Lessons from 10 Years of Demand Response Research - Smart Energy for Customers?

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***Abstract*— In order to accommodate more energy from renewable sources, the existing paradigm in the electricity grid where supply follows demand, has its limitations. Demand response, on the other hand, aims to exploit the available flexibility in consumption of electricity to follow the supply of renewables. This is possible by decoupling the demand for electricity from the demand of the associated services (such as heating, cooling, hot water). This f brings many challenges, especially if flexibility is harvested at a local scale. For 10 years, research groups worldwide have looked into demand response. In this paper, the open challenges of demand response in a residential context are sketched, and different coordination mechanisms outlined that optimize market profit, mitigate technical issues, reach prosumer objectives, or a combination of these. Several considerations are added on how these cyber-physical solutions need to be complemented by other, non-technical, fields in order to get the customers engaged.**

***Index Terms*— demand response, distributed coordination, smart grid**

I. Introduction

ELECTRICITY is a secondary energy source. Apart from lightning discharge and some fauna (e.g. Electrophorus Electricus) that use electricity to paralyze prey, we do not find it in nature – at least not in harvestable amounts. Nevertheless, electricity counts for about 20% of the final energy use in a country like Belgium [1], and it is expected to rise to 33% by 2050 according to the Belgian Federal planning Office [2]. This paramount usage is because electricity is a convenient energy carrier that can easily transport power from remote production sites into cities, all the way to the end consumer; it does not smell and –if cables are underground– it is even invisible. It has a very small footprint, and can be installed and handled easily if it is tensionless. The physics of electricity however also imply that it is difficult to store electricity in large amounts in a reversible way and with reasonable efficiency. Because of this, the electric power system has always been operated in a way that yields an instantaneous match between the demand for electricity and its supply. Therefore, conversion towards electricity (i.e. production) has been implemented from controllable sources mainly, both classical–nuclear, fossil fuels– and renewable –biofuels, hydropower.

When the demand for electricity is predictable, and the supply is from controllable sources (that can be turned on or off, or can be modulated), it is straightforward to create this balance by determining which power plants need to run at which moments in time. This technical goal has been complemented by a market, which forces that control to be executed in a cost-effective way.

Europe's 'Roadmap for moving to a competitive low carbon economy in 2050' (COM/2011/0112 final) implies an enormous increase of electricity generation from renewable sources. Hence, the current electrical system needs a profound remake (technically and market-wise) to deal with the associated variability if we do not want to decrease the reliability, the security-of-supply or the attained comfort levels. Smart grids are an important enabler of such a roadmap. In line with the digitization of society, they rely on an information and communication infrastructure to monitor and control assets in energy networks. Consequently, an enormous amount of smart grid projects are taking place across Europe and elsewhere, see Fig. 1 [3].

The electrification of the energy services at the customer side is partly due to the abovementioned roadmap towards a carbonless society: when homes and office buildings become better insulated, this often results in a decreased demand for natural gas or oil, so that the investment in a fossil fuel fired boiler is not cost effective. As a result, the residual heat demand is covered by electricity as the energy carrier. Examples are manifold. Heat pumps, which use electricity to pump environmental or earth heat to higher temperature levels, are increasingly used in many European countries. In low-energy buildings, the heat and cooling demands are often covered electrically, and new requirements for ventilation and air conditioning are implemented via electrical appliances as well. Sanitary hot water – if ecologically produced via solar thermal panels – often needs auxiliary heating, which is done electrically. In addition, induction cooking and increased use of information technology and gadgets raise the electricity consumption at local levels. At the same time, also electric mobility is accelerating fully. The importance of electricity as energy carrier of choice will thus increase further. If this happens in an uncontrolled way, it will increase the peak powers to be transported to the final customers, causing a need

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Fig. 1 Overview of smart grids projects in Europe (http://ses.jrc.ec.europa.eu/)

to redesign a power grid to support such peak capacity. However, if this additional electricity use can be moved to valley periods in which excess electricity is available, the peak power will not increase and the capacity of the grid will be used more optimal. This is where demand response comes in.

Demand response (also called active demand, or demand side management), allows changing the size or the timing of the demand for electricity e.g. in order to better follow the variable supply. This is not new and demand response has been applied for more than forty years, e.g. to provide sufficient electrical load by steering residential demand towards the night period, such that base load power plants can run at optimal efficiency also during that part of the day. Electric appliances with a night demand for electricity (e.g. electric accumulation heating) and Day/Night tariff schemes that stimulate consumers to start white appliances only in off-peak periods are examples of these.

