MODEL AND ALGORITHMS FOR THE REAL TIME MANAGEMENT OF RESIDENTIAL ELECTRICITY DEMAND

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ABSTRACT
Household Demand Side Management (DSM) systems play a key role in improving the efficiency of the entire electrical system. An efficient management of the energy resources can indeed allow spreading domestic energy loads in a smart way in order to reduce the peak power of the overall demand. To achieve this goal, home appliances and energy storage systems have to be controlled through the definition of energy plans for future periods (offline) and the real time control of energy resources (online). In this paper, we propose an optimization model and a set of heuristics for the online demand side management, to properly react in real time to events which were unexpected in a previous offline stage of the home management system, such as wrong weather forecasts or user’s misbehaviours. The final goal is to reschedule the energy consumption and production coherently with the energy plan defined in the offline phase, taking into account the real production of renewable energy sources and the capacity of storage devices. Along with the heuristics, we show the numerical results obtained by applying them on realistic instances of the problem.

Index Terms— Energy Demand Management, Residential Buildings, Smart Grid, Heuristics;

1. INTRODUCTION
Demand side management systems are receiving a growing attention in the development of the future smart grid. In fact, the application of a functional DSM system can significantly improve the efficiency of the energy production and distribution, in particular in residential contexts. The residential sector represents one of the most promising scenarios for using DSM capabilities. Domestic users, in fact, are one of the major contributors to the national energy balances, and an even more critical situation is forecast for the near future since the home energy consumption will probably exceed 40% of the total yearly consumption in most of the western countries. A DSM can be used to modify or reduce residential users energy demand through an offline and/or online approach. In the offline approach, the DSM defines the optimal energy plan for future periods by scheduling loads, deciding when to buy or sell energy and so on, according to forecasts (PV production, devices usage, etc.). In the online case, the DSM defines in real-time the energy plan of households based on the actual situation of the energy market and on users needs.

In this paper, we propose a part of the DSM system developed within the BEE Project [1]. This system has been designed for managing the electricity consumption of residential users, with the objectives of minimizing the energy bills and improving the efficiency of the electricity grid. To this purpose, we combine the offline and online approaches. The offline demand optimization model [2] has been designed to schedule the next day house appliances activities and power exchanges with the grid. In order to define the future energy plan, the optimization model requires predictions on the photovoltaic panels production and the users preferences about the home devices future usage. The outcome of this offline DSM is the 24 hour profile representing the energy that is planned to be purchased\sold from\to the grid for the next day. This information can be used by the energy retailer to optimize the grid management. Unfortunately, predictions are naturally subject to uncertainty, so the real energy demand and supply are often different from the planned profiles. For this reason, the advantages obtained by adopting the offline method are nullified. In this paper, we propose an online DSM model, which deals with real time events that were unexpected or wrongly forecast. The final goal is to optimally reschedule home devices activities and decide when to store\buy\sell energy to the grid, coherently with the offline plan.

The remainder of this paper is organized as follows. In Section 2 we review previous works on offline and online demand side management. In Section 3 we describe the basic characteristics of the offline model designed within the BEE project. In Section 4 we present an online model and two heuristics developed to quickly react to real time events. Section 5 reports the numerical results that we have obtained by testing the algorithms based on realistic data. Finally, the paper is concluded in Section 6.
2. RELATED WORK

Demand side management has been deeply studied by the scientific community because of the possible advantages achievable through this kind of mechanism, such as the peak shaving and load shifting. The execution of many home appliances, for example, may be postponed with only a little discomfort for households. Even just optimizing this procedure may lead to significant peak reductions.

