# Contextual Intelligent Load Management Considering Real Time Pricing in a Smart Grid Environment

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# Contextual Intelligent Load Management Considering Real-Time Pricing in a Smart Grid Environment

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***Abstract* — The use of demand response programs enables the adequate use of resources of small and medium players, bringing high benefits to the smart grid, and increasing its efficiency. One of the difficulties to proceed with this paradigm is the lack of intelligence in the management of small and medium size players. In order to make demand response programs a feasible solution, it is essential that small and medium players have an efficient energy management and a fair optimization mechanism to decrease the consumption without heavy loss of comfort, making it acceptable for the users. This paper addresses the application of real-time pricing in a house that uses an intelligent optimization module involving artificial neural networks.**

***Index Terms*— Artificial Neural Network, Demand Response, Load Management, Multi-Agent Systems, Real-Time Price.**

## I. Introduction

The recent liberalization of electricity markets must be followed by the restructuration of power systems towards the practical implementation of smart grids [1]. This new paradigm, besides other concepts, comprises the active participation of small and medium players in the smart grid environment. The integration of small and medium players will increase the complexity of the smart grid's management. Despite this, only the active participation of such players will enable the success of smart grids.

The integration of small and medium players can be done through Demand Response (DR) programs [2][3]. The aggregation between the players allows them to be represented by an external entity that can interact with high level players of the grid. The aggregation of players enables small and medium players to participate in large programs formerly exclusive to large players.

The aggregation of resources belonging to small and medium players can be achieved with new players, such as Virtual Power Players (VPP) [4] and Curtailment Service Providers (CSP). They act as mediators between the Independent System Operator (ISO) and the aggregation composed of the small and medium players.

The use of DR programs can be seen in works such as [5], [6] or [7]. Moreover, to enhance the potential of DR programs it is mandatory to test these programs outside of a simpler simulated environment. The impact motivated by DR programs in people daily life can lead to the non-acceptance of DR programs by real consumers.

To solve the problem of the negative impact of DR in the daily life, this paper uses a Multi-Agent System (MAS) to simulate a smart grid environment and it uses a combination of physical and simulated loads to represent a house. Using this integration between physical and simulated worlds it is possible to test the real impact of DR programs in a house.

This paper also uses a load management system entitled SCADA House Intelligent Management (SHIM) which deals with environmental variables. The existence of an optimization module is almost mandatory to enable small and medium players to participate in DR programs in an autonomous and efficient way.

An appropriated optimization module is crucial to achieve the integration of small and medium players in the smart grid environment. DR programs can bring economic benefits to the small and medium players, but for users, the importance of DR programs is the impact they produce in their lives. That is the reason why this paper deals with DR programs from the point of view of the consumers' comfort used for this project. The minimization of the DR negative impact must be controlled not to intimidate the small and medium players. In previous works, the authors demonstrate the learning capabilities of the optimization module [8] and the benefits of the optimization during DR programs [9]. In this paper, the authors focus on the users' comfort, showing three case studies that illustrate optimization module ability to address

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This work is also supported by FEDER Funds through the "Programa Operacional Factores de Competitividade – COMPETE" program and by National Funds through FCT "Fundação para a Ciência e a Tecnologia" under the projects FCOMP-01-0124-FEDER: PEst-OE/EEI/UI0760/2011, and PTDC/SEN-ENR/122174/2010).

the environment conditions, keeping a satisfactory level of comfort to the users.

After this initial introductory section, Section II presents the proposed system based on the MAS methodology and the physical laboratory. Section III presents the SHIM and describes this module regarding the optimization processes, giving particular attention to the use of the Artificial Neural Networks (ANN). Section IV presents the case study considering three scenarios that show the impact of Real-Time Price (RTP) inside the house. Finally, Section V presents the most important conclusions of the presented work.

## II. SYSTEM'S ARCHITECTURE

This section will address the system architecture used to test the proposed methodology. The two sub-sections will discuss the Multi-Agent System used to simulate a realistic smart grid environment with all the main players, and the physical laboratory used to simulate the analyzed house.

