Backtracking search algorithm for total cost optimization of hybrid renewable PV/wind system coupled with battery storage

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Abstract: - Hybrid renewable energy sources can be seen as one of the most used way to electrify remote area. They are more suitable for loads with variation in a daily basis demand. In order to size up optimally the hybrid PV/Wind system coupled with battery storage, the proposed technique is based on meteorological data to determine the electrical power produced by PV panels and wind turbine generators. Once this power is determined, the total renewable energy cost per year and the system reliability are optimized for two different scale factor f. To do so, a Backtracking Search algorithm (BSA) is used and thoroughly described throughout this paper. Moreover, some results are carried out concerning the penalty factor ϖ to highlight the impact of this factor on the rate of renewable energy (RELD).

Key-Words: - BSA, Optimization, PV, Wind, battery.

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1 Introduction

Hybrid stand-alone systems provide the electrical power next to the point of user demand; they seem to be the best way to electrify remote areas where the support of remote infrastructure such as utility grid could not be offered [1]. The battery-integrated Renewable Energy Sources (RES) —Photovoltaic cells and wind turbines for instance, are considered in this study and proved tangible enhancements in terms of system cost and reliability.

In isolated area, the primarily power supply source could be a diesel generator, even though this solution is conceptually and technically simple it suffers from many drawbacks related to pollution [1-2].

In the literature there are several software tools dealing with battery-integrated RES systems, among these tools we found RETScreen [3] and HOMER [4].This software allows comprehensive identification, assessment and optimization of the technical and financial viability of the intermittent energies in use (in this case PV and wind power sources) and by the way exhibit the best energy efficiency scenario.

Recently many studies have been done to size stand-alone hybrid RES: a control system are proposed in [5] to determine the most optimal hybrid system, while other studies were interested on optimizing the power provided by the hybrid system in order to minimize the total system cost [6].

The design and control of such hybrid systems are typically complex due to intermittency of the renewable energy supplies and to the nature of load demand. The optimization task cannot be done by the most classical algorithms.

During the past decades several studies use evolutionary algorithms to address these limitations. In [7], the Genetic Algorithm (GA) was used to design a hybrid PV/Diesel system, the designed system is compared to another one fed only by PV sources. The results showed the advantage of the hybrid system.

This paper proposes a multi-objective Backtracking Search Algorithm (BSA) to optimize the renewable energy power by taking into account the total cost and the system reliability. In this context, Backtracking Search optimization algorithm is an evolutionary algorithm proposed to manage continuous optimization problems. The PV panels and the wind turbines are conjunctively used to satisfy the load demand in the first place, along with the batteries may be invoked to tackle the stochastic nature of the power supplies (variable solar radiation, wind speed and load demand).

The paper is organized as follows: section 2 presents the model of the system under study. The objective functions and the BSA algorithm are presented in section 3.Simulations and results are addressed in section 4 and some conclusions are given in section 5.

2 Hybrid system model

2.1 PV array model

The mathematical model of power produced by renewable technologies varies from deterministic and probabilistic approaches. All of them are calculated based on climatic data [2].
In this section the electrical power from the PV arrays and a wind turbine generator is determined, then the power reliability factor is calculated.
The power output of the PV system is calculated based on climatic data (E_{dirc}, E_{difc}) and nominal power (Ppv) as shown in eq.(1)

$$P_{pv} = (E_{dirc} + E_{difc}) . \frac{P_{pvc}}{E_n} \qquad (1)$$

2.2 Wind turbine model

The power of the wind turbine depends to the wind speed, on the air density and the radius of the rotor [8]. This power varies at different wind speeds. The mathematical model is expressed as follows:

$$W = \begin{cases} 0, & v \prec v_d \\ \frac{1}{2} \cdot \rho \cdot \pi \cdot R^2 \cdot V^3, & v_d \le v \prec v_n \\ P_n, & v_n \le v \prec v_c \\ 0, & v \ge v_c \end{cases} \qquad (2)$$

Where W is the wind power, V is the wind speed, Vd is the boot speed Vn is the rated speed, Vc is the shutdown speed.

