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Physically-Based Load Demand Models for Assessing Electric Load Control Actions

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***Abstract*—Simulation, by resorting to suitable models, is often used by electric utilities in studies related with load forecasting, system reliability, power flow and demand-side management activities, among others. Nowadays, in restructured electricity market scenarios, activities involving buying and selling energy can also be studied through simulation. Different goals for those studies require different load representation and modeling. Since some activities at the demand-side level may lead to changes in load demand shape and levels, it is necessary to foresee such impacts before their implementation. Moreover, whenever such actions involve the remote control of end-use loads a careful assessment must be done in order to avoid undesirable effects, such as payback or strong reduction in revenues without other counterparts. The use of suitable load models contributes to avoid or greatly reduce both the need for pilot programs, which may be a costly and time consuming activity, and the risk of reducing revenues/profits. This work presents the results of using physically-based air conditioner models to simulate load control actions and to analyze the impacts of such actions on the demand, on the revenues, and on the comfort of consumers.**

***Index Terms*-- Air conditioning, Load management, Load modeling, Load shedding, Monte Carlo methods, Power demand, Power systems.**

I. Introduction

Simulation is an analytical tool very often used in power systems. Several diverse situations may be studied and analyzed by resorting to appropriate models to simulate the real-world conditions. The capability of anticipating the impacts of any action to be implemented in power systems is of utmost importance, independently of the type of study being carried out. Previous assessment of actions may help preventing potential undesirable effects. For instance, changes on demand can impact on losses, reliability and revenues, among other issues. Different goals for the analysis require different load representation and modeling. Thus, while econometric or behavioral models, generally based on historical data, are suited for load forecasting and load flow studies, the appraisal of load management (LM) programs asks for a different approach. This can be based on data collected through load research programs, possibly with the implementation of pilot actions, or based on simulation by resorting to suitable models with the ability to reproduce the behavior of the loads with and without the implementation of LM actions.

LM measures include direct load control, interruptible power and voluntary load shedding. The remote control of end-use loads has been implemented by several utilities with diverse objectives [11], [18]. Since these actions usually lead to changes in load demand shape and levels, it is necessary to foresee such impacts before their implementation. Therefore, a careful assessment must be done in order to avoid undesirable results such as the payback effect or a strong reduction in revenues without other counterparts. The payback effect is an increase in maximum demand during the restoration of loads after a period of forced supply interruption, when compared with the demand that would exist if no load management actions have been applied. The use of suitable load models for simulating the actions to be implemented and assessing their results contributes to avoid or, at least, to greatly reduce the need for pilot programs, which are generally a costly and time consuming activity. Thus, this kind of programs can be more effective when there is the capability to predict the consequences of remote load control actions on the load diagram - both from the point of view of maximum demand reductions and the payback effect.

Usually, loads used in LM activities are thermostatic ones, meaning that the power demand of such loads is imposed by a thermostat. The demand of these loads is determined by the temperature of the fluid being cooled/heated. The cooling/heating device is powered when the temperature rises above/falls below the upper/lower limit of the thermostat dead band, and it is disconnected when the temperature reaches the lower/upper limit of the thermostat dead band. In this type of loads, when the regular working cycle is changed by an external action the demand pattern over the subsequent periods of time may also be changed. Since LM activities change the normal functioning of loads under control, the models used in LM programs must be able to capture such behavior. Thus, models based on data collected when loads are on its normal state are not suited for LM studies, and most texts about LM refers to models based on the energy balance that exists in loads used for control [1], [9], [22]. These are the so-called physically-based load models (PBLM). These models reproduce the demand of end-use loads, such as air conditioners, by simulating both the physical phenomena

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occurring in that type of loads and the behavior of the thermostat, which determines the demand of the load [1], [9], [15], [25]. Software tools allowing the simulation of load diagrams (LD), also with the capability of capturing the effects of LM actions, are useful for a previous assessment of these actions.

