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Firefly-inspired algorithm for optimal sizing of renewable hybrid system considering reliability criteria

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ABSTRACT

Renewable energy sources are usually seen as a response to actual environmental, social and economic issues. However, the random nature of these sources requires the development of sizing rules and the use of these systems for their exploitation. This article presents the results of a developed hybrid PV/wind optimization sizing method, taking into account the strong combination between the intermittent energy resource (solar and wind), the storage capacity and a given load profile. This optimization method is based on the use of metaheuristic techniques. These algorithms, often inspired by nature, are designed to solve complex optimization problems. Among the most recent metaheuristics, we used the Firefly Algorithm (FA), considering the Load Dissatisfaction Rate (LDR) criteria and the Electricity Cost (EC) indicator for power reliability and system cost. The suggested method determines the system optimum configuration, which can achieve the desired LDR with minimum EC. To achieve this aim, an objective function is formulated for the EC. It must be kept to a minimum while respecting the reliability constraints ($LDR_{desired}$). The effectiveness of the FA in solving a hybrid system optimization problem is scrutinized and its performance is compared to other renamed optimization algorithms. To highlight the propounded method performance a real case study has been conducted and the results are discussed.

1. Introduction

To face the climate change challenges, increasing energy demand, fossil fuels scarcity and their fluctuating prices, and the adverse effects on the environment, many countries around the world have changed their energy policies. The first strategy was to make energy savings. For example, Algeria aims at saving energy at about 63 million TOE by 2030 by implementing programs in order to reduce consumption and improve energy efficiency in industry, residential sector, and tertiary and transport (Nouveau programme national de développement des énergies renouvelables (2015–2030)). The second strategy is to use renewable energy sources in autonomous systems as well as in large-scale energy production. Now, the energy produced by systems using these resources is known to be less competitive than the one produced by conventional production systems, mainly due to the relatively high system cost. In addition, the random and intermittent nature of renewable energies makes them difficult to control. Therefore, it is necessary to characterize as accurately as possible changes occurring in these resources. However, they have several advantages, such as reducing dependence on fossil fuels and reducing greenhouse emissions into the atmosphere. The impact of their random nature may be reduced by coupling two or more sources of energy, renewable–renewable or conventional, connected to a power grid, or supplying an isolated load (autonomous systems) in a Hybrid System for Renewable Energy Sources (HSRES).

In order to design efficient, reliable and economic hybrid system, the optimal sizing must be pursed. The design of such hybrid system is a very complex problem because it is necessary to model each system component (Fathy, 2016). In this context, numerous optimization methods for hybrid system sizing have been reported in the literature. Thus, Hossain et al. (2017) have used the HOMER software to optimize the design of several configurations of hybrid systems. The results showed that a PV/wind/diesel/battery choice is further viable economically in comparison with diesel generator only.

A further techno-economic survey of various configurations of hybrid systems in three small rural communities in Colombia was presented in Haghighat Mamaghani et al. (2016). Seven configurations have been proposed and assessed based on

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combinations of PV panels, wind turbines, and diesel generators. The net present cost (NPC) and energy unit cost (EUC) were selected as the economic indicators. The results showed that combined diesel-renewable configurations have a low carbon footprint and are most economically relevant.

Yahiaoui et al. (2016) proposed a new method to optimize the PV/Diesel/Battery hybrid system. The Particulate Swarm Optimization (PSO) algorithm was applied to simultaneously minimize the system global cost, loss of load probability (LLP) and CO_2 emission. The optimization results reveal the interest of using the PV and battery subsystems. Without their contribution, the annual cost of diesel generator becomes substantially high.

In Al-Sharafi et al. (2017), a new methodology allowing the optimal selection of the hybrid energy system configuration has been presented. In a case study, a system composed of photovoltaic panels/wind turbines/diesel generator/batteries was studied. This multi-source system is designed to supply a residential unit in the Dhahran area, KSA. Taking into account economic and environmental considerations, two performance valuation cases were investigated. In the economical case, emphasis was made on reducing the cost of energy (COE) without taking into account the environmental impact of the system. In this case, the EC is 0.611 $/kW h; however, the renewable contribution (RC) of this system is only 50%. In the second case, the importance was given to the environmental impact. In this case, RC is 100%; however, the COE with this system is relatively high up to 0.938 $/kW h.

A study to determine the optimal configuration of a hybrid PV/wind system was performed by Maleki et al. (2015) in various remote areas of Iran. Authors studied the effectiveness of five modified PSO technics and three more algorithms viz: tabu search, simulated annealing and harmony search. The authors concluded that PSO-CF was the most performing PSO variant and PV–battery based hybrid systems are suitable for most areas of the country due to the good solar radiation availability and low windy nature.

In order to minimize the total annual cost of a hybrid PV/Wind/Battery system, Maleki and Pourfayaz (2015) have used seven heuristic algorithms. Authors found that Artificial Bee Swarm Optimization (ABSO) showed more promising results than the other six algorithms. A new optimization method of hybrid PV/wind/diesel/battery system using a multi-objective evolutionary algorithm (MOEA) to minimize the total net present cost (TNPC) and maximize human development index (HDI) and job creation (JC) was presented by Dufo-López et al. (2016). HDI depends on the electricity consumption and JC depends on the evolution of technology. The resulting values showed that the three objectives were often contradictory so a Pareto-optimization MOEA is a good option to obtain a set of possible solutions in which no solution is better than another one for all three objectives (optimal Pareto set).

With a view to optimally size of hybrid PV/wind system, Ahmadi and Abdi (2016) proposed an efficient method based on Hybrid Big Bang–Big Crunch (HBB–BC) algorithm to minimize the total net present cost (TNPC). To evaluate the performance of the suggested algorithm, a comparison was made with two other algorithms namely: Discrete Harmony Search and PSO. Simulation results confirm the high precision of HBB-BC to find the optimal solution and its superiority on two mentioned algorithms.

A new optimal sizing approach based on Cuckoo Search (CS) algorithm to minimize the total system cost of a hybrid PV/wind system was presented in Sanajaoba and Fernandez (2016). Three system configurations namely: PV-Battery, Wind-Battery and PV-Wind-Battery systems applicable to isolated locations in India have been considered in this study. In order to assess the performance of the proposed algorithm, a comparison was made with two other algorithms viz: Genetic Algorithm and PSO. The optimization results show that a PV/wind/battery alternative is more reliable and economical compared to PV/battery system or Wind/Battery for the study area.

Maleki et al. (2016) presented the modeling and optimization of a hybrid PV/wind generation system for electrification of remote rural communities in Rafsanjan, Iran by Particle Swarm Optimization Algorithm-based Monte Carlo Method. Their results proved that the Monte Carlo Simulation Method could provide a novel approach to tools already used in the field of optimization. In addition, the case study showed that the Wind/battery option was the most reliable and economical.

In this paper, a PV/wind hybrid optimization method, which employs one of the most recent Nature Inspired Algorithm (NIA), called Firefly Algorithm (FA), considering the Load Dissatisfaction Rate (LDR) criteria and the Electricity Cost (EC) indicator for power reliability and system cost is presented. The recommended method determines the system optimum configuration, which can attain the desired LDR with minimum EC. For this purpose, an objective function is formulated for the EC. It must be kept to a minimum while respecting the reliability constraints ($LDR_{desired}$). The effectiveness of the FA in solving a hybrid system optimization problem is scrutinized and its performance is compared to other well-known optimization algorithms. To highlight the proposed method performance a real case study has been carried out and the results are inspected.

2. Hybrid system overview

The hybrid energy production system in its most general view is the one that combines and exploits several readily available sources. The studied system consists of two energy production parts (PV generator and wind turbine) passing through an electrochemical storage. Fig. 1 presents the synoptic scheme of the studied system.

3. Hybrid system model

Modeling is an essential step before any optimal sizing phase. The studied hybrid system is composed of three energy sources namely: wind turbine, PV generator and batteries as shown above (Fig. 1). The modeling of each component is detailed below.

