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ABSTRACT

In competitive electricity markets with deep concerns for the efficiency level, demand response programs gain considerable significance. As demand response levels have decreased after the introduction of competition in the power industry, new approaches are required to take full advantage of demand response opportunities.

This paper presents DemSi, a demand response simulator that allows studying demand response actions and schemes in distribution networks. It undertakes the technical validation of the solution using realistic network simulation based on PSCAD. The use of DemSi by a retailer in a situation of energy shortage, is presented. Load reduction is obtained using a consumer based price elasticity approach supported by real time pricing. Non-linear programming is used to maximize the retailer's profit, determining the optimal solution for each envisaged load reduction. The solution determines the price variations considering two different approaches, price variations determined for each individual consumer or for each consumer type, allowing to prove that the approach used does not significantly influence the retailer's profit.

The paper presents a case study in a 33 bus distribution network with 5 distinct consumer types. The obtained results and conclusions show the adequacy of the used methodology and its importance for supporting retailers' decision making.

1. Introduction

The concept of Electricity Markets (EMs) appeared in the most developed countries as a consequence of power system deregulation and power sector restructuring [1]. Traditionally, the entities involved in power systems have determined tasks and are remunerated according to defined regulations. EMs involve a large number of players that are expected to act in a competitive environment, taking advantage of the adequate opportunities and strategies to accomplish their individual goals. Moreover, the whole power system should be able to attain global requirements, guaranteeing demand satisfaction within accepted reliability levels.

The implementation of EMs was expected to lead to relevant advantages concerning the increase in power system efficiency and price reduction due to the end of monopolies [1]. However, the experience has proved that some problems can occur [2–4], due to the very specific electrical energy characteristics which make some rules and methods usually used in other commodities markets not useful in the EMs context. This is mainly due to the unique characteristic of electrical energy that is a commodity, for which the balance between supply and demand must be assured at all moments. Moreover, electrical energy can only be stored in very limited quantities, because of technical and economic reasons.

One of the areas expected to grow in the scope of EMs is the Demand Response (DR), as it appears as a very promising opportunity for consumers and brings several advantages for the whole system [5,6]. This is due to the fact that power systems' infrastructure is highly capital-intensive and DR is one of the cheaper resources available to operate the system [7]. On the other hand, DR programs can provide the system operator with a determined load curtailment capacity which is highly valuable to deal with unexpected changes in both supply and demand levels.

The actual state of DR around the world has been summarized in [8]. Experiences of DR in the wholesale market are taking place in the United States [9], Europe [10], China [11] and also in other places around the world [2]. Some difficulties in the transition from a traditionally regulated industry to a competitive environment can be justified by the lack of retail demand response. However, it is accepted that time-dependent pricing (e.g. RTP) can benefit the sector's operation and investment [8].

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DR is not being as successful as expected in the context of competitive markets. In some cases, the EM implementation caused a reduction in demand participation [7], [12–15]. In the United States load management (LM) decreased 32% between 1996 and 2006 because of weak load management services offered by utilities [12]. This can be explained by the 10% reduction of the money spent in LM programs since 1990. Between 1996 and 2004, 32% of utilities stopped providing LM programs.

Demand Side (DS) has been unable to use all the business opportunities in the scope of EMs in a satisfactory way. This participation difficulty is verified for large DS players and also obviously applies to small DS players. Aggregation is being more and more used, therefore, the EM players can join their resources and efforts to obtain competitive advantage [14] in EM. However DR has very specific needs that even large aggregators face serious difficulties in dealing with.

In response to this, grid operators and utilities are taking new initiatives, recognizing the value of DR for grid reliability and for the enhancement of organized spot markets' efficiency [16]. However, the current state of the art does not answer the pointed problems and does not show any sign of finding the correct path so that the required solutions are obtained in a short time period. As the efforts that have been put in DR issues are very relevant, the poor results evidence the need to use a different approach to address DR issues [17].

This paper presents a work that contributes to such an approach which is centered in DemSi, a DR simulator developed by the authors. DemSi constitutes a platform to support decision making concerning DR in the scope of distribution networks, including technical validation of the solutions.

The paper also presents the use of DemSi by a retailer, to address a situation of energy shortage due to an incident in the network. Strategic load curtailment is obtained using real time pricing, fixing the price variations for each consumer or consumer type so as to maximize retailer's profit.

After this introduction, Section 2 presents the most important concepts related to demand response, shows the importance of demand response in the context of electricity markets, and explains the recent DR experiences. Section 3 describes the Demand Response Simulator (DemSi), with special focus on practical application in the presented case study. Section 4 presents a case study concerning the procurement of a load reduction by the retailer. Finally, Section 5 presents the most important conclusions of the presented work.

2. Demand response concepts and programs

The management of consumers' behavior or the actions that result from this management are usually referred as demand response, load management and Demand Side Management (DSM). Traditionally this is done in the context of utility load management programs, during the periods of higher demand [18], essentially with the objective of peak shaving.

DR includes all intentional electricity consumption pattern modifications by end-use customers and the incentive payments that are intended to change the timing, level of instantaneous demand, or total electricity consumption [19]. These incentives are mainly used at times of high wholesale market prices or when system reliability is jeopardized [12].

The way that electric energy is bought and sold is being changed by new business opportunities created by electricity markets. These opportunities include consumer participation which can directly influence market results [14,15,20] and can be defined over longer or shorter periods either in the context of capacity markets or directly through bilateral contracts.

2.1. Price elasticity

Price elasticity rate is a measure used in economics to evaluate a good or service demand response to a change in its price, i.e. percentage change in the demanded quantity on response to one percent change in price [21]. The formula for the price elasticity of demand is expressed in (1), where *Quantity* is the quantity of the usage of the good or service and *Price* is the price of this good or service [22].

$$\varepsilon = \frac{\Delta \mathrm{Quantity}/\mathrm{Quantity}}{\Delta \mathrm{Price}/\mathrm{Price}} \tag{1}$$

In the case of electricity consumption, this is a measure of the intensity on how the usage of electricity changes when its price changes by one percent.

