International Journal of Engineering & Applied Sciences (IJEAS)
Vol.6, Issue 2(2014)52-63

APPLICATION OF ANT COLONY OPTIMIZATION (ACO) FOR DESIGNING A HYBRID SYSTEM

Alireza Askarzadeh [a*]

[a] *Department of Energy Management and Optimization, Institute of Science and High Technology and Environmental Sciences, Graduate University of Advanced Technology, Kerman, Iran*
[*]*E-mail address*: *a.askarzadeh@kgut.ac.ir, askarzadeh_a@yahoo.com*

Abstract

Inspired by the behavior of ants seeking the shortest path between their nest and a food source, ant colony optimization (ACO) is the most popular technique to effectively solve combinatorial optimization problems. Combinatorial optimization is a branch of optimization which is concerned with the optimization of functions with discrete decision variables. Finding optimum size of a PV/wind/battery hybrid system belongs to combinatorial optimization problems with the aim of determining three discrete decision variables, namely, number of PV panels, wind turbines and batteries. This paper proposes ACO to optimally size a PV/wind/battery hybrid system for having a reliable system. In order to evaluate the effectiveness of the proposed methodology, ACO performance is compared with that of two other well-known metaheuristic algorithms, namely, harmony search (HS) and particle swarm optimization (PSO). It is observed that ACO yields more promising results than the other studied methodologies.

Keywords: hybrid system, optimum sizing, combinatorial optimization, ant colony optimization.

1. Introduction

Among the renewable energy sources, PV/wind/battery hybrid system is one of the most popular ones because by use of this system the probability of having continuous electrical power increases. The schematic of this system is shown in Fig. 1. In such system, an inverter is used before the load to convert the DC power to AC as well as a backup generator is provided to use when there is no enough energy and the storage batteries are low.

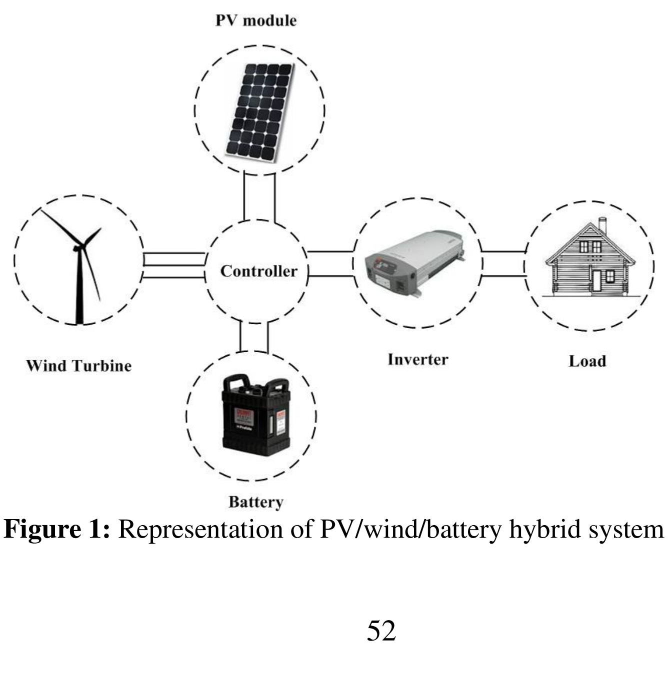

Figure 1: Representation of PV/wind/battery hybrid system

Considering economic aspects, optimum sizing of a PV/wind/battery hybrid system is essential. Finding optimum size means to determine number of PV panels, wind turbines and batteries with the aim of minimizing the total annual cost of the system so that the load demand is satisfied. Since the decision variables (number of PV panels, wind turbines and batteries) are discrete, optimum sizing of such system belongs to combinatorial optimization problems. Combinatorial optimization is a branch of optimization which is concerned with the optimization of functions with discrete decision variables. To optimally size the hybrid system, an optimization algorithm suitable for combinatorial problems should be used.

Study of literature indicates that many attempts based on probabilistic, analytical and heuristic methods have been proposed for optimum sizing of hybrid systems. Diaf et al. have used accurate mathematical models for characterizing PV module, wind generator and battery to develop sizing algorithms [1]. They have optimized the system size according to loss of power supply probability (LPSP) and the levelized cost of energy (LCE). Their study shows that the optimal configuration is obtained with respect to meeting the desired system reliability requirements with the lowest LCE. Moreover, it is found that the device system choice plays an important role in cost reduction and as well as in energy production. Loss of load probability (LLP) concept has been introduced by Borowy and Salameh for finding the optimal size of the PV/wind hybrid system [2]. In this case, the system operation is simulated for various combinations of PV array and battery sizes and the LPSP is calculated for each combination. Then, for the desired LPSP, the PV array versus battery size is plotted and the optimal solution, which minimizes the total system cost, is defined as the point on the sizing curve. According to energy generation simulation for various numbers of PVs and batteries using suitable models for the system devices, Shrestha and Goel have presented a methodology for optimal sizing [3]. In this study, the number of PVs and batteries guarantees that reliability indices like the loss of load hours (LOLH), the lost energy and the system cost are satisfied. Markov chain modeling has been used for the solar radiation so that the number of PVs and batteries are selected based on the desired system performance level (SPL) requirement, which is defined as the number of days that the load cannot be satisfied and it is expressed in terms of probability [4]. A design method for hybrid PV/wind systems, based on energy balance, has been proposed by Kellogg et al. [5]. An methodology for optimization of PV/wind system is presented by Prasad and Natarajan based on deficiency of power supply probability (DPSP), relative excess power generated (REPG), unutilized energy probability (UEP), life cycle cost (LCC), levelized energy cost (LEC) and life cycle unit cost (LUC) of power generation with battery bank [6]. Nonlinear programming has been proposed to find the optimum capacity and the location of wind turbines connected to the network [7]. A simple iterative search methodology has been developed for size optimization of a PV/wind hybrid system [5]. HOMER has been used for optimum size and control strategy of a hybrid system [8].

