Recent Trends in Demand-Side Flexibility

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Abstract. Renewable energy generation is inherently stochastic, and it rarely aligns with the periods of peak demand. Consequently, and despite continuous developments in storage technology, there is still a significant potential in using demand-side flexibility to balance generation and demand. The flexibility arises in many contexts, e.g., in the heating of buildings, and by shifting the demand, we can substantially reduce the need for infrastructure investments. However, it is not trivial to utilize the flexibility in a scalable manner. Energy customers are highly diverse (residential, commercial, industrial, etc.), and in most cases, their energy demand cannot be controlled directly. Furthermore, flexibility is both a *dynamic* and *stochastic* quantity. When the flexibility is used, it cannot be used at a later point in time as well. In this paper, we describe the Smart Energy Operating System, which is a framework for scalable exploitation of demand-side flexibility. It combines hierarchical forecasting with hierarchies of controllers and models. A key part of this framework is the Flexibility Function. It describes the energy demand of a flexible asset in response to a price signal, and it is continuously updated based on the actual demand. An aggregator can use it to predict the energy demand of the underlying flexible assets and participate in flexibility markets on their behalf. In other words, the Flexibility Function serves as a minimum interoperability mechanism (MIM). An important prerequisite is that markets must account for the dynamic and stochastic nature of flexibility, and we discuss current limitations and opportunities.

Keywords: Smart Buildings · Smart Grids · Flexibility · Demand-Response

1 Introduction

Demand-side flexibility (DSF), as defined by smartEn, is "*the capability of any active customer to react to external signals and adjust their energy generation and consumption in a dynamic time-dependent way, individually as well as through aggregation*" [1]. A well-known example of such external signals is dynamic pricing, where end-users are equipped with local controllers that can quickly react to changes in price without manual interventions. Another example is a demand response signal that can directly adjust energy consumption of active customers' flexible loads such as air-conditioners [2,3].

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Regardless of the external signal choice, DSF can unlock a range of benefits at both distribution (DSO) and transmission (TSO) system operator levels. The report [1] outlines the benefits of such flexibility based on the 'Fit for 55' objectives [4] and REPowerEU Communication [5] in the low- and medium-voltage grids as 11.1–29.1 billion EUR savings in investment needs across the 27 EU countries annually between 2023 and 2030. This represents between 27% and 80% of today's forecast in investment needs for low- and medium-voltage distribution grids, between 43% and 66% of saving in balancing costs in European balancing markets by 2030, 2.7 billion EUR annual savings by 2030 through enabling 60 GW of DSF rather than installing peak generation units across EU to ensure supply security, and 61% less (15.5 TWh annually) curtailment in renewable energy generation in Europe, which will improve the economics of wind and solar energy and increase the availability of decarbonized electricity to consumers.

Similarly, some large-scale projects in Denmark, such as the "Center for IT-Intelligent Energy Systems (CITIES)" [6] and "Flexible Energy Denmark (FED)" [7], have demonstrated solutions for demand-side flexibility in a number of Living Labs. The solutions have demonstrate savings from 10% to 85%.

A recent study by an Australian DSO indicates that curtailment of distributed PV generation in 2029 will be two to four times higher than the current values [8]. At these levels, solar customers are set to experience solar curtailment as the norm rather than the exception. The number of low-voltage sections that experience voltage non-compliance will also increase from the current $\sim$4k to at least $\sim$10k by 2036. DSF can provide an economic way to meet technical standards around voltage, safety and performance.

For price-responsive customers, prices can be used to control the load as first suggested in [9]. Methods for using experimental data to estimate the energy flexibility of households with a price-responsive load were suggested at least as early as 2009, as part of the FlexPower project [10]. In [11], it is shown how the variations in penalties can be used to shift the load from peak hours to off-peak hours. The authors in [12,13] went a step further and described how the frequency and voltage in power grids can also be controlled by this method.

However, a model for forecasting how clusters of consumers in, e.g., a DSO area will respond to a particular sequence of prices is needed. [14] introduced the so-called *Flexibility Function*, which is simply a map between the response (e.g., the load) and incentivizing signal (e.g., the price). A detailed stability analysis of this flexibility function is presented in [15]. The flexibility function could be implemented using any type of dynamical model, and it is suggested as one of the fundamental MIMs for energy systems [16].

While the current options for offering and trading such flexibility is rather limited, different jurisdictions are moving in this direction. For example, Nord Pool has introduced the "flexi order", which is the most appropriate product for utilising energy flexibility on the day-ahead market. It is a classical block order with a flexible start and accept hour [17,18]. In Australia, a Wholesale Demand Response market allows demand side participation at any time, however, most likely at times of high electricity prices and electricity supply scarcity. Demand Response Service Providers classify and aggregate the demand response capability of large market loads for dispatch through the standard bidding and scheduling processes [19].

