Agent Cooperatives for Effective Power Consumption Shifting

Charilaos Akasiadis and Georgios Chalkiadakis
Electronic and Computer Engineering
Technical University of Crete
Kounoupidiana Campus, Chania, Greece, GR73100
{akasiadi, gehalk}@intelligence.tuc.gr

Abstract
In this paper, we present a directly applicable scheme for electricity consumption shifting and effective demand curve flattening. The scheme can employ the services of either individual or cooperating consumer agents alike. Agents participating in the scheme, however, are motivated to form cooperatives, in order to reduce their electricity bills via lower group prices granted for sizable consumption shifting from high to low demand time intervals. The scheme takes into account individual costs, and uses a strictly proper scoring rule to reward contributors according to efficiency. Cooperative members, in particular, can attain variable reduced electricity price rates, given their different load shifting capabilities. This allows even agents with initially forbidding shifting costs to participate in the scheme, and is achieved by a weakly budget-balanced, truthful reward sharing mechanism. We provide four variants of this approach, and evaluate it experimentally.

Introduction
The expanding application of Smart Grid and “clean” energy production technologies necessitates the adoption of novel, “intelligent” techniques to better coordinate and run the future power production and distribution process [Fang et al., 2011; Ramchurn et al., 2012]. As technology evolves and electricity demand rises, the task to keep it precisely balanced with supply at all times becomes especially challenging [MIT authors, 2011]. Maintaining demand curve stability, in particular, can alleviate the risk of disastrous electricity network collapses, and leads to financial and environmental benefits—as then some generators can be run on idle, or even be shut down completely [MIT authors, 2011].

To this end, several load control programs have been proposed, where electricity consumers are encouraged to abridge their consuming activities, or shift them to off-peak hours in order to reduce peak-to-average ratio (PAR) [MIT authors, 2011; Davito, Tai, and Uhlanger, 2010]. Apart from industrial and other large-scale consumers, the participation of residential customers is also possible, provided that smart meters or similar electricity management systems are available [Sastry et al. 2010, van Dam et al. 2010]. Typically, such schemes either involve an intermediary company which manages consumers who agree to contribute to the “trimming down” of the demand curve in the event of an impending critical period; or provide a reduced “flat” electricity consumption rate or rebate to consumers for lowering their consumption over a prolonged time period; or require the use of dynamic, real-time pricing (RTP) [Albadi and El-Saadany, 2008; Asmus, 2010; Bushnell et al. 2009]. Most of the “flat-rate” based schemes can be easily manipulated by individuals, however [Bushnell et al. 2009]; while 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, RTP can require user manual response or the continuous monitoring of smart meters, leading to difficulties in application. Recent work also shows that RTP mechanisms do not necessarily lead to PAR reduction, because large portions of load may be shifted from a typical peak hour to a typical non-peak hour [Mohsenian-Rad and Leon-Garcia, 2010]. Other approaches aim to optimize consumption schedules via searching for Nash equilibria in specific game settings [Ibars et al. 2010, Mohsenian-Rad et al. 2010], but require players to retain fixed strategies, which is unrealistic for large, open environments.

At the same time, recent work in the multiagent systems community has put forward the notion of Virtual Power Plants (VPPs). These correspond to coalitions of electricity producers or consumers, who cooperate in order to meet market demands, mimic the reliability characteristics of traditional power plants, and deal efficiently with the issues that accrue [Asmus, 2010; Ramchurn et al., 2012]. In particular, the work of [Kota et al., 2012] has proposed the formation of consumer Cooperatives for Demand Side Management (CDSMs), with the aim of “selling back” to the electricity market the amount of load that was not consumed due to proactive reduction measures. In their scheme, which comes complete with certain incentive compatibility guarantees, consumers form cooperatives with the purpose to participate in the wholesale electricity markets as if they were producers, essentially selling energy negawatts in the form of reduction services. Though visionary, their approach requires a legislature change in order to be applied in real life. Moreover, no guidelines whatsoever as to where to shift consumption to are provided by that model, and deals agreed...
there involve reduction promises only.

