People's Democratic Republic of Algeria
Ministry of Higher Education and Scientific research
M'hamed Bougara University, Boumerdes
Institute of Electrical and Electronic Engineering,
Laboratory of Signals and Systems (LSS)

ALGERIAN JOURNAL OF SIGNALS AND SYSTEMS

ISSN : 2543-3792

Title: **Design of Standalone Micro-Grid Systems Using Teaching Learning Based Optimization**

Authors: **Abdelmadjid RECIOUI and Khaled DASSA**

Affiliations:
Laboratory of Signals and Systems, Institute of Electrical and Elctronic Engineering, University M'hamed Bougara of Boumerdes, Avenue de l'indépendance, 35000, Algeria
Page range: **75- 85**

Volume : 2 Issue : 2 (June 2017)

Laboratory of Signals and Systems
Address : IGEE (Ex-INELEC), Boumerdes University, Avenue de l'indépendance, 35000, Boumerdes, Algeria
Phone/Fax : 024 79 57 66
Email : lss@univ-boumerdes.dz ; ajsyssig@gmail.com

Design of Standalone Micro-Grid Systems Using Teaching Learning Based Optimization

Abdelmadjid RECIOUI* and Khaled DASSA
(1) dept. Laboratory of Signals and Systems, Institute of Electrical and Elctronic Engineering, University M'hamed Bougara of Boumerdes, Avenue de l'indépendance, 35000, Algeria.
*a_recioui@univ-boumerdes.dz

Abstract: Meeting the load demand reliably and efficiently is the most important issue of any electrical system. Installing huge off grid hybrid power systems to deliver enough power is economically unwise. Therefore, it is necessary to minimize the size and number of units of the off-grid power system components and operate the system under an appropriate power management strategy to ensure efficient system operation. The successfulness of installing an off grid power system in remote areas depends on the total net present cost occurs during the lifetime of the project. In this work, optimization of off grid power system component sizing is performed using two tools: Homer and a metaheuristic optimization method that has been recently developed, the Teaching Learning Based Optimization (TLBO).

Keywords: Renewable energies, standalone systems, TLBO, Homer.

1. INTRODUCTION

In recent years, a considerable growth in using renewable energy resources has been observed. Especially solar and wind energy are infinite, site-dependent, clean and high potential sources for alternative energy production. Hybrid energy systems are the best suited to reduce dependence on fossil fuel using available wind speed and solar radiations. The integration of renewable energy sources is not a straightforward operation but it needs a techno-economical analysis and requires the data of the renewable resources.

Sizing hybrid systems has been in the last two decades a large research field and many methods have been suggested to solve that problem. Particularly, research is carrying on the modeling accuracy of the component of the hybrid system and the followed power management strategies. The control strategy is the heart beating of any algorithm subjected to optimize a hybrid system, in 1996 Barley and Winn improved the control strategies model of introducing new parameters that have become of great importance in the control strategies of the software tools HYBRID2, HOMER and HOGA.

HOMER (Hybrid Optimization Model for Electric Renewables), developed by NREL (National Renewable Energy Laboratory in USA), is the most-used optimization software for hybrid systems. It uses a predictive control strategy where the charging of the batteries depends on the prediction of the demand and the energy expected to be generated by means of renewable sources, with this strategy, the energy loss from the renewable energies tends to decrease. Homer has a special control strategy, another method used to optimize the system which has a quite similar control strategy with predicting side, the method is one of the most recent stars in the field of metaheuristic methods, it is called "Teaching-learning-based algorithm" (TLBO). The suggested TLBO use the loss of power supply probability (LPSP) as the reliability restriction.

Usually, the optimum design is carried out minimizing the Net Present Cost (NPC: investment costs plus the discounted present values of all future costs during the lifetime of the system) or by minimizing the Cost of Energy (COE: total cost of the entire hybrid system divided by the energy supplied by the hybrid system), the results obtained by each used tool will be evaluated by that economic criterion.

2. MODELING OF COMPONENTS

The power output of a single unit of wind turbine (model: BWXL) and solar panel were imported from Homer results, therefore the model is not needed for these two components.

Battery model

Modeling the battery bank includes: the energy content (which is directly related to the state of charge), the maximum charge power , the maximum discharge power, energy in, energy out , annual throughput and the expected life, those will be explained shortly.

