Applied Soft Computing 37 (2015) 396–415

Contents lists available at ScienceDirect

Applied Soft Computing

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

Weighted Superposition Attraction (WSA): A swarm intelligence algorithm for optimization problems – Part 2: Constrained optimization

Adil Baykasoğlu*, Şener Akpinar

Dokuz Eylül University, Faculty of Engineering, Department of Industrial Engineering, Izmir, Turkey

ARTICLE INFO

Article history:
Received 14 May 2015
Received in revised form 27 July 2015
Accepted 27 August 2015
Available online 4 September 2015

Keywords:
WSA algorithm
Non-linear programming
Constrained global optimization
Design optimization
Constraint handling

ABSTRACT

This paper is the second one of the two papers entitled "Weighted Superposition Attraction (WSA) Algorithm", which is about the performance evaluation of the WSA algorithm in solving the constrained global optimization problems. For this purpose, the well-known mechanical design optimization problems, design of a tension/compression coil spring, design of a pressure vessel, design of a welded beam and design of a speed reducer, are selected as test problems. Since all these problems were formulated as constrained global optimization problems, WSA algorithm requires a constraint handling method for tackling them. For this purpose we have selected 6 formerly developed constraint handling methods for adapting into WSA algorithm and analyze the effect of the used constraint handling method on the performance of the WSA algorithm. In other words, we have the aim of producing concluding remarks over the performance and robustness of the WSA algorithm through a set of computational study in solving the constrained global optimization problems. Computational study indicates the robustness and the effectiveness of the WSA in terms of obtained results, reached level of convergence and the capability of coping with the problems of premature convergence, trapping in a local optima and stagnation.

1. Introduction

Optimization consist all of the endeavours within the purpose of systematically improving the effectiveness of a system or designing a system as efficient as possible. In other words, optimization procedures aim at finding the optimum values for the decision variables of the problem on hand by realizing some specific rules. During the optimization process it is possible to use different optimization procedures. The key issue is to determine the proper one thereby the most powerful optimization method, since the classical optimization techniques impose some limitations on solving complex optimization problems [1]. Within this context, many researchers have been interested in developing effective optimization procedures or improving the effectiveness of the existing optimization procedures for different optimization problems, which may arise in such fields of science, engineering and operational research.

The domain of the decision variables of an optimization problem specifies the type of the optimization problem. Optimization problems are divided into three categories by the means of the domain of decision variables: (i) problems having exclusively discrete decision variables, (ii) problems having exclusively continuous decision variables, and (iii) problems having both discrete and continuous decision variables. The optimization problems belonging into these three categories may also be classified into two groups: constrained and unconstrained global optimization problems. This current paper is about to tackle the constrained global optimization problems via Weighted Superposition Attraction (WSA) algorithm, which was developed by Baykasoğlu and Akpınar in the Part-I of this paper as a new member of swarm based meta-heuristic algorithms and used to solve unconstrained global optimization problems [2].

Global optimization, a branch of applied mathematics and numerical analysis, is a challenging research field, since many real word applications could be formulated as a global optimization problem. Engineering design, production management, computational chemistry, and environmental pollution management are some of the application fields of the global optimization. The rapidly developed global optimization techniques has taken interest in different scientific domains such as applied mathematics, operations research, industrial engineering, management science and computer science. Within this context, this current part of this paper

* Corresponding author. Tel.: +90 232 301 16 00; fax: +90 232 301 76 08.
E-mail addresses: adil.baykasoglu@deu.edu.tr (A. Baykasoğlu), sener.akpinar@deu.edu.tr (Ş. Akpinar).

http://dx.doi.org/10.1016/j.asoc.2015.08.052
1568-4946/

Notations of WSA and their definitions

Notation	
Maxiter	Iteration number (stopping condition)
Iteration	Current iteration number
AA	Number of artificial agents
D	Number of dimensions of the problem
τ	User defined parameter
λ	User defined parameter
φ	User defined parameter
UL	Upper limit for the dimensions
LL	Lower limit for the dimensions
$f(i)$	Fitness of the current point of agent *i*
$f(tar)$	Fitness of the target point
weight	Weight of the current point of an agent
$\vec{x}$	Current position vector of an agent
$\rightarrow tar$	Position vector of the target point
$\rightarrow gap$	Vector combines an agent to target point
$\rightarrow direct$	Move direction vector of an agent
sign()	Signum function
sl	Step length

mainly focus on analysing the performance of WSA algorithm on the well-known constrained mechanical design optimization problems, which are formulated as complex nonlinear programming models.