There are two types of price elasticity of demand, namely own-price elasticity and substitution elasticity. Own-price elasticity measures how customers will change the consumption due to changes in the electricity price, regardless to the period of variation. This rate is expected to be negative since a price increase should cause a reduction on load. Substitution elasticity is related to the time shifting the electricity consumption of electricity within a certain period (e.g. a day or a week).

A DR approach using the price elasticity has been presented in [7]. This work uses an optimal power flow for economic dispatch including load forecast. The market prices for each period of the next day are calculated considering the price elasticity, and a new load forecast is obtained. With the new load forecast, market prices are updated to verify the positive influence of demand response in market prices. The effectiveness of DR programs in case of system contingency is demonstrated.

In [23], price elasticity has been used to fix the demand participation in several DR programs. These programs are ordered in function of the priority from the point of view of the ISO, utility, customer, and regulator. Weights are associated to operation criteria and adjusted for each type of player. It had been referred that the presented algorithm can be used as a toolbox to overcome market operation problems.

Generally, studies considering the concept of price elasticity of demand combine market conditions and consumer's flexibility to analyze the benefits of DR whereas the present work uses price elasticity to determine the market signals (energy price) which are necessary for obtaining the desired response level of demand, for example in case of a supply shortage.

2.2. Characteristics of DR programs

Demand response programs can be divided in two wide groups, namely price-based demand response and incentive-based demand response [12].

Price-based demand response is related to the changes in energy consumption by customers in response to the variations in their purchase prices. This group includes time-of-use (TOU), real time pricing (RTP) and critical-peak pricing (CPP) rates. For different hours or time periods, if the price varies significantly, customers can respond to the price structure with changes in energy use. Their energy bills can be reduced if they adjust the time of the energy usage taking advantages of lower prices in some periods and reducing consumption when prices are higher. Currently, the response to price-based demand response programs by adjusting the time of consumption is entirely voluntary. However, some advantages of mandatory response can be found (see Section 2.3).

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TOU includes different prices for usage during different periods, usually defined for periods of 24 h. This rate reflects the average cost of generating and delivering power during those periods.

For RTP the price of electricity is defined for shorter periods of time, usually 1 h [24], reflecting the changes in the wholesale price of electricity. Customers usually have the information about prices on a day-ahead or hour-ahead basis.

CPP is a hybrid of the TOU and RTP programs and is harder to implement. The base program is TOU and a much higher peak pricing is used in specified conditions (e.g. when system reliability is compromised or when supply costs are very high).

Incentive-based demand response includes programs that give customers fixed or time varying incentives in addition to their electricity rates. These can be established by utilities, load-serving entities, or by a regional grid operator. Some of these programs penalize customers that fail the contractual response when events are declared. This group includes the 6 programs listed below [25,26]:

- Direct Load Control (DLC) is a program that considers a remote shut down or cycle of a customer's electrical equipment by the program operator. These programs are primarily offered to residential or small commercial customers;
- Interruptible/Curtailable Service (ICS) is based on curtailment options integrated into retail tariffs that provide a rate discount or bill credit by agreeing to reduce load during system contingencies and includes penalties for contractual response failures. These programs are traditionally offered to larger industrial customers;
- In Demand Bidding/Buyback (DBB) programs, customers offer curtailment capacity bids and large customers are normally preferred;
- Emergency Demand Response (EDR) can be seen as a mix of DLC and ICS and is targeted for periods when reserve becomes insufficient;
- In Capacity Market (CM) programs, customers offer load curtailment as system capacity to replace conventional generation or delivery resources;
- Ancillary Services Market (ASM) programs are basically similar to DBB programs, whereas in this case the offer is just made for the ancillary services market. As in traditional ancillary services, the remuneration can be paid for reserve and energy provision of energy separately.

Fig. 1 [12] shows the integration of DR programs in the electric system operation and planning, from a time horizon point of view, in the context of electricity markets.

An important demand side resource that can be considered independently, but not necessarily disconnected from the above described DR programs is the energy efficiency. This has to be considered in the long time system planning.

2.3. Real-time pricing (RTP)

In 2001 California's electricity market exhibited very high prices for electricity and threats of shortages. In [27], it is argued that the problems that appeared in California and other markets are intrinsic to the market design and DR is pointed as a promising solution. A long-run study of RTP efficiency is conducted in [28] being demonstrated that efficiency gains from RTP are significant even where the elasticity of demand is very low. In addition, it is demonstrated that the Time Of Use (TOU) tariff, that is, a simple peak and off-peak pricing tariff, presents very small efficiency gains when compared with RTP. The present paper is focused on real-time pricing (RTP) applied to a set of customers, demonstrating RTP gains from the point of view of retailers.

A frequently discussed topic about RTP is the mandatory or voluntary implementation for a given class of customers. Usually RTP is associated with large customers; therefore this program should be mandatory for these customers. In practice, all the programs in the U.S. are voluntary [29]. In this paper, RTP is considered for all types of customers, from small commerce to large industrial customers. It is important to clarify that mandatory RTP does not mean necessarily that customers need to be exposed to the full risk of the electricity market. Forward contracts are a good opportunity to reduce this risk since it can reduce the volatility of costs they pay, in comparison with those they would pay if they purchased all the power at the spot price. In spite of this, many market participants still argue that RTP should be voluntary. A voluntary program can be attractive although it creates efficiency difficulties that do not exist when RTP is mandatory. Thus, voluntary programs must be designed so that customer participation does not work as a subsidy to non-participating customers.

