Coordinating Distributed and Flexible Resources: A Case-study of Residential Cooperatives

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***Abstract*—The increasing number of residential energy co-operatives raises the importance of forming a local *prosumer marketplace* that is capable of managing energy and flexibility exchange efficiently. However, the *coordination* and *control* of independently operated flexible resources (e.g. storage, demand response) imposes critical challenges arising from the heterogeneity of the flexible resources, conflict of interests, and impact on the grid. Therefore, designing a simple yet efficient coordination mechanism that works on these distributed resources is of the utmost importance. We introduce a simulation model to study energy exchange with flexibility coordination while working towards an efficient allocation mechanism. A case study analysing different allocation mechanisms and consequent losses (compared to a base-case of *No flexibility*) in numerical experiments over real demand/generation profiles of the Pecan Street dataset elucidates the efficacy in energy and flexibility allocation while promoting cooperation between co-located flexibilities in residential cooperatives through local exchange.**

***Index Terms*—Market Design, Exchange Mechanism, Energy Cooperative, and Multiagent System.**

I. Introduction

Energy Cooperatives (ECs) of prosumers are gaining considerable traction due to their potential for efficient energy management, reduced grid dependency, and increased usage of distributed renewable energy. One of the paramount challenges an EC faces is establishing an efficient and fair prosumer marketplace. An efficient trading mechanism of the commodities in a prosumer marketplace is essential since such mechanism is capable of reconciling the losses due to the diversity in transport and storage activation produced by the round-trip efficiencies of locally controlled flexible resources. A generic prosumer marketplace can be envisaged as a multiagent system that hosts heterogeneous services with a large number of participant prosumers which take actions autonomously [1]. The necessity of establishing a local prosumer market (in the sense of the scope and proximity of the served area) that fulfills the requirements of decentralized production and consumption is therefore of paramount importance [2], [3]. The local market facilitates the management of distributed renewable generation that needs to be consumed as *locally* as possible [4]. Flexibility, on the other hand, can be enabled by facilitating *demand response* [5], which is an important element in the prosumer-centric energy market. While previous works have highlighted the need for forming a local market for *demand response* in addition to *energy*, they have not considered small-scale prosumers as market participants. One example considers stakeholders such as DSO, TSO (as *buyers*), aggregators and customers (as *sellers*) [6]. However, market interactions down to the level of prosumers are not considered. Another work presented an effort-based DR service where the DR participants are benefited against the time of their *stalling effort* and showed that by doing so, the system achieves socially efficient allocations [7]. However, the implications of such innovative design on the real energy market scenarios are not entertained.

Coordination of flexible resources/devices while aggregating the flexibility of devices usually requires a detailed understanding of device characteristics [5] which may be hard to obtain in many scenarios and hinders the scalability of the system. Furthermore, in order to optimally manage and control flexibility in demand side, previous works deploy an aggregator [8] that essentially combines the available flexibilities and trade them on the customers' behalf. However, this is not a straightforward process and may rise to caveats such as integrating and optimizing large amount of data provided by participant prosumers coupled with high transaction costs of managing, arranging, optimizing and balancing the prosumer relations within the aggregator's vicinity [9].

Therefore, the prosumer marketplace requires a simple yet effective coordination mechanism – of locally controlled flexible resources – that is capable of reducing the loss induced by flexibility activation and of promoting cooperation between flexibilities in an EC. In light of the related works, this paper aims at contributing to the state of the art by:

- Providing a simulation model to study local markets with energy loss resulting from flexibility deployment in residential ECs.
- Proposing real-time exchange mechanisms that ensure optimal and efficient exchanges in local EC with coordination of heterogeneous and individually-controlled flexible devices. Due to the near real-time execution, these mechanisms inherently reduce the uncertainties imposed by renewable generations as well as prosumers'

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behavior.

- Proposing a reward structure that encourages the prosumers to participate in the exchange mechanism by rewarding them according to their marginal contributions to the overall system efficiency.

