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## **A multi-level Demand-Side Management algorithm for offgrid multi-source systems**

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### **Abstract**

The use of renewable sources for electricity supply of islands is faced with technical and economic constraints. To ensure that demand is fully met in the event of low generated power, batteries and gensets are often used and these can be expensive due to fuel import and battery costs. To provide more degrees of freedom for these offgrid networks, a multi-level algorithm based on several Demand Side Management strategies is proposed in this paper. The simulated case study concerns an island supplied by a multi-source system including solar, wind, tidal, wave energies and a battery storage solution. To limit the inconvenience for users, a hierarchical application of the proposed strategies is studied, according to a day-ahead forecast. Strategies based on anticipation are firstly applied for electric room heaters and water heaters in order to use the excess of generated power. For the most critical situations, strategies based on load shifting and load shedding are studied. In these cases, the best solution is found using a genetic algorithm. The application of the proposed Demand Side Management algorithm was found to help reduce the unmet load demand rate and adapt load demand according to the power generated.

### **Keywords**

Demand Side Management, Offgrid, Multi-source system, Marine renewable energy

## 1. Introduction

In recent years, a lot of research and industrial developments have been carried out in the field of renewable energy use in isolated maritime areas [1] to increase the penetration of renewable energy and replace diesel generators [2]. More and more studies support obtaining 100% of electric power generation from renewable sources. For example, the use of wind and solar energies was studied for Ometepe Island (Nicaragua) in [3] and the Island of Korcula (Croatia) [4]. Islands often present high potential for harnessing renewable energy but the electricity supply of islands faces more severe constraints than that in continental areas. To ensure that demand is fully met, gensets are mainly used as is the case on some French islands for example [5]. However, some drawbacks exist such as the pollution generated. Moreover, fuel import is also highlighted to be an important issue according to the logistical constraints and the resulting costs for the case of using gensets [6]. Otherwise, the use of storage solutions is increasingly considered on islands thanks to the recent development of several technologies [7]. Batteries are one of the most promising solutions in island areas as they represent a good compromise between capacity, cost and technical maturity [8]. Thus, they represent more than half of the installed storage capacity on islands worldwide [7]. While storage technologies have been significantly improved in recent years, they remain expensive [8]. Also the recent development of marine renewable energies, such as wind, tidal or wave energies, has opened up new perspectives for electricity supply on islands [9]. However, the use of renewable energies suffers from constraints linked to intermittency and variability although the diversification of sources helps non-production hours to be reduced [10]. Thus, the Energy Management System (EMS) of an island network needs a degree of freedom to avoid both large storage capacity requirements which increase costs and also black-out situations caused by low generated power and low battery charge levels.

Among the possible solutions, a mix of storage solutions, several examples of which are reviewed in [11], and Demand Side Management (DSM) are the solutions given the most consideration in the literature [12]. This paper discusses the application of DSM strategies. Demand Side Management consists of modifying the shape of the load profile according to the available power to achieve goals related to reliability and costs [13] and it can be broadly divided into Demand Response (DR) strategies and energy efficiency measures [14]. Several kinds of strategies are defined in the literature: peak clipping, valley filling, load shifting, strategic load conservation, strategic load growth and flexible load shape [13]. These strategies are based on different time and amplitude modulation principles with or without initial demanded energy conservation. According to several surveys explaining DSM concepts and schemes [15–17], DSM programs are applied thanks to the variable prices or incentives offered to the consumer. A lot of benefits deriving from the application of DSM programs have been

observed. There are economic impacts for customers (electricity bill reductions) and operators (electricity production costs) [14]. Moreover, many technical benefits have been observed such as improved reliability [14,18], increased degrees of freedom [14], reduced battery ageing [19], etc. There are a lot of papers dealing with DSM strategies for smart grids but only a few papers seem to deal with DSM for remote areas supplied by renewable sources. For example, D. Friedrich and G. Lavidas observed in [20] the positive effects of DSM application on a solar-wind-wave-genset system as it allows the reduction of sizing costs and pollution. Savings in sizing costs due to DSM application is also discussed in [21]. In [22], G. Zizzo et al. proposed a feasibility study of the implementation of DSM on Lampedusa island. According to [23], the application of DSM programs in islands could help reduce investments and favour the integration of renewable energies. The state of the art shows that few papers deal with DSM applied to an offgrid system only based on the use of renewable energies without connection to a mainland network and Diesel generators. Thus, given academics' and industrials' strong interest in the development of 100% renewable energy systems on islands, the necessity to enhance the flexibility of such systems by managing demand seems to be a key step.

To manage load demand efficiently in isolated maritime areas, a DSM algorithm is proposed in this paper for an offgrid multi-source system based on the use of solar, wind, tidal and wave energies, without mainland network connection and Diesel generators. This algorithm consists of applying DR strategies based on load shifting and/or load shedding according to the evaluation of the batteries state of charge in the coming hours on the basis of a day-ahead scheduling. A hierarchical approach is proposed in order to use the energy produced by the renewable sources as effectively as possible and to avoid load shedding which would be a source of some discomfort for consumers. For this purpose, the island load profile was split into three parts: water heaters, electric room heaters and other loads which cannot be shifted. The performances of the proposed algorithm were validated by simulation. In addition, a sensitivity analysis was carried out to assess the impact of the algorithm parameters.

The paper is organized as follows. Section 2 presents the considered multi-source system and the loads used for DSM application. Section 3 explains the designed DSM strategies and the multi-level algorithm. Simulation results and a sensitivity analysis are presented in Section 4. Conclusions and ideas for future work are given in Section 5.

## 2. Multi-source system modelling

A multi-source system using solar, wind, tidal and wave energies is considered in this study. As generated power can be weak in the event of low levels of available resources, a battery storage solution is also used to supply the load demand. An overview of the considered multi-source system is given in Fig. 1. A detailed description of the sources, the loads and the batteries is given in the following sections.

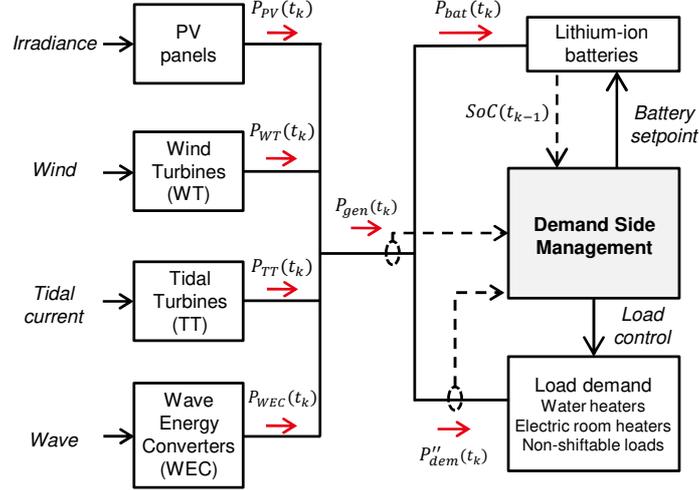


Fig. 1. Overview of the considered multi-source system

### 2.1. Sources models

The models used for the calculation of the power generated by each source are detailed in [19] and consist of the evaluation of generated power according to the harnessed resources. At each time sample  $t_k$ , the total generated power  $P_{gen}$  is defined by:

$$P_{gen}(t_k) = P_{PV}(t_k) + P_{WT}(t_k) + P_{TT}(t_k) + P_{WEC}(t_k), \quad P_{gen}(t_k) \leq P_{gen\ max}(t_k) \quad (1)$$

where  $P_{PV}$  is the power generated by all the photovoltaic panels [W],  $P_{WT}$  the generated power by all the wind turbines [W],  $P_{TT}$  the power generated by all the tidal turbines [W],  $P_{WEC}$  the power generated by all the wave energy converters [W] and  $P_{gen\ max}$  the maximum power which could be generated by all the energy sources according to the natural resources available. The relationship between  $P_{gen}$  and  $P_{gen\ max}$  will be given by the energy management algorithm described in section 2.3.

### 2.2. Load model

The load power considered in this article concerns the hourly load profile for Ouessant Island located on the west coast of France. This island's electricity demand mostly involves domestic usage. To apply DSM strategies to different kinds of loads, the island load profile based on the data available in [24] was separated into three

load profiles, namely water heaters, electric room heaters and non-shiftable loads according to the hypotheses detailed in [19]. At each time sample  $t_k$ , the total requested power  $P_{dem}$  is defined as:

$$P_{dem}(t_k) = P_{WH}(t_k) + P_{HT}(t_k) + P_{NS}(t_k) \quad (2)$$

where  $P_{WH}$  is the power related to the total water heater demand [W],  $P_{HT}$  the power related to the total electric room heater demand [W] and  $P_{NS}$  the power related to the total non-shiftable demand [W]. These powers are considered to be positive. The modified total load demand  $P'_{dem}$  resulting from DSM strategies application will be defined as:

$$P'_{dem}(t_k) = P'_{WH}(t_k) + P'_{HT}(t_k) + P'_{NS}(t_k) \quad (3)$$

where  $P'_{WH}$ ,  $P'_{HT}$  and  $P'_{NS}$  are the powers allocated to water heaters, electric room heaters and the non-shiftable loads for the whole island after DSM strategies application [W]. The power  $P''_{dem}$  in Fig. 1 represents the load power observed on the microgrid which allows the power balance to be met. This power can be different from  $P'_{dem}$  if the batteries and the sources are not able to supply the load demand (see the section 2.3).

### 2.3. Battery model

A storage system based on batteries is considered to supply the load in the event of a low level of generated power. The state of charge  $SoC$  of the batteries is calculated at each time sample by [25]:

$$SoC(t_k) = \begin{cases} SoC(t_{k-1}) \times (1 - \sigma)^{\frac{\Delta t}{24}} + \frac{P_{bat}(t_{k-1}) \times \Delta t \times \eta_{bat}}{C_{bat\ ref}} & \text{if } P_{bat}(t_k) > 0 \text{ (Charge)} \\ SoC(t_{k-1}) \times (1 - \sigma)^{\frac{\Delta t}{24}} + \frac{P_{bat}(t_{k-1}) \times \Delta t}{\eta_{bat} \times C_{bat\ ref}} & \text{if } P_{bat}(t_k) < 0 \text{ (Discharge)} \end{cases} \quad (4)$$

where  $C_{bat\ ref}$  is the total capacity of the batteries [Wh],  $P_{bat}$  the operating power of the batteries [W] which is considered as positive during charge (when  $P_{gen} > P''_{dem}$ ) and negative during discharge (when  $P_{gen} < P''_{dem}$ ),  $\Delta t$  the time step [h],  $\sigma$  the daily self-discharge rate and  $\eta_{bat}$  the batteries efficiency.