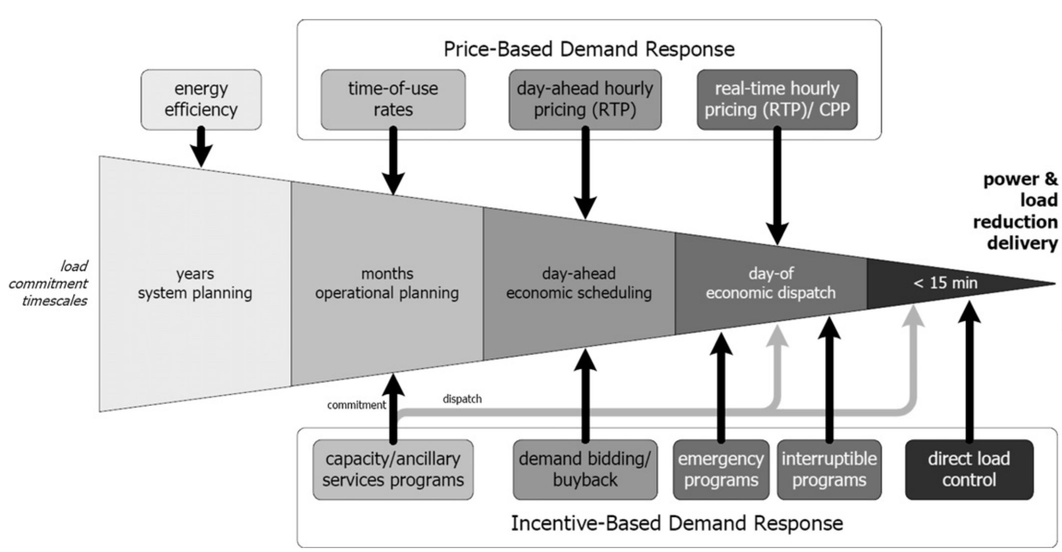

Fig. 1. Demand response in electric system planning and operations [12].

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3. Demand response simulator

This section presents DemSi, a Demand Response simulator that has been developed by the authors to simulate the use of diverse DR programs.

3.1. DemSi in the scope of DR tools

The positive impact of DR on power systems and on the involved players' business may be enhanced by adequate tools which are able to simulate DR programs and events, from the point of view of the relevant players. Several tools have been developed to support decision making and validation concerning demand response programs. A list of some tools can be found in [30]. Generally, the existing software aims to assess the cost savings opportunities based on building and load characterization (HVAC, ventilation, lighting, electronic, etc.). As an example, a simulator from the U.S. Department Of Energy (DOE) with these characteristics has been upgraded to a new version (DOE-2) and includes a link to MATLAB/Simulink which integrates the control logic. These simulators generally advise users about the best DR programs at each specific context.

References [31] and [32] describe tools that deal with commercial customers. [31] presents a tool which considers end-use resources costs (primary energy, storage, control, monitoring and measurement, and communication) to provide customers with the ability of evaluating DR opportunities. [32] presents a method to validate DR tools.

Recently advanced building control systems have been designed to improve the control mechanism for energy efficiency. New studies on how to use existing control systems in commercial buildings to integrate energy efficiency and demand response are reported in [33].

DemSi, the DR simulator presented in this paper, presents several innovative features when compared with other existing tools. One important point is that the other tools deal with specific installations (e.g. commercial or residential buildings) whereas DemSi is able to deal with the application of DR programs to a large set of consumers. Moreover, it uses realistic models that allow to simultaneously take into account detailed contractual constraints and to undertake the technical validation from the point of view of the electrical behavior of the power system.

DemSi considers the players involved in the DR actions and results can be analyzed from the point of view of each specific player. This includes three types of players: electricity consumers, electricity retailers (suppliers) and Distribution Network Operators (DNO). This paper considers the point of view of the retailer, but the analysis can also be done from the point of view of the consumers (both individually or in the scope of a load aggregator) or the DNO.

Another advantage of DemSi is that it includes a diversity of DR programs. Although this paper focuses on the application of real time pricing, DemSi allows choosing among a large set of DR programs, each one modeled according to its specific characteristics.

3.2. Loads characterization

Detailed knowledge of demand side behavior is crucial for the success of the use of demand response. From the point of view of each consumer or of an aggregated set of consumers, this allows to take the best advantage of existing opportunities. From the point of view of DNOs or retailers, this allows to take decisions that usually minimize operating costs. The present work explores the maximization of retailers' profit.

From the point of view of demand response, loads mainly differ on the conditions they impose for reduction, under specific situations. Some approaches consider the existence of flexible supply contracts between consumers and retailers and/or the consideration of critical loads which should be supplied in every situation. This paper applies the concept of demand elasticity to represent the response of the loads.

For the elasticity value of each consumer a default value is assumed, according to the type of load. However, the simulator allows choosing distinct values for each load, not depending on the load type. For a realistic simulation, some constraints like maximum price and power variations are considered for each load. This implementation is fully discussed in Section 4.3, of the paper. The consideration of several DR programs running in the same simulation and the simultaneous participation of each load in more than one program is supported by DemSi.

As explained above, loads can be characterized according to the consumer type. Loads belong to one of 5 types which have been created according to peak power consumption, destination of energy, and load diagram. These types are:

- Domestic (DM);
- Small Commerce (SC);
- Medium Commerce (MC);
- Large Commerce (LC);
- Industrial (IN).

After defining the consumer type, default values of several parameters of the load contracts are attributed. The user can easily change these values to better characterize the loads that are involved in a DR simulation study.

3.3. Mathematical formulation

DemSi allows the implementation of resource management methodologies. Let us consider the retailers' point of view, aiming at maximizing retailers profit when there is a need of consumption reduction. This problem's characteristics lead to a non-linear model.

The power that can be considered to supply the loads (P_{Supply}) is equal to the available power ($P_{\text{Available}}$) minus the required reserves (P_{Reserve}) and the power losses (P_{Loss}) (2). The value of power losses is estimated for each run. In fact, this value is obtained from PSCAD simulation before the implementation of demand response, but after this implementation load flow changes, resulting in a slightly different power losses value.

$$P_{\text{Supply}} = P_{\text{Available}} - P_{\text{Reserve}} - P_{\text{Loss}} \tag{2}$$

The objective function can be expressed by (3) and expresses the aim of maximizing the profit of the retailer who provides energy to the set of considered customers. This profit is the difference between the earnings of the retailer due to selling energy to consumers and the costs that it bears (electricity acquisition costs and other operational costs).

$$\begin{aligned}&\text{Maximize}\\ &\text{Profit} = \sum_{c=1}^{\text{nc}} \left[\left(E_{\text{Load}(c)} - E_{\text{LoadRed}(c)}\right) \times \left(\text{Price}_{\text{EnergyInitial}(c)}\right.\right.\\ &\left.\left.+\text{Price}_{\text{EnergyVar}(c)}\right)\right] - E_{\text{Supply}} \times \text{Price}_{\text{Supply}} - \text{Price}_{\text{Other}}\end{aligned} \tag{3}$$

