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Optimization PV/Batteries System: Application in Wouro Kessoum Village Ngaoundere Cameroon

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Abstract

This paper presents the optimization of the PV/battery system including extrapolation of the electrical demand. Matlab software was chosen to implement the algorithm. PVC, the number of PV modules and battery capacity increase with increasing electrical demand. This makes it possible to predict the device according to the electrical demand. Particle swarm optimization is used to minimize the total cost of the system over 20 years. The average cost of energy is $0.369/kWh.

Keywords

Optimization, Extrapolation, Increasing, Electrical Demand, Particle Swarm Optimization

1. Introduction

In Cameroon, 81% of households in rural areas and 12% in urban areas still do not have electricity [1]. The average solar radiation in Cameroon is 4.9 kWh/m²/day for the whole country. This solar potential is sufficient for the development of energy uses [2]. The government continues to promote the use of the photovoltaic system. In an autonomous installation, photovoltaic energy is compared to the energy demand in a given locality. [3] estimated the daily energy demand in a village which is 1523 KWh. Similarly [4], also identified energy demand in a locality in Nigeria. However, they did not include variation in energy demand. To satisfy the demand for energy, an optimization study is needed. [5] optimized the autonomous PV system in a residence by an objec-

tive function. [6] identified the solar potential in Cameroon. They show that the global solar radiation received in Cameroon varies between 2.9052 kWh/m²/day and 4.9709 kWh/m²/day for Yaounde, 3.1159 kWh/m²/day and 6.2602 kWh/m²/day for Garoua, 2.8535 kWh/m²/day and 5.9245 kWh/m²/day for Bamenda. The average solar potential in Cameroon is 7.431×10^8 GWh per year. This potential is exploitable and Cameroon is a country which abounds in solar potential.

2. Mathematical Model of the PV Module

There are two main types of photovoltaic model [7]: the electrical model or the equivalent model (with one diode or two diodes). Voltage and current are a function of solar irradiation and temperature. The energy model where the power supplied by the solar module is a function of the efficiency of the solar module, its area, the temperature of the module and solar irradiation

2.1. The Electrical Model

A photovoltaic cell behaves simply as an ideal current source which produces a current I proportional to the incident light power, in parallel with a diode which corresponds to the p-n transition area of the cell PV (**Figure 1**) [7].

According to Pouillet's law:

$$I_{Ph} = I_D + I \tag{1}$$

$$I = I_{Ph} - I_s \left[\exp\left(\frac{qV}{nKT}\right) - 1 \right] \tag{2}$$

I_s: The reverse saturation current of the diode, q: The charge of the electron = 1.6×10^{-19} (C), k: Boltzmann's constant = 1.38×10^{-23} (J/K), T: The temperature of the junction.

I_d: The current flowing in the diode.

This model is theoretical and does not reflect the behavior of a photovoltaic cell in real conditions. It does not take into account the loss of voltage and leakage current. There are other models, admittedly theoretical, but which more accurately reflect the behavior of the photovoltaic cell (**Figure 2**).

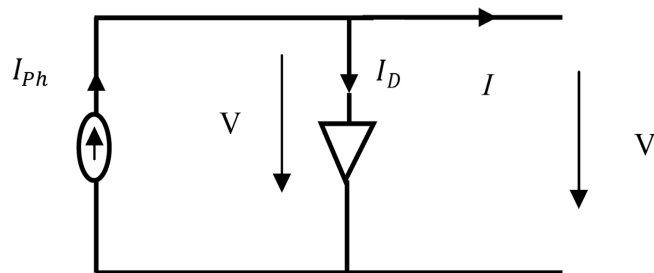$$I = I_{ph} - I_D - I_p \tag{3}$$
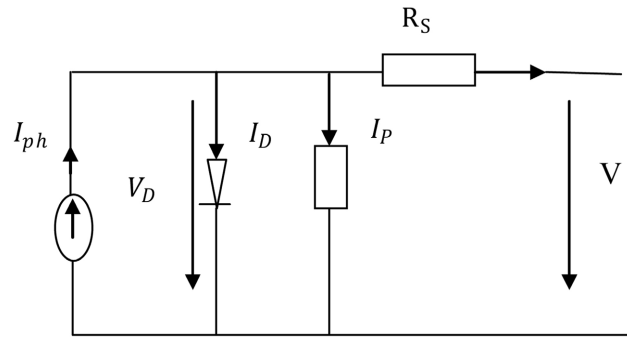

Figure 1. Model of a PV cell.

