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Application of the Hybrid Big Bang–Big Crunch algorithm for optimal sizing of a stand-alone hybrid PV/wind/battery system

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ABSTRACT

In this paper an efficient method based on Hybrid Big Bang–Big Crunch (HBB–BC) algorithm is presented for optimal sizing of a stand-alone hybrid power system including photovoltaic panel, wind turbine and battery bank. The optimization is carried out to continuously satisfy the load demand with minimizing the total present cost (TPC) of the system. TPC includes all the costs throughout the useful life of the system, which are translated to the initial moment of the investment. In the optimization problem, the reliability index of energy not supplied (ENS) is also considered to have a reliable system. The HBB–BC algorithm is an effective and powerful method that has high accuracy and fast convergence as well as its implementation is easy. This algorithm using the Particle Swarm Optimization (PSO) capacities improves the capability of the Big Bang–Big Crunch (BB–BC) algorithm for better exploration. In addition, the HBB–BC uses a mutation operator after position updating to avoid local optimum and to explore new search areas. This study is applied to a village in Qazvin, Iran that still lacks access to grid electricity due to economic and geography issues. The performance of the proposed algorithm is compared with PSO and Discrete Harmony Search (DHS) algorithms. Simulation results confirm that HBB–BC algorithm with high accuracy can find the optimal solution and it has the best performance in comparison with two mentioned algorithms.

1. Introduction

The need for energy-efficient and reliable electric power in remote rural villages is a driving force for research in this area. Fuel transportation problems, high operating costs, fluctuation in fuel cost, the depletion of the fossil fuel resources and environmental problems have forced many utilities to explore hybrid energy systems for inexhaustible energy development and environmental pollution prevention. Photovoltaic (PV) panels and Wind turbines (WTs) are the most promising technologies for supplying load demand in remote areas. Because of unpredictable nature of these power sources and dependence on environmental conditions, hybrid energy systems must be used by combining the wind and solar energies along with battery storage. Hybrid systems have greater reliability and lower cost than a PV-only system or a wind-only system. In order to have a cost-effective hybrid system, optimal sizing is necessary.

In previous studies, different methods have been presented for the optimal sizing of hybrid power systems. Kellogg et al. (1998) presented a simple numerical algorithm for generation unit sizing. It has been used to determine the optimum generation capacity and storage needed for a stand-alone, wind, PV, and hybrid wind/PV system for an experimental site in a remote area in Montana with a typical residential load. Dufo-López and Bernal-Agustín (2005) have developed a program that uses the Genetic Algorithm (GA) for sizing and operation control of a PV–Diesel system. The program has been developed in C++. Nelson et al. (2006) performed an economic evaluation of a hybrid wind/photovoltaic/fuel cell (FC) generation system for a typical home in the Pacific Northwest. In this configuration the combination of a FC stack, an electrolyser, and hydrogen storage tanks is used as the energy storage system. A new method for optimization of a wind–PV hybrid system for a specific location employing an iterative scheme has been addressed by Prasad and Natarajan (2006). Yang et al. (2008) presented an optimal sizing method for a stand-alone hybrid solar–wind system employing battery banks Based on the genetic algorithm. This method can achieve the desired loss of power supply probability (LPSP) with a minimum annualized cost of system. A triple multi-objective design of isolated hybrid systems minimizing, simultaneously, the total cost throughout the useful life of the installation, pollutant emissions (CO_2) and unmet load is presented

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Nomenclature

$A_i^{(k,j)}$	ith component of the jth candidate generated in the kth iteration
$A_i^{c(k)}$	ith component of the center of mass in the kth iteration
$A_i^{gbest(k)}$	the global best position up to the iteration k
$A_i^{lbest(k,j)}$	the best position of the jth particle up to the iteration k
$A_{i\max}$	upper limit for the ith control variable
$A_{i\min}$	lower limit for the ith control variable
C_{BA}	unit cost of battery bank ($)
$C_{BA,M}$	annual maintenance cost of battery ($/year)
C_{CON}	unit cost of converter ($)
C_{INV}	unit cost of inverter ($)
C_{PV}	unit cost of PV panel ($)
$C_{PV,M}$	annual maintenance cost of PV panel ($/year)
C_{REC}	unit cost of rectifier ($)
C_{REG}	unit cost of charge regulator ($)
C_{WT}	unit cost of wind turbine ($)
$C_{WT,M}$	annual maintenance cost of wind turbine ($/year)
$CPV(\,)$	cumulative present value
DOD	maximum depth of discharge
ENS	energy not supplied during the year (kW)
$ENS(\%)$	percentage of energy not supplied during the year
$ENS_{\max}(\%)$	allowable percentage of energy not supplied during the year
f_j	fitness function value of candidate j
G	perpendicular radiation at array's surface (W/m^2)
$InfR$	inflation rate
$IntR$	interest rate
$INVESTC$	investment cost ($)
m	number of control variables
$MAINC$	maintenance cost ($/year)
N	population size
N_{BA}	number of battery bank
N_{CON}	number of converter
N_i	number of component i
$N_{i\text{-max}}$	maximum number of the component i
$N_{i\text{-min}}$	minimum number of the component i
N_{INV}	number of inverter
N_{PV}	number of PV panel
N_{REC}	number of rectifier
N_{REG}	number of charge regulator
N_{WT}	number of wind turbine
P_{BA}	charge quantity of the battery bank (kW h)
$P_{BA\text{-max}}$	maximum charge quantity of battery bank (kW h)
$P_{BA\text{-min}}$	minimum charge quantity of battery bank (kW h)
P_{Load}	load demand (kW)
P_m	mutation probability
P_{PV}	output power of each photovoltaic panel (kW)
$P_{PV\text{-rated}}$	rated power of each PV panel (kW)
P_{WT}	output power of each wind generator (kW)
$P_{WT\text{-rated}}$	rated power of each wind generator (kW)
r_j	random number from a standard normal distribution
$REPLACEC$	replacement cost ($)
S_{BA}	nominal capacity of battery bank (kW h)
T	economic life cycle of the hybrid system (year)
TPC	total present cost of the system ($)
v	wind speed (m/s)
V_{ci}	cut-in speed of the wind turbine (m/s)
V_{co}	cut-out speed of the wind turbine (m/s)
V_r	rated speed of the wind turbine (m/s)
α_1	parameter for limiting the size of the search space
α_2, α_3	adjustable parameters
η_{BA}	charge efficiency of the battery bank
η_{CON}	efficiency of the converter
η_{INV}	efficiency of the inverter
η_{MPPT}	efficiency of MPPT system
η_{REC}	efficiency of the rectifier
σ	hourly self-discharge rate

