Optimization with Energy Management of PV Battery Stand-Alone Systems over Life Cycle

Julien Seigneurbieux, Gaël Robin, Hamid Ben Ahmed, Bernard Multon

OPTIMIZATION WITH ENERGY MANAGEMENT OF PV BATTERY STAND-ALONE SYSTEMS OVER THE ENTIRE LIFE CYCLE

Julien SEIGNEURBIEUX, Gaël ROBIN, Hamid BEN AHMED, Bernard MULTON
SATIE CNRS UMR 8029
ENS de Cachan, Brittany Branch - Ker Lann Campus
35170 BRUZ (France)
julien.seigneurbieux@bretagne.ens-cachan.fr
http://www.satie.ens-cachan.fr

ABSTRACT: Photovoltaic (PV) installations are typically optimized on the basis of simplified considerations that draw design conclusions from insolation data and heavily-averaged consumption trends (e.g. using daily averages) and/or standard consumption profiles. The analysis proposed herein begins with the premise of working on averaged time series data using much narrower time intervals (e.g. 1-hour series). Design of both the installed PV power and storage capacity (lead-acid battery technology for purposes of this article, yet the underlying principle remains applicable to any other technology) is optimized by incorporating accumulator cycling aging. The energy management strategy that serves, among other things, to reduce cycling costs (sizable in the case of lead-acid batteries [1]) can in turn be optimized according to this design procedure. The solid correlation between design and energy management functions is also taken into account herein. The objectives (optimization criteria) considered in this approach are not limited to the classical notion of financial costs, but instead encompass environmental energy costs as well (Global Energy Requirement, or GER), in addition to the rate of consumer satisfaction (load shedding has been envisaged).
Keywords: Battery storage and control, Lifetime simulation, PV system.

1. INTRODUCTION

Given the sizable initial outlay for an autonomous installation producing photovoltaic electricity, the design process must be highly exacting and detailed. In order to ensure thoroughness, all components placed in the power system would naturally have to be considered during this process.

The present article proposes an original approach to optimizing the design of an autonomous photovoltaic energy production facility associated with a storage system. The objectives behind this approach were chosen so as to provide the design team not just with a unique optimal solution, but with a whole array of tradeoff configurations, each capable of standing out based on at least one criterion. In order to incite an effective convergence routine leading to compromise solutions, the objectives to be minimized must be contradictory. These solutions are all displayed in the form of a Pareto front.

Through application of a technical-economic analysis tool previously developed and [2], we are now able to simulate, using data presumed to be deterministic, the electrical and energy operations of each installation component and then deduce total system costs as well as system capacity to meet consumer needs.

Both the models and analysis tool generated for this purpose rely upon insolation profiles and hour-by-hour sampled consumption data over a 15-year period (other durations could obviously be studied as well). A timely and accurate analysis can thus be conducted of a complete production system: from the PV panels to the undulator, including the storage system.

This "step-by-step" simulation allows computing energy flux as it varies with production/consumption cycles; moreover, it serves to refine the more typical design methods that use constant daily consumption patterns and overly-averaged renewable output. The battery state of charge (SOC), which determines the efficiency during charging or discharging, may be computed at any point in time.

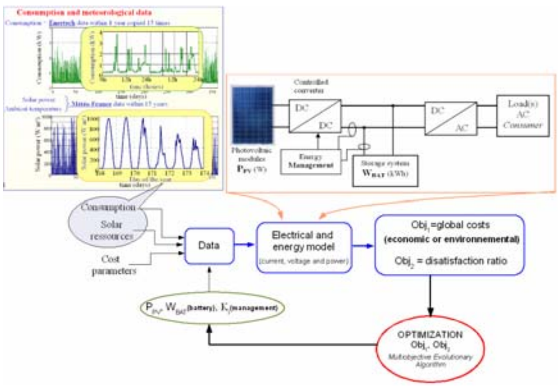

Figure 1: Method for a design and energy management optimization using life-cycle simulation: General overview

2. MODELING SET-UP FOR THE INSTALLATION

The installation considered comprises a variable number of photovoltaic panels, in association with DC/DC converters that enable adjusting the power generated (up to the MPPT operating threshold, i.e. the full extent of solar resources).