In contrast, here we propose a simple power consumption shifting scheme which can be applied directly, including residential, commercial and industrial customers. Our scheme motivates self-interested business units, represented by autonomous agents that potentially form coalitions, to shift power consumption from peak intervals to lower demand ones, in order to receive lower electricity price rates for their contribution. In more detail, the independent system operator (ISO), usually the national Grid, gives information a day ahead for the time intervals that consumption needs to be reduced at, and those that it is best to shift to. Consumption during these preferred non-peak intervals is granted a better price. Then, consumers weigh own costs and potential profits, and choose to participate in a shifting operation or not. The employment of a strictly proper scoring rule, CRPS, incentivizes agents to report their predicted shifting capabilities as truthfully and accurately as possible.

Now, it is conceivable that the Grid would be willing to promise significantly lower electricity rates for considerable shifting efforts only, which cannot normally be undertaken by any consumer alone (due to small reduction capacity or high shifting costs). As a result, agents are motivated to join forces in a cooperative, to coordinate their actions so as to reach the expected reduction levels and make their participation in the scheme worthwhile. This is similar to group buying in e-marketplaces, where some members can obtain items that cost more than they are able to pay for alone, but due to group internal price fluctuations set by corresponding mechanisms, the purchase finally becomes advantageous to all [Li et al., 2003; Yamamoto and Sycara, 2001].

Inspired by work in that domain, we devise an individually rational, incentive compatible, and budget-balanced reward sharing mechanism which determines variable reduced electricity prices for coalescing agents via internal money transfers, and incentivizes them to participate in the consumption shifting scheme. We propose four variants of this mechanism, and evaluate their effectiveness.

To the best of our knowledge, this is the first specific protocol and mechanism that achieves large-scale electricity demand shifting under uncertainty, imposing the necessary constraints to avoid the event of new peaks arising; it does so without the use of “intermediary parties” or real-time pricing; and provides further testimony to the benefits arising from the formation of agent cooperatives in the Smart Grid.

**Model and Shifting Scheme**

The electricity pricing scheme used in many countries consists of two different rates, a daily and a nightly one. In our model, we also assume that there exist exactly two different price levels \( p_{\text{high}} > p_{\text{low}} \), that characterize each specific time interval \( t \) based on a demand threshold \( \tau \) under which electricity generation costs are lower. The high demand intervals with \( p_{\text{high}} \) price are considered to be peak ones, at which demand needs to be reduced. We denote these as \( t_h \) in a \( T_H \) set, as opposed to low price intervals \( t_l \in T_L \).

Now, given the daily consumption pattern known to the Grid, it would ideally like consumption to drop to a safety limit \( s_l \) that is placed below \( \tau \). Consuming at the safety limit would ensure that some low cost generated load is available in case of an emergency, minimizing the risk that high-cost generators would have to be turned on. That is, the Grid ideally wants to curtail consumption by \( Q^{sh} \geq q^{sh} \), where (i) \( Q^{sh} \) is the load normally consumed over the safety limit at \( t_h \), and (ii) \( q^{sh} \) is the minimum amount of load whose potential removal can, under the Grid’s estimations, allow for a better electricity price to be offered to contributing reducers.

Intuitively, \( q^{sh} \) 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 \( q^{sh}_i \), and that shifted by \( i \) to some \( t_l \) as \( q^{sl}_i \). The following must then hold: (1) \( \sum_i q^{sh}_i \geq q^{sh} \) that is, the amount of load reduced must be higher than the minimum needed at \( t_h \); (2) \( \sum_i q^{sh}_i \leq \sum_i q^{sh}_i \), \( \forall i \) 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); (3) \( \sum_i q^{sh}_i \leq Q^{sh}, \forall t_h \in T_H \), i.e., the sum of all reducing agents shifted load to all non-peak intervals must be at most equal to \( Q^{sh} \), assuming that the Grid has no interest in further reducing consumption, once it has reached \( s_l \); and (4) \( \sum_i q^{sh}_i \leq q^{sh}_i, \forall t_l \in T_L \), namely, the total load shifted to each \( t_l \) must not exceed the \( q^{sh}_i \) quantity originally available under \( s_l \) at \( t_l \). The objective is to keep demand close to \( s_l \) in as many intervals as possible.

