Surveys in Operations Research and Management Science 20 (2015) 35–42

Contents lists available at ScienceDirect

Surveys in Operations Research and Management Science

journal homepage: www.elsevier.com/locate/sorms

Review

Evolutionary many-objective optimization: A quick-start guide

Shelvin Chand[a,*], Markus Wagner[b]

[a] University of New South Wales, Canberra, Australia
[b] University of Adelaide, Adelaide, Australia

HIGHLIGHTS

- This article presents an overview of the recent developments in the area of many-objective optimization.
- It looks at the challenges that are associated with many-objective optimization and the progress that has been made so far.
- A number of algorithms and real world applications are identified.
- The authors also suggest future research directions within many-objective optimization.

ARTICLE INFO

Article history:
Received 4 May 2015
Received in revised form
2 July 2015
Accepted 27 August 2015

ABSTRACT

Multi-objective optimization problems having more than three objectives are referred to as many-objective optimization problems. Many-objective optimization brings with it a number of challenges that must be addressed, which highlights the need for new and better algorithms that can efficiently handle the growing number of objectives. This article reviews the different challenges associated with many-objective optimization and the work that has been done in the recent-past to alleviate these difficulties. It also highlights how the existing methods and body of knowledge have been used to address the different real world many-objective problems. Finally, it brings focus to some future research opportunities that exist with many-objective optimization.

We report in this article what is commonly used, be it algorithms or test problems, so that the reader knows what are the benchmarks and also what other options are available. We deem this to be especially useful for new researchers and for researchers from other fields who wish to do some work in the area of many-objective optimization.

© 2015 Elsevier Ltd. All rights reserved.

Contents

1. Introduction

Multi-objective optimization refers to the simultaneous optimization of multiple conflicting objectives. It gives rise to a set of

* Corresponding author.
E-mail address: chand.shelvin@gmail.com (S. Chand).

http://dx.doi.org/10.1016/j.sorms.2015.08.001
1876-7354/© 2015 Elsevier Ltd. All rights reserved.

optimal solutions (known as the Pareto-optimal solutions), instead of a single optimal solution [1]. None of the optimal solutions can claim to be better than any other with respect to all objective functions.

Surveys have highlighted this to be one of the fastest growing fields of research and application among all computational intelligence topics [2]. It is also a field of research that attracts interest from people of different backgrounds including mathematicians, computer scientists, economists and engineers [2].

Evolutionary multi-objective optimization (EMO) methods have shown to be highly successful in finding well-converged and well-diversified non-dominated solutions for optimization problems with two and three objectives [3]. Some of these successful methodologies include Strength Pareto Evolutionary Algorithm (SPEA) [4], SPEA2 [5], Non-dominated Sorting Genetic Algorithm (NSGA) [6], NSGA-II [1] and Pareto Archived Evolution Strategy (PAES) [7].

While all these methodologies have shown good success, it is important to consider that many real world problems have more than three objectives. Scalability tests for these methodologies highlight a number of problems relating to convergence, diversity and computation time [8]. As a result, it is important to come up with new methodologies or to improve existing ones to be able to deal with a higher number of objectives. Multi-objective problems having more than three objectives are referred to as many-objective optimization problems [9,10]. Many-objective optimization gives rise to a new set of challenges that must be addressed. It also opens doors for new research opportunities which can allow us to solve more complex real world problems.

While many-objective optimization is a fairly new area of research, it is important to take note that some work on this had already begun in the early 1990s. One of the earliest algorithms which has been applied to many-objective problems is MOGA [11]. MOGA was tested on the four objective Pegasus gas turbine engine optimization problem [11]. Since then a number of researchers have attempted to solve different real world and simulated many-objective optimization problems. Majority of the work in this area has taken place within the last decade.