In context of the roadmap towards a carbonless society, the varying supply from renewables and the decrease of classical conversion technology in the overall energy mix, necessitate the reactivation of demand side management to keep the balance. Hence, we need to move from a supply-follows-demand to a demand-follows-supply paradigm. This becomes more feasible if there is more flexibility in the demand side, which is – due to increased electrification – more and more the case.

The flexibility in the electricity consumption comes from the energy reservoirs, such as heat buffers (storage tanks or vessels connected to electric boilers or heat pumps), building thermal mass (driven by HVAC systems), cold buffers (refrigerators, deep freezers, cooling cells) or batteries (from electric vehicles and plugin hybrid electric vehicles, or stand-alone batteries). These reservoirs allow the decoupling in time of the demand for electricity from the demand for the energy service (hot water for a shower, keeping the building between temperature comfort limits, have a charged car before departure, etc.). Using the heat pump to heat up water electrically and storing it in a vessel, allows a later use of this hot water to keep the room warm; the heat does not have to be generated when the heating service is needed, hence it is decoupled. A similar story can be told about electricity use in commercial, office and industrial environments, mutatis mutandis, where the involved amounts of power and energy are larger. Demand response will use this flexibility to move the electricity use to a different period in time as when the energy services are required. This flexibility can be used locally, or in an aggregated way, and can target economic, ecologic or technical objectives.

Most importantly, demand response, which is a requirement for the future infrastructure, must support the customers. They need to be engaged and willing to contribute, without being hassled with technicalities or organizational challenges. It shall be as invisible as the electricity infrastructure itself, but provide the energy service in a more sustainable way that is in line with the roadmap to a carbonless society.

This paper synthesizes 10 years of demand response research at EnergyVille, identifying the main lessons learned, and reflecting on how it supports the infrastructure and customers. The major challenges are laid out, as well as a proposal on how to move forward in the next decade.

II. Characteristics of Demand Response

The flexibility of individual appliances and their energy buffers at a local, residential scale is mostly limited to some kVA power modulation (e.g. 2-4 kW for a monophasic electric boiler, 20 kVA for a three-phase electric vehicle charging station), and up to some tens of kWh energy storage (e.g. 8 kWh for an electric boiler, 20 kWh for an electric vehicle’s battery).

This flexibility is often sufficient to pursue local objectives, such as to maximize consumption of electricity from local renewables that are behind the same point of common coupling and metering equipment, or to minimize the electricity injection into the local grid. It can also be used for providing grid support, i.e. to mitigate voltage issues on weak distribution feeders. Such local objectives can be driven by economic incentives (minimizing cost of electricity), ecologic ones (maximizing the use of electricity from local renewables) or technical ones (avoiding power quality problems or minimizing grid losses).

This electrical flexibility from individual households can also be used in an aggregated way, i.e. together with the flexibility of other households or other actors. While this requires that a communication and control infrastructure be in place, the accumulated flexibility can grow several orders of magnitude and reach MW of power and MWh of energy. This allows for flexibility trading at wholesale markets, both for energy services (on the day-ahead or intraday market), as well as for ancillary services (markets for balancing or frequency support, for congestion avoidance, etc.). In the latter case, the flexibility from the demand side has to compete with the classical power plants, but many transmission system operators are opening up their markets for these types of smaller scale demand response (e.g. http://www.elia.be/en/products-and-services/product-sheets).

Before elaborating on demand response coordination, it is important to understand the asymmetry of the flexibility, its longevity and its uncertainty. While stand-alone batteries can be kept at an average state-of-charge (SoC) of 50%, as to enable them to both take electricity from the grid and inject it into the grid as needed, the physical properties and usage characteristics

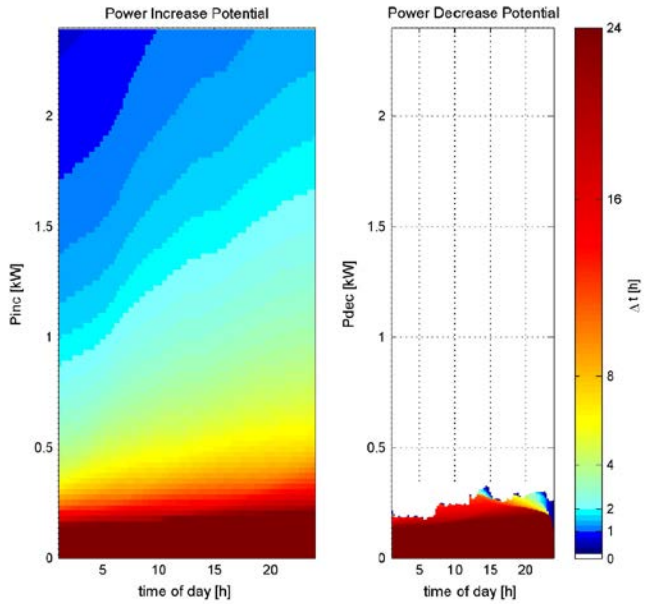

Fig. 2 Flexibility potential of an average domestic hot water buffer from the LINEAR pilot (Figure taken from [4])

