# Control Structures for Smart Grid Balancing

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*Abstract*—This work addresses the problem of maintaining the balance between consumption and production in the electricity grid when volatile resources, such as wind and sun, account for a large percentage of the power generation. We present control structures for Smart Grid balancing services on three different levels: portfolio, larger scale individual power units, and aggregations of small power units. Our focus is on illustrating the connection between coordination and control algorithms.

*Index Terms*—Smart Grids, Energy management, Optimal scheduling, Distributed control

## I. INTRODUCTION

During recent years, there has been a growing desire to increase the amount of renewable energy from wind and sun in the overall electricity generation. This presents the issue of how to maintain the balance between consumption and production when a large part of the electricity generation comes from resources with partially uncontrollable characteristics. An important concept that comes into play is that of demand management, namely using existing flexibilities to shift consumption from times when renewable resources are scarce, to periods when resources are ample [1], [2].

A portfolio containing both traditional power plants and controllable consumers is considered and the balancing problem is addressed at the different levels. We first consider the high-level task of scheduling and coordinating production and consumption as an off-line planning process. Consumers are actively included in this planning, only if they present some level of flexibility, in the sense that some temporal shifts of the power consumption incur no relevant drawbacks compared to normal operation. We then look into the real-time operation and control for following the power references from the planning process.

The units of the portfolio can be individual entities, for instance large producers as power plants, as well as large and medium scale consumers. In particular, commercial refrigeration systems (e.g. supermarkets, cold storages) have been shown to have a high potential for demand response implementations [3]. For these, there exists two separate demand response schemes: optimization of the cost of operation or direct management of the power consumption for balancing services [4]. In this work we combine the two schemes and perform demand management for commercial refrigeration systems such that objectives of both refrigeration system and higher level service provider are accommodated.

A portfolio unit may also refer to an aggregation of smaller individual units, such as wind turbines collected in a farm, or a number of aggregated small scale consumers that can collectively be considered as a single medium scale consumer. In particular, we focus here on the power flexibility of residential thermostatic loads. These have a good potential for automatic demand response and viable control strategies have received increased scientific interest. For example, collective thermostat set-point manipulation was proposed by [5], while [6] analyzed the effectiveness of two types of control with preplanned activation windows. In this work, we use a collective on-off manipulation with randomization as proposed in [7] and [8].

The hierarchical layers of the balancing are illustrated in Fig. 1, showing the separation between off-line planning and real-time operation. In the planning process the portfolio owner (PO) schedules the power consumption and/or production of the units as an iterative process, according to the external balance objective and the local optimization model of each unit. The local optimization encompasses specific operational costs and constraints of each unit. At the end of the planning process, each unit has acquired a power schedule in form of a reference to be tracked during real-time operation.
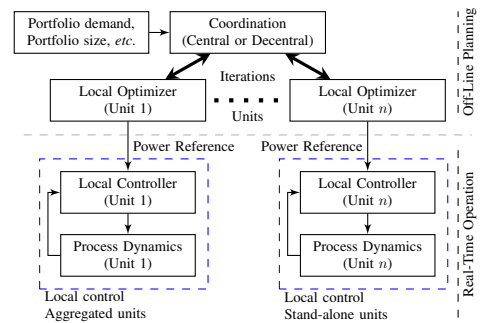


Fig. 1. Hierachical illustration of the off-line planning and coordination of portfolio units, and real-time operation of each unit governed by local controllers.

The coordination mechanism and planning process of the portfolio are presented in Section II. Section III presents the control structure for a supermarket refrigeration system considered as an individual unit in the portfolio. Section IV presents the control structure for a portfolio unit that is an aggregation of residential refrigerators devices with small individual consumption. Numerical experiments are presented in Section V and Section VI provides closing remarks.

