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# Demand-Side Management Strategy in Stand-Alone Hybrid Photovoltaic Systems with Real-Time Simulation of Stochastic Electricity Consumption Behavior

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**ABSTRACT**—Demand-side management (DSM) represents a potential way to improve the profitability of renewable energy systems. In this paper, power management including a new DSM strategy in a stand-alone hybrid Photovoltaic (PV)/ Diesel/ Battery system with multiple customers has been studied. A new probabilistic model of the consumer behavior based on Bayesian network and Monte Carlo simulation has been carried out so as to capture the real-time and stochastic aspect of the demand. The analysis has been made by means of a one-year period simulation of the whole system. Statistical data on consumers and meteorological observation data have been used to set the simulation's parameters. Numerical results showed that with the implementation of DSM, energy costs are reduced by 11.3% for equal total consumption, and the use of solar energy resources rose to 54%. This provides insight on the significant performance enhancement offered by a DSM scheme in such a system.

**KEYWORDS**— Stand-Alone Hybrid PV/ Diesel/ Battery System, Power Management, Demand-Side Management (DSM), Energy Cost, Photovoltaic (PV) Penetration, Electricity Consumption Behavior.

## 1. Nomenclature & Abbreviations

$C_{BAT}$	Rated capacity of the batteries	Ah
$C(s)$	Transfer function of the corrector inside the Optimizer	--
$e$	Error between the total consumption and its set point	W
$l_{BAT}^*$	Elementary cost of the lead-acid battery ageing	€/Wh
$l_{Diesel}^*$	Basic cost of diesel	€/liter
$l_{kWh\_Op}$	Operating cost per kWh (energy cost)	€
$l_{Op}$	Total operating cost during the simulation time	€
$N$	Number of CMAs (or subscribers)	--
$P_{Del}^*$	Maximum power subscribed for controllable loads	W
$P_{Diesel}$	Production of the diesel generator	W
$P_{load}^*$	Total maximum power subscribed	W
$\sum_{i=1}^N P_{load}$	Total consumption of all N subscribers	W
$P_{PV}$	PV production	W
$\dot{P}_{PV}$	PV productivity	W
$S_{Conv\_BAT}$	Rated power of the batteries' converter	kVA
$S_{Conv\_PV}$	Rated power of the MPPT DC/AC converter	kVA
$S_{Diesel}$	Rated power of the diesel generator	kVA
$S_{PV\_max}$	Peak photovoltaic generation	kW
$t_{sim}$	Simulation duration	hour
$\Delta t$	Time step	min
$T_{Use_i}$	Period of use of the $i^{\text{th}}$ home appliance	hour
$V_{BAT\_init}$	Batteries' voltage's initial value	V
$V_{BAT\_max}$	Maximum value of the batteries' voltage	V
$V_{BAT\_min}$	Minimum value of the batteries' voltage	V
$V_{Diesel\_on}$	Batteries' voltage at which the diesel generator starts	V
$V_{Diesel\_off}$	Batteries' voltage at which the diesel generator stops	V
$W_{max}^*$	Maximum daily energy consumption subscribed	Wh
CMA	Communication Measurement and Activation Device	
DLC	Direct Load Control	
DSM	Demand-Side Management	

EMS	Energy Management System
LC	Local Controller
MPPT	Maximum Power Point Tracking
PV	Photovoltaic

## 2. Introduction

NOWADAYS, hybrid photovoltaic (PV) stand-alone systems have become an efficient and reliable way to provide electricity for rural regions where the main grid is nonexistent or too distant. However, the problem in designing such a system remains primarily economic in nature. In order for stand-alone hybrid renewable energy systems to offer satisfactory performance and reasonable energy cost, efficient energy management strategies have to be studied right from the design phase [1-5]. In a multi-source configuration, the energy management system (EMS), whose role can be compared to an orchestra conductor, *may include or not a demand response program* in order to help to reinforce:

- the stability of the system’s operations by ensuring a better balance between intermittent renewable energy production and consumption;
- the economic efficiency of the operations by reducing the batteries’ ageing and/ or fossil fuel consumption, knowing that usually these operating cost components make up the biggest share of energy costs.

In [6], the authors advise that a combination of forecasting, efficient EMS, and demand response program should take part in future renewable energy systems in order to achieve greater robustness.

Practically-speaking, in most stand-alone hybrid PV systems that are currently studied and/ or operating all around the world, *demand response programs are not included* [7-14]. For the design and optimization of such systems, the work carried out in the references [7-14] has a very similar approach where, demand is considered to be deterministic (average load profile). The goal of the optimization algorithm then consists of finding the system’s parameters that optimize criteria while entirely ensuring the predetermined load.

However, in recent literature, DSM has been attracting interest among researchers working in the field of stand-alone hybrid renewable energy systems. B. Sivaneasan et al. [15] presented a new demand response algorithm for dynamically managing the building’s air conditioning and mechanical ventilation so as to ensure the best balance between PV production intermittency and demand. Y. Zheng et al. [16] developed a load shifting algorithm based on renewable energy generation and time-of-use tariff, using economic linear programming to minimize the operating cost of a biomass combined heat and power-based microgrid. R. In [17], a priority load control algorithm has been developed in order to gain optimal energy management and guarantee the energy supply for critical loads. X. Wang et al. [18] used the receding horizon optimization strategy implemented with demand response with the aim of minimizing the overall operating and environmental costs of a stand-alone PV/ wind system for single-family residential homes. M. Marzband et al. [19] proposed a stochastic optimization method considering variation in the load consumption model to achieve the best performance in isolated systems.

Some of those DSM strategies aimed at utilizing specific loads having a significant impact on supply-demand balance [15, 16]; others focused on the management of domestic demand which is of interest to our works. To our knowledge, in literature, there are two main approaches of managing domestic loads that are:

- direct load control (DLC) aimed at ensuring priority loads and shedding non-priority load if necessary in order to meet supply [17];
- day-ahead scheduling which is a dynamic pricing mechanism-based method [18, 19].

In our judgment, on the one hand, traditional DLC creates an efficient way to enhance load shaping, but it may compromise the domestic users’ comfort, since the utility remotely controls specific loads on the user side. On the other hand, the pricing mechanism-based method with its high complexity may experience difficulties achieving efficiency [20, 21], but particularly so when *supply is highly uncertain* in the case of stand-alone renewable energy systems. According to X. Wang et al. [18], and O. Elma et al. [18, 22], even though energy management at small-scale stand-alone systems can be far less complicated compared with the management of renewable energy generation applied to a large-scale network, stand-alone system may experience even more potential uncertainties related to electricity generation.

In the context of DSM development in the smart grid, the French Government’s National Research Agency has invested in the SOLEDO project, seeking the *design and implementation of ecological and economically efficient stand-alone hybrid PV systems* for domestic usage. Complementary to the approach taken in the cited studies [7-14], the real-time management of loads is integrated into the design and optimization of the system. Indeed, the temporal demand profile is not considered deterministic, but stochastic with probabilistic and hazardous aspects. Hence, *the EMS contains a real-time DSM strategy* that helps customers to appropriately modulate their consumption in order to better achieve the critical requirement of supply and demand balance. To address the highly uncertain aspect of the supply, and independently from existing works, we have conceived a new DSM strategy, called “load shaping & authorization dispatching”, which can be grasped as an *enhanced and adapted DLC for domestic loads in a multi-subscriber configuration within a stand-alone renewable energy system*. The DSM strategy has been simulated and has proved its benefits with regard to the enhancement of system’s performance.

