Multiple Criteria Decision Support by Evolutionary Computation

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Abstract

This paper describes the use of Evolutionary Algorithms (EAs) as a decision support tool in environmentally relevant decision problems. Though various methods from Artificial Intelligence as well as from Computational Intelligence have been successfully integrated into Environmental Decision Support Systems (EDSS), the use of Evolutionary Computation has so far remained marginal in this context. On the other hand EAs are popular in solving large-scale optimization problems in diverse engineering disciplines, where complex, non-linear models make the use of traditional optimization techniques difficult or impossible. In addition, they can handle multiple criteria simultaneously, being able to generate efficient solutions even for problems where the number of alternatives is very large or only implicitly defined, which makes them a promising tool in environmental decision making.

1 Introduction

All areas of human interaction with its environment involve decision situations and decision making. Sustainable decision making should ideally be based on a complete knowledge of the decision alternatives at hand as well as their consequences. As the complex nature of the system under concern often renders exact predictions impossible, one usually has to rely on models, which shall provide tractable approximations of the reality. Here, systems analysis plays an important role (Bell et al. 1977), since only a well-informed decision maker will be in a position to take good, responsible, and sustainable decisions.

In systems analysis, three different steps can be distinguished based on different points of interest:

- Modeling: What are the mechanisms that produce certain behavior or output on a given input, and how can they be described?
- Simulation: What output is produced by the model for a given input?

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- Optimization: What input need to be provided to the model in order to receive a desired output?

The optimization part can be seen as a decision problem, and vice versa: The input to the system can be modeled by decision variables of arbitrary domains. All (feasible) settings of these variables form the set of decision alternatives. The criteria to judge each decision relate to the output they produce. Quantitative criteria are usually referred to as objectives (Kaliszewski 1994).

Environmentally relevant decision situations typically involve multiple criteria or objectives. In many cases they are incommensurable, which means that are not comparable with respect to magnitude and value, and non-cooperative, which means that at some point one objective cannot be improved without decreasing the value of another. The insight into these trade-offs (e.g. risk vs. profit, labor cost vs. social security, greenhouse gas emissions vs. nuclear waste) is of crucial importance for sustainable decision making.

Depending on the set of alternatives, Multiple Criteria Decision Making (MCDM) can involve a choice problem (when there is a small, explicit list of alternatives) or a design problem (when an infinite set of alternatives is implicitly defined by constraints) (Steuer 1986). The different approaches to Multiple Criteria Decision Making (MCDM) can be classified according to the time when the decision maker's preferences enter the formal decision making process (Hwang and Masud 1979):

- no articulation of preference information,
- a priori articulation of preference information,
- progressive articulation of preference information, or
- a posteriori articulation of preference information.

This paper focuses on the fourth class of method dealing with the design problem type, where the complete set of efficient solutions is to be generated - or at least approximated - before preferences come into play to choose the most appropriate out of this solution pool. Its relevance for Environmental Decision Support Systems (EDSS) is discussed in the next section. In section 3 Evolutionary Computation is presented as an appropriate tool to solve this task, and a possible way to integrate this into EDSS is described. Finally, we sketch some basic applications.

2 Environmental Decision Support Systems

The role of Information Technology in providing support for environmental decision making has become very important (Denzer et al. 2000), covering tasks from providing and managing information, executing system models, evaluation and production of alternative solutions. Environmental Information Systems (EIS) address the first point. The second aspect refers to computer models which are used to simulate the system under concern, including computer based tools for data analysis, model calibration and verification, sensitivity analysis and so forth. The purpose of Environmental Decision Support Systems (EDSS) is to support human decision making in environmental issues. They provide options (decision alternatives) to the user and help to judge and to compare them (Guariso and Werthner 1989) and are thus mainly related to the third issue.

In many cases, EDSS deal with a small number of (a priori specified) alternatives which can be evaluated by the model and – in case of conflicting outcome – be judged using Multiple Criteria Decision Analysis. On the other hand, the desired task of (automatically) producing alternatives from an only implicitly defined and potentially infinitely large set has not received much attention so far. This is certainly not due a lack of demand, since an automated procedure to help in these kinds of ”search” or “planning” problems would allow many complex problems to be handled which so far have only been accessible via simplification. The reason seems to a mere technical one as the corresponding mathematical optimization techniques are mostly limited to a specific problem structure that fit to a very limited number of system models. Examples are (Gheorghe et al. 1995), where a Dynamic Programming approach was applied, and (Booty et al. 2001) for Linear Programming. However, it is important to emphasize that complex environmental models usually do not have a structure which can be exploited by traditional optimization techniques and have thus to be regarded as “black box” models. In the following section we present an alternative approach based on evolutionary computation, which can deal with virtually any type of black box optimization problems.

3 Evolutionary Multi-criterion Optimization in EDSS

Evolutionary Algorithms model the basic evolutionary principles population, self-replication, variation, and selection (Bäck et al. 1997) and can serve as all-purpose optimization methods solving even large scale optimization problems in academia and industry. On the other hand, they can as well be used to gain insight into the general principles of self-adaptation and self-organization in natural processes (Kursawe 1993). Together with Neural Networks and Fuzzy Logic, Evolutionary Computation forms part of the field Computational Intelligence (Zurada et al. 1994), but – unlike Neural and Fuzzy Computation – has not gained access to Environmental Decision Support Systems yet.

