

# Decentralized Large-Scale Electricity Consumption Shifting by Prosumer Cooperatives

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**Abstract.** In this work we address the problem of coordinated consumption shifting for electricity prosumers. We show that individual optimization with respect to electricity prices does not always lead to minimized costs, thus necessitating a cooperative approach. A *prosumer cooperative* employs an internal cryptocurrency mechanism for coordinating members decisions and distributing the collectively generated profits. The mechanism generates cryptocurrencies in a distributed fashion, and awards them to participants according to various criteria, such as contribution impact and accuracy between stated and final shifting actions. In particular, when a scoring rules-based distribution method is employed, participants are incentivized to be accurate. When tested on a large dataset with real-world production and consumption data, our approach is shown to provide incentives for accurate statements and increased economic profits for the cooperative.

## 1 Introduction

Demand-side management (DSM) in Smart Grid environments generally aims to induce changes to the consumers' demand curves, so as for the total demand to match the production [10, 26, 22]. In order to provide incentives for consumption rescheduling to the actors, variable pricing techniques are often used. This means that instead of applying a flat pricing scheme, time-of-use (TOU), or real-time pricing (RTP) are employed [7, 20]. By setting higher electricity price values for buying energy during intervals of high demand, and lower values during intervals of low demand, it is possible for an electricity consumer to reduce her expenses by rescheduling her energy usage to the most profitable intervals [2]. This is a task that becomes even more important (and challenging) when it comes to *electricity prosumers*. As prosumers both produce and consume energy [3, 24], they can take advantage of fluctuations in prices, and generate even more profit [14].

However, increased participation to DSM schemes often leads to herding effects. As such, the estimated consumption curve could significantly change, both endangering the Grid's stability, and leading to substantially different economic outcomes [28]. For this reason, the formation of consumer cooperatives or virtual power plants has been proposed [2, 5, 13, 28], an approach which, however, requires a centralized entity to serve as the cooperative manager.<sup>2</sup> To overcome both herding effects and the need for cooperative manager determination, in this work we champion the use of a purpose-designed

*cryptocurrency protocol for distributed prosumer cooperative coordination*. Cryptocurrencies and blockchain-oriented algorithms run distributedly, and are transparent. Additionally, they use encryption methods, which guarantee that the transactions are secure, and that no third-parties need to take part in the exchanges [8]. A first generation cryptocurrency protocol has already been used in a setting with electricity prosumers, and is called NRGcoin [15]. Although it incentivizes demand and production balancing, that protocol does not promote large-scale cooperative consumption shifting. In our work, we envisage a next-generation, special-purpose cryptocurrency software, which is executed by each cooperative member in a decentralized fashion, and is used for coordinating electricity consumption shifting actions and the sharing of the rewards.

Thus, here we combine for the first time cryptocurrency with mechanism design for cooperatives formation, to achieve large-scale coordinated shifting of electricity prosumers consumption. The cooperative shifting activities result to increased prosumer profits from electricity trading. Using a cryptocurrency protocol, prosumers autonomously create a *virtual* wholesale mediator between the end-users and the Grid. The protocol takes into account prosumer shifting capacity statements, and distributes personalized rewards given the final collective profits achieved, and the cooperative's profits sharing policy of choice. The coins awarded represent shares on the total cooperative profits.

Summarizing, our work has several contributions. First, we model *prosumers* in a market setting with variable prices, and present a *distributed consumption shifting approach for prosumer cooperatives*, which guarantees monetary gains to the participants. We apply a *novel cryptocurrency model* for the coordination and management of the cooperative shifting actions. In the proposed model, the rewards from prosumer participation are determined in a personalized manner, in the form of newly mined coins. We examine different coin mining methods, and champion one that evaluates prosumers via a scoring rule [9] assessing the difference between promised and final actions. *This is the first time that cryptocurrency mining and scoring rules are combined into one method*. By penalizing inaccuracy, this method incentivizes prosumers to provide truthful promises. We propose specific formation techniques, which select members for participation in cooperative actions.

Our approach can be applied in conjunction with any existing regulations or pricing schemes. We evaluate our scheme experimentally on a large dataset that extends over a one-year period, and which is based on real consumption and renewable production data. Simulation results confirm that adopting our mechanism leads to increased profits for the cooperative participants, stabler variable electricity prices, and achieves lower Peak-to-Average Ratio (PAR) values for the difference between electricity supply and demand. Especially

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<sup>2</sup> The term cooperative refers to conglomerations of prosumers that organize and operate largely on a democratic manner [1]; which is not necessarily the case for Virtual Power Plants.

when using a scoring rules-based reward redistribution method, accuracy is explicitly incentivized with increased gains for the accurate participants.

This paper is further structured as follows: In Section 2 we present the system setting and the individual prosumer financial decisions model. Section 3 presents the cooperative model, the cryptocurrency protocol and three different approaches for personalized reward sharing, as well as methods for contributor selection for cooperative actions. Section 4 presents the experimental results, and, finally, in Section 5 we conclude.

## 2 A Prosumer Consumption Shifting Model

We assume a setting encompassing *prosumers*, which both import and export energy from and to the Grid; and a *prosumer cooperative*, which is a large coalition of prosumers trading energy as a unique entity. The Grid is regulated by the *distributed system operator (DSO)*, responsible for the transmission of energy and its pricing.

Actors need to take decisions regarding trading at some day-ahead electricity market, or consuming electricity at specific 1 to  $T$  intervals during the course of a day (the day-ahead).<sup>3</sup> Each actor  $i$  is characterized by the amount of electricity (kWh) imported  $q_{i,t}^-$ , and the amount exported  $q_{i,t}^+$ , during the time interval  $t$ . The aggregate demand and supply levels for each time interval are given by  $Q_t^- = \sum_i q_{i,t}^-$ , and  $Q_t^+ = \sum_i q_{i,t}^+$  kWh. We assume reliable renewable production and demand forecasting techniques that can achieve high precision—lower than 2% mean absolute percentage error [11, 25]. Predictions are noted as  $\tilde{q}_{i,t}^-$ , and  $\tilde{q}_{i,t}^+$  kWh, for imports and exports respectively. The predicted demand and supply for the planning horizon are noted as  $\tilde{Q}_t^-$  for the total imports, and  $\tilde{Q}_t^+$  for the total predicted exports.

