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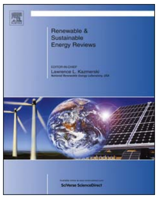

Swarm intelligence-based optimization of grid-dependent hybrid renewable energy systems

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ABSTRACT

Recently, with the stringent environmental regulations and shortage fossil-fuel reserve, power generation based on renewable energy sources is seen as a promising solution for future generation systems. A combination of these sources with an optimized configuration can face the climate change obstacles, permit better reliability, and reduce the cost of the generated energy. This paper presents a proposed particle swarm optimization (PSO) algorithm for an optimized design of grid-dependent hybrid photovoltaic-wind energy systems. This algorithm uses the actual hourly data of wind speeds, solar radiation, temperature, and electricity demand in a certain location. The PSO algorithm is employed to obtain the minimum cost of the generated energy while matching the electricity supply with the local demand with particular reliability index. The algorithm has been tested by considering a real case study used the actual situation to supply the electricity demand from utility grid at electricity market prices to estimate how significant are the cost saving compared to the actual situation costs. Results showed that the proposed algorithm responds well to changes in the system parameters and variables while providing a reliable sizing solution.

1. Introduction

Lately, various renewable energy sources (RES) have been exploited for power generation to confront the energy crisis, high fuel cost, and reduce the environmental pollution [1]. However, the capital cost of these sources is typically high; therefore, reducing capital costs with an optimized installation is one of the imperative prospects of today's research [2]. To achieve the optimal installation with a specific set of parameters and variables, different optimization techniques are being utilized. In perspective of the complexity of optimization of hybrid renewable energy systems (HRES), it was pressing to discover effective optimization methods to achieve a good engineering solution. A literature review has been carried out to properly evaluate the present state of research on HRES optimization. Most of the accessed researches focused on sizing of the grid-independent HRES using different optimization techniques. Some of these researches used the iterative optimization technique which is usually time-consuming and may not obtain accurate results. The work in these researches has the same target of determining the optimal size of HRES but with different objective functions, constraints, and input parameters [3–7]. The authors in [3–5] introduced a model for sizing and optimization of hybrid PV/wind/battery energy systems using the iterative optimization technique. The model considers loss of load probability (*LOLP*) and cost of energy (*COE*) as the optimization objectives. The iterative optimization technique has been presented in [6] to determine the optimum size of hybrid PV/wind/battery energy systems in order to minimize the investment cost. The author in this study assumes that the battery capacity is infinite to determine the maximum capacity of the battery and the minimum size of the supply. After that determines the optimum number of wind turbines (WTs), and PV arrays capable of supplying the load demand with certain value of *LOLP*. An approach using iterative optimization technique has been introduced in [7] for techno-economic optimization of hybrid PV/wind/battery systems with and without an uninterruptible power supply (UPS). The minimum *COE* was the objective function of the optimization problem. The authors in this research compared the exhibitions of HRES with and without the UPS and reported that the system configuration effects on the value of *COE* and the state of charge of the battery (*SOC*), particularly at low windy locales.

Some other researchers used the graphical construction technique to determine the optimum integration of PV array and battery in a hybrid PV/wind/battery energy system [8]. The system has been

