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Local Energy Markets in Energy Communities and Their Impact on Energy Poverty

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***Abstract*—Local energy markets and energy communities have emerged as novel solutions to efficiently coordinate demand for locally generated renewable energy. This study presents a hierarchical multi-stage optimisation framework for the day-ahead scheduling of demand and determination of energy transactions within an energy community. Special pricing when trading with peers in the community is extended to vulnerable households facing energy poverty. The research study emphasizes the importance of mitigating energy poverty and evaluates the effect of various local energy market approaches on the reduction of energy costs through simulation analysis. Application of the proposed methodology is demonstrated through a case study involving a UK-based community of 200 households. Substantial reductions in electricity costs exceeding 13% are achieved across all market structures explored in this paper, particularly when flexibility and optimisation are combined with community trading. Prosumers experience the greatest savings exceeding 32.2%, while energy-poor households gain over 11.1% on average benefiting from reduced tariffs at the community trading stage, however, this is accompanied with diminished gains on behalf of prosumers.**

I. Introduction

Small-scale renewable energy sources (RES) and power-producing prosumers are expected to play a pivotal role in the energy transition, however the increased decentralisation accompanying these developments poses significant challenges for the grid operation. Emerging solutions to such challenges are local energy markets (LEMs) including community, peer-to-peer (P2P) and transactive energy, which aim to exchange, trade and optimise energy at a local level first, before interacting with the wider power grid and larger energy markets. This trend is evidenced by the significant growth in the academic literature [1], [2], pilot and commercial projects deployed at a global level and the significant change in the regulatory landscape observed in the last 5 years. One example is the effort of the European Union to legislate towards supporting energy communities, as shown by two recent EU directives supporting renewable and citizen energy communities [3], [4].

A LEM is a marketplace that coordinates energy and flexibility from distributed assets (generation, storage, demand response) within a confined geographical area, while energy communities refer to citizens jointly investing in renewable generation assets, energy sharing and/or energy trading [5], [6]. Significant benefits of LEMs and energy communities reported in the academic literature include promoting renewable energy adoption, community empowerment, enhancing resilience and reducing energy costs. As such, energy communities can be a promising tool in tackling energy poverty (EP) [7]. EP (or fuel poverty as known in several countries) is a measure of the people's affordability regarding energy costs. The actual definition of EP varies across regions, but generally depends on three main factors, the household income, household energy requirements and fuel/energy prices. The issue of EP is of great importance and bears significant social implications. According to a leading energy poverty charity group, over 6 million households are in EP, and over 10,000 deaths are caused each winter in the UK due to EP [8].

EP mitigation methods include retrofitting, grants or loans for adoption of RES technologies and energy efficiency measures, and discounts on energy bills. This work is the result of a Transition Engineering approach [9] that aims to explore whether LEMs, demand flexibility and optimisation in the context of energy communities can address EP by reduction of energy costs. The main contributions of our work are:

- A hierarchical multi-stage optimisation method is proposed for the day-ahead energy demand scheduling and derivations of optimal energy transactions in the context of a local energy community. The method promotes first the consumption of self-generation at a household level, then the consumption of local RES generation produced in the community, and finally trading with the main grid through the typical energy supplier.
- Various approaches of LEM design are explored. These evaluate how demand flexibility, optimisation, community trading and their combination, affects household energy costs. Reduced pricing is offered to vulnerable consumers and the effects on all end-users segments are estimated.
- Finally, an application of the methodology is shown for a UK-based local energy community of 200 households.