In this paper, we will show how demand-side flexibility can be described using the concepts of a stochastic flexibility function, and it will be outlined how a hierarchy of controllers and multi-objective control can be used to take into account the dynamics linked to various flexible assets. By the use of stochastic control theory, we address the uncertainty from wind and solar generation and propose a new market design as well as grid and balancing services for the future weather-driven energy system.

2 Hierarchical Control for Utilising Flexibility

This section describes how sequential dynamic optimization, implemented as controllers in a multi-level or hierarchical control setup, can be used to solve both grid performance and balancing problems. Here, we use buildings as an illustrative example to showcase the flexibility utilisation. Briefly speaking, we will describe how the physics (dynamical formulations) of the buildings and grids can be linked to the conventional electricity markets which are characterised by bidding and clearing (static formulations). We will then briefly outline how these principles can be generalised to multi-level and hierarchical control problems.

First, we explain how to control the electricity demand for smart buildings by generating energy prices such that the building *reacts* and *adapts* its consumption according to some criteria. For instance, in a peak shaving application, smart buildings aggregate demand should follow a reference respecting a maximum allowable load. The basic concept is illustrated by Fig. 1, where a smart building takes an input (price) which results in an output (demand). Data-driven techniques are used to estimate the price-demand relationship, known as the Flexibility Function. This function can then be used to predict demand as a dynamic function of price.

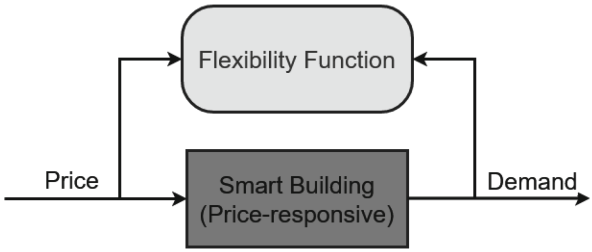


Fig. 1. The Flexibility Function can be used to predict the demand of a smart building a function of prices.

Given a Flexibility Function for the building, a second controller can be formulated where the objective is to control the building's demand according to some criteria, and the decision variable is the price (say, electricity price as a function of time). As shown in Fig. 2, the Flexibility Function along with a secondary controller can be used to generate prices such that the demand follows a reference. The reference could be given by the expected local PV production or any other desired energy consumption in time. Notice how the demand acts as the feedback to the controller, closing the loop.

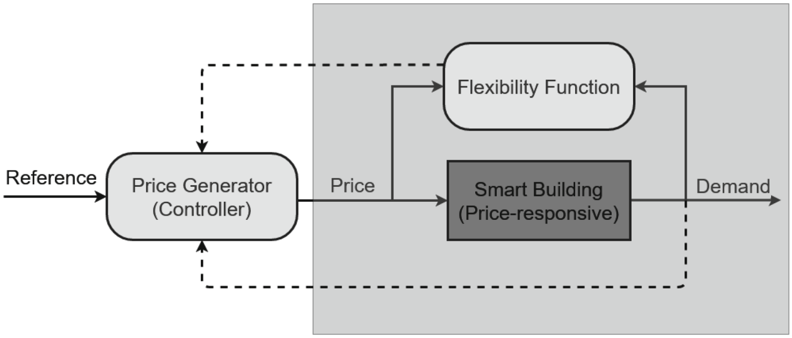


Fig. 2. A price generator implemented as a controller uses the FF and demand feedback to generate price signals for controlling the demand.

Let FF be the Flexibility Function that takes energy prices as input and provides the building's expected demand as output, while r_l is a reference load profile. Then, a simple upper-level controller (the price generator in Fig. 2) can be defined as the following optimization problem

$$\min_{C_u} \quad (\mathrm{FF}(C_u) - r_l)^2, \tag{1}$$

where C_u is the future energy prices. An example of such a controller is the minimum variance controller [20], but these controllers typically lead to high variability of the control signal; i.e. the prices in this case. Obviously, it might be necessary to impose limits on how much the price can change or requirements on the average value, and a more sophisticated optimization problem than the minimum variance formulation can be formulated, as discussed in [21]. Combining this optimization problem with the lower-level optimization problem of the building's heating system, the Flexibility Function couples the two levels:

$$\begin{array}{lll} \min\limits_{C_u} & (\mathrm{FF}(C_u) - r_l)^2 & \text{Upper level} \\ \hline \min\limits_{u_k} & \sum\limits_k C_u^\top u_k & \text{Lower level} \\ s.t. & \mathrm{d}x = f(x,u,d,t)\mathrm{d}t + g(x,u,d,t)\mathrm{d}\omega, & \\ & \Pr(x_{\min} \le x \le x_{\max}) \ge 1 - \alpha & \end{array} \tag{2}$$

where the functions f and g are the drift and diffusion coefficients of the grey-box model of the flexible asset. Here, the grey-box model is formulated as a set of stochastic differential equations for the temporal evolution of the states x of the considered asset with u and d as controllable and uncontrollable input, respectively. Such grey-box models for buildings are presented in numerous papers ([22–24]). In this case, the lower optimization problem is formulated as an economic MPC problem with chance constraints [25,26].