by Dufo-López and Bernal-Agustín (2008). For this task, a multi-objective evolutionary algorithm (MOEA) and a genetic algorithm have been used in order to find the best combination of components of the hybrid system and control strategies. An advanced variation of Particle Swarm Optimization algorithm is used by Kashefi Kaviani et al. (2009) to optimal design of a hybrid wind/photovoltaic/fuel cell generation system to reliable supply of the demand. The aim of the design is minimization of annualized cost of the hybrid system over its 20 years of operation. Hakimi and Moghaddas-Tafreshi (2009) used the particle swarm optimization algorithm for optimal sizing of a stand-alone hybrid power system. This study is performed for Kahnouj area in south-east Iran. Ekren and Ekren (2010) performed Simulated Annealing (SA) algorithm for optimizing size of a PV/wind integrated hybrid energy system with battery storage. The proposed methodology is a heuristic approach which uses a stochastic gradient search for the global optimization. Mohammadi et al. (2012) presented an optimized design of microgrid in distribution systems with multiple distributed generation units under different market policies such as pool/hybrid electricity market. Proposed microgrid includes various energy sources such as photovoltaic array and wind turbine with energy storage devices such as battery bank. The particle swarm optimization algorithm has been implemented for the optimization of the microgrid cost. A discrete simulated annealing algorithm (DSA) for finding the optimum design of hybrid PV/wind system is presented by Askarzadeh (2013b). The DSA algorithm is then expanded by using the merits of two other heuristic algorithms, namely, harmony search and chaotic search. Kazem et al. (2013) presented a method for optimal sizing of a standalone PV system for remote areas in Sohar, Oman. PV array tilt angle as well as the size of the system's energy sources are designed optimally for better performance and lower energy cost. A methodology based on iterative technique is presented by Smaoui et al. (2015) to perform the optimal sizing of a stand-alone hybrid photovoltaic/wind/hydrogen system supplying a desalination unit which feeds the area's inhabitants with fresh water. The methodology aims at finding the optimal technical–economic configuration among a set of systems components. Fetanat and Khorasaninejad (2015) employed ant colony optimization (ACO) for continuous domains based integer programming for size optimization in a hybrid photovoltaic–wind energy system. The objective function of this system design is the total design cost. The optimal sizing and tilting of a hybrid photovoltaic/battery/diesel generator system are performed by Jeyaprabha and Selvakumar (2015) for the remote locations in India, using artificial intelligence techniques (AIT) without the metrological data. Maleki et al. (2015) evaluated the performance of different variants of particle swarm optimization algorithms on the sizing problem of PV/wind/battery systems. The optimal size of system components has been studied under various performance conditions using real-time information and meteorological data from each of Iran's southern, north-west, and north-east regions.

The Big Bang–Big Crunch (BB–BC) optimization algorithm is a global optimization method that relies on one of the theories of the evolution of the universe, namely, BB–BC theory. It has several advantages over other evolutionary methods: the inherent numerical simplicity of the algorithm with relatively few control parameters, quick convergence, and easy implementation (Tang et al., 2010). Superiority of the BB–BC algorithm over improved and classical genetic algorithms for many benchmark test functions was shown by Erol and Eksin (2006). The results for design of space trusses indicated that the BB–BC has better performance than either the ACO or GA approaches (Camp, 2007). The HBB–BC algorithm was employed by Sedighizadeh et al. (2013) for multi-objective reconfiguration of balanced and unbalanced distribution systems in a fuzzy framework. Numerical results demonstrated the efficiency and robustness of the HBB–BC method compared to other heuristic algorithms.

This paper presents an efficient method to solve the problem of optimal sizing of a stand-alone hybrid power system including photovoltaic panel, wind turbine and battery bank using Hybrid Big Bang–Big Crunch algorithm. The objective function is minimizing the total present cost (TPC) of the system. TPC includes all the costs throughout the useful life of the system, which are translated to the initial moment of the investment. To have a reliable system, the reliability index of energy not supplied (ENS) is also considered. The number of PV panels, wind turbines and batteries are considered as the control variables. This study is performed for electrification to a remote area located at Qazvin, Iran. Simulation results are compared with Particle Swarm Optimization (PSO) (Maleki and Askarzadeh, 2014) and Discrete Harmony Search (DHS) (Askarzadeh, 2013a) algorithms to indicate the efficient performance of the HBB–BC algorithm.

The rest of the paper is organized as follows: In Section 2, the modeling of the hybrid system components and problem formulation are described. In Sections 3 and 4, the BB–BC and HBBBC algorithms are introduced, respectively. Section 5 explains the application of the HBB–BC algorithm to optimal sizing of hybrid power system. Simulation results are presented in Section 6. The results demonstrate the efficiency of the proposed algorithm. Finally, Section 7 gives the conclusions.

2. Problem formulation

As it can be seen in Fig. 1, the studied hybrid system consists of the photovoltaic (PV) panel and wind turbine (WT) as main power sources, the battery bank for backup power, converter and charge regulator. Components mathematical model are summarized in the following sections.