ϱ is the air density, R is the radius of the rotor and Pn is the nominal power.

2.3 Battery model

The model of the battery is based on the kinetic battery model proposed by Manwell and McGowan [9]. In this model, the battery is depicted by two bound with charges separated by a conductance k. The first bound with charge immediately available Q1 to be used by the load and the second bound charge Q2 chemically depends on the parameter k.

Conductance k corresponds to the chemical reaction by which the bound charge becomes available. The rate at which the bound charge becomes available is considered to be proportional to the level difference of the charges [9]. According to the kinetic battery model, the diffusion reaction is assumed to be of first-order rate. It is also assumed that a current regulator is placed between the battery and the load, which ensures that power drawn and hence current is constant over the time step [9].

The model characterizes the battery with a set of three constants, the rate constant of the charge diffusion (k), the fraction of the battery capacity that holds the available charge (c) and the maximum battery capacity (Qmax). These parameters can be estimated from the battery test data [10]. The constitutive relations for the available and the bound charges are as follows:

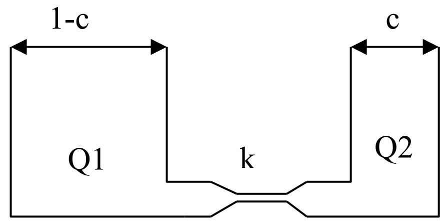


Fig.1: Battery kinetic model

The maximum amount of energy Q1max is expressed in terms of the quantity Q of battery power and a constant characterizing the battery c.

$$Q_{1\max} = c \cdot Q \qquad (3)$$

$$Q_{2\max} = (1-c) \cdot Q \qquad (4)$$

$$Q_1(i) = Q_1(i-1) \times e^{-k\Delta t} + \frac{(Q(i-1) \times k \times c - P_{bat}) \times (1-e^{-k\Delta t})}{k} + \frac{P_{bat} \times c \times (k \times \Delta t - 1 + e^{-k\Delta t})}{k} \qquad (5)$$

$$Q_2(i) = Q_2(i-1) \cdot e^{-k\Delta t} + Q(i-1) \cdot (1-c) \cdot (1-e^{-k\Delta t}) + \frac{P_{bat} \cdot (1-c) \cdot (k\Delta t - 1 + e^{-k\Delta t})}{k} \qquad (6)$$

$$Q(i) = Q_1(i) + Q_2(i) \qquad (7)$$

$$SOC = \frac{Q(i)}{Q} \qquad (8)$$

$$P_{bat\max} = \frac{k \cdot Q_1(i-1) \cdot e^{-k\Delta t} + Q(i-1) \cdot k \cdot c \cdot (1-e^{-k\Delta t})}{1-e^{-k\Delta t} + c \cdot (k\Delta t - 1 + e^{-k\Delta t})} \qquad (9)$$

3 Problem formulations

3.1 Objective function

This paper proposes a multi-objective optimization of PV/wind/Battery system. The method is based on heuristic algorithm. In this section we define the two objective functions, the total cost and the system reliability.

The total cost of the hybrid system is given by [11]:

$$y1 = C_{p}^{a}.P_{pv} + C_{w}^{a}.W + C_{bat}^{a}.P_{bat} \tag{10}$$

Where C_{p}^{a} is the total cost of the PV power per year, C_{w}^{a} is the total cost of wind power per year, C_{bat}^{a} is the total cost of batteries per year, P_{pv}, W and P_{bat} are the installed power of the PV panels , wind generators and batteries respectively.