This paper is organized as following: section 3 presents the new strategy for DSM in a stand-alone hybrid PV system. Section 4 describes a new stochastic domestic consumption model, based on a Bayesian network and Monte-Carlo simulation, in order to capture the real-time and stochastic aspect of demand. Section 5 presents the simulation of the whole system during a one-year cycle. The key contributions of this paper are: firstly, the real-time simulation platform of stand-alone hybrid PV systems including the simulation of the new DSM strategy associated the real-time stochastic electricity consumption behavior model; secondly, the economic and ecological analysis enabling the *evaluation of the benefits of DSM in the enhancement of the system’s performance*. The financial benefits for customers offered by this DSM program will also be discussed. Finally, a parametric study is performed to determine the gain of DSM with varying diesel prices and installed battery capacity. The numeric results will be compared with

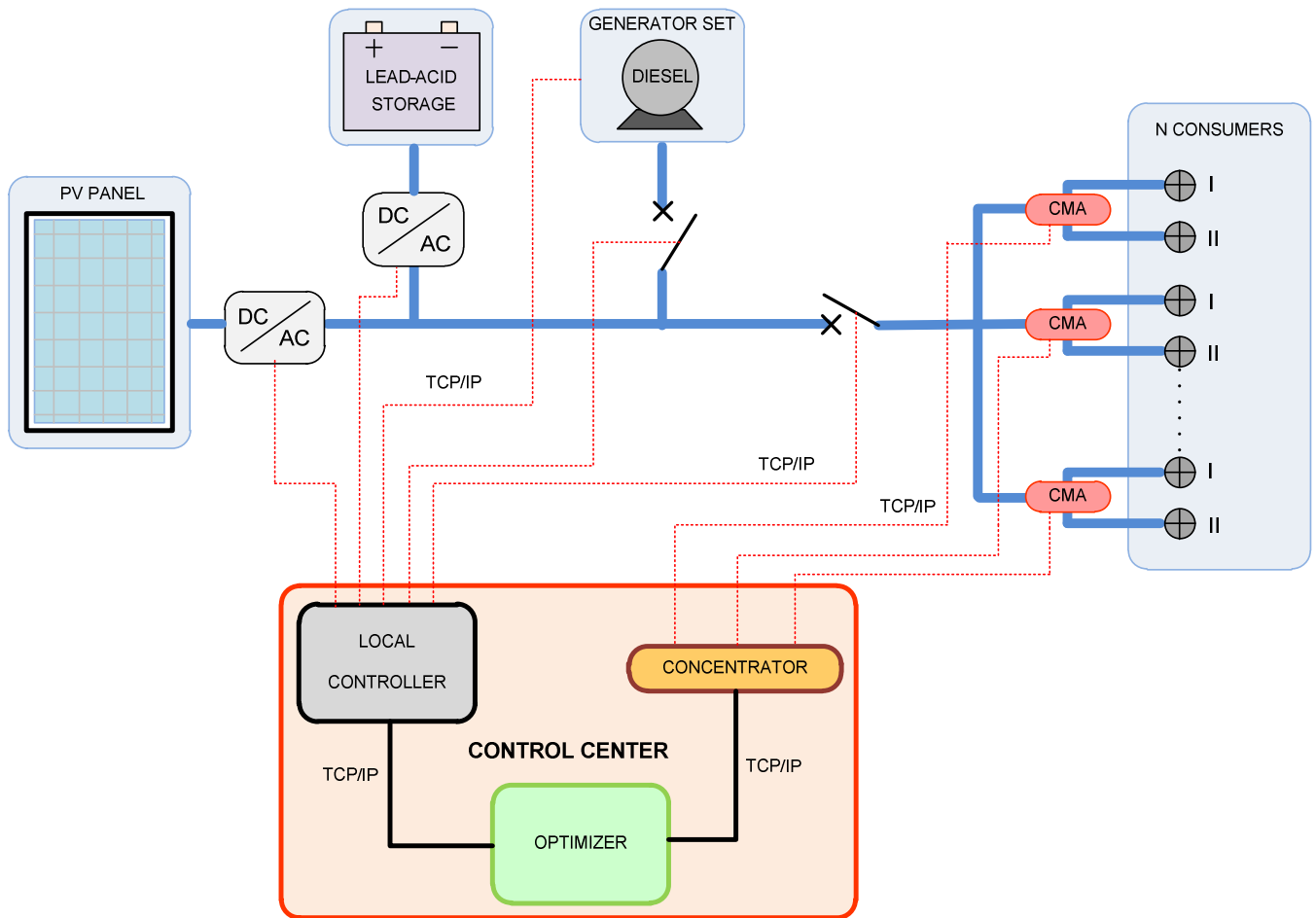


Figure 1: SOLEDO system in an off-grid configuration.

other studies in literature. The last section (section 6) concludes the paper and provides directions for future work.

### 3. Demand-Side Management Strategy in a Stand-ALone Photovoltaic System with Multiple Subscribers

According to Figure 1, the implementation of the DSM strategy mainly relies on two physical devices:

- CMAs (Communication Measurement and Activation) which are located at each consumer's home.
- A 'Optimizer', which is located at the control center.

Like a smart-meter, CMA (developed by Landis & Gyr) enables the interactive communication between customers and the utility. It allows information about customers' real-time consumption to be sent to the utility via a Local Area Network (LAN). It receives the control signal from the control center and executes it. CMA contains not only a tool which measures the consumed power and energy, but also two switches. According to their importance, domestic loads are classified into two categories: priority loads and controllable loads. CMA's switches can be used to shed only the controllable loads (Switch II), or both priority and controllable loads (Switch I) (cf. Figure 2). Figure 2 also illustrates the composition of CMA. The three CMA's parameters, corresponding to the subscribed thresholds by each user, are listed in Table 1. CMA has five different control modes:

- *Mode 0*: normal operation mode where the requested power is equal to the supplied power.
- *Mode 1*: if the total power needed by the user is greater than  $P_{Del}^*$ , then Switch II is open for 30 minutes.
- *Mode 2*: an external order (from the Optimizer) can force Switch II to be closed or opened.
- *Mode 3*: if the total power needed by the user is greater than  $P_{load}^*$ , then Switch I is open for 10 minutes.
- *Mode 4*: if the daily energy is greater than  $W_{max}^*$ , Switch I is open. It is programmed to be reset at 6 AM the next day.

Note that the CMA's action following *Mode 1*, *3* and *4* provide the means to prevent excessive overconsumption and undesirable peak loads.

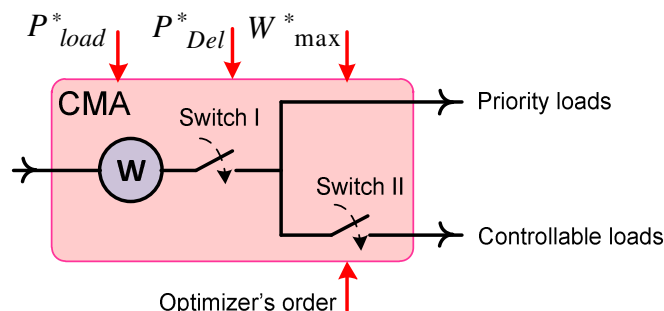


Figure 2: CMA: Electrical load management device on the customer's side

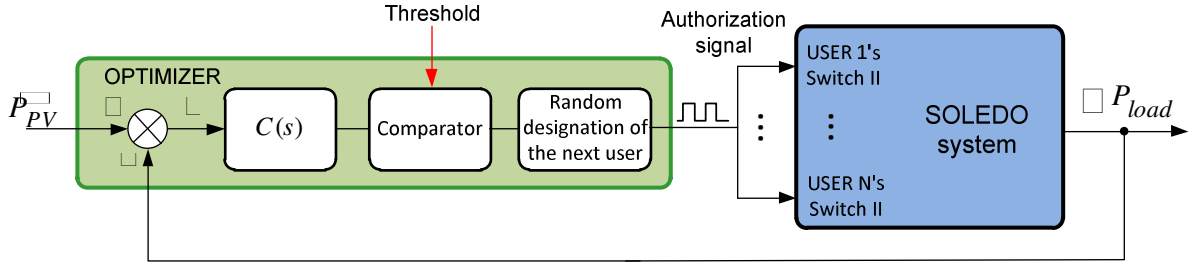


Figure 3: Graphic representation of the SOLEDO system in a closed-loop

Among the control center's components, the Optimizer is intended for the DSM, where the "load shaping & authorization dispatching" algorithm is implemented. The critical role of the Optimizer is to authorize users to consume their controllable loads at different appropriate times. For this, the component acts on Switch II of every CMA. Real-time power and energy consumption data of all customers is centralized in the 'Concentrator' (Figure 2) which communicates with the Optimizer. The Optimizer also collects every system's real-time data from the Local Controller, which is responsible for the supply-side management, also located at the control center (Figure 2).