## II. DECENTRALIZED POWER PORTFOLIO PLANNING

We consider a participant in the energy market, who manages a portfolio composed of different units, as outlined in Fig. 2(Left). Specifically, the portfolio includes consumption units with flexible consumption. We assume that the PO has

committed to an overall power schedule, so that the portfolio must be operated to comply with this schedule. Since the portfolio contains both production and consumption units, the total output of the portfolio can be managed by adjusting either the production or the flexible consumption. Operating the portfolio entails that the PO must create individual power schedules for each unit in the portfolio. This should be done in an economical way, meaning that the PO must minimize operating costs, while obeying operational constraints of each unit.
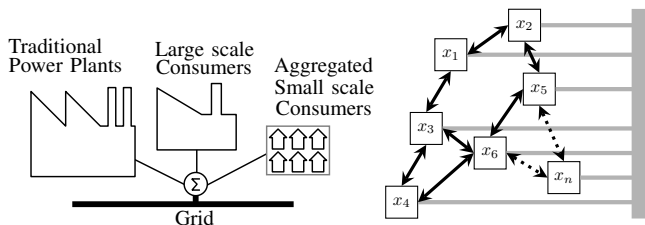


Fig. 2. **Left:** The portfolio consisting of both traditional power plants, large scale consumers and aggregated small scale consumers. **Right:** Graph structure of the portfolio, where units should only communicate with a few neighboring units.

The units in the portfolio are distributed across geographical areas. Further, the number of units in the portfolio, when including a large number of controllable consumers, can make the portfolio very large. Consequently, both collecting and distributing data across the portfolio, as well as optimizing individual power schedules in a centralized manner, may become cumbersome. Therefore, we propose to solve the problem in a distributed fashion as illustrated in Fig. 2(Right). In the figure, each box illustrates a unit of the portfolio that operates independently, the black arrows indicate communication paths used to coordinate units, and the gray lines indicate the power grid. All units are connected to the power grid, but each unit is only allowed to communicate with a few neighboring ones. The following outlines how satisfactory operation of the collected portfolio may be maintained, even when enforcing such distributed computation and communication structure.

### A. Technical approach

Let $\mathcal{T} = \{1, \ldots, N\}$ denote the discrete time-frame for which the portfolio balancing is conducted. Let the portfolio consist of $n$ units, and let each portfolio unit $i \in \mathcal{S} = \{1, \ldots, n\}$ be characterized by a strictly convex cost function $f_i : \mathbf{R}^N \to \mathbf{R}$, and convex local constraints, denoted $\mathcal{P}_i$. Letting $c \in \mathbf{R}^N$ denote the energy schedule to be honored by the PO, the overall optimization problem is formulated as

$$
\begin{aligned}
\underset{p_i, \ i \in \mathcal{S}}{\text{minimize}} \quad & \sum_{i \in \mathcal{S}} f_i(p_i) \\
\text{subject to} \quad & p_i \in \mathcal{P}_i \\
& \sum_{i \in \mathcal{S}} p_i = c,
\end{aligned} \tag{1}
$$

where $p_i \in \mathbf{R}^N, i \in \mathcal{S}$ is the power consumed (or produced) by each portfolio unit. Problem (1) is convex and may be readily solved in a centralized fashion. However, as mentioned, we desire to derive a decentralized approach, that does not rely on centralized computations. A method that has proved viable in several contexts ([9], [10]) and can also be shown to work in this case, is the method of dual decomposition, following the approach:

1) Initialize: $k = 0, \nu^{(1)} \in \mathbf{R}^N, \epsilon > 0, \{\alpha^{(j)}\}, j \in \mathbf{N}$
2) Let $k = k + 1$, and $p_i^{\star(k)} = \underset{p_i \in \mathcal{P}_i}{\arg\inf}(f_i(p_i) + p_i^T \nu^{(k)})$
3) $g^{(k)} = \sum_{i \in \mathcal{S}} p_i^{\star(k)} - c$
4) $\nu^{(k+1)} = \nu^{(k)} + \alpha^{(k)} g^{(k)}$
5) If $\|g^{(k)}\| \geq \epsilon$, repeat from item 2

Above, $k$ is an iteration index and $\nu^{(k)}$ are Lagrange multipliers for the power accumulation constraint. These multipliers are updated at each iteration. Dual decomposition separates the main problem (1) into smaller subproblems that can be solved locally by each unit (Step 2 above), and utilizes that $g^{(k)}$ can be shown to be a gradient to the dual of Problem (1). Thus for suitable choices of $\alpha^{(k)}$, the iterative method converges. The drawback is however that the implementation of this strategy requires a central unit to collect $p_i^{\star(k)}, \forall i$, and calculate as well as distribute $\nu^{(k+1)}$ for the following iteration. The work by [11] showed how this can be avoided by the reformulation

$$
\overline{p}^{(k)} = \frac{1}{n} \sum_{i \in \mathcal{S}} p_i^{\star(k)}, \quad g^{(k)} = n\overline{p}^{(k)} - c.
$$

