Quality Assessment of Multiobjective Optimisation Algorithms in Component Deployment

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ABSTRACT

Measuring the quality of the approximate sets in a quantitative way is important to asses the performance of multiobjective optimisation algorithms and decide which algorithm performs best in a problem domain. In the case of component deployment optimisation of automotive systems, despite the wide range of optimisation methods already published, it is still unknown which algorithm is the optimal choice. Several studies can be found in the literature that address the problem of comparing approximate sets in a quantitative manner, reflecting a specific feature of the optimisation method, i.e. either convergence or diversity. However, both convergence and diversity are important quality aspects and both should be considered to define dominance relations. The aim of this study is a new quality assessment method for approximate sets, which will indicate dominance relations based on both convergence and diversity.

Categories and Subject Descriptors

D.2 [**Software**]: Software Engineering

General Terms

Performance

1. INTRODUCTION

The quality of embedded systems in the automotive industry is highly dependent on the design decisions that map software components to hardware hosts [4]. Since this problem is known to be NP hard, approximate methods should be employed. Moreover, the component deployment problem often involves simultaneous optimisation of several competing quality objectives and constraints. The solution to such problems is usually a set of design alternatives, which assures a tradeoff between the conflicting qualities, referred to as *Pareto front*. The employment of approximate methods for multiobjective optimisation yields *approximations of the Pareto front*, known as *approximate sets*.

Many approximate optimisation methods exist in the literature for the component deployment optimisation problem [4, 5]. While researchers generally agree on using approximate methods for component deployment optimisation, the performance of these methods is not considered. As Blum [2] states, the performance of an approximate optimisation method is highly related to the context in which it is being used. Accordingly, knowledge about the performance would not only enable monitoring and improving the optimisation method but also it would provide means for comparing and contrasting the performance of different optimization methods in a specific problem domain.

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Unfortunately, measuring the performance of multiobjective optimisation methods is a non-trivial task. Zitzler et al. [10] suggest three aspects to define appropriate quality-measures for approximate sets: (i) The distance of the resulting approximate set to the Pareto front should be minimized, (ii) A good, i.e uniform, distribution of the solutions should be found, and (iii) The extent of the obtained approximate set should be maximized. The first one deals with the quality of the solutions, known as *convergence property*. The latter two deal with the distribution of solutions, which is known as *diversity property*. To measure the quality of approximate sets, various quality metrics exist in the literature [12]. However, it is not very clear what the advantages and disadvantages of these quality measures are, and in what way they relate to each other [12]. Moreover, despite of the variety of the quality metrics, none of them indicates how good an approximate set is with respect to both the desired features, i.e. diversity and convergence properties.

As Laumanns et al. [7] points out, the diversity of solutions is as important as the convergence to the Pareto front. Accordingly, the main goal of component deployment optimisation problem is to find an approximate set that is as close as possible to the Pareto front and covers a wide range of diverse solutions. This study aims to develop a new method to measure the quality of approximate sets which will indicate both the convergence of the algorithm and the preservation of diversity of the solutions.

2. RELATED WORK

Optimisation Methods: Considerable research has been done to help the designers find an optimal deployment of software components on the hardware platform [3]. Typical representatives of optimisation algorithms in the component deployment optimisation problem are Evolutionary Algorithms [4], Simulated Annealing [5], and Tabu Search [6]. The main problems with these algorithms are the time complexity for the convergence to the Pareto front and their proneness to confinement in local optima.

Because of their probabilistic nature, approximate optimisation algorithms behave differently. Some of these algorithms can only generate a part of the solutions in the real

Pareto front while others obtain a "good" rather than the Pareto set. Moreover, their performance is strictly bounded to the problem-domain [2]. In order to reveal the strengths and weaknesses of optimisation methods and identify the most promising techniques in component deployment optimisation problem, quality metrics are needed.

Quality Metrics: Many quality assessment methods have been developed to define dominance relations on approximate sets and evaluate various qualities of multiobjective optimisation results. A wide range of these quality metrics relate to the diversity of the solutions [12, 11, 9], while other quality metrics deal with the convergence aspect [8, 12].

One of the few recommended metrics is the *hypervolume indicator* [11, 12]. This metric treats the size of the dominated area in the objective space as the indicator of diversity. However, it may be misleading if the approximate set is non-convex [11]. Another well established metric for the diversity indication is the *front spread indicator* [9]. This metric indicates the size of the objective space covered by an approximate set. Nevertheless, this quality indicator does not consider the number of solutions found.

The *proximity indicator* [8] is a convergence metric and measures the distance from a set of approximate solutions to the Pareto front. Unfortunately, it requires the generation of the Pareto front. The *front occupation indicator* [8] is another approach which states how many points are available in the approximate set. However, being only a quantity metric, it does not consider how far these points from each other are. Zitzler et al. [12] propose two quality metrics, i.e. *enclosing hypercube indicator* and *objective vector indicator*. Although these two metrics are recommended according to the current status of knowledge, there exist particular scenarios where they fail to represent dominance relations [12].

To summarise, the use of quality indicators is restricted and not quite clear. Zitzler et al. [12] provide a comprehensive review of quality indicators for multiobjective optimisation, finding that many commonly used metrics do not reliably reflect dominance relations.

3. PROBLEM STATEMENT AND APPROACH

Quality indicators found in the literature represent problem-dependent knowledge with respect to a single feature of the algorithm, being either diversity or convergence property. The trade-off between the goals of convergence and diversity is an important quality aspect of different multiobjective optimisation algorithms. Accordingly, both convergence with respect to the Pareto front and diversity along the finally obtained set of approximate solutions should be considered as a quality measure to compare different algorithms.

In this study, the outperformance relation will represent a formal description of an approximate set being better than another with respect to both, diversity and convergence properties. Diversity brings crucial knowledge to the decision maker, informing him about the range of the good solutions and will guarantee that the possible efficient solutions are explored. On the other hand, the main goal of every approximate optimisation method is to approach as much as possible to the Pareto front. Considering either diversity or convergence is not enough to decide upon the optimal algorithm for component deployment optimisation. A method which addresses both issues will have the power of representing in a quantitative manner which algorithm is the best choice in our problem domain.

To validate this approach, the method should be proven to be compatible and complete with respect to dominance relations [12]. Considering the stochastic nature of approximate methods, statistical testing will be applied using multiple runs of the optimisation algorithms on realistic case studies taken from the automotive industry. As an experimental framework the Archeopterix tool [1] will be employed.

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