According to Fig. 1 and the energy management rules presented in [26], the batteries must operate at a power  $P_{bat}$  allowing the power balance to be ensured at each time sample  $t_k$ :

$$P_{gen}(t_k) = P''_{dem}(t_k) + P_{bat}(t_k) \quad (5)$$

However, the limits related to the state of charge and the batteries power must also be taken into account:

$$P_{disch\ max} \leq P_{bat}(t_k) \leq P_{ch\ max} \quad (6)$$

$$SoC_{min} \leq SoC(t_k) \leq SoC_{max} \quad (7)$$

where  $P_{ch\ max}$  is the maximum power in charge [W],  $P_{disch\ max}$  the maximum power in discharge [W],  $SoC_{max}$  the maximum state of charge and  $SoC_{min}$  the minimum state of charge. The operating power  $P_{bat}$  of the batteries, the generated power  $P_{gen}$  and the load power  $P''_{dem}$  are calculated according to the energy management algorithm proposed in Fig. 2, in which different cases are distinguished according to the power and the state of charge limits. So as to ensure the power balance, a power curtailment is considered for the load in the cases 1 and 2 ( $P''_{dem} < P'_{dem}$ ) and for the sources in the cases 4 and 5 ( $P_{gen} < P_{gen\ max}$ ).

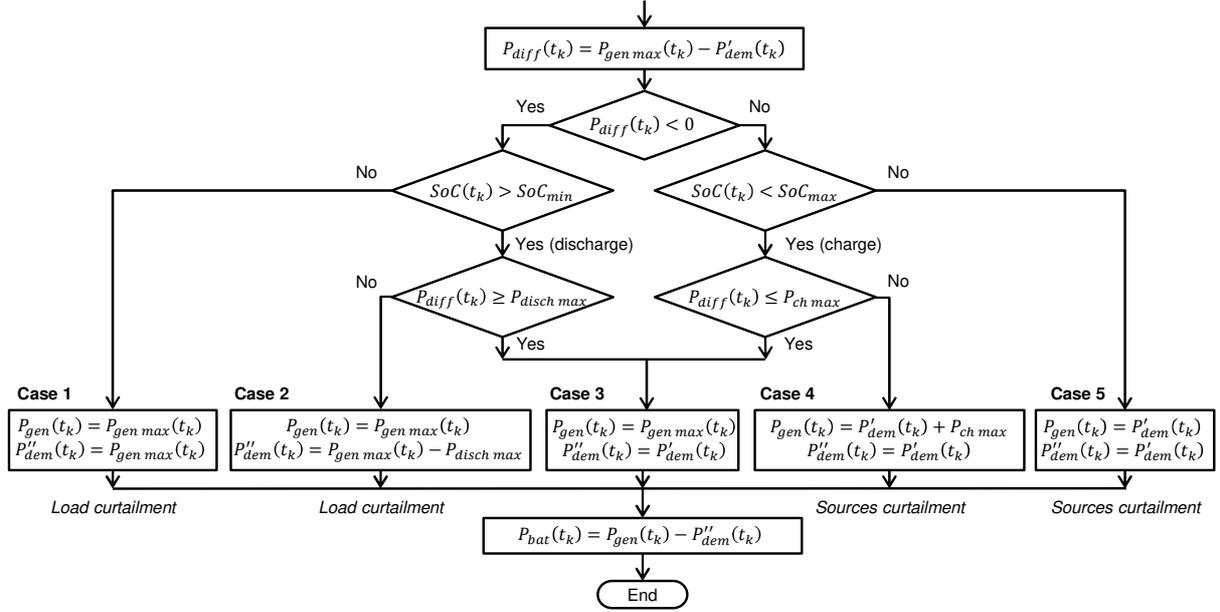


Fig. 2: Flowchart of the energy management algorithm considered for the calculation of the powers  $P_{bat}$ ,  $P_{gen}$  and  $P''_{dem}$

#### 2.4. House thermal model

To evaluate the possible loss of comfort caused by DSM strategies, a house thermal model using convectors was studied. Based on the first order model described in [27], the room air temperature  $T_{in}$  is evaluated at each time sample  $t_k$  by:

$$T_{in}(t_k) = \lambda T_{in}(t_{k-1}) + (1 - \lambda)(R_b \times P_{HT,h}(t_{k-1}) + T_{out}(t_{k-1})) \quad (8)$$

$$\lambda = e^{-\frac{\Delta t}{R_b \times C_b}} \quad (9)$$

where  $C_b$  is the house equivalent thermal mass [Wh/°C],  $P_{HT,h}$  the electric room heaters total power for one house [W],  $R_b$  the house equivalent thermal resistance [°C/W],  $T_{in}$  the room air temperature [°C],  $T_{out}$  the outside air temperature [°C] and  $\Delta t$  the time step [h]. The following values were considered in this paper:  $C_b = 2200$  Wh/°C and  $R_b = 0.01$  °C/W. A set point temperature of 20°C is considered in normal conditions (without DSM application).

### 3. Proposed Demand-Side Management strategies

Different kinds of DSM strategies are proposed in this article. To use any excess of generated power which may occur, DSM strategies based on load shifting by anticipation are studied first. For the most critical situations, DSM strategies based on load shifting and load shedding are studied. To modify the power of the electric room heaters, it is assumed that the room air temperature setpoint could be sent to the consumer remotely. Moreover, it is assumed that the water heaters could also be turned on and off remotely using a control system connected to the network. The DSM strategies proposed in this section are evaluated according to the timeline given in Fig. 3. A scheduling period of  $K$  hours is considered corresponding to a day-ahead evaluation, such as:

$$k \leq j < k + K, \quad j, k, K \in \mathbb{N} \quad (10)$$

where  $k$  is the starting sample of DSM strategy evaluation corresponding to time  $t_k$  and  $j$  the sample during the scheduling period corresponding to time  $t_j$ . The DSM algorithm is computed at time  $t_{k-1}$ , so that the results can be applied at time  $t_k$ . The proposed strategies will be evaluated over a simulation period of  $N$  time samples and an hourly time step  $\Delta t = 1$  h. To take into account the need for DSM in the forthcoming hours without lengthening the simulation time, an update time step of  $\delta$  hours is considered and defined as:

$$0 < \delta \leq K, \quad \delta \in \mathbb{N} \quad (11)$$

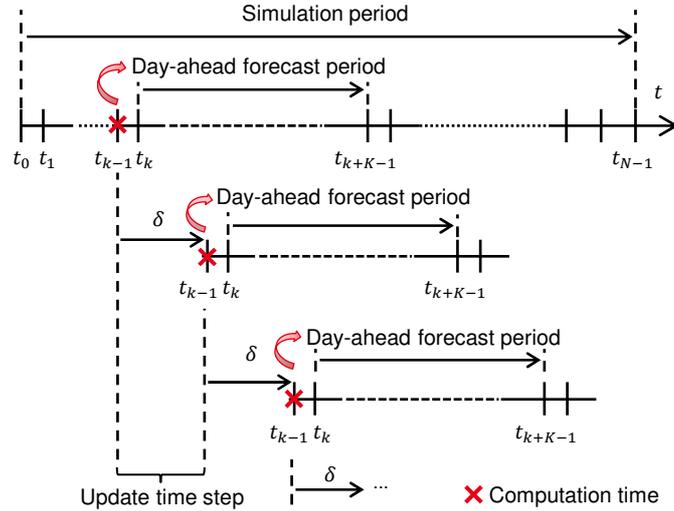


Fig. 3. Timeline of the simulation with rolling horizon for day-ahead scheduling

#### 3.1. Evaluation without Demand-Side Management

The normal EMS operating mode is to charge the batteries when the generated power  $P_{gen\ max}$  is greater than the load power  $P_{dem}$  and discharge the batteries in the opposite case according to the state of charge and power

constraints described in Section 2.3. The total load power is shed if at time  $t_j$  the batteries state of charge is at its minimum level or if the power requested from the batteries is lower than  $P_{disch\ max}$ . This load shedding is carried out without distinction between the three kinds of loads, according to:

$$P'_{dem}(t_j) = \begin{cases} P_{gen\ max}(t_j) & \text{if } SoC(t_j) = SoC_{min} \text{ and } P_{gen\ max}(t_k) < P_{dem}(t_k) \\ P_{gen\ max}(t_j) - P_{disch\ max} & \text{if } P_{gen\ max}(t_k) - P_{dem}(t_k) < P_{disch\ max} \\ P_{dem}(t_j) & \text{otherwise} \end{cases} \quad (12)$$

Thus, the corresponding unmet load power  $P_{UL}$  could be defined as:

$$P_{UL}(t_j) = P_{dem}(t_j) - P'_{dem}(t_j) \quad (13)$$

This load shedding would lead to a cut in the power supply to a part of the island. To avoid such a situation where the demand is not fully met, different DSM strategies are proposed in the following sections. These strategies allow some loads to be shifted (electric room heaters and water heaters) and enabled to distinguish which loads needed to be shed.

### 3.2. Demand-Side Management strategies based on load anticipation

Firstly, to limit the load profile modification, DSM strategies based on time shifts are proposed according to the rule-based strategies described in [19]. The anticipation of the demand from water heaters and electric room heaters initially planned over the coming hours is considered if at time  $t_j$  the batteries state of charge is at its maximum level and if the excess of power  $P_{exc}$ , defined as:

$$P_{exc}(t_j) = \begin{cases} P_{gen\ max}(t_j) - P_{dem}(t_j) & \text{if } P_{gen\ max}(t_j) > P_{dem}(t_j) \text{ and } SoC(t_j) = SoC_{max} \\ 0 & \text{otherwise} \end{cases} \quad (14)$$

is strictly positive. This excess of power  $P_{exc}$  is used to supply these two shiftable loads initially planned for the forthcoming hours according to the proposed rule-based strategies described in the following sections. No postponement consumption is considered for these kinds of DSM strategies.

