Intelligent Load Management for a Shopping Mall model in a smartgrid enviroment

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***Abstract*— The future electricity demand is expected to increase as well as the will to exploit in deeper the generation from renewable resources. These facts will make necessary to achieve more flexibility in managing the electrical systems. One effective way to manage distribution networks with this increase of demand, is to apply all the different techniques that smart grid technologies bring such as load balancing, load shifting and peak shaving through intelligent load management (ILM). The aim of this work is to present a model of a shopping mall used as a study case for ILM, in order to evaluate and compare the different results achieved using a predictive rate control algorithm to control the power consumption of the electrical loads. All the models, algorithms and simulations have been implemented in MATLAB.**

***Index Terms*—Intelligent Load Management, peak shaving, smartgrid, Demand Side Management, Demand Response (DR)**

I. Introduction

Nowadays the electrical loads are active players in the electricity market and their possibility to decide when be or not connected to the network can significantly influence the management of the power system. This situation is due to the well-known process of liberalization of the electrical market that is already happened, or still in act, in a very large number of countries worldwide. Many studies and researches have demonstrated the important of the role that the Demand Side Management (DSM) can cover into a power system context, with several advantages as for example the reduction of the spike phenomenon in the energy demand [1].

Moreover, in the context of the liberalized market, the flexibility, that the loads management gives to the system operator, assumes a great value also in the solution of congestion problems that often emerge from the results of the day ahead market (interruptions upon notice), or in the real time operations (interruption without notice) sometimes necessary to preserve the grid from overload problems due to the increase of Renewable Energy Sources (RES) penetration.

Furthermore the new increase of electricity and intermittent generation ask for more flexibility of load to proper manage distribution networks [2-6].

In recent literature several studies analyze different methods and effects of using the Intelligent Load Management (ILM): in [7] the authors propose to use an Intelligent Load Shedder module connected to non-critical loads in order to detect the conditions where these loads can be disconnected when the microgrid is in island configuration and the DG present is not enough to meet all the energy demand. In [8] the DSM is used to orient the demand peak and to obtain a significant peak shaving effect by providing real time price signals directly to the users. In [9] the use of Artificial Neural Network approach is explored to support machine-learning in residential load management system and to develop users absorption profiles in order to better manage the DR and meet the consumption targets. In [10] the authors propose an architecture for DSM in a residential building to manage a system with different dynamic loads, in multiple time scales and to integrate different techniques for operation control, scheduling and dynamic pricing.

In this paper a case study is presented based on a model of a Mall, where several loads are present and each one is characterized with its own absorption profile. In Section II the load control algorithm and the simulation methodology are illustrated. The Section III presents the shopping mall model, Section IV presents the simulations while in Section V several results are reported. Finally Section VI contains the conclusions and the future development of the study.

II. Algorithm for the ILM

The object of the algorithm is to contain the energy consumption below of a predetermined threshold, defined by the contractual agreement based on its evaluations and in the future received by the Distribution System Operator (DSO) or a Load aggregator [1], [11-13]. In particular, once defined a target power MP (*Mean Power*) as the average value in the range of time T, the objective of these controller is to ensure that the final energy at the end of the period T is equal to or less than MP * T.

The proposed predicted rate controller measures the expected slope of average energy consumption at a regular sampling interval and compares it with the instantaneous energy consumption at that particular time [12]. This

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information is used to dynamically set up a curve of expected consumption for the remaining time within the sampling period. If the predicted line indicates that the desired value E_{max} can be exceeded the controller commands a disconnection, while if the predicted consumption is lower than E_{max} other loads can be connected. Therefore the controller acts on the instantaneous power, switching on/off the loads according to the inputs received from the algorithm.

The main controller is connected to all breakers through a bus through which the information about the need to shed or restore loads and the priority level is shared [14]. A priority level is attached to each breaker by means of a look-up table previously defined.

The priority level is update at each cycle and the operation of disconnection and reconnection of each load is actuated in accordance to this level as reported in the flow-chart (see Figure 1).