II. Market Structure and Coordination Mechanisms

In this section, we define real-time exchange mechanisms that operate on a local prosumer marketplace with associated market offers that are necessary for the market formation. Prosumers in a cooperative are represented by software agents, therefore, we will use the terms agent and prosumer interchangeably. While we discuss it in the context of storage flexibility from batteries, it is applicable to the flexibility of demand response as well. Additionally, prosumers are equipped with photovoltaic (PV) for renewable generations. A *market offer* $o = (c, p, b)$ is defined as a tuple comprising a *commodity* $c \in \mathcal{C}$ with a price tag p and a *flag* stating whether the offer is a bid ($f = 1$) or an ask ($f = 0$). A commodity is a marketable item (typically, a good or a service) produced to satisfy demand or need. In the context of the electric power market, a commodity comprises power time series, giving rise to several interesting classes as services. The energy commodity, $\mathcal{C} = (\mathbf{q}, \mathbf{t})$, where $\mathbf{q}$ and $\mathbf{t}$ are equal-length vectors of time and quantity respectively, defining a time series with $\forall i : q_i \geq 0$.

A. Coordination Mechanisms

In this section, we describe four different scenarios (that correspond to the proposed coordination mechanisms) with increased order of complexity, i.e., considering flexibility and local exchange. Later, we will analyze these mechanisms from the perspective of allocative efficiencies, which in turn is measured by the ability to reduce the system loss arising from flexibility activation. Throughout this paper, we interchangeably refer the mechanisms by their names and numbers.

- *No flexibility (Mechanism 0):* This baseline case considers the simplest case where there is no exchange and the flexibility is deactivated (i.e. batteries are not considered). Since the agents are not capable of providing flexibility and are not participating in the local exchange, the net-demand is always resolved by interacting with the main Grid.
- *Individual control (Mechanism 1):* Here, the agents individually control their batteries by charging with excess PV and by discharging to serve their own load. Agents are again not allowed to exchange energy with each other.
- *Exchange and control (Mechanism 2):* In this case agents are allowed to exchange energy. We assume a centralized exchange is responsible of performing optimal allocation (see Section II-C) from the participants' offers. The batteries are controlled to balance residual load after the exchange.
- *Efficient exchange and control (Mechanism 3)* Similar to the previous mechanism, however, in addition to net demand, the offer comprises *round-trip efficiency* of their flexibility (e.g. battery efficiency). By doing so, our proposed mechanism is able to improve allocative efficiency by resolving flexibility needs with the most efficient means. The mechanism is detailed in Section II-D

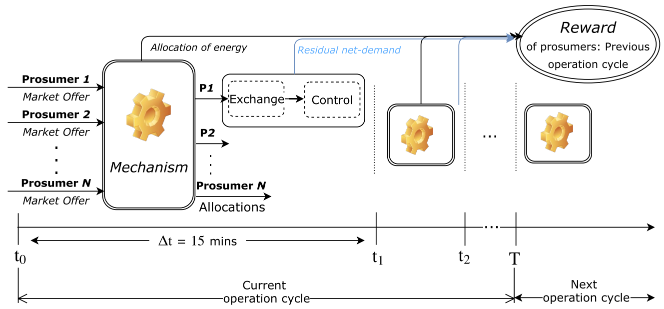

Fig. 1. High-level operational outline of the coordinating exchange mechanisms followed by reward computation.

B. Operation outline

The market protocol proceeds in rounds where every agent submits a bid (or ask), allocations are computed by matching bids and asks, establishing the market equilibrium. In this paper, however, we have assumed all bids (and asks) are cleared by a local exchange market. We assume that the intelligence of exchange market is hosted in one of the prosumers' energy management system. The exchange market clears the offers in near real-time and provides the allocations back to the agents. The high-level operational outline of the proposed mechanism is shown in Figure 1. In brief, the mechanism periodically accepts offers from prosumers, computes the allocated exchange quantities by matching offers, and responds back to the prosumers with those allocations. The rewards are calculated retrospectively after a predefined *operation cycle* of T discrete time periods is completed. Specifically, the algorithm proceeds as follows:

- *Step 1:* For each time $t \in T$, repeat *Step 1.1* to *Step 1.5*.
  - *Step 1.1:* Collect the *market offer*s from all prousmers, segregating *bids* and *asks* based on the embedded f flag.
  - *Step 1.2:* Tabulate the quantities (with round-trip efficiencies for *Mechanism 3*) of each flexible devices of sellers (detailed in Section II-C and in Section II-D).
  - *Step 1.3:* Determine the *allocations*, using the *bids* (and *efficiencies* of the devices) after applying the perspective exchange mechanism.
  - *Step 1.4:* Respond back to the prosumers with the allocations, where the prosumers realize the exchange and deploy batteries.
  - *Step 1.5:* Transact the prosumer-specific residual net energy with the Grid.
- *Step 2:* Determine the reward of prosumers as detailed in Section II-E.