### 2.1 Promoting Demand-Side Management

Many methods have been proposed for modelling individual consumption profiles [10, 20, 27]. In our work, we examine the rescheduling of *shiftable loads*, which are those loads that it is possible to shift to in later or earlier time intervals, with minimum impact on the consumer's well being, e.g., battery charging, water-heaters, washing-machines, etc. Now, to promote demand side management operations, prosumers should be offered better prices to counterbalance the associated shifting costs. Following existing dynamic pricing mechanisms, which promote the balancing of demand and renewable energy supply [15], we assume that billing functions are in place (by the DSO) for selling  $B_t^{sell}()$ , and buying  $B_t^{buy}()$  energy to/from the Grid, each with specific properties. First, they are functions of the quantity of energy produced  $q_{i,t}^+$  and consumed  $q_{i,t}^-$ , respectively. Next, and in order to satisfy the supply and demand balancing requirements [23], both also need to be functions of aggregate supply,  $Q_t^+$ , and demand,  $Q_t^-$ . Specifically,  $B_t^{sell}()$  must take maximum values for fixed  $q_{i,t}^-$ s and  $q_{i,t}^+$ s, during intervals when  $Q_t^+ = Q_t^-$ . This incentivizes prosumers to produce exactly the quantity that is required for consumption (since their income is then maximized). Intuitively, it is to the DSO's interest that prosumers decide to sell when  $Q_t^+ = Q_t^-$ , since this defers the need to import or export energy.

**Assumption 1 ([15])** *The pricing for selling energy to the Grid during a time interval  $t$ , is a function of the sold quantity, the aggregate quantity produced, and the aggregate quantity consumed during that interval,  $B_t^{sell}(q_t^+, Q_t^+, Q_t^-)$ ; and for fixed  $q_t^+$ , it is maximized as  $Q_t^+ - Q_t^- \rightarrow 0$ .*

Note that, assuming the electricity production of prosumers originates mainly from wind turbines and photovoltaic panels, the quantity produced  $q_t^+$  cannot be easily controlled [23]. Moreover, the selling prices are also functions of aggregate demand  $Q_t^-$ , which we later optimize by shifting consumption tasks in a large-scale cooperative manner.

The  $B_t^{buy}()$  on the other hand, should produce lower prices with higher renewable production excess, prompting prosumers to buy energy from the Grid (and perhaps store it future use). Intuitively, it is more efficient to consume the cheap renewable energy produced locally, than import from some external balancing market where prices are in general far worse [23]. This is because exporting or importing electricity involves additional expenditures, e.g. transmission lines, electricity resellers, etc. By contrast,  $B_t^{buy}()$  produces higher values as renewable energy supply decreases.

**Assumption 2 ([15])** *The pricing for buying energy from the Grid during a time interval  $t$ , is a function of the acquired quantity, the aggregate quantity produced, and the aggregate quantity consumed during that interval,  $B_t^{buy}(q_t^-, Q_t^+, Q_t^-)$ ; and for fixed  $q_t^-$ , it is minimized as  $Q_t^+ - Q_t^- \rightarrow +\infty$ .*

### 2.2 Shifting to Profitable Time Intervals

Given this model, a prosumer can control the quantity consumed during time intervals by shifting consumption tasks. We now characterize each time interval as *peak* or *non-peak*. Peak intervals  $t_h$  are those intervals during which reducing consumption can be considered profitable for the prosumer. Specifically, due to Assumptions 1 and 2, this happens when aggregate demand is higher than supply:

**Definition 1 (Peak intervals  $t_h$ )** *Consider a non-negative threshold  $\tau$ . A time interval  $t$  is considered to be a peak interval,  $t_h$ , if  $\tilde{Q}_t^+ - \tilde{Q}_t^- < \tau$ .*

Non-peak intervals  $t_l$  are those intervals during which, increasing consumption levels up to the reduced amount of energy that was decreased during  $t_h$ , results to lower expenses due to a reduced buying price. Specifically, due to Assumptions 1 and 2, this happens when demand is lower than supply:

**Definition 2 (Non-peak intervals  $t_l$ )** *Consider a non-negative threshold  $\lambda$ . A time interval  $t$  is considered to be a non-peak interval,  $t_l$ , if  $\tilde{Q}_t^+ - \tilde{Q}_t^- > \lambda$ .*

Intuitively, variables  $\tau$  and  $\lambda$  correspond to load difference thresholds that allow profitable shifting actions. Their values can be based on the statistics of  $\tilde{Q}_t^+$  and  $\tilde{Q}_t^-$ , according to each actor's business goals.

Now, we assume that each prosumer can alter her baseline demand value  $q_i^-$ . More specifically, during peak intervals prosumers can reduce down to  $q_{i,t_h}^- - \hat{r}_i^{t_h}$ ; while for the non-peak intervals consumption can be increased up to  $q_{i,t_l}^- + \hat{r}_i^{t_h}$  where  $\hat{r}_i^{t_h}$  is the *stated reduction capacity* of each actor  $i$ . Also, as in [2], there is a *shifting cost*  $c_{i,t_h \rightarrow t_l}^{t_h}$  associated with shifting from a peak to a non-peak interval. The *actual reduction capacity*  $r_i^{t_h}$ , refers to the load that is reduced during a  $t_h$ , and is shifted to some other, non-peak interval

<sup>3</sup> A decision theoretic optimization approach for a single prosumer operating in such a setting was proposed by [3, 4]. However, they did not include cooperative electricity trading, nor dealt with consumption shifting.

$t_l$ . These values can be obtained by using appropriate smart metering equipment.

We now discuss the price differences induced when a prosumer shifts  $\hat{r}_i^{t_h}$  from a peak interval to a non-peak interval. When prosumers decrease their consumption during peak intervals, they accrue gains from the lower buy prices, and the higher sell prices. Namely, the *estimated profit* by the induced price variations for reducing at  $t_h$  is given by:

$$\begin{aligned} profit_i^{t_h}(\hat{r}_i^{t_h}) &= B_{t_h}^{sell}(\tilde{q}_{i,t_h}^+, \tilde{Q}_{t_h}^+, (\tilde{Q}_{t_h}^- - \hat{r}_i^{t_h})) \\ &\quad - B_{t_h}^{sell}(\tilde{q}_{i,t_h}^+, \tilde{Q}_{t_h}^+, \tilde{Q}_{t_h}^-) + B_{t_h}^{buy}(\tilde{q}_{i,t_h}^-, \tilde{Q}_{t_h}^+, \tilde{Q}_{t_h}^-) \\ &\quad - B_{t_h}^{buy}((\tilde{q}_{i,t_h}^- - \hat{r}_i^{t_h}), \tilde{Q}_{t_h}^+, (\tilde{Q}_{t_h}^- - \hat{r}_i^{t_h})) \end{aligned} \quad (1)$$

The result from subtracting the second term in Eq. (1) from the first, indicates the profit from the price differences for selling energy; selling during a peak interval  $t_h$ , with lowered aggregate demand,  $(\tilde{Q}_{t_h}^- - \hat{r}_i^{t_h})$ , grants better prices than with the initial demand,  $\tilde{Q}_{t_h}^-$  (cf. Assumption 1 & Definition 1 above). Now, the last two terms give the difference in the bill that the prosumer will pay for consumption during  $t_h$ . Thus, to calculate this quantity, we subtract the billing paid by the prosumer for the reduced consumption  $(\tilde{q}_{i,t_h}^- - \hat{r}_i^{t_h})$  from the initial estimated bill  $B_{t_h}^{buy}(\tilde{q}_{i,t_h}^-, \tilde{Q}_{t_h}^+, \tilde{Q}_{t_h}^-)$ .

