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Performance analysis and feasibility study of ant colony optimization, particle swarm optimization and cuckoo search algorithms for inverse heat transfer problems

Udayraj [a], Konica Mulani [b], Prabal Talukdar [a,*], Apurba Das [c], R. Alagirusamy [c]

[a] Department of Mechanical Engineering, Indian Institute of Technology Delhi, New Delhi 110016, India
[b] Department of Mechanical Engineering, Harcourt Butler Technological Institute, Kanpur, UP 208002, India
[c] Department of Textile Technology, Indian Institute of Technology Delhi, New Delhi 110016, India

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ABSTRACT

In the present work, three recently developed metaheuristic algorithms (ant colony optimization, cuckoo search and particle swarm optimization) are examined for a class of heat transfer problems. Unknown boundary heat fluxes are estimated for conduction, convection and coupled conduction–radiation problems. Direct problems are solved to determine temperature distribution assuming known boundary heat flux. Inverse method is then used to estimate boundary heat flux with the help of the temperature previously determined from the direct problem. To replicate experimental error, effect of noise on temperature data is introduced to examine the robustness of all the algorithms. Effect of time step size and regularization are studied. It is found that all the algorithms are promising and can be used for this class of inverse heat transfer problems. Performance of all the algorithms is comparable. Efficiency of the three algorithms is compared in terms of CPU time. Ant colony optimization algorithm is found to be most efficient followed by particle swarm optimization and cuckoo search algorithms for all the considered heat transfer problems. All the algorithms are also applied to estimate diffusion coefficient of a food material (mushroom) using experimental data.

1. Introduction

Inverse heat transfer has emerged as an important engineering tool in the recent past. Difficulties in direct measurement of heat flux and temperature at various complicated locations and extreme conditions (re-entry vehicle, combustion chamber) in actual situations and associated high cost; complexities in measuring heat transfer coefficient, thermo-physical and radiative properties (if not impossible), attracted researchers towards the inverse heat transfer. Inverse heat transfer problems are ill-posed and hence requires special methods. Various methods like iterative regularization [1], conjugate gradient iterative algorithm [2,3], function specification method [4,5], combined regularization and function estimation method [6,7] and filtering techniques [8–10] have been used to obtain stable solution. These conventional methods are very efficient computationally and applied to almost all types of problems [11]. Many books dealing with such methods are available [3,12,13].

Although these conventional methods are efficient, it was found that some of these conventional methods are not able to converge to the global optimum. Apart from this, conventional methods requires information regarding the gradients (which are sometimes hard to determine or involves more computational time) and are problem specific. Situations can become complex when problem involves non-linearity and large number of parameters [12]. It is very hard (if not impossible) to apply such methods in problems involving shape optimization of heat exchangers [14], discrete optimal locations of the heat sources [15,16] and size and location of tumors [17,18]. Stochastic search based methods (Genetic algorithm, ant colony optimization, particle swarm optimization, simulated annealing, etc.) with a suitable "governing mechanism" leading to the optimal solution are good alternatives. These methods usually does not suffer with the problem of local convergence. Moreover, these methods are blind (not problem specific) and gradient information is not required. Hence, these methods are more robust. Computational time is of course a concern for these methods [16] but with ever growing computational power, parallelization [19], modifications [20–22] and development of hybrid methods [23–25], these methods can substitute

* Corresponding author. Tel.: +91 11 26596337.
E-mail address: prabal@mech.iitd.ac.in (P. Talukdar).