The energy content

The initial battery state of charge is assumed to be 100% and during the charging process is expressed as:

$$en_{content}(t) = en_{content}(t-1) + \eta b_{ch} \times \left(PV_{out} + Pwind_{out} + \frac{Gen_{out} - load}{\eta_{inv}}\right) \quad (1)$$

$en_{content}(t)$ is the energy content at the current hour, $en_{content}(t-1)$ is the energy content at the previous hour, PV_{out} is the output power of the PV arrays, $Pwind_{out}$ is the output power of the wind turbines, Gen_{out} is the output power of the diesel generator, $load$ is the load at the current hour t, η_{inv} is the inverter efficiency, ηb_{ch} is the battery charging efficiency which is the square root of the round trip efficiency: $\eta b_{ch} = \sqrt{\eta_{rntr}}$

The energy content for the discharging process:

$$en_{content}(t) = en_{content}(t-1) - \frac{1}{\eta b_{dis}}\left(\frac{load - Gen_{out}}{\eta_{inv}} - PV_{out} - Pwind_{out}\right) \quad (2)$$

ηb_{dis} is the discharging efficiency : $\eta b_{dis} = \eta b_{ch} = \sqrt{\eta_{rntr}}$.

The maximum charge power

As described in Homer's Help, HOMER imposes three separate limitations on the battery bank's maximum charge power. The first limitation comes from the kinetic battery model. As described in [ ], the maximum amount of power that can be absorbed by the two-tank system is given by the following equation:

$$P_{batt,max1} = \frac{kQ_1 e^{-k\Delta t} + Qkc\left(1 - e^{-k\Delta t}\right)}{1 - e^{-k\Delta t} + c\left(k\Delta t - 1 + e^{-k\Delta t}\right)} \quad (3)$$

Where

Q_1 is the available energy [kWh] in the battery at the beginning of the time step,

Q is the total amount of energy energy [kWh] in the battery at the beginning of the time step,
c is the battery capacity ratio [unitless],
k is the battery rate constant [h^{-1}], and
Δt is the length of the time step [h].
A second model can be written as:

$$P_{batt,max2} = \frac{\left(1 - e^{-\alpha\Delta t}\right)(Q_{max} - Q)}{\Delta t} \quad (4)$$

The third limitation relates to the battery's maximum charge current. The maximum battery bank charge power corresponding to this maximum charge current is given by the following equation:

$$P_{batt,max3} = \frac{N_{batt} I_{max} V_{nom}}{1000} \quad (5)$$

Where N_{batt} is the number of batteries in the battery bank.
I_{max} is the battery's maximum charge current [A]. V_{nom} is the battery's nominal voltage [V].
HOMER sets the maximum battery charge power equal to the least of these three values, assuming each applies after charging losses, hence:

$$P_{batt,max} = \frac{MIN(P_{batt,max1}, P_{batt,max2}, P_{batt,max3})}{\eta b_{ch}} \quad (6)$$

The maximum discharge power:

The maximum amount of power that the battery bank can discharge over a specific length of time is given by the following equation:

$$P_{batt,max1} = \frac{-kcQ_{max} + kQ_l e^{-k\Delta t} + Qkc\left(1 - e^{-k\Delta t}\right)}{1 - e^{-k\Delta t} + c\left(k\Delta t - 1 + e^{-k\Delta t}\right)} \quad (7)$$

HOMER assumes that the discharging losses occur after the energy leaves the two-tank system; hence the battery bank's maximum discharge power is given by the following equation: $P_{batt,maxdis} = P_{batt,max}\eta b_{dis}$.

Other measures of battery performance include:

- Energy in, energy out: is the energy that goes inside the battery bank or the energy that goes out of the battery and it simply the difference between the energy content of the current hour and the precious one.
- Annual throughput: is the amount of energy that cycles through the battery bank in one year. Throughput is defined as the change in energy level of the battery bank, measured after charging losses and before discharging losses.

The expected life

The expected lifetime of the battery is given as:

$$Life_{batt} = min\left(\frac{N_{batt}Q_{lifetime}}{Q_{thrpt}}, Float_{life}\right) \quad (8)$$

In HOMER, two independent factors may limit the lifetime of the battery bank: the lifetime throughput and the battery float life. In other words, batteries can die either from use or from old age.

Converter/inverter

The converter/inverter is a modeled as a linear device whose output is a fraction of the input:

$$\frac{conv}{inv}_{out} = \eta_{inv} \times \frac{conv}{inv}_{in} \quad (9)$$

η_{inv} is the efficiency of invesion/rectification which is taken as 90%.

The feasibility (reliability) of a system

For the feasibility, Homer simulates each system chronologically and verifies that the load is always met. Another way to test the feasibility is to calculate the reliability at each time step. The reliability is measured by the loss of power supply (LPS) which is defined by:

$$LPS(t) = load(t) \times \Delta t - \left((PV_{out} + Pwind_{out} + Gen_{out})\Delta t + en(t-1) - en(t)\right) \quad (10)$$

$en(t-1) \quad en(t)$ is the difference between the energy stored in the battery in the current and previous hour.

$(PV_{out} + Pwind_{out} + Gen_{out})\Delta t$ is the energy produced from hour t-1 to hour t.

The above difference cannot be negative, so when it is negative it will be replaced by 0.

