOOPs, it has been recognized that there is no algorithm considered as the best approach to solve all types of problems. In the last years a new paradigm of algorithms combining characteristics of two or more meta-heuristics has arisen [2].

GECCO'13 Companion, July 6–10, 2013, Amsterdam, The Netherlands.
ACM 978-1-4503-1964-5/13/07.

A hybrid algorithm is proposed combining the advantages of Evolutionary Algorithms (EAs), Simulated Annealing (SA) and the incorporation of preferences to deal with a real-world problem.

2. THE HESA ALGORITHM
The Hybrid Evolutionary Simulated Annealing (HESA) algorithm has been developed in the spirit of a memetic approach, combining EvABOR-III (Evolutionary Algorithm Based on Outranking Relation) with a local search method. EvABOR-III [3] incorporates preferences into genetic operators (crossover, mutation and selection of the next generation) and it obtains a set of non-dominated solutions belonging to the best class of merit using the ELECTRE TRI method [4]. Preferences are elicited from the DM using different sets of parameters, and this information is used to sort solutions into ordered classes of merit. Despite the good performance proved by EvABOR-III in previous works [3], the hybridization with a local search technique is proposed to improve the convergence of the algorithm to solutions more in accordance with those preferences. After the crossover and the mutation operators are applied according to its probabilities and to the preference information (see [3] for details), the non-dominated offspring solutions are obtained and classified into classes of merit using the ELECTRE TRI method. The local search is triggered when a solution belonging to a new (higher) class of merit is found. The underlying idea is to intensify the exploitation in the neighborhood of that new solution to increase the convergence to solutions belonging to a better class of merit than the current one. In the selection of the non-dominated solutions to constitute the next generation, priority is given to the solutions belonging to the best class of merit, as in EvABOR-III. The SA algorithm has been chosen to perform the local search due to its capability to exploit promising regions of the search space, namely in combinatorial optimization problems. An innovative aspect of this approach is the incorporation of preferences also in SA aiming at obtaining a set of non-dominated solutions belonging to the best class of merit.

2.1 Incorporation of Preferences into SA
An archive is used during local search to store the solutions belonging to the best current class of merit. This archive is initialized with the offspring belonging to the new best class of merit found after crossover and mutation operators. The neighbor solutions of each offspring in the archive are obtained using a set of neighborhood structures (moves) specifically designed for the problem at hand, which are selected at random. These solutions

are evaluated and classified using the ELECTRE TRI method based on the preferences elicited from the DM. Three main cases are considered in this phase to carry out a new exploitation of these solutions:

1) If the new neighbor solution dominates the current solution (consequently it belongs to the same or a higher class of merit), the current solution is replaced by the neighbor solution in the archive.

2) If the neighbor solution and the current solution are non-dominated then the acceptance depends on the quality of the solution according to the preferences elicited. If the class of merit of the neighbor solution is the same, or higher, than the class of the current solution, then the neighbor solution is added to the archive. If the class of merit of the neighbor solution is inferior to the class of the current solution then the neighbor solution can be accepted depending on the value of the credibility degree (an indicator of the quality of the solution used in ELECTRE TRI and based on the preferences elicited).

3) If the neighbor solution is dominated with respect to the current solution and both solutions belong to the same class of merit then the acceptance depends on the credibility degree, else a probability acceptance function is used (in this case the current solution belongs to a higher class than the neighbor solution). The probability acceptance function depends on the characteristics of the problem at hand. In this work the strong probability acceptance function is used.

Non-dominated solutions are filtered, before the exploitation of a new solution in the archive is carried out. Then priority is given to the non-dominated solutions belonging to the best (and new) classes of merit. After all solutions in the archive are exploited, the annealing temperature is successively decreased and solutions in the archive are again exploited until a pre-defined minimum temperature is achieved.

3. EXPERIMENTAL EVALUATION

The HESA algorithm has been applied to a direct load control problem [5] to obtain a set of curtailment patterns according to preferences elicited from a DM. The aim is to design and select load control strategies that allow to minimize the maximum peak power demand in a sub-station and in two power transformers, minimize the maximum continuous time interval in which discomfort is imposed to consumers, minimize the total time discomfort occurs, minimize the total time in which loads are in curtailment and maximize profits with the sale of electricity. Obtaining solutions to this combinatorial problem is a hard task also due the number of objective functions and their conflicting nature.

Results obtained with HESA have been compared to the ones obtained with EvABOR-III for the same set of preference parameters. Despite the two approaches have similar results concerning the quality of non-dominated solutions, in the sense that both are capable to achieve a set of non-dominated solutions belonging to the best class of merit, the HESA algorithm shows its superiority achieving this with a time reduction of about 50%. Considering the runs where all non-dominated solutions belong to the best class of merit, the average time spent by EvABOR-III is 7074 seconds, while the HESA algorithm spent in average 3752 seconds.

4. CONCLUSIONS

An Evolutionary Algorithm Based on Outranking Relation (EvABOR-III) has been hybridized with SA. The motivation to include a local search phase in EvABOR-III lies on the difficulty, in some runs, to complete the population with solutions belonging to the best class of merit after having obtained one solution in this class. The hybridization with SA has revealed to increase the performance of the algorithm. With the local search triggered when this first solution is obtained, the HESA algorithm completes the population with solutions in the best class much more quickly reducing substantially the overall computational time.

5. ACKNOWLEDGMENTS

This work has been partially supported under project grant[s] PEst-C/ EEI/UI308/2011, ICIS (CENTRO-07-ST24-FEDER-002003), and EMSURE (CENTRO-07-0224-FEDER-002004).

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