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Nomenclature

c_1	cognitive coefficient
c_2	social learning coefficient
c_p	specific heat, J/kg K
D_{eff}	effective moisture diffusivity, m^2/s
G	incident radiation, W/m^2
GE	number of generations
h	height of channel, m
I	radiative intensity, W/m^2 sr
J	objective function, defined by Eq. (16)
IT	maximum iterations in ACO algorithm
k	thermal conductivity, W/m K
L	length of domain, m
M	moisture content, kg/kg
N	number of ants (ACO algorithm) or number of cuckoo (CS algorithm)
P	number of particles
q	heat flux, W/m^2
RE	Average relative error, %
$\vec{r}$	position vector
$\hat{s}$	unit vector in the direction of radiative intensity
t	time, s
T	temperature, °C
u	velocity in x-direction, m/s
v	particle velocity, m/s
w	inertial weight
x, y	coordinate directions
Y	temperature with noise, °C, defined in Eq. (17)

Greek symbols

α	narrowing parameter in ACO algorithm
β	evaporation rate in ACO algorithm; extinction coefficient (m^{-1}) in Eq. (14)
Γ	Gamma function
ρ	density, kg/m^3
κ	absorption coefficient, m^{-1}
λ	Levy exponent
θ	polar angle (rad)
φ	azimuthal angle (rad)
ϕ	phase function
σ_s	scattering coefficient (m^{-1}),
σ	standard deviation in measurements, °C
ω	random number from normal distribution
γ	regularization parameter

Subscripts

b	blackbody
e	equilibrium
in	inlet
m	mean
max	maximum
min	minimum
o	initial
R	radiative
∞	represents surrounding condition

Superscripts

GE	generations
S	sensor

the conventional methods. Growing interest in metaheuristic algorithms in the field of heat transfer (including inverse heat transfer) is already evident from almost ten percent increase in the articles published using such methods in the last decade [26].

Various algorithms were developed in the past like ant colony optimization (ACO), particle swarm optimization (PSO), genetic algorithm (GA), cuckoo search (CS), artificial bee colony optimization (ABC) etc. based on foraging behavior of species, swarm intelligence, natural selection etc. These are called nature-inspired algorithms as nature is in the heart of all of the above mentioned algorithms and provides the necessary governing mechanism to efficiently explore the search space. Among these, biologically-inspired, swarm intelligence based algorithms is of primary interest here. Nature is perfectly designed and so the species living in it. All of the species (and we 'human') are provided with the capabilities (best required characteristics) which help us to survive under present conditions. If required, with changing environmental conditions these species can evolve as per the conditions over a period of time. Researchers studied the behavior of many species around us over the decades and extracted the best from the nature to optimize our real life problems by developing various algorithms.

ACO was proposed and initially developed by Marco Dorigo and colleagues in early nineties [27,28] based on the foraging behavior and concept of exploitation of the shortest path by the ants. Ants leave a chemical substance (pheromone) while traveling from ant-hill to food source and it is the intensity of pheromone which governs motions of the whole community. Subsequently, intensity of pheromone becomes very high along the shortest path and all of them converge to the same. Good review related to origin, development and application areas of ACO is presented by Blum [29]. Over the years it has been successfully used for various types of problems like traveling salesman problem [28,30,31] routing problems [32] and many industrial problems [33–35].

It is only very recently that ACO attracted people working in thermal sciences and they started analyzing feasibility of it in the field of heat transfer. It has been used to estimate unknown boundary conditions- heat flux [36] and heat transfer coefficient [37] for heat conduction problem. Zhang et al. [38,39] used ACO in 1-D coupled radiation-conduction case to estimate thermal conductivity, scattering coefficient and absorption coefficient of a medium. FVM was used to simultaneously solve energy equation and radiative transfer equation (RTE).

The cuckoos are species of birds which never build their own nest and cleverly utilize other bird species' nest for development and care of its young ones. Female cuckoos are specialized in laying eggs similar to host bird in their nest and replace one of the eggs of the host bird with their egg within seconds. This way young cuckoo enjoys the motherhood of the host species except for few odd cases when host bird somehow identifies the cuckoo's egg. In the later case, host bird either throws the cuckoo egg out of their nest or permanently abandon the nest to build a new one. Based on this interesting and rather awkward way of survival of the cuckoo species, Yang and Deb [40] in 2009 developed an optimization algorithm known as cuckoo search (CS) algorithm.

Cuckoo search has been applied successfully since then in various fields [41] ranging from mechanical design [42–44], structural design optimization [45,46] and optimization of machining