A Multiple Objective Decision Support Model for the Selection of Remote Load Control Strategies

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***Abstract*—Utilities frequently use remote load control as an effective means to achieve suitable network operational conditions. This procedure, usually designated Load Management (LM), is a part of the resources considered under the general designation of Demand-Side Management (DSM).**

However, the use of LM in electric distribution network management is a problem that involves different conflicting aspects such as reducing peak demand, maximizing utility profits and minimizing discomfort caused to consumers. Hence, the problem is multiobjective in nature: economical, technical and quality of service aspects must all be explicitly accounted for in mathematical models.

This paper presents a multiobjective decision support model which allows the consideration of the main concerns that have an important role in LM: minimize peak demand as perceived by the distribution network dispatch center, maximize utility profit corresponding to the energy services delivered by the controlled loads, maximize quality of service in the context of LM.

***Index Terms*—Load management, Multiobjective programming, Load modeling, Energy management.**

I. Introduction

ELECTRICITY distribution network management activities encompass situations where it is convenient, or even indispensable, to control maximum demand. This may happen either due to economic reasons (to reduce losses and increase load factor as a means of reducing energy purchase costs to the distributor) or due to physical limitations of the network equipment (namely associated with lines and transformers).

To face this situation, it is usual to consider the adoption of demand-side management (DSM) programs, by means of which the consumers are encouraged to modify their load patterns through the use of adequate stimuli. Time-of-use rates or rates based on spot prices are examples of such stimuli, together with advising campaigns or funding programs to encourage the use of more efficient end-use equipment or smart clocks which prevent the use of energy by some loads at certain periods of the day.

An alternative exists for the utilities, consisting in remotely controlling customer loads, acting behind the meter according to some pre-defined contractual terms. This procedure is designated load management (LM) and it is usually considered as a DSM option. In situations of highly constrained operation due to capacity shortage, LM is a very effective means of avoiding high losses and low voltage levels at delivery nodes. On the other hand, even when no such critical constraints exist, LM helps reducing network losses in peak periods also reducing energy purchase costs to the utility. The loads most frequently used in this type of remote control procedures are those which deliver energy services whose quality is not substantially affected by supply interruptions of short duration. In the residential sector such typical loads are those associated with some form of thermal energy storage, e. g. water heaters and air conditioners.

Traditionally, utilities have carried out demonstration or pilot test programs to verify the cost-effectiveness of direct load control. A pilot test program allows the utility to forecast load shape impacts and may help it to develop marketing strategies. Two sets of customers are normally selected - one to test the program and a second one as a control group to be used as the reference case. This methodology is very expensive and may not produce accurate results [9]. A utility can avoid pilot testing programs and proceed directly to a program implementation if it designs and conducts a proper load research program in which average customer usage and instantaneous demand are determined as a function of the variables that affect each of them. The use of models such as the one described in this paper can significantly reduce the initial costs associated with the prior economical and technical evaluation of load management programs implementation.

In order to achieve a successful implementation of LM programs, consumers' acceptance is a vital issue. Direct load control, concerning both water heating and air conditioning, affects comfort of final users. Therefore, the issue of how to minimize the inconvenience caused to consumers has to be assigned a high priority whenever a LM program is considered. Thus, it is desirable that the model of load control used to assess the LM program can accommodate the interests of the participant consumers.

Some approaches presented in the literature on the optimization of remote load control programs address the problem in a relatively narrow perspective and may basically be divided in two categories, in accordance with the intended goals. One concerns minimizing peak demand ([6], [12], [15]) and the other one concerns minimizing operational costs ([3], [4], [7], [10], [14]). Other approaches, mentioned below, reveal concerns on other aspects of a more diversified nature.

The model proposed by Chu *et al.* [5] attempts to cope with the negative impact on comfort, by defining the minimization of the amount of load reduction as the goal of load control in order that the peak demand does not exceed a given maximum threshold.

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The approach presented by Lee and Breipohl [15] considers the use of direct load control to reduce spinning reserve, thus providing significant cost savings and often a limited inconvenience for the participant consumers.