If LPS=0, it means that the load is well fitted; otherwise it is not.

The loss of power supply probability (LPSP) is defined as:

$$LPSP = \frac{\sum_{t=1}^{8760} LPS(t)}{\sum_{t=1}^{8760} load(t)} \quad (11)$$

LPSP=0 means that the load is always satisfied, LPSP=1 means that the load is never be satisfied.

3. PROBLEM SPECIFICATIONS

The system considered

The hybrid system is considered as shown in Fig. 1. XL1: is manufactured by Bergy Windpower and it has a capacity of 1 Kw and a lifetime of 20 years and a Hub height of 30m. Gen10: is 10Kw gasoline generator which has linear consumption of fuel. T-105: is manufactured by Trojan Battery Company and it is a 6V battery with 225 Ah nominal capacity, 865Kwh lifetime throughput, the minimum state of charge is 30% and the Round Trip Efficiency is 85%. PV: Generic flat plate PV can generate up to 1Kw and it has lifetime of 25 years. The converter has a lifetime of 15 years and an inverting efficiency of 90% and rectifying efficiency of 90%.

The annual nominal interest rate (nri) of this project is 8% with an expected inflation rate f of 2% which gives a real interest rate of 5.88%

For the dispatch strategy the Load following and Cycle charging dispatch strategies have been considered both to see which one is better. For simplicity the operating reserve is not considered.

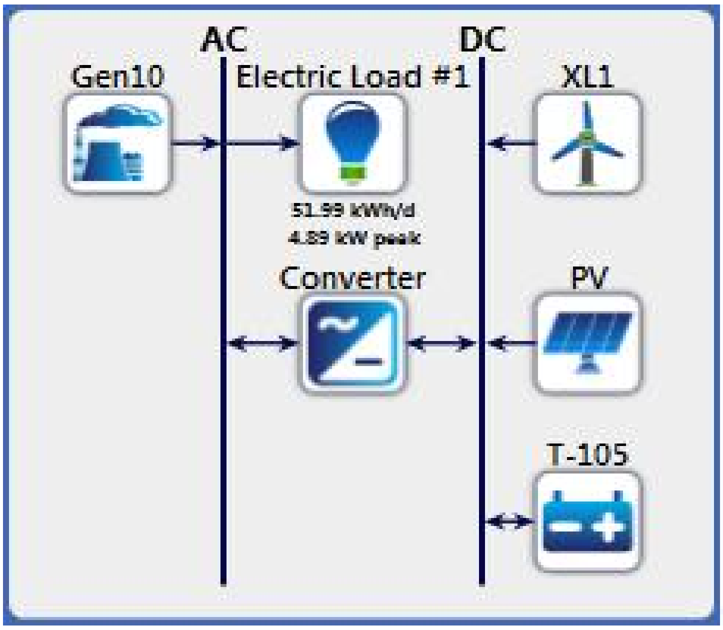


Fig. 1 The system to be optimized.

The power management strategies

The power management is split into two parts like Homer: Cycle Charging (CC) and Load Following (LF).

A. Cycle charging strategy

The cycle charging (CC) dispatch strategy works as the following steps:

- In each time step, the mode is checked, mode 1 is the mode of charging the battery where the battery should be charged until $SOC \geq 80\%$ then the system is switched to mode0 where the battery can be discharged if it is needed or charged it there is an excess energy.

- The load is always served by the renewable components if they can otherwise the battery bank energy or the generator power will be used depending on the lowest marginal cost of the current load for the generator and the current load inverted for the battery bank.

-if the renewable components and the battery cannot serve the load, the generator goes ON without checking the marginal cost and in that case the mode will be switched to mode 1.

-At the end of the time step, the system reliability is calculated (LPS) to be summed with other LPSs after computing the last LPS ($LPS(8760)$).

It should be noticed that the generator cannot generate a power less than 25% of its rated power.

B. The Load Following

Under the load following (LF) strategy, the battery bank can be charged by the excess energy and the generator will goes ON if it is necessary only to serve the load not to charge the battery bank.
The criterion of marginal cost is also considered here but the marginal cost is exactly the wear cost, it is also noticed that the marginal cost for the battery is calculated for the inverted load minus the total renewable output i.e. when the renewable output and the battery bank are able to serve the load, the system has two choices: either serving the load by the total renewable output and the energy stored in the batteries or serve the load by the generator and the renewable output and the excess energy goes to the battery bank, in that case the system will make a decision by comparing the value of the following functions:

$$marg_{gen}(load) = C_{gen,ma} \times load + C_{gen,fixed} \quad (12)$$

If $marg_{batt}(load) < marg_{gen}(load)$, then the load is served by the renewable outputs and the battery bank, otherwise the generator is ON where its outputs is exactly equal to the demand (load) and any excess energy from the generator or the non-dispatchable sources will charge the batteries.

