Demand Response and Its Sensitivity to Participation Rates and Elasticities

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***Abstract*—Activating the demand-side of the electric system is a comeback of an old idea. What decades ago did not work out due to the lack of proper technology, today raises hopes to meliorate some of the most problematic situations in electric system operation such as ever higher peak demands and high wind generation during low demand periods. Smart grid infrastructures are currently implemented in many countries. This communication and control infrastructure allows consumers to receive information on system conditions, for example in the form of price signals, and thus to react to these and reduce, increase or shift their electricity consumption.**

This paper presents the modelling of demand shifting with two Demand Response mechanisms, Direct Load Control and Dynamic pricing. The outcome of both mechanisms depends, to a great extent, on two parameters: the maximum share of load which consumers are able and willing to shift and the elasticities used to express consumer's level of responsiveness in the dynamic pricing mechanism. An analysis of the sensitivity of the impact of Demand Response is carried out by varying these two parameters over a large range. Results regarding demand participation shares, cost savings, demand variation patterns and used generation technologies are compared for the different sensitivity cases. We find that cost saving increases are not proportional to increments in the maximum share of participating demand and in responsiveness to prices.

I. INTRODUCTION

The concept of Demand Side Management (DSM) comprises all activities which aim to change the demand profile in time or shape. However, Demand Response includes only those activities which involve reacting to price signals. Changes in the shape of the demand profile may have, among others, peak shaving, load shifting, valley filling or a more flexible load shape as their objective (see [1] for more information). Load shifting implies a decrease of consumption in peak demand hours to be recovered during off-peak hours. This flexibility of consumers to move their demand to other hours may help to tackle difficult situations in current and future electric systems. These include situations in which a growing fraction of increasing peak demand during daytime has to be supplied with intermittent energy sources. In other cases high electricity generation from intermittent energy sources needs to be absorbed in low load times. Demand shifting may help manage both situations and will thus be the focus of this paper.

DSM programs or mechanisms must be implemented to achieve these load shape changes. A classification of those mechanisms can be found in the works of [2] or [3]. They are classified into economic load reductions, dynamic pricing and ancillary services. Economic load reductions comprise all those mechanisms which offer a financial incentive, be it in the form of billing discount or rate-payback, when consumption is lowered. Dynamic pricing includes those mechanisms which let the price vary depending on system conditions. Time-of-use rates, critical peak pricing and real-time pricing belong to this class as well as demand bidding in markets. When demand is offering ancillary services it is contributing to system reserves. Within this third category demand can respond for reserve in similar ways either via economic load response or via dynamic pricing.

The modelling of two response mechanisms out of each category will be presented in section II. Economic load response will be represented via Direct Load Control (DLC). This is a fairly straightforward approach as DLC implies that control about switching on and off or reducing the consumption level of electric devices is given to the system operator. The system operator decides centrally depending on the overall system conditions time and quantity of consumption changes of these devices. The second mechanism considered in this paper belongs to the category of dynamic pricing: real-time pricing. In this DSM mechanism demand variations are caused by variations in price. The decision on shifting demand is taken decentrally by each consumer whose responsiveness to prices is expressed via elasticities which are included in a demand function explained in subsection II-C. The results depend crucially on the assumption of shares of participating demand for the first mechanism and on the chosen elasticities in the second mechanism. As no other study in the literature has been found to study those two aspects in the context of DSM in detail, a sensitivity analysis will be carried out in this paper. Data specifications are explained in section III and results for the sensitivity analysis are shown in section IV.

These results give details on how much efforts in increasing the share of active demands are compensated and on which consumer groups certain DSM mechanisms should be focussed (see more in section V). This information may be useful for policy makers and regulators who want to design and implement such DSM programs.

II. MODEL

The modelling approach is divided into various parts. An underlying system operation model is explained briefly in subsection II-A. The different DSM mechanisms are modelled in two different ways to be explained in subsections II-B and II-C.