2.1. Photovoltaic panel

The output power of each photovoltaic panel with respect to the solar radiation power, can be calculated by Eq. (1).

$$P_{PV} = \frac{G}{1000} \times P_{PV\text{-}rated} \times \eta_{MPPT} \tag{1}$$

where G is perpendicular radiation at array's surface (W/m^2), $P_{PV\text{-}rated}$ is rated power of each PV panel at $G = 1000$ W/m^2, and η_{MPPT} is the efficiency of PV's DC/DC converter and maximum power point tracking (MPPT) system. PV systems are usually equipped with MPPT systems to maximize the power output. A PSO-based MPPT for PV systems under partially shaded as well as variable temperature and insolation conditions was presented by Sarvi et al. (2015). The proposed method with high accuracy can track the real peak power point under different conditions. In current study it is assumed that η_{MPPT} is 95% (Kashefi Kaviani et al., 2009).

2.2. Wind turbine generator

Wind power is one of the most important sources of renewable energy. The main advantage of this energy source is the absence of greenhouse gas emissions and its economic efficiency (Maleki and Pourfayaz, 2015). For a wind turbine, if the wind speed exceeds the cut-in value, the wind turbine generator starts generating. If the wind speed exceeds the rated speed of the wind turbine, it generates constant output power; and if the wind speed exceeds the cut-out value, the wind turbine generator stops running to protect the generator. The output power of each wind generator is described in terms of the wind speed by Eq. (2) (Maleki et al., 2015).

$$P_{WT} = \begin{cases} 0 & \text{if } v \leqslant V_{ci} \text{ or } v \geqslant V_{co} \\ P_{WT\text{-}rated} \times \frac{v - V_{ci}}{V_r - V_{ci}} & \text{if } V_{ci} \leqslant v < V_r \\ P_{WT\text{-}rated} & \text{if } V_r \leqslant v < V_{co} \end{cases} \tag{2}$$

where v is the wind speed; V_{ci}, V_{co} and V_r are cut-in, cut-out and rated speed of the wind turbine, respectively; and $P_{WT\text{-}rated}$ is the wind generator rated power.

2.3. Battery

The battery bank is widely used for hybrid power systems to store extra electrical energy and to supply load demand in case of deficiency of wind turbine and/or PV panel output power. Due to the stochastic behaviors of PV panels and wind turbines, the battery bank capacity constantly changes in hybrid system. In such system, state of charge (SOC) of the battery is stated as follows (Maleki and Pourfayaz, 2015).

When the total output power of PV panels and wind turbines is greater than the load demand, the battery bank is in charging state. The charge quantity of the battery bank at time t can be obtained by:

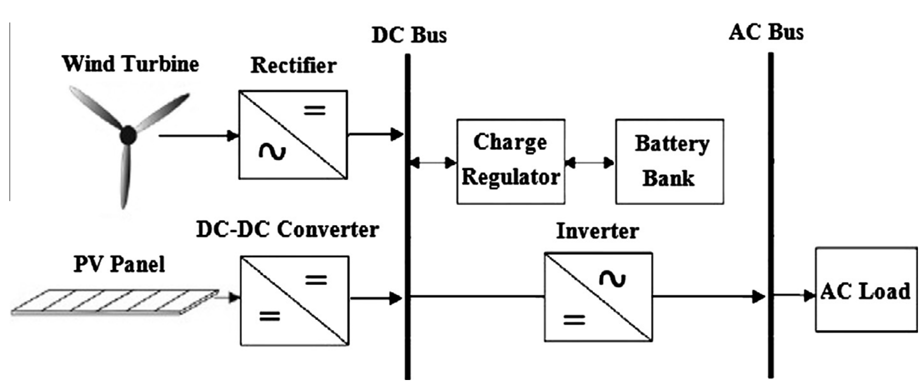

Fig. 1. Diagram of a hybrid PV/wind/battery system.

$$P_{BA}(t) = P_{BA}(t-1) \times (1-\sigma) + \left[(N_{PV} \times P_{PV}(t) \times \eta_{CON} + N_{WT} \times P_{WT}(t) \times \eta_{REC}) - \frac{P_{Load}(t)}{\eta_{INV}} \right] \times \eta_{BA} \tag{3}$$

where $P_{BA}(t)$ and $P_{BA}(t-1)$ are the charge quantities of the battery bank at time t and $t-1$, respectively. σ is the hourly self-discharge rate, η_{CON}, η_{REC} and η_{INV} denote the efficiency of the converter, rectifier and inverter, respectively. $P_{Load}(t)$ is the load demand, and η_{BA} is the charge efficiency of the battery bank.

When the total output power of PV panels and wind turbines is less than the load demand, the battery bank is in discharging state. In this paper, the discharge efficiency of battery bank is assumed to be 1. Therefore, the charge quantity of the battery bank at time t can be obtained by:

$$P_{BA}(t) = P_{BA}(t-1) \times (1-\sigma) - \left[\frac{P_{Load}(t)}{\eta_{INV}} - (N_{PV} \times P_{PV}(t) \times \eta_{CON} + N_{WT} \times P_{WT}(t) \times \eta_{REC}) \right] \Big/ \eta_{BA} \tag{4}$$

In this paper, temperature effects on the battery bank are ignored

2.4. Objective function

The objective function of the optimal sizing problem is the minimization of the total present cost (TPC) of the system. TPC is sum of the investment cost (*INVESTC*), maintenance cost (*MAINC*) and replacement cost (*REPLACEC*) throughout the useful life of the system, which are translated to the initial moment of the investment. The optimization is carried out to continuously satisfy the load demand considering the reliability index of energy not supplied (ENS). The problem is mathematically formulated as follows:

$$\text{Minimize TPC} = INVESTC + MAINC + REPLACEC \tag{5}$$

The investment cost which includes the costs of the wind turbine, photovoltaic panel, battery bank, rectifier, charge regulator, inverter and converter is obtained by Eq. (6).

$$INVESTC = (C_{PV} \times N_{PV}) + (C_{WT} \times N_{WT}) + (C_{BA} \times N_{BA}) + (C_{REC} \times N_{REC}) + (C_{REG} \times N_{REG}) + (C_{INV} \times N_{INV}) + (C_{CON} \times N_{CON}) \tag{6}$$

where C_{PV} is unit cost of PV panel, C_{WT} is unit cost of wind turbine, C_{BA} is unit cost of battery bank, C_{REC} is unit cost of rectifier, C_{REG} is unit cost of charge regulator, C_{INV} is unit cost of inverter and C_{CON} is unit cost of converter. N_{PV} is the number of PV panel, N_{WT} is the number of wind turbine, N_{BA} is the number of battery bank, N_{REC} is the number of rectifier, N_{REG} is the number of charge regulator, N_{INV} is the number of inverter and N_{CON} is the number of converter.

