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## Simultaneous concept-based evolutionary multi-objective optimization

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#### ABSTRACT

In contrast to traditional multi-objective problems the concept-based version of such problems involves sets of particular solutions, which represent predefined conceptual solutions. This paper addresses the concept-based multi-objective problem by proposing two novel multi objective evolutionary algorithms. It also compares two major search approaches.The suggested algorithms deal with resource sharing among concepts, and within each concept, while simultaneously evolving concepts towards a Pareto front by way of their representing sets. The introduced algorithms, which use a simultaneous search approach, are compared with a sequential one. For this purpose concept-based performance indicators are suggested and used. The comparison study includes both the computational time and the quality of the concept-based front representation. Finally, the effect on the computational time of both the concept fitness evaluation time and concept optimality, for both the sequential and simultaneous approaches, is highlighted.

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#### **1. Introduction**

Multi-objective problems (MOPs) exist in a vast number of engineering and scientific applications [\[1\]. S](#page--1-0)olving such problems with multiple and often conflicting objectives is, in general, a very difficult problem. Evolutionary algorithms possess several characteristics, which make them suitable for solving this type of problem [\[2\]. T](#page--1-0)his paper deals with a unique type of MOP and suggests an evolutionary multi-objective optimization (EMO) approach to solve it. It concerns a concept-based MOP and a solution approach, which is motivated by the way humans, such as engineers solve a problem [\[3,4\]. T](#page--1-0)he notion of a conceptual solution, as understood in engineering design [\[3–5\],](#page--1-0) is associated with abstractive ideas, which are generated by humans, describing a generic solution to a problem. For example, a conveyor and a manipulator are potentially two conceptual solutions to the problem of moving an object from one location to another. Due to its inherent lack of details it is difficult, and often impossible, to evaluate a conceptual solution in the regular sense of performances. In comparison with conceptual solutions, particular solutions, are sufficiently detailed such that each has a one-to-one relationship with a point in the objective space (as in the classical MOP). In certain problems multiple particular solutions might be associated with a conceptual solution and performance evaluation models might be available for each concept by way of its associated particular solutions (see Section [2.2\).](#page-1-0) In such a case, a concept-based MOP can be defined and used to support both the selection of a concept and the selection of a particular solution.

In the concept-based MOP, which is addressed here following the s-Pareto definition of [\[3\],](#page--1-0) the focus is on finding all the Pareto-optimal concepts, where each such concept has at least one member of its set being a non-dominated solution with respect to the entire feasible set of solutions from all concepts. In the conceptbased approach such as in [\[3\], a](#page--1-0)nd in the current paper, concepts are predefined by the designers. It should be noted that conceptbased MOPs could be solved using a sequential approach. In such an approach each concept is considered separately, and the obtained independent fronts are subsequently used to produce the final front [\[5\].](#page--1-0) In contrast, the purpose of the simultaneous concept-based EMO is to reach, by a simultaneous evolution of the concepts, the Pareto-optimal set or at least its approximation, with adequate representation of the concepts. The term 'simultaneous' indicates that all concepts are participating during the same evolution process. This resembles competing species in nature, and could be viewed as the evolution of species towards and along a Pareto front. Adequate representation of the concepts means that the resulting set

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<span id="page-1-0"></span>should contain individuals from all the Pareto-optimal concepts. Furthermore, an adequate representation means that the resulting sub-sets are well distributed on the front, as further explained in this paper.

Section 2 provides an extensive background on the relevant issues and a detailed discussion on the research needs. Section [3](#page--1-0) of this paper presents the fundamental problem definitions for the classical and the concept-based MOPs and exposes their equivalence. Section [4](#page--1-0) outlines two search approaches, sequential and simultaneous, and discusses their comparison. Section [5](#page--1-0) provides details on the algorithms, which are proposed here based on a simultaneous solution approach, and includes a comparison with the sequential approach. Section 6 includes some examples, which demonstrate the special features of the suggested algorithms, as well as a representation of the effect of the concepts on the computational time, both for the sequential and the simultaneous approach. In Section 7 a discussion of the results and the needs for future research is carried out. Finally, Section 8 provides a summary of the conclusions.

#### **2. Background**

#### 2.1. Evolutionary multi-objective optimization

According to a recent review by Coello [\[1\], e](#page--1-0)volutionary multiobjective optimization (EMO) has reached a matured stage, and its development has consistently been followed by applications in engineering, product development, management, and science. The development of Pareto-based evolutionary algorithms has been initiated by the procedure suggested by Goldberg [\[6\].](#page--1-0) Surveys and descriptions of such algorithms can be found in several references (e.g., [\[1,7–11\]\).](#page--1-0) The use of EMO to solve concept-based MOPs is relatively new, and constitutes a modification of classical EMO. This issue is discussed in the following section.