Several approaches to physically-based modelling can be found in the literature. Despite some diversity, which is related not just with the individual load models but also with the load aggregation process, all of them have in common the same objective: the reproduction of physical phenomena that occur in thermostatic loads. At the individual level, the main differences are due to the eventual need for some simplifications that are necessary in order to make the detailed and complex individual models suitable for practical use, even if it is a specific usage. Some of the complexity arises from the stochastic behavior of the demand of loads usually used in the LM programs. Such behavior comes from the energy service usage, which is random in nature, and from the weather factors, which largely influence the demand of some loads, namely air conditioners and space heaters. Other issue that also deserves some attention is the incorporation of load models into more general tools. For example, PBLM are well suited for LM studies, meaning that besides the demand of loads the tool should be able to reproduce LM actions in conjunction with the load demand. This integration is essential for the evaluation of those actions.

On the other hand, recent changes in power systems structure and ownership require the ability to evaluate LM actions at different levels of demand aggregation, since the entity interested in such activities may change from one situation to another [4], [7], [11], [12], [18]. LM programs can be very attractive for a retailer dealing with volatile wholesale prices and fixed, over a certain time period, retail prices. Thus, load modeling methodologies used in LM studies should enable to simulate:

- power demand without and with load control strategies applied to loads under control;
- demand at different levels of load aggregation.

The remaining of the paper is structured as follows. Section II presents a deeper analysis of LM programs and their objectives. In section III the individual air conditioner (AC) model is described, as well as the approach implemented based on Monte Carlo simulations for aggregating demand. A case-study is present in section IV, while in section V some conclusions are drawn.

II. Load Management

LM activities have been implemented by some electric utilities as a way to improve economic efficiency also leading to operational benefits, such as increasing load factor, reducing maximum power demand as well as losses and costs. The implementation of LM actions is referred to in [11], [16], [18], [27], among others. Even in present scenarios of unbundling and restructuring of power systems, these activities may be attractive [11], [12], mainly due to the volatility and spikes of wholesale electricity prices. Besides a “traditional” utility that owns the wires and sells electricity, other entities may be interested in such activities. For instance, a retailer may be interested in evaluating the local effects on demand of load control actions implemented over some loads of a group of consumers and, at the same time, he/she can be interested in assessing the impact on the total revenues or the global demand (of all the customers of this retailer).

An appropriate software framework able to simulate the demand of loads under control and the LM actions to be applied over the loads, and simultaneously capture the effects of LM actions on load demand, can be used in the identification of LM actions (on/off patterns to be applied over the loads – duration and location during a certain time frame):

- to reduce the risk associated with the implementation of the control actions;
- to reduce the need for intensive data gathering;
- to characterize the demand-side resources;
- to assess the impact of the LM actions.

In the scientific literature several issues have being addressed: direct load control (DLC) objectives to be achieved and constraints to be satisfied in the implementation; load modeling (global demand / demand under control); assessment of the effects of LM actions; design and selection of LM actions. [20] assess the impact of LM actions in the cold load pickup and diversity factor**,** while in [5] and [7] the main goal is to study the impact of DLC in the spinning reserve and the consequent reduction in the costs. However, the reduction in the peak power demand and in the costs are often the main objectives of the studies related with LM. Such objectives can be found, for instance, in [3], [4], [13], [14], [17], [27] and [30]. The maximization of the utility’s profits is the objective pursuit by [26]. In recent works, besides the objectives referred to above, some authors introduce also some objectives (or constraints) related with the quality of energy service provided to the customers [3], [9], [15], [27], [29]. The aim is to maintain a suitable level of acceptance of such actions, namely by introducing some constraints in the duration of power curtailment actions (maximum time off and minimum time on). As already referred to above the economic interest has increased enormously in more recent implementations [11], [12]. In Table I the objectives of the programs reported in these works are summarized.