Similarly, the *estimated loss* generated by increasing consumption during non-peak intervals  $t_l$  is given by:

$$\begin{aligned} loss_i^{t_l}(\hat{r}_i^{t_h}) &= B_{t_l}^{sell}(\tilde{q}_{i,t_l}^+, \tilde{Q}_{t_l}^+, \tilde{Q}_{t_l}^-) \\ &\quad - B_{t_l}^{sell}(\tilde{q}_{i,t_l}^+, \tilde{Q}_{t_l}^+, (\tilde{Q}_{t_l}^- + \hat{r}_i^{t_h})) \\ &\quad + B_{t_l}^{buy}((\tilde{q}_{i,t_l}^- + \hat{r}_i^{t_h}), \tilde{Q}_{t_l}^+, (\tilde{Q}_{t_l}^- + \hat{r}_i^{t_h})) \\ &\quad - B_{t_l}^{buy}(\tilde{q}_{i,t_l}^-, \tilde{Q}_{t_l}^+, \tilde{Q}_{t_l}^-) \end{aligned} \quad (2)$$

To calculate the *estimated gain* for an actor  $i$ , for shifting from a  $t_h$  to a  $t_l$ , we subtract the estimated loss at  $t_l$  and the shifting costs  $c_i^{t_h \rightarrow t_l}$  per kWh from the estimated profit at  $t_h$ :

$$g_i^{t_h \rightarrow t_l}(\hat{r}_i^{t_h}) = profit_i^{t_h}(\hat{r}_i^{t_h}) - loss_i^{t_l}(\hat{r}_i^{t_h}) - \hat{r}_i^{t_h} c_i^{t_h \rightarrow t_l} \quad (3)$$

**Definition 3 (Eligible interval pairs)** *Eligible shifting interval pairs for a prosumer  $i$  are those  $(t_h, t_l)$  pairs for which the gain associated with the shifting is positive, i.e.  $g_i^{t_h \rightarrow t_l}(\hat{r}_i^{t_h}) > 0$ , where  $\hat{r}_i^{t_h}$  is the actual quantity of the shifted consumption.*

Summarizing, the strategy for individual consumption rescheduling is to find those shifting interval pairs for which the estimated gain is maximized, and shift accordingly.

### 2.3 Shifting Without Coordination

When optimizing individually, each agent does not take into account other agent rescheduling actions, and considers their consumption to be the baseline. Thus, the optimizer can exhaustively calculate the  $g_i^{t_h \rightarrow t_l}(\hat{r}_i^{t_h})$  values for each shifting interval pair, for a stated reduction capacity  $\hat{r}_i^{t_h}$ . Then, rescheduling takes place (e.g., shifting to the most profitable ones). However, without coordination or constraint enforcements, and since every prosumer optimizes individually, herding effects take place, resulting to substantially different prices during the intervals with the lowest/highest prices, than those anticipated by the prosumers. These ‘‘unexpected’’ price fluctuations are not in favor of the prosumer, as the estimated gains can end up turning to losses:

**Lemma 1** *If every participant is rational, and billing follows Assumptions 1 and 2, optimizing the rescheduling of consumption individually does not guarantee positive final gains.*

Intuitively, Lemma 1 states that non-coordinated shifting actions in such settings cannot be expected to always lead to monetary gains for the participants, and cooperation is essential. It is straightforward to show this, considering the fact that estimated gains are calculated based on the values  $\tilde{Q}_{t_h}^- - \hat{r}_i^{t_h}$  and  $\tilde{Q}_{t_l}^- + \hat{r}_i^{t_h}$ , which are used in the first and last term of Eq. (1), and the second and third term of Eq. (2), respectively. However, since participants are rational, every one acts the same manner, resulting to substantially different values finally realized, i.e. final  $B^{sell}()$ ,  $B^{buy}()$  prices are calculated using  $\tilde{Q}_{t_h}^- - (\hat{r}_i^{t_h} + \sum_{j \in C \setminus i} \hat{r}_j^{t_h})$  and  $\tilde{Q}_{t_l}^- + (\hat{r}_i^{t_h} + \sum_{j \in C \setminus i} \hat{r}_j^{t_h})$ , resulting to lower  $B^{buy}()$  and higher  $B^{sell}()$ . Moreover, if the total shifting capacity is not constrained, the conditions in Def. 1 and 2 can stop holding, rendering the intervals ineligible for profitable shifting.

### 3 Distributed Shifting and Reward Sharing

Now, cooperatives can be key for the effective coordination of consumption shifting actions [2]. Here we describe the workings of *prosumer* cooperatives, allowing members to both sell and buy energy as a single entity. We assume that cooperative members share common estimates regarding the total production and consumption per interval  $\tilde{Q}_{t_h}^+$  and  $\tilde{Q}_{t_h}^-$  (obtained, e.g., via the summation of communicated individual estimates). Also, participants execute a novel cryptocurrency mechanism, allowing for distributed management, transparency, and personalized rewards. The mechanism awards contributors with new coins, according to specific participation performance measures.

For the scheme to work, each individual  $i$  must announce only two values for each shifting interval pair: (a) her reduction capacity,  $\hat{r}_i^{t_h}$ ; and (b) her confidence  $\hat{\sigma}_i$  for meeting her reduction promises. The confidence represents the variance of a normal distribution (with mean value 0) over the error between the stated and the final action. This is in line with past approaches [2, 21].

