ORIGINAL RESEARCH

Modeling and sizing optimization of hybrid photovoltaic/wind power generation system

Mohammad-Ali Yazdanpanah

Abstract The rapid industrialization and growth of world's human population have resulted in the unprecedented increase in the demand for energy and in particular electricity. Depletion of fossil fuels and impacts of global warming caused widespread attention using renewable energy sources, especially wind and solar energies. Energy security under varying weather conditions and the corresponding system cost are the two major issues in designing hybrid power generation systems. In this paper, the match evaluation method (MEM) is developed based on renewable energy supply/demand match evaluation criteria to size the proposed system in lowest cost. This work is undertaken with triple objective function: inequality coefficient, correlation coefficient, and annualized cost of system. It provides optimum capacity of as many numbers of supplies as required to match with a load demand in lowest investment, so it can handle large-scale design problems. Meteorological data were collected from the city of Zabol, located in south-east of Iran, as a case study. Six types of wind turbine and also six types of PV modules, with different output powers and costs, are considered for this optimization procedure. A battery storage system is used to even out irregularities in meteorological data. A multi-objective particle swarm optimization algorithm has been used for the prediction of an optimized set of design based on the MEM technique. The results of this study are valuable for evaluating the performance of future stand-alone hybrid power system. It is worth mentioning that the proposed methodology can be effectively employed for any composition of hybrid energy systems in any locations taking into account the meteorological data and the consumer's demand.

Keywords Sizing study · Match evaluation method (MEM) · Electricity match rate (EMR) · Hybrid renewable energy systems

Introduction

Countries are trying to decreasing their dependence to fossil energy by integrating renewable energy sources to their energy policies. Several projects in the field of renewable energy system (RES) are developed in the last two decades. Growing evidence of global warming phenomena, rapid depletion of fossil fuel resources and fast escalation in world's population caused widespread attention to seek energy from RES. Solar and wind energy are commonly used RES to supply power for consumers in the remote area. The reason is that they are non-polluting, no fuel cost, renewable and available in most sites. A hybrid system using a combination of these sources has the advantage of reliability and stability. Utilization of solar and wind energy has become increasing significant, attractive and cost-effective, since the oil crises of early 1970s (Wei et al. 2010). However, substantial fluctuates of climate and meteorological conditions may decrease the reliability of the system. Therefore, batteries are required to even out irregularities in the solar irradiation and wind speed. Hou et al. (2013) have used sensitivity coefficients to predict climatic variation.

Optimally sized design of hybrid RES is an important issue in hybrid systems. In large-scale problems, optimum size of each component of hybrid energy systems will require complex computer program and will need much time for computing. This paper presents an optimization

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process for finding the optimum size of different hybrid renewable energy configuration which maximizes the electricity match rate (EMR) between supplies and demand in lowest cost. The purpose is to provide the best configuration among all cases which can meet the load demand in lowest cost. For this task, six types of wind turbine (WT) and six types of PV module, with different output powers and costs, are considered. To find the optimum configuration which is economical and efficient, sizing optimization method is necessary. Optimum match design will guarantee the lowest investment and optimal use of hybrid energy resources. Various optimization techniques in sizing of hybrid energy resources have been reported in the literatures. The design of hybrid systems is usually done by searching the configuration and/or control with the lowest total cost throughout the useful life of the installation or pollutant emissions. Classical optimization techniques may consume excessive CPU time or even be unable to take into account all the characteristics associated with the posed problem. Dufo-Lopez and Bernal-Agustin (2008) presented a multi-objective design of hybrid systems by minimizing the total cost, pollutant, emission and unmet load. Vafaei (2011) confirms that hybrid stand-alone electricity production systems are usually more reliable and less costly than systems that use only single source of energy. The optimization procedure can be done in different methods. Proper design of stand-alone hybrid RESs using loss of power supply probability technique is discussed by Xu et al. (2005), Yang et al. (2008), Wei (2007), Wei and Hongxing (2007), Nelson et al. (2005, 2006). Zhao et al. (2006) have optimized the wind/PV hybrid power system with particle swarm optimization algorithm (PSO) to have higher capacity and faster search efficiency. Dhillon (2009) proposed the non-dominated sorting genetic algorithm (NSGA-II) algorithm to simultaneously minimizing the total system real power losses in transmission network and cost by satisfying power balance equation. Proper sizing of a wind/PV hybrid system has obtained with NSGA-II procedure by Xu et al. (2006). The use of genetic algorithm (GA) in unit sizing of photovoltaic/wind generator systems is discussed by Koutroulis et al. (2006). Luna-Rubio et al. (2012) reviewed different sizing technique developed in the recent years. Another sizing technique, which is developed in the current paper, is based on match evaluation method (MEM) (Yazdanpanah Jahromi et al. 2012). The MEM is based on the coordination criteria between generation and consumption intervals.

In this paper, a PSO-based multi-objective algorithm called multi-objective particle swarm optimization (MO-PSO) is applied to different wind/PV hybrid systems in the optimization of supply and demand matching. The results are validated by NSGA-II. The MEM technique is developed to find the optimum system among all different possible configurations, which offers to guarantee the lowest investment with full use of the PV and wind turbine components. Inequality coefficient (IC) and correlation coefficient (CC) together can obtain good EMR for hybrid systems. IC provides a relative measure of forecast accuracy in terms of deviation from the perfect forecast (Henderson 2010). CC measures how well the predicted values from a forecast model "fit" with the real-life data (Yuan and Yu 2012). IC gives the match magnitude, while CC deals with trend matching. Hence, IC and CC are selected together to check the EMR between supplies and load demand. Optimization algorithm selects the optimal sizing of stand-alone wind/PV generator system with the help of PSO and genetic algorithm. PSO and GA are the most suitable algorithms in terms of global optimization, stochastic nature of these renewable energies and particular nature of sizing method. To have a perfect generation, a storage battery bank system is considered in the optimization algorithm. The excess generated power is used to charge the battery. On the other hand, battery supplies the power when the total generated power cannot meet the load.

The first step is the modeling of components in the proposed hybrid system. Optimization procedure of this hybrid system according to IC, CC and cost concepts is the second step. By applying these two steps to each configuration of proposed hybrid system, optimal configuration among all cases, which can meet the maximum match between demand and supplies, is obtained.

Modeling of hybrid wind/PV system components

To develop an overall power management strategy for the proposed hybrid system and to investigate the system performance, mathematical modeling of the components has been developed. Various models for hybrid wind/PV system have been reported in the literature. A brief description for modeling wind/PV hybrid system is shown in the following subsection.

The wind turbine model

There are six possible different WTs, shown in Table 1. These WTs are most commonly used in the USA and Europe for small wind power applications. It has been considered a 30 m tower to be used with all turbines. The price was obtained from reference (Rios Rivera 2008). The lifetime of all WTs is supposed to be 20 years.