By employing the graph structure of the portfolio outlined in Fig. 2(Right), the average vector $\overline{p}^{(k)}$ can be computed locally by each unit, through data-exchange only with neighboring units in the graph [12]. This allows a local update of the Lagrange multipliers. Employing averaging eliminates the need for a central unit for gathering/scattering data. Inaccuracies in the local calculation of $\overline{p}^{(k)}$ for each node, entail that this approach does not converge to the global optimum. However, it was shown by [11] that these inaccuracies can be made arbitrarily small, and convergence can therefore be guaranteed to a point arbitrarily close to the global optimum.

The algorithm supplied above comprises the top-level off-line coordination algorithm, rendering run-time power references for the portfolio units. The following sections describe how portfolio units can participate in the coordination process, as well as track the resulting references in real-time. As mentioned, we focus on consumption for thermal processes, in the two cases of large scale consumers and aggregated small scale consumers.

### III. COORDINATION OF LARGE SCALE CONSUMERS

A typical supermarket refrigeration system (SRS) is composed of several compressors placed in one or two racks (for instance in a booster configuration), several display cases, and freezer rooms. The main power consuming components of the system are the compressors. Supermarket refrigeration systems have significant potential for thermal energy storage, which is not currently used for grid balancing. In this part of the work, we focus on how to manage the operation of a supermarket in a power flexible manner and have it connected as a node to the power portfolio of Section II. For this purpose we first derive and validate a dynamical model of the SRS, which is also capable of predicting the power consumption of the system. Secondly, we formulate the minimization of the SRS operating cost, as a strictly convex optimization problem, for participating in the top-level coordination. Finally, a supervisory controller is needed to regulate the power consumption to the assigned reference, during real-time operation.

The SRS is already equipped with various controllers distributed across the installation. These have the primary purposes of maintaining the food temperatures within safety regulations, and nominal operating conditions for the refrigeration equipment. The control approach for power flexibility is to keep the standard local controllers, and design a supervisory control, responsible for providing required set-points, as shown in Fig. 3.
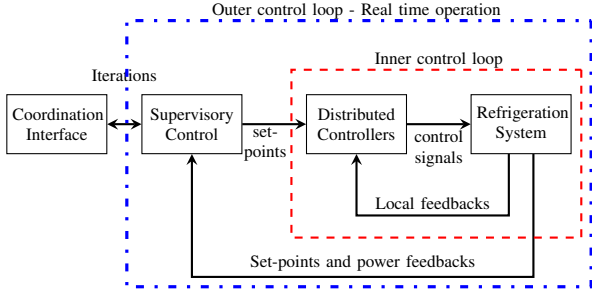


Fig. 3. Supermarket control system structure [13], along with interface to high-level coordination.

### A. Dynamic Model

A modular, nonlinear, continuous time model, suitable for supervisory control design in the smart grid, is developed by [14]. The modeling is based on a first principle approach, where the complete system is separated into modules, each addressed and validated separately. This modularity leaves open the possibility of modeling various configurations for different supermarkets. Each module, as well as the overall integrated system, is validated against measured data, collected from a supermarket in Denmark. For an elaboration on the modeling and validation, the reader is referred to [14].

### B. Cost Optimization

The objective of the local optimization problem the SRS is to keep operation close to ideal conditions. To elaborate on this, we let $p(t), \eta(t) \in \mathbf{R}$ denote the total power consumption and common coefficient of performance (COP) of the compressors, and let

$$u(t) = (u_1(t), \cdots, u_m(t)) \in \mathbf{R}^m, \quad t \in \mathcal{T}$$

denote the cooling capacity applied by each of $m$ cooling units. The coherence between the electrical power consumption and cooling capacity is

$$p(t) = \sum_{i=1}^{m} u_i(t)/\eta(t), \quad \forall t \in \mathcal{T}, \qquad (2)$$

and we let $p = (p(1), \dots, p(N)) \in \mathbf{R}^N$. In general, both $u(t)$ and $\eta(t)$ are nonlinear functions of other manipulated variables of the refrigeration system. However, [15] and [16] explain how $u(t)$ can be dealt with as a fictitious manipulated variable, and further how $\eta(t)$ can be obtained by a linear estimation process. It is further possible to set-up a linear dynamical model that uses $u(t)$ as input and acts as a high-level approximation of the supermarket operating conditions:

$$x(t+1) = Ax(t) + Bu(t) + B_\mathrm{d}d(t),$$

where $d(t)$ encapsulates disturbances, *e.g.*, building indoor thermal conditions. The state vector $x(t)$ contains food and air temperatures for the display cases in the SRS. The details of the model are elaborated in [15].

We denote by $\bar{x}(t)$ the desired operating conditions as set-point values for the states. Given estimates of the model parameters for all $t \in \mathcal{T}$, an optimization problem that gives the power consumption reference for the SRS is expressed as

$$
\begin{aligned}
\underset{u,p}{\text{minimize}} \quad & \sum_{t \in \mathcal{T}} ||x(t) - \bar{x}(t)||^2 + \nu^T p \\
\text{subject to} \quad & x(t+1) = Ax(t) + Bu(t) + B_\mathrm{d}d(t) \\
& x_{\min} \le x(t) \le x_{\max} \\
& 0 \le u(t) \le u_{\max} \\
& \Delta u_{\min} \le u(t) - u(t-1) \le \Delta u_{\max} \\
& t \in \mathcal{T},
\end{aligned}
\qquad (3)
$$

where the connection between $p$ and $u$ is still governed by (2).

Above $x_{\min}, x_{\max}, u_{\max}$ denote upper and lower bounds on states and actuators. Similarly, $\Delta u_{\min}$ and $\Delta u_{\max}$ denote upper and lower bounds on the rate of change of cooling capacity $u(t)$ between time-steps. This is both to avoid large oscillations in the cold storage temperatures, and further to produce smoother power consumption trajectories that are more appropriate to track during real-time operation. The final term $\nu^T p$ in the cost, is on account of the high-level coordination of Section II.

Problem (3) corresponds to a single subproblem in the overall balancing described by (1). Let $\mathcal{S}_{\mathrm{srs}} \subset \mathcal{S}$ denote the part of the portfolio consisting of SRS's. Then given the correspondence between cooling capacity and power in (2), the subproblem (3) defines $f_i$ and $\mathcal{P}_i$ for all $i \in \mathcal{S}_{\mathrm{srs}}$.

### C. Power management

The SRS optimization described in (3) is the local optimizer that coordinates the SRS to the rest of the portfolio as illustrated in Fig. 1. After convergence of the coordination, the SRS should follow the power consumption profile agreed with the higher level service provider. For this, a model predictive control (MPC) scheme with a 5 minute sampling time is considered. A sampling time larger than four minutes ensures that the mass flow dynamics inside the evaporators are in steady state, and their dynamics may thus be neglected. Further, assuming constant pressure set-points for the suction manifold gives a linearized relation between the cooling capacity and the opening degree of expansion valves (as manipulated variables). The details of the controller are elaborated in [14].

## IV. COORDINATION OF SMALL SCALE CONSUMERS

Residential power consumption is currently inflexible in practice, as it is not directly affected by prices from the energy markets and is not controlled by other mechanisms except complete load shedding in exceptional cases. However, as for SRS's, there exists an obvious potential for flexibility. We focus here on thermostatic appliances, in particular cooling devices such as residential refrigerators and freezers. These can be regarded as many small and leaky thermal energy storages each consuming power in an on/off pattern determined by the thermostat control.

We consider an aggregator that is responsible for the power consumption of a large population of such thermostatically

controlled appliances. The objective is to include the aggregator as a single flexible consumption node in the power portfolio presented in Section II.

### A. Dynamic model

Let $\mathcal{F}$ denote the set of all refrigerators in the population, with cardinality $|\mathcal{F}| = F$. Also, let $p_i(t)$ denote the power consumption for $\mathbf{F}_i \in \mathcal{F}, i \in \{1, \ldots, F\}$, and let

$$p(t) = \sum_{\mathbf{F}_i \in \mathcal{F}} p_i(t)$$

denote the total population consumption for $t \in \mathcal{T}$. Strictly speaking, $p(t)$ is a quantized variable, however, under the assumption of large population size $F$, we will take $p(t)$ to be continuous. Each unit $\mathbf{F}_i \in \mathcal{F}$ is modeled with first-order dynamics and equipped with a local logical controller $\mathbf{K}_i$ that has the main function of a thermostat. In addition, the logical controller can switch the on/off state of the refrigerator as a response to a broadcast signal from the aggregator, see also Section IV-C, but only if doing so does not contravene with the safety of the local operation.