In the framework of stand-alone PV systems, the desired total load is ideally the profile of the PV productivity. PV productivity (i.e. the maximum electrical power that PV panels can produce by considering meteorological conditions) is to be differentiated from the PV production (i.e. the power that actually flows out of the MPPT (Maximum Power Point Tracking) DC/AC converter taking into account eventual shedding of the PV production). Indeed, consuming during the high PV productivity period requires neither the batteries nor the diesel generator, the associated operating costs would then be minimized. This step aims at defining the desired aggregate load profile, and constitutes the "load shaping" phase of the strategy.

This DSM approach can be regarded as a centralized control with a feedback loop which tries to minimize the real-time error between total consumption and its set point (Figure 3). The Optimizer records this dynamic error and uses it to decide if the system's permission should be allowed. A corrector is implemented in order to generate an appropriate control signal from the dynamic error. At each time step, decision-making is based on a comparison performed between the value of the control signal and a fixed threshold, meaning:

$$\begin{cases} \text{if } C(s).e < \text{Threshold} & \text{No permission is granted} \\ \text{if } C(s).e \geq \text{Threshold} & \text{System's permission is granted} \end{cases}$$

$$\text{Where: } e = \dot{P}_{PV} - \dot{P}_{load} \quad (1)$$

In the case where the system's permission is allowed, in order to designate the next user to whom the system grants authorization in the next time step (10 min), a random selection with equitable opportunities is performed among customers who do not currently have permission. This selection process is carried out at each time step until all customers have authorization. This step consists of the "authorization dispatching" phase of the strategy.

In a multi-subscriber configuration, the authorization to use controllable loads is being granted only to one new user at each time step. From the moment when the system's permission is given, the customer is authorized to consume for 3 hours (this duration is fixed in this case study, otherwise it should be an optimization parameter in future work). During these 3 hours, when the load is started, it's up to the consumer; hence several controllable loads can be started at the same time. A timer associated with the CMA is provided to display to the user the remaining authorized time. At the end of this time frame, Switch II is open, and all controllable loads will be shed. The customer has to wait for another authorization from the Optimizer that they may use their controllable appliances again. Obviously, there are no constraints on the total number of users that are being authorized at each time step.

Note that the system's permission is granted only according to the difference between the PV productivity and the aggregate load. Indeed, even though real-time consumption data of every user is gathered to the control center, only the aggregate consumption data is necessary to dispatch the authorization to a specific user, i.e. a common meter for all subscribers should be sufficient for the operation of this DSM scheme. Nonetheless, the SOLEDO system is designed with two-way communication between customers and the utility so that we would be able in the future to extend the DSM strategy to a more sophisticated scheme. Besides, all loads that have been defined as priority will not be submitted to the Optimizer's action.

The proposed demand-side management in this stand-alone PV system can be identified as a rule-based method, rather like DLC. However, compared to traditional DLC strategy, the control center in this framework doesn't directly control specific non-priority home appliances in the domestic area, but only the total users' consumption. Hence, we expect that consumers in this DSM scenario should have a *more important flexibility to schedule their loads compared to traditional DLC*. Otherwise, the Optimizer's *control action*, which does not exist in the dynamic pricing mechanism, should allow a more efficient "load shaping".

However, the following questions may arise: 1) how does this DSM scheme effectively help to enhance the economic and ecological features of the PV system? 2) does this strategy drastically deteriorate the customers' accustomed behavior and comfort?

These questions will be answered, in the next sections. Before, we will present the simulation of the whole system. In the system approach, like other system's components' model (supplies, batteries, etc.), the consumption model must interact with the other components' model (i.e. Optimizer, CMAs). This requirement leads us to focus on studying an original dynamical model of the domestic electricity consumption.

#### 4. Real-Time Modeling of the Domestic Electricity Consumption Behavior

Electricity consumption modeling is a familiar research area in power networks nowadays. At all hierarchical levels of the power grid, load modeling provides the means to forecast future consumption, therefore helping utility companies to make decisions on the grid's operation, planning and infrastructure development [23].

In our study, however, the purpose of the load modeling is not to forecast future consumption, but to simulate the action of the DSM strategy on consumption patterns so that its potential benefits may be evaluated. As mentioned before, we need to build an appropriate electricity consumption model according to the so-called system approach. Indeed, the load's model must integrate the Optimizer's control signal as an input in such a way that if an authorization is granted, electricity consumption obeys the consumer's behavior, otherwise, all loads are shed, i.e. consumption is strictly zero. We assume along this study that consumer behavior and the system's permission are two independent events. Besides, in our framework, the consumption of each user is separately altered by the Optimizer's control order which has a binary characteristic (Section 3). Consequently, we need to build a load model with a bottom-up approach so that the consumption behavior at each single household's level can be taken into account.

To build our model, we selected a probabilistic method that relies on a Bayesian network [24]. This network is intended to determine the start time of a home appliance; this step involves a graphic representation of the causal links between different events leading to the electrical load's starting. Moreover, a Bernoulli trial has allowed the random aspect of the consumer's behavior to be taken into account.

##### 4.1. Probabilistic aspect

This part of the paper focuses on assessing the probability of starting a home appliance. In reality, this event depends on a multitude of factors, such as the consumer's presence at home, the consumer's need relative to a specific load, etc. This need also depends on several parameters (e.g. the current state of the load either running or switched off, the user's habits, household size, weather conditions, the day of the week, seasons and so on). In order to facilitate the assessment of the electrical load's starting probability, the number of causal parameters has been reduced; however, the Bayesian graphic representation facilitates increasing the model complexity.

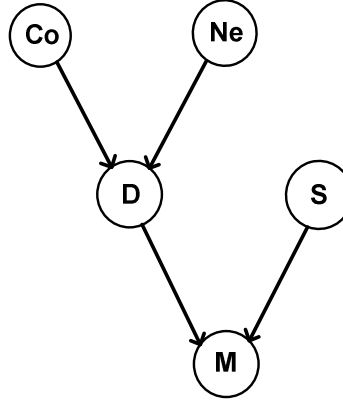


Figure 4: Bayesian network representing the causal links between events leading to the starting of a specific home appliance

The Bayesian network lays out the causal links between events. The nodes represent random variables symbolizing events, while the links reflect causal relationships between events. In Figure 4, the event "M" is the effective start of the load. According to Figure 4, this event depends directly on two other events, namely:

- Event "D": the consumer's decision to switch on the load.
- Event "S": authorization granted by the system to switch on the load.

Hence, within the SOLEDO system, the start of a load is subjected not only to the consumer's decision but also to the ability of the system to supply this load. The system may refuse to switch on a load for three following reasons:

- Refusal from the Local Controller when there is a lack of energy (batteries and diesel generator set tanks are both empty),
- Refusal from CMA when the user's consumption has exceeded one or more parameters' threshold,
- Refusal from the Optimizer, in order to minimize the system's operating costs.

As assumed above, the independence between the consumers' behavior and the system's permission is thus translated by the decoupling between the probability of event "D" and event "S". The probability of event "M" can be calculated by using the following equation:

$$p(M, D, S) = p(M | D, S) \cdot p(S) \cdot p(D) \quad (2)$$

where  $p(M | D, S)$  symbolizes the probability that event "M" happens knowing that event "D" and event "S" take place.

Furthermore, the event "D" also depends on two other independent events, namely:

- Event "Co": consumer's presence at home,
- Event "Ne": consumer's need with respect to the load.

The lack of home automation in our system does become a major assumption in this model: the consumer's presence is essential to start an electrical load. Consequently, the probability of the event "M" can be assessed as in (3). Each part of this equation will be determined so as to establish the probability of starting a load.

$$p(M, Co, Ne, S) = p(M | S, D) \cdot p(S) \cdot p(D | Co, Ne) \cdot p(Co) \cdot p(Ne) \quad (3)$$

#### 4.1.1. Probability of the consumer's presence $p(Co)$

A survey was conducted permitting the collection of statistical data on the consumer's presence at home in the considered location. The campaign consisted of different consumer profiles. In a survey form, 24 columns represent 24 hours of a day and each line represents a day where ordinary days, weekend days and holidays are distinguished. For each day category, several sample-days were registered during a year. In case of missing days, existing data was adequately replicated so as to obtain 365 days. Participants in our campaign were encouraged to take a minute every day in order to fill in each line with 1 if they were at home; and with 0 if not at home at each hour of the day. From this data, we defined an average day where the probability of the consumer's presence at home  $t = H$  with  $H \in \{0, \dots, 23\}$  as the mean value of every value in the  $H^{th}$  column.