Figure 2. PV cell model taking into account voltage loss and leakage current.

$$I_p = \frac{V_D}{R_P} = \frac{V + IR_s}{R_P} \tag{4}$$

$$I = I_{ph} - I_s \left[\exp\left(\frac{q(V + IR)}{aKT} \right) - 1 \right] - \frac{V + IR_s}{R_P} \tag{5}$$

This model does not include the radiation effect as there is exchange between the air and the photovoltaic module. Thus (Yahya *et al.* 2008) [8] held account the radiation effect. The model is described by the following equation:

$$I = I_{cc} \left[\alpha - \beta \left(e^{y(V - V_{co} + R_s \cdot I)} \right) \right] + \lambda \left(T - T_{ref} \right) - \frac{V + I \cdot R_s}{R_{sh}} \tag{6}$$

$$\beta = 1 + \frac{R_s}{R_{sh}} \tag{7}$$

$$y = \frac{1}{V_T} \tag{8}$$

$$\alpha = \frac{\psi}{1000} \tag{9}$$

λ is a coefficient characterizing variation of power as a function of temperature. T_{ref} is the temperature of the module under standard conditions, Ψ the luminous flux (W/m²). V_{co} the open circuit voltage. The electric model allows knowing the electrical quantities. For a photovoltaic system, the energy model is the most appropriate. Many of the works do not take into account. Also, there are several models which describe the temperature of the solar module noted T_c. Models that take into account ambient temperature and solar irradiation [9]. And others are differentiated by the nominal operating cell temperature *NOCT* [10].

$$P_{pv}(t) = P_{max} \times \left(\frac{R}{R_{ref}} \right) \times \left[1 + \alpha_T \left(T_c - T_{a-ref} \right) \right] \tag{10}$$

with

$$T_c = T_a + \left[\frac{NOCT - 20}{800} \right] \times R \tag{11}$$

$P_{pv}(t)$ is the power generated in time t expressed in (W), P_{max} is the nominal power of the panel, R and R_{ref} are the solar and reference irradiation (W/m²). T_{a-ref} is the temperature under normal conditions. T_c is cell temperature (˚C). T_a is the ambient temperature (˚C). The temperature of the solar module was presented under another model [11] [12].

$$T_c = T_a (1 + 1.25\xi) \tag{12}$$

with ξ solar radiation.

The present cost value (*PVC*) of PV generator is given in the following relationship [13] [14] [15]:

$$PVC_{PV} = I_{PV} + c_{omr,PV} \left(\frac{1+i}{r-i} \right) \left[1 - \left(\frac{1+i}{1+r} \right)^n \right] - s_{PV} \left(\frac{1+i}{1+r} \right)^n \tag{13}$$

2.2. Modeling of the Battery

A 1000 Ah, 48 kW·h Nickel Iron battery (Ni-Fe) bank with 80% DOD and 1% self-discharge per day have been used in this work, the usable energy of the battery is 50 kW·h. An MPPT (Maximum Power Point Tracker) charge control with a maximum of 100 A outputs has been used with the battery bank with a typical 99% efficiency. Since the lifetime of the battery bank is 20 years, which is equal to the project lifetime. The available battery bank capacity [16] [17]:

$$C_{bat}(t) = C_{bat}(t-1)(1-\sigma) + (surpluspower)\eta_b \tag{14}$$

On the other hand, when the available energy generated is less than load demand, the battery bank is in discharging state.