In recent years, owing to the ability of global search, metaheuristic algorithms have attracted significant attention to solve the sizing problem. Metaheuristics are approximate algorithms used to obtain good enough solutions for hard optimization problems in a reasonable amount of computational time. A detailed review of these methods for optimum sizing of hybrid systems can be found in [9]. Genetic algorithm (GA) [1,10,11], particle swarm optimization (PSO) [12], simulated annealing (SA) [13] and artificial bee colony (ABC) [14] have been introduced as promising methods to optimally size the hybrid systems. Nevertheless, these algorithms have been originally proposed for continuous optimization and using a method suitable for combinatorial problems may lead to finding better result.

Ant colony optimization (ACO) is a metaheuristic technique for solving hard combinatorial optimization problems which was initially introduced by Marco Dorigo in 1992 in his PhD thesis. ACO originates from the ability of real ants for finding the shortest path between their nest and a food source. The basic idea in ACO is to utilize a chemical substance named pheromone used by real ants as a medium for communication and as an indirect form of memory for previously found solutions. The effectiveness of ACO has led to its application to various combinatorial optimization problems.

In this paper, ACO is proposed to optimally size a PV/wind/battery hybrid system. For this aim, the optimum sizing problem is mapped into a graph form and the ants are driven by a probability rule to choose their solution to the problem, known as a tour. The pheromones are then updated and this process continues until optimum number of PV panels, wind turbines and batteries is found. To evaluate the efficiency of the proposed ACO algorithm, the obtained results are compared with the results found by particle swarm optimization (PSO) and harmony search (HS).

The rest of this paper is as follows: Section 2 provides the formulation of the hybrid system sizing problem; in Section 3, the proposed methodology is introduced and explained in detail; simulation results are discussed in Section 4; and conclusion is given in Section 5.

2. Problem definition

2.1. Objective function

The objective function of the optimum design problem is the minimization of the total annual cost (C_T). The total annual cost consists of the annual capital cost (C_{Cpt}) and the annual maintenance cost (C_{Mtn}). To optimally design the hybrid generation system, the optimization problem, defined by Eq. (1), should be solved using an optimization technique.

$$Minimize \quad C_T = C_{Cpt} + C_{Mtn} \tag{1}$$

Maintenance cost occurs during the project life while capital cost occurs at the beginning of a project.

In order to convert the initial capital cost to the annual capital cost, capital recovery factor (*CRF*), defined by Eq. (2) is used.

$$CRF = \frac{i(1+i)^n}{(1+i)^n - 1} \tag{2}$$

where i is the interest rate and n denotes the life span of the system.

By breaking up the capital cost into the annual costs of the wind turbine, PV panel, battery, inverter and backup generator, Eq. (3) is obtained.

$$C_{Cpt} = \frac{i(1+i)^n}{(1+i)^n - 1}\left[N_{Wind} \times C_{Wind} + N_{PV} \times C_{PV} + \left(\frac{n}{LS_{Batt}}\right) \times N_{Batt} \times C_{Batt} + \left(\frac{n}{LS_{Inv}}\right) \times C_{Inv} + C_{Backup}\right] \tag{3}$$

where N_{Wind} is the number of wind turbines, C_{Wind} is unit cost of wind turbine which is defined by sum of turbine price (T_p) and turbine installation fee (T_{if}), N_{PV} is the number of PV panels, C_{PV} is unit cost of PV panel which is defined by sum of panel price (P_p) and panel installation fee (P_{if}), LS_{Batt} is battery's life span because battery is vulnerable in the renewable generation system, N_{Batt} is the number of batteries, C_{Batt} is unit cost of battery, LS_{Inv} is the inverter's life span, C_{Inv} is the inverter cost and C_{Backup} is the cost of the backup generator.