All installation component models have been validated experimentally ([2], [3]). We decided to focus this part of the article on modeling accumulators for the purpose of explaining the role of management parameters within the optimization process. The model incorporates the influence of both battery charge state and instantaneous recharge power on accumulator efficiency. This specific feature in our set-up will allow determining the impact of management parameters on overall output (which also takes accumulator cycling into account).

We have made use of the electric model from CIEMAT [4]. It proves difficult to overcome the Coulomb (electrical) orientation inherent in this model, which derives the battery charge state at each instant; the CIEMAT model however offers a good compromise between resolution speed and model detail.

This model has been based on the electrical diagram shown in Figure 2, which describes the battery with just two elements (whose characteristics depend on a whole set of parameters): voltage source, and internal resistance.

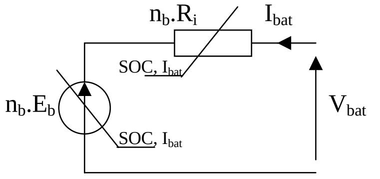

Figure 2: Equivalent electrical diagram of *nb* battery elements in series

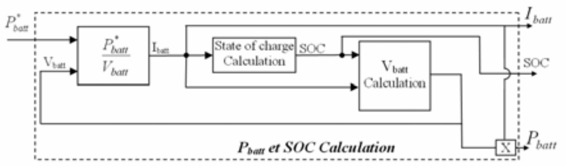

Figure 3: Computation algorithm for battery modeling

Both the accumulator charge and discharge, as depicted in Figure 4, modify the battery state of charge, which in turn affects the level of efficiency (especially due to variations in internal resistance *Ri*). Figure 5 illustrates this dependence of instantaneous accumulator efficiency on state of charge.

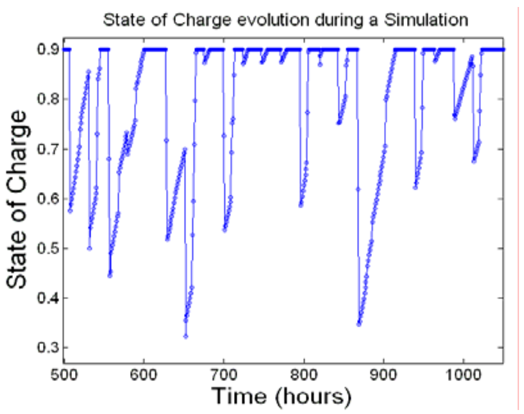

Figure 4: Evolution in State Of Charge

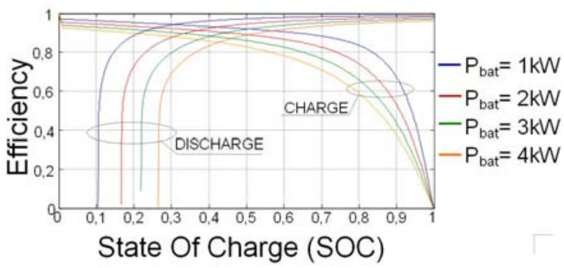

Figure 5: Evolution of storage efficiency during both the charge and discharge, as a function of the state of charge, at constant power (24 VRLA batteries – C_{10} = 325 Ah or W_{bat} = 15.6 kWh)

Acting upon energy flux via the storage system, by means of adapting recharge power to the level of available energy, makes it possible to add one degree of freedom to the system. The optimization algorithm must then determine the most pertinent management strategy in terms of energy efficiency and accumulator aging, so as to minimize optimization objectives. This strategy corresponds to the choice of *Ki* factors that represent the ratio of recharge power to available power. In this case:

$$K_i = \frac{P_{Batt}}{P_{available}} = \frac{P_{Batt}}{P_{PV_{producible}} - \dfrac{P_{user}}{\eta_{DC/AC}}}$$

Battery aging, also to be taken into account during simulations, constitutes a key factor when calculating the system's financial and environmental costs. The cycling of these accumulators, particularly if poorly managed, can wind up as the installation's primary investment expense. Manufacturers' data have guided us in modeling accumulator aging by associating the life cycle duration with a constant quantity of total exchanged energy, i.e.:

(Number of cycles * Depth of Discharge = Cste)

Cycling 2,700 kWh for W_{bat} = 1 kWh installed

Although this cycling-based life cycle modeling has been simplified, it still yields a reasonable approximation for this factor.