The coupled upper and lower level controller structure (2) relies on a fixed FF. However, the price-demand dynamics are time-varying, influenced by factors such as seasonal changes and shifts in consumption behavior due to abnormally high energy prices. This variability necessitates an adaptive mechanism capable of tracking these dynamic changes. An adaptive flexibility function is proposed in [27]. It can update the price signal based on changes in price-demand dynamics without requiring explicit identification of the flexibility function. Furthermore, this approach eliminates the need for a manual, customized modeling-and-control procedure for each flexibility resource. Therefore, the adaptive flexibility function can be seamlessly deployed across different assets in a plug-and-play fashion, facilitating mass adoption.

As it will be explained more in Sect. 6, the main reason why the Flexibility Function is suggested as one of the fundamental MIMs for energy systems is that the FF is instrumental for interoperability between the building level and the upper level representing the grids and aggregators.

Notice how the two optimization problems are solved independently from each other, thus preserving autonomy and privacy for the building owners while simultaneously allowing a stakeholder (e.g., supplier, aggregator, or balance responsible party) to utilize the energy flexibility. In practice, there will be many smart buildings for each aggregator, each with independent control problems and preferences.

The development of building energy management systems and smart buildings is left open to competition among commercial stakeholders, while the flexibility function remains agnostic to specific types and technologies of controllers. Finally, this method scales well since the computational burden for the upper-level remains constant with the Flexibility Function simply representing the expected aggregated response from the relevant cluster of smart buildings [21].

3 Using the Flexibility for Multi-purpose Control

In the previous sections, the upper-level controller received the load reference as input and created a sequence of prices to make the building demand follow the desired reference. This optimization was based on the known flexibility dynamics represented by the Flexibility Function. This setting is appropriate if we want to establish demand-side load management, which could be useful for peak-shaving or for maximizing self-consumption, e.g., in the case of local PV production.

The sketched methodology, however, can be generalized into other situations. Let us for instance consider the problem of voltage control with a reference

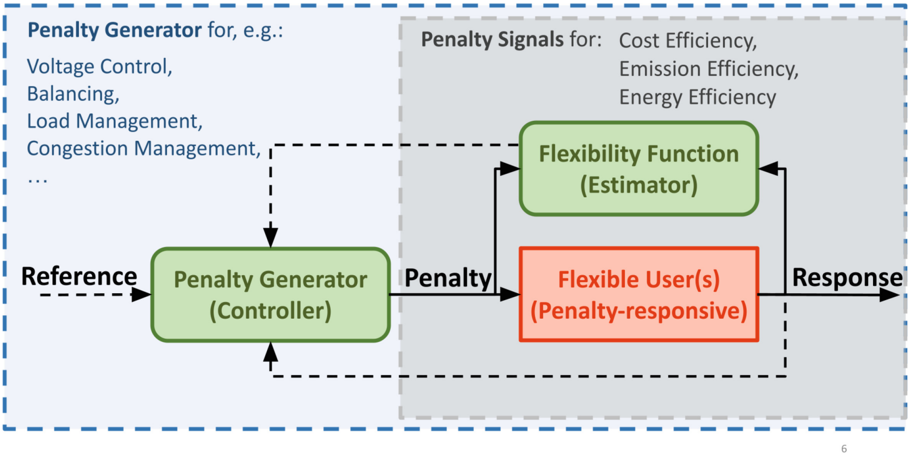


Fig. 3. Hierarchical control for utilising flexibility

voltage $r_{voltage}$. Then, the voltage controller can be defined as the upper-level controller

$$\min_{C_u} \quad (\mathrm{FF}_{voltage}(C_u) - r_{voltage})^2, \tag{3}$$

where the $\mathrm{FF}_{voltage}$ is a flexibility function describing the dynamical relations between prices and voltage for the considered low-voltage distribution area.

Such an upper-level controller can be used to, e.g., postpone costly investments and ensure safe operations of power transformers, which are one of the most costly assets in power grids. Without such settings and due to the increasing levels of electricity demand and distributed generation, transformers are more likely loaded above their rated limits, which may cause serious lifetime reductions and increase failure rates. While transformer ratings are traditionally set in a controlled environment with conservative margins, it has been shown in [28] that a digital twin model of transformers can be used for **dynamic transformer ratings**, where it can be dynamically overloaded up to 60% without any risks for damages.

