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A cooperative distributed protocol for coordinated energy management in prosumer communities

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Abstract The power system is experiencing a rapid introduction of uncontrollable renewable power sources, and an increase ability to store power, sense usage patterns, and control consumption. While standard demand management methods such as price-based demand response can be characterized as a "demand management from the supply-side", we propose a coordinated energy management of prosumers communities that can be characterized as a "demand management from the demand-side". In this a approach, prosumers (producers and consumpers) coordinate their power consumption and generation, balancing their power usage, and reducing cost without sacrificing quality of life. In the present article we provide the main concepts of coordinated energy management and illustrate its benefits by comparing it to price-based demand response for the case of day-ahead appliance scheduling. The proposed approach is a compelling solution for enhancing the power system, implementing a prosumer society, and enabling the further introduction of renewables.

Key words Coordinated energy management, cooperative distributed protocol, prosumer community, smart community, demand-side management, demand response.

1. Introduction

The traditional power system is basically a uni-directional, centralized system, where only the generation is controlled and the demand is not controlled. This system assumes that a large demand is aggregated, so that consumption peaks are smoothen, making the generation control easier, increasing system stability.

During the last 30 years, information and communication technologies have been introduced in the power grid, namely in the generation, transmission and distribution systems, seeking to improve reliability and reduce the need to operate and build peaking generation. The use of information and communication technologies in the power grid is commonly known as the smartgrid.

The introduction of smartgrid technologies in developing countries has been used to manage the increasing generation capacity and to improve system stability. However, in developed countries the priority is no longer to increase generation capacity, but *i*) to better manage their energy consumption, mainly due environmental concerns and demographics changes (e.g. decrease in population size), *ii*) and to change and diversify the generation mix to reduce costs and to increase energy security. As a consequence, many countries have started to suppress redundant energy usage (e.g. through the introduction of power efficient appliances), and to reduce high consumption peaks (e.g. by modifying the consumption timing). Examples of this are the so-called demand respond programs and the introduction of energy management systems at homes, offices and factories.

In recent years, due to the decrease in cost of renewables (such as PV and wind) and batteries, and due to government policies encouraging the implementation of renewables (such as the feed-in tariff scheme), consumers have started to install their own local generation and energy storage systems. This has reduced the dependency on traditional power sources, but it is requiring to re-think the power system, because the generation is no longer centralized and now the demand can be controlled.

To address these issues, each end-user should be considered as potential prosumer, i.e. as a consumer and a producer of energy, and therefore energy management systems for a society of prosumers are needed. From the social point of view, the introduction of such a system implies that a new market should emerge, where the end-users will be able to *i*) buy and sell power energy and capacity, and *ii*) decide which energy they are willing to buy (based e.g. on energy origin and type). To implement such prosumer community, new methods and technologies are required.

The current article presents the main concepts for the implementation of the energy management system for a prosumer community. More specifically, we propose a *cooperative distributed protocol for the coordinated energy management of prosumer communities*. This work is part of larger endeavor [1], where 3 additional components for demand management are also being developed: *i*) a smart-tap network [2], *ii*) an energy on demand protocol [3] [4], and *iii*) a power flow coloring protocol.

The structure of this paper is as follows, we first describe existing energy management paradigms, followed by the here proposed one (Section 2.). We continue by presenting the proposed coordinated energy management and comparing it against price-based demand response (Section 3.). Afterwards we present illustrative results in a simulated scenario (Section 4.). We then discuss issues related to required technological developments (network, sensor and control technologies), and societal issues (e.g user's quality of life and energy market) required for the acceptance of proposed approach (Section 5.), to finally conclude (Section 6.).