#### 3.2.1. Water heaters

The next operating occurrence initially planned at  $t_{j+A}$  is shifted at  $t_j$  whatever the power balance expected at  $t_{j+A}$ . A duration of 10 hours is the basis for this calculation ( $1 \leq A \leq 10$ ). The initial operating cycle of water heaters starts at 9 p.m. and the greatest consumption of hot water occurs in the morning which means that the water does not need to be heated before 11 a.m. The amount of shifted water heater consumption is defined according to the amount of excess power at  $t_j$ , resulting in two cases:

- Case WH1: if  $P_{exc}(t_j) \geq P_{WH}(t_{j+A})$ , all the water heater demand is shifted from  $t_{j+A}$  to  $t_j$ . Thus, the modified demand becomes:

$$P'_{WH}(t_j) = P_{WH}(t_j) + P_{WH}(t_{j+A}) \quad (15)$$

$$P'_{WH}(t_{j+A}) = 0 \quad (16)$$

- Case WH2: if  $P_{exc}(t_j) < P_{WH}(t_{j+A})$ , a partial load shifting is applied, constrained by the available excess power (not all the water heaters are concerned by this shift):

$$P'_{WH}(t_j) = P_{WH}(t_j) + P_{exc}(t_j) \quad (17)$$

$$P'_{WH}(t_{j+A}) = P_{WH}(t_{j+A}) - P_{exc}(t_j) \quad (18)$$

### 3.2.2. Electric room heaters

The demand from electric room heater is shifted from  $t_{j+B}$  to  $t_j$  only if a lack of power  $P_{def}$  is expected at  $t_{j+B}$ , defined by:

$$P_{def}(t_{j+B}) = \begin{cases} P_{dem}(t_{j+B}) - P_{gen\ max}(t_{j+B}) & \text{if } P_{gen\ max}(t_{j+B}) < P_{dem}(t_{j+B}) \\ 0 & \text{otherwise} \end{cases} \quad (19)$$

The time duration is limited to two hours ( $B = 1$  or  $2$ ) to limit temperature fluctuations. The amount of shifted consumption depends on the excess of power  $P_{exc}$  at  $t_j$  and the lack of power  $P_{def}$  at  $t_{j+B}$ , according to one of the four cases described in Fig. 4.

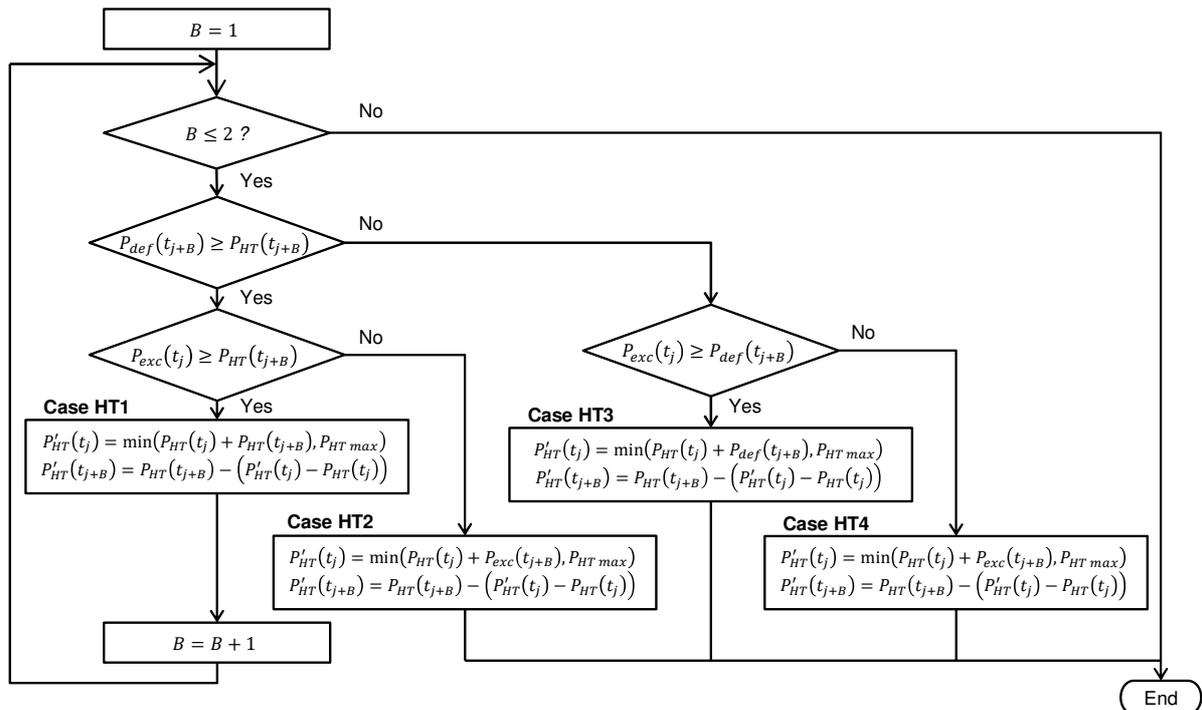


Fig. 1. Flowchart of the anticipation based DSM strategy for electric room heaters demand

The modified power is constrained by an upper limit  $P_{HT\ max}$  corresponding to the power of all the electric room heaters of the island operating at maximum power. If the lack of power at  $t_{j+B}$  is greater than the electric room heaters demand, this consumption is shifted as much as possible and only constrained by the excess of power at  $t_j$  : in case HT1, the demand is totally shifted whereas in case HT2, only a partial shift is carried out. When the lack of power at  $t_{j+B}$  is found to be lower than the electric room heaters demand, the shifted demand is defined according to the lack of power at  $t_{j+B}$  and the power available at  $t_j$  (cases HT3 and HT4).

### 3.3. Demand-Side Management strategies for critical situations

If a lack of available power is expected during the  $K$  forthcoming hours (i.e. due to a low batteries state of charge and a low generated power), a new load scheduling must be proposed to consumers to avoid a power system black-out. Anticipation-based strategies are sometimes not sufficient to avoid this kind of situation which means a new DSM scheme including load shifting and load shedding is required. To limit consumer discomfort caused by the application of DSM strategies during critical situations, a weighted objective function is proposed allowing the DSM actions on each load to be distinguished and prioritized. For the scheduled period, load shifting based strategies for demand from water heaters and electric room heaters are preferred and load shedding is limited as much as possible, being penalized by the objective function's weighting coefficients.

#### 3.3.1. Decision variables

The DSM strategies considered for the three load profiles are defined according to the following equations and variable decisions:

- Water heaters

A strategy based on load shifting and load shedding is proposed. A binary decision variable  $\alpha$  allows the water heaters to be turned on or not at each time sample  $t_j$ :

$$P'_{WH}(t_j) = P_{WH,K} \times \alpha(t_j), \quad \alpha(t_j) \in \{0,1\} \quad (20)$$

$$A = [\alpha(t_k) \quad \alpha(t_{k+1}) \quad \cdots \quad \alpha(t_j) \quad \cdots \quad \alpha(t_{k+K-1})] \quad (21)$$

where  $A$  is the vector of decision variables related to the modified water heaters demand for a scheduling period of  $K$  hours. The island's water heaters are all scheduled to be turned on and off at the same times.  $P_{WH,K}$  is the power related to water heaters demand expected during the scheduled period [W], defined as:

$$P_{WH,K} = \frac{1}{K_{WH \text{ init}}} \sum_{j=k}^{k+K-1} P_{WH}(t_j) \quad (22)$$

where  $K_{WH \text{ init}}$  is the number of operating hours of the water heaters included in the scheduled period.

- Electric room heaters

A load power modulation is included in the electric room heaters DSM strategy. At each time sample  $t_j$ , the modified power is related to the maximum power demand of the electric room heaters  $P_{HT \text{ max}}$  according to a real valued decision variable  $\beta$ :

$$P'_{HT}(t_j) = P_{HT \text{ max}} \times \beta(t_j), \quad 0 \leq \beta(t_j) \leq 1, \quad \beta(t_j) \in \mathbb{R} \quad (23)$$

$$B = [\beta(t_k) \quad \beta(t_{k+1}) \quad \cdots \quad \beta(t_j) \quad \cdots \quad \beta(t_{k+K-1})] \quad (24)$$

where  $B$  is the vector of decision variables related to the electric room heaters demand for the scheduled period. If  $\beta(t_j)$  is set to zero, all the electric room heaters are turned off and if  $\beta(t_j) = 1$ , all the electric room heaters are considered to work at their maximum power level. This load power modulation involves changing the temperature setpoint for each home.

- Other loads (Non-shiftable loads)

The DSM strategy proposed for the rest of load profile only involves load shedding as some loads such as lighting cannot be shifted. Thus, a real valued decision variable  $\gamma$  is included for each time sample, leading to the vector of decision variables  $C$ :

$$P'_{NS}(t_j) = P_{NS}(t_j) \times \gamma(t_j), \quad 0 \leq \gamma(t_j) \leq 1, \quad \gamma(t_j) \in \mathbb{R} \quad (25)$$

$$C = [\gamma(t_k) \quad \gamma(t_{k+1}) \quad \cdots \quad \gamma(t_j) \quad \cdots \quad \gamma(t_{k+K-1})] \quad (26)$$

### 3.3.2. Constraints

A set of inequality constraints is defined. These constraints have to be negative or zero for the solution to be admissible. To avoid water heaters' over-consumption,  $g_1$ , defined as

$$g_1(A) = \left( \sum_{j=k}^{k+K-1} \alpha(t_j) \right) - K_{WH \text{ init}} \quad (27)$$

is constrained to be negative or zero. In the same way,  $g_2$ , defined as

$$g_2(B) = \sum_{j=k}^{k+K-1} \left( \beta(t_j) \times P_{HT \max} - P_{HT}(t_j) \right) \quad (28)$$

is constrained to be negative or zero to avoid electric room heaters' over-consumption. Finally, a third inequality constraint related to the power balance is defined. The sources and the batteries have to be able to satisfy the modified load power at each time. Thus,  $g_3$ , defined as

$$g_3(A, B, C) = \max_{k \leq j < k+K} \left( P'_{dem}(t_j) - P_{gen}(t_j) + P_{bat}(t_j) \right) \quad (29)$$

is constrained to be negative or zero.

### 3.3.3. Objective function

The objective function  $f$  of the scheduling optimization problem is defined to minimize the initial demand modification. Each load modification is normalized and penalized according to a weighting factor  $w_i$  ( $w_i \geq 0$ ,  $w_i \in \mathbb{R}$ ) which meant a hierarchy of DSM actions could be defined. The objective function  $f$  is defined as:

$$f(A, B, C) = \frac{\sum_{i=1}^5 w_i \times y_i}{\sum_{i=1}^5 w_i} \quad (30)$$

where  $y_1$  represents the term related to the load shedding of water heaters:

$$y_1(A) = 1 - \frac{\sum_{j=k}^{k+K-1} P'_{WH}(t_j)}{\sum_{j=k}^{k+K-1} P_{WH}(t_j)} \quad (31)$$

The variable  $y_2$  represents the term related to the load shifting of electric room heaters:

$$y_2(B) = \frac{1}{K} \sum_{j=k}^{k+K-1} \frac{|P'_{HT}(t_j) - P_{HT}(t_j)|}{\max(P_{HT \max} - P_{HT}(t_j), P_{HT}(t_j))} \quad (32)$$

The variable  $y_3$  represents the term related to the load shedding of electric room heaters:

$$y_3(B) = 1 - \frac{\sum_{j=k}^{k+K-1} P'_{HT}(t_j)}{\sum_{j=k}^{k+K-1} P_{HT}(t_j)} \quad (33)$$

The variable  $y_4$  represents the term related to the shedding of the other loads:

$$y_4(C) = 1 - \frac{\sum_{j=k}^{k+K-1} P'_{NS}(t_j)}{\sum_{j=k}^{k+K-1} P_{NS}(t_j)} \quad (34)$$

The last term  $y_5$  is related to the energy provided by the batteries:

$$y_5(A, B, C) = \frac{\sum_{j=k}^{k+K-1} (SoC'(t_j) - SoC'(t_{j-1}))^2}{\sum_{j=k}^{k+K-1} (SoC(t_j) - SoC(t_{j-1}))^2} \quad (35)$$

where  $SoC$  is the batteries state of charge obtained with DSM (Mode 4) and  $SoC'$  the batteries state of charge obtained without DSM (Mode 1). This term is introduced to allow the discharge of batteries to be slowed down and the largest state of charge diminutions to be penalized more than the smallest variations. Through this term, load shifting is favoured.