The maintenance cost of the system components is obtained by Eq. (7).

$$MAINC = CPV(C_{PV,M} \times N_{PV} + C_{WT,M} \times N_{WT} + C_{BA,M} \times N_{BA}) \tag{7}$$

where $C_{PV,M}$, $C_{WT,M}$ and $C_{BA,M}$ are the annual maintenance costs of PV panel, wind turbine and battery, respectively. The maintenance costs of rectifier, charge regulator, inverter and converter are neglected. *CPV*( ) is the cumulative present value which translates all the costs throughout the useful life of the system to the initial moment of the investment and is obtained by Eq. (8).

$$CPV(f) = f \sum_{t=1}^{T} \left(\frac{1 + InfR}{1 + IntR} \right)^{t} \tag{8}$$

In this equation, *IntR* is the interest rate, *InfR* is the inflation rate and T is the economic life cycle of the hybrid system.

The replacement cost of the system components regarding to their lifetime can be obtained as follow:

$$REPLACEC = CPV(C_{BA} \times N_{BA} + C_{REC} \times N_{REC} + C_{REG} \times N_{REG} + C_{INV} \times N_{INV} + C_{CON} \times N_{CON}) \tag{9}$$

Since that the lifetime of the PV panel and wind turbine is equal to the useful life of the system, the replacement cost is not considered for them.

2.5. Constraints

The constraints considered in this study are as follows:

– The minimum and maximum number of the hybrid system components.

$$N_{i\text{-min}} < N_i < N_{i\text{-max}} \tag{10}$$

where N_i is the number of component i, $N_{i\text{-min}}$ and $N_{i\text{-max}}$ are the minimum and maximum number of the component i, respectively.

– Energy not supplied amount during the year

In the hybrid power system, for having a reliable system the concept of the energy not supplied should be considered.

$$ENS(\%) \leqslant ENS_{\max}(\%) \tag{11}$$

$ENS_{\max}(\%)$ is the allowable percentage of energy not supplied during the year and $ENS(\%)$ is the percentage of energy not supplied during the year which is obtained by Eq. (12).

$$ENS(\%) = \frac{ENS}{\sum_{t=1}^{8760} P_{Load}(t)} \times 100 \tag{12}$$

where *ENS* is the energy not supplied during the year and is calculated as follows:

$$ENS = \sum_{t=1}^{8760} [P_{Load}(t) - (N_{PV} \times P_{PV}(t) + N_{WT} \times P_{WT}(t) + P_{BA}(t))] \tag{13}$$

– The minimum and maximum charge quantity of the battery bank

$$P_{BA\text{-min}} \leqslant P_{BA} \leqslant P_{BA\text{-max}} \tag{14}$$

$P_{BA\text{-max}}$ is the maximum charge quantity of battery bank which is considered equal to the nominal capacity of battery bank (S_{BA}). $P_{BA\text{-min}}$ is the minimum charge quantity of battery bank which is obtained by maximum depth of discharge (*DOD*).

$$P_{BA\text{-min}} = (1 - DOD) \times S_{BA} \tag{15}$$

3. BB–BC optimization algorithm

The BB–BC optimization algorithm was introduced by Erol and Eksin (2006). It was inspired by one of the theories of the evolution of universe, namely, the Big Bang–Big Crunch theory. Its key advantages are the low computational time, easy implement and fast convergence. The BB–BC optimization algorithm consists of two main steps. In the first step, Big Bang phase, candidate solutions are randomly distributed over the search space and in the next step, Big Crunch phase, candidate solutions are drawn into a single representative point via a center of mass or minimal cost approach. Then candidate solutions are spread about the center of mass or the individual with minimal cost to be used as the next Big Bang. Initial population is randomly generated within the search space similar to other evolutionary algorithms. The center of mass is computed regarding the current positions of each candidate solution in the population and its associated cost function value as given in Eq. (15).

$$A_i^{c(k)} = \frac{\sum_{j=1}^{N} \frac{1}{f_j} \cdot A_i^{(k,j)}}{\sum_{j=1}^{N} \frac{1}{f_j}} \qquad i = 1, 2, \ldots, m, \tag{16}$$

where $A_i^{c(k)}$ is the ith component of the center of mass in the kth iteration; $A_i^{(k,j)}$ is the ith component of the jth candidate generated in the kth iteration; f_j is the fitness function value of candidate j; N is the population size in Big Bang phase; and m is the number of control variables.

The new candidates for the next iteration of the Big Bang are normally distributed around the center of mass or best fit individual and the standard deviation of this normal distribution function decreases as the iterations elapse:

$$A_i^{(k+1,j)} = A_i^{c(k)} + \frac{r_j \alpha_1 (A_{i\max} - A_{i\min})}{k+1}, \qquad i = 1, 2, \ldots, m, \tag{17}$$

where r_j is a random number from a standard normal distribution which changes for each candidate; α_1 is a parameter for limiting the size of the search space; and $A_{i\max}$ and $A_{i\min}$ are the upper and lower limits for the ith control variable, respectively.

The successive Big Bang and Big Crunch steps continue until a stopping criterion has been met.

4. Proposed HBB–BC algorithm

The HBB–BC algorithm uses the PSO capacities as introduced by Kaveh and Talatahari (2009) and a mutation operator to improve the exploration ability of the BB–BC algorithm and avoid the trapping into the local optimum.