Figure 6 shows, given a set of 4 *Ki* parameters, the normalized battery charge command for all available power during the cycle.

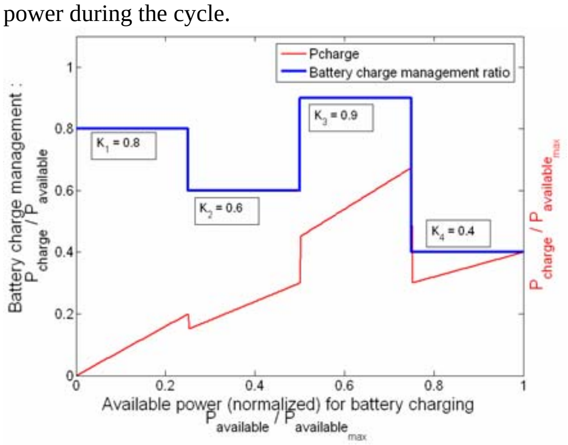

Figure 6: Management parameters: 4 discrete values - A configuration example

Figure 7 shows the result derived from the principle of managing charge power (negative) throughout the life cycle. The charging power command (negative) is smaller than available power: the *Ki* coefficients (which correspond with a given available power range) serve to attenuate this power in establishing the set value. Each coefficient would then correspond with an available power threshold and is optimized over the life cycle like other parameters (P_{PV} and W_{bat}).

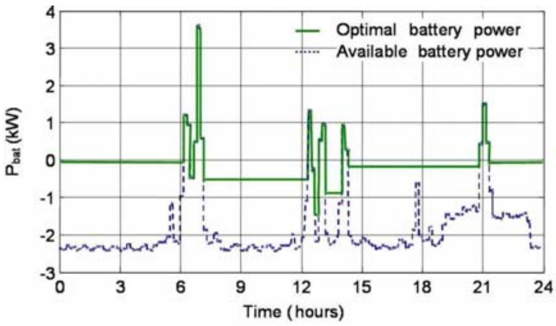

Figure 7: Managing battery charge power during the simulation, for different levels of available power

3. LIFE CYCLE-BASED SIMULATION

The models featured herein (electrical, energy and system aging - emphasis on batteries) are simulated over a 15-year life cycle (131,496 hours). The deterministic simulation thus imposes generating a database on insolation and consumption over the entire simulation period. Consumption data are based on actual trends from French household measurements, not including hot water and heating usage. Insolation values have been drawn from a Météo-France meteorological recording of solar radiation near a laboratory site in Rennes. Figure 8 shows the shapes of the hourly input profiles. To enhance clarity, these profiles have been averaged over daily time intervals to generate annual profiles and, conversely, averaged over the year to yield the daily profiles.

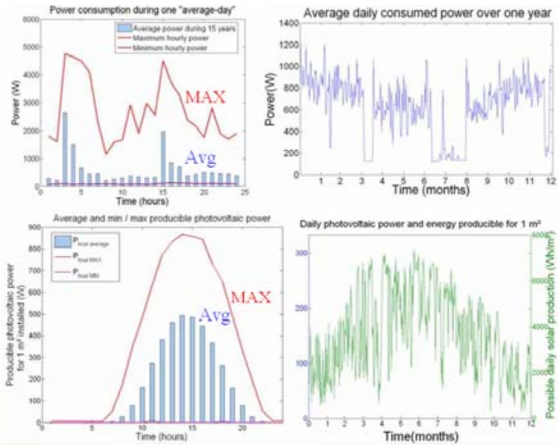

Figure 8: Consumption and solar resource profiles: 15 years or 131,496 hours

Beyond the "actual" consumption profile based on actual trends from French household measurements, we examined the results from an optimization conducted on various consumption profiles: at a constant level of service, i.e. for the same quantity of electrical energy supplied to the consumer (82 MWh over 15 years), both the installation cost and optimal parameters will depend on how the energy is getting consumed, and in particular on its correlation with electrical energy produced by the PV panels. In all, three profiles were studied: the original composed using on-site measurements; the second simply held constant, with the power consumed at any instant corresponding to average power; and the third in phase with solar production.

