Simulation of a Decentralized Optimal Demand Response Algoritm

Aldo Rondoni, Administración Nacional de Usinas y Trasmisiones Eléctricas (UTE)
Álvaro Giusto, Facultad de Ingeniería de la Universidad de la República
and Marcelo Rey, Administración Nacional de Usinas y Trasmisiones Eléctricas (UTE)

***Abstract*—Demand Response will be a fundamental component in the future of smart grids, and it will be helpful to reduce peak loads and adapt elastic demands to the fluctuations of distributed generation provided by Renewable Energy. In this paper we consider customers who may operate different equipments, and an approach to Demand Response, based on maximizing the overall welfare of society (Social Welfare) with a similar methodology to classical economic theory treatment. Under certain conditions, with the help of price signals, individual optimization and social optimization can be aligned, ie, when customers selfishly optimize their own benefit, social welfare is being optimized. This fact, beyond its social and economic implications, enables a distributed technology solution where each customer is planning its consumption so as to maximize their net benefit with the information available. To do this each device (heating, washing machines, etc.) is modeled by a utility function that depends on the consumption pattern over the day and volume of consumption in that day. The electric company can then dynamically manage prices to manage demand to the benefit of the overall system. In this paper, an algorithm for Demand Response proposed in the recent literature, based on an iteration / negotiation between customers and the electric company, is implemented, and the results of the simulation of an scenario with 12 clients is presented.**

***Index Terms*—Demand Response, Optimization, Smart Grids.**

I. Introduction

There is many literature on the various ways to implement demand side management (DSM), or Demand Response, ranging from the classic aproach, to the latest direct control of Prices in real time. Particularly direct load control has been implemented, and optimization methods have been proposed to minimize generation costs, maximize income from the electric company, or minimize the deviation from the desired customer behavior. Most demand response programs are focused in large commercial or industrial users, and do not tinclude the domiciliary ones. This is mainly due for two reasons: The first, is that demand response is used only to support a large increase in demand due to weather, or a drop in supply due to failures during peak demand. The second is that the lack of communication systems in the current infrastructure does not allow to control a large number of users with different requirements of electricity usage. Both reasons promote a simple static mechanism involving few large users that is enough to control the occasional need of a modified load profile. There are many reasons to change that paradigm. Distributed generation can fluctuate rapidly in large scale. As the penetration of renewable electric generation continues increasing, the need for fast back up generation will increase with its high cost problem. Another approach could be by mean of demand response in real time strategies. The current state of technology , suggests that demand response will not be used only to flatten peaks and transfer charges for economic benefits, but they will be used to improve safety, and reduce rotating reserve. Demand response in this context must allow participation of big scale users, be dynamic, and distributed. In this work, simulation scenarios in Optimal Demand Response based on written articles by Steven Low, LijunChen, Na Li and Jiang Libin, [1-3] are presented. In these articles, optimal welfare of society is achieved, from an economic point of view, through a process of negotiation between a Load Serving Entity (LSE) and customers. On one hand, each customer tends to maximize profits according to the price signals given by the LSE. The optimum Social welfare is reached, in certain conditions established in [1], through price signals consisting of the marginal cost of energy per hour, as the same time that customers try to optimize their own benefit. This method does not depend on the global knowledge of the utility functions of the customers. The algorithm that implements the mentioned method also provides a benchmark against that can be compared with other mechanisms of demand response.

II. Equipment and users modelling

The objective in this work is to show simulation models of equipment and user behavior in the use of such equipments, and propose applications strategies to achieve demand management based on optimization criteria, maximizing welfare. To achieve this objective, a survey of the literature was conducted, and based on this, we developed an optimization tool. The equipments are divided in four types:

Type 1: Elements of thermal conditioning (water heaters, air conditioners, refrigerators, electric stoves, radiant slabs, panels heating);

Type 2: Charging electric cars, washing machines, dishwashers;

Type 3: Lighting;

Type 4: TV, DVD, computers, video games, entertainment in general.