In some works DLC is seen as a system resource that can be dispatched. The available capacity depends on the amount of load under control, time of day and the consumer lifestyle, meaning that the available DLC capacity depends on the diversified demand of the loads under control. However, the available capacity for dispatch in each moment (between the minimum and a maximum value) is not a continuum but a set of discrete values. Due to its similarity (availability and dispatch ability) with the resources in supply side, some authors consider DLC available for unit commitment [4], [13], [14]. The amount of DLC dispatched can be fixed as in [4] or variable. [17] try to identify when the off period begins and how long it lasts, while [26] determine the number of groups powered off in each control interval and how many intervals they are powered off. However, most actual implementations use some kind of cycling strategy [1], [4], [24].

TABLE I
OBJECTIVES TYPICALLY PURSUIT BY LOAD MANAGEMENT PROGRAMS.

	Athow and Law (1994)	Bhattacharyya and Crow (1996)	Chen et al. (1995)	Fotuhi-Firuzabad and Billiton (2000)	Gomes et al. (2004)	Hsu and Su (1991)	Huang et al. (1998)	Jorge et al. (2000)	Kurucz et al. (1996)	Ng and Sheblé (1998)	Rautenbach and Lane (1996)	Lefébvre and Desbiens (2002)	Wei and Chen (1995)
Minimize peak demand					√		√	√	√		√		√
Minimize costs	√	√	√	√		√	√						√
Discomfort caused to customers		√			√			√			√		
Minimize bill											√		
Maximize utility's profits					√			√		√			
Assess impacts on reliability, spinning reserve, cold load pickup or diversity factor				√								√	

Two issues must be dealt with whenever LM actions are at stake: design and selection of the DLC actions. Most studies reported in the literature just address the second issue; that is, they consider optimization problems in which DLC actions are selected from a previously identified set of actions. However, the design of appropriate on/off patterns to be applied over the loads under control is a key task. Traditionally, LM actions are identified based on empirical or past knowledge (due to experiments) generally based on pilot programs or on cycling strategies in which a pre-defined and fixed on/off patterns are used. Moreover, pilot programs should be implemented carefully and only in a small scale as they can be costly and time consuming. Few authors studied the action design phase; for instance, [9], [10], [15] and [17] use an optimization approach for this purpose.

III. LOAD MODELS

Demand simulation is often based on diversified load diagrams possibly resulting from load research programs [28]. [2] use probabilistic models (random variables with Gaussian behavior) to reproduce the demand. Demand modeling and simulation (both demand under control and global demand) are essential issues in LM studies since, besides the demand, it should be possible to simulate the LM actions [1], [10], [15], [21].

Different approaches may also be found for the simulation of the aggregate demand. [21] suggests that all efforts about the aggregation should be done on the evolution of the thermostat state since the demand of individual loads is imposed by the thermostat. [6] and [9] use Monte Carlo simulations of individual models to obtain the demand of groups of loads. [19] use a statistical approach to compute the aggregate demand.

A. Individual models

The PBLM of air conditioners is a detailed one. The heat load of a space is given by $Q_T(t) = Q_L(t) + Q_S(t)$, where

$Q_T(t)$ [W] – total heat load,
$Q_L(t)$ [W] – latent load,
$Q_S(t)$ [W] – sensible load.

The diagram in Fig. 1 shows all the contributions for the heat load in a space being cooled by an air conditioner.

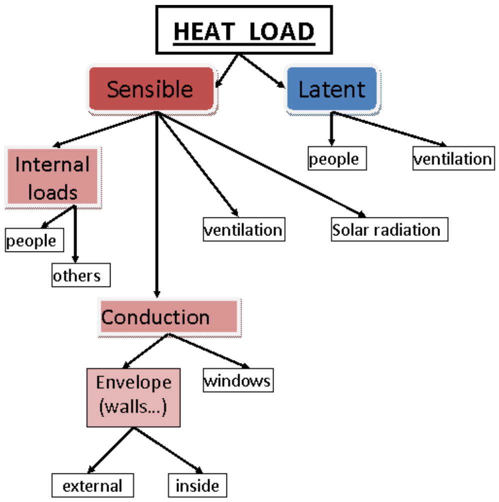

Fig. 1. Contributions for heat load.