According to different obtained average days, we can distinguish three types of occupancy behavior depending on the observable peaks: 1) high day and evening, 2) double peak, and 3) day focus. In general, consumers are most likely present at home during meal times: 1) in the morning (everybody gets up, this is breakfast time before going to work or to school); 2) in the evening (family members gather after work for dinners and other family activities), 3) at noon (time for a break and for lunch). Given these observations, we propose the following model for the consumer's presence probability during an average day as a sum of three Gaussian functions:

$$p(Co) = \sum_{k=1}^3 A_k \cdot \exp\left[-\frac{1}{2} \left(\frac{t - t_k}{s_k}\right)^2\right] \quad (4)$$

- $A_k$  : amplitude of the  $k^{th}$  Gaussian function,
- $t_k$  : time at the maximum of the  $k^{th}$  Gaussian function,
- $s_k$  : standard deviation of the  $k^{th}$  Gaussian function.

This model has the advantage of being easily fitted to different occupancy behaviors by adjusting  $A_k, t_k, s_k$ .

Figure 5 shows the model for the "high day & evening" behavior presenting three peaks. Various parameters linked to the different occupancy behaviors are given in Table 1.

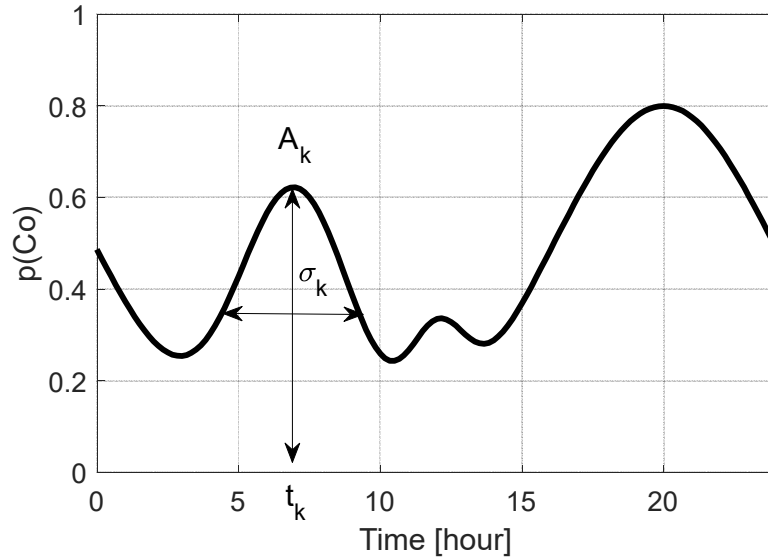


Figure 5: Probability of the consumer presence according to the "high day & evening" occupancy behavior during the average day over the observed year

#### 4.1.2. Probability of the consumer's need $p(Ne)$

This probability represents the consumer's need to start a specific home appliance. This event is supposed to be independent from the consumer's presence. Even though consumer's need may vary depending on many factors, our model will only take into account its usual and repetitive aspect.

Let's consider hereafter the different load states. The probability of the consumer's need to start a load should depend on its current state. Four states have been defined:

1. *State 0 - Wait before starting:* The consumer's need relative to this load will linearly increase during this time until the effective load's start. The evolution of this probability is depicted in Figure 6, where:

- $t_{ini}$  : the initial point in time when State 0 occurs
- $T_{Use_j}$  : the period of use of the  $i^{th}$  home appliance. This period is equal to the average time between the two successive starts of the load. This is also a statistical data, given in Table 1.

The probability linked to the consumer's need increases from its initial value 0 to 1 during the period of use of the load.

2. *State 1 - The load is operating:* While the load is running, the probability of need equals zero.

3. *State 2 - The load has been shed:* When the load has been shed, the need to restart this load is at its maximum, in which case the probability is equal to 1.

4. *State 3 - The load cycle is complete:* When the period of use is over, the probability is again equal to zero until reaching State 0.

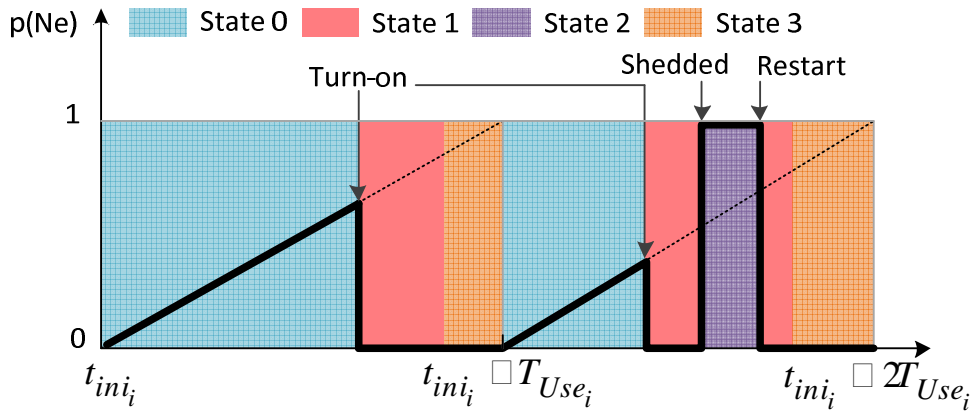


Figure 6: Probability of the consumer's need relatively to different states of a load

#### 4.1.3. Conditional probability of $p(D|Co, Ne)$

This term means the conditional probability of the consumer's decision to start a specific home appliance knowing that he is present at home and he needs to use this load. For simplicity's sake, we suppose that there is a monotonically increasing function between the users' decision and their need: the more important the need, the more probability that the decision takes place. The same reasoning is adopted for the relationship between customers' decisions and their presence. We adopted a multivariate normal distribution which is tractable for the simulation purpose (Figure 7).

$$p(D|Co, Ne) = \frac{\exp\left\{-\frac{1}{2}(P - m)^T \hat{a}^{-1} (P - m)\right\}}{2\pi \sqrt{|\hat{a}|}} \quad (5)$$

- $P = \begin{pmatrix} p(Co) \\ p(Ne) \end{pmatrix}$
- $m$ : mean vector
- $\hat{a}$ : covariance matrix

The mean vector and the variance matrix are defined so as to have:

$$\begin{cases} p(D|Co, Ne) = 1 & \text{while } p(Co) = p(Ne) = 1 \\ p(D|Co, Ne) = 0 & \text{while } p(Co) = p(Ne) = 0 \end{cases} \quad (6)$$

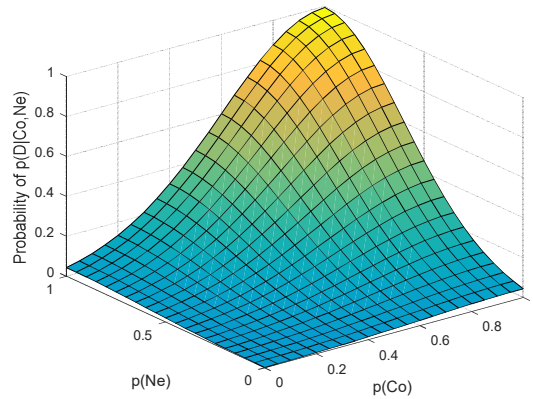


Figure 7: Probability of the consumer's decision to start a specific home appliance

#### 4.1.4. Probability of $p(M|S, D), p(S)$

The term  $p(M|S, D)$  represents the conditional probability that a specific home appliance will be triggered knowing that the user has decided to use it and the system permission has been given, while  $p(S)$  means the probability that the system gives permission at each time step. Since the variable representing the system's permission can only have binary values 0 or 1. At each time step, this probability can be determined as following:

$$\begin{cases} \text{if } S = 0 \text{ } p(S) = 0 \text{ } p(M|D, S), p(S) = 0 \\ \text{if } S = 1 \text{ } p(S) = 1 \text{ } p(M|D, S), p(S) = 1 \end{cases} \quad (7)$$

In (7), in the case where the system's permission is given, we supposed that  $p(M|D, S) = 1$  ( $= p(D)$ ), meaning that a home appliance will certainly be started, knowing that the user has decided to use it while the system's authorization has been given. This assumption is made for the sake of the model's simplicity: it ignores for example the condition of the apparatus (whether healthy or broken).