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Nomenclature

$u(h)$	wind speed at the hub height of WT
$u(h_g)$	wind speed at anemometer height
α	roughness factor, 0.14
P_W	the output power of WT
P_r	the rated output power of WT
u_c	cut-in wind speed
u_r	rated wind speed
u_f	cut-off wind speed
$P_{WT,av}$	the WT average power generated
C_F	capacity factor
c	scale parameter
k	shape parameter
NWT	average number of WT
$P_{L,av}$	average annual load demand
ω_m	WT rotational speed
ω_{mopt}	optimum rotational speed of WT
$C_p(\lambda, \beta)$	WT power coefficient
λ	tip speed ratio
β	blade pitch angle
R	radius of swept area of WT blades
H_t	solar radiation on tilted surface
$\mu_c(t)$	instantaneous PV cell efficiency
η_{PC}	power conditioning system efficiency
γ	azimuth angle
β	angle between tilted surface and horizontal
TIC	total investment cost
IC	capital cost
OMC	operation and maintenance cost
RC	replacement cost
NC	number of controllers
NV	number of converters
x	size optimization variables; x=NWT, PVA, NC, and NV
GSC	cost of surplus energy
GDC	cost of deficit energy
T	system lifetime
IC_{PV}	initial cost of PV energy system
IC_{WT}	initial cost of WT energy system
$IC_{controller}$	operation and maintenance cost of PV energy system
$IC_{converter}$	operation and maintenance cost of PV energy system
OMC_{PV}	operation and maintenance cost of PV energy system
OMC_{WT}	operation and maintenance cost of WT energy system
$OMC_{controller}$	operation and maintenance cost of controllers
$OMC_{converter}$	operation and maintenance cost of converters
r	net interest rate
i	inflation rate
RC_{PV}	replacement cost of PV energy system
RC_{WT}	replacement cost of WT energy system
$RC_{controller}$	replacement cost of controllers
$RC_{converter}$	replacement cost of converters
NR_{PV}	no. of replacements of PV energy system
NR_{WT}	no. of replacements of WT energy system
$NR_{controller}$	no. of replacements of controllers
$NR_{converter}$	no. of replacements of converters
C_{RC}	capacity of the replacement units
C_U	cost of replacement units
PSV	present value of scrap of the HRES components
SV	value of scrap
ST	salvage times
E_{PV}	total annual energy of PV system
E_{WT}	total annual energy of WT system
E_{GD}	total annual energy purchased from grid
E_L	total annual load energy
P_L	load power
P_{PV}	PV system power
P_W	WT system power
P_{SG}	surplus power supplied to grid
P_{DG}	deficit power purchased from grid
η_{CO}	controller efficiency, 95%
η_{CV}	converter efficiency, 95%
P_G	grid power
$LOLP_{new}$	the old value of loss of load probability
$LOLP_{old}$	the old value of loss of load probability
$LOLP_{index}$	the designed values of loss of load probability counter
P_i	best experience for each particle
G_i	global best particle
$x_i(g)$	position vector
$v_i(g)$	velocity vector
i	index number of every particle in the swarm
M	dimension of the search space
g	iteration number
c_1	self-confidence
c_2	swarm-confidence

simulated for various integrations of PV array, battery sizes, and different values of *LOLP*. At certain value of *LOLP*, the PV array size has been plotted versus battery size and the optimal solution, which minimizes the system cost, has been picked. This kind of graphical procedures doesn't permit including more than two parameters in the optimization process (i.e. PV/wind, wind/battery, or PV/battery).

Another researchers used linear programming technique [9–11], mixed integer linear programming [12], Monte-Carlo simulation approach [13,14], dynamic programming technique [15,16] probabilistic approach [17,18], whereas others used fuzzy logic controller with multi-objectives optimization [19].

Some other researches depend on the existent optimization software, such as the hybrid optimization model for electric renewable (HOMER), and the hybrid power system simulation model (HYBRID2). HOMER software has been used in [20] for the optimization of a hybrid PV/wind/battery system and its performance for a typical community load in Bangladesh. The main limitation of HOMER software is that the sizing of the system components assumes many simplifications during the optimization process. This may has a significant impact on the accuracy of results deduced from HOMER software. In addition, the analysis requires more information on resources, economic constraints, and control methods which might be hard to be accessed. Therefore, the lowest price obtained with HOMER software is not always the optimum solution but it may be the best possibility from the available possibilities entered for each component as a data. The authors in [21] applied HYBRID2 software in conjunction with a simplified time-series model to analysis and size a hybrid PV/wind system to supply electricity to about one-third of the non-grid connected households in Inner Mongolia. Sizing of the major components of the system has been determined based on the trade-off between the cost of the system and the percent unmet load. The authors showed that using PV to the wind system in conjunction with battery storage reduces the unmet load by over 75%. Although HYBRID2 can simulate the hybrid systems with remarkably high precision calculations, it does not optimize the size of the system components.

A group of researchers relies in their work on short-term or unreal meteorological data of wind speed, solar radiation, temperature, and load data. This may weaken the analysis and reduces the sizing accuracy of the system [22–25].

Another different researches developed optimization methodologies based on various optimization approaches such as genetic algorithm