Economic Modeling

Economic modeling is exactly the same with that of Homer. The capital cost, replacement cost, operating and maintenance cost are also the same whereas the search space is larger than HOMER since TLBO has the ability to find the global minimum in large search spaces.

The fitness function

The criterion for the TLBO to know which configuration is the fittest is defined as:

$$f_i(x) = \sqrt{TNPC^2(i) + 10^{10} \times LPSP(i)} \quad (13)$$

The fitness function is considered as a vector whose components are the TNPC (total net present cost) and the LPSP (loss of power supply probability). The LPSP determines the feasibility of the system and the COE represents its economic factor. Since the change of the LPSP is too small with respect to the TNPC, its value were not squared but rather multiplied by a huge factor (10^{10}) in order to be significant enough against the COE.
The fitness value of each configuration is the smallest value fitness values for the cycle charging strategy and the load following.

Sizing the converter/inverter

The size of the inverter/converter does not affect the LPSP function it affects only the TNPC. In fact the size of the converter/inverter is determined after the last time step and it is given as the maximum power that travels from DC bus to the AC bus or vice versa.
However, another method inspired from Homer results is suggested which is:

- If the size of the converter is less than the inverter size: rerun the dispatch strategy and if inversed power exceeds the limit (size of the converter) switch ON the generator and charge the batteries by the renewable output power, this process occurs only in the cycle charging.

For the load following dispatch strategy: rerun the dispatch strategy don't let the inversed power exceeds the old size decremented, if that happens switch ON the generator

4. THE TEACHING LEARNING OPTIMIZATION ALGORITHM (TLBO)

Mechanism of TLBO

Most of the metaheuristic methods are inspired from nature i.e. they mimic the behavior of nature. For example in Genetic Algorithm inspired from Darwin's theory, the strongest is the one who survive, Particle swarm is inspired from the movement of a flock of bird, a school of fish, or a swarm of bees that are looking for food, Artificial Bee Colony (ABC) simulates the intelligent forging of honey bee swarm, Ant colony shows how ants search for food and how to find an optimal way to it,…etc. They prove their effectiveness in solving many engineering optimization problems but each one of them requires its own algorithm specific control parameters.For example, Genetic Algorithm (GA) uses mutation rate and crossover rate. Similarly ¨Particle Swarm Optimization (PSO) uses inertia weight, social and cognitive parameters. The improper tuning of algorithm specific parameters either increases the computational effort or yields the local optimal solution. Considering this fact,recently Rao et al. (2011, 2012), Rao&Savsani (2012) and Rao & Patel (2012) introduced the Teaching-Learning Based Optimization (TLBO) algorithm which does not require any algorithm specific parameters. In this way TLBO obtain global solutions for continuous nonlinear functions with less computational effort and high consistency [ ].

TLBO is a teaching-learning process inspired algorithm based on the effect of influence of a teacher on the output of learners in a class. Teacher and learners are the two vital components of the algorithm and describes two basic modes of the learning, through teacher (known as teacher phase) and interacting with the other learners (known as learner phase). The output in TLBO algorithm is considered in terms of results or grades of the learners which depend on the quality of teacher. So, teacher is usually considered as a highly learned person who trains learners so that they can have better results in terms of their marks or grades. Moreover, learners also learn from the interaction among themselves which also helps in improving their results [ ].

TLBO is population based method. In this optimization algorithm, a group of learners is considered as population and different design variables are considered as different subjects offered to the learners and learners' result is analogous to the 'fitness' value of the optimization problem. In the entire population the best solution is considered as the teacher. The working of TLBO is divided into two parts, 'Teacher phase' and 'Learner phase'. Working of both the phases is explained below.

A. Teacher phase

In this phase the best student is chosen from the population (the class) according to the fitness function and set as a teacher. Since the teacher is the highest learned person in the class, he puts effort to disseminate knowledge among students so that he tries to bring the mean level of the class up to his level, the new mean of the class depends on two things:

- The ability of the teacher i.e. his method in teaching is good or bad and this is represented by a factor t_f called "teaching factor", it can be 1 or 2 (those values are concluded from experiments).
- The ability of the student to receive and understand concepts from his teacher.

B. Learner phase: as known, when a student does not understand his teacher or he wants to have more knowledge, he will interact with one of their fellow students. If he finds his friend better than himself he will learn from him otherwise he will not [].

Implementation of TLBO Algorithm for optimization

Step1: formulate the optimization problem, the objective function and the side constraints:

Minimize (objective function) $y = f(x_1, x_2, \dots, x_{n-1}, x_n)$ such that: $x_j^{min} \le x_j \le x_j^{max}$ Where j=1, 2, 3,……,D those are the side constraint which specify the limit of each design variable i.e. the maximum and minimum level in each course of any student.