of many appliances imply that it is easier to increase electricity consumption than to decrease it. For example, consider an electric boiler for domestic hot water that is kept at a certain average temperature (corresponding to a particular SoC). Depending on the consumer behavior (hot tap water profile), such boiler would be turned off e.g. 80% of the time. When it is off, it can be turned on (until the maximal temperature is reached), but it can only decrease its electrical consumption in the 20% of time that it is actually running. Additionally, the temperature (or comfort) limits determine how long this flexibility can be provided. The LINEAR project (Local Intelligent Networks and Energy Active Regions, www.linear-smartgrid.be) analyzed the flexibility potential in a large-scale pilot that comprised 418 smart appliances in 186 households in Belgium [4]. Fig. 2 shows the flexibility potential of an average domestic hot water buffer, with its potential to increase electrical consumption (P_{inc}) or to decrease (P_{dec}) it. It also shows that the hot water consumption profile influences this potential during the day. The colors indicate how long this increase or decrease can hold, i.e. the flexibility's longevity.

Longevity is not only an issue with boilers, but with all types of flexible devices. MacDougall *et al.* provide a detailed analysis of the longevity of heat pumps for residential use [5]. Additionally, when flexibility has been used, there might be a certain time-period required to recover the flexibility (e.g. keeping a heater off for a particular period to allow the temperature to decrease, recharging a battery for some hours.). Approaches that use flexibility should consider such aspects.

A final aspect is the uncertainty, which comes from the user behavior and the amount of information that is transferred to the entity that controls the demand response actions. Consider an electric boiler to be used for demand response that does not send explicit information about its individual state-of-charge and dimensions, nor about its future requirements to deliver hot water. This means that the central controller can only assume average boiler behavior for an average consumer. As such, the

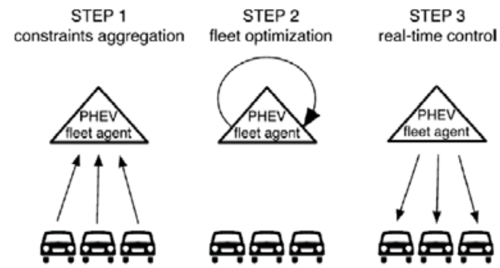

Fig. 3 Three-step approach for charging a PHEV fleet (Figure taken from [6])

response to an action for increasing or decreasing consumption will be less predictable than when the detailed state-of-charge data and the forecasted future usage is sent to an aggregator. In general, demand response solutions need to be able to adapt to the uncertainty caused by unexpected used behavior and incomplete view on the state of the electrical appliance.

III. Residential Demand Response for Different Purposes

When small amounts of flexibility from individual devices are aggregated at a higher level, to be relevant for market trading, scalability is of utmost importance.

If demand response is coordinated in order to achieve sufficient aggregation to participate in the energy market, a three-step approach, as indicated in Fig. 3 is useful. Consider, e.g. the example of charging a large fleet of plug-in hybrid electric vehicles (PHEV) [6], where the aggregated flexibility is used to trade on the day-ahead energy market.

In the first step, the flexibility of the individual vehicles is considered, together with its constraints (derived from the expected departure time of the vehicle, and the state-of-charge of the battery). This local willingness to charge of each PHEV results in a priority value. This priority value p_t increases over time as the need for immediate charging becomes larger. The constraints of the individual cars, both in terms of charging power and in terms of energy are then aggregated as constraints of the fleet (or of the aggregator that uses the fleet to participate on the energy market). This is illustrated in Fig. 4.

