Potential analysis of Residential Demand Response using GridLAB-D

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***Abstract*—Demand Response (DR) is getting the focus of the energy efficiency directives in European energy commission. It counts as an important instrument for improving efficiency of the energy system from final consumption to generation, transmission and distribution system. Integration of the DR into the electricity market is one of the measures which can take part in ensuring the reliability and security of the energy system in near future. In this regard various methods and tools developed to analyze the effect of DR in the different domains which range across voltage regulation, regulating reserve, market efficiency and transmission congestion management. This paper will not introduce a new method but will analyze the potential of DR in Austrian residential sector using GridLAB-D. A case-study generator is developed to generate any desired test cases and the results were analyzed in order to assess the residential demand response potential.**

Keywords—Residential Demand Response; Distribution System Analysis; Smart Grid; Active Market

I. INTRODUCTION

Rapid growth and uptake of renewable energy resources create new challenges for the power system. The stochastic and intermittent nature of renewable resources increases the need of flexibility in the energy system. Since the ability of the current power system in response to the brisk dynamic changes of generation side is limited, demand side management can play an important role by incrementing the degrees of network flexibility in order to enhance the reliability and stability of the electricity grid.

Demand response is not a new approach in the history of energy systems. In 1980, Schweppe et.al. introduced homeostasis control concept in order to keep the state of equilibrium in the power system with DR measures which based on shifting load according to the frequency deviation in the grid and real time price of the electricity [1]. In 1981, following the rising price of oil and gas, load management solution presented for reducing the peak demand as well as the operation of oil-gas fired generators [2]. In 1986, Rosenfeld explored the effect of dynamic pricing on the peak load reduction [3]. The potential of 10-20% for peak shaving in household sector has been estimated. In this era, implementation of DR was limited to the intensive energy consuming industries because of lack of installed enabling technologies like interval meters in small business and residential sectors. The large industrial and commercial (I&C) have long participated in the utilities program such as conventional direct control load (DCL) and interruptible tariffs and provided DR services.

By emerging the idea of smart grid and massive rollout of smart meters as a major component of smart grids, DR again got the focus of the research works and energy industries and has been introduced by European energy commission as a key instrument for improving energy efficiency of the energy system. Although results of some investigations declare that I&C customers are still of big interest for utilities because of their large potential and easy coordination, at the same time the carried out studies mentioned although the potential of individual households are not considerable, the aggregation is also not negligible. By introducing smart grid, above all advances metering infrastructure (AMI), access on small business and residential consumers is also possible and considerable potential in these sectors would be achieved by aggregating the individual available DR potential. Introducing novel energy market design, billing system and regulatory structure are additional drivers for integration of DR in various energy sectors. Referring to the study supported by the Federal Energy Regulatory Commission (FERC) if there is no regulatory and market barrier for participating in the DR programs, the impact of the residential sector would be even higher than that of I&Cs [4]. In [5] the residential DR is also addressed as a long-term solution and the potential range of 10-23% were calculated.

In order to assess the potential of DR, many worldwide demonstration projects were carried out and are ongoing. The GridWise project is an American demonstration project which had two major research focuses, energy pricing and smart appliances demonstration project. For the first time a dynamic real time price for electricity which varies each 5 min. was tested. The grid friendly appliances were also able to respond to the under-frequency events once a day. The demonstration project shows 15% peak demand reduction as well as 10% cost saving in the energy bill.

E-Energy is a ICT-based project funded by the Federal Ministry of Economics and Technology (BMWi) in Germany

[6]. In the framework of this project, a platform called "internet of energy" is developed in order to better exploit the grid's information and improve stability and reliability of energy network. The results of this demonstration project show a 10% DR potential achieved by controlling heat pumps, washing machine, dryer and dish washer of households.

EcoGrid is another ongoing large scale Smart Grids demonstration project in Europe which introduces a real time market-based mechanism in order to release the potential of balancing capacity through DR measures.