### A. *Multi-Agent System*

To be able to test DR programs, the project uses a MAS to simulate a smart grid environment. The use of MAS applied to distributed energy systems for management and test purposes has been shown to be feasible and very useful [10][11]. The MAS has been chosen due to the existing abstraction in the code that each agent executes, ensuring that the Installation Agent, studied in this paper, may be added to any other MAS that would like to deal with a facility with real loads and not only simulated loads.

In order to adequately test the methodology proposed in this paper, two MAS are used:

- MASCEM – a modeling and simulation tool developed for studying complex restructured electricity markets [12];
- MASGriP – a simulation platform that allows studying the integration of small and medium players in a smart grid perspective [13].

From the combination of these two systems a unique MAS emerges, accommodating several distinct players with their own characteristics and goals. This creates a perfect environment of agents capable of communicating among themselves and pursuing their personal goals. This system provides the opportunity for simulating DR programs and testing their impact in a real facility. Figure 1 presents the integration of MASCEM and MASGriP.

The system also allows the use of three types of consumer players:

- Virtual Consumer – in this case all loads present in the player are simulated by a computer;
- Physical Consumer – with regard to players that use only physical loads;
- Hybrid Consumer – in this case the player had a mixture of Virtual and Physical loads.

These three types of players enable the system to be more than a conventional virtual simulator, enabling it to accommodate physical players.

All agents have an Extensible Markup Language (XML) file to define their configurations and actions in the smart grid. The communications between agents are made by internet sockets, allowing a multi-machine system. For now, these communications use XML to structure messages and their information. Furthermore, the communications will be standardized by the FIPA-ACL, opening this MAS to outside players [14].

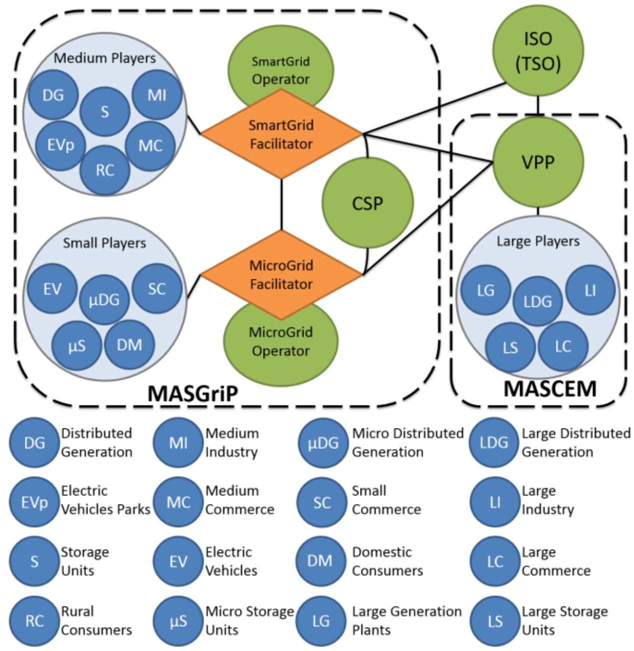


Figure 1. MAS platform for smart grid simulation.

### B. *Physical Laboratory*

In order to analyze the impact of DR programs and the load optimization that most DR events require, this paper will focus on a Hybrid Consumer, from now on referred to as Installation Agent that combines simulated loads and physical loads.

The physical loads of the Installation Agent are located at the Intelligent Energy Systems Laboratory (LASIE), at GECAD (the Knowledge Engineering and Decision Support Research Center) – Polytechnic of Porto [15][16]. LASIE includes physical loads controlled and managed by the Installation Agent, making this a very realistic simulator.

Besides the physical loads the agent also deals with virtual loads simulated by the agent, enabling the inclusion of loads that are not physically available.

The control of the loads can be done with:

- Switches – only the physical loads can be controlled by physical switches;
- Computer – all the loads can be controlled and managed by a computer with the appropriate software;
- Mobile Device – all the loads can be controlled and managed through an application that runs in android devices.

When the users use a Computer or a Mobile Device to control the loads, in addition to manage the loads, they can also access to information regarding DR programs, the previous consumption and the energy prices of the last hours.