The contributions for the thermal load of the space that have been taken into account are:

- internal heat sources,
- heat transfer through the walls,
- heat transfer through the windows,
- ventilation.

The heat transfer through the walls depends not only on the physical characteristics of the walls, which influences the heat transfer by conduction and by convection and takes into account the thermal resistance of the walls, but it is also a function of the solar insulation that depends on the orientation of the building and the characteristics of the walls, more specifically the thermal capacity. A similar situation occurs with windows, but their thermal capacity is very low meaning that almost all insolation load goes through these elements of the envelope. On the other hand, this thermal load first heats the floor, interior walls or furniture that exists in the space conditioned. Then, part of this load is released to the surrounding air. Both the solar insolation according to the orientation of the space and the amount of the heat released to the interior air can be found in the literature. Some other contributions to the global thermal load are the ventilation, internal heat sources and the use of the space. Moreover, the coefficient of performance (COP), which is the ratio between the amount of energy removed from the space and the amount of electricity consumed by the equipment, characterizes the air conditioner and depends on the external temperature. When the AC is on, the available energy for cooling the room is given by $P_{AC}(t) - Q_T(t)$, $P_{AC}(t) = P_{AC} * COP(t)$, where P_{AC} is the power of the AC and $COP(t)$ is its coefficient of performance. The COP, which varies with the temperature, is the ration between the heat load removed from the room and the energy consumed by the AC for removing the heat load.

If the AC is on, the temperature will be given by

$$T(t+\Delta t) = T(t) - \frac{[P_{AC}(t) - Q_T(t)]\Delta t}{mc_p}.$$

If the AC if off then the temperature will be given by

$$T(t+\Delta t) = T(t) + \frac{[Q_T(t)]\Delta t}{mc_p},$$ where

T(t) – temperature inside the room in the time instant t [ºC]
m – air mass [kg]
cp – specific heat of air [J/kgºC]
Δt – elemental time interval
$Q_T(t)$ – total heat load [W]

The AC model implemented has been experimentally validated. This model allows assessing both the demand of the AC and the temperature inside the room being cooled. The AC demand pattern, as well as the inside and outside temperature, is depicted in Fig. 2.

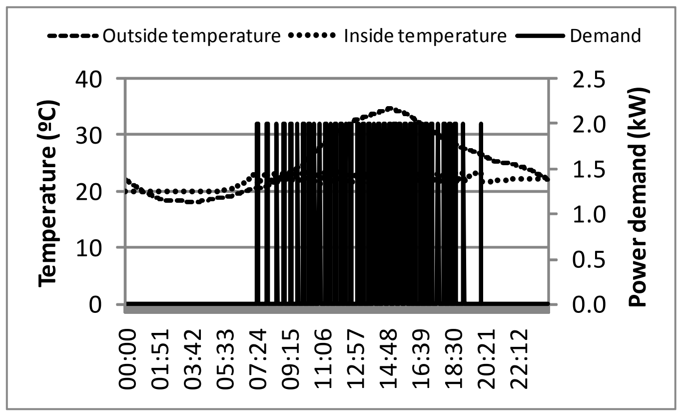

Fig. 2. Air conditioner demand pattern, and inside and outside temperature.

In Fig. 3 the evolution of inside and outside temperatures are shown.

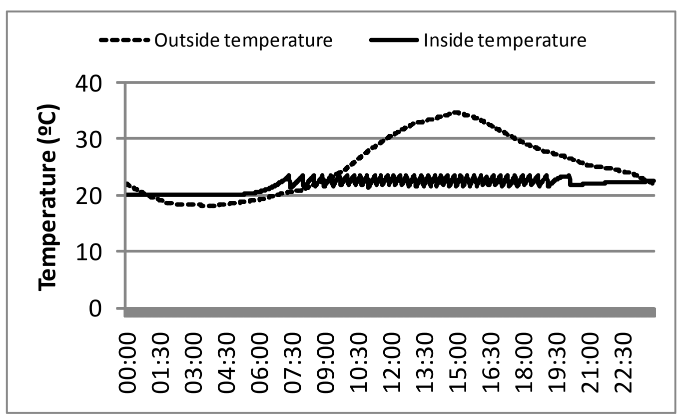

Fig. 3. Inside and outside temperature.

