Flexibility Offering and Rating for Multi-objective Energy Balancing

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***Abstract*—In the course of the energy transition novel solutions are needed to solve challenges that arise. Many customer owned energy resources become connected and shall contribute to the demand–supply balancing process, eventually. Small size suggest to solve related volatility issues also locally. Flexibilities of customer appliances provide the means to mitigate/manage the impact of volatile energy production close to the source. This paper presents an approach to rate appliance specific flexibility offers. Provider and user needs are addressed independently via the metrics *benefit* and *quality*. Introducing the problem and the proposed 2D-rating, we sketch exemplarily how PV and electric room heating flexibility can be predicted, offered, and used.**

***Index Terms*—Smart energy systems, demand side management, flexibility, load prediction, energy scheduling.**

I. INTRODUCTION

The path to a climate-neutral European Union by 2050 will be paved with a plethora of interrelated, heterogeneous, distributed solutions. Only a variety of approaches and systems will together enable the intended net-zero CO_2 budget, and eventually a renewable (cyclic) power system [1]. Photovoltaic electricity generation (PV), and a massive integration of private distributed energy resources (DER) in general, will play an essential part [2]. However, PV provides power only when the sun is shining. In some regions, the peak PV production around noon enforces curtailment, which is neither economic nor ecologically proper. Scaled up, more transition hindrances will appear because the energy market is not designed to handle volatile renewable energy sources (RES).

Figure 1 sketches the common energy system, where electric power conduction is shown on the bottom and electricity trading on the top. The left side covers the electricity consumers (appliances) and their users, the customers. The right side holds the appliances that convert some other form of energy into electricity, and their operators, who sell electric energy to the brokers on the energy market.

Active Customers (ACs) and Energy Communities (ECs) specified in the European *Clean Energy Package* [4]–[8] are entitled to participate in all energy markets, e.g., similar to *Aggregators* shown top left in Figure 1. Regulatory requirements shall be fulfilled likewise [6], [8]. Among peers, ACs and ECs can share RES and DER, and trade energy on a private basis. Neither ACs nor ECs are necessarily self-sufficient in their energy demand. Commonly, ACs and the members of ECs remain clients of their individual energy supplier [7, Article 4]. What they can trade, though, is excess power from private generation and the flexibility of loads they can control.

Top right, Figure 1 shows the *Balancing group*, which bills reserve energy to energy suppliers according to the deviation between energy purchased on the market and actually consumed by their customers [6, Article 6]. Physical balancing is commonly managed by the Transmission System Operator (TSO) who controls all electricity generation connected directly or indirectly to their transmission grid [7, Article 40].

Flexibility is a novel concept intended for *local balancing*, on a smaller scale and in addition to the wide area reserve market mechanisms. It addresses the end-customer and shall enable the connection of more RES and DER to the local grids managed by the distribution system operators (DSOs), who are mostly excluded from any form of energy trading by unbundling regulations.

The paper sketches a concept to offer and use end-customer flexibilities. Section II introduces a two-dimensional rating scheme for flexibility offers, followed by section III on demand and flexibility modelling. The scheduling challenge is intro-

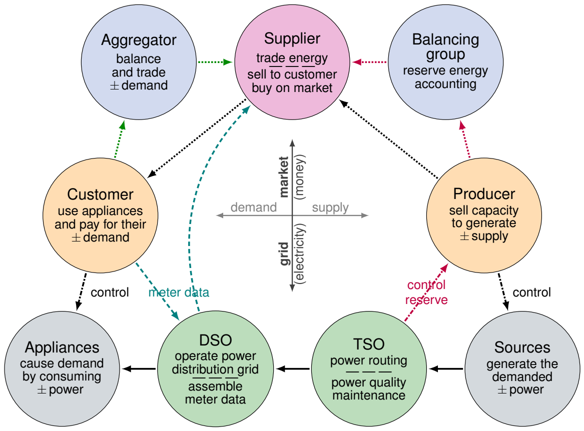

Fig. 1. Simplified model of the Energy System [3]

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duced in section IV, together with an initial heuristic to solve the multi-objective selection problem. Section V concludes the presented work and provides an outlook on next steps.

II. TWO-DIMENSIONAL FLEXIBILITY RATING

Flexibility is the native approach to address volatile RESs from a local perspective: Either clean energy production peaks become curtailed, or the demand has to be temporarily increased to effectively consume peaks. The latter is a variant of Demand Side Management (DSM), which inverts the traditional control paradigm where production follows demand. With DSM, a controllable part of the demand shall follow the current capacity to produce clean energy from renewable sources. The average power system flexibility required is for example analysed in [9].