In the second step, the aggregated flexibility is compared with the market price for electricity in every timeslot. An optimization algorithm allows finding the cheapest cost trajectory that charges all cars within the aggregated flexibility

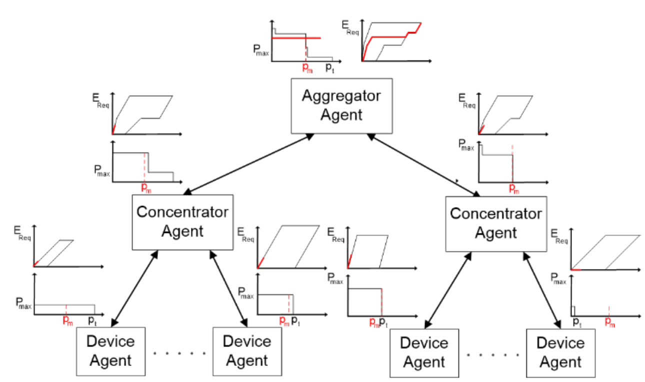

Fig. 4 Aggregation of power and energy constraints for a cluster of flexibility devices, and resulting control for the three-step approach (Figure based on [6])

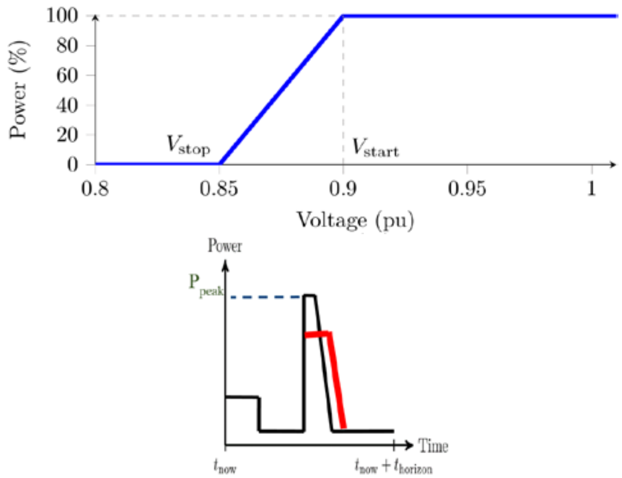

Fig. 5 Droop function of the local controller, that lowers the charging power if there is an under voltage issue, and resulting power profile with (in red) lower peak due to the droop function. (Figure based on [7])

constraints. This optimal trajectory to be followed is indicated in red in the energy constraint of the aggregator agent in the top right of Fig. 4, and a corresponding aggregated required power consumption for the entire fleet follows from there. At every time step, this results in a priority value pm where this line with the required power crosses the aggregated power (top left of Fig. 4).

In the third step, this priority value pm is broadcast to all individual devices, which can automatically derive their individual set point from this value, and every vehicle hence knows whether it should charge (if pt<pm) or not (if pt>pm). This broadcasting, together with the optimization at the aggregated level, leads to a scalable approach, both in number of vehicles to be included in the optimization, as in time horizon over which the optimization is considered [6].

While this market-driven approach works well in strong grids, where there are no technical constraints, it might be not technically feasible to implement this in a weaker grid. Taking only market prices and the business case of the aggregator into account, can indeed lead to simultaneous actions of many devices (the so-called syncing effect). This creates new peaks in the power consumption when the price is low, and hence could lead to local voltage problems. In [7], this has been elegantly solved by adding a local droop function to the electric vehicle charging as indicated in Fig. 5; if the local voltage deviates too much from its nominal value, this event is captured by the local controller and the vehicle will charge at a lower power than required, in order not to aggravate the voltage problem. The three-step approach is hence complemented with a local control mechanism that considers the technical constraints. The ability of the three-step approach to deal with dynamic behavior will imply that the charging takes longer in order to reach the same SoC. But, such an event-driven dual coordination mechanism has in general very limited impact (<2%) on the aggregator's business case, while getting rid of almost all voltage problems [7].

This approach is an example of combining the use of aggregated flexibility from electric vehicles both for market objectives and for technical objectives (i.e. voltage support).

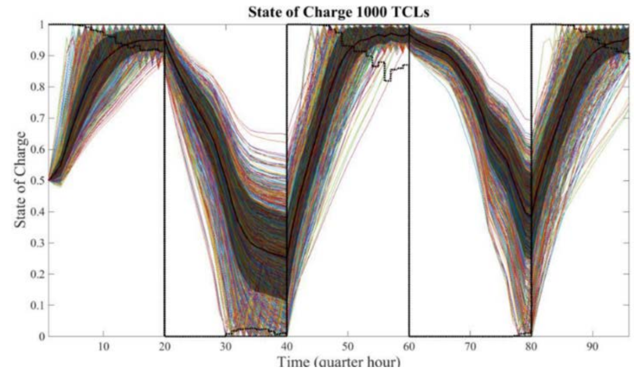

Fig. 6 State-of-charge of 1000 thermostatically controlled loads; physical differences imply different dynamics. The straight black line represents the on-off signal, while colored lines show the device dynamics; the curly black line is the aggregated, scaled power consumption. (Figure taken from [10])

This shows that grid operators should not be scared that their grids would collapse when demand response considers market prices. While here illustrated for homogeneous flexibility providers (electric vehicles only), it can be easily extended to heterogeneous flexibility providers (e.g. electric vehicles, white appliances, electric boilers) [8], or to deal with more advanced technical constraints. Examples of the latter include phase imbalance in a three-phase system, or dealing with congestion management to avoid overloading and accelerated aging of a transformer [9].