Wind speed height correction

The recorded anemometer data at a reference height (h_r) should be adjusted to the desired hub center (h) using the

Table 1 Small wind turbines rating and price

Type of wind turbine	Small wind turbine parameters			
	Product	Turbine MSRP (US$)	Tower price (US$)	Watt at 12.5 m/s
1	SouthWest (Air X)	600	804.86	400
2	SouthWest (Whisper 100)	2,085	804.86	900
3	SouthWest (Whisper 200)	2,400	804.86	1,000
4	SouthWest (Whisper 500)	7,095	1,157.19	3,000
5	SouthWest (Skystream 3.7)	5,400	1,157.19	1,800
6	Aeromax Engineering (Lakota S, sSC)	1,591	804.00	800

wind power law. This can be done through the following expression (Borowy and Salameh 1996)

$$v(t) = v_r(t)\left(\frac{h}{h_r}\right)^{\gamma} \qquad (1)$$

where v is the wind speed at the desired height h, v_r is wind speed measured at known height h_r, γ is wind shear exponent coefficient which varies with pressure, temperature and time of day. A commonly used value for open land is one-seventh.

Weibull probability density function

Probability density function (pdf) is the best description for variation of wind speed. The pdf calculated the probability that an event will occur between two end points. Note that the pdf curve shape and its height provide in some way that the area under the pdf curve from 0 to infinity is exactly 1. This means that blowing of wind speed will be between 0 and infinity (m/s). There are various notations for Weibull pdf in papers. In this paper, the Weibull PDF is defined as:

$$f(v) = \frac{\beta}{\eta}\left(\frac{v}{\eta}\right)^{\beta-1} e^{-\left(\frac{v}{\eta}\right)^{\beta}} \qquad (2)$$

where β is the shape factor and v is wind speed. Figures 1 and 2 are the plots of f vs. v for different values of η and β in (8), respectively. The value of β controls the curve shape and hence is called the shape factor. The smaller shape factor shows that the distribution of wind speed is near the average. The scale factor (η) shows how the bulk distribution lies and how it stretched out. For wind speed profile shown in Fig. 3, the Weibull probability distribution function has been shown in Fig. 4.

Wind turbine output energy

The output power of wind can be calculated using probability distribution function for a specific site. The output energy from the wind turbine can be estimated using wind turbine power curve. The wind turbine power curve usually given by manufacturer shows the output power of wind turbine at any wind speed. The available energy for a wind speed profile can be calculated as Rios Rivera (2008):

$$E_{wt} = (\text{days})(\text{hours}) \cdot P_c f(v, \beta, \eta) \qquad (3)$$

where E_{wt} is the generated energy of wind turbine in kWh for a specific site. The multiplication of days by hours gives the

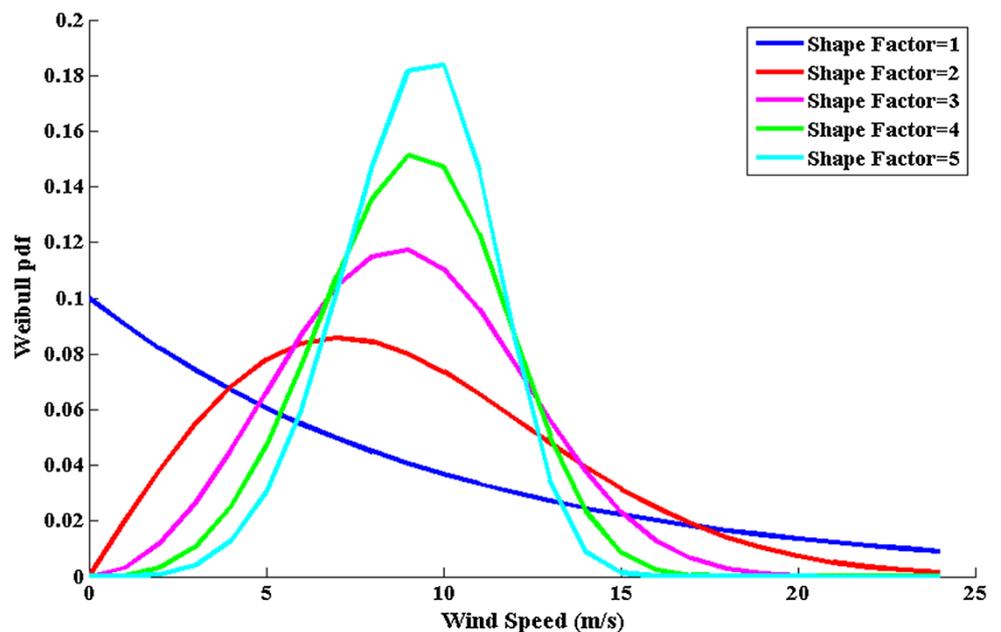**Fig. 1** Weibull PDF with scale factor $\eta = 10$ and shape factor $\beta = 1, 2, 3, 4, 5$

Fig. 2 Weibull PDF with shape factor $\beta = 2$ and scale factor $\eta = 6, 7, 8, 9, 10, 11, 12$
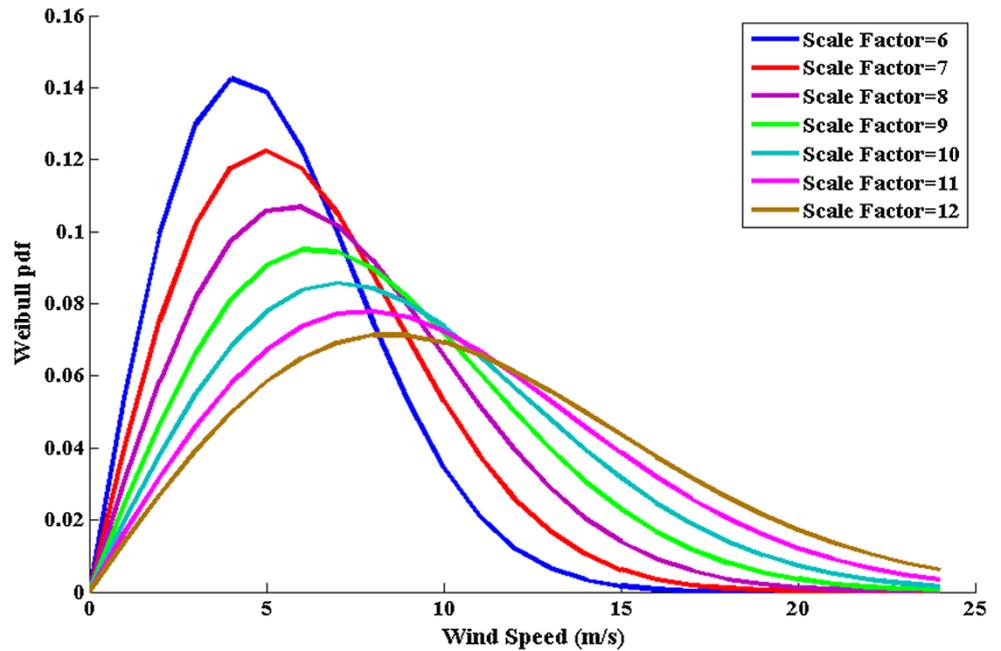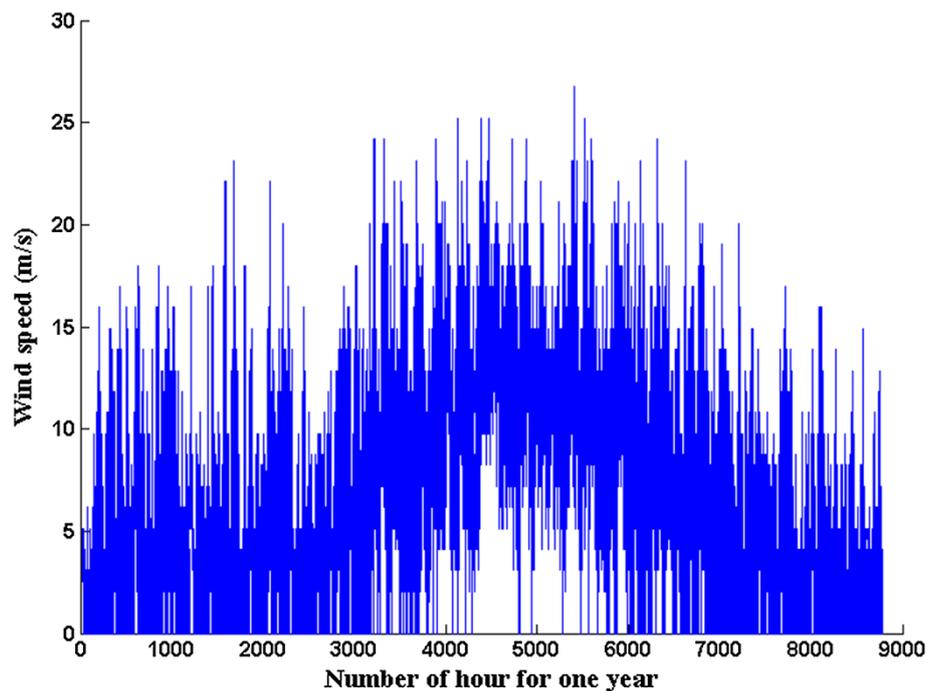