The least desirable load modification has to be penalized by a weighting factor  $w_i$  with a high value whereas the best accepted strategy has to be penalized by a small weighting factor  $w_i$  so as to be applied as much as necessary. Thus, the scheduling optimization problem consists of finding the best decision variables to minimize the objective function:

$$[A_{opt}, B_{opt}, C_{opt}] = \arg \min f(A, B, C) \quad (36)$$

Subject to the  $N_{ic} = 3$  inequality constraints and the variable decisions bounds:

$$g_c(A, B, C) \leq 0, \quad c = 1, \dots, N_{ic} \quad (37)$$

$$\alpha(t_j) \in \{0,1\} \quad (38)$$

$$0 \leq \beta(t_j) \leq 1, \quad \beta(t_j) \in \mathbb{R} \quad (39)$$

$$0 \leq \gamma(t_j) \leq 1, \quad \gamma(t_j) \in \mathbb{R} \quad (40)$$

According to this formulation, the considered scheduling optimization problem corresponds to a MINLP problem (Mixed-Integer Non Linear Programming).

#### 3.3.4. Problem solving by a genetic algorithm

The optimization problem involves a large number of decision variables ( $3 \times K$  real and binary variables) and the solving time has to be limited, so a meta-heuristic method based on a genetic algorithm has been chosen as done in several papers dealing with heuristic optimization for DSM [28–31]. An individual (i.e. a chromosome) corresponds to a set of the  $A$ ,  $B$  and  $C$ , leading to a chromosome made of  $3 \times K$  genes. The genetic algorithm used is based on the genetic algorithm proposed in [32] and consists of the following steps, considering the parameters given in Table 1:

1. *Initialization*: an initial population of  $N_{ind}$  individuals is randomly created;
2. *Evaluation*: the performance of each chromosome is evaluated according to the objective function;
3. *Genetic operations application*: selection, crossover and mutation operators are applied in order to keep the best solutions and to bring diversity. The application of the genetics operators leads to a new generation of  $N_{ind}$  individuals.
4. Steps 2 and 3 are repeated until the stopping criteria is satisfied (if the maximal number of generations  $N_{gen}$  is reached or if no change of the objective function is observed since  $N_{gen\ stop}$  generations).

Table 1: Genetic algorithm parameters

Parameter	Value
Population size $N_{ind}$	100 individuals
Number of generations $N_{gen}$	8000
Crossover rate $C_r$	0.3
Mutation rate $X_r$	0.2
Selection	Roulette
Stopping criteria $N_{gen\ stop}$	4000

### 3.4. Multi-level algorithm

To limit the discomfort caused by using DSM, the previously described strategies were applied in a hierarchical manner using a multi-level DSM algorithm for which a flowchart is given in Fig. 5. The proposed algorithm is based on the *SoC* profile expected for the  $K$  forthcoming hours, for which different zones of DSM application are defined according to *SoC* threshold values, as shown in Fig. 6:

- Mode 1: the multi-source system operation is assessed without DSM ;
- Mode 2 and 3: if the state of charge without DSM is expected to be lower than a chosen threshold value  $SoC_a$  during the scheduling period, anticipation strategies (Section 3.2) are used. Anticipation of electric room heaters (Mode 3) is only carried out if the water heaters' load shifting (Mode 2) did not allow the occurrence of *SoC* values lower than  $SoC_a$  to be avoided.
- Mode 4: if an occurrence of fully discharged batteries is expected in the  $K$  forthcoming hours even by applying the DSM strategies based on load anticipation, the load scheduling procedure (Section 3.3) is applied.

To take into account the rebound effect caused by the electric room heaters turning off [33], the electric room heater energy lost during the scheduling period is recovered once the *SoC* reaches its maximum value,

considering that the electric room heaters operate at their maximum power. A summary of the developed DSM strategies is given in Table 2.

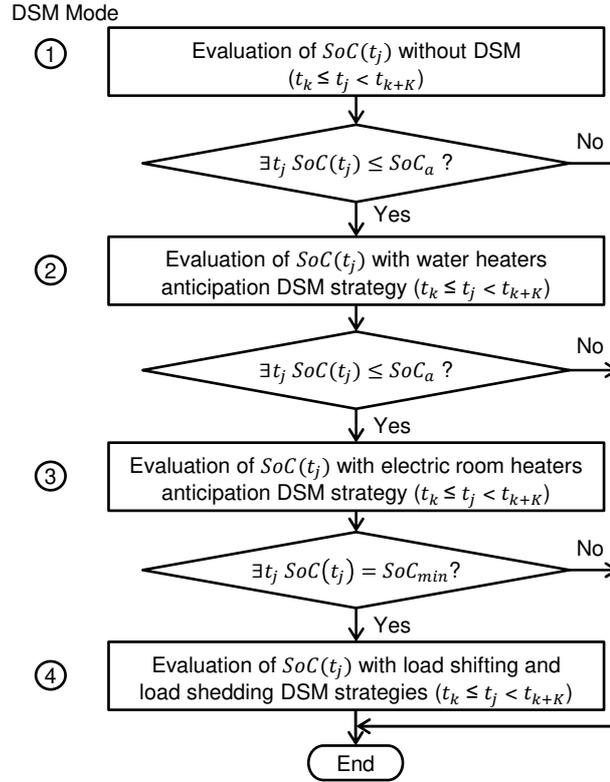


Fig. 5. Flowchart of the multi-level DSM algorithm

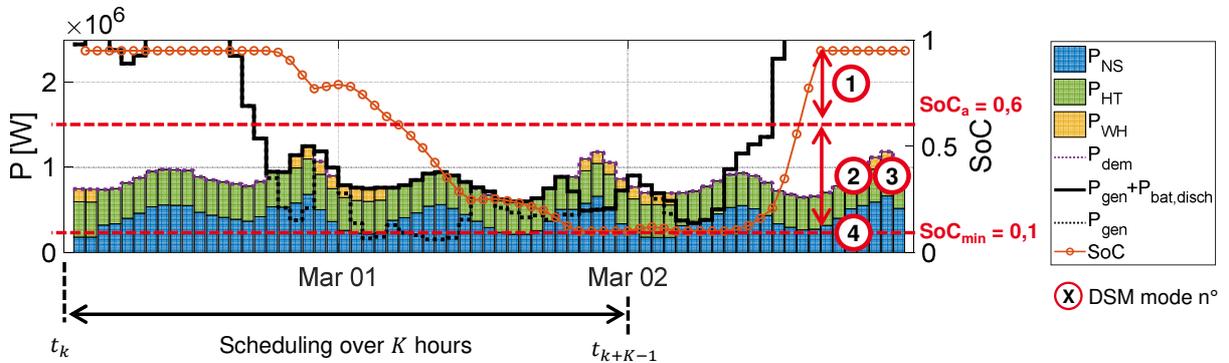


Fig. 6 : DSM modes according to the threshold SoC values

The multi-level DSM algorithm is performed at time sample  $t_{k-1}$ . The necessary data for the computation of each DSM mode is presented in Fig. 7. To assess the performances of the proposed DSM strategies for the  $K$  forthcoming hours at time  $t_{k-1}$ , the forecasted data related to the generated and demanded powers expected for this period and the batteries state of charge at  $t_{k-1}$  are required. In this article, a perfect forecasting ability was achieved by evaluating the generated and demanded powers according to the resources and load data time series. The application of the multi-level DSM algorithm leads to a demand planning which can be different from the

initial load profile. Moreover, the occurrence of fully discharged batteries will be avoided by computing the proposed DSM algorithm.

Table 2: Summary of the proposed DSM modes

DSM mode n° (priority order)	DSM strategy	Main goal	Method/Tool	Load and DSM strategy considered	Trigger condition	Described in Section/Figure
1	Without DSM	Evaluate the expected state of charge evolution over the scheduling period	Rule-based	None	None	Section 3.1
2	Water heaters anticipation	Use the excess of generated power when it occurs whatever the power balance in the future	Rule-based	Water heaters load shifting by anticipation	At least one occurrence for which $SoC$ is lower than $SoC_a$ is expected during the $K$ coming hours	Section 3.2.1
3	Electric room heaters anticipation	Use the excess of generated power when it occurs if a lack of power is expected in the future	Rule-based	Electric room heaters load shifting by anticipation	At least one occurrence for which $SoC$ is lower than $SoC_a$ is expected during the $K$ coming hours	Section 3.2.2 Fig. 4
4	Scheduling for critical situations	Schedule the three load profiles while limiting the modification of initial demand	Genetic algorithm	Water heaters and electric room heaters loads: load shifting and load shedding Other loads: load shedding	At least one occurrence of $SoC_{min}$ is expected during the $K$ coming hours	Section 3.3

After the application of one of the DSM modes over the scheduling period, the unmet load demand rate  $UL$  over a given period is assessed [21]:

$$UL = 1 - \frac{\sum_{j=k}^{k+K-1} P'_{dem}(t_j)}{\sum_{j=k}^{k+K-1} P_{dem}(t_j)} \quad (41)$$

Loss of comfort is evaluated according to the heating degree-hours indicator  $DH$  [34], expressed in °C.h, representing the variations of room air temperature under ( $DHL$ ) and above ( $DHH$ ) the normal temperature (20°C):

$$DHL = \sum_{j=k}^{k+K-1} \max(20 - T_{in}(t_j), 0) \times \Delta t \quad (42)$$

$$DHH = \sum_{j=k}^{k+K-1} \max(T_{in}(t_j) - 20, 0) \times \Delta t \quad (43)$$

