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Cooperative electricity consumption shifting

Charilaos Akasiadis *, Georgios Chalkiadakis

School of Electrical and Computer Engineering, Technical University of Crete, Kounoupidiana Campus, 73100 Chania, Crete, Greece

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ABSTRACT

In this paper, we propose the formation of agent cooperatives offering large-scale electricity demand shifting services, and put forward a complete framework for their operation. Individuals, represented by rational agents, form cooperatives to offer demand shifting from peak to non-peak intervals, incentivized by the provision of a better electricity price for the consumption of the shifted peak load, similar to economy of scale schemes. We equip the cooperatives with a novel, directly applicable, and effective consumption shifting scheme, that allows for the proactive balancing of electricity supply and demand. Our scheme employs several algorithms to promote the formation of the most effective shifting coalitions. It takes into account the shifting costs of the individuals, and rewards them according to their shifting efficiency. In addition, it employs internal pricing methods that guarantee individual rationality, and allow agents with initially forbidding costs to also contribute to the shifting effort. The truthfulness of agent statements regarding their shifting behaviour is ascertained via the incorporation of a strictly proper scoring rule. Moreover, by employing stochastic filtering techniques for effective individual performance monitoring, the scheme is able to better anticipate and tackle the uncertainty surrounding the actual agent shifting actions. We provide a thorough evaluation of our approach on a simulations setting constructed over a real-world dataset. Our results clearly demonstrate the benefits arising from the use of agent cooperatives in this domain.

1. Introduction

Electricity is undoubtedly one of the most important commodities in our world, affecting almost every aspect of daily life, from industrial production processes and commercialism, to people's heating, well-being and recreation. Existing systems for electricity generation mainly produce electricity by the burning of fossil fuels. Apart from the fact that their sources are depleting, their use is harmful to the environment as their extraction might harm surrounding areas, and their burning produces gases which help exacerbate the so-called "greenhouse effect".

As a remedy for these concerns, recent trends propose "greener" approaches that will help future electricity production become less polluting, introducing the hope for a more sustainable development [1–3]. The emerging *renewable energy* generation sources can be organized in a non-industrial and decentralized manner, allowing the average household to contribute and benefit from its participation to the electricity production process [4,5]. Despite the positive effects from using renewable energy sources, new challenges arise for electricity production and demand management. This is because weather-dependent electricity sources are by definition intermittent, and potentially unreliable regarding their output size.

Against this background, the contemporary *Smart Grid* agenda of research aims to create a more secure, reliable and efficient electricity networks infrastructure, with energy produced mostly by "green" sources, production costs minimized, and affordable electricity made easily and reliably available to the public [6,7,1]. Now, due to the scale and complexity of electrical networks management, artificial intelligence (AI) and multiagent systems (MAS) solutions are in high demand in the emerging markets involving business entities providing Smart Grid services [8,3]. Many such entities have already adopted a business model that pulls together the resources and abilities of multiple economically-minded individuals. Specifically, the emergence of *virtual power plants (VPPs)* or *cooperatives* of small-to-medium size electricity producers, consumers, or even prosumers[1] – that operate as a virtually single entity – has been hailed as a means to create large, efficient,

* Corresponding author.
E-mail addresses: akasiadi@intelligence.tuc.gr (C. Akasiadis), gehalk@intelligence.tuc.gr (G. Chalkiadakis).

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[1] A prosumer is an entity that both produces and consumes energy.

trustworthy providers of renewable energy production or electricity consumption reduction (peak-trimming) services [8–11,3,12]. VPPs can also deliver a range of *demand side management (DSM)* services. In DSM, consumers contribute to the stability of the electricity grid in exchange for certain, usually monetary, rewards. DSM services can be loosely divided into three categories: consumption reduction programs, load management programs, and energy conservation programs [13,10,14]. Now, although reduction and conservation can obviously contribute to the reliability and sustainability of the power system, they require large investments for equipment and infrastructure upgrade [15]. Moreover, these efforts can reach a maximum effectiveness level, beyond which further reductions cannot be tolerated, because such actions begin to interfere with consumer comfort and well being [16]. In any case, any DSM technique should make sure that consumer needs are accommodated and consumer tasks are eventually completed—even at earlier or later times than originally scheduled. Furthermore, load-management schemes are an alternative to *electricity storage*—a problem difficult by its nature, and the tackling of which requires the use of expensive equipment [17].

In this paper, we take the provision of electricity load management solutions one step forward, by proposing the formation of *agent cooperatives for demand shifting services*. In particular, our work demonstrates how to perform *large-scale, collective electricity consumption shifting*. To the best of our knowledge, ours is the first ever complete mathematical framework for collective electricity consumption shifting, which comes with several desirable properties and guarantees, and which is also evaluated extensively via simulations on a real-world consumption dataset.

Our scheme motivates self-interested business units, represented by autonomous agents to join forces in a cooperative and shift power consumption from peak intervals to others with lower demand, in order to receive lower electricity price rates for their contribution. This is similar to economy of scale approaches, where groups of buyers join together to finally buy larger good numbers at a better price each [18,19]. Consumption re-scheduling can be performed a day-ahead, thus avoiding the dangers and risks of last-minute action. In this way, our scheme *proactively balances future supply and demand*, without any losses affected to the utility of the contributors.

Now, for the cooperative to be successful at *large-scale* shifting effort, it is obvious that *coordinated joint shifting efforts* have to take place, carried out by *demand shifting coalitions*. Inspired by work in the *cooperative games* and related MAS literature [20], we propose several methods for the formation of shifting coalitions. These *coalition formation* methods group together agents based on criteria such as their perceived shifting contribution potential, and their expected economic gains from participation. We also devise *internal pricing* mechanisms that determine *variable*, and *individual-specific* reduced electricity prices for our agents, via implementing *expected gain transfers* among the coalescing consumers. The resulting *internal price balancing* incentivizes even agents with initially forbidding shifting costs to participate in the cooperative effort.[2] We put forward several such internal price balancing techniques: a heuristic mechanism; and five alternative ones. All of our proposed internal pricing methods satisfy budget-balancedness.

Thus, our mechanism employs coalition formation and internal pricing techniques in order to facilitate the shifting of sizeable electricity consumption amounts from peak to non-peak time intervals. The effectiveness of the joint coalitional shifting actions naturally depends on the accuracy of the members' statements regarding their shifting capabilities, and their confidence about meeting their forecasted goals. These statements, however, might not be accurate forecasts, as consumers might not be able to accurately predict their shifting capabilities, or are not truthful (due to low trust towards their partners, or similar concerns). Therefore, to promote truth-telling and efficiency in load shifting, we employ a *strictly proper scoring rule*, the *continuously ranked probability score (CRPS)*, proposed in the mechanism design literature [22]. The use of *CRPS incentivizes* agents to truthfully and precisely report their predicted shifting capabilities.

Of course, even if participating agents are perfectly truthful regarding their abilities and corresponding uncertainty, their reports and estimates can still be highly inaccurate. This can be due to, for example, communication problems, malfunctioning equipment, or prejudiced beliefs and private assumptions—e.g., a truthful reporting agent might be overly pessimistic or optimistic. As a result, monitoring the performance of individuals and correctly predicting their future contributing potential is of utmost importance to any organization relying on the services of selfish, distributed, autonomous agents. To this end, several approaches try to explicitly estimate agent electricity consumption and production amounts, by incorporating prediction models that rely on agent geographical location and weather forecasts, or the processing of macroeconomic data [23,24]. However, such methods cannot immediately predict the actual behaviour of a specific agent, which might be motivated by private knowledge or business concerns, neither do they account for errors due to equipment malfunction. By contrast, here we propose the application of *generic* prediction methods, which are nevertheless able to adapt to a specific agents behaviour and generate accurate estimates. In particular, we propose the use of stochastic filtering methods to keep track of the parameters that best describe agent behaviour, and to effectively predict future agent performance.

An extensive experimental evaluation of the proposed mechanisms and methods was performed on a large dataset containing real consumption patterns from the Kissamos district at western Crete, Greece. Our experiments confirm that granting a low enough price to the consumers incentivizes cooperative consumption shifting—as long as this price allows the agents to (collectively) overcome their shifting costs. Moreover, our results indicate that the coalition formation method that yields the best results with respect to load shifting effectiveness and actual monetary gains for the participants, is one that creates agent coalitions that maximize in expectation both the eligible amount for shifting, and the expected gains of their members. We also assess the behaviour of the various internal pricing methods we propose, and conclude that our heuristic price balancing approach, in particular, is the most appropriate for use in this domain. Further, we demonstrate that employing *CRPS* is effective: inaccurate agents suffer penalties that are higher than those of their more accurate counterparts, and individual agents and coalitions alike are incentivized to be truthful and accurate regarding their stated shifting capacities. Finally, our experiments show that employing stochastic filtering techniques for agent performance monitoring improves our mechanism's effectiveness and quality. In particular, we show that stochastic filtering leads to greater (near 100%) accuracy *wrt.* forecasted shifting performance; higher collective peak consumption reduction; and increased financial gains for the shifting cooperative.

Summing up, our work here provides several contributions to the state of the art. This is the first time that a complete framework for effective large-scale demand shifting is provided in the literature. We propose a variety of novel coalition formation methods that can be used by consumers wishing to join forces

2 This is similar to group purchasing in e-marketplaces, where agents collectively get better prices for their purchases; and where, due to group-internal price fluctuations set by corresponding mechanisms, the purchase finally becomes advantageous to all—even though some members would not be able to obtain the items even at the better rate promised [21,19].

for cooperative demand shifting, along with several novel internal pricing techniques, the application of which incentivizes even agents with low shifting capacities to offer their services in the scheme. Our mechanisms come with individual rationality, truthfulness, and (weak) budget-balancedness guarantees. As such, the design of our mechanism promotes *broad participation opportunities*, guaranteeing that consumers of any category or type, have strong economic incentives for participation in the scheme, as verified theoretically and also proven by our simulations. Moreover, we are the first to propose and evaluate the use of stochastic filtering techniques in this domain. Finally, our proposed scheme is easy-to-use and directly applicable, as it requires no legislature changes whatsoever—it only requires the willingness of national authorities (or perhaps even utility companies that adopt DSM as part of their business) to provide better prices for joint, large-scale demand shifting.

The remainder of this paper is structured as follows. In Section 2 we give a detailed description of our problem and setting. Section 3 then discusses the details of methods for forming effective shifting coalitions. Section 4 describes our internal price balancing methods, and Section 5 discusses the scheme's properties and complexity. Section 6 presents our proposed performance monitoring techniques, while Section 7 describes our experiments and corresponding results. Section 8 reviews related work; and, finally, Section 9 concludes this article.[3]

2. A generic electricity consumption shifting model

In this section we begin by describing the problem setting and the required notation (see Table 1). After defining the complete model, we proceed to discuss the necessary constraints that must hold in order to guarantee the feasibility of collective demand shifting efforts. Next, we analyse the incentives of participation for each agent and identify the relationships between shifting costs and prices offered for consumption. Based on these, we propose a pricing scheme that grants lower prices for consuming the (possibly collectively) shifted demand during non-peak intervals; and equip our mechanism with a strictly proper scoring rule to promote accuracy and effectiveness in the coordinated efforts.

To begin, power supply must continuously meet demand that varies between time intervals. To meet this need and in order to provide incentives for consumption at times where production and power supply are cheap, the electricity pricing scheme used in many countries consists of two different pricing rates, one for day-time and one for night-time consumption. Such prices are often set by the various power authorities, or, in many cases, by a nationwide independent system operator (ISO), managing the electricity grid [26]. In our work here, we term such authorities as “the Grid” for convenience.

In our model, we also assume that there exist exactly two different price levels $p_h > p_l$.[4] These, however characterize *each specific time interval* t, based on a demand threshold τ^t under which electricity generation costs are lower, e.g. when renewable energy levels are higher:

$$p^t = \begin{cases} p_h, & \text{if } D^t \geq \tau^t \\ p_l, & \text{if } D^t < \tau^t \end{cases} \qquad (1)$$

where D^t is the energy demand during t. The intervals during which $p^t = p_h$ are considered to be peak-intervals, at which consumption needs to be reduced. We note peak intervals as $t_h \in T_H$ and non-peak ones as $t_l \in T_L$.

Now, given the daily consumption pattern known to the Grid, it would ideally like consumption to drop under *a safety limit* that is placed below τ. Dropping below the safety limit would ensure that some low cost generated load is available in case of high uncertainty or an emergency, thus minimizing the risk that high-cost generators would have to be turned on. That is, the Grid would ideally want to reduce consumption by $Q_{\max}^{t_h} \geq q_\tau^{t_h}$, where:

1. $Q_{\max}^{t_h}$ is the load normally consumed over the safety limit at t_h (that is the maximum load eligible for shifting), and
2. $q_\tau^{t_h}$ is the minimum amount of load whose potential removal can, under the Grid's estimations, allow for a better electricity price[5] to be offered to contributing reducers.

Intuitively, $q_\tau^{t_h}$ is a sizable load quantity that makes it cost-effective for the Grid to grant a very low electricity rate, in anticipation of reaching a demand level that is close to the safety limit. We denote the load reduced by some agent i at a t_h as $r_i^{t_h}$, and that shifted to each $t_l \in T_L$ as $q_i^{t_l}$.

2.1. Scheme overview

We now provide an overview of the proposed shifting scheme. First, the Grid gives information for the time intervals that consumption needs to be reduced at, and those that it is best to shift consumption to. The consumption of the shifted load during these preferred non-peak intervals is granted a better price. Then, the consumer side weighs its costs and potential profits, and chooses to participate in a shifting operation or not. The exact procedure is:

1. The Grid announces peak and non-peak time intervals[6] with high and low consumption prices and asks agents to announce their willingness to shift some of their production from peak to non-peak intervals, promising them a better consumption price for doing so.
2. The agents put forward bids to shift specific amounts from peak to non-peak intervals, along with their costs for doing so, and their *uncertainty* (in the form of a probability distribution) regarding their ability to honour their bids. If the agents represent a cooperative, deliberations internal to the cooperative occur, in order to determine its bids, as we detail later.[7]
3. A *clearing process* takes place, determining the accepted agent bids.
4. During the next day,[8] the agreed consumption shifting activities take place.

The clearing process, apart from determining the expected gains from participation, also guarantees the feasibility of the efforts, by

[3] Parts of this work, namely the model and *some* of our coalition formation and internal pricing algorithms were presented in a preliminary conference paper, and were evaluated with a limited number of experiments conducted on a small dataset involving industrial consumption [25].

[4] By contrast, real-time approaches result to the use of more than 2 different price levels. We discuss such approaches briefly in Section 8.

[5] The specific nature of the authority maintaining or setting the prices is not relevant to our mechanism.

[6] We must note that time intervals can be of any size. In this work, we consider them to be 24 h intervals per day, that is a pretty common division in the energy domain.