#### 4.2. Hazardous aspect

The effective start of each home appliance depends on a Bernoulli trial conducted on the probability  $p(M, Co, Ne, S)$ . At each time step and for each load, a random variable  $c$  generated by following a uniform distribution will determine the starting of the load:

1.  $c \leq p(M, Co, Ne, S)$  The load starts
2.  $c > p(M, Co, Ne, S)$  The load does not start

Ultimately, the higher the probability, the greater the chance that the load will be started. In this way, the unusual and hazardous aspect of the consumer's behavior is henceforth simulated. This implementation constitutes the Monte-Carlo simulation using the acceptance-rejection method.

Based on pre-defined simplifying assumptions and experimental data of consumer behavior, we obtained the stochastic electricity consumption model compatible with the DSM approach. We are now ready to carry out the simulation of the whole stand-alone PV system.

### 5. Analysis of the Benefits of Demand-Side Management In a Stand-Alone Hybrid Photovoltaic System

#### 5.1. Simulation platform of the SOLEDO system

The main assumptions adopted for the simulation are:

- Only the active power flux is considered.
- The ohmic losses in transmission lines are neglected.
- Consumers are not equipped with distributed generators and storage.
- Consumers are supplied with an AC 230V 50 Hz grid.

However, power electronic converters losses, battery efficiency and ageing, and diesel generator efficiency are all taken into account [25, 26]. In this study, the two main performance criteria are targeted: the system operating cost per kWh (also called energy cost) and the PV penetration, respectively corresponding to the economic and ecological criteria.

Firstly, the energy cost is a major indicator of the economic effectiveness of a hybrid PV system. It is defined as the ratio between total operating cost and total consumption. In this study, the operating cost has two main components: diesel consumption and battery ageing. For the sake of brevity, the detailed computation of the total operating cost is already specified in our earlier work [26].

$$l_{kWh\_Op} = A \frac{l_{Op}}{t_{sim} \cdot N} \int_0^1 P_{load}(t) dt \quad (8)$$

Secondly, the PV penetration is defined as the ratio between PV production and total productivity. This indicator represents the effectiveness in which solar resources can be exploited by the system:

$$PV \text{ penetration} = A \frac{\int_0^{t_{sim}} P_{PV} dt}{\int_0^{t_{sim}} (P_{PV} + P_{Diesel}) dt} \quad (9)$$

Unlike most existing work where the day-by-day energy cost is computed based on the system's daily operating cost, herein, we study the SOLEDO system's long-term operation by means of a one-year period simulation. In our case, the solar energy resource cyclically varies for a period of one year. Otherwise, in this simulation the time granularity is 10 minutes.

The simulation includes the model of PV panels, MPPT DC/AC converters, lead-acid batteries, AC/DC reversible converter associated with the batteries and diesel generator. These models have already been developed and described in our earlier work [25-27]. Every system's true scale parameters are given in Table 1. For the calculation of the PV production, real data on temperature and sunlight recorded every 10 min for one year at the considered location are provided by Météo France [28]. Then, the total PV panel's surface area is calculated so as to provide on average 18 kWh/ user/ day, which reflects a standard comfort level. The rated capacity of the batteries is sized so as to be able to supply all users for 48hr in case of total generation loss, equivalent to 1800Ah (Table 1). The rated power of the diesel generator is dimensioned to be able to supply the highest peak load while there is no PV production and all battery banks are empty.

The simulation also includes the control system whose key component is the Local Controller (LC). This component helps to dispatch available energy sources in order to meet demand, i.e. the supply-side management. It monitors every real-time measurement of the system and makes decisions based on the current batteries' voltage. The LC's operation can be described as follows. In case of PV underproduction, the power coming from the batteries will be dispatched in priority until their voltage drops below  $V_{Diesel\_on}$  (Table 1). Then the LC sends a control signal to start the diesel generator. In the extreme case where there isn't any PV production, the battery bank and diesel generator set tanks are both empty, all loads would be shed. Otherwise, in case of PV overproduction, the LC manages the batteries' charging until their voltage reaches  $V_{Diesel\_off}$  (Table 1), then eventual operating diesel generators will be stopped. And if their voltage continues to increase until it exceeds  $V_{BAT\_max}$ , then the LC will control gradually shedding of the PV production. The LC directly controls the PV production (via the MPPT DC/AC converter), the charge/ discharge cycle of the batteries (via the AC/DC reversible converter), and the start/ stop sequence of the diesel generator (Figure 8) [26].

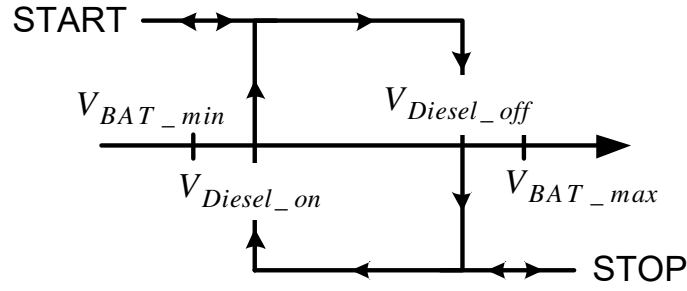


Figure 8: Hysteresis cycle describing the operations of the diesel generator by the Local Controller.

The “load shaping & authorization dispatching” algorithm is implemented inside the Optimizer of the control system as mentioned in Section 3. For the time being, this DSM study is exploratory. And due to the high complexity of the hybrid PV system, concerning the synthesis of the corrector inside this component (Figure 3), a proportional corrector has been chosen:

$$C(s) = K_p \quad (10)$$

Table 1  
SOLEDO System Parameters

SIMULATION PARAMETERS		PARAMETERS OF THE GAUSSIAN FUNCTIONS DESCRIBING p(Co)			
$t_{sim}$	365 days	<b>Mode</b>	$t_k$	$A_k$	$s_k$
$Dt$	10 min	<i>High day &amp; evening (9 subscribers)</i>			
CMA'S PARAMETERS IN EACH CONSUMER'S HOME		1	07:00 AM	0.6	2h
		2	12:00 AM	0.2	1h
		3	08:00 PM	0.8	4h
$P_{load}^*$	20000 W	<i>Double Peak (9 subscribers)</i>			
$P_{Del}^*$	15000 W	1	07:00 AM	0.6	2h
$W_{max}^*$	30000 Wh	2	08:00 PM	0.8	4h
SOLEDO SYSTEM'S COMPONENTS PARAMETERS		<i>Day focus (2 subscribers)</i>			
$N$	20	1	07:00 AM	0.6	2h
$S_{PV\_max}$	80 kW	2	12:00 AM	0.6	2h
$PV\ panels' \ surface$	650 m <sup>2</sup>	3	08:00 PM	0.8	2h
$S_{Conv\_PV}$	80 kVA	<b>CONTROLLABLE LOADS</b>			
$C_{BAT}$	<b>1800 Ah</b>	<b>Type</b>	<b>Power</b>	<b>During</b>	$T_{Use}$
$S_{Conv\_BAT}$	80 kVA	Washing machine	1200 W	2h	Random $\hat{I}$ [48; 96 ]h
$V_{BAT\_max}$	460 V	Dishwasher	1050 W	2h	Random $\hat{I}$ [24; 48 ]h
$V_{BAT\_min}$	340 V	Iron	2000 W	30min	Random $\hat{I}$ [48; 96 ]h
$V_{Diesel\_on}$	390 V	Vacuum cleaner	1000 W	30min	Random $\hat{I}$ [24; 48 ]h
$V_{Diesel\_off}$	430 V	Water pump	1000 W	2h	Random $\hat{I}$ [48; 96 ]h
$V_{BAT\_init}$	400 V	Tumble dryer	1800 W	2h	Random $\hat{I}$ [48; 96 ]h
$S_{Diesel}$	80 kVA	Kettle	2000 W	10min	Random $\hat{I}$ [24; 48 ]h
ECONOMIC PARAMETERS		Toaster	850 W	10min	Random $\hat{I}$ [24; 48 ]h
$l_{BAT}^*$	0.4 €/Wh	Kitchen hood	250 W	1h	Random $\hat{I}$ [24; 48 ]h
$l_{Diesel}^*$	<b>1.5 €/liter</b>	Additional heating	2000 W	30min	Random $\hat{I}$ [12; 24 ]h
		Hair dryer	1000 W	10min	Random $\hat{I}$ [12; 24 ]h
		Electric plates	10000 W	30min	Random $\hat{I}$ [12; 24 ]h
		Oven	2500 W	30min	Random $\hat{I}$ [24; 48 ]h
		Microwave	1500 W	10min	Random $\hat{I}$ [12; 24 ]h
		Coffee maker	1000 W	10min	Random $\hat{I}$ [24; 48 ]h
		Food mixer	150 W	10min	Random $\hat{I}$ [24; 48 ]h