On the one hand, demonstration projects are very helpful in order to foresee implementation problems of suggested DR programs prior to their execution but on the other hand they are too expensive and each can just focus on the limited issues. The individual enabling technologies in various demonstration projects have different impacts on the operation of the distribution/transmission system and can exhibit unexpected behaviors. In this regard, a simulation tool for modeling the DR resources and their interaction with the electricity grid and energy market is required. Most of the developed simulation tools are either implemented considering a single, monolithic domain or they are based on a manually integration of different simulation tools and models. The following tools are developed based on multi agent algorithm and are able to simulate smart grids of any size.

The Mosaik is a framework which allows simulation of a Smart Grid based on the existing heterogeneous models of consumers and producers of any kind as well as the components of the power grid [8]. It offers a powerful test bed for evaluating ICT based Smart Grid coordination mechanisms and analyzes their potential in a real world environment whereas the market module is still not integrated.

GridLAB-D is another powerful simulation tool developed by the Pacific Northwest National Laboratory (PNNL) in cooperation with industrial partners. It is an open-source simulation tool which is utilized for simulating the impacts of smart grid technologies. Smart grid energy technologies ranges from power flow calculations with distribution automation to distributed energy resources and energy market can be modeled by GridLAB-D [9].

The aim of this paper is to estimate the market based DR potential in residential sector by using GridLAB-D as a validated developed tool. The paper is organized as follows: chapter II gives a general description about Demand Response Resources in domestic sector. Chapter III gives an overview about the implemented control strategies in GridLAB-D and describes the case study generator which is developed in this paper in order to easily create various cases in energy market and DR component in residential sector; Chapter IV assesses the results of executed simulations for generated case studies. Chapter V is a comprehensive conclusion of the presented work in this paper.

II. DEMAND RESPONSE RESOURCES IN DOMESTIC SECTOR

There are numerous studies that analyze the demand response potential of domestic sector. O'Dwyer et.al. estimated this potential considering wet-, cool- and space/water heating devices up to 6% of the total demand. The results are based on an incentive-based method that looks specifically at the ability of residential loads to provide reserves through the use of direct load control by a third party aggregator [10]. Schneider et.al. extended the direct load control strategy according to developed communication technologies and introduced an automated control system which operates based on a price signal [11]. The saving potential increases up to 10% by using automated control system for space heating and cooling system.

Various studies show that the probability of accessing space cooling/heating within a day is higher than that of the other household devices [12][13][14]. A market based thermal resources distribution in the building can control the thermal energy need in the building without imposing any extra costs and technical changes in the existing building management systems. Thermostat controlled devices present a large portion of the domestic load and can be characterized as very flexible resources since they are connected to the naturally integrated heating storage of building. They can operate, under aggregation, in a way similar to battery storage since they are not characterized by any time constraints like the other investigated devices.

Heat pumps are one of the demand response resources which support the well-known EU energy target 20-20-20 by reducing the energy demand and consequently greenhouse gas (GHG) emission. Figure 1 presents the market development of heat pumps in some EU countries [7]. Since EU directives support their market integration as a medium for increasing energy efficiency and optimal integration of renewable energy sources, they would be a potential candidate for participating in the domestic DR programs.

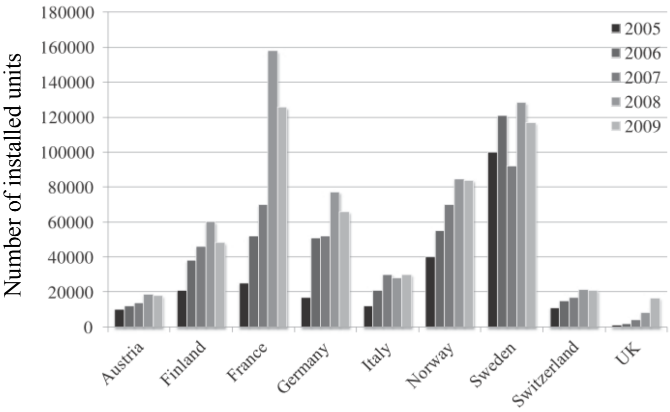

Fig. 1. Penetration of Heat pumps in some EU countries

Besides proper DR resources, type of load control action is another issue which should be considered in the DR programs. DR actions can be executed either manually or automatically. Generally, manually executed programs are more suitable for large I&C sector while for achieving reliable results by aggregating many households and small businesses, automated execution actions is likely to be the better choice. DR events will be initiated after receiving an external control signal. Price signal is one of the triggers for DR control systems since it includes information about the availability of generation and requested demand and can support the stability of the energy system. The focus of this paper is assessing the potential of residential demand response including space heating/cooling devices based on an automated control system using dynamic price signal as a trigger for adjusting the heating/cooling setpoint in the desired range defined by the users.