An *optimistic estimate* of the cooperative shifting capacity is then collectively calculated as  $\tilde{R}_C^{t_h} = \sum_{i \in C} \hat{r}_i^{t_h}$ , and a *pessimistic estimate*, by  $\tilde{r}_C^{t_h} = \sum_{i \in C} (1 - \hat{\sigma}_i) \hat{r}_i^{t_h}$ . Then, the cooperative determines the shifting interval pairs  $(t_h, t_l)$ , as well as the target shifting capacity that will lead to increased profits. In order to guarantee profits, the target shifting capacity is the maximum  $r^{*,t_h}$  values to be rescheduled such that Assumptions 1, 2 continue to hold. That is, for each shifting interval pair  $(t_h, t_l)$ :

$$\text{maximize } r^{*,t_h} \text{ s.t.}$$

$$\tilde{Q}_{t_h}^+ - (\tilde{Q}_{t_h}^- - r^{*,t_h}) < \tau \quad (4)$$

$$\tilde{Q}_{t_l}^+ - (\tilde{Q}_{t_l}^- + r^{*,t_h}) > \lambda \quad (5)$$

Next, the estimated by the members cooperative gains (minimum and maximum) are calculated, given the total expected consumption and production values of the cooperative for each time interval,  $\tilde{q}_{C,t}^- = \sum_{i \in C} \tilde{q}_{i,t}^-$ ,  $\tilde{q}_{C,t}^+ = \sum_{i \in C} \tilde{q}_{i,t}^+$ , and the estimates  $\tilde{R}_C^{t_h}$ , and  $\tilde{r}_C^{t_h}$ :

$$\tilde{G}_C^{t_h \rightarrow t_l} = profit_C^{t_h}(\tilde{R}_C^{t_h}) - loss_C^{t_l}(\tilde{R}_C^{t_h}) \quad (6)$$

$$\tilde{g}_C^{t_h \rightarrow t_l} = profit_C^{t_h}(\tilde{r}_C^{t_h}) - loss_C^{t_l}(\tilde{r}_C^{t_h}) \quad (7)$$

To continue, the estimated gains per kWh are calculated:

$$\tilde{G}_{C,kWh}^{t_h \rightarrow t_l} = \frac{\tilde{G}_C^{t_h \rightarrow t_l}}{\tilde{R}_C^{t_h}}, \tilde{g}_{C,kWh}^{t_h \rightarrow t_l} = \frac{\tilde{g}_C^{t_h \rightarrow t_l}}{\tilde{r}_C^{t_h}} \quad (8)$$

For shifting interval pairs  $\{t_h, t_l\}$  that

$$\tilde{g}_{C,kWh}^{t_h \rightarrow t_l} > 0 \quad (9)$$

holds, the shifting procedure is expected to be profitable, and the shifting interval pair along with its  $\tilde{G}_C^{t_h \rightarrow t_l}$  and  $\tilde{g}_C^{t_h \rightarrow t_l}$  values are announced to the members. If  $r^{*,t_h} \geq \hat{r}_C^{t_h}$ , every available contributor can participate in the shifting operations. However, in case  $r^{*,t_h} < \hat{R}_C^{t_h}$ , the constraint of Eq. (4) does not yet hold and gains are not certain, so some agents must be excluded from action. We will examine different approaches for this in the following section.

Finally, if the cooperative actually reduces  $r_C^{t_h} \leq r^{*,t_h}$  given actual  $Q_t^-$  &  $Q_t^+$ , the final actual cooperative gain is:

$$g_C^{t_h \rightarrow t_l}(r_C^{t_h}) = profit_C^{t_h}(r_C^{t_h}) - loss_C^{t_l}(r_C^{t_h}) \quad (10)$$

Of course, in order for the final gain levels to be inside the estimated range, two conditions must hold. First, the statements  $\hat{r}_i^{t_h}$ ,  $\hat{\sigma}_i$ , and the predictions  $\tilde{Q}_t^-$  &  $\tilde{Q}_t^+$  must be accurate. As mentioned earlier, the accuracy of  $\tilde{Q}_t^-$  &  $\tilde{Q}_t^+$  can be ensured by known methods [11, 25]. We examine how we can achieve the accuracy of  $\hat{r}_i^{t_h}$ ,  $\hat{\sigma}_i$  in the next section. Second, the cooperative must be sizeable, meaning that it is the only actor that can induce significant price changes by consumption rescheduling. This helps overcome the problems raised by Lemma 1.

**Definition 4 (Sizeable cooperative)** *A cooperative C is sizeable, if its pessimistic reduction capacity estimate is much greater than the sum of external parties capacity, i.e. when*

$$\sum_{i \in C} (1 - \hat{\sigma}_i) \hat{r}_i^{t_h} \gg \sum_{j \notin C} \hat{r}_j^{t_h}, \forall t_h \quad (11)$$

**Remark 1** *The cooperatives that are formed are sizeable, because, due to Lemma 1, every rational agent avoids optimizing individually, thus seeks to cooperate.*

**Lemma 2** *If statements  $\hat{r}_i^{t_h}$ ,  $\hat{\sigma}_i$ , are accurate, and the cooperative C is sizeable, then, the cooperative's shifting suggestions include only eligible shifting interval pairs for C, in other words C will have  $\tilde{g}_C^{t_h \rightarrow t_l} > 0$ .*

**Proof** Since the cooperative has accurate knowledge of the total shifting capacity range  $\hat{R}_C^{t_h}$ , and  $\hat{r}_C^{t_h}$ , and it is sizeable, the  $\tilde{g}_C^{t_h \rightarrow t_l}$  and  $\tilde{G}_C^{t_h \rightarrow t_l}$  estimates are more accurate than others calculated based on partial knowledge, thus the following holds:  $\tilde{g}_C^{t_h \rightarrow t_l} < \hat{g}_C^{t_h \rightarrow t_l} < \tilde{G}_C^{t_h \rightarrow t_l}$ . Now, due to the enforcement of the constraints from Eq. 4, 5, and 9, for the suggested interval pairs, the minimum gain estimate per kWh is positive,  $\tilde{g}_C^{t_h \rightarrow t_l} > 0$ . Thus the shifting interval pairs suggested by the cooperative are eligible.  $\square$

In conjunction with Remark 1, this Lemma is important for the following reason. While the calculations above do not take the individual shifting costs into account, cooperative members must weigh the expected gain per kWh (if these are accurate) with their own shifting costs  $c_i^{t_h \rightarrow t_l}$  and decide whether they will finally contribute or not. Now, Lemma 2 shows that the cooperative can take advantage of the predicted price differences and create profit by rescheduling consumption. Moreover, since C is sizeable, no other actor can significantly affect prices so that the cooperative does not meet its goals. Therefore, the  $\tilde{g}_C^{t_h \rightarrow t_l}$  are accurate (assuming the  $\hat{r}_i^{t_h}$ ,  $\hat{\sigma}_i^{t_h}$  are too); and then individuals can safely weigh these against own shifting costs to decide participation. The overall process can be achieved as shown in Alg. 1. The complexity for solving the algorithm's first step,

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**Algorithm 1** Coordinated shifting for a  $(t_h, t_l)$  interval pair