Bhattacharyya and Crow [2] present a methodology that seeks to optimize both the customer satisfaction and the reduction of production costs to the utility. This approach is based on fuzzy logic techniques aimed at optimizing the balance between consumer preferences, utility resources and demand uncertainty.

The model presented by Laurent *et al.* [13] aims at optimizing interruption schedules for large aggregations of controlled electric water heating loads within a load management program. In this approach, the objective is to obtain the maximum system peak reduction while maintaining an acceptable level of service to consumers participating in the program.

Electric distribution network management is a problem that involves generally different conflicting aspects. When LM is also considered, the integration of demand-side in the decision process associated with dispatch activities contributes to increase the conflicting aspects both in number and intensity. For example, decreasing peak demand may correspond to also decrease utility revenues. Hence, the problem is multiobjective in nature: economic, technical and quality of service aspects must be explicitly accounted for in the mathematical models. By means of multiobjective models, the decision maker (DM) may grasp the conflicting nature of the objectives and the trade-offs to be made in order to obtain satisfactory compromise solutions.

In the decision support model developed and presented herein, the aim is not optimizing a single objective function of technical or economical nature (for example, to reduce peak demand or to minimize operational costs), but to explicitly incorporate into the mathematical model the distinct, conflicting and incommensurate aspects that are at stake for the network manager. This enables not just to extend the range of potential alternative plans, but also gives an important role to the network manager's structure of preferences to evaluate and select a satisfactory compromise solution, since no feasible solution exists which optimizes simultaneously all objective functions.

This paper describes a multiobjective decision support model that allows the explicit consideration of the main concerns that have an important role in LM: minimizing peak demand as perceived by the distribution network dispatch center, maximizing profits resulting from energy sale, maximizing the quality of service delivered by the controlled loads.

In Section II a multiple objective model for decision support is presented and a description is made of an interactive process to support the DM in selecting a compromise solution. In Section III the decision support environment is outlined and it is described how the control strategies are generated by means of a physically-based load model. A case study is described in Section IV and some results of the multiple objective model are presented. Some conclusions are drawn in Section V.

II. A Multiple Objective Model for the Selection of Control Strategies

The multiobjective model allows the DM to grasp the conflicting nature of the objectives in a LM program and to make trade-off in order to obtain satisfactory compromise solutions from the set of nondominated solutions. In a multiobjective context the concept of optimal solution gives place to the one of nondominated solutions (feasible solutions for which no improvement in any objective function is possible without sacrificing at least one of the other objective functions).

This model to provide decision support in the selection of control strategies allows to take into account the main concerns in an adequate remote load control program: to minimize peak demand of the load diagram perceived by the distributor, to maximize profit and to maximize quality of service. The use of this multiple objective model allows the DM to select, of a set of predefined strategies, a satisfactory control strategy to apply to each group of controlled loads in order to guarantee a compromise (nondominated) solution between the three objectives. The computed nondominated solutions depend on the time of occurrence of the peak of the forecasted network load diagram and on the network manager's preferences.

The model can be used to select satisfactory remote load control strategies for an existing system. At a preliminary design stage, it is also suited to make a previous economic analysis for evaluating the attractiveness of new LM programs, since it involves investments, namely in communication equipment and load switching interfaces.

The multiobjective model does not depend on the type of controlled load, though it has been applied only to the control of groups of electric water heaters. The information on the electricity consumption of the load groups and on hot water temperatures with or without the application of the control strategies to the load groups is obtained with a physically-based load model [8]. Control strategies define the on/off schedule of load groups, during the period of time where maximum demand control is to be achieved.