The PSO algorithm was initially proposed by Kennedy and Eberhart (1995). It was inspired by the social behavior of bird flocking and fish schooling. PSO consists of a swarm of particles as candidate solutions for the optimization problem. Each particle adjusts its trajectory toward its own best previously visited position (local best) and the global best position of the swarm found (global best). In HBB–BC algorithm similarly in addition to the center of mass, the local best and the global best are also used to generate the new candidates as (Kaveh and Talatahari, 2009):

$$A_i^{(k+1,j)} = \alpha_2 A_i^{c(k)} + (1-\alpha_2)\left(\alpha_3 A_i^{gbest(k)} + (1-\alpha_3) A_i^{lbest(k,j)}\right) + \frac{r_j \alpha_1 (A_{i\max} - A_{i\min})}{k+1} \qquad \left\langle \begin{array}{l} i = 1, 2, \ldots, m \\ j = 1, 2, \ldots, N \end{array} \right., \tag{18}$$

where $A_i^{lbest(k,j)}$ is the best position of the jth particle up to the iteration k and $A_i^{gbest(k)}$ is the global best position up to the iteration k; α_2 and α_3 are adjustable parameters controlling the effect of the global best and local best on the new position of the candidates, respectively.

A discrete solution is achieved by using Eq. (18).

$$A_i^{(k+1,j)} = round\left(\alpha_2 A_i^{c(k)} + (1-\alpha_2)\left(\alpha_3 A_i^{gbest(k)} + (1-\alpha_3) A_i^{lbest(k,j)}\right) + \frac{r_j \alpha_1 (A_{i\max} - A_{i\min})}{k+1}\right), \tag{19}$$

where $round(X)$ is a function which rounds the elements of X to the nearest integers.

Now, we use the mutation operation to prevent the HBB–BC from trapping into the local optimum and to explore new search areas as follow:

$$A_i^{(k+1,j)} = round(A_{i\min} + rand() \times (A_{i\max} - A_{i\min})) \quad \text{if } rand() < P_m, \tag{20}$$

Here, $rand(\,)$ is the uniformly generated random number within the interval of [0, 1] and P_m is mutation probability.

5. Application of the HBB–BC algorithm for optimal sizing problem

In the proposed algorithm, the number of PV panels, wind turbines and batteries are considered as the control variables. The HBB–BC algorithm is applied for the problem of the optimal sizing of the hybrid power system as follows:

- Step 1: Define the input data. In this step, the input data are defined including the costs of investment, maintenance and replacement of hybrid system components, the data related to the load demand, solar insolation and wind speed in the studied area, the rated power and efficiency of system components, the number of population, limiting parameter of the size of the search space (α_1), adjustable parameters (α_2, α_3), mutation probability (P_m), and the number of iterations.
- Step 2: Generate the initial population. Initial population is randomly generated within the search space.
- Step 3: Evaluate the objective function and check the problem constraints. If the problem constraints are not satisfied, the corresponding objective function is penalized.
- Step 4: Calculate the center of mass $\left(A_i^{c(k)}\right)$ using Eq. (16) and determine the best position of each particle $\left(A_i^{lbest(k,j)}\right)$ and the global best position $\left(A_i^{gbest(k)}\right)$.
- Step 5: calculate new candidates according to Eq. (19). Then, apply the mutation operation to prevent the HBB–BC from trapping into the local optimum.
- Step 6: Repeat steps 3–5 until a termination criterion is satisfied. In this paper, the stopping criterion is considered the number of iteration. Furthermore, if the maximal iteration number is satisfied, algorithm is terminated.

At last, the proposed algorithm is achieved the optimal number of the hybrid system components and the total present cost of the corresponding system.

Fig. 2 shows the flowchart of the proposed algorithm.

6. Simulation results

The proposed algorithm for optimal design of the hybrid power system has been applied to a village in Qazvin that still lacks access to grid electricity due to economic and geography issues. The experimental data used here for wind speed and solar insolation in 2011 is extracted from meteorological organization. These data have been recorded every ten minutes and their mean for each hour is used in this study. Figs. 3–5 show the hourly profiles of wind speed, solar insolation and area estimated load during a year (8760 h), respectively. The costs related to the hybrid system components are given in Table 1. Technical specification of the wind turbine is also presented in Table 2.

MATLAB environment is used to code and implement the algorithms. To compare the performance of the proposed algorithm with PSO (Maleki and Askarzadeh, 2014) and DHS (Askarzadeh, 2013a) algorithms, 50 independent runs are implemented and the results are presented. The parameters of the algorithms used in this paper to optimize the objective function are adjusted as follows:

HBB–BC: population size (N) = 50, α_1 = 1, α_2 = 0.4, α_3 = 0.8, P_m = 0.01, maximum iteration = 150.