[7] Note that, instead of communicating individual agent shifting costs, it would be possible for the cooperative to announce a marginal shifting cost that would allow profitable participation; then the agents would decide whether they contribute or not (see, e.g., [27]). However, this removes the ability to perform internal price balancing, i.e. most profited agents granting a small part of their gain to necessary, but potentially non-profited agents, so that to make shifting profitable for everyone, as we discuss later in Section 4.

[8] Our mechanism can be employed for any future date of our choice.

Table 1
Notation.

Symbol	Meaning
i	Agent ID
t	Time interval
t_h	Peak time intervals
t_l	Non-peak time intervals
p^t	Price of electricity during t
p_h	Peak time price
p_l	Non-peak time price
p_g	Better price granted for consumption shifting efforts
τ^t	Demand threshold that characterizes peak and non-peak intervals
sl	Safety limit $\leq \tau$
D^t	Electricity demand during t
$q_\tau^{t_h}$	Amount of load whose removal can allow for a better price
$Q_{\max}^{t_h}$	Maximum amount of load eligible for a better price when shifted from t_h
$q_{\min}^{t_h}$	Minimum amount of load eligible for a better price when shifted from t_h
$r_i^{t_h}$	Load reduced by i at t_h
$q_i^{t_l}$	Load shifted by i to t_l
$q_{sl}^{t_l}$	Load quantity available under sl during a t_l
$\hat{r}_i^{t_h}$	Stated agent shifting capacity (amount of load pledged to be removed from t_h)
$\tilde{r}_i^{t_h}$	Cooperative estimate over the agent's reduction capacity
$c_i^{t_h \to t_l}$	Agent cost for shifting one kWh from t_h to t_l
$\hat{\sigma}_i$	Stated agent uncertainty regarding stated $\hat{r}_i^{t_h}$
$\hat{p}_i$	Agent i's reservation price for shifting to specific t_l
ξ_i	Agent i's contribution potential
$\alpha_i^{t_h}$	"Accuracy factor": a random variable that indicates the $\hat{r}_i^{t_h}$–$r_i^{t_h}$ relationship
$\tilde{\alpha}_i^{t_h}$	Estimate for $\alpha_i^{t_h}$
r^*_{i,t_h}	A "trusted index" that substitutes $\hat{r}_i^{t_h}$
p_i^{eff}	Agent i's "effective price"—i.e., price eventually paid by i at t_l
$\hat{r}_C^{t_h}$	Stated cooperative shifting capacity
$\hat{\sigma}_C$	Stated cooperative uncertainty regarding stated $\hat{r}_C^{t_h}$
G_C	Cooperative expected gain
p_C	Price awarded for cooperative action
B_i	Electricity bill for i
b_i	Cooperative contributor's bill

Note: the key parameters of our scheme are only the prices p_l, p_h, $p_g(\cdot)$, and $Q_{\max}^{t_h}$, and $q_{\min}^{t_h}$, which are essentially determined by the Grid.

applying specific constraints, which we describe in the following subsection. In reality, of course, such efforts are expected to be best conducted by consumers joining forces in *cooperatives*, as this is the only way to actually deliver substantial – and thus effective – power consumption shifting. We explain the formation of the cooperatives in Section 3 below.

2.2. Constraints

We came up with specific constraints that must hold in order to safely shift demand. These constraints are checked during the demand shifting operations and actually limit the eligible load for reduction by our mechanism. Such limits are important, in order to tackle herding effects. Note that the constraints do not attempt to directly control consumers actions, just characterize which amounts of load are considered eligible for shifting. If the consumer deviates and constraints no longer hold, then the standard fares are applied.

To begin,

$$\sum_i r_i^{t_h} \geq q_\tau^{t_h} \tag{2}$$

that is, the amount of load reduced must be higher than the minimum needed at t_h. In order for the Grid to be profited, the reduction must be above certain levels, guaranteeing that the peak will be trimmed.

Second,

$$\sum_{t_l} q_i^{t_l} \leq \sum_{t_h} r_i^{t_h}, \quad \forall i \tag{3}$$

meaning that every reducer shifts to a subset of non-peak intervals an aggregate load amount of at most the load reduced over the t_h intervals he participates in. Note that the consumer might consume during a t_l more than reduced during t_h, as we do not explicitly restrict power flow. In such situations, the better price of Section 2.4 is charged only for the eligible amount, and the excess is charged according to the original prices that would be charged during t_l.

Moreover,

$$\sum_i \sum_{t_l} q_i^{t_l} \leq Q_{\max}^{t_h}, \quad \forall t_h \in T_H \tag{4}$$

has to hold, meaning that the sum of all reducing agents shifted load to all non-peak intervals must be at most equal to $Q_{\max}^{t_h}$, assuming that the Grid has no interest in further reducing consumption, once it has dropped under τ^{t_h}.

Finally,

$$\sum_i q_i^{t_l} \leq q_{sl}^{t_l}, \quad \forall t_l \in T_L. \tag{5}$$

Namely, the total shifted load at each t_l must not exceed the $q_{sl}^{t_l}$ quantity which is actually available under the safety limit, in order to avoid the creation of a new "peak" at t_l. The objective is to keep demand close to the safety limit in as many intervals as possible.

2.3. Agent incentives

The participation of each agent in the scheme obviously depends on his individual costs and potential gains. Suppose that an agent i ponders the possibility of altering his baseload consumption pattern by shifting some electricity consumption r_i from an interval t_h to t_l. This shifting effort is associated with a *cost* $c_i^{t_h \to t_l}$ for the agent. The *gain* that an agent has for shifting r_i to t_l given t_l's lower price p_l, is equal to

$$gain(i|p_l) = r_i(p_h - p_l - c_i^{t_h \to t_l}) \tag{6}$$

since the agent would be able to consume r_i at t_l for a lower rate. However, under normal circumstances this gain is *negative* for the agent, that is,

$$p_l + c^{t_h \to t_l} > p_h \tag{7}$$

because if not, then the agent would have already been able to make that shift (and its baseload pattern would have been different than its current one).

Now, if the Grid is able to grant an *even lower* rate p_g for consumption of $r_i \geq q_{\min}^{t_h}$ at t_l s.t.

$$p_g + c^{t_h \to t_l} \leq p_h \tag{8}$$

then the agent will be incentivized to perform the shift, as his perceived $gain(i|p_g)$ would now be non-negative.

Lemma 1 (*Better Price*)**.** *The better price must lead to non-negative gains.*

Proof. Assume that p_g rate is better than p_h by at least $c_i^{t_h \to t_l}$. Then:

$$p_g \leq p_h - c_i^{t_h \to t_l} \Leftrightarrow \tag{9}$$

$$(p_h - p_g - c_i^{t_h \to t_l}) \geq 0. \tag{10}$$

Since r_i denotes the amount of kWh shifted, its value is always positive and multiplication does not change the sign:

$$r_i(p_h - p_g - c_i^{t_h \to t_l}) \geq 0. \tag{11}$$

As defined by Eq. (6), this is the gain of an agent for shifting from a peak interval to another non-peak one where a price rate p_g is given, so the following finally holds:

$$gain(i|p_g) \geq 0. \tag{12}$$

Thus, the gain for every agent is non-negative, and individual rationality is guaranteed. □

2.4. Group price

Our scheme allows the shifting of sizable load consumption from peak to non-peak intervals. The eligible load for coordinated shifting is granted an *even lower*, "*group*" *price* $p_g < p_l$, which is a function of the actual load reduced at t_h, $r_i^{t_h}$, in a way that for larger load portions, the price becomes better. We term this price as p_g because such reduction will likely be possible only by groups of agents. Thus, the group price is given as:

$$p_g(r_i^{t_h}) < p_l \tag{13}$$

and it is awarded if *the actual quantity of the load shifted* from t_h exceeds some minimum value $q_{\min}^{t_h}$, set by the Grid given its knowledge of $q_\tau^{t_h}$ (e.g., it could be $q_{\min}^{t_h} = q_\tau^{t_h}$). The function can actually be linear or non-linear, as long as it is descending and complies with the incentive analysis of Section 2.3.

To elaborate further, the Grid is not willing to offer a lower price to every consumer, as then it would only need to lower the p_l rates. Instead, p_g is awarded only to adequately large participant numbers, those whose coordinated consumption shifting finally reduces the Grid's generation costs. This is analogous to what happens in *economy of scale* and *group buying* paradigms [18,19] which takes place for several years in actual real world trades.

2.5. Continuously ranked probability score

Now, to promote efficiency in load shifting and (in the face of the global constraints described in our model) avoid Grid interaction with unreliable participants, the agents need to be motivated to precisely report their true reduction capabilities. To achieve this, we employ a *strictly proper scoring rule*, the *continuous ranked probability score (CRPS)* [22], which has also been recently used in [12] to incentivize renewable energy-dependent electricity *producers* to accurately state their estimated output when participating in a cooperative. A scoring rule $S(\hat{P}, x)$ is a real valued function that assesses the accuracy of probabilistic forecasts, where $\hat{P}$ is the reported prediction in the form of a probability distribution over the occurrence of a future event, and x the actual occurrence itself. For a scoring rule to be *proper* the following must hold [28]: $S(P, P) \geq S(P, Q), \forall P, Q$. Then, for a scoring rule to be *strictly proper*, the equality must hold if and only if $P = Q$, which means that the forecasters are better off stating *their true beliefs* accurately, i.e. $\hat{P} = P$, since this is the only value that gives the best score. As such, a mechanism can exploit a rule's strict propriety property, to ensure that scores that are lower than the best result to lower returns (e.g., via the use of penalties) to the participants—and, by so doing, ensure the *incentive compatibility* [29] of the agent reports. The use of *CRPS*, in particular, allows us to directly evaluate probabilistic forecasts, and the score is given by:

$$CRPS(\mathcal{N}(\mu, \sigma^2), x) = \sigma \left[\frac{1}{\sqrt{\pi}} - 2\phi\left(\frac{x-\mu}{\sigma}\right) - \frac{x-\mu}{\sigma}\left(2\Phi\left(\frac{x-\mu}{\sigma}\right) - 1\right) \right]. \tag{14}$$

In our setting, $\mathcal{N}(\mu, \sigma^2)$ is the uncertainty stated over the expected *absolute relative errors*[9] regarding the reduction capacity, as reported by an agent; while x is the actually observed error, ϕ the PDF, and Φ the CDF of a standard Gaussian variable. A *CRPS* value of zero signifies a precise forecast, while a positive value shows the distance between prediction and occurrence. For convenience, we normalize *CRPS* values to [0, 1], with 0 assigned when we have exact forecast, and 1 assigned when the forecast gets far from the occurrence. To improve readability, we also henceforth note $CRPS(\mathcal{N}(\mu, \sigma^2), x)$ as *CRPS* without the arguments and write $CRPS_i$ to denote the *CRPS* rule applied to agent i's performance, while the stated agent uncertainty over its error is considered to be zero mean, $\mathcal{N}(0, \hat{\sigma}^2)$, so this confidence measure will be sometimes simply referred to as $\hat{\sigma}$. Given this notation, an agent i whose bid to shift some load from t_h to t_l is accepted, is charged an electricity bill B_i,[10] given its actual contribution $r_i^{t_h}$,[11] and its additional consumption $q_i^{t_l}$ at the low-cost time interval t_l:

$$B_i^{t_l} = (1 + CRPS_i) q_i^{t_l} p_g(r_i^{t_h}). \tag{15}$$

Note also that it can be $q_i^{t_l} < r_i^{t_h}$, since an agent can shift $r_i^{t_h}$ to multiple t_ls.

Lemma 2. *The payment rule $B_i^{t_l}$, as defined in (15), is strictly proper.*

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[9] The mean μ and variance σ^2 of this distribution can be estimated by each agent through private knowledge of its consumption requirements and business needs.

[10] $B_i^{t_l}$ is the bill the agent receives for the $q_i^{t_l}$ quantity it shifted to t_l. The agent might have been billed a separate amount for any quantity already being consumed at t_l before shifting.

[11] Note that $r_i^{t_h}$ is the *actual amount reduced* at t_h, which also determines the electricity price p_g for i at t_l; while $q_i^{t_l}$ is the quantity shifted from t_h to t_l and consumed there.

Proof. Eq. (15) shows that $B_i^{t_l}$ is an affine transformation of $CRPS_i$, which is a strictly proper scoring rule. According to [30] any affine transformation of a strictly proper scoring rule is also strictly proper. Thus, $B_i^{t_l}$ is strictly proper. □

To summarize, *CRPS* provides a scoring function for evaluating the accuracy of a forecast, given its actual occurrence. When agent-stated forecasts are off the occurrences, contributors are "fined" proportionally to their *CRPS* score. However, while this *mechanism design* technique provides the agents with strong incentives to stay truthful (and, indeed, provides theoretical guarantees for statement truthfulness), it does not guarantee agent statements accuracy, as have already explained in Section 1.

3. Forming effective demand shifting coalitions

In the general case, it is very rare for reducers to have shifting capacity greater than $q_{\min}^{t_h}$, even for large industrial consumers. Therefore, the agents need to organize into cooperatives in order to coordinate their actions and achieve the better rates promised by the Grid for effective consumption shifting. As we have already mentioned, shifting is meaningful only for substantial quantities, such that the Grid can guarantee better prices, which make participation worthwhile. Consequently, cooperative action is needed. We envisage a cooperative as being composed by hundreds or even thousands of consumers. In what follows, we explain how bids are formed for the cooperative case, and what is actually charged at the end of the shifting efforts to the participants. In this section we detail different methods for the formation of demand shifting coalitions i.e., that act to carry out specific "shifting contracts", inside the cooperative, and discuss their final billing, which also incorporates a *CRPS* score.

Naturally, at every given time interval t_h earmarked for potential consumption reduction, only a subset $\mathbb{C}^{t_h}$ of cooperative members might be available for shifting services. We assume that every member agent announces its availability for every such t_h to a cooperative manager agent, along with its reduction (shifting) capacity $\hat{r}_i^{t_h}$; its confidence $\hat{\sigma}_i^2$ on its ability to reduce that amount at t_h (specifically, the agent's expected relative error with respect to $\hat{r}_i^{t_h}$ reduction is normally distributed according to $\mathcal{N}(0, \hat{\sigma}_i^2)$); and the set of low cost intervals t_l that he pledges to move consumption to.

Even so, more often than not, it is impossible for all agents in $\mathbb{C}^{t_h}$ to participate in the cooperative effort. This is because their shifting costs might be so high that they would not allow their inclusion in any profitable cooperative bid. Therefore, only a subset C of $\mathbb{C}^{t_h}$ will be selected for participation in the bid. Such a shifting bid is composed by the following parts: t_h, the high cost interval to reduce consumption from; $\hat{r}_C$, the amount C pledges to reduce at t_h; a pair (T_l, Q_l) that determines the set of low cost intervals t_l to shift consumption to, along with the set of corresponding quantities that will be moved to each t_l; the per kWh *shifting costs* $c_i^{t_h \to t_l}$ associated with moving consumption from t_h to t_l; and a probabilistic estimate of its $\hat{\sigma}_C^2$, in the form of a normal distribution describing the joint relative error on predicted r_C, $\mathcal{N}(0, \hat{\sigma}_C^2)$.