A. Mathematical Model

Notation:

i	Elementary time interval index (i $= 1, \cdots,$ n)
j	Load group index (j $= 1, \cdots,$ m)
k	Control strategy index (k $= 1, \cdots,$ q)
ΔT	Total control period
Δt	Elementary control time interval in minutes.
A_{jk}	Total number of loads in group j whose minimum comfort threshold is violated when subject to control strategy k, during the control period.
B_{jk}	Maximum number of loads in group j whose minimum comfort threshold is simultaneously violated when subject to control strategy k, during the control period.
b_j	Maximum number of loads in group j that are allowed to simultaneously violate the minimum comfort threshold.
c_{ijk}	Difference at interval i between load group j demand when control strategy k is applied to it and load group j demand without any control action.
D_{jk}	Measure of discomfort defined as a function of A_{jk} and B_{jk}.
L_i	Average forecasted network demand at interval i without load control
P	Forecasted network peak demand without control

r Decision variable that represents the network peak demand reduction

R_{jk} Profit variation corresponding to the consumption variation in group j when subject to control strategy k

m_{ij} Net revenue perceived by the utility per kWh at interval i by selling energy to group j.

X_i Average network demand at interval i with load control

x_{jk} Binary decision variable that assumes the value 1 if control strategy k is selected to be applied to group j, and 0 otherwise.

Objective Functions: The network load diagram is assumed to be known by means of a load forecast procedure. The total control period, that must be as long as needed in order to prevent a new peak demand caused by the payback phenomenon, is divided into n equal intervals ($\Delta t = \Delta T/n$). Supply interruptions, as defined by the control strategies, always begin at the start of a Δt interval and last for an integer number of intervals.

Under load control, demand at each elementary interval is given by:

$$X_i = \sum_j \sum_k (c_{ijk} x_{jk}) + L_i \quad \mathrm{i = 1, \cdots, n} \tag{1}$$

Minimize peak demand consists in minimizing the maximum network controlled demand, that is:

$$Min\, Max\{X_1, X_2, \cdots X_n\}$$

This objective can be formulated in an alternative way: maximizing the minimum value of the difference between the forecasted peak demand and the instantaneous controlled power demand, that is, maximizing the peak demand reduction.

$$Max\, Min\{P - X_1, P - X_2, \cdots, P - X_n\}$$

The optimization of this objective is not a linear problem, but it can be transformed into a linear problem considering a new decision variable r as the network peak demand reduction.

Thus, the $max\, min$ problem can be re-written:

$$Max\, r$$

subject to:

$$\begin{aligned} &P - X_i - r \geq 0 \qquad (\mathrm{i = 1, \cdots, n}) \\ &r \geq 0 \end{aligned} \tag{2}$$

The optimization of profit is equivalent to maximizing revenue variation caused by electricity consumption variation achieved with the application of control strategies.

Thus, maximizing profit may be stated as:

$$Max \sum_j \sum_k (R_{jk} x_{jk}) \tag{3}$$

where R_{jk} is given by:

$$R_{jk} = \frac{\Delta t}{60} \sum_i c_{ijk} m_{ij} \tag{4}$$

The measurement of discomfort caused by control actions is based on the number of loads for which the minimum comfort threshold has been violated. In the case of electric water heating loads, it corresponds to the number of water heaters whose water temperature is below an admissible minimum. The lower the number of water heaters that violate the minimum comfort threshold, the higher the quality of service.

Minimizing discomfort caused to consumers corresponds to minimizing the following function:

$$Min \sum_j \sum_k D_{jk} x_{jk} \tag{5}$$

where D_{jk} is given by:

$$D_{jk} = \alpha_A A_{jk} + \alpha_B B_{jk} \tag{6}$$

Parameters α_A and β_B are coeffcients of importance with respect to the accumulated value (A_{jk}) and the maximum number (B_{jk}) of loads in group j that violate the minimum comfort threshold, when subject to control strategy k.

Model constraints: One control strategy can be applied, at most, to each load group:

$$\sum_k x_{jk} \leq 1 \qquad (\mathrm{j = 1, \cdots, m}) \tag{7}$$

There is a maximum number of loads that are allowed to violate the minimum comfort threshold. Control strategies that lead to a higher number of loads in such situation are rejected.