The Installation Agent is responsible for the physical loads, the simulated loads and the connection between these loads and the smart grid environment (Figure 2). In Figure 1, the Installation Agent is considered a Small Player and it can be seen as a Domestic Consumer.

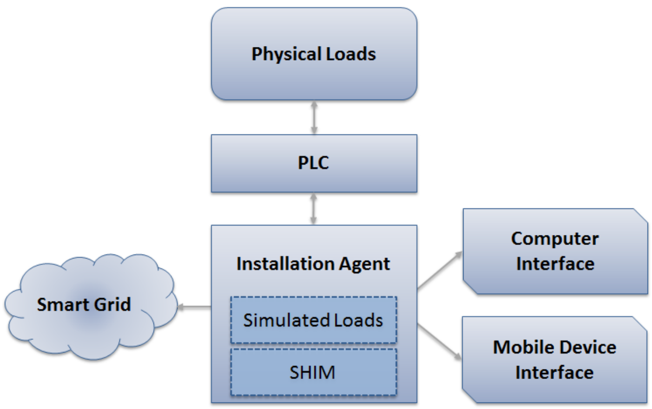


Figure 2. Communications of the Installation Agent.

The Installation Agent corresponds to a small house in the smart grid. This agent is prepared to manage the loads and manage DR programs launched in the grid. The DR programs are treated according to the user's will; for this reason the agent has a configuration file (in XML) with information on the actions of each DR program in which the user wants to participate. For this paper the main goal of the Installation Agent is to save money for the user, through the participation of DR events, while maintaining the comfort level of the house.

The Installation Agent, described in this paper, uses a SCADA House Intelligent Management (SHIM) that is responsible for reducing the consumption in real time. This intelligent module uses ANNs and General Algebraic Modeling System (GAMS) to achieve its reduction goal (Section III).

The SHIM uses the ANN to define the priorities of the loads at the time of the reduction in the consumption. These priorities are modelled by preference factors and they are the values that will indicate if the user wants a certain load to maintain its initial state (initial state is the state before the optimization process) [8].

## III. SCADA HOUSE INTELLIGENT MANAGEMENT

The optimization of loads from the consumer's standpoint is critical to participate in DR programs, which mainly culminates in a reduction in the consumption on the consumer's side. This section will present the structure of the SHIM integrated in the Installation Agent.

### A. Optimization

The optimization present in the Installation Agent can be executed for three different reasons: when the user intends to; when a DR event (that the facility must or may react to) occurs; and when an offset of consumption is defined and the user exceeds the offset of consumption.

The process of optimization is composed of the initial context characterization, using the environmental variables, such as the inside temperature, the inside clarity, the season of the year, the day of week, the time of the day, the number of people in the facility and the people's locations.

After knowing the context, the Artificial Neural Network (ANN) will transform this context into preference factors regarding each load in the facility. The preference factors are numerical representations of the user preference for each load. After the optimization, the ANN can learn through the user interaction, recording this data into the users' profile [8].

The last step of the optimization combines the loads states and the preference factors to proceed with an optimization according to the preference factors, the loads that are turned on and the cut that is requested.

To execute the optimization, this paper uses GAMS to achieve an optimal, or near to optimal, solution for the reduction of consumption.

The optimization problem in GAMS can be formulated as follows:

- Objective function:

$$Minimize\ \ f =$$

$$Min\begin{bmatrix} \sum_{Load=1}^{NLoad} \lambda_{Load} \cdot P_{Load} + \lambda_{Down}.Reg_{Down} \\ +\lambda_{UP}.Reg_{Up} \end{bmatrix} \quad (1)$$

GAMS is responsible for the actual optimization process, deciding the loads that are left turned on and the loads that will be turned off. GAMS also provides the consumption for each load, being prepared to work with variable loads and with discrete loads.