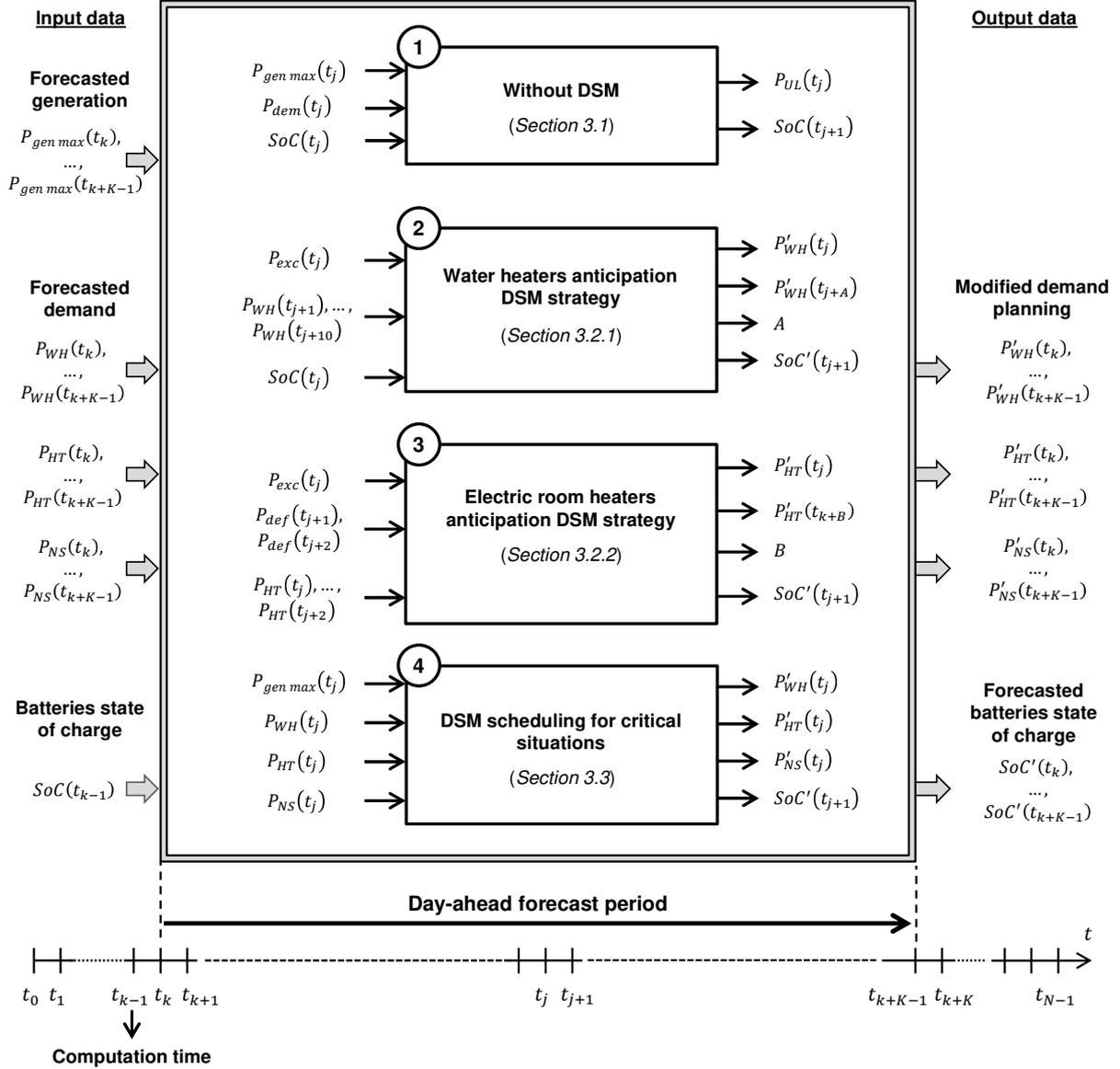


Fig. 2. Overview of necessary data in the four DSM modes

#### 4. Results and discussion

The proposed multi-level DSM algorithm was applied to the multi-source system over a simulation period of  $N$  hours according to the simulation flowchart given in Fig. 8 and involving a rolling horizon with the update period  $\delta$  and an hourly time step  $\Delta t = 1$  h. The simulation is performed using Matlab 2017b software on an Intel® Core™ i7-6500U CPU @ 2.5 GHz processor.

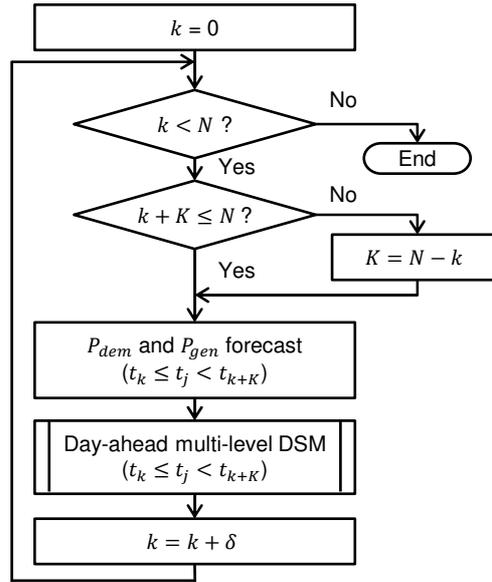


Fig. 8. Flowchart of the simulation

The simulation was carried out using the following parameters:  $K = 36$ ,  $\delta = 6$ ,  $N = 72$  and  $SoC_a = 0.6$ . The following weighting factors of the objective function are used:  $w_1 = 200$ ,  $w_2 = 1$ ,  $w_3 = w_4 = 1000$  and  $w_5 = 500$ . These values enable the load shedding of electric room heaters and other loads to be equally penalized ( $w_3$  and  $w_4$ ) limiting room air temperature fluctuations around to the setpoint value ( $20^\circ\text{C}$ ). The values chosen for  $w_1$  and  $w_2$  enable to shift the water heaters and electric room heaters loads as much as possible.

The devices and technical data related to the sources are given in [19] in addition to data related to resources and the load for the case study of Ouessant Island. For the batteries, the lithium-ion technology is chosen because it represents an effective compromise between capacity, power and costs in comparison with other technologies (lead-acid, redox, etc.). The batteries used in this work correspond to ten units of the battery Max+20M from Saft manufacturer. The main characteristics of the batteries storage system are:  $C_{bat\ ref} = 10.9$  MWh,  $P_{ch\ max} = 22$  MW,  $P_{disch\ max} = -25$  MW,  $\sigma = 0.166\%$ /day and  $\eta_{bat} = 0.96$ . The state of charge was limited by  $SoC_{min} = 0.1$  and  $SoC_{max} = 0.95$  to avoid a premature ageing which can occur for  $SoC$  values close to 0 and 1 as has been discussed in several articles [35,36]. The power  $P_{HT\ max}$  related to all the electric room heaters of the island when operated at maximum power was  $P_{HT\ max} = 1$  MW, occurring when the air temperature  $T_{out}$  was  $2^\circ\text{C}$ .

In Section 4.1, the multi-level algorithm was applied over a three-day period in order to show the impact of each DSM strategy. For the fourth DSM mode, the use of the genetic algorithm has been validated in Section 4.2

according to a convergence analysis and a sensitivity analysis of the weighting factors. Finally, the impacts of the temporal parameters and the *SoC* threshold values of the proposed algorithm are studied in the Section 4.3.

#### 4.1. Application of the multi-level Demand-Side Management algorithm over a few days period

The performances of the multi-level DSM algorithm application over a period of three days ( $N = 72$ ) were evaluated first. A summary of the numerical results obtained at each step of the multi-level DSM algorithm is given in Table 3.

The results obtained without DSM are presented in Fig. 9. By applying only the Mode 1 of Fig. 5, the unmet load reaches 5.68%, corresponding to nine hours of fully discharged batteries. The heat discomfort degradation *DHL* reaches 49.26 °C.h.

When the DSM strategies based on anticipation were applied (Modes 2 and 3), the unmet load becomes 3.6%, corresponding to seven hours for which batteries were fully discharged as shown in the results given in Fig. 10. The heat discomfort level *DHL* was reduced to 34.59 °C.h. Thanks to the application of both these DSM modes (2 and 3), the first occurrence of the batteries becoming fully discharged is postponed, but this situation cannot be avoided.

Thus, the fourth step of Fig. 5 was applied. No energy was lost thanks to the use of the genetic optimization algorithm over this period. As the results presented in Fig. 11 show, the water heaters demand has been shifted before and after the critical period when the generated power is greater than the demand. Moreover, as Fig. 11 and Fig. 12 show, pre-heating was proposed before the 1<sup>st</sup> of March. The modified heating profile leads to a heat discomfort of 31.03 °C.h for temperatures lower than normal temperature (*DHL*) and 12.3 °C.h for temperatures higher than normal temperature (*DHH*), due to pre-heating.

According to these results, the application of the proposed DSM algorithm effectively reduced the unmet load energy *UL* and improved thermal comfort compared to a case where no DSM was applied. The fourth step of the algorithm increases the computational time due to the computation of the genetic algorithm but the obtained time (150 s) remains short in comparison with the hour given to the algorithm to propose a new planning.

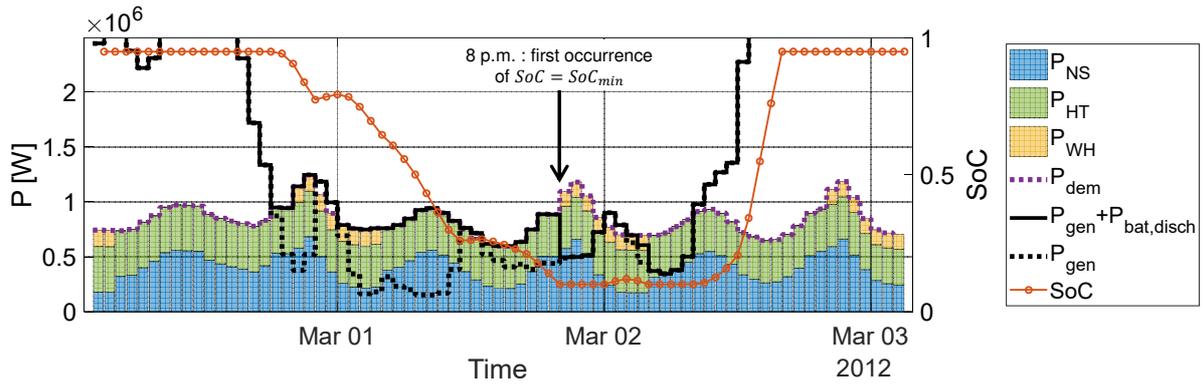


Fig. 9. Power and SoC profiles for simulation without DSM (Mode 1)