$$\sum_k B_{jk} x_{jk} \leq b_j \qquad (\mathrm{j = 1, \cdots, m}) \tag{8}$$

Summarizing, the multiobjective model is thus:

$$\begin{aligned} &Max\, r \\ &Max \sum_j \sum_k (R_{jk} x_{jk}) \\ &Min \sum_j \sum_k D_{jk} x_{jk} \end{aligned}$$

subject to:

$$\begin{aligned} &P - L_i - \sum_j \sum_k (c_{ijk} x_{jk}) - r \geq 0 && (\mathrm{i = 1, \cdots, n}) \\ &\sum_k x_{jk} \leq 1 && (\mathrm{j = 1, \cdots, m}) \\ &\sum_k B_{jk} x_{jk} \leq b_j && (\mathrm{j = 1, \cdots, m}) \\ &x_{jk} = 0\, or\, 1 && (\mathrm{j = 1, \cdots, m;\ k = 1, \cdots q}) \\ &r \geq 0 \end{aligned}$$

B. Interactive Process

Since there is no solution which is superior to all the others (within the nondominated set) in all aspects of evaluation, the simple computation of nondominated solutions does not convey sufffficient information to select a final (compromise) solution. Once the multiobjective problem has been formulated, the available methods for dealing with it can be schematically classified as (see also [17]): - generating methods; - methods in which there is apriori articulation of the DM's preferences; - methods in which there is a progressive articulation of the preferences (interactive methods).

Generating methods are aimed at computing the whole nondominated solution set. The DM must then select the nondominated solution to be implemented. The exhaustive computation of all nondominated solutions becomes cumbersome beyond certain limits, and, more important than that, this effort is not worthwhile in most situations. In fact, presenting the DM with a large set of solutions, in many cases with just slight differences among the objective function values, may further complicate an already complex decision problem.

Another way to tackle this problem is to consider that a utility function is explicitly known, which is supposed to be the analytical expression of the DM's preferences. Under this assumption, the computation of the optimal solution, which maximizes the utility function, is then a scalar optimization problem. However, that is not a realistic assumption in most problems.

Interactive methods are nowadays considered to address the main drawbacks of the previous approaches (computational and decision complexity). In interactive methods, phases of decision (dialog) involving the DM are alternated with phases of computation. The DM intervenes in the solution search process by inputting information into the procedure which in turn is used to guide the search process in order to compute a new solution which more closely corresponds to his/her preferences. Thus, interactive methods reduce the computational burden and the number of irrelevant (from the point of view of the DM's preferences) solutions generated.

In this work, STEM [1] interactive method has been adopted to provide decision support in selecting remote load control strategies, both because of the simplicity of its computation and dialog phases as well as its capability to deal also with integer variables. Whenever integer variables are considered, nondominated solutions located to the interior of the convex hull (defined by the set of nondominated solutions) may exist. These solutions cannot be computed simply by optimizing a weighted sum program, as it is done in some approaches, because they are dominated by a convex combination of vertex solutions (no set of weights exists which defines a supporting hiperplane for them; that is, a duality gap exists). For this reason, though they are nondominated, they are generally called convex dominated solutions or unsupported (nondominated) solutions (see Fig. 1). But, since those solutions are actually nondominated, they must be considered as potential compromise solutions and consequently the method must accommodate for their computation.

These concepts are illustrated in Fig. 1 for the two-objective case, where both objective functions must be maximized. Solutions 1 and 2 are the nondominated solutions which maximize $f_1(\underline{x})$ and $f_2(\underline{x})$ objective functions, respectively. Solutions 3, 4 and 5 are vertex nondominated solutions. Solution 6 is a nondominated solution, even though it is dominated by a convex combination of solutions 3 and 4 (which belong to the nondominated boundary of the convex hull). Solution 7 is dominated by solution 5. z^* is the so-called ideal solution.

The type of scalarization (that is, transforming the multiple objective problem into a scalar optimization problem such that an optimal solution to this latter is a nondominated solution to the former) which is used in the framework of STEM (minimizing a weighted Tchebycheff distance to the ideal solution) enables to compute both supported and unsupported nondominated solutions.

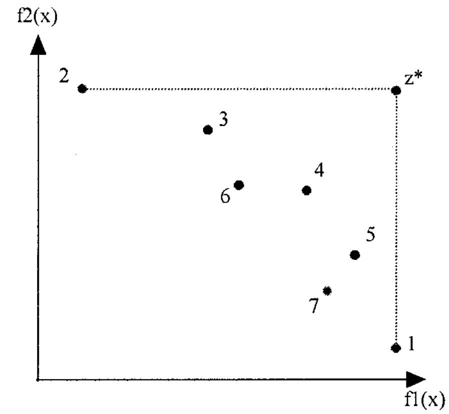

Fig. 1. Nondominated, convex dominated, dominated and ideal solution.