On the other hand, the system cost within one year consists of the sum of capital, maintenance and replacement costs. It is expressed by:

$$C^{a} = C_{cap}^{a} + C_{main}^{a} + C_{rep}^{a} \tag{11}$$

The capital cost of each component (PV cells, wind turbines and batteries) during one year is given bellow:

$$C_{cap}^{a} = C_{cap} \frac{i(1+i)^{Lt}}{(1+i)^{Lt}+1} \tag{12}$$

Where C_{cap} is the initial capital cost, L_t is the project life time and i is the annual real interest rate which is linked to the intensity of nominal interest rate and to the annual inflation rate by the following expression:

$$i = \frac{j-f}{1+f} \tag{13}$$

The replacement cost per year is the annualized value of all the replacement costs occurring throughout lifetime of the project, taking into account the inflation rate .It can be expressed by:

$$C_{rep}^{a} = C_{rep}.\frac{i}{(1+i)^{Lt}-1} \tag{14}$$

The reliability of the system is defined as the disparity between renewable energy and load demand RELD [11]. For a period T the RELD is determined by:

$$y2 = \frac{1}{L_t T} \sum_{y=1}^{L_t} \sum_{t=1}^{T} \frac{D\left[E_g(y,t) - E_l(y,t)\right]}{E_l(y,t)} \tag{15}$$

$$D[x] = \begin{cases} (1+\omega)x \text{ if } x \succ 0, \\ -(1-\omega)x \text{ if } x \leq 0, \end{cases} \tag{16}$$

Where E_g is the expected Energy, E_l is load Energy, T is the period of the calculation, and ω is a penalty factor [11].

Theoretically, the penalty factor can be in the range from 0 to 1. However, this factor is used to penalize the energy excess in a minimization problem, then using high values close to 1 means that we minimize the disparity without caring about the lack of energy. Then, we will take the penalty factor in the range from 0 to 0 5.

3.2 Algorithm

BSA is an Evolutionary Algorithm (EA) proposed in [12], and it is composed of five main processes: initialization, selection-I, mutation, crossover and selection-II. The general temple of BSA is shown below.

Initialization
Repeat
II.Selection I
Generation of trail population
III.Mutation
IV.Crossover
End
V.Selection II
Until stopping conditions are met

Fig.2: Flowchart of the BSA

- **Initialization**

The BSA initializes the population P by a uniform distribution as shown in eq. (17).

$$P_{i,j} \sim U(low_j, up_j)$$

$$i= 1; 2; ... ;N; j = 1; 2; ... ;D; \tag{17}$$

Where N and D are the population size and the problem dimension respectively.Lowj and upj is the lower boundary and upper boundary. They are determined by the range of the variables that must be resolved.

- **Selection I**

This selection defines the historical population old P, which is used to calculate the search direction. It is initialized in Eq. (18) before starting the first iteration, and it will be determined at the beginning of each iteration using Eq. (19) and permutation function in Eq. (20), respectively.

The OldP represents the population of the previous generation randomly selected for use in the generation of research-management matrix and

partial advantage of previous experiences to generate a new test population.
OldP is the major difference between BSA and other EAs.

$$oldP_{i,j} \sim U(low_j, up_j) \quad (18)$$

$$if \ a \prec b \text{ then } oldP \coloneqq P \left| a,b \sim U(0,1) \right| \quad (19)$$

$$oldP \coloneqq permuting(oldP) \quad (20)$$

- **Mutation**

In this step BSA generates the trail population defined in eq. (18), where F value determines the amplitude of search direction.

$$\text{Mutant}=P+F*(oldP-P)$$

$$F = 5*randn, \text{ where } randn \sim N(0,1) \quad (21)$$

- **Crossover**

BSA unique-cross process consists of two main stages. The First step is to define a binary N×D matrix (Map), where two different ways are selected to define the card as shown in the equations (23) and the mixture flow rate setting (in mix-rate) controls the number of elements which mutate. The second step is to update the population of the track depending on the card fined. This type of crossing process is quite different from traditional differential evolution.