In contrast, here we propose a simple power consumption shifting scheme which can be applied directly, including residential, commercial and industrial customers. Our scheme motivates self-interested business units, represented by autonomous agents that potentially form coalitions, to shift power consumption from peak intervals to lower demand ones, in order to receive lower electricity price rates for their contribution. In more detail, the independent system operator (ISO), usually the national Grid, gives information a day ahead for the time intervals that consumption needs to be reduced at, and those that it is best to shift consumption to. Consumption during these preferred non-peak intervals is granted a better price. Then, consumers weigh own costs and potential profits, and choose to participate in a shifting operation or not. The employment of a strictly proper scoring rule, CRPS, incentivizes agents to report their predicted shifting capabilities as truthfully and accurately as possible.

Now, it is conceivable that the Grid would be willing to promise significantly lower electricity rates for considerable shifting efforts only, which cannot normally be undertaken by any consumer alone (due to small reduction capacity or high shifting costs). As a result, agents are motivated to join forces in a cooperative, to coordinate their actions so as to reach the expected reduction levels and make their participation in the scheme worthwhile. This is similar to group buying in e-marketplaces, where some members can obtain items that cost more than they are able to pay for alone, but due to group internal price fluctuations set by corresponding mechanisms, the purchase finally becomes advantageous to all [Li et al., 2003; Yamamoto and Sycara, 2001].

Inspired by work in that domain, we devise an individually rational, incentive compatible, and budget-balanced reward sharing mechanism which determines variable reduced electricity prices for coalescing agents via internal money transfers, and incentivizes them to participate in the consumption shifting scheme. We propose four variants of this mechanism, and evaluate their effectiveness.

To the best of our knowledge, this is the first specific protocol and mechanism that achieves large-scale electricity demand shifting under uncertainty, imposing the necessary constraints to avoid the event of new peaks arising; it does so without the use of “intermediary parties” or real-time pricing; and provides further testimony to the benefits arising from the formation of agent cooperatives in the Smart Grid.

**An Efficient Consumption Shifting Scheme**

An agent \( i \) that wishes to participate in the consumption shifting scheme, is characterized by (a) its reduction capacity \( r_i \), namely the amount of load that it is willing to curtail (e.g., by shifting) at a time interval \( t \), and (b) its shifting cost \( c^{sh}_{t_i} \), that is the cost that occurs if consumption of a unit of energy is shifted from (a peak interval) \( t_h \) to (a non-peak) \( t_l \). Given the above, the exact shifting protocol is as follows.

Every day, the Grid announces the forecasted (according to its own information/uncertainty) peak intervals \( T_H \) and the most preferable non-peak intervals \( T_L \); and also announces the (quantity-dependent) price rates it awards for consumption in \( T_l \) (we elaborate below). It then waits for shifting proposals by business units. Each business unit (consisting of a single consumer or more), can interact with the Grid and state its overall load reduction capability during announced \( T_H \) intervals, and a number of intervals \( t_i \in T_L \) to which it is willing to shift consumption to. This procedure is called bidding. Note that for each \( t \in \{ T_H \cup T_L \} \) there can be more than one bidder. Furthermore, bidders can pledge to shift some load from one high consumption \( t_h \) interval to several low consumption \( t_l \) ones. Moreover, each bidder has
we have exact forecast, and CRPS
tion from t
consumption requirements and business needs); while
reduced electricity bill
accepted after consideration of the constraints
future event, and x the actual occurrence itself. The rule is
strictly proper if it incentivizes forecasters to state their true
beliefs P only, and it does so by maximizing expected re-
ward only when \( P = P \). Use of CRPS allows us to directly
evaluate probabilistic forecasts, and the score is given by:

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

(1)

In our setting, \( \mathcal{N}(\mu, \sigma^2) \) is the uncertainty over the expected
relative error regarding the reduction capacity, as reported
by an agent (and estimated given its private knowledge of
consumption requirements and business needs); while x is
the actually observed error, \( \phi \) the PDF and \( \Phi \) the CDF of
a standard Gaussian variable. A CRPS value of zero signi-
fies a precise forecast, while a positive value shows the dis-
tance 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 \( \text{CRPS}(\mathcal{N}(\mu, \sigma^2), x) \) as CRPS, and write CRPS\( i \) to denote the CRPS rule applied to \( i \)'s performance.

