A Scalable Multi-objective Test Problem Toolkit

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Abstract. This paper presents a new toolkit for creating scalable multi-objective test problems. The WFG Toolkit is flexible, allowing characteristics such as bias, multi-modality, and non-separability to be incorporated and combined as desired. A wide variety of Pareto optimal geometries are also supported, including convex, concave, mixed convex/concave, linear, degenerate, and disconnected geometries.

All problems created by the WFG Toolkit are well defined, are scalable with respect to both the number of objectives and the number of parameters, and have known Pareto optimal sets. Nine benchmark multi-objective problems are suggested, including one that is both multi-modal and non-separable, an important combination of characteristics that is lacking among existing (scalable) multi-objective problems.

1 Introduction

There have been several attempts to define test suites and toolkits for testing multi-objective evolutionary algorithms (MOEAs) [1, 2, 3, 4]. However, existing multi-objective test problems do not test a wide range of characteristics, and are often poorly designed. Typical defects include not being scalable and being susceptible to simple search strategies. Moreover, many problems are poorly constructed, with unknown Pareto optimal sets, or featuring parameters with poorly located optima.

As suggested for single-objective problems by Whitley et al. [5] and Bäck and Michalewicz [6], test suites should include scalable problems that are resistant to hill climbing strategies, are non-linear, non-separable[1], and multi-modal. Such requirements are also a good start for multi-objective test suites, but unfortunately are poorly represented in the literature.

Addressing this problem, this paper presents the Walking Fish Group (WFG) Toolkit, which places an emphasis on allowing test problem designers to construct scalable test problems with any number of objectives, where features such

[1] Separable problems can be optimised by considering each parameter in turn, independently of one another. A non-separable problem is thus characterised by parameter dependencies, is more difficult, and is more representative of real world problems.

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as modality and separability can be customised as required. Test problems in the WFG Toolkit are defined in terms of a simple underlying problem that defines the fitness space and a series of composable, configurable transformations that allow the test problem designer to add arbitrarily levels of complexity to the test problem. Problems created by the WFG Toolkit are well defined, are scalable with respect to both the number of objectives and the number of parameters, and have known Pareto optimal sets.

The next section of the paper introduces the multi-objective terminology used throughout. Section 3 briefly examines previous multi-objective test suites, highlighting the deficiencies with them. Section 4 specifies our new WFG Toolkit, generalising the concepts introduced in these previous test suites to produce a configurable toolkit that allows for the construction of scalable, well-behaved test problems. Section 5 then describes how the WFG Toolkit can be used to construct an example test problem. Some experimental results are presented in Section 6. A suite of nine test problems are proposed in Section 7 that exceeds the functionality of previous test suites. Section 8 concludes the paper.

2 Terminology

Consider a multi-objective optimisation problem given in terms of a search space of allowed values of n parameters $x_1, \ldots, x_n$, and a vector of M objective functions $\{f_1, \ldots, f_M\}$ mapping parameter vectors into fitness space. The mapping from the search space to fitness space defines the *fitness landscape*.

In multi-objective optimisation, we aim to find the set of optimal trade-off solutions known as the *Pareto optimal set*. The Pareto optimal set is the set of all Pareto optimal parameter vectors, and the corresponding set of objective vectors is the *Pareto optimal front*. The Pareto optimal set is a subset of the search space, whereas the Pareto optimal front is a subset of the fitness space.

The following types of relationships are useful because they allow us to separate the convergence and spread aspects of sets of solutions for a problem. A *distance parameter* is one that when modified only ever results in a dominated, dominating, or equivalent parameter vector. A *position parameter* is one that when modified only ever results in an incomparable or equivalent parameter vector. All other parameters are *mixed parameters*.

When the projection of the Pareto optimal set onto the domain of a single parameter, the parameter optima, is a single value at the edge of the domain, then we call the parameter an *extremal parameter*. If instead the parameter optima cluster around the middle of the domain, then it is a *medial parameter*. Extremal parameters can be unduly favoured by truncation based mutation correction strategies, whereas medial parameters can be favoured by EAs that employ intermediate recombination [7].