$\text{Price}_{\text{Supply}}$ is the price at which the retailer buys the energy and $\text{Price}_{\text{Other}}$ represents the other operational costs he has. The values of these variables to be used in a specific context for which a reduction need is required are the values of the above referred

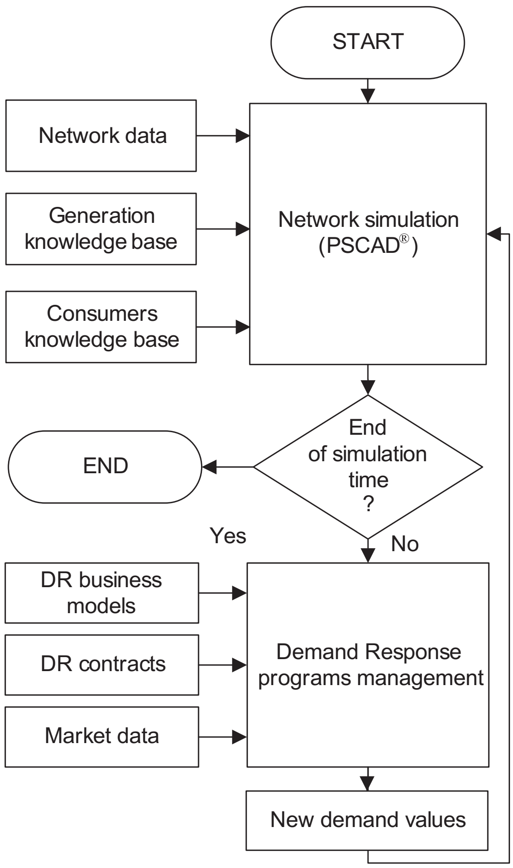

Fig. 2. DemSi general architecture.

Table 1
Network loads.

Bus	Load (kW)
1	143.7
2	126.6
3	125.0
4	123.7
5	80.1
6	264.5
7	262.4
8	75.9
9	77.0
10	56.9
11	77.5
12	77.6
13	154.1
14	77.4
15	77.4
16	78.1
17	115.1
18	129.5
19	128.9
20	128.8
21	128.7
22	125.2
23	573.6
24	568.9
25	79.7
26	79.3
27	78.4
28	155.6
29	251.0
30	191.6
31	267.8
32	76.4
Total	4956.58

costs in the considered context. $\text{Price}_{\text{Supply}}$ is the mean price at which the retailer buys energy in the considered situation (if the retailer buys energy from several suppliers, $\text{Price}_{\text{Supply}}$ is evaluated as the weighted mean of those suppliers' prices). In certain situations, $\text{Price}_{\text{Supply}}$ can significantly increase if the retailer aims at supplying high load demand. If $\text{Price}_{\text{Supply}}$ is considered too high without demand response, the retailer uses DemSi to determine the optimal parameters for the RTP use and to undertake the

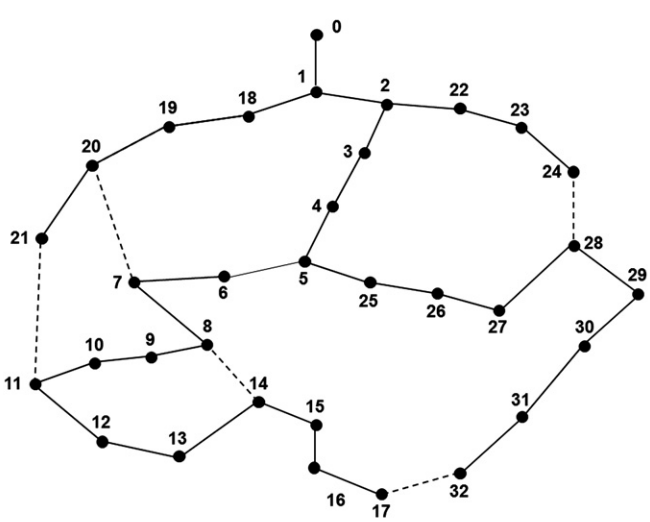

Fig. 3. Network configuration.

network simulation in this context. Having reached a feasible solution, RTP is scheduled to be triggered for the period to which the reduction need is required.

The response of consumers to price variation cannot be assumed as totally flexible; therefore, the following constraints are considered in this optimization problem. Maximum limits have to be imposed for load reduction (4); price caps are also considered (5). The balance between load and generation, which is the main constraint of any power system, has to be guaranteed (6). The consideration of load response is formulated based on price elasticity of demand (7), therefore the elasticity should be included in the formulation, since it shows the relation between power and price variation and makes them mutually dependent. Assuming a constant value for each consumer's elasticity, changes on price imply a corresponding change in the load consumption. Solving the optimization problem corresponds to finding the optimal values for load reduction and price variation for all the considered loads.

$$P_{\text{LoadRed}(c)} \leq \text{Max}P_{\text{LoadRed}(c)} \tag{4}$$

$$\text{Price}_{\text{EnergyVar}(c)} \leq \text{MaxPrice}_{\text{EnergyVar}(c)} \tag{5}$$

Table 2
Scenarios characterization.

	AC	BC	AT	BT
Price cap	1.5	2.5	1.5	2.5
Price variation	Individual price variation, not dependent from the customers type		Same price variation for every customer of the same type	
Power cap	15%			

Table 3
Loads characterization.