A. *The Unit Commitment Model*

For the modelling of those two DSM mechanisms, an underlying short-term unit commitment model is used. The objective function of this basic model seeks to minimise operation costs. It includes no-load, variable and start-up costs as well as the cost of non-served energy. Its restrictions include an energy balance to equal the total of generation and demand in each hour. Furthermore, the requirement to have certain up- and downward spinning reserve guarantees enough generation flexibility to increase or decrease electricity output in the real-time if demand or wind variations, or a generator outage, make it necessary. This reserve can be provided either by thermal generators or by hydro or pump storage hydro units. Minimum and maximum power output limits are defined for each generation unit. Ramping constraints assure that power output can be increased or decreased only at a certain rate. Minimum up and down times are considered for thermal generators. Pumping storage hydro units are provided production and consumption targets to help schedule water use along the year, considering the reservoirs weekly or yearly work cycle. The unit commitment model comprises the logic sequence of unit commitments and start-up and shut-down decisions.

B. *Direct Load Control*

When introducing the DSM mechanism of DLC, load is represented as a variable (in the basic model demand was a parameter). The new demand d_p for each period p consists now of the formerly given demand D_p minus demand decreases $\Delta d_{p,down}$ plus demand increases $\Delta d_{p,up}$ (see equation (1)). This new variable is included in the energy balance equation (2) where W_p expresses wind and other distributed generation and nse_p non-served energy. Furthermore, $\underline{G_t}$ stands for the minimum output of each generator, and $uc_{p,t}$ for the unit commitment status. The variable $g_{p,t}$ is the production above the minimum of thermal generators t and $g_{p,h}$ is the production of hydro unit h. The set b refers to pump storage hydro units.

$$d_p = D_p + \Delta d_{p,up} - \Delta d_{p,down} \tag{1}$$

$$d_p - W_p - nse_p = \sum_t \underline{G_t} \cdot uc_{p,t} + g_{p,t} + g_{p,h} - g_{p,b} \tag{2}$$

Moreover, it is assumed that the demand shifts take place within the same day. This implies that the sum of all demand decreases must equal the sum of all demand increases on that day, which is expressed in equation (3). The share of demand which is able and willing to participate in this DSM mechanism is limited (see equation (4)) by the participation limit of L, which is equal for up- and down changes to consumption. This topic will be treated in depth in section III-A.

$$\sum_p \Delta d_{p,up} = \sum_p \Delta d_{p,down} \tag{3}$$

$$L \cdot D_p \geq \binom{\Delta d_{p,down}}{\Delta d_{p,up}} \geq 0 \tag{4}$$

C. *Dynamic Pricing*

Introducing into the basic operation model the dynamic pricing DSM mechanism leads to another modelling approach. Given that in dynamic pricing, such as real-time pricing, consumers face varying prices throughout the day, their reaction can be modelled with demand functions using elasticities to express consumers' sensitivities to price changes. The price-demand elasticity expresses how much percent of demand would change when a change in price of 1% occurs (see equation (8) and subsection III-B for more explications). The demand function is approximated assuming a reference point when no DSM mechanism is applied. This point corresponds to a reference demand D_p and a reference price Pr_p (coincident with the marginal cost). The slope of the demand function is represented with elasticities ε_{up} and ε_{down}, according to equations (5) and (6). We assume the demand function to be linear which may differ slightly from reality. Due to the absence of real-time pricing schemes in Spain and thus the lack of data to construct a demand function and other models to be found in the literature using the assumption of linearity as for example [4].