Thus, at a given time interval t_h the cooperative has to select C agents to cooperate and shift demand to some t_l. Without loss of generality and for ease of presentation, let us assume that t_l is just one specific time interval (though in reality it is just one interval among many in T_l). Assume also that $|C| = n$, and thus the total stated reduction capability of C at t_h is:

$$\hat{r}_C^{t_h} = \sum_{i=1}^{n} \hat{r}_i^{t_h}. \tag{16}$$

Given this, the collective expected gain by this shifting operation, assuming the stated quantity $\hat{r}_C^{t_h}$ and corresponding stated confidence $\hat{\sigma}_C$ are *accurate forecasts*, is [12]:

$$G_C = \hat{r}_C^{t_h}(p_h - p_g(\hat{r}_C^{t_h}) - \overline{c}^{t_h \to t_l}) \tag{17}$$

where $\hat{r}_C^{t_h}$ is the amount of load pledged to be shifted, with $q_{\min}^{t_h} \leq \hat{r}_C^{t_h} \leq Q_{\max}^{t_h}$ and $p_g(\hat{r}_C^{t_h})$ is the price corresponding to the shifting forecast. Cost $\overline{c}^{t_h \to t_l}$ denotes the (expected) weighted mean shifting cost:

$$\overline{c}^{t_h \to t_l} = \frac{\sum_{i=1}^{n} \hat{r}_i^{t_h} c_i^{t_h \to t_l}}{\sum_{i=1}^{n} \hat{r}_i^{t_h}} \tag{18}$$

where $\hat{r}_i^{t_l}$ is the load pledged to be shifted by each agent.

Obviously, the cooperative has to select a C so that G_C is non-negative in Eq. (17) above. Notice that in order for inequality $\overline{c}^{t_h \to t_l} < p_h - p_g(\hat{r}_C^{t_h})$ to hold, it is not required that each $c_i^{t_h \to t_l}$ is less than the price difference too, because the quantity of shifted load also matters. This allows for the possibility that reducers with high shifting costs but low shifting capacity can also contribute in the cooperative bid.

Moreover, the cooperative needs to be able to estimate its confidence $\hat{\sigma}_C$ over the expected performance of any subset of an acting set of agents C. This confidence is also calculated using the weighted mean formula of Eq. (18), where, however, instead of individual costs, individual confidence estimates are now used:

$$\hat{\sigma}_C = \frac{\sum_{i=1}^{n} \hat{r}_i^{t_h} \hat{\sigma}_i}{\sum_{i=1}^{n} \hat{r}_i^{t_h}}. \tag{19}$$

Now, there are several ways to determine the subset C of agents to be selected for shifting. Also, due to the uncertain nature, the estimation of the reduction quantity that C will contribute at t_h is also another issue which can be addressed with different approaches. We proceed to describe the process by which the cooperative determines the subset C of $\mathbb{C}^{t_h}$ to participate in its bid at t_h.

3.1. Choosing the acting coalitions

In more detail, suppose a set of n agents that constitute the cooperative. As already explained, in order for the cooperative to place a bid, each contributing agent i must state its reduction capacity, $\hat{r}_i^{t_h}$, at t_h high-consumption (peak) intervals, and corresponding shifting costs $c_i^{t_h \to t_l}$ for moving consumption to non-peak, t_l, intervals. Agents are also required to state their uncertainty over their *expected relative error* regarding their reduction capacity, in a form of a normal distribution $\mathcal{N}(\mu_i, \hat{\sigma}_i^2)$.[13]

Next, the cooperative assigns an estimate of each agent's expected performance $\tilde{r}_i^{t_h}$, which is a function $\mathcal{F}$ of its stated capacity $\hat{r}_i^{t_h}$ and its error distribution $\mathcal{N}(\mu_i, \hat{\sigma}_i^2)$. Function $\mathcal{F}$ can correspond

12 This is assuming that all $\hat{r}_C^{t_h}$ pledged to be shifted is actually later on consumed at t_l. If only $q_C^{t_l} < \hat{r}_C^{t_h}$ is consumed at t_l, then the gain is $G_C = \hat{r}_C^{t_h} p_h - p_g(\hat{r}_C^{t_h}) q_C^{t_l} - \overline{c}^{t_h \to t_l} q_C^{t_l}$.

13 As stated earlier, we set $\mu_i = 0$. This simply assumes that random relative errors, over a long enough time range, will be normally distributed around a mean of 0.

to various performance prediction methods, as we will be explaining in Section 6.[14]

$$\tilde{r}_i^{t_h} = \mathcal{F}(\hat{r}_i^{t_h}, \mathcal{N}(\mu_i, \hat{\sigma}_i^2)). \tag{20}$$

With $\tilde{r}_i^{t_h}$ at hand, the absolute relative error between the actual reduction and the expected one is given by:

$$x_i^{t_h} = \frac{|r_i^{t_h} - \tilde{r}_i^{t_h}|}{\tilde{r}_i^{t_h}}. \tag{21}$$

This value is used for the computation of agent i's *CRPS* score (cf. Eq. (14)).

Then, each agent's *reservation price* $\hat{p}_i$ is calculated as the difference between the price paid for consuming at the "high-cost" t_h intervals, and the agent i's costs for shifting consumption to t_l intervals with lower electricity charges:

$$\hat{p}_i = p_h - c_i^{t_h \to t_l}. \tag{22}$$

Thus, this $\hat{p}_i$ quantity is the highest price i is willing to pay for shifting consumption from t_h to t_l without suffering a monetary loss. Now, the agent's *contribution potential* ξ_i can be calculated as the product of the expected reduction and reservation price:

$$\xi_i = \tilde{r}_i^{t_h} \hat{p}_i. \tag{23}$$

The contribution potential is a measure that compactly captures the impact of the individual agents contribution to the coalition. It is higher when more load is offered for shifting and agent reservation prices are high, meaning they are in less need for compensation, and, as such, their employment would cost less to the Grid side; and it is lower for agents with low reduction capacities, and low reservation prices (i.e., greater compensation demands for shifting).

The agents are then ranked by some ξ_i-related *ranking criterion* of the cooperative's choosing (cf. below), and *shifting coalitions* are formed by the number of top agents that meet any set of requirements determined by the cooperative (e.g., "maximize the shifting capacity", etc.). Selected coalition agents are awarded low, *variable prices* for shifting to t_l, determined by the *group price* $p_g \leq p_l$ which is guaranteed by the Grid, and by monetary *gain transfers* that make it worthwhile for everyone selected to participate in the shift, as described in Section 4 below.

Thus, in order to form the acting coalitions, one must first check, for every i, whether $\hat{p}_i \leq 0$. If that holds for all i, we stop; the problem is infeasible (as *all* agents need to *be paid* with a rate equal at least $\hat{p}_i$ in order to participate). Furthermore, if for all i it holds that $\hat{p}_i \leq p_g^{\min}$ (where $p_g^{\min}$ is the best possible quantity-dependent group price that can be granted), then the problem is again infeasible and we stop (as *all* agents need to be *paid* with a rate at least equal to $p_g^{\min} - \hat{p}_i$ in order to participate). If that is not the case, then there exist some agents in $\mathbb{C}^{t_h}$ for which there is a price they can accept to pay so as to move some of their consumption to t_l without suffering a loss. We now present four different coalition formation methods that one can use in order to identify such agents.[15]

3.1.1. Rank by contribution potential and maximize expected capacity (method CF1)

The algorithm ranks all agents in $\mathbb{C}^{t_h}$ by their *contribution potential*, i.e., $\xi_i = \tilde{r}_i^{t_h} \hat{p}_i$, in decreasing order. Then, starting from the agent with the highest ξ_i value, we sum these values up in decreasing order, and add the respective agents in a group C. Intuitively, the algorithm attempts to add in the coalition members with high "potential" to contribute to reduction—that is, members with potentially high $\tilde{r}_i$ to contribute, while being able to accept a relatively high (though reduced) energy price $\hat{p}_i$. This process continues until the following conditions are met for the *maximum possible* group of agents C:

$$\sum_{i \in C} \xi_i \geq \tilde{r}_C p_C \tag{24}$$

$$\tilde{r}_C \geq q_{\min}^{t_h} \tag{25}$$

$$\tilde{r}_C \leq Q_{\max}^{t_h} \tag{26}$$

where $q_{\min}^{t_h}$ and $Q_{\max}^{t_h}$ are the minimum and the maximum quantity admitting a group price at t_h, respectively;

$$\tilde{r}_C = \sum_{i \in C} \tilde{r}_i; \tag{27}$$

and

$$p_C = p_g(\tilde{r}_C) \tag{28}$$

is the price rate offered by the Grid for reduction $\tilde{r}_C$.

To provide further intuition, note that the expected gain of every agent in some group C given p_C is:

$$gain(j|p_C) = \tilde{r}_j(\hat{p}_j - p_C). \tag{29}$$

If we were simply given a C for which this gain was positive for every member, then each agent would have been able to just pay p_C and enjoy the corresponding gain. However, the reducing set C has to be dynamically determined by the cooperative—and, in order to guarantee individual rationality, so is the price paid by each one of its members. Note also that by progressively adding agents with lower ξ_i values to C, the agents j preceding them can only become better-off, in terms of expected gain, as the group price p_C expected to be attained drops.

Now, if *all* agents in $\mathbb{C}^{t_h}$ are inserted in C and $\tilde{r}_C$ is still lower than $q_{\min}^{t_h}$ (i.e., there is a violation of the constraint of Eq. (25)), the problem is infeasible and we stop. Likewise, if all agents are in C and $\sum_{i \in C} \xi_i - \tilde{r}_C p_C < 0$ (violation of the constraint of Eq. (24)), the problem is again infeasible and we have to stop.

Assume that this has not happened, and both conditions have been met for *maximal* C.[16] This means that there is *at least* one agent j in C that has a positive gain, given p_C. That is,

$$gain(j|p_C) = \tilde{r}_j(p_h - c_i - p_C) = \xi_j - \tilde{r}_j p_C > 0.$$

If not, then no agent has a positive gain, and thus $\sum_{iC} \xi_i - \tilde{r}_i p_C \leq 0$, leading to $\sum_{iC} \xi_i \leq \tilde{r}_C p_C$, contradicting condition of Eq. (24) above. This also means that agents in C are collectively willing to pay a total amount for moving their $\tilde{r}_i$ consumptions to t_l, which is greater than what their group will be asked to pay for (assuming accurate forecasts), given the Grid's offer p_C for $\tilde{r}_C$ reduction.

Thus we have ended up with the maximal C so that Eqs. (24) and (25) hold, and which contains some agents with positive and some agents with negative gain given p_C. This means that the cooperative bid is actually formed as $\tilde{r}_C$. We will later (in Section 4) use these agents to implement a gain transfer scheme so that all individual agents in C end up with non-negative gain themselves.

[14] One potential estimate is the *conservative* one, i.e.: $\tilde{r}_i^{t_h} = \hat{r}_i^{t_h} - \hat{\sigma}_i \hat{r}_i^{t_h}$.

[15] In what follows, we relax the notation somewhat, by dropping time indices where these are clearly implied.

[16] That is, assume that C was actually constructed so that, after a subset of agents L has met $\tilde{r}_L \geq q_{\min}^{t_h}$, we kept adding agents to L until by adding an agent k we constructed some C' so that $\sum_{i \in C'} \xi_i - \tilde{r}'_C p'_C$ has turned to negative, in which case we remove k from the list C' so that we end up with a C that has $\sum_{i \in C} \xi_i - \tilde{r}_C p_C \geq 0$.

3.1.2. Rank by contribution potential and meet minimum expected capacity requirements (Method CF2)

When using $CF2$, we form coalitions in the same manner we did when employing $CF1$, with the difference that we stop adding agents in the coalition at the point when the reduction capacity $\tilde{r}_C$ becomes equal or more than the minimum amount of load eligible for a better price $q^{t_h}_{\min}$. This way, coalitions with the minimum shifting capacity are formed. Thus, $CF2$ runs the risk of proving overly "optimistic" wrt. its final shifting performance estimates. This fact was actually verified by our experiments in Section 7.2.

3.1.3. Rank by expected gain and maximize expected capacity (Method CF3)

Here we rank the available agents by their *expected gain* (cf. Eq. (29)) with respect to the p_g offered at the very moment they are to be included in the coalition. Then, the agents are added in the coalition under formation given this ranking, as long as the "feasibility constraints" of Eqs. (24), (25), and (26) hold.

Note that the ranking used in this particular method, encompasses an insight regarding the expected gain given the better price offered (Eq. (29)). By contrast, $CF1$ and $CF2$ rank the agents by contribution potential. However, having a high contribution potential does not necessarily mean that the gain of an agent is also high. For instance, assume two agents, the first of which with $\tilde{r}_1 = 100$, $\hat{p}_1 = 0.05$, and thus $\xi_1 = 5$; and the second one with $\tilde{r}_2 = 20$, $\hat{p}_2 = 0.06$, and thus $\xi_2 = 1.2$. Assume $p_C = 0.055$. Then, we get (expected) gains $gain(1|p_C) = -0.5$ and $gain(2|p_C) = 0.1$ respectively. In this case, $CF1$ would rank agent 1 before agent 2, while $CF3$ would do the opposite.

This results to the potential exclusion from the acting coalition of agents that could contribute much to the joint gain—because by the time their inclusion is examined by $CF1$, the feasibility constraints[17] have already been violated, and formation has stopped. For this reason, one would expect that using $CF3$ would give rise to coalitions with an increased gain potential and a higher number of agents, which is naturally linked to increased shifting ability. This was verified by our experiments in Section 7.2.

However, employing $CF3$ is computationally more expensive. This is because whenever an agent enters the coalition, the total reduction capacity increases, and consequently p_g changes. This price change induces further changes in the expected gain of the agents, the criterion by which agents get ranked, and thus the respective values have to be recalculated with every new addition. The added complexity is of order $\mathcal{O}((n-k)^2)$, where n is the number of the possible contributors, and k is the number of agents that form the minimum coalition.

3.1.4. Random selection of contributors and maximize expected capacity (method random)

Here we *do not* rank agents by any criterion whatsoever, but those included in the coalitions are simply chosen randomly. The random inclusion continues until the maximum capacity is reached, just as it was the case in $CF1$.

At this point we must note that any simpler approaches than the ones we mention, comes with no incentive compatibility guarantees. The method that ranks agents by their contribution potential ($CF1$) and the one that randomly selects them (*Random*) are our baseline approaches.