In each iteration of STEM a nondominated solution is computed, which minimizes a weighted Tchebycheff distance to the ideal solution. The so-called ideal solution is the one that would optimize all the objective functions simultaneously, which is not feasible whenever the objective functions are conflicting.

The problem to be optimized in iteration h reflects the DM choices in the preceding interaction phases, through the reduction of the feasible region by imposing additional constraints on the objective function values. In each computation phase of STEM a problem of the following type

$$\begin{aligned} &\min \mathrm{v} \\ &\text{s.t.} \quad \alpha_k(z_k^* - f_k(\underline{x})) \le v \quad , \quad k = 1, \cdots, p \\ &\qquad \underline{x} \in X_h \\ &\qquad v \ge 0 \end{aligned}$$

is solved. Without loss of generality, all the objective functions are considered to be maximized. z_k^* is the maximum of the objective function $f_k(\underline{x})$ in the feasible region X of the original problem. The α_k values are the product of two terms which aim at placing the most weight on the objectives with the greatest relative range and normalizing (using the L_2-norm) the objective functions. The feasible region for iteration h X_h results from the introduction of additional constraints on the objective function values with respect to the initial feasible region X. v is a variable used to transform the min-max problem (that is, minimizing the Tchebycheff distance) into a linear problem.

The nondominated compromise solution computed in each iteration by minimizing a weighted Tchebycheff distance to the ideal solution is presented to the DM. If the values of the objective functions are considered satisfactory the process stops, otherwise the DM must specify those which he/she is willing to relax, and by how much, in order to improve the other objectives. A reduced feasible region for the next iteration is then constructed by introducing additional constraints on the objective functions, in the following way:

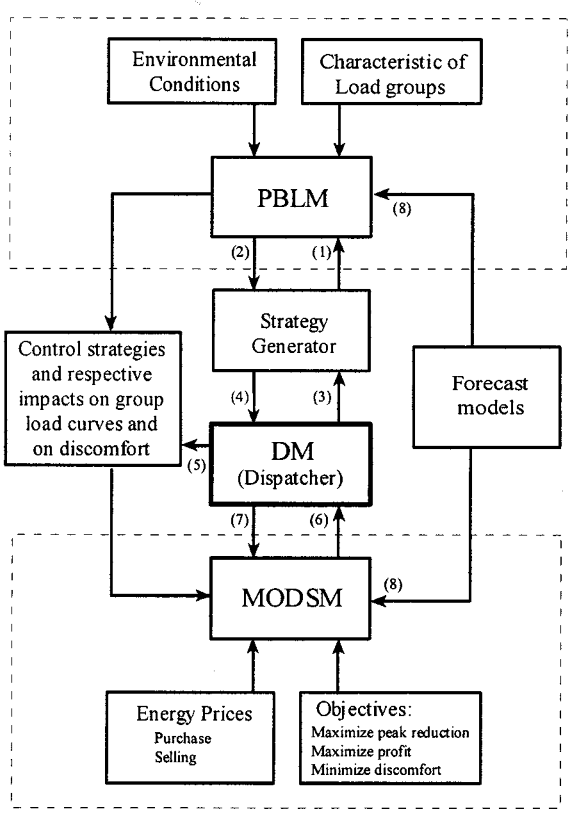

Fig. 2. Decision support environment.

$f_k(\underline{x}) \geq f_k(\underline{x}^h)$, if the value of objective function k computed in iteration h has not been considered satisfactory;

$f_k(\underline{x}) \geq f_k(\underline{x}^h) - \Delta_k$, if the value of objective function k computed in iteration h has been considered satisfactory and the DM is willing to specify a relaxation quantity Δ_k in order to improve the remaining objectives whose values have not been considered satisfactory. The weight $\alpha_k = 0$ for each objective function that it is relaxed.