3.1. PV generator model

The output power delivered by the PV module depends on the module temperature, T_{cell} and the irradiance incident on the module plane, G_β (Huld et al., 2010):

$$P(G_\beta, T_{cell}) = P_{STC}\frac{G_\beta}{G_{STC}}\eta_{rel}(G', T') \tag{1}$$

With P_{STC} is the power module at the standard test conditions (STC) and η_{rel} is the instantaneous relative efficiency given by:

$$\eta_{rel}(G', T') = 1 + k_1 \log G' + k_2[\log G']^2 + T'(k_3 + k_4 \log G' + k_5[\log G']^2) + k_6 T' \tag{2}$$

where G' and T' are normalized parameters with respect to the standard conditions, defined by:

$$\mathrm{G}' = \left(\frac{G_\beta}{\mathrm{G_{STC}}}\right) \tag{3}$$

And

$$\mathrm{T}' = (\mathrm{T}_{cell} - \mathrm{T}_{STC}) \tag{4}$$

The coefficients k_1-k_6 must be found by fitting the model to the experimental data measured in one or more test sites.

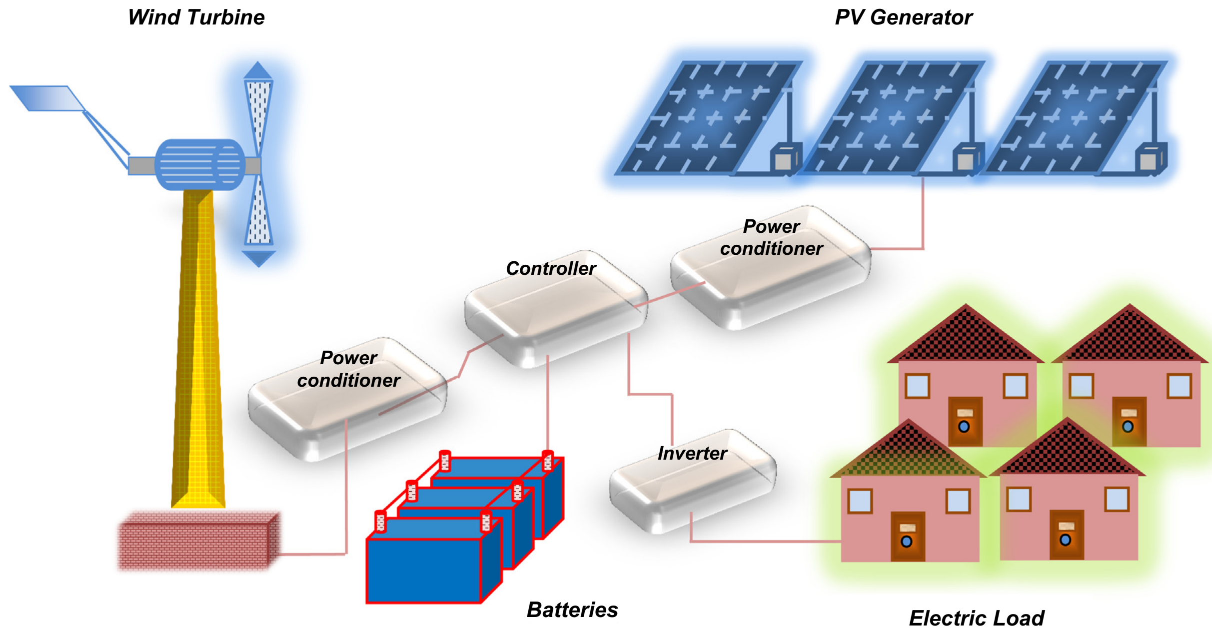

Fig. 1. Schematic diagram of grid-independent hybrid PV/wind/system with battery storage.

T_c in Eq. (5) is given by Tahani et al. (2015) and Xydis (2013):

$$T_{cell} = T_{amb} + [(NOCT - 20)/800]G_\beta \tag{5}$$

where T_{amb} is the ambient temperature (°C) and $NOCT$ is the nominal cell operating temperature (°C).

3.2. Wind turbine model

The output power of a wind turbine $P_{out}(v)$ at different wind speeds is formulated as follows (Kaabeche et al., 2011).

$$P_{out}(v) = \begin{cases} a v^k + b, & v_C \leqslant v \leqslant v_R \\ P_R, & v_R \leqslant v \leqslant v_F \\ 0, & Otherwise \end{cases} \tag{6}$$

where P_R is the rated power; k is Weibull shape factor; v_C is the cut-in speed; v_R is the rated speed; and v_F is the cut-off speed. Constants a and b may be found through the subsequent formulas:

$$a = \frac{P_R}{(v_R^k - v_C^k)} \tag{7}$$

$$b = \frac{P_R v_c^k}{\left(v_c^k - V_R^k\right)} \tag{8}$$

P_{out} (v) at a given site depends essentially on wind speed at hub height and speed characteristics of the turbine (Fig. 2). Wind speed at hub height can be calculated by using power-law equation (Soheyli et al., 2016; Wen et al., 2009):

$$V_{mes} = V_{est}\left(\frac{h_{hub}}{h_{ref}}\right)^{\alpha} \tag{9}$$

where V_{mes} and V_{est} are the measured and estimated wind speeds at the reference height, h_{ref} and hub height, h_{hub} respectively. α is a coefficient which depends on the considered ground roughness.

3.3. Battery bank model

The charge and discharge of the energy stored in the battery bank depends on the difference between the energy produced by the renewable sources and the energy consumed by the load. During charging, the battery state of charge can be calculated as follows (Singh et al., 2016):

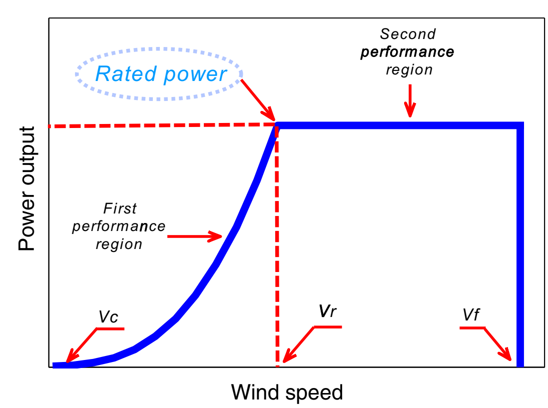

Fig. 2. A typical wind turbine output characteristics.

$$E_{Bat}(t) = E_{Bat}(t-1) + [E_{Prod}(t) - E_{Load}(t)/\eta_{inv}] \cdot \eta_{Bat} \tag{10}$$

In the discharge phase, it is given by Singh et al. (2016):

$$E_{Bat}(t) = E_{Bat}(t-1) - [E_{Load}(t)/\eta_{inv} - E_{Prod}(t)] \tag{11}$$

where $E_{Bat}(t)$ and $E_{Bat}(t-1)$ are the energy stored in battery bank (W h) at hour t and t − 1, respectively; $E_{Prod}(t)$ is the overall energy produced by PV and wind turbine generators; $E_{Load}(t)$ is load demand at the time t; η_{inv} and η_B are the efficiency of inverter and charge efficiency of battery bank, respectively.

4. Formulation of optimization problem

4.1. Objective function

In this study, the objective function of the optimum design problem is the minimization of the Electricity Cost (EC). EC is defined as the sum of the discounted costs of energy production divided by the amount of energy consumed. To optimally design the hybrid system, the optimization problem described by Eq. (12), should be resolved using an advanced optimization algorithm.

$$Minimise\ EC\ (\$/\text{kW h}) = \frac{LCC \times CRF}{\sum_{t=1}^{8760} E_{Load}(t)} \quad (12)$$

where *LCC* is the life cycle cost and *CRF* is the capital recovery factor given by Baneshi and Hadianfard (2016) and Nacer et al. (2016):

$$CRF(d, L_S) = \frac{d(1+d)^{L_S}}{(1+d)^{L_S} - 1} \quad (13)$$

In which d is the interest rate and L_S is the system lifespan in years (25 years).

The *LCC* can be expressed as follows:

$$LCC\ (\$) = C_{Init} + C_{main} + C_{rep} \quad (14)$$

where C_{Init} is the initial cost of the system components (incorporating costs of civil work, installation and connections), and C_{main} and C_{Rep} are maintenance and replacement costs respectively. These two costs are recurrent throughout the system life cycle. They require discounted over time. The cumulative cost of replacement is calculated as follows (Messenger and Ventre, 2010):

$$C_{rep} = P_{wor,fact} \times C_{acq} \quad (15)$$

where C_{acq} is the component acquisition cost and $P_{wor,fact}$ represents the present worth factor of this cost if the component would be purchased n years later. This factor is given by Messenger and Ventre (2010):

$$P_{wor,fact} = \left[\frac{1+i}{1+r}\right]^n = X^n \quad (16)$$

With

$$X = \left[\frac{1+i}{1+r}\right] \quad (17)$$

i represents the inflation rate which is a measure of the lasting decline in the value of money. r is the discount rate per year; this is the percentage return on investment (remuneration for advanced capital) and n represents the number of years from now on.