Fig. 3 Meteorological conditions of wind speed

total hours in the period of simulation, P_c is the output power of wind turbine; $f(v)$ is the Weibull PDF for wind speed v; β is the shape factor and η is the scale factor (Fig. 5).

Modeling of PV generator

There are six possible different PV generators, presented in Table 2. The price was obtained from reference (Rios Rivera

2008). Each hybrid system will include one of them. The mathematical model of PV modules is given in forthcoming subsections. The lifetime of all PV modules is 20 years.

Photovoltaic power

Simulation of PV array performance has been done by considering the modeling of the maximum power point
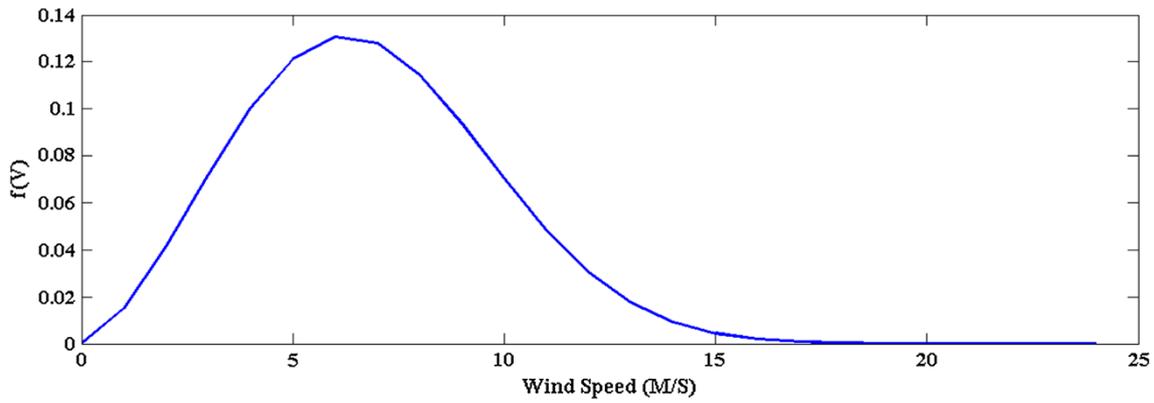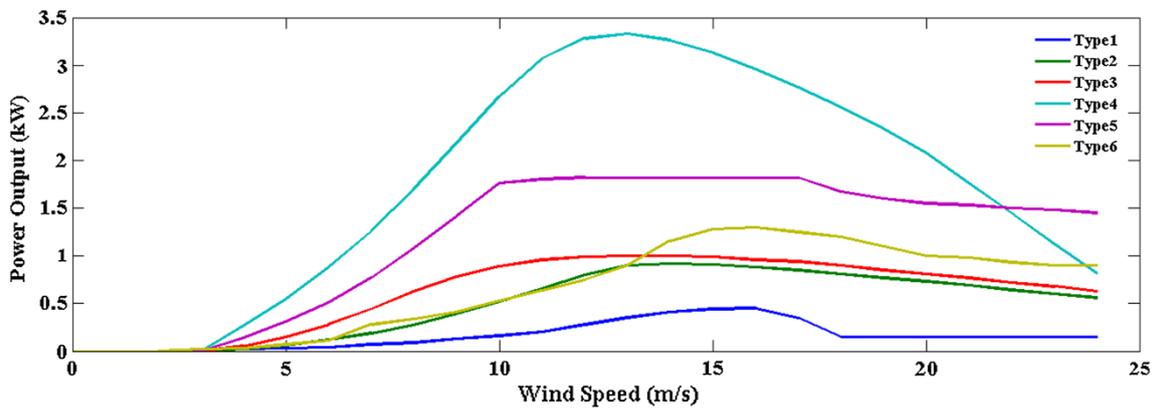
Fig. 4 Weibull probability density function [$f(v)$]

Fig. 5 Wind turbine power curves (the *symbols* represent data sampled from the power curve graphs given by the manufacturer)

Table 2 Solar module power at STC rating and price

Type of PV module	PV panels parameters			
	Product	PV MSRP (US$)	Watt at 1,000 W/m²	Efficiency
1	Kyocera Solar (KC200)	800.00	200	0.20
2	BP Solar (SX 170B)	728.97	170	0.17
3	Evergreen (Spruce ES-170)	731.00	170	0.17
4	Evergreen (Spruce ES-180)	774.00	180	0.18
5	Evergreen (Spruce ES-190)	817.00	190	0.19
6	Solar World (SW-165)	709.97	165	0.17

tracking (MPPT) controller at any PV module temperature in this modeling procedure. This model can predict output power of PV panel in different temperatures and various irradiation levels. The output power of a PV panel can be calculated using the following equation (Ortiz Rivera 2006):

$$I(V) = \frac{Ix}{1 - \exp\left(-\frac{1}{b}\right)} \cdot \left[1 - \exp\left(\frac{V}{b \cdot Vx} - \frac{1}{b}\right)\right] \quad (4)$$