Summarizing, the Grid announces peak intervals \( t_h \) that
need consumption reduction, and \( t_l \) intervals to which shifting
is acceptable. The Grid determines and announces a bet-
ter price rate \( p_{\text{group}}(q) \) to offer for the consumption of load \( q \)
at (any) \( t_l \) instead of \( t_h \). This price is awarded if the quantity
of the load shifted from \( t_h \) exceeds \( q_{\text{min}} \). Consumers then
make their bid collectively or alone, and state their expected
reduction capacity \( q_{\text{min}} \) and corresponding uncertainty, along with
the intervals that they are willing to shift to. Bids are accepted after consideration of the constraints (1)-(4) stated above. Finally, an agent \( i \) whose bid was accepted, receives a reduced electricity bill \( B_i \) given its actual contributed reduction \( \bar{r}_{i_h} \) at \( t_h \), and its final consumption at \( t_l, q_{i_l}^h \), as follows:

\[
B_i = (1 + \text{CRPS}_i) q_{i_l}^h p_{\text{group}}(\bar{r}_{i_h})
\]

(2)

Strict propriety is maintained in Eq. 2, since the only factor
depending on agent forecasts is the \( 1 + \text{CRPS}_i \) one.

**Agent Incentives and Decisions** The participation of each
agent in the scheme obviously depends on its individual
costs and potential gains. Suppose that an agent \( i \) ponder-
the possibility of altering its baseload consumption pattern\( ^1 \)
by shifting some electricity consumption \( q \) from an inter-
val \( t_h \) to \( t_l \). This shifting is associated with a cost \( c_{i_h + t_l}^l \)
for the agent. The gain that an agent would have for shifting
\( q \) to \( t_l \) given \( t_i \)’s lower price \( p_{\text{group}} \), would be equal to
gain \( (i) \mid p_{\text{group}} = q(p_{\text{high}} - p_{\text{low}} - c_{i_h + t_l}^l) \) since the agent
would be able to consume \( q \) at \( t_l \) for a lower rate. How-
ever, under normal circumstances this gain is negative for
the agent; if not, then the agent would have already been able
to make that shift (and its baseload pattern would have been different). Now, if an even lower rate \( p_{\text{group}} \) is granted for con-
sumption of \( q \geq q_{\text{min}} \) at \( t_l \) s.t. \( p_{\text{group}} + c_{i_h + t_l}^l \leq p_{\text{high}} \),
then the agent is incentivized to perform the shift.

**Agent Cooperatives**

In the general case, it is very rare even for large industrial
consumers to have reduction capacity \( \geq q_{\text{min}} \). Therefore, the
agents need to organize into cooperatives in order to coordi-
nate their actions and achieve the better rates promised by
the Grid for effective consumption shifting. At every given
time interval \( t_h \) earmarked for potential consumption redu-
tion, only a subset \( C^{th} \) of cooperative members might be
available for shifting services. We assume that every mem-
ber agent announces its availability to a cooperative manager
agent, along with its reduction capacity \( r_{i_h}^l \); its confidence
\( \mathcal{N}(\mu, \sigma^2) \) on actually reducing that amount at \( t_h \);
and the set of \( t_l \) intervals that it pledges to move consumption to.

Even so, more often than not, it is impossible for all agents
in \( C^{th} \) to participate in the cooperative effort. This is be-
because their shifting costs of some of them might be so high
that do not allow their inclusion in any profitable cooperative
bid. Therefore, only a subset \( C \) of \( C^{th} \) will be selected for
participation in the bid. Any such shifting bid is composed by
four parts: \( t_h \), the high cost interval to reduce consump-
tion from; \( r_C \), 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 move consumption to, along the set of corresponding quan-
tities that will be moved to each \( t_l \); and an estimate of its
\( \mathcal{N}(\mu_C, \sigma^2_{C,t_h}) \) joint relative error on predicted \( r_C \). The bid
is determined so that the collective expected gain from the
shifting operation is non-negative (we provide the details of
how this is ensured below). Assuming that \( C \) was selected
and reduced by \( r_C \), the bill \( B_C \) charged to the cooperative
for consuming \( q_C^l \) is given by Eq. 2 (substituting \( C \) for \( i \)):

\[
B_C = (1 + \text{CRPS}_C) q_C^l p_{\text{group}}(r_C)
\]

Now, even if the collective expected gain from the bid is
positive, it is not certain that all individuals in \( C \) have a pos-
itive expected gain as well. Nevertheless, with positive col-
lective expected gain, the possibility of internal gain trans-
fers is raised, allowing non-negative (expected) gain for all
participants. These transfers have to be performed in such a
way so that the budget-balancedness of any cooperative bid
is ensured, at least in the weak sense. We now describe the
process by which the cooperative determines its bid at \( t_h \).