2. Energy management paradigms

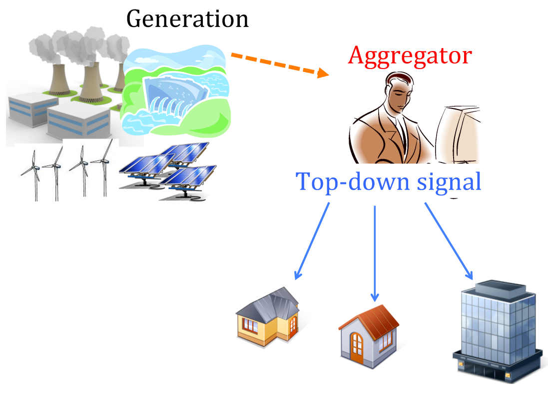
2.1 Supply management paradigm

Traditionally, the power system is designed based on three main assumptions: *i*) the generation is controllable, *ii*) the demand is uncontrollable (but it can be forecast), and *iii*) the generated power is distributed from a central location to the consumers. Taking these into account, there are four mechanisms that any standard power system uses to maintain stability and reduce total economic cost: *i*) unit commitment, *ii*) economic dispatch, *iii*) frequency restoration mechanism, and *iv*) contingency reserves.

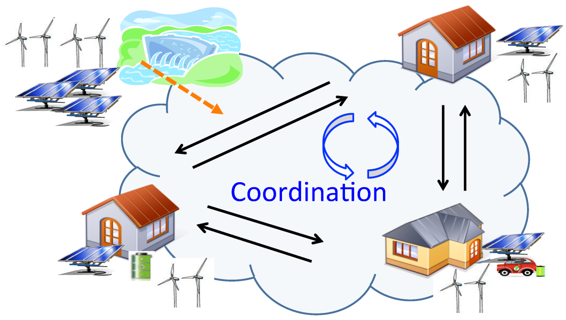
Unit-commitment and *dispatch* are used for scheduling generation and for online control of generation, respectively, and they are managed by an independent system operator (ISO) seeking to reduce total economic cost. *Frequency restoration* is required due to the difference between nominal demand and scheduled generation, while *contingency reserves* are required to respond when large loss of power supply occurs.

2.2 Demand management paradigms

In the supply management paradigm, the demand is completely uncontrolled, and therefore high consumption peaks may occur. These peaks of high demand require having expensive operational reserve just to supply enough power during those high peaks. Being able to manage the demand can reduce peaks of very high demand, reducing costs due to high peak generation. Similarly, being able to manage the demand could allow adjusting consumption pattern to closely match, e.g., fluctuating uncontrollable renewable generation.



(a) Demand response



(b) Prosumer community coordination

Figure 1 Demand management paradigms. Top: example of *demand management from the supply-side* (a.k.a. "demand response"). Bottom: example of *demand management from the demand-side* (implementing a "prosumer community coordination").

Demand management from the supply-side

The common approach to manage the demand can be characterized as *demand management from the supply-side*, with methods in this category usually known as Demand Response (DR) or Demand-Side Management [5] [6]. In the following we will use the term "Demand Response (DR)" only to refer to methods that implement a *demand management from the supply-side*.

In DR, a third party "aggregator" or "operator" serves as an intermediary between the generation and the loads, with this aggregator negotiating curtailment bids with the ISO (or to the utility). After the power usage has been defined, the aggregator seeks to manage the demand to achieve a given consumption pattern.

Demand response programs have a centralized architecture, with the aggregator sending a top-down signal to the demand (see Fig. 1 (a)). Demand response implementations deal with three basic challenges: *i*) DR should manage the power usage without causing important losses in the user's quality of life (QoL), while also compensating the user when load curtailment occurs. *ii*) In general, each end-user has a lower bound in the required total energy. This means that

DR, has to shift the power consumption time rather than only reducing total energy consumption. *iii*) Due to the shifting in power usage to off-peak periods, peak rebounds (recovery peaks) may occur. This last point is one of the main problems of many demand response methods.

