

# Energy Contract Settlements through Automated Negotiation in Residential Cooperatives

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**Abstract**—This paper presents an automated peer-to-peer (P2P) negotiation strategy for settling *energy contracts* among prosumers in a Residential Energy Cooperative (REC) considering heterogeneous prosumer preferences. The heterogeneity arises from prosumers' evaluation of *energy contracts* through multiple societal and environmental criteria and the prosumers' private preferences over those criteria. The prosumers engage in *bilateral negotiations* with peers to mutually agree on periodical *energy contracts/loans* that consist of an energy volume to be exchanged at that period and the return time of the exchanged energy. The prosumers keep an ordered *preference profile* of possible *energy contracts* by evaluating the contracts from their own valuations on the entailed criteria, and iteratively offer the peers contracts until an *agreement* is formed. A prosumer embeds the valuations into a *utility function* that further considers uncertainties imposed by demand and generation profiles. Empirical evaluation on real demand, generation and storage profiles illustrates that the proposed negotiation based strategy is able to increase the system efficiency (measured by *utilitarian* social welfare) and fairness (measured by *Nash* social welfare) over a baseline strategy and an individual flexibility control strategy. We thus elicit system benefits from P2P flexibility exchange already with few agents and without central coordination, providing a simple yet flexible and effective paradigm that may complement existing markets.

**Index Terms**—Automated Negotiation, Energy Contract, Multi-agent System, P2P energy exchange.

## I. INTRODUCTION

The joint coordination of prosumers' distributed energy resources (DER) in a Residential Energy Cooperative (REC) has the potential to shape the overall demand and to mitigate fluctuations caused by renewable integration. However, properly incentivizing the prosumers to coordinate their locally owned distributed resources is quite a challenge, and justifiably a field of active research in Smart Grids. Local energy exchange may offer incentives to the prosumers to engage in competition and in local trading [1]. For energy communities, these mechanisms may need to take into account and balance several objectives, including, next to efficiency, altruism, or fairness of allocations [2]. Prosumers in a REC may have diverse preferences over how their energy profiles are valued due to various societal and environmental factors. For instance, the prosumers may evaluate *energy contracts* based on several criteria, e.g. *self-sufficiency* or *autarky*, *cost of energy*, *loss in flexibility*, *sustainability*, and so on [3],

resulting in a private valuation. While complete preferences would need to be computed and revealed for market based solutions, peer-to-peer (P2P) negotiation proceed iteratively, reducing the amount of information revealed.

Automated negotiation is an organic process of joint decision making where multiple stakeholders – typically represented by autonomous agents – with conflicting interests engage and make a decision [4]. The negotiation approach contrasts market-based approaches, and its iterative nature provides a more natural model for low liquidity settings, in which personalized solutions need to be found in large outcome spaces. P2P negotiation within REC's is still a widely unexplored area of research, with a few exceptions; e.g., an automated negotiation protocol has been applied to address energy exchange between off-grid smart homes [5]. However, their designed protocol imposes several key restrictions, in which only two *exchange periods* over a day in which only equal amounts *energy volume* can be exchanged.

We present an *automated negotiation approach* as an energy exchange mechanism to settle P2P energy contract as loans between prosumers in a REC. During each negotiation session, a pair of prosumers (represented by software agents) engage in *bilateral negotiation* by exchanging and eventually agreeing on *energy contracts*, comprised of several *negotiation issues* (here *energy volume* and *return time*). The proxy agents evaluate *offers* based on criteria that model the heterogeneous preferences of the users they represent: 1) *loss in flexibility* (in local storage), and 2) *autarky* or sustainability of the *offers*. The agents are able to weigh these criteria differently, thereby enabling heterogeneity and trade-offs between the agents.

The main contributions of this paper are as follows.

- We propose a novel and intuitive *negotiation* based strategy that considers *heterogeneity* in prosumers through a *distributed* and *autonomous* agent model.
- We evaluate the performance of the proposed *negotiation* based strategy over real residential demand, generation, and storage data to elucidate the efficiency of the strategy in increasing the social welfare over a baseline strategy and an individual flexibility control strategy.

