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A multi-objective hyper-heuristic based on choice function

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ABSTRACT

Hyper-heuristics are emerging methodologies that perform a search over the space of heuristics in an attempt to solve difficult computational optimization problems. We present a learning selection choice function based hyper-heuristic to solve multi-objective optimization problems. This high level approach controls and combines the strengths of three well-known multi-objective evolutionary algorithms (i.e. NSGAII, SPEA2 and MOGA), utilizing them as the low level heuristics. The performance of the proposed learning hyper-heuristic is investigated on the Walking Fish Group test suite which is a common benchmark for multi-objective optimization. Additionally, the proposed hyper-heuristic is applied to the vehicle crashworthiness design problem as a real-world multi-objective problem. The experimental results demonstrate the effectiveness of the hyper-heuristic approach when compared to the performance of each low level heuristic run on its own, as well as being compared to other approaches including an adaptive multi-method search, namely AMALGAM.

1. Introduction

Most real-world problems are complex. Due to their (often) NP-hard nature, researchers and practitioners frequently resort to problem tailored heuristics to obtain a reasonable solution in a reasonable time. Generally, there are two recognized types of hyper-heuristics (Burke et al., 2013): (i) heuristic *selection* methodologies: (meta-) heuristics to choose (meta-) heuristics, and (ii) heuristic *generation* methodologies: (meta-) heuristics to generate new (meta-) heuristics from given components. A selection hyper-heuristic framework manages a set of low level heuristics and chooses one to be applied at any given time using a performance measure for each low level heuristic (Burke et al., 2013). The interest in selection hyper-heuristics has been growing in the recent years. However, the majority of research in this area has been limited to single-objective optimization.

A limited number of studies on selection hyper-heuristics have been introduced for multi-objective problems (see Table 1). Burke, Landa-Silva, and Soubeiga (2003) presented a multi-objective hyper-heuristic based on tabu search (TSRoulette Wheel), applying it to space allocation and timetabling problems. Veerapen, Landa-Silva, and Gandibleux (2009) described another hyper-heuristic approach comprising two phases, applying it to the multi-objective traveling salesman problems. McClymont and Keedwell (2011) used a Markov chain-based learning selection hyper-heuristic (MCHH) for solving a real-world water distribution networks design problem. A new hyper-heuristic approach based on a multi-objective evolutionary algorithm i.e. NSGAII (Deb & Goel, 2001) was proposed in Gomez and Terashima-Marín (2010). NSGAII learned to choose from a set of rules representing a constructive heuristic for 2D irregular stock cutting. In Furtuna, Curteanu, and Leon (2012) a multi-objective hyper-heuristic for the design and optimization of a stacked neural network is proposed. The proposed approach is based on NSGAII combined with a local search algorithm (Quasi-Newton algorithm). Rafique (2012) presented a multi-objective hyper-heuristic optimization scheme for engineering system design problems. A genetic algorithm, simulated annealing and particle swarm optimization are used as low-level heuristics. de Armas, Miranda, and León (2011) and Miranda, de Armas, Segura, and León (2010) described a representation scheme to be used in hyper-heuristics for multi-objective packing problems. Kumari, Srinivas, and Gupta (2013) presented a multi-objective hyper-heuristic genetic algorithm (MHypGA) for the solution of a multi-objective software module clustering problem. In MHypGA, different methods of selection, crossover and mutation operations of genetic algorithms incorporated as a

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Table 1
Heuristic components and application domains of hyper-heuristics for multi-objective optimization.

Component name	Application domain/test problems	Reference(s)
Tabu search	Space allocation, timetabling	Burke et al. (2003)
	Travelling salesman problems	Veerapen et al. (2009)
Markov chain, evolution strategy	Real-world water distribution networks design \DTLZ, WFG	McClymont and Keedwell (2011)
NSGAII	Irregular 2D cutting stock	Gomez and Terashima-Marín (2010)
	Strip packing and Cutting stock	de Armas et al. (2011) and Miranda et al. (2010)
NSGAII, quasi-Newton algorithm	Stacked neural network	Furtuna et al. (2012)
Number of Operations from NSGAII, SPEA2 and IBEA	A number of continuous multi-objective test problems	Vázquez-Rodríguez and Petrovic (2013)
Number of selection, crossover and mutation operations of evolutionary algorithms	Software module clustering	Kumari et al. (2013)
Hypervolume	Dynamic-mapped island-based model	Len et al. (2009)
Particle swarm optimization, adaptive metropolis algorithm, differential evolution	Water resource problems/a number of continuous multi-objective test problems	Vrugt and Robinson (2007), Raad et al. (2010) and Zhang et al. (2010)
Memory strategy, genetic and differential operators	Dynamic optimization problems/a number of continuous multi-objective test problems	Wang and Li (2010)
Genetic algorithm, simulated annealing, particle swarm optimization	Engineering system design problems/a number of classical multi-objective test problems	Rafique (2012)
Simulated annealing	Shelf space allocation	Bai et al. (2013)