The vital assumption is that on-request increased energy usage does not change the over-all energy demand too much, and thus, at other times consumption is accordingly reduced [10]. The latter shall occur when less renewable capacity is available, such that effectively the generation of non-renewable energy is reduced. In that respect, curtailing RES is no option. DSM works best where energy can be buffered, e.g., where an energy storage system (ESS) or well isolated heat reservoir is used. Also buildings buffer thermal energy in ceilings and walls. Electric room heating and cooling may as well be considered a controllable load, within strict limits to preserve the comfort and health of people living or working in affected areas [11]. Similarly can cooling devices like refrigerators be used to slightly shift energy demands [12].

Comfort and convenience is the first parameter to consider for flexibility rating. Customers will not easily provide a flexibility that causes them discomfort. Probably, they will not want any third party to control their appliances directly. How much discomfort is accepted will depend on the *benefits* gained in return. Still, there are flexibilities that cause nearly no discomfort, e.g., excess electricity production capacity or increased temperature in a hot water boiler.

The second parameter is the reliability of a flexibility offer. Temporary excess power from a PV system may instantly vanish if a cloud passes by. The reliability metric shall tell how likely an offered flexibility can actually be delivered when called upon. For the party that purchases flexibility, this *quality* of an offer is essential to choose what best fits their demand.

In general, these two metrics cannot be easily combined into a scalar rating factor without loss of essential information. The best offer depends on the problem to solve. To enable multi-objective selection we propose the two-dimensional rating shown in Figure 2. Five levels per dimension seem appropriate, still could be reduced to three $[-|\bigcirc|+]$. Offers in the lower left (gray) area can be neglected as these please neither the provider nor the purchaser. Flexibility with assured availability (top bar) are the only offers applicable for safety related measures. Whereas bargaining reliability versus cost is probably the selection approach for the remaining offers and reasons to utilise flexibility.

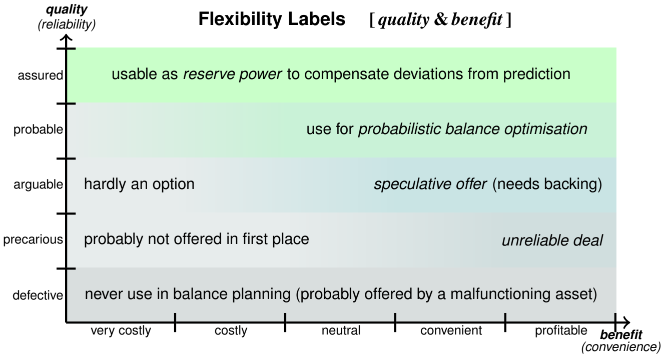

Fig. 2. Labeling flexibility offers with expected cost and reliability

III. FLEXIBILITY MODELLING

To offer flexibility it is necessary to know what is available. Offers need to be made ahead of time based on prediction. Flexibility from curtailing RES is upper bounded by the electricity that would be delivered with no curtailment. Similarly, load can be increased only if an appliance is not already drawing maximum power. Flexibility of an ESS is bound by the peak (dis-)charging current and the state of charge. Likewise, current and future states of controllable appliances need to be known and predicted to assess the flexibility that may be offered.

To grasp the complexity, have a look at the load and production distribution of the modelled end-customer sketched in Figure 3. The modelled household has a 12 kWp PV system,

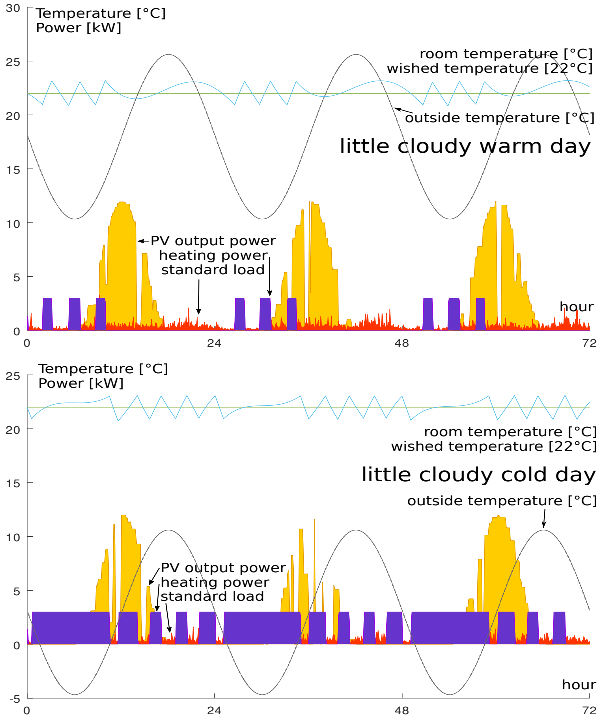

Fig. 3. Load and temperature development across three subsequent little cloudy days in a warm and a cold environment