The variables $x_1, x_2, \dots, x_{n-1}, x_n$ represent the level of student $\mathbf{X}$ in each course so x_1 is the level of $\mathbf{X}$ in the first course.

Decide how many student you will use or the population size, also the number of generation. Here a minimization problem is considered; the maximization is similar.

Step 2: initialization: suggest a population (that will be developed to reach the final solution) or students randomly according to the following equation:

$$x_{(i,j)}^{1} = x_j^{min} + rand_{(i,j)} \times \left(x_j^{max} - x_j^{min}\right) \quad (14)$$

i:refer to student number, so this is the ith student, *i*=1, 2, …,P

j:refer to the course number, $x_{(i,j)}$ is the level of the ith student at the jth course, *j*=1, 2,…,D

The small number 1 refer to the generation number, it's the first generation.

After manipulating the above equation $P \times D$ times, a $P \times D$ matrix which represents the population is obtained:

$$population^1 = \begin{bmatrix} x_{(1,1)}^1 & \cdots & x_{(1,D)}^1 \\ x_{(2,1)}^1 & & x_{(2,D)}^1 \\ \vdots & \ddots & \vdots \\ x_{(P,1)}^1 & \cdots & x_{(P,D)}^1 \end{bmatrix} \quad (15)$$

So $X_1^1 = (x_{(1,1)}^1, \quad x_{(1,2)}^1, \dots, x_{(1,D)}^1)$ is student number 1 in the first generation.

Choose the teacher: the best student is the one which has the minimum fitness function.
Step 3: teacher phase
Mathematically, how the best student teaches the others:

$$X_{i,new} = X_i + (X_{teacher} - t_f \times mean) \tag{16}$$

t_f is the teaching factor, it can be 0 or 1.

- A comparison between the new student $X_{i,new}$ and the old one X_i should be made, if $X_{i,new}$ is better than X_i, replace the old by the new one otherwise keep the old one.

$i = 1, 2, \ldots, P.$ $if\ f(X_{i,new}) < f(X_i)\ then\ X_i = X_{i,new}\ else\ do\ nothing$

Step 4: learner phase
This phase shows the interaction between students.
For each student i we pick another student j randomly and compare their level (fitness function), the first student i will learn from the second j (get close to him) if he is better than him otherwise he will go far from him, according to the formula: $if\ f(X_{i,new}) < f(X_i)\ then\ X_i = X_{i,new}\ else\ do\ nothing$

$$X_{i,new}^g = \begin{cases} X_i^g + rand_i^g \times (X_j^g - X_i^g), & iff(X_i^g) < f(X_j^g)\ better \\ X_i^g + rand_i^g \times (X_i^g - X_j^g), & iff(X_i^g) \geq f(X_j^g)\ worst \end{cases} \tag{17}$$

After completing the process for all the population, the fittest student is set as teacher.
Step 5: if $g \neq numberofgeneration$ go to step 3 else stop.
The flowchart of the TLBO algorithm is shown in Fig. 2.