As long as there exist any objective function values for which the DM is willing to trade-off in order to improve the others, the interactive process goes on.

III. The Decision Support Environment

In functional terms, the multiple objective model described in Section II is one of the components of a wider support environment to a DM in charge of planning short-term load management programs or, as they may be alternatively designated, load dispatch schemes. The diagram in Fig. 2 represents this environment.

The block identified by MODSM (multi-objective decision support model) is interactively accessed by the DM in the way previously described (flows (6) and (7)). It is fed with different kinds of data: short-term demand forecasts (flow (8)), electricity prices as seen both by consumers and by the utility, load control strategies and their impacts on load diagrams. Data on these strategies and respective impacts are obtained through the interaction between the DM and the block PBLM (physically-based load modeling) through the interface designated "Strategy Generator" (flows 1 to 4).

The PBLM block represents a simulation environment where detailed individual physically-based load models are used as the essential components of large scale load representations. The load model also takes into account the payback phenomenon effect that occurs after the restoration of electricity supply to loads. In some previous works such as Chen *et al.* [4] and Kurucz *et al.* [12] this effect is accounted for through an empirical approach. In the case study, an individual electric water heater (EWH) model is used, which needs several data to be able to provide information on the rate of electricity consumption, on the water temperature inside the tank and on the rate of energy losses through the envelope. Inputs such as the physical characteristics of the tank's envelope, air temperature, inlet water temperature, thermostat setting, and water consumption pattern are needed to operate the model. Groups of loads, in the context of PBLM, are made up of EWH which have similar average physical characteristics and are subject to similar environmental conditions. Additional concerns should be present when designing groups, such as the geographical vicinity among the loads to be controlled, or the total number of control points in each group. The first, for the sake of feasibility of the actual control system and its communication requirements. The second, because the pay-back effect when supply is restored to a group of curtailed loads is the more important the higher is the number of loads within a group.

Several hot water consumption patterns may be used, which usually result from previous consumption research actions. Randomization is used to ensure an appropriate spreading of hot water consumption among the EWH in each group. The initial water temperature inside the tank, when simulation starts, is also randomized among the EWH. Besides, a 24 hour period is simulated only to allow for the stabilization of load behavior, before results are actually used. Loads may be simulated with or without shedding actions. In the absence of control, the model output provides quantitative information on the spontaneous contribution of controllable loads to the network load diagram, as the base case. When shedding actions are considered, the physically-based nature of the underlying load model automatically allows a quantitative assessment of the demand modifications to the base case. Additionally, detailed information is also available on a major comfort indicator: water temperature inside the EWH tanks. It may be used to assess the adequacy of a certain control scheme as regards to the quality of the energy service provided to customers under control, and may be compared to a value defined by the DM – the lower water temperature comfort limit.

In the context of PBLM block not only the data needed for the procedures previously described are defined, but also the EWH groups and load control strategies (time schedules of supply curtailment and restoration).

Within the Strategy Generator block the DM conducts the definition of the control strategies which reveal to be the most appropriate for feeding the MODSM block. The DM's relation with the Strategy Generator is interactive (flows 3 and 4). It

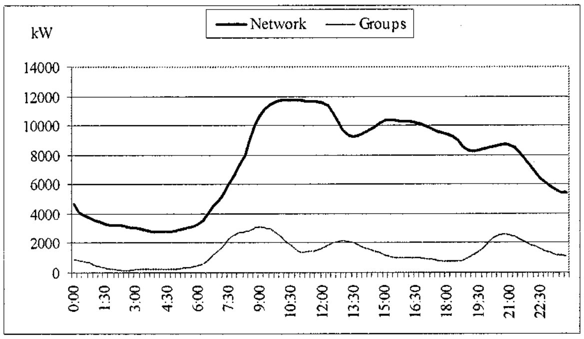

Fig. 3. Network and total group load curves.

needs, in the first place, the definition of a network power demand limit (PDL) that should not be overpassed. PBLM performs the simulation according to the parameters previously defined until a situation occurs where PDL would be violated in the absence of load control. Here, the DM may use a bi-objective linear programming model that helps selecting the strategy best suited for minimizing load shedding and discomfort to customers, complying with the defined PDL. It configures a load leveling approach, in the sense that only the indispensable shedding actions are taken in order to comply with the PDL. The time interval used may be of 5, 10, 15 or 30 minutes. After each time interval, information is available on the network base case power demand, the total number of EWH violating the lower water temperature limit and the power demand of each EWH group. The chosen control strategies are retained to be used in MODSM. The DM may always delete some of them if he/she considers that a too big number of strategies have already been retained (flow (5) in Fig. 2).

