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ORIGINAL RESEARCH

Comparative study between classical methods and genetic algorithms for sizing remote PV systems

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Abstract Uncertain renewable energy supplies, load demands and the non-linear characteristics of some components of photovoltaic (PV) systems make the design problem not easy to solve by classical optimization methods, especially when relevant meteorological data are not available. To overcome this situation, modern methods based on artificial intelligence techniques have been developed for sizing PV systems. However, simple methods like worst month method are still largely used in sizing simple PV systems. In the present study, a method for sizing remote PV systems based on genetic algorithms has been compared with two classical methods, worst month method and loss of power supply probability (LPSP) method. The three methods have been applied to a PV lighting system with orientation due south and inclination angles between 0° and 90° in Adrar city (south Algeria). Because measured data for the chosen location were not available, a year of synthetic hourly meteorological data of this location, generated by PVSYST software, have been used in the simulation. Genetic algorithms and worst month methods give results close to each other between 0° and 60° but the system is largely oversized by the worst month method when the tilted angle is over 60°. The results obtained by LPSP method show that the system is very undersized. Hence, a proposition has been made to improve results obtained by this method.

Keywords Cost · Genetic algorithms · Lighting · LPSP · Optimization · Photovoltaic · Worst month

Introduction

Conventional methodologies (empirical, analytical, numerical, hybrid, etc.) are used for sizing photovoltaic (PV) systems, especially when the required weather data (irradiance, temperature, humidity, clearness index, wind speed, etc.) and the information concerning the location of PV system are available [1–4]. These methods present a good solution for sizing PV systems under the above conditions. However, such techniques cannot be used for sizing PV systems where the required data are not available. Moreover, the majority of the above methods need long-term meteorological data, such as total solar irradiance, air temperature, and wind speed, for their operations. To overcome this situation, newer methods have been developed for sizing the parameters for PV systems based on artificial intelligence techniques [5]. However, these methods require complex implementation and powerful calculators to reduce time calculation which makes simple methods, like worst month method, still largely used in sizing simple remote PV systems.

A wide range of literature is available in this area. Chen [6] proposes a sizing procedure based on the long-term trend of the observed extremes of solar radiation. In [7] the sizing and designing of a standalone photovoltaic electricity generation system for a small household load performed using the locally acclimatized simulation program is discussed. In [8] a hybrid approach, combining analytical sizing equations with long-term performance, for an optimal design of a standalone PV battery system is proposed. In [9] after the sizing of PV generator in conventional irradiation and ambient temperature conditions, the proper battery capacity has been estimated with iterative simulations. Becherif et al. [10] deal with the design, modeling, sizing and control of a photovoltaic standalone Home to

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Vehicle (HV) application that can fully charge the Battery Electrical Vehicles (EV) overnight at home. Brenna et al. [11] instead deals with the capability of PV and EV in grid-connected systems based on daily average solar irradiance as a function of the site coordinates. In [12] a methodology for optimum design of solar array and battery bank for a solar array-exclusive standalone photovoltaic system using energy balance concept is presented. The constraint of system cost function based on loss of power supply probability (LPSP) has been implemented using genetic algorithms (GA). In [13] one optimum sizing method based on genetic algorithm, for solar lighting system with battery banks, was recommended. In [14] the authors study the sizing and economic optimization of a standalone photovoltaic–wind hybrid system with storage batteries, installed in a semi-arid region of Algeria supplying a farm. Two methods were developed. The first method is based on the average annual monthly values in which the size of photovoltaic and wind generators was determined from the average monthly contribution of each component. In the second method, the determination of these two system components size is based on the worst month. Zaninelli and Leva [15] introduces hybrid photovoltaic–wind–diesel generation systems supplying a remote power load. A cost investment valuation is performed on a real plant showing the effect of sustainable economical saving. In [16] a cost investment evaluation is performed on a real plant showing the effect and the weight of sustainability economical saving. The possibility to introduce a fuel cell generation device is also investigated. Simonov et al. [17] discusses the role of evolutionary computational tools and some issues related to the variability and uncertainty in the operations where PV plants are potentially fully connected to the power grid in a future scenario.

Recently, using PV lighting systems has been considerably increased in Algeria. This is motivated by the enormous potential of PV energy, especially in the south. For example, in Adrar city (27.51°N, 0.17°W), the annual mean insolation incident on a horizontal surface equals to 5.68 kWh/m^2/day [18]. Consequently developing powerful methods to optimum sizing of these systems becomes very necessary.

In the present study, a method for sizing remote PV systems based on GA [19] has been compared with two classical methods, worst month method [1] and LPSP method [20]. The three methods have been applied to a PV lighting systems with orientation due south and inclination angles between 0° and 90° in Adrar city (south Algeria).

Because measured data for the chosen location were not available, a year of synthetic hourly meteorological data of this location, generated by PVSYST software, have been used in the simulation.

The PV lighting system studied is shown in Fig. 1.