The cumulative cost of maintenance is obtained as follows:

$$C_{main} = (C_{m0}) \times \left[\frac{1-X^n}{1-X}\right] \times (X) \quad (18)$$

where C_{m0} is the maintenance cost in the first year. This cost is expressed as a fraction of the component cost.

4.2. Constraints

The constraints considered in this studied hybrid system are as follows:

– The minimum and maximum number of system components.

$$N_i^{Min} \leqslant N_i \leqslant N_i^{Max} \quad (19)$$

where N_i is the number of component i, N_i^{Min} and N_i^{Max} are the minimum and maximum number of the component i, respectively. N_i^{Min} is considered equal to zero in this study.

– The minimum and maximum energy stored in the battery bank.

$$E_{Bat,Min} \leqslant E_{Bat}(t) \leqslant E_{Bat,Max} \quad (20)$$

$E_{Bat,Max}$ and $E_{Bat,Min}$ being the maximum and minimum storage energies allowed.

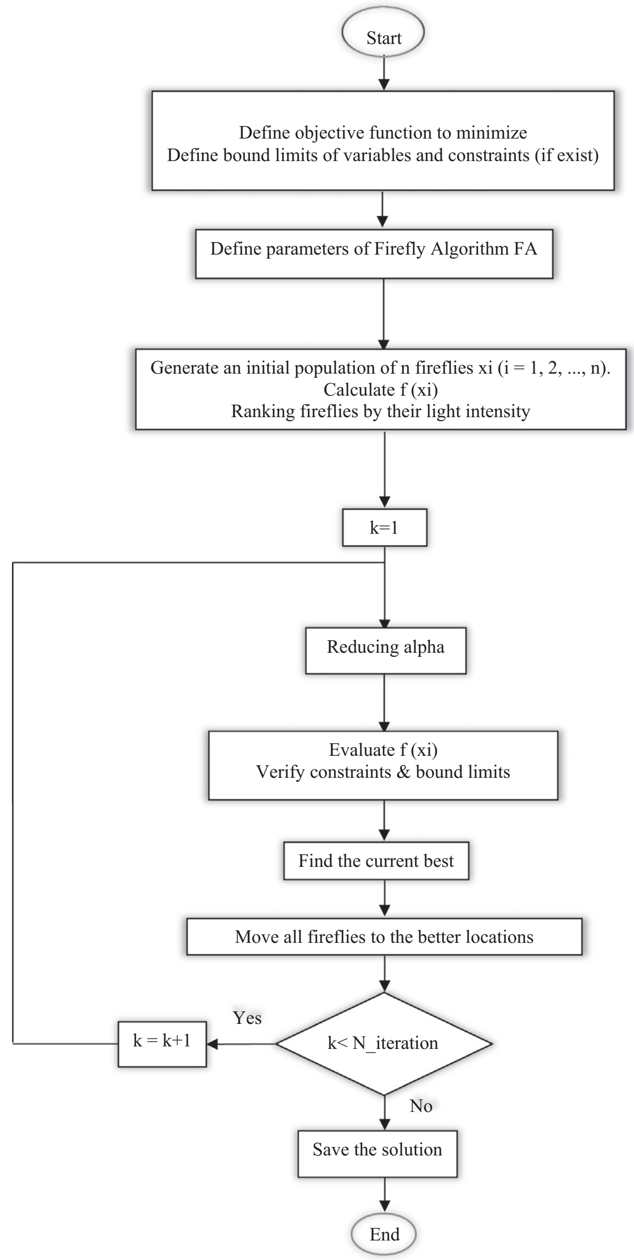

Fig. 3. Flowchart of firefly algorithm for hybrid system optimization.

– In the design process of hybrid systems, reliability of power supply system is considered a primary criterion. In our study, the system reliability is expressed in terms of Load Dissatisfaction Rate LDR (%). The LDR varies between 0 % (total load satisfaction) and 100 % (total load shedding). Thus, LDR is defined by the ensuing equation:

$$LDR = \frac{\sum_{t=1}^{T}(E_{Load}(t) - E_{Supp}(t))}{\sum_{t=1}^{T} E_{Load}(t)} (\%) \quad (21)$$

where $E_{Load}(t)$ is the required energy at hour t, T is the period analysis of the system, and $E_{Supp}(t)$ is the hourly energy actually provided to the user. $E_{Supp}(t)$ is given by the subsequent expression:

$$E_{Supp}(t) = [E_{Prod}(t) + E_{Bat}(t-1) - E_{Bat,Min}]\eta_{inv} \quad (22)$$

Table 1
Technical and economic parameters values used for the studied hybrid energy system (Kaabeche and Ibtiouen, 2014).

Description	Data
Financial parameters	
Interest rate d (%)	8
Inflation rate i (%)	4
Discount rate r (%)	4
Specifications of the PV module	
Type	BP 3160
P_{max}	160 W
Unit Price (US$/W)	2.29 (US$/W)
Maintenance cost in the first year (%)	1% of price
Life time (year)	25
Specifications of the wind turbine	
Type	Bergey BWC XL1
Rated power	1 kW
Unit Price (US$/W)	3 (US$/W)
Maintenance cost in the first year (%)	3% of price
Life time (year)	20
Specifications of the single battery	
Type	Fiamm FG 2M009
Nominal capacity	200 Ah
Minimum state of charge (%)	50%
Round-trip efficiency (%)	85%
Unit Price (US$/W h)	0.213 (US$/W h)
Maintenance cost in the first year (%)	3% of price
Life time (year)	4
Specifications of the inverter	
Unit Price (US$/W)	0.711 (US$/W)
Maintenance cost in the first year (%)	0%
Life time (year)	10
Efficiency (%)	90%

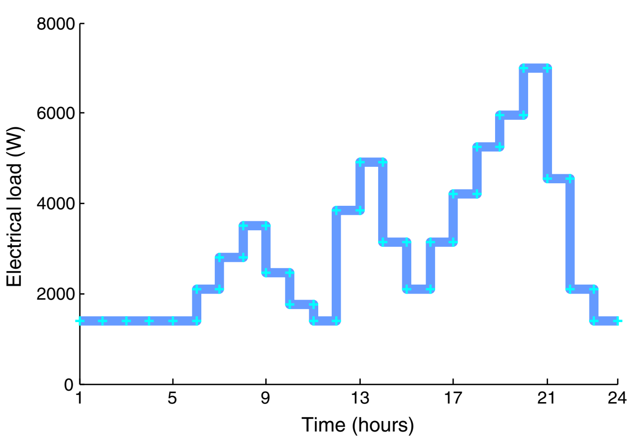

Fig. 4. Hourly load profile.