The recovery rate is controlled by the cutoff frequency parameter (Cr), and makes it easy to realize crossing process, as shown in the equation (11).

$$Map_{i,rand(D)} = 1 \quad (22)$$

$$Map_{i,u\left(1:\lceil mixrate*rand*D\rceil\right)} = 1; u = permuting\left(1,2,3,....,D\right)$$

$$Crossover = P + (map.*F).*(oldP - P) \quad (23)$$

$$T_{i,j} = rand*(up_j - low_j) + low_j \quad (24)$$

if $T_{i,j}$ beyond the boundary

- **Selection II**

In BSA selection II level, the individual in the trail population T that have the best fitness value is used to replace the individual in original population. Besides, if the algorithm process finds an individual with the best fitness value than the global optimal value, the global minimizer is updated to be Pbest , and the global minimum value is updated to be the fitness value of Pbest.

4 Simulation and results

Fig. 2 presents the flowchart of BSA; it starts by initializing the population (Npv, Nw, Nbat) using the uniform distribution which generates the trial population Ts. Thereafter, we apply the selection operation I, which determines the historical population Ps to be used to calculate the search direction. Afterwards, BSA evaluates the fitness function, generates a mutant population.

The crossover process generates the final form of trial population. When it comes to the Selection II, the Ts that have better fitness values than the corresponding Ps are used to update the Ps based on a greedy selection (selection that moves away from the local minimum to approach the optimal solution).

In the simulation process, we take the duration T=15min, the interest rate j=3.5 and the inflation rate f =1.5. In this paper BSA is simulated by MATLAB. The parameters used in the simulation are listed as follow: population size: 40, crossover: CR=0.9, mutation: Mu=0.2 and maximum iteration: epoch=120.

The rules for the selection of the BSA control parameters are quite different that their validity is limited to the values of the parameters taken into account in the respective investigations. The speed and the robustness of the search are assigned mainly to the change in the scale factor parameters.

To show this phenomenon, we have chosen scale factor f=3 and f=5 .fig.4 and fig.5 illustrate the importance of choosing this factor.

The value of the scale factor f affects the plot and also the value of total cost, it means that the system with scale factor f=3 is more steady than the system with scale factor of f=5. In our case, the system with f=3 converges in less than 10 generations while in the system with f=5 needs more time.

We remark also that the scale factor affects the value of the cost function, because the scale factor determines the search direction of the algorithm. We mention that several studies use Burger's chaotic map to adjust this factor during mutation process [13].
To see the impact of the scale factor f on the Rate of Renewable Energy Load Demand (RELD), we plot this monthly rate for the three different scenarios (wind only, PV only and both wind/PV) fig.6.