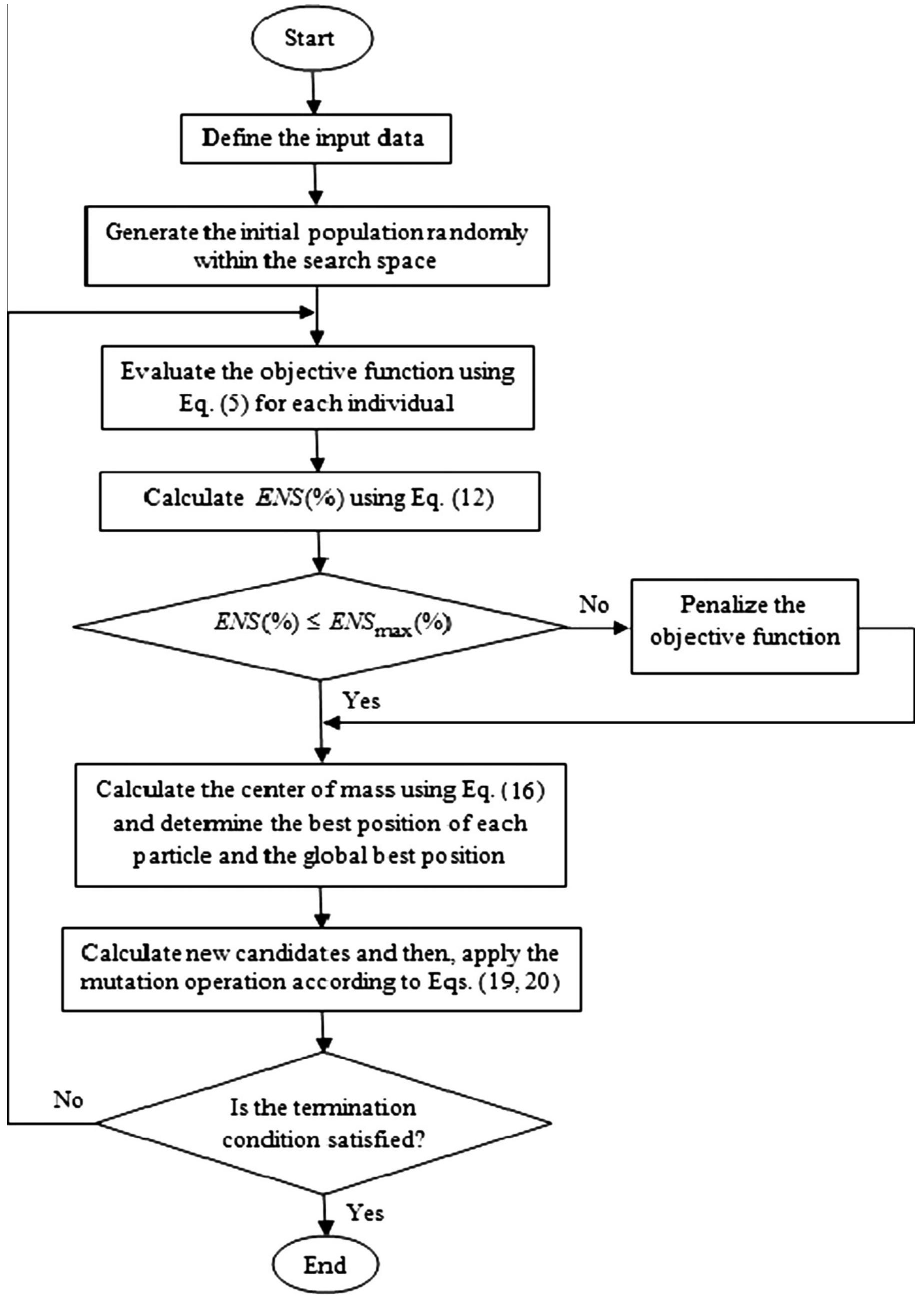

Fig. 2. Flowchart of the proposed HBB–BC algorithm.

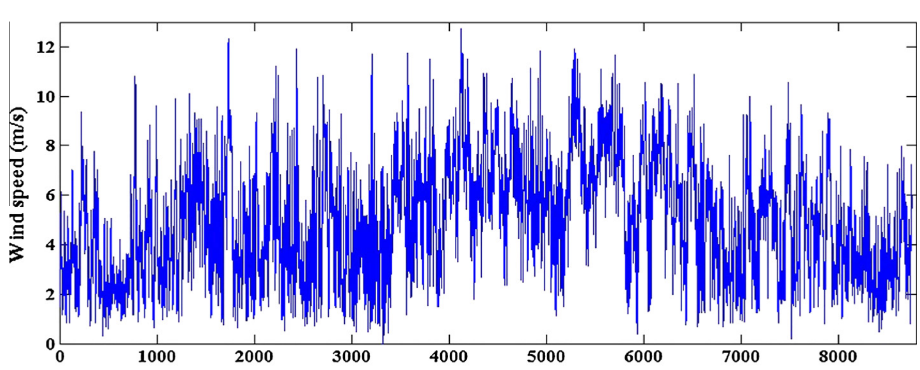

Fig. 3. Hourly profile of wind speed during a year.

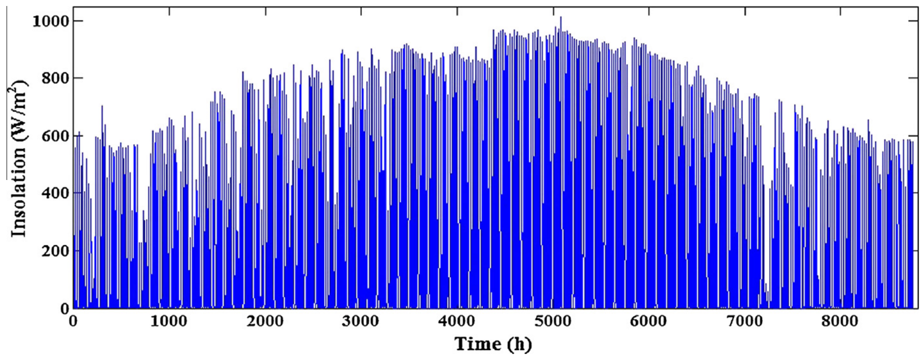

Fig. 4. Hourly profile of insolation during a year.

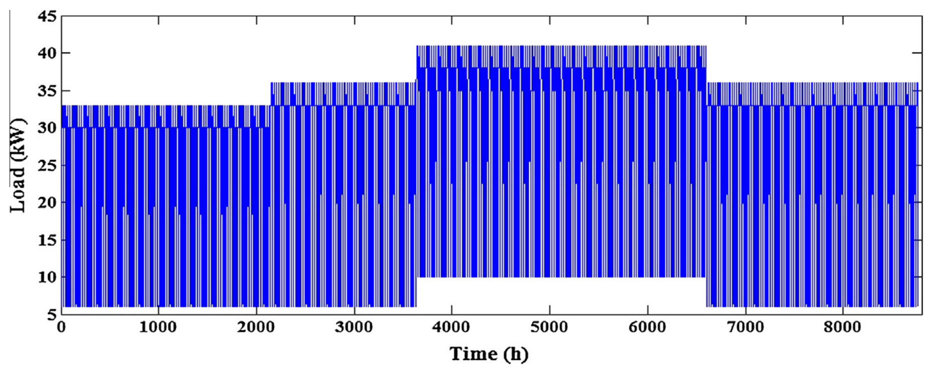

Fig. 5. Hourly load profile during a year.