C. Optimization: Exchange and control

The optimal allocation for pooled resources is computed by solving a centralized linear program. This counter-factual scenario proceeds independent of the market and uses private information to provide the optimal allocation given the net demand as bids. For this purpose, a single period optimization is devised, i.e. no time-coupled constraints are required. The objective of such optimization is to maximize the local energy exchange.

Let, $ex_b(s) \in \mathbb{R}^+$ be the energy traded from seller $s \in S$ to buyer $b \in B$; where B and S are the set of all buyers and all sellers (both including the Grid $\{\mathcal{G}\}$), respectively. Aligning with the *Commodity classes of Energy* (defined at Section II), at any discrete time interval t, the buyers and sellers approach to the real-time exchange market by providing a quantity q as $E_b(t)$ and $E_s(t)$, respectively. Therefore, for a buyer b the bid structure looks like $c \leftarrow (q = E_b(t), t)$ and the *market offer* is $o = (c, p = 0, f = 0)$. As the central exchange currently does not consider pricing, we set the price $p = 0$. Similarly, for a seller s, the bid structure and the *market offer* are represented by $c \leftarrow (q = E_s(t), t)$ and $o = (c, p = 0, f = 1)$, respectively.

Typically, the quantities are the net demand (the difference between near real-time demand and generation) of perspective buyers or sellers. After receiving the quantities as bids from prosumers, the exchanger decides on the allocation that maximizes energy exchange locally (equivalently, minimizes energy transaction with the Grid[1]).

The objective function for this problem is devised as,

$$\min_{ex} \sum_{b \in B - \{\mathcal{G}\}} ex_b(\mathcal{G}) + \sum_{s \in S - \{\mathcal{G}\}} ex_{\mathcal{G}}(s). \tag{1}$$

The above objective function is subjected to the following balancing equations for buyers and sellers, respectively.

$$\begin{aligned} E_b &= \sum_{s \in S} CM(b,s) \cdot ex_b(s) \quad \forall b \in B - \{\mathcal{G}\}, \\ E_s &= \sum_{b \in B} CM(b,s) \cdot ex_b(s) \quad \forall s \in S - \{\mathcal{G}\}. \end{aligned} \tag{2}$$

where CM is a "boolean" connectivity matrix representing possible trading restrictions due to the electrical network topology of the cooperatives. These constraints ensure that the demand (and the supply) is met entirely through the exchange with physically connected prosumers. In this paper, we assume that the network is not restrictive, modeled by a fully-connected topology i.e. $CM(b,s) = 1, \forall b \in B$ and $\forall s \in S$.

Finally, a prosumer resolves the residual demand (i.e. post-exchange step in Figure 1) by activating local flexible device and charge or discharge accordingly. Typically, the flexible devices (e.g. battery) are subjected to a degradation loss of the usable capacity. In this paper, we modeled a battery as the flexible device and utilize a linear loss function to model the degradation.

[1]The mechanism does not actually allocate any *grid exchange* with prosumers. Rather, it provides the optimal allocation *among* the prosumers.

The mechanism obtains the allocation based on the net-demand while minimizing the *grid exchange*. However, the mechanism might still yield inefficient allocations as depicted in the following example.

Example: Consider a single buyer who requires 3kWh for the next period, submits an *ask* to the exchanger. At the same time, two sellers, $Seller_1$ and $Seller_2$, both capable of providing 3kWh for that period, submit their associated *bids* to the exchanger. Consider, without loss of generality, that the round-trip efficiencies of the local flexible resources (e.g. batteries) controlled by these sellers are 80% and 90%, respectively. A mechanism that does not consider these efficiencies into the decision making might end up assigning the buyer to $Seller_2$, which consequently leads to an inefficient allocation. The reason for the inefficiencies links to the phenomenon that $Seller_1$ needed to trade the energy earlier due to its relatively higher loss in battery coupled with the degradation loss than that of $Seller_2$. However, the *Mechanism 2* may allocate otherwise and thereby increase the overall loss in the system.