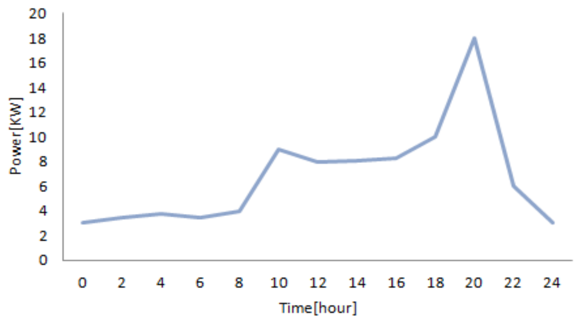


Fig.3: Household load profile

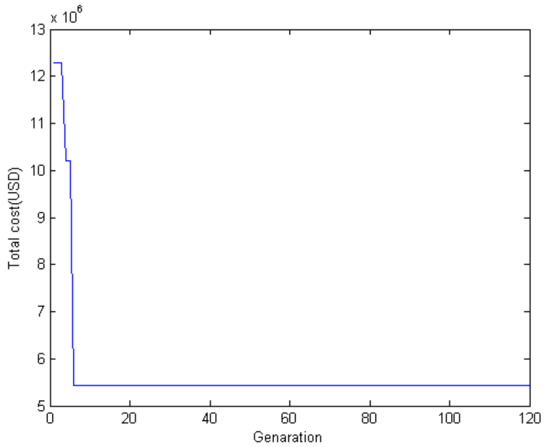


Fig.4: Total cost for scale factor f=3

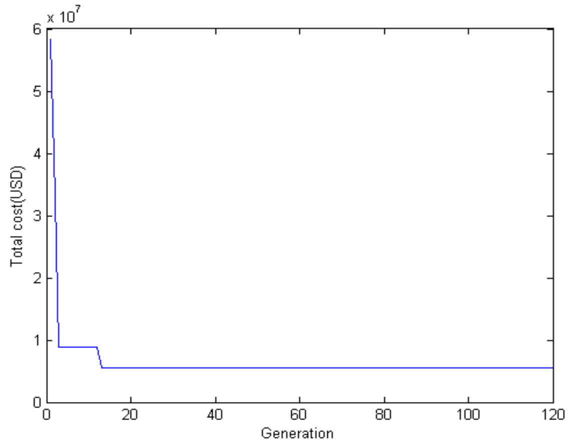
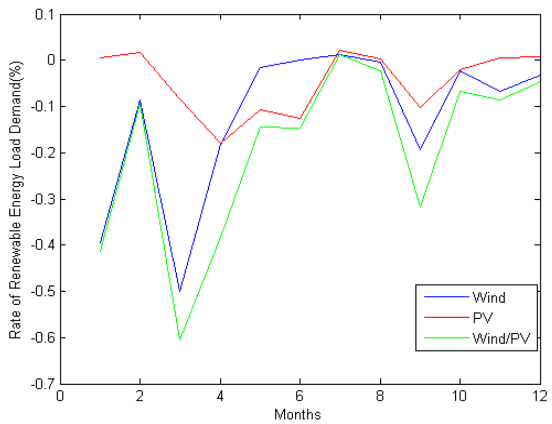
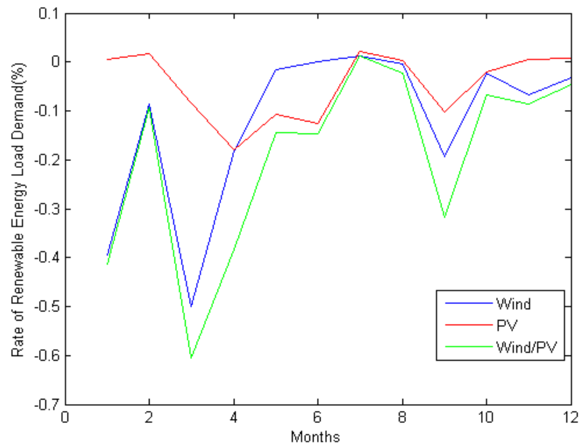


Fig.5: Total cost for scale factor f=5



(a)



(b)

Fig.6: Rate of Renewable Energy Load Demand (RELD) for three installation scenarios for f=3 (a), and f=5 (b).

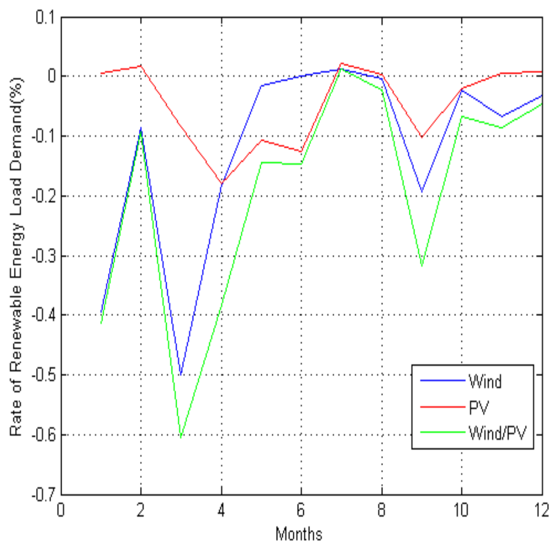
The algorithm used in the optimization process is utilized for three installation scenarios: wind generation power only, PV generation power only and finally wind and PV both.

Fig.6 shows the rate of renewable energy load demand (RELD) for scale factor *f*=5 and *f*=3. We remark that there is no difference between the plots. It means that the factor *f* doesn't affect the rate of RELD.