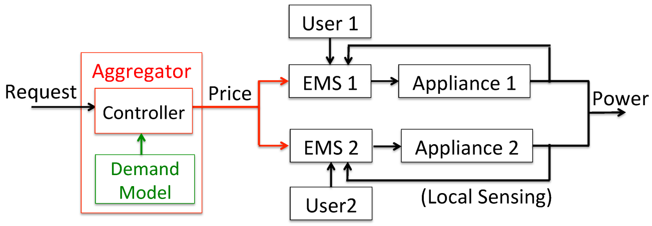
DR methods can be roughly arranged in two categories: *event-based*, and *price-based*. In *event-based DR* approaches, the aggregator has direct control of the appliances, and it remotely controls the appliances and the associated loss or gain in QoL. Common examples of event-based DR are direct load control (DLC), emergency and curtailment programs, and demand bidding programs. In *price-based DR* programs, the aggregator sends the same price-signal to all end-users, seeking to modify their consumption patterns. Then, each end-user independently decides his/her power usage based on the price signal. Given that the aggregator cannot directly control appliances, it requires an accurate model of how the demand responds to price signals, because the top-down price signal controls is a feed-forward, open loop, control. Common examples of price-based DR include time-of-use (TOU), critical-peak-pricing (CPP) and real-time-pricing (RTP).

Demand management from the demand-side

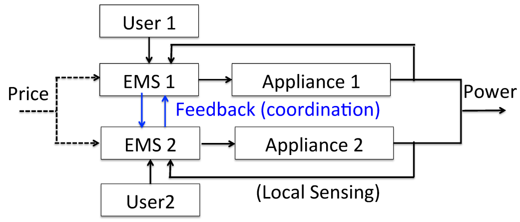
One of the main problems with DR approaches is that most methods are either open loop or that they cannot minimize the impact on the end-users' QoL. As an alternative, the distributed control of power usage has been proposed (see e.g. [7] [8] [9] [10] [11]). In the literature, this kind of approach has been refereed to as distributed DR [10] and coordinated DR [11], with most methods addressing the same issues of demand response, but in a distributed fashion. These methods can be characterized as *demand management from the demand-side*.

We propose a demand management approach that can be characterized as *coordinated energy management of prosumer communities* (see Fig. 1 (b)), where the prosumers in a community perform a coordinated management of their power consumption and generation. While this approach shows some similarities with some of the methods mentioned above, there are two main differences: *i*) the coordination does not need to respond to external requests, and *ii*) each end-user can be a producer and a consumer, i.e. there is no need to distinguish demand and supply.

We think that this *energy management of prosumer communities* will enhance the existing power system, by enabling the coordinated management of end-users' consumption and distributed generation, and that this is an important step to build a bi-directional power network that will further facilitate the introduction of renewables and help achieving full control and responsiveness in the demand.



(a) Price-based demand response



(b) Community Coordination

Figure 2 Control schemes. Example for the case of two end-users, each one consisting of an EMS controlling a single appliance. The control in (a) works as a *feed-forward* control, thus the controller requires an accurate model of the aggregated demand. In (b) a *feedback* control is realized through the coordination (communication) among EMSs.

3. Comparative analysis

From a control point-of-view, it has been argued that direct load control is the best alternative among demand response programs [12]. Direct load control, however, has the drawback of remotely controlling the appliances, making it difficult to manage the end-user's QoL and to integrate uncontrollable distributed generation in the distributed control. On the other hand, price-based demand response is the most popular demand response approach, mainly because it allows the user to self manage the trade-off between QoL and energy cost. However, price-based demand response has several drawbacks, in particular in terms of control capability.

In the following we present the basic formulation and benefits of the proposed coordinated energy management approach, while contrasting it against price-based demand response.

3.1 Control Scheme

In price-based demand response, the power is managed by each end-user independently, with an aggregator sending the same price signal to all users (see Fig. 2 (a)). A key point is that after the price signal has been sent each end-user, the end-user decides his/her power usage without communicating this information to the aggregator (nor to other end-users) until after the power has been consumed. In other words, price-based DR acts as a feed-forward control, and as such it requires a very good model of the demand to achieve a successful control.

In coordinate energy management, the end-users communicates to coordinate their power usage, with this communication implementing a feedback control loop among EMS agents (see Fig. 2 (b)). From a control point-of-view, this allows achieving full control responsiveness (i.e. fast and predictable control), as opposed to a slow and unpredictable control of price-based demand response.