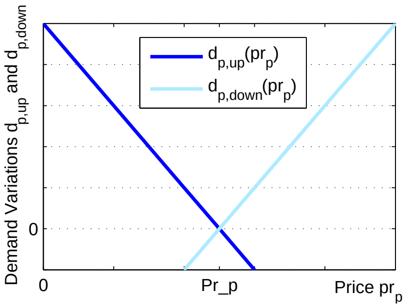

Fig. 1. Demand functions

Fig. 1 shows these demand functions. The reference price Pr_p is the point where demand variations in both directions are zero, i.e. when no DSM exists and the demand corresponds to the reference demand D_p. When the price pr_p is below this reference price Pr_p, which is indicated in the figure, upwards demand variation $\Delta d_{p,up}$ go along the dark blue line. At the same time this lower price would result in a negative downwards demand variation $\Delta d_{p,down}$ (light blue line). As demand variations are obliged to be positive, equations (5) and (6) are expressed as inequalities. In that way, it is assured that $\Delta d_{p,up}$ and $\Delta d_{p,down}$ cannot happen at the same time. $\Delta d_{p,down}$ is zero when $\Delta d_{p,up}$ is positive and vice versa. It has been assumed perfect competition in the market, so that the marginal cost corresponds to the price which consumers see. This assumption neglects possible market distorsions but is widely used in the literature. As we will compare the scenarios changing only two variables, participation limits and elasticies, among each other, this assumption is very unlikely to affect results. The variable price pr_p must be as close as possible to the marginal price. As the merit order is affected as well by no-load or start-up cost, these will be taken into account. This is expressed in equation (7) where CF_t, CV_t and CS_t are no-load, variable and start-up costs, respectively and $uc_{p,t}$ and $on_{p,t}$ represent the unit-commitment and start-up decisions. This equation cannot be expressed as equality because we want the price pr_p to be equal to the most expensive extended variable cost and pr_p depends on other decision variables $uc_{p,t}$ and $on_{p,t}$ which is not viable in mixed-integer programming. Hence, equation (7) is expressed as an inequality. Equations (1) and (2) remain the same. As the elasticity is the critical parameter in this equation, a sensitivity analysis for it is undertaken, to be explained in subsection III-B. All demand variations over one day have to sum up zero, as in the former approach (equation (3)). In this approach no load participation limit is applied. Demand variations will result solely from the demand functions.

$$\Delta d_{p,up} \geq \varepsilon_{up} \cdot D_p \cdot \left(\frac{pr_p}{Pr_p} - 1\right) \tag{5}$$

$$\Delta d_{p,down} \geq \varepsilon_{down} \cdot D_p \cdot \left(1 - \frac{pr_p}{Pr_p}\right) \tag{6}$$

$$pr_p \geq \left(\frac{CF_t}{G_t} + CV_t\right) \cdot uc_{p,t} + \frac{CS_t}{G_t} \cdot on_{p,t} \tag{7}$$

More details about the mathematical model formulation can be found in [5].

III. DATA FOR THE ELECTRIC SYSTEM AND DSM MECHANISMS

The sensitivity analysis will be applied to the case of mainland Spain and the study horizon will be the year 2016 as this was the time horizon studied in the CENIT-VERDE project mentioned in the acknowledgements on page 6. The model is run for each day of the year. Installed capacities of conventional generation technologies have been oriented by a government estimates [6]. Forecasts of Renewable Energies' installed capacities have been taken from [7]. Hourly demand profiles are derived from historic time series available in [8] taking into account energy (321 TWh) and peak demand (59 GW) estimates for 2016 from [7]. Upwards regulation reserves take into account ranges of possible demand and wind generation variations and the failure of the biggest generation unit. Reserve requirements for demand and wind variations are set in a way that 95% of variations are covered. Downwards regulation reserves do not include failures in generation equipment, but consider the rest of components included in the upward ones. Data on heat rate and fuel cost have been approximated using expert knowledge. Hydro generation is classified into hydro plants and pump storage hydro units. Hourly electricity generation for wind, biomass and biogas, thermosolar and photovoltaic and small hydro as well as cogeneration and waste units are based on time series taken from [8] and scaled with the estimates of installed capacities in 2016 from [7]. Data needed for modelling the DSM mechanisms are first and foremost participation rates and elasticities to be explained in detail next.

A. Participation Rates

The share of all consumers which are able and willing to participate in each DSM mechanism can vary depending on the region, the economic and technical circumstances. First, whether consumers are able to participate depends mainly on the technical requirements to participate in each DSM mechanism. Direct load control as well as real-time pricing implies the use of an infrastructure able to communicate and to produce and transmit control signals. In both cases this comprises the use of smart meters able of two-way communication. Furthermore, electric appliances need to be intelligent or come with intelligent plugs so that these can react to the price signals by modifying their electricity consumption. Authors in [9] give information on the cost of these devices for the Spanish domestic market. They consider as well an automated response DSM mechanism and examine the change in cost associated with four different DSM penetration rates. Although they find that costs exceed benefits by far at the moment, they acknowledge that not all possible future benefits have been included. Having more DSM options, higher renewables shares and the integration of electric cars may change the social benefits of introducing this intelligent metering infrastructure. Authors in [10] give an overview of international experiences about costs and benefits of smart metering. Given the increasing exigencies on the flexibility of generation and demand facing steadily growing rates of renewables, the introduction of smart metering seems to be an imperative.

In the literature, participation rates for peak shaving range between 5% and 27% in the work of [1]. Authors studying the case of Spain determine peak reduction rates of 5% in [11] or 10-15% in [12].

