EVOLUTIONARY LARGE-SCALE GLOBAL OPTIMIZATION: AN INTRODUCTION

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Many real-world optimization problems involve a large number of decision variables. The trend in engineering optimization shows that the number of decision variables involved in a typical optimization problem has grown exponentially over the last 50 years [7], and this trend continues with an ever-increasing rate. The proliferation of big-data analytic applications has also resulted in the emergence of large-scale optimization problems at the heart of many machine learning problems [1, 8]. The recent advance in the area of machine learning has also witnessed very large scale optimization problems encountered in training deep neural network architectures (so-called deep learning), some of which have over a billion decision variables [2, 4]. It is this "curse-of-dimensionality" that has made large-scale optimization an exceedingly difficult task. Current optimization methods are often ill-equipped in dealing with such problems. It is this research gap in both theory and practice that has attracted much research interest, making large-scale optimization an active field in recent years. We are currently witnessing a wide range of mathematical and metaheuristics optimization algorithms being developed to overcome this scalability issue. Among these, metaheuristics have gained popularity due to their ability in dealing with black-box optimization problems.

In this tutorial, we provide an overview of recent advances in the field of evolutionary large-scale global optimization with an emphasis on the divide-and-conquer approaches (a.k.a. decomposition methods). In particular, we give an overview of different approaches including the non-decomposition based approaches such as memetic algorithms and sampling methods to deal with large-scale problems. This is followed by a more detailed treatment of implicit and explicit decomposition algorithms in large-scale optimization. Considering the popularity of decomposition methods in recent years, we provide a detailed technical explanation of the state-of-the-art decomposition algorithms including the differential grouping algorithm [5] and its latest improved derivatives, which outperform other decomposition algorithms on the latest large-scale global optimization benchmarks

[3]. We also address the issue of resource allocation in cooperative co-evolution and provide a detailed explanation of some recent algorithms such as the contribution-based cooperative co-evolution family of algorithms [6]. Overall, this tutorial takes the form of a critical survey of the existing methods with an emphasis on articulating the challenges in large-scale global optimization in order to stimulate further research interest in this area.

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