IV. Case Study

In this section a case study is described corresponding to 4000 water heaters aggregated into 8 groups. Each group has 500 water heaters and is associated with several typical households each one characterized by a water consumption pattern. A computer application using a physically-based load model has been used to generate the group load curves with and without remote control actions. In Fig. 3 the network load curve is displayed. The network peak demand is 11 750 kW at 10:30. Without control actions, the load curve pertaining to all groups has a peak demand of 3110 kW at 9:00.

Eight control strategies have been generated for each load group by using a PBLM. The computational load model has also been used to determine the impact of the different load control strategies on customers' discomfort and on load group curves. Discomfort is measured through the number of water heaters that violate the minimum comfort threshold. This condition is violated whenever the water temperature inside the tank is below 45°C (113°F).

The nondominated solutions that individually optimize each objective function (F1 - reduction peak demand, in kW, F2 - profit variation, in Portuguese escudos, F3- discomfort) and the corresponding control strategies are presented in Table I (the underlined values denote the optimal value of each objective). The strategies are ordered by groups and identified by a number that represents the control strategy in the group. For instance, the solution which optimizes F1 consists in applying strategy 1 to group 1, strategy 2 to groups 2 and 5-8, strategy 8 to group 3 and strategy 3 to group 4. These solutions have been determined imposing that network peak demand can not be greater than its initial value of 11 750 kW and the variation of profit must be positive.

TABLE I
Individual Optimal Solutions and Control Strategies

	F1 (kW)	F2 (PTE)	F3	Control Strategies
Optimal solution F1	<u>514</u>	8109	4420	1, 2, 8, 3, 2, 2, 2, 2
Optimal solution F2	293	<u>15403</u>	7360	8, 8, 8, 8, 8, 8, 8, 8
Optimal solution F3	17	2975	<u>980</u>	6, 3, 3, 6, 6, 3, 6, 7

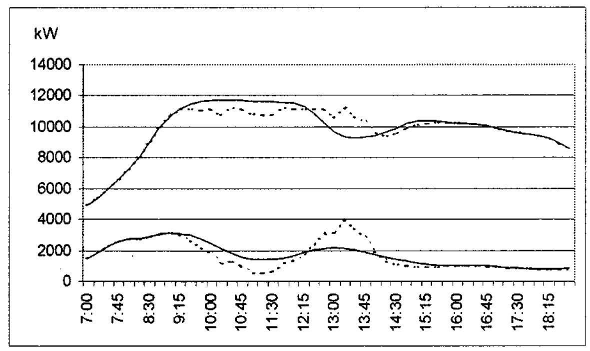

Fig. 4. Solution that optimizes F1.

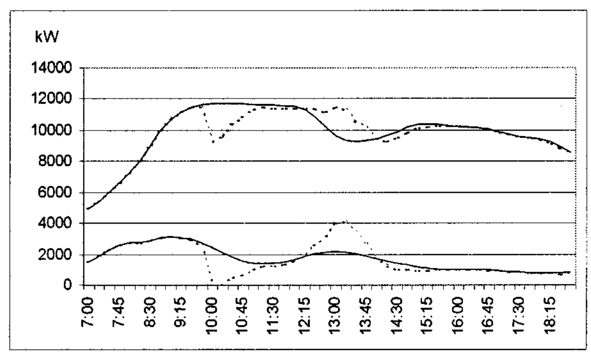

Fig. 5. Solution that optimizes F2.

The load curves corresponding to the nondominated solutions that individually optimize each objective function are displayed in Figs. 4 to 6. Full lines correspond to the uncontrolled situation, while doted lines correspond to the effects of remote load control. The upper curves are global network load curves and the lower ones pertain to the load groups under control.