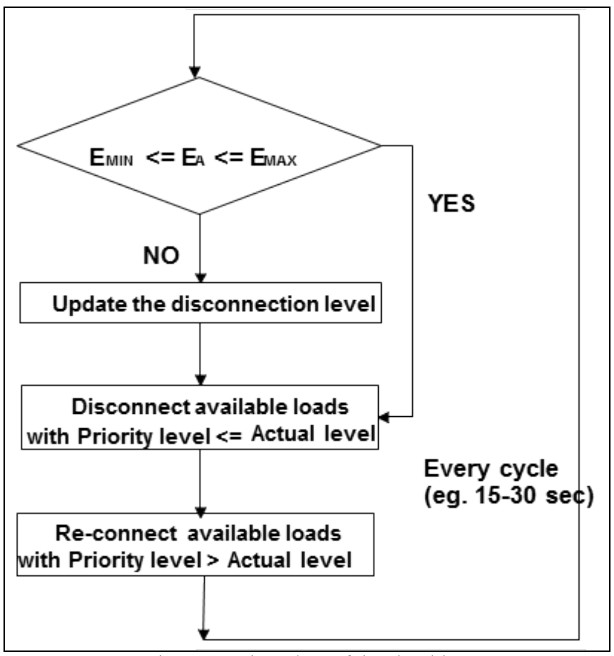

Figure 1 – Flow chart of the algorithm

III. Study Case: Shopping Mall Model

The model of the shopping mall studied is composed by 100 main users shared among 3 different categories (Restaurants, Large Shops, Small Shops); it has been assumed that there are 25 users for the first and the second category, while 50 are the small shops. For each category some different loads are assigned as shown in the list below:

1. Restaurants *(Illumination, Kitchen, Dishwasher, Fridge, Heat Ventilation and Air Conditioning (HVAC))*
2. Large Shops *(Main Illumination, Stock room illumination, Power wiring, HVAC)*
3. Small Shops *(Illumination, Power wiring, HVAC)*

Finally, also three loads (*illumination, Power and HVAC)*, that represent the power need to the mall operation, are added [11]. In Figure 2 a functional layout of the structure proposed for the mall is reported.

The three main loads directly connected to the primary bus, and one example for each type of user that is assumed to be in the mall are individuated.

Totally there are 378 electrical loads and each load has its own reference switch.

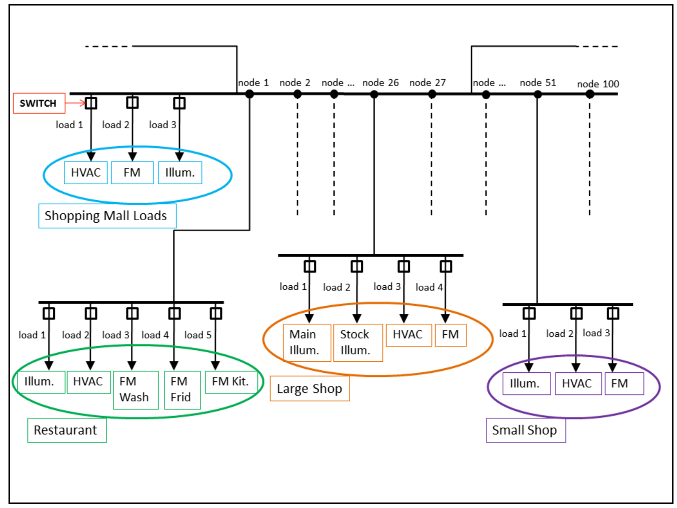

Figure 2: General layout of the shopping mall model.

The model has been created as a *struct* matrix of MATLAB. According to the Figure 2 for each load three characteristics have been defined: name, rated power and a one-day long power absorption profile, based on historical data. Moreover a value of priority and an availability state are assigned to each switch; this is a critical assignment due to the methodology of the Controller that during the operation will disconnect, when necessary, firstly the loads with the lowest priority level. This logic of control, presented in [12] has been embedded in the main switch of the network that commands the low voltage switch of each load.

A. *Load Profiles*

The consumption profiles are one day long and they have been modeled using the seconds as time unit (24 hours = 86.400 seconds) and a per-unit scale of values for the intensity.