[17] Usually Eq. (26), due to the addition of agents with high capacity but low gain potential.

3.2. Cooperative bidding and billing

Above we defined coalition formation methods to determine which agents to actually include in the acting coalitions, and we showed how to compute specific values that characterize the coalition in terms of expected performance. Given these, the actual bid that the cooperative submits for a peak interval t_h, consists of:

1. The sets of non-peak intervals that the coalescing agents agree to shift to, namely the t_ls.
2. The total expected reduction capacity $\tilde{r}_C$.
3. The total confidence of the coalition $\hat{\sigma}_C$, as calculated using Eq. (19).

Next, the shifting actions take place, and the cooperative is billed according to its shifting performance, as we now explain. Assuming that a coalition C was selected for shifting and eventually acted, the total cost (or, the electricity bill) charged by the Grid to the cooperative for consuming $q^{t_l}_C$ after curtailing $r^{t_h}_C$ is given as:

$$B_C = (1 + CRPS_C) q^{t_l}_C p_g (r^{t_h}_C) \tag{30}$$

with $CRPS_C$ being calculated using the cooperative confidence (Eq. (19)), and the collective absolute relative error realized after shifting. Note that *strict propriety* is maintained in this rule, since the only factor depending on agent forecasts is $(1 + CRPS_C)$.

However, even if G_C (Eq. (17)) is positive, it is not certain that all individual agents in C have a positive gain (and thus an incentive to participate) as well. Nevertheless, with $G_C \geq 0$, the possibility of allowing *all* agents in C to make a non-negative gain arises, via "price balancing" and the use of internal *gain transfers*. These transfers also have to be performed in such a way so that the budget-balancedness of any cooperative bid is ensured—that is, the sum of the n members' bills will have to be equal to B_C (or, if not, definitely not be less than it). We now proceed to discuss potential ways that achieve these goals.

4. Internal pricing

As a next step, the cooperative must pre-assign different *effective price* rates p^{eff}_i to each contributor, producing bills that must sum up *at least* to B_C, i.e., the bill charged to the shifting team C. This is done with the understanding that a member's final effective price will eventually be weighted according to its individual contribution, given also that an acting coalition C of agents will receive an actual price rate that is dependent on its *CRPS* score. Moreover, in order to allow even negative gain agents to be included in the coalition, their prices must be reassigned in order to ascertain that no contributor suffers a gain loss, and maintain individual rationality.

In short, an *internal price balancing* or "*gain balancing*" process is employed, assigning p^{eff}_i effective prices that guarantee that each agent will be granted non-negative gains from participation. More specifically, we propose certain (weakly) budget-balanced internal pricing mechanisms, which meet the goals above, and also ensure that the gains derived from cooperative shifting efforts are shared among its members in intuitively fair ways (e.g., larger and more accurate contributors can still expect after internal price balancing to rank higher than smaller and less accurate ones in terms of gain). The first pricing method we propose is a heuristic gain balancing algorithm. That is then followed by five additional pricing methods based on different mathematical programming formulations. Note that gain balancing takes place only if the collective (expected) gain is positive, and under no circumstances leads to negative (expected) gains for any of the individual participants.

4.1. Heuristic internal price balancing

The heuristic algorithm actually balances the gains of the participants, such that nobody ends up with negative expected gain, and that the most favoured ones grant some of their gain to achieve this. However, *the new ranking maintains the same order*, i.e. the one who used to have the most gain, ends up also with the most after the balancing takes place. The procedure is described in detail by Algorithm 1. To begin, the cooperative initially computes individual reservation prices and corresponding gains and proceeds to rank agents in C in decreasing order with respect to their *expected gain* (Lines 1–3), that is:

$$gain(i|p_i^{eff} = p_C) = \tilde{r}_i(\hat{p}_i - p_C). \tag{31}$$

If all agents already have non-negative *gain*, then everyone pays p_C and expects to achieve $gain(i|p_C)$ without need of balancing (Line 1). If negativities exist (Line 4), then we must rearrange p_i^{eff} such that agents with the highest gain provide some of their surplus to those with negative, to make their participation individually rational. The first step is to count the total negative gain existing and assign negative gain agents a reduced p_i^{eff} so that their gain becomes exactly zero (Lines 5–6). These agents are added in the set of negative gain participants, denoted as G^-. In Lines 7–32, an iterative process takes place, where the gain of the top agents is reduced until it reaches the gain of those below. This is achieved by the following procedure: having ranked the contributors based on their expected gains, we increase p_i^{eff} of the top agent until its gain drops to the point that it is equal to the g_j gain of the $j = i+1$ agent below (as long as $g_j \geq 0$). The value of p_i^{eff} is calculated by:

$$p_i^{eff} = \frac{\xi_i - g_j}{\tilde{r}_i} \tag{32}$$

with g_j being the target gain i.e., the gain of the agent below (Lines 20–22).

Then we do the same for the second top agent, until its gain reaches that of the third. We continue in this manner until all requested gain is transferred (Lines 16–17, 24–25), or one's gain reaches zero (Lines 12–14). If the latter happens, we move to the top again and repeat (Line 8).

The p_i^{eff} prices thus determined represent internally pre-specified prices, agreed upon by all the agents, and set ahead of the actual shifting operations. The actual bill b_i that an agent $i \in C$ will be called to pay, however, is determined *after* the actual shifting operations have taken place, and depends on its actual performance wrt. the performance of other agents also, as follows:

$$b_i = \frac{(1 + CRPS_i)p_i^{eff} q_i}{\left(\sum_{j \in C\setminus\{i\}} (1 + CRPS_j)p_j^{eff} q_j\right) + p_i^{eff} q_i} B_C. \tag{33}$$

Strict propriety is ensured by this rule, as it is an affine transformation of a member's $CRPS_i$ score; if the sum in the denominator was over all agents including i, i.e. if $\sum_{j \in C}(1+CRPS_j)p_j^{eff} q_j$ then Eq. (33) would not have been an affine transformation of i's $CRPS$ score. By contrast, Eq. (33) is an affine transformation of $CRPS_i$. As such, its strict propriety is maintained [30]. Moreover, the sum of the b_i bills is always at least as much as the overall bill B_C charged to C, making the mechanism *weakly budget balanced*, and generating some small *cooperative surplus* (which could be used for cooperative administration expenses, maintenance, or other similar purposes).

In this approach, the amount of gain that needs to be transferred in order for required but high-shifting cost agents to contribute with no losses, is provided from the most profitable ones. However, the heuristic internal price balancing method is such, that after the application, the ranking with respect to gains does not change. This means that (a) no contributor suffers losses and also (b) that those who gained more than other agents, still gain more than those specific agents. Summarizing, the internal price balancing informally provides incentive compatibility guarantees for the stated shifting cost values.

Algorithm 1 The Heuristic Internal Price Balancing Method

Input: $p_C, \tilde{r}_i, c_i \forall agent_i \in C$
Output: $p_i^{eff} \forall agent_i \in C$
1: Assign $p_i^{eff} = p_C, \forall i \in C$
2: Compute reservation prices $\hat{p}_i$ and gain $g_i = gain_i, \forall i \in C$
3: Sort agents by gain in decreasing order
4: **if** Negative expected gain agents exist (i.e., the set G^- is non empty) **then**
5: Count total negative gain $L = \sum g_j, \forall j \in G^-$
6: Assign agents $\forall j \in G^-, p_j^{eff} = \hat{p}_j$
7: $donation := 0$
8: **while** $donation < L$ **do**
9: **for all** Positive gain agents **do**
10: **if** $donation < L$ **then**
11: **if** $agent_i$ is the last positive gain agent in sorted gain list **then**
12: **if** $donation + gain_i \leq L$ **then**
13: $donation = donation + gain_i$
14: $p_i^{eff} = \hat{p}_i$
15: **else**
16: $donation = L$
17: Assign p_i^{eff} s.t. only the remaining gain needed is transferred
18: **end if**
19: **else**
20: **if** $donation + (gain_i - gain_{i+1}) \leq L$ **then**
21: $donation = donation + (gain_i - gain_{i+1})$
22: Assign p_i^{eff} s.t. the amount of i's gain is equal to that of $i+1$'s
23: **else**
24: $donation = L$
25: Assign p_i^{eff} s.t. only the remaining gain needed is transferred
26: **end if**
27: **end if**
28: **else**
29: Assign $p_i^{eff} = p_C$
30: **end if**
31: **end for**
32: **end while**
33: **end if**
34: **return** $p_i^{eff}, \forall i \in C$

4.2. Internal pricing as a constrained optimization problem

It is often desired to formulate problems in a form of constrained minimization or maximization, in order to be able to apply generic solving methods. In our case, the problem of dividing the aggregate profit of the cooperative to the individuals could be optimized according to various criteria. The initial approach that was discussed in the previous subsection, had as a criterion to change as few prices as possible, without violating any constraints. Also, when the algorithm had to change the prices due to the existence of negative gains of participants, it chose to alter those of the *highest gain* agents first. Here, by adding specific constraints we can guarantee that the outcomes, despite the optimization criterion, will maintain the individual rationality and budget balancedness properties. Furthermore, each cooperative might set different optimization criteria, according to its own interests. Then, off-the-shelf, practically efficient methods can be applied to solve the optimization problems. Later, in Section 7.7, we study the effects that each of these optimization criteria has on the agents payoffs. In what follows, we present the general form of our optimization problem, and five different criteria for gain balancing.

Eq. (34) describes the general constrained optimization problem that we will be solving, but for each of the following cases, different objective functions $f(\mathbf{p}^{eff})$[18] are going to be used:

$$\begin{aligned} \underset{\mathbf{p}^{eff}}{\text{opt}} \quad & f(\mathbf{p}^{eff}) \\ \text{s.t.} \quad & \mathbf{p}^{eff} \leq \hat{\mathbf{p}} \\ & gain(\hat{\mathbf{p}}|\mathbf{p}^{eff}) \geq \mathbf{0} \\ & \mathbf{r}^{\top}\mathbf{p}^{eff} = r_C p_C. \end{aligned} \tag{34}$$

The opt operator can mean either minimize, or maximize. The first constraint guarantees that each agent will pay at most its reservation price, and the second constraint, that its gain will be non-negative (*individual rationality*). The third constraint dictates that the sum of individual monetary charges will be equal to the total amount that the cooperative is charged for the shifted consumption of electricity. After using an off-the-shelf method to solve the problem described by Eq. (34) and thus calculate the p_i^{eff} effective prices, the actual b_i bills that agents pay are once again determined via employing Eq. (33). We now present the objective functions $f(\mathbf{p}^{eff})$ that are to be optimized, and form affine problems [31] with optimal solutions.

1: Minimize maximum individual gain loss. Namely:

$$\underset{\mathbf{p}^{eff}}{\text{minimize}} \ \max\{gain(\hat{\mathbf{p}} \mid \mathbf{p}^{eff}) - gain(\hat{\mathbf{p}} \mid \mathbf{p}_C)\}. \tag{35}$$

This case measures the gain differences for each agent induced by the internal pricing change, and tries to minimize the maximum of these differences.

2: Maximize sum of individual gains. Namely:

$$\underset{\mathbf{p}^{eff}}{\text{maximize}} \sum gain(\hat{\mathbf{p}} \mid \mathbf{p}^{eff}). \tag{36}$$

This case sums up individual gains of the cooperating agents, and strives to maximize this particular sum.

3: Minimize sum of gain loss. Namely:

$$\underset{\mathbf{p}^{eff}}{\text{minimize}} \sum\{gain(\hat{\mathbf{p}} \mid \mathbf{p}^{eff}) - gain(\hat{\mathbf{p}} \mid \mathbf{p}_C)\}. \tag{37}$$

This objective sums up the total gain loss of agents induced by the price balancing, and aims at minimizing this particular sum.

4: Minimize the maximum individual gain loss and the sum of gain loss (sum of objectives 1 and 3). Namely:

$$\begin{aligned} \underset{\mathbf{p}^{eff}}{\text{minimize}} \ & \max\{gain(\hat{\mathbf{p}} \mid \mathbf{p}^{eff}) - gain(\hat{\mathbf{p}}|\mathbf{p}_C)\} \\ & + \sum\{gain(\hat{\mathbf{p}}|\mathbf{p}^{eff}) - gain(\hat{\mathbf{p}}|\mathbf{p}_C)\} \end{aligned} \tag{38}$$

This case is a combination of cases 1 and 3, that is it minimizes the sum of the maximum gain loss of agents and also the sum of all agents' gain loss.

5: Minimize price differences. Namely:

$$\underset{\mathbf{p}^{eff}}{\text{minimize}} \ \|\mathbf{p}^{eff} - \mathbf{p}_C\|_1. \tag{39}$$

By introducing the ℓ_1-norm as an objective function, what we actually manage to do is to induce the minimum number of gain transfers required inside the cooperative. As such, this case is expected to produce outputs that are very similar to those of our previously proposed heuristic gain balancing scheme—with one important difference: *criterion* 5 does *not* guarantee that the initial ranking of participants *wrt.* gains is maintained. The experimental simulations in Section 7.7 actually confirm our expectations regarding this method's behaviour.

[18] For ease of notation, $\mathbf{p}^{eff}$ refers to the vector containing all p_i^{eff}s.

Moreover, note that the initial gain ranking is not maintained by *any* of the objective functions proposed here, since this would require the enforcement of additional constraints that would change dynamically according to the number of participants in each shifting coalition. This fact makes the optimization problem formulation more complex, and have negative impacts on the genericness of such approaches.

5. Mechanism properties

The mechanism that we described in the previous sections, although simple, it exhibits certain desirable properties. First of all, participation in shifting coalitions is individually rational in expectation, since non-negative gains are guaranteed for every coalescing agent, by the application of the constraints and the internal price balancing; the latter also allows the inclusion of even agents with high shifting costs, that otherwise could only lose by participating.

Another property that is ascertained is the weak budget balancedness. Eq. (33) in particular, dictates that no loss can be generated by the cooperative, as participants are asked to pay a proportion of the cooperative bill, respective to each one's performance and contribution. Note though, that the proportions might sum up to more than 1, so there are cases when the cooperative generates (small) profit. Also, the cost is divided "fairly" among the individuals, judging by their load quantity, their calculated effective price, and, of course, their deviation between promises and final actions, as measured by the *CRPS*.