For thermostatically controlled devices (such as deepfreezes or electric boilers, or a heat pump that use the thermal mass of building as flexibility provider), it might be quite difficult to track the state-of-charge of the energy buffer, and hence to know the flexibility. This is due to the differences in device types (e.g. size, insulation levels), local circumstances (e.g. external temperature) or the user behavior (e.g. opening doors or windows); see Fig. 6. If the flexibility of all individual appliances would have to be modelled before it can be aggregated, it would become intractable to optimize the use of the flexibility. In such context, it can help to identify 'tracers' in the population of flexibility providers, so that a scalable approach is obtained [10]. A few tracers can track the population behavior of thousands of individual devices, at a much lower computational and communicational cost. A cross-entropy method can be used to identify such relevant tracers, and then apply the optimization step (step 2 of the three-step approach mentioned above) on the reduced order tracer models.

These tracers are an example of how machine learning can be added to the three-step approach, in order to learn the flexibility of a cluster of devices [10]. In addition, Vandael *et al.* have applied machine learning to determine the electric vehicle cluster behavior together with the energy market behavior. This enables them to optimally benefit from the flexibility on the market [11].

Machine learning can also be applied to learn the flexibility of individual devices in a data driven way. Ruelens *et al.* have applied this to an electric boiler, where boiler characteristics and market prices are taken into account together with user behavior [12]. Based on fitted Q-iteration, it directly learns a control policy that determines when an electric boiler needs to charge, depending on its state of charge, time of day and price

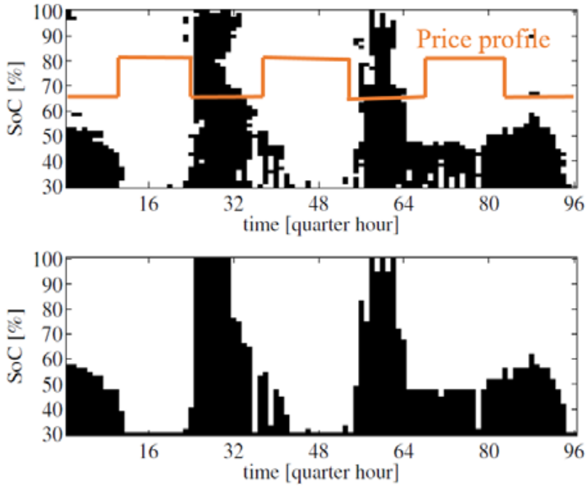

Fig. 7 Learned policy for boiler control, depending on current state-of-charge and price. Black = boiler on, White = boiler off. Learned policy (top) and smoothed policy (bottom). (Figure taken from [12])

of electricity. Based on a combination of the exploration of the design space, and the exploitation of earlier knowledge, it is able to find a good control policy in less than 20 days.

Recently, Engels *et al.* [13] have showed an example of using the flexibility for multiple purposes at the same time. Based on stochastic optimization techniques, it combines the use of a battery for providing frequency support to the system operator, with this battery's usage for maximizing self-consumption. The first objective requests guaranteed response, but is not often activated, while the second one allows for increasing the customer benefits by using the spare capacity for increasing the consumption of locally generated electricity. The varying power and energy bands in Fig. 8 indicate the remaining flexibility for the self-consumption objective, while the rest is reserved for the frequency support. The different colored lines results from the stochastic scenarios that are underlying the optimization methodology.

Beside data-driven approaches towards flexibility aggregation for combined objectives (e.g. market & technical), it is also possible to rely on game-theoretic analysis to determine where it is most beneficial to use the flexibility [14].