Some profiles are derived from a previous real measurement campaign (e.g. the energy absorption profile of the fridge), instead some others are modeled with a procedure that starts from operating points with samples at 15 minutes. Starting from these data a routine has been implemented to obtain profiles which respect the mean consumption rate, in a quarter of hour, but present a random noise that represents the errors of the devices and the variability of the loads.

As example the fridge absorption profile (reported in Figure 3) has been modeled starting from real measures, it is characterized with a number of cycles of power consumption due to the assumed use of this device during the day.

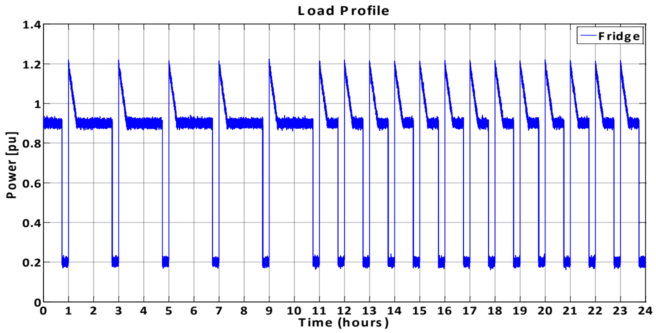

Figure 3: MF fridge power absorption profile during an entire day

B. *Pay-Back Effect*

It is well known how the power absorbed by thermal loads is strictly depending from the difference between the external and the target temperature (for example 4°C for the fridge loads) of the devices. This phenomenon is called pay-back effect and it has been implemented for any thermal load present in the model.

More in detail the absorption profile of these loads is increased to the maximum value every time that a thermal load is switched on after a previous disconnection in order to model the restoration of the target temperature (thermostatic behavior). The change in the power demand lasts less for the fridges (one minute) than for the air conditionings (three minutes) because it is assumed that the thermal capacity of the fridge is lower than the room space.

IV. SIMULATIONS

The simulations are one day long and they cover three different scenarios, in which the effects of the predictive controller are evaluated. The analysis starts from a scenario called Base Case so composed:

- 378 loads with a peak absorption of 1.639 MW totally
- Each load has its own breaker with a defined level of priority within 1 and 9
- The time period for the main controller T (I_{CTRL}) is equal to 900 seconds (15 minutes), the cycle time for the priority level is 50 seconds.
- The parameter E_{max} is equals to 275 kWh/15 minutes.

The choice of E_{max} implies that the desired value of energy consumed in an hour is less than 1100 kWh.

The other two scenarios are so defined:

- In Case 1 the breakers are characterized with a more detailed level of priority within 1 and 45, moreover the cycle time of the algorithm is reduced to 5 seconds.
- In Case 2 the logical operation of the controller is changed a little: when the forecasted energy consumption oversteps the upper limit, the algorithm tries to estimate directly the priority level below which all the loads have to be disconnected immediately to meet the target consumption in the end of the period T.

In the TABLE 1 the priority values assigned to each load in the Base Case (column 2) and in the Case 1 and 2 (column 3) are reported:

TABLE 1: Priority values for each type of load

Shopping Mall Loads		
Load Name	***Priority Value (Base Case)***	***Priority Value (Case 1-2)***
HVAC	2	7
Power	6	30
Illumination	9	45
Restaurant Loads		
Load Name	***Priority Value (Base Case)***	***Priority Value (Case 1-2)***
Illumination	9	45
HVAC	Random (1-3)	Random (1-5)
Dishwasher	7	35
Fridge	5	25
Kitchen	6	30
Large Shop Loads		
Load Name	***Priority Value (Base Case)***	***Priority Value (Case 1-2)***
Main illumination	9	45
Stock illumination	6	30
HVAC	Random (1-3)	Random (1-5)
Power	8	40
Small Shop Loads		
Load Name	***Priority Value (Base Case)***	***Priority Value (Case 1-2)***
Illumination	8	40
HVAC	Random (1-3)	Random (1-5)
Power	4	20

V. RESULTS

C. *Base Case*

A simulation of one day has been performed for the Base Case. In Figure 4 is represented half hour (two periods) of controller operation in order to explain the logic of the algorithm: every time that the black line (the energy consumed) oversteps the upper limit (blue line) the controller increases the priority level reached by one and all the breakers with that priority value are opened. Then the energy consumed reduces its slope, if the lower bound (red line) is crossed the controller reduces the priority level reached and all the breakers with that priority value are closed.