Moreover, the use of the *CRPS* scoring rule ensures that the presented mechanism is *truthful* with respect to their shifting capacity-related statements. An agent has to be as accurate as possible regarding shifting capacity and corresponding uncertainty, as otherwise it will suffer a gain loss due to a bad *CRPS* score. The truthfulness of the agent statements regarding their shifting costs is more difficult to formally guarantee. Since the agents operate in a large, dynamic, and open environment, one cannot determine an incentive compatible mechanism in the Bayes-Nash sense, because analysing Bayes-Nash equilibria properties is computationally infeasible in such settings. Indeed, it is next to impossible for a member agent to reason on the unknown capabilities or availability of thousands of other agents, and no common prior determining such properties can be reasonably assumed. So, given this uncertainty, the best that an agent can do is to be truthful regarding its shifting costs: If the agent states inflated shifting costs, it runs the danger of not being selected for C. Similarly, if the agent states shifting costs lower than its real ones, then it risks suffering a high reduction in expected gain (since the lower these costs are, the higher its p_i^{eff} effective price). In addition, the sheer size and dynamic nature of the problem makes it improbable that a rational consumer would be willing to utilize, on a daily basis, the resources necessary to estimate potentially beneficial fake shifting costs, in order to game the scheme. The internal price balancing mechanism makes this even more complex. In practice, the cooperative could use estimates of industry-dependent shifting cost limits, to fend off any such attempts. Moreover, if an agent is able to and chooses to stick to promised actions, this will allow him to achieve high returns.

Additionally, the proposed mechanism is fair[19] for both the Grid and the contributors, in the following sense: first, the Grid

[19] We use the term "fair" a bit loosely, without referring to some formal notion of fairness, such as *max–min fairness* or *the Shapley value* [20]. Note however that *CRPS* payments punish non-accurate agents and "boost" the gains of accurate ones. In this sense, *CRPS* itself could be seen as constituting a formal notion of fairness: agents realize that their final billing will take place using *CRPS*, and that their bill is proportional to what they deliver and to what others have promised to deliver and finally deliver.

is the one that sets the thresholds, safety limits, and group price functions, according to the expected savings that will come up. Next, at the consumer side, fairness is promoted in various ways: (a) our mechanism guarantees that there will be no loss in expectation, (b) accurate participants achieve larger gains, and (c) we give contribution opportunity to negative gain agents, when required. Even when internal to the coalition price balancing is applied[20] the mechanism is still fair in the case of the heuristic approach.

Last but not least, the pricing schemes and coalition formation methods employed by the mechanism, can be readily used by cooperatives offering electricity demand management services, as they are simple enough and require no legislature changes whatsoever—in sharp contrast to *real-time pricing* approaches [8].

Computational complexity. Let $|A|$ be the number of the agents in the cooperative; for each peak interval that is announced, only the $|\mathbb{C}^{t_h}| \leq |A|$ available agents communicate their information. Thus, the determination of potential contributors subject to the grids constraints, is of order $\mathcal{O}(|\mathbb{C}^{t_h}|)$. Next, we rank the $|\mathbb{C}^{t_h}|$ agents by their contribution potential $\tilde{r}_i\hat{p}_i$, paying the cost of an off-the-shelf algorithm such as $\mathcal{O}(|\mathbb{C}^{t_h}|\log(|\mathbb{C}^{t_h}|))$. The formation of the minimum coalition of $|c| \leq |\mathbb{C}^{t_h}|$ agents, as required by the coalition formation methods $CF1$ and $CF2$ (Section 3.1), involves two summations and two conditional checks, i.e., it has $\mathcal{O}(|c|)$ complexity. Now, method $CF1$ needs additional $\mathcal{O}(|C|-|c|)$ calculations to expand to the maximal coalition, where $|C|, |c| \leq |C| \leq |\mathbb{C}^{t_h}|$, is the final number of agents in the coalition. In case negative gain agents exist and price balancing needs to be initiated, an additional ranking according to expected gain is needed, adding $\mathcal{O}(|C|\log(|C|))$ to the complexity when the heuristic internal price balancing is used. Final calculations regarding p_i^{eff}s and b_is add a linear increase of $\mathcal{O}(|C|)$. Thus, the complexity for the planning of shifting operations during a single peak interval can be kept just linearithmic to $|\mathbb{C}^{t_h}|$—that is, it increases less than quadratically with the number of available individuals during a peak interval t_h. However, if the cooperative employs the constrained optimization problem formulations of Section 4.2 for internal price balancing, then the complexity rises to $\mathcal{O}(|C^3|)$, i.e. the typical complexity of quadratic programming algorithms, which can be used to solve affine problems such as ours [31].

6. Performance monitoring and performance prediction

In this section we present two different methods for monitoring and predicting agent actions in a power consumption shifting scheme: a Histogram Filter, and a Gaussian Process Filter. These two methods are very generic, and have wide areas of application. Their employment in the power consumption shifting domain ensures that member agents can be ranked by the cooperative according to their perceived consumption shifting capacities. In this way, inaccurate agent statements regarding their capacity and corresponding uncertainty will not be able to jeopardize the overall mechanism governing the cooperative business decisions (e.g., which agents to select for cooperation). This is key for the economic viability of any such cooperative.

By the discussion in Section 3 it is obvious that agent statements greatly affect cooperative decisions, and, if inaccurate, endanger the scheme's stability and effectiveness. As such, accurately estimating the expected reduction capacity via Eq. (20) is an extremely important factor, determining the joint demand shifting performance. An initial approach is to apply a *conservative index* $\tilde{r}_i^{t_h}$ for the expected performance of participants, based exclusively on what the agents state in their bid:

$$\tilde{r}_i^{t_h} = \hat{r}_i^{t_h} - \hat{\sigma}_i\hat{r}_i^{t_h}. \tag{40}$$

However, as already noted in the introduction, even if agent statements are rendered truthful via the use of an appropriate mechanism (e.g., the use of a strictly proper scoring rule like the one employed in our work here), they might still be subject to inaccuracies due to unexpected reasons, for example faulty equipment, or agent prejudiced beliefs. This is why a *trusted index* r_{i,t_h}^* is required—an index that is neither stated explicitly by i, nor relies exclusively on i's statements, but nevertheless reveals the distribution best describing future agent actions. This index can then be used instead of $\tilde{r}_i^{t_h}$ to provide a more accurate indicator of an agent i's expected performance (and, subsequently, a more accurate contribution potential ξ_i). The employment of performance monitoring techniques like the ones we propose in this section will help us derive such trusted indices.

To begin, we denote the *actual* amount of load reduced by $r_i^{t_h}$. In general, it can be assumed to be provided by a transformation of the stated $\hat{r}_i^{t_h}$ amount:

$$r_i^{t_h} = \alpha_i^{t_h}\hat{r}_i^{t_h} \tag{41}$$

with the (observed) "accuracy factor" $\alpha_i^{t_h}$ corresponding to a random variable characterizing the accuracy of the statement regarding the promised shifting amount during the peak interval. This variable follows some unknown probability distribution.

The objective of our work in this section is to build models of the agents' performance *by approximating the distributions that* $\alpha_i^{t_h}$s follow. We can then sample such a distribution to obtain *a better* $\alpha_i^{t_h}$ estimate, denoted $\tilde{\alpha}_i^{t_h}$. We then use this estimate to obtain our trusted index r_{i,t_h}^* to replace $\tilde{r}_i^{t_h}$, as follows:

$$r_{i,t_h}^* = \tilde{\alpha}_i^{t_h}\hat{r}_i^{t_h}. \tag{42}$$

As a result, more accurate predictions about individual agent and cooperative shifting abilities can be obtained.

Given all underlying uncertainty, an individual agent's final behaviour most likely corresponds to a complex, non-linear function of its past behaviour. Therefore, we chose to test two filtering approaches that are expected to fit such a function well: (a) a filter utilizing a *Gaussian Process (GP)* [32], and (b) the *Histogram Filter (HF)* [33], a non-parametric filtering technique.[21]

The GP uses historically observed pairs of agent statements and final actions values to fit normal distributions for the underlying random variables for each statement value. The HF ignores user stated uncertainty over the performance and takes into account only past observations for its predictions. On the other hand, GP assumes that final actions are functions of user stated uncertainty and performs accordingly. These methods are generic, with very wide areas of application. Moreover, not only are they able to fit the dynamics of the processes governing agent performance, but can also imbibe the potential errors of electricity metering or information transmission devices. Here we employ them to enhance the performance of our energy consumption shifting mechanism. By so doing, more accurate agent rankings can be obtained, and inaccurate statements will not be able to jeopardize the stability and effectiveness of the mechanism. We now describe the stochastic filtering methods and their application to our setting in detail.

20 Recall that internal price balancing only takes place when negative gain agents exist, but this is not always the case. The frequency depends on the specific settings.

21 All methods require an adequate amount of historical data collected, in order to form an initial model that can be sampled. To this purpose, the *conservative estimate* can be employed at first, and then get replaced by one of the proposed methods once enough data is available.

6.1. Histogram filter

Histogram filters decompose a continuous state space to a finite set of areas or bins:

$$dom(X) = \mathbf{x}_1 \cup \mathbf{x}_2 \cup \cdots \cup \mathbf{x}_K.$$

The HF uses a histogram to map a probability p_k to each of the bins $\mathbf{x}_k$. The value of each p_k depends on the frequency of the observations in the range of bin k.

With this approach, agent forecasts $\hat{\sigma}$ are completely ignored and only past observations of $\alpha_i^{t_h}$ are taken into account. Every time an agent participates in a consumption shifting coalition, its actions are monitored and stored. A histogram is calculated over the set of available observations. Then, according to each bin's height, a coloured roulette wheel is constructed that can be sampled to obtain the most probable ranges of $\alpha_i^{t_h}$, i.e. the more frequent values appear in a bin the more probable its range is selected. So, we sample the corresponding roulette wheel, and come up with a specific bin $\mathbf{x}_k$. The final $\tilde{\alpha}_i^{t_h}$ estimate is another sample from a uniform distribution normalized to have range equal to that of the bin obtained —i.e., for $\mathbf{x}_k$ with lower limit $\mathbf{x}_k^-$, and upper $\mathbf{x}_k^+$ we have:

$$\tilde{\alpha}_i^{t_h} \sim \mathcal{U}(\mathbf{x}_k^-, \mathbf{x}_k^+). \tag{43}$$

The advantage of HF is that it requires no prior knowledge about the form of the distribution that $\alpha_i^{t_h}$ follows, and adapts effectively to all kinds of non-linearities [33]. On the other hand, it needs a number of measurements before it starts working accurately and performance might be unacceptable in initial stages with no actual measurements. Another drawback is that if the distribution changes over time, the length of a history window must be re-set, in order to get rid of expired measurements interference. Also, it does not take into account the error variance $\hat{\sigma}$ that is, the agent-stated confidence.

6.2. Gaussian process filter

Here we describe the application of Gaussian processes for probabilistic regression, to construct a filter that is going to be used for monitoring and prediction purposes.[22] For a set of training samples, $\mathcal{D} = \{(\mathbf{x}_j, y_j), j = 1, \ldots, n\}$ ($\mathbf{x}_j$ inputs and y_j noisy outputs) we need to predict the distribution of the noisy output at some test locations $\mathbf{x}_*$. We assume the following model:

$$y_j = f(\mathbf{x}_j) + \epsilon_j, \quad \text{where } \epsilon_j \sim \mathcal{N}(0, \sigma_{noise}^2)$$

with σ_{noise}^2 the variance noise.

GP regression is a Bayesian approach that assumes a priori that function values follow: $p(\mathbf{f}|\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n) = \mathcal{N}(\mathbf{0}, K)$ where $\mathbf{f} = [f_1, f_2, \ldots, f_n]^T$ is the vector of latent function values, $f_j = f(\mathbf{x}_j)$ and K is the covariance matrix that is computed by a covariance function $K_{jk} = k(\mathbf{x}_j, \mathbf{x}_k)$. The joint GP prior and the independent likelihood are both Gaussian with mean and variance as follows:

$$GP_\mu(\mathbf{x}_*, \mathcal{D}) = K_{*,f}(K_{f,f} + \sigma_{noise}^2 I)^{-1}\mathbf{y} \tag{44a}$$

$$GP_\sigma(\mathbf{x}_*, \mathcal{D}) = K_{*,*} - K_{*,f}(K_{f,f} + \sigma_{noise}^2 I)^{-1}K_{f,*}. \tag{44b}$$

GPs also require value assignments to the vector $\theta = [\mathbf{W}\, \sigma_f\, \sigma_{noise}]$ that contains the hyperparameters, with $\mathbf{W}$ holding the distance measure of each input in its diagonal, σ_f being the variance of the input and σ_{noise} the variance of the process noise. We can find the optimal values for θ by maximizing the log likelihood:

$$\theta_{\max} = \arg\max_\theta \{\log(p(\mathbf{y}|\mathbf{X}, \theta))\}. \tag{45}$$

Finally, the estimate of future agent behaviour can be calculated by:

$$\tilde{\alpha}_i^{t_h} = GP_\mu(\hat{\sigma}_i, \mathcal{D}) + u_\tau \tag{46}$$

with noise u_τ following $\mathcal{N}(0, GP_\sigma(\hat{\sigma}_i, \mathcal{D}))$.

7. Experimental evaluation

In this section we conduct extensive experimental simulations of our mechanism on real consumption patterns. We first present our real world dataset, and explain how we augmented it to also contain information which is still unavailable and cannot be obtained, but is nevertheless required in order to illustrate the mechanism's performance. We then proceed to evaluate the coalition formation methods of Section 3.1 and the monitoring techniques of Section 6. Following that, we examine the effects of using variable group prices and employing the *CRPS* scoring rule or not; and, finally, study the differences among our various internal price balancing techniques.

7.1. The simulations dataset

To experimentally evaluate our methods, we created a simulations dataset based on real electricity consumption data,[23] from Kissamos, a municipality at the greek island of Crete. The dataset contains hourly consumption values for the year 2012, as well as contract types and geographical locations, and a summary of its contents appears in Table 2. We note that participants in our setting belong to two classes of realistic, highly plausible agent behaviour. First, 50% of the participants are mainly confident, and also have a high probability to deliver what they promised (they belong to the *BB* class of agents presented in the Appendix); while 50% of the agents are uncertain predictors, which might or might not follow stated forecasts. The exact definition of these two classes of agents appears in the Appendix. Note that once the necessary (due to the lack of real data) agent shifting costs are calculated, the only additional parameters that one might need to adjust for experimentation are $p_g(\cdot)$, $q_{\min}$, and $Q_{\max}$.

7.1.1. Key parameters of the shifting scheme

We assume a threshold τ for our model, to the 93% of the maximum demand value among all time intervals, and is fixed for all of them—though, it could also be variable across time intervals. The safety limit is 97.5% of τ.

We report that in our simulations there are on average 6.2 peak intervals and 14.9 non-peak intervals per day.