In other words, while price-based demand response can be understood as a best-effort control of many independent users, coordinate energy management implements a best-effort control of the community.

3.2 Formulation

For illustration purposes we consider the case of day-ahead scheduling of power usage. We assume a network consisting of $N = |\mathcal{N}|$ agents, with each agent $i \in \mathcal{N}$ having an associated decision variable $x_i \in \mathbb{R}^T$ representing the power profile of agent i, T the number of time slots, and $x_{i,t}$ the power used by agent i at time slot t. For simplicity, we consider the case where the profile x_i is controlled by an energy management system (EMS), i.e. the agent i (appliance/household/factory/office). Note that in general $x_{i,t}$ can be either positive (power is consumed) or negative (power is generated).

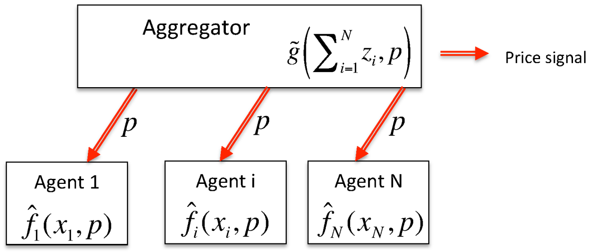
Price-based demand response

Most price-based demand response programs can be formulated as a two-step process (see Fig. 3 (a)). Firstly an aggregator determines the price signal using an approximated model of the aggregated response. Secondly, each end-user independently realizes its power usage taking into account the received price signal, but without communicating again with the aggregator nor with other end-users. This two-step process can be formalized as follows:

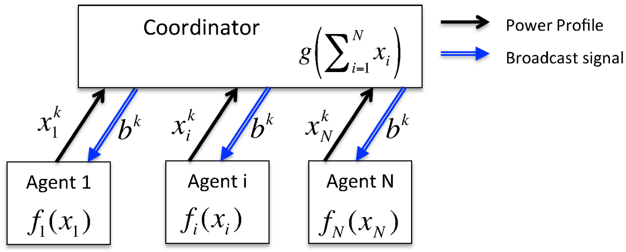
$$\begin{aligned} \bar{y}, p^* &= \underset{\bar{y},p}{\operatorname{argmin}}\ \tilde{g}(N\bar{y}, p), \\ x_i^* &= \underset{x_i}{\operatorname{argmin}} \hat{f}_i(x_i, p^*)\ \forall i \in \mathcal{N}. \end{aligned} \tag{P1}$$

The function $\tilde{g}(N\bar{y}, p)$ is minimized by the aggregator and depends on two variables, the energy price p that the agents pay, and the average power profile $\bar{y} \in \mathbb{R}^T$. In general we can think of p as price vector of the same dimension, $\mathbb{R}^T$, as $\bar{y}$. The function $\hat{f}_i(x_i, p)$, minimized by agent i, measures the cost (dissatisfaction) of agent i for selecting a profile x_i given the energy price p.

Note that if there is a gap between the aggregator's scheduled power profile and the nominal power profile is not zero ($\bar{y}_t N - \sum_i x_{i,t}^* \neq 0$), this cannot be compensated due to the lack of feedback in the control. While the first step in (P1) can formalized in a more general way, e.g. by adding an specific model for each end-user, $\min_{\{z_i\},p} \sum_{i \in \mathcal{N}} \tilde{f}_i(z_i, p) +$



(a) Top-down price-based control



(b) Coordinated energy management

Figure 3 Control architectures. Top: the aggregator determines the price signal, and then each agent independently determines his/her power usage. Bottom: the agents, with the help of a coordinator, minimize $\sum_{i \in \mathcal{N}} f_i(x_i) + g(\sum_{i \in \mathcal{N}} x_i)$, minimizing the community objective and each end-user's objective.