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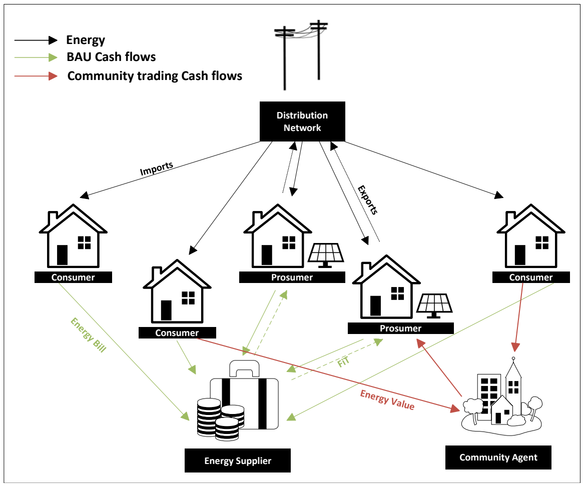

Fig. 1. Business as usual and community trading energy and cash flows

Section II of the paper presents the agent-based modelling and optimisation process, Section III discusses the case study and simulation scenarios , Section IV presents the results of the simulation analysis and Section V concludes the work.

II. Agent modelling and methodology

The methodology follows an agent-based modeling approach. An energy community comprises several households, each being an autonomous agent $\omega \in \Omega$, i.e. a computational entity, which takes decisions on behalf of the household occupiers based on an *optimisation process*. Agents that own power-producing assets, such as rooftop PV panels, are called *prosumers* (Ω_p: set of prosumers) or otherwise *consumers* (Ω_c: set of consumers). We assume that all agents are rational and non-strategic, and act to minimise their energy bills. Each agent $\omega \in \Omega$ has an electricity demand D_ω composed of must-run demand D_{mr_ω} that is not controllable, and flexible demand D_{flx_ω}, e.g. smart controllable appliances or energy assets that can be shifted in time. Prosumers also produce their own power G_ω from RES assets installed in their premises.

While traditionally end-users procure energy through an energy supplier, in this work alternative market arrangements are explored. In the business-as-usual (BAU) case, end-users are imposed to a time-of-use (TOU) grid import price of $p_{imp}^{(t)}$ and are rewarded with a grid export tariff price of $p_{exp}^{(t)}$ for any energy exported back to the grid. However, export tariffs are usually very low, hence an alternative market scheme benefiting both prosumers and consumers is a community trading scheme, where end-users trade their energy surplus with peers in the local community, with a price $p_{com}^{(t)}$, where $p_{exp}^{(t)} \leq p_{com}^{(t)} \leq p_{imp}^{(t)}$, the value of which lies in the diversification of the end-users load profiles. Community trading is coordinated by a community agent, as shown in Fig. 1.

A. Optimisation process

In this section, a *multi-stage hierarchical optimisation* process is proposed, where agents perform individual optimisations at different stages with the objective to minimise their energy bills over the course of one day. Optimisations result in the discovery of the day-ahead optimal schedule of each agent's flexible assets and energy transactions. To explain, assume that v_ω is the value attained from altering the shape of (flexible) demand, then the objective function can be formulated as the maximisation of the value gained from demand shifting. If demand and generation profiles can be estimated based on historical data, we can treat flexible demand as a vector of tasks $D_{flx_{n,\omega}}$, where $n \in \mathcal{N} = \{1, ..., N\}$ denotes the usual time interval when task n is served. Following a typical optimisation formulation for task scheduling (bounded Knapsack problem with divisible item sizes), for agent $\omega \in \Omega$, task $n \in \mathcal{N}$ and time interval $t \in \mathcal{T}$, the objective function is equal to the double summation of the product of tasks, decision variables and value obtained from demand shifting:

$$\max_x f_\omega = \max_x \sum_{t \in \mathcal{T}} \sum_{n \in \mathcal{N}} x_{n,\omega}^{(t)} v_{n,\omega}^{(t)} D_{flx_{n,\omega}} \tag{1}$$

where

$$f_\omega = \sum_{n \in \mathcal{N}} D_{flx_{n,\omega}} \sum_{t \in \mathcal{T}} x_{n,\omega}^{(t)} v_{n,\omega}^{(t)} \tag{2}$$

and $x_{n,\omega}^{(t)}$ the decision variables stating that task n is allocated at time t. When flexible demand is not shifted, then $t = n$ for all flexible jobs. Value $v_{n,\omega}^{(t)}$ is equal to the sum of value obtained by cost savings $v_{cost_{n,\omega}}^{(t)}$ and value lost from a cost or penalty factor experienced when shifting demand $v_{shift_{n,\omega}}^{(t)}$:

$$v_{n,\omega}^{(t)} = v_{cost_{n,\omega}}^{(t)} + v_{shift_{n,\omega}}^{(t)}, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \tag{3}$$