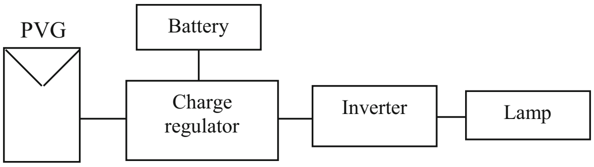

Fig. 1 Studied system

Mathematical modeling

Photovoltaic array output modeling

The “four-parameter” equivalent circuit model that considers a PV cell as an “ideal” irradiance-dependent current source in parallel with a diode was used to model the PV module [21]. The four parameters are module photocurrent at reference conditions (I_L, ref), diode reverse saturation current at reference conditions (I_0, ref), empirical diode PV curve fitting factor (d_1), and module series resistance (R_s) [22]. The total current (I) is calculated as follows [23]:

$$I = I_L - I_0\left[\exp\left(\frac{q}{d_1 k T_c}(V + IR_s)\right) - 1\right] \tag{1}$$

The values of parameters $d1$ and Rs are fixed for a given PV cell. The photocurrent (IL) is linearly proportional to the incident irradiance:

$$I_L = I_{L,ref}\frac{I_T}{I_{T,ref}} \tag{2}$$

where $I_{L,ref}$ is the photocurrent at the reference conditions and I_T and $I_{T,ref}$ represent incident irradiance at any time and reference insolation, respectively, where the reference insolation is equal to 1000 W/m^2.

The reverse saturation current (I_0) is expressed in terms of material characteristics and PV module temperature (T_c):

$$I_0 = I_{0,ref}\left(\frac{T_c}{T_{c,ref}}\right)^3 \exp\left[\frac{q\varepsilon}{dk}\left(\frac{1}{T_{c,ref}} - \frac{1}{T_c}\right)\right] \tag{3}$$

where d is equal to d_1/n_s; n_s is the number of cells in the module connected in series; ε is the semiconductor band-gap energy; and $I_{0,ref}$ and $T_{c,ref}$ are reverse saturation current and module temperature, respectively, at reference conditions.

The values of the parameters $I_{L,ref}$, $I_{0,ref}$, d_1 and R_s have been calculated in [24] and are given in Table 1.

The photovoltaic generator (PVG) reference characteristic parameters used in the study are shown in Table 1.

Storage modeling

Several models are proposed in the literature for battery storage modeling. A simple model proposed in [25] has

Table 1 PV module characteristic parameters

Parameter	Value
Module short-circuit current at reference conditions	3.45 A
Module open-circuit voltage at reference conditions	43.5 V
Temperature at reference conditions	298 K
Irradiance at reference conditions	1000 W/m^2
Maximum power point voltage at reference conditions	35.0 V
Maximum power point current at reference conditions	3.15 A
Semiconductor band gap	1.12 eV
Number of cells in the module connected in series	72
Module photocurrent at reference conditions	3.45 A
Diode reverse saturation current at reference conditions	2.86.10–6 A
Empirical diode PV curve fitting factor	120
Module series resistance	0.2421 Ω

been chosen. This model allows calculating storage capacity according to the produced power by PV generator and the load. This model does not consider temperature effect.

During the charge, battery capacity is described by the following equation:

$$C_{\text{bat}}(t) = \text{Min}\left(C_{\text{N}}, C_{\text{bat}}(t-1)\cdot(1-\sigma) + \left(P_{\text{pv}}(t) - \frac{P_{\text{c}}(t)}{\eta_{\text{inv}}}\right)\cdot\eta_{\text{bat}}\right) \tag{4}$$

where C_{N} nominal capacity of the battery (Wh), $C_{\text{bat}}(t)$ battery capacity at t time, $C_{\text{bat}}(t-1)$ battery capacity at $t-1$ time, σ self-discharge rate, $P_{\text{pv}}(t)$ produced power by the PV generator at t time, $P_{\text{c}}(t)$ charge demand at t time, η_{inv} DC/AC inverter efficiency, η_{bat} battery efficiency.

During the discharge, battery capacity is described by the following equation:

$$C_{\text{bat}}(t) = \text{Max}\left(C_{\text{N}}\cdot(1-\text{DOD}), C_{\text{bat}}(t-1)\cdot(1-\sigma) + \left(P_{\text{pv}}(t) - \frac{P_{\text{c}}(t)}{\eta_{\text{inv}}}\right)\right) \tag{5}$$

where DOD is the depth of discharge.

Since the studied system is a lighting system, some particularities must be considered. During the charge phase, i.e. during the daylight, there is no charge demand, so $P_{\text{c}}(t)$ is equal to zero. During discharge phase, i.e. during the night, PV generator does not produce any power, so $P_{\text{pv}}(t)$ is equal to zero. Moreover, load is constant because it is a lamp. Therefore, charge and discharge models became:

$$C_{\text{bat}}(t) = \text{Min}(C_{\text{N}}, C_{\text{bat}}(t-1)\cdot(1-\sigma) + (P_{\text{pv}}(t))\cdot\eta_{\text{bat}}) \tag{6}$$

for charge and:

$$C_{\text{bat}}(t) = \text{Max}\left(C_{\text{N}}\cdot(1-\text{DOD}), C_{\text{bat}}(t-1)\cdot(1-\sigma) - \left(\frac{P_{\text{c}}}{\eta_{\text{inv}}}\right)\right) \tag{7}$$

for discharge.

In this study η_{c} and η_{bat} have been taken equal to 0.9; σ has been taken equal to zero.

Meteorological data computation

Monthly meteorological data available on the NASA Web site [18] have been used for generating hourly synthetic meteorological data (horizontal global irradiance and ambient temperature) with the aid of PVSYST software [26].