#### 2.2. Concept-based multi-objective search

The proper selection of a design concept is crucial to company competitiveness [\[12\]. T](#page--1-0)he significance of this problem, and in particular with conflicting objectives, has been reflected in an increasing effort to develop methodologies and computational tools to support optimal concept selection. A recent review by Mattson and Messac [\[3\]](#page--1-0) provides an overview on existing concept selection methods with a focus on efforts towards multi-objective selection of concepts. Among such efforts is the development of the concept-based Interactive Evolutionary Computation (IEC) approach [\[4,13–16\].](#page--1-0) The major motivation for the development of the concept-based IEC methodology has been the support of engineering design. Yet, exploring conceptual solutions (concepts) in MOPs has a much broader scope as demonstrated in [\[13\].](#page--1-0) As indicated in [\[4\],](#page--1-0) the use of conceptual solutions improves human–machine interface, and enables evaluating concepts, rather than just specific solutions. Moreover, it allows the incorporation of human subjective preferences towards concepts and sub-concepts. In dealing with engineering design problems, a progressive goal approach has been taken, with a simultaneous evolution of concepts [\[4\].](#page--1-0) In [\[13–16\], a](#page--1-0)n algorithm has been presented that interactively evolves such conceptual solutions by a Pareto-directed, rather than a progressive goal approach. The technique has been extended to deal with conceptual solutions, which are represented by a hierarchical tree of sub-concepts, [\[14\],](#page--1-0) and for robustness considerations [\[15,16\]. T](#page--1-0)he concept-based MOP approach of [\[4,13–16\], a](#page--1-0)nd of the current paper, follows that of Li and Azarm [\[17\], C](#page--1-0)rossley et al. [\[18\], M](#page--1-0)attson and Messac [\[19\], a](#page--1-0)nd Andersson [\[5\].](#page--1-0)

In contrast to a classical MOP, a concept-based MOP involves the association of multiple particular solutions with a concept. Moreover, each particular solution from any concept is associated with a point in the objective space. The objective space is usually common to all concepts. It is assumed that the performances of each particular solution are computable. Each conceptual solution, and its associated particular solutions, may be characterized by different models, different search spaces, and/or different range of variables. The following provides an example for concepts with different models and identical search spaces. Consider the concept of a two-arm manipulator with prismatic joints, vs. the concept of a two-arm manipulator with revolute joints. Furthermore, consider that the search spaces for both concepts involve identical variables including the arms' material and their cross sections, as well as the same objectives of minimizing both the Integral Square Error (ISE) and the deflection of the end-effecter. The evaluations of the performances of solutions, which belong to these concepts, are done by different models due to the different configuration. An example for concepts with the same models but with different range of variables is the MOP, which involves the maximization of the volume while minimizing the weight of the empty containers. Two different concepts are considered, both involving prismatic containers. The first is of large base and short height and the second is of small base and medium height. Yet, the above examples are not the general case as concepts to solve a MOP may be as remote as a plane and a car, both valid concepts to solve a traveling problem between two cities. Such a conceptual design involves different concepts related to different models and to different search spaces.

Mattson and Messac [\[19\]](#page--1-0) introduced the s-Pareto notion involving Pareto-optimal solutions that are associated with the considered concepts, and have extended their method to include measures to compare concepts along the front [\[3\].](#page--1-0) The current paper, and [\[13–16\], f](#page--1-0)ollows the s-Pareto approach of representing Pareto-optimal sets of concepts. However, in contrast to Mattson and Messac, who have used non-evolutionary methods to generate the front, the approach taken here, and in [\[13–16\],](#page--1-0) is based on EMO. Andersson [\[5\]](#page--1-0) developed a sequential MOEA approach to display and compare concept-related fronts. In the sequential approach of Andersson each set of solutions that represents a concept is evolved separately. Similarly, Rai and Allada [\[20\]](#page--1-0) introduced a sequential approach to tackle the modular product family design problem. AMOEA approach has been taken by Simpson and D'Souza [\[21\]](#page--1-0) to deal with product family design. They used NSGA-II [\[11\]](#page--1-0) to facilitate a structured genetic algorithm [\[22\]. T](#page--1-0)he objectives of the problem in [\[21\]](#page--1-0) are the variation in design variables and a deviation function from a given goal. However, in the MOEA approach of [\[21\]](#page--1-0) each "family" is associated with one point in the objective space and not with a set of points as in the concept-based approach.

The major originality of our approach, in [\[13–16\], t](#page--1-0)o the solution of the concept-based MOP, in comparison with the sequential technique, [\[5\], i](#page--1-0)nvolves the simultaneous evolution of several concepts. The simultaneous approach, in [\[13–16\], h](#page--1-0)as been motivated by considerations for human interactivity towards concepts. The simultaneous evolution of concepts, in [\[13–16\],](#page--1-0) has been facilitated by sharing resources, among the evolving concepts, using a modified NSGA algorithm. The proper distribution of resources is also a major issue in the current study. Apparently, the notion of sub-populations and resource sharing is not unique to the conceptbased EMO as outlined in the following section.

#### 2.3. Resource sharing and sub-populations

In biology the term species refers to the most basic biological classification. It is comprised of individuals that are able to breed with each other but not with others.

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