For the purpose of off-line planning, we will model the aggregated population as a single, leaking energy storage. Let $E(t)$ denote the virtual stored energy,

$$E(t + 1) = aE(t) + T_s p(t),$$

where $a \in (0, 1)$ is a leakage parameter. We define the flexibility of the population as an interval of virtual energy levels, $E_{\min} \leq E(t) \leq E_{\max}$. A reference $p(t)$ is defined to be valid as long as, starting from an initial $E_0$, it maintains the virtual energy level within this interval. A valid reference may be successfully tracked by the power management structure of the population.

Numerical simulations show that, while simple, this model and the associated constraints provide an efficient way of characterizing the power consumption flexibility of the refrigerator population under our chosen flexibility control. The parameters of the leaky storage model ($a$, $E_{\min}$, $E_{\max}$, $E_0$) have to be estimated using Monte Carlo simulations of the thermostat load population under step power references.

### B. Cost optimization

As previously, let $p = (p(1), \ldots, p(N)) \in \mathbf{R}^N$. Further, let $p_{\text{bas}} \in \mathbf{R}^N$ denote the preferred baseline of the aggregated consumption for the population of refrigerators across the horizon $\mathcal{T}$. Given the modeling described above, the flexibility of the consumers can be managed through the local optimization

$$\begin{aligned}
\underset{p}{\text{minimize}} \quad & \|p - p_{\text{bas}}\|^2 + \nu^T p \\
\text{subject to} \quad & E(t+1) = aE(t) + T_s p(t) \\
& E_{\min} \leq E(t) \leq E_{\max} \\
& 0 \leq p(t) \leq p_{\max},
\end{aligned} \tag{4}$$

where $p_{\max}$ is the hard upper limit for the population consumption. The last term $\nu^T p$ is the coordination contribution from the top-level coordination algorithm. Similarly to the previous case of the SRS, problem (4) makes up the local optimization for one of the portfolio units in the main problem (1).

### C. Power management

The overall approach for enabling the power flexibility of the refrigerator population consists of a two-level control structure; a supervisor and the local controllers $\mathbf{K}_i$, see Fig. 4. The supervisory controller measures the total power output $p(t)$ of the population, predicts the consumption one step-ahead in time and compares the prediction with the predetermined reference trajectory. The differences are balanced out by broadcasting an $\epsilon$-signal to refrigerator population. The $\epsilon$-signal influences the on/off switching of the local controllers $\mathbf{K}_i$ and represents a randomized dispatch strategy. Details are included in [7], and we note that technique is similar to that proposed in [8].
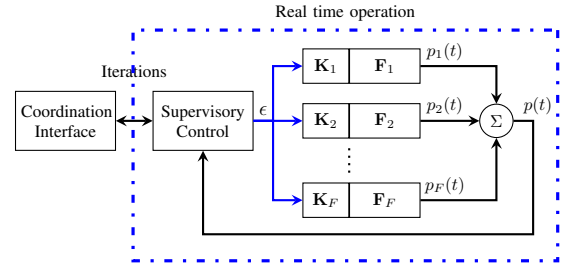


Fig. 4. Overview of the control approach, along with interface to the high-level coordination.

## V. NUMERICAL EXPERIMENTS

The following presents a combined numerical experiment illustrating the different hierarchical levels of the balancing strategy outlined in the previous sections:

A. top level portfolio balancing and coordination
B. reference tracking by large scale and aggregated small scale consumers

### A. Portfolio balancing

We consider a small portfolio consisting of a supermarket, an aggregated population of 1000 household refrigerators, and a power plant. The coordination and local optimization from the supermarket and refrigerator population, are performed as described in the previous sections. The power plant is modeled similar to the work of [17], as a third order system $G_{\text{pp}}(s) = 1/(s\tau_{\text{pp}}+1)^3$, describing the closed loop transfer function from power reference to actual power production. The power plant is subject a maximum capacity constraint of 20 kW, as well as a ramping constraints on the input, *i.e.*, the power reference. The power plant optimization attempts to minimize a quadratic fuel cost pertaining to the power production.