Module temperature

To determine module temperature, a simple equation has been developed in [21] using module ambient temperature and incident insolation data. The correlation equation is given as follows:

$$T_C = T_A + 0.031\, I_T \tag{8}$$

Predicting hourly solar irradiance on inclined surface

In many sites, at best, only global irradiances on horizontal planes are available. Because most systems using solar energy are tilted, these data are clearly insufficient. A number of models to estimate global irradiance on an inclined surface, from the irradiance on a horizontal surface, are available. However, these models require information at the same time on the global and the direct or diffuse irradiance on a horizontal surface. In [27], two models requiring only the global irradiance on horizontal planes as input parameter were developed. The present work uses the model given in Eq. 9, which yields better results:

$$I_{T,\beta} = I_{\text{G}}\left(0.1 + \frac{\rho}{2} + \left(0.1 - \frac{1}{2}\rho\right)\cos\beta + 0.8(\cos\theta/\cos\theta_z)\right) \tag{9}$$

where $I_{T,\beta}$ total irradiance received on a tilted surface, I_{G} the horizontal global irradiance, θ_z zenith angle calculated by [28]:

$$\cos\theta_z = \sin\delta\,\sin\phi + \cos\delta\cos\phi\cos\omega \tag{10}$$

δ declination of day D calculated by [29]:

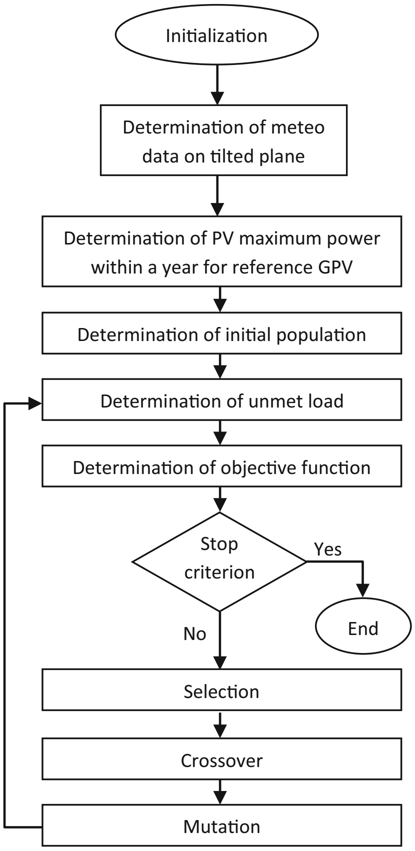

Fig. 2 Flowchart of the method

$$\delta(D) = 0.4093 \sin\left(2\pi \frac{D - 81}{365}\right) \tag{11}$$

ρ albedo (in this work, the value of albedo have been taken constant and is equal to 0.2), ϕ geographic latitude, ω hour angle, and θ angle of incidence for an arbitrarily inclined surface oriented toward the equator calculated by the following:

$$\cos\theta = \sin\delta\ \sin(\phi - \beta) + \cos\delta \cos(\phi - \beta)\cos\omega \tag{12}$$

Genetic algorithms method

The flowchart of this method is shown in Fig. 2.

The algorithm works with a Boolean vector containing the PVG pick power correction coefficient (k_1) and battery nominal capacity correction coefficient (k_2). The algorithm uses N_{pop} vectors (k_1, k_2).

By determining k_1, PVG optimum peak power has been obtained using Eq. 14. Coefficient k_1 has been used also to approximate the maximum power produced by the PVG each hour during the year by multiplying the power of the reference PVG, calculated once a time at the beginning of the program, by that coefficient. This is a good approximation that allows avoiding recalculating maximum power for each element of the vector, so the method became faster.

By the same manner, determining k_2 allows to obtain battery capacity using Eq. 15.

Objective function

The objective function to be minimized includes the following costs:

- Cost of PV panel acquisition
- Cost storage battery acquisition
- Cost of unmet load.

Costs of the other system components have been considered as constant and so omitted in the objective function because they have no effect on the behavior of the results. Hence the objective function is as follows:

$$ff = N_{\text{ul}} \cdot C_{\text{ul}} + P_{\text{P}} \cdot C_{\text{GPV}} + C_{\text{N}} \cdot C_{\text{Bat}} \tag{13}$$

where N_{ul} unmet load (number of hours), C_{ul} cost of 1 h of unmet load (Euro), P_{P} PV generator peak power (Wp), C_{GPV} one PV generator Wp cost, C_{N} battery nominal capacity (Wh), C_{Bat} one battery Wh cost.

Cost of unmet load should be taken sufficiently high, this will lead to a very large value of the term $N_{\text{ul}} \cdot C_{\text{ul}}$; so the only solution to minimize the objective function is to enforce N_{ul} to be equal to zero (because this value is admissible). This ensures that we obtain a system with a total autonomy without using a multi-objective optimization.

P_{P} and C_{N} are determined as follows:

$$P_{\text{P}} = k_1 \cdot PP_{\text{r}} \tag{14}$$

$$C_{\text{N}} = k_2 \cdot CN_{\text{r}} \tag{15}$$

where PP_{r} and CN_{r} are references of PV generator peak power and battery nominal capacity, respectively. In this study they have been taken equal to 110 Wp and 1000 Wh, respectively.

k_1 and k_2 are the correction coefficients determined by GA to optimize system cost.

The main objective of this study is comparing performance of the methods under different tilt angles, so contribution of O and M costs, interest rate, inflation rate etc. to the objective function has been omitted.