Type of Consumer	Loads	Elasticity	Electricity Price (€/kWh)
Domestic	5, 8, 9, 10, 11, 12, 14, 15, 16, 25, 26, 27, 32	−0.14	0.18
Small Commerce	2, 3, 4, 17, 22	−0.12	0.19
Medium Commerce	1, 13, 18, 19, 20, 21, 28, 29, 30	−0.20	0.20
Large Commerce	6, 7, 31	−0.28	0.16
Industrial	23, 24	−0.38	0.12

$$P_{\text{Supply}} = \sum_{c=1}^{\text{nc}} P_{\text{Load}(c)} - \sum_{c=1}^{\text{nc}} P_{\text{LoadRed}(c)} \tag{6}$$

$$\text{Elasticity}_{(c)} = -\frac{P_{\text{LoadRed}(c)} \times \text{Price}_{\text{EnergyInitial}(c)}}{P_{\text{Load}(c)} \times \text{Price}_{\text{EnergyVar}(c)}} \tag{7}$$

where

$\text{Elasticity}_{(c)}$ Price elasticity of consumer c
$E_{\text{Load}(c)}$ Consumer c electricity consumption not considering the reduction
$E_{\text{LoadRed}(c)}$ Reduction of consumer c electricity consumption
$\text{MaxPrice}_{\text{EnergyVar}(c)}$ Maximum variation permitted in energy price for consumer c
$\text{Max}P_{\text{LoadRed}(c)}$ Maximum variation permitted in power for consumer c
nc Number of consumers
$\text{Price}_{\text{EnergyInitial}(c)}$ Initial electricity price for consumer c
$\text{Price}_{\text{EnergyVar}(c)}$ Variation in consumer c electricity price
$\text{Price}_{\text{Supply}}$ Price of the energy supplied to the retailer
$\text{Price}_{\text{Other}}$ Value of other costs
$P_{\text{Available}}$ Power available for the resources scheduling
P_{Loss} Power losses
$P_{\text{LoadRed}(c)}$ Variation in consumer c power consumption
$P_{\text{Load}(c)}$ Initial power for consumer c
P_{Reserve} Reserve power
E_{Supply} Energy available for the considered scenario
Profit Retailer profit (earnings minus costs)

Using this approach and having knowledge on load profile to establish supply contracts, the retailer can manage the loads in order to optimize its operation. The optimized individual load reductions ($P_{\text{LoadRed}(c)}$) and the electricity price variations ($\text{Price}_{\text{EnergyVar}(c)}$) for each consumer are obtained solving the formulated optimization problem.

Some case studies consider the obligation of having the same price variation for the loads of the same type as formulated in (8):

$$\text{Price}_{\text{EnergyVar}(c)} = \text{Price}_{\text{EnergyVar}(T)}, \forall c \in T \tag{8}$$

where T is the consumer type.

3.4. Software implementation

DemSi aims to provide a flexible tool to analyze demand response actions and schemes, providing realistic simulation results. This requires modeling all relevant demand response programs and also a realistic network simulation. After some preliminary experiences, PSCAD® [34] is being used for network simulation evidencing good results. PSCAD® allows to have detailed models of electrical equipment and to consider transient phenomena. On the other hand, it also allows the realistic modeling of distributed generation resources. This had a strong influence in the decision of using PSCAD® because we aim at applying the developed simulator to study demand response in the context of future electrical networks, which are characterized by intensive use of distributed generation and the need of adequate management of distributed energy resources.

To fully attain our goals, PSCAD® is linked with MATLAB™ [35] and GAMS™ [36]. These links allow using programmed modules able to model the relevant players' behavior and all the relationships among them, namely the contracts between clients and suppliers. The solution of the formulated optimization problem is found using MATLAB™ and/or GAMS™. Using diverse approaches for solving the optimization problems, it is possible to derive the best approach for each type of situation. This is important because our ultimate goal is to develop a software application that can be used by several types of players to optimize their resource management. Fig. 2 shows the general architecture of DemSi.

Every time the simulation starts, an initial state (e.g. value of loads, state of breakers, etc.) is considered as the departing simulation point. Apart from this initial state, the required inputs can be divided in three major groups:

- Network data: The simulator requires detailed data concerning network equipment (e.g. lines, transformers, VAR compensators). This includes the characteristics of electrical equipments and an equivalent model for the upstream network that are considered in the PSCAD simulation;
- Generation knowledge base: Detailed technical data concerning each generation plant allowing their PSCAD models to be created. This includes the electrical characteristics, generation limits and resource forecasting for renewable based plants. Resource forecasting is required for the entire duration of the simulation study;
- Consumers knowledge base: The simulator requires having knowledge on the consumers which can be divided in three different types:
  - Electric characteristics of consumers' loads so that they can be modeled in PSCAD;
  - Load forecasting and price elasticity for the entire duration of the simulation study;

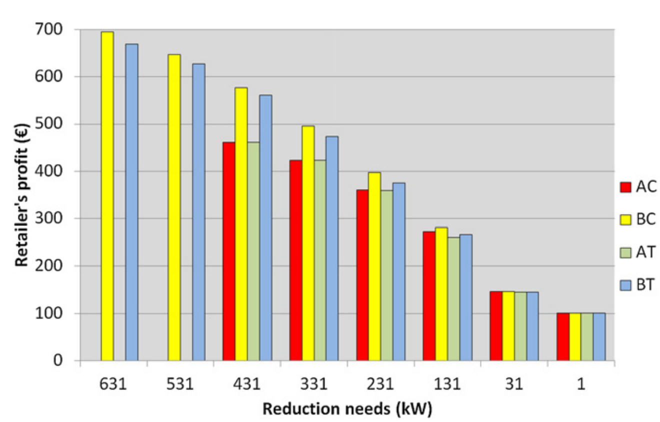

Fig. 4. Values of the objective function for each approach and reduction need.