This model enables to perform deeper and more detailed analyses. Fig. 4 shows the inside temperature and the demand of an air conditioner between 13:00 and 17:59h.

PBLM allow capturing the impact of changes in different parameters in the demand of air conditioners. For instance, the impact of changes in outside temperature on the demand of air conditioners can be easily captured by this model. Also, if any external action imposes a change in the "regular working" cycle of the equipment (for instance, by imposing some periods of forced supply interruption) the PBLM capture the changes both on the AC demand pattern and the inside temperature. Supposing two periods of forced interruption between 12:00-12:15 and 13:00-13:14h have been imposed on the AC, the impacts on power demand and the inside temperature are shown in Figures 4 and 5.

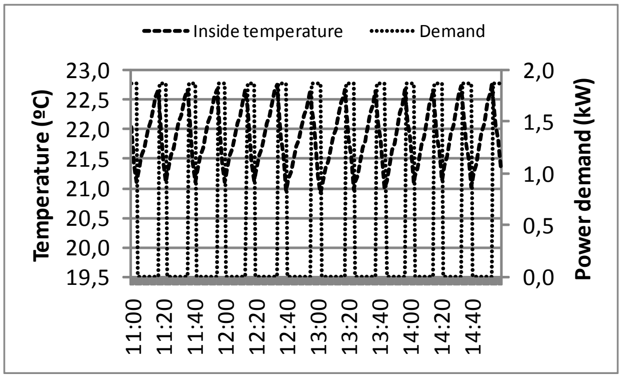

Fig. 4. Power demand and inside temperature without load shedding.

B. The aggregation process – Monte Carlo simulation

Individual load models are essential for evaluating the impacts of LM actions at individual end-use level. A detailed evaluation of such actions requires the quantification of the power and energy changes and also the assessment of the quality of the energy service provided. However, when such activities are provided and supported by, for example, an electricity marketer, the assessment of LM programs from its point of view is also necessary. In order to proceed with this evaluation, the impacts of LM actions must be evaluated at a given aggregate demand level. Once again, both demand and LM actions should be simulated for a detailed evaluation of the LM actions to be carried out.

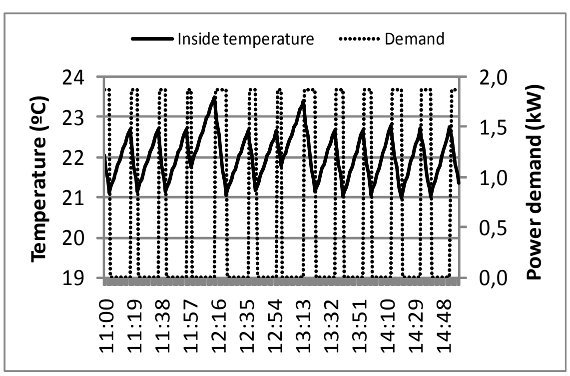

Fig. 5. Power demand and inside temperature with load shedding.