Table 1
The costs related to the hybrid system components.

Item	PV panel	Wind turbine-generator	Battery bank	Inverter, converter, rectifier, charge regulator
Rated power	1 (kW)	1 (kW)	1 (kW h)	1 (kW)
Useful lifetime (year)	20	20	5	10
Investment cost ($)	2000	3200	100	700
Maintenance cost ($/year)	33	100	5	0

PSO: $N = 50$, $c_1 = 2$, $c_2 = 2$, $\beta = 0.99$, $w_0 = 1$, maximum iteration = 150.
DHS: $N = 50$, $HMCR = 0.95$, $PAR_{\max} = 0.7$, $PAR_{\min} = 0.1$, $bw_{\max} = 1$, $bw_{\min} = 0.01$, maximum iteration = 150.

which are determined by a trial-and-error method by using computer simulations. In this study, the minimum and maximum bounds of the control variables are set to 0 and 400 for the PV panels and wind turbines and set to 0 and 900 for the battery banks.

To perform the simulation, different cases are considered as follow:

– Hybrid system consists of PV panel and battery bank.
– Hybrid system consists of wind turbine and battery bank.
– Hybrid system consists of PV panel, wind turbine and battery bank.

Table 2
Technical specification of the wind turbine.

Rated power (kW)	1
Cut-in speed (m/s)	2.5
Rated speed (m/s)	11
Cut-out speed (m/s)	13

In each case study, the simulation is performed for three different values of $ENS_{\max}(\%)$ (2%, 5% and 10%). Table 3 indicates the results of optimal sizing problem which obtained by HBB–BC algorithm. The number of PV panels, wind turbines and battery banks, total present cost of the system and $ENS(\%)$ are presented in the table. As can be seen, the hybrid PV/wind/battery system is the most cost-effective hybrid system for different $ENS_{\max}(\%)$. Also the hybrid PV/battery system has lower cost than hybrid wind/battery system.

Table 3
The results of optimal sizing problem obtained by HBB–BC algorithm.

Hybrid systems	$ENS_{\max}(\%)$	$ENS(\%)$	N_{PV}	N_{WT}	N_{BA}	Total present cost ($)
PV/battery	2	1.995	330	0	555	2,185,948
	5	4.999	237	0	515	1,778,456
	10	9.998	185	0	440	1,466,196
Wind/battery	2	1.9998	0	363	843	3,560,149
	5	4.999	0	277	529	2,551,783
	10	9.997	0	210	343	1,860,223
PV/wind/battery	2	1.9997	186	57	434	1,794,824
	5	4.998	141	56	338	1,468,857
	10	9.998	106	57	222	1,159,472

Table 4
Comparison of the results obtained by the algorithms for $ENS_{\max}(\%) = 2\%$.

Hybrid system	Algorithm	Mean	Std.	Best				Worst			
				N_{PV}	N_{WT}	N_{BA}	TPC ($)	N_{PV}	N_{WT}	N_{BA}	TPC ($)
PV/battery	HBB–BC	2,185,948	0	330	0	555	2,185,948	330	0	555	2,185,948
	PSO	2,185,962	89	330	0	555	2,185,948	328	0	560	2,186,584
	DHS	2,193,509	10,852	330	0	555	2,185,948	308	0	627	2,220,202
Wind/battery	HBB–BC	3,560,150	0	0	363	843	3,560,150	0	363	843	3,560,150
	PSO	3,560,150	0	0	363	843	3,560,150	0	363	843	3,560,150
	DHS	3,563,805	3697	0	363	843	3,560,150	0	385	773	3,577,012
PV/wind/battery	HBB–BC	1,794,835	40	186	57	434	1,794,824	180	63	426	1,795,060
	PSO	1,794,867	76	186	57	434	1,794,824	180	63	426	1,795,060
	DHS	1,805,291	10,322	186	57	434	1,794,824	215	35	479	1,844,931

Table 5
Comparison of the results obtained by the algorithms for $ENS_{\max}(\%) = 5\%$.

Hybrid system	Algorithm	Mean	Std.	Best				Worst			
				N_{PV}	N_{WT}	N_{BA}	TPC ($)	N_{PV}	N_{WT}	N_{BA}	TPC ($)
PV/battery	HBB–BC	1,778,456	0	237	0	515	1,778,456	237	0	515	1,778,456
	PSO	1,778,470	65	237	0	515	1,778,456	241	0	506	1,778,790
	DHS	1,786,320	9550	237	0	515	1,778,456	221	0	577	1,818,823
Wind/battery	HBB–BC	2,551,784	0	0	277	529	2,551,784	0	277	529	2,551,784
	PSO	2,551,805	139	0	277	529	2,551,784	0	284	504	2,552,775
	DHS	2,560,275	11,363	0	277	529	2,551,784	0	311	438	2,605,399
PV/wind/Battery	HBB–BC	1,468,926	231	141	56	338	1,468,858	146	53	338	1,469,708
	PSO	1,468,944	261	141	56	338	1,468,858	145	52	344	1,469,770
	DHS	1,478,610	11,017	142	56	336	1,469,342	114	94	294	1,521,650

Table 6
Comparison of the results obtained by the algorithms for $ENS_{\max}(\%) = 10\%$.