The rest of the paper is organized as follows: Section II describes a residential prosumer model, and defines the *energy contract* that is used in the negotiation process. Section III presents the negotiation based energy exchange strategy and the contextual notion of allocative efficiency. Simulation case

studies are presented in Section IV. Finally, Section V concludes the paper with a glimpse of possible follow-up research.

## II. MODELING PROSUMERS AND ENERGY CONTRACTS

In this section, we present a prosumer by systematically modeling their load and generation profiles integrated with batteries. Later, we define *energy contracts* with associated concepts, uncertainty management in planning, and aspects of the negotiation process.

### A. Prosumer Model

A prosumer is assumed to be equipped with a renewable power generation unit (e.g. Solar Photovoltaic, PV) and a flexible resource (e.g. battery energy storage system). We represent a prosumer as a software agent,  $i \in N$ , where  $N$  is the set of agents in the cooperative. Let the (predicted) generation profile (through PV panels) of an agent  $i$  be represented by  $\widetilde{Pv}_i(t)$ ,  $\forall t \in T$ , where  $T$  is the set of time-periods. Similarly, the predicted load profile of the agent  $i$ , at  $t$  is represented by  $\widetilde{Ld}_i(t)$ . In addition, the battery dispatch (load) profile is denoted as  $Pb_i(t)$ , and a choice of agent  $i$ . The battery state of charge is modeled by the following equation

$$X_i(t) = X_i(t-1) + \eta_b \times Pb_i(t) \times \Delta t - \epsilon_b, \quad (1)$$

where,  $X_i(t)$  is state of charge (SOC) of the battery at  $t$  and is operated within a limit. The constant degradation of the battery is represented by  $\epsilon_b$ . The dispatched battery power,  $Pb_i(t)$  is constrained to operate within a limit. The efficiency of the battery,  $\eta_b$  is dependent on whether the battery is being charged (with efficiency  $\eta_b^c$ ) or discharged (with efficiency  $\eta_b^d$ )

$$\eta_b = \begin{cases} \eta_b^c, & \text{if } Pb_i(t) \geq 0 \\ \frac{1}{\eta_b^d}, & \text{otherwise} \end{cases} \quad (2)$$

After self-consumption, the net demand of agent  $i$  becomes

$$\widetilde{Ld}_i^{net}(t) = \widetilde{Ld}_i(t) - \widetilde{Pv}_i(t). \quad (3)$$

An agent  $i$  engages in a trade with a subset of peers  $j \in J \subseteq N$  at  $t$ , and the volume of energy being traded with each other is denoted as  $ex_{i,j}(t)$ . The residual of agent  $i$  – after self-consumption, followed by the (cumulative) exchange with the peers and the local battery activation – is the energy either wasted or to be traded on the external market, and is presented by the following energy balancing equation.

$$\widetilde{Ld}_i^{res}(t) = \widetilde{Ld}_i^{net}(t) + \sum_{j \in J} ex_{i,j}(t) + Pb_i(t). \quad (4)$$

### B. Energy Contracts: P2P energy lending

A simple but effective contract to exchange flexibility in energy systems are *energy loans* [6], which we here adapt to the P2P setting. In automated multi-issue negotiation, agents negotiate over several *issues* with a target to achieve an agreement – a value attribution to those issues – that generates a socially optimal outcome for the participating agents. We consider energy loans parameterized by two important *issues* over which the agents negotiate:

1. The volume of energy to be traded between two agents (denoted by  $q \in \mathcal{Q} \subseteq \mathbb{R}$ , where  $\mathcal{Q}$  is a discrete set of energy volumes).
2. The time of receiving the energy back (denoted by  $\tau \in \mathcal{T} \subseteq \mathbb{Z}_{>0}^+$ , where  $\mathcal{T}$  is a discrete set of positive time periods).

A *negotiation domain*  $\Omega$  comprises all possible *energy contracts*, i.e.  $\Omega = \mathcal{Q} \times \mathcal{T}$ . Every  $\omega = (q, \tau) \in \Omega$  is a potential *energy contract* (or loan) within the multi-issue negotiation that specifies a value for each *issue*.