The p_l, p_h price levels correspond to the day/night prices provided by PPC, the greek public power company, i.e. $p_l = 0.0785$ €/kWh and $p_h = 0.094$ €/kWh. The p_g group price rate ranges from $p_g^{\max} = 0.05625$ to $p_g^{\min} = 0.0214$ €/kWh, depending on the reduction size q:

$$p_g(q) = \frac{0.0214 - 0.05625}{(Q_{\max}^{t_h})^\kappa - (q_{\min}^{t_h})^\kappa}(q^\kappa - (q_{\min}^{t_h})^\kappa) + 0.05625 \tag{47}$$

22 Note that in a previous short paper [34], we also explored the use of *GP-UKF*, an *unscented Kalman filter combined with Gaussian process regression*. However, in order to exploit the full power of that technique, in reality one needs to have access to a realistic model of the stochastic dependencies among the past $\hat{\sigma}_i$ agent statements. Without such a model, no significant differences exist between using *GP-UKF* and *GP* alone.

23 The dataset was provided by the Hellenic-Public Power Company (PPC, www.dei.gr).

Table 2
Kissamos 2012: Size and corresponding individual average consumption and bills for each consumption contract type.

Type	Count	Avg daily Individ. Cons. (kWh)	Avg daily/type (kWh)	% Of total	Avg. Individ. Bill cost (€) over 100 days
Residential	5889	7.294	42956.721	35.410	61.66
Commercial	1381	25.080	34636.032	28.550	213.20
Agricultural	271	111.473	30209.372	24.901	933.17
Municipal	295	13.776	4063.979	3.349	113.30
Public	68	76.361	5192.588	4.280	645.36
Industrial	38	107.257	4075.785	3.359	903.74
Public law	12	14.921	179.053	0.147	120.13
Total	7954	–	121313.532	100	–

Table 3
Average results over a 100 days simulation period.

		CF1	CF2	CF3	Random
Exp. Coop. gain (€/day)	μ	52.15	4.31	62.66	7.22
	σ	22.18	2.09	16.75	7.94
Actual Coop. gain (€/day)	μ	33.16	−6.35	38.35	4.59
	σ	14.02	3.33	10.41	5.22
Total gain (100 days)	Σ	3316.03	−635.63	3835.61	459.59
Coop. "Surplus" (€/day)	μ	0.18	1.13	0.43	0.09
Expected reduction (kWh/day)	μ	1153.975	355.924	1341.691	216.499
	σ	496.659	155.061	372.472	235.063
Final reduction (kWh/day)	μ	966.400	301.963	1125.482	190.791
	σ	410.780	132.343	308.096	206.762
Peak (Demand $\geq \tau$) trimmed (%)	μ	71.31	22.42	83.33	15.36
	σ	23.83	8.23	3.35	17.17
Avg. reducing coalition size	μ	191.11	17.98	239.22	337.14
Gain per participant (€/day)	μ	0.17	−0.52	0.16	0.01

with q ranging from $Q^{t_h}_{\max}$, that is the amount of load above τ, to some minimum $q^{t_h}_{\min}$, which we set to $0.3Q^{t_h}_{\max}$.

To also account for non-linear group pricing functions, the reduction size q, as well as $Q^{t_h}_{\max}$ and $q^{t_h}_{\min}$, are raised to a power of κ. By assigning different values to κ, we can achieve various slopes of the pricing function. For the rest of the experiments, the value assigned to κ is 1, unless otherwise stated.

7.2. Evaluation of the proposed coalition formation methods

In our first set of experiments we compare the performance of the different coalition formation methods described in Section 3.2.[24] Recall that $CF1$ maximizes contribution potential and expected capacities, $CF2$ maximizes contribution potential but meets minimum capacity requirements, $CF3$ maximizes expected gain and capacities, and *Random* selects the contributors at random. Since ours is the first approach to large scale coordinated demand shifting, there exist no benchmark methods to compare ours to.

Table 3 shows the average results for the four methods—with each one of them applied on the same input values with the others per day, over a 100 days simulation horizon. We can observe that the most successful coalitions with respect to the amount of actual gain are formed by employing $CF1$ and $CF3$. The $CF3$ formation method, in particular, generates the highest amounts of expected and actual final gains, apparently due to its ability to rank agents with respect to expected gain. In addition, $CF3$ achieves larger consumption reduction (shifting) amounts, leading to higher percentage of peak load trimmed. This is due to the fact that acting coalitions sizes are on average larger when $CF3$ is in use, for the reasons explained in Section 3.2; a fact that also means that their members errors with respect to shifting abilities are "cancelling out" better, and performance improves. Moreover, $CF3$ appears to more robust overall when compared to $CF1$, since $CF3$ results come with a variance that is consistently lower.

By contrast, the other two methods, $CF2$ and *Random*, do not do as well. $CF2$ does not seem to be effective, neither with respect to shifted quantities, nor with respect to gain. This is because $CF2$ forms coalitions that appear to secure the minimum required reduction amount; however, typically the agents are not capable of delivering their promises, and as such, the coalition's final actual gain is negative. *Random*, on the other hand, does manage to generate positive gain, but judging from the actual reduction amount (which is the minimum of all the methods), it fails to select effective and efficient participants. That was to be expected, since when *Random* is employed the contributors are selected in an entirely random fashion.

Table 4 contains additional information regarding the 100-day simulation results. Specifically, it presents the most active participants from each consumption category, when using the different coalition formation methods.

We see there that the most active participants, participating in the scheme dozens of times per month, gain approximately 0.03 euros per kWh shifted, as illustrated in Table 5. This performance leads to electricity bills that are reduced up to approximately 20% for the most active residential participants when $CF1$ or $CF3$ is used, *wrt.* the average bill of the respective category. Even participants that are much less active can expect to make substantial gains from scheme participation: Table 6 depicts the gains of agents that participate in the scheme at least 15 times in a month. As illustrated there, these agents can reduce their monthly bill by 1.4%–3.5% on average. Notice that these rates are comparable to discount rates commonly used in consumer rewards programs, and definitely much higher than bank deposit accounts interest rates currently (2016) in effect in most countries in Europe and North America.

[24] The internal price balancing method used in this and all subsequent experimental subsections up to 7.7, is our heuristic price balancing technique.

Table 4
Shifting performance of the most active participants per consumer class and coalition formation method, over 100 days.

Method	ID	Consumer class	Participations	Total load shifted (kWh)	Total gain (€)	Gain/kWh (€)
*CF*1	288	Ind.	368	5987.004	174.46	0.029
	372	Pub.	337	1832.405	43.86	0.024
	1955	Comm.	292	934.892	25.26	0.027
	7528	Res.	237	363.520	12.32	0.033
*CF*2	288	Ind.	326	5700.062	−169.68	−0.029
	372	Pub.	218	1329.302	−31.81	−0.023
	1955	Comm.	147	599.539	−15.32	−0.025
	7528	Res.	83	188.214	−3.37	−0.017
*CF*3	288	Ind.	398	6602.649	129.19	0.019
	372	Pub.	353	1841.574	47.76	0.025
	1474	Comm.	317	1072.027	25.51	0.023
	7528	Res.	280	414.244	14.00	0.033
Random	5287	Res.	44	5.648	0.07	0.014
	1941	Comm.	41	7.312	0.38	0.052
	349	Pub.	38	0.273	0.03	0.125
	293	Ind.	35	3.577	0.22	0.061

Table 5
Monthly financial gains for the four most active participants.

Class	Avg. monthly bill (€)	Gain/kWh (€)		Total gain/month (€)		Bill reduction %	
		*CF*1	*CF*3	*CF*1	*CF*3	*CF*1	*CF*3
Industrial	301.24	0.029	0.019	58.15	43.06	19.3%	14.29%
Public	215.12	0.024	0.025	14.62	15.92	6.7%	7.4%
Commercial	71.06	0.027	0.023	8.42	8.50	11.8%	11.9%
Residential	20.55	0.033	0.033	4.10	4.66	19.9%	22.67%

Table 6
Average gains for participants with 15 or more participations per month.

Class	Avg. monthly bill (€)	# of agents	Total load shifted (kWh)	Gain/kWh (€)	Total gain (€)	Bill reduction %
CF1						
Residential	20.55	559	16.776	0.037	0.62	3.0%
Commercial	71.06	109	42.635	0.031	1.34	1.8%
Public	215.12	11	114.004	0.027	3.13	1.4%
Industrial	301.24	25	173.025	0.031	5.37	1.7%
CF3						
Residential	20.55	559	19.828	0.036	0.72	3.5%
Commercial	71.06	109	47.507	0.032	1.54	2.1%
Public	215.12	11	119.567	0.029	3.51	1.6%
Industrial	301.24	25	190.272	0.026	5.12	1.7%

In the case of *CF*2, the numerical results of Table 4 indicate once again that it is not an appropriate method for coalition formation, as even the most active consumers lose from participation. Finally, the use of *Random* does not grant losses to the most active participants, however the gain is very small for every consumer type, indicating that its use does not provide adequate incentives for the shifting of electricity demand.

In conclusion, employing *CF*3 appears to be the most profitable, effective and robust of our proposed coalition formation techniques. Also, *CF*1 is another effective demand-reducing coalition formation method, which could also be considered as an alternative. For the rest of the experiments, however, *CF*3 is our coalition formation method of choice, unless otherwise stated.

7.3. Assessing the effect of different group pricing slopes

We now apply different κ values to the $p_g(q)$ pricing function of Eq. (47), and observe their impact on the total cooperative gain and the percentage of peak-load trimmed. Changing κ from negative to positive values results to different non-linear forms, and to concave and convex curves respectively, as illustrated in Fig. 1. For each κ value we used the *CF*3 coalition formation method, and the *Conservative* approach for estimating the reduction capabilities of the participants. The results over 100 days, are presented in Table 7.

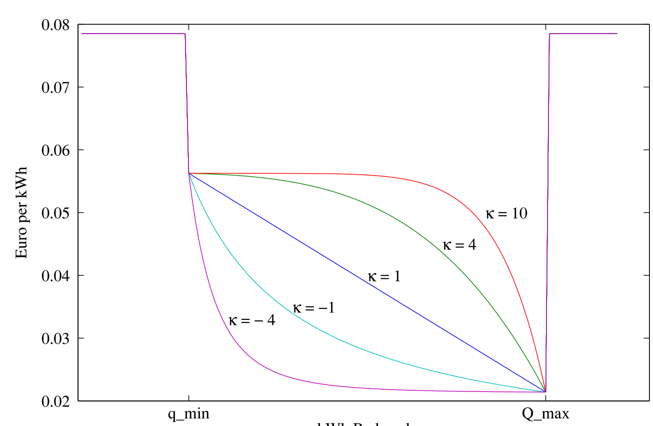


Fig. 1. Forms of p_g for different values of κ.

As we can see, for $\kappa = -4$, where $p_g(q)$ reaches low values faster, the total cooperative gain grows larger when compared to the other four cases. Also, the average percentage of peak-demand

Table 7
Results from an 100 days simulation for different values of κ in the group pricing function.

		$\kappa = -4$	$\kappa = -1$	$\kappa = 1$	$\kappa = 4$	$\kappa = 10$
Peak (Demand $\geq \tau$) trimmed (%)	μ	82.86	81.65	81.36	81.47	81.50
	σ	3.17	4.18	3.57	3.98	3.23
Total gain (100 days)	Σ	4951.71	4641.15	3835.61	2714.37	1397.49

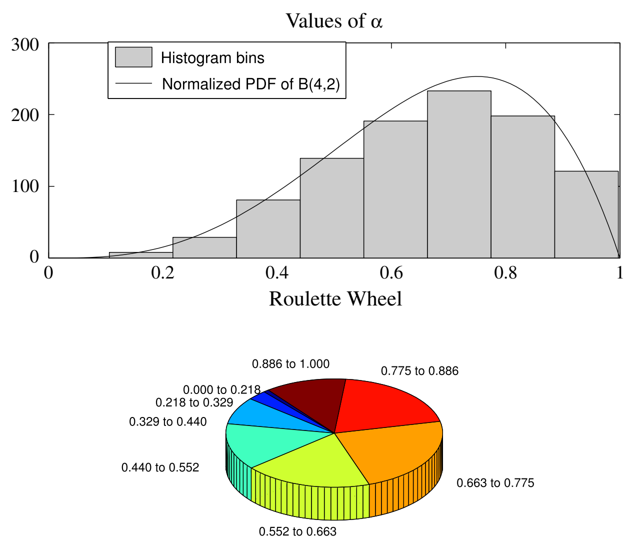


Fig. 2. Agent population vs. average agent shifting cost.

trimmed is slightly higher, with lower standard deviation. This means that this particular $p_g(q)$ form is the most incentivizing for the consumer side, and respectively demands larger discounts from the Grid's side. As the κ value increases, the total cooperative gain become gradually smaller, without significant changes in the percentage of the trimmed peak-load. In the rest of our experiments below, we adopt the $p_g(q)$ given by $\kappa = 1$ as the middle ground solution.

7.4. Evaluation of monitoring techniques

To test-evaluate the performance of our two monitoring techniques, we first applied them on a single agent of the *BB* class, trained over 1000 past value couples that were generated using the same distributions as in the simulation. Figs. 2 and 3 show the outcomes for the *HF* and *GP*, respectively. We can observe that although the *HF* does not take into account agent $\hat{\sigma}_i$ statements, it fits well to the real underlying distribution.[25]values are statistically independent.

The *GP*, on the contrary, does take agent commitments into account. In Fig. 3(a) we can see the *GP* fit an arbitrary non-linear scenario, proving that non-linearities can be handled. Fig. 3(b) presents the trained variances and means for a typical agent participating in the cooperative shifting process for the setting where $\hat{\sigma}_i$ and α_i^{th} follow $\mathcal{B}(1,5)$ and $\mathcal{B}(4,2)$ respectively. In this case, there is no function of a specific known form for the Gaussian Process to approximate, as the points are both random variables following different distributions. Despite that, *GP* has converged to some relationship between input and output values. We can infer that this estimated complex function is meaningful, by the fact that most "test points" fall within the shaded area representing the *GP* output variance; the "test points" plotted in this case are random $\hat{\sigma}_i$, α_i^{th} values, sampled by the $\mathcal{B}(1,5)$ and $\mathcal{B}(4,2)$ respectively. Thus, *GP* is apparently able to produce meaningful predictions, even when the relationships between variables are governed by some highly complex function. We can observe that the main mass of the observations is in the upper left quadrant ($E[\hat{\sigma}_i] \approx 0.16$ and $E[\alpha_i^{th}] \approx 0.66$) and that the trained means are close to that area. Note that because $\mathcal{B}(1,5)$ gives very low to zero probability for $\hat{\sigma}$ values between 0.7 and 1, the number of corresponding training points is very low, so uncertainty in that region is very high. This is not an issue, as *GP* is not likely to be asked to provide predictions in that range.

Next, we employ these techniques in conjunction with both our two most successful coalition formation methods, *CF*1 and *CF*3, in our cooperative consumption shifting simulation scenario. For training, we used 100 $(\hat{\sigma}_i, \alpha_i^{th})$ couples generated from the same distributions; these were considered to be the historical values. We compare the gains produced when using the two stochastic filtering techniques to those accrued when using "conservative" estimates for performance prediction. The *conservative*, *HF*, and *GP* estimates are calculated as described in Section 6.