Modeling a equipment eventually involves a physical model, for example heat, and, from the point of view of optimization, each of these devices have associated restrictions on use and a utility function according to [1-3]. These utility functions should be combined with the costs associated with the generation, both renewable and non-renewable, in order to maximize the overall welfare. In this paper, we consider that equipment groups are commanded by intelligent devices (IEDs) that are responsible of negotiating with the load server entity (LSE) a vector of daily hourly rates. Each IED represents a user who has multiple equipments. For each of these equipments, user has a economic "utility" function, that together with the signal price transmitted by the LSE, conforms particular benefit that the user, represented by the intelligent device, seeks to maximize. In the articles collected, is established an iteration/negotiation step by step between the user and the energy supplying entity, that maximizes the total social welfare. In the figure 1, the scheme is summarized.

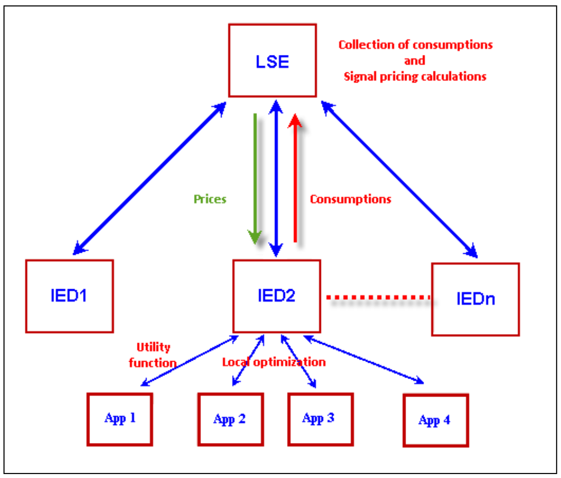

Fig. 1. Actors Interaction

A. UTILITY FUNCIONS

The utility funtions represent the welfare that a customer gets by the use of some kind of equipment. Utility funtions are developed in [1], [2] and [3]. Utility functions for the different types of equipment are:

1) Type I Equipment:

$$U_{ia}(T_{ia}(t)) = c_{ia} - b_{ia}(T_{ia}(t) - T_{ia}^{Comfort})^2 \qquad (1)$$

where:
U_{ia} : Utility function for the equipment a of customer i
$T_{ia}(t)$: Temperature obtained by the equipment a of customer i
$T_{ia}^{Comfort}$: Temperature that maximizes user's comfort obtained by the use of equipment a of customer i
c_{ia}, b_{ia} : Parameters of the utility function

2) Type II equipment:

$$U_{ia}(Q) = c_{ia} + b_{ia}Q \qquad (2)$$

where:
U_{ia} : Utility function for the equipment a of customer i
Q : Total power consumed by the equipment
c_{ia}, b_{ia} : Parameters of the utility function

III. OPTIMIZATION PROCCES

$$Max \sum_{\epsilon cliente_{iq}} U_{ia}(q_{ia}) - \sum_t p(t)Q_i(t) \qquad (3)$$

$$Max_q \sum_i (\sum U_{ia}(q_{ia})) - \sum_t C(\sum_i Q_i(t)) \qquad (4)$$

where:

C : is the cost of energy for a t time-slot.

$$\bar{q}_{ia}^{k+1}(t) = q_{ia}^k(t) + \gamma(\frac{\partial}{\partial q_{ia}^k} U_{ia}(q_{ia}) - p_k) \qquad (5)$$