This short and compact review represents an update over existing surveys on this topic, such as the ones done by Wagner et al. [12, 22 references in total], Ishibuchi et al. [13, 55 references in total] and the recent one by von Luecken et al. [14, 112 references in total]. We extend those by putting over 60 new articles into the context of many-objective optimization. We highlight some of the current challenges and bring focus to the work that has been done to address these difficulties. We also identify a combination of old and recently developed methods which have shown success with many-objective optimization. There also exists quite a bit of literature on application research. We highlight some of the recent application research done in this area. We conclude by bringing focus to some of the future research opportunities that exist with many-objective optimization.

2. Definitions & basic principles

Without loss of generality, a simple multi-objective problem[1] can be formulated as:

$$\min \quad F(x) = (f_1(x), f_2(x), \dots, f_m(x))^T \quad x \in X \subset \mathbb{R}^n \tag{1}$$

where $x = (x_1, \dots, x_n)$ is a vector of n decision variables and X is an n-dimensional decision space. m is the number of objectives to be optimized. When $m \geq 4$, the problem becomes a many-objective problem.

In the context of multi-objective optimization, the optimal solutions are also referred to as non-dominated solutions. In a minimization problem, a solution x dominates another solution x* when no objective value of x* is less than x and at least one objective value of x* is greater than x [6].

Convergence and diversity are the main goals of any multi-objective optimization algorithm. Convergence refers to finding a set of solutions that lie on or close to the true Pareto-optimal front [2]. Diversity refers to finding a set of solutions which are diverse enough to represent the entire range of the Pareto-optimal front [2].

To measure the performance of EMO algorithms, a number of quality indicators have been proposed over the years. Some of the most widely used quality indicators are the inverted generational distance (IGD), hypervolume and the R2 indicator. IGD measures the average distance for all members in the true Pareto-optimal set to their nearest solutions in the obtained solution set (opposite of generational distance (GD)) [15]. The hypervolume of a set of solutions measures the size of the portion of objective space that is dominated by those solutions collectively [16]. The IGD and the hypervolume can be used to measure both the spread of the solutions and convergence to the Pareto-front. The family of R-indicators (R1, R2, R3) can be used to assess and compare Pareto set approximations on the basis of a set of utility functions [17]. In particular the R2-indicator [18] was explored recently because it is weakly monotonic and computationally efficient [19,20].

A list of other quality indicators are given in Table 1.[2]

3. Challenges

3.1. Non-dominated population

Most of the EMO algorithms use the concept of Pareto Dominance in order to compare and identify the best solutions [28]. An increase in the number of objectives causes a large portion of a randomly generated population to become non-dominated [28]. Having a population which is largely composed of non-dominated solutions does not give room for creating new solutions in every generation [3,13]. This slows down the overall search process.

Some research has been done on tackling this problem and finding alternatives to the Pareto dominance approach. Sato et al. [29] proposed a novel multi-objective evolutionary algorithm that uses Pareto partial dominance. It calculates dominance between solutions using a subset of the objectives which are switched after a fixed number of generations. Their approach was able to give better convergence in comparison to conventional NSGA-II for the many-objective 0/1 knapsack problem. Aguirre and Tanaka [30] proposed a method to search on many-objective problems by partitioning the objective space into sub-spaces and performing one generation of the evolutionary search in each sub-space. Their method showed good performance on the MNK Landscapes with 4–10 objectives.

The ϵ-domination principle [31,3] which is used for approximating the Pareto-front can also be used to address the problem of a large non-dominated set [32]. The use of this principle will make all points within an ϵ-distance from a set of Pareto-optimal points ϵ-dominated. This process will allow for the generation of a finite number of Pareto-optimal points as the target [3]. It will also allow for a more diverse set of solutions. Algorithms based on the ϵ-domination principle include the ϵ-MOEA [33], ϵ-NSGA-II [34], Borg-MOEA [35] and AGE-II [36]. Other domination principles such

[1] As above-mentioned, many-objective problems are multi-objective ones with more than three objectives. Thus, the definitions here hold for many-objective problems as well.

[2] This is a summary and extension of Table 1 from [21].

Download English Version:

https://daneshyari.com/en/article/1131462

Download Persian Version:

https://daneshyari.com/article/1131462

Daneshyari.com