Method description

The method has been implemented in the following way:

First, the parameters used in the optimization are set (see Table 1). Then the irradiation on a tilted surface is calculated using the model described above. The irradiation is

Table 2 Worst month of each tilt angle

Tilt angle (°)	Worst month	Mean daily global irradiation (Wh/m^2.day)	Mean daily charge (Wh/day)
0	December	3315.0	432.6
15	December	4258.8	432.6
30	December	4877.6	432.6
45	December	5225.2	432.6
60	December	5211.6	432.6
75	July	2809.6	340.6
90	June	1281.2	324

calculated with a step time of 1 hour. The irradiation during a year is applied to the model of a 110 Wp PVG to determine the PVG maximum power ($P_{\max\,110}(t)$) produced during every hour of the year. To determine the optimum PV peak power, the 110 Wp PVG is used as a reference, then corrected by the coefficient k_1. After that, N_{pop} vectors are obtained randomly. These vectors have been described above, each one representing a possible configuration of PVG peak power and battery capacity. For each vector, the maximum power $(k_1 \cdot P_{\max\,110}(t))$ is applied to the storage model to determine the unmet load parameter N_{ul}. In the model of charge described in Eq. 6, $P_{\mathrm{pv}}(t)$ is substituted by "$k_1\, P_{\max\,110}(t)$". As mentioned above, this is a good approximation to obtain faster method. The objective function is evaluated for each vector. Best vectors (fittest) have a greater probability of reproducing themselves, crossing with other vectors. In each cross of two vectors, two new vectors are obtained (descendants).

The descendants are evaluated and the best of them replace the worst individuals of the previous generation (iteration).

To find the optimal solution and not to stay in local minimal, some solutions randomly change some of their components (mutation). The mutations can affect the change of a bit of k_1 or k_2. The individuals (vectors) obtained from reproduction and mutation are evaluated, making the next generation.

The process continues until a determined number of generations have been evaluated.

Worst month method

For this method, peak power of the PVG and battery nominal capacity are determined as follows:

$$P_{\mathrm{P}} = \frac{E_{\mathrm{d}}}{Kt \cdot \eta_{\mathrm{bat}} \cdot I_{\mathrm{rd}}} \tag{16}$$

$$C_N = \frac{E_{\mathrm{d}} \cdot D}{\eta_{\mathrm{inv}} \cdot \mathrm{DOD}} \tag{17}$$

where E_d daily mean demand during the worst month, Kt temperature correction coefficient of the PVG (0.67), η_{bat} battery efficiency (0.9), I_{rd} daily mean irradiation on tilted plane of the worst month, D number of days of autonomy, η_{inv} DC/AC inverter efficiency (0.9), DOD dept of discharge (0.5).

For each tilted angle, the worst month is determined by calculating the fraction $I_{\mathrm{rd}}/E_{\mathrm{d}}$ for the twelve months. The worst month correspond to the lowest value of this fraction.

Table 2 shows the worst month of each tilted angle and the corresponding data.

System cost for this method is calculated as follows:

$$\cos t = P_{\mathrm{P}} \cdot C_{\mathrm{GPV}} + C_{\mathrm{N}} \cdot C_{\mathrm{Bat}} \tag{18}$$

This equation is the same as Eq. 13 but the term of unmet load $N_{\mathrm{ul}} \cdot C_{\mathrm{ul}}$ is eliminated.

Lowest cost of the system has been obtained by searching the lowest autonomy duration that allows non-unmet load. This duration has been obtained by trial and error process.

This method has been implemented as follows:

First, autonomy duration is chosen, and then PVG and Battery capacities are calculated using Eqs. 16 and 17. Then, k_1 and k_2 are calculated based on Eqs. 14 and 15. These values are applied to the storage model to calculate unmet load with the same manner as for GA method.

If unmet load is zero the autonomy duration is decremented and the process continues until unmet load became non-zero. If unmet load is non-zero the autonomy duration is incremented and the process continues until unmet load became zero.

LPSP method

To make results obtained more accurate, a second classical method has been employed in this work. This method has been proposed in [20]. Unlike to the two above methods, that one uses daily data for PV system sizing. First the daily energy output of the solar array is calculated by:

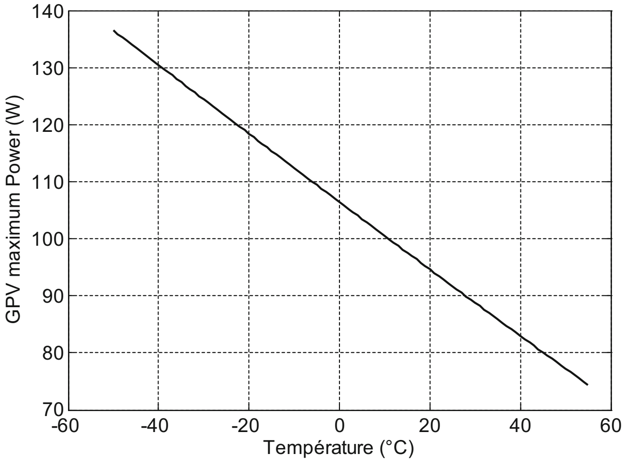

Fig. 3 Maximum power with respect to ambient temperature

$$P_{\mathrm{pv}} = P_{\mathrm{pv\,max}} * [1 + *(T_c - 25)] * \mathrm{PSHs} * \eta_{\mathrm{c}} * \eta_0 \qquad (19)$$