Until now the purpose of the low-level controller has been to minimize the operational cost. However, it is possible to change the low-level controller. For example, if we use real-time CO2 emissions associated with electricity consumption as the penalty signal, then the controller will minimize the carbon footprint of the system. This example of low-level controllers is used in, e.g., [29,30] for controlling the temperatures in summer houses with a swimming pool such that the carbon footprint is minimized.

As explained in [29] and shown in Fig. 3, by changing the cost function, the low-level controllers can be used for i) cost minimization, ii) carbon footprint minimization, or iii) energy efficiency optimization. Note that a goal of modern regulation for the energy sector would be to ensure that, e.g., cost and emission optimization go hand-in-hand. Unfortunately, this is often not the case today. For instance, as explained in [31], wastewater treatment plants could only save up to 50% on their carbon footprint due to the embedded flexibility.

4 Controllers and Markets

The ultimate goal of the future smart energy system is to establish a connection between the lower-level local controllers and upper-level markets operating at large scales. This includes coupling sectors and establishing dynamic markets to reflect an increasingly dynamic supply and demand of energy. At the same time, the established markets and controllers must ensure that power systems on all temporal and spatial scales are balanced. Essentially, it means that a spectrum of all relevant spatial aggregation levels (building, district, city, region, country, etc.) has to be considered. Consequently, data-intelligent solutions for operating flexible electrical energy systems have to be implemented on all spatial and temporal scales.

Traditionally, power systems are operated by sending bids to a market. However, in order to balance the systems on all relevant horizons, several temporal-specific markets are needed. Examples are day-ahead, intra-day, balancing, and regulation markets. The bids are typically static and consist of a volume and duration. Given all the bids, the so-called supply and demand curve for all the operated horizons can be found. Mathematically, these supply and demand curves are static and deterministic. *Merit order dispatch* is then used to optimise the cost of generation. However, if the production is from wind or solar power, the supply curve must be stochastic, and the demand flexibility has to be described dynamically - e.g., by use of the introduced Flexibility Function. Consequently, it is believed that introducing new digitised markets, which are *dynamic* and *stochastic*, is necessary. Also instead of using a large number of markets for various purposes (frequency, voltage, congestion, etc.) and on different time frmas, we propose utilizing concepts based on the Flexibility Function and stochastic control theory; exactly as described in the previous section for the two-level case. We call this the Smart Energy Operating System (OS) [13,16,30], which will be explained further in Sect. 6 and illustrated in Fig. 5.

If we zoom out in space and time, i.e., consider the load in a very large area on a horizon of days, or maybe the next day, then both the dynamics and stochasticity start to matter less (and might be disregarded), and hence we can use conventional market principles as illustrated in Fig. 4. If we zoom in on higher temporal and spatial resolutions (like for instance a house), the dynamics and stochasticity become important, and consequently, we will suggest using the control-based methods for the flexibility as discussed previously.

Having a smart Energy OS implies that a real-time connection between controllers and the flexible assets (e.g., buildings) is handled by a one-way communication, i.e., broadcasting the price signal. The consumer can then easily self-dispatch according to prices without any further complications, e.g., having to submit bids.

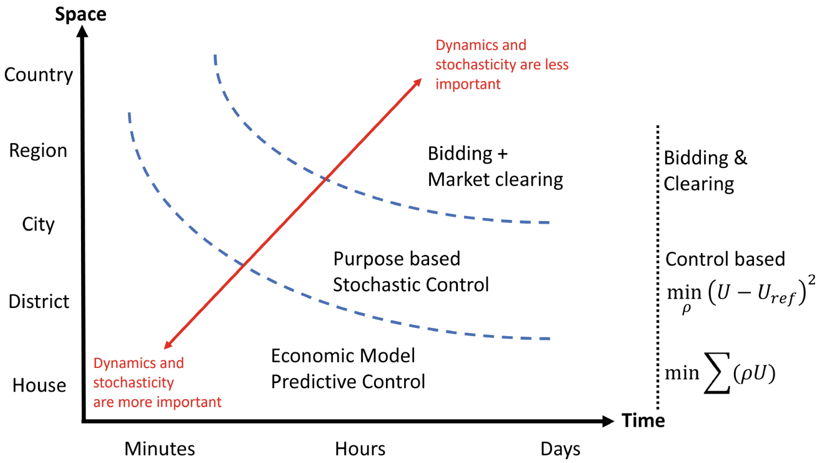


Fig. 4. Hierarchical control and markets.