\( ^1 \)Note that this is constantly monitored by the Grid given agent
consumption over long time periods, and not “stated” by the agent.
Cooperative Bid Determination Since the Grid-awarded group rate depends on quantity reduced, we (originally) assume that the cooperative attempts to select a subset $C$ with maximal reduction capacity (we modify this assumption in subsequent algorithm variants). We now present an algorithm that achieves this, while ensuring that $C$ and each one of its members has a non-negative gain, and that budget-balancedness is ensured. In what follows, we drop time indices where these are clearly implied.

To begin, let $\hat{p}_i = (p_{\text{high}} - c_i)$ be agent $i$’s (implicitly stated) reservation price, that is, the highest price that $i$ is willing to pay for moving from $t_0$ to $t_1$ (in order to not suffer a loss). The algorithm then proceeds as follows.

First, for every $i$, we check 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). If that is not the case, then there exist some agents in $C^h$, for which there is a price they can accept to pay so as to move some of their consumption to $t_1$ without suffering a loss.

The algorithm then sets $r_i := r_i - \sigma r_i$ for all agents in $C^h$, that is, the cooperative makes a pessimistic estimate of an agent’s expected performance, given its stated uncertainty. The algorithm then ranks the agents by $r_i \hat{p}_i$ in decreasing order. Then, starting from the agent with the highest $r_i \hat{p}_i$ value, 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 $q_i$ to contribute, while being able to accept a relatively high (though reduced) energy price $\hat{p}_i$. This process continues until both of the following conditions are met for the maximum possible group of agents $C$:

(i) $\sum_{i \in C} r_i \hat{p}_i \geq r_C p_C$; and (ii) $r_C \geq q_{\text{min}}$

where $q_{\text{min}}$ is the minimum quantity admitting a “group price”, $r_C = \sum_{i \in C} r_i$, and $p_C = p_{\text{group}}(r_C)$ is the price rate offered by the Grid for reduction $r_C$.

To provide further intuition, note that the expected gain of every agent in some group $C$ given $p_C = \text{gain}(j | p_C) = r_j (\hat{p}_j - p_C)$. 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 $C$ and individual effective price of its members have to be dynamically determined by the cooperative, so that individual rationality is ensured.

Now, if all agents in $C^h$ are inserted in $C$ and $r_C$ is still lower than $q_{\text{min}}$, the problem is infeasible and we stop. Likewise, if all agents are in $C$ and $\sum_{i \in C} r_i \hat{p}_i - r_C p_C < 0$, the problem is again infeasible and we have to stop.

Assume that this has not happened, and both conditions have been met for maximal $C$.\footnote{That is, after a subset $C$ has met $r_C \geq q_{\text{min}}$, we kept adding agents to $C$ until by adding some $k$ we constructed a $C'$ for which $\sum_{i \in C'} r_i \hat{p}_i - r_C p_C < 0$, in which case $k$ is removed from $C'$.}

This means that there is at least one agent $j$ in $C$ with positive expected gain, given $p_C$. That is, $\text{gain}(j | p_C) = r_j (p_{\text{high}} - c_j - p_C) = r_j \hat{p}_j - r_j p_C > 0$; if not, then no agent has a positive gain, and thus $\sum_{i \in C} r_i \hat{p}_i - r_C p_C \leq 0$, leading to $\sum_{i \in C} r_i \hat{p}_i \leq r_C p_C$, contradicting condition (i) above. This also means that agents in $C$ are collectively willing to pay a total amount for moving their $r_i$ consumptions to $t_1$, which is greater than what their group is asked to pay for, given the offer $p_C$ for $r_C$.

Thus we have ended up with the maximal $C$ so that (i) and (ii) hold, and which contains some agents with positive and some with negative gain given $p_C$, and which we can now use to implement a gain transfer scheme so that all individual agents in $C$ end up with non-negative gain themselves.

Setting variable effective prices At this point the cooperative pre-assigns different effective price rates $p_i^{\text{eff}}$ to each contributor, producing bills that must sum up at least to $B_C$. 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 $C$ will receive an actual price rate that will be dependent on its CRPS score.

