Available online at www.sciencedirect.com

ScienceDirect

Solar Energy 118 (2015) 96–106

SOLAR ENERGY

www.elsevier.com/locate/solener

Multi-objective optimal design of hybrid renewable energy systems using preference-inspired coevolutionary approach

Zhichao Shi[a,*], Rui Wang[a], Tao Zhang[a,b]

[a] College of Information System and Management, National University of Defense Technology, Changsha 410073, China
[b] State Key Laboratory of High Performance Computing, National University of Defense Technology, Changsha 410073, China

Received 5 January 2015; received in revised form 6 March 2015; accepted 30 March 2015

Communicated by: Associate Editor Mukund R. Patel

Abstract

As the increasing energy demand and rapid depletion of conventional fossil fuel resources, renewable energy has caused great attention of the public. The main drawback of the renewable resources is their unpredictable nature. A hybrid renewable energy system (HRES) that integrates different resources in proper combination is a promising solution to overcome this challenge. In this context, the preference-inspired coevolutionary algorithm (PICEA) has been applied for the first time to the design of multi-objective hybrid renewable energy system. We propose an enhanced fitness assignment method to improve the preference-inspired coevolutionary algorithm using goal vectors (PICEA-g) in the optimization process minimizing, simultaneously, the annualized cost of system (ACS), the loss of power supply probability (LPSP) and the fuel emissions. As an example of application, a stand-alone hybrid system including PV panels, wind turbines, batteries and diesel generators has been designed to find the best combination of components, achieving a set of non-dominated solutions from which the decision maker can select a most adequate one.

Keywords: Hybrid renewable energy systems; Optimization; Preference-inspired coevolutionary algorithm

1. Introduction

The worldwide rapid depletion of conventional energy sources such as coal and natural gas has made it an urgency to search for alternative energy resources to meet the present energy demand. Alternative energy resources like solar and wind have attracted energy sectors due to their advantages over conventional energy sources such as a decrease in external energy dependence and carbon emissions. However, a common drawback of solar and wind energy is their unpredictable nature and dependence on weather and climatic conditions. A hybrid renewable energy system (HRES), integrating different energy resources in a proper combination, can overcome the problems caused by the uncertainties of solar and wind. HRESs are becoming increasingly popular both in theory and engineering due to their higher reliability and lower cost.

The optimal design of HRESs is a multi-objective optimization problem (MOP) in nature, that is, multiple objectives need to be optimized simultaneously. Due to the complexity of the optimal design of an HRES, traditional optimization methods cannot solve it either effectively or efficiently (Dufo et al., 2007). Hence, different meta-heuristics methods were developed to find the optimal sizing of an HRES in the last decade. These studies can be divided into single objective and multi-objective

---

* Corresponding author. Tel.: +86 8457 3554.
E-mail addresses: nkshizc@163.com (Z. Shi), ruiwangnudt@gmail.com (R. Wang), 197697@qq.com (T. Zhang).

http://dx.doi.org/10.1016/j.solener.2015.03.052
0038-092X/

Nomenclature

PICEA	preference-inspired coevolutionary algorithm
ACS	the annualized cost of system ($)
LPSP	loss of power supply probability
MOP	multi-objective optimization problem
MOEA	multi-objective evolutionary algorithm
SOC	battery state of charge
δ	solar declination (°)
θ	earth's inclination to the plane of its orbit (°)
h	solar elevation angle (°)
φ	geography of the latitude (°)
τ	hour angle (°)
lt	local time
S_t	incident radiation on the tilted surface (W/m^2)
S	horizontal component of solar radiation (W/m^2)
S_p	solar radiation perpendicular to the tilted panel (W/m^2)
$T_C(t)$	cell temperature (°C)
$T_A(t)$	ambient temperature (°C)
NCOT	nominal cell operating temperature (°C)
I_{SC}	short-circuit current (A)
$I_{SC,STC}$	short-circuit current under STC (A)
V_{OC}	open-circuit voltage (V)
$V_{OC,STC}$	open-circuit voltage under STC (V)
K_I	short-circuit current temperature coefficient (A/°C)
K_V	open-circuit voltage temperature coefficient (V/°C)
$P_M(t,\beta)$	power output of PV (W)
N_P	number of PV modules connected in parallel
N_S	number of PV modules connected in series
FF(t)	fill factor
C_{ainv}	annualized cost of initial investment ($)
C_{aom}	annualized cost of operation and maintenance ($)
C_{arep}	annualized replacement cost ($)
C_{inv}	initial investment cost of each component ($)
C_{om}	operation and maintenance cost ($)
C_{rep}	replacement cost of each component ($)
$P_{avail}(t)$	available power supply at time t (W)
$P_{load}(t)$	load demand at time t (W)
$F_{emission}$	fuel emissions (kg)
Ef	emission factor
$P_r^n(t)$	total power produced by renewable
P_{WG}	output power of wind turbine (W)
v	wind velocity (m/s)
C_P	performance coefficient
ρ	air density (kg/m^3)
P_{WGR}	wind turbine rated power (W)
V_c	cut-in wind speed (m/s)
V_r	rated wind speed (m/s)
V_f	cut-off wind speed (m/s)
H_{wg}	wind turbine height (m)
v_r	measured reference wind speed (m/s)
H_r	reference height (m)
γ	power law coefficient
$P_{bat}(t)$	battery input/output power (W)
V_{bus}	DC bus voltage (V)
η_{bat}	round-trip efficiency
C_n	total nominal capacity of the battery bank (A h)
N_{bat}	total number of batteries
n_{bs}	number of batteries connected in series
C_{bat}	nominal capacity of each battery (A h)
V_{bat}	nominal voltage of individual battery (V)
F_{cons}	fuel consumption of a diesel generator (l)
P_{r_dg}	generator's rated power (W)
P_{dg}	generator's output power (W)
F_s	the fitness of a candidate solution s
F_g	the fitness of a preference g
n_g	number of solutions that satisfy the preference g
G_c	goal vectors set after genetic variation
G	initial goal vectors set resources (W)
$P_L^n(t)$	power consumed by the load (W)
F_{obj}	objective function
N_{pv}	number of PV panels
N_{wg}	number of wind turbines
N_{dg}	number of diesel generators
β	PV panel slope angle (°)
H_{low}	wind turbine tower lower limit (m)
H_{high}	wind turbine tower upper limit (m)
SBX	simulated binary crossover
PM	polynomial mutation

optimization problems according to the number of objectives in the model. Single objective optimization problems are considered in many articles, for example, genetic algorithm (Koutroulis et al., 2006) and stochastic simulated annealing algorithm (Giannakoudis et al., 2010) are used to minimize the system cost objective, respectively. Unlike single objective optimization, there are only a few articles using MOPs for optimal design of an HRES.

Katsigiannis et al. (2010) developed a bi-objective optimization model to generate Pareto front of an HRES minimizing the total cost and total greenhouse emissions during its lifetime by using NSGA (Srinivas and Deb, 1994). An optimal sizing method based on genetic algorithm (GA) was developed by Yanget al. (2008) to calculate the optimum configuration of a hybrid solar-wind system employing battery banks, which aims to achieve the required LPSP with a minimum annualized cost of system (ACS). Trivedi (2007) applied the multi-objective genetic algorithm (MOGA) (Fonseca and Fleming, 1998) to solve a nonlinear multi-objective optimization problem for scheduling a wind/diesel system minimizing the fuel cost as well as SO_2 and NO_x emissions. With a tri-objective