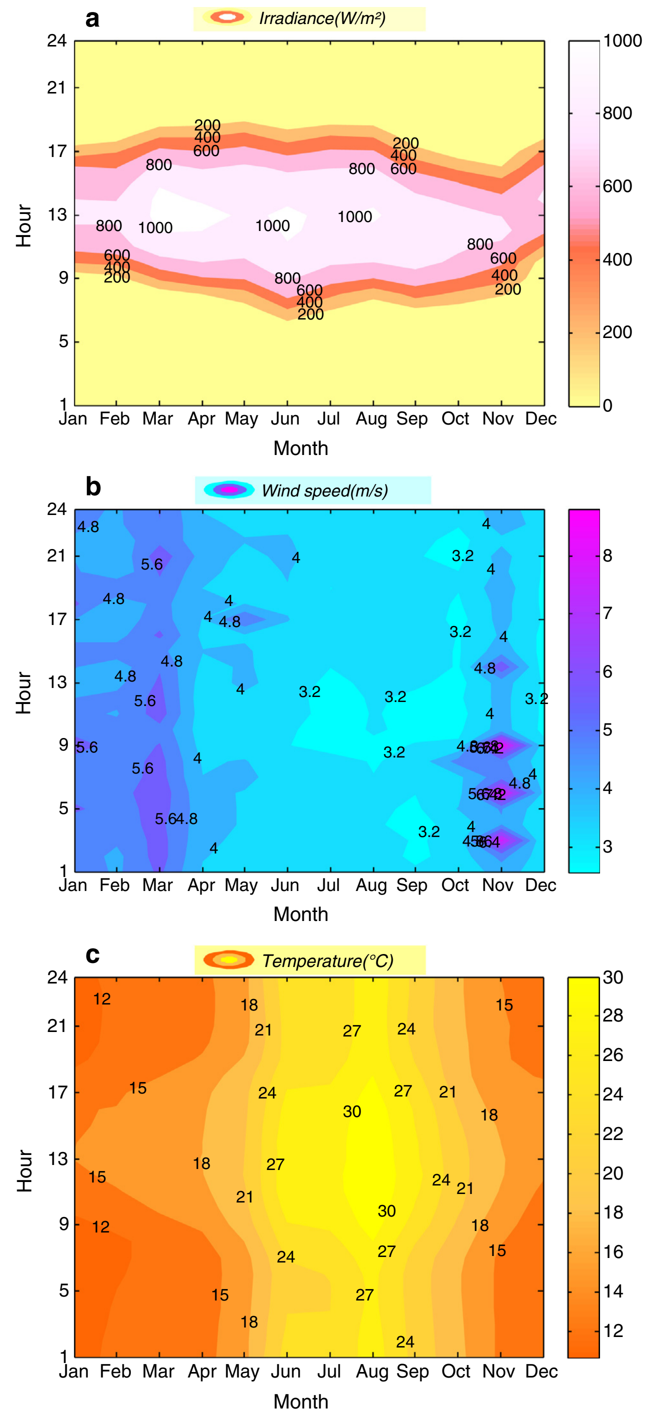

Fig. 5. Meteorological conditions for optimal design. (a) Solar irradiation on horizontal plane, (b) wind speed and (c) Ambient temperature.

To highlight the relevance of reliability criterion represented by the LDR, the following constraint is taken into consideration during the optimization process:

$$LDR \leqslant LDR_{Desired} \tag{23}$$

where $LDR_{Desired}$ is the maximum admissible LDR, which is specified by the user.

5. Methodology

As the optimal sizing problem is formulated as a constrained nonlinear optimization problem, Firefly-inspired metaheuristic algorithm is utilized in this paper to solve the objective optimization problem and its performance is compared with other well-known optimization algorithms like Accelerated Particle Swarm Optimization (APSO) algorithm, Generalized Evolutionary Walk Algorithm (GEWA), and Bat algorithm (BA).

5.1. Firefly algorithm

Firefly Algorithm (FA) is a metaheuristic algorithm for global optimization proposed by Xin-She Yang in late 2007/early 2008 (Yang, 2010a, 2010b). The FA was inspired by the flashing of fireflies in nature. There are thousands of species of fireflies, the majority of which generate bioluminescence of their abdomen (Lewis and Cratsley, 2008). Each species of firefly produces its

Table 2
The results of optimal sizing problem obtained by Firefly (FA) algorithm for various reliability levels.

Hybrid system	$LDR_{Desired}$ (%)	N_{PV}	N_{WT}	N_{BAT}	EC ($/kW h)
PV/wind/battery	0	232	7	92	**1.8306**
	0.01	242	4	82	**1.6480**
	1	221	6	43	**1.1666**
PV/battery	0	250	0	107	**2.9728**
	0.1	250	0	95	**2.6172**
	1	280	0	48	**1.9562**
Wind/battery	0	0	163	428	**10.3882**
	0.1	0	163	404	**9.9325**
	1	0	163	428	**8.1862**

Table 3
Comparison of the results obtained by the algorithms for $LDR_{Desired}$ (%) = 0%.

$LDR_{Desired}$ = 0%											
Hybrid system	Algorithm	Mean	Std.	Best				Worst			
				N_{PV}	N_{WT}	N_{BAT}	EC ($/kW h)	N_{PV}	N_{WT}	N_{BAT}	EC ($/kW h)
PV/wind/battery	FA	**1.8760**	**0.0341**	232	7	92	**1.8306**	347	17	70	**2.0207**
	APSO	1.9821	0.1083	232	7	92	**1.8306**	377	42	46	2.4018
	GEWA	2.0165	0.1151	233	7	92	1.8366	350	41	56	2.4520
	BAT	2.0562	0.1331	238	7	92	1.8479	142	17	145	2.5806
PV/battery	FA	**2.1167**	**0.1652**	250	0	107	**1.8781**	851	0	104	**2.9728**
	APSO	2.7634	0.6253	250	0	107	**1.8781**	1076	0	339	**2.6172**
	GEWA	2.3231	0.4085	250	0	107	1.8838	1314	0	104	3.8453
	BAT	2.6102	0.5523	250	0	107	1.8951	133	0	350	4.7234
Wind/battery	FA	**9.6619**	**0.1357**	0	163	428	**9.5471**	0	102	616	**10.3882**
	APSO	11.2949	1.5659	0	163	428	**9.5471**	0	324	751	17.6622
	GEWA	10.2179	0.7703	0	163	428	**9.5471**	0	56	1117	15.5546
	BAT	10.8460	1.0449	0	164	429	9.5848	0	502	349	17.0572

Table 4
Comparison of the results obtained by the algorithms for $LDR_{Desired}$ (%) = 0.1%.

$LDR_{Desired}$ = 0.1%											
Hybrid system	Algorithm	Mean	Std.	*Best*				*Worst*			
				N_{PV}	N_{WT}	N_{BAT}	EC ($/kW h)	N_{PV}	N_{WT}	N_{BAT}	EC ($/kW h)
PV/wind/battery	FA	**1.6741**	**0.0217**	242	4	82	**1.6480**	346	16	52	**1.7666**
	APSO	1.7901	0.1087	250	4	81	1.6505	132	14	141	2.4360
	GEWA	1.7842	0.0958	242	4	82	**1.6480**	223	0	138	2.2183
	BAT	1.8332	0.1135	243	4	83	1.6625	167	20	114	2.3119
PV/battery	FA	**1.9792**	**0.1763**	250	0	95	**1.7267**	756	0	90	**2.6172**
	APSO	2.6064	0.6441	248	0	96	1.7356	1076	0	339	6.3617
	GEWA	2.1628	0.4098	250	0	95	**1.7267**	1365	0	89	3.7522
	BAT	2.4234	0.5202	248	0	97	1.7482	1408	0	125	4.2874
Wind/battery	FA	**9.3607**	**0.1286**	0	163	404	**9.2443**	0	113	558	**9.9325**
	APSO	11.0504	1.6271	0	163	404	**9.2443**	0	324	751	17.6622
	GEWA	9.9217	0.8122	0	163	404	**9.2443**	0	56	1117	15.5546
	BAT	10.5133	1.1611	0	162	409	9.2823	0	60	1271	17.5979

Table 5
Comparison of the results obtained by the algorithms for $LDR_{Desired}$ (%) = 1%.

$LDR_{Desired}$ = 1%											
Hybrid system	Algorithm	Mean	Std.	*Best*				*Worst*			
				N_{PV}	N_{WT}	N_{BAT}	EC ($/kW h)	N_{PV}	N_{WT}	N_{BAT}	EC ($/kW h)
PV/wind/battery	FA	**1.1725**	**0.0103**	221	6	43	**1.1666**	166	19	39	1.3387
	APSO	1.2957	0.1266	221	6	43	**1.1666**	424	27	32	1.9373
	GEWA	1.2846	0.1102	222	6	43	1.1685	115	5	126	1.9889
	BAT	1.3290	0.1309	247	4	44	1.1780	500	18	42	1.9809
PV/battery	FA	**1.3457**	**0.1487**	280	0	48	**1.1903**	740	0	40	**1.9562**
	APSO	2.0465	0.6529	280	0	48	**1.1903**	982	0	276	5.3897
	GEWA	1.4737	0.3204	280	0	48	**1.1903**	1223	0	41	2.8790
	BAT	1.7840	0.5012	298	0	46	1.1990	1294	0	77	3.4670
Wind/battery	FA	**6.9441**	**0.1314**	0	140	260	**6.8504**	0	60	525	**8.1862**
	APSO	8.9707	1.8471	0	139	262	6.8505	0	556	232	16.9361
	GEWA	7.4712	0.6753	0	141	259	6.8629	0	462	127	13.2526
	BAT	8.3350	1.2739	0	140	260	**6.8505**	0	568	130	15.9504

own model of flashes. For many species, the male is attracted to a sedentary female. In other species, the female can copy the signal of a different species, so that the males of this species are attracted to it. The flashing can also be used to send information between fireflies. The idea of this attractiveness and passing information is what leads to inspiration for the FA. The FA idealizes many aspects of firefly in nature. First, real fireflies flash in discrete patterns, whereas the modeled fireflies will be treated as always glowing. Then, three rules can be applied to manage the algorithm and develop a modeled firefly behavior (Yang, 2009).