During the last two decades, Evolutionary Computation methods have been successfully extended to solve multi-objective optimization tasks. For their population concept and inherent parallelism they are regarded to be especially well suited to search for even a large number of efficient solutions in parallel (Deb 2001).

Figure 1 shows how Evolutionary Algorithms can serve as a decision support tool

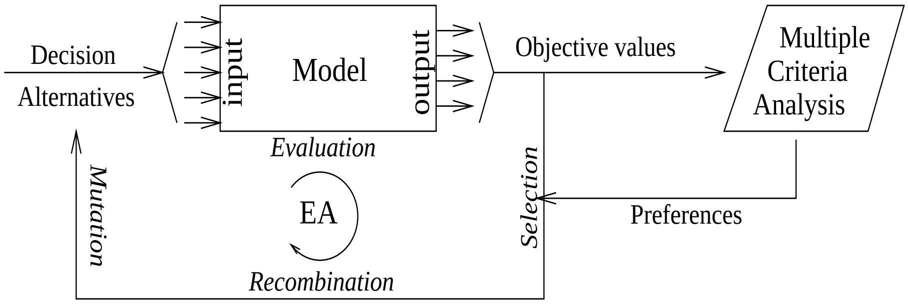

Figure 1: Integration of Evolutionary Algorithms (EA) into a decision support system based on a simulation model. Each decision alternative is a distinct combination of input parameter values, for which the model can be executed to calculate the corresponding objective values. If the number of different alternatives is small, they can be directly processed further, e.g. by Multiple Criteria Analysis. If the number of possible combinations is large, an iterative approach is recommended: From a small set of initial alternatives, the better performing are chosen and used to create new solutions by variation (recombination and mutation, first feedback loop). While the variation step is driven randomly, the selection step can incorporate preference information obtained in parallel from MCA (second feedback loop).

in environmentally relevant decision problems and how they can be integrated into Environmental Decision Support Systems. Different individuals in the population represent different decision alternatives which are used as input to the model and evaluated according to its corresponding output. Selection distinguishes better individuals from worse, here the Pareto-dominance principle can be used in case of multiple conflicting outcomes. While worse individuals are deleted, the better ones are used to produce new offspring by random variation (recombination and mutation). Thus, by mimicking natural evolution a feedback loop can be integrated into EDSS which implements exactly the two decision support tasks referred to in the previous section: Routine decisions (discarding bad alternatives, remembering good ones) are automatically taken by the selection operation, the automatic generation of new alternatives is achieved by the variation operation.

4 Applications and Outlook

After discussing the integration of Evolutionary Computation techniques into a EDSS framework we present three simple application examples to highlight the broad range of applicability of the approach. A larger scale application can be found in (Chetan et al. 2001). Details of the first project are given in (Laumanns et al. 2001), while the latter two are still in experimental status and subject of ongoing research.

Design of Road Trains as an alternative in long-distance fright traffic In freight traffic the importance of trucks grows constantly, while the higher traffic load will certainly be accompanied by increased environmental impact. One technological possibility to avoid this effect is to extend the vehicle load. To avoid road damages, however, the maximum load per axle of today has to be kept constant. Here, we study a road train concept, consisting of a semi-trailer truck and two semi-trailers, connected by a dolly. Based on different simulation scenarios, the evolution shall produce combinations of overall weight, gear box, engine, and driving strategy to minimize fuel consumption and emissions, optimizing the driving performance and increasing driving convenience.

Airline Network Optimization In the airline business the question which routes and connections are to be offered is a major strategic decision which must be taken with respect to several different criteria. With our evolutionary model we study the trade-offs between operating costs, customer satisfaction, and emissions, and how different preferences of the decision maker relate to certain structures in the final network.

Optimal Control of Repowered Power Plants Liberalization in the power market leads to considerable changes not only in the customers' behavior, but also in the preferences of the suppliers: While public enterprises were mainly concerned with reliability and other political criteria (security, employment, avoidance of imported fuel), today's private companies tend to focus mainly on market requirements and hence on production costs. In this project a new technological approach to improve existing coal fired steam power plants is evaluated under multiple criteria: the parallel repowering using the High Efficiency Coal & Gas cycle (HE–C&G). Possible advantages are the use of existing infrastructure, reduction of CO_2 and NO_x emissions, and a higher flexibility of the plant concerning power load over time and fuel mix. Evolutionary Algorithms are used to find the trade-offs between fuel costs, emissions, and overall efficiency.

These example problems contain multiple conflicting objectives as well as very large search spaces where the number of decision alternatives is either uncountable or combinatorial. The use of Evolutionary Algorithms in connection with a simulation model automatically generates of a number of efficient solution in parallel that can – a posteriori or interactively – be presented to the decision maker as an approximation of the Pareto-optimal set. This allows for preferences articulation from an informed position (since possible trade-offs are known) and not from an information vacuum prior to the search, which can be of considerable advantage in environmental decision situations involving multiple criteria, multiple interest groups, and a large number of possible decision alternatives.

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