The simplicity of broadcasting price signals to activate demand-response, needed for instance by a DSO, implies that basically all appliances can contribute to unlocking the needed flexibility at the relevant spatial and temporal coordinates. At the same time, end-users can still customize their local preferences in the Home Energy Management Systems (HEMS) by prioritizing factors such as comfort, cost, emissions, and energy efficiency [32]. The overall simplicity of the proposed setup ensures quick adaptation and encourages widespread use of flexibility and demand response technologies in the market. A comprehensive model, integrating these concepts into a TSO-DSO coordination framework, is presented in [33].

Basically, the setup distributes the computational effort across multiple levels of the hierarchy, where each level (e.g., TSO, BRP and DSO) has a controller linked to some well-defined criteria and constraints. Such a setup with a simple broadcast of a price signal also provides a direct possibility for sector coupling and multi-energy supply systems. For instance, air-to-air heat pumps can be used jointly with natural gas heating systems and HEMS can easily switch from natural gas to electricity when electricity prices are low. This setup would accelerate the transition to green energy and offer extra flexibility, thereby reducing the instances when, for example, wind turbines are stopped by grid operators.

5 Market Design Challenges

5.1 Market Design for Activating Local Flexibility

Several projects and initiatives have studied the possibility of controlling, e.g., the load in a distribution grid by setting up a local DSO market [34,35]. However, it has been concluded that conventional market mechanisms are not suitable here [30]. First of all, the number of potential bidders and the market size is very limited. Moreover, even for larger flexible assets, energy flexibility is only of secondary concern. As an example, we can consider the conclusion from a series of workshops for wastewater treatment plants organized by Energinet and Center Denmark. Wastewater treatment can be very flexible, but the primary concern for the operator of wastewater treatment plants is to avoid overflow in the city. The second priority is to keep the flow at the plant below some given values to ensure that the active part of the sludge stays on the plant, while saving money due to energy flexibility is at best a third priority. Given even a small probability of a severe rain event, wastewater plants will not bid into the markets. Furthermore, they found the price-volume bidding strategy to be difficult or impossible to use. The suggestion was to introduce an aggregator which trades on the electricity markets and then broadcasts a dynamic price signal to the wastewater plants. However, from the wastewater treatment plant's perspective, it does not matter where this dynamic price signal comes from. [31] demonstrated savings up to around 50%. The savings can be shared between the aggregator and the wastewater treatment plant.

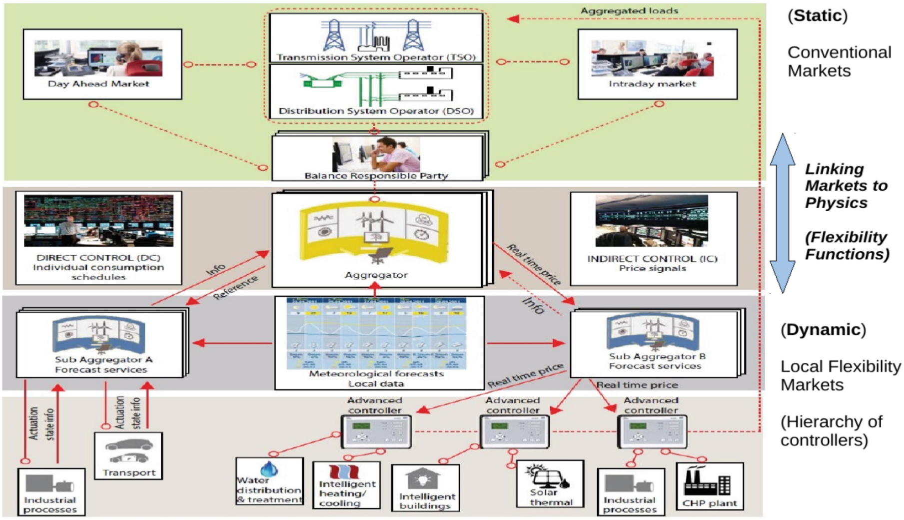


Fig. 5. The Smart Energy OS

5.2 Where Does the Market Stop and the Physics Begin?

Another barrier is the fact that the conventional market design with merit order bidding and subsequently clearing represents a *static problem*, but the local flexibility represents a *dynamic problem*. Therefore, the bidding formats of traditional market mechanisms do not offer enough expressive richness to capture the temporally coupled characteristics of the new market players [36].

Consider a supermarket where the cooling system serves as a flexible asset. The problem is that if the supermarket reduces its electricity usage for cooling in a particular hour, it may not be possible to offer a similar flexibility for the subsequent hour because it is necessary to keep the goods within specific temperature ranges (typically below 5–6° C). However, at higher aggregation levels, e.g., day-ahead at price-zones operated at the Nord Pool spot market, the existing market mechanisms should be preserved since they act as an important mechanism to find the overall level for the electricity prices.