Thus, the cooperative initially sets $p_i^{\text{eff}} = p_C$, $\forall i \in C$, given the price $p_C$ expected, and proceeds to rank in decreasing order agents in $C$ according to their expected gain, that is $\text{gain}(i | p_i^{\text{eff}} = p_C) = r_i (\hat{p}_i - p_C)$. If all agents already have non-negative gain, then everyone pays $p_C$ and expects gain $(i | p_C)$ without need of balancing. If negativities exist, then we must rearrange $p_i^{\text{eff}}$ s.t. 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 $p_i^{\text{eff}}$ s.t. their gain becomes exactly zero. Then, we increase $p_i^{\text{eff}}$ of the top agent until its gain is equal to the $g_j$ gain of the $j = i + 1$ agent below (as long as $g_j \geq 0$). Then we do the same for the second top agent, until its gain reaches that of the third. We continue this way until all requested gain is transferred, or one’s gain reaches zero. If the latter happens, we move to the top again and repeat.

The $p_i^{\text{eff}}$ prices thus determined represent internally pre-agreed prices 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:

$$b_i = \frac{(1 + \text{CRPS}_i) p_i^{\text{eff}} q_i}{(\sum_{j \in C \setminus \{i\}} (1 + \text{CRPS}_j) p_j^{\text{eff}} q_j) + p_i^{\text{eff}} q_i} B_C \quad (3)$$

Strict propriety is ensured by this rule, as it is an affine transformation of a member’s CRPS, score; and 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.

Properties and Algorithm Variants The reward transfer scheme and the overall cooperative bid determination algorithm presented above have several desirable properties. Apart from (weak) budget balancedness, individual rationality is ascertained for all agents in $C$, as they all have non-negative expected gain from participation.

Moreover, the transfer scheme presented is truthful. Of course, since the agents operate in a large, dynamic, and
open environment, one cannot determine an incentive compatible mechanism in the Bayes-Nash sense, since analysing Bayes-Nash equilibria properties is computationally infeasible in this setting. 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. Given this uncertainty, the best that an agent can do is to be truthful regarding its shifting costs, capacity, and corresponding confidence: 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 \( p^{\text{eff}} \) 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. Also, in practice the cooperative could use estimates of industry-dependent shifting cost limits, to fend off any such attempts. Finally, an agent has to be as accurate as possible regarding shifting capacity and corresponding uncertainty, or will suffer a gain loss due to a bad CRPS score.

Last but not least, the computational cost of the overall bid determination process (which is in any case actually performed offline and a day in advance) is quite reasonable. Specifically, it is proportional to the cost of sorting at most \(| C^{t_h} | \) agents in every \( t_h \), twice (once when ranked according to \( r; p_h \), and once when ranked according to perceived gain).

Now, the scheme presented aims to achieve the lowest possible group price, through the addition of as many agents as possible into the reducing set of agents in any given \( t_h \), as long as budget balancedness and individual rationality are respected. Though this is clearly efficient for the Grid (since it apparently promotes the maximum possible reduction at any \( t_h \)), it is not necessarily efficient for the reducing coalition at \( t_h \). That is, it does not necessarily maximize the sum of the members expected gains: since agents with potentially high costs keep being added until it is possible for the coalition to sustain them through “gain transfers”, there might exist different reducer sets with higher overall gain.

The bid determination mechanism proposed above can thus be summarized as **Method 1**: Rank agents by potential and maximize expected capacity. We now proceed to consider 3 variants of that approach. We note that all variants include a reward transfer phase, and that, unless stated otherwise, retain all the good properties of our original approach. **Method 2**: Rank by potential, meet minimum capacity requirement. This method is exactly the same as the original one, with the difference that we stop adding agents in \( C \) the moment when the \( q_{\min} \) requirement is met.

**Method 3**: Rank by potential, maximize expected capacity, exclude agents with negative expected gain. This method is exactly the same as the original one, but once \( q_{\min} \) is met, an agent in the ranked list is added in the coalition only if its expected gain is non-negative wrt. \( p_{\text{group}} \) at the moment of its entry (otherwise the search for contributors continues).

**Method 4**: Rank by expected gain, maximize expected capacity. This method ranks prospective contributors by their expected gain wrt. \( p_{\text{group}} \) offered at the moment they are checked for entering \( C \). However, whenever an agent enters \( C \), \( p_{\text{group}} \) changes, and so does the expected gain of every \( C \) member. Thus, it has to be recalculated with every new entry, which increases computational complexity.