The total power and energy generated by the wind turbines at time t are obtained by:

$$P^t_{Wind} = N_{Wind} \times P^t_{Wind-Each} \tag{4}$$

$$E^t_{Wind} = P^t_{Wind} \times \Delta t \tag{5}$$

where P^t_{Wind} is the power generated by the wind turbines, $P^t_{Wind-Each}$ is the power generated by each wind turbine and Δt denotes the time between the samples.

In the same way, for PV panels the total power and energy are obtained by:

$$P^t_{PV} = N_{PV} \times P^t_{PV-Each} \tag{6}$$

$$E^t_{PV} = P^t_{PV} \times \Delta t \tag{7}$$

where P_{PV}^{t} is the power generated by the PV panels and $P_{PV-Each}^{t}$ is the power generated by each PV panel.

Thanks to the random behaviors of PV panels and wind turbines, the battery bank capacity constantly changes correspondingly in hybrid systems. When the total output of PV panels and wind generators is greater than the load energy, the battery bank is in charging state. The charge quantity of the battery bank at time *t* can be obtained by

$$E_{Batt}^{t} = E_{Batt}^{t-1} \times (1-\sigma) + \left[\left(E_{PV}^{t} + E_{Wind}^{t} \right) - \frac{E_{Dmd}^{t}}{\eta_{Inv}} \right] \times \eta_{Batt} \tag{8}$$

where E_{Batt}^{t} and E_{Batt}^{t-1} are the charge quantities of battery bank at time *t* and *t* - 1, σ is hourly self-discharge rate, η_{Inv} denotes the inverter efficiency and η_{Batt} is the charge efficiency of battery bank.

On the other hand, when the total output of PV panels and wind generators 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

$$E_{Batt}^{t} = E_{Batt}^{t-1} \times (1-\sigma) - \left[\frac{E_{Dmd}^{t}}{\eta_{Inv}} - \left(E_{PV}^{t} + E_{Wind}^{t} \right) \right] \tag{9}$$

For the annual maintenance cost the following equation is used:

$$C_{Mnt} = \left[C_{Mnt}^{Wind} \times \sum_{t=1}^{24} E_{Wind}^{t} + C_{Mnt}^{PV} \times \sum_{t=1}^{24} E_{PV}^{t} \right] \times 365 \tag{10}$$

where C_{Mnt}^{Wind} is the wind turbine's maintenance cost per kW h, C_{Mnt}^{PV} is the PV panel's maintenance cost per kW h. The maintenance costs of battery bank and inverter are neglected.

2.2. Constraints

Eqs. (1)-(10) show the description of the objective function in detail. In addition to these equations, some constraints need to be regarded during the optimization process. The constraints are as follows:

$$N_{Wind} = Integer, \quad 0 \le N_{Wind} \le N_{Wind}^{\max} \tag{11}$$

$$N_{PV} = Integer, \quad 0 \le N_{PV} \le N_{PV}^{\max} \tag{12}$$

$$N_{Batt} = Integer, \quad 0 \le N_{Batt} \le N_{Batt}^{\max} \tag{13}$$

where $N_{Wind}^{\max}$, $N_{PV}^{\max}$ and $N_{Batt}^{\max}$ are the maximum available number of wind turbines, PV panels and batteries, respectively.

At any time, the charge quantity of battery bank should satisfy the constraint of $E_{Batt}^{\min} \le E_{Batt}^{t} \le E_{Batt}^{\max}$. The maximum charge quantity of battery bank ($E_{Batt}^{\max}$) takes the value of nominal capacity of battery bank (S_{Batt}) and the minimum charge quantity of the battery bank ($E_{Batt}^{\min}$) is obtained by maximum depth of discharge (*DOD*).

$$E_{Batt}^{\min} = (1 - DOD) \times C_{Batt} \tag{14}$$

3. Ant colony optimization

In the real world, ants are able to discover the shortest path between their nest and a food source. For finding food source, ants initially search the vicinity of their nest in a random manner. When an ant finds a food source, it evaluates the quality of that food and returns to the nest while depositing a pheromone trail on the ground. The quantity of the pheromone deposited, which may rely on the quality of the food, will lead the other ants to the food source. During the time, the pheromone of a path evaporates if other ants lay down no more pheromone on that path. If many ants select a specific path and lay down pheromone, the quantity of pheromone on that path increases, and accordingly, that path has more chance to attract more and more ants. In ACO, each ant is a simple agent to conduct the task and obeys the following rules:

- It lives in a discrete-time environment.
- It selects its path by a probability related to the pheromone laid on the connections.
- It deposits pheromone when its tour is completed.