The energy volume  $q$  and the return time  $t + \tau$  influence respective energy profiles for both negotiating agents and consequently affect their local flexibility dispatch. As depicted before, agents may have varied preferences over a predefined set of criteria, i.e. the agents tend to weigh the criteria differently. Let  $\mathbb{C}$  represent the set of criteria upon which the agents state their preferences. In this paper, we assume an agent evaluates an energy profile – resulting from an *energy contract* – based on two criteria: *loss in flexibility* and *autarky* i.e.  $\mathbb{C} := \{c_1 = \text{loss in flexibility}, c_2 = \text{autarky}\}$ . The weight an agent  $i$  places on criterion  $c \in \mathbb{C}$  can be represented as a scaler  $\lambda_c^i$  (where  $\lambda_c^i$  are normalized weights, i.e.  $\sum_c \lambda_c^i = 1$ ) and is private to  $i$ . We assume, the weights are known to agent. An *evaluation function*,  $e_{c,t}^i(\omega)$  is defined that denotes how an *energy contract* performs, at  $t$ , from the perspective of criterion  $c$  given the private preferences of agent  $i$ . Additionally, an agent maintains a planning horizon,  $w$  that represents how far ahead of the agent looks while deciding about the *contracts*. The planning horizon depends on the uncertainty on the demand/generation prediction.

*Criterion 1:* Criterion *loss in flexibility* measures the emergent loss (in energy) due to the round-trip efficiency of the flexibility (e.g. battery) dispatch resulting from implementing an *energy contract*. The *evaluation function* associated with *loss in flexibility* is defined as

$$e_{c_1,t}^i(\omega) = \sum_{k=t}^{k=t+w} Pb_i(k) + \Theta(\mathbf{X}_i), \quad (5)$$

where  $\Theta(\mathbf{X}_i)$  is the offset power required to adjust the resulting SOC. Therefore,  $\omega$  directly influences the battery dispatch power  $Pb_i(t)$  through the energy balancing equation, i.e. Eq. 4.

*Criterion 2:* Autarky in an *energy contract* signifies the sustainability of the contract, which actually measures the total (estimated) energy to be traded on the external market provided that the *energy contract* is implemented. The *evaluation function* associated *autarky* is formally defined as

$$e_{c_2,t}^i(\omega) = \sum_{k=t}^{k=t+w} |\widetilde{Ld}_i^{res}(k)|. \quad (6)$$

Agent aggregates the weighted *evaluation function* of individual criterion to measure the quality of an *energy contract*. The *utility function* is defined as

$$f_{i,t}(\omega) = \sum_c \lambda_c^i e_{c,t}^i(\omega). \quad (7)$$

### C. Dealing with Uncertainty

The load profile  $\tilde{L}_i(t)$  and generation profile  $\tilde{P}_i(t)$  of an agent  $i$  are predicted signals and are potential sources of uncertainties. The *utility* function defined in Eq. 7 is, therefore, unable to provide robust scheduling of local flexibilities. We utilize a set of stochastic scenarios of predicted net load profiles  $\tilde{L}_i^{net}$  and calculate the *expected utility* of an *energy contract* [7]. The scenarios of predicted net load profile are generated by taking samples from a *Gaussian Process* comprising of 1) *Gaussian* error Probability Density Functions (PDF), for each of the discrete lags  $l$  in planning horizon  $w$ , i.e.  $l = 1, \dots, w$ , and 2) a *Gaussian* PDF that models the interdependency between net load of two consecutive periods. The predicted net load for scenario  $s \in \mathcal{S}$  is then determined as  $\tilde{L}_i^{net}(t+l|t, s) = \tilde{L}_i^{net}(t+l|t) + d_i(l, s)$ , where  $d_i(l, s)$  is sampled from the aforementioned *Gaussian Process* and  $\tilde{L}_i^{net}(t+l|t)$  is the predicted net demand for period  $t+l$  when predicted at  $t^1$ . Now, we can define the *expected utility* an *energy contract* could provide by

$$\mathbb{E}[f_{i,t}(\omega)] = \sum_{s \in \mathcal{S}} Pr(s) \cdot f_{i,t}(\omega, s), \quad (8)$$

where  $Pr(s)$  is the probability of the scenario  $s$  and  $f_{i,t}(\omega, s)$  is the modified *utility* of an *offer*  $\omega$  considering the net predicted load scenario  $s$ . We assume the scenarios are equiprobable, and thus  $Pr(s) = 1/|\mathcal{S}|$ . Therefore, in the *negotiation process*, the agents distributively search through the  $\Omega$  to jointly agree on an *energy contract* that maximizes their perspective *expected utilities*.