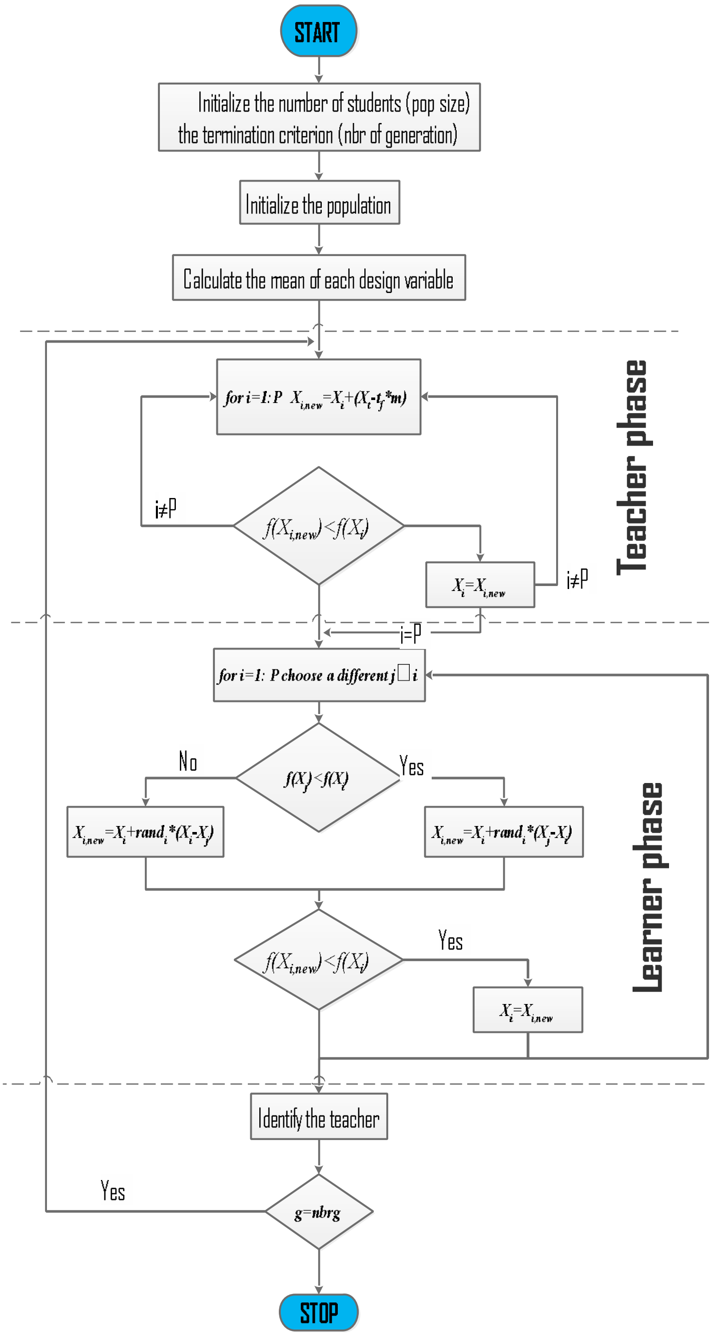


Fig. 2 Flowchart of TLBO Algorithm

5. RESULTS AND DISCUSSIONS

The results of the optimization process are summarized in the table below

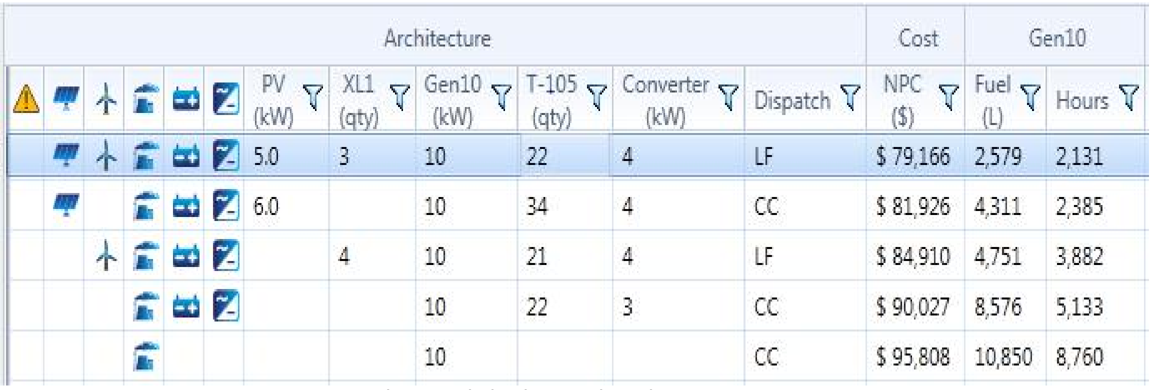
TABLE 1 Results of the optimization process

BWXL1	PV	Batts	Con/Inv	Gen	LPSP	TNPC	Oph	Fuel [liter]
3	3	33	4	1		8201	2567	3150.1
4	5	34	5	1	0	79846	1012	1239.2
3	5	34	5	1	0	78918	1440	1752.5
3	5	29	5	1	0	7889	1573	1910.9

3	5	30	5	1	0	78839	1542	1873.2
3	**5**	**27**	**5**	**1**	**0**	**78753**	**1636**	**1985.5**
3	**5**	**27**	**5**	**1**	**0**	**78753**	**1636**	**1985.5**
3	**5**	**27**	**5**	**1**	**0**	**78753**	**1636**	**1985.5**
3	**5**	**27**	**5**	**1**	**0**	**78753**	**1636**	**1985.5**
3	**5**	**27**	**5**	**1**	**0**	**78753**	**1636**	**1985.5**

The results in the above table are not ranked according to their TNPCs like Homer but they are the best solutions ever gotten in the ten iterations. The last 8 solutions are identical because after the second iteration the algorithm didn't find any solution better than that.

Fig. 3 shows results of Homer for the same inputs



Architecture						Cost	Gen10	
PV (kW)	XL1 (qty)	Gen10 (kW)	T-105 (qty)	Converter (kW)	Dispatch	NPC ($)	Fuel (L)	Hours
5.0	3	10	22	4	LF	$ 79,166	2,579	2,131
6.0		10	34	4	CC	$ 81,926	4,311	2,385
	4	10	21	4	LF	$ 84,910	4,751	3,882
		10	22	3	CC	$ 90,027	8,576	5,133
		10			CC	$ 95,808	10,850	8,760

Fig. 3 optimization results using HOMER

In order to specify the differences between Homer and TLBO, each dispatch strategy was optimized alone. Table 2 shows the optimization results of TLBO for the load following. **Erreur ! Source du renvoi introuvable.** presents the same with HOMER

