Evolutionary Algorithms For Optimization Practitioners

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1 Introduction

Evolutionary algorithms (EAs) are simplified formal models of organic evolution. At least three different approaches can be distinguished by their history: Evolutionary programming (EP) [Fog62, FOW66], evolution strategies (ES) [Rec65, Sch65], and genetic algorithms (GAs) [Hol62, Hol75].

Taking advantage of valuable preparational work done in the early 1960s [Bre62], these general purpose algorithms unfolded during the 1960s and 1970s. Nevertheless, optimization practitioners nowadays still experience some difficulties when applying EAs to real-world optimization problems. Our approach is problem oriented and should give optimization practitioners a working knowledge of evolutionary algorithms. Similar to the approach presented in [Kle87], we will take a look at evolutionary algorithms from the viewpoint of an optimization practitioner. We will demonstrate how problem specific knowledge can be integrated into genetic operators, and how coding and hybridization with traditional gradient search procedures can improve the algorithm's performance. Additionally, we will discuss multiple criteria optimization problems and imprecise (stochastically disturbed) objective functions.

Taking several optimization tasks as examples, we will show how to analyze these optimization problems, how to select suitable evolutionary operators, coding and procedures, and finally how to tune the parameters of the specified algorithms. Therefore, guidelines to develop efficient and powerful EAs for real-world optimization tasks are presented in this tutorial.

The tutorial is structured as follows: Sec. 2 gives an overview over typical applications of EAs, Sec. 3 introduces basic features of evolutionary algorithms, especially parameter design and adaptation. Since stochastically disturbed fitness function values occur in many real-world optimization problems, this issue is covered in Sec. 4. Advantage of parallelization and of different population structures are presented in Sec. 5. Sec. 6 summarizes the evolutionary approach presented here.

2 Some EA-Applications

In the following, we will present some typical examples to demonstrate the applicability of evolutionary algorithms to real-world optimization problems. One of the 'classics' in this context is the contour optimization of a nozzle for a two-phase flow to maximize the efficiency of converting thermal into kinetic energy [Sch68], see Fig. 1. More recent optimization problems are e.g. minimal weight truss layout (structural optimization) [Spr95] or an optical filter optimization problem [SS96].

The population based approach of evolutionary algorithms might be beneficial for multi criteria optimization (MCO) problems. Digital circuit design [BDFP02], airfoil design [NWBH02] and mold temperature optimization[MMBS03] can be mentioned here. The elevator supervisory group controller (ESGC) problem [MAB$^+$01, BEM03] is an interesting example to demonstrate how EAs can cope with noisy fitness function values.

Extensive empirical investigations have shown that combinations out a simple EA and neighborhood search methods are competitive optimizers for several vehicle routing problems.

We will summarize some common features of problems for which EAs are suitable optimization algorithms.

Figure 1: Optimization of a nozzle for a two-phase flow with an ES. No simulation model was available at the time [Sch68]. Schwefel performed an experimental optimization using an $(1+1)$ ES. The nozzles were built of conical pieces such that no discontinuity within the internal shape was possible. In this way every nozzle shape could be represented by its overall length and the inside diameters at the borders between the segments (every 10mm). Despite the use of a very simple (1+1) ES without recombination this first ES using gene duplication and deletion produced astonishingly good results leading to a 'strange' nozzle shape shown on the right. The unintuitively formed shape has been understood only after further investigations. On the left, the starting shape is shown.

3 EA Basics

3.1 Algorithm

We will present the basic elements of evolutionary algorithms, see Fig. 2. This includes items such as population, selection, recombination, mutation, and termination criterion. We will discuss differences and similarities between GA, GP, and ES. Furthermore, hybrid approaches will be considered.

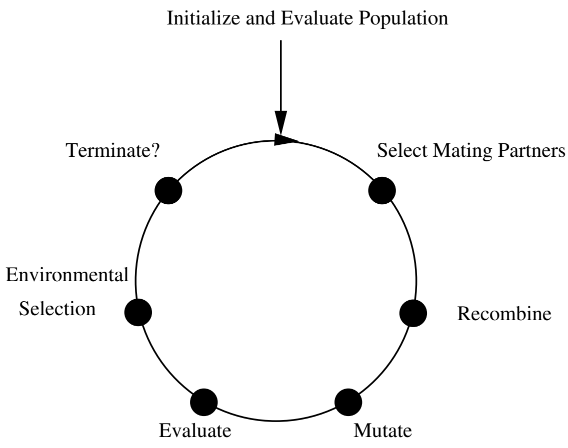

Figure 2: Evolutionary algorithms.

3.2 Optimization Model and Representation

Although EAs do not need more than a representation of the search space and an objective function (which can be treated as a 'black box'), it is often advantageous to integrate problem specific knowledge to improve and secure the optimization process.