$$C_{bat}(t) = C_{bat}(t-1)(1-\sigma) - (deficitpower) \tag{15}$$

where $C_{bat}(t)$ and $C_{bat}(t-1)$ are the available battery bank capacity (Wh) at hour t and $t-1$, respectively; η_b is the battery efficiency during discharging process, the battery discharging efficiency was set equal to 1 and during charging, the efficiency is 0.65 - 0.85 depending on the charging current [18]. the lifetime of the battery bank is 20 years, which is equal to the project lifetime, its replacement cost is zero. PVC_{Bat} of the battery bank can be calculated as:

$$PVC_{Bat} = I_{Bat} + c_{omr,bat} \left(\frac{1+i}{r-i} \right) \left[1 - \left(\frac{1+i}{1+r} \right)^n \right] - S_{Bat} \left(\frac{1+i}{1+r} \right)^n \tag{16}$$

3. Load Profile (Electrical Demand)

The electrical demand is that of the work of [19]. Load demand profile (electrical demand) varies with the variation of households in Wouro Kessoum village. The variation of load profile is given by the extrapolation with the following equation [19]:

$$P_{load}^t = N * Pd^t \tag{17}$$

The extrapolation of electrical demand will be is included in the algorithm for optimization.

Total energy demand over a period of one year (Pt_{load}) can be expressed as follow

$$Pt_{load} = \sum_{t=1}^{T} P_{load}^{t} , \quad T = 8760 \tag{18}$$

4. Problem Formulation

Objective Functions

We have tree objectives function:

$$\text{Object } 1 = \min f\left(N_{pv}, N_{WT}, E_{ESS}\right) = N_{pv} \cdot C_{pv} + C_{ESS} \cdot E_{ESS} \tag{19}$$

$$\text{Object } 2 = \min\left(COE\right) \tag{20}$$

$$\text{Object } 3 = \min\left(TNPC\right) = \min\left(\frac{PVC,tot}{CRF}\right) \tag{21}$$

$$COE = \frac{PVC,tot}{E_{served}} \tag{22}$$

with

$$E_{served} = E_{PV} + E_{WT} \tag{23}$$

$$PVC,tot = PVC_{PV} + PVC_{WT} + PVC_{Bat} \tag{24}$$

$$CRF = \frac{i(1+i)^{n}}{(1+i)^{n} - 1} \tag{25}$$

Constraints:

- PV power limits:

$$P_{pv\min} \leq P_{pv}(t) \leq P_{pv\max} ; \quad N_{PV} \geq 0 \tag{26}$$

- ESS stored energy and power limits:

$$E_{ESS\min} \leq E_{ESS}(t) \leq E_{ESS\max} \tag{27}$$

$$E_{ESS\min} = (1 - DOD) \cdot E_{ESS\max} \tag{28}$$

- Power balance:

$$P_{pv}(t) \pm P_{ESS}(t) \geq P_{load}(t) \tag{29}$$

with $P_{load}^{t} = N * Pd^{t}$.

The system reliability was reliability (the hybrid system satisfied the load by 100%).

5. Particle Swarm Optimization

Particle swarm optimization is an evolutionary algorithm that uses a population of candidate solutions to develop an optimal solution to the problem. This algorithm has been proposed Russel Eberhart and James Kennedy in 1995 [20]. He was originally inspired by the living world, more precisely by behavior of animal living in swarms, flights groups of birds. Indeed, we can observe in these animals movement dynamics relatively complex, whereas individually each individual

has an "intelligence" limited, and has only local knowledge of her situation in the swarm. Local information and the memory of each individual are used to decide their shifting. Simple rules, such as "stay close to other people", "go in the same direction" or "going at the same speed", are sufficient to maintain cohesion of the swarm, and allow the implementation of complex collective behaviors and adaptive. The particle swarm is a population of simple agents called particles. Each particle is considered as a solution of problem, where it has a position (the solution vector) and a speed. In addition, each particle has a memory allowing him to remember his best performance (in position and in value) and the best performance achieved by the "neighboring" particles (informants): each particle has in fact a group of informants, historically called its neighborhood. Each individual in PSO represents a possible solution assumed to have two properties: velocity and position. Each particle wanders through in the solution area and recalls the best objective function value (position), which has already been discovered; the fitness value is saved and known Pbest. When a particle captures all the best population as its topological neighbors, the superior value is a global best and it is called Gbest. The particles flight with a certain velocity in the D-dimensional space to find the optimal solution. Let the variable (x_i) refers to the position of particle (i) in the study space and its speed is (v_i), so the (i_{th}) from the particle can be represented as (Lu *et al.*, 2015):