The nondominated solutions computed by STEM interactive method are summarized in Table II. The initial solution present by the method is (123,12607, 4030). To begin the interactive process let us suppose that the DM decided to relax F2 by $\Delta 2 = 3500$ in order to improve the other functions. The new nondominated solution computed by STEM is (364, 9265, 2450). The

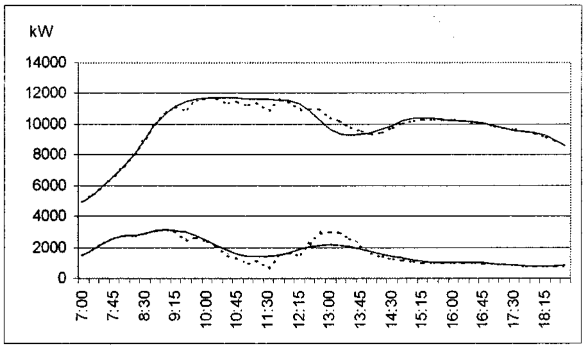

Fig. 6. Solution that optimizes F3.

TABLE II
SOLUTIONS COMPUTED BY STEM INTERACTIVE METHOD

	F1 (kW)	F2 (PTE)	F3	Control Strategies
Solution 1	123	12607	4030	7, 8, 8, 2, 8, 8, 1, 1
Solution 2	364	9265	2450	7, 4, 6, 4, 2, 8, 1, 2
Solution 3	283	8071	1910	7, 3, 2, 4, 6, 8, 5, 1
Solution 4	310	8000	2100	2, 4, 4, 2, 2, 8, 1, 1
Solution 5	318	10255	2810	7, 7, 7, 2, 8, 7, 1, 1

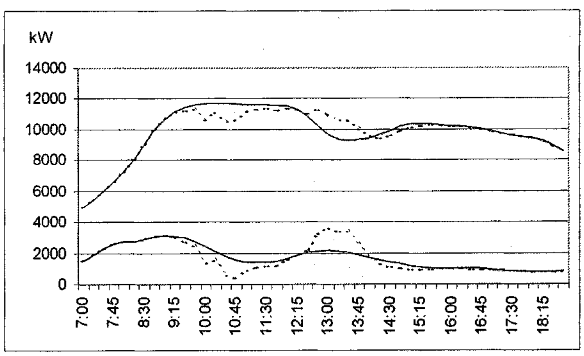

Fig. 7. A compromise solution among the three objectives.

interactive process proceeds then in the same way until the DM considered solution 5 a satisfactory compromise solution.

The load curves corresponding to solution 5 are displayed in Fig. 7.

V. CONCLUSIONS

The multiple objective model described in the paper aims at providing decision aid to select control strategies, which are to be applied to load groups through the load remote control dispatcher. This model takes into account the main concerns in a load management program: to minimize peak demand (or maximize peak demand reduction), to maximize utility profits and to minimize discomfort caused to consumers.

STEM interactive method has been used to aid the DM in the progressive and selective search of nondominated solutions, by using the knowledge about the problem acquired in the preceding iterations and accommodating the DM's preferences.

The sets of control strategies, and their impact on group load curve and discomfort caused to consumers, are generated by a physically-based load model. The load model also takes into account the payback phenomenon effect.

An advantage of this multiple objective model, when compared with other approaches consists in the use of binary variables instead of continuous variables. This enables the model to select (or not) a control strategy to be applied to a whole load group and not to a part of it. For instance, Laurent *et al.* [13] define a percentage of water heaters in a group that are affected by a specific control strategy, considering that the control system has the ability to perform this action. This provides a more flexible load control, but it increases the complexity of load addressing by the control system.

The multiple objective decision support model is independent of the load type, even though it has been illustrated with a case study involv ng control of water heaters. The load model associated with each load type must give the following information to each control strategy: group load curves and number of loads that violate a minimum comfort threshold.

The use of multiobjective models in the framework of nteractive decision support environments seems a very promising research avenue to aid DM's in selecting remote load control strategies.

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