The time horizon of the example spans 24 hours, with a 5 minute sample time. The power schedule $c(t)$ that the PO has to comply with, is shown in Fig. 5(Top) along with the accumulation of the portfolio references obtained from the distributed coordination process described in Section II. It can be seen that the committed PO schedule is closely followed by the coordination.

For comparison, Fig. 6 shows the schedule in the case when the power plant is acting alone without contributions from the flexible demand units. In particular, due to the capacity constraint, the power plant alone cannot meet the schedule.
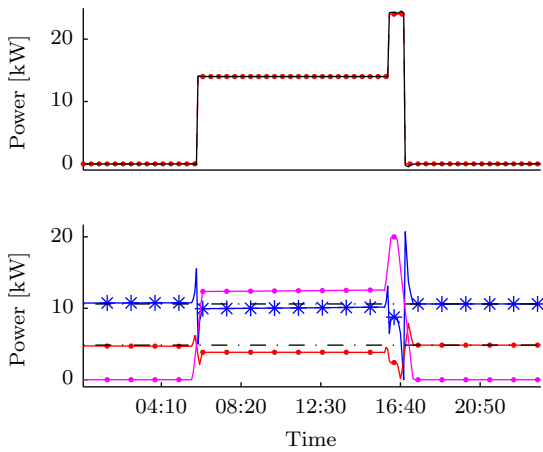
Fig. 5. **Top:** The power demand (solid, black) and the accumulated portfolio references (dotted, red), after coordination. **Bottom:** The coordinated references for the power plant (dotted, magenta), the population (asterisk, blue), and SRS (circles, red), as well as baseline consumptions (dashed, black).
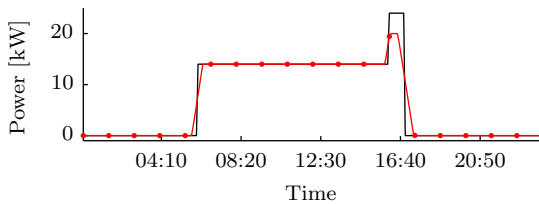


Fig. 6. The demand (solid, black), and the best obtainable demand tracking from the power plant alone (circles, red).

### B. Reference tracking

The power references to be tracked in real time by the supermarket and the refrigeration population respectively, can be seen in Fig. 5(Bottom). Following the MPC scheme outlined previously for the SRS, results in the reference tracking presented in Fig. 7(Top). Similarly, by the aggregated controller outlined in Section IV, the demand tracking of the refrigerator population is presented in Fig. 7(Bottom).
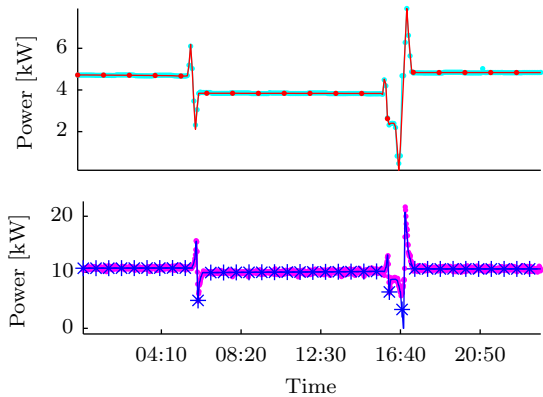


Fig. 7. **Top:** The coordinated reference (circled, red), and the runtime power consumption (dotted, cyan), of the SRS. **Bottom:** The coordinated reference (asterisk, blue), and the runtime power consumption (dotted, magenta), of the consumer population.

Both the SRS and refrigerator population controller manage to track their respective references closely, with only minor deviations. Overall, the tracking results indicate that the balance

obtained by the off-line coordination illustrated in Fig. 5 will be closely maintained during real-time execution as well.

## VI. CONCLUSION

This work has addressed the task of maintaining the balance between consumption and production in the electrical grid. We have considered this issue on different hierarchical levels, encompassing both distributed off-line coordination, as well as the real-time execution and reference tracking. Our work has focused on controllable consumption, and we have shown how a balanced grid can be maintained by consumption control, both for large scale consumers, as well as aggregations of a population of small scale consumers. Our numerical example has illustrated how controllable consumption can assist and improve the grid balancing, compared to the case where exclusively traditional power plants maintains balance.

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