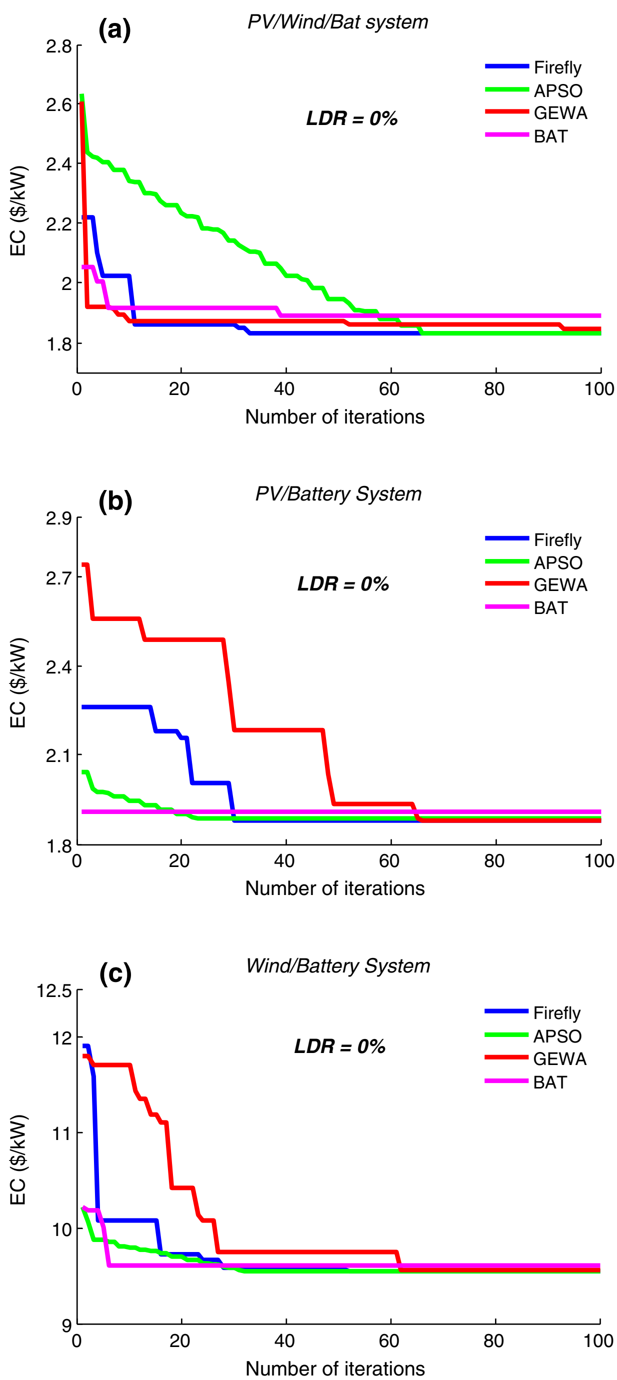

Fig. 6. Convergence process of the algorithms for finding the optimum size of the (a) PV/wind/Batt; (b) PV/Batt system; (c) Wind/Batt hybrid systems.

1. All fireflies are unisexual, therefore positively attracted to each other.
2. The attractiveness is proportional to the brightness and both decrease when their distance increases. Thus, for any two flashing fireflies, the less brighter one will move to the brighter one. If there is no other brighter source, the firefly will move at random.
3. The firefly brightness is influenced by the objective function topology.

The light intensity varies exponentially with distance as follow:

$$I(r) = I_0 e^{-\Upsilon r} \tag{24}$$

where $I(r)$ is the light intensity; r is distance between two flies; I_0 is the initial light intensity; Υ is light absorption coefficient.

As a firefly's attractiveness is proportional to the light intensity seen by adjacent fireflies, we can now define the variation of attractiveness β with the distance r by:

$$\beta(r) = \beta_0 e^{-\Upsilon r^2} \tag{25}$$

where β_0 is the initial attractiveness at r = 0.

The distance between any two fireflies i and j at x_i and x_j respectively, is given by the Euclidean distance equation,

$$r_{ij} = ||x_i - x_j|| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{26}$$

where $x_{i,k}$ is the kth component of the spatial coordinate x_i of ith firefly.

The movement of a firefly i is attracted to another, more attractive firefly j as determined by:

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\Upsilon r^2}(x_j^t - x_i^t) + \propto_t \epsilon_i^t \tag{27}$$

Where the second term is due to the attraction. The third term is randomization with α_t being the randomization parameter, and ϵ_i^t is a vector of random numbers drawn from a Gaussian or other distribution at time t.

5.2. Application of the firefly algorithm (FA) for optimal sizing problem

In this article, a Firefly-inspired metaheuristic algorithm is applied to solve the objective optimization problem, particularly in finding the optimal sizing of the recommended hybrid system. The control variables, in this study are: the number of PV modules, wind turbines and batteries. Thus, the use of FA for this application type can be described in the following steps:

Step 1: 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 irradiation, ambient temperature and wind speed in the considered region, the rated power and efficiency of system components, the number of fireflies (n), the randomness factor (α), the initial attractiveness of a firefly (β_0), the light absorption coefficient of medium (Υ), and the iterations number.
Step 2: Generate initial population of fireflies placed at random positions within the n-dimensional search space, xi. Define the light absorption coefficient, Υ.
Step 3: Define the light intensity of each firefly, I_i, as the value of the cost function for x_i.
Step 4: For each firefly, x_i, compare its light intensity, I_i, with the light intensity, I_j, of every other firefly, x_j.
Step 5: If I_i is less than I_j, then move firefly x_i towards x_j in n-dimensions using Eq. (27).