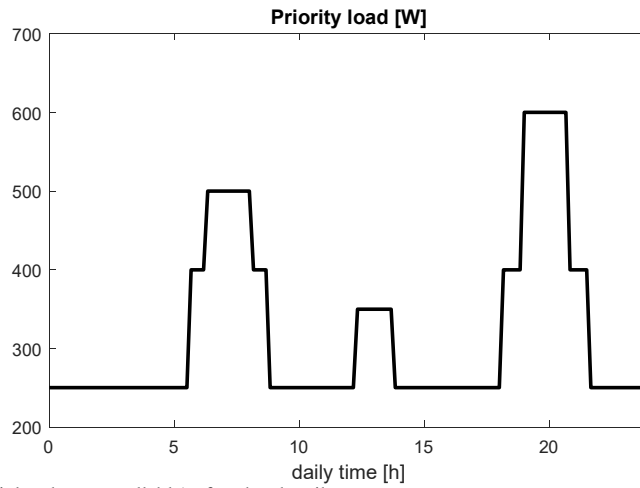


Figure 9: Daily priority load profile (essential and uncontrollable) of each subscriber.

Finally, this case study relies on 20 subscribers. Each subscriber has a part of priority loads and 16 typical controllable loads. Priority loads are uncontrollable loads such as refrigerators, electronic devices on standby mode and lights, while controllable loads are listed in Table 1. The priority load profile is defined as a deterministic curve in Figure 9, while the use of controllable loads is determined by using the probabilistic model described in Section 4. According to this definition, the priority electrical consumption equals 7.7 kWh/ user/ day. The usage patterns of typical home appliances are provided by measurements, given also in Table 1.

## 5.2. Results & discussions

### 5.2.1. Effects of DSM on the stand-alone hybrid PV system's performance

To illustrate the operation of the proposed DSM on the consumption and on the system's operation (PV production, batteries, diesel generators), a comparison between two scenarios, *with and without the Optimizer*, has been made. The key condition for this comparison is that the total consumption in two scenarios must be equal (Table 2), which approximately represents the same service rendered to consumers. Figure 10 (a) and (b) shows the system's variables depending on time, while Table 2 sums up the principal performance features for both cases. Without loss of generality, in the case of the Optimizer, the proportional corrector has been set to  $K_p = 0.1$ .

According to Figure 10 and Table 2, some remarks can be made:

- *The efficiency of "load shifting"*: much of the load during PV production's off-peak hours was moved to high PV production hours. Indeed, in Figure 10 (b) and compared to Figure 10 (a), we observe a creation of consumption peaks at midday. High consumption periods are more in correlation with the PV production time; and there are fewer loads at night.
- *The enhancement of the solar resource usage*: as the consumption is more coincident with the PV generation, the shedding conducted on the PV production is reduced in Figure 10 (b), compared to Figure 10 (a). Hence, we can make more use of the available solar energy and less waste with DSM. In a stand-alone hybrid system, PV penetration of 50% is considered to be very high [29].
- *The enhancement of the system's economic and ecological performance*: the total operating cost for one year has been reduced by 11.1% which offers consumers a reduced energy cost of 11.3%. PV penetration is enhanced by +17.4%, for the same service rendered to consumers (18.5 kWh/ user/ day). CO<sub>2</sub> emissions are reduced by 14,4% (from 27,6 tons/ year to 23,6 tons/ year).

### 5.2.2. Discussions on the consumer comfort

By participating in the DSM program, it could provide economic interest for customers: they may benefit from reduced energy costs of 11.3 % for an unchanged total daily consumption (18.5 kWh/day).

But in return it is clear that they will have to progressively change their consumption habits. Nevertheless, we think that there still should be a necessary flexibility for customers to consume while participating in this DSM program. Let's look deeply into the consumption of one subscriber among 20 others. Simulation results in Figure 10 (c) give us an illustration of the system's authorization sequence distributed to a specific user and his load patterns. Without loss of generality, user N°1 is highlighted. There is an average of 3 permissions per day. Hence, users can freely schedule and consume their different controllable loads up to 9 hours each day. Therefore, this DSM strategy may probably provide some flexibility for consumers.

Another aspect of the flexibility offered by this DSM scheme is that its use does not consist of totally upsetting customers' habits. According to simulation results in Figure 10 (a), a part of the consumption is naturally beneficial for the system, i.e. the consumption under the PV production curve. Therefore, the proposed DSM strategy does not consist of completely changing consumer behavior, but instead, encourages people to move some, though not all, of their loads from low PV production hours to high PV production hours. And according to the statistical information on the actual consumer's behavior presented in Section 4, the probability of the user's decision to consume during authorization time intervals has non-zero values, meaning that people may have the ability to consume during "appropriate time". Remember that this DSM algorithm only concerns the use of controllable loads, and that priority loads defined by users (which constitutes 41.6% of the total load in this case study) are not subjected to the DSM action. Therefore, consumers will not have to sharply change their habits in order to consume 'better'.

Due to all the above advantages, we can conclude that "load shaping & authorization dispatching" DSM strategy could be beneficial for both utility and consumers of the stand-alone hybrid PV system.