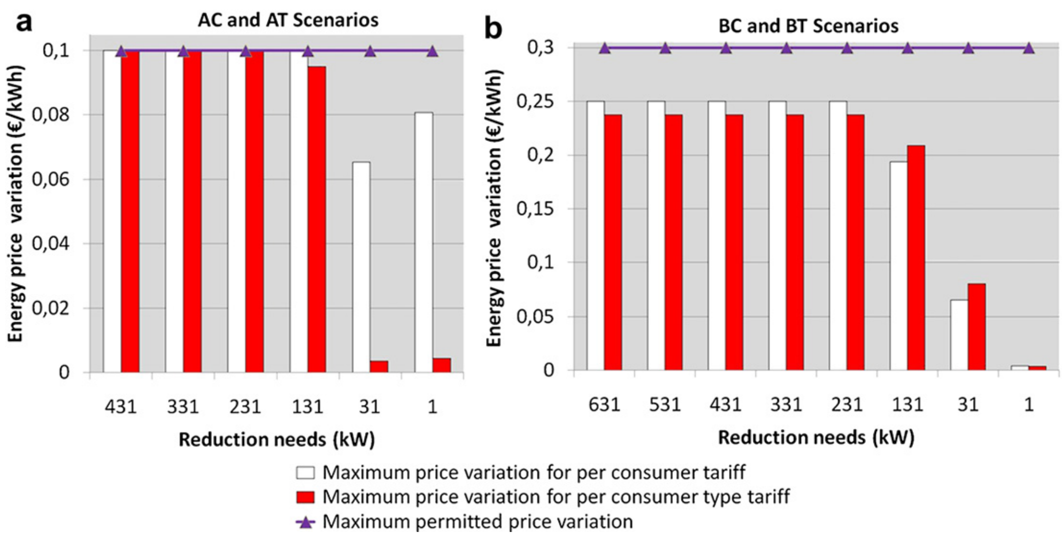

Fig. 5. Maximum price variations for each approach and reduction needs.

- Detailed information concerning consumers' contracts with their suppliers, including the contracts that refer to demand response. For each demand response contract, this information includes its type (e.g. Direct Load Control, Real Time Pricing, Critical-Peak Pricing) and the specific relevant information for each contract (e.g. trigger logic, advance notification time, sustained response period, minimum reduction amount, allowance for aggregated participation).

An event timeline is used, allowing the simulator to consider the occurrence of demand response events. For each declared event, the situation is analyzed in terms of the balance between supply and demand. The demand response management module is ran, implementing the corresponding demand response programs. Once the optimized solution is achieved, the new load values are fed into the network simulation module. The simulation goes on, reflecting the consequences of the declared demand response events and pursuing through the event timeline.

4. Case study

This section presents a case study that illustrates the use of the developed demand response simulator DemSi. Let us consider a distribution network with 32 buses, from [37], as seen in Fig. 3. The dashed lines represent reconfiguration branches that are not considered in the present case study.

In an incident situation, DR can be used to reduce the incident's impact, strategically determining what loads should be shed when there is a lack of supply. Consequently, DR use allows a significant reduction in the Value of Lost Load (VOLL) even if the non supplied load value remains the same [15]. This case study considers this network in an updated scenario, regarding load evolution from the initial scenario in 2008. All the results presented in this paper are obtained for a period for which the load demand is presented in Table 1. These values result from the load power values obtained from [37], corrected with the forecasted load evolution till the present.

4.1. Case characterization

For the present case study, four scenarios based on consumer response capability have been considered. The differences between the scenarios arise from the following aspects:

- Limits imposed for the maximum price and power variations (power and price caps);

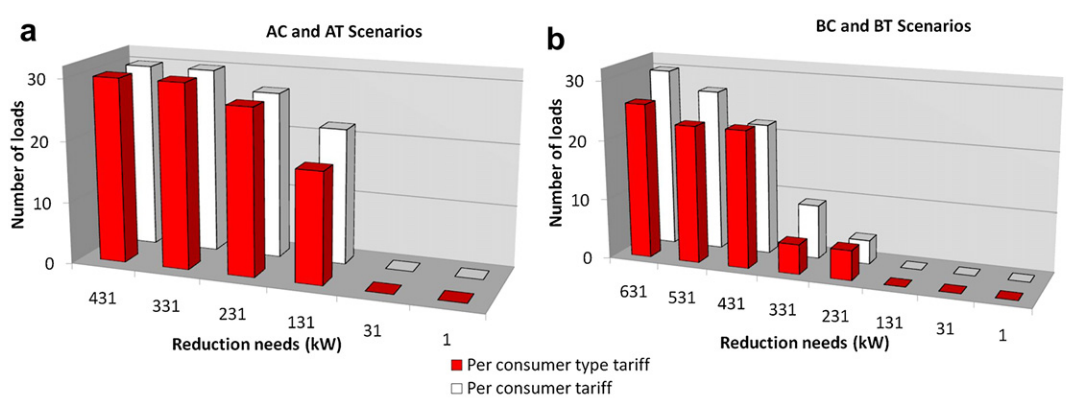

Fig. 6. Number of loads that reached the price limit (a) and the power reduction limit (b).

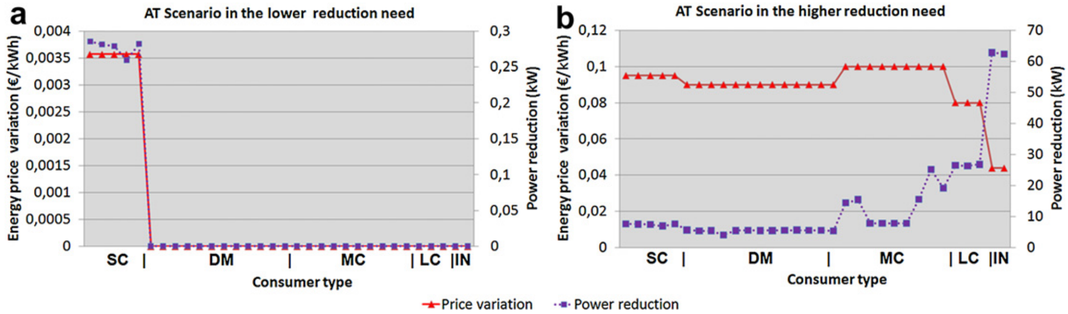

Fig. 7. Price and power variations for AT scenario for the lower and higher reduction needs.

- Imposition or not of the same price variation for the customers of the same type.

Table 2 summarizes the characteristics of these four scenarios. Power cap is the same for all the scenarios and corresponds to the reduction of 15% in the power consumption value of each customer. Reference [12] reports values of potential load reduction, in percentage, depending on the classification of the consumer. Using the results published in [12], the value of 15% is a prudently weighted value which has been chosen for this case study. The load reduction value is assumed as equal for all consumer types, to simplify the results' analysis.

In what concerns the price variation limits (price cap), two different values are considered: a maximum increase of 50% and 150% in the value of energy price for each customer (labeled as *A* and *B* data, respectively).

The other variation in the scenario characteristics is the fact of considering or not equal price variations for all the customers of the same type. Approach *C* considers individual price variations for each customer whereas approach *T* imposes the same price variation for every customer of each customer type. In the text bellow, "*A*" and "*B*" indices are related to *A* data and *B* data, respectively, and "*C*" and "*T*" indices are used for approaches *C* and *T* respectively. In total, we have 4 scenarios that combine the above referred characteristics: AC, BC, AT, and BT scenarios.

Table 3 shows the group of 32 customers classified in the five consumer types. In this case study, a fixed value of elasticity is used for all the customers of the same type. The last column presents the default values of the electricity price, which correspond to the values of flat-rate tariffs.

The consumer types are usually strongly related to the activity sector, and depend on the used studies. A report concerning some of these studies is presented in [38]. The data presented in Table 3, concerning the consumer classification (type) and the corresponding elasticity values, is derived from [38] and on [12].

All the obtained results consider a load reduction requirement. The load reduction requirement can be evaluated as the total initial load demand level, minus the available generation amount, and corresponds to the quantity of load that the retailer wants to reduce, which should be obtained through the use of demand response.

4.2. Results

The case study has been solved by the DemSi DR programs' management module, using the GAMS solver CONOPT (CONtinuous global OPTimizer) [39], which is based on the Generalized Reduced Gradient (GRG) method [40].

Fig. 4 presents the values of the objective function (OF) for each approach and for each considered reduction need.

From the results shown in Fig. 4, it is possible to conclude that when there is load flexibility to respond to higher reduction needs, the retailers benefit from this characteristic and various opportunities of higher profits will occur.

Analyzing Fig. 4, one can see that for lower load reduction needs, the differences between the results for the four analyzed scenarios are insignificant. However, for higher reduction needs, it is clear that the values of the objective function are lower for the scenarios using *A* data, indicating lower profits for the retailer. This means that the retailer's profit can be increased with the increase of the price variation limit. If the retailer uses a part of this additional profit as an incentive for consumers, additional demand response can be obtained.

For the scenarios using *A* data there is no solution for the highest reduction needs. The additional price variations allowed in the scenarios using *B* data allow obtaining feasible solutions for all considered reduction needs.

The comparison of the results obtained by the optimization algorithm for scenarios considering a normalized tariff for each consumer type with the results of the corresponding scenario, considering individual consumer tariffs (i.e. comparing the results of AC with AT and of BC with BT), shows that the normalization of tariffs by consumer type does not significantly affect the maximum

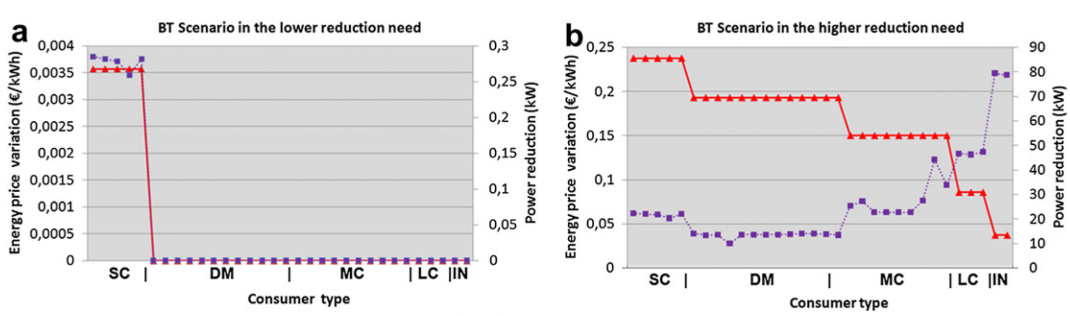

Fig. 8. Price and power variations for BT scenario for the lower and higher reduction needs.

Table 4
Network load and losses.

	Initial	Reduction need (kW)							
		1	31	131	231	331	431	531	631
Load (MW)	4.956	4.955	4.925	4.825	4.725	4.625	4.525	4.425	4.325
Losses (MW)	0.233	0.230	0.228	0.216	0.203	0.191	0.179	0.168	0.161
Losses (%)	4.7	4.6	4.6	4.5	4.3	4.1	4.0	3.8	3.7
Load + Losses (MW)	5.189	5.186	5.153	5.042	4.929	4.816	4.705	4.593	4.487

retailer profit (the maximum difference is below 26 Euros, in this case study). Considering normalized tariffs for each consumer type is a fairer strategy in comparison with applying different tariffs for consumers of a same type, being more prone to be well accepted by the consumers. This is an important conclusion to be taken into account for retailers' decision making.

An important aspect to be analyzed for the use of demand response programs is the optimal variation on the energy tariff to encourage customers to reduce their power consumption so that the retailer's profit is maximized. Fig. 5 presents the maximum variations in energy price obtained for both *A* and *B* scenarios.

From the results presented in Fig. 5b) it can be concluded that, for *B* data (i.e. when larger load reduction margins are allowed), the highest price variation never reaches the maximum permitted value. On the other hand, the results presented in Fig. 5a) show that for *A* data the load response is limited by the price cap, for the higher load reduction needs.

For the scenarios using *A* data, the maximum energy price variation is generally lower for the normalized tariff for each consumer type approach. For this approach, the reduction need tends to be divided by all the customers of the same type, while the approach applying different tariffs for consumers of the same type obtains the required load reduction from a smaller number of customers (those with lower reduction tariffs). For the scenarios using *B* data this rule does not apply to 31 kW and 131 kW reduction needs for which a larger number of customers is used by the *C* approach than by the *T* approach.

As mentioned, *A* and *B* data have as major distinction the predominant cap parameter (price for *A* and power for *B*). Thus, Fig. 6 presents, for each reduction need, the number of loads that reached the limit of price and power variations, for *A* and *B* data, respectively in Fig. 6a) and in Fig. 6b).

For other combinations, namely price variation for *B* data and power variation for *A* data, it has been concluded that there are no loads reaching the variation limits. For lower reduction needs, there are no loads reaching any variation limit. As we increase the reduction needs, more loads reach the variation limits and it can be seen that for the higher reduction needs there are not any differences in the results obtained for *A* and *B* data.