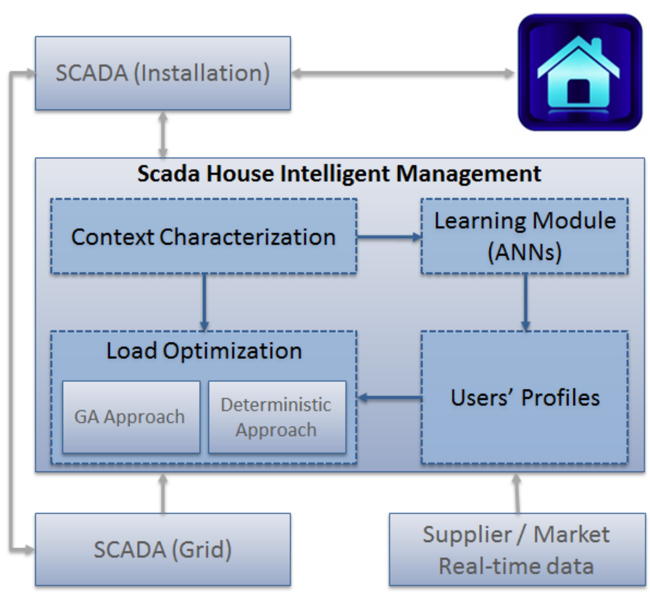


Figure 3. Scada House Intelligent Management.

### B. *ANN Structure*

ANN can be used to predict future situations based on past events [8][17][18]. The SHIM uses the ANN to predict preference factors regarding users' preferences for each individual load in the facility, every time the optimization is requested. After obtaining the preferences factors, the SHIM will use GAMS to thereby conclude the optimization.

Because GAMS produces an optimal or near optimal solution, the outputs produced by the ANN are critical to obtain a plausible optimization according to the user preferences. Changing the weights of the preference factors we can obtain a totally different result after the execution of the optimization.

The structure of the ANN, integrated in the SHIM, is of feedforward backpropagation type and it is composed of a single hidden layer of 77 nodes (the amount achieved through thorough tests). The Levenberg–Marquardt algorithm is used to train the structure of the ANN. The implementation of the ANN was done in MATLAB, using the Neural Network Toolbox.

As inputs, the ANN uses the following variables of context acquired during the initial step of the optimization:

- Temperature – this value represents the average temperature, in Celsius degrees, in the facility;
- Clarity – this value represents the average clarity, or visibility, in the facility;
- Season – the season of the year (0 – Spring; 1 – Summer; 2 – Autumn; 3 – Winter);
- Day – the day of the week (from 0 to 6);
- Hour – the time of the day (from 0 to 23);
- People – this parameter represents more than one input, creating one input for each room in the facility, indicating the number of people inside that room.

The retraining of the ANN is made based on the users' actions after the optimization process takes place. After the optimization executes and changes the state of the loads to achieve the desired consumption limit, users cannot agree with all the changes and turn back on a load that was turned off by the optimization. These types of behaviors are recorded in the system for a further retraining of the ANN (a process that can be seen in [8])

## IV. CASE STUDY

This case study uses the Demand Response (DR) program of Real-Time Price (RTP) [19], which produces real-time variations of the price of energy (EUR/kWh), allowing consumers, such as the Installation Agent, to act in the best way according to their goal. For this case study the Installation Agent must create offsets of consumption when a high price of energy is detected.

This DR program has the advantage of not overloading network communications in the smart grid. Being the management core centralized on the consumer side, it is the consumer player that manages the reaction, if there is any, of the DR program.

The SHIM present on the Installation Agent of this case study will use the following variables of context as inputs of the ANN:

- Temperature;
- Clarity in the facility;
- Season;
- Day;
- Hour;
- Position of the people in the facility.

This case study will analyze the impact of the RTP event in the Installation Agent present on the MAS proposed, which was described in Section II-a. This Installation Agent will represent the Physical Laboratory, described in Section II-b, and use the SHIM with the ANN, described in Section III.

This case study will not analyze the learning carried out by the ANN. The learning process can be seen in detail in [8]. This case study will only analyze the impact of the optimization in real time according to the users' position inside the house.

To correctly analyze the impact of the RTP, the case study will present similar scenarios differing only on the number of people and their distribution in the facility.

On this case-study, the prices will be given by the ISO agent. The Installation Agent, studied on this case-study, will access the prices of energy and act according to its XML configuration file.