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**Input:**  $\tilde{Q}_{t_h}^+, \tilde{Q}_{t_h}^-, \tilde{Q}_{t_l}^+, \tilde{Q}_{t_l}^-, \{\tilde{q}_{i,t}^-\}_C, \{\tilde{q}_{i,t}^+\}_C$   
1: Determine and announce  $\tilde{G}_{C,kWh}^{t_h \rightarrow t_l}, \tilde{g}_{C,kWh}^{t_h \rightarrow t_l}$   
2: Receive agent bids  $\{\hat{r}_i^{t_h}\}_C, \{\hat{\sigma}_i^{t_h}\}_C$ ,  
3: Check constraints and select agents  
4: Wait for shifting actions realization,  $\{q_{i,t}^-\}_C, \{q_{i,t}^+\}_C$   
5: Distribute revenues to contributors

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i.e. finding the peak and non-peak intervals, and respective loads and gains for the daily planning horizon, is a function of the number of time intervals. For example, if the cooperative adopted a constrained optimization approach, it would be  $\mathcal{O}(t^3)$ , where  $t$  is the number of time intervals. Next comes the selection of the actual contributors during each peak interval, that of Line 3. The duration of this procedure depends on the selection method that each cooperative adopts. The most expensive step of the selection methods we present in Section 3.3 below, is that of ranking, whose complexity is  $\mathcal{O}(n^2 t)$  in the worst case, i.e.  $\mathcal{O}(n^2)$  for sorting [18], times  $t$  time intervals.

### 3.1 Cooperative Balance Increase

As already discussed (Eq. (10)), prosumers generate gain from the price differences for both buying and selling electricity. However, the gain part from buying is immediately awarded to each prosumer in the form of reduced bills, and cannot be redistributed among the members easily. Better sell prices, on the other hand, result to larger income for the cooperative, and this profit can be concentrated into a collective account. The achieved cooperative balance increase by each collective shifting operation is given by:

$$\begin{aligned} bal\_inc(r_C^{t_h}) &= B_{t_h}^{sell}(q_{C,t_h}^+, \tilde{Q}_{t_h}^+, (\tilde{Q}_{t_h}^- - r_C^{t_h})) \\ &\quad - B_{t_h}^{sell}(q_{C,t_h}^+, \tilde{Q}_{t_h}^+, \tilde{Q}_{t_h}^-) - B_{t_l}^{sell}(q_{C,t_l}^+, \tilde{Q}_{t_l}^+, \tilde{Q}_{t_l}^-) \\ &\quad + B_{t_l}^{sell}(q_{C,t_l}^+, \tilde{Q}_{t_l}^+, (\tilde{Q}_{t_l}^- + r_C^{t_h})) \end{aligned} \quad (12)$$

This equation is derived from Eq. (1) and (2) after removing the parts that include  $B_{t_h}^{buy}$ , and represents the achieved gain from sell prices alone. Assuming that the initial balance of the cooperative is zero, the cooperative balance over the time horizon of shifting operations is simply the sum of the per time step balance increases:

$$b_{COOP} = \sum_{t_h} bal\_inc(r_C^{t_h}) \quad (13)$$

However, since each participant contributes to the increase differently, the distribution of rewards must be different as well. A straightforward procedure for this redistribution is to generate and award new coins, which, nevertheless, are returned to the prosumers based on each one's behavior. For this reason we propose a cryptocurrency protocol that is used simultaneously, to both coordinate, and reward prosumers.

### 3.2 COOPcoin for Prosumer Cooperatives

To achieve effective rescheduling of prosumers consumption, and reward back members according to their behavior, we propose the employment of a specialized cryptocurrency algorithm, designed for the coordination of prosumer cooperative actions. In existing cryptocurrency schemes, the same protocol is used by all members of the community, and each member executes a program that is linked with a distributed database, called the *blockchain* [6, 12].

The program performs certain calculations—e.g., in our case, consumption and production measurements, gain calculations, and so on, which implement Alg. 1. The individual results are then compared with those of other members, and, if validated—i.e. compared and matched, are written to each user’s database that is, added to the blockchain and stored as history. If validation fails for a member, the adopted result is the one calculated by most members. This distributed execution approach removes the need for cooperative managers.

Note that the distributed nature of such an algorithm is guaranteed with the use of existing cryptocurrency protocols. Such protocols offer many desirable features, e.g. distributed consensus, transaction transparency, and anonymized data sharing [19]. Particularly, although data are shared among all participants freely, they are encrypted, and only the issuer and trusted parties can actually recover actual information, and link data with real persons. Increased privacy, transparency, and the ability to operate democratically without a “manager”, are important for cooperatives [1]. Moreover, by ensuring these properties via the use of cryptocurrency, our approach can naturally extend to virtual power plants [5, 21] (where the trust among the constituting entities is even lower).

Our cryptocurrency scheme is specifically designed for prosumer cooperatives, and is called *COOPcoin*. The proposed cryptocurrency protocol “mines” coins according to a small number of measurements and calculations regarding the shifting behaviors, and *does not* require computationally intensive operations like other existing cryptocurrency algorithms, e.g. Bitcoin [12]. Here, “mining”<sup>4</sup> is performed collectively, i.e. utility is generated by the better electricity rates as a result of collective shifting, and in place of the Bitcoin’s “proof-of-work” concept [12], we use what we term “proof-of-physical-action”: in order to get rewarded with COOPcoins, certain actions (i.e., electricity consumption shifting actions) must take place in the real world. For the sharing of the rewards, the protocol generates COOPcoins based on the collectively achieved profit and uses these to distribute that profit to the participants. The actual number of COOPcoins returned to each prosumer is determined based on their shifting behavior.

More specifically, the number of COOPcoins awarded depends on two terms: the first,  $bal\_inc(r_C^{t_h})$ , is the actual balance increase due to the shifting operations, given by Eq. (12); and the second one,  $s_k$ , is a scaling factor used for the personalized rewarding.

$$b_{i,t_h}^+ = bal\_inc(r_C^{t_h}) \cdot s_k^{i,t_h} \quad (14)$$

Now, the value of  $s_k$  that actually scales each participant’s share over the balance, depends on the reward sharing policies of each cooperative. We examine three approaches:

The *proportionate to estimated reduction (PROPest)* approach distributes back the balance increase to participants in a proportionate manner, according to their capabilities stated prior to the rescheduling actuation.

$$s_{PROPest}^{i,t_h} = \frac{(1 - \hat{\sigma}_i) \hat{r}_i^{t_h}}{\sum_{i \in C} (1 - \hat{\sigma}_i) \hat{r}_i^{t_h}} \quad (15)$$

The *proportionate to actual reduction (PROPact)* approach rewards

according to the achieved individual reduction.

$$s_{PROPact}^{i,t_h} = \frac{r_i^{t_h}}{\sum_{i \in C} r_i^{t_h}} \quad (16)$$

The *accurate (ACCU)* approach uses the normalized *continuously ranked probability score (CRPS)*, a strictly proper scoring rule, to assess the absolute relative error  $\epsilon_i$  between promised  $\hat{r}_i^{t_h}$ , and actual  $r_i^{t_h}$  performance, with  $\hat{\sigma}_i$ :

$$s_{ACCU}^{i,t_h} = \frac{1 - CRPS(\mathcal{N}(0, \hat{\sigma}_i), \epsilon_i)}{\sum_{j \in C \setminus \{i\}} (1 - CRPS(\mathcal{N}(0, \hat{\sigma}_j), \epsilon_j)) + 1} \quad (17)$$

CRPS has been used in the past [2, 21] to rank production and consumption reduction forecasts. Here, it reduces the prosumer COOPcoin reward when her actual performance is not inside the stated confidence range. It is used in negative orientation and is normalized, so that perfect forecasts generate a value of zero, while the worst ones produce a value of 1. This incentivizes participants to be accurate.