To this end, we extend the formulation presented in Eq. 1 and associated constraints to support an *Efficient Exchange and control* strategy, which keeps the benefits of being device-agnostic while considering round-trip efficiencies, resulting in a more efficient allocation (as experimentally shown in Section III-B).

D. Optimization: Efficient Exchange and control

In addition to submission of the net demand to the centralized exchanger, the mechanism assumes that the agents (the sellers, in particular) submit the round-trip efficiencies of their locally controlled flexible devices. Therefore, the bids are restructured as $c \leftarrow (q =< E_s(t), \eta_s >, t)$ where η_s be the round-trip efficiency of battery (or other flexibility) of seller $s \in S - \mathcal{G}$. The mechanism makes use of these submitted round-trip efficiencies into the decision making process. The objective is still to maximize the local energy exchange and thereby minimizing the *grid exchange*. Therefore, the formulation should produce allocations that are capable of minimizing the *grid exchange* while improving the allocative efficacies exemplified in Section II-C.

In order to do so, for a particular seller s, the exchanger reformats η_s to η_s^b, $\forall b \in B$ and assigns $\eta_s^b = \infty$ when $b \in \{\mathcal{G}\}$ or $s \in \{\mathcal{G}\}$. The transformation can be written as, $\forall s \in S$

$$\eta_s^b = \begin{cases} \infty, & \text{if } b \in \{\mathcal{G}\} \text{ or } s \in \{\mathcal{G}\} \\ \eta_s, & \text{otherwise.} \end{cases} \tag{3}$$

The following objective function serves the purpose of minimization of the *grid exchange* with improved allocative efficiencies

$$\min_{ex} \sum_{b \in B} \sum_{s \in S} \eta_s^b \cdot ex_b(s). \tag{4}$$

The objective function is subjected to the same set of constraints defined in Section II-C.

E. Resolving conflict of interest

In this section, we detailed the phenomenon of *conflict of interests* of the prosumers emerging from applying the mechanisms. Typically, the prosumers may not participate in any of the exchange mechanisms if the resultant allocation and consequent flexible resource control go against the interest of the prosumers. We introduce a loss function followed by a reward mechanism that essentially encourages the agents to participate in the exchange mechanisms. The *Loss in the system* introduced by applying a particular mechanism is defined by the total increase in (net) demand compared with the baseline mechanism of *No flexibility* (i.e. *Mechanism 0*). The loss therefore, be directly linked to the round-trip efficiencies of the activated flexible resources. There is no system loss when *Mechanism 0* is applied.

Let N be the number of prosumers and T be the total simulation period. Further, let the demand and (PV) generation of agent i at time t be $d_i(t)$ and $pv_i(t)$, respectively. The cumulated net demand after applying *Mechanism* m and deploying local battery of agent $i \in N$ is defined as:

$$D_i^m = \sum_{0}^{T} \left(d_i(t) - pv_i(t) + Ex_{i,-i}^m(t) + pb_i(t) \right), \quad (5)$$

where $Ex_{i,-i}^m(t)$ is the total energy agent i received from other agents $-i$ at time t utilizing *Mechanism* m.[2] Therefore, Ex_i essentially is the agent specific decision yielded from the exchanger described in Section II-C and II-D. However, since *Mechanism 1* does not impose any exchange, $Ex_{i,-i}^1(t) = 0$ for all $i \in N$. The dispatched battery power of agent i at t is $pb_i(t)$, where $pb_i(t) < 0$ when the battery is discharged. Again in *Mechanism 0*, $pb_i(t) = 0$ since the flexibility is not activated. Finally, the loss in the system after applying *Mechanism* $m \in \{1, 2, 3\}$ is given by

$$L^m = \sum_{i=1}^{N} \left(D_i^m - D_i^0 \right). \quad (6)$$

Typically, the losses are socialized among the participated prosumers. Therefore, the loss per prosumer is calculated by taking the average (i.e. $L_i^m = \frac{L^m}{N}$). This socialized loss function could form a mean of rewarding the agents.