Table 2 Results with load following strategy

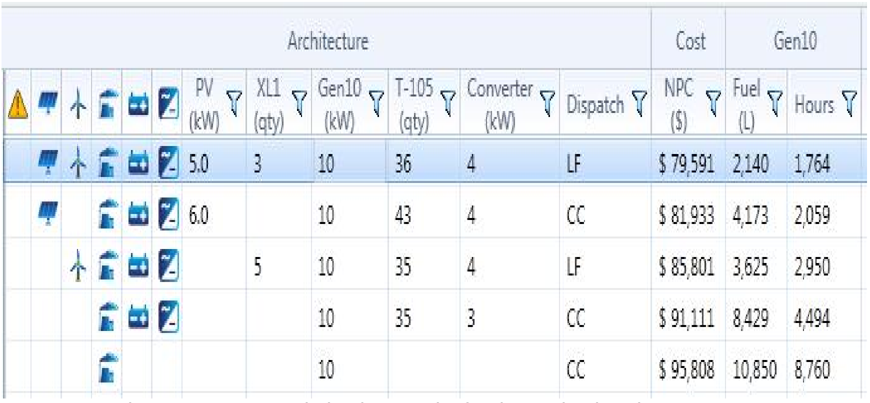
BWXL1	PV	Batts	Con/Inv	en	TNPC [$]	Oph	Fuel [liter]	LPSP
4	5		5	1	79603	104	1466.9	0
4	5	27	5	1	79603	1204	1466.9	0
3	5	33	5	1	78889	1459	1774.1	0
3	**5**	**27**	**5**	**1**	**78753**	**1636**	**1985.5**	**0**
3	**5**	**27**	**5**	**1**	**78753**	**1636**	**1985.5**	**0**
3	**5**	**27**	**5**	**1**	**78753**	**1636**	**1985.5**	**0**
3	**5**	**27**	**5**	**1**	**78753**	**1636**	**1985.5**	**0**
3	**5**	**27**	**5**	**1**	**78753**	**1636**	**1985.5**	**0**
3	**5**	**27**	**5**	**1**	**78753**	**1636**	**1985.5**	**0**
3	**5**	**27**	**5**	**1**	**78753**	**1636**	**1985.5**	**0**

For the load following the results are different and that is due to the difference in the power management, the optimal solution for the TLBO has a TNPC smaller than the optimal solution of HOMER.

Table 3 shows the optimization results of TLBO for the cycle charging and Figure 5 does the same with HOMER.

Table 3 TLBO optimization results for the cycle charging strategy

BWXL1	PV	Batts	Con/Inv	Gen	TNPC [$]	Oph	Fuel [liter]
5	3	53	5	1	83941	720	1648.4
3	4	56	5	1	80506	914	2224.1
3	4	54	5	1	80183	933	2231.2
3	4	51	5	1	79806	967	2251.7
3	5	45	4	1	79671	918	1848.4
3	4	47	4	1	78929.1	1063	2334.9
3	4	47	4	1	78929.1	1063	2334.9
3	4	47	4	1	78929.1	1063	2334.9
3	4	47	4	1	78929.1	1063	2334.9
3	4	47	4	1	78929.1	1063	2334.9



Architecture						Cost	Gen10	
PV (kW)	XL1 (qty)	Gen10 (kW)	T-105 (qty)	Converter (kW)	Dispatch	NPC ($)	Fuel (L)	Hours
5.0	3	10	36	4	LF	$ 79,591	2,140	1,764
6.0		10	43	4	CC	$ 81,933	4,173	2,059
	5	10	35	4	LF	$ 85,801	3,625	2,950
		10	35	3	CC	$ 91,111	8,429	4,494
		10			CC	$ 95,808	10,850	8,760

Fig. 5 HOMER's optimization results for the cycle charging strategy

Obviously TLBO solutions are less costly than HOMER solution, the results are not the same and that is due to some facts:

- Homer considers the self-discharging of the battery bank.
- The amount of power generated to charge the batteries in the cycle charging in Homer depends on the future renewable outputs and that's the prediction control strategy.

The second notice on HOMER is the possibility fall in local optima. The beginner user of HOMER has no experience in choosing the right search space, and if he chooses a large search space like the one associated with TLBO the simulation will take days to end.

6. Conclusions

This study accomplished also the optimization of a hybrid standalone Wind/Solar/Diesel based energy system has been considered for the site of In Salah. The region proves that it possess a large potential of both solar and wind energies which can be a better alternative sources of electricity than those connected to grid especially in remote areas.