Load shifting is a quite different approach as it does not involve net reductions in demand. Load shifting potentials have been studied far less. The author in [13] concludes that potential of domestic appliances is between 5 to 20%. Authors in [14] keep within this range with 19% of consumers joining DSM mechanisms. In the work in [5], where our model is presented in detail, a conservative limit of 8% was applied for the whole demand including domestic as well as commercial and industrial consumers. In this work, presented in section IV of this paper, participation rates will range from 5% to 25% of total demand. This range encompasses common values found in the literature.

B. Elasticities

Elasticities are the measure of sensitivity of consumer reactions regarding the price. An elasticity of -0.2 expresses that an increase of 10% in price p with respect to a reference price p_0 would lead to a decrease in demand d of 2% with respect to the reference demand d_0.

$$\epsilon = \frac{\Delta d/d_0}{\Delta p/p_0} \tag{8}$$

Authors in [15] classify elasticities into short-term and long-term ones. Long-term elasticities do take into account further price effects that are added to the short-term elasticity.

The so far mentioned elasticities are called self or own elasticities. In contrast, cross or substitution elasticities relate price and demand levels of different time periods such as peak and off-peak periods. Authors in [16] describe the difference of self and cross elasticities in a very simple way. Self elasticities measure how a price increase in one product changes the consumption of that product. So, a price increase in peak hours causes demand in these peak hours to decrease. In contrast, cross elasticities measure how a price increase of a product causes, next to a decrease in the consumption of that product, an increase in that of another product. This may happen when a price increase in peak hours leads to an increase of demand in offpeak hours. While self elasticities are negative, cross-elasticities are positive. Authors in [15] mention cross-elasticities in connection with time-of-use programs and provide numbers for systems in which two tariffs are applied. In the work of [17] where electricity conservation and shifting for industrial and commercial consumers is examined, substitution elasticity is defined as the change in the ratio of peak to off-peak hour demand as a reaction to changes of off-peak to peak hour prices, see equation (9). In this equation a and b indicate two different time periods such as peak and off-peak.

$$\epsilon_{ab} = \frac{\Delta d_a/d_0}{\Delta p_b/p_0} \tag{9}$$

If all cross effects shall be measured then an elasticity matrix is used, in which the diagonal represent the self elasticities.

$$\begin{pmatrix} \Delta d_a/d_0 \\ \Delta d_b/d'_0 \end{pmatrix} = \begin{pmatrix} \epsilon_{aa}\, \epsilon_{ab} \\ \epsilon_{ba}\, \epsilon_{bb} \end{pmatrix} \begin{pmatrix} \Delta p_a/p_0 \\ \Delta p_b/p'_0 \end{pmatrix} \tag{10}$$

The work in [15] provides an extensive survey of elasticities to be found in the literature. Data on elasticities varies significantly depending on the electric system, its characteristics and the applied tariffs. Short-term self-elasticities range from -0.04 to -1.113, in contrast, long-term elasticities range from -0.09 to -3.39 (see [15]). Self elasticities for time-of-use tariffs described in [15] range from -0.003 to -2.57 for off-peak hours and -0.002 to -1.41 for peak hours. Cross elasticities vary from 0.003 to 1.57 depending on the study. Authors in [3] find these elasticities to amount from 0.02 to 0.27. They find elasticites under a real-time pricing regime to be higher than those under time-of-use or critical-pricing regimes.

Overall, very little has been published on cross elasticities. As detailed data for Spain is not available to derive a matrix for cross elasticities, another approach is chosen. Only self elasticities are used and a restriction for the sum of all demand shifts within one day is implied (explained in subsections II-B and II-C in equation (4)). This approach is similar to other approaches, like those presented in the work of [15, Table 2], which use only self elasticities and neglect cross sensitivities. In the following sensitivity analysis elasticities range from -0.1 to -1.0. this seems a reasonable range considering the data found in the literature.

IV. SENSITIVITY ANALYSIS AND ANALYSIS OF RESULTS

In the this section, results of the sensitivity analysis carried out are presented. Participation limits and Elasticities in the two modelled DSM mechanisms are modified as shown in table I.

