Application of GA, PSO and ABC in Optimal Design of a Stand-Alone Hybrid System for North-West of Iran

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Abstract

In this paper, a novel intelligent method is applied to the problem of optimal design hybrid power system for supplying the isolated load demand. The purpose of this design is to optimize the costs during the 20-year operation system. This system includes photovoltaic, wind and a lead-acid battery bank. Using optimization methods of Artificial Bee Colony (ABC), Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) the optimal capacity of these sources is determined. The objective function is minimized and the efficiency of this system in different operation situations. The input data of this paper is real and north western remote areas of Iran is studied. Covering the load demand under various weather conditions is the main constraint in this study.

1. Introduction

The absence of an electrical network in remote regions or the prohibitively high connection cost leads the organizations to explore alternative solutions. A stand-alone power system is one of the most problems. For a long time, the diesel power generation for these regions has been used as the most economical and reliable alternative.

Renewable energy resources can enhance diversity in energy supply markets, secure long-term sustainable energy supply, and reduce local and global atmospheric emissions [1].

Nowadays, due to several practical problems (high operating costs, fuel transportation problems, complicated maintenance, etc.), the diesel power generation is not always the best solution. On the other hand, with more concerns about environmental issues and the steady progress in renewable energy technologies, renewable energy resources appear to be one of the most efficient solutions for sustainable energy development and environmental pollution prevention. The use of different energy sources allows to improve the system efficiency and the reliability of the energy supply. On the other hand, with the complementary characteristics between solar and wind energy resources for certain locations, hybrid solar/wind power generation systems with storage banks offer a high reliable source of power [2].

Photovoltaic (PV) and Wind Generation (WG) units are the most promising technologies for supplying load in remote and rural regions [3]. A drawback, common to these units, is unpredictable nature of solar and wind energy sources. Additionally, the variations of these sources may not match with the time distribution of demand [4]. As another approach, hybrid PV/WG systems efficiently combine complementary characteristics of solar and wind sources to enhance the system's reliability and reduce its costs.

Because of intermittent characteristic of wind speed and solar radiation, most important challenge in design of such systems is reliable supply of demand under varying weather conditions, considering operation and investment costs of the components. Hence, the goal is optimal design of a hybrid system for reliable and economical supply of the load [5]. In this way, literature offers a variety of methods for optimal designing of hybrid PV/WG generating systems [2-9].

In the previous studies, different methods have been presented for the optimal design of wind turbines and photovoltaic cells. In [6], a method based on nonlinear programming has been presented according to different scenarios for selecting optimum capacity and the location of wind turbines connected to the network that reducing the costs and optimizing the energy. In [7], a simple iterative search algorithm is proposed for optimal sizing of a hybrid PV/WG/battery system. In [8], HOMER used for design model that determines the optimal architecture and control strategy of the hybrid system. In [2-4] Genetic Algorithm finds optimal sizes of the hybrid system components. In some later works, Particle Swarm Optimization (PSO) algorithm has been used in a WG/PV for the configuration of optimal capacity of the dimensions of the system and the cost function. [5,6,9].

In this paper, ABC, PSO and GA are used for optimal design of a stand-alone hybrid power system configuration. The results of three procedures are compared to each other. In this study ABC is successfully implemented for optimal sizing of hybrid stand-alone power systems, assuming continuous and reliable supply of the load. This paper is organized as follows: Description of the hybrid system components is presented in Section. 2. Fitness function and Constraints are presented in Section. 3. Section. 4 describes optimization procedures. Section. 5 describe simulation results. Finally conclusion is presented in Section. 6.

2. Description of hybrid system components

The block diagram of a typical stand-alone hybrid WG/PV system is shown in Fig. 1. Battery chargers connected to a DC bus, are used to charge the battery bank from the respective PV and WG input power sources, which are usually configured in multiple power generation blocks according to the devices nominal power ratings and the redundancy requirements.

On the design point of view, optimization of the size of a hybrid plant is very important, and leads to a good ratio between cost and performances. Before the system sizing, it's necessary to have enough information about each component of the system. Therefore, they are presented in the following sections.