In a broad sense, there are two main approaches for obtaining the demand of groups of loads. In one of them an attempt to describe the aggregate demand is done usually based on some kind of statistical inference about data gathered in a load research program [19]. In a second approach, physically-based modeling is used, usually in conjunction with data collected in load research programs. The focus herein is the on/off time of the loads as a function of the temperature [25] or identifying how long it takes to go from temperature T1 to temperature T2 [23]. Other authors focus on the time evolution of the thermostat [8], given that the demand of loads is determined by this device. The analogy with electrical circuits is also used to represent the exchange of heat through the envelope of the space [25]. Within physically-based modeling a very interesting alternative is the one in which the demand of groups of loads is obtained by the aggregation of individual demands. This bottom-up way of reproducing the aggregate demand presents a great advantage over some other alternatives because it enables the simulation of the demand of small groups of loads. Thus, the analysis of a power transformer, feeding several end-users in which some AC have been identified for potentially being used in a LM program, is possible. This capability is more difficult to attain in other approaches used for aggregation, since some of them need a high number of devices for being statistically significant. The demand of groups of loads is built up by aggregating average demands of individual loads. The average individual demand is obtained through Monte Carlo simulations of the individual demands. In these simulations some parameters may change according to a normal probability distribution while some other parameters present a static behavior. For instance, the physical characteristics of the envelope and the COP of the AC are static while weather parameters, the use of the cooling energy service and some other stochastic parameters change according to probability distributions that have been identified.

Fig. 6 shows the demand of 80 AC and the total demand of the power transformer feeding them.

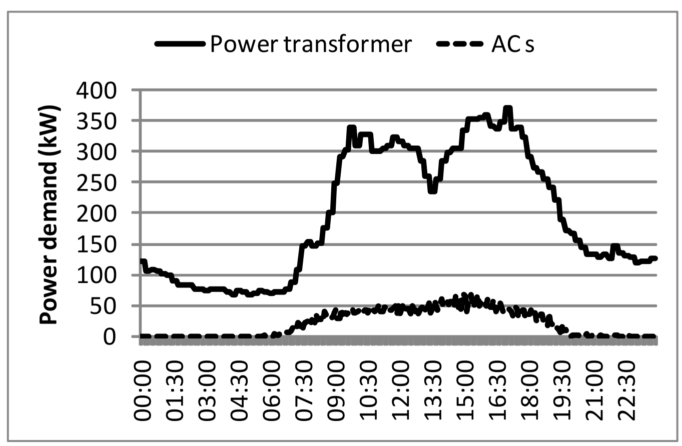

Fig. 6. Demand at power transformer level and demand of 80 air conditioners.

IV. Simulation Based Case Study

The load under control is usually grouped according to some physical (and possibly other) characteristics and the same control strategy is applied over all the loads belonging to the same group. Besides, the amount of loads under control and the objectives of the LM program determine the number of groups and the size of each group. In actual power systems restructuring scenarios it is very important to be able to assess the impacts of LM actions at several demand aggregation levels since different entities may be interested in such activities.

A power transformer (PT) feeding mainly small services and commerce customers has been chosen to exemplify the application of the methodology described above. The power transformer is operating near its maximum capacity and implementing DLC is an alternative that may be studied. The maximum peak demand is 370kW, occurring at 17:00h. Among all customers fed through this PT, 80 air conditioners able for remote control have been identified. Most air conditioners are mono-split units ranging from 1.3kW to 3.8kW, with the evaporator inside the room and with the condensate outside the room being cooled. The maximum demand of this 80 ACs are 69.5kW, occurring at 15:00h.

The load curtailment actions being simulated for four groups of loads are shown in Fig. 7.