where $P_{\mathrm{pv\,max}}$ is the maximum power output of the solar array under a solar radiation of 1000 W/m^2. ρ is the negative temperature coefficient of power with respect to solar cell temperature; this coefficient is the slop of the line represented in Fig. 3. This curve has been obtained using the model described in Eq. 1. η_{c} and η_0 are the factors representing connection loses and other loses such as those caused by accumulative dust for example. In this study, these factors have not been considered. PSHs is the peak sun hours equivalent to the length of time in hours at a solar radiation level of 1000 W/m^2. The charge/discharge model used here is the same one described in "Storage modeling". However, time step is not one hour but one day.

The loss of power supply probability (LPSP) is adopted in [20] to describe reliability of power supply to load. It is defined here as

$$\mathrm{LPSP} = \frac{\sum_{n=1}^{N} \mathrm{LPS}(n)}{\sum_{n=1}^{N} E_{\mathrm{L}}(n)} \qquad (20)$$

Where $E_{\mathrm{L}}(n)$ is the load demand on day n; and $\mathrm{LPS}(n)$ is the loss of energy supply on day n which has been expressed in [20] as:

$$\mathrm{LPS}(n) = E_{\mathrm{L}}(n) - (E_{\mathrm{pv}}(n) + C_{\mathrm{bat}}(n-1) - C_{\mathrm{bat\,min}}) * \eta_{\mathrm{inv}} \qquad (21)$$

For a desired LPSP different size combinations of solar array and battery size can meet the given load demand. Optimum combination is obtained by minimizing Eq. 18.

Meteorological data

The Insolation Incident on a horizontal surface (kWh/m^2/day) for Adrar is shown in Table 3 [19]. These data have been used for generating hourly synthetic meteorological data (horizontal global irradiance and ambient temperature) with the aid of PVSYST software.

Table 3 Insolation incident on a horizontal surface (kWh/m^2/day) for Adrar

Jan	Feb	Mar	Apr	May	Jun	
3.68	4.74	5.90	6.84	7.32	7.70	
Jul	Aug	Sep	Oct	Nov	Dec	Ann
7.45	6.96	5.86	4.60	3.83	3.32	5.68

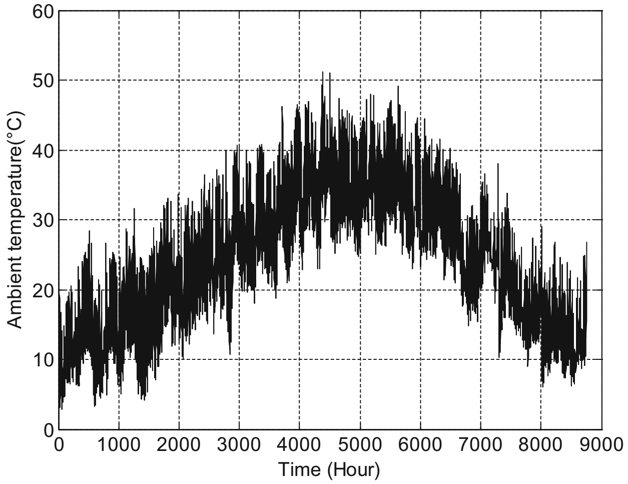

Fig. 4 Ambient temperature for Adrar

Figures 4 and 5 show the synthetic meteorological data generated by PVSYS for Adrar located in Southwest Algeria (27.51°N, 0.17°W).

Load profile

Figure 6 shows the daily load profile during a year. Since the studied system is a lighting system, the demand is present during the night. In this study the night is considered when the horizontal global irradiation is less than 50 W/m^2.

Results

Using the three methods described above, a photovoltaic lighting system located in Adrar (Algeria) has been sized. The three methods have been implemented using Matlab software. The parameters used for the GA method are the following:

The crossover rate is 0.8, the mutation rate is 0.1, number of generations is 100 and number of individuals per generation is 100.