**Theorem 1** *When using ACCU for electricity prosumers cooperative reward sharing, participants are incentivized to be accurate regarding their statements.*

**Proof** A scoring rule is a function  $S(P, Q)$  that assesses the distance between a predictive distribution  $P$  and an actual distribution  $Q$ . When the rule is *strictly proper*, then  $S(Q, Q) \geq S(P, Q)$ , with the equality holding iff  $P = Q$ , i.e. the value is maximized for exact forecasts [9]. Since CRPS is used here in negative orientation, and is normalized, i.e.  $CRPS \in [0, 1]$ , we have that  $CRPS(Q, Q) \leq CRPS(Q, P)$ , with the equality holding if and only if  $Q = P$ . Also, because any affine combination of a strictly proper scoring rule is also strictly proper [16], we exclude agent’s  $i$  CRPS from the denominator of Eq. (17), guaranteeing that  $s_{ACCU}^i$  is also strictly proper. Now, due to CRPS placement in Eq. (17) for fixed  $r_i^{t_h}, r_C^{t_h}$ , the share from the positive balance increase (Lemma 2) for the participant  $i$  is maximized when CRPS=0, leading to  $s_{ACCU}^{i,t_h}(Q, Q) \geq s_{ACCU}^{i,t_h}(Q, P)$  with the equality holding iff  $Q = P$ . Thus, the reward for  $i$  is maximized when the forecast  $\hat{\sigma}_i$  is accurate.  $\square$

Note that, to maintain strict propriety,  $i$  is excluded from the denominator, leading to a small surplus of gain not being directly awarded to the participants in the form of COOPcoins. This *weak budget balancedness* does not affect the other properties of our approach, and the surplus can be returned to the actors in various ways (e.g., via the purchase of new equipment, or as bonus to new members).<sup>5</sup>

### 3.3 Selection of Contributors

As pointed out earlier, it is probable that shifting capacity is larger than the maximum eligible for profitable actions. In such cases, the cooperative must select only a subset from the available participants in  $C$  to include in shifting operations. The actual method used for the selection can vary among cooperatives, according to their business plans and policies. In any case, it is to the actors’ best interest to form reliable cooperatives in order to both achieve gains, and contribute to Grid stability. Here, we examine three selection methods.

<sup>4</sup> Since cryptocurrency is not issued by a central authority, the process that creates new coins is performed by end-users and it is called *mining*. According to this procedure, users check if the data of the available transactions are valid, i.e. signatures are genuine, amounts in transactions are correct, etc., and are given newly created coins as a reward [17].

<sup>5</sup> Alternatively, considering that COOPcoins represent shares, if no surplus redistribution actions are performed, the result is an increase to the exchange rate between the COOPcoin and the “external” currency used to pay the cooperative, benefiting this way everyone with COOPcoins in their possession.

The *Random selection* method picks contributors uniformly until the required  $\tilde{R}_C^{t_h}$  is covered for each  $t_h$ .

The *Reduction Capacity selection* method sorts contributors *wrt.* reduction capacity for each shifting interval pair, in an ascending order. Then, it starts including from the one with the lowest value, until  $\tilde{R}_C^{t_h}$  is covered for each  $t_h$ . The objective here is to include as many contributors as possible.

The *Engagement selection* method ranks contributors *wrt.* their wealth in COOPcoins. Then, starting from the richer one, it continues with the rest, until  $\tilde{R}_C^{t_h}$  is covered for each  $t_h$ . The intuition is to include active and valuable members, since the wealth in COOPcoins does not only indicate participation frequency, but overall effectiveness as well.

Following selection, the accepted contributors are called for action, and rewards are dispensed after the actions occur.

## 4 Experimental Evaluation

In this section we present the dataset and the results from the simulation. First, we report the origin of our dataset, and describe its augmentations to account for missing values. Next, we show the different impacts of individual and cooperative shifting actions, as well as selection methods comparison results; the stability of our proposed scheme is illustrated with a sensitivity test and, finally, we show how different COOPcoin reward sharing techniques incentivize statement accuracy.

### 4.1 Simulations Setting

Our simulations employ a dataset based on consumption data from Kissamos, a district of Crete, Greece, and renewable production data from Galicia,<sup>6</sup> Spain, both in 2012. The consumption data represent hourly demand from different contract categories, and include seasonal variabilities.<sup>7</sup> In particular, the load profiles come from *residential, commercial, industrial, agricultural, public, and municipal* customers. However, due to the nature of agricultural and municipal demand profiles (i.e. mainly pumps, street lighting, etc.), which are tasks that cannot be shifted in time, these two categories do not participate in the prosumer cooperative of our simulation. In total, there are 7,376 prosumers in our setting.

The production data come from real wind generators and solar power plants, and have been scaled and divided, so as to represent the production of each prosumer. Prosumers are equipped either with both wind generators and solar panels, or with a single type of generation only. The average daily prosumer electricity production in our setting is 7.68kWh. The numerical results presented in this section are averages over 10 yearly iterations—that is, averages over 10 simulation runs, with each simulation run encompassing 344 days in 2012.<sup>8</sup>

**External Variable Pricing.** Now, as the external currency to our mechanism, we assume that the NRGcoin protocol is adopted by the

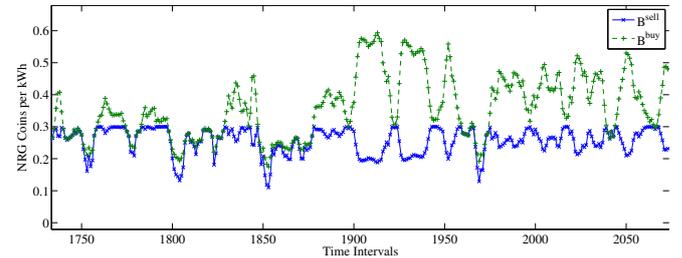
market and thus  $B_t^{sell}()$  and  $B_t^{buy}()$  are calculated based on the formulations shown in [15]:

$$B_t^{sell}(q_t^+, Q_t^+, Q_t^-) = (0.1 \cdot q_t^+) + \frac{0.2 \cdot q_t^+}{e^{\frac{(Q_t^+ - Q_t^-)^2}{Q_t^-}}} \quad (18)$$

and

$$B_t^{buy}(q_t^-, Q_t^+, Q_t^-) = \frac{(0.65 \cdot Q_t^-) \cdot q_t^-}{Q_t^- + Q_t^+} \quad (19)$$

Both billing functions satisfy our assumptions regarding variable pricing, as explained in Section 2.1. The parameter values 0.1, 0.2, 0.65 are set arbitrarily, so that Eq. (18) and Eq. (19) to produce reasonable results. An illustrative example of the  $B_t^{buy}$  and  $B_t^{sell}$  values during the eleventh and twelfth weeks of the simulation, are shown in Fig. 1.