III. GRIDLAB-D TOOL FOR DR ANALYSIS

GridLAB-D is an open source simulation environment developed by the US Department of Energy at Pacific Northwest National Laboratory which includes the physical model of end-use devices as well as distribution automation control models which utilize price signal as a means to control end use devices.

The residential-end-user model implemented in this tool is using the equivalent thermal parameter (ETP) model to calculate indoor air temperature as a function of climate data, building parameters and installed HVAC system.

The tool also features energy market model which makes it possible to analyze various market strategies and assess their effect on the operation of grid and end-use devices and energy market itself.

A. Control strategies

As described by Schneider in [11], different levels of control system developed in this tool among which passive and active controller are in the focus of this paper.

- "Passive controller" is similar to what is currently implemented. Customers use their appliances without information being sent to or received by the utility. The function of household appliances using passive controller are price inelastic.
- "Active controller" is akin to the passive controller which is additionally provided by information such as dynamic price so that the controllers' setting can be adjusted accordingly. Active controller controls end-use devices to automatically react to price information. End-use appliances alter their consume schedule according to the price signal but they are not capable of biding back into the market and influencing the market price.

Depending on the type of appliance, a controller may reconfigure the thermostat setpoints or directly turn them on and off. In this paper the operation of HVAC system in residential buildings were controlled by adjusting their thermostat setpoints according to the real-time price information.

Naturally, heating occurs when the actual indoor temperature drops below the heating setpoint and cooling occurs when the indoor temperature exceeds the cooling setpoint.

According to [11], the appliance related variables like thermostat setpoint have an intuitive relation to their power consumption. The tighter the deadband of the thermostat, the more energy is consumed to maintain the indoor temperature between the adjusted setpoints. By using a price signal as a trigger for control action, in the time of high prices the controller lowers the heating setpoint and raises the cooling setpoint, thus the deadband gets wider and as a result the energy consumption of HVAC decreases. Conversely, at times of low prices the controller adjusts higher heating and lower cooling setpoint which leads to a tighter deadband and consequently preheating and pre-cooling actions which increases the power demand.

B. Case study generator

GridLAB-D uses special input files, called Grid Lab Model (GLM), to describe the simulations and set up the related configuration. In GLM file, each component and its relationship to others (i.e. transformers, transmission lines, houses, controllers, etc.) need to be explicitly defined. The input file can get considerably huge in size by simulating a complex system. In order to avoid writing each case study manually, a generic tool was developed to simplify the generation of large GLM input files and to generate any desired case study automatically (see Figure 2).

The tool consists of a number of input masks for specifying the relevant GLM parameters such as population composition, building parameters, electrical consumer, energy market and controller configurations. A VBA-based generator defines the related relations between components and creates the corresponding GLM simulation file. This greatly simplifies the setup process, as new scenarios with minimum time effort can be prepared.

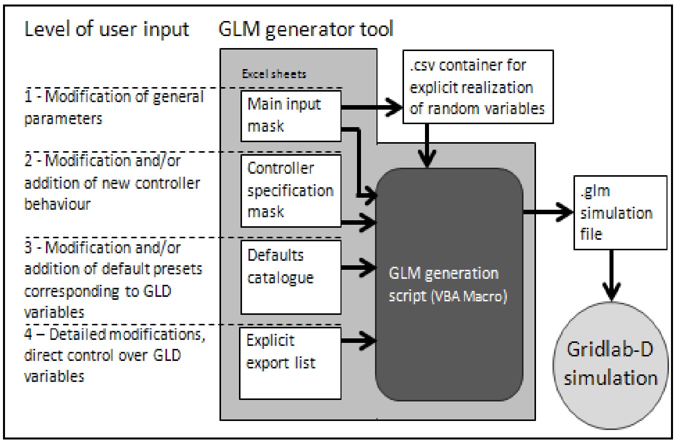

Fig. 2. Operation diagram of the GLM generator tool

Another advantage of the generator is that it gives direct control over any random variable that may be used. Typically, a DR case study contains a population of houses with their associated end-use appliances such as HVAC system and water heater.