For a more detailed analysis, let us focus on the lower and higher reduction needs. Fig. 7 presents the results for the price and power variations for *A* data, for the lower reduction need in Fig. 7a) and for the higher reduction need in Fig. 7b). The results are presented only for *AT*, since *AC* results are similar. Note that buses are grouped by type of customers and are ordered from lower to higher elasticity values.

For the lower reduction need, only small commerce consumers participate, since they have the lowest elasticity and therefore they are the first choice for the profit maximization. On the contrary, industrial customers, who have the highest elasticity, only participate in higher reduction needs if the retailer's profit maximization approach is used. If a consumers' cost minimization approach was used, industrial customers would be preferably chosen to satisfy lower reduction needs due to their high elasticity.

Fig. 8 shows the results of a similar analysis that has been used for obtaining Fig. 7 but for *B* data. For the lower reduction, results are similar to those obtained with *A* data. For the higher reduction, in Fig. 8b), it is important to note that its absolute value is higher (631 kW) than the one of Fig. 7b), which is equal to 431 kW. The increase in the maximum permitted load reduction causes an increase of consumer participation in DR.

Table 4 presents the load and loss values for the initial network state and for all the considered reduction needs, considering demand response, for *BT* scenario.

4.3. Sensitivity analysis

A sensitivity analysis has been performed in order to reach conclusions concerning the impact of changes in the study input parameters on the obtained solutions. These conclusions are relevant so that decision agents are aware of the risk involved in considering, for each input, values that may differ from the real ones, in smaller or higher extent.

Table 5
Sensitivity analysis of the objective function value (in €) with respect to the variable parameters' values.

Input variable	Value change	Reduction need (kW)							
		1	31	131	231	331	431	531	631
Power cap (%)	−10	100.79	144.58	266.86	374.34	471.70	552.91	606.39	642.81
	−5	100.79	144.58	266.86	374.70	472.53	557.40	618.14	656.45
	0	100.79	144.58	266.86	374.93	473.23	560.61	627.68	669.13
	5	100.79	144.58	266.86	375.03	473.79	562.36	633.85	680.83
	10	100.79	144.58	266.86	375.03	474.23	563.34	638.74	691.56
Electricity price (€/kWh)	−0.04	–	–	36.79	125.42	206.33	278.50	332.57	365.55
	−0.02	1.45	41.11	151.81	250.16	339.77	419.55	480.13	517.34
	0.00	100.79	144.58	266.86	374.93	473.23	560.61	627.68	669.13
	0.02	200.12	248.05	381.92	499.73	606.71	701.66	775.23	820.92
	0.04	299.46	351.52	496.99	624.54	740.20	842.71	922.79	972.71
Elasticity	−0.10	111.74	325.17	660.80	894.99	1032.47	1099.69	1144.74	1159.74
	−0.05	102.35	178.29	375.74	533.20	673.66	781.42	848.87	892.07
	0.00	100.79	144.58	266.86	374.93	473.23	560.61	627.68	669.13
	0.05	100.14	130.70	218.47	298.52	372.00	437.90	492.34	528.78
	0.10	99.79	123.13	191.76	254.96	313.07	365.63	411.10	443.39

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The sensitivity study considered the influence of three different input variables in the results of the objective function (that represents the profit obtained by the retailer), in function of the reduction need. Therefore, the reduction need can be seen as the 4th variable of this study. The results of the sensitivity study are shown in Table 5. The discrete values of changes in these variables, in percentage or absolute values, are displayed in the second column. These changes are applied equally to all the consumers.

The first input variable is the power cap, for which increasing and decreasing percentage changes are considered. For the second input, the electricity price, positive and negative increments of 0.02 €/kWh are considered. For the simulations considering the changes in the electricity price, the values of price caps, which were considered as a percentage of the electricity price, were also updated. For the last considered input, the value of elasticity, positive and negative increments of 0.05 are considered.

From the analysis of the results shown in Table 5, it can be seen that the solutions are highly sensitive to the elasticity value. For this variable, the sensitivity increases with the increase of the reduction need. The power cap is the input to which the solutions are less sensitive. Changes increase with the increase of reduction needs, and present lower absolute values. In the study of the electricity price influence, it can be seen that there are two situations for which there are no solutions for the problem.

These results allow concluding that an erroneous evaluation of consumer elasticity may result in significant errors in the identified optimal solutions. On the other hand, variations in the allowed power caps do not bring significant changes for the objective function value.

5. Conclusions

Although demand response is not a new concept, it can have a much more relevant importance in the context of competitive electricity markets. In the scope of a competitive market, with technical and economic issues having to be equally considered, active demand players can bring the additional required flexibility to attain the envisaged efficiency operation levels.

This paper presented the most important demand response concepts and programs, as well as some relevant experiences in this field. Increasing interest on this area is leading to an increasing number of works. However, new approaches are required in order to take full advantage of demand response in benefit of electricity market operation and electricity market players.

This paper presented DemSi, a demand response simulator that allows studying demand response actions and schemes, using a realistic network simulation based on PSCAD. DemSi allows simulating a variety of demand response methodologies and to optimally achieve a solution according to the available demand response opportunities.

DemSi is used to support the case study presented in the paper. This case study is based on the retailer's perspective and includes a set of events with a load reduction level being envisaged for each one. The study considers both price and load reduction caps for each consumer. For each envisaged load reduction, the optimal demand response solution is determined using a non-linear programming approach. Results show that customer's demand depends on price elasticity of demand, and on the real-time pricing tariff. The optimal solution also depends on the imposed price caps according to the concerned DR programs.

The study includes simulations considering a normalized tariff for each consumer type and considering individual consumer tariffs. When comparing the results obtained imposing the use of a normalized tariff and those resulting from the consideration of individual consumer tariffs, it can be concluded that the retailer's benefits are almost the same. Considering normalized tariffs for each consumer type is a fairer strategy in comparison with applying different tariffs for consumers of a same type, being more prone to be well accepted by the consumers. This is an important conclusion to be taken into account when DR programs are designed.

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