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Research paper

A novel meta-heuristic optimization algorithm: Thermal exchange optimization

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ABSTRACT

This paper introduces a new optimization algorithm based on Newton's law of cooling, which will be called Thermal Exchange Optimization algorithm. Newton's law of cooling states that the rate of heat loss of a body is proportional to the difference in temperatures between the body and its surroundings. Here, each agent is considered as a cooling object and by associating another agent as environment, a heat transferring and thermal exchange happens between them. The new temperature of the object is considered as its next position in search space. The performance of the algorithm is examined by some mathematical functions and four mechanical benchmark problems.

1. Introduction

In engineering design, choosing design variables that fulfill all design requirements and have the lowest possible cost is concerned, i.e. the main objective is to comply with basic standards but also to achieve economic designs [1]. In practice, a designer is usually satisfied with good solutions, which are obtained by heuristic or metaheuristic algorithms. Meta-heuristics represent a family of approximate optimization techniques that have gained a lot of popularity in the past two decades. These are among the most promising and successful techniques. Metaheuristics provide acceptable solutions in a reasonable time for solving hard and complex problems in science and engineering [2].

Some of the metaheuristic approaches are inspired by nature. These can be classified into three categories in terms of the source of inspiration:

(a) Evolutionary Algorithms. The Evolutionary Algorithm (EA) proposed by Fogel et al. [3], De Jong [4] and Koza [5], and the Genetic Algorithm (GA) proposed by Holland [6] and Goldberg [7] are inspired by biological evolution, such as reproduction, mutation, recombination and selection.

(b) Swarm Algorithms. These methods mimic the processes of decentralized, self-organized systems, which can be either natural or artificial in nature. Studies on animal behavior led to Ant Colony Optimization (ACO) proposed by Dorigo et al. [8] which follows the processes of an ant colony searching for food, the navigation ability of dolphins was mimicked in Dolphin echolocation proposed by Kaveh and Farhoudi [9], Grey wolf optimizer formulated by Mirjalili et al. [10] that mimics the hunting process of grey wolves, Eberhart and Kennedy's Particle Swarm Optimizer (PSO) [11] imitates animal flocking behaviors.
This class of algorithms are often inspired by animal's behaviors of looking for food, locating, flocking and their other smart techniques.

(c) Physical algorithms. These methods are inspired by the physical laws. Of these, Water Evaporation Optimization (WEO) proposed by Kaveh and Bakhshpoori [12] imitate the evaporation of a tiny amount of water molecules, Charged System Search (CSS) introduced by Kaveh and Talatahari [13] which utilizes the governing Coulomb law from electrostatics and the Newtonian laws of mechanics. Simulated Annealing proposed by Kirkpatrick et al. [14] is inspired from annealing in metallurgy, the Big Bang–Big Crunch algorithm proposed by Erol and Eksin [15] that mimics the Big Bang and Big Crunch theory, Hsiao, et al. [16] developed the Space Gravitational Optimization and Gravitational Search Algorithm (GSA) presented by Rashedi et al. [17] that is based on the law of gravity and the Vibrating Particles System (VPS) developed by Kaveh and Ilchi Ghazaan [18] mimics the free vibration of single degree of freedom systems with viscous damping.

In recent years a big number of novel methods have been developed and applied to different multidisciplinary optimization

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problems. Some of these methods are listed in the following: Glowworm Swarm Optimization (GSO) [19], Firefly Algorithm (FA) [20], Monkey Search (MS) [20], Bat Algorithm (BA) [21], Krill Herd (KH) Algorithm [22], Bird Mating Optimizer (BMO) [23], Tug of war optimization [24], Social Spider Optimization (SSO–C) [25] and Water Cycle Algorithm (WCA) [26].

A wide range of algorithms have been introduced, improved and applied by the first author and his students which some of them are mentioned above.

The main objective of this paper is to present a new optimization algorithm based on principles from physics, which is called Thermal Exchange Optimization (TEO). In this, each agent is considered as a cooling object and by associating another agent as surrounding fluid, a heat transferring and thermal exchanging happens between them. This algorithm utilizes Newton's law of cooling to update the temperatures. The process is repeated until the satisfaction of the termination conditions.

Simulated annealing (SA) is a well-known metaheuristic algorithm [14]. Partly, SA and TEO use common terminologies, but their operations are technically different. SA's operation can be summarized as follows:

SA models the physical process of heating a material and then slowly lowering the temperature to decrease defects and to produce crystals, thus minimizing the system energy. At each iteration of SA, a new position is randomly generated. The distance of the new position from the current position, or the extent of the search, is based on a probability distribution with a scale proportional to the temperature. The algorithm accepts all new points that lower the objective, but also, with a certain probability, positions that raise the objective. By accepting positions that raise the objective, the algorithm avoids being trapped in local minima in early iterations and is able to explore globally for better solutions.