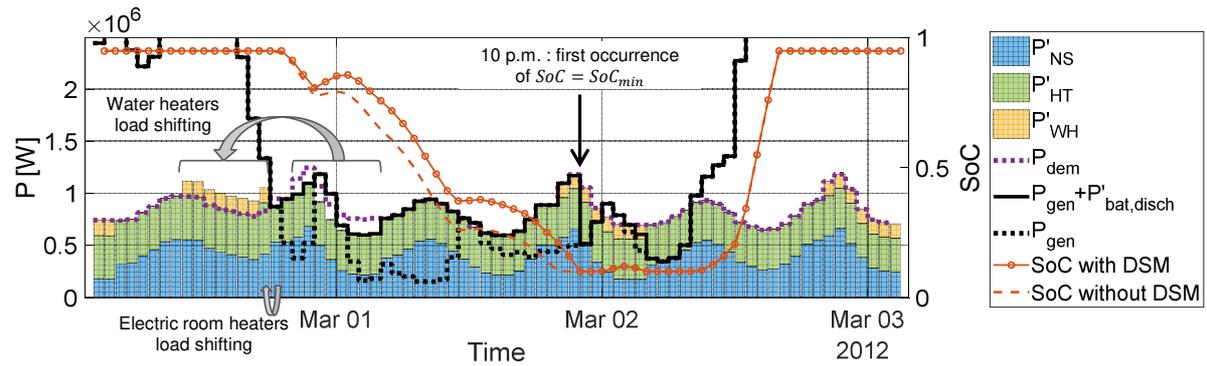


Fig. 10. Power and SoC profiles for simulation with DSM based on anticipation (Modes 2 and 3)

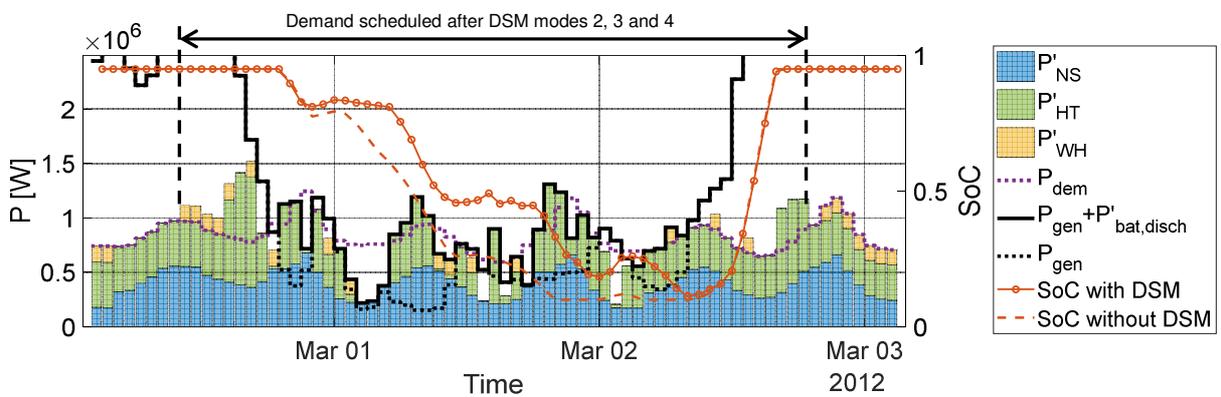


Fig. 11. Power and SoC profiles for simulation with DSM based on anticipation and scheduling according to load shedding and load shifting (Mode 4)

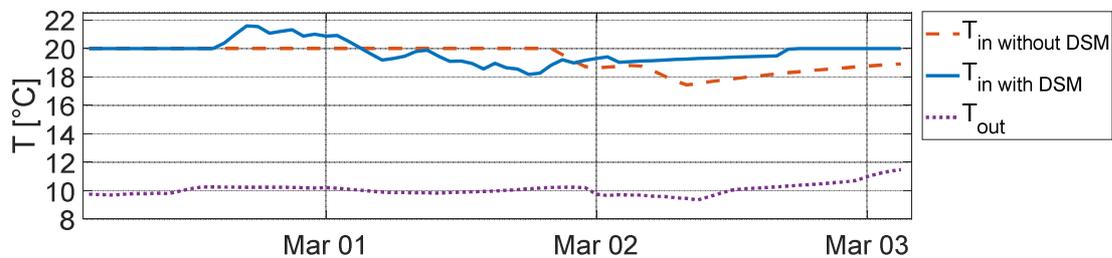


Fig. 12. Room air temperature evolution (Mode 4)

Table 3: Summary of the results obtained after application of each step of the multi-level DSM algorithm

Level of DSM algorithm	UL [%]	Number of hours of fully discharged batteries	DHL [°C.h]	DHH [°C.h]	Computational time [s]
1: without DSM (Fig. 9)	5.68	9	49.26	0	0.26
2: after application of water heaters anticipation DSM strategy	3.73	7	36.01	0	0.35
3: after application of electric room heaters anticipation DSM strategy (Fig. 10)	3.6	7	34.59	0.08	0.4
4: after genetic algorithm computation (Fig. 11)	0	0	31.03	12.3	150

#### 4.2. Validation of Demand-Side Management strategy for critical situations (Mode 4)

The proposed DSM strategy for critical situations (Mode 4 of DSM algorithm) is based on the use of a meta-heuristic method (genetic algorithm) which means that the convergence of the method needs to be validated and the impact of the weighting factors assessed. In this section, the genetic algorithm was run over a period of  $K = 36$  hours presented in Fig. 13, corresponding to a part of the profile used in Fig. 9.

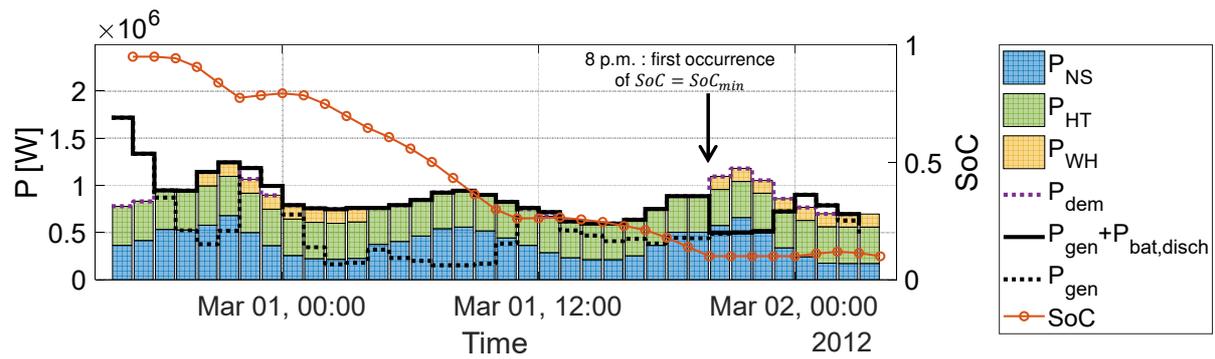


Fig. 3. Period considered for the validation of the genetic algorithm convergence, without DSM

##### 4.2.1. Convergence and reproducibility validation

To ensure that the objective function could reach a value close to the minimum in short time, the number of generations  $N_{gen}$  is set at 8000. The results obtained are presented in Fig. 14 and Table 4. Although the unmet load energy  $UL$  is reduced ( $UL = 2.46\%$ ) compared to a case without DSM, it does not reach zero. Indeed, the power generated was found to be larger than the demand for only two hours (the first two hours of the Fig. 13 period) which were used for the load shifting of water heaters and electric room heaters. Thus, load shedding could not be avoided during this period. The solution proposed by genetic algorithm for this period leads to a loss of energy of 5.34% for other loads, 0% for electric room heaters and 0% for water heaters.

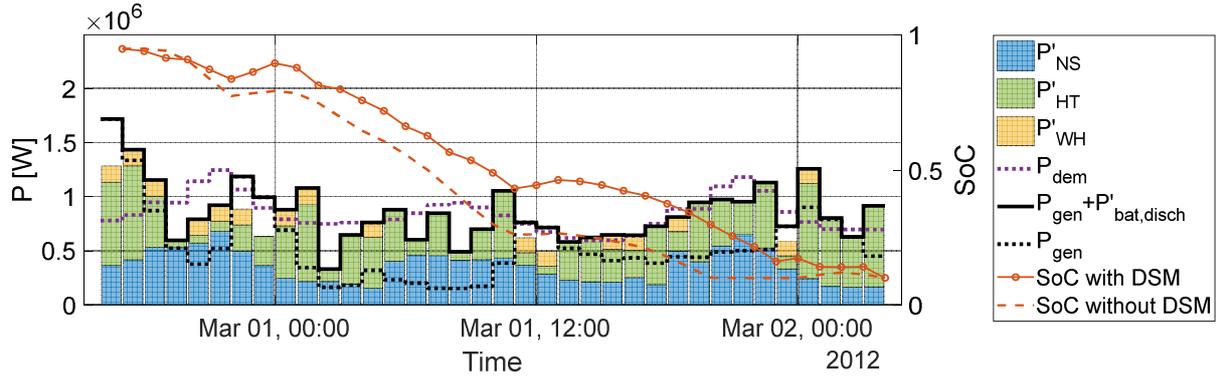


Fig. 4. Results obtained after execution of the genetic algorithm

Table 4: Summary of the results obtained after application of the genetic algorithm

Level of DSM algorithm	$UL$ [%]	Number of hours of fully discharged batteries	$DHL$ [ $^{\circ}C.h$ ]	$DHH$ [ $^{\circ}C.h$ ]
1: without DSM (Fig. 13)	6.74	5	8.95	0
4: after genetic algorithm computation (Fig. 14)	2.46	0	8.05	9.28

The evolution of the objective function during the genetic algorithm execution for this period is given in Fig. 15, according to the iteration number. The results show that the chosen number of generations is sufficient to ensure convergence as the objective function value reached a value close to the minimum in short time. For a number of generations  $N_{gen}$  set to 8000 and a scheduling period of  $K = 36$ , the computation time was found to be around 150 seconds.

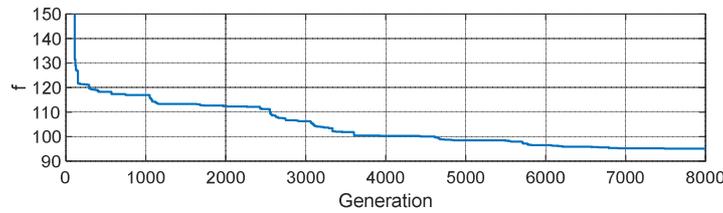


Fig. 5. Evolution of the objective function according to the generation number

To check and approve the meta-heuristic method used for critical situations, reproducibility and convergence were validated by running the genetic algorithm multiple times for the same scheduling period (Fig. 13). The unmet load  $UL$  and rates of the lost energy for each load, corresponding to the terms  $y_1$ ,  $y_3$  and  $y_4$  of the objective function, are given in Table 5 for ten executions of the genetic algorithm. The results obtained show a convergence with the same distribution of energy losses. The average unmet load  $UL$  reached 2.471% due to the shedding of non-shiftable loads, while the electric room heaters' demand and the water heaters' demand were retained. The calculation of standard deviation shows a low dispersion of the results.