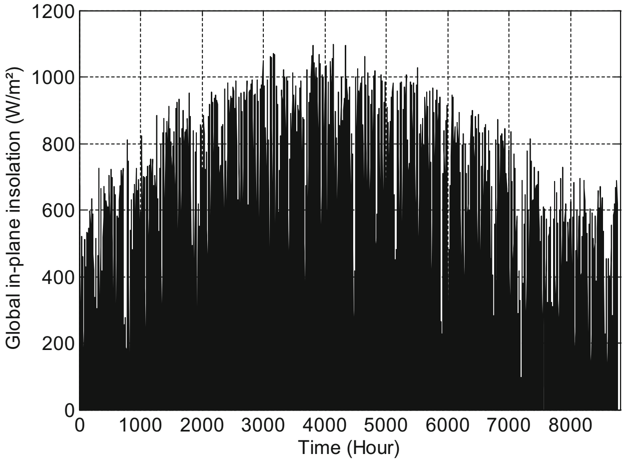

Fig. 5 Global in-plane insolation for Adrar

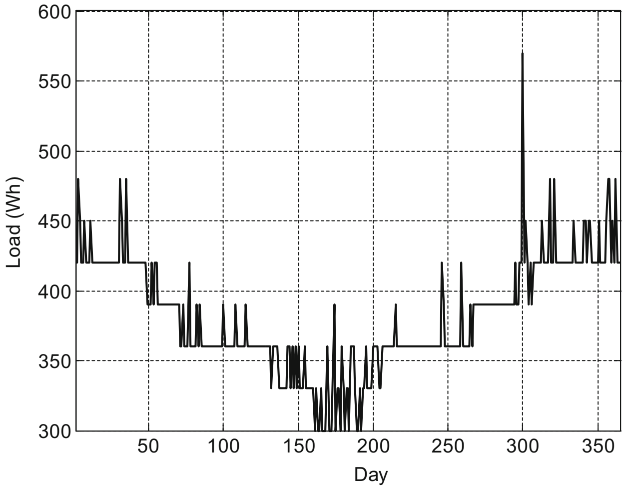

Fig. 6 Load profile

Table 4 GA method results

	GA method		
Tilt angle (°)	PV generator peak power (Wc)	Battery capacity (Wh)	System cost (€)
0	202	2789	1203
15	155	2859	1103
30	135	2875	1054
45	126	2899	1041
60	135	2891	1060
75	212	2408	1133
90	499	2250	1810

The cost of 1 Wp of the PVG has been taken constant and equal to 2.5€, the cost of 1 Wh of the battery capacity 0.25€ [30, 31] and the depth of discharge (DOD) 50 %.

Table 5 Worst month method results

	Worst case conditions method			
Tilt angle (°)	PV generator peak power (Wc)	Battery capacity (Wh)	System cost (€)	Autonomy duration used (days)
0	217	2699	1218	2.8
15	169	2796	1122	2.9
30	148	2757	1059	2.9
45	138	2796	1044	2.9
60	138	2892	1069	3
75	202	4555	1644	6
90	421	7148	2841	9.9

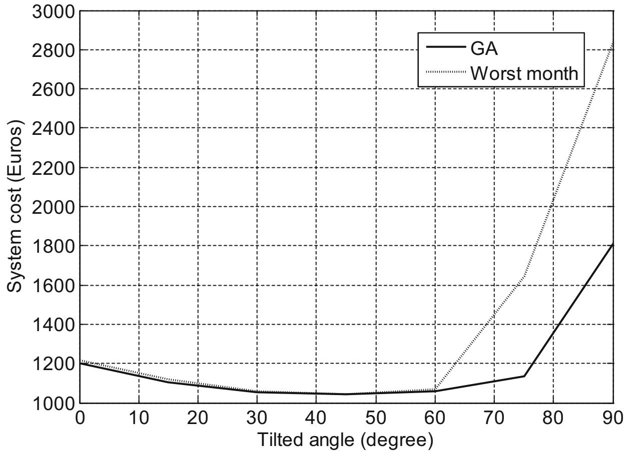

Fig. 7 Comparison between system cost obtained by the two methods

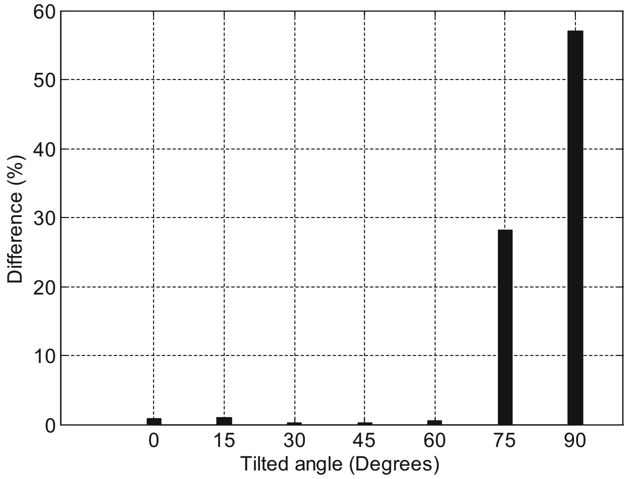

Fig. 8 Cost difference between the two methods

Results obtained for GA and worst month methods are shown in Tables 4 and 5. Figures 7 and 8 show that from 0° to 60° the costs obtained by the two methods are very close to each other and the difference is in general less than 1 %. Nevertheless, by increasing tilted angle above 60°, the difference between the two methods is very significant and GA method gives lowest cost.

Figure 9 shows PVG peak power for the two methods. It can be seen that the PVG for the classical method is oversized for tilted angle less than 60°, and undersized for tilted angle between 60° and 90°; nevertheless the difference is not very significant between the results obtained by the two methods; except for tilted angles close to 90°. In general the PVG size given by the two methods is not very different and we can conclude that classical method, despite of its simplicity, gives good sizing for PVG.