### III. A NEGOTIATION BASED EXCHANGE MECHANISM

Agents engage in a *bilateral negotiation* to seek for an agreement on an *energy contract*. Given the residential energy cooperative settings of several connected prosumers, the process may be understood as a *multilateral negotiation*, emerging from multiple bilateral P2P pairwise negotiations<sup>2</sup>. As the *negotiation protocol*, we implement the *alternating offers protocol* [4], which is commonly used in automated multi-issue negotiation settings. We assume that each agent is limited to interact once with one other agent in each particular time period. Several important aspects of the negotiation process are detailed in the following.

**Agreement:** An *agreement* is an *energy contract* that is approved by both negotiating agents, and can be denoted by  $\omega^* = (q^*, \tau^*)$ .

**Reservation value:** The private value a negotiating agent keeps as a criterion to accept an offer. Additionally, it also represents the outside option in case of a disagreement. In this paper, an agent  $i$  sets the *reservation value* as a *quantile* of the distribution of  $\mathbb{E}[f_{i,t}(\omega)]$ ,  $\forall \omega \in \Omega$  for negotiating at  $t$ .

<sup>1</sup>Pseudo-predictions of the net demand are generated by adding *Gaussian* noise to the real net demand signal.

<sup>2</sup>An alternative approach could be *multi to multi negotiation*. We do not entertain that option since *multi to multi negotiation* typically require a mediator or a centralized coordination, as per the current state of the research.

Additionally, the *energy contracts* that generate *expected utility* higher than the *reservation value* forms a so-called *aspiration region*.

**Deadline:** The maximum number of rounds of a negotiation before which the agents should reach an outcome. If no *agreement* is formed after the *deadline*, the negotiation fails.

**Preference profile:** A negotiating agent contains a *preference profile* that accumulates an ordered set of the issues in the *negotiation domain*. The agent creates such a profile by ordering the issues according to their *expected utility*, defined in Eq. 8.

**Fair outcome:** An important measure to quantify the fairness in an *outcome* could be conducted by determining the *Nash solution*. The *Nash solution* is essentially the outcome that maximizes the product of the utilities (Eq. 8), achieved from an *energy contract*, of negotiating agents (e.g. agent  $i$  and  $j$ ).

$$\omega_{\text{Nash}}(t) = \max_{\omega \in \Omega} \mathbb{E}[f_{i,t}(\omega)] \cdot \mathbb{E}[f_{j,t}(\omega)]. \quad (9)$$

Figure 1 shows an exemplary *negotiation domain* and the associated *expected utility* (normalized within unit-range) of all possible *energy contracts* calculated from the perspective of an agent that has a *reservation value* quantile of 70% of the distribution that results in a value of 0.46 in the normalized scale. The demarcation of the *aspiration regions* in the *negotiation domain* are outlined through the contoured line. The figure illustrates that *expected utility* is smooth over quantity and nonlinear over return-time.

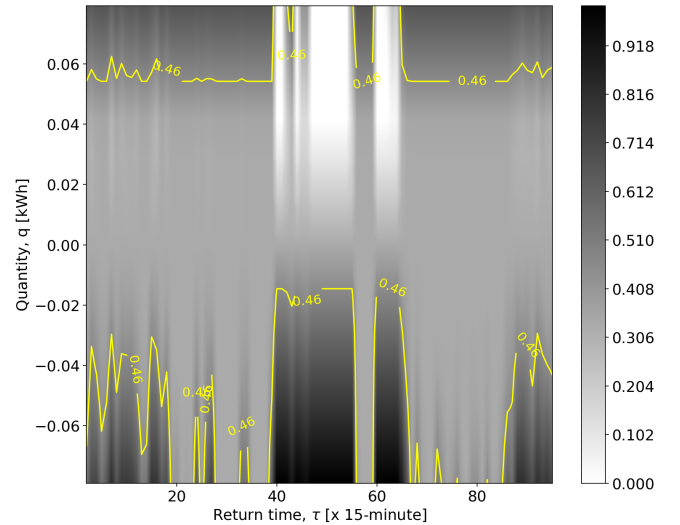


Fig. 1. An exemplary *negotiation domain*. The *issues* are presented at the axes whereas the *expected utility* of the contracts is plotted as a heat-map. The contoured regions are the *aspiration region* as they contain the preferred *energy contracts* with the *expected utility* higher than the *reservation value*.