However, if the agents are rewarded just by considering the socialized loss component without taking their marginal contributions to loss reduction, the system might exhibit unfairness due to the consequent increase in the *conflict of interests* amongst prosumers. Therefore, we adopted a measure, namely *difference evaluation function*, which has been widely utilized in Multiagent learning for its performance in extracting excellent behavior in numerous multiagent applications [10]. The *difference evaluation function* of an agent i defines the marginal contribution of i reaching a joint system state $\mathbb{S}$ utilizing *Mechanism* m. Formally,

$$DE_i(\mathbb{S}|m) = G(\mathbb{S}|m) - G_{-i}(\mathbb{S}|m). \quad (7)$$

[2]Negative $Ex_{i,-i}$ implies outgoing energy from agent i.

We can break the joint system state $\mathbb{S}$ down to two components; *loss reduction* (Eq. 6) and *grid exchange minimization* (Eq. 1 and Eq. 4) as $\mathbb{S}_1$ and $\mathbb{S}_2$, respectively. Finally, an agent i could be rewarded by taking a linear combination of its marginal contributions to both the states

$$R(i|m) = \alpha \times DE_i(\mathbb{S}_1|m) + (1 - \alpha) \times DE_i(\mathbb{S}_2|m), \quad (8)$$

where α represents a reward contribution factor. Therefore, we could say that an agent i chooses *Mechanism* m over other mechanisms if the *Mechanism* m maximizes its reward defined in Eq. 8. The agents are provided with a payment that essentially is an *affine transformation* of the reward function. However, since the reward function requires the joint system states as functional parameters, the payment is made in retrospect. The agents are paid weekly based on their marginal contributions to the joint system states acquired over that week.

III. A Case Study of local energy exchange and Discussions

In this section, we present experimental results of a case study applying the mechanisms described in Section II-A. First, we describe the used residential data [11] and experimental setup and then we present results considering the following points:

- *Scalability*: The number of prosumers is varied to elucidate the effect of prosumer scalability over different mechanisms. The number of prosumers analyzed is taken from a list of 3, 10, 20, and 50 prosumers.
- *Diversity*: The round-trip efficiency of the flexible resources are assumed to *Normally Distributed* over the number of prosumers.

A. Data and Setup

The experiments are conducted by taking samples of prosumers over 150 households that are collected from the Pecan Street dataset. The prosumers are assumed to be equipped with a battery.[3] Due to homogeneity in the geographical location, the PV generation patterns of the prosumers are positively and highly correlated. Therefore, the demand/supply patterns (i.e. the timings of prosumers to be *consumer* and *producer*, respectively) are positively correlated. In order to form a local market platform, the PV generation patterns of a set of randomly chosen prosumers are shifted uniformly with a span of [0,6] hours. The conducted simulation period is set out to be 7-days where the exchange is performed quarter-hourly i.e. the *trading and exchanging* period is 15-minutes. Note that due to the near real-time *bidding* and exchange, the exchange mechanisms inherently reduce the necessity of predicting demand and generation that are required for *bidding* in the day-ahead market.

[3]A typical residential Lithium-ion battery of capacity 6.8kWh with rated charging and discharging power of 3kW and 1.3kW, respectively. The round-trip efficiency is assumed as 90% while the SOC is allowed to operate within 10% to 90% of the capacity. The degradation rate of the battery is fixed as 0.1% of the capacity.

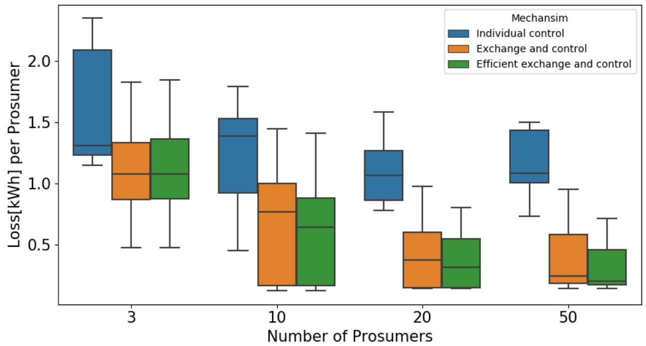

Fig. 2. System loss per prosumer emerges from different mechanisms. The proposed mechanisms (green and orange) obtained better results than individual control (blue).

