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General framework for localised multi-objective evolutionary algorithms

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Many real-world problems have multiple competing objectives and can often be formulated as multi-objective optimisation problems. Multi-objective evolutionary algorithms (MOEAs) have proven very effective in obtaining a set of trade-off solutions for such problems. This research seeks to improve both the accuracy and the diversity of these solutions through the local application of evolutionary operators to selected sub-populations. A local operation-based implementation framework is presented in which a population is partitioned, using hierarchical clustering, into a pre-defined number of sub-populations. *Environment-selection* and *genetic-variation* are then applied to each sub-population. The effectiveness of this approach is demonstrated on 2- and 4-objective benchmark problems. The performance of each of four best-in-class MOEAs is compared with their modified local operation-based versions derived from this framework. In each case the introduction of the local operation-based approach improves performance. Further, it is shown that the combined use of local *environment-selection* and local *genetic-variation* is better than the application of either local *environment-selection* or local *genetic-variation* alone. Preliminary results indicate that the selection of a suitable number of sub-populations is related to problem dimension as well as to population size.

1. Introduction

Multi-objective problems (MOPs) regularly arise in real-world design scenarios, where two or more objectives are required to be optimised simultaneously. As such objectives are often in competition with one another, the optimal solution of MOPs is a set of trade-off solutions, rather than a single solution. Due to the population-based approach, multi-objective evolutionary algorithms (MOEAs) are well suited for solving MOPs since this leads naturally to the generation of an approximate trade-off surface (or Pareto front [22]) in a run [6,9].

A variety of MOEA approaches has been proposed [63]: (1) Pareto dominance (and modified Pareto dominance) based MOEAs, e.g. MOGA [17,19,21],NSGA-II [12], SPEA2 [65], ϵ-MOEA [11] and Pareto Cone ϵ-dominance based MOEA [2], (2) indicator (hypervolume [66]) based MOEAs, e.g. IBEA [64], SMS-EMOA [4], HypE [1], (3) scalarising function based MOEAs, e.g. MSOPS [26], MOEA/D [62], and, latterly, (4) preference-inspired co evolutionary algorithms (PICEAs), e.g. PICEA-g [48,58,59]. All of these approaches strive to converge quickly to a satisfactory approximation to the Pareto front (convergence) and that this approximation be well distributed with a good coverage of the front (diversity).

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Pareto dominance based MOEAs were one of the earliest approaches and it is accepted that they perform well on MOPs with 2 and 3 objectives. However, their search capability often degrades significantly as the number of objectives increase [46,27]. This is because the proportion of Pareto-optimal (or non-dominated) objective vectors in the population grows large when MOPs have more than 3 objectives i.e. many-objective problems. As a result, insufficient selection pressure can be generated toward the Pareto front [47,36]. Relatively recently, there has been considerable effort invested in other types of MOEAs that might perform more effectively on many-objective problems. In particular, PICEA-g, HypE and MSOPS are MOEAs that claim to perform better on many-objective problems [55,58].

In general, a MOEA can be described as

$$P(t+1) = S_s(v(S_v(P(t))), P(t)) \tag{1}$$

where $P(t)$ are the candidate solutions (population) at iteration t, S_v is the *selection-for-variation* operator, v is the *genetic-variation (recombination and mutation)* operator, S_s is the *environment-selection* operator, and $P(t+1)$ are the newly generated solutions [47]. Thus, a set of candidate solutions is evolved by successively applying recombination, mutation, and selection to yield better solutions in an iterative process.

In many cases, S_s and v are executed on the entire population (described as a global operation). Accordingly, an evolutionary operator that is executed on sub-populations is denoted a local operation. Global operations are held to be beneficial for speed of convergence. However, global operation increases the probability of recombining solutions distant from one another and so produce lower performance offspring known as lethals [19,47,31]. The issue of lethals were originally considered in single objective optimisation by Deb & Goldberg as a response to the problems of fitness sharing [22]. The superfluous production of lethals, known as dominance resistance [47], will consequently reduce the efficiency of the optimisation process and affect convergence towards the Pareto optimal front. It has been argued that the use of local operations may achieve a better overall performance, taking account of both convergence and diversity [7,37]. For example, Sato et al. [49,50] demonstrated that the execution of Pareto dominance and recombination on neighbouring solutions could produce more fruitful solutions and so improve the performance (convergence and diversity) of MOEAs. Although local operation has been investigated in some studies[1] [39,49,50,31,57], no generalised MOEA framework is available for the implementation of local operations. In this study we first propose a local operation based framework and then present a specific implementation for using this framework. In this implementation, a clustering technique first partitions the global population into a number of sub-populations. Then, the operators, S_v and v, are executed on each sub-population independently. The proposed framework shares some similarities with parallel MOEAs, particularly, the island model based MOEAs (in which the population is divided into sub-populations, each sub-population is associated with an island and an optimiser evolves the sub-population with occasional migration of individuals between sub-populations). A specific instantiation of the framework is evaluated by comparing the performance of MOEAs and their modified *local* versions (LMOEAs) derived from the new framework on 2- and 4-objective real-parameter test problems. The MOEAs selected for the evaluation are four best-in-class algorithms: NSGA-II (Pareto dominance), HypE (indicator-based), MSOPS (scalarising function) and PICEA-g (co-evolutionary). Since MOEA/D [62] includes local operators – local selection and local replacements – it is not selected for this study [32]. Overall, the main contributions of this paper are as follows:

- A local operation based framework is proposed and a specific implementation for using this framework is presented. The effectiveness of this local framework is demonstrated to work well on four different types of MOEAs.
- The probability p of doing local operations is discussed. Experimental results show using fixed setting of p is worse than using different p (changed according to a relationship defined in Eq. (3)) during the search.
- The effect of the independent use of local *environment-selection* or local *genetic-variation* is discussed. Experimental results show applying both the local operations jointly is better than applying one of the operations on its own. Moreover, local *genetic-variation* is more effective.
- The effect of the number of sub-populations (k) to the performance of the framework is discussed. It is found k is impacted by both population size and problem dimension. Some suggestions are provided for the choice of a suitable k.

The remainder of the paper is structured as follows. In Section 2, MOPs and MOEAs are introduced and related work is briefly reviewed. This is followed, in Section 3, by a description of the new MOEA framework for implementing local operations. Section 4 provides a systematic performance comparison of individual MOEAs and LMOEAs. Section 5 examines the effectiveness of this new framework over other existing local operation based algorithms. Section 6 provides a further discussion of this framework. Section 7 offers concluding remarks and future research.

2. Basic features of MOPs and MOEAs

In this Section, the formulation of MOPs and some fundamental concepts in multi-objective optimisation are first introduced, then some features relating to the development of existing MOEAs are described and some related studies on the use of local operations are briefly reviewed.

[1] In [57], local operators are implemented in PICEA-g as part of a preliminary study.