Algorithm 1 describes the high-level algorithm of the negotiation process between two agents  $A$ , and  $B$  at time  $t \in T$ . The process starts with creating negotiation domain  $\Omega$  that will be used by both agents. Agents then generate perspective ordered *preference profiles* by evaluating all possible contracts in  $\Omega$  while considering their *expected utility* over a planning

**Algorithm 1: NEGOTIATE-Contract( $A, B, t, Q, T$ )**


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begin
   $\Omega \leftarrow \text{createNegotiationDomain}(Q, T)$ 
   $A.\text{generateOrderedPreferenceProfile}(\Omega, t)$ 
   $B.\text{generateOrderedPreferenceProfile}(\Omega, t)$ 
   $r \leftarrow 0$ 
   $\text{offerAccepted} \leftarrow \text{False}$ 
  while  $r < \text{deadline}$  AND NOT  $\text{offerAccepted}$  do
    if  $r \% 2 = 0$  then
       $\text{offer} \leftarrow A.\text{makeOffer}(t)$ 
       $\text{offerAccepted} \leftarrow B.\text{acceptOffer}(\text{offer}, t)$ 
    else
       $\text{offer} \leftarrow B.\text{makeOffer}(t)$ 
       $\text{offerAccepted} \leftarrow A.\text{acceptOffer}(\text{offer}, t)$ 
     $r \leftarrow r + 1$ 
  if  $\text{offerAccepted}$  then
     $A.\text{implementContract}(\text{offer}, t, B)$ 
     $B.\text{implementContract}(\text{offer}, t, A)$ 
  else
     $A.\text{implementReservePlan}(t)$ 
     $B.\text{implementReservePlan}(t)$ 
  return  $\text{offerAccepted}$ 

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horizon  $w$ . Subsequently, an *alternating offers protocol* is implemented where, in each round, one of the agents proposes an offer (picked from the ordered *preference profile*) to the other agent until an *agreement* is reached or the *deadline* is encountered. In case an *agreement* is reached, the agents implement the agreed *energy contract*. Otherwise, the plans associated with the *reservation values* are implemented by each agent. While implementing an *energy contract*, an agent (for instance,  $A$ ) amends to an existing exchange pool by stating *how much* energy ( $q^*$ ) to be traded with *whom* (for instance,  $B$ ) and *when* ( $t$ ) as well as by listing the *same* volume of energy ( $-q^*$ ) is committed to be traded back at  $(t + \tau^*)$  from  $B$ .

#### A. Efficiency and Fairness

In this section, we define the following strategies – apart from the proposed negotiation based energy exchange – to illustrate the efficiency of the proposed strategy.

- *No flexibility*,  $s_0$ : The prosumers do not activate their batteries and only trade residuals with external market.
- *Individual control*,  $s_1$ : This strategy is being currently utilized in the real residential setting, where the prosumers activate their local batteries, individually control the batteries and trade the residuals with external market. However, prosumers do not engage in trading with each other.
- *Negotiation and control*,  $s_2$ : The proposed strategy where prosumers engage in bilateral negotiation over *energy contracts* with peers, implement the *agreement*, and finally activate their batteries to control the residual energy. The remaining energy is traded in external market.

The properties of the strategies are briefed in Table I. Now, we define the *utility* of an agent achieved by applying a particular strategy. Note that, it differs from the *utility function* defined in Eq. 7 which measured the quality of an *energy contract*. The *utility* of the proposed strategy  $s_2$  considers the realized energy profile, after periodically negotiating and implementing the

TABLE I  
PROPERTIES OF THE STRATEGIES.