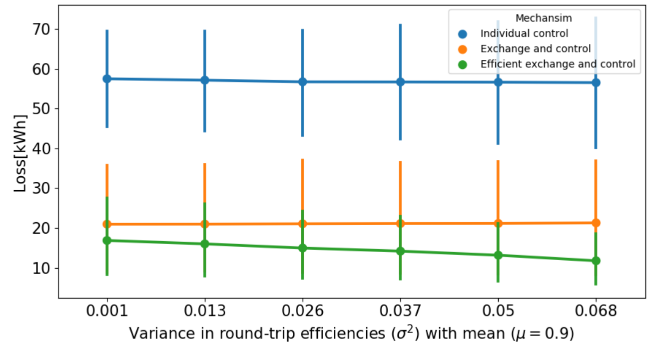

Fig. 3. System loss pattern with increasing variance in the distribution of round-trip efficiency over 50 prosumers. The efficient exchange and control mechanism (green) reduces the loss as the diversity of the round-trip efficiencies increases.

B. Experiment: Loss Reduction

Here, we analyze the performance of derived mechanisms with respect to the *Loss in the System*, as described in Section II-A and Eq. 6. In order to clarify the statistical properties of the Loss reduction phenomenon over different prosumer scales and diversities, the experiments are performed over a number of trials, where each trial contains an independently chosen subset of the prosumers (the superset of prosumers contains 150 prosumers). First, the experiments are performed considering the *scalability* of prosumers and then, we evaluate the effects of *diversity* of the prosumers' batteries.

The sensitivities of the system loss with the increasing number of prosumers depict that the proposed mechanisms obtain better results than individual control. The incurred system loss per prosumer with the scale of the EC is shown in Figure 2. The distribution of the round-trip efficiencies of the locally controlled batteries is assumed to be $\mathcal{N}(\mu = 0.9, \sigma^2 = 0.01)$ (i.e. the *Diversity* is kept relatively more static). The influences of the devised mechanisms on the reduction of system loss are quite apparent from the Figure. The *Efficient exchange and control* mechanism minimizes the Loss regardless of the number of prosumers with better results than the other mechanisms. As the scale of the cooperative grows, so does the dominance of *Mechanism 3* over the other two compared mechanisms. Evidently the prosumers are encouraged to participate in exchange coordinated by *Mechanism 3*.

Now, we turn to analyze the effects of *diversity* in the mechanisms. The increasing variances in the distribution of round-trip efficiencies over 50 prosumers are shown in Figure 3. Interestingly, the system loss is not sensitive to the distribution of round-trip efficiencies when *Mechanism 1* and *Mechanism 2* are applied since these mechanisms are unable to take the advantage of having diversity in flexible devices. The *Mechanism 3*, on the other hand, takes the round-trip efficiencies into consideration and reduces the loss further with greater diversity.

Next, we evaluate the impact of the mechanisms in terms of reverse power flow gathered from aggregated PV generation. Assuming the EC working as a Microgrid, increased PV

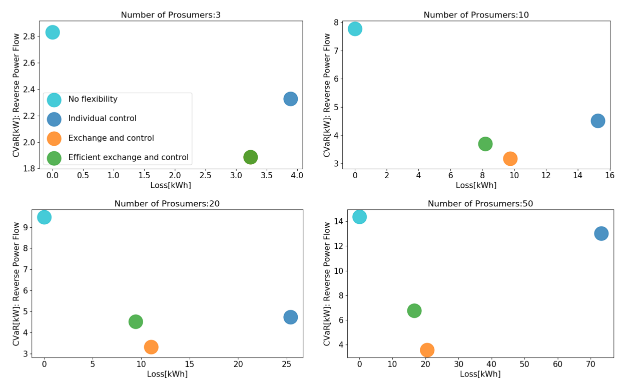

Fig. 4. The trade-off between Loss and CVaR of reverse power flow over increasing number of prosumers resulted from applying different coordination mechanisms. The proposed mechanisms obtained lower CVaR and loss than individual control.

generation may lead to reverse power flows at the transformer located at the point of common coupling (PCC) [12]. Such reverse power flow influences costly degradation in reliability and thus needs to be minimized. Conditional Value at Risk (CVaR) is a coherent measure of risk [13], which we adopt from the financial literature as a rigorous quantification of