The numerical results from the two 100 days simulation are presented in Table 8 for the case of *CF*1, and in Table 9 for that of *CF*3. All three estimators generate *expected* gain and reduction values that are pretty close to each other, though estimates differ among the two coalition formation cases. However, when one examines the *final outcomes*, it becomes obvious that the *HF* and *GP* filtering methods perform much better than the *conservative* one. The *HF* and *GP* performance is comparable, with *GP* generating slightly better actual gains and better precision for individual forecasts, as indicated by its lower "unallocated" cooperative surplus (cf. Eq. (33)). To better illustrate these points, the average final gains generated when using our members performance estimation methods are shown in Fig. 4.

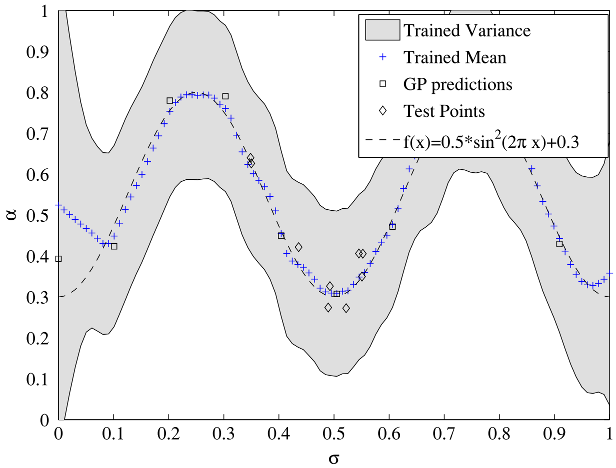
The figure clearly illustrates that the average final gain increases with the adoption of performance monitoring methods (instead of relying on – albeit conservative – performance estimates based solely on agent statements), and that *GP* is the technique most successful in generating gains.

Returning to the numerical results of Tables 8 and 9, we observe that the final performance of the shifting coalitions reaches prediction accuracy values that exceed 94% for the two filtering techniques. Moreover, *GP* is able to achieve 97.66% peak trimming performance when coalition formation method *CF*3 is used.

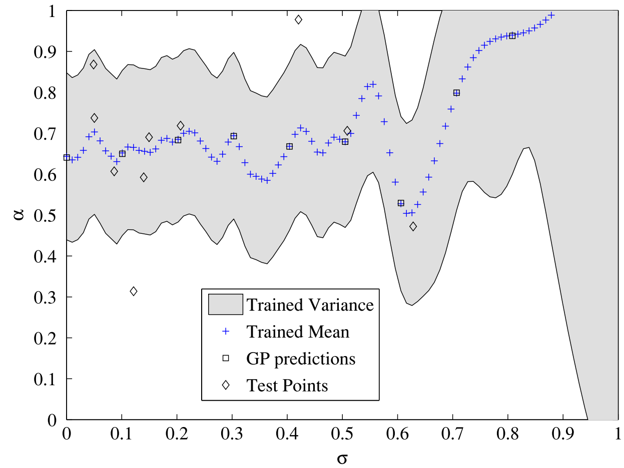
Summarizing, the evaluation demonstrates that *GP* is potentially the most effective of the prediction techniques examined. This is best illustrated by its better performance with respect to prediction accuracy, and its nearly perfect effectiveness in terms of peak load trimmed. Recall that for the *HF*, agent forecasts are not taken into account, so potentially important information is ignored. Intuitively, *GP* can effectively learn and adapt to the underlying model that relates agent forecasts and final actions, thus enabling the cooperative to choose reducing coalitions that often deliver what they promised. *GP* is the monitoring method used in the rest of our experiments. *HF*, however, exhibits a strong performance also. Thus, in a nutshell, our results indicate that both filtering techniques examined are strong candidates for monitoring the accuracy of selfish agent statements in Smart Grid consumer cooperatives.

Finally, we also report that when using *GP*, the most active participants achieve higher gains (approximately 0.04 €/kWh shifted),

[25] In our setting, the $\hat{\sigma}_i$, α_i^{th}.



(a) Illustrating *GP*: fitting an arbitrary non-linear function.



(b) Fitting of the behavioural function of the Kissamos dataset.

Fig. 3. *GP* fits. Illustration of *GP* training for two non-linear cases.

Table 8
Average results from an 100 days simulation when using *CF*1.

		Conserv.	HF	GP
Expected Coop. gain (€/day)	μ	55.79	54.87	54.61
	σ	20.94	22.36	22.53
Actual Coop. gain (€/day)	μ	35.38	47.04	51.10
	σ	14.16	20.04	21.46
Coop. “Surplus” (€/day)	μ	0.19	0.56	0.12
Expected reduction (kWh/day)	μ	1239.135	1219.125	1211.522
	σ	466.138	501.049	504.137
Final reduction (kWh/day)	μ	1038.433	1155.718	1204.058
	σ	395.930	483.849	504.177
Accuracy (%)	μ	83.80	94.79	99.38
Peak (Demand $\geq \tau$) trimmed (%)	μ	74.70	82.88	85.99
	σ	19.95	24.43	25.89
Avg. reducing coalition size	μ	207.14	272.99	284.59

Table 9
Average results from an 100 days simulation when using *CF*3.

		Conserv.	HF	GP
Expected Coop. gain (€/day)	μ	63.78	63.90	64.00
	σ	17.18	17.16	17.13
Actual Coop. gain (€/day)	μ	39.00	54.47	59.89
	σ	10.85	16.02	16.03
Coop. “Surplus” (€/day)	μ	0.20	0.68	0.11
Expected reduction (kWh/day)	μ	1368.003	1372.307	1373.888
	σ	379.318	380.762	379.835
Final reduction (kWh/day)	μ	1125.705	1298.333	1361.656
	σ	309.521	365.489	372.946
Accuracy (%)	μ	82.28	94.60	99.10
Peak (Demand $\geq \tau$) trimmed (%)	μ	81.36	93.41	97.66
	σ	3.67	3.57	2.48
Avg. reducing coalition size	μ	233.79	322.02	339.36

as compared to those achieved when using the conservative technique for estimating future agent performance. In addition, participants with 15 participations or more within a month, receive bills that are reduced by 2.4% for the *CF*1 method and 2.6% for the *CF*3.

7.5. Coalition size vs. group price range

Overall, it is clear that in order for shifting to take place, the Grid must grant a p_g range that provides enough gain to the agents, in order to overcome the underlying individual shifting costs. Here we study the dynamics associated with this p_g range selection. Specifically, we examine the average reducing coalition size formed at each t_h, given variable p_g prices granted for collective consumption shifting. To do so, we simultaneously add an offset to both the p_g^{max} and group p_g^{min} values produced by Eq. (47), with the offset ranging from −0.015, to +0.025 of their initial values; then, following formation, we observe the average number of agents in reducing coalitions for each peak interval.

Fig. 5 demonstrates this concept, where average coalition sizes over 50 simulation days are plotted against group price range variations. If the *CF*1 method is applied, it is obvious that as p_g

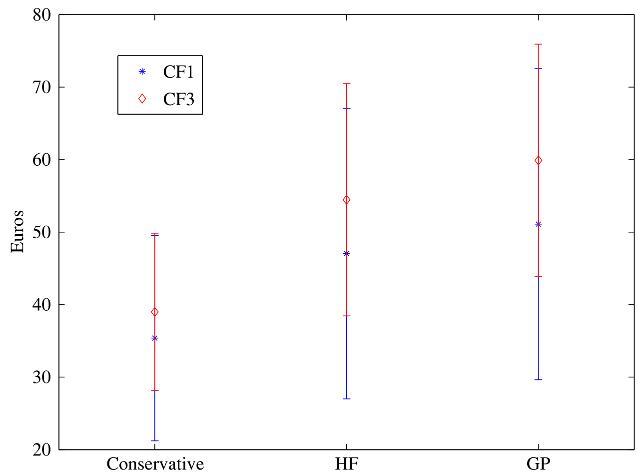


Fig. 4. Average final gain and standard deviation generated by each prediction method when using $CF1$ and $CF3$.

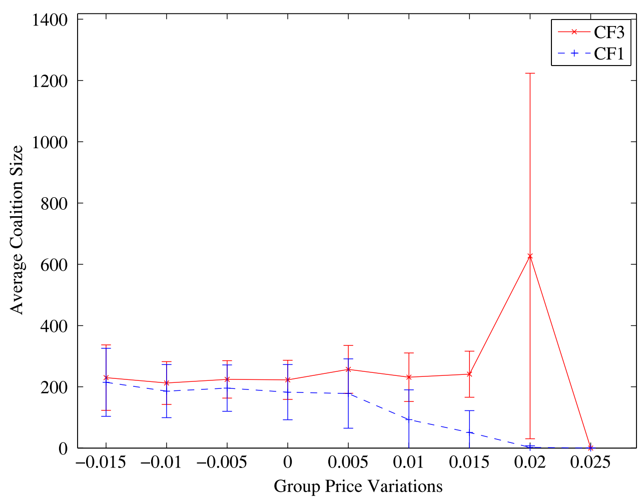


Fig. 5. Average coalition size vs. p_g increase for the coalition formation methods $CF1$ and $CF3$.

increases to get closer to p_{low}, fewer agents decide to contribute—and, subsequently, less consumption is finally shifted. In the case of $CF3$, however, we observe that the average coalition size is in general more stable; moreover, for a $p_g^{max} = 0.05625 + 0.015 = 0.07125$ and above (i.e., for p_g^{max} values close to p_l), the $CF3$ mean and standard deviation of the average coalition size increases, in contrast to $CF1$—and both methods reach the value of zero for the maximum offset added (i.e., when p_g^{max} exceeds p_l and p_g^{min} is also high, it is no longer possible to form profitable coalitions).

This difference in the behaviour is explained as follows. First, recall that $CF1$ ranks contributors according to their contribution potential ξ_i, not accounting for the expected monetary gains to be created. This is acceptable in settings where agents have low shifting costs, and the formation of shifting coalitions is relatively easy, i.e. there is abundance of shifting capacities for the offered prices. On the other hand, when the better price p_g is high, it becomes harder to come up with a coalition of contributors offering large shifting quantities at such high prices. Thus, it becomes more probable to create infeasible coalitions that violate one of the constraints of Eqs. (24)–(26) during the $CF1$ process. Hence, the average coalition size gradually drops to zero.

In the case of $CF3$, however, contributors are ranked according to their expected gain, which is a very good indicator of the coalition's feasibility potential. This method is able to guarantee the coalition's feasibility, even if a larger number of participants is required in order to achieve it. This is in fact illustrated in Fig. 5: when few agents in the population can profit directly from the granted p_g price, the required shifting amount is more difficult to gather, and more agents have to join in the coalition to do so.

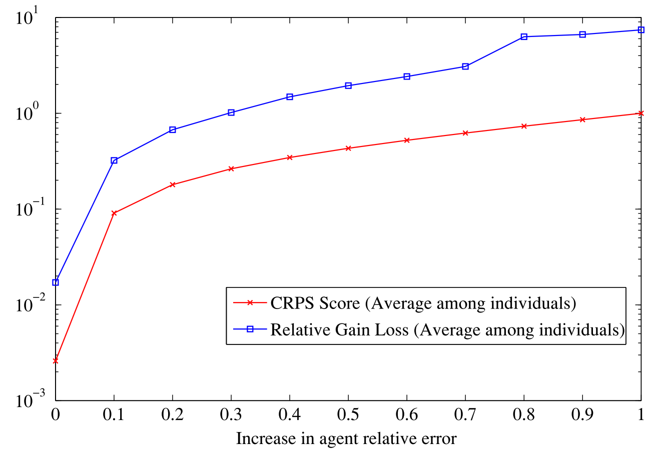


Fig. 6. Average losses in gain (increase in bill) due to *CRPS*, as induced by increasing participant inaccuracies, across all intervals.

7.6. Assessing the CRPS effect

In this set of experiments, we gradually increase the relative errors of the agents and measure the drop in their final gains after applying the *CRPS* scoring rule. Specifically, the relative error of each agent was progressively increased from 0 to 1 by 0.1 over 11 complete runs of 20 simulation days each. This naturally leads to a higher (i.e., worse) *CRPS* score for the individual agents, and thus a bad *CRPS* score for their corresponding reducing coalitions. Fig. 6 plots together the *CRPS* score and losses in gain,[26] for the average individual. We observe that as an individual agent's *CRPS* score gets worse, its gain losses increase. In the vertical axis, we present the relative difference d between the final bill payed b_i (calculated *after* the *CRPS* rule has already been applied) and the $p_i^{eff} q_i$ expected to be paid at the time of the formation of the coalition (i.e., *before* applying *CRPS*):

$$d = \frac{b_i - p_i^{eff} q_i}{p_i^{eff} q_i}. \tag{48}$$

Notice that this relative difference might be much larger than 2 for a "highly inaccurate" agent. This is because, firstly, if the difference between the statements and the final actions is very high, applying the *CRPS* can double the price (cf. Eq. (15)). Secondly, rising individual *CRPS* scores correspond to reduced cooperative effectiveness, and thus the final effective group price (and cooperative bill) is higher than anticipated, resulting to lower-than-expected gains.

It is therefore clear that *CRPS* can induce substantial "penalties" on erroneous agents and coalitions. Thus, employing *CRPS* provides definite incentives for the agents to produce accurate statements regarding their shifting capacities.

CRPS penalizing only cooperative performance. In this part we also test a case where the *CRPS* is applied for producing the *overall* cooperative bill (Eq. (30)) only, but *not* for determining the

26 Note that this does not mean the average gain is negative, just that it decreases as a result of *CRPS*-generated penalties.

Table 10
Average differences between expected and final gain per contribution, with and without internal *CRPS* penalization.

All surplus and gain values average over participations	Without internal penalty	With internal penalty
Cooperative "surplus" (€/day)	0	0.10
Exp. gain per participation for agents with $CRPS > 0.2$	0.03132	0.03132
Final gain per participation for agents with $CRPS > 0.2$	0.02703	0.02646
Difference	0.00429	0.00486
Exp. gain per participation for agents with $CRPS \leq 0.2$	0.03076	0.03076
Final gain per participation for agents with $CRPS \leq 0.2$	0.03060	0.03095
Difference	0.00016	−0.00019

individual bills of the participants. That is, instead of using Eq. (33), the final bill of the individuals b_i is calculated by

$$b_i = \frac{p_i^{eff} q_i}{\left(\sum_{j \in C} p_j^{eff} q_j\right)} B_C \tag{49}$$

where B_C is given by Eq. (30).