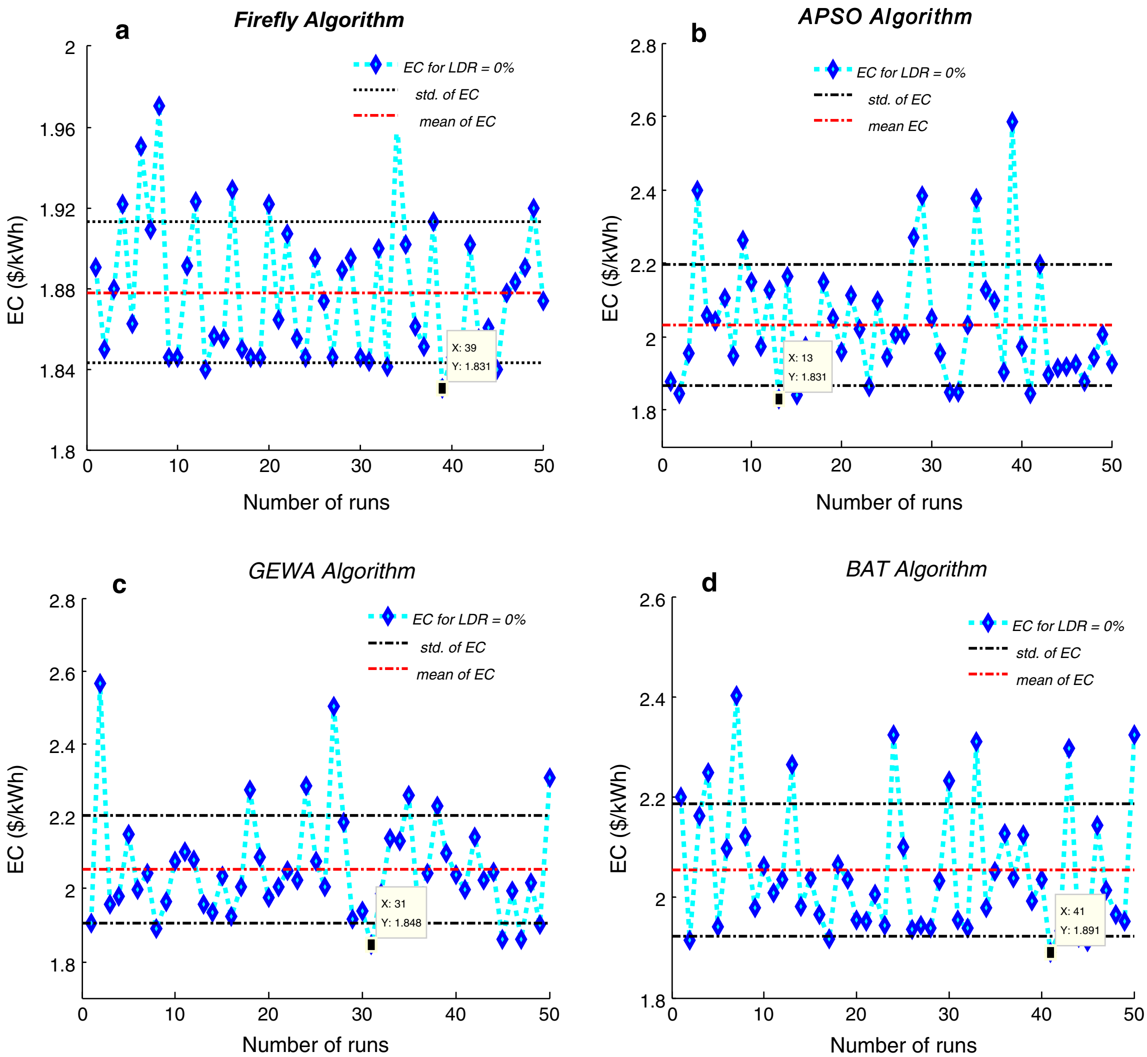

Fig. 7. Evolution of EC obtained via metaheuristic algorithms for the hybrid PV/wind system after 50 runs (a) applying FA algorithm; (b) applying APSO algorithm; (c) applying GEWA algorithm; (d) applying BAT algorithm.

Step 6: Calculate the new values for the cost function for each fly, x_i, and update the Light Intensity, I_i.
Step 7: Rank the fireflies and determine the current 'best'.
Step 8: Repeat steps 3 to 7 until definite termination conditions are met, such as a pre-defined number of iterations or a failure to make progress for a fixed number of iterations.

Finally, the suggested algorithm is reached the optimal number of the hybrid system components and the Electricity Cost (EC) of the corresponding system. The flowchart for firefly algorithm in hybrid system optimization is presented in Fig. 3.

6. Results and discussion

6.1. Case study

In order to highlight the recommended method, a case study is lead to scrutinize a PV/wind hybrid system, which is designed to supply a group of twenty households, located in Bouzaréah, Algeria (36°48′N, 3°1′E, 345 m). The considered hybrid system components include PV subsystem, wind power subsystem, a power conditioning unit and battery bank storage, whose the technical and economic specifications are itemized in Table 1. The average hourly load demand considered in this study is presented in Fig. 4. Hourly data of solar radiation on horizontal surface, wind velocity as well as ambient temperature recorded at Bouzaréah (Algeria) for the year 2012 are used in system optimal sizing. Fig. 5 shows the meteorological conditions for the considered site. MATLAB software is used to implement and execute the nature-inspired metaheuristic algorithms. To effectively compare performance of proposed algorithm with those of APSO, GEWA and BA algorithms, fifty independent runs are executed and the results are presented. The suggested algorithm parameters are adjusted as follows:

FA: population size (N) = 40, $\alpha = 0.5$, $\beta = 0.2$, $\gamma = 1$, maximum iteration number = 100.
APSO: population size (N) = 40, $\beta = 0.8$, $\gamma = 0.99$, maximum iteration number = 100.
GEWA: population size (N) = 40, $\alpha = 0.5$, maximum iteration number = 100.
BAT: population size (N) = 40, $Q_{min} = 0$, $Q_{max} = 2$, A = 0.25, r = 0.75, maximum iteration number = 100.

In this study, the minimum and maximum control variables bounds are set to 0 and 400 respectively for the PV modules and

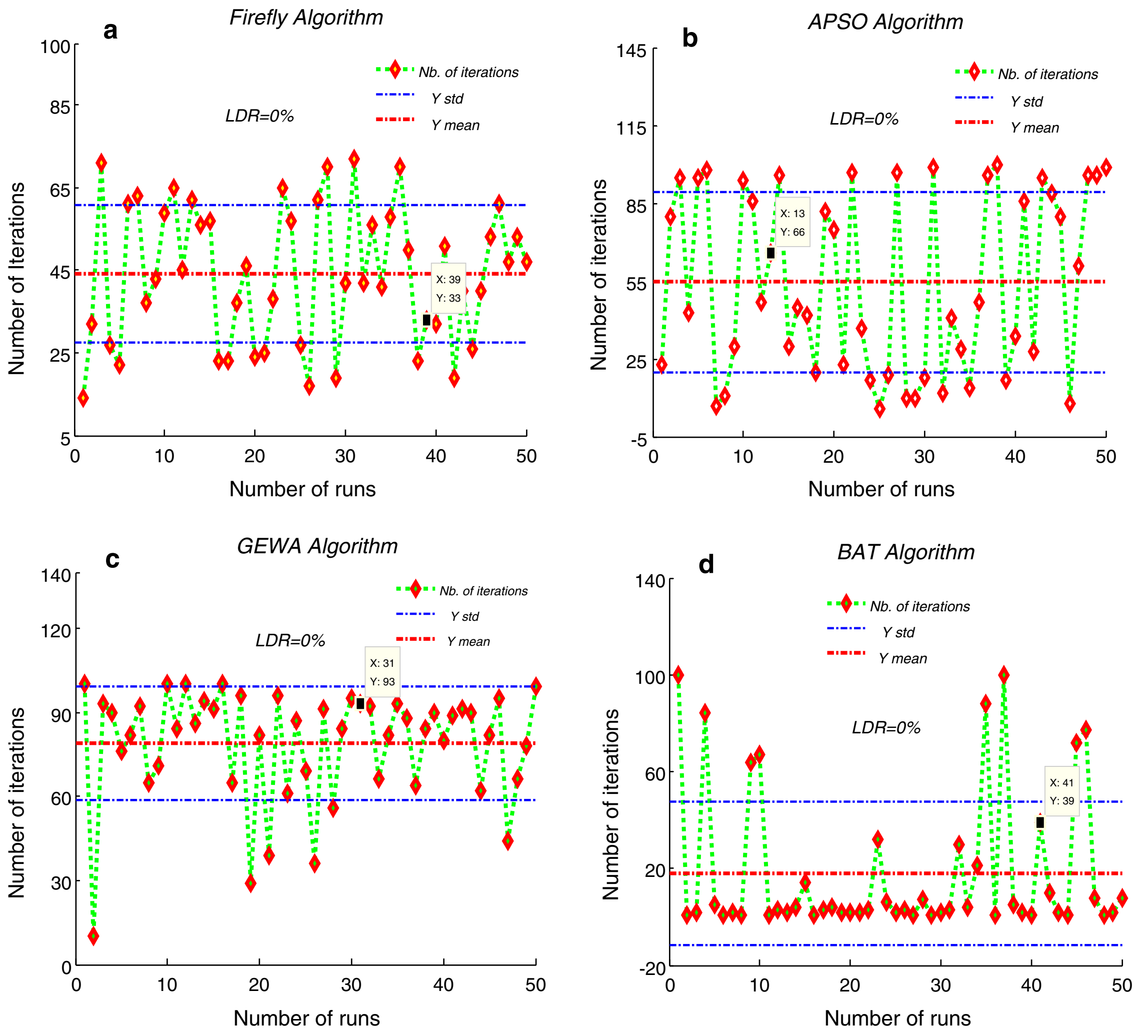

Fig. 8. Variation of iterations number vs. number of runs for the studied hybrid system (a) applying FA algorithm; (b) applying APSO algorithm; (c) applying GEWA algorithm; (d) applying BAT algorithm.

wind turbines and set to 0 and 900 respectively for the battery banks. To perform the simulation, different configurations are considered such as:

– Photovoltaic system only with batteries.
– Wind system only with batteries.
– Hybrid PV/wind system with batteries.

In each case study, the simulation is performed for three different values of LDR (0%, 0.001% and 0.01%). Table 2 indicates the results of optimal sizing problem which obtained by Firefly (FA) algorithm. The number of PV panels, wind turbines, battery banks and Electricity Cost (EC) are presented in this table. As can be seen, the hybrid PV/wind/battery system is the most cost-effective hybrid system for different LDR (%). In addition, the single-source PV/Battery system has lower cost than single-source Wind/Battery system. Simulation results also show that reduction of LDR (%) and reliability improvement leads to increase the system costs. For the hybrid PV/wind/battery system and LDR (%) = 0%, Electricity Cost is obtained 1.8306 $ which is more than EC for LDR (%) = 0.1% (1.6480 $) and LDR (%) = 1% (1.1666 $).