4. THE MULTI-OBJECTIVE OPTIMIZATION STRATEGY

4.1 Introducing the Global Energy Requirement (GER)

Minimizing financial costs most certainly represents the primary objective behind any photovoltaic installation design method. Within a context dictated however by environmental concerns and in the presence of strong disparities in installation financing and subsidization, environmental costs may in some instances serve as a better indication for drawing comparisons between installations, based on intrinsic technological criteria. We used data from life cycle analyses in order to determine, for illustration purposes, the values of equivalent primary energy necessary for the installation over its entire life cycle, i.e. "from cradle to grave". These data were drawn from research conducted in [5]; cost data may be further refined and has been used herein strictly for methodology validation.

Table I: Global Energy Requirement data

Total Energy Requirement	Primary fossil fuel equivalent
Photovoltaic panels (for 1 Wp)	12.5 kWh_{th}
VRLA batteries (for 1 kWh)	422 kWh_{th}
DC/AC converter (for 1 W)	0.833 kWh_{th}

The kWh_{th} unit is basically used to relate costs. It represents the primary fossil fuel equivalent energy used to produce and maintain a system. In order to compare the system costs and service, the following equivalence may be used: $1\ kWh_{th} \leftrightarrow 0.4\ kWh_{el}$, which implies that the global efficiency of electricity production is 40%.

4.2 Second objective: Dissatisfaction ratio (%)

In order to provide a set of tradeoff solutions (called "Pareto solutions"), we introduce as a second (minimization) objective the consumer's dissatisfaction ratio, which consists of the proportion of total energy (82 MWh) demanded by the consumer that is unable to be supplied. The cumulative load-shedding time has been limited, through adding a constraint, to 10% of total time. This objective enables studying the influence of consumer behavior on system design and, over the long run, identifying specific actions taken on the consumption profile that could lower system costs.

The formation of a Pareto front during convergence of the genetic NSGA-II algorithm [6] serves to characterize a dichotomy between minimized overall system costs and fulfillment of consumer needs.

5. RESULTS

5.1 Influence of consumption profile

It obviously appears that correlations between consumption and production will give rise to a key design factor. Acting upon the consumption profile may even further reduce costs and improve the satisfaction of consumer needs.

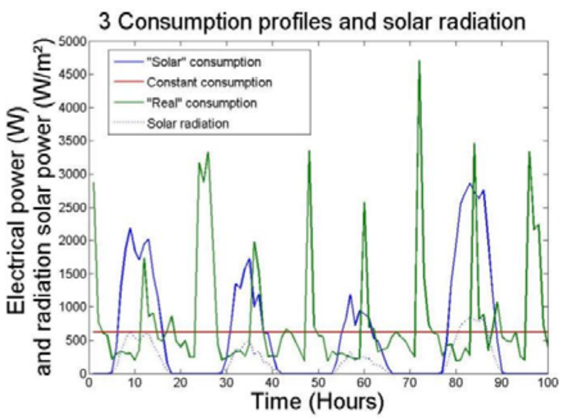

Figure 9: Definition of consumption profiles used for optimization and solar radiation:
The total energy consumed over the cycle (15 years) is the same (82 MWh) in all profiles.

Figure 10 indicates the optimization results obtained for three types of consumption profiles (Figure 9):

- constant consumption,
- consumption proportional to solar production, and
- "actual" consumption established from on-site measurements (see Figure 8).