Hybrid system	Algorithm	Mean	Std.	Best				Worst			
				N_{PV}	N_{WT}	N_{BA}	TPC ($)	N_{PV}	N_{WT}	N_{BA}	TPC ($)
PV/battery	HBB–BC	1,466,197	0	185	0	440	1,466,197	185	0	440	1,466,197
	PSO	1,466,197	0	185	0	440	1,466,197	185	0	440	1,466,197
	DHS	1,470,118	5229	185	0	440	1,466,197	175	0	482	1,496,638
Wind/battery	HBB–BC	1,860,224	0	0	210	343	1,860,224	0	210	343	1,860,224
	PSO	1,860,225	7	0	210	343	1,860,224	0	207	354	1,860,257
	DHS	1,877,672	23,988	0	210	343	1,860,224	0	177	532	1,969,650
PV/wind/battery	HBB–BC	1,159,481	25	106	57	222	1,159,472	103	63	207	1,159,556
	PSO	1,159,485	26	106	57	222	1,159,472	103	63	207	1,159,556
	DHS	1,166,839	11,403	106	57	222	1,159,472	68	95	212	1,226,184

Simulation results also show that reduction of $ENS_{\max}(\%)$ and reliability improvement leads to increase the system costs. For the hybrid PV/wind/battery system and $ENS_{\max}(\%) = 2\%$, total present cost is obtained 1,794,824$ which is more than TPC for $ENS_{\max}(\%) = 5\%$ (1,468,857$) and $ENS_{\max}(\%) = 10\%$ (1,159,500$).

Simulation results for optimal sizing problem obtained by HBB–BC, PSO and DHS algorithms are presented in Tables 4–6. In these tables, the mean (Mean), standard deviation (Std.), worst (Worst) and best (Best) indexes of each algorithm for each case are given. The indexes have been reported over 50 runs.

With comparison of the different indexes, it can be concluded that HBB–BC algorithm yields better result than the other algorithms in all cases. Also PSO algorithm is better than DHS algorithm. The small values of HBB–BC's Std. denote the robustness of this algorithm. Std. index for DHS algorithm has high values and this algorithm cannot find the best solution in most trials.

For example, for the hybrid wind/battery system and $ENS_{\max}(\%) = 5\%$, the mean and standard deviation values of TPC obtained by HBB–BC over 50 runs are 2,551,784 ($) and zero, respectively. Therefore HBB–BC in all trials can find the best solution. These values are obtained 2,551,805 ($) and 139 by PSO and 2,560,275 ($) and 11,363 by DHS. According to these results, PSO cannot find the best solution in some trials and DHS does not yield the acceptable result.

Fig. 6 shows the generated power, the load demand and the charge quantity of the battery bank for hybrid system consists of PV panel, wind turbine and battery bank with $ENS_{\max}(\%) = 2\%$. As can be seen, during the hours that the load demand is greater than generated power, the battery bank supplies the load demand and is in discharging state and during the hours that the load demand is less than the generated power, the battery bank is in charging state.

Fig. 7 illustrates the convergence characteristic of HBB–BC algorithm for the hybrid PV/wind/battery system and $ENS_{\max}(\%) = 2\%$. It is observed that the proposed algorithm quickly finds the optimum sizing of the hybrid systems.

7. Conclusion

This paper evaluates the performance of HBB–BC optimization for optimal sizing of hybrid PV/wind/battery system to minimize the total present cost (TPC) of the system. TPC includes all the costs

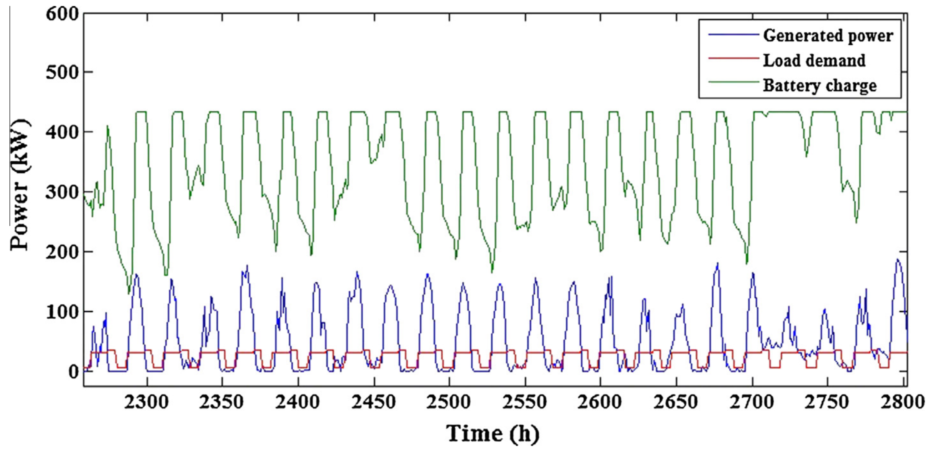

Fig. 6. Sample of hourly performance of hybrid PV/wind/battery system for $ENS_{max}(\%) = 2\%$.

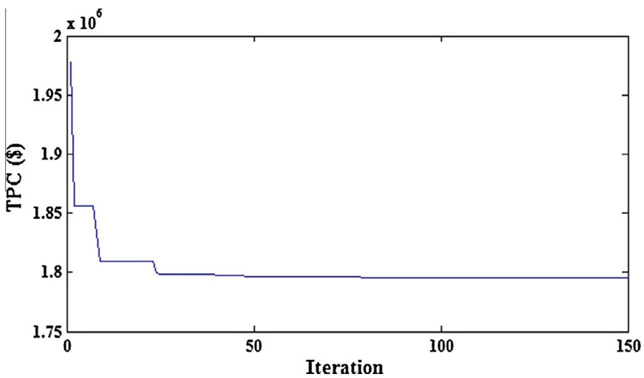

Fig. 7. Convergence characteristic of HBB–BC for the hybrid PV/wind/battery system and $ENS_{max}(\%) = 2\%$.

throughout the useful life of the system, which are translated to the initial moment of the investment. To have a reliable system, the reliability index of energy not supplied is also considered. In HBB–BC algorithm PSO capacities and mutation operation are used to improve the exploration ability of the BB–BC algorithm and avoid local optimum. This study is applied to a village in Qazvin that still lacks access to grid electricity due to economic and geography issues. The HBB–BC algorithm is compared with PSO and DHS algorithms. The results indicate the better performance of the proposed algorithm than two other algorithms. Also can be concluded, the hybrid PV/wind/battery system is the most cost-effective hybrid system for different $ENS_{max}(\%)$ (2%, 5% and 10%).

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