$$q_{ia}^{k+1} = [\bar{q}_{ia}^{k+1}]^S \qquad (6)$$

IV. SIMULATION SETUP AND RESULTS

We have considered two profiles of consumption: First profile: simulates a home that is habitated by people all day, so there will be interest in using the apparatus during the time interval [8h, 23h]. Second profile: simulates a home where there are no people in the house during working hours, which is not important to use certain equipment for heating. The time interval which aims to use is [18h, 23h]. It is assumed that outside the ranges above scheduled, no heating equipment or washing are turned on, but refrigeration is used, which should keep the cold over the 24 hours. From the twelve simulated clients, there are four that matchs the first profile, while the remaining eight meets the second profile. In this case each client has three different equipment that can control its temperature, consisting of one air conditioning as a heating system, one water heater and one refrigerator, besides a washing machine. These equipments have the following characteristics: Air conditioning: During the hours of comfort, each user needs to maintain the temperature in the range [18 , 22] with an ideal temperature of 20 , which maximizes his utility. Water heater: During comfort hours, in which the user wants to have hot water in his home, the temperature needs to be maintained in the range [40, 80] with an ideal temperature of 60. Refrigerator: It is intended that all day temperature was maintained in the range of [4 , 8] with an ideal temperature of 6 . Washing Machine: This is a type 2 equipment, where the total energy consumed is controlled, keeping it between a minimum and a maximum value. During all previous simulations, the minimum total consumption were considered for each of these equipments randomly selected in the interval [1400Wh, 1600Wh], while the highest consumptions were chosen equally randomly between [2000Wh, 2500Wh]. Has also established an additional constraint which is that in each time slot, the maximum consumption did not exceed 1500 Wh. Both scenarios considered, are presented graphically

A. Without Demand Response

In the following figures the result of a free use of equipment is presented.

In this scenario, customers adjust their appliance usage according with maximizing the local utility funcion.

Global welfare is a decrescent function.

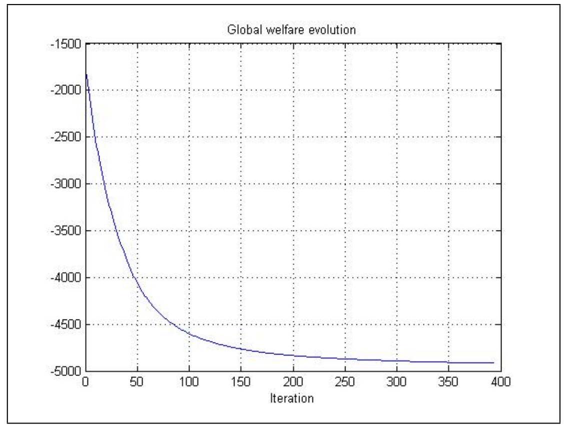

Fig. 2. Global welfare evolution without Demand Response

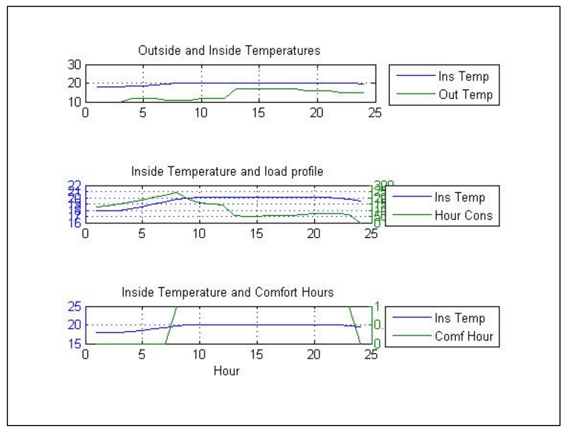

Fig. 3. Household temperature without Demand Response

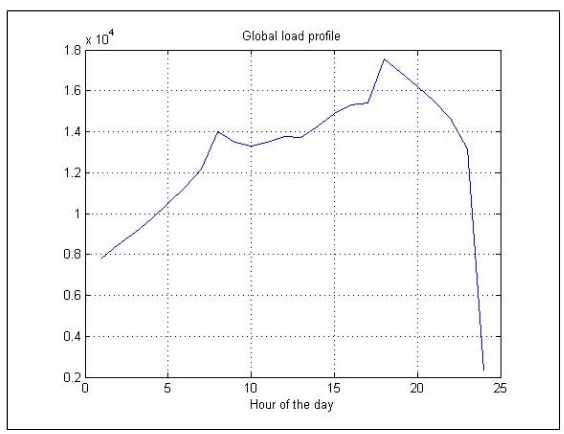

Fig. 4. Global load profile without Demand Response

B. Double hourly price

In the following figures the result of a double hourly price strategy is presented. To obtain the desired temperature profile, there is a peak of load just before the start of the high price period.