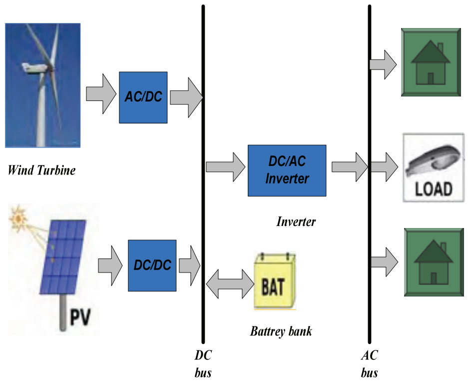

Fig. 1. Block diagram of a hybrid system.

2.1. Wind Generator

Fig. 2. Shows output power of wind turbine generator versus wind speed. A wind turbine generator needs to consider the cut-in wind speed and the cut-out wind speed. If the wind speed exceeds the cut-in value, the wind turbine generator starts generating. If the wind speed exceeds the rated wind speed, then it generates constant output, and if the wind speed exceeds the cut-out value, the wind turbine generator stops running to protect the generator, [10,11]. The power of the wind turbine is described in terms of the wind speed by(1) [12].

$$P_{WG} = \begin{cases} 0 & V_W \le V_C, V_W \ge V_F \\ P_R \times \left(\dfrac{V_W - V_C}{V_R - V_C} \right)^3 & V_C \le V_W \le V_R \\ P_R & V_R \le V_W \le V_F \end{cases} \tag{1}$$

Where,
P_{WG}: The wind turbine output power (Watt).
P_R: The wind turbine rated power (Watt).
V_W: The wind speed (m/s).
V_C, V_F, V_R: Cut-in, cut-out and rated or nominal speed of the wind turbine (m/s).

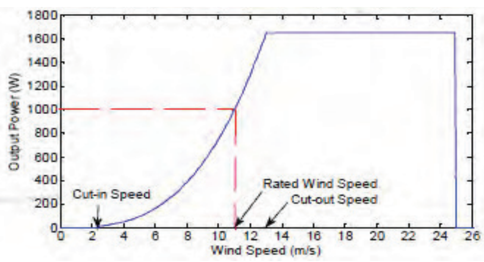

Fig. 2. Power output characteristic versus wind speed.

2.2. PV cells output model

The output power of each PV array, with respect to the solar radiation power, can be calculated by (2).

$$P_{pv} = \frac{G}{1000} \times P_{pv,rated} \times \eta_{MPPT} \tag{2}$$

Where, G is perpendicular radiation at array's surface (W/m^2), $P_{pv,rated}$ is rated power of each PV array at G= 1000W/m^2, and η_{MPPT} is the efficiency of PV's DC/DC converter and Maximum Power Point Tracking System (MPPT). PV systems are usually equipped with MPPT systems to maximize the power output, therefore it is reasonable to believe that the PV array working states stay around the maximum power point [4]. Using these systems, usually leads to about 30% increase in the average amount of the extracted energy from PV arrays and, as a result, it is economically reasonable to incorporate them into hybrid systems [3]. Thus, in current study it is assumed that PV arrays are equipped with 95% efficient MPPT systems which provide a 48 V DC at DC bus side. It should be noted that, temperature effects are neglected here.

2.3. The battery output model

Since the output of the PV cells and the turbine is a random behavior, the battery storage capacity are constantly changing correspondingly in hybrid systems. When the total output power of the turbine and PV cells is greater than the load power, the battery is in the state of charging, and the charged quantity of the battery at the moment of (t) is expressed by (3) [13]:

$$P_b(t) = P_b(t-1).(1-\sigma) + [P_z(t) - P_l(t)/\eta_{inv}].\eta_{bc} \tag{3}$$

When the total output power of the turbine and PV cells is less than the load power, the battery is in the state of discharging, and the charged quantity of the battery at the moment of (t) is expressed by (4) [13]:

$$P_b(t) = P_b(t-1).(1-\sigma) + [P_l(t)/\eta_{inv} - P_z(t)]/\eta_{bf} \tag{4}$$

Where,
P_b (t) : Battery charged quantity at time (t).
P_b (t-1): Battery charged quantity at time (t-1).
σ: Battery self-discharge rate per hour.
P_z(t): The total output power of the turbine and PV cells in the time interval (t-1, t).
P_l(t): The total load power in the time interval (t -1, t).
η_{inv}: Inverter efficiency.
η_{bc}: Battery charging efficiency.
η_{bf}: Battery discharging efficiency.