The operation of these appliances is usually defined by schedules describing desired indoor temperature and water demand respectively. In order to avoid synchronous behavior and implement kind of coincident factor, each appliance is usually assigned a random initiation time and/or a random selection from a number of predefined schedules.

For a case study with a various number of variables, these random properties can be generated and saved once at the beginning of a simulation and reloaded for subsequent simulation runs, thereby ensuring the consistency of the population throughout each scenario.

IV. DR CASE STUDIES

A. Capacity of thermal storage for different residential buildings

One of the issues in implementing DR is how practical the application of DR measures in various building types is. Therefore, three buildings with the same characteristics except for their thermal transmittance characteristic, which is based on available Austrian building standards [15] [16], were simulated:

1. An energy efficient building with thermal insulation according to passive house standards
2. Building insulated according to current building regulations for residential buildings
3. Building with thermal transmittance characteristics typical for 1960's construction practices

Figure 3 shows that the annual energy consumption of HVAC system in the building is strongly correlated to its thermal integrity. Also, the saving potential is highest for the well-insulated house while almost negligible for an old, poorly insulated building.

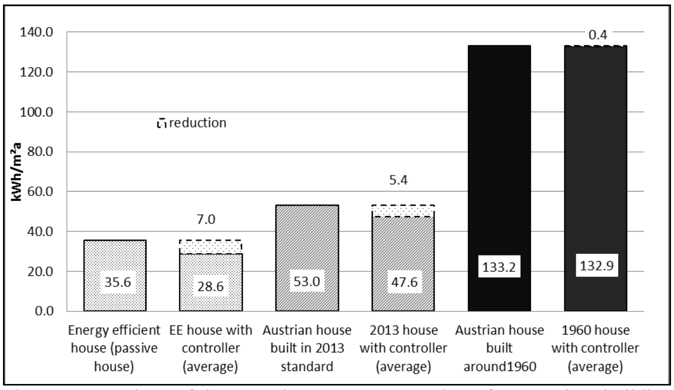

Fig. 3. Comparison of the annual energy consumption of HVAC in a building with good Insulation (passive house standard), statutory Insulation and average Insulation built in the 1960's

Since passive building is not the dominating construction standard for the new buildings yet, despite of their better insulation, the simulations and analysis from now on are based on the Austrian statutory building regulations for residential buildings.

As stated above, indoor air temperature is a function of climate data, building parameters and function of HVAC system. Figure 4 presents the HVAC average load profile over a day for 100 up to 10000 houses. Since the outdoor temperature, the thermal resistance and the HVAC system is the same for all simulated samples and only average floor area is defined by using a normal distributed function, the pattern of average energy consumption of HVAC system for different sample size are highly correlated.

In order to perform different scenarios and analyze the results, a sample size of 1000 houses has been considered which will be scalable for any desired number of households. According to the Statistic Austria, in 2012 about 37.700 dwellings were authorized in new residential buildings among which 14000 were detached houses. Based on the study carried out by ministry of transport, innovation and technology the annual installed number of heat pumps in Austria is about 12000. Based on these available statistic data the penetration rate of 85% for heat pumps in detached houses is considered for estimation of DR potential in the following section.

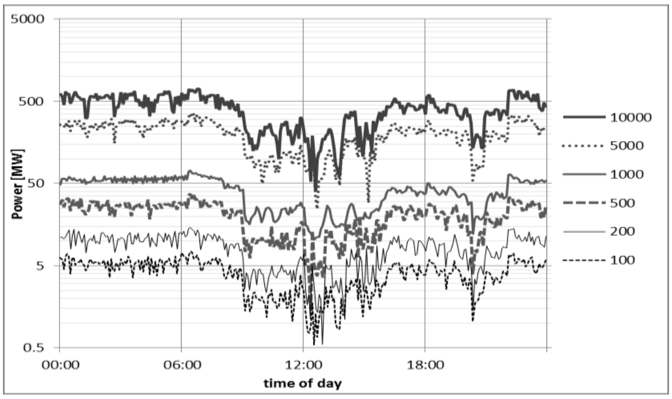

Fig. 4. Average power consumption for different population sizes

B. Impact of dynamic price signal

One essential issue in analyzing the potential of DR is the pattern of price signal. It is important to assess which type of price signal has a better impact on the response of heat pumps and which can optimally exploit the available capacity of thermal storage in the building envelope.

In this regards, the effects of 5 different price signals with 5 min. time resolution for month January (see Table I) were investigated. All price data are based on real clearing prices from the Austrian spot market in January 2012 which is identified with "base" signal in the following. The other four signals introduce additional peak events at pseudo-random times. A peak price event occurs when the price reaches a price cap for a certain amount of time. In the "base" signal, for example, ten peaks with a duration between one and eight hours occur during the simulation period in January. The total peak duration of 19 hours (2.6% total simulation time) and therefore, average peak duration of 1.9 hours was identified in the "base" price signal.

TABLE I. PRICE SIGNALS

Price signals	January 2012		
	Description	***Number of events***	***Total event duration***
Base	Real price signal from Austrian spotmarket 2012	10	19 h
Half Hour	additional half-hour peaks	40	34 h
Thin Peaks	additional peaks, mostly one hour in duration	23	32 h
Long Noons	additional 5h peaks	14	35 h
Long Evenings	additional 5h peaks	14	35 h

Figure 5 shows the distribution of peak price durations for the five different price signals. The table depicts the share of total peak duration rather than the individual peak events.

Therefore the Base signal's relative share is greater than the other signal's in some categories. In case of 2.5-3.5h peak duration for example the actual number of peaks for all signals is identical, while the total event duration, and thus the relative share of this category, is different.

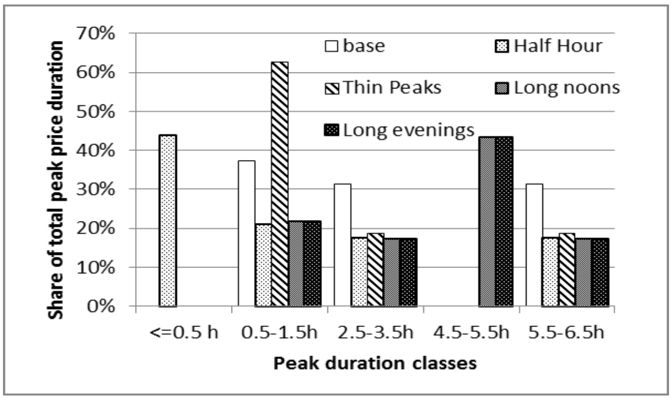

Fig. 5. Distribution of peak price duration

C. *Temperature variation*

Another important issue to consider is the adjustment band of indoor temperature, as it is closely related to the effectiveness of a controller. Four types of temperature controls are considered in the simulation. The main property of the HVAC controller investigated in this paper is essentially its operational range. The range (measured in °C) specifies the maximum deviation from the desired thermostat temperature. For example, a range setting of 1°C allows the controller to reduce the heating setpoint at times of high prices or decrease the cooling setpoint when prices are low by 1°C. Therefore, a larger range allows more radical control while a narrow range offers only limited controlling possibilities.

TABLE II. CONTROLLER BREAKDOWN

Controller	*Description*	*max. setpoint deviation at peak price (range)*	*max. setpoint deviation at floor price (range)*
1	conventional controller	1°C	1°C
2	dynamic setpoint range	3°C	1°C
3	dynamic setpoint range	5°C	1°C
4	dynamic setpoint range	3°C	0°C
5	dynamic setpoint range	5°C	0°C

The different range settings for the investigated controllers are shown in Table II. Controller 1 features standard settings for a HVAC controller with a fixed range of 1°C. Depending on the price signal, it can modify the setpoint up to 1°C (but does not have to, if the price is not significantly above or below the moving average). Although this is a fairly solid configuration when aiming to reduce a household's electricity bill, it is less suited for reacting to peak price events due to its narrow range. Therefore, controllers 2-5 employ a dynamic range, which is directly proportional to the price itself. Thus at peak price events, when the price increases to multiples of its average, the allowed range of operation is simultaneously widened, while on the other hand the controller operates within regular boundaries during non-critical times, ensuring a stable indoor climate and user comfort.

In fact, from the critical peak control point of view, the controller is not required to adjust the thermostat setpoint outside of critical peak times at all. Furthermore, extensive setpoint manipulation causes indoor temperature fluctuations, which are detrimental to user comfort. Therefore controllers 4 and 5 were defined with a 0-3°C and 0-5°C range respectively. This means that in the duration of low prices these controllers have to strictly follow the scheduled setpoint, while they are still allowed a wide range during peak price events. The effects of these range settings are demonstrated in Figure 6. As can be seen, both controllers 2 and 4 have the same range available during the peak price event, but the range of controller in off-peak duration 4 is very narrow compared to 2, forcing it to follow the initial setpoint schedule more tightly.

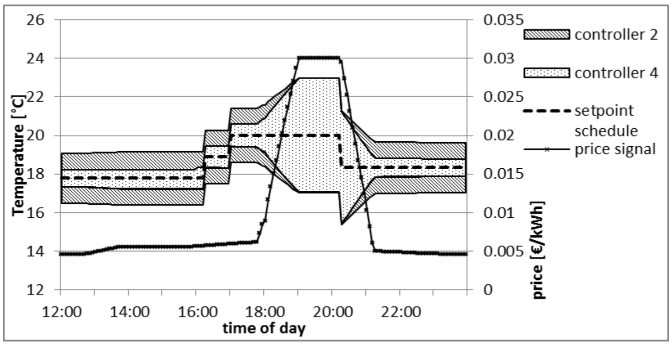

Fig. 6. Setpoint range for controllers 2 and 4

Figure 7 shows a simple example of the indoor temperature development during a peak price event on January 16th for two controllers with maximum range of 3°C and two controllers with 5°C. The average outdoor temperature in this example is approx. -3°C. The peak price events start at around 9 am, at which the controllers immediately adjust their setpoints to the minimum allowed temperature (i.e. 17°C and 15°C respectively). Initially, the indoor temperature for all cases is just above 20°C, the former setpoint, but begins to decrease. Once the indoor temperature reaches the new setpoint, the heating system switches on again and the load-deferring effect of the controller ends.

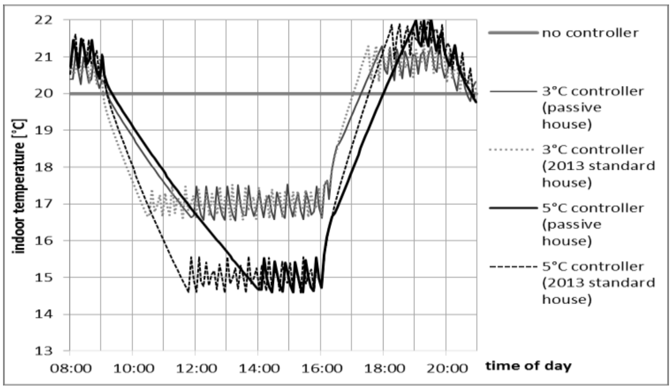

Fig. 7. Indoor temperature at peak price events for various controllers

As can be seen, the effective duration for which a controller can react to a peak price is limited by two major factors: the maximum range, which the temperature is allowed to drop, and the insulation of a building, which determines the rate of decline. In this case, the effective peak duration for the 3°C controller with standard insulation is only about one-and-a-half hours, whereas the 5°C controller with passive house insulation can defer heating for up to 5 hours. Generally, the shorter the peak duration is, the higher the chance that a controller can defer heating for the entire duration.

In terms of user comfort, a temperature variation of 5°C from the desired setpoint is not feasible if it occurs during the time of use. In fact, many customers may not even accept a 1°C drop in the time of active use i.e. when the building is occupied.

For the purpose of this paper the setpoint schedules are not divided into "time of active use" and "time of passive use" (when the building is not occupied e.g. holidays or working hours) but for future research it might be interesting to introduce this parameter to the controller and adjust the range of the controller accordingly.