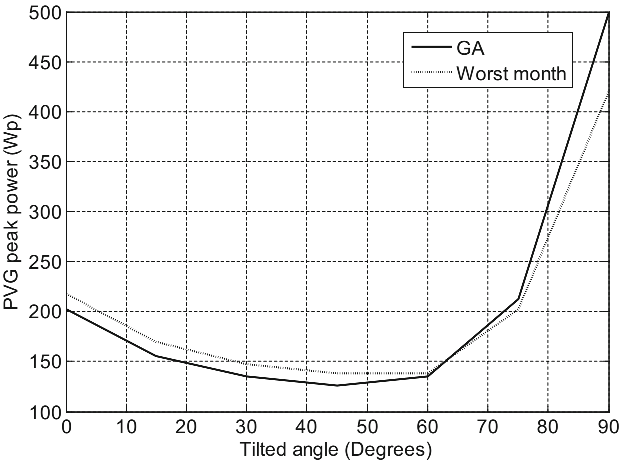

Fig. 9 Comparison of PVG peak power

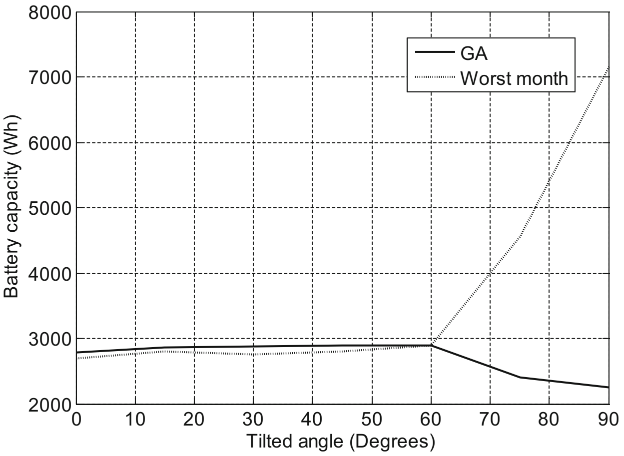

Fig. 10 Comparison of battery capacity

Figure 10 shows battery capacity for the two methods, it can be seen that the battery for classical method is undersized for tilted angle less than 60° but still not very far from optimum size given by GA method, and oversized for tilted angle between 60° and 90°. The difference became exponential when tilted angle is over 60°. This result shows that the worst month method is not a good solution for sizing the battery when the tilted angle became over 60°.

By examining Figs. 9 and 10 it can be seen that, despite of the little difference between battery and PVG sizes given by the two methods, when tilted angle is less than 60°; the cost of the system obtained by the two methods still practically the same. It means that there is some possible flexibility for choosing the size of system components.

In addition, oversizing the PVG can be compensated by undersizing the battery to obtain a reasonable cost of the system. Nevertheless, undersizing the PVG has a damaging effect on total cost of the system; because it needs an important oversizing of the battery, which leads to an exaggerated total system cost.

Results given by the worst month method are obtained using an “optimum” autonomy duration. Increasing this duration will lead to an oversizing of the battery, hence to a higher cost of the system. Nevertheless, decreasing this duration will lead to an unmet load. Therefore, the most difficult task with the worst month method is the determination of the optimum autonomy duration.

Results obtained with LPSP method, with an LPSP equal to zero, are shown in Table 6. A comparison between system cost obtained by this method and GA method is shown in Fig. 11. The results show that system cost obtained by LPSP method is much lower in comparison with GA method. Nevertheless the system is largely undersized because the unmet load calculated with the same manner as

Table 6 LPSP method Results

Tilt angle (°)	PV generator peak power (Wc)	Battery capacity (Wh)	System cost (€)	Unmet load (h)	Unmet load (%)
0	73	870	378.5	1521	32.71
15	72	950	417.5	1276	27.44
30	74	1070	452.5	1139	24.49
45	77	1605	593.75	1205	25.91
60	85	1045	473.75	1340	28.82
75	96	1150	527.5	1653	35.55
90	121	710	480	2470	53.12

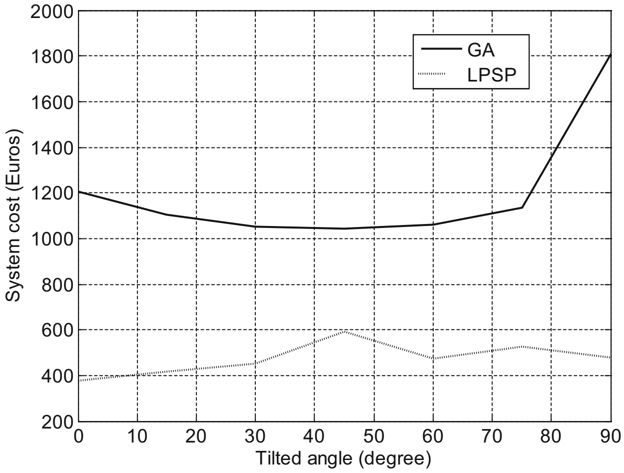

Fig. 11 Comparison between system cost obtained by GA and LPSP methods

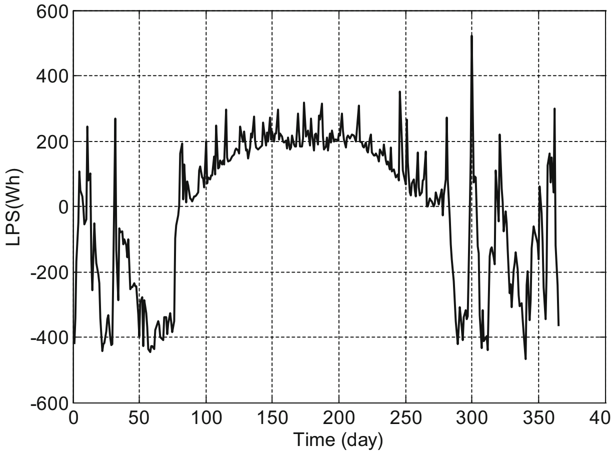

Fig. 12 Daily loss of energy supply

Table 7 Negative LPS method Results

Tilt angle (°)	PV generator peak power (Wc)	Battery capacity (Wh)	System cost (€)	Unmet load (h)	Unmet load (%)
0	189	1690	895	51	1.1
15	145	1825	818.75	51	1.1
30	162	1515	783.75	32	0.69
45	161	1470	770	31	0.67
60	119	1980	792.5	262	5.63
75	166	1650	827.5	424	9.12
90	357	960	1132.5	527	11.33