Simulation results for optimal sizing problem obtained by FA, APSO, GEWA and BA algorithms are presented in Tables 3–5. In these tables, the mean (Mean), standard deviation (Std.), worst (Worst) and best (Best) indexes of each algorithm for each configuration and with various reliability levels are given. The indexes have been reported over 50 runs. With comparison of the different indexes, it can be concluded that FA algorithm yields better result than the other algorithms in all cases. In addition, APSO algorithm is better than GEWA and BA algorithms. The low values of FA's Std. show the robustness of this algorithm. Std. index for BA algorithm has higher values than FA and this algorithm cannot find the best solution in most trials.

For example, for the hybrid PV/wind/battery system and LDR (%) = 0%, the mean and standard deviation values of EC obtained by FA over 50 runs are 1.8760 ($/kW h) and 0.0341, respectively. Therefore, FA in all cases can find the best solution. On the other hand, APSO give 1.9821 ($/kW h) and 0.1083, GEWA give 2.0165 ($/kW h) and 0.1151, and BA give 2.0562 and 0.1331. According to these results, APSO and GEWA could not find the best solution in some cases and BA did not give any satisfactory result.

Fig. 6 shows the convergence process of algorithms for finding the optimum design for the hybrid, PV/Wind/Battery, PV/Battery and Wind/Battery systems for LDR = 0%. In this figure, the minimum EC (corresponding to the best performance) during the iterations has been shown. As the figure shows, during the iterations, the EC decreases. This means that the optimization technique reduces the energy cost by moving toward the optimum

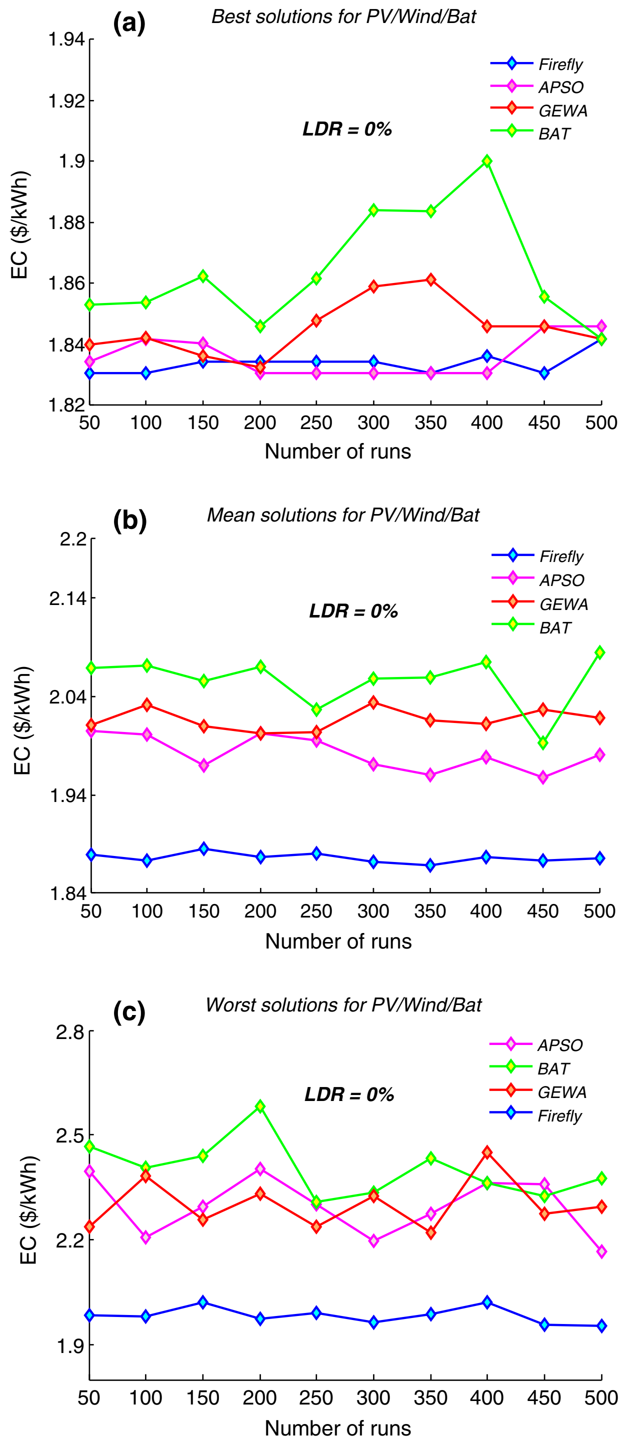

Fig. 9. Evolution of EC obtained via the methods after several runs for sizing of PV/wind hybrid energy system (a) Case of best solutions; (b) Case of mean solutions; (c) Case of worst solutions.

size. For such system, there is no information about the optimum size. Therefore, any reduction of the cost function is significant because it leads to having more knowledge about the optimal sizing. It is also shown that FA converges to the optimal solution more quickly than APSO, GEWA and BA.

Fig. 7 presents the evolution of EC obtained via metaheuristic algorithms for the hybrid PV/wind system after 50 runs. Fig. 7a presents the different performance indexes obtained by FA algorithm. The best solution value which is 1.831($/kW h) is obtained after 39 runs. The mean value and the standard deviation for EC are 1.8760 ($/kW h) and 0.0341, respectively. The same performance indexes obtained by APSO algorithm have been presented in Fig. 7b, with a best solution of 1.831 ($/kW h) obtained in 13 runs. The mean value and the standard deviation are 1.9821 ($/kW h) and 0.1083 respectively. Fig. 7c displays the same performance indexes given by GEWA algorithm with a best solution value of 1.848 ($/kW h) obtained after 31 runs. The corresponding mean value and the standard deviation are 2.0165 ($/kW h) and 0.1151 respectively. The similar performance indicators obtained by BAT algorithm are shown in Fig. 6d, with a best solution of 1.891 ($/kW h) obtained after 41 runs. The mean value and the standard deviation are 2.0165 ($/kW h) and 0.1151 respectively. These results validate further the overall superiority of the FA algorithm performances compared to the APSO, GEWA and BAT algorithms.

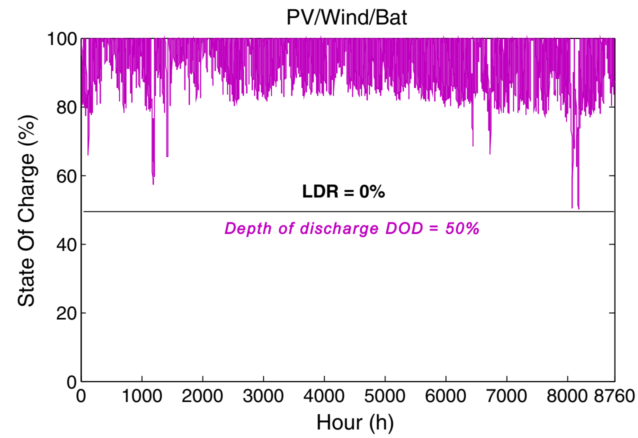

Fig. 10. Hourly variation of the SOC of battery bank for optimal hybrid PV/wind system (LDR = 0%).

Fig. 8 presents the variation of iteration number vs. run number for the studied hybrid system and LDR = 0%. Fig. 8a illustrates this variation in applying Firefly algorithm. It can be seen from this figure that the best solution (EC = 1.831 $/kW h for LDR = 0%) is obtained after 33 iterations and 39 runs. The same optimal value (EC = 1.831 $/kW h) has been obtained with APSO algorithm after 66 iterations and 13 runs (Fig. 8b). Otherwise, GEWA and BAT algorithms cannot find the best solution. Thus, the solution found by GEWA is 1.848 $/kW h after 93 iterations and 31 runs, while the one obtained by BAT is 1.891 $/kW h after 39 iterations and 41 runs.

Fig. 9 presents the evolution of EC obtained via the different algorithms after several runs for sizing of PV/wind hybrid energy system for the year concerned. It can be seen that the lowest values of the EC relatively to the three indexes (Best, Mean and Worst solutions) presented in Fig. 9a, b and c are obtained with FA. On the other hand, the highest values of EC are obtained with the BAT algorithm. These simulation results show that FA can find the optimal solution with high accuracy and it has the best performance compared to the three others algorithms. It sustains also, that FA is very effective in dealing with multimodal, highly nonlinear problems.