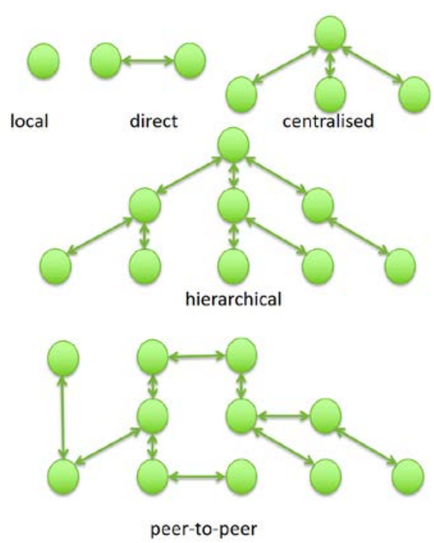

Fig. 9 Relevant control paradigms for local and coordinated control

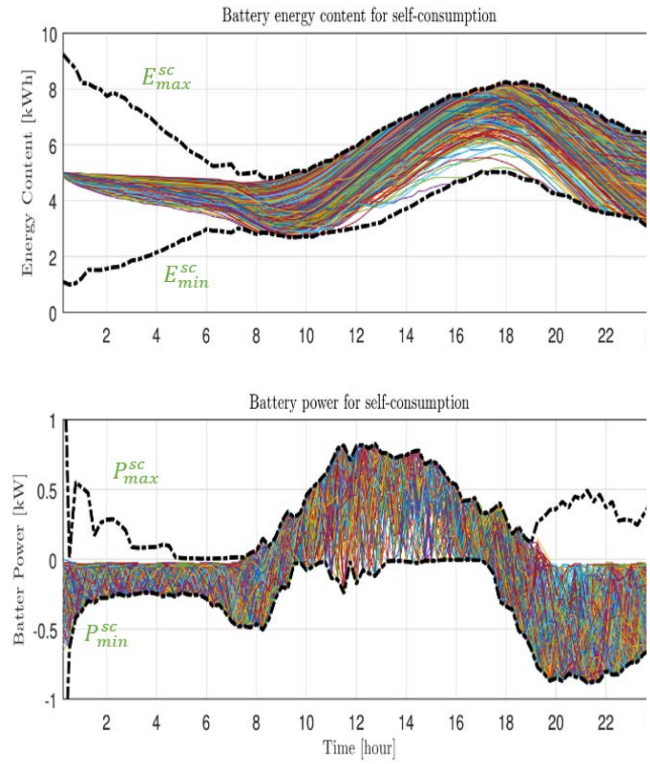

Fig. 8 Varying energy and power constraints to deliver frequency support, and associated battery behavior for maximizing self-consumption (Figure taken from [13])

IV. Challenges for Demand Response

Many technical and non-technical challenges remain for a widespread adoption of demand response, and they require additional research. Let us look at four challenges in more detail: scalability, distribution of control, uncertainty and aggregation aspects.

A first element is the scalability issue. If a certain aggregated demand response (in terms of required power reduction/increase for a determined time period) is fulfilled with large industrial loads, then often one or two industrial loads are enough and the control can be dedicated, taking all process features into account. If commercial loads are used, probably some tens of them are needed to cover the request, but still the problem remains tractable and detailed process information can be taken into account to reach a global optimum. However, if residential loads are considered then thousands or more of these are required to fulfil the request and a model-based approach becomes too cumbersome. A data-driven approach is needed instead, where the flexibility of the devices is learned from the data delivered by them. This is more scalable than the a-priori definition of device models.

A second element is the question, which is the most appropriate paradigm for the distribution of control (Fig. 9). In a case with only local control, there is no communication between devices, and control decisions are only taken based on locally measured parameters (voltage, power, known price profiles …). Often it is beneficial however to coordinate control between entities, such that it is not only based on local sensor information, but also on information from other entities that is

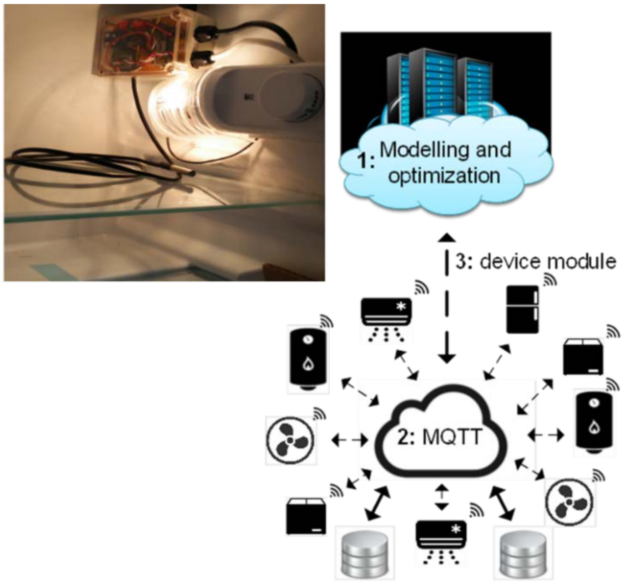

Fig. 10 Device model and architecture of demand response proof of concept

communicated to them. This can be done in different ways.