3. Problem formulation

The aim of this study is to achieve a stand-alone hybrid generation system, which should be appropriately designed in terms of economic, reliability, and environmental measures subject to physical and operational constraints/strategies.

3.1. System Cost

There are many ways to calculate the economic viability of distribution generation and energy efficiency projects. The capital and replacement costs, the operation and maintenance costs must be combined in some manner so that a comparison may be made with the costs of not doing the project. In this project we don't need fuel cost because of not using fuel. We choose Net Present Cost (NPC) for calculation of system cost.

1) Net Present Cost

The Net Present Cost (NPC) of each component is defined by (5) [14] :

$$NPC = N\times(\text{Capital cost} + \text{Replacement cost} \times K + \text{Operation maintenance cost} \times \frac{1}{CRF(ir\,,\,R)})$$

Where, N may be number (unit), R is the useful lifetime of the project (here, 20 years). ir is the real interest rate (here, 6%) which is a function of nominal interest rate ($ir_{nominal}$) and annual inflation rate (fr), defined by [15]:

$$ir = \frac{ir_{nominal} - fr}{1 + fr} \tag{6}$$

Also, CRF and K are capital recovery factor [4] and single payment present worth [15], respectively, which are defined as follows:

$$CRF(ir, R) = \frac{ir \times (1+ir)^R}{(1+ir)^R - 1} \tag{7}$$

$$K_i(ir, L_i, y_i) = \sum_{n=1}^{y_i} \frac{1}{(1+ir)^{n\times Li}} \tag{8}$$

Where, L and y are useful lifetime and number of replacements of the component during useful lifetime of the project, respectively. Number of replacements of each component is a simple function of useful lifetimes of the component and the project, it can be calculated by:

$$y_i = \left[\frac{R}{L_i}\right] - 1 \quad \text{if R is dividable to Li} \tag{9}$$

$$y_i = \left[\frac{R}{L_i}\right] \quad \text{if R is not dividable to Li} \tag{10}$$

2) Objective Function

The objective function is the sum of all net present costs.

$$NPC = NPC_{wg} + NPC_{pv} + NPC_{bat} + NPC_{inv} \tag{11}$$

3.2. Constraints

1) Power balance constraint, For any period t, the total power supply from the hybrid generation system must supply the total demand P_{LOAD} with a certain reliability criterion. This relation can be represented by:

$$P_{PV} + P_{WG} + P_{BAT} \geq P_{LOAD} \tag{12}$$

2) The constraints of the number of turbines, PV cells and batteries:

$$N_{WG}\ , N_{PV}\ , N_{BAT} \geq 0 \tag{13}$$

3) The constraints of the capacity of batteries:

$$\text{Pbmin} \geq \text{Pb} \geq \text{Pbmax} \tag{14}$$

Where,
P_{bmax}: The maximum allowable capacity of batteries, which is generally set to rated battery capacity.
P_{bmin}: The minimum allowable battery capacity, which is determined by the maximum depth of discharging *DOD*, that calculated by (15):

$$P_{bmin} = (1\text{-DOD}).P_{bmax} \tag{15}$$

4. Optimization procedures

Different approaches have been reported for optimization of various problems such as linear and nonlinear programming, probabilistic approach, dynamic programming, and iterative techniques. In this paper, the ABC and PSO and GA based algorithms are applied for optimal design of a stand-alone hybrid power system configuration.