To participate in the RTP, the Installation Agent was configured as shown in Table I, where are indicated the offsets of consumption defined by the user. These offsets define the maximum consumption allowed during a time of a certain price of energy, saving therefore users' money.

TABLE I.
OFFSETS CONFIGURED ON THE AGENT FOR THE RTP EVENTS

| Price (EUR/kWh) | Offset |
|---|---|
| Less than 0.12 | None |
| More than 0.12 and less than 0.14 | 4 kW |
| More than 0.14 and less than 0.16 | 2.5 kW |
| More than 0.16 and less than 0.18 | 2.7 kW |
| More than 0.18 and less than 0.20 | 2 kW |
| More than 0.20 | 1.75 kW |

According to the correct offset for a given period of time, the Installation Agent will proceed, if require, to the optimization process in order to minimize the consumption in the facility.

To analyze the impact, Table II shows seven scenarios tested in the Installation Agent. These seven scenarios can be aggregated into three groups: I and II; III and IV; and V to VII. These three groups have similar start points, differing on the number of people and their distribution in the facility.

As we can see in Table II, the optimization process was successfully capable of reducing the consumption to a value closed to the offset desired in each scenario.

TABLE II.
CHARACTERISTICS OF THE DIFFERENT PERIODS

| | I | II | III | IV | V | VI | VII |
|---|---|---|---|---|---|---|---|
| Temperature (ºC) | 23 | 23 | 7 | 7 | -10 | -10 | -10 |
| Clarity (%) | 70 | 70 | 5 | 5 | 0 | 0 | 0 |
| Season | Summer | Summer | Winter | Winter | Winter | Winter | Winter |
| Day | Monday | Monday | Wednesday | Wednesday | Friday | Friday | Friday |
| Hour | 12h00 | 12h00 | 19h00 | 19h00 | 20h00 | 20h00 | 20h00 |
| Persons | 0 | 1 (Kitchen) | 1 (Living Room) | 2 (Living Room, Kitchen) | 0 | 2 (2xRoom) | 3 (2xLiving Room, Kitchen) |
| Consumption (W) | 4544 | 4544 | 2906 | 2836 | 3066 | 3076 | 3086 |
| Price of Energy (EUR/kWh) | 0.15 | 0.15 | 0.18 | 0.18 | 0.16 | 0.16 | 0.16 |
| Offset (W) | 2500 | 2500 | 2000 | 2000 | 2500 | 2500 | 2500 |
| Consumption After Optimization (W) | 2474 | 2538 | 1990 | 1998 | 2420 | 2408 | 2550 |

According to Table II, the changes of the number and location of people does not affect the optimization process, although in Figure 4 we can see that the optimizations are very different from each others.

The table shows the global context of the facility before and after the optimization occurs. Figure 4 shows the consumptions before and after the optimization process, according to the type of components and rooms of the house. And easily observe the impact of the optimization and the effects on the loads according to the type of components and rooms of the house.

In scenarios I and II, it is visible the impact that the position of the person represents on the optimization process. The reduction in the consumption is similar in both scenarios, but as it can be seen, in scenario II the loads are mostly found in the kitchen, being this one the location of the user.

Another important aspect of the data presented in Figure 4 is the HVAC loads. Even with a temperature of 23ºC, scenario I show the HVAC loads turned on, but in scenario II, when a user is in the facility, the HVAC loads are turned off, so the loads inside the kitchen can be remain turned on. On the other hand, in scenarios III and IV the HVAC loads were kept turned on after the optimization because of the low temperature of the day (7ºC).

Scenarios V, VI and VII feature a temperature of -10ºC, even when users are in the facilities, the HVAC loads remained turned on, despite being forced to reduce their consumption in order to be capable of dealing with the existence of several users in the facility.

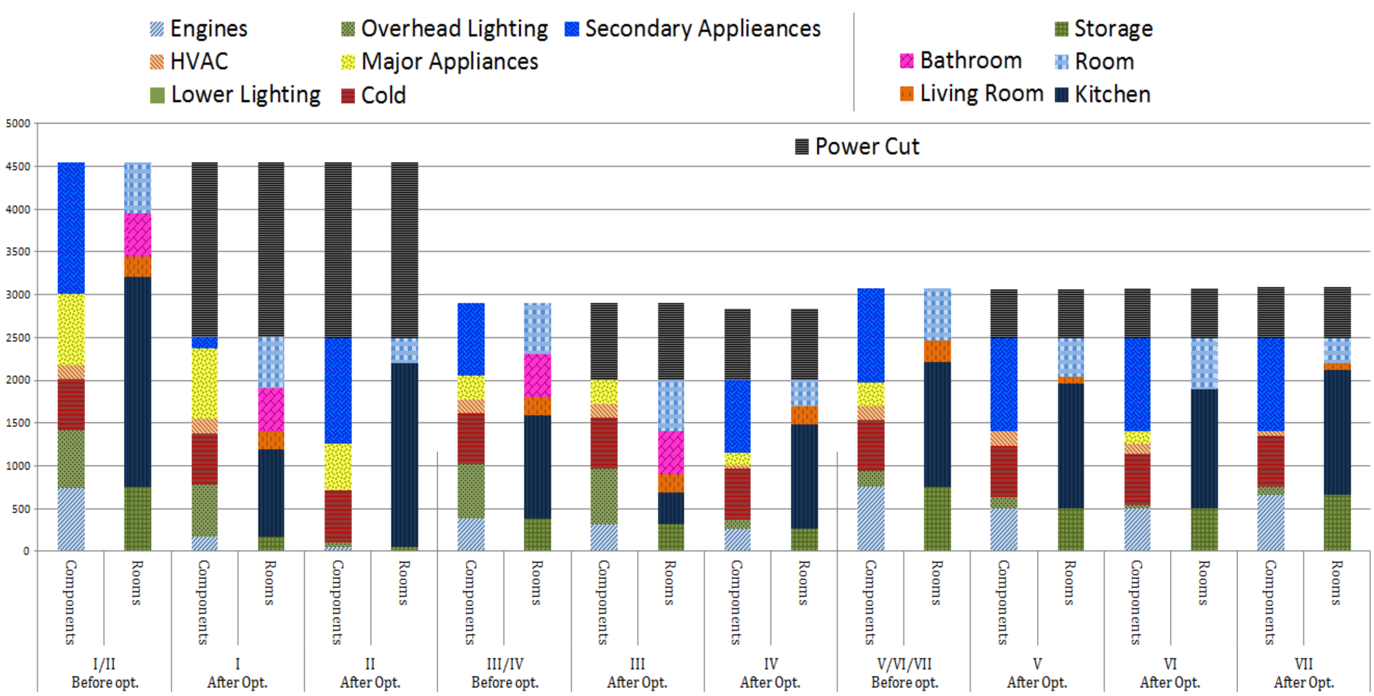


Figure 4. Results of the optimization mechanism in seven periods.

## V. CONCLUSIONS

Electricity markets and smart grids brought a new paradigm to the power systems operation. To deal with this new paradigm distributed generation and the active participation of small and medium players must be ensured.

The participation of small and medium players is made possible by Demand Response programs in the smart grid context. These programs can be triggered by any kind of player that aggregates, physically or contractually, other players.

Although the use of Demand Response is often advocated in a smart grid environment to increase the performance of the grid, this implies a correct management inside the small and medium players and it causes a direct impact on the consumer's daily life. Besides the wide amount of Demand Response programs, the majority of these programs leads to a reduction of consumption from the small and medium players.

This paper proposes an optimization methodology that can be integrated into small and medium players to prevent a negative impact by the Demand Response programs. Using Artificial Neural Networks to learn the users' preferences, and using an optimal, or near to optimal, optimization it is possible to create an optimization module capable of producing different optimization results according to the context that we are in. The case study is the proof that an optimization according to contexts is possible.

The integration of small and medium players in the smart grid environment is mandatory to produce automatic responses that are not invasive to users and does not produce a negative impact in users' daily life. Otherwise, the inclusion of small and medium players will pass through a path of problems and discomfort to users.

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