multi-Multi-Objective Optimization Problem and Its Solution by a MOEA

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Abstract. In this paper, a new type of Multi-Objective Problems (MOPs) is introduced and formulated. The new type is an outcome of a motivation to find optimal solutions for different MOPs, which are coupled through communal components. Therefore, in such cases a multi-Multi-Objective Optimization Problem (m-MOOP) has to be considered. The solution to the m-MOOP is defined and an approach to search for it by applying an EMO algorithm sequentially is presented. This method, although not always resulting in the individual MOPs' Pareto fronts, nevertheless gives solutions to the m-MOOP problem in hand. Several measures that allow the assessment of the introduced approach are offered. To demonstrate the approach and its applicability, academic examples as well as a "real-life," engineering example, are given.

Keywords: Communality, Family of designs, Engineering design.

1 Introduction

Sharing components among products is an effective way to cut costs. Expenses are decreased through the reduction in components design time as well as through savings in manufacturing costs and inventory (see e.g., [1]). Robertson and Ulrich, [2], point out that ‘‘By sharing components and production processes among products, companies can develop differentiated products efficiently, increase the flexibility and responsiveness of their manufacturing processes, and take market share away from competitors that develop only one product at a time." An example of the importance of sharing is Black & Decker’s universal electric motor. According to Lehnerd [3], in the 1970s Black & Decker developed a family of universal motors for their power tools in response to a new ‘double insulation’ safety regulation. Prior to that, they used different motors in each of their 122 basic tools with hundreds of variations. By paying attention to standardization and exploiting platform scaling around the motor stack length, material costs dropped from \$0.77 to \$0.42 per motor while labor costs fell from \$0.248 to \$0.045 per motor, yielding an annual savings of \$1.82M per year.

Most of the attempts to share components between products are associated with the design of a product family. A product family is a group of related products that share common components and/or subsystems – yet satisfy a variety of market niches (e.g., [4]).

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A design for components' commonality, is not restricted to hardware components as done e.g., in [1], but is also associated with software components. According to [5], software product families, aim at decreasing the costs and time required to produce a customer specific product. Oftentimes, commonality of software components is referred to as Component Based Software Development (CBSD). According to [6], there are two main benefits specific to CBSD. First, it gives structure to system design and system development, thus making system verification and maintenance more tractable. Second, it allows reuse of development effort by allowing components to be re-used across products and in the longer term by paving the way for a market for software components. Studies and approaches for CBSD may be found in many citations (e.g. [7],).

The focus of this paper is on the commonality of hardware components rather than on software components. According to [1], two types of component sharing can be used when selecting a product platform. The first is *component sharing*, in which one or more components are common to several products. The second is the sharing of “scaled” versions of components. Mathematically this can be described as *variable sharing*.

Successful engineering design of products generally requires the resolution of various conflicting design objectives ([8]). In case of contradicting objectives within a MOP, there is no universally accepted definition of an 'optimum' as in a single-objective optimization (see [9]). In such a case, there is no single global solution and it is often useful to determine a set of solutions that fits a predetermined definition for an optimum and let a Decision Maker (DM) choose between them. The predominant concept in defining such a set point is that of Pareto optimality ([10]). By definition, Pareto solutions, which belong to the Pareto optimality set, are considered optimal because there are no other designs that are superior in all objectives (e.g., [11]). The current focus is on different products whose designs require the solution of a MOP for each, and share common components.

The search for optimal solutions for a MOP is commonly termed Multi Objective Optimization (MOO). A comprehensive survey and comparison between most multi-objective optimization techniques and algorithms can be found in [12].

Searching a multi-objective design space, for optimal solutions, by Evolutionary Computation (EC) approaches (such as genetic algorithms) is commonly referred to as Evolutionary Multi-objective Optimization, (EMOO/EMO). Multi-Objective Evolutionary Algorithm (MOEA) is an EMOO algorithm, which searches for a solution in a multi-criteria space using some inspiration from evolutionary theories. Most MOEAs use genetic algorithms for the evolutionary search.

Research on MOEA has grown considerably in the last few years (see: Coello's web site http://www.lania.mx/~ccoello/EMOO/EMOObib.html). A number of algorithms, such as the Multiple Objective Genetic Algorithm (MOGA) of [13], are known to advance the use of EMO to solve MOPs. These algorithms utilize the non-dominancy notation ([14]), to direct the search towards a Pareto front. They use 'sharing' to allow the spreading of solutions along the front. According to Coello, ([15]), the later generation of Pareto-based algorithms, such as NSGA-II, ([16]), involves three major elements. The first element concerns the creation of a search pressure towards the Pareto set. This is commonly achieved by one of the known Pareto-based fitness assignment (dominance-based) techniques. The second element