However in TEO, temperature of each object is its position and by grouping the objects, they start to exchange it. New temperatures will be their new positions.

The rest of this paper is organized as follows. In Section 2, a brief overview of the TEO is presented. Section 3 uses benchmark functions to compare TEO with some other popular optimization methods. Section 4 verifies the parameters of the algorithm and its performance during iterations. Finally, conclusions are derived in Section 5.

2. Thermal exchange optimization

2.1. Back ground

2.1.1. Newton's law of cooling

Newton's law of cooling states that the rate of heat loss of a body is proportional to the difference in temperatures between the body and its surroundings. The following is the Newton's law of cooling in his own words:

"The iron was laid not in a calm air, but in a wind that blew uniformly upon it, that the air heated by the iron might be always carried off by the wind and the cold air succeed it alternately; for thus equal parts of air were heated in equal times, and received a degree of heat proportional to the heat of the iron", as shown in Fig. 1, Refs. [27,28].

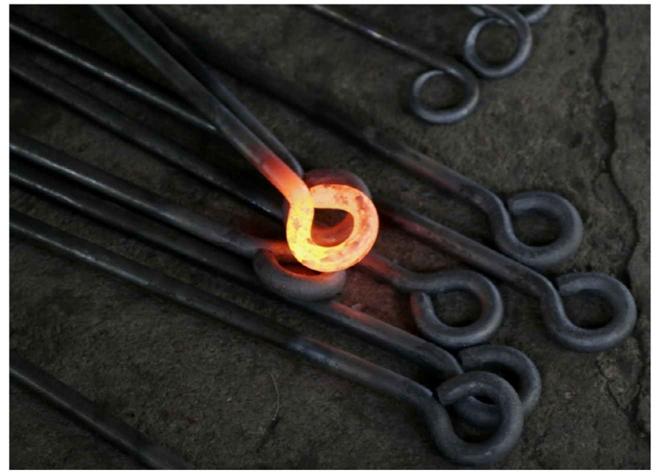

Fig. 1. Hot iron objects, transferring heat to the surrounding environment.

2.1.2. Theory

The modern lumped parameter approach to transient cooling is given in many textbooks, e.g. [29,30]. We assume the overall heat transfer coefficient to be h, and the physical properties are constant. The shape of the solid region is irrelevant (except that it will affect the calculation of h). The object starts at time $t = 0$ at a high temperature T_0 and is suddenly placed in a different environment where it is cooled by surrounding fluid at a constant temperature T_{b}. The volume of the solid is V and its surface area is A. The rate of heat loss from the surface is:

$$\frac{dQ}{dt} = h(T_a - T_b)A \tag{1}$$

where

$A =$ area for heat flow m^2, $T =$ temperature K

$h =$ heat transfer coefficient $W\ m^{-2}K^{-1}$, $t =$ time s

The heat loss in time dt is $h(T_a - T_b)A\,dt$ and this equals the change in stored heat as the temperature falls dT, i.e.

$$V\rho c dT = -hA(T - T_b)dt \tag{2}$$

where

$V =$ volume m^3, $\rho =$ density $kg\ m^{-3}$ and $c =$ spaecific heat $J\ kg^{-1}K^{-1}$

Integration gives

$$\frac{T - T_b}{T_0 - T_b} = \exp\left(-\frac{hA}{V\ \rho c}\mathrm{t}\right) \tag{3}$$

The integration is only valid when $\frac{hAt}{V\ \rho c}$ is constant, i.e. not a function of T, so we can write

$$\beta = \frac{hA}{V\ \rho c} \tag{4}$$

And from Eq. (3):

$$\frac{T - T_b}{T_0 - T_b} = \exp(-\beta \mathrm{t}) \tag{5}$$

This equation can be rearranged as:

$$T = T_b + (T_0 - T_b)\exp(-\beta t) \tag{6}$$

2.2. Presentation of thermal exchange optimization

The main objective of this section is to formulate the new effective physically-based meta-heuristic algorithm which is called Thermal Exchange Optimization (TEO).

2.2.1. Inspiration

In TEO algorithm, some agents are defined as the cooling objects and the remaining agents are supposed to represent the environment, then we do it contrariwise. Choosing the cooling objects and environment ones are similar to the grouping of bodies in CBO and ECBO [31–33].