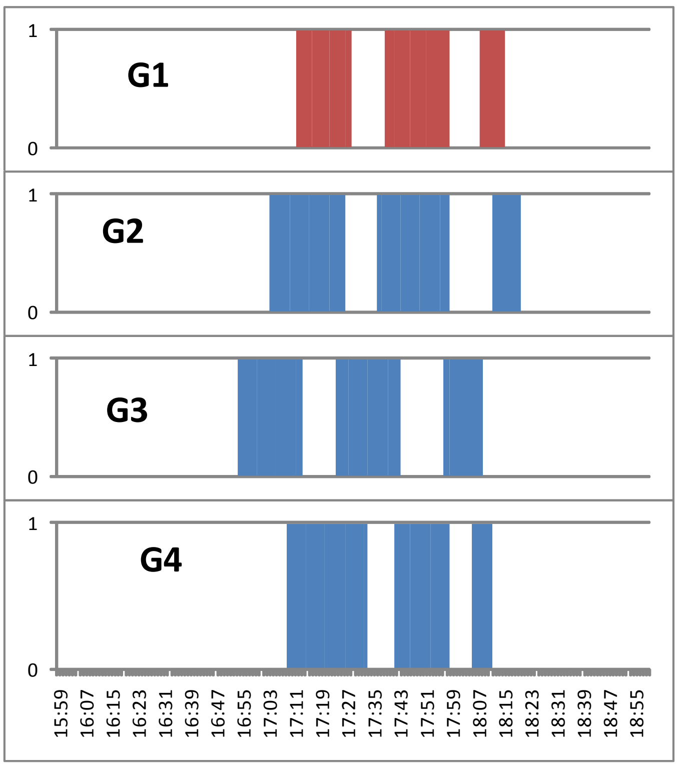

Fig. 7. Load curtailment patterns.

With the load shedding patterns shown in Fig. 7 is was possible to reduce the maximum demand at the power transformer to 354 kW (a reduction of 4.3%) – Fig. 8.

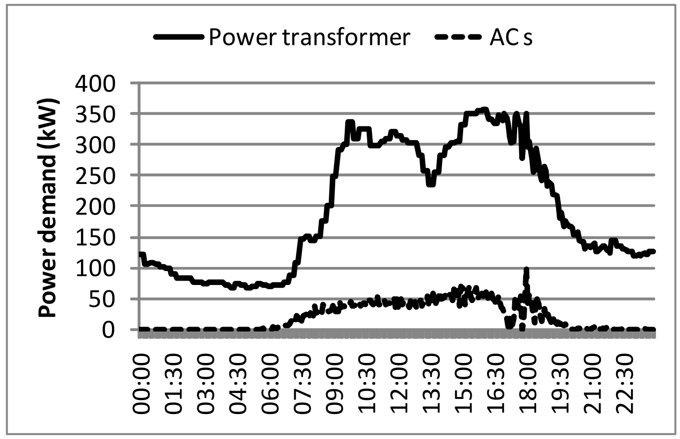

Fig. 8. Demand at PT level and AC demand with load curtailments.

The impacts of load curtailments can also be evaluated at the inside temperature level. Fig. 9 shows the temperature in one the loads of group 2.

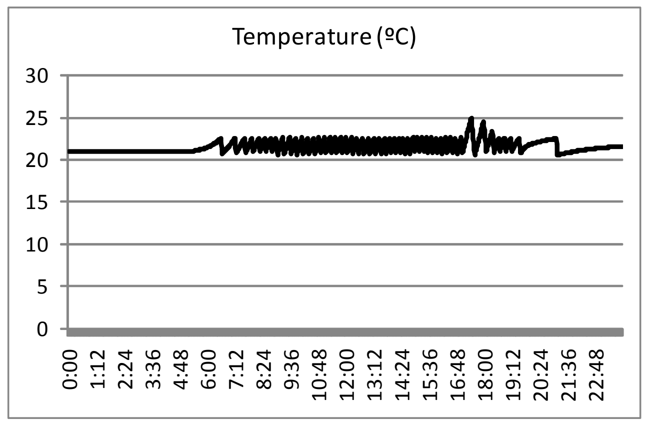

Fig. 9. Inside temperature in a room cooled by an AC belonging to the group number 2.

V. Conclusions

The selection of adequate load shedding actions to be implemented over sets of loads, grouped according to some criteria, is essential for avoiding undesirable effects in LM programs. Despite being very demanding for data, PBLM are well suited for simulating LM actions in a realistic manner. Since these models are able to track the temperature of the fluid, they enable the identification of the load profile without and with load curtailments. PBLM may also be useful in the determination of the groups and total number of loads to be controlled, as well as in the study of schedules of shedding/restoration sequences to obtain the load curtailment patterns leading to the maximum demand reduction that minimizes the undesirable effects to customers, both for off-line studies and for on-line decision support.

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VII. BIOGRAPHIES

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