These three profiles (Figure 9) all consume the same amount of energy accumulated over the cycle (82 MWh).

Figure 11 provides an example of optimization parameter distribution within the constant consumption profile, which consists of the peak photovoltaic power and maximum storage capacity of each optimal configuration.

Figure 10 clearly shows that the Pareto front is "compressed" in the case where the consumption profile is positioned in phase with production (i.e. the "solar profile"); in this case, consumer load-shedding will only be due to poor solar panel sizing. With this specific consumption profile, an optimal Pareto front boundary is obtained: regardless of the selected consumption profile, no single profile will lead to a "best solution".

On the other hand, in the case of a sizable difference between production and consumption profiles, it can be observed that even the slightest consumer load-shedding considerably decreases the quantity of batteries / solar panels installed. The quantity of batteries installed constitutes the parameter that initially enables heavily reducing costs, while guaranteeing minimum load-shedding for the consumer.

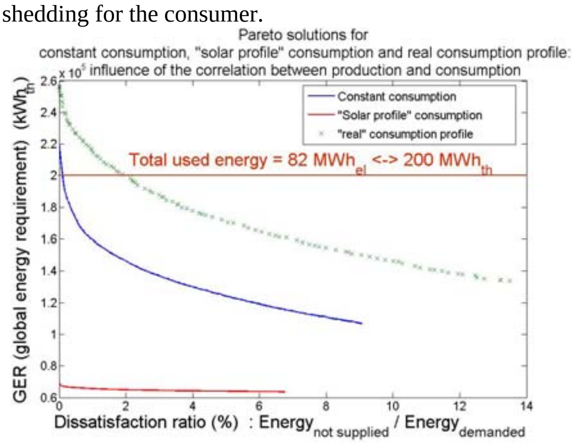

Figure 10: 3 optimization results for 3 consumption profiles: The same total energy is being supplied to the consumer (82 MWh_{th}), yet the curve has been modified.

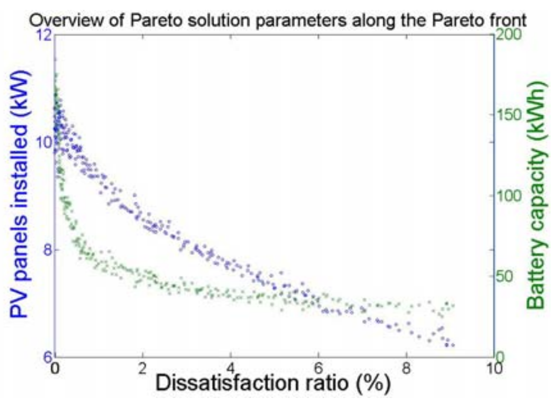

Figure 11: Main Pareto solution parameters (P_{PV} and battery capacity): Distribution along an increasing dissatisfaction ratio, in the constant consumption case

5.2 Influence of energy management parameters

The optimization results presented in Figure 12, as obtained using 0, 1 and 5 optimized energy management parameters, show that the influence of these parameters ultimately proves to be quite small with respect to the final optimization result.

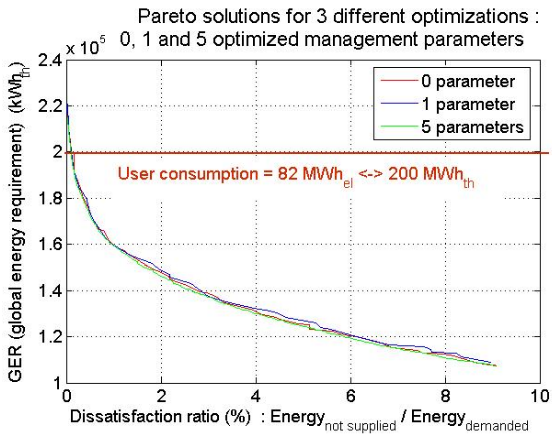

Figure 12: Optimization results for three different types of optimization (constant consumption profile): 0, 1 and 5 management parameters optimized

Their utility principally lies in providing insight when several storage and/or production means are combined (network connection would also be included herein). This feature is primarily due to the fact that battery recharge power is naturally limited by the gassing phenomenon (see Figure 13), which "naturally" clips the recharge power, even if the set point remains very high. Under this configuration therefore, managing just the recharge set point provides for automatic adjustment. The optimization procedure however may identify different solutions in the case where one degree of freedom gets added: network connection, additional storage, etc.