Decision variables $x_{n,\omega}^{(t)}$ are bounded by the conditions:

$$0 \leq x_{n,\omega}^{(t)} \leq 1, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \tag{4}$$

$$\sum_{t \in \mathcal{T}} x_{n,\omega}^{(t)} \leq 1, \forall n \in \mathcal{N} \tag{5}$$

Eq. (5) states that up to $D_{flx_{n,\omega}}$ can be shifted. A detailed description of the optimisation at each stage is shown below.

B. Stage 1: Matching flexible demand to self-generation

At *Stage 1*, prosumers maximise the use of self-generation, i.e. each prosumer $\forall \omega \in \Omega_p$) solves the optimisation problem stated in Eq. (1)-Eq. (5) with the additional constraint that flexible demand can only be shifted at times when there is excess generation ($\forall t \in \mathcal{T} : G_\omega^{(t)} - D_{mr_\omega}^{(t)} > 0$), as in Eq. (6):

$$\sum_{n \in \mathcal{N}} x_{n,\omega}^{(t)} D_{flx_{n,\omega}} \leq G_\omega^{(t)} - D_{mr_\omega}^{(t)}, \forall t \in \mathcal{T} : G_\omega^{(t)} - D_{mr_\omega}^{(t)} > 0 \tag{6}$$

At times of surplus generation, cost savings are equal to the difference between the grid import price the agent would have paid if demand was not shifted $p_{imp_{n,\omega}}$ minus the export price $p_{exp_\omega}^{(t)}$ the agent would have been rewarded with, if utilising excess generation for export purposes rather than self-consumption, i.e. $\forall n \in \mathcal{N}$:

$$v_{cost_{n,\omega}}^{(t)} = p_{imp_{n,\omega}} - p_{exp_\omega}^{(t)}, \forall t \in \mathcal{T} : G_\omega^{(t)} - D_{mr_\omega}^{(t)} > 0 \tag{7}$$

After completion of Stage 1, unserved demand and surplus generation not utilised are made available for Stage 2.

C. Stage 2: Matching demand to community generation

At *Stage 2*, agents engage in *community energy trading*, the coordination of which is overseen by a *community energy coordinator*, who plays a pivotal role in orchestrating the optimisation process and facilitating peer trading. The role of the community coordinator is twofold: to discover how the aggregate RES production should be allocated to each agent, and to determine the community trading price $p^{(t)}_{com_\omega}$.

Prosumers and consumers perform their own individual optimisation process, taking as an input part of the community production assigned to them by the community coordinator agent equal to $G2^{(t)}_{Share_\omega}$, which is discovered by the community agent through the iterative process described in Algorithm 1. For prosumers the value obtained from demand shifting depends on $G2^{(t)}_{Share_\omega}$ and the surplus production $G2^{(t)}_{\omega}$ offered at Stage 2 by each agent. Demand shifted can be served by any combination of power originating from the agent's own production $G2^{(t)}_{own,\omega}$ or local peers in the community $G2^{(t)}_{com,\omega}$, affecting accordingly the value estimation. Moreover, the actual quantity of power that can be absorbed at Stage 2 is estimated as shown in Algorithm 1. To deal with the differentiation in value estimation, the optimisation decision variables are split into two parts: (i) $x^{(t)}_{1n,\omega}$ when self-generation is utilised, (ii) $x^{(t)}_{2n,\omega}$ when energy is supplied by local peers ($x^{(t)}_{n,\omega} = [x^{(t)}_{1n,\omega} | x^{(t)}_{2n,\omega}]$). Similarly, the cost value achieved is $v^{(t)}_{cost_{n,\omega}} = [v^{(t)}_{cost1_{n,\omega}} | v^{(t)}_{cost2_{n,\omega}}]$, where $\forall n \in \mathcal{N}$:

$$v^{(t)}_{cost1_{n,\omega}} = p_{imp_{n,\omega}} - p^{(t)}_{exp_\omega}, \forall t \in \mathcal{T} : G2^{(t)}_{own,\omega} - D^{(t)}_{mr_\omega} > 0 \tag{8}$$

and

$$\begin{gathered} v^{(t)}_{cost2_{n,\omega}} = p_{imp_{n,\omega}} - p^{(t)}_{com_\omega}, \\ \forall t \in \mathcal{T} : G2^{(t)}_{com,\omega} - (D^{(t)}_{mr_\omega} - D^{(t)}_{mr,own_\omega}) > 0 \end{gathered} \tag{9}$$

$\forall n \in \mathcal{N}$ and $\forall t \in \mathcal{T}$, the prosumers' objective function is:

$$f_\omega = \sum_{n \in \mathcal{N}} D_{flx_{n,\omega}} \sum_{t \in \mathcal{T}} (x^{(t)}_{1n,\omega} v^{(t)}_{1_{n,\omega}} + x^{(t)}_{2n,\omega} v^{(t)}_{2_{n,\omega}}) \tag{10}$$

where $v^{(t)}_{1_{n,\omega}} = v^{(t)}_{cost1_{n,\omega}} + v^{(t)}_{shift_{n,\omega}}$ and $v^{(t)}_{2_{n,\omega}} = v^{(t)}_{cost2_{n,\omega}} + v^{(t)}_{shift_{n,\omega}}$. In summary, prosumers perform the optimisation problem described by Eq. (1) and Eq. (10) under the constraints set by Eq. (4), Eq. (5), Eq. (8) and Eq. (9), while consumers perform Eq. (1), Eq. (2) under the constraints set by Eq. (3)-Eq. (8), where $G^{(t)}_\omega = G2^{(t)}_{Share_\omega}$. Flexible demand not shifted is made available for optimisation at Stage 3.

D. Stage 3: Matching flexible demand to TOU tariffs

At *Stage 3*, agents perform optimisation as in Eq. (1)-Eq. (5) with the additional constraint of Eq. (11). The value obtained from demand shifting is given by:

$$v^{(t)}_{cost_{n,\omega}} = p_{imp_{n,\omega}} - p^{(t)}_{imp_\omega}, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \tag{11}$$

where savings are equal to the difference between the grid import price the agent would have paid if demand was not rescheduled ($p_{imp_{n,\omega}}$) minus the import price ($p^{(t)}_{imp_\omega}$) the agent pays at the time when demand is actually allocated.

In summary, the optimisation is hierarchical and promotes, first the local matching of demand and supply at an individual agent level, then community self-consumption and trading, followed by a final stage that allows optimisation of the imported energy from the grid. The next section presents the case study used to demonstrate the methodology proposed.

Algorithm 1 COMMUNITY TRADING COORDINATION

Collect each prosumer's surplus from Stage 1 & compute the aggregate community RES production
Assume all agents are active for community trading & share community production equally
Assume agents' own generation is absorbed at Stage 2
repeat {*Discover* $G2^{(t)}_{Share_\omega}$}
    repeat {*Discover* $G2^{(t)}_{own,\omega}$}
        Agents perform optimisation with $G2^{(t)}_{Share_\omega}$
        Discover production absorbed & Correct $G2^{(t)}_{own,\omega}$
    until {*RES generation absorbed converges*}
    Remove agents without change in flexible demand
    Reallocate community production to remaining agents
until {*No active agents remain*}
Return excess to prosumers & Finalise allocation
Final optimisation with final allocated RES production