$$Vx = s \cdot \frac{E_i}{E_{iN}} \cdot \text{TCV} \cdot (T - T_N) + s \cdot V_{\max}$$
$$- s \cdot (V_{\max} - V_{\min}) \cdot \exp\left(\frac{E_i}{E_{iN}} \cdot \ln\left(\frac{V_{\max} - V_{oc}}{V_{\max} - V_{\min}}\right)\right) \quad (5)$$

$$Ix = p \cdot \frac{E_i}{E_{iN}} \cdot [I_{sc} + \text{TC}i \cdot (T - T_N)] \quad (6)$$

$$P(V) = \frac{V \cdot Ix}{1 - \exp\left(\frac{-1}{b}\right)} \cdot \left[1 - \exp\left(\frac{V}{b \cdot Vx} - \frac{1}{b}\right)\right] \quad (7)$$

where P is the output power of the photovoltaic panel (W), $I(V)$ is the output current of the photovoltaic panel (A), V is the output voltage of the photovoltaic (V), I_{sc} is the short-circuit current at 25 °C and 1,000 W/m², V_{oc} is the

open-circuit voltage at 25 °C and 1,000 W/m², V_{max} is the maximum open-circuit voltage at 25 °C and 1,200 W/m² (usually, V_{max} is close to 1.03 V_{oc}), V_{min} is the minimum open-circuit voltage at 25 °C and 200 W/m² (usually, V_{min} is close to 0.85 V_{oc}), T is the solar panel temperature (°C), E_i is the effective solar irradiation impinging on the cell in W/m². T_w is 25 °C standard test condition (STC), TCi is the temperature coefficient of V_{oc} in V/C, Ix is short-circuit current at any given E_i and T; Vx is open-circuit voltage at any given E_i and T; s is the number of photovoltaic panels in series, p is the number of photovoltaic panels in parallel. b is characteristic constant based on I–V curve.

The characteristic constant, b, usually varies from 0.01 to 0.18 and can be calculated using (8) with iterative procedures

$$b_{n+1} = \frac{V_{op} - V_{oc}}{V_{oc} \cdot \ln\left(1 - \frac{I_{op}}{I_{sc}} \cdot \left(1 - \exp\left(\frac{-1}{b_n}\right)\right)\right)}. \tag{8}$$

Photovoltaic energy

To calculate the available output energy of PV array at a specific site, the following equation is used:

$$E_{PV} = P_{out}(E_x) \cdot (\text{SolarWindow}) \cdot (\text{TotalDay}) \tag{9}$$

where E_{pv} is the production of photovoltaic energy in kW, "SolarWindow" is the total time hours the sun hits the PV module at an average hourly solar irradiation, the product of "TotalDay" is to change from daily to monthly or yearly quantities, $p_{out}(E_x)$ is the PV module power output at an

average hourly solar irradiation (E_x). The solar radiation profile has shown in Fig. 6. The P–V and I–V curves for different PV modules are shown in Fig. 7.

Battery storage system

The batteries are the most widely used devices for energy storage in different applications. The stochastic nature of available energy from the wind/PV system makes it necessary to select a right size of battery bank that the system will satisfy the load at any hour of a typical day. The battery sizing is mainly depends on the number of days that the battery bank itself can supply the load without being recharge by supply resources which is called "autonomy days". Another important factor in battery sizing procedure is the battery depth of discharge (DOD). The battery can have the maximum life if the DOD is set to 30–50 %, for instance DOD = 50 %. Temperature can also affect the performance of batteries (T_{bat}). High temperature decreases the battery lifetime. The batteries are normally installed inside a building where the temperature is not expected to change drastically. It is recommended to keep the battery at 25 °C. In this temperature, the derate factor (D_f) is one. The required battery band capacity can be calculated as Rios Rivera (2008):

$$C_{BR} = \frac{L \cdot (\text{Autonomy Days})}{\text{DOD}_{max} \cdot D_f} \tag{10}$$

where C_{BR} is the required battery bank capacity (Ah), L is the amp-hour consume by the load in a day (Ah/Day). The

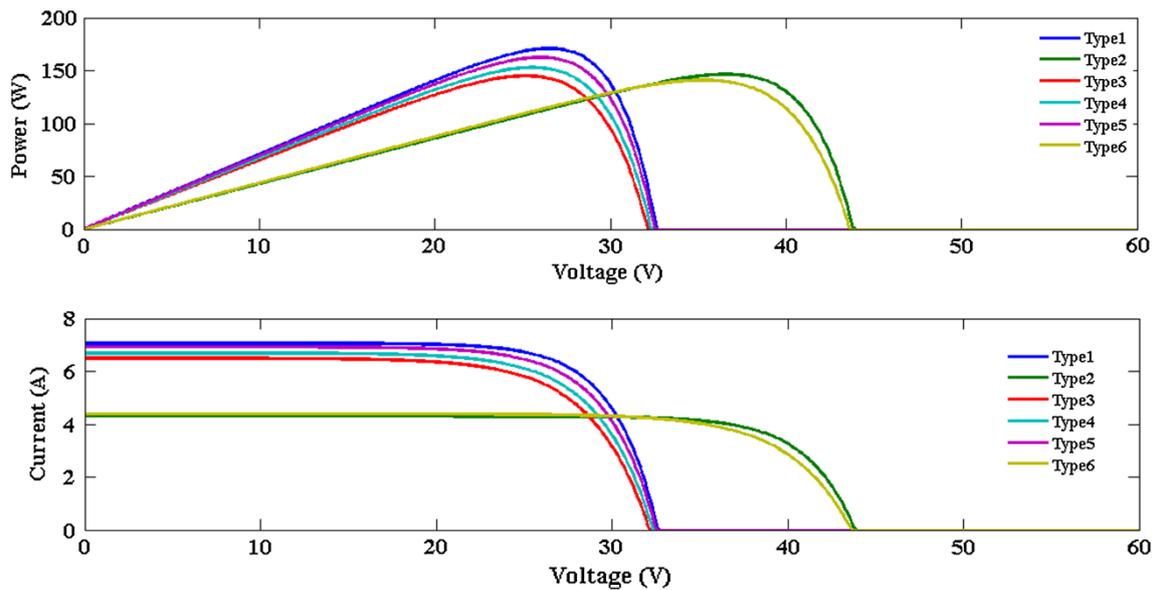**Fig. 6** Meteorological conditions of solar radiation
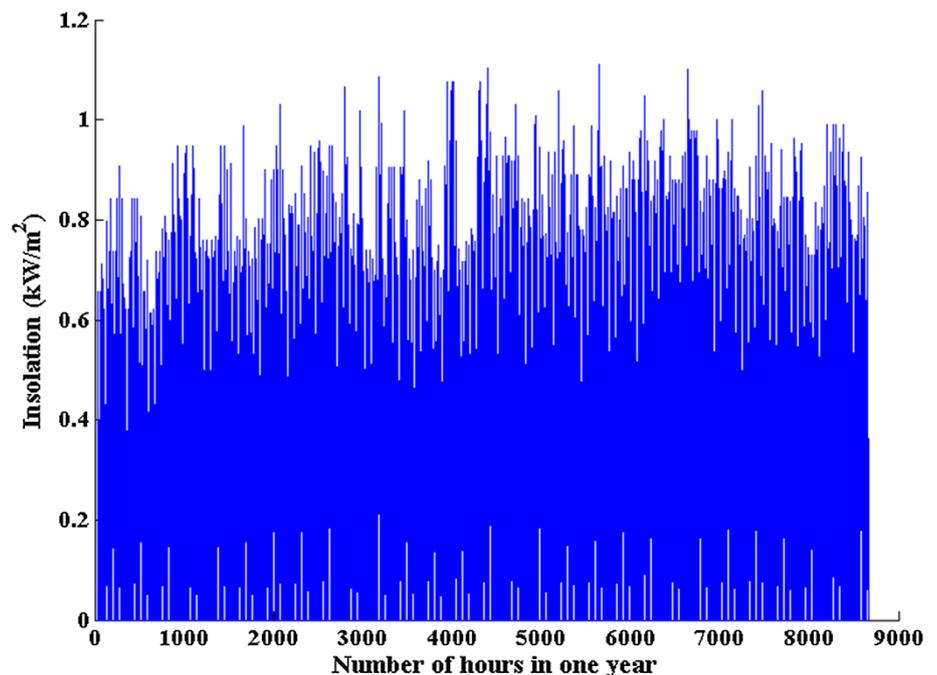
Fig. 7 P–V and I–V curves for different PV modules