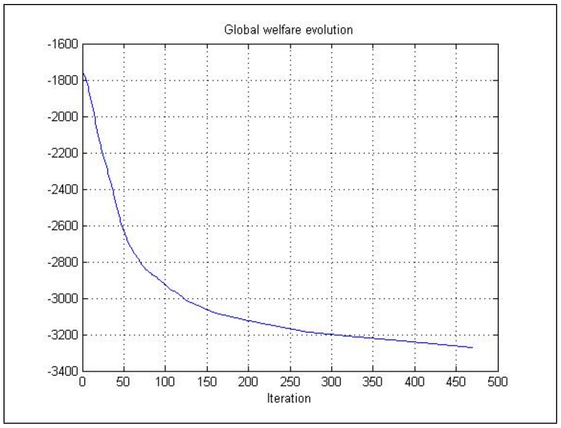

Fig. 5. Global welfare with double hourly prices

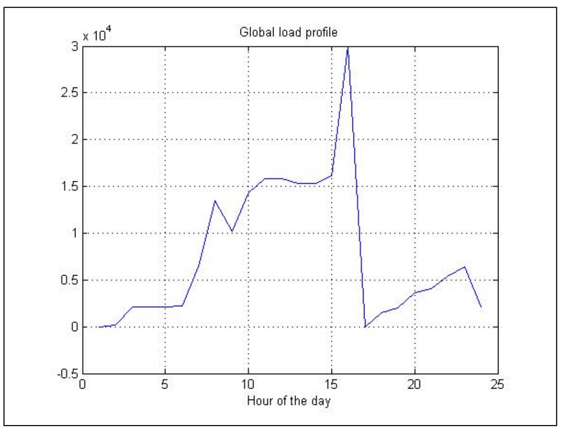

Fig. 6. Load profile with double hourly prices

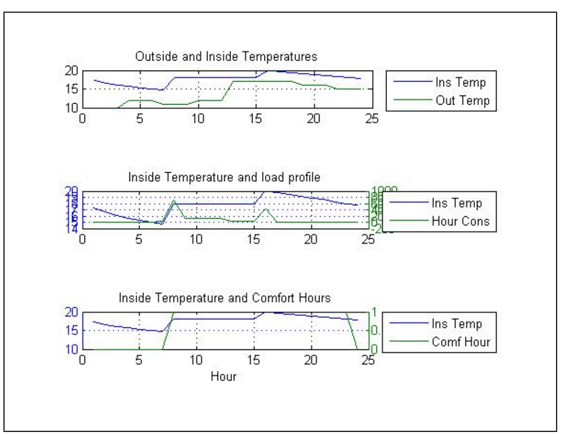

Fig. 7. Household temperature with double hourly prices

C. Full Optimization

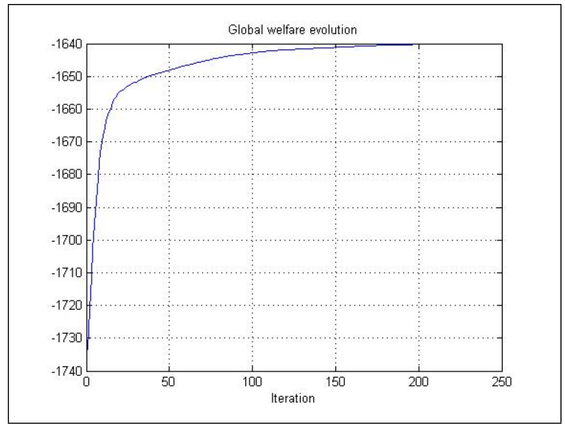

Fig. 8. Welfare evolution with Demand Response

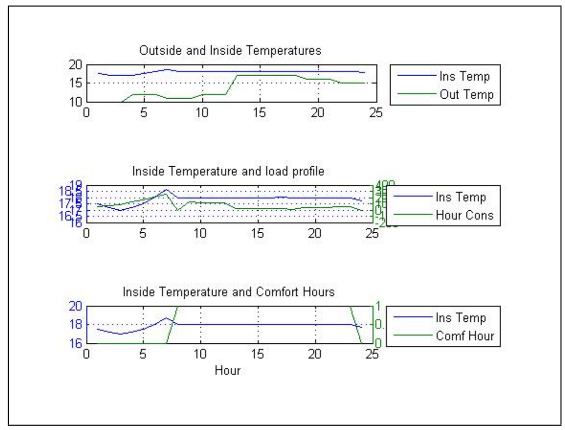

Fig. 9. Household temperature with Demand Response

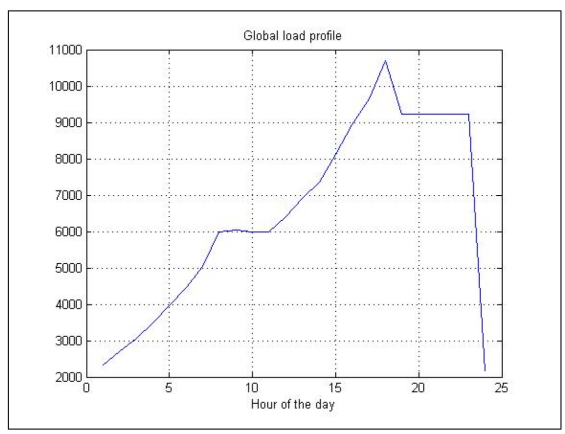

Fig. 10.

V. Some remarks

The results obtained in the simulations are consistent with the pricing strategies presented. In the case without demand Response, customers tend to maximize their utility, while in the other cases they tend to consume the least amount of energy satisfying the constraints of the equipment. This work has established a simulation environment that allows the study of different pricing policies and customer behavior. Particularly, the classical multiple price rates is simulated and compared with the optimal strategy. On future works, the utility functions and equipment models will be improved to represent real cases.

References

[1] Na Li, Lijun Chen and Steven H. Low. Optimal Demand Response Based on Utility Maximization in Power Networks.

[2] Libin Jiang and Steven Low. Multi-period Optimal Energy Procurement and Demand Response in Smart Grid with Uncertain Supply

[3] LijunChen, Na Li,Libin Jiang, and Steven H. Low. Optimal demand response: problem formulation and deterministic case