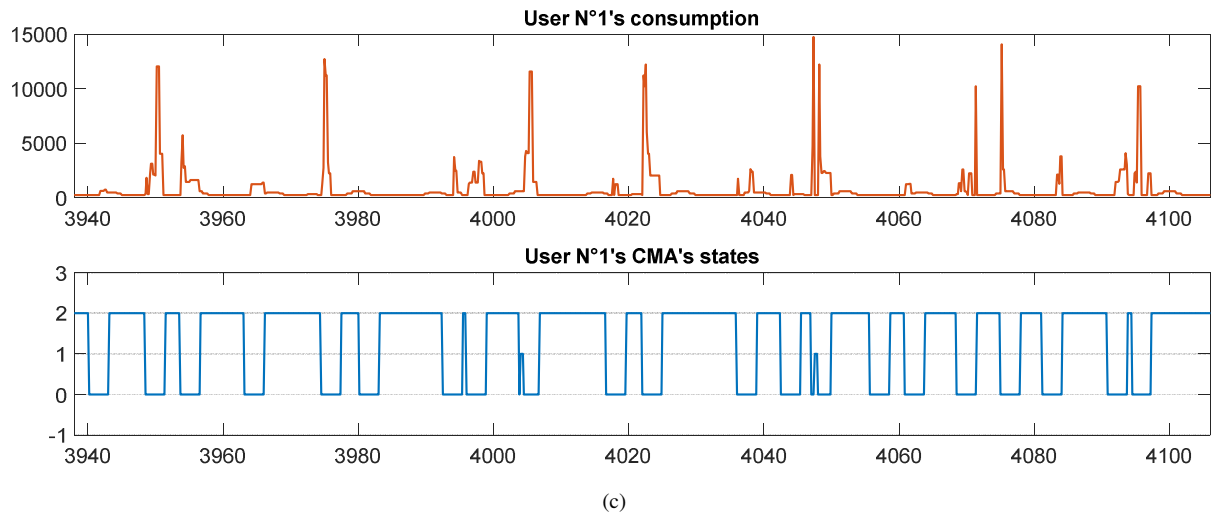
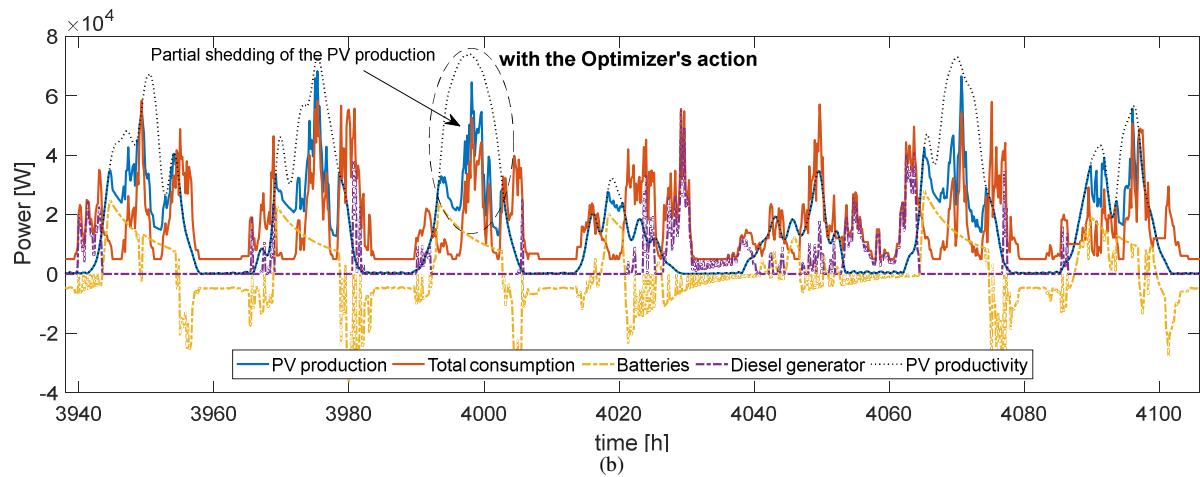
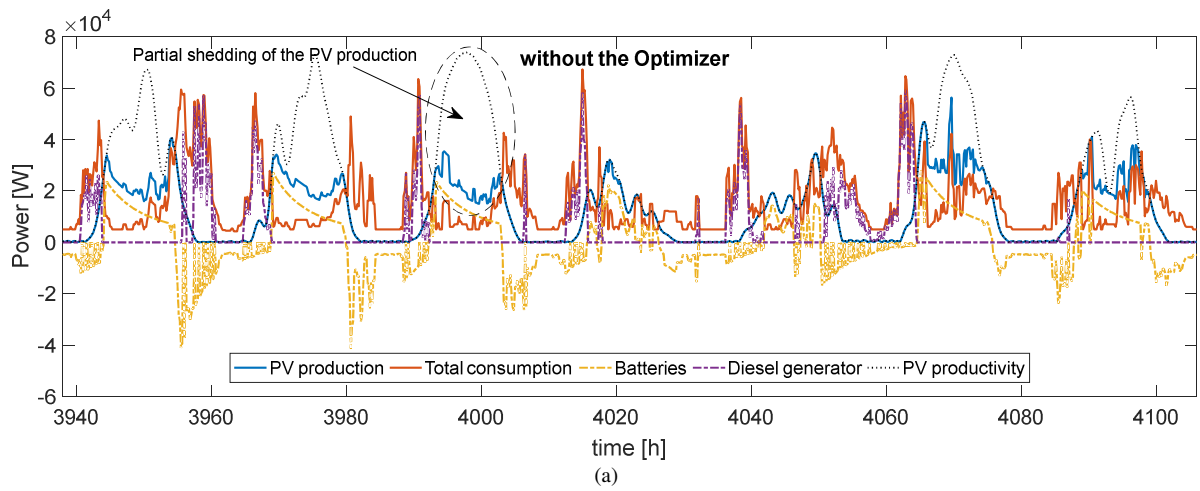


Figure 10: Load profile and system's operation without DSM (a) and with DSM (b); Consumption and authorization signal linked to the user N°1 (c).

**Table 2**  
Comparison Of Some Principal Performance Features Between Two Scenario: With & Without DSM

Variables	Without the Optimizer	With Optimizer's action
Total consumed energy by all subscribers per year [kWh]	134951	134701
Consumption per user per day [kWh]	18.5	18.5
Operating cost per kWh (energy cost) [€ cents/kWh]	17.7	15.7
Total operating cost [€], where:	23899	21256
– Operating cost due to the battery ageing [€]	5857	5814
– Operating cost due to the diesel consumption [€]	18041	15441
CO <sub>2</sub> emissions per year [kg]	27663	23676
PV penetration	45%	54%

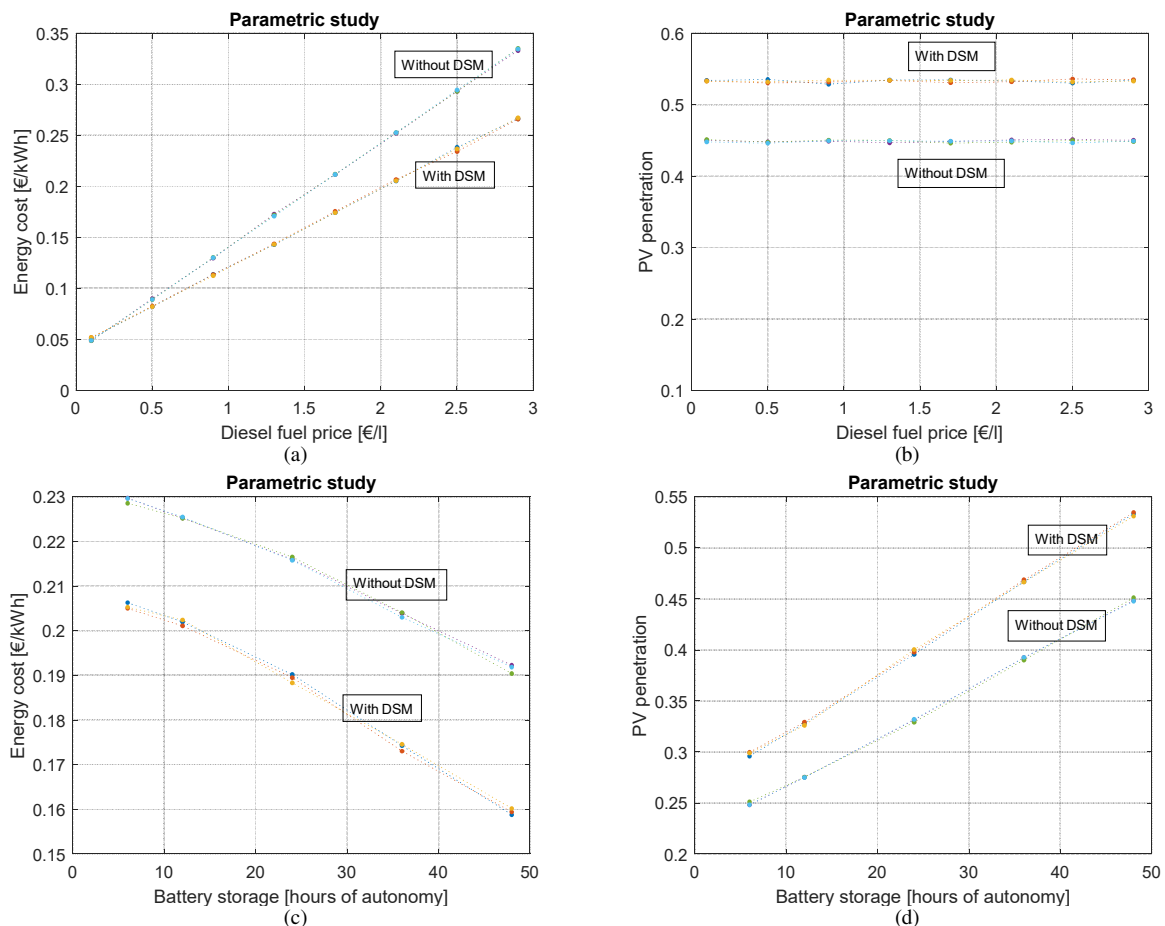
### 5.2.3. Parametric study on the effects of DSM on a stand-alone hybrid PV system's performance and comparison with published data

In section 5.2.1, the simulation results of the whole system show that the DSM strategy may reinforce the system's economic and ecological performance. In this section, a parametric study will complete this result. Energy cost and PV penetration are criteria that depend highly on diesel costs, battery storage capacity, insolation and demand. In this part of the paper, we suppose that the PV's peak power and the number of subscribers at the demand-side are fixed. We will proceed with the variation of diesel costs and with total installed battery capacity so as to analyze how those factors can influence the system's performance in two cases: *with and without the demand-side management strategy*.