**Figure 1.** Time-series of  $B_t^{buy}$  and  $B_t^{sell}$  used in the simulation as the Grid’s pricing mechanism.

**Shifting Behaviours.** Unfortunately, no shifting costs and capacities were available in the dataset, and we are not aware of any datasets including such values. Thus, we assumed shifting capacities that were on average 35% of the demand, varying among categories (e.g. higher for industrial prosumers, and lower for residential ones).

Shifting costs increase inversely proportionally to the prosumer baseline demand, meaning that shifting to an interval which typically has less demand, induces increased comfort loss. In this setting, the shifting costs result to an average value of 3.9 profitable interval pairs/day, for each prosumer.

Moreover, participants are divided into two different accuracy classes that describe the relationship between agent confidence statements  $\hat{\sigma}_i$ , and final realized shifting actions. The first one contains the *accurate* predictors; this describes the realistic case where agents are mainly confident about their statements, and also have a high probability to deliver what they promised. The second one, corresponds to the *inaccurate* predictors, where prosumers might or might not follow stated forecasts. For *accurate* predictors, the confidence statements and the parameters for calculating the absolute relative error  $\epsilon_i$ , are sampled from  $\mathcal{B}(1, 5)$  and  $\mathcal{B}(4, 2)$  respectively; note that the actual  $r_i^{t_h}$  is calculated by the product of a sample  $\alpha_i^{t_h}$  and the stated shifting capacity  $\hat{r}_i^{t_h}$ , i.e.  $r_i^{t_h} = (1 - \alpha_i^{t_h})\hat{r}_i^{t_h}$ . For *inaccurate* agents, confidence statements  $\hat{\sigma}_i$  are sampled from a “wider” Gaussian  $\mathcal{N}(0.5, 0.15)$ , and the  $\alpha_i^{t_h}$  parameter is set to  $1 - \hat{\sigma}_i$ . About 50% of the participants in our setting belong to the accurate class, with the rest being inaccurate agents (since agents are assigned to a specific class with 50% probability).

<sup>6</sup> <http://www.sotaventogalicia.com>

<sup>7</sup> The production and consumption values in a Matlab file format can be obtained from <http://intellix2.intelligence.tuc.gr/~akasiadi/ProsumerCoop/>.

<sup>8</sup> Note that since the simulated time horizon extends to a year, all seasonal variabilities and additional uncertainties (e.g. individual agent availability, individual reduction capacities for each time interval) are sufficiently taken into account.

**Parameters  $\tau$  and  $\lambda$ .** To calculate the  $\tau, \lambda$  parameters for each day, we first determined the average kWh difference between supply and demand,  $Q_t^+ - Q_t^-$ , across the 24 values. Then,  $\tau$  is placed at the 75% of the distance between the average and minimum difference value, while  $\lambda$  at the 25% of the distance between the average and the maximum difference value. Nevertheless, these particular values are application specific, and other algorithms can be used for their calculation as well, according to each cooperative’s capabilities and business goals. We now proceed to describe the numerical results from our experiments.

## 4.2 Individual vs. Cooperative Action

We first compare two different scenarios, one with the prosumers shifting according to individually optimized plans, and a second where they shift according to the cooperative suggestions. Contributors are selected randomly, and everyone is accurate with respect to their promises and final actions, i.e. no specific “accuracy” classes are used for this set of experiments. Table 1 shows the difference in the total bills of the prosumers, and the average across all year daily peak-to average ratio (PAR) values, for the total demand and supply difference, buying, and selling prices.

**Table 1.** Performance of individual and cooperative action.

Method	Total bill difference	Avg. PAR $ Q_t^+ - Q_t^- $	Avg. PAR $B^{sell}$	Avg. PAR $B^{buy}$
Initial	-	1.96	1.28	1.21
Individ.	-2.4%	4.75	1.38	1.19
Coop.	-4.4%	1.86	1.24	1.19

First, we observe that the “collective bill” when prosumers cooperate drops by a factor of 2 (-4.4% vs. -2.4%) compared to its reduction when they do not. Additionally, the cooperative approach outperforms individual optimization in terms of peak-to-average ratio (PAR) values (average across 344 days) for the  $|Q_t^+ - Q_t^-|$  and  $B^{sell}$  columns. Lowering the PAR of  $|Q_t^+ - Q_t^-|$  means that demand and supply difference is flattened, thus less electricity is exchanged to the balancing market, and consumption of locally produced electricity is promoted. By contrast, the increase of the PAR for the individual approach shows the scale of the herding effects that take place. Furthermore, reduction in the PAR value of the selling price when cooperating, means smaller fluctuations, a fact that allows for more realistic planning. Lastly, both cooperative and individual optimization leads to buying prices that are quite stable.

## 4.3 Evaluating Contributor Selection Methods

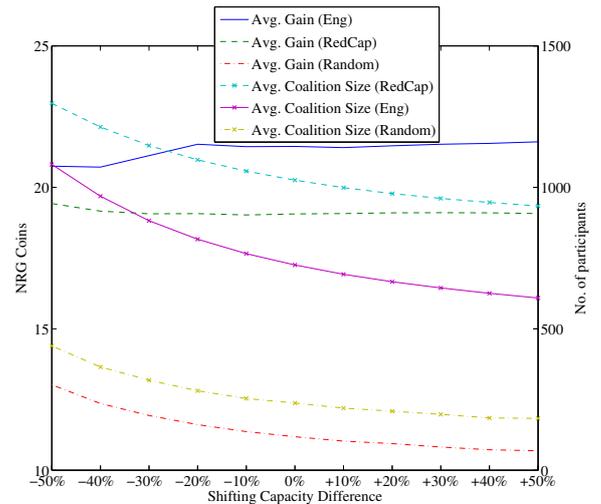
Henceforth, we assume that each prosumer belongs to the two different accuracy classes introduced earlier. In this setting, we first evaluate the three different contributor selection approaches we put forward, namely *Engagement*, *Reduction Capacity* and *Random*. Table 2 presents the (average) total cooperative gains and balance for 2012, for each of the three proposed contributor selection methods, in NRG coins. The prior COOPcoin wealth distribution required by the *Engagement selection*, is determined by conducting simulations using *Reduction Capacity selection* and ACCU reward sharing. We can observe that *Engagement* achieves the highest cooperative gains, and, consequently, the highest cooperative balance. *Reduction Capacity* also performs well wrt. gains in NRG coins. Lastly, *Random* has the worst outcome, which, nevertheless, is still profitable.