Table 3 Battery characteristics

| | Volt | Rated capacity (Ah) | Price (US$) | Dimensions (m) | | | Weight (kg) | Lifetime (years) |
				Width	Length	Height		
	12	50	87	0.132	0.239	0.205	17.1	5

number of batteries that should be connected in parallel to reach the amp hours required by the system can be calculated using (11)

$$B_{\text{paralel}} = \frac{C_{\text{BR}}}{C_{\text{B}}} \tag{11}$$

where C_{B} is the capacity of the selected battery (Ah). The number of batteries that should be connected in series to reach the voltage required by the system can be calculated using (12)

$$B_{\text{series}} = \frac{V_{\text{N}}}{V_{\text{B}}} \tag{12}$$

where V_{N} is the DC system voltage (Volt) and V_{B} is the battery voltage (Volt).

Finally, the total number of required batteries can be expressed as:

$$N_{\text{B}} = B_{\text{paralel}} \cdot B_{\text{series}}. \tag{13}$$

The selected battery characteristic is presented in Table 3 (Industrial Power Battery 2013).

Load model

The hourly load demand is presented in Fig. 8. This is the yearly variation of domestic load profile in the region.

Problem formulation

After modeling the hybrid components, the design problem of the hybrid wind/PV system is formulated as a multi-objective optimization problem. The MEM technique is used to check the match rate. Three objectives (Inequality coefficient, correlation coefficient, and total system cost) are considered. The number of WTs and PV modules is a decision variable in this procedure. The aim is to seek the optimal system configuration which gives the acceptable EMR and low total system cost. The following three subsections describe the objective definitions in detail.

Correlation coefficient

The maximization of EMR between demand and supplies in hybrid RESs is an important subject in power systems. In

Fig. 8 Yearly variation of domestic load profile
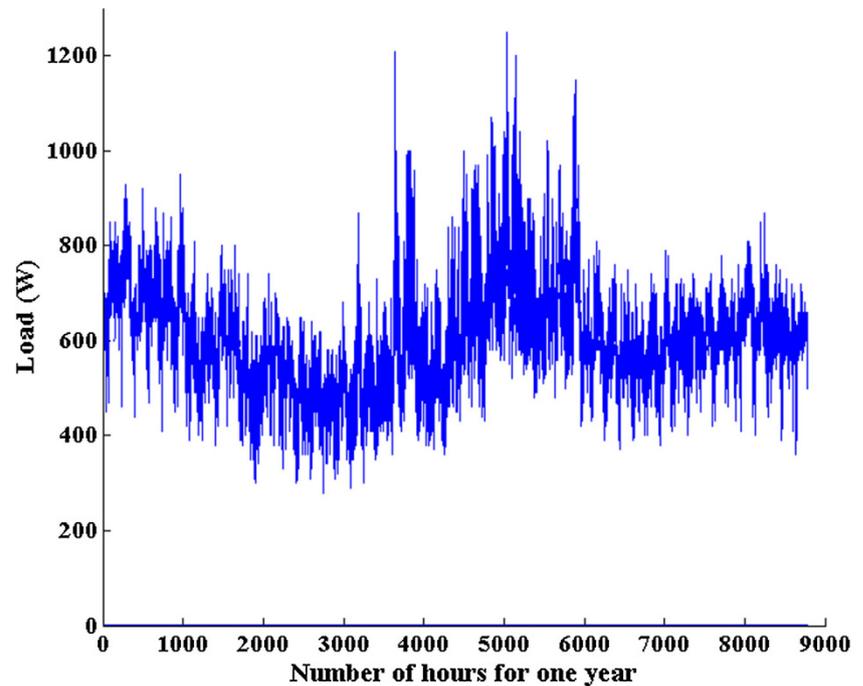
other words, generation periods of renewable generators should nearly match with consumption periods. For quantifying the deviation between two set of data variables, the least squares (LS) approach can be used (Scheaffer et al. 2011). The following equation describes LS:

$$LS = \sum_{t=0}^{n} (D_t - S_t)^2. \tag{14}$$

It is clear that the answer of LS is always a positive value. The value of zero for it shows a perfect match. Several authors have discussed and investigated the concepts of correlation in differences methods. Zeng and Li (2007) proposed a method for calculating the correlation coefficient of fuzzy sets. Spearman's rank correlation coefficient is one of the objectives which can describe the correlation between supply and demands. CC can vary from −1 to 1. "1" shows the perfect positive match and "−1" shows perfect negative correlation, while "0" represents no match. The correlation coefficient can be expressed as follows (Born 2001):

$$CC = \frac{\sum_{t=0}^{n} (D_t - d) \cdot (S_t - s)}{\sqrt{\sum_{t=0}^{n} (D_t - d)^2 \cdot \sum_{t=0}^{n} (S_t - s)^2}} \tag{15}$$

where D_t is the demand and S_t is the supply at time t, d and s are demand and supply average over time period n, respectively. S_t is composed of two parts; S_1 and S_2 are the energy supply sources, PV modules and wind turbines,

respectively. The higher correlation coefficient gives more electricity match between supplies and demands. Note that as said before, the upper limit of CC is 1.

Inequality coefficient

The other objective function which can be ideally used to describe match rate is inequality coefficient. This objective defines the inequality in time-series due to three sources: unequal tendency (mean), unequal variation (variance) and imperfect co-variation (co-variance) (Born 2001). The smaller IC gives us the larger match rate. The inequality coefficient can vary in the range of 0–1 and can be given by the following equation (Born 2001):

$$IC = \frac{\sqrt{\frac{1}{n} \sum_{t=0}^{n} (D_t - S_t)^2}}{\sqrt{\frac{1}{n} \sum_{t=0}^{n} (D_t)^2} + \sqrt{\frac{1}{n} \sum_{t=0}^{n} (S_t)^2}}. \tag{16}$$

Value of IC between 0 and 0.4 shows good matches and value above 0.5 represents bad match (Waqas 2011). IC is the best criterion for matching between supplies and demand. However, CC is also good but not as good as IC.