$$x_i = [x_{i1}, x_{i2}, x_{i3}, \cdots, x_{iD}] \tag{30}$$

The best past position of the ith particle is saved under the name vector and calculated by:

$$P_i = (p_{i1}, p_{i2}, \cdots, p_{iD}) \tag{31}$$

where $i = 1, 2, 3, \cdots, N$ is the number of particles in a swarm,

$$v_i(t+1) = w(t)v_i(t) + c_1 r_1 (P_i(t) - X_i(t)) + c_2 r_2 (G(t) - X(t)) \tag{32}$$

The r_1 and r_2 are random real numbers drawn from [0, 1], c_1 and c_2 are acceleration constants that pull each particle towards. The procedure for the implemented PSO is as the following Set PSO parameters: population size (N_{Pop}) = 200, (c_1) = 1.8, (c_2) = 2, χ = 0.7, total number of iteration = 100, the Set dimension of the search variables: the lower and upper bound respectively: lower and upper bound of number of PV systems (0, 50). Lower and upper bound of number of battery banks (0, 100).

6. Results and Discussion

Study focuses on the economic optimisation. Three objective functions are defined. Objective function base on minimization of the cost of energy production (COE), total net present cost (TNPC) and number of PV module and batteries (N_{PV}, N_B) taking account some constraints like the rising of the electrical demand, PV power limits, and batteries power limits. The PSO algorithm was developed by Matlab. The data of solar energy, wind energy temperature and air

density was inserted. The location of Wouro Kessoum (Ngaoundere), Cameroon (Latitude 7˚20'N, Longitude 13˚34'E, Altitude 1120 m) is used as site for the case study. The global horizontal solar irradiance (**Figure 3**) is minimal in November, December, January and February. Ambient temperature (**Figure 4**) is minimal in June, July and August. The data were taken from the reception center of the Vantage Pro2 station of the IUT of Ngaoundere and used to calculate the Output powers of the PV and WT. The characteristic of PV modules and batteries are presented in **Table 1**. Optimal combination system is presented in **Table 2**. In this table, the TNPC increase with the increase in the number of household. For n = 50, the TNPC is \$275,253.02. With the increase of the population in village, the algorithm allows predicting the TNPC and the components (N_{PV}, N_{WT}, E_{ESS}).
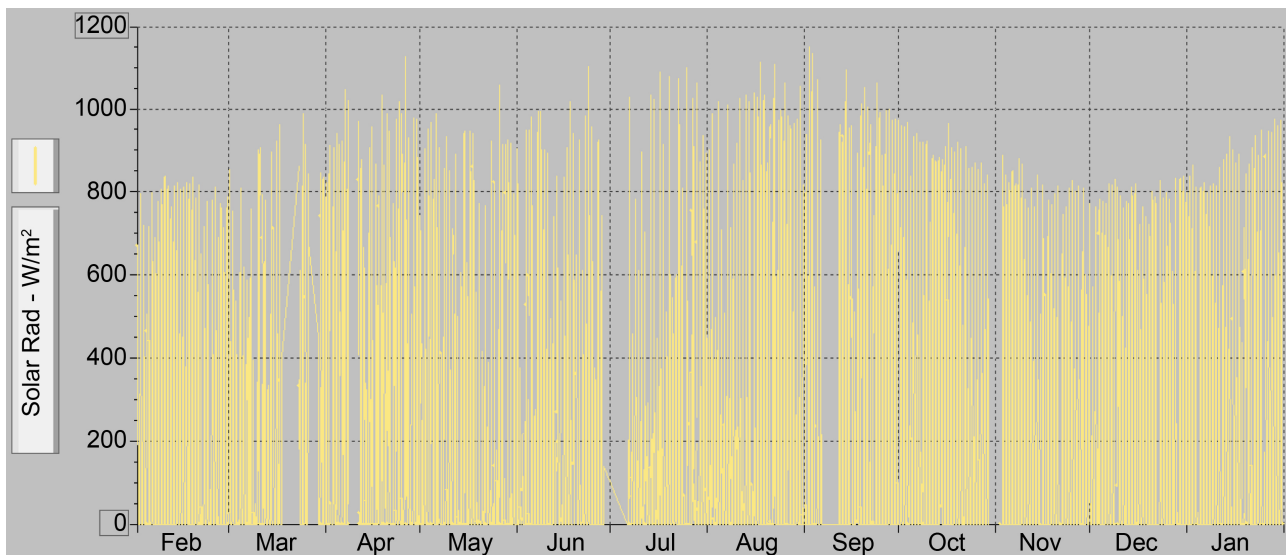

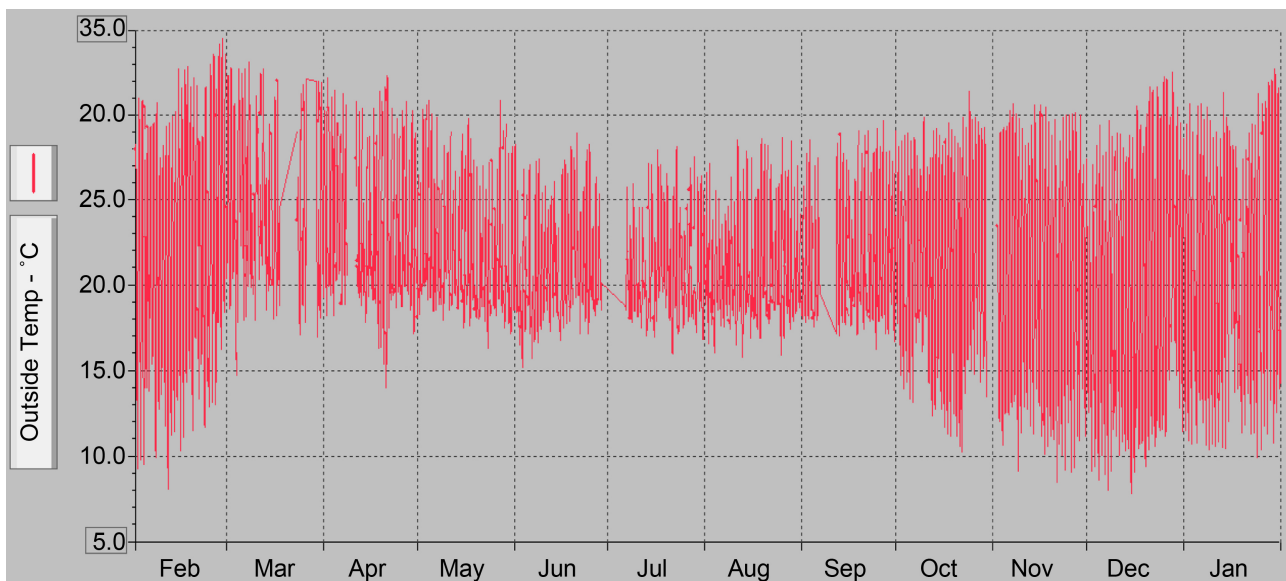**Figure 3.** Monthly global solar irradiation of the year (W/m²).

Figure 4. Monthly ambient temperature of the year (˚C).

For $n = 100$; 150; 195, the TNPC are \$321,141.10; \$460,725.20; \$490,920.17. **Figure 5** shows the variation of the Cost of Energy (COE) for a year. The minimal cost of the energy is in July and August (\$0.346) and the maximal cost of the energy is in November and December (\$0.433). Diminution of energy increases the cost of energy (Equation (22)). The average cost energy per kWh for a year is \$0.369/kWh. This is the price that the population of this village can pay as the price per kilowatt hour.

Table 1. Components characteristics and their corresponding costs.

Photovoltaic		Batteries bank	
Parameters	Values	Parameters	values
The rated power	255 W	Price	\$(42,250)
efficiency η	90%	Efficiency η	71%
The lifetime	20		
Price/PV (30 kW)	\$(42,000)	Rated energy	50 kW·h
		Nominal voltage	100v

Table 2. Optimal combination system.

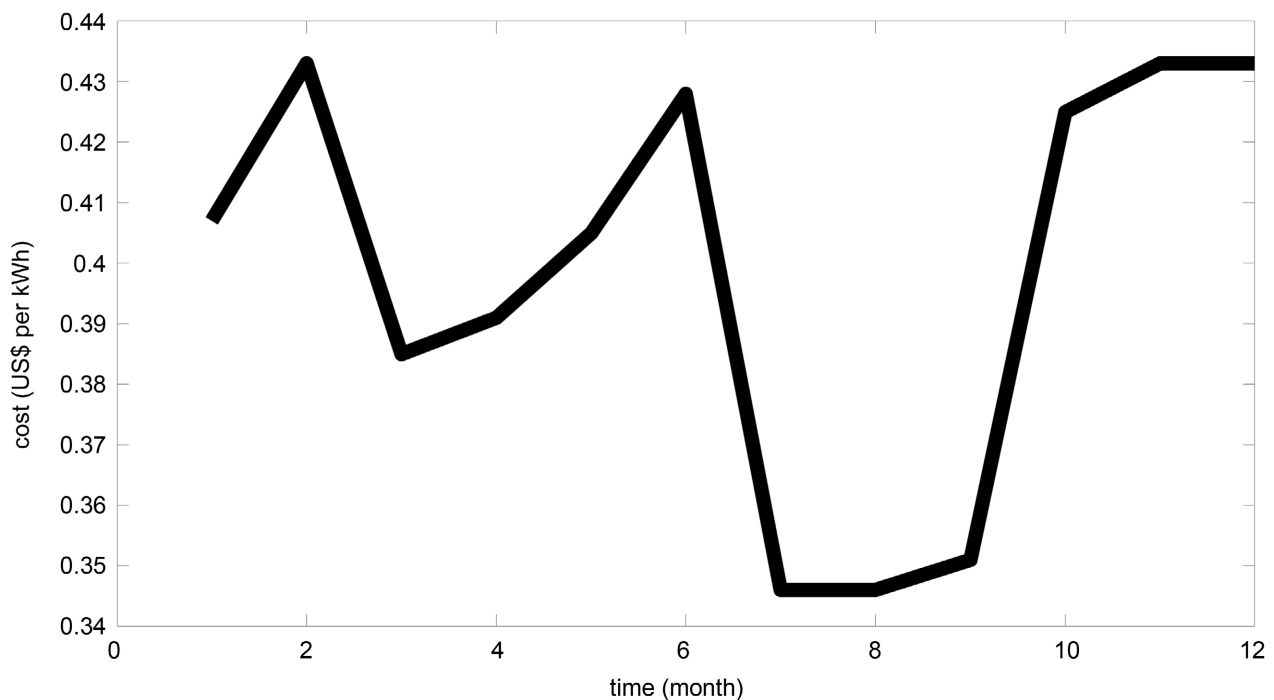|	$n = 50$	$n = 100$	$n = 150$	$n = 195$	$n = 250$
Number of PV module	48	55	79	84	85
Number of battery (kWh)	210	461	512	632	639
TNPC (\$)	275,253.02	321,141.10	460,725.20	490,920.17	531,764.11

Figure 5. Cost of energy (US\$per kWh).

7. Conclusion

This work highlights the optimum costs, the number of PV modules and the size of the batteries. To do this, the characteristics of the elements were evaluated. The particle swarm method has been chosen to optimize. The optimization constraints have been determined. The constantly increasing demand for energy in a locality is an important factor. Why this factor was taken as constraint. The cost of energy in this locality is $0.369/kWh.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Nomenclature

COE, Cost of energy	CRF, Capital recovery factor
PVC, Present cost value	i, inflation rate
TNPC, Total net present cost	r, interest rate
PV, Photovoltaic	P_{load}, total electrical demand
n, useful lifetime	N, number of household
η, efficiency	Pd, electrical demand for one household