To apply ACO to optimum sizing of the PV/wind/battery hybrid system, the graph that describes the settings of the decision variables (number of PV panels, wind turbines and batteries) is mapped on the ACO graph (search space), which is the space that ants will walk. Fig. 2 shows the search space for the sizing problem. The decision variables are shown by the stages j (j = 1, 2, 3). Number of nodes in each stage is equal to all the possible candidate discrete settings for the corresponding decision variable. For example, the nodes in stage 1 are valued from 0 to $N_{PV}^{\max}$, where $N_{PV}^{\max}$ is maximum number of PV panels. Each ant starts its tour and moves from the nest to the food source by probabilistically selecting one of the possible paths. The steps of ACO used here are as follows:

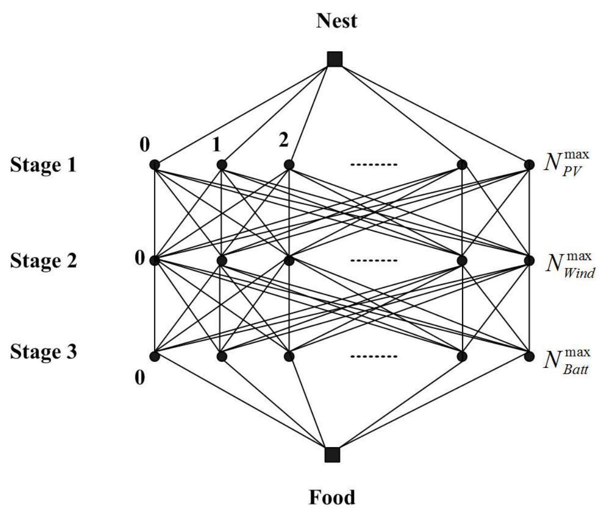

Figure 2: Search space of the sizing problem

Step 1. Initialization

A number of ants, N_{ant}, are placed in the nest. They perform a tour based on the node transition rule explained below. ACO constructs a complete tour for the first ant prior to the second ant starting its tour. At the beginning of the algorithm, the initial pheromones laid on the connections are set to a small value, $\tau_0 > 0$.

Step 2. Node transition rule

Each ant moves from a node of the current stage to a node in the next stage by using node transition rule. The transition probability from node i to node j for the kth ant in tth iteration, $p_{ij}^{k}(t)$, is defined as

$$p_{ij}^{k}(t) = \frac{\tau_{ij}(t)}{\sum_{r=1}^{p} \tau_{ir}(t)} \tag{15}$$

where τ is the intensity of pheromone on the connection and p denotes the number of nodes of the next stage.

Step 3. Pheromone updating rule

At the end of each iteration, ants will complete their tour. Consequently, the pheromone of all the connections will be evaporated by Eq. (16). Reducing the amount of pheromone on all the possible paths is known as local updating.

$$\tau_{ij}(t+1) = (1-\xi)\times\tau_{ij}(t) \qquad (16)$$

where ξ is the pheromone evaporation factor.

Then, global updating is performed by updating the pheromone on the best path found so far as

$$\tau_{best}(t+1) = \tau_{best}(t) + N_{pass}\times\Delta\tau \qquad (17)$$

where τ_{best} is the amount of the pheromone on the best path, N_{pass} is the number of ants that selects the best path in iteration t and $\Delta\tau$ is computed by Eq. (18).

$$\Delta\tau = \gamma\frac{f_{best}}{f_{worst}} \qquad (18)$$

where γ is the attractiveness factor, f_{best} denotes the minimum cost value obtained in iteration t and f_{worst} is the maximum cost value obtained in iteration t.

The ants continue their tours until maximum number of iterations, t_{max}, is reached. Accordingly, the decision variables of the best path found are considered as the optimal size values of the hybrid system. During solving the optimal sizing problem since the constraint of $E_{Batt}^{\min} \le E_{Batt}^{t} \le E_{Batt}^{\max}$ should be satisfied, some paths of Fig. 1 will be infeasible. If an ant chooses an infeasible path, the path will be abandoned by that ant.

4. Simulation results

ACO is coded in the MATLAB program and applied to a test system. In ACO, the parameters are adjusted as: N_{ant} = 100; t_{max} = 200; ξ = 0.5; γ = 2; τ_0 = 1. The average hourly power generated by each PV panel ($P_{PV-Each}^{t}$) and each wind turbine ($P_{Wind-Each}^{t}$) in a day are same as the characteristics used by Kellogg et al. [5] and reported by Geem [15]. The powers have been obtained from a remote area in South-Central-Monatana to supply a house. These characteristics have been illustrated in Figs. 3 and 4. The average hourly load demand (P_{Dmd}^{t}) considered in this paper is as Fig. 5. Table 1 lists the system parameters. At initial time, it is assumed that the charge of each battery is 30 percent of its nominal capacity.

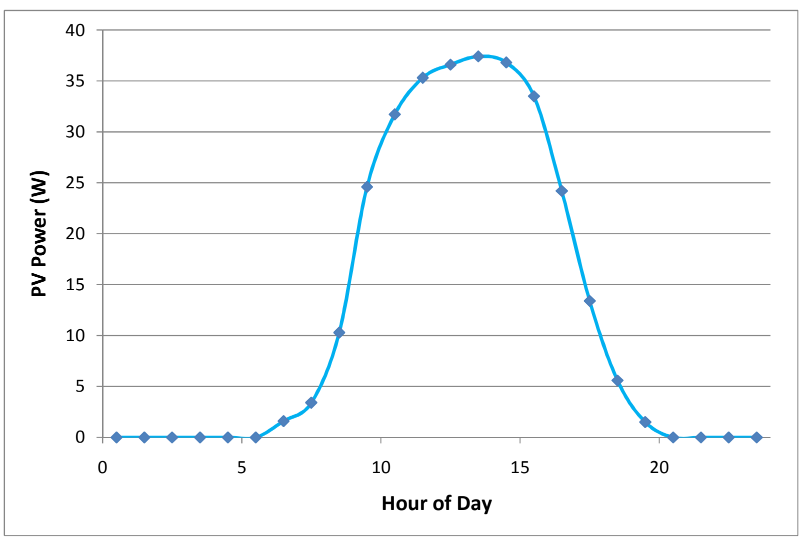

Figure 3: Average hourly power generated by a PV panel in a day

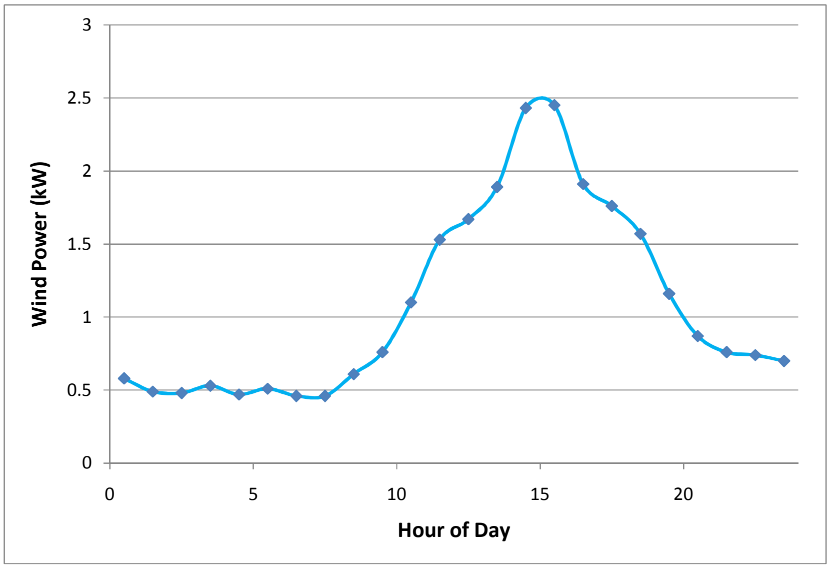

Figure 4: Average hourly power generated by a wind turbine in a day

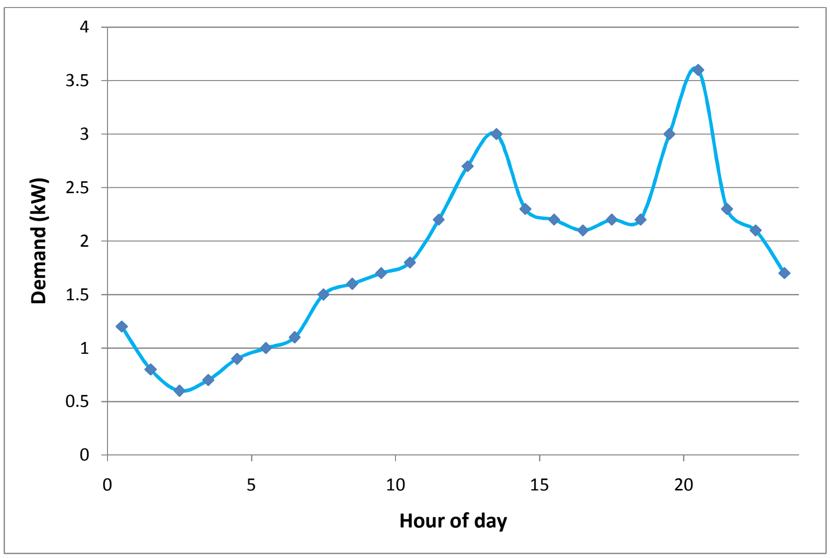

Figure 5: Average hourly load demand in a day

Table 1. Design parameters of the studied PV/wind/battery hybrid system

Parameter	Value
i	6 %
n	20 years
T_p	20000 \$/turbine
T_{if}	$0.25 \times T_p$
P_p	350 \$/panel
P_{if}	$0.5 \times P_p$
C_{Batt}	170 \$
C_{Backup}	2000 \$
S_{Batt}	2.1 kW h
Δt	1 h
LS_{Batt}	4 years
C_{Mnt}^{PV}	0.005 \$/kW h
C_{Mnt}^{Wind}	0.02 \$/kW h
C_{Inv}	2200 \$
LS_{Inv}	10 years
σ	0.0002
η_{Inv}	80 %
η_{Batt}	85 %
$N_{Wind}^{\max}$	100
$N_{PV}^{\max}$	100
$N_{Batt}^{\max}$	100
DOD	0.8

Metaheuristic algorithms have stochastic nature and the result of a run may differ from another run. In order to statistically study the ACO performance, the results are reported considering 50 independent runs. Table 2 shows mean (*Mean*), standard deviation (*Std.*), best (*Best*) and worst (*Worst*) values for the obtained cost functions over 50 runs. The results have been obtained for hybrid, PV alone and wind alone systems. To assess the capability of ACO, the results obtained by two other well-known algorithms, particle swarm optimization (PSO) and harmony search (HS), have been also shown in Table 2. For having a fair comparison, the number of objective function evaluations in ACO, PSO and HS is equal, namely, 100 × 200 = 20000. Since the basic forms of PSO and HS can only handle continuous variables, the search process is conducted in a continuous space and the solution found is rounded to have integer values for the decision variables.

As Table 2 shows, for the hybrid system, the optimal size is $N_{PV} = 7$, $N_{Wind} = 2$ and $N_{Batt} = 15$ with the cost of 6730.989 \$ which is found by ACO. In this case, considering all the indexes (*Mean*, *Std.*, *Best* and *Worst*), the best result belongs to ACO. In terms of the *Best* index, PSO and HS have same performances, but in terms of the other indexes (*Mean*, *Std.* and *Worst*) PSO outperforms HS. The best solution found by PSO and HS is $N_{PV} = 7$, $N_{Wind} = 2$ and $N_{Batt} = 17$ with the cost of 6879.203 \$. The overriding point is that the *Worst* index found by ACO is smaller than the *Mean* indexes of PSO and HS algorithms. Considering the PV alone system, the optimum size is obtained $N_{PV} = 168$, $N_{Wind} = 0$ and $N_{Batt} = 44$ with the cost of 11599.084 \$. For PV alone system $N_{PV}^{\max}$ is set to 200. In this case, the performance of ACO is superior and this algorithm yields better results than PSO and HS in terms of the *Mean*, *Std.* and *Worst* indexes. When the wind alone system is considered, the optimum size is obtained $N_{PV} = 0$, $N_{Wind} = 2$ and $N_{Batt} = 24$ with the cost of 7073.768 \$ which is found by ACO, PSO and HS. In this case, although the result of ACO in terms of the *Best* index is similar to PSO and HS, the best performance in terms of the

Mean, *Std.* and *Worst* belongs to PSO and HS is in the second rank. By comparing the obtained results of this case, it is seen that using the hybrid system leads to having the minimal total annual cost (6730.989 $). Also, the wind alone system with the total annual cost of 7073.768 $ is more economic than the PV alone system which has the total annual cost of 11599.084 $. Fig. 6 indicates the convergence process of ACO related to the *Best* index for hybrid, PV alone and wind alone systems which illustrates minimum total annual cost found at each iteration.

Table 2. The performance of ACO, PSO and HS for finding the optimum size of the hybrid, PV alone and wind alone systems (case study 1)

	Algorithm	Index				Optimum design		
		Mean	*Std.*	*Best*	*Worst*	N_{PV}	N_{Wind}	N_{Batt}
Hybrid	ACO	6980.526	168.820	6730.989	7462.702	7	2	15
	PSO	7730.448	521.471	6879.203	9148.487	7	2	17
	HS	7854.940	694.159	6879.203	9667.391	7	2	17
PV alone	ACO	11652.072	42.085	11599.084	11747.298	168	0	44
	PSO	11848.270	133.181	11599.084	12247.568	168	0	44
	HS	11906.992	179.789	11599.084	12423.499	168	0	44
Wind alone	ACO	7662.120	567.433	7073.768	9074.654	0	2	24
	PSO	7336.106	266.459	7073.768	7963.050	0	2	24
	HS	7439.856	401.933	7073.768	8778.226	0	2	24

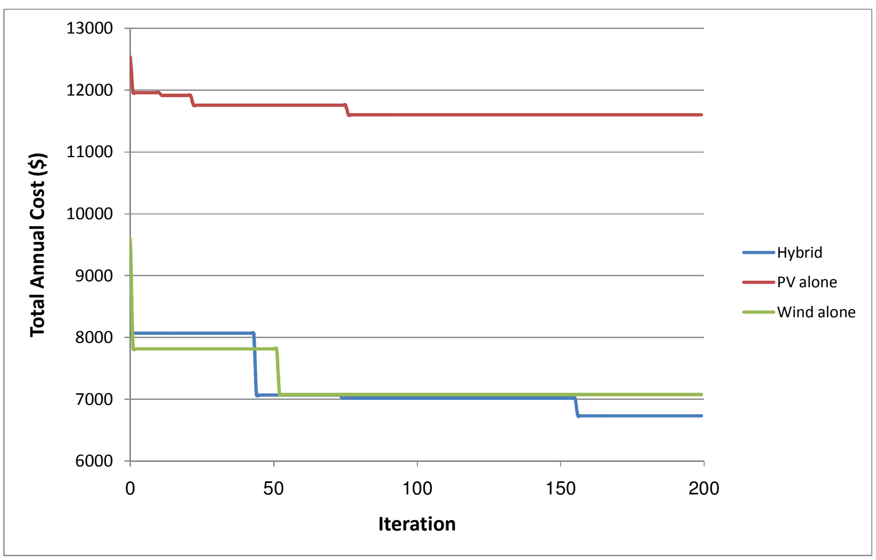

Figure 6: Convergence process of ACO for finding the optimum size of the systems (case study 1)