III. CASE STUDY ANALYSIS & SIMULATION SCENARIOS

A practical application of the methodology proposed in Section II is shown for a UK-based community of 200 households. Demand data are from real households from the Thames Valley Vision project. Prosumers have solar PV installed at their premises with a capacity ranging from $3 - 6kWp$, the RES production of which was derived by solar irradiance data obtained from the UK Met Office at the location of Kirkwall, Orkney. 40% of consumers are considered as energy poor (EP). The mean absolute percentage error (MAPE) method was applied to demand and generation data across a year in order to identify 4 days that represent the average profiles across seasons (Winter and Summer) and day types (Weekday and Weekend). Next, we performed a simulation analysis for all 4 representative days, assuming daily half-hourly time series data, i.e. 48 data points for each day. The penalty factor applied when demand patterns are changed depends on the willingness of an agent to shift its demand α_ω, which may differ across households, and the distance between the original time slot n and the actual time slot when demand is reallocated t expressed in monetary values:

$$v^{(t)}_{shift_{n,\omega}} = -\alpha_\omega \mid n - t \mid, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \tag{12}$$

The furthest away demand is allocated with respect to the original time slot n, the greater the penalty incurred. Grid import $p^{(t)}_{imp_\omega}$ and export prices $p^{(t)}_{exp_\omega}$ are real TOU tariffs from a UK energy supplier (Octopus Agile) for 2019. The tariff for community trading was set based on the mid-market rate [10] between grid import and grid export prices for every t:

$$p^{(t)}_{com_\omega} = (p^{(t)}_{imp_\omega} + p^{(t)}_{exp_\omega})/2 \tag{13}$$

Finally. in several scenarios in our analysis, EP households have access to a lower community trading price equal to:

$$p^{(t)}_{comEP_\omega} = (p^{(t)}_{com_\omega} + p^{(t)}_{exp_\omega})/2 \tag{14}$$

Simulation analysis aims to explore the impact of optimisation, flexibility and community trading on household energy bills. Moreover, an evaluation of the reduced price offering to EP consumers is required. For these reasons, the following scenarios were investigated:

- *Scenario 1 Business as usual (BAU)*: It serves as the benchmark scenario against which all other scenarios are compared. In this case, agent households buy/sell energy only from/to the energy supplier at the designated prices. Agents are not flexible, do not perform optimisations, and do not engage in community trading.
- *Scenario 2 No FLX - Community trading Single Price:* Agents are not flexible and do not perform optimisations. Community trading is allowed at a single uniform price for all agents, as in Eq. (13).
- *Scenario 3 No FLX - Community trading EP Price:* This is the same as Scenario 2 with the difference that EP consumers have access to a reduced price, as in Eq. (14).
- *Scenario 4 FLX - No community trading:* Agents are flexible and can alter their demand patterns, however no community trading is allowed. In this scenario, agents optimise their demand individually according to the grid ToU tariffs. Prosumers engage in optimisations described at Stage 1 and Stage 3, while consumers at Stage 3.
- *Scenario 5 FLX - Community trading Single Price:* Here agents are flexible and community trading is allowed, hence prosumers engage in the hierarchical optimisation described in Stages 1-3, while consumers at Stages 2-3. Community trading is allowed at a single uniform price for all agents, as in Eq. (13).
- *Scenario 6 FLX - Community trading EP Price:* This is the same as Scenario 5, however EP consumers have access to a reduced price, as in Eq. (14).