TABLE I
PARAMETER VARIATION FOR SENSITIVITY ANALYSIS CASES

Case	1	2	3	4	5
Participation Limits	5%	8%	15%	20%	25%
Case	I	II	III	IV	V
Elasticities	-0.1	-0.2	-0.35	-0.5	-1.0

A. Results for the Variation of Participation Limits

First, the effects of varying the participation limits of demand in the Direct Load Control mechanism are analysed with cases 1 to 5 according to table I. The participation limit determines the maximum allowed size of demand increases or decreases in each hour, as explained in subsections II-B and II-C. Increasing the participation limit increases the share of consumption which is shifted if total cost over one day can be further reduced. The average variation of demand in each hour amounts from 3.95% to 12.71% (from case 1 to 5). In each case, the participation limit is a binding restriction in many hours of the year (in over 5000 hours for the case of 5% participation limit going down to around 1800 hours in the 25% participation limit case). The high number of hours that demand would be higher without such an imposed participation limit is partly due to the negation of any costs of transaction. Shifting demand may cause extra costs, for example in the case of organisation of night shifts in factories. As the focus of this paper is to analyse the sensitivity of the effects of DR to two specific parameters, the consideration of possible transaction costs is out of scope. The reader is referred to the work in [5] for a case with transaction cost. As all considered scenarios don´t take into account transaction cost and we compare them among each other with the non-consideration of transaction costs possible distorsions due to different transaction costs among consumers are avoided.

We analysed as well the increase in cost savings and demand variations resulting from an increase in the demand participation limit and found out that the relationship between these variables is not proportional, as can be seen in Fig. 2. For example, a participation limit rise from 15 to 20% (that is an increase in participation of 33%), causes an increase in the average demand variation level of 19% and a cost saving rise of 12%. Thus, relative cost savings and demand variations are lower than participation limit changes.

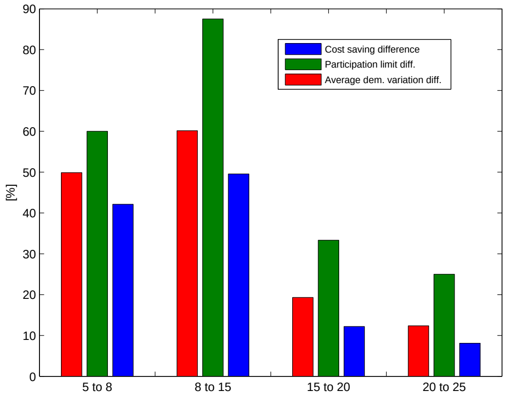

Fig. 2. Comparison between cost saving and participation limit increases

Now, we analyse the hourly cost savings of the average day (obtained through averaging the results in each hour). Hourly cost savings are obtained by the difference of marginal cost between the cases without and with DSM. Cost savings are the higher the higher the participation limit is in peak hours (8 a.m. till 1 p.m. and 6 p.m. till 9 p.m.) on weekdays. On weekends this applies only for the evening peak hours. For the rest of the hours on weekends as well as on weekdays no correlation exists between cost savings and participation limit increases. Cost savings are as well much lower on these off-peak hours. They range between -3% and 2% on weekdays and -3% and 7% on weekends in comparison to up to 17% on weekdays and 15% on weekends. This correlation between cost saving and participation limit increases in peak hours can be explained with the minimum load of generation plants. In peak hours almost every demand reduction leads to a reduction of committed generation units. Thus, marginal and overall costs sink. In contrast, in off-peak hours demand can increase without committing a new generation unit up to the maximum generation output. Thus, increases in marginal cost are either very small or zero.

These results, especially the lack of proportionality between cost savings and participation limits, imply that DSM mechanisms and their costs should be evaluated carefully before being implemented. Benefits from introducing such a Direct Load Control mechanism in general are high, but efforts to further enhance it should be evaluated well in advance, since cost savings do not increase at the same pace.

B. Results for the Variation of Elasticities

Second, the effect of changes in the elasticity of consumer decisions to price signals is analysed. We modelled a dynamic pricing approach using demand functions as explained in subsection II-C and changed elasticities in cases I to V from -0.1 to -1 according to table I. Increasing the elasticity (both, in the positive as well as in the negative direction) involves a higher demand reaction. An elasticity of -0.1 corresponds to a 1% decrease in demand when prices increase by 10%. The same price increase leads to a decrease of 2% of demand when the elasticity amounts to -0.2 and so on.

Now, we analyze the share of demand which is increased or reduced in each hour. Averaging this hourly share for the whole year and comparing cases I to V (i.e. with an increasing consumers sensibility), we find this share to change very little. Increases range from 18.30% to 20.82%.

