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Optimization of energy systems based on Evolutionary and Social metaphors

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Abstract

Optimization problems that arise in energy systems design often have several features that hinder the use of many optimization techniques. These optimization problems have non-continuous mixed variable definition domains, are heavily constrained, are multimodal (i.e. have many local optima) and, foremost, the functions used to define the engineering optimization problem are often computationally intensive. Three methods are tested here: (a) a Struggle Genetic Algorithm (StrGA), (b) a Particle Swarm Optimization Algorithm (PSOA), and (c) a PSOA with Struggle Selection (PSOStr). The last is a hybrid of the evolutionary StrGA and the socially inspired PSOA. They are tested in four purely mathematical and three energy systems thermoeconomic optimization problems. All of the methods solved successfully all the problems. The PSOStr, however, outperformed the other methods in terms of both solution accuracy and computational cost (i.e. function evaluations).

Keywords: Energy systems; Particle swarm optimization; Evolutionary programming

1. Introduction

The complex simulation models of energy systems, their structure, the various technological alternatives to be considered and the large number of design, technology and operational constraints make energy systems optimization a hard problem for most available algorithms. In addition, these optimization problems have discrete as well as continuous independent (decision) variables.

Two broad classes of optimization methods, that can handle the aforementioned problem characteristics efficiently are the socially inspired and evolutionary algorithms. Evolution inspired algorithms are a broad class of optimization methods loosely based on the processes and phenomena of biological evolution and adaptation in nature [1]. Evolutionary algorithms have been successfully applied to engineering optimization problems for at least the past two decades. A relatively new optimization algorithm is particle swarm optimization (PSO), which is inspired by the social behavior of flocking populations (swarms), such as birds, fish, insects or, even, humans. This optimization technique was first introduced by Kennedy and Eberhart [2].

The main benefit of bio and socially inspired algorithms over the conventional optimization methods (i.e. Newton-based techniques, linear programming, interior point methods, etc.) is that they do not require derivatives of functions, they can operate with non-continuous functions, even with tabulated data, they are not trapped easily in local optima and they can efficiently handle both continuous and discrete independent variables.

In this study the applicability of evolutionary and/or socially inspired algorithms to multimodal, mixed-variable energy system optimization problems, is investigated. Two well-known bio-inspired algorithms and the PSO method have been extended to deal with mixed-variable optimization problems. In addition, a novel algorithm, which is a hybrid of evolutionary and socially inspired techniques, has been used. All three algorithms have been tested with certain mathematical and energy system optimization problems. The performance of each algorithm has been

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Nomenclature

c	constant
C_c	capital costs
c_f	specific cost of fuel
C_{op}	operating costs
d	distance
f, F	objective function
f_P	constraint penalty factor
FCR	fixed charge rate
g	inequality constraint function
h	equality constraint function
H_u	ower heating value of fuel
$\dot{m}_f$	fuel mass flow rate
n	number of variables, functions, components, intervals, etc.
N	population size
p	probability
r	random number
t	pseudo-time—generation index
T_H	number of consecutive iterations with no improvement of the objective function
v	velocity term (PSOA)
w	inertia term (PSOA)
$\mathbf{x}$	set of independent variables

Greek letters

$\Delta\tau$	duration of a time interval
ϕ	installation costs factor

Subscripts

b	binary variable
cr	craziness
cross	crossover
e	euclidean
h	hamming
INT	integer variable
lb	lower bound
mut	mutation
r	real variable
sel	selection
str	struggle
ub	upper bound

Superscripts

*	optimum value

assessed in terms of its capability to locate the global optimum and of the computational cost, expressed by the number of required objective function evaluations. In the terminology of evolutionary optimization the objective function, is also referred as "fitness" function, a term also used in this work when necessary.

2. Description of algorithms

2.1. Struggle Genetic Algorithm (StrGA)

The Struggle Genetic Algorithm (StrGA) is an evolutionary algorithm that has been designed for multimodal function optimization with special characteristics for maintaining population diversity through the whole optimization procedure, in order to avoid premature convergence to local optima [3,4]. StrGA does not require any special encoding for the independent variables; all variables are treated in their natural code format (i.e. real, integer, and/or binary). It must be noted that StrGA has been successfully applied to energy system optimization problems in the works of Pelster and Olsommer [5,6].

The selection mechanism of StrGA is designed to maintain diversity of the population and thus to minimize the risk of convergence to a local optimum. The first parent to be used for subsequent reproduction is selected via binary tournament selection. In binary tournament selection, two individuals are selected at random from the whole population, their fitness values are compared, and the one having the better fitness value is selected as parent. The selection method of the second parent is probabilistically decided with a pre-determined probability threshold. A uniform random number between 0 and 1 is drawn and if it is less than p_{str}, the individual in the population most similar to the first parent in terms of an appropriate distance metric is selected. Otherwise, the second parent is selected by the same selection method used for the first parent.

Since the algorithm has been designed for addressing mixed variable problems, appropriate distance metrics have been employed for real, integer and binary variables accordingly. For real and integer variables the normalized Euclidean distance metric was used:

$$d_e(x_1, x_2) = \sqrt{\sum_i \left(\frac{x_{1,i} - x_{2,i}}{x_{ub,i} - x_{lb,i}}\right)^2}, \quad i = 1, \ldots, n_r \quad or \quad i = 1, \ldots, n_{int} \tag{1}$$

while for binary variables the Hamming distance metric was used:

$$d_h(x_1, x_2) = \sum_i \left|x_{1,i} - x_{2,i}\right|, \quad i = 1, \ldots, n_b. \tag{2}$$

The total distance metric between two individuals, both consisting of real, integer and binary variables, has been selected to be the sum of the respective