It can be seen in Figure 8 that the controller with higher degree of freedom (larger temperature range) has the better response in reducing the peak load and the shorter the peak price event, the more responsive the controller.

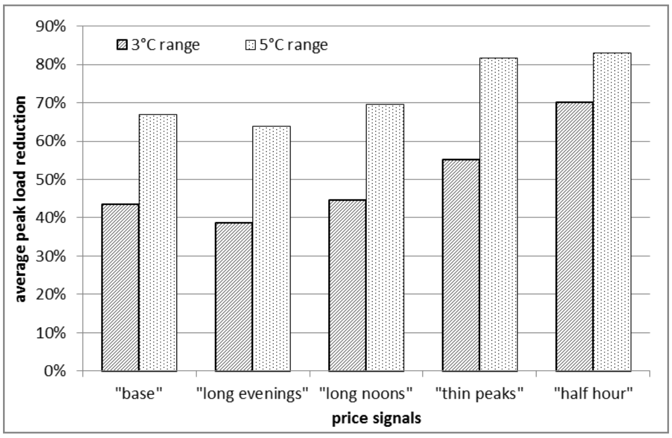

Fig. 8. Comparison of average load reduction between controller with 3°C and 5°C range

D. *Rebound effect*

The effectiveness of each controller can be assessed based on different criteria. Controllers 3 & 5 have a better performance regarding to peak load reduction while controller 4 & 5 keep the indoor temperature closer to the desired temperature of the consumers. As can be seen in Figure 9, indoor temperature drops up to 3°C below the reference adjusted temperature in the duration of the peak price but in the normal operation of the system the scheduled indoor temperature can be fulfilled.

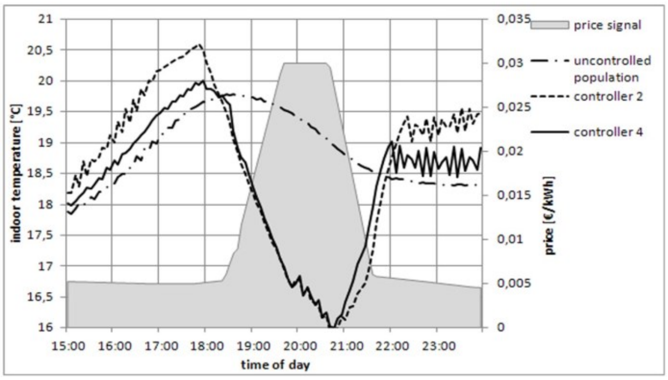

Fig. 9: Fig. 9.Averag indoor temperature of an uncontrolled and controlled population at a peak price event on the 4.january

Figure 10 shows the power distribution during this peak price event. As can be seen, both controllers 2 and 4 have similar load reduction during the peak, but controller 2 due to its higher base range, has a larger rebound effect.

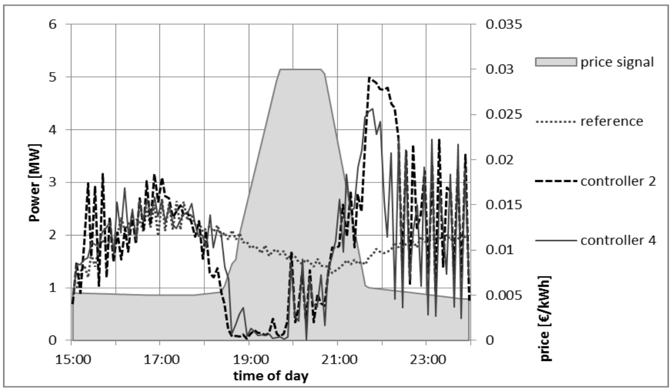

Fig. 10. consumption profile of heat pumps without controller and with controller 2 & 4

In order to find a compromise between the advantages of various controllers, the relation between their effective demand reduction during peak events and deferred rebound effect during off-peak hours was analyzed and depicted in Figure 11. Unsurprisingly, control parameters with high deferring potential also suffer from higher rebound effects. Furthermore, the relative performance of the controller is mostly the same for the different price signals. This highlights the sensitive relation between controller effectiveness, outdoor temperature and building thermal integrity, as discussed in section C.