In summary, we need an interoperability mechanism to define the link between the high-level static markets and the low-level physics. Later on, we will suggest the previously introduced Flexibility Function as a fundamental MIM for this purpose, and hence for describing the link between the markets and the physics. The MIMs [37] are now becoming an important instrument in the twin transition in Europe and globally, as they are approved by ITU and 17 member organisations [38].

6 The Smart Energy OS

Principles for forecasting, control and optimisation constitute the so-called Smart Energy OS, which is a framework used to develop, implement, and test solutions (layers: data, models, optimisation, control, communication) for the hierarchical and coherent operation of flexible electrical energy systems at all scales. See [13,30,39] for further information.

An efficient implementation of the future low-carbon energy system requires the electricity demand to follow the weather-driven energy production at all scales of the power system. The future calls for more coordination between the low- and high-voltage system operators and, consequently, there is a need for coherence between actions taken by the TSO and DSOs, who operate at different spatial scales. The coordination in Smart Energy OS goes beyond previously introduced hierarchical control. As an example, a method for hierarchical forecasting of wind power production suggested in [40] has led to a significant improvement of wind power generation forecasts and at the same time the forecasting hierarchy ensures that the forecasts seen by the TSO and the DSOs are coherent. In [41], similar hierarchical forecasting techniques are used for improved load forecasting in all four price areas in Sweden.

The Smart Energy OS principle is using the Flexibility Function as one of the fundamental MIMs to ensure minimal but sufficient interoperability between all relevant levels. For many applications, low-cost solutions can be established using mobile phones, smart home management systems, and similar edge computing technologies. Data is often collected at the edge, but aggregated on higher levels of the hierarchy, and computations are carried out, in a *coherent hierarchy* consisting of edge, fog, and cloud computing levels with privacy, transparency, and fairness in mind.

The Smart Energy OS is a hierarchical setup as indicated in Fig. 5. At the top level, it consists of conventional markets, but at the lower levels, it consists of methods for combined direct and indirect control. The experience at, e.g., the smart energy hub, Center Denmark, is that most of the building related demand response methodologies are based on indirect price-based control.

At the same time, the Smart Energy OS is designed as a hierarchical system for energy data spaces, i.e., for data handling and information exchange frameworks, ensuring a unique coherence across all relevant spatial and temporal aggregation scales, and with a focus on multi-objective criteria like energy efficiency and flexibility.

Conceptually, the Smart Energy OS relies on the MIMs roadmap, which aims at providing building blocks for an efficient digitalization of the society in general, and in providing functionality across different but related domains like energy, transportation and water. The intention is not to replace existing market mechanisms but to accomplish this with a MIMs-compliant framework for an efficient scale-up of local flexibility concepts (e.g., for large-scale integration of wind and solar energy) while supporting local initiatives like district heating and local energy communities.

Data for energy systems forecasting and services is an important example being built upon the Smart Energy OS concepts. Here, unique frameworks and data spaces for the exchange of information between all relevant aggregation levels have been established. More specifically, the Smart Energy OS concept contains a framework of spatial and temporal hierarchies for ensuring that forecasts of, for instance, the wind power generation are coherent across all relevant aggregation levels, as explained, e.g., in [42].

Integrity - including privacy, transparency, security, and reliability - has foremost importance in the Smart Energy OS, and in all essential cases such issues are dealt with by design in a consistent and verifiable way. The one-way broadcast of prices in the Smart Energy OS ensures privacy by design.

A key element of the data exchange framework between, e.g., residential homes and grid operators is the Flexibility Function [14], as previously introduced in Sect. 5.2. The Flexibility Function is one of the fundamental MIMs-related features within the Smart Energy OS setup, and it represents a condensed data exchange framework which is used, for instance, to create a coherent link between the low-level physics (e.g., the thermal inertia of the buildings) and high-level electricity markets.

The Flexibility Functions are used also for sector coupling and for hybrid energy systems; an example being buildings with both district heating and heat pumps. Finally, the Flexibility Function can be used at all aggregation levels, e.g., for the appliance, the house, the district, the city, and larger regions.

Another key element of the Smart Energy OS is the data-driven digital twin or grey-box models. The grey-box models allow for real-time data from sensors and measurements to improve the forecast and control performance. Moreover, the Smart Energy OS manages to keep privacy-related information at the edge. This is possible due to the fact that the Flexibility Function contains all relevant information for instance for the balance responsible parties as well as for the distribution grid operator [26].

The Smart Energy OS concepts, and in particular the integrated standard Flexibility Function for activating flexibility at all levels and across all relevant energy vectors, imply that flexibility and interoperability can be obtained everywhere using low-cost technology. The simplicity of broadcasting price signals for activating demand-response implies that basically all appliances can contribute to unlocking the needed flexibility at the relevant spatial and temporal coordinates. At the same time, the end-user can set up local preferences in a weighted combination of a focus on costs, emissions and energy efficiency. The overall simplicity of the concepts ensures fast adaptation and stimulates an effective scale up of the use of flexibility and demand response technologies in the market [26].