### Experimental Evaluation

In our experiments, we use simulated consumption patterns for 4968 agents, generated from distributions derived after a statistical analysis of 36 small and medium scale actual industrial consumers from India\(^3\) for a number of (simulated) days. Each simulation day is divided in 48 half-hour intervals. The \( \tau \) threshold is fixed to 96.5% of the maximum demand across all time intervals. The safety limit is set to 99% of \( \tau \), while \( q_{\text{high}} \) to 1% of the total load at \( t_h \); and the \( p_{\text{high}} \) & \( p_{\text{low}} \) values are set to the day-night prices specified by the public utility company of a given country. The \( p_{\text{group}} \) rate (in €/KWh) ranges from \( p_{\text{group}}^{\text{max}} = 0.05625 \) to \( p_{\text{group}}^{\min} = 0.0214 \), depending on reduction size \( q \):

\[
p_{\text{group}}(q) = \frac{p_{\text{group}}^{\min} - p_{\text{group}}^{\max}}{Q^{\text{h}} - q_{\min}^{\text{h}}} \cdot (q - q_{\min}^{\text{h}}) + p_{\text{group}}^{\max}
\]

with \( q \) ranging from \( q_{\min}^{\text{h}} \) to a maximum \( (t_h,\text{-specific}) Q^{\text{h}} \).

Individual shifting preferences are generated as follows. A beta distribution \( (a = 1, b = 43.444) \) is sampled twice per agent, giving the means (a higher and a lower) of 2 Gaussians (with \( \sigma = 0.01 \)) which are then sampled for each interval, resulting to the actual agent shifting cost. The higher-mean Gaussian is used for shifts from intervals with baseline consumption above the agent’s daily average to ones below that average; and the lower-mean one is used for all other shifting operations. Average shifting costs classify the agents into 3 cost levels: high / medium / low, numbering 811.86 / 2809 / 1347.14 agents respectively on an average run. Reduction capacities are estimated based on the variance of each agent baseline consumption, as this is a good indicator for its demand elasticity. Agent uncertainty stated for bidding, is provided by sampling a beta distribution, with \( a = 1, b = 5 \) (i.e., the great mass of the agent population has low to average uncertainty) and actual agent shifting actions are provided by sampling another beta, with \( a = 4, b = 2 \) (modeling the realistic case that at best the agents deliver what they promised, but often fail to do so).

In our experiments, we first assume that all 4968 agents participate in the cooperative. Note that running one simulation day involving all agents takes on average only 1.5 sec on a 3.3 GHz PC (with a further 110 sec for demand curves and shifting costs initialization period before simulation starts).

#### Methods Comparison

First, we simulated 100 days and compared the aforementioned methods, in order to choose one for further evaluation. Results are shown in Table 1.

**Method 2** clearly ranks lower than all others both in terms of cooperative gains and trimming effectiveness. This is

\(^3\)The exact same consumers as in the experiments of [Kota et al., 2012]; we thank that paper’s authors for providing the dataset.
because it forms coalitions of a “minimum” size, capable in expectation to shift just qmin. Thus, due to uncertainty governing actual agent behaviour, profits suffer when agent promises fail to materialize (and qmin is not reached).

In contrast, Methods 1, 3 and 4 all trimmed more than 98% of peak load, and have similar performance. When adopting Method 3 though, it is possible for an agent that could be favoured by the final pgroup price to be excluded from the coalition, if its contribution potential was checked early-on in the process, when the pgroup price awarded at that point happened to grant negative expected gain to that agent. Method 4 results to the highest cooperative gain, and highest consumption reduction, but is the most expensive computationally. Moreover, from the Grid’s point of view, it is probably not worth it to hand over an additional €37.28/day, 4.1% of the amount “paid” to Method 1, for a mere 0.35% increase in consumption reduction. Therefore, Method 1 appears to be the most appropriate for our purposes, as it is comparable to the rest both in terms of cooperative gains and trimming ability; is cheaper for the Grid to use; and allows even agents with initially negative expected gains to participate in the scheme. For those reasons, we chose Method 1 for further evaluation in this paper.