Regardless to the type of price signal, controller 4 has the best ratio of deferring potential to rebound effect compared to the other type of controllers. According to the Fig.10, it can reduce the demand in a sample of 1000 households equipped with controllable heat pumps up to 1.8 MW for an evening peak price event.

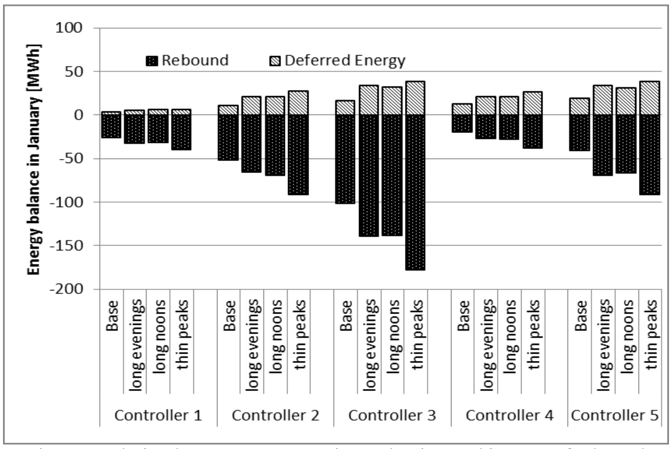

Fig. 11. Relation between consumption reduction and impact of rebound effect for various controller and price signals in January

E. *Day time and Seasonal effect*

Day time and seasonal changes in the outdoor temperature and solar gain of the building has also considerable impact on the available DR potential of the building. In order to present these effects three sample winter days has been selected with the average temperature about +8, 0 and -8 degrees which are tagged with mild, normal and extreme cold days respectively. In order to get more realistic results the permitted setpoint range distributed heterogeneously with a uniform distribution function in the sample of 1000 buildings as it is described in the table III.

Table III DISTRIBUTION OF SETPOINT RANGE IN SAMPLE OF 1000 BUILIDNGS

Population size	Responsiveness	Average allowed setpoint deviation [°C]
250	None	0
500	Moderate	0.5
250	High	1.5

Based on the results in section C, effective price signal of half an hour was applied to every half an hour within a day. Fig.12 depicts that constrained setpoint setback in the sample reduces the maximal DR potential of 1.8 MW to 900 kW. Besides, the available potential depends strongly on the time of day. Considering the time and type of the day available DR potential varies between 0 to 900 kW.

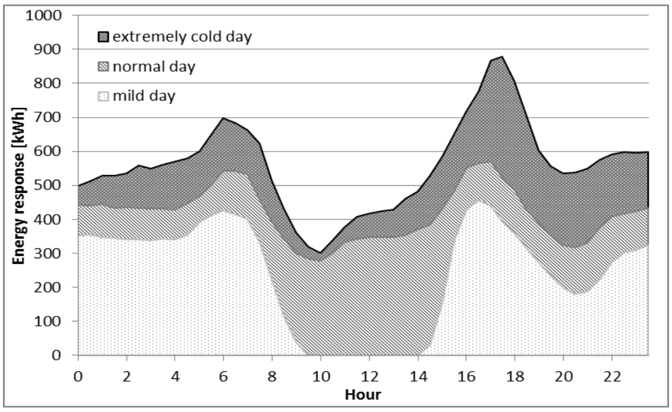

Fig. 12. Demand response potential within a day for mild, normal and extreme cold days

V. CONCLUSION

Demand response programs can be used in order to reduce the peak load or provide balancing energy in the power system by efficient exploiting the stored thermal energy in the residential buildings. In this paper, heat pumps combined with the available thermal energy storage of the residential buildings were used as DR enabling technology which response to the price signals by adjusting their setpoint. Simulation results confirm that price-based adjustable setpoints within the user given deviation range can reduce the demand up to 1.8 MW for 1000 households with ±3°C deviation range of indoor temperature. However this potential will be limited to 900 kW for tighter setpoint range. Time of day and seasonal temperature changes has also considerable impact on the actual rate of response. DR is an interim short term solution for preventing blackouts/brownouts however its variability and uncertainty still needs to be discussed.

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