Total system cost

A cost analysis of the system is performed for each configuration according to the concept of annualized cost of system (ACS). For all wind/PV configurations, the ACS is

composed of the annualized capital cost (ACC), annualized operation and maintenance cost (AOC), and annualized replacement cost (ARC). It is supposed that the life time of the project is 20 years. ACS can be calculated as:

$$
\begin{aligned}
\text{ACS} = {} & \text{ACC(PV + Wind + Tower + Battery)} \\
& + \text{AOC(PV + Wind + Tower + Battery)} \\
& + \text{ARC(Battery)}
\end{aligned}
\tag{17}
$$

Annualized capital cost (ACC)

ACC of each component is as follows:

$$
\text{ACC} = C_{\text{cap}} \times \text{CRF}(i, n)
\tag{18}
$$

where C_{cap} is capital cost of each component and CRF is capital recovery factor, defined as:

$$
\text{CRF}(i, n) = \frac{i(1+i)^n}{(1+i)^n - 1}.
\tag{19}
$$

The project life time is n and the annual interest rate (i) consists of nominal interest rate (i_{loan}, the rate at which a loan can be obtained) and the annual inflation rate, f, by the equation given below:

$$
i = \frac{i_{\text{loan}} - f}{1 + f}
\tag{20}
$$

Operation and maintenance cost (AOC)

The maintenance cost of each component can be calculated as follows:

$$
\text{AOC} = \text{AOC}(1) \times (1+f)^n
\tag{21}
$$

where AOC (1) is the maintenance cost of that component for the first year of the project.

Annual replacement cost (ARC)

The components which have a lifetime less than the lifetime of the project need to be replaced during the project lifetime. The ARC can be calculated from the following equation:

$$
\text{ARC} = C_{\text{rep}} \times \text{SFF}(i, n_{\text{rep}})
\tag{22}
$$

where C_{rep} is replacement cost of units, SFF is sinking fund factor which depends on lifetime of units (n_{rep}) and interest rate (i) as follows:

$$
\text{SFF}(i, n_{\text{rep}}) = \frac{i}{(1+i)^{n\text{rep}} - 1}.
\tag{23}
$$

The cost parameters used in this paper are presented in Table 4 (Wei 2007; Vafaei 2011).

## Multi-objective optimization procedure using MOPSO

By mathematical formulation of optimization design problem and applying it to each configuration of hybrid system, the best combination of components (minimizing IC and ACS and also maximizing CC) has been obtained. The proposed objective functions conflict with each other. It is not possible to improve them simultaneously and there is always a trade-off between them. The optimization design problem has nonlinearity characteristic due to the nonlinear behavior of the hybrid components. To reach the best combination for IC, ACS and CC, long-term system performance is required. Daily and seasonal variations of RES and the load demand make design problem more complex, as well as mismatch between them.

Implementation of MOPSO and NSGA-II in various engineering and business applications has been done in the recent years. These two algorithms are well suited to solve these kinds of problems. The reason is that they are population based and this property allows them to find an entire set of Pareto-optimal solution in one single simulation run. They can seek for the best configuration among all possible cases in somehow the electricity production periods have better match with the consumption periods than others, in the lowest total system cost. With the same number of iteration and population, MOPSO has higher speed than NSGA-II. The good sizing algorithm is the one which can find the optimal size of each component in each configuration to maximize the EMR between demand and supplies. By employing the MOPSO algorithm to each configuration, a set of possible solutions (Pareto set) will be obtained. These solutions validated with NSGA-II. The

Table 4 Economic parameters of the project

Lifetime (years)	Wind turbines maintenance cost for the first year (US$)	Wind tower maintenance cost for the first year (US$)	PV modules maintenance cost for the first year (US$)	Inflation rate f (%)	Interest rate i_{loan} (%)
20	95	6.5	65	2	5

Fig. 9 The scheme of
optimization using MOPSO
(or NSGA-II)
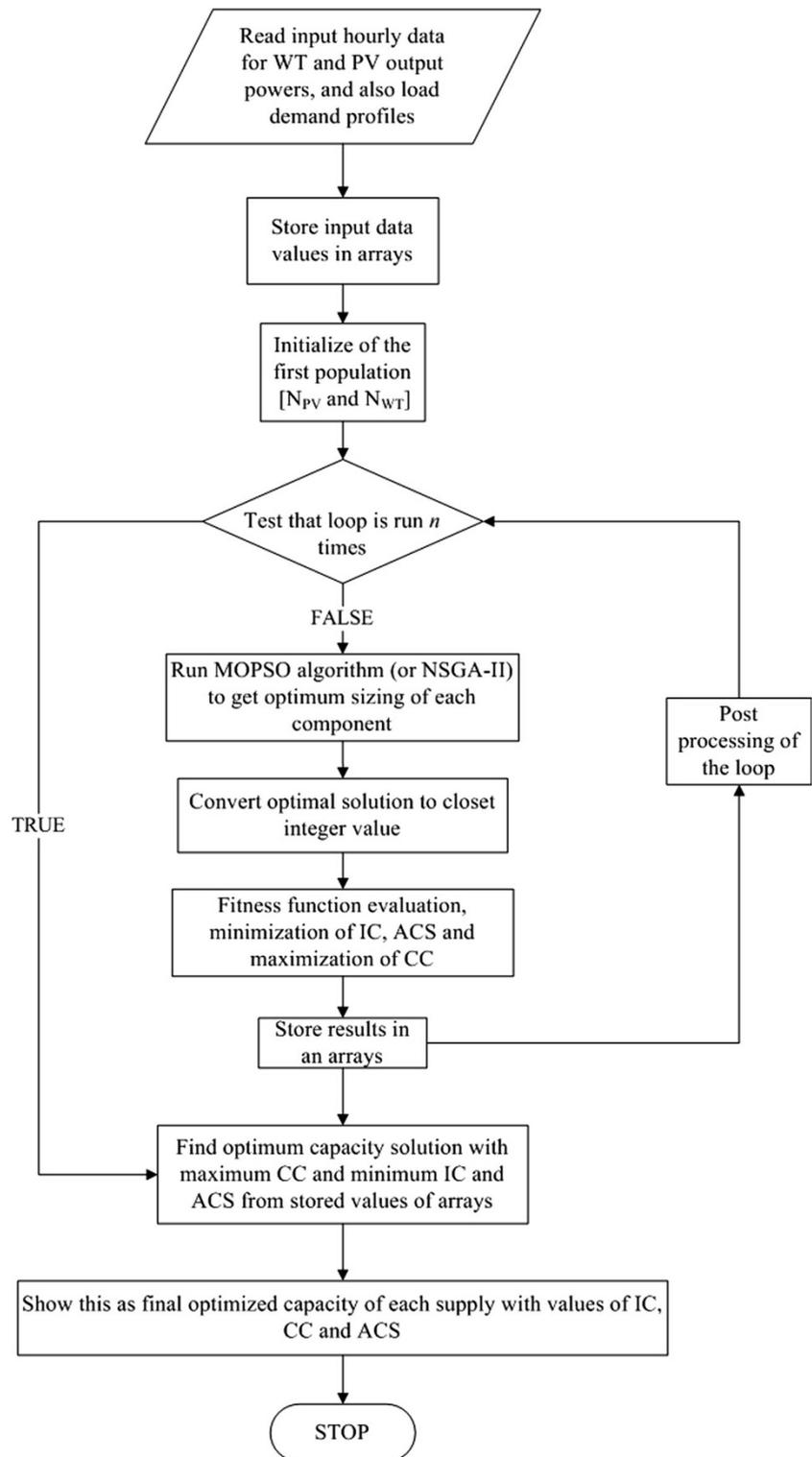
number of PV panels and wind turbines is a design variable. The minimum value (lower limit) of design variables is selected as 1 to be sure that there is at least one of each supply in the system and the upper bound of them is set as $\max(D)/\min(S_n)$. Where max (D) and min (S_n) are the maximum and minimum values of demand and supplies over considered time period, respectively. The flow chart of the MOPSO algorithm is shown is Fig. 9.