In the Smart Energy OS framework, the computations are done at many levels of the system hierarchy. The Smart Energy OS for can be used to provide grid and balancing services for power systems, as illustrated in this paper. However, also for Community Energy Management Systems (CEMS), and Home Management Information Systems (HMIS) the concepts can be used to provide information about the aggregated flexibility which can be offered from a particular building, a cluster of buildings or an energy community. The concept has been demonstrated at scale in the ebalanceplus [43], Flexible Energy Denmark [44], and SmartNet projects (EU H2020) [30], to provide flexibility using a hierarchy of controllers at multiple levels.

7 Real Life Examples

7.1 Demand Side Flexibility Extraction via Market Level

Smart Energy OS setup offers a new possibility for specialized aggregators, which can take advantage of domain expertise (summer houses, wastewater treatment plants, supermarkets, etc.), and use the flexibility function for their pool of assets to buy more electricity on the high-level markets when the electricity is cheap and then use the flexibility function to find the price to broadcast to their cluster of users in order to incentivize an optimal demand-side response [26]. In the existing Scandinavian market, only the so called flexi orders exist. Flexi orders consist of an interval, an amount of energy, and a duration. For example, during the interval 8:00 to 12:00, we will buy 1 MWh of energy for 2 h (duration), and with the Smart Energy OS setup, we will purchase 1 MWh in the cheapest 2 h within the given time interval. This can be combined with regular spot market bids to obtain the final flexibility.

The Smart Energy OS setup and the use of the flexibility function are illustrated in Fig. 6. The specialized aggregator takes advantage of the Flexibility Function for buying more energy on the conventional markets when the prices are low, as well as for broadcasting the price signal to the energy flexible system. For the particular example illustrated in Fig. 7, we see the normal base load (green curve) and the spot price (grey area). The orange curve shows that the aggregator takes advantage of the flexibility and buys more energy when it is cheap and less when it is expensive. The dark-grey area in Fig. 8 shows the price signal broadcasted to the actual cluster of flexible assets. This setup, where the

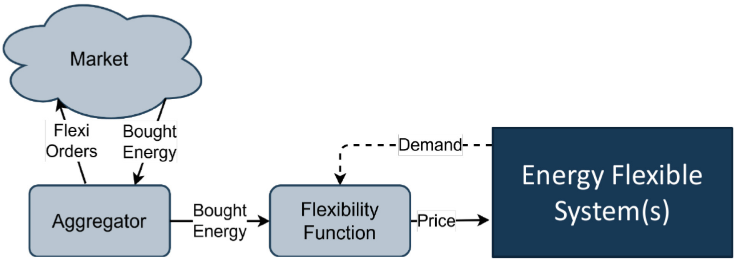


Fig. 6. The setup used by the specialized aggregator, which uses the Flexibility Function for optimal market participation

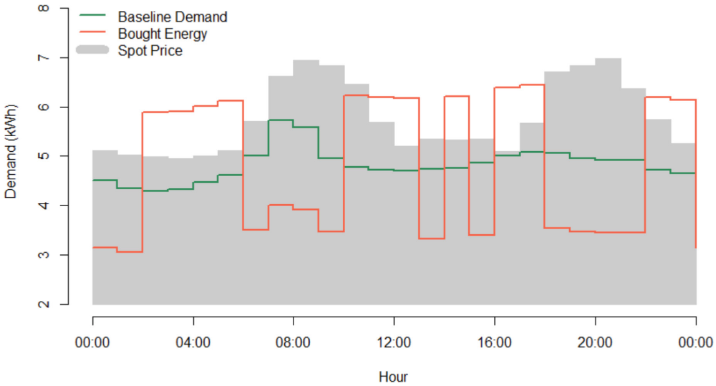


Fig. 7. Spot price, based-load and bought energy

Smart Energy OS is used by an aggregator, is for instance used to save electricity costs for the operation of water towers [18], and in [45], the concept is used for water pumping.