Table 5: Reproducibility of the genetic algorithm

Run	Unmet Load $UL$ [%]	$100y_1$ [%] (water heaters lost energy)	$100y_3$ [%] (electric room heaters lost energy)	$100y_4$ [%] (other loads lost energy)
1	2.467	0	0	5.342
2	2.500	0	0	5.414
3	2.467	0	0	5.342
4	2.471	0	0	5.351
5	2.468	0	0	5.345
6	2.464	0	0	5.336
7	2.471	0	0	5.351
8	2.467	0	0	5.342
9	2.467	0	0	5.342
10	2.466	0	0	5.340
Average value	2.471	0	0	5.35
Standard deviation (relative to the average value)	0.01 (0.4%)	0 (0%)	0 (0%)	0.02 (0.4%)

#### 4.2.2. Impact of weighting factors

To assess the impact of the weighting factors considered in the objective function, a sensitivity analysis was carried out by running the genetic algorithm over the period of 36 hours used in Fig. 13 and changing only one weighting factor value each time. The results are summarized in Table 6 in which the first line represents the basic configuration discussed in sections 4.1 and 4.2.1.

Table 6: Loss of energy and comfort degradation according to weighting factor values

$w_1$	$w_2$	$w_3$	$w_4$	$w_5$	$UL$ [%] (Without DSM: 6.74%)	$100y_1$ [%] (water heaters lost energy)	$100y_3$ [%] (electric room heaters lost energy)	$100y_4$ [%] (other loads lost energy)	$DHL$ [°C.h] (Without DSM: 8.95°C.h)	$DHH$ [°C.h] (Without DSM: 0°C.h)
200	1	1000	1000	500	2.46	0	0	5.34	8.05	9.28
100	1	1000	1000	500	2.47	6	0	4.37	8.88	8.94
500	1	1000	1000	500	2.46	0	0.15	5.18	13.78	17.00
200	500	1000	1000	500	2.59	0	0	5.62	6.08	6.99
200	1	500	1000	500	2.47	0	5.31	0.02	22.08	10.25
200	1	2000	1000	500	3.22	0	0	6.98	6.80	8.38
200	1	1000	500	500	3.42	0	0	7.40	10.81	15.79
200	1	1000	2000	500	2.47	0	5.31	0.02	21.44	11.88
200	1	1000	1000	50	2.47	0	0.08	5.26	10.16	8.89
200	1	1000	1000	1000	2.46	0	0.01	5.33	11.65	8.97

By reducing  $w_1$ , the loss of water heater energy was found to increase, as this loss was penalized less. When the weighting factor  $w_2$  was increased, the variations of electric room heater power around the initial value were limited leading to a greater loss of energy and lower thermal discomfort. The increase of  $w_3$  was found to improve thermal comfort but if its value is larger than  $w_4$ , more shedding occurs for the other loads. To give more priority to the other loads, the weighting factor  $w_4$  must be greater than  $w_3$ . However, this distribution of weighting factors was found to lessen thermal comfort. Finally, changes applied to  $w_5$  showed that decreasing it enabled the reduction of other loads shedding but thermal comfort was lessened. A small  $w_5$  corresponds to a

lower penalization of the batteries discharge which means that the load shedding during occurrences of batteries discharge can be avoided.

#### 4.3. Sensitivity analysis

A sensitivity analysis of the parameters used in the proposed algorithm was carried out over the same period than the period considered in Fig. 9 ( $N = 72$ ) by applying the multi-level DSM algorithm given in Fig. 5.

Firstly, the impacts of the scheduling period  $K$  and the update time  $\delta$  were assessed. The results presented in Fig. 16 show that a long scheduling period allows the total unmet load rate  $UL$  to be reduced because the DSM strategies based on load shifting (water heaters and electric room heaters) can be applied early enough to avoid load shedding. However, a long scheduling period requires a long-term weather forecast which decreases the predicted reliability of the results. Also, a long scheduling period increases the computation time, especially for the genetic algorithm, as the number of decision variables increases. However, as Fig. 17 shows, the computation time of the multi-level DSM algorithm is always smaller than the shortest update time step ( $\delta = 1$  h) whatever the duration  $K$  of the scheduling period considered. For example, the computation time was found to be about 150 seconds for  $K = 36$  and did not exceed three minutes for the longest value ( $K = 48$ ). Thus, the proposed algorithm is computationally efficient for use in a real time system. Moreover, a short update period ( $\delta = 6$ ) allows the occurrence of a low state of charge to be detected earlier compared to the case where  $\delta = 12$  (Fig. 16), which decreases the total unmet load rate  $UL$ . An update time step of 6 hours corresponds to the duration between two updates of the weather forecasts. Thus, the case with  $K = 36$  and  $\delta = 6$  seems to be a good compromise between load scheduling optimization, algorithm performance and data prediction effectiveness .

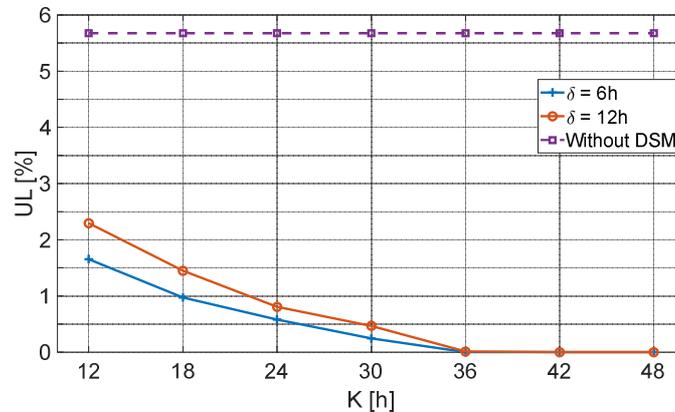


Fig. 6. Influence of the scheduling period duration and the update period on the unmet load rate

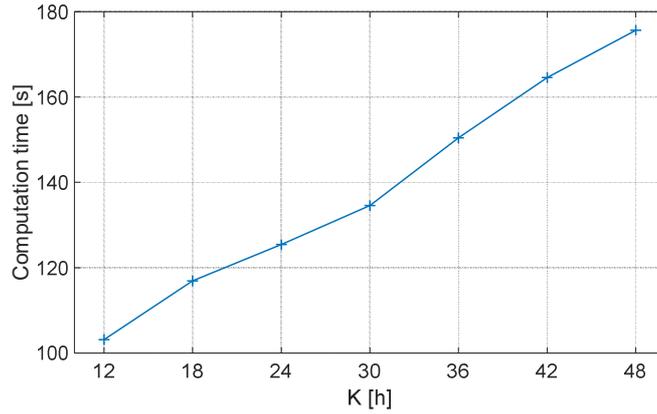


Fig. 17 : Influence of the scheduling period duration on the computation time of the multi-level DSM algorithm

Finally, the effect of the state of charge threshold value  $SoC_a$  included in the DSM algorithm (Fig. 5 and Fig. 6) was studied. This parameter corresponds to the value which activates the application of strategies based on load anticipation. Thus, a sensitivity analysis was carried out according to different  $SoC_a$  and  $K$  values by applying steps 2 and 3 of the DSM algorithm over the period presented in Fig. 5, as done in the third case of the Table 3. The results presented in Fig. 18 show that the increase of  $SoC_a$  allowed the unmet demand rate  $UL$  to be reduced because the DSM strategies were applied earlier. In the case of a low  $SoC_a$  value (0.2 for example), less occurrences of the power generated being greater than the load power were found over the scheduling period which limits the possibilities to shift consumption. Moreover, a broad time window ( $K = 36$  for example) was found to improve the unmet demand reduction.

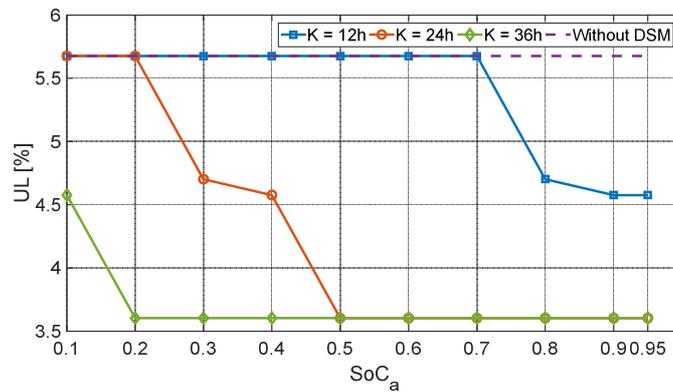


Fig. 7. Impact of threshold SoC value triggering the application of strategies based on anticipation, considering only the DSM modes 1, 2 and 3

## 5. Conclusion

This paper presents a set of DSM strategies which can be used to enhance flexibility in the energy management of an offgrid system based on the use of different renewable sources. The considered DSM

strategies are based on load shifting and load shedding and were applied to water heaters, electric room heaters and other loads according to the proposed algorithm. The starting assumption was that the first two kinds of loads could be controlled remotely. The hierarchical algorithm was found to favour load shifting by anticipating shiftable loads when an excess of generated power occurs and before critical situations. To prevent and avoid situations in which the batteries become discharged, a new load schedule has been proposed using a genetic algorithm, allowing load shedding and load shifting actions to be weighted according to user preferences. The main results obtained from this study show the benefits of anticipating shiftable loads when enough energy is generated by the sources according to the reduction of the unmet load rate. As such strategies cannot always avoid critical situations, some load shedding is sometimes required. Thus, a compromise is needed to share the loss of energy between the three load profiles to prevent thermal comfort being lessened as much as possible. The sensitivity analysis carried out shows a sufficiently long scheduling period and a short update period are required to reduce energy loss as much as possible. A zero unmet load rate was achieved thanks to the proposed algorithm and the load shifting strategies. This is an improvement on the results obtained in a previous study done for the same multi-source system with only DSM strategies based on load anticipation [19]. A zero unmet load rate cannot always be achieved in studies dealing with DSM according to the results presented in [21,37].

Future work will attempt to assess the impact of the proposed DSM algorithm on the multi-source system sizing in terms of unmet load rate and costs. Moreover, an analysis of the most suitable sources among the four considered herein will be carried out according to the strategies proposed. The proposed DSM algorithm could be modified by considering more types of loads if their power can be forecasted for the  $K$  forthcoming hours. Additional *SoC* levels could also be added to the multi-level algorithm so as to trigger the strategies considered for these loads. Finally, the algorithm needs to be computed on a real-time test bench to ensure that it is computationally efficient and can interact with external data.

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## References

- [1] Kuang Y, Zhang Y, Zhou B, Li C, Cao Y, Li L, et al. A review of renewable energy utilization in islands. *Renew Sustain Energy Rev* 2016;59:504–13. doi:10.1016/j.rser.2016.01.014.
- [2] Gioutos DM, Blok K, van Velzen L, Moorman S. Cost-optimal electricity systems with increasing renewable energy penetration for islands across the globe. *Appl Energy* 2018;226:437–49. doi:10.1016/j.apenergy.2018.05.108.