To increase the certainty of the powerfulness of the area and to study the heart of Homer, another way is suggested for optimizing hybrid system which the optimization by TLBO. A proposed TLBO is developed for optimizing hybrid systems. The fitness function was taken as combination of TNPC and LPSP index, TLBO in the end proves its great ability in the optimization, the main advantage of TLBO over Homer is the globality certainty. Metaheuristic methods characterized by their ability to reach the global optimum.

REFERENCES

[1] Rusawasatt Lutato, Minimising Excess energy in Sizing of Hybrid Renewable Power Systems, SCIE Journals, 2012.
[2] Kashefi Kaviani, et al ,Soft Computing in Green and Renewable Energy Systems, Springer, 2009
[3] Farouk Chellali, Adballah Khellaf , Adel Belouchrani , Abdelmadjid Recioui ,A contribution in the actualization of wind map of Algeria, Elsevier, Renewable and Sustainable Energy Reviews 15 (2011) 993–1002
[4] HOMER energy modeling software. National Renewable energy laboratory. Available from: http://en.openei.org/wiki/HOMER.

[5] Pei Yi Lim, Power Management Strategies for Off-Grid Hybrid Power Systems, Doctor of Philosophy of Curtin University, October 2011.
[6] Mohammadi M, Hosseinian SH, Gharehpetian GB, GA-based optimal sizing of microgrid and DG units under pool and hybrid electricity markets. Int J Elect Power Energy Syst 2012;35(1):83e92.
[7] Optimization of micro-grid system using MOPSO Hanieh Borhanazad a, Saad Mekhilef a, Velappa Gounder Ganapathy b, Mostafa Modiri-Delshad, Ali Mirtaheri Renewable Energy 71 (2014) 295e306
[8] Erdinc O, Uzunoglu M. Optimum design of hybrid renewable energy systems: overview of different approaches. Renew Sustain Energy Rev 2012;16(3): 1412e25.
[9] Luna-Rubio R, Trejo-Perea M, Vargas-V azquez D, Ríos-Moreno GJ. Optimal sizing of renewable hybrids energy systems: a review of methodologies. Sol Energy 2012;86(4) 1077e88.
[10] Bogdan, S. B. and Salameh, Z. M. Methodology for optimally sizing the combination of a battery bank and PV array in a wind/PV hybrid system. IEEE Transactions on Energy Conv. 11(2), 367-375, 1996
[11] Bin, A., Hongxing, Y., Shen, H., Xianbo, L, Computer aided design for PV/Wind hybrid system. Renewable Energy 28,1491-1512, 2003
[12]J. F. Manwell and J. G. McGowan, Lead acid battery storage model for hybrid energy systems, Solar Energy,(1993) Vol. 50, pp. 399–405.
[13] Said Diaf, Djamila Diaf, Mayouf Belhamel, Mourad Haddadi, Alain Louche, A methodology for optimal sizing of autonomous hybrid PV/wind system. Energy Policy, Elsevier, 2007, 35,pp.5708-5718.
[14] Kaabeche A, Belhamel M, Ibtiouen R. Techno-economic valuation and optimization of integrated photovoltaic/wind energy conversion system. Sol Energy 2011;85(10):2407e20.
[15] Deshmukh MK, Deshmukh SS. Modeling of hybrid renewable energy systems. Renew Sustain Energy Rev 2008;12(1):235e49.
[16] Recioui.A, Bentarzi.H, Chellali.F, Stand-alone system optimization and assessment of wind energy potential of a remote area in Algeria, International Symposium on Environment Friendly Energies in Electrical Applications, 2-4 November 2010.
[17] R. Venkata Rao, Vivek Patel, Comparative performance of an elitist teaching-learning-based optimization algorithm for solving unconstrained optimization problems, Growing Science 2012.
[18] Matej Cˇrepinšek, Shih-Hsi Liu, Luka Mernik, A note on teaching–learning-based optimization algorithm, Information Sciences 212 (2012) 79–93.
[19] R.V. Rao, V.J. Savsani, D.P. Vakharia, Teaching-learning-based optimization: A novel method for constrained mechanical design optimization problems, Computer-Aided Design 43 (2011) 303–315.
[20] R. Venkata Rao , Vivek Patel, An improved teaching-learning-based optimization algorithm for solving unconstrained optimization problems, Elsevier Scientialranica, Volume 20, Issue 3, June 2013, Pages 710–720
[21] R.V. Rao, V.J. Savsani, D.P. Vakharia, Teaching–Learning-Based Optimization: An optimization method for continuous non-linear large scale problems, Elsevier Information Sciences 183 (2012) 1–15
[22] K.R. Krishnanand2, Bijaya Ketan Panigrahi1, P.K. Rout2, and Ankita Mohapatra, Application of Multi-Objective Teaching-Learning-Based Algorithm to an Economic Load Dispatch Problem with Incommensurable Objectives, SEMCCO 2011, Part I, LNCS 7076, pp. 697–705, 2011.