**Table 2.** Total cooperative gains and balance in 2012 for each selection method (NRG coins).

Measure	<i>Engagement</i>	<i>Reduction Capacity</i>	<i>Random</i>
Total Coop. Gains	133805.51	123813.43	80714.62
Total Coop. Balance	68116.49	58134.89	15029.42

## 4.4 Shifting Capacity Sensitivity Test

In this set of experiments we gradually change the shifting capacity of every individual, from -50%, to +50% of their initial, and examine the impacts to the average individual gains and average coalition sizes during 2012. Note that during all experiments we enforced two constraints: (a) shifting capacity cannot exceed the hourly demand, and (b) shifting capacity cannot be negative. Results are presented in



**Figure 2.** Average individual gains during 2012, and average shifting coalition sizes vs. shifting capacity changes for all three selection methods.

Figure 2. As we observe, the average size of the shifting coalitions drops when the shifting capacity of the prosumers increases, for all selection methods. This is natural, since increase in the shifting capacity helps meeting cooperative shifting requirements with fewer members. Regarding the individual gains of participants for 2012, we can see that *Engagement* and *Reduction Capacity* selection methods are not significantly affected by the difference in the shifting capacity of the individuals. Also, differences in the shifting capacity do not induce changes in the selection methods relative ranking; for all values, *Random* consistently ranks last, while *Engagement* produces higher gains than the *Reduction Capacity*.

The increase in average individual gain for the *Engagement* selection is due to the fact that “better” performing agents are selected continuously, resulting to the gain being shared by fewer agents. Lastly, when contributors are selected using the *Random* method, the average individual gain decreases for higher shifting capacity percentages. This happens because shifting operations are overtaken by fewer members, who, however, are not examined wrt. their truthfulness. Thus, it is highly probable that the final cooperative shifting actions deviate from those promised, leading to less overall gain.

Figure 3 presents the *total cooperative balance* in 2012, for different shifting capacity percentages. As we can see, the balance of the cooperative *decreases* for all methods as prosumers’ shifting capacity

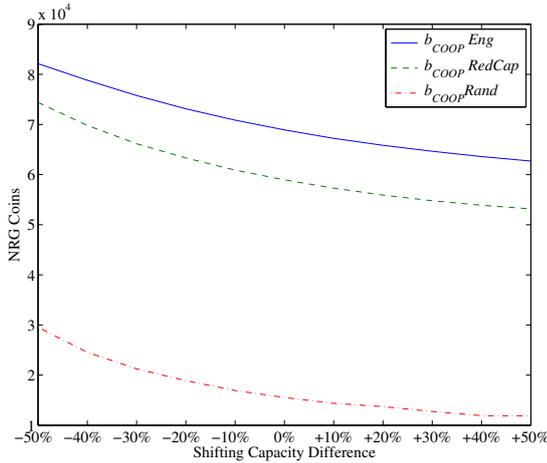


Figure 3. Cooperative balance in 2012 vs. shifting capacity changes for all three selection methods.

increases. This can be interpreted if we consider the average coalition size values from Fig. 2: when the number of acting prosumers decreases, each individual inaccuracy regarding the shifting operation has a larger impact on the cooperative performance, leading to reduced cooperative gains. When actors come in large numbers, their individual errors have less impact, since they cancel out by others to the opposite direction. Regardless of the observed balance reduction, we can see that *Engagement* selection method consistently produces the highest balance, with *Reduction Capacity* following, and *Random* producing the least, irrespective of the way the shifting capacity changes.

#### 4.5 Reward Sharing Methods Evaluation

Finally, we use the three reward sharing methods with each selection method, in order to find the one incentivizing accurate statements the most. Figure 4, presents the *difference* in the total COOPcoin wealth between accurate and inaccurate actors when using different selection and reward sharing approaches. We observe that, for every selection method, this difference is higher when the *ACCU* approach is used for rewarding. Also, as expected, when using *ACCU* redistribution combined with *Engagement selection*, the difference in COOPcoin wealth between accurate and inaccurate participants reaches its highest levels. Interestingly, when using *ACCU*, accurate participants are rewarded more, even when the selection criterion does not distinguish between the two classes (i.e., when using *Reduction Capacity* and *Random* selection). For all these reasons, *ACCU* is clearly the most effective in promoting statements accuracy.

### 5 Conclusions and Future Work

In this work, we presented a cooperative prosumer consumption shifting scheme that employs a distributed cryptocurrency mechanism for the coordination of members' actions. We proposed contributor selection and reward sharing methods which incentivize truthfulness, guarantee increased profits from the trading of electricity, and help flatten electricity demand curve. Though illustrated in the domain of prosumer cooperatives, our approach immediately applies to the broader domain of prosumer virtual power plants as well.

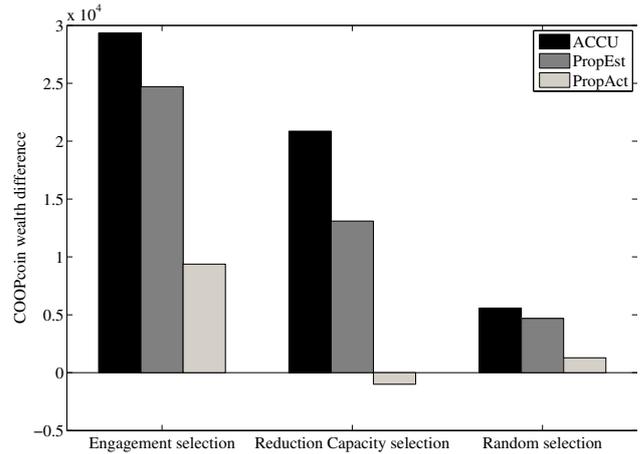


Figure 4. COOPcoin total wealth difference between accurate and inaccurate actors after 344 days.

In future work, we will study settings with multiple cooperatives that can even exchange members. Also, additional selection and rewarding techniques with specific properties will be tested and compared against each other. Furthermore, in the near future we aim to work closely with partners from the European Federation for Renewable Energy Cooperatives [1], in order to see these ideas adopted by real-world Smart Grid businesses.

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