3 kW electric heating, and heat loss of approximately 0.1 °C per hour and ΔT (temperature difference between interior and outside). The daily temperature cycle is $\sim$15 °C and simplified to a sinusoid. More accurate thermal modelling of rooms and buildings is possible [13], but not necessary for basic considerations. The room temperature fluctuates due to the heating control hysteresis. To maintain the intended temperature of 22 °C, the heating system is activated when the room temperature drops below 21 °C, and deactivated when 23 °C are reached. This causes the typical on-off cycles of heating systems, as for example shown in [14].

If DSM usage of the heating system is restricted to (de-)activation within the control hysteresis only, the effect on comfort is marginal. In this case, DSM triggers earlier (de-)activation, achievable only when the heating system is not permanently on or off. A heating system is consequently a temporal DSM asset, availability depends indirectly on the outside temperature. For a short period it could be used also during on or off periods, although only once, and only if the temperature is currently below or above the intended temperature, respectively.

The traces also show potential electricity production offered by the modelled PV system (approximated by a sine-square curve). The model is yet not considering seasonal irradiation difference and assumes a sunny day with sporadic clouds passing by (*little cloudy*). We note that the majority of the heating intervals occurs at times when no direct power from PV is available. The standard load of households is here assumed less technically controllable because many of the significant household demands are triggered by people. Stochastic modelling can add these loads to complete the picture [15].

Regarding the flexibility rating factors, we notice that cutting back the PV inverter output is always possible, either by control or caused by a passing cloud, having the same effect. If the current inverter output is known, the possible instant cut-back can be assured. Vice versa can an increase never be assured. For the heating system we need to know the current on-off cycle times, the current system state, and the momentary room temperature, to tell which flexibility can be reliably offered in the near future. Depending on the system state (on/off) either a load decrease or an increase is possible, never can both be offered at the same time.

Flexibility offers that reach beyond the current operation cycle of an electric appliance shall be considered probabilistic offers because their availability cannot be assured in general. Averaging over thirty of the days sketched in Figure 3, we get the predicted flexibilities shown in Figure 4. The on-off heating phases and the ditches in PV production due to passing clouds differ day-to-day. Still, at some times there is flexibility predicted due to the similarity of the modelled days. Whether such a predicted flexibility can be executed is not assured. The associated reliability, shown close to the baseline, indicates the probability of availability.

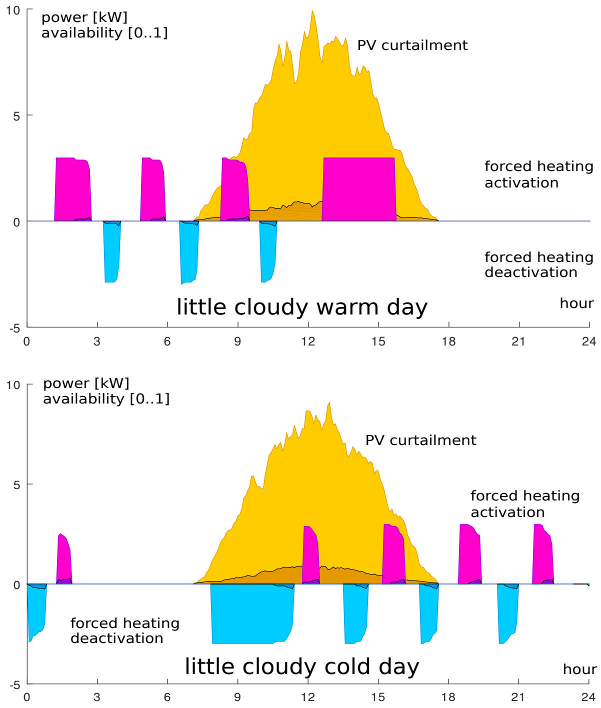

Fig. 4. Predicted flexibilities of controlable loads (room heating, PV inverter) calculated from averaging thirty simulated days with identical characteristics.