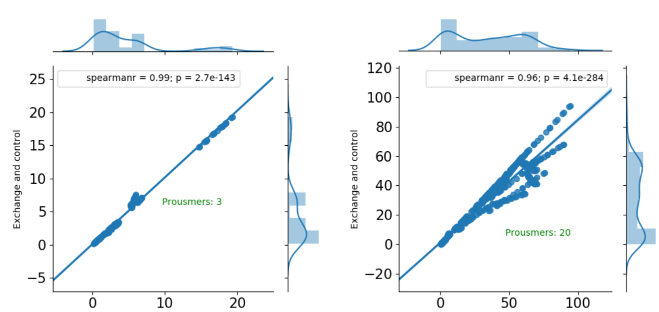

Fig. 5. The improvements in *loss reduction* using *Exchange and control* and *Efficient exchange and control* strategies over *Individual control* and their correlations performed over different number of prosumers in the cooperative

reverse power flow risk. The relationship between CVaR (of aggregated reversed power flow) and loss is depicted in Figure 4. The reverse power flow from the cooperative could not be avoided entirely due to the high and positive correlation amongst the PV generation patterns in prosumers. The exchange mechanisms (*Mechanism 2* and *3*) reduce the CVaR and minimize the loss regardless of the scale of the cooperative compared to the individual control (*Mechanism 1*).

In order to evaluate the Statistical significance of the relative *Loss reduction* while applying *Exchange and control* and *Efficient exchange and control* over *Individual control*, we have employed Spearman correlation test (with a confidence level 0.05). The Spearman correlation is a non-parametric rank test that measures the monotonicity of two datasets and does not assume the datasets to be normally distributed. As depicted in Figure 5, the marginal distributions of the relative *Loss Reduction* are not normal. Further, the figure shows that the relative *Loss Reductions* are positively correlated (regardless of the number of prosumers) while two-sided $p-value$ points that these values are statistically independent.

C. *Experiment: Resolving* conflict of interests

In order to resolve the conflict of interests of prosumers in participating in the proposed mechanisms, we devise a reward function that forms the basis of payment. In this experiment, we show that the *Efficient exchange and control* mechanism is capable of maximizing the agents' reward. The relative change in rewards imposed by the *Efficient exchange and control* mechanism – over *Individual Control* mechanism – applied on an energy cooperative with 10 prosumers is shown in Table I. The *difference evaluation functions* for two optimized system states ($\mathbb{S}_1$ and $\mathbb{S}_2$), namely *Loss Reduction* and *Grid Exchange Reduction* are presented in the Table. Notably, prosumers *4*, *7*, and *9* yield negative reward in *loss reduction* (highlighted in the Table). In other words, these prosumers contributed negatively while reducing system loss when the system is exposed to *mechanism 3*. The same set of prosumers, however, positively contributed to the system while reducing the *grid exchange* volume. Finally, the improvement in rewards, as defined in Eq. 8, experienced by prosumers are listed on the table (for $\alpha = 0.5$). Therefore, empirically the *Mechanism 3* increases the reward of each prosumer in the cooperative.

IV. Conclusion

Our first contribution are two flexibility device-agnostic near real-time exchange mechanisms that ensure optimal and efficient exchanges in residential ECs. As a second contribution, we introduce a reward-mechanism that forms the payment function for the participating prosumers based on their marginal contributions to the joint system states (i.e. *loss reduction* and *grid exchange minimization*). Such a reward-mechanism encourages the prosumers to participate in the exchange market, resolving the *conflict of interest* of the prosumers that arise from shifting from an *individual control* mechanism. The paper further contributes to a detailed simulation model for various scales of EC with infused diversifications from underlying flexible devices and to a follow-up sensitivity analysis of these features in achieving *loss reduction*. An immediate follow-up research will seek for the payment mechanism that ensures the *truthfulness* of the agents in bidding while increasing the *social welfare* and *fairness* of the system. Additionally, the mechanisms only focus on the local market, the interactions with markets such as retail, wholesale, and ancillary services are not explored.

TABLE I

Prosumers improvement in rewards while choosing *Efficient exchange and control* mechanism over *Individual control* mechanism.

Prosumer	Contribution to reduction		Reward
	Loss	*Grid exchange*	
1	6.29	136.42	71.35
2	5.61	9.13	7.37
3	4.83	30.33	17.58
4	**-0.66**	66.59	32.96
5	4.95	16.77	10.86
6	7.73	13.98	10.85
7	**-6.47**	22.44	7.99
8	0.28	121.93	61.11
9	**-4.23**	16.76	6.26
10	2.52	32.46	17.49

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