- In direct control there is a direct interaction between two entities, for instance an intelligent electric vehicle charger that determines the optimal moment to charge the car.
- With centralized control, a central agent controls all flexibility, for instance a distribution system operator that sends an interruption signal to specific loads to be shed.
- With a hierarchical approach, there are intermediate levels that ensure some scalability, such as the concentrator agents shown in Fig. 4 above.
- Within a peer-to-peer approach, components only interact with some physical or logical neighbors in a flat hierarchy.

Which one of these control paradigms is better suited, depends on the type of application for which the flexibility will be used, and the actors involved (Table 1).

A next challenge is the uncertainty of the response to the control signal. Whether or not individual devices will be able to deliver the required flexibility, can depend on the user behavior, the grid behavior, the local circumstances and external (e.g. weather) parameters. In addition, energy markets (day ahead and intraday or balancing markets) are sources of uncertainty. Many different techniques exist that deal with these uncertainties, from stochastic variants of model-based optimization techniques over game theoretic to data-driven approaches. If the uncertainty implies that a control algorithm always considers the worst-case situation for a guaranteed expected response, then much of the available flexibility will remain unused. Alternatively, if an average scenario is considered, there is a non-negligible probability that the demand response request will not be fully fulfilled. The larger the uncertainty on the flexibility, the more conservative the algorithm has to behave.

A final challenge has to do with the aggregation aspects related to the heterogeneity of flexibility providers and their geospatial location. If the flexibility from a homogenous set of devices is included, some indirect synchronization might appear because of the device usage; e.g., all electric vehicles arrive home after work and leave again in the morning. This

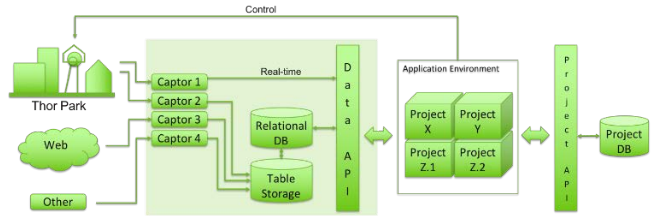

Fig. 11 Cloud-based SmarThor data platform

leads to a rather high simultaneity factor. Increasing the heterogeneity by e.g. combining flexibility from electric boilers, vehicles, white appliances and heat pump-heated buildings, can spread out the available flexibility over time. Also, the geospatial location of the flexibility provider (e.g. feeder to which device is connected, or its phase) might play a role if technical objectives are pursued. In contrast, when flexibility is traded at a regional or national market level, this locality information is not relevant.

V. Ways Forward

Thanks to the tremendous advantages in information technology and communication infrastructures, e.g. internet-of-things, big data and cloud technology, it becomes more possible to interconnect flexibility providers to controllers, and to use the flexibility for the different objectives described above.

In the recent years this has led to many new protocols and standardization initiatives that try to harmonies the way to deal with flexibility. Examples include the OpenADR Alliance (www.openADR.org) in 2010 “created to standardize, automate and simplify DR to enable utilities to cost-effectively meet growing energy demand, and customers to control their energy future”), USEF (Universal Smart Energy Framework) (“international common standard that ensures smart energy technologies and projects are connectable at lowest cost. Its component parts enable the commoditization and market trading of flexible energy use and specify all stakeholder roles (new and existing), how they interact and how they can benefit by doing so.”, since 2014, see www.usef.org), or the extensions to the IEC 61850 series “Communication networks and systems for power utility automation”. However still, many proprietary protocols within closed systems continue to exist.

As an example of combining demand response with innovative communication technology, the author’s team at KU Leuven, together with colleagues from UC Berkeley, developed a proof-of concept controller for demand response in refrigerators [10]. Based on a device module that works in parallel with the built-in controller of a fridge (in order to ensure

Table 1: Advantages and disadvantages of centralized vs decentralized control paradigms

Centralized	Decentralized
more simple	more scalable
single point of control	no single point of failure
SCADA-compatible • requires dedicated communication architectures • e.g. master/slave	internet-compatible • fits with many architectures: overlays, peer-to-peer … • e.g. publish/subscribe
control structure per application	interface to many control applications
more compatible with integrated energy companies with few actors	more compatible to a liberalized, open market model with many actors
…	…

the temperature constraints), the MQTT protocol is used to aggregate the flexibility information from all appliances, and a centralized controller sends out the demand response requests (Fig. 10) [15]. MTTQ is the Message Queuing Telemetry Transport, a standardized publish-subscribe protocol that is often used in social media applications.