Table 5 Pareto front/optimal solutions obtained from multi-objective optimization algorithm

Solution number	Optimization algorithm made in MOPSO and NSGA-II				
	N_{PV}	N_{WIND}	IC	CC	ACS
1	7	1	0.1528	0.9223	7,683/30
2	6	1	0.1563	0.9224	6,804/00
3	5	1	0.1830	0.9218	5,924/80
4	4	1	0.2319	0.9202	5,045/57
5	4	2	0.1282	0.9119	6,574/20
6	2	2	0.2056	0.9037	4,815/70
7	6	2	0.1480	0.9172	8,332/70
8	2	4	0.1301	0.8981	7,873/00
9	5	2	0.1283	0.9149	7,453/40
10	3	2	0.1549	0.9083	5,694/96

Results

The output powers of PV array and wind turbine were calculated according to the model which described before by specifications of wind turbine and PV module given in Tables 1 and 2. The output power of PV panels calculated with considering MPPT controller. The battery sized based on the given characteristic on Table 3. The DC voltage of the battery system will be 48-V. The number of autonomy days is supposed to be 3 days. The DOD is selected 50 % for longevity of battery lifespan. The derate factor is 1 because the batteries are kept at a temperature of 25 °C. Taking into account the above consideration, the total

number of batteries is defined as 12 (4 batteries in series and 3 batteries in parallel).

The optimization process which dynamically searches the optimal configuration to minimize the IC and ACS and also maximize the CC is employed. The results of these studies suggest the choice of Kyocera Solar (KC200) PV module and Southwest (Air X) wind turbine for the proposed hybrid power system, compared to the other configurations. This configuration provides the lowest cost in larger EMR. Other configurations, either have not optimal IC range ($0 \leq$ IC ≤ 0.4) or optimal CC range (CC = +1, −1) or have higher cost than the selected configuration. For this configuration, results obtained for the capacities of WT and PV modules from multi-objective algorithms (MOPOS and NSGA-II), and the Pareto front are recorded in Table 5 which shows the optimal solutions. As said before, to have a good EMR, IC values must be as low as possible. The values lower than 0.4 are acceptable for providing good match rate between supplies and demand. The ACS cost needs to be as low as possible. Higher CC is another criterion for this process. Note that the upper limit of CC is one.

It is important to know that IC is the main objective function which is most importantly desirable (Waqas 2011). Although the algorithm involves CC and ACS as other objectives for optimization procedure, but it does not provide equal importance as that of IC. CC is also more important objective with respect to ACS. Owing to the above considerations, the Pareto front has been plotted for IC and CC, IC and ACS, and also CC and ACS whose obtained curves are shown in Figs. 10, 11 and 12, respectively. The