As another test, a same problem with the following changes will be investigated: $P^t_{Wind-Each} \leftarrow 0.8 \times P^t_{Wind-Each}$ and $P^t_{PV-Each} \leftarrow 0.5 \times P^t_{PV-Each}$. Table 3 lists the performance of the algorithms on this problem. For the hybrid system, the optimum design is N_{PV} = 0, N_{Wind} = 2 and N_{Batt} = 9 with the total annual cost of 6056.663 $ which is found by ACO. For the PV alone system and considering $N_{PV}^{\max} = 300$, the optimum design is N_{PV} = 224, N_{Wind} = 0 and N_{Batt} = 44 with the total annual cost of 14162.310 $ which is found by ACO. For the wind alone system, the optimum design is N_{PV} = 0, N_{Wind} = 2 and N_{Batt} = 9 with the total annual cost of 6056.663 $ which is obtained by ACO, PSO and HS algorithms. For all the systems, ACO finds the best solution and for the hybrid and PV alone system ACO produces better results than PSO and HS in terms of all the indexes. As the previous investigation, the hybrid generation system has the minimal total annual cost and is recommended for using in the present case study. Fig. 7 indicates the convergence process of ACO related to the *Best* index.

Table 3. The performance of ACO, PSO and HS for finding the optimum size of the hybrid, PV alone and wind alone systems (case study 2)

	Algorithm	Index				Optimum design		
		Mean	*Std.*	*Best*	*Worst*	N_{PV}	N_{Wind}	N_{Batt}
Hybrid	ACO	6592.630	337.150	6056.663	7656.846	0	2	9
	PSO	7217.403	647.149	6195.194	8982.435	3	2	9
	HS	7645.829	796.091	6130.770	9491.500	0	2	10
PV alone	ACO	14205.725	33.787	14162.310	14282.594	224	0	44
	PSO	14456.631	142.903	14190.240	14765.968	223	0	45
	HS	14558.564	236.240	14190.240	15109.691	223	0	45
Wind alone	ACO	6877.768	823.199	6056.663	9391.472	0	2	9
	PSO	6194.502	183.336	6056.663	7094.160	0	2	9
	HS	635.013	345.042	6056.663	7835.228	0	2	9

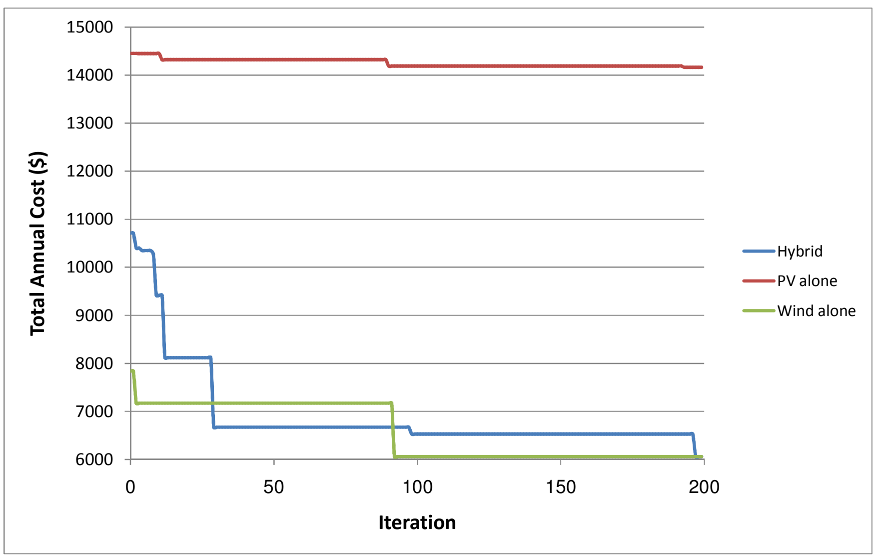

Figure 7: Convergence process of ACO for finding the optimum size of the systems (case study 2)

5. Conclusion

This paper proposes ACO for optimum sizing of PV/wind/battery hybrid system, because ACO can effectively handle combinatorial optimization problems. In order to evaluate the efficiency of the proposed methodology, ACO is used to find the optimum size of a test system and its results are compared with the results obtained by PSO and HS. It is observed that ACO produces more promising results than PSO and HS. For the test system, PV/wind hybrid system is more economic than PV alone and wind alone systems for 20 years life span. It can be concluded that ACO could be an efficient tool for optimum sizing of hybrid systems.