**Coalition Size vs. Group Price Range** Next, we examine the average reducing coalition size formed at each th given different pgroup prices granted for collective consumption shifting. More specifically, we simultaneously increase the pmax and pmin values produced by Eq. 4 up to +0.05 of their initial values, and observe the average number of agents in reducing coalitions for each peak interval. Figure 1 shows this concept, where average coalition sizes over 100 simulation days are plotted against group price range variations. It is obvious that as pgroup increases to get closer to plow, fewer agents decide to contribute—and, subsequently, less consumption is finally shifted. Thus, in order for shifting to take place, the Grid must grant a pgroup range that provides enough gain to the agents, given individual shifting costs.

**Other Observations and Further Insights** We measured that an average number of agents participating into each reducing coalition at some th is 47.7 individuals. The 30.6% of these are low shifting cost agents, whereas 57.8% are medium and 5.6% high cost. When the reward transfer scheme is enforced, the actual amount transferred on average during a gain balancing operation at a given th is negligible, in the order of €10^-3, and is granted by either low cost or medium cost consumers.

It is worth noting that the Grid each day grants back to consumers an average of only €895.56, from its average daily income of €354064.3. Note that we cannot account for the Grid profits emerging due to reduced generation costs from the evasion of peak intervals, because such an analysis would require information that is typically not disseminated by the Grid operators. However, since we observe that in an average simulation run an 98.616% of the peak load is “safely” shifted, we can infer that the Grid stands to gain from the shifting operations. Another positive side-effect is, of course, that power outages (and resulting costs) become more distant possibilities as the demand curve flattens out.

We also verified experimentally that CRPS incentivizes agent accuracy and efficiency. Specifically, we progressively increased the relative error of reducing agents every 10 simulation days with a step of 0.1 (over a period of 110 days). This leads to an almost linearly increasing (worsening) CRPS score for the agents and their reducing coalitions, with a corresponding reduction in their profits.

In a final set of experiments, we considered settings with considerably fewer consumers participating in the cooperative. With 30% of the agents participating, it is still possible to shift 98.52% of peak load, while 10% of the population manages to shift 93.82% of peak load. With 7% of agents participating, 75% of the total peak load is shifted; while 4% and 3% of all agents shift 51.86% and 12.66% of peak load respectively. Finally, 2.5% of all agents shift only 0.8% of the peak load. Thus, membership clearly has to reach a “critical mass” for the cooperative to be effective.

<table>
<thead>
<tr>
<th>Expected Cooperative Gain (€/day)</th>
<th>Method 1</th>
<th>Method 2</th>
<th>Method 3</th>
<th>Method 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Cooperative Gain (€/day)</td>
<td>895.56</td>
<td>24461.93</td>
<td>899.34</td>
<td>2139.38</td>
</tr>
<tr>
<td>Cooperative “Surplus” (€/day)</td>
<td>6.20</td>
<td>-273.89</td>
<td>6.20</td>
<td>6.13</td>
</tr>
<tr>
<td>Expected Reduction (KWh)</td>
<td>32856.45</td>
<td>12868.40</td>
<td>32861.60</td>
<td>32919.06</td>
</tr>
<tr>
<td>Final Reduction (KWh)</td>
<td>24454.32</td>
<td>9471.053</td>
<td>24461.93</td>
<td>24539.96</td>
</tr>
<tr>
<td>Peak (Demand ≥ τ) Trained (%)</td>
<td>98.616 (σ=0.75)</td>
<td>42.511 (σ=5.86)</td>
<td>98.619 (σ=0.73)</td>
<td>98.639 (σ=0.75)</td>
</tr>
<tr>
<td>Avg. Reducing Coalition Size</td>
<td>47.70598</td>
<td>15.49350</td>
<td>47.82045</td>
<td>49.06499</td>
</tr>
<tr>
<td>High Cost Participants (%)</td>
<td>5.609709</td>
<td>4.396607</td>
<td>5.384088</td>
<td>4.151036</td>
</tr>
<tr>
<td>Medium Cost Participants (%)</td>
<td>57.78608</td>
<td>56.61016</td>
<td>57.91386</td>
<td>55.56619</td>
</tr>
<tr>
<td>Low Cost Participants (%)</td>
<td>36.60421</td>
<td>38.99323</td>
<td>36.70205</td>
<td>40.28277</td>
</tr>
</tbody>
</table>

Table 1: Average Results (100 days simulation); σ denotes standard deviation from average values.
References


MIT authors. 2011. Engaging electricity demand. In MIT Interdisciplinary Study on the future of the electric grid. MIT.