4.1. Artificial Bee Colony Algorithm

The colony of artificial bees contains three groups of bees: employed bees, onlookers and scouts. A bee waiting on the dance area for making decision to choose food source is called an onlooker and a bee going to the food source visited by it previously is named employed bee. A bee carrying out random search is called scout. In the ABC algorithm, first half of the colony consists of employed artificial bees and the second half constitutes the onlookers. For every food source, there is only one employed bee. The employed bee whose food source is exhausted by the employed and onlooker bees becomes a scout. At initialization stage, a set of food source positions are randomly selected by the bees and their nectar amounts are determined. These bees come into hive and share the nectar information of sources with the bees waiting on the dance area within the hive. After sharing the information, every employed bee goes to the food source area visited by her at the previous cycle since that food source exists in her memory, and then chooses a new food source by means of visual information in the neighborhood of the present one. Then an onlooker prefers a food source area depending on the nectar information distributed by the employed bees on the dance area. As the nectar amount of a food source increases, the probability with which that food source is chosen by an onlooker increases, too. After arriving at the selected area, employed bee chooses a new food source in the neighborhood of the one in the memory depending on visual information. Visual information is based on the comparison of food source positions. When the nectar of a food source is abandoned by the bees, a new food source is randomly determined by a scout bee and replaced with the abandoned one. In this model, at each cycle one scout goes outside for searching a new food source and the number of employed and onlooker bees were equal. The probability P*i* of selecting a food source *i* is determined by using (16):

$$P_i = \frac{fit_i}{\sum_{n=1}^{S_n} fit_n} \tag{16}$$

Where *fiti* is fitness of the solution represented by food source *i* and *SN* is total number of food sources. After all onlookers have selected their food sources, each of them determines a food source in the neighborhood of his chosen food source and computes its fitness. The best food source among all the neighboring food sources determined by the onlookers associated with a particular food source *i* will be the new location of the food source *i*. If a solution represented by a particular food source does not improve for a predetermined number of iterations then that food source is abandoned by its associated employed bee and it becomes a scout. This tantamount to assigning a randomly generated food source to this scout and changing its status again from scout to employed. After the new location of each food source is determined, another iteration of ABC algorithm begins. The whole process is repeated again and again till the termination condition is satisfied. The food source in the neighborhood of a particular food source is determined by altering the value of one randomly chosen solution parameter and keeping other parameters unchanged. Suppose each solution consists of *d* parameters and let Xi = (Xi1, Xi2, Xi3…… Xid) be a solution..In order to determine a solution vi in neighborhood of Xi, a solution parameter j and other solution Xk=(Xk1, Xk2, Xk3…… Xkd) are selected randomly. Except for the values of the selected parameter j, all other parameter values of vi are same as Xi ,i.e., vi=(Xi1, Xi2 …… Xi(j-1), Xij, Xi(j+1), … Xid). The value vi of the selected parameter j in vi is determined by (17):

$$v_{ij} = x_{ij} + u(x_{ij} - x_{kj}) \tag{17}$$

Where *u* is an uniform variate in [-1, 1]. If the resulting value falls outside the acceptable range of *j*, it is set to the corresponding extreme value in that range[16-18].

4.2. Particle Swarm Optimization Algorithm

PSO is a population based stochastic optimization technique developed by Eberhart and Kennedy in 1995. The PSO algorithm is inspired by social behavior of bird flocking or fish schooling.

PSO shares many similarities with evolutionary computation techniques such as GA. The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. Compared to GA, the advantages of PSO are that PSO is easy to implement and there are few parameters to adjust. PSO has been successfully applied in many areas. A good bibliography of PSO applications could be found in [19, 20].

The standard PSO algorithm employs a population of particles. The particles fly through the n-dimensional domain space of the function to be optimized (in this paper, minimization is assumed). The state of each particle is represented by its position $x_i = (x_{i1}, x_{i2}, ..., x_{in})$ and velocity $v_i = (v_{i1}, v_{i2}, ..., v_{in})$, the states of the particles are updated.

