Information Sciences 316 (2015) 457–486

Contents lists available at ScienceDirect

Information Sciences

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

Decomposition-based evolutionary algorithm for large scale constrained problems

Eman Sayed *, Daryl Essam, Ruhul Sarker, Saber Elsayed

School of Engineering and Information Technology, UNSW-Canberra, Canberra, Australia

ARTICLE INFO

Article history:
Received 20 November 2013
Received in revised form 8 September 2014
Accepted 12 October 2014
Available online 24 October 2014

Keywords:
Large scale constrained problem optimization
Decomposition approach
Variable interaction identification

ABSTRACT

Cooperative Coevolutionary algorithms (CC) have been successful in solving large scale optimization problems. The performance of CC can be improved by decreasing the number of interdependent variables among decomposed subproblems. This is achieved by first identifying dependent variables, and by then grouping them in common subproblems. This approach has potential because so far no grouping technique has been mainly developed for constrained problems. In this paper, a new variable interaction identification technique to identify the dependent variables in large scale constrained problems is proposed. The proposed technique is tested on both a new test suite of constrained problems with medium and high dimensions, which include overlapping subproblems and different levels of complexity and nonseparability and also the established DED problem. The experimental results have shown that the proposed technique contributes to the decomposition approach over a range of high dimensions, in comparison with other state-of-the art grouping techniques. It achieves better performance with higher feasibility ratios and less computational time.

1. Introduction

Many real life problems (i.e. industry [44,69], environment [45], bio-computing [4], shape design (such as turbine blades [78], aircraft wings [87], and heat exchangers [26]), and operations research (such as optimization of water management problem [35], optimization of Norwegian natural gas production and transport [71], optimizing US army stationing [18]) are large scale optimization problems. The increased need for high quality decision making for such problems, has made the topic of solving large scale optimization problems a valuable and challenging research area. Moreover, the challenge increases when solving large scale constrained optimization problems. Although evolutionary algorithms (EAs) are an effective optimization technique [40], the performance of EAs eventually deteriorates with increasing dimensionality [64]. Applying a decomposition approach can reduce the dimensionality problem of EA by decomposing a large scale problem into smaller subproblems. However, to be more effective, before starting the optimizing process an EA should use a technique to identify and group the dependent variables of the large problem into smaller scale subproblems, in a way that decreases the interdependency among the subproblems.

Using a decomposition approach for large scale unconstrained problems is not new in the literature. The logic of understanding the complexity of systems through decomposition is found in the publications of Descartes and Veitch [19] and

* Corresponding author.
E-mail addresses: e.hasan@student.adfa.edu.au (E. Sayed), d.essam@adfa.edu.au (D. Essam), r.sarker@adfa.edu.au (R. Sarker), s.elsayed@adfa.edu.au (S. Elsayed).

http://dx.doi.org/10.1016/j.ins.2014.10.035

Simon [77]. One of the well-known decomposition approaches is the cooperative coevolution (CC) technique [68]. CC with global search was designed to handle Large Scale optimization problems by decomposing a large scale problem into smaller scale subproblems [99]. The size of the subproblems is problem dependent [90,94]. However, the subproblem size can be adaptively tuned to suit different problems [91]. CC uses problem decomposition, but does not identify the dependency of variables [95]. This can negatively affect the performance, because when two dependent variables are optimized in two different subproblems, the overall performance of the optimization approach decreases [68]. These two dependent variables in such a case are defined as interdependent variables. Two variables in a problem are interdependent if the optimal setting for one variable depends on the setting of the other variable [38]. Therefore CC, which neglects dependency identification, is not efficient with nonseparable and complex optimization problems [68,86].