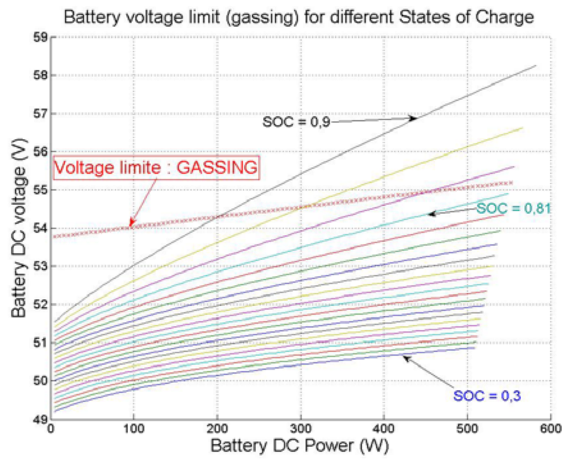

Figure 13: Gassing limit for battery voltage:
Vbat = *Vgassing* if recharging power is too high
(dependent on SOC = [0.3:0.03:0.9])

6. CONCLUSION

For the purpose of optimizing autonomous photovoltaic electricity production systems, we have implemented a multi-objective optimization tool that yields, for any given situation, a set of optimal solutions. Simulations were run over long life cycles (15 years) in order to effectively incorporate cycling aging of the accumulator used.

Moreover, system design was performed by optimizing not just the standard parameters P_{PV} and W_{bat}, but the battery recharge management as well. Three consumption profiles were also analyzed as part of this research effort.

Optimization results, obtained using the evolutionary (NSGA-II) algorithm and displayed in the form of Pareto fronts, have highlighted the following:

- The optimized battery recharge management strategy does not appear extremely relevant within the simplified configuration examined herein (PV production alone on an isolated site), in part due to the forced recharge power limitation as a result of the gassing phenomenon.
- Consumer behavior (given the same level of energy supplied) exerts considerable influence on installation design.

Furthermore, the assignment of optimization objectives has allowed identifying dichotomous objectives that we found pertinent to the problem of improving overall energy efficiency, especially as regards the rate of satisfying consumer energy needs.

It should be pointed out that this article has purposely been confined to optimizing a photovoltaic installation at an isolated site so as to focus attention on the method employed. This "life-cycle" design tool however may be applied to more complex configurations; the utility of these techniques in managing instantaneous energy fluxes may be enhanced for multi-source systems or grid-connected systems.

7. REFERENCES

[1]. Alsema EA. “Environmental life cycle assessment of solar home systems”, Report NWS-E-2000-15, Dept. Science Technology and Society, Utrecht Univ., NL, 2000.

[2]. O. Gergaud, G. Robin, B. Multon, H. Ben Hamed, “Analysis and Experimental Validation of Various Photovoltaic System Models”, 7th International ELECTRIMACS 2002 Congress.

[3]. O. Gergaud, G. Robin, B. Multon, H. Ben Hamed, “Energy modelling of a lead-acid battery within hybrid wind / photovoltaic systems”, European Power Electronics, 2003.

[4]. J.B. Copetti, E. Lorenzo, F. Chenlo, “A general battery model for PV system simulation”, Progress in Photovoltaics: Research and Applications, Vol. 1, pp. 283-292, 1993

[5]. C.J. Rydh, B. A. Sanden, “Energy analysis of batteries in photovoltaic systems. Part II: Energy return factors and overall battery efficiencies”, Energy Conversion and Management 46, Elsevier, 2004.

[6]. K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, “A fast Elitist Multiobjective Genetic Algorithm: NSGA-II“, IEEE Transactions on Evolutionary computation, Vol. 6, April 2002.