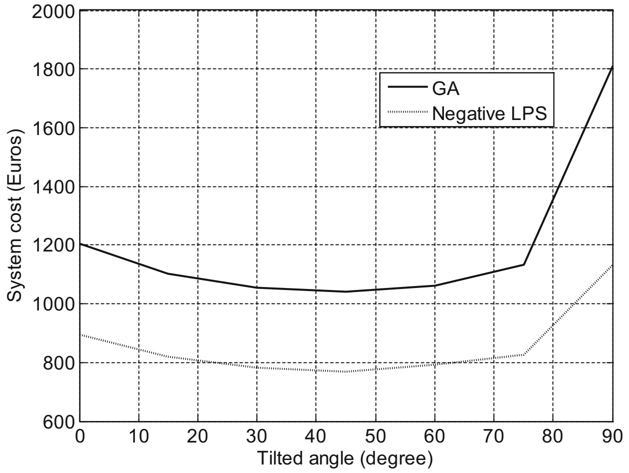

Fig. 13 Comparison between system cost obtained by GA and Negative LPS methods

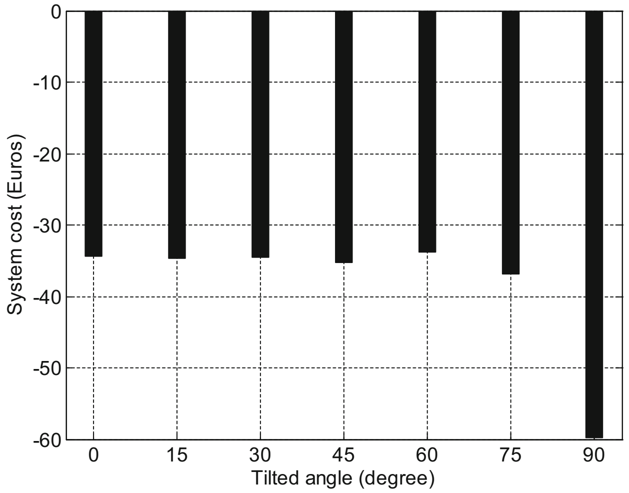

Fig. 14 Cost difference between GA and Negative LPS methods

for GA method, is more than 24 % for all tilt angles and reached 53 % for tilted angle equal to 90°. This is due to the fact that this method does not take into account the load variations during a day. Figure 12 shows the daily loss of energy supply (LPS) during a year for tilted angle equal to 90°. On some days, LPS is negative which means that the energy produced exceeds energy consumed. Nevertheless, in some days LPS is positive, hence the load is not met. However, integration of LPSs throughout a year gives practically zero, and hence LPSP is equal to zero, despite of large unmet load seen in Table 6 and Fig. 12.

To improve results obtained by this method, LPSP as defined in Eq. 20, has been replaced by a set of size combinations of solar array and battery those verify the following condition:

$$\mathrm{LPS}(n) \le 0; \qquad n \in [0, 365]$$

Optimum size is obtained by taking the combination minimizing Eq. 18.

The results obtained using this proposition are shown in Table 7. A comparison between system cost obtained by this method and GA method is shown in Fig. 13.

Results show that the objective of total autonomy of the system is not reached. Results for tilted angle more than 60° are not acceptable because unmet load is more than 5 %. Figure 14 shows that with allowing minor unmet load, system cost is considerably decreased. For example, for tilted angle of 45°, allowing an unmet load of 0.67 % decreases system cost more than 35 %.

Conclusion

In this study, a comparison has been achieved between a GA method and two classical methods for sizing a photovoltaic lighting system located in Adrar (Algeria).

The results obtained, by GA method and the worst month method, are very close to each other for tilted angle from 0° to 60°. Nevertheless, by increasing tilted angle above 60°, the difference between the two methods is very significant and GA method gives the lowest cost. These results show that very simple method, like worst case method, can give good results under particular conditions, but the problem is to determine the adequate autonomy duration to obtain the lowest cost with non-unmet load. In this study, this duration has been obtained by trial and error process. The comparison between results, obtained by GA method and LPSP method, shows that the system is very undersized by LPSP method because the LPSP model do not take into account the load profile during one day. Therefore, to improve the results obtained with this method, LPSP has been replaced by another condition (Negative LPS). Results show that the objective of total autonomy of the system is not obtained. Results for tilted angle more than 60° are not acceptable because unmet load is more than 5 %. In addition, by allowing minor unmet load, system cost is considerably decreased.

Author contribution statement Salim Makhloufi received his Magister degree in Electronic Engineering from the University of Batna, Algeria, his Master degree in Automatics from Ecole Centrale de Nantes, France, and his Doctorate degree from the University of Batna, Algeria in 2002, 2003 and 2013, respectively. At present, he is a lecturer at the University of Adrar, Algeria. His research interests include photovoltaic systems and intelligent control methods.

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