When looking at differences in demand variations between the five elasticity cases I to V the average day (averaging demand variations in each hour over the whole year) will be taken for the analysis. Differences are most clearly seen in off-peak hours at night (1 to 7 o'clock a.m.) and peak hours in the evening (6 to 12 o'clock p.m.). Then, a lower elasticity allows less demand to be shifted. Demand variations in some peak hours are shown in table II. In the hours in between both periods higher elasticity levels do not necessarily lead to larger demand variations. This is due to fact that high price signals sent during peak-hours lead to demand being shifted to those hours with the lowest reference prices during night. When price signals and elasticity levels are high, then more demand is changed in peak and off-peak hours.

TABLE II
DEMAND VARIATIONS FOR DIFFERENT ELASTICITY CASES IN PEAK HOURS

	h18	h19	h20
Δd with $\epsilon = -0.1$	-5.61%	-14.48%	-17.57%
Δd with $\epsilon = -0.2$	-5.75%	-14.84%	-17.57%
Δd with $\epsilon = -0.35$	-6.30%	-15.28%	-17.56%
Δd with $\epsilon = -0.5$	-6.61%	-15.22%	-17.58%
Δd with $\epsilon = -1.0$	-7.10%	-16.13%	-18.53%

We compare now the average cost saving, which is the average of the hourly cost savings over the year. These hourly cost savings are determined by the difference between results of the model without and the ones with DSM. Hardly any changes are observable between cases I to V (they range from 2.83% to 2.77%). When we analyze hourly cost saving in an average day (averaging the cost saving of each hour) we observe an inverse behaviour in peak hours. The more elastic demand is, the more cost saving decelerate during these peak hours. Cost savings are slightly lower from case I to case V; this situation is shown in Fig. 3 for the evening peak hours. In other hours this behaviour has not been found. This reaction in peak-hours seems counter-intuitive, as having more elastic demand should reduce costs because more elastic demand gives more flexibility to the system. This may be related to the fact that required reserves do not change although demand is changing. All the decisions taken in the model are day-ahead decisions. Although demand is reduced in peak hours, reserve requirements do not change. So, the output of thermal plants is reduced, but reserves need to be provided anyway. Thus, there may be more generation units at their load minimum in the high elasticity case V than in the low elasticity case I causing higher marginal costs in the former.

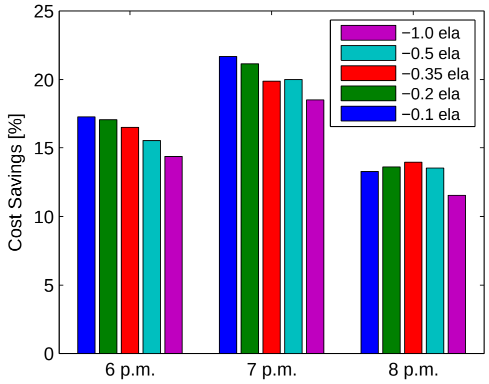

Fig. 3. Comparison between cost saving and elasticity decrease in peak hours

Providing a tariff which reflects the real system cost incurred at each moment to which consumer can react, brings about cost savings. However, efforts to increase demand elasticities may not necessarily result in higher cost savings during critical hours such as peak hours. This finding may influence the target group of specific DSM programs. Very elastic demands may create during some hours higher cost to the system than less elastic consumers. In any case, having an elastic demand has important advantages and increases the flexibility of the system.

A point that has not been considered in this paper but is subject of ongoing work by the authors, is the modelling of the ability of demand to provide system reserves. This should reduce the amount of committed thermal generation plants aimed at providing reserve and make the electric system more flexible. Further DSM options as the use of electric vehicles as shown in [18] or [19] may be considered in future work.

V. CONCLUSIONS

In this paper the modelling of Direct Load Control and Dynamic Pricing to shift load from peak to off-peak hours has been presented. A sensitivity analysis has been carried out to investigate the influence of two parameters, crucial to these modelling designs, on the benefits from Demand Response. First, the maximum participation level of demand in a Direct Load Control mechanism has been changed from 5% to 25%. Then, price-demand elasticities have been changed in the dynamic pricing mechanism from -0.1 to -1.0. Results show that cost savings do not grow at the same pace as load participation limits do. Moreover, we have found out that a more elastic demand may lead in peak-hours to a deceleration of cost savings. This is important to know at the moment of designing and implementing DSM programs and to focus financial efforts effectively.

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