7.2 Demand Side Flexibility Potential of HVAC System

To demonstrate the effectiveness of connecting the high and low levels of the hierarchy in the Smart Energy OS using an identified flexibility function, we use data from a new development in Fredrikstad, Norway, as part of the syn.ikia project [46]. This development is the largest plus-energy housing project in Norway, with a strong focus on energy sharing and flexibility within the neighborhood. The HVAC system in this neighborhood, illustrated in Fig. 9(a), consists of a heat pump and a storage tank. The heat pump generates thermal energy, while the storage tank stores a significant amount of hot water for the building. Given the high flexibility potential of the HVAC system, we aim to control it using a model predictive controller [47]. The connection between the levels of hierarchy is facilitated by the identified flexibility function. This function receives informa-

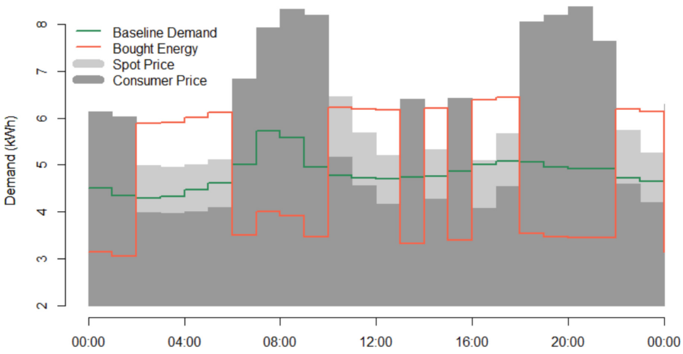
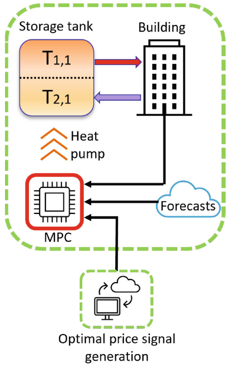
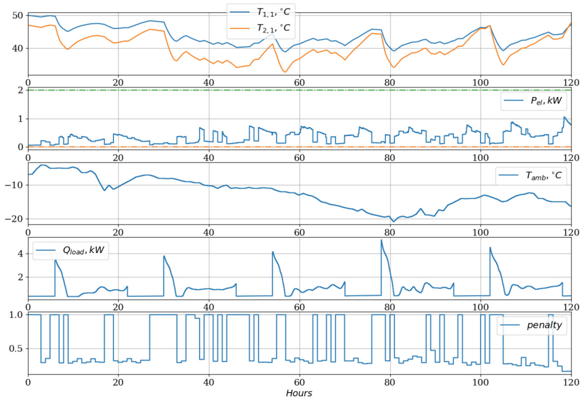


Fig. 8. The price-signal sent to the end-users for an optimal activation of the flexibility



(a)



(b)

Fig. 9. (a) Building energy management system with HVAC system control. (b) Simulation results of the MPC using optimal penalty signal.

tion about the day-ahead purchased energy from an aggregator and generates an optimal price signal as discussed in (2).

Simulation results demonstrating the efficacy of the employed controller with optimal penalty signal generation are shown in Fig. 9(b). The top panel displays the water temperature at the top and bottom of the tank, while the second panel illustrates the electricity consumption for heating the water. The third panel presents the ambient temperature, and the fourth and fifth panels show the requested load of the tank and the optimal penalty signal, respectively. The results indicate that the controller effectively shifts the demand to periods with lower penalty signals and maintains the tank temperature within specified limits. Furthermore, the optimal penalty signal ensures that the demand aligns with the purchased energy.

8 Summary

Exploiting demand-side flexibility is key to enabling the green transition to a fossil-free society, and it can reduce the need for expensive expansions of the electricity grid. Furthermore, demand-side flexibility can be used for a number of purposes (e.g., load shifting and voltage control) and in both local distribution networks and the overall power and transmission system. However, it is not straightforward to exploit demand-side flexibility at scale, and it requires a significant level of digitalization and smart controllers for automating the process.

We argue that such a highly digitalized and automated system must be *modular*, with interactions between relevant parts facilitated by MIMs. For instance, an aggregator interacts with the underlying flexible assets and trades on their behalf. We propose using Flexibility Functions as MIMs. They are data-driven models of flexible assets' energy demand over time as functions of a time-varying price signal (typically, electricity price). They enable aggregators to 1) predict the amount of flexibility they can trade on flexibility markets and 2) indirectly control the aggregated energy demand of the flexible assets. However, we also discuss important limitations of current market structures that complicate the adoption of this approach. Specifically, flexibility is traded as a *static* commodity although it is a highly *dynamic* quantity with a strong temporal coupling. For instance, if a flexible asset uses all of its flexibility in a given hour, it cannot trade flexibility in the following hour. Additionally, flexibility is considered to be a deterministic quantity, but it is often uncertain and stochastic in nature. Thus, we claim that flexibility markets should account for this temporal coupling, and we propose to use the Flexibility Function for this purpose as well.

Finally, the hierarchy of controllers (used by the flexibility aggregators and sub-aggregators) must be complemented with forecasting of energy production and demand. Furthermore, the forecasts at the different levels (e.g., at DSO and TSO levels) need to be consistent in order to ensure interoperability. We call this combined hierarchy of controllers and consistent forecasts the Smart Energy Operating System, and we argue that it is the most effective and realistic approach for achieving scalable and fair exploitation of demand-side flexibility.

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