[4] Libin Jiang and Steven Low. Real-Time Demand Response with Uncertain Renewable Energy in Smart Grid

[5] C. E. Lin, G. L. Viviani. Hierarchical Economic Dispatch for Piecewise Quadratic Cost Functions

[6] Stephen Boyd, LievenVandenberghe. Convex Optimization

[7] Mokhtar S Bazaraa, Hanif D. Sherali and C.M Shetty. Nonlinear Programing, Theory and Algorithms

[8] David G. Luenberger, Yinyu Ye. Linear and Nonlinear Programming

[9] Miao WeiWei, JIA HongJie,WangDan,ParkinsonSimon, Crawford Curran and Djilali Ned. Active power regulation of wind power systems through demand response.

[10] Jean-Yves Le Boudec and Dan-Cristian Tomozei. A Demand-Response Calculus with Perfect Batteries

[11] Safdar Ali, Rashid Ahmad, DoHyeun Kim. A Study of Pricing Policy for Demand Response of Home Appliances in Smart Grid Based on M2M

[12] MichalisKanakakis, MarilenaMinou, Costas Courcoubetis, George D. Stamoulis, George Thanos. An Iterative Price-Based Approach for Optimal Demand Response

[13] PedramSamadi, Amir-HamedMohsenian-Rad, Robert Schober, Vincent W.S. Wong, and JuriJatskevich. Optimal Real-time Pricing Algorithm Based on Utility Maximization for Smart Grid.

[14] SeyedAtaollahRaziei and HamedMohsenian-Rad. Optimal Demand Response Capacity of Automatic Lighting Control

[15] R.E.Mortensen, K.P.Haggerty. A stochastic computer model for heating and cooling loads.

[16] BadriRamanathan, and Vijay Vittal. A Framework for Evaluation of Advanced Direct Load Control With Minimum Disruption

[17] LazarosGkatzikis, TheodorosSalonidis, NidhiHegde, Laurent Massouli'e. Electricity Markets Meet the Home through Demand Response