- [3] Meza CG, Zuluaga Rodríguez C, D'Aquino CA, Amado NB, Rodrigues A, Sauer IL. Toward a 100% renewable island: A case study of Ometepe's energy mix. *Renew Energy* 2019;132:628–48. doi:10.1016/j.renene.2018.07.124.
- [4] Dorotić H, Doračić B, Dobravec V, Pukšec T, Krajačić G, Duić N. Integration of transport and energy sectors in island communities with 100% intermittent renewable energy sources. *Renew Sustain Energy Rev* 2019;99:109–24. doi:10.1016/j.rser.2018.09.033.
- [5] Notton G. Importance of islands in renewable energy production and storage: The situation of the French islands. *Renew Sustain Energy Rev* 2015;47:260–9. doi:10.1016/j.rser.2015.03.053.
- [6] Blechinger P, Cader C, Bertheau P, Huyskens H, Seguin R, Breyer C. Global analysis of the techno-economic potential of renewable energy hybrid systems on small islands. *Energy Policy* 2016;98:674–87. doi:10.1016/j.enpol.2016.03.043.
- [7] Rodrigues EMG, Godina R, Santos SF, Bizuayehu AW, Contreras J, Catalão JPS. Energy storage systems supporting increased penetration of renewables in islanded systems. *Energy* 2014;75:265–80. doi:10.1016/j.energy.2014.07.072.
- [8] Sabihuddin S, Kiprakis AE, Mueller M. A Numerical and Graphical Review of Energy Storage Technologies. *Energies* 2015;8:172–216. doi:10.3390/en8010172.
- [9] Khan N, Kalair A, Abas N, Haider A. Review of ocean tidal, wave and thermal energy technologies. *Renew Sustain Energy Rev* 2017;72:590–604. doi:10.1016/j.rser.2017.01.079.
- [10] Roy A, Auger F, Dupriez-Robin F, Bourguet S, Tran QT. Electrical Power Supply of Remote Maritime Areas: A Review of Hybrid Systems Based on Marine Renewable Energies. *Energies* 2018;11:1904. doi:10.3390/en11071904.
- [11] Argyrou MC, Christodoulides P, Kalogirou SA. Energy storage for electricity generation and related processes: Technologies appraisal and grid scale applications. *Renew Sustain Energy Rev* 2018;94:804–21. doi:10.1016/j.rser.2018.06.044.
- [12] Lund PD, Lindgren J, Mikkola J, Salpakari J. Review of energy system flexibility measures to enable high levels of variable renewable electricity. *Renew Sustain Energy Rev* 2015;45:785–807. doi:10.1016/j.rser.2015.01.057.
- [13] Gellings CW. The concept of demand-side management for electric utilities. *Proc IEEE* 1985;73:1468–70. doi:10.1109/PROC.1985.13318.
- [14] Jabir H, Teh J, Ishak D, Abunima H. Impacts of Demand-Side Management on Electrical Power Systems: A Review. *Energies* 2018;11. doi:10.3390/en11051050.
- [15] Vardakas JS, Zorba N, Verikoukis CV. A Survey on Demand Response Programs in Smart Grids: Pricing Methods and Optimization Algorithms. *IEEE Commun Surv Tutor* 2015;17:152–78. doi:10.1109/COMST.2014.2341586.
- [16] Haider HT, See OH, Elmenreich W. A review of residential demand response of smart grid. *Renew Sustain Energy Rev* 2016;59:166–78. doi:10.1016/j.rser.2016.01.016.
- [17] Palensky P, Dietrich D. Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads. *IEEE Trans Ind Inform* 2011;7:381–8. doi:10.1109/TII.2011.2158841.
- [18] Strbac G. Demand side management: Benefits and challenges. *Energy Policy* 2008;36:4419–26. doi:10.1016/j.enpol.2008.09.030.
- [19] Roy A, Auger F, Bourguet S, Dupriez-Robin F, Tran QT. Benefits of Demand Side Management strategies for an island supplied by marine renewable energies. 2018 IEEE Int. Conf. Renew. Energy Res. Appl. ICRERA, Paris: 2018.
- [20] Friedrich D, Lavidas G. Evaluation of the effect of flexible demand and wave energy converters on the design of hybrid energy systems. *IET Renew Power Gener* 2017;11:1113–9. doi:10.1049/iet-rpg.2016.0955.
- [21] Chauhan A, Saini RP. Size optimization and demand response of a stand-alone integrated renewable energy system. *Energy* 2017;124:59–73. doi:10.1016/j.energy.2017.02.049.
- [22] Zizzo G, Beccali M, Bonomolo M, Di Pietra B, Ippolito MG, La Cascia D, et al. A feasibility study of some DSM enabling solutions in small islands: The case of Lampedusa. *Energy* 2017;140:1030–46. doi:10.1016/j.energy.2017.09.069.
- [23] Pina A, Silva C, Ferrão P. The impact of demand side management strategies in the penetration of renewable electricity. *Energy* 2012;41:128–37. doi:10.1016/j.energy.2011.06.013.
- [24] EDF SEI. Open Data EDF îles du Ponant n.d. <https://opendata-iles-ponant.edf.fr/explore/dataset/conso-3-iles-final/> (accessed March 14, 2018).
- [25] Bridier L, Hernández-Torres D, David M, Lauret P. A heuristic approach for optimal sizing of ESS coupled with intermittent renewable sources systems. *Renew Energy* 2016;91:155–65. doi:10.1016/j.renene.2016.01.021.
- [26] Zaibi M, Cherif H, Champenois G, Sareni B, Roboam X, Belhadj J. Sizing methodology based on design of experiments for freshwater and electricity production from multi-source renewable energy systems - ScienceDirect. *Desalination* 2018;446:94–103.

- [27] Lefebvre S, Desbiens C. Residential load modeling for predicting distribution transformer load behavior, feeder load and cold load pickup. *Int J Electr Power Energy Syst* 2002;24:285–93. doi:10.1016/S0142-0615(01)00040-0.
- [28] Logenthiran T, Srinivasan D, Shun TZ. Demand Side Management in Smart Grid Using Heuristic Optimization. *IEEE Trans Smart Grid* 2012;3:1244–52. doi:10.1109/TSG.2012.2195686.
- [29] Graditi G, Silvestre MLD, Gallea R, Sanseverino ER. Heuristic-Based Shiftable Loads Optimal Management in Smart Micro-Grids. *IEEE Trans Ind Inform* 2015;11:271–80. doi:10.1109/TII.2014.2331000.
- [30] Rahim S, Javaid N, Ahmad A, Khan SA, Khan ZA, Alrajeh N, et al. Exploiting heuristic algorithms to efficiently utilize energy management controllers with renewable energy sources. *Energy Build* 2016;129:452–70. doi:10.1016/j.enbuild.2016.08.008.
- [31] Reddy SS. Optimizing energy and demand response programs using multi-objective optimization. *Electr Eng* 2017;99:397–406. doi:10.1007/s00202-016-0438-6.
- [32] Houck CR, Joines JA, Kay MG. *A Genetic Algorithm for Function Optimization: A Matlab Implementation*. 1996.
- [33] Saker N, Petit M, Vannier J-C, Coullon J-L. Cold Load Pick-Up with Electrical Space Heating Loads Under Demand Response Actions. 2011 IEEE PES PowerTech, Trondheim: 2011.
- [34] Silva DD, Duplessis B, Adnot J. A methodology for evaluating the energy, peak load and comfort effects of demand response control strategies for electric heating, 2011.
- [35] Li X, Huang Y, Huang J, Tan S, Wang M, Xu T, et al. Modeling and control strategy of battery energy storage system for primary frequency regulation. 2014 Int. Conf. Power Syst. Technol., 2014, p. 543–9. doi:10.1109/POWERCON.2014.6993760.
- [36] Ding H, Zhang W, Chen M, Li S, Hou T, Zhou X, et al. Multi-Objective Optimal Configuration of Distributed Wind-Solar Generation Considering Energy Storage. 2018 2nd IEEE Conf. Energy Internet Energy Syst. Integr. EI2, 2018, p. 1–6. doi:10.1109/EI2.2018.8582361.
- [37] Kallel R, Boukettaya G, Krichen L. Demand side management of household appliances in stand-alone hybrid photovoltaic system. *Renew Energy* 2015;81:123–35. doi:10.1016/j.renene.2015.03.024.

## Figures/Tables captions

Figure/Table	Caption	Size	Color
Fig. 1	Overview of the considered multi-source system	Single column	No
Fig. 2	Fig. 2: Flowchart of the energy management algorithm considered for the calculation of the powers $P_{bat}$ , $P_{gen}$ and $P_{dem}''$	Double column	No
Fig. 3	Timeline of the simulation with rolling horizon for day-ahead scheduling	Single column	No
Fig. 4	Flowchart of the anticipation based DSM strategy for electric room heaters demand	Double column	No
Fig. 5	Flowchart of the multi-level DSM algorithm	Single column	No
Fig. 6	DSM modes according to the threshold SoC values	Double column	Yes
Fig. 7	Overview of necessary data in the four DSM modes	Double column	No
Fig. 8	Flowchart of the simulation	Single column	No
Fig. 9	Power and SoC profiles for simulation without DSM (Mode 1)	Double column	Yes
Fig. 10	Power and SoC profiles for simulation with DSM based on anticipation (Modes 2 and 3)	Double column	Yes
Fig. 11	Power and SoC profiles for simulation with DSM based on anticipation and scheduling according to load shedding and load shifting (Mode 4)	Double column	Yes
Fig. 12	Room air temperature evolution (Mode 4)	Double column	Yes
Fig. 13	Period considered for the validation of the genetic algorithm convergence, without DSM	Double column	Yes
Fig. 14	Results obtained after execution of the genetic algorithm	Double column	Yes
Fig. 15	Evolution of the objective function according to the generation number	Single column	No
Fig. 16	Influence of the scheduling period duration and the update period on the unmet load rate	Single column	Yes
Fig. 17	Influence of the scheduling period duration on the computation time of the multi-level DSM algorithm	Single column	No
Fig. 18	Impact of threshold SoC value triggering the application of strategies based on anticipation, considering only the DSM modes 1, 2 and 3	Single column	Yes
Table 1	Genetic algorithm parameters	Single column	No
Table 2	Summary of the proposed DSM modes	Double column	No
Table 3	Summary of the results obtained after application of each step of the multi-level DSM algorithm	Double column	No
Table 4	Summary of the results obtained after application of the genetic algorithm	Double column	No
Table 5	Reproducibility of the genetic algorithm	Double column	No
Table 6	Loss of energy and comfort degradation according to weighting factor values	Double column	No