IV. SCHEDULING APPROACH

Scheduling is the art to optimise the arrangement of events in time. Comparable problems are the knapsack and the travelling salesman problems, which are known to be NP-hard, i.e., not in general solvable in polynomial time [16]. However, the hard problem is finding the actually optimal solution and not achieving some fitting solution. Where parameters are not perfectly known, the aim shall be a viable heuristic, i.e., a solution finding approach that yields sufficiently good solutions with least necessary effort.

For flexibility scheduling, the objective is to most reliably mitigate any apparent power balance issues by utilising a set and sequence of offered flexibilities. We need to handle not only the two rating parameters, *benefit* (convenience) and *quality* (reliability), but also the combination and sequencing of flexibilities over time. This yields a multi-dimensional problem space. In addition, dynamic dependencies shall be considered because using a flexibility alters what is available afterwards.

In a first approach, we schedule one flexibility after the other. This fits very well into an event-based simulation, but is a responsive, not a predictive control approach. Still, it is the fall-back operation required in case predictions fail to meet reality sufficiently well to safely operate the system. How to aggregate and select flexibilities with respect to their origin is outlined in [17]. In the ongoing study, we intend to extend this to also consider well balanced mixtures of flexibilities and less transparent offers.

An underlying assumption is that in some near future every customer first balances the own energy demand and thereby already shifts loads to better use own resources. These shifts are not a necessity; not performing them can be offered as flexibility. Other flexibilities, for example discharging the battery of an electric vehicle into the grid, will not be for free.

An energy community controller, as for example sketched in Figure 5, or some public flexibility market, basically another intra-day trading platform, will rarely know the physical source of a flexibility offer. It will receive and deal with *amounts* and associated *quality* and *benefit* metrics only.

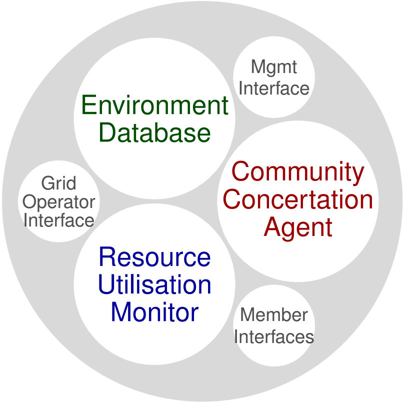

Fig. 5. Community Energy Management System modules and interfaces [18]

The multi-objective flexibility concertation aim is to *find the least costly, most reliable combination of flexibility offers*. That can be approximated using the heuristic

$$\min \sum_{i \,\in\, \Delta^{\text{called}}} \frac{\text{cost}(\delta_i) + \text{const}}{\text{reliability}(\delta_i)} \tag{1}$$

where δ_i are the selected flexibility offers *called* to be executed, and Δ^{called} is the set of all foreseen δ_i. The *const* shall cover possibly negative costs, i.e., $\mathit{const} \geq \max\left[-\mathit{cost}(\delta_i)\right]$, to prevent incorrect and non-converging optimisation. Chosen larger it reduces the number of δ_i called, accepting higher cost.

This objective function needs to be solved in compliance with a number of side constraints that specify operational requirements. For example, an offered flexibility δ_i must not be exceeded or inverted to negative numbers. Some offers may be binary, i.e., can be used either in full or not at all, and continuity/adjacency constraints can integrate grid topology related requirements.

V. CONCLUSIONS AND OUTLOOK

This paper proposes to rate flexibilities such that these can be used for local electric power balancing, utilising end-customer equipment as good as possible, which is applicable in parallel, additionally, and independently of the established reserve energy markets and mechanisms. Preliminary simulation showed potential power flexibility prediction. Future work will investigate practicable multi-objective scheduling strategies.

An additional aspect identified is that the largest electricity consumers (heating, cooling, hot water) and the production of renewable energy, all depend more or less on the weather. Reliable weather forecasts are thus critical for flexibility prediction. Therefore, it will be necessary to back predictive flexibility scheduling up with a robust fall-back mechanism that assures grid safety and reliable power supply even if predictive control is misled by incorrect forecasts.

DISCLAIMER

The content and views expressed in this material are those of the authors and do not necessarily reflect views or opinion of the transnational joint programming platform (JPP) ERA-Net SES or the funding bodies. Any reference given does not necessarily imply endorsement by ERA-Net SES, FFG, or KLIEN.

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