To improve the efficiency of the decomposition approach, it is necessary to detect the dependent variables and to then group them in subproblems to minimize the interdependent variables among the subproblems. Considering variable dependency is thus a critical factor that should be considered when designing a decomposition technique [100]. In the literature, limited research proposals have been carried out to develop decomposition techniques that are able to identify the dependencies of the variables, and to hence decrease interdependencies among the subproblems of the unconstrained problems [9,65,70,74,92,94]. Some of the recently developed techniques for the unconstrained problems are: Random Grouping (RG) [64,94], correlation based Adaptive Variable Partitioning (AVP) [70], Delta Grouping (DG) [65], Variable Interactive Learning (VIL) [9], Statistical variable interactive Learning (SL) [80], Dependency Identification (DI) technique [74], and Differential Grouping technique [63]. The decomposition approach also exists in the area of multiobjective problems. One of the recent techniques that was developed for decomposing a multiobjective problem into subproblems with smaller objectives is MOEA/D [101], which uses the Tchebycheff Approach [58].

In RG, the decision variables are grouped randomly into smaller subproblems. Although RG does not have a systematic way to group variables or to detect their dependencies, it achieves good performance in the literature [94]. Afterwards, AVP [70] was developed. This technique calculates a correlation coefficient that depends on the current population, and then decomposes the problem into two subproblems based on a threshold value of the correlation coefficients. This technique uses correlation coefficients as a measure of the variables dependency. Hence it only detects linear dependency between two variables; it does not detect nonlinear dependencies among variables. In DG, the decision variables are grouped according to the sorted absolute magnitude of change that is measured between two consecutive generations, during the evolution of the subproblems. Despite the reasonable concept of this technique, it is less efficient when a large scale problem has more than one group of rotated variables [65].

In regards to VIL [9], a large scale optimization problem is decomposed into one-dimension subproblems and the current and previous populations are tested after optimizing each subproblem. Then subproblems are merged if they have changed and affected each other. One of the disadvantages of this technique is that it starts with one-dimension based subproblems, which thereby creates subproblems and is hence computationally expensive. VIL uses up to 60% of the available computational resources for this testing and merging. Moreover, VIL is more suitable for separable large scale problems, rather than for the nonseparable problems [95]. SL [80] is able to quantify, for unconstrained problems, the degree of interdependencies among variables by statistical variable interdependence learning. This technique checks the change that every pair of variables have on each other. Although it captures the variable interdependencies by using a statistic method successfully, it requires a large amount of computation to check every pair of a large scale problem. The DI technique that is proposed in [74] identifies the dependent variables in the unconstrained problems by generating variant groups of the variables in the subproblems and by then selecting the arrangement of variables that has the least difference between the overall fitness value and the summation of each subproblems' fitness. This difference is derived from the definition of problem separability. This technique was able to identify better arrangements for the variables in the subproblems of large scale unconstrained optimization problems.

The DI technique achieved good performance at the large dimensions of 1000 and 4000 when compared to RG. Although the performance of DI decreased when solving spliced overlapping problems over dimension 1000, it achieved reasonable performance for these complex problems at dimension 4000 and outperformed the aggregation approach [73]. A major drawback of these techniques is that the subproblem size or the number of subproblems needs to be predefined. Differential Grouping [63] is a simple decomposition technique that decomposes a large scale unconstrained problem into smaller subproblems. This technique is also derived from the definition of problem separability, but it overcomes one drawback of the previous techniques as the determination of the subproblem size is automated. Moreover, Differential Grouping is a contribution-based scheme which dedicates more resources to subproblems with higher contributions in the problem. Differential Grouping was evaluated on 1000 dimensions using the CEC 2010 benchmark problems and it was capable of grouping interacting variables with great accuracy for the majority of the tested benchmark problems. However, it has a threshold value which is sensitive to change, which affects its accuracy in detecting the interactions between the variables. Moreover, the mechanism of Differential Grouping may lead to its failure to detect variable interaction in fully nonseparable problems. Even though some of these techniques have limitations and others are successful, these decomposition techniques were developed for unconstrained problems and none of them is applicable on the constrained optimization problems.

The decomposition of constrained optimization problems is more challenging than that of the unconstrained problems due to the structure of the constraint problems. A number of researchers have considered decomposing constraint problems, but they have not considered variable dependencies as part of their [7,15,23,31,39,72] approaches. For example, Dantzig and Wolfe [15] introduced a decomposition technique for linear optimization problems. This technique is applied on problems