Strategy	Local trading	Flexibility activation
<i>No flexibility</i>	No	No
<i>Individual control</i>	No	Yes
<i>Negotiation and control</i>	Yes	Yes

*agreement*. The *utility* is, therefore, similar to Eq. 7 but taking into account the realized energy profile and the consequent battery dispatch.

$$u_i(s_2) = \lambda_1 \times \left[ \sum_t^T P b_i(t) + \Theta(\mathbf{X}_i) \right] + \lambda_2 \times \left[ \sum_t^T |L d_i^{res}(t)| \right]. \quad (10)$$

For strategy  $s_0$ , the  $u_i(s_0)$  only considers the *autarky* components (without the energy exchange component, i.e.  $\sum_{j \in J} ex_{i,j}(t)$  in Eq. 4). And for strategy  $s_1$ , the  $u_i(s_1)$  considers both criteria, but again without the flexibility component. In order to validate the efficiency of the strategies  $\mathbb{S} := \{s_0, s_1, s_2\}$  in improving the social welfare, we define the *utilitarian social welfare* as  $sw_s = \sum_i^N u_i(s)$  for all  $s \in \mathbb{S}$ . Moreover, we quantify the relative fairness of a strategy  $s$  (to another strategy  $h$ ) based on the *Nash social welfare* criterion, an established concept of fairness [8], as following

$$nw_{s|h} = \prod_i^N (u_i(s) - u_i(h)). \quad (11)$$

#### IV. NUMERICAL SIMULATION AND DISCUSSION

In this section, we consider two cases of varied scaled cooperatives to empirically evaluate different aspects of the proposed strategy.

- Case 1: *Cooperative of 2 agents* presents the effects of the proposed strategy on the residual demand and consequent battery dispatch, and the agents' *negotiation domain* exploring phenomena.
- Case 2: *Cooperative of 9 agents* verifies the quality of the allocation achieved by the proposed strategy from the perspectives of efficiency and fairness.

The aforementioned cases assume the local flexibility (i.e. battery) is owned privately and controlled individually by the prosumers<sup>3</sup>.

##### A. Case 1: Cooperative of 2 Agents

Flexibility activation through battery enhances the potential benefits as two agents could negotiate even when their net demand status are equal (i.e. both positive or negative). The specification of the agents with associated battery information is provided in Table II. The charging and discharging rates

<sup>3</sup>The total simulation period is taken as 20 days with 15-minute of granularity, i.e.  $\Delta t = 15$ . The planning horizon  $w$  is set out to be 48-hours. The number of scenarios  $|\mathcal{S}|$  is set to 100. The set  $\mathcal{Q}$  contains 10 discrete energy quantities, and the set  $\mathcal{T}$  contains discrete time steps of  $\{2, 3, \dots, w \times \Delta t\}$ . The *deadline* of a negotiation session is set out to be 5000 rounds.