The upper and lower bound curves represent the border of the forecasted energy within a period.

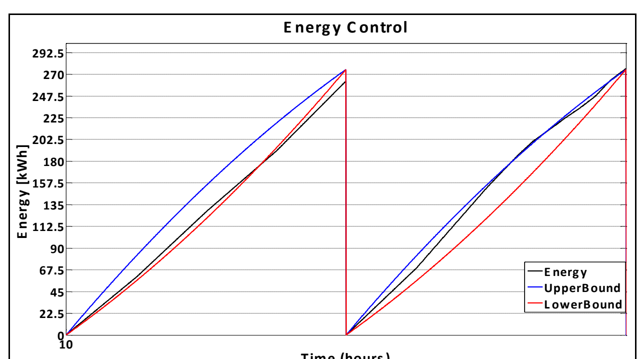

Figure 4: Operation of the Controller between 10 am and 10:30 am

During the simulation the Controller operates only in the central hours of the day when the energy demand grows up significantly. A zoomed view of this hours is proposed in Figure 5.

In the results of the Base Case it is possible to notice that sometimes the operation of the controller is not sufficient and the energy consumed exceeds the limit, for example at t=12:45 the energy absorbed is more than the threshold decided. Some other times the controller actions are oversize and more loads than necessary are disconnected.

These facts are probably due to the cycle time of the controller that is too high to allow a reconnection of those loads disconnected in the previous period and to the little variability between the priority values assigned to the loads that result to be a too strict constrain.

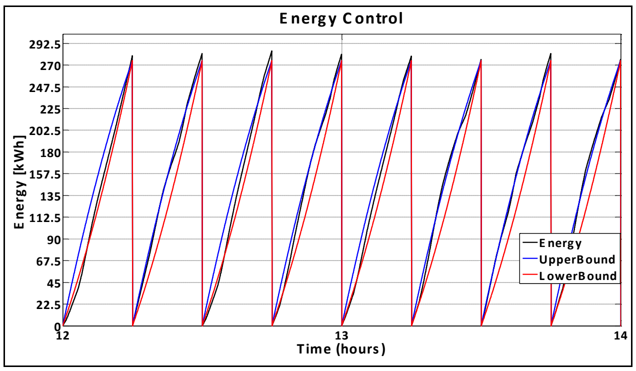

Figure 5: A zoom view of the energy absorption between 12 am and 2 pm, in the Base Case

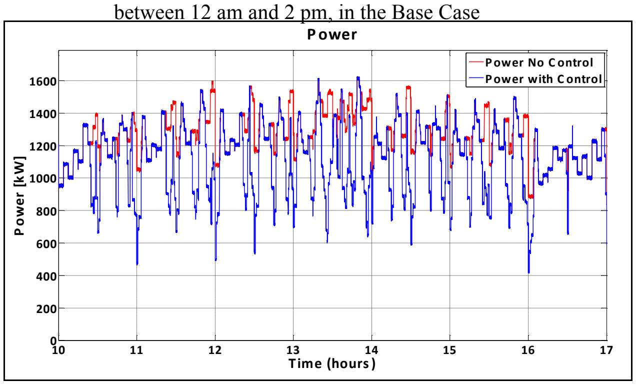

Figure 6: Instantaneous active power consumption with (blue line) and without (red line) predictive controller

The maximum value of priority achieved by the controller is equal to 8, it means that almost all the loads have been disconnected during the most critical situations of the day, as it is showed in Figure 6 where the active power consumption (blue line) never reaches the zero during the controller operation hours.