Several research groups from the collaborative research centers *Design and Management of Complex Technical Processes and Systems by Means of Computational Intelligence Methods* and *Modeling of Large Logistic Networks* (SFB 531 and SFB 559, University of Dortmund, Germany) are investigating in the integration of problem specific knowledge [SWW02] in EAs with respect to their efficiency and usefulness for real-world optimization tasks.

Results from these research groups will be presented, i.e. how problem specific knowledge might result in non-standard operators for EAs. As a 'classical' example we will present different recombination methods for the traveling salesperson problem (TSP): Partial ordered crossover (PMX), ordered crossover (OX), and cyclic crossover (CX).

Additionally, metric based evolutionary algorithms present a systematic approach and give guidelines for the design of genetic operators and the representation of the phenotype space [DW00].

Hybridizations of EAs and neighborhood search methods may result in a good balance between intensification and diversification.

3.3 Adaptation

Whereas canonical GAs consider mutation as a background operator, mutation is essential for evolution strategies. We will discuss the importance of endogenous strategy parameters that enable self-adaptation of the strategy. The 1/5th rule, correlated mutations and cumulative step-size adaptation schemes will be introduced [Rud92, HO97].

3.4 EA Parameter Design Considerations

In contrast to endogenous strategy parameters that can be adapted during the search process, exogenous strategy parameters (i.e. population size and selective pressure) have to be selected before the optimization run is started [BS02]. The setting of the exogenous parameters might have a significant influence on the behavior of stochastic search algorithms (this refers not only to EAs, but also to particle swarm optimization or simulated annealing etc.) Design of experiments and response surface methods are useful statistical tools to find improved exogenous parameter settings in an efficient and effective manner.

3.5 Multi-Criteria Optimization

Multi-criteria optimization (MCO) problems can be modeled with populations of candidate solutions which are a common feature of EAs. Mold temperature optimization[MMBS03] is used to demonstrate the applicability of this approach.

4 How to Cope with Noise

Methods to handle stochastically disturbed fitness function values are summarized and discussed in this section. Due to their step-size adaptation mechanism ES affords a greater degree of robustness than other direct search methods such as the direct pattern search algorithm (Hooke and Jeeves), the simplex method (Nelder and Mead), Torczon's multi-directional search algorithm, or the implicit filtering method (Gilmore and Kelley) [AB03].

The idea of threshold selection [MAB$^+$01, BM02, BMS$^+$02, BEM03] and its relationship to statistical hypothesis testing is presented here. The elevator supervisory group controller problem gives an interesting example in this context.

5 The Advantages of Parallelism

Various approaches are known for parallelizing evolutionary algorithms, choosing an appropriate one first requires some knowledge about the available hardware and the optimization problem dealt with. Driving forces for parallelization are often minimization of wall-clock time needed for achieving a specified solution quality or increased robustness of the optimization process. It must be noted that parallelization usually leads to modified algorithms, so that discussing results in terms of speedup becomes difficult. We only present three of the most common approaches [AT02] below.

5.1 Global Parallelism

If network latency times on the given hardware are well below the time needed for computing the objective function, factoring out evaluations, also referred to as the global parallelism approach, usually leads to considerable speedup.

The EA as depicted in figure 2 is then run on a master node and only the evaluations (step Evaluate) are sent out to client nodes that hand back the results. A similar method can help if the objective function is separable.

5.2 Island Models

If communication on the underlying hardware is rather slow or very unreliable, island models should be considered. They utilize several EA instances concurrently running on the available nodes. The separate EAs are coupled by exchange of current solutions (migration, pollination) without strict synchronization.

5.3 Diffusion Models

Diffusion Models are like Island Models well suited to parallel architectures with slow communication. They utilize a huge number of tightly coupled subpopulations usually arranged as a grid. Each of these only interacts with subpopulations within a defined neighborhood.

5.4 Means of Implementation

Several software libraries and virtual platforms exist that support implementation of the communication needed by parallel EAs: message passing interfaces like MPI and PVM, the OpenGrid, the DREAM platform [ACE$^+$02], and specialized libraries for specific parallel hardware architectures.

6 Summary and Outlook: The Evolutionary Methodology

Summarizing, we can classify our approach as an evolutionary method (similar to the approach proposed in [BD87]). Three steps are important:

1. Problem analysis: this results in problem specific operators (noise, problem representation, genetic operators, constraint handling mechanisms etc. are determined).

2. Algorithm tuning: exogenous algorithm parameters are specified.

3. Validation: discussion of the results. Do the results lead to new questions?

Evolutionary optimization can be regarded as communication between the engineer and the optimization practitioner. The applicability and usefulness of this concept has been demonstrated at the Collaborative Research Centers 531 and 559 at the University of Dortmund (Germany) [SWW02].

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