$\tilde{g}(\sum_{i \in \mathcal{N}} z_i, p)$, unless $\tilde{f}_i(z_i, p)$ is a very accurate model of $\hat{f}_i(z_i, p)$, it is not possible to realize an effective control due to the lack of feedback.

Coordinated energy management

The community coordination is formulated as a sharing problem:

$$\underset{(x_i)_{i \in \mathcal{N}}}{\text{minimize}} \sum_{i \in \mathcal{N}} f_i(x_i) + g\Big(\sum_{i \in \mathcal{N}} x_i\Big), \tag{P2}$$

where $f_i : \mathbb{R}^T \to \mathbb{R}$ is the cost of the agent $i \in \mathcal{N}$, with $x_i \in \mathbb{R}^T$ the decision variable of agent i, and $g : \mathbb{R}^T \to \mathbb{R}$ a global cost shared among all agents $i \in \mathcal{N}$. Note that unlike problem (P1), here the price of energy paid by each end-users is not explicit in the formulation.

For agent i, the cost function $f_i(x_i)$ can measure QoL, economic cost/benefit, and physical constraints associated x_i. The cost function $g(\sum_{i \in \mathcal{N}} x_i)$ can measure economic cost/benefit, a constraint, and flatness associated to the aggregated profile $\sum_{i \in \mathcal{N}} x_i$.

3.3 Cooperative distributed protocol

Now we present the basic protocol for the coordinated management of prosumer communities for the case of a day-ahead scheduling. More complete descriptions and extensions of this work, including the case of on-line coordination, can be found in [13] [14] [15].

Distributed algorithm. To solve problem (P2), we use the Alternating Direction Method of Multipliers (ADMM) [16], which in our case corresponds to solving the following iterative algorithm (for a detail derivation see [13] [15]):

$$
\begin{aligned}
x_i^{k+1} &:= \arg\min_{x_i} \left(f_i(x_i) + \frac{\rho}{2}||x_i - x_i^k + b^k||_2^2 \right), \forall i \in \mathcal{N}, \\
\bar{z}^{k+1} &:= \arg\min_{\bar{z}} \left(g(N\bar{z}) + \frac{N\rho}{2}||\bar{z} - \bar{x}^{k+1} - \bar{\nu}^k||_2^2 \right), \\
\bar{\nu}^{k+1} &:= \bar{\nu}^k + \bar{x}^{k+1} - \bar{z}^{k+1},
\end{aligned}
\tag{1}
$$

where $\bar{\nu}$ is a Lagrange multiplier, $b^k := \bar{x}^k - \bar{z}^k + \bar{\nu}^k$, $\rho > 0$ a constant, and we have used the notation $\bar{a}$ to refer to the average of a set of variables $\{a_i\}_{i\in\mathcal{N}}$ (i.e. $\bar{a} = \frac{1}{N}\sum_{i\in\mathcal{N}} a_i$). This algorithm yields convergence without assumptions such as strict convexity of f_i and g [16].

Distributed implementation. We implement the distributed algorithm in Eq. (1) using the distributed protocol illustrated in Fig. 3 (b). The shared cost, $g(N\bar{z})$, is managed by a coordinator-agent that is not in $\mathcal{N}$, and that we will refer to as "coordinator". Each remaining agent $i \in \mathcal{N}$ manages it own cost function f_i, and the coordinator has no access to it, increasing privacy and independence. Also, the variable x_i is not visible to other agents. Note that this algorithm is profile-based, and that no local control variable (e.g. appliance starting time or conditioning set-point) is communicated.

The first step (x_i-step) in Eq. (1) is solved concurrently by the agents (agent i only needs to know b^k), while the second and third steps are evaluated by the coordinator, which needs to aggregate $\{x_i^{k+1}\}_i$, to later calculate $\bar{x}^{k+1}$, $\bar{z}^{k+1}$ and $\bar{\nu}^{k+1}$, and finally broadcast b^{k+1} to all agents. The variable b^k helps guiding the coordination, and measures the gab between $\bar{x}^k$ and $\bar{z}^k$ plus the scaled Lagrange multipliers $\bar{\nu}^k$. After convergence the value $b^K = \bar{\nu}^K$ can be interpreted as clearing prices of an exchange market [16]. Thus, the coordination determines both the optimal power usage and the clearing prices.

To take part of the coordination, the basic requirement for agent i, is to be able to solve the optimization problem $\text{prox}_{f_i/\rho}(v) = \arg\min_x f_i(x) + \frac{\rho}{2}||x - v||^2$, i.e. implement a proximal operator [17] [18]. The coordinator has to implement a proximal operator and a linear update.

4. Simulated evaluation

To illustrate the proposed approach, we consider the example application where N agents, each consisting of a single appliance, balance their power profile. In this setting, $x_i \in \mathbb{R}^T$ corresponds to the power profile of agent i, with $T = 144$ the number of time slots (10-min per time slot for a total duration of 24 hours), and $x_{i,t}$ the power used by agent i at time slot t.

The shared goal for the community is to flatten the aggregated power usage profile $v = \sum_i x_i$, measured by the cost function $g(v) = \beta||v||_2^2$, with $\beta = 2 * 10^{-6}$. During the coordination we use the value $\rho = 0.1 * 10^{-6}$ (ρ controls the convergence speed).

We consider a simple agent model to illustrate the benefits of the coordination (see [13] for a more general model). Each load can have profiles of the form

$$
x_i = (\underbrace{0,\ldots,0}_{t_i}, \underbrace{1000,\ldots,1000}_{T_d}, \underbrace{0,\ldots,0}_{t_i^r}), \tag{2}
$$

with $T_d = 18$ the power usage duration (fixed value), t_i the power usage starting time (control variable), $t_i^r > 0$ and $t_i + T_d + t_i^r = T$. Thus, the power consumption pattern is fixed, and can only be shifted (this could be a very simple model of a laundry machine or electric vehicle charging).

The dissatisfaction of agent i for selecting a profile x_i is measured using the cost function $f_i(x_i) = \min_{t_i\in\mathbb{U}_i} ||t_i - t_i^0||_2^2/\sigma_i^2 - \log \Pi_{[x_i=\psi_i(t_i)]}$, with t_i^0 the preferred power usage starting time for agent i, σ_i a measure of agent's i starting time flexibility (large σ_i implies larger flexibility), Π the indicator function, and $\{\psi_i(t_i)\}_{t_i\in\mathbb{U}_i}$ the set of possible profiles with shapes as indicated in Eq. (2). In the experiments we consider that the agents have a preferred staring time t_i^0 uniformly distributed in $[50, 75]$.

For price-based demand response we consider the agent cost given by $\hat{f}_i(x_i, p) = f_i(x_i) + ||x_i||_{W_p}^2$, with $W_p =$ diagonal(p) and $p \in \mathbb{R}^T$ a price vector, while for coordinated energy management we consider the solution of $\sum_i f_i(x_i) + g(\sum_i x_i)$ as obtained using the coordination given by Eq. (1).

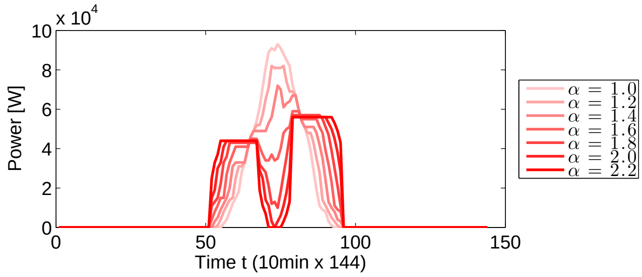
Aggregated profiles. We consider the case of $N = 40$ agents, with $\sigma_i = 3$ for all agents, and analyze the obtained aggregated profiles. In Fig. 4 (a) we can observe the profiles obtained for critical-peak-price (CPP) signals of the form $p(\alpha) = (1,\ldots,1,\alpha,\ldots,\alpha,1,\ldots,1)$, for values of $\alpha \in \{1, 1.2, \ldots, 2.2\}$. In Fig. 4 (b) we can observe the power profiles obtained during the iterations of a single run of coordinated energy management.