The three key parameters to PSO are in the velocity update equation. First is the momentum component, where the inertial constant w, controls how much the particle remembers its previous velocity [21]. The second component is the cognitive component. Here the acceleration constant C_1, controls how much the particle heads toward its personal best position. The third component, referred to as the social component, draws the particle toward swarm's best ever position; the acceleration constant C_2 controls this tendency. The flow chart of the procedure is shown in Fig. 3.

During every iteration, each particle is updated by following two "best" values. The first one is the position vector of the best solution (fitness) this particle has achieved so far. The fitness value $p_i = (p_{i1}, p_{i2}, ..., p_{in})$ is also stored. This position is called pbest. Another "best" position that is tracked by the particle swarm optimizer is the best position, obtained so far, by any particle in the population. This best position is the current global best $p_g = (p_{g1}, p_{g2}, ..., p_{gn})$ and is called gbest.

$$v_i^{k+1} = wv_i^k + c_1 r_1 (p_{best} - x_i^k) + c_2 r_2 (g_{best} - x_i^k) \tag{18}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{19}$$

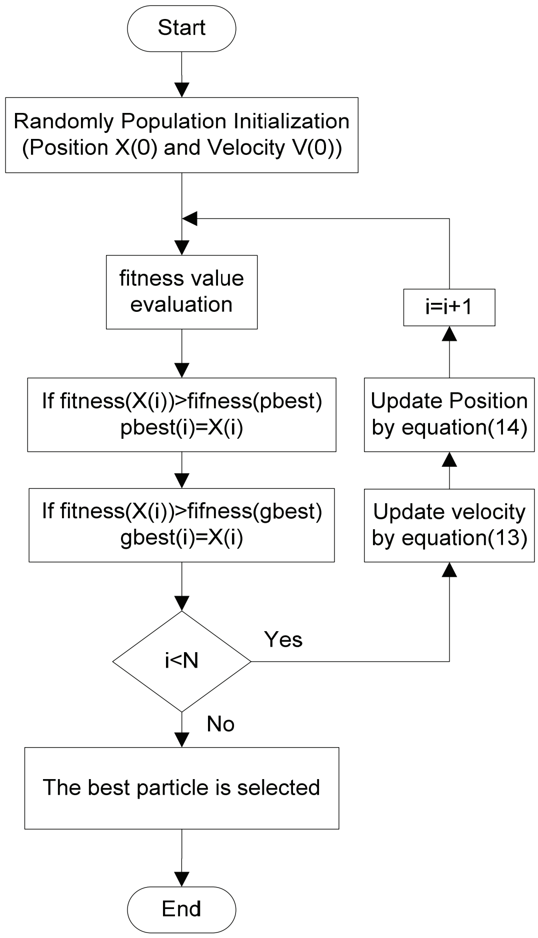

Fig. 3. PSO flow chart

4.3. Genetic Algorithm

It is well known that GAs work according to the mechanism of natural selection – stronger individuals are likely to be the winners in a competitive environment. In practical applications, each individual is codified into a chromosome consisting of genes, each representing a characteristic of the individual. For identification of the unknown parameters of a model, parameters are regarded as the genes of a chromosome, and a positive value, generally known as the fitness value, is used to reflect the degree of goodness of the chromosome. Typically, a chromosome is structured by a string of values in binary form, which the mutation operator can operate on any one of the bits, and the crossover operator can operate on any boundary of each two bits in the string [2-4,22]. Since in our problem the parameters are real numbers, a real coded GA is used, in which the chromosome is defined as an array of real numbers with the mutation and crossover operators. Here, the mutation can change the value of a real number randomly, and the crossover can take place only at the boundary of two real numbers. More details of proposed GA is shown in Fig. 4.