In TABLE 2 some indexes, that have been created to better evaluate the simulation results, are reported:

- E_{nd} stays for Energy Not Supplied and is the amount of energy (expressed in MWh) that is not dispatched to the loads due to the operation of the Controller
- T_{disc} measures the overall disconnection time of the loads. It can be expressed in hours/minutes/seconds or in percentage compared to the global operating time of all the loads calculated as:

$$\text{Number of Loads x 24 hours} = 9072 \text{ h} \tag{2}$$

- N_{int} is the number of loads disconnected at least once during the simulation
- e_{max} represents the maximum percentage error committed by the controller at the end of the period T compared to the desired threshold E_{max} equals to 275 kWh
- E_{tot} is the sum of the errors committed in each period T expressed in energy (kWh)

TABLE 2

E_{ns} [MWh]	1,124 MWh
T_{disc} [hh:mm:ss]	341:00:00
$T_{disc\%}$ [% of T_{global}]	3.76%
N_{int}	252
e_{max} [%]	3.75%
E_{tot} [kWh]	449,2 kWh

Remembering that there are 378 loads it can be observed that not all the loads are disconnected during the simulation, but the total amount of the errors committed is almost 450 kWh, which means that globally the controller has not respected the desired target of energy consumption.

D. *Case 1*

In Case 1 in order to make more performing the Controller by pushing the energy consumed closer to the target value to better describe the variability of the loads the priorities assigned to each switch spread between 1 and 45 according to TABLE 1. The cycle time of the controller (I_{CTRL}) has been reduced from 50 to 5 seconds to make the algorithm able to reach the higher priority values in time.

The Figure 7 shows the results obtained by the Controller in the more critical interval of the simulation. A comparison between Figure 7 and Figure 5 permits to evaluate the better behavior of the algorithm and the better results achieved in term of energy consumption.

In Figure 8 the power consumption between 10 am and 5 pm is reported and it can be notice that during the simulation a complete detachment of the loads never happens.

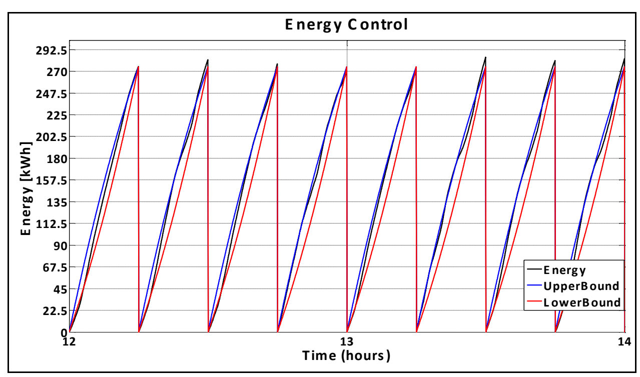

Figure 7: A zoom view of the energy absorption between 12 am and 2 pm in Case 1

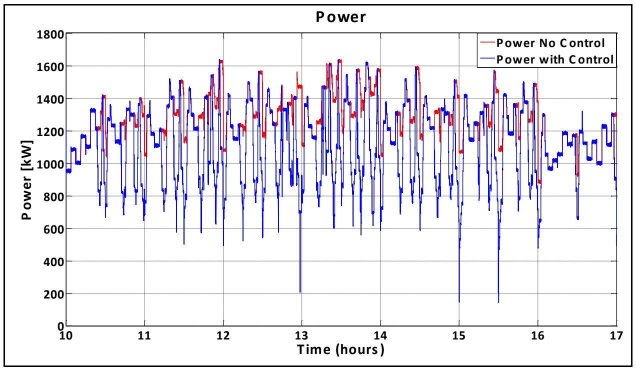

Figure 8: Instantaneous active power consumption with (blue line) and without (red line) predictive controller in Case 1

The TABLE 3 reports the significant indices for the evaluation of the Case 1 and shows that despite the number of disconnected loads is increased the total error has been reduced to 251 kWh.