Fig. 10 2D Pareto front for the last generation. Inequality coefficient (IC) vs. correlation coefficient (CC)
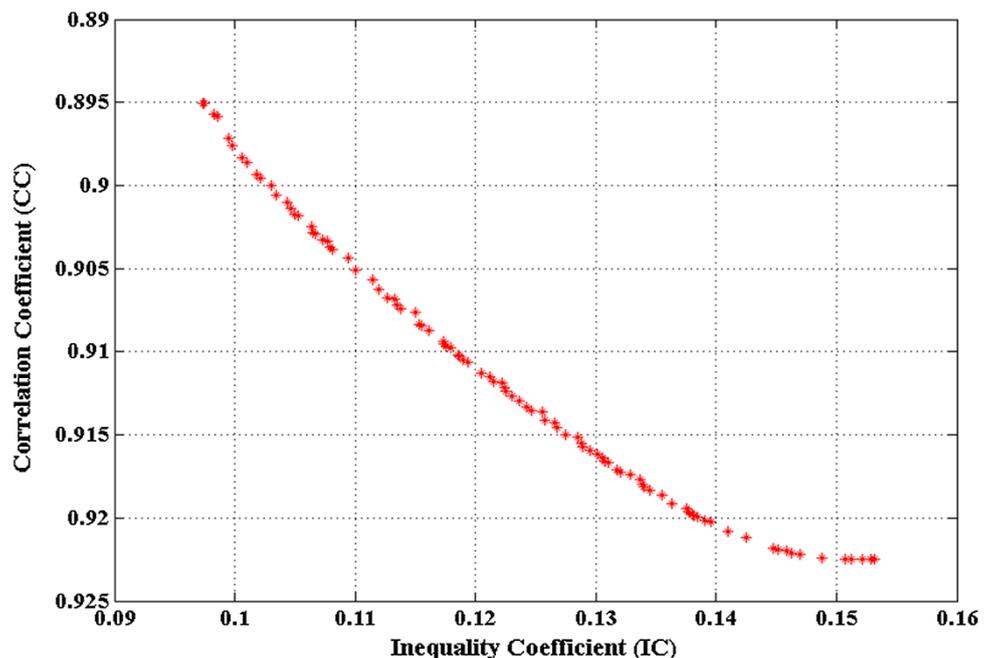
Fig. 11 2D Pareto front for the last generation. Inequality coefficient (IC) vs. annualized cost of system (ACS)
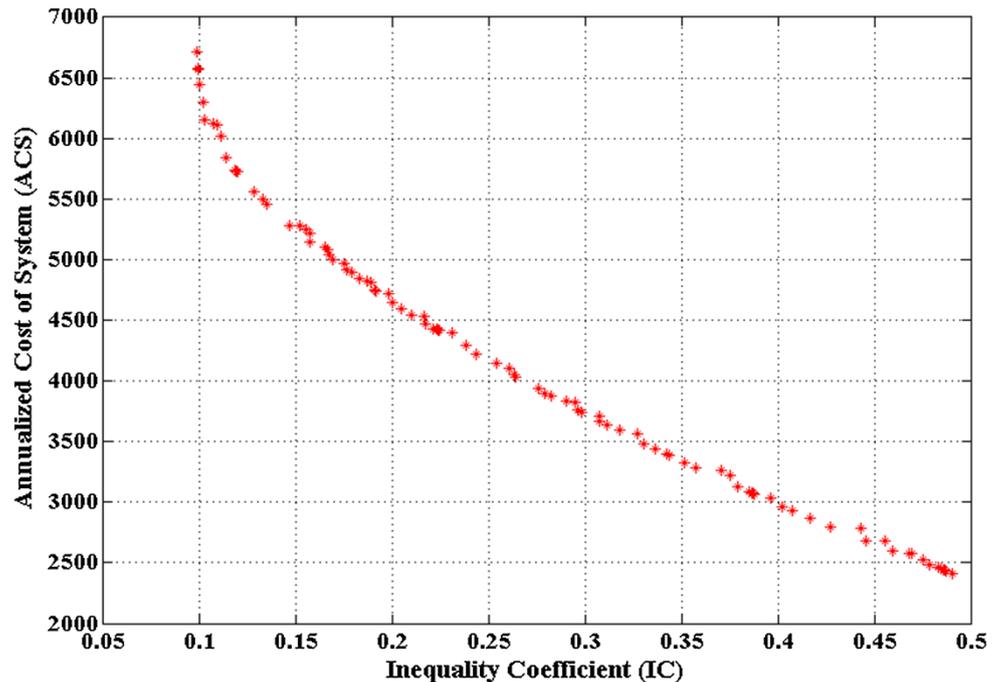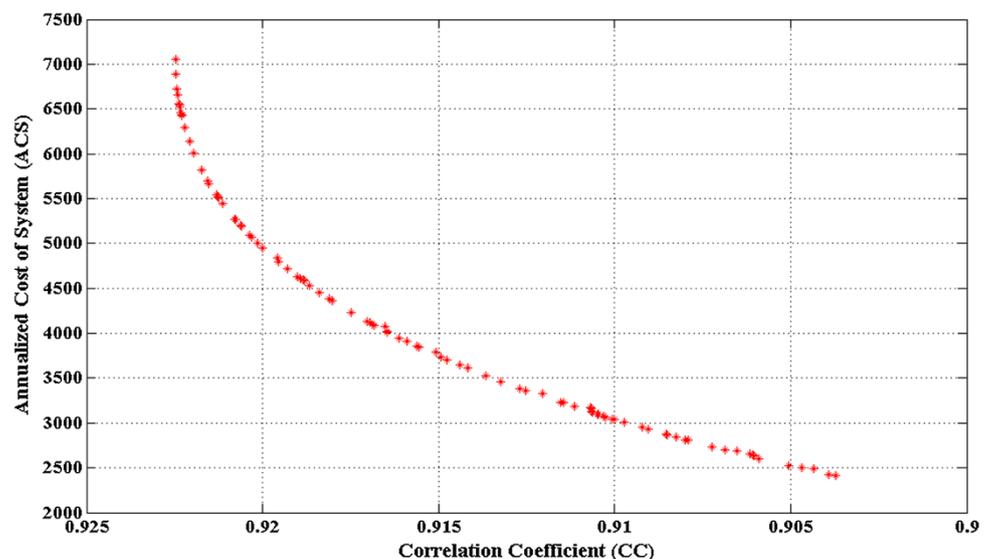

Fig. 12 2D Pareto front for the last generation correlation coefficient (CC) vs. annualized cost of system (ACS)


evolution of the 3D Pareto front can be observed in Fig. 13. When a pre-specified iteration count ($N = N_{max}$) is reached, MOPSO is terminated. $N_{max} = 200$ and a population size of $N_{pop} = 200$ are considered.

The solutions found by these optimization algorithms are shown in Table 5. These results show the optimum combination of equipment needed to supply the energy to the load at the lowest cost possible. The 10 best sizing selections from 30 runs in Matlab for best configuration have been obtained. The designer can select the solution that most appropriate to the requirements from the set of solutions obtained, studying for each solution its IC, CC and ACS. Hence, the designer can limit the acceptable upper and lower bounds of each objective function, and consider several solutions, which agree with the limits that have been imposed. The results show good EMR between supplies and demand, and the practical utility of this procedure. Table 5 shows sizing number of 2 for both PV modules and WT, and gives the minimum cost in acceptable EMR.

Fig. 13 3D Pareto front for the best configuration
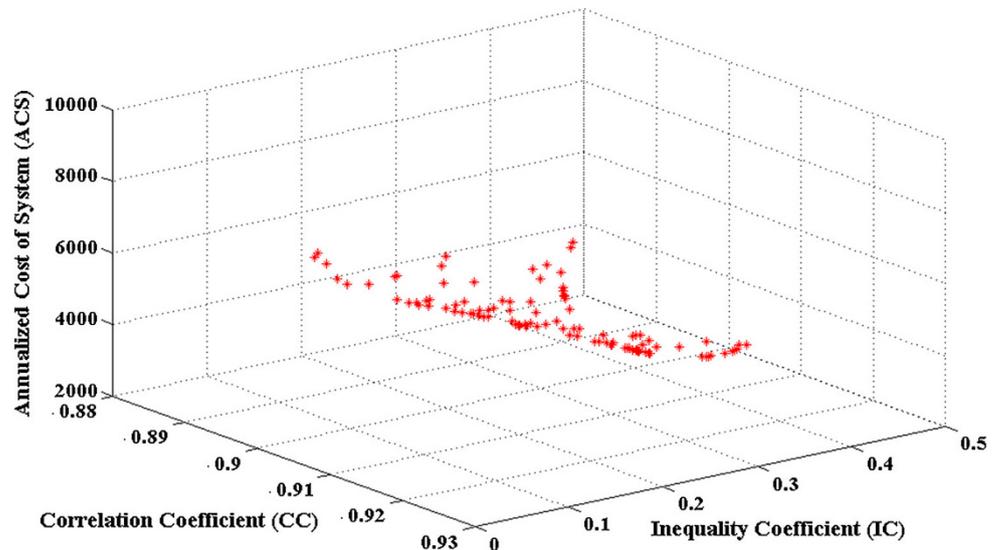
Conclusion

In this paper, a new sizing method has been applied to the multi-objective design of hybrid wind/PV systems of electrical energy generation. The MEM is developed to calculate the optimal size of each component based on MOPSO algorithm and NSGA-II. The both selected algorithms have the ability to attain the global optimum solution. The best solutions, that the applied algorithm has found, simultaneously consider three objectives: Inequality coefficient, correlation coefficient and ACS. Battery storage systems are used to even out irregularities in the solar irradiation and wind speed. Obtained solutions are non-dominated and they form the Pareto front. Results suggest the choice of Kyocera Solar (KC200) PV module and Southwest (Air X) wind turbine for the proposed hybrid power system, among all configurations. Simulation results show that a configuration with two PV and two WTs has the minimum ACS value compared to other configurations, in acceptable EMR. The designers can select other configurations among the Pareto set which fits their desire. It is worth mentioning that the proposed methodology can be effectively employed for any composition of hybrid energy systems in any locations taking into account the meteorological data and the consumer's demand.

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