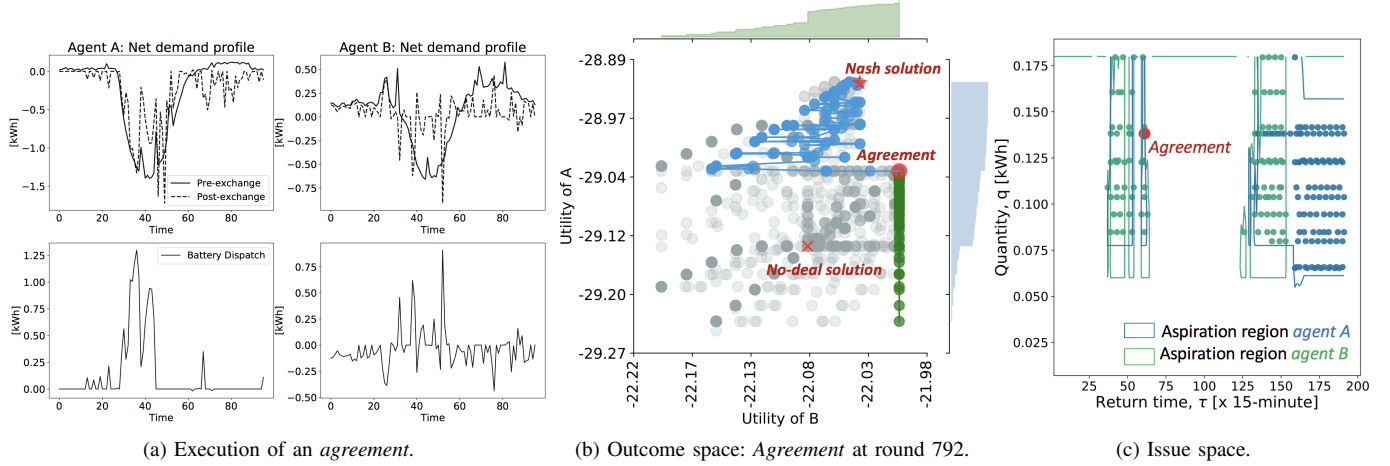


Fig. 2. (a) Effects of executing *agreements* – on net demand and battery dispatch profiles – reached through negotiation between two agents. (b) An exemplary outcome space of *agent A* and *agent B* with marginal cumulative distributions of their *expected utilities*. The *Nash solution*, *agreement* and *No-deal solution* are plotted to illustrate the relative distances. (c) The *negotiation domain* with the juxtaposed *aspiration regions* bounded by contour lines for both agents. The negotiation traces, represented by the colored scatters, depict the behavior of the agents with the opponents as both of them converge to the *agreement*.

TABLE II  
AGENT SPECIFICATIONS.

Agent	Reservation (%)	$\lambda_{c_1}$	$\lambda_{c_2}$	Capacity[kWh]	Efficiency
<b>A</b>	52	0.33	0.67	6.8	0.9
<b>B</b>	50	0.71	0.29	7.0	0.8

of these batteries are 1.3kW and 3.3kW, respectively. The SOC the batteries are operated within 20% to 90% of the respective capacity, and the degradation rate is set as 0.4% of the same. As pointed in the Table, *agent A* values criterion  $c_2$  than criterion  $c_1$ ; that is the agent places higher preferences on *autarky*, while *agent B* prefers *loss in flexibility* more.

Figure 2(a) shows effects of energy exchange (through negotiation) and resulting battery dispatch between *agent A* and *agent B*. The residual demand profiles resulting from negotiation clearly reflect the preferences of the agents. For instance, the battery dispatch profile of *agent B*, who cares more about the *loss in flexibility*, exhibits a relative fluctuating signal that results in an almost neutralized losses. The apparent fluctuations in the battery dispatches are due to the fact that they both implement a naive battery scheduling technique, as described in Section II-A. However, in the proposed framework, agents can easily mitigate such fluctuations by integrating an additional cost function (that penalizes such behavior) into their utility function, and placing a higher weight on that cost function.

Now, we analyze the exploration of *negotiation domain* by agents while reaching an *agreement*. The battery specifications of the agents are kept identical and similar to *agent A*. The *reservation quantile* are kept as 95% for the agents. Figure 2(b) depicts a two-dimensional outcome space that emerges from the negotiation interactions between the agents, and their marginal cumulative distributions of (expected) *utility* over *negotiation domain*. Noticeably, while the *agreement* generates

the highest *utility* for *agent B*, *agent A* needs to compromise to reach the *agreement*. Although, the *agreement* does not reach the *Nash solution*, it still yields *utilities* that are located over 95% quantile range of the distributions. The *no-deal solution* defines the situation when the agents do not engage in negotiation, and consequently do not exchange energy. The trace of negotiation – from the perspective of individual agents – illustrate the power of heterogeneous preferences and the multi-issue setting, because the agents are able to explore their *iso-utility curves*, and concede until an *agreement* is found. The corresponding *negotiation domain*, with the issues and *aspiration regions* of both the agents are illustrated in Figure 2(c). The *agreement* is located at one of the intersections of the agents' contoured region of *aspiration value*.

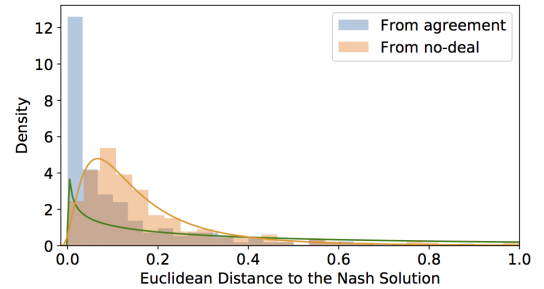


Fig. 3. Distributions of the Euclidean distance (fitted via *F-distributions*) to the *Nash solution* from the *agreements* and the *no-deal solutions* in the *utility/outcome space*. The resulting *agreements* are more inclined to be the *Nash solutions*, hence confirm the fairness of the energy allocations.