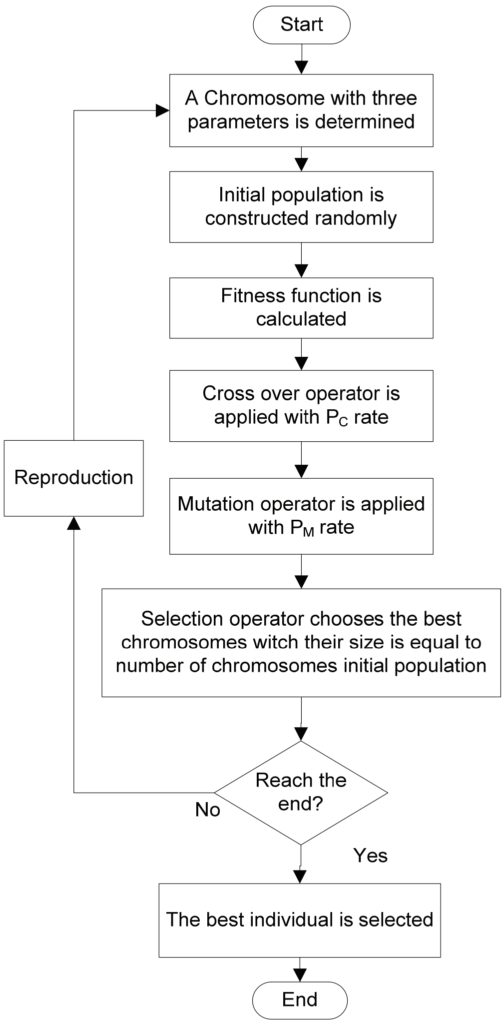

Fig. 4. GA flow chart.

5. Simulation Results

The technical characteristics and the related capital and maintenance costs of the hybrid system devices, which are input to the optimal sizing procedure, are shown in Tables 1-4 [2,3,13,23]. The installation cost has been included in the capital cost of the devices and maintenance cost of each unit per year. The maintenance cost is expressed as a fraction of the component cost. In this study, it is assumed to be 1% of capital cost for PV, battery and inverter and 3% of capital cost for wind generator [2]. To perform the cost assessments, it is necessary to simulate the systems through a year with 1-h time steps. The available data consist of hourly averages of wind speed and solar radiation in one of the northwestern provinces of Iran, i.e. Ardebil (latitude: 38_170, longitude: 48_150, altitude: 1345 m). The chosen load profile is the IEEE household consumptions with a peak of 1 kW. For the sake of simplicity, we have considered the weekly mean in input data in our simulation. The data are the wind velocity, solar radiation and the demand in every one hour in a day. So, an average of the input data in each hour is calculated during a week. In a year, we have 1248 (52 × 24) data about the wind velocity and demand. These data are shown in Figs. 5–7 [5,9].

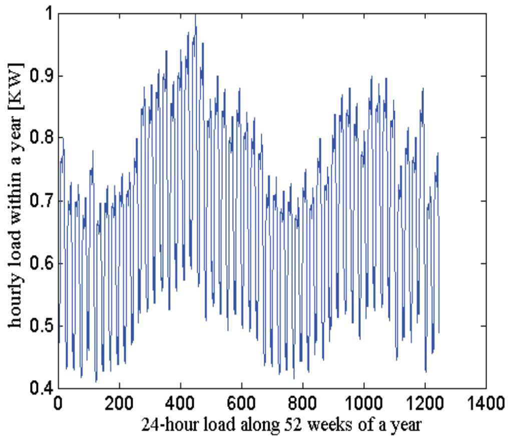

Fig. 5. Load profile

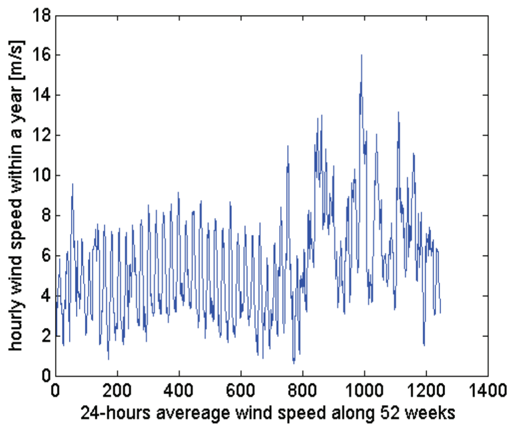

Fig. 6. Wind speed in a year the Ardebil city

Table 1. Wind generator specifications [2,3]

Power rating (W)	Cut-in wind speed m/s	Rated wind speed m/s	Cut-out wind speed m/s	Capital cost (US$/W)	Maintenance cost (US$/year)	Lifetime (year)
1000	2.5	11	24	3.000	3% of capital cost	20

Table 2. PV modules specifications [2,3,23]

Power rating (W)	Open circuit voltage (v)	Short circuit current (A)	Capital cost (US$/W)	Maintenance cost (US$/year)	Lifetime (year)
110	21	7.22	4.86	1% of capital cost	20

Table 3. Battery bank specifications [2,3,13,23]

Nominal capacity (A h)	Voltage (v)	DOD (%)	Battery charging and discharging efficiency	σ (%)	Capital cost (US$/W)	Maintenance cost (US$/year)	Lifetime (year)
230	12	80	85%	0.02	0.171	1% of capital cost	4

Table 4. DC/AC inverter specifications [2,3]

Power rating (W)	Efficiency (%)	Capital cost (US$/W)	Maintenance cost (US$/year)	Lifetime (year)
1500	80	0.707	1% of capital cost	10

Table 5. Hybrid system optimal sizing results

Optimization technique	Population size	Iteration number	Time (s)	Optimum values of parameters			Total cost (€)	Comments
				N_{WG}	N_{PV}	N_{BAT}		
GA	30	200	526.31	1	35	12	109002.92	$P_c = 0.3$ $P_m = 0.7$
PSO	30	200	438.63	1	35	12	109002.92	$C_1 = 2$ $C_2 = 2$
ABC	16	100	352.17	1	34	13	108877.01	Number of employed bees = 8

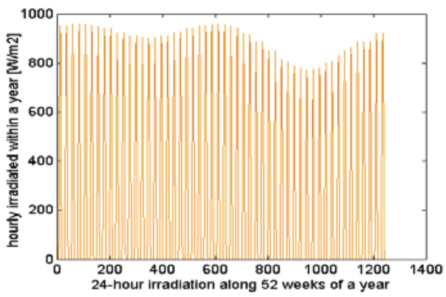

Fig. 7. Hourly solar radiation in the Ardebil city

Software is run for the base case on a Pentium IV, 2.8 GHz CPU and 512 MB of RAM. The optimal sizing results of system devices included in Tables 1-4, are shown in Table 5. In case that the power source consists either only of WGs or only of PV modules are tabulated in Tables 6 and 7 respectively. It is observed that in both cases, result in substantially higher total system cost compared to the hybrid PV/WG system design. The total cost of the optimized system showed that the system can deliver energy in a stand-alone installation with an acceptable cost. Convergence curves of the GA, PSO and ABC algorithms, are depicted in Fig. 8. It can be seen that, the ABC algorithm converges to the optimal fitness value after, more or less, 30 iterations. So, 100 iterations can be considered as a fair termination criterion.

Table 6. Optimal sizing results for WG-only power source

Optimization technique	N_{WG}	N_{PV}	N_{BAT}	Total cost (US$)
GA	13	0	78	439119.125
PSO	14	0	63	438219.306
ABC	15	0	48	437319.487

Table 7. Optimal sizing results for PV-only power source

Optimization technique	N_{WG}	N_{PV}	N_{BAT}	Total cost (US$)
GA	0	49	15	114918.359
PSO	0	51	12	113531.152
ABC	0	51	12	113531.152

As seen from the results in Table 5-7, the ABC algorithm can converge to the minimum of cost function. In other words, this proves that the ABC algorithm has the ability of getting out of a local minimum in the search space and finding the global minimum. In the ABC algorithm, while the exploration process carried out by artificial scouts is good for global optimization, the exploitation process managed by artificial onlookers and employed bees is very efficient for local optimization. The SOC battery for optimal solution, results of ABC algorithm shown in Fig. 9. Its observed that the state of charge battery bank never gets less than 24% so the fifteenth relation, constraint of the minimum capacity of batteries is always satisfied. In order to inspection to operation of system according to power management strategy by SOC battery, Fig. 10 is presented. In this figure, operation of battery bank in a typical day and normal weather condition on 24 hours term is shown. The total cost of the hybrid system through 20 years of operation in the best state is 108877.01(US/$) and the breakdown of cost analysis of configuration is depicted in Fig. 11.

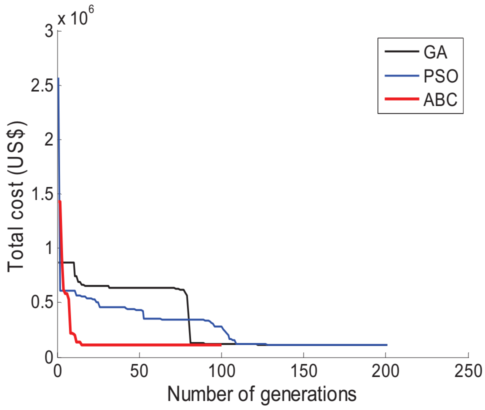

Fig. 8. Convergence of optimization of algorithms.

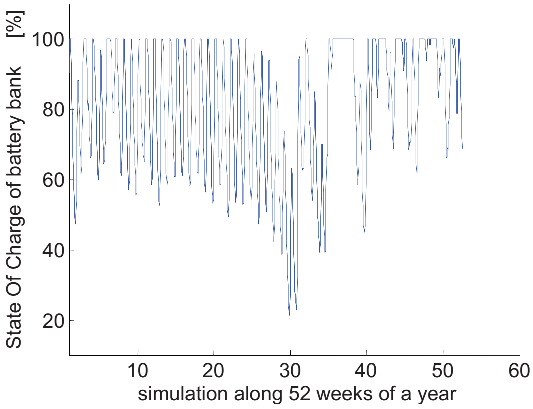

Fig. 9. Simulated state of charge of battery bank corresponding to the optimal solution during the year.

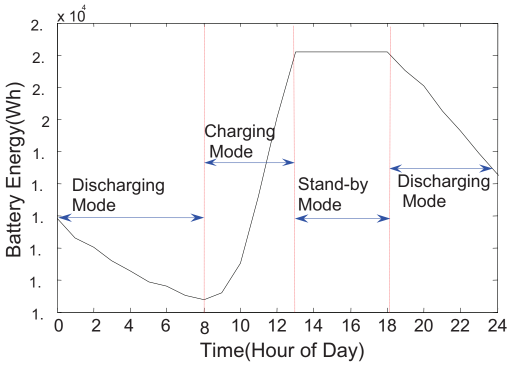

Fig. 10. Energy of battery during 24 hours.

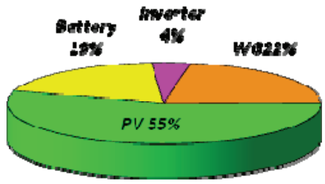

Fig. 11. Breakdown of cost analysis of the configuration.

6. Conclusion

The main object for designing hybrid photovoltaic-wind generating systems is reliable supply of the load, under varying weather conditions, with minimum cost. In this paper, a stand-alone hybrid WG/PV generating system with battery storage has been designed for a 20-year period of operation. The 20-year round total system cost is equal to the sum of the respective components capital and maintenance costs. The cost (objective) function minimization is implemented using Artificial Bee Colony algorithm, which compared to conventional optimization methods, such as GA and PSO algorithm have the ability to attain the global optimum with relative computational simplicity. The proposed method has been applied to the design of a hybrid power generation system in order to supply a residential household. The simulation results of three algorithm verify that the hybrid PV/WG systems result in lower system cost compared to cases where either exclusively WG or exclusively PV sources are used. In order to demonstrate the performance of the ABC algorithm, PSO, GA and ABC algorithms were tested for optimal design a stand-alone hybrid wind-solar generating systems. From the simulation results it was concluded that the proposed algorithm has the ability to get out of a local minimum and can be efficiently used for multivariable, multimodal function optimization. It shows that the method used in this paper can be used for the operation purposes in which accuracy, cost and time are important.

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