Table 10 summarizes the differences between skipping internal penalization (via using Eq. (49)) and not. The first thing to observe is that the "cooperative surplus" is non-existent when *CRPS* is not applied internally, as expected since the exact amount of the cooperative bill is now split among the participants (charged via Eq. (49)). Then, to better illustrate the desired effect of the internal *CRPS* penalization, we measure the difference between expected and final gain for agents with *CRPS* score higher than 0.2 (which we can consider as inaccurate participants) and for those with score lower than 0.2 (accurate participants). As shown in the middle column of Table 10, when there is no internal penalty applied to cooperative members, there exists a difference in final gains and in "losses *wrt.* expected gains" between the highly erroneous and less erroneous agents. However, when applying internal individual penalization, these "losses" for the erroneous participants rise, while for the non-erroneous ones the average final gain exceeds the value of the expected gain. Note that the expected gain is given by Eq. (29), that does not preclude the possibility that initial gain estimates are pessimistic. Thus, making more gains than expected when being accurate, in the presence of highly inaccurate participants is not overly surprising. This exacerbates the differences in gain transfers between these two agent classes: it really pays to be truthful and accurate. In a nutshell, applying the *CRPS* "internally", clearly incentivizes the individual agents to be accurate and deliver what they promised.

7.7. Experimenting with different price balancing techniques

In this subsection, we compare the performance of the various optimization criteria of Section 4 with respect to resulting price assignments and resulting gain per participant. We employ the *cvx* toolkit of *Matlab* to obtain the solutions of the various mathematical programming methods of Section 4.2. All different pricing methods operate on the same input data. In this way, the difference in behaviour occurring by using the various criteria is clearly demonstrated, as shown in Figs. 7 and 8. The x-axis shows the agent IDs coalescing to shift demand at a t_h, in this case from 1 to 68. Note that agent IDs are ranked in *descending order* with respect to the gains granted by considering p_C as the price paid.

Fig. 7 in particular, depicts the participant $\hat{p}_i$s and p_i^{eff}s, where the latter are calculated with the various methods that we explained earlier. As we observe, certain pairs of criteria perform similarly: specifically, criteria 2 (maximize sum of individual gains) and 3 (minimize sum of gain losses), criteria 1 (minimize max individual gain loss) and 4 (sum of criterion 1 and criterion 3), and our proposed heuristic balancing and criterion 5 (minimize price differences).

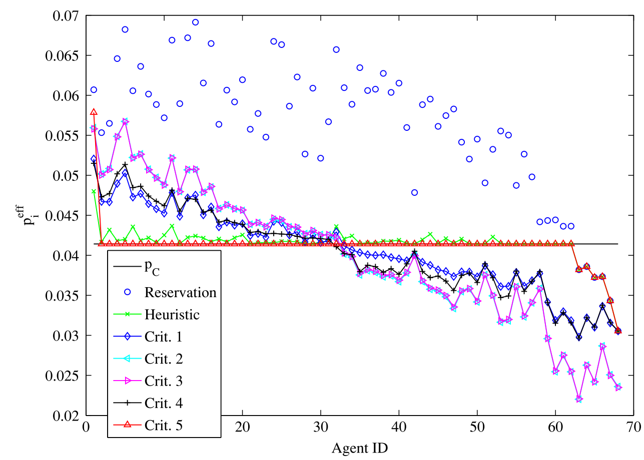


Fig. 7. Prices (€/kWh shifted) assigned to each individual for a sample peak interval as a result of employing our pricing methods.

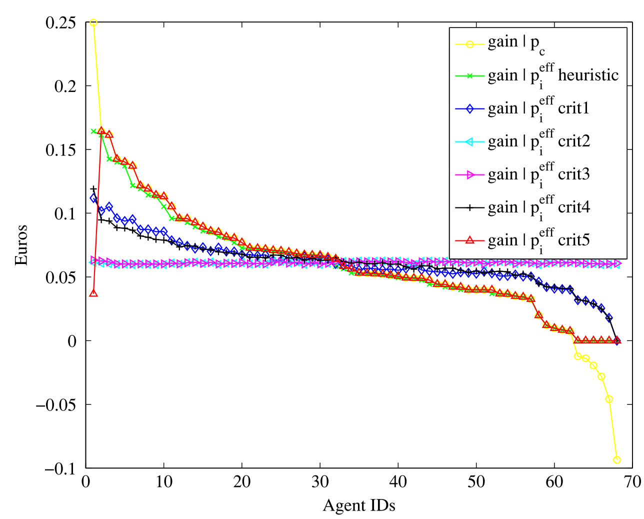


Fig. 8. Expected gains for each participant for a sample peak interval, when applying different reward sharing approaches.

The actual effects of variable pricing can be seen in Fig. 8, where we present the gains for each agent, when assigning the calculated $\mathbf{p}^{eff}$; also, the gain before we perform internal price balancing is shown with the yellow curve. It is clear from the figure that optimization methods 2 and 3 tend to dispense the amount of gain equally (within some tolerance levels) among the contributors. This can be considered as a violation of the mechanism's fairness, as participants end up enjoying the same amount of gain regardless of the value of their individual contribution.

By contrast, the heuristic price balancing technique (green curve), maintains the ranking with respect to the gain amount, and so does optimization criterion 5, except for the higher gain participant. The performance of criterion 5 is mainly due to the l_1 norm application, which tries to change values in as few p_i^{eff}s

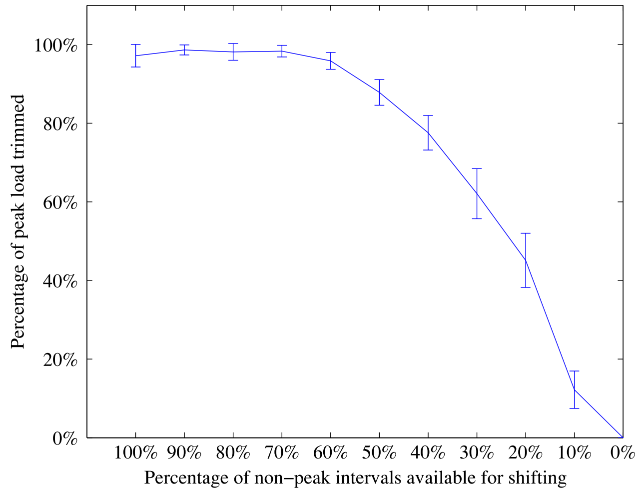


Fig. 9. Cooperative effectiveness versus contributor availability.

as possible. Notice however that, unlike the heuristic balancing method, this criterion does not guarantee that the original agents ranking *wrt.* gain is maintained after balancing. Criteria 1 and 4, on the other hand, appear to maintain this ranking, but are more generous to lower ranking agents (thus, the gain-related "gap" or "social distance" among the agents appears to be closing up when using these methods).

Last but not least, it is important to note that no gain is lost in expectation when adopting any of the proposed internal pricing methods. As we observe in Fig. 8, despite the existence of (originally) negative gain agents (the yellow curve for which lies below zero), there are no negative expected gains for any of the participants after internal pricing (regardless of the specific method used).

7.8. Participant availability

Finally, we examine the relationship between agent availability and cooperative effectiveness. In particular, we ran the simulator for 11 iterations, each lasting for 30 days. Now, in each iteration, we raise the probability of an agent being unavailable for participation during a time interval.

Results are shown in Fig. 9, where we can observe that the cooperative achieves nearly 100% peak load trimming effectiveness when agents are available for at least 70% of the time. After that point, cooperative effectiveness drops in a nearly linear manner proportionally to the percentage of time intervals during which agents are available. Thus, the higher the participants availability, the greater the effectiveness of the shifting scheme.

8. Related work

Here we brief-review related work and outline its connections to our approach. To begin, the beneficial nature of cooperative *producer* VPPs is demonstrated in [9], where the benefits arising from distributed energy resources coalescing to profitably sell energy to the Smart Grid. Our approach also advocates the creation of cooperative VPPs, but on the *consumer* side—and details a complete framework for the cooperative shifting of consumption loads, to achieve the proactive and effective large-scale electricity demand curve balancing.

Kota et al. [10] were actually the first to propose a demand side management scheme involving electricity consumer cooperatives. Their scheme comes complete with certain incentive compatibility guarantees, but differs to ours in many important ways. In their scheme, consumers represented by agents form cooperatives with the purpose to participate in the (wholesale) electricity markets *as if they were producers*, essentially selling energy *nega-watts* in the form of reduction services. However, their approach would, in most countries, require legislature changes in order to be applied in real life. Moreover, agents in their scheme have to essentially sign strict contracts with the Grid to participate in the market, and cooperative members risk the danger of being significantly "punished" for not meeting their obligations through what might appear to a small-scale, household consumer as a complicated protocol. Thus, real consumers might prove reluctant to join cooperatives and participate in their scheme. By comparison, in our scheme, agents simply run the danger of being granted less profit for their actions than originally promised. Importantly, they are also capable of minimizing this risk, due to the fact that they are guided a priori (and have agreed) to the time slots where they can actually *shift* consumption to. Indeed, no guidelines whatsoever as to where to shift consumption to are provided in [10], and deals agreed there involve *reduction promises* only. Our approach allows for a more relaxed agent-Grid interaction, for explicit power consumption *shifting* to targeted time intervals.

Other approaches, like those in [35] and [36], aim to optimize consumption schedules via searching for Nash equilibria in specific game settings. We chose not to follow this line of research, because it requires that every "player" retains a specific and fixed strategy. This cannot be realistically assumed to hold – let alone be guaranteed – in any large, open multiagent environment.

Several simple reduction schemes, that promise reduced flat electricity rates for lower consumption levels over prolonged periods of time, are already in place in the real world [8]. Unfortunately, most of those schemes can be easily manipulated in "unethical" ways by individuals. For instance, they have no means to exclude consumers that simply happened to be able to not demand electricity over some period; that is, an individual could go away on holiday for a month, and collect a cash reward for doing so. Our scheme does not suffer such problems, as it *(a)* rewards consumption reduction – and, importantly, promotes *consumption shifting* – on essentially an hour-to-hour basis (planned a day ahead), and *(b)* rewards these "short-term" services based on how successfully they were delivered.

Returning to the demand management schemes, in recent years economists have been advocating the use of "dynamic", *real-time pricing (RTP)* schemes as a means to avoid market inefficiencies and the aforementioned shortcomings of existing demand reduction schemes [37]. However, RTP has been strongly criticized for promoting the complete liberalization of household energy pricing. In addition, due to increased levels of consumer uncertainty regarding imminent price fluctuations, it may also require user manual response or the continuous monitoring of smart meters, leading to difficulties in application. Moreover, recent work shows that RTP mechanisms do not necessarily lead to peak-to-average ratio reduction, because large portions of load may be shifted from a typical peak hour to a typical non-peak hour [38]. By contrast, our scheme explicitly takes into account the Grid's perspective on which time intervals are preferable for shifting consumption to, and imposes the necessary constraints to avoid – to the extent possible – the event of new peaks arising. The work of Gottwalt et al. [15], assumes variable electricity prices and presents an environment that simulates the behaviour of house tenants participating in demand side management efforts. However, it makes no references to the potential discrepancies between expected and final actions. By contrast, our model captures such uncertainties, and uses specific techniques to promote efficiency, as we have explained in Sections 3 and 6.

Another field related to our work here is performance monitoring and prediction. Stochastic filtering techniques, Kalman filters and their variants in particular, have been widely used in a variety of domains; here we mention only a couple of examples that are most relevant to our work. In [39], authors use an *extended Kalman filter (EKF)* whose parameters are given by a *particle swarm optimization* algorithm, to compute the synaptic weights of a neural network. This neural network is then used to predict wind turbine production; however, *EKF* is prone to errors due to inaccurate approximations. The approach in [40], on the other hand, employs Gaussian process regression for learning motion and observation models by some training measurements. Resulting *GP* parameter values are fed in to an *unscented Kalman filter (UKF)*, in order to perform tracking of an autonomous micro-blimp. The approach successfully tackles precision problems that appear from the combination of noisy observations and uncertainty in the model. *GP*s have also been used recently by [41] to forecast electricity demand, and the predictions are tested in the electricity market simulation of PowerTAC.

Finally, various *scoring rules* have been widely used to incentivize agents to act by the rules and not deviate intentionally. The work of [42] proposes the use of scoring rules that compensate *forecasting experts* for the utility loss they suffer by stating truthful forecasts. Other recent works in the Smart Grid domain, use the *spherical* scoring rule to incentivize participants to accurately predict aggregate electricity demand or demand response actions [43,44]. We chose to use the *CRPS* instead of the spherical scoring rule, because the *CRPS* is indifferent between the sign of the error, while the spherical is not [45]: our goal here was to incentivize precise forecasts, and deviations to either side – i.e., either lower, or higher than stated – should be penalized equally.

9. Conclusions and future work

In this paper, we presented a complete framework for large-scale cooperative electricity consumption shifting, to promote the proactive balancing of the demand curve. Our proposed shifting scheme is directly applicable, and promotes agent efficiency in the face of uncertainty. No additional infrastructure or specialized equipment is required for deployment: off-the-shelf smart metering and transmission equipment can be readily employed, and the computational complexity of the overall mechanism planning the cooperative shifting operations is low. This is achieved via the use of effective coalition formation methods we developed; and via employing the *CRPS* strictly proper scoring rule (which incentivizes truthful and accurate forecasts), alongside with specific stochastic filtering techniques (that allow the effective prediction of agent demand shifting performance). Furthermore, our mechanism is equipped with internal pricing schemes that employ gain transfers within a cooperative, to make it worthwhile for individuals to participate in shifting operations and thus guarantee the scheme's effectiveness and profitability. Our mechanism possesses desirable theoretical properties: individual rationality, truthfulness, and (weak) budget balancedness. We ran extensive simulations based on real consumption data, and demonstrated experimentally the effectiveness of our methods. Based on our results, we believe our methods could bring tangible benefits to energy cooperatives and other business entities operating in this domain.

Future plans include the acquisition of a real dataset regarding *shifting costs* and more testing in real world scenarios. These are difficult or next to impossible to acquire, either because, to the best of our knowledge at the time of writing, they do not exist, or because they are not publicly available. Moreover, we plan to devise a realistic model defining possible stochastic dependencies (or "transitions") among past $\hat{\sigma}$ forecasts of the agents, and operate upon it with *GP* combined with extended Kalman filtering, for improved monitoring ability. For this, we will employ crowdsourcing combined with serious games techniques. In addition, we intend to develop methods for automatically clustering and re-clustering consumers with respect to inferred preferences. Moreover, in ongoing work we investigate the use of cryptocurrencies [46] for decentralized computation of the agents' payments, without the need of a trusted cooperative manager, and without the need of transmission of sensitive data, such as personal shifting costs [27]. Finally, we plan to transform our software suite to an integrated simulations environment—for the benefit of academic research, and of energy companies and cooperatives alike.

Acknowledgment

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at http://dx.doi.org/10.1016/j.segan.2016.12.002.

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