A theoretical background of the engineering design optimization problems was reported by Belegundu [3] and the basic concepts and methods for these problems were described by Arora via some examples [4]. For the global optimization problems, the developed methods should monitor the approach of the algorithms towards the optimum point via a descent function [4] refers to the cost function of the problem. Nevertheless, the descent function must be aware of the feasibility for the constrained global optimization problems. For that reason, it is required to construct the descent function by adding a penalty to the current value of the cost function in case of the constraint violations and researchers would rather derive the penalty value via some formulations named as constraint handling methods.

An improvement for the conventional constraint handling methods was introduced by Coello [5,6]. Their notation uses adaptive penalty factors for a Genetic Algorithm (GA) implementation, however, it has the potential of to be generalizing to any meta-heuristic. Coello and Mezura-Montes proposed another constraint handling method in order to overcome the constraint violations through the selection operator of GA [7,8]. A simple evolution strategy based approach, which does not require a penalty function, was presented by Mezura-Montes et al. [9]. Coello and Becerra proposed a cultural algorithm, which builds the map of the feasible region during the evolutionary process in order to avoid infeasibility and improves the performance of an evolutionary programming technique [10]. Another evolutionary-based approach free from penalty functions was proposed by Mezura and Coello in order to identify and maintain infeasible solution close to feasible region located in promising areas [11]. Furthermore, Akhtar et al. and Ray and Liew presented solution approaches based on the phenomenon of society and civilization for constrained engineering design optimization problems [12,13].

Ray and Sani presented a swarm based approach that realizes a Pareto ranking scheme as a constraint handling method [14]. A feasibility preserving Particle Swarm Optimization (PSO), which is a well-known member of swarm based algorithms, was developed by Hu et al. [15]. A constraint handling approach named as fly-back method, makes any individual to return to its previous position it violates any problem constraint, was realized by He et al. in order to improve the performance of PSO while solving mechanical design optimization problems [16]. Parsopoulos and Vrahatis tested the performance of a unified PSO method by realizing a penalty function and a feasibility preserving modification of the algorithm [17]. A constraint handling technique based on feasibility and sum of constraints violation was realized by Aguirre et al. while tackling the constrained optimization problems via PSO [18]. He and Wang incorporate a co-evolution model into PSO for the first time and their approach realized two types of swarms, multiple swarms for searching satisfactory solutions and a single swarm for evolving suitable penalty factors [19]. A novel hybrid PSO was also presented by He and Wang with a feasibility-based rule has the aim of overcoming the deficiencies of penalty function methods [20]. Tomassetti proposed another hybrid PSO, which was inspired from evolutionary algorithms and realizes multi-start approach, randomly reinitializing the swarm and updating the inertia factor multiplying the previous velocity of the swarm with the aims of enlarging the exploration space, accelerating convergence to the optimal solution and avoiding the algorithm to remain trapped into local minima, respectively [21]. Cagnina et al. proposed a PSO with simple pairwise-comparison based constraint handling method and their method adds an amount of violation, normalized with respect to the largest violation stored far, for the infeasible solutions [22]. A new tool based on PSO proposed by Maruta et al. and it is applicable for a broad class of non-convex problems directly [23]. Kim et al. and Chun et al. proposed a PSO algorithm with a constraint handling method that transforms the given constrained optimization problem into an unconstrained problem without introducing extra problem-dependent parameters such as penalty factors or Lagrange multipliers [24,25].

From the previous two paragraphs, it can be obviously seen that GA, PSO and evolutionary strategies were widely used for solving constrained global optimization such as mechanical design optimization problems. Besides these solution methodologies, some other meta-heuristic algorithms (Artificial Bee Colony Algorithm (ABC) [26,27], Differential Evolution (DE) [28], Harmony Search Algorithm (HSA) [29,30], Cuckoo Search Algorithm (CSA) [31], Bat Algorithm [32], Great Deluge Algorithm (GDA) [1] and Firefly Algorithm (FA) [33,34] were also preferred by varied researchers with the aim of tackling the related problems. Additionally, it must be stated that current competitive market and manufacturing conditions result many problems concerning design optimization and manufacturing parameters estimation. At this point, these problems required to be solved optimally and design optimization/manufacturing parameters estimation via meta-heuristics is a growing and challenging research field as can be realized from the existing literature [35–42].

The main research concern of this current paper is to analyze the performance of WSA algorithm on the well-known constrained mechanical design optimization problems. The WSA algorithm was originally designed for unconstrained continuous global optimization problems in the first part of this paper, thus it requires to be redesigned so as to solve constrained problems and a constraint handling approach must be inserted into WSA. Within this context, we select 6 different constraint handling approaches for implementing WSA through them and analyze if the performance of WSA is strongly related with the used constraint handling approach or not. By the way we will have the ability of providing concluding remarks about the robustness of WSA for solving constrained mechanical design optimization problems at the end of the computational study of this paper.

The remainder of this paper is organized as follows. In section 2, the WSA algorithm and the selected constraint handling methods are depicted. Comparative computational study is given in Section