We can note that for the best case of price-based DR ($\alpha = 1.6$), the peak consumption is about 6KW, while the coordination obtains a peak consumption about 3KW after 100 iterations. Thus, coordinated energy management performs a better control, almost halving the maximum peak, while also taking into account the preference of each end-user in the control.

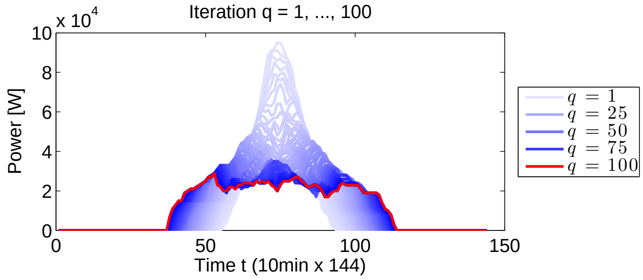
Scalability. In Fig. 5 we analyze the control ability for increasing values of N (the number of agents) and for different levels of agent flexibility (as measured by σ_i). To evaluate the control ability of the methods, we use the

Coincidence Factor (CF), which defined as $\mathrm{CI}(\{x_i\}_{i\in\mathcal{N}}) = \sum_i \max_t(x_{i,t})/\sum_i \max_t(\hat{x}_i^0)$, with $\hat{x}_i^0$ the power profile of agent i when the control $t_i = t_i^0$ is applied. The CI measures how flat is the aggregated profile (in terms of the maximum peak) when compared to the non-managed aggregated profile (worst case). Thus, smaller values of CI are better. For the case of price-based demand response we consider two types of prices: critical peak pricing (as done in Fig. 4 (a)), and a price that is proportional to the non-coordinated aggregated profile $\hat{x}_i^0$.

From Fig. 5 (a) it is interesting to note that using CPP can help flattening the aggregated profile, but the flattening work worst results for larger flexibility (larger σ_i). This is due to the peak rebounds caused by the control strategy due to the lack of feedback. In the case of proportional price Fig. 5 (b), the flattening works better that CPP, but larger peak occur when the flexibility is large $\sigma_i = 6$. In the other hand, coordinated energy management achieves very low CI values, especially for large values of σ_i and the results do not depend much on the number of agents N.



(a) Price-based demand response



(b) Coordinated energy management

Figure 4 Aggregated profiles. Top: obtained power profiles for various price signals. Bottom: Evolution of the aggregated profiles for a single coordination. Note that for the best case of price-based DR, the peak consumption is 6KW, while for the coordination the peak consumption is 3KW.

5. Discussion

5.1 Real-time coordination

In Section 3.3, the case of coordination for day-ahead scheduling considering controllable agents was considered. That formulation can be extended to the online (intra-day) coordination in cases where the agents do not follow the scheduled plan or where the community objective functions change over time [14] [15]. However, our goal is to deal in real-time with uncontrollable power consumption (associated to the users' unpredictable living activities) and with uncontrollable power generation (associated to external conditions, such as weather in the case of photovoltaics). This requires the development of new technologies and methodologies, and their integration. In particular this requires the development of real-time methods for the cooperative management protocol, the estimation and prediction of renewables fluctuation, the estimation of power consumption, the estimation of living activities, and for a market model for the community.

To implement the coordination, in particular in the real-time case, a reliable and fast communication network is required. While the presented coordination is robust to package losses and communications problems [15], the implementation of a real-time coordination will require communication networks and smart meters that can communicate at fast communication rates. Communication networks currently used in power systems are not sufficient, and that the Internet might not be fast and reliable enough for the required real-time management.

5.2 Social issues

To have a high user acceptance, social issues are very important. One of such issues is *privacy*, which in the proposed protocol was addressed through a profile-based distributed protocol where the agents do not disclose their objective function. In this protocol the coordinator sends the same broadcast signal to all agents, which increases *transparency*. Another important issue is achieving *fairness* for all agents in terms of the minimization of each agent's objective functions [15], and also in terms of how the cost of energy cost for the community is split among agent according to each agent effort [19]. All these issues are very relevant to encourage users to be part of the prosumer community, and they need to be studied in deep.