Notations

C_{Cpt}	annual capital cost ($)
C_{Mtn}	annual maintenance cost ($)
C_T	total annual cost ($)
i	interest rate
n	life span of the system (years)
T_p	turbine price ($)
T_{if}	turbine installation fee ($)
P_p	panel price ($)
P_{if}	panel installation fee ($)
C_{Batt}	cost of battery ($)
C_{Backup}	cost of the backup generator ($)
S_{Batt}	nominal capacity of battery bank (kW h)
Δt	time between the samples (hour)
LS_{Batt}	battery's life span (years)
C_{Mnt}^{PV}	PV panel's maintenance cost ($/kW h)
C_{Mnt}^{Wind}	wind turbine's maintenance cost ($/kW h)
C_{Inv}	inverter cost ($)
LS_{Inv}	inverter's life span (years)
σ	hourly self-discharge rate
η_{Inv}	inverter efficiency
η_{Batt}	charge efficiency of battery bank
$N_{Wind}^{\max}$	maximum number of wind turbines
$N_{PV}^{\max}$	maximum number of PV panels
$N_{Batt}^{\max}$	maximum number of batteries
DOD	maximum depth of discharge
N_{Batt}	number of batteries
N_{PV}	number of PV panels
N_{Wind}	number of wind turbines
P_{Wind}^{t}	power generated by the wind turbines (W)
$P_{Wind-Each}^{t}$	the power generated by each wind turbine (W)
P_{PV}^{t}	power generated by the PV panels (W)
$P_{PV-Each}^{t}$	power generated by each PV panel (W)
E_{Batt}^{t}	charge quantity of battery bank at time t (W h)
E_{Batt}^{t-1}	charge quantity of battery bank at time $t-1$ (W h)

References

[1] Diaf, S., Diaf, D., Belhamel, M., Haddadi, M., Louche, A., 2007. A methodology for optimal sizing of autonomous hybrid PV/wind system. Energy Policy 35, 5708-5718.

[2] Borowy, B.S., Salameh, Z.M., 1996. Methodology for optimally sizing the combination of a battery bank and PV array in a wind/PV hybrid system. IEEE Transactions on Energy Conversion 11, 367–373.

[3] Shrestha, G.B., Goel, L., 1998. A study on optimal sizing of stand-alone photovoltaic stations. IEEE Transactions on Energy Conversion 13 (4), 373–378.

[4] Maghraby, H.A.M., Shwehdi, M.H., Al-Bassam, G.K., 2002. Probabilistic assessment of photovoltaic (PV) generation systems. IEEE Transactions on Power Systems 17 (1), 205–208.

[5] Kellogg, W.D., Nehrir, M.H., Venkataramanan, G., Gerez, V., 1998. Generation unit sizing and cost analysis for stand-alone wind, photovoltaic and hybrid wind/PV systems. IEEE Transactions on Energy Conversion 13 (1), 70–75.
[6] Prasad, A.R., Natarajan, E., 2006. Optimization of integrated photovoltaic–wind power generation systems with battery storage. Energy 31, 1943–1954.
[7] Roy, S., 1997. Optimal planning of wind energy conversion systems over an energy scenario. IEEE Transactions on Energy Conversion 12, 248-253.
[8] Rohani, A., Mazlumi, K., Kord, H., 2010. Modeling of a hybrid power system for economic analysis and environmental impact in HOMER. Iranian Conference on Electrical Engineering (ICEE), 819-823.
[9] Luna-Rubio, R., Trejo-Perea, M., Vargas-Vázquez, D., Ríos-Moreno, G.J., 2012. Optimal sizing of renewable hybrids energy systems: A review of methodologies. Solar Energy 86, 1077-1088.
[10] Koutroulis, E., Kolokotsa, D., Potirakis, A., Kalaitzakis, K., 2006. Methodology for optimal sizing of stand-alone photovoltaic/wind-generator systems using genetic algorithms. Solar Energy 80, 1072-1088.
[11] Yang, H., Zhou, W., Lu, L., Fang, Z., 2008. Optimal sizing method for stand-alone hybrid solar–wind system with LPSP technology by using genetic algorithm. Solar Energy 82, 354-367.
[12] Kaviani, A.K., Baghaee, H.R., Riahy, G.H., 2009. Optimal sizing of a stand-alone wind/photovoltaic generation unit using particle swarm optimization. Journal of Simulation 85, 89-99.
[13] Ekren, O., Ekren, B.Y., 2010. Size optimization of PV/wind hybrid energy conversion system with battery storage using simulated annealing, Applied Energy 87, 592-598.
[14] Javadi, M.R., Mazlumi, K., Jalilvand, A., 2011. Application of GA, PSO and ABC in optimal design of a stand-alone hybrid system for north-west of Iran. ELECO 2011 7th International Conference on Electrical and Electronics Engineering, Bursa, Turkey, 204-211.
[15] Geem, Z.W., 2012. Size optimization for a hybrid photovoltaic–wind energy system. International Journal of Electrical Power & Energy Systems 42, 448-451.