Based on the 1-year simulation data, Fig. 10 describes the hourly state of charge (SOC) variations of battery bank for optimal configuration of hybrid power generation system and for high reliability level (LDR = 0%). Generally speaking, the seasonal changes of the battery SOC are well marked. It can be seen that the maximum depth of discharge is approximately 49.4%, thus indicating the system capability to supply reliably the consumer load. As seen also in Fig. 10, the lower limit of SOC is achieved mainly in

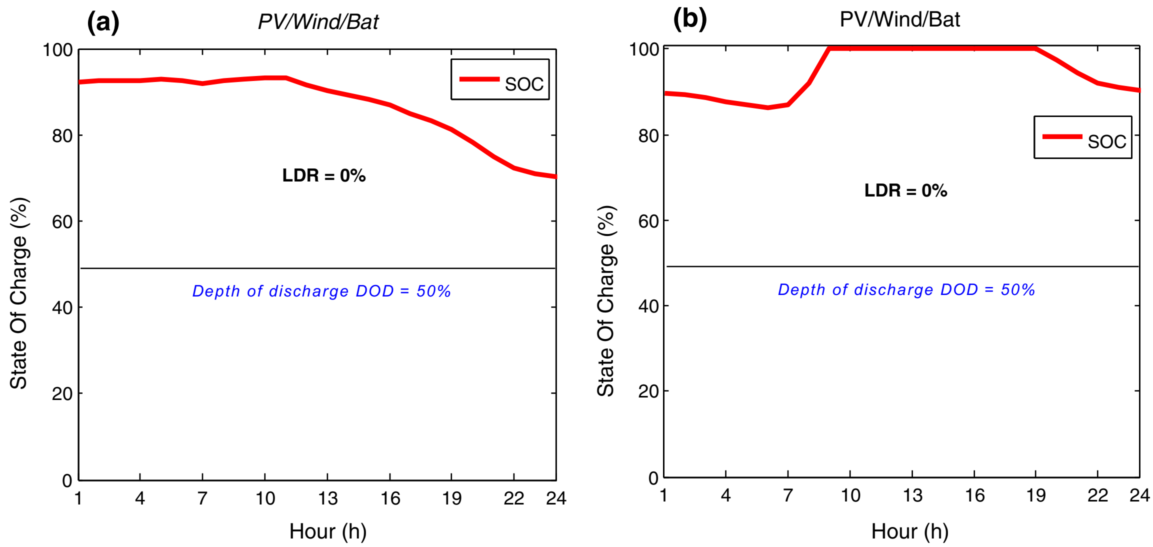

Fig. 11. Hourly variation of the SOC of battery bank for optimal hybrid PV/wind system in a day (a) case of theleast-sunny day of the year; (b) case of the sunniest day of the year.

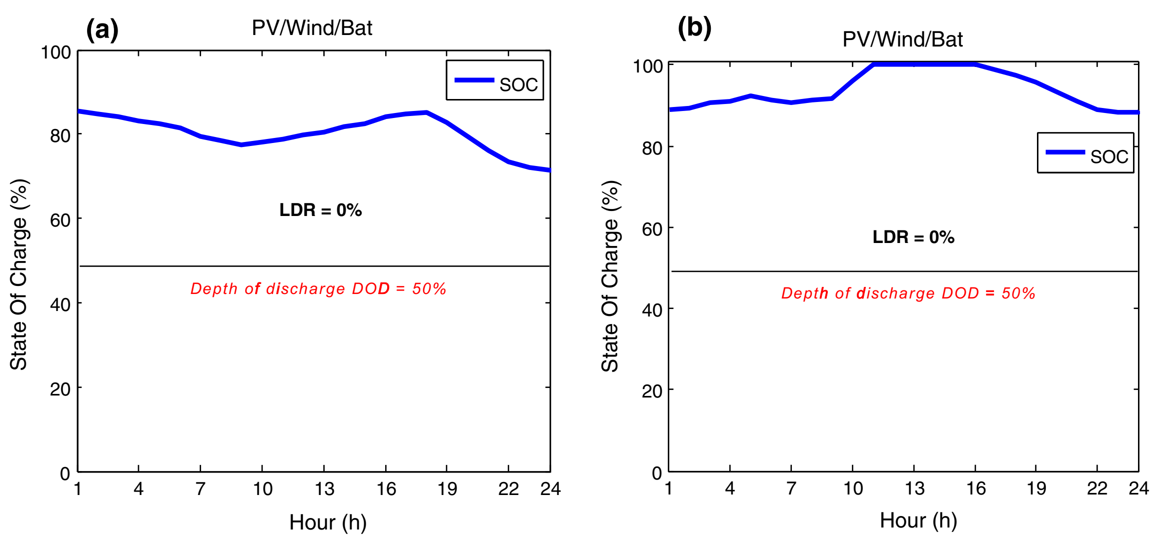

Fig. 12. Hourly variation of the SOC of battery bank for optimal hybrid PV/wind system in a day (a) case of the least-windy day of the year; (b) case of the windiest day of the year.

February (between 1197 h and 1238 h) and in December (between 8054 h and 8176 h), which perfectly meets the objective set in the management and control strategy of the battery.

Fig. 11 shows the hourly variation of the state of charge (SOC) of battery bank for optimal hybrid PV/wind system during a day. Fig. 11a illustrates this variation for the least-sunny day of the year. It can be seen that SOC between 01am and 11am is almost constant with a SOC of 93%, and it decreases to 70% at midnight. Otherwise, the variation of the SOC for the sunniest day of the year is illustrated in Fig. 11b. A clear feature is that SOC increases between 7 am and 9 am to reach 100%, and it remains full up to 07 pm. This increase of observed battery state of charge (SOC) corresponds well to the daytime period when solar radiation is available.

In Fig. 12, the hourly SOC variation for optimal hybrid PV/wind system during a day has been presented. Fig. 12a illustrates this variation for the least-windy day of the year. It can be seen that the state of charge oscillates between 72% and 87% with low charging and discharging phases during the day and this, according to the energy balance involved in the system. Moreover, Fig. 12b illustrates the variation of the SOC for the windiest day of the year. It can be seen that the SOC reaches the maximum state of charge (100%) between 11am and 04 pm and varies during the rest of the day, depending on production and consumption conditions (According to the wind speed evolution and load demand level).

7. Conclusions

This paper proposes a PV/wind hybrid optimization method, which employs one of the most recent Nature Inspired Algorithm (NIA), called Firefly Algorithm (FA), considering the Load Dissatisfaction Rate (LDR) criteria and the Electricity Cost (EC) indicator for power reliability and system cost. The recommended method determines the system optimum configuration, which can attain the desired LDR with minimum EC. For this purpose, an objective function is formulated for the EC. It must be kept to a minimum while respecting the reliability constraints ($LDR_{desired}$). The effectiveness of Firefly algorithm (FA) in solving hybrid system design problem is scrutinized and its performance is compared to other well-known optimization algorithms such as Accelerated Particle Swarm Optimization (APSO) algorithm, Generalized Evolutionary Walk Algorithm (GEWA) and Bat Algorithm (BA).

In order to highlight the recommended method, a case study is lead to scrutinize a PV/wind hybrid system, which is designed to supply a group of twenty households located in Bouzaréah, Algeria (36°48′N, 3°1′E, 345 m). The algorithm input data set consists of hourly solar radiation on the horizontal surface, wind velocity, ambient temperature recorded at Bouzaréah for the 2012 year, the energy requirements expressed by the load throughout the year and the specifications of the system devices.

The PV/wind hybrid system is simulated by running the developed computer program. Fifty independent runs are executed and the results are presented. From the optimization viewpoint, it is found that Firefly algorithm (FA) yields more promising results than Accelerated Particle Swarm Optimization (APSO) algorithm, Generalized Evolutionary Walk Algorithm (GEWA) and Bat Algorithm (BA), in terms of the Electricity Cost (EC). It can be also conducted that the PV/wind/battery choice is more economically viable compared to the stand-alone wind and stand-alone PV systems. The results also show that more the consumer tolerates shedding, more the hybrid system is undersized and therefore cheaper in terms of electricity costs. Indeed, there is a considerable variation in the cost (up to 36%) between the sizing of a system that provides 99% and 100% of the electrical requirements of the user.

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