Quality of live (QoL) & sensor networks. We have already discussed that the coordination can manage the power of each user and of the community, while also taking into account the QoL of the users. While in event-based demand response programs the QoL is managed by the suppliers, in coordinated energy management the QoL is managed locally by each agent (it is implicit in the agent's cost function).

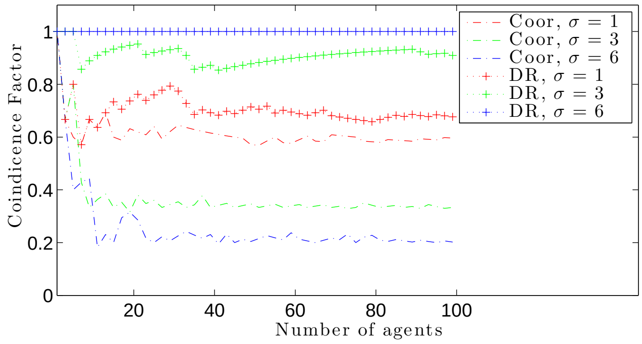
In order to take into account the user's QoL during the energy management, it is important to have a prediction of future living activities, a real-time estimation of the current living activities, and an estimation and prediction of local environmental conditions (e.g. weather). Therefore, the further development of sensor and sensor network technologies will be important for the successful implementation of energy management systems at homes, offices and communities.

Exchange market. As the end-users are becoming prosumers (producers and consumers), they will be an active part of the energy market. While the presented coordination can be interpreted as an exchange market, in a more general case each prosumer should be able to buy and sell power energy and power capacity, and also to decide which energy is willing to buy based on characteristics such as origin and type of energy. Such issues need to be considered in the design of the real-time coordination.

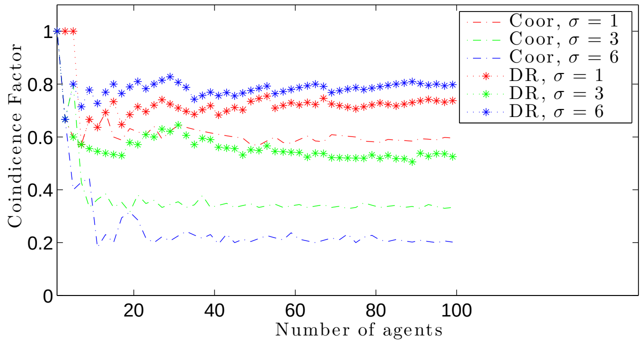
6. Conclusions

We have proposed the concept of coordinated energy management for prosumer communities. This energy management approach can be characterized as a "demand management from the demand-side" where users can be producers and consumers. We presented an implementation of this concept for day-ahead scheduling of appliances, where the users coordinate and plan their aggregated power usage pattern, allowing an effective control of their energy usage without sacrificing quality of live.

The proposed approach was illustrated in a simulated scenario and compared with price-based demand response. The proposed approach presents very good control capabilities, while preserving privacy and QoL. We believe that coordinated energy management is a compelling solution for enhancing the power system, for implementing a prosumer society, and for enabling the further introduction of distributed renewables. Future work includes extending the proposed approach to allow real-time coordination and cooperation, in particular to take into distributed uncontrollable fluctuating power consumption and generation, and distributed storage.



(a) Critical peak pricing DR and coordination.



(b) Proportional price DR and coordination.

Figure 5 Coincidence Factor (CF) of demand response (DR) and community coordination for different number of agents and agent flexibility (σ). Two cases of price-base demand response are considered. Top: Price-based DR with critical peak price versus coordination. Bottom: Price based DR (price signal is proportional to the non-coordinated profile) versus coordination. Note that coordination achieves a smaller CF, in particular for larger σ_i (flexible loads) and independently of the size of the number of agents).

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