low-level heuristics. Vázquez-Rodríguez and Petrovic (2013) proposed a multi-indicator hyper-heuristic for multi-objective optimization. This was approach based on multiple rank indicators that taken from NSGAII (Deb & Goel, 2001), IBEA (Zitzler & Künzli, 2004) and SPEA2 (Zitzler, Laumanns, & Thiele, 2001). Len, Miranda, and Segura (2009) proposed a hypervolume-based hyper-heuristic for a dynamic-mapped multi-objective island-based model. Bai, van Woensel, Kendall, and Burke (2013) proposed a multiple neighborhood hyper-heuristic for two-dimensional shelf space allocation problem. The proposed hyper-heuristic was based on a simulated annealing algorithm.

Different frameworks have been proposed for mixing a set of existing algorithms applied to different problems, such as an adaptive multi-method search (AMALGAM) (Vrugt & Robinson, 2007; Raad, Sinkse, & Vuuren, 2010; Zhang, Srinivasan, & Liew, 2010) and multi-strategy ensemble multi-objective evolutionary algorithm (Wang & Li, 2010).

None of the above have used multi-objective evolutionary algorithms (MOEAs), with the exception of Gomez and Terashima-Marín (2010), Vrugt and Robinson (2007) and Rafique (2012) and none of the standard multi-objective test problems are studied, except in McClymont and Keedwell (2011), Vrugt and Robinson (2007), Len et al. (2009) and Vázquez-Rodríguez and Petrovic (2013). Moreover, none of the previous hyper-heuristics make use of the components specifically designed for multi-objective optimization that we introduce. This paper highlights the need for scientific study in the research area of multi-objective evolutionary algorithms and hyper-heuristics. We focus on an online learning selection choice function based hyper-heuristic, to solve continuous multi-objective optimization problems, and their hybridization with multi-objective evolutionary algorithms which controls and combines the strengths of three well-known multi-objective evolutionary algorithms (NSGAII (Deb & Goel, 2001), SPEA2 (Zitzler et al., 2001), and MOGA (Fonseca & Fleming, 1998)). The choice function was successful when used as a selection method for single-objective optimization (Cowling, Kendall, & Soubeiga, 2002; Kendall, Cowling, & Soubeiga, 2002). To the best of our knowledge, no work been reported in the literature that utilizes the choice function as selection method within a hyper-heuristic framework for multi-objective optimization.

Our hyper-heuristic for multi-objective optimization addresses the research areas of multi-objective evolutionary algorithms and hyper-heuristics. Section 2 discusses each one of these areas. The rest of the paper is organized as follows. Section 3 provides the details of the proposed hyper-heuristic framework for multi-objective optimization. The empirical results comparing our approach to the well known multi-objective evolutionary algorithms that are used as the low level heuristics are presented in Section 4. The comparison of our multi-objective hyper-heuristic to other approaches over benchmark test problems and a real-world problem are presented in Sections 5 and 6 respectively. Section 7 summarizes and discusses possible future research directions.

2. Multi-objective optimization

A multi-objective optimization problem (MOP) comprises several objectives, which need to be minimized or maximized depending on the problem. In the literature, many similar techniques are presented for multi-objective optimization. An example is a posteriori search is conducted to find solutions for the objective functions. Following this, a decision process selects the most appropriate solutions often involving a trade off. Examples of this methodology are multi-objective evolutionary optimization (MOEA) methods, whether non Pareto-based or Pareto-based methods. The Pareto-based evaluation is a method used to evaluate the quality of MOP solutions. In Pareto-based methods, all objectives are simultaneously optimized by applying Pareto dominance concepts. The idea behind the dominance concept is to generate a preference between MOP solutions since there is no information regarding the objective preference provided by the decision maker. Tan, Lee, and Khor (2002) and Coello, Veldhuizen, and Lamont (2007) present a more formal definition of Pareto dominance.

Definition 1. A vector $u = (u_1, \ldots, u_k)$ is said to dominate another vector $v = (v_1, \ldots, v_k)$ (denoted by $u \preceq v$) according to k objectives, if and only if, u is partially less than v, i.e., $\forall i \in \{1, \ldots, k\}, u_i \leqslant v_i \wedge \exists i \in \{1, \ldots, k\} : u_i < v_i$.

In the literature, various features for multi-objective optimization test problems are presented. Those features are designed to make the problems difficult enough to examine algorithmic performance. Examples of these features are deception (Goldberg, 1987; Whitley, 1991), multimodality (Horn & Goldberg, 1995), noise (Kargupta, 1995), and epistasis (Davidor, 1991). Moreover, other features of test problems are suggested in Deb (1999), such as multi-modality, deceptive, isolated optimum and collateral noise.