### B. Case 2: Cooperative of 9 Agents

In this case, we analyze a higher scaled cooperative with 9 agents comprising similar battery configuration (as *agent A* in Case 1) and having similar *reservation values*. Figure 3 elucidates the quality of the outcome –i.e. *agreement* – through



the distribution of the Euclidean distance from the *agreement* to the *Nash solution*, and how the *agreement* outperforms the *no-deal solution* by being more likely to be the *Nash solution*. The distances are measured for each negotiation session over the whole simulation periods and normalized within unit range. Now, we turn the analysis toward the allocative efficiency of the proposed negotiation strategy, and how the strategy establishes itself preferable for all agents over a baseline strategy of *no flexibility* and a strategy of *individual control* of flexibility without any P2P exchange. Figure 4 presents the relative increase in utility for each prosumer of an EC with 9 agents, comparing the improvements of *individual control* strategy and *negotiation and control* strategy over *No flexibility* strategy. As seen in the figure,  $(u_i(s_2) - u_i(s_0))$  dominates over  $(u_i(s_1) - u_i(s_0))$  by placing itself over the dashed line. Therefore, it implies that the *social welfare* criteria, both *utilitarian* and *Nash* are maximized by the proposed *negotiation and control* strategy.

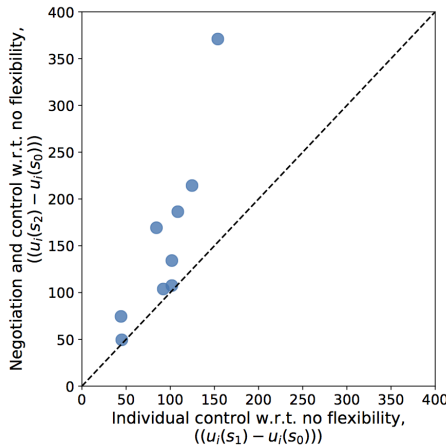


Fig. 4. Agents utility improvement of *individual control* strategy (horizontal) and *negotiation and control* strategy (vertical) over *no flexibility* baseline. Agents are above the dashed equal improvements line, hence our newly proposed strategy dominates *individual control*, while also improving relative fairness ( $nw_{s_2|s_0} \approx 1.38 \cdot 10^{19} > nw_{s_1|s_0} \approx 3.35 \cdot 10^{17}$ ).

## V. CONCLUSION

A residential cooperative potentially exhibits inefficiencies due to renewable power integration and uncoordinated activations of locally owned distributed energy resources of heterogeneous prosumers. Automated negotiation – a natural model of interaction – has the ability to alleviate these inefficiencies by accommodating the heterogeneous preferences of prosumers in joint decision making. In this paper, we have presented a P2P automated *bilateral negotiation* strategy for *energy contract* settlement between prosumers. The prosumers jointly seek for an *agreement* on *energy contracts/loans* – consisting of energy volume to be exchanged and the return time of the exchanged energy – that maximise their preferences by evaluating the realized energy profiles and the consequent flexibility dispatch. Although we consider a predefined set of criteria for the agents to have the preferences on, in reality,

the agents may have a diverse set of mutually exclusive constraints that shape up their personal preferences. The proposed negotiation strategy allows the agents to effortlessly stack-up those local constraints weighing by preferences while settling for the *contracts*. The proposed negotiation based strategy is applied to real energy profiles, and results in an improved *utilitarian* social welfare as well as improved fairness w.r.t. *Nash* social welfare; which is remarkable considering that the allocations are achieved from single pairwise interactions amongst prosumers.

In this paper, we assume the weights an agent places on the criteria to be predefined, whereas in practice, an agent may be uncertain about the preferences and may need to elicit them from prosumers in a cost-effective way [9], [10]. Future work may investigate the case where the agents exhibit uncertainty over the preferences and are required to negotiate successfully with partial preferences.

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