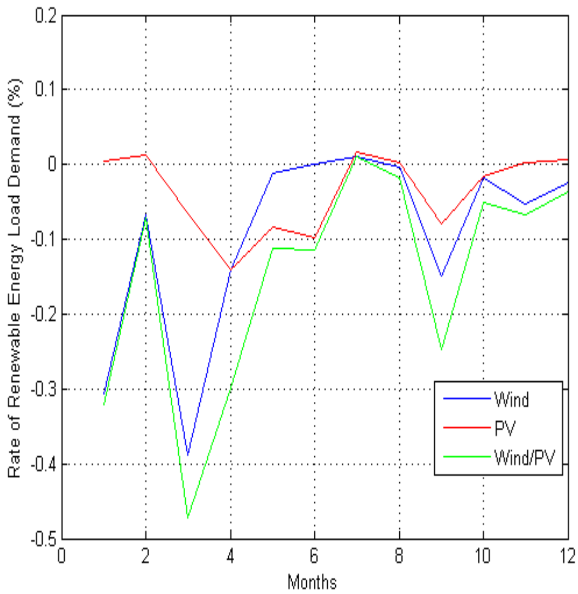
In order to show the performance of the proposed algorithm according to the RELD factor, fig.7 presents this factor for different generation scenarios for **ω** =0.1 (c) and **ω** =0.3 (d) .Then for **ω** = 0.1 fig. (7, c) the minimum value of the Rate Renewable Energy Load Demand achieved by both (Wind and PV) is 0.6 (60%), while in fig. (7.d) this value is less than 0.4 (40%). That means that **ω** has a big influence on the factor RELD.

In Fig.8 we take the Wind/PV generation system with different value for the penalty factor **ω**. Thus

here for the same system we have different curve depending on the factor **ω**. So the designer of the system can decide whether to gain in terms of RELD rate or in penalty factor **ω**. Here we can see the important of the penalty factor **ω** and his influence both on the rate of renewable energy and load demand.
The simulated load profile used in fig.3 corresponds to typical household power consumption within 24 hours.



(c)



(d)

Fig.7: Rate of Renewable Energy Load Demand (RELD) per month for w=0.1 (c) and w=0.3 (d).

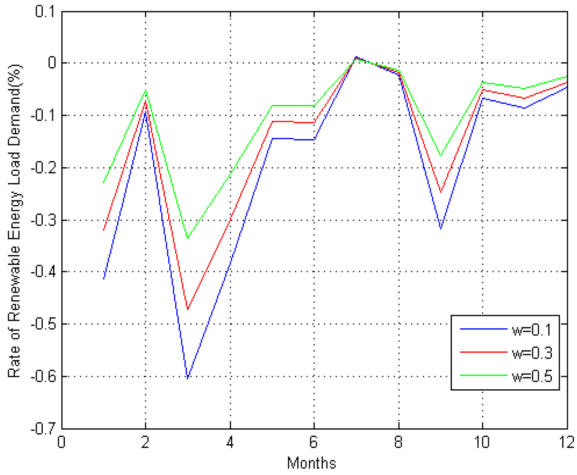


Fig.9: RELD per month for different

Conclusion

The aim behind this work is to optimize the total cost per year of the studied system (renewable energy coupled with a battery storage) by taking into account the Rate of Renewable Energy Load Demand (RELD). Firstly we determined the power produced by each power source separately, and next the total cost per year was optimized.

The first objective function defined by equation 10 was optimized for two different scale factor f; the metaheuristic optimization algorithm called Backtracking Search Algorithm (BSA) was used. The carried out results showed the importance of this parameter in determining the search direction. Furthermore, we saw also the influence of this factor on the second objective function defined by equation 15. However and according to fig. 7, it has been shown that the scale factor f didn't affect the RELD of the system.

Finally, a comparative study has been fulfilled for three configurations (Wind only, PV only and both PV/Wind) with two different values of the penalty factor ω.

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