Although the diesel cost is very different from one country to another, the general trend is that the price of fossil fuel will keep rising. First of all, we propose to vary diesel costs from €0.1/liter to €2.9/liter. Since the consumption behavior model is stochastic, the simulation was run 3 times for each parameter set. In Figure 11 (a), the dependence of energy cost on diesel prices is plotted. Energy cost increases proportionally with diesel costs, however, the rate of increase is reduced by the application of the DSM strategy (€0.08/kWh per €/liter) compared to "without DSM scenario" (€0.11/kWh per €/liter). Therefore, the DSM strategy in stand-alone hybrid PV systems can help lower the rate of energy cost increase as the diesel prices increase. Besides, Figure 11 (b) shows that PV penetration is rather independent from the price of diesel. With DSM, PV penetration is enhanced from 45% to 54%.

Second of all, we propose to vary the installed battery capacity from 225 Ah to 1800 Ah (equivalent to an autonomy of 6hr to 48hr with regard to the average consumption of 18 kWh/ user/ day). Let us note that in this study, energy cost is computed by taking into account only the operating cost (diesel consumption and battery ageing). Hence, the investment cost linked to the installation of PV panels, batteries, converters, diesel generators, and other system components is not taken into account in the energy cost. Figure 11 (c) shows that energy cost (€/kWh) decreases as the battery storage capacity increases; indeed, the rate of energy cost decrease is slightly higher with DSM (-€0.0034/kWh for additional 100Ah) than without DSM scenarios (-€0.0026/kWh for additional 100Ah). In Figure 11 (d), the PV penetration can be strongly enhanced with greater battery storage capacity. Nevertheless, the rate of PV penetration increase is higher (+1.48 % for additional 100Ah) with DSM than without DSM (+1.24 % for additional 100Ah).

In any case (except in case of very low diesel costs), the application of DSM strategy significantly helps to reduce the energy cost and increase the PV penetration of a stand-alone hybrid PV system.



**Figure 11:** Results of the parametric study. (a) and (b): Evolution of energy price and PV penetration with the varying diesel prices; (c) (d): Evolution of these two criteria with the varying installed battery storage capacity.

The performances of SOLEDO system versus systems all around the world are summed up in the following table, showing the realistic aspect of the simulation results, noting that most systems in literature don't include any DSM strategies. However, this table is not made for the purpose of comparing systems (a real comparison is difficult to obtain because of the difference in adopted assumptions and criteria computational methods), but of situating the obtained results.

**Table 3**  
Stand-alone hybrid PV systems' performance: some examples from the literature

System	PV peak power	Diesel generator rated power	Batteries' capacity	Annual demand	Diesel price	Energy cost	PV penetration	Computational software tool
PV/ diesel/ batteries (SOLEDO), France	80 kW	80 kVA	1800 Ah (48 h of autonomy)	≈ 13500 kWh	1.5 €/liter	0.177 €/kWh (without DSM) 0.157 €/kWh (with DSM)	45% (without DSM) 54% (with DSM)	SOLEDO simulation platform (described in this paper)
Wind/ PV/ batteries United States [18]	230W	--	1200Wh	single-family residential home	--	0.181 \$/kWh (without DSM) 0.172 \$/kWh (with DSM)	Not specified	Not specified
PV/ diesel/ batteries Saudi Arabia [7]	2.5MW	4.5MW	1 h of autonomy	15943 MWh	0.1 \$/liter	0.170 \$/kWh	27%	HOMER <sup>1</sup>
PV/ diesel/ batteries Turkey [11]	3 kW	1 kW	6 × 245 Ah	2353 kWh	Not specified	≈0.16 €/kWh	79%	HOMER
PV/ diesel/ batteries Malaysia [12]	1200 kW	2 × 400 kW	2160 kWh	Not specified	0.8 \$/liter	0.302 \$/kWh	42%	HOMER
PV/ diesel/ batteries Greece [9]	4 kW	Not specified	600 Ah	4730 kWh	1.1 €/liter	0.657 €/kWh	Not specified	“PHOTOV-DIESEL III” algorithm

## 6. Conclusions and Future Works

The exploitation of demand-side management (DSM) within a stand-alone hybrid PV system still constitutes a challenging problem in order to enhance the profitability of renewable energy. Recently, DSM has been attracting a large interest among researchers working in the field of stand-alone hybrid renewable energy systems.

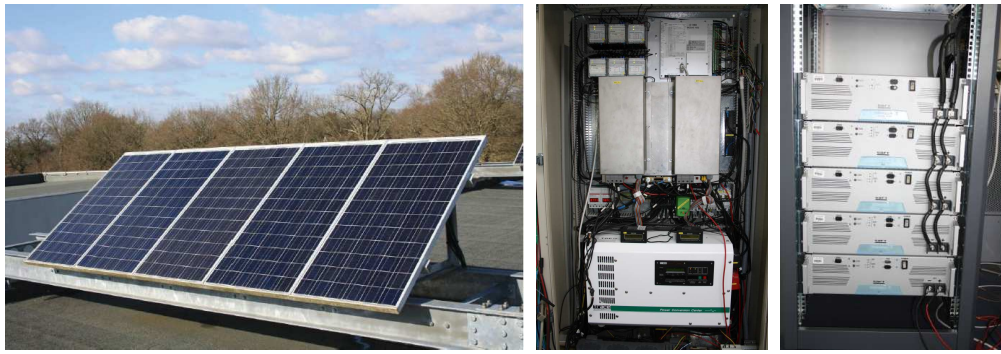
This paper presented the analysis of stand-alone hybrid PV/ Diesel/ Batteries systems including a new DSM strategy, called “load shaping & authorization dispatching”, which can be identified as an *enhanced and adapted direct-load control* for domestic loads in a multi-subscriber configuration. The simulation results showed that the proposed DSM may offer a noteworthy enhancement of economic and ecological performance to the hybrid PV system. The key contributions of this study are: 1) the proposal of the new DSM algorithm and presentation of the innovative infrastructure for the implementation of this strategy; 2) a new and original model for consumer behavior based on a Bayesian network and Monte-Carlo simulation, which permits us to simulate the real-time and stochastic aspect of the demand; 3) utilization of real data on meteorological conditions and consumers' statistical data; 4) analysis of the benefits that the DSM may give to both the system and its users.

The simulation relies on 20 users, each one has a part of the priority load and controllable loads. The numerical results showed that the application of DSM may offer a notable enhancement of economic and ecological performance to the hybrid PV system. Indeed, customers may experience the benefits of a reduced energy cost of 11.3 % for an unchanged daily consumption (18.5 kWh/day). Meanwhile, the solar resource is better exploited with photovoltaic penetration rising to 54% in this case study. We have also discussed the consumer comfort, and the flexibility for them to consume according to their usual habits by subscribing to this DSM program. Moreover, a parametric study on the benefits of DSM to stand-alone hybrid PV system has been carried out. Parametric results showed that the benefits from DSM can be better emphasized when the diesel prices rise and/ or the total installed battery capacity increases.

To take a broader view, the idea of setting a desirable set point for aggregate load during critical situations, as developed in this article, may constitute an interesting way of improving the efficiency of DSM deployment in smart grids nowadays. In addition, this new DSM strategy would also be of interest for off-grid micro-grids managers and consumers to share the available limited energy resource.

As we are in the design phase of the high efficiency stand-alone hybrid PV systems, this paper aims mainly at developing the novel DSM strategy for this context, and to analyze, through simulation, its benefits with respect to the system's performance and the user's comfort. Our work continues to progress toward the full development of the system. At the SATIE-CNRS laboratory, experimental conditions are being developed with the goal of validating the effectiveness of the proposed DSM strategy (Figure 12). Besides and interestingly, “load shaping & authorization dispatching” is a compatible approach with the pricing mechanism approach as well: energy price fluctuations can be introduced at different moments of the day so as to motivate people to even more effectively adapt their consumption behavior. In this case, the complexity of the Bayesian network may increase to take into account the consumer behavior in response to energy prices.

<sup>1</sup> HOMER is software for the simulation and optimization of distributed power generation systems developed by the National Renewable Energy Laboratory (NREL)



**Figure 12:** Construction of the SOLEDO system's test bench: from left to right, 2kW<sub>p</sub> PV systems, MPPT inverters, 10 kWh Lithium-Ion battery storage at the SATIE-CNRS laboratory.

## Acknowledgment

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