Besides communication as an enabling technology for demand response, also the information itself exchanged between devices and controllers is of paramount importance. Historical flexibility profiles of devices and consumption profiles of households capture a huge amount of knowledge that can improve e.g. machine learning-based demand response algorithms. This can be further optimized by also including data that pertains to related phenomena that more indirectly affect the choice to shift demand; examples are the forecasted and actual values of renewable energy production, of weather conditions and of energy market prices. Big data and related cloud technologies have proven their worth to collect, process and manage this abundance of data in a timely, reliable, scalable and secure manner.

Fig. 11, for example, presents such a cloud-based approach, called SmarThor, which is being developed at EnergyVille. Besides data collection, management, and provisioning, SmarThor provides a platform-as-a-service application environment to host long running demand response and optimization applications, and, crucially in smart grids, a control interface to, amongst others, the building management systems at the local building. While designed and built as a generic and reusable data platform, the first application to make use of the SmarThor platform implements demand response to maximize self-consumption of locally produced renewable energy to charge a fleet of (hybrid) electrical vehicles.

VI. Considerations

A number of interesting paradoxes pop up if one considers the broader infrastructural perspective of demand response within smart grids.

A first paradox is that the flexibility which is added to the electricity system by the demand response makes the electricity generation (i.e. supply) less flexible. Indeed, when demand response becomes more widely available in order to accommodate electricity generation from renewables better, the less there will be incentives to modulate the less-flexible classical power plants (such as nuclear or coal-fired power plants), effectively leaving them in the market.

A second paradox is about the increased resilience and increased vulnerability of the electrical grid infrastructure. With more and more bottom up control and distributed intelligence, the resilience of the grid can be increased: outages can be detected more quickly and be covered more locally. However, this decentralized control can also start interfering with the higher-level top-down control mechanisms, leading to oscillations in set points or to cascading effects of failures. Additionally, the need of information and communication technology for operating the grid brings in an additional point of failure.

The different objectives for which demand response is used (market, technical or prosumer objectives) can also lead to conflicting incentives towards the devices that provide flexibility. Low electricity prices could lead to an increase in demand by some demand response applications, while the resulting under voltage would call for a decrease in demand by the same flexibility providers. The value of flexibility still is a hot research topic [14], [16].

This increase in demand response opportunities also results in both new actors in the energy field; e.g. aggregators, ESCOs (energy service company), prosumer, or existing actors taking up new roles; e.g. system operators, utilities. This has its implications on the regulatory and legal frameworks that need to be in place. In Europe, this has been driven since the late nineties by directives concerning the market openings, and in the fourth package of directives (the so-called winter package "Clean Energy for all Europeans", outlined end of 2016 and to be implemented by 2020), Europe fully envisages an active role of the consumer/prosumer, who can interact directly with its neighbors concerning energy trade.

In this context, the individual customer, engaged towards energy efficiency and economic delivery of electricity, plays an ever more important role. Bottom-up groups in society, cooperatively working together to increase their sustainability and decrease their carbon footprint are eager to take on this path of being an active customer. They are actively seeking for alternative solutions that do not require central control. Instead, they want to remain in control themselves and are sensitive to privacy issues, etc. In this context, new technologies such as peer-to-peer energy trading and smart grid control [17], [18], or smart contracts and blockchain technology (e.g. Energy Web Foundation, www.ewf.org) are fully taking ground. This is in line with the introduction to this special issue, emphasizing the trend towards decentralization in the provisioning of services, either within the energy infrastructure system itself, or in competition with established infrastructure (such as road infrastructure). Examples include a prosumer with solar panels on their roof or one with an electric car that is used to provide public transport services.

Other researchers look into the possibilities of complementary currencies, as policy instrument, to engage customers for energy-saving behavior [19]. Just like frequent flyer programs from airlines, these are based on credits that are rewarded when one behaves energy-efficiently, and that can be spend on more energy-efficient appliances or services [20].

The final paradox is that only a limited amount of people are interested in the environmental effects of their own energy consumption pattern, and that apathy (or even adversity) drives many people away from digitization and increased automation. Studies have shown that even tech-savvy consumers lose their attention and interest their consumption patterns after some weeks or months. Engineers need to reach out towards social sciences to get the consumers involved; seeing technical infrastructures as socio-economic ones is a condition-sine-qua-non the European vison towards a carbonless society around 2050 can be met.

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