IV. Results and Discussion

This section discusses the main simulation results. The following case was assumed: out of a population of 200 agents, 30% are prosumers (60) and 70% are consumers (140). 40% of consumers are energy-poor (EP) (56) and the remainder (84) are non-EP. For all scenarios described in Section III, we performed simulations for 4 representative days that estimated the optimal day-ahead demand scheduling for 200 agents in the local community and computed their daily electricity cost, from which we estimated their yearly electricity cost. The average electricity cost across all agent segments can be seen in Fig. 2. The average agent electricity cost for the BAU case is equal to £508.04. As seen in Fig. 3, the maximum reduction of agents' electricity cost is realised for scenario 5 at 13.4% and £440.08, followed by scenario 6 at 12.8% and £442.81, i.e. when agents willing to shift their demand and practice trading with peers in the community. Over all the agent population, a reduction of approximately 6% can be achieved when allowing community trading, even without any demand flexibility (scenarios 2 and 3). If agents are flexible, but no community trading is allowed they are able to reduce their electricity cost by approximately 6% (scenario 4). Prosumers achieve the largest cost savings with respect to BAU across all scenarios. Prosumers can achieve significant cost savings when community trading is allowed, even in the case when no flexibility is assumed (19.8% and 14.4% for scenarios 2 and 3, respectively). This is almost double the electricity cost savings that flexible prosumers can achieve when they perform individual optimisations, but no community trading is allowed (9.9% reduction is achieved in scenario 4). When flexibility and community trading are combined, prosumers can achieve an average improvement in electricity costs of 32.2% and 25.7% for scenarios 5 and 6, respectively. The reduced EP price offering means that prosumers gain less than in scenarios with a single community trading price. Comparison of scenarios 2 to 3 shows that prosumers achieve 3.4% less cost reduction while EP consumers improve by 1.6%, while comparison of scenarios 5 to 6 shows a prosumer cost reduction of 6.5% leads to 1.6% EP consumer gains. EP consumers can reach a maximum reduction of approximately 11.1%, when flexibility and community trading are combined (scenario 6). EP prefential price does not have a significant effect on non-EP consumers, who can reach a reduction of over 9.5% in scenarios 5 and 6.

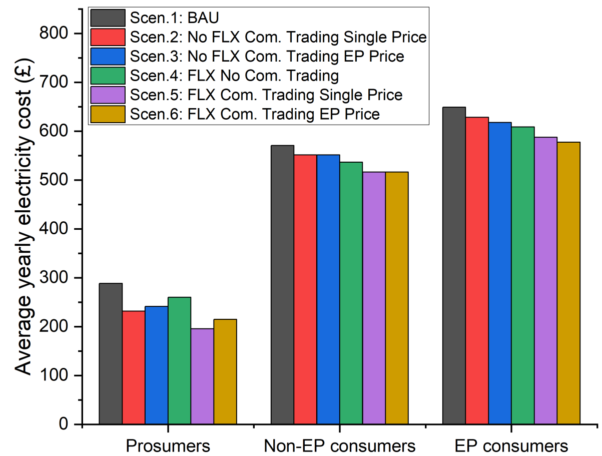

Fig. 2. Average electricity cost for all agent segments under different scenarios

We also studied how the electricity cost reduction evolves as more agents install RES generation. The reduction in electricity costs for scenario 6 compared to BAU scenario is shown in Fig. 4 for the cases when 20%, 30% and 40% of agents are prosumers. At each case, 40% of consumers are considered to be EP. The largest reduction is realised by prosumers followed by EP consumers and last non-EP consumers. As the prosumer rate increases, electricity costs

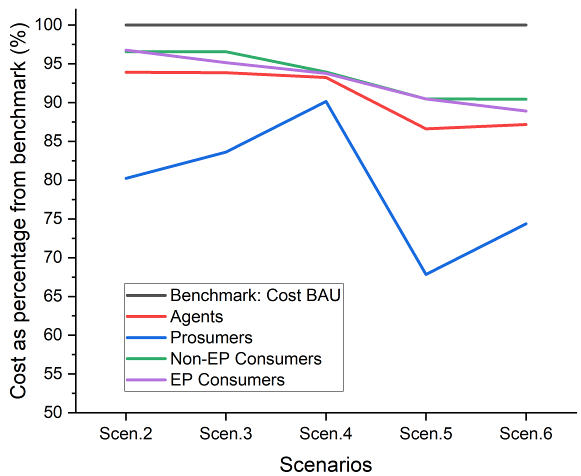

Fig. 3. Average electricity cost for all agent segments under different scenarios