TABLE 3

E_{ns} [MWh]	1,244 MWh
T_{disc} [hh:mm:ss]	375:30:30
$T_{disc\%}$ [% of T_{global}]	4.14%
N_{int}	327
e_{max} [%]	3.64%
E_{tot} [kWh]	251 kWh

E. Case 2

In the second case the controller algorithm has been modified starting from the system configuration analyzed in Case 1 in order to obtain better performances in terms of runtime of the algorithm. In particular, referring to Figure 9, when the consumed energy (black line) oversteps the upper limit (blue line) the algorithm tries to estimate how much power has to be disconnected to respect the energy target in the ongoing period. This estimation is based on the assumption that the power demand remains constant during the period, so the amount of power in excess is calculated dividing the energy gap for the remaining time to the end of the period. The information about the not-to-dispatch power is compared to a step-curve which represents the total power consumption for each priority value. In this way the controller can detect up to which priority value is necessary to remove power to obtain the desired result.

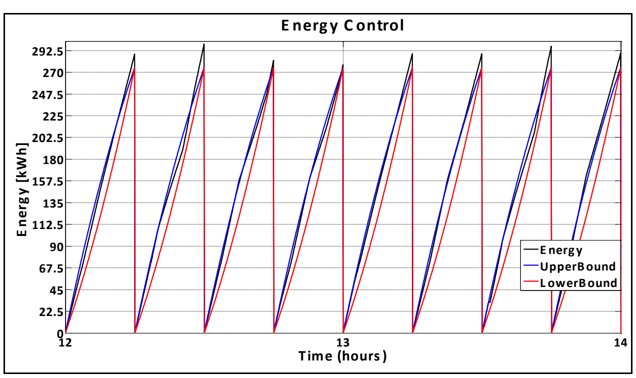

Figure 9: A zoom view of the energy absorption between 12 am and 2 pm in Case 2

The effects of this different logic in the controller algorithm is showed in Figure 10 where is possible to notice that all the loads have been disconnected several times in the central hours of the day. In particular, sometimes the complete disconnection has been actuated several times in the same period.

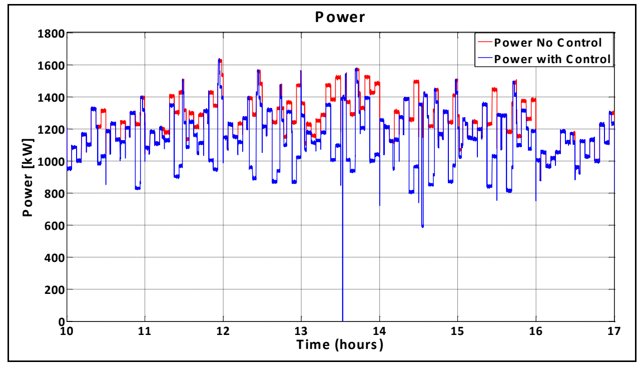

Figure 10: Instantaneous active power consumption with (blue line) and without (red line) predictive controller in Case 2

Finally, in TABLE 4 the same indices used for the previous Cases are reported in order to allow a numerical comparison between the different algorithm logics.

TABLE 4

E_{ns} [MWh]	0,826 MWh
T_{disc} [hh:mm:ss]	249:34:08
$T_{disc\%}$ [% of T_{global}]	2.75%
N_{int}	378
e_{max} [%]	9.67%
E_{tot} [kWh]	1258 kWh

It can be noticed that the results provided by this different control logic are getting worse compared with previous simulations. In particular, despite all the loads have been disconnected the error committed is increase and the energy consumed is 1,26 MWh more than desired.

VI. Conclusions and Development

The methodology proposed for the load management, based on a predictive rate controller, allows to achieve good results in term of peak shaving and respect of the target consumption for tertiary sector buildings, opening the pace of ILM and indirect load control from DSO in future distributions networks .

In particular, in Case 1 it has been observed that by using more priority values to characterize the loads it is possible to better contain the energy consumption because the controller has a large variability of priority between which choose the loads to disconnect. Indeed this is the case where the minimum value for total error in term of undesired energy consumption has been obtained.

In Case 2 a different methodology has been proposed to achieve better results with a lower runtime of the algorithm but the results do not show any improvement. This fact is probably due to the assumption made to have a constant power demand to calculate how much power needs to be disconnected.

Future studies will regard the exploration of the control logic (used in Case 2) and the implementation of the "standard" controller (proposed in Case 1) in a more complex model by introducing hierarchy levels for the switches and using also the market price to decide the loads status.

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