In literature, two kinds of demand side management are proposed: offline and online. In the offline scenario, DSM mechanisms [3], [4], [5] are designed to define the optimal energy plans of households for future periods, based on data forecasts. In the online scenario, a real time energy plan is defined according to events that occur during the day. In [6] an optimization model is presented to adjust the hourly load level of a given consumer in response to electricity prices. The objective of the model is to maximize the utility of the consumer, subject to several constraints such as minimum daily energy consumption levels and limits on hourly loads. Real time management is also discussed in [7]. In this case a multi-level optimization framework for demand-side load management of a group of houses is proposed. The control algorithm provides predictions on energy consumption and the possibility of adjusting the energy allocation in real time is introduced, to cope with errors in the forecast energy consumption. Finally, in [8] the authors propose a system which works as an online smart demand response solution and is based on an explicit demand-based power supply control. By applying the method it is possible to reduce the energy consumption without damaging the comfort of domestic users. Moreover, energy retailer companies are allowed to set and modify power ceiling values based on contracts with consumers.

With respect to most of these papers, our online model is based on the outcome provided by an offline demand side management model and its goal is to react to real time events by rescheduling the energy consumption coherently with the offline plan. Moreover, more attention has been spent on modeling household contexts: we take into account a realistic domestic scenario (domestic loads, PV generators, batteries, energy prices) as well as the user requirements.

3. BEE PROJECT FRAMEWORK

The BEE (Bright Energy Equipment) Project [1] is a research activity of Politecnico di Milano. The purpose of the project is to provide advanced tools to residential users in order to make them an active part of future Smart Grids. In the considered scenario, houses can be equipped with PhotoVoltaic (PV) panels, batteries and sensors (e.g. power meters for the monitoring of the energy consumption of home devices). The core of the framework is the BEE box, a smart processing unit which manages and optimizes the home energy plan and exchanges data with the other actors of the electrical system.

The home energy management is performed in two different steps, offline and online. The offline DSM optimization model [2] is introduced with the task of scheduling the house appliances activities and power exchanges with the electricity network for the next day. This model uses the predictions on PV production and devices future usage. For the PV plant, we defined an ad-hoc learning method which predicts the panels production based on the weather forecast. Similar algorithms have also been introduced to predict the house load demand [9] (i.e. which home appliances will be used and at what time of the day) based on data provided by the power meter sensors. The offline optimization model designed in the BEE Project [2] is shortly presented in the following subsection.

3.1. Offline Optimization Model

The problem is modelled as a Mixed Integer Linear Programming (MILP) model. The 24 hour daytime is divided into 96 time slots of 15 minutes each (set $T$). In order to schedule house appliance activities (set $A$), a set of binary variables $x_{at}^{OFF}$ is defined for each activity $a \in A$ and for each time slot $t \in T$, equal to 1 if the activity $a$ starts in the time slot $t$, 0 otherwise. Besides, the continuous non-negative variables $y_t^{OFF}$ and $z_t^{OFF}$ represent the amount of bought and sold energy, respectively, in each time slot $t$.

Objective Function The objective of the model is to minimize the daily energy bill. Denoting with $c_t$ and $g_t$ respectively the cost of bought and sold energy in the time slot $t$, the objective function can be defined as:

$$\min \sum_{t \in T} (c_t \cdot y_t^{OFF} - g_t \cdot z_t^{OFF})$$

Activity scheduling For every activity $a \in A$, associated with the execution of a house appliance, the devices prediction algorithm presented in [9] automatically computes its earliest starting time, $ST_a$, and its latest starting time, $ET_a$, that define a time window in which the activity can be launched. Constraints:

$$\sum_{t = ST_a}^{ET_a} x_{at}^{OFF} = 1 \quad \forall a \in A$$

guarantee that the activity $a$ is carried out in the required interval $(ST_a, ET_a)$.

Battery constraints The charge and discharge rates are represented by the continuous non-negative variables $cr_t^{OFF}$ and $dr_t^{OFF}$. Such variables are bounded, for each $t \in T$, according to the following constraints, where $\tau_{max}$ and $\varphi_{max}$ are the maximum charge and discharge rates, respectively:

$$cr_t^{OFF} \leq \tau_{max}, \quad dr_t^{OFF} \leq \varphi_{max} \quad \forall t \in T$$
In each time slot, the battery energy depends on the energy in the previous time slot, and on the charge and discharge rates, according to the following constraints:

\[ e_t^{\text{OFF}} = e_{(t-1)}^{\text{OFF}} + cr_t^{\text{OFF}} - dr_t^{\text{OFF}} \quad \forall t \in T \]  

(4)

Finally, the energy charge level of the battery can’t exceed its capacity \( \gamma^{\max} \):

\[ e_t^{\text{OFF}} \leq \gamma^{\max} \quad \forall t \in T \]  

(5)

**Balancing constraints** These constraints force the balance between the acquired energy (first member) and the consumed energy (second member) in each timeslot:

\[ y_t^{\text{OFF}} + \pi_t^{\text{OFF}} + d_t^{\text{OFF}} = z_t^{\text{OFF}} + \sum_{a \in A} p_{at}^{\text{OFF}} + cr_t^{\text{OFF}} \quad \forall t \]  

(6)

where \( \pi_t^{\text{OFF}} \) represents the predicted PV production in the time slot \( t \) and \( p_{at}^{\text{OFF}} \) is the energy consumed by the device \( a \) in the slot \( t \), depending on its starting timeslot.

Based on data forecasts (PV panels production and load demand) and energy tariffs, the optimization model defines an energy plan for the next day which minimizes the daily bill. The model, in particular, schedules when to buy and sell energy (i.e. \( y_t^{\text{OFF}} \) and \( z_t^{\text{OFF}} \), see Figure 1) and when to start home appliances. The output is an energy plan which can be used by the energy retailer to optimize its production/distribution.

Since in the offline model the 24 hour daytime is divided into 96 timeslots of 15 minutes each (set \( T \)), this model is conceived to be solved at the beginning of each timeslot. In real-time, anyway, we no longer have inaccurate data but precise data. In particular, at any time slot \( t \), we know the set of devices which have been used or are still running (\( z_{a(t+1)}^{\text{ON}} \)), the overall consumption of the devices in the current time slot (\( \sum_{a \in A} p_{at}^{\text{OFF}} \)), the energy charge level of the battery \( e_{(t-1)}^{\text{OFF}} \) and the real energy production of the photovoltaic panel (\( \pi_t^{\text{OFF}} \)).

Based on these data, the online model has to define the value of the following variables for the current time slot \( t \), satisfying the constraints presented in Section 3.1: battery charge or discharge rates \( cr_t^{\text{ON}} \) and \( dr_t^{\text{ON}} \), amount of energy to buy and sell, respectively \( y_t^{\text{ON}} \) and \( z_t^{\text{ON}} \) and the schedule of the appliances for the current and future timeslots \( z_{a(t,t+1)}^{\text{ON}} \). The final objective of the model is to keep the demand and supply profiles as close as possible to those defined by the offline phase (i.e. \( y_t^{\text{OFF}} \) and \( z_t^{\text{OFF}} \)). We call Profile Error \( (PE_t) \) for each timeslot \( t \) the difference between the real profile and the scheduled one:

\[ PE_t = | y_t^{\text{ON}} - y_t^{\text{OFF}} | + | z_t^{\text{ON}} - z_t^{\text{OFF}} | \]  

(7)

Every 15 minutes, the energy plan is rescheduled according to the following objective function:

\[ \min PE = \sum_{t=1}^{96} PE_t \]  

(8)

subject to the same constraints as the offline model, where we substitute the \( OFF \) variables with the respective \( ON \) variables defined above. Note that these variables are treated as parameters for the timeslots prior to the actual \( t \). Minimizing PE allows avoiding high peaks due to unexpected demands of high amounts of energy.

As a new schedule is required almost instantly, in the following we will present two heuristics to efficiently solve this problem. The heuristics differ in the time scale used to reschedule the energy plan, which can be single slot or multi slot. The single slot heuristic reschedules activities only for the current time slot \( t \), with the goal of minimizing \( PE_t \), while the multi-slot heuristic minimizes the value of \( PE \) by reoptimizing through the remaining portion of the day. In this case, the day ahead forecasts are reused for the timeslots subsequent to the actual one.

**4. ONLINE OPTIMIZATION MODEL**

The offline method presented in Section 3.1 requires the prediction of some parameters which are naturally subject to uncertainty, so the user energy demand and supply may actually be different from the planning. For this reason we propose a new optimization model which reschedules home activities (appliance executions, storage operations) in real-time, with the goal of obtaining a demand and supply profiles (i.e. \( y_t^{\text{OFF}} \) and \( z_t^{\text{OFF}} \)) which are as close as possible to the offline profiles.

4.1. Single-Time Slot Online Heuristic

In the single time slot scenario, in every time slot \( t \), the online algorithm has to define the energy demand and supply profile in \( t \) (i.e. \( y_t^{\text{ON}} \) and \( z_t^{\text{ON}} \)) with the aim of minimizing the profile error \( PE_t \). In order to achieve this goal, the algorithm can both charge or discharge the battery and reschedule the devices that have still to be used. The algorithm used for minimizing \( PE_t \) performs the following four steps:

**Step 1) No Battery and Appliances Scheduling** The algorithm verifies if it is possible to use the same demand and
supply profile defined by offline model (i.e. \( y_t^{ON} = y_t^{OFF} \) and \( z_t^{ON} = z_t^{OFF} \)), with no changes in the schedule of the devices and without using the battery. For this reason \( cr_t^{ON} \) and \( dh_t^{ON} \) are both set to 0 and the appliance execution for the future time slots is unchanged, so that \( x_{a(t,t+1,...,96)}^{ON} = x_{a(t,t+1,...,96)}^{OFF} \). The balancing constraint (6) is updated according to the real time value of the photovoltaic panel production and of the energy consumed by home devices in the current time slot \( t \):

\[
y_t^{OFF} + a_t^{ON} = z_t^{OFF} + \sum_{a \in A} p_{at}^{ON} \tag{9}
\]

If equation (9) is verified, then it is possible to use the same demand and supply defined by offline model, \( PE_t \) is equal to 0 and the algorithm stops. Notice that in this case, since \( cr_t^{ON} \) and \( dh_t^{ON} \) are both equal to 0, the battery constraints (3), (4), (5) are satisfied as well as the appliances scheduling constraint (2), since the devices scheduling has not been modified. If equation (9) is not verified, the algorithm goes to step 2 to balance the input and output energy of the system described in (9) using the battery:

Step 2) Battery The algorithm readapts the charge and discharge rates. Two different cases may occur:

(a) If the input energy (i.e. the first term of equation (9)) is greater than the output energy, the battery can be charged to minimize \( PE_t \). In this case, \( dh_t^{ON} \) is still set to 0 and \( cr_t^{ON} \) is set to the difference between the input and the output energy, so that the updated balancing constraint (10) is verified:

\[
y_t^{OFF} + a_t^{ON} = z_t^{OFF} + \sum_{a \in A} p_{at}^{ON} + cr_t^{ON} \tag{10}
\]

If the battery constraints (3), (4), (5) are satisfied for the new values of \( cr_t^{ON} \) and \( dh_t^{ON} \) then it is possible to use the same demand and supply defined by the offline model (i.e. \( y_t^{ON} = y_t^{OFF} \) and \( z_t^{ON} = z_t^{OFF} \)), \( PE_t \) is equal to 0 and the algorithm stops. Otherwise the algorithm computes the maximum value of \( cr_t^{ON} \) which satisfies the battery constraints. For the new charge rate value, the difference, \( D \), between the input and output energy in the constraint (10) is computed and the algorithm goes to step 3.

(b) If the input energy of equation (9) is less than the output energy, the same kind of procedure described for the above case a) is performed except for the fact that in this case the battery has to be discharged in order to minimize \( PE_t \).

Step 3) Appliances Scheduling The algorithm changes the schedule of appliances. In this procedure, we start, in the current time slot \( t \), one or more among the devices that still have to be used. Once again, two possible scenarios can occur:

(a) The difference, \( D \), between the input and output energy in the balance constraint is positive: in this case, it is required to increase the output energy in the balance constraint (hence, the energy consumed by devices \( \sum_{a \in A} p_{at}^{ON} \)) by the amount \( D \). For this purpose, we group the appliances which still have to be launched (we call this set \( B \subseteq A \)) and we define a subset of devices \( C \subseteq B \) which may be started in the current time slot without violating the constraint (2):

\[
C = \{ b \in B : t \in [ST_b, ET_b] \}
\]

Each of these devices is characterized by the corresponding power consumption \( p_c \). The problem is to decide which devices belonging to \( C \) have to be started in the time slot \( t \) to increase the devices total consumption by the amount \( D \). This is a particular case of the 0-1 knapsack problem, a well known problem in combinatorial optimization: given the set of items \( C \), each with a weight and a value (in this case both equal to \( p_c \)), determine which item to include in a collection so that the total weight is less than or equal to a given limit (in this case \( D \)) and the total value is maximized. The knapsack problem is an NP-hard problem but it can be efficiently solved by a number of algorithms [10]. After having defined the optimal subset of appliances to start in the time slot \( t \), the balancing constraint (10) is updated with the new value of the amount of energy consumed by the devices in the current time slot (i.e. \( \sum_{a \in A} p_{at}^{ON} \)). If the difference \( D \) between the input and output energy is 0, it is possible to use the same demand and supply defined by the offline model, \( PE_t \) is equal to 0 and the algorithm stops. Otherwise the algorithm goes to step 4.

(b) The difference, \( D \), between the input and output energy in the balancing constraint is negative: the algorithm goes straight to step 4. Indeed, in this case, it would be required to decrease the output energy and hence the amount of energy consumed by the devices. Unfortunately, in our model appliances activities are non preemptable so that it is not possible to stop devices that have already started.

Step 4) New Energy Demand and Supply The algorithm equally distributes on \( y_t^{ON} \) and \( z_t^{ON} \) the difference \( D \) in the balance constraint between input and output energy. In this case the value of the profile error \( PE_t \) is equal to \( D \).

4.2. Multi-Time Slot Online Heuristic

In the multi time slot scenario, in every time slot \( t \), the online model has to define the energy demand and supply profile in \( t \) (i.e. \( y_t^{ON} \) and \( z_t^{ON} \)) with the aim of minimizing the mean value of the profile error, \( PE \), computed through all the day long. In order to achieve this goal, the system can both charge/discharge the battery and reschedule the devices that still have to be used. The heuristic used for minimizing \( PE \) performs the following two steps:

Step 1) Single-Time Slot Mechanism The algorithm presented in Section 4.1 is applied to the current time slot in order to define the values of \( y_t^{ON} \) and \( z_t^{ON} \) that minimize the profile error \( PE_t \) based on the real time value of the PV production and the energy consumed by home devices. The same algorithm is also applied to every future time slot \( h \) (i.e. for \( h = t+1, t+2...,96 \)) based on the PV panel and devices usage forecast also considered in the offline step (real time data are not yet available for these slots) as to minimize \( PE_h \). At this
point we compute the mean value, here called $PE^r$, of the profile error. If $PE_i$ is less than $PE^r$, the algorithm goes to step 2 to try and increase the error experimented in the current time slot with the aim of decreasing $PE^r$, otherwise it stops. In fact, if $PE_i$ is greater than the error mean value, it would be useless to further increase its value: we know for sure that in time slot $t$ we would make a very high error, while the next time slots may still be subject to errors, because of the uncertainty of the forecasts used for planning the energy demand for these slots.

Step 2) Slot Selection The algorithm selects the first time slot $i (i = t + 1, t + 2, \ldots, 96)$ in which the error $PE_i$ is greater than $PE^r$. Let $I = PE_i - PE$. We apply the single-time slot heuristic to the current time slot $t$ with the goal of obtaining a Profile Error Value (PEV) equal to:

$$PEV = \begin{cases} PE_i + I & \text{if } PE_i + I \leq PE^r \\ PE^r & \text{otherwise} \end{cases}$$  \hspace{1cm} (11)$$

where $PE_i$ is the error obtained in the current time slot $t$ in the first step of the algorithm. Subsequently, the single slot mechanism is reapplied to every future time slot $h$ (i.e. for $h = t + 1, t + 2, \ldots, 96$) using the photovoltaic panel and devices usage forecast also considered in the offline step to minimize $PE_h$. Finally, the new mean value of the profile error, $PE_{new}$, is computed. If it is less than the one previously obtained $PE^r$, then $PE^r$ is set equal to $PE_{new}$ and the algorithm performs again the step 2 starting from $i = t + 1$. Otherwise $PE^r$ is not updated and $i$ is increased by one before executing again the step 2.

5. NUMERICAL RESULTS

The online heuristics have been implemented in C++ and have been tested on several instances. We considered a configuration obtained from data relevant to the Italian standard user [11]. It consists of a residential household having 11 home appliances, whose load consumption profiles have been defined based on literature [12]. Moreover, the house is equipped with a 1 kWp PV panel and a 3 kWp storage battery with a capacity of 10 kWh or 30 kWh. With regard to the dimension of the starting time window of each appliance (constraints (2)), we considered two different flexibility levels: low ($ET_a - ST_a = 3$) and medium flexibility ($ET_a - ST_a = 5$). Finally, we used the dynamic pricing tariff also adopted in [2].

We solved each instance with the offline optimization model, to define the energy plan for the next 24 hours. Afterwards, the online algorithms have been applied to reschedule the energy plan during the day. As for the photovoltaic panel we have tested two particular scenarios: in the first case the production of a sunny day is forecast but a cloudy day occurs in real time; in the second case, the production of a sunny day is forecast but a rainy day occurs in real time, inducing a larger prediction error. We also evaluated the performance of the online heuristics when errors in the device start time forecast occur. For this purpose we have generated errors according to the probability distribution function of the prediction error experimentally obtained for the devices start time forecast algorithm presented in [9].

Table 1 shows the results of our tests for the wrong photovoltaic prediction case. For each online algorithm, we report the decreasing percentage of the mean value of the profiles error $PE$ with respect to an unmodified plan (i.e. the energy plan defined in the offline stage is still used during the day even if errors in the prediction occur). Results show that both the online algorithms are able to reduce the profiles error caused by wrong predictions in the photovoltaic production. As expected, the multi-time slot approach doesn’t introduce a major improvement on the performance of the system. In this case, in fact, predictions are still used for defining the energy plan of future time slots. Therefore, if future time slots are affected by forecast errors, as happening in our test scenarios, this procedure turns out to be ineffective. This result is also confirmed by the performance evaluation obtained for the second scenario (sunny is the predicted weather and rainy the real one, Table 1(b)). In minimizing the profile error, a key role is played by the battery that gives the online methods the flexibility to buy or sell energy (by charging and discharging the battery) just to use the same demand and supply defined by the offline model. For this reason, the greater the battery capacity is, the more the performance of the online mechanisms improves. Moreover, when no battery is available, the performance of the online algorithms are badly affected thus confirming the importance of this element in taking decisions to fix wrong forecasts.

<table>
<thead>
<tr>
<th>Battery Storage Capacity</th>
<th>Sunny-Cloudy</th>
<th>Sunny-Rainy</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 kWh</td>
<td>307.64 W</td>
<td>411.51 W</td>
</tr>
<tr>
<td>10 kWh</td>
<td>311.49 W</td>
<td>434.12 W</td>
</tr>
<tr>
<td>30 kWh</td>
<td>656.11 W</td>
<td>609.24 W</td>
</tr>
</tbody>
</table>

Table 1. Mean value of the profiles error $PE$ for two PV forecast error scenarios ((a) predicted sunny/real cloudy, (b) predicted sunny/real rainy) with a medium flexibility level.

<table>
<thead>
<tr>
<th>Battery Storage Capacity</th>
<th>Sunny-Cloudy</th>
<th>Sunny-Rainy</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 kWh</td>
<td>294.12 W</td>
<td>421.6 W</td>
</tr>
<tr>
<td>10 kWh</td>
<td>311.49 W</td>
<td>434.12 W</td>
</tr>
<tr>
<td>30 kWh</td>
<td>656.11 W</td>
<td>609.24 W</td>
</tr>
</tbody>
</table>

Table 2. Mean value of the profiles error $PE$ for two PV forecast error scenarios (case (a) predicted sunny/real cloudy, case (b) predicted sunny/real rainy) with a 10 kWh battery.
Table 2 shows the important role of the devices scheduling flexibility: the greater the flexibility is, the more the system is able to react to incorrect forecasts by advancing or delaying the devices activities so to match the energy demand and supply defined by the offline model. Similar considerations can be done for the numerical results, represented in Table 3, obtained in testing the performance of the online algorithms when errors occur in the device start time forecast. In this case, as expected, a larger flexibility mitigates the effects of errors in the prediction of the start time of appliances.

(a) Battery Storage Capacity

<table>
<thead>
<tr>
<th>Battery Storage Capacity</th>
<th>0 kWh</th>
<th>10 kWh</th>
<th>30 kWh</th>
</tr>
</thead>
<tbody>
<tr>
<td>No online</td>
<td>201.09 W</td>
<td>247.31 W</td>
<td>443.95 W</td>
</tr>
<tr>
<td>Singe Slot</td>
<td>-11.41 %</td>
<td>-77.56 %</td>
<td>-98.95 %</td>
</tr>
<tr>
<td>Multi Slot</td>
<td>-16.31 %</td>
<td>-85.19 %</td>
<td>-98.96 %</td>
</tr>
</tbody>
</table>

(b) Scheduling Flexibility

<table>
<thead>
<tr>
<th>Scheduling Flexibility</th>
<th>Low</th>
<th>Medium</th>
</tr>
</thead>
<tbody>
<tr>
<td>No online</td>
<td>239.99 W</td>
<td>247.31 W</td>
</tr>
<tr>
<td>Singe Slot</td>
<td>-61.34 %</td>
<td>-77.56 %</td>
</tr>
<tr>
<td>Multi Slot</td>
<td>-65.18 %</td>
<td>-85.19 %</td>
</tr>
</tbody>
</table>

Table 3. Mean value of the profiles error PE with a medium flexibility level (a) and a 10 kWh battery (b).

6. CONCLUDING REMARKS

In this paper we proposed a DSM online model developed within the BEE Project [1], along with two efficient heuristics. These algorithms can be used to properly react to errors in the offline energy profiles. The final goal is to plan the household operations with the objective of minimizing the difference between the real time demand\supply profiles and the ones defined through the offline stage. The proposed methods have been tested on data relevant to the Italian electric market in order to correctly appreciate the performance of each algorithm. Tests confirm the benefits of using a proper online DSM model along with an offline plan. As expected, a key role is played by the storage devices, which can be effectively integrated in the smart grid to guarantee the effectiveness of a priorly scheduled plan.

Although having discussed the efficacy of the online algorithms, the proposed work represents just one first cut analysis and further investigation is therefore required. The model, in particular, can be extended as to consider the possibility of interrupting the execution of any appliances, or to be integrated into a cooperative multi-house context.

7. REFERENCES