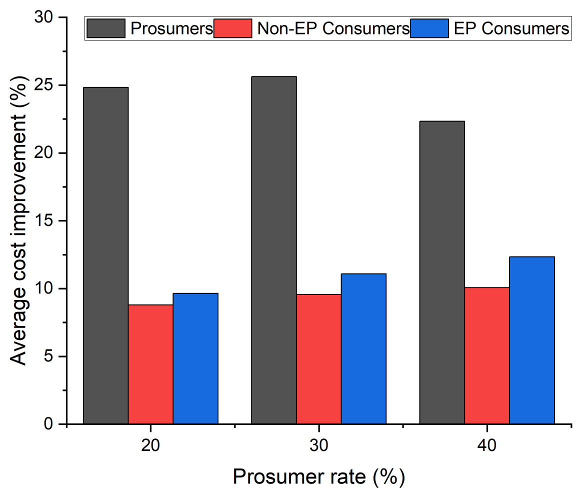

Fig. 4. Average electricity cost reduction for increasing prosumer rates

decrease for consumers as they can utilise more renewable production at the community trading stage. The largest cost improvement for prosumers is realised in the case of a 30% prosumer rate. If too many agents become prosumers then the RES production increases, however there is a limit up to which no demand can be further shifted. In addition to electricity cost improvements, community trading and flexibility has the ability to better match local demand to generation and use more RES production locally. Res utilisation increased by 12.93%, 16.31% and 16.65% for the 20%, 30% and 40% prosumer rate cases, respectively.

V. Conclusions & Future Work

In this work, a hierarchical multi-stage optimisation process was developed for the day-ahead demand scheduling in a LEM applied an energy community of 200 households. The optimisation process included three stages, first promoting the use of self-generation at prosumer level, then promoting matching of local demand to local generation through peer-to-community energy trades, and finally allows for optimal demand scheduling with respect to TOU energy tariffs offered by the energy supplier. We investigated the role that community trading has on the electricity cost for each agent, the role of flexibility and smart optimisation, and the effect of a reduced price offering to vulnerable consumers at the community trading stage by exploring 6 different scenarios. We found that all LEM approaches followed in the scenarios yield to a reduction of all household electricity costs. Community trading can achieve significant reduction even without flexibility and smart optimisation applied. Benefits however are maximised when flexibility and optimisation are combined with community trading. Prosumers can realise greater savings, followed by EP and non-EP consumers. The price reduction offered to EP consumers does, however, result in less cost reduction for prosumers. In addition, we found that local demand matches better local generation. While in this work, we only investigated electricity costs, future work will explore how LEMs can reduce other parts of the energy bill, e.g. by decreasing charges related to the use of network. Moreover, we will consider other RES technologies and business models, such as the possibility of prosumers to invest in community size wind generators or the combination of wind and solar.

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References

[1] T. Capper, A. Gorbatcheva, M. A. Mustafa, M. Bahloul, J. M. Schwidtal, R. Chitchyan, M. Andoni, V. Robu, M. Montakhabi, I. J. Scott *et al.*, "Peer-to-peer, community self-consumption, and transactive energy: A systematic literature review of local energy market models," *Renewable and Sustainable Energy Reviews*, vol. 162, p. 112403, 2022.

[2] J. M. Schwidtal, P. Proadpran, M. Troncia, R. Chitchyan, M. Montakhabi, C. Francis, A. Gorbatcheva *et al.*, "Emerging business models in local energy markets: A systematic review of peer-to-peer, community self-consumption, and transactive energy models," *Renewable and Sustainable Energy Reviews*, vol. 179, p. 113273, 2023.

[3] European Union, "Directive EU/2019/944 on common rules for the internal electricity market," 2019. [Online]. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32019L0944

[4] ——, "Directive EU/2018/2001 on the promotion of the use of energy from renewable sources," 2018. [Online]. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32018L2001

[5] S. Norbu, B. Couraud, V. Robu, M. Andoni, and D. Flynn, "Modelling the redistribution of benefits from joint investments in community energy projects," *Applied Energy*, vol. 287, p. 116575, 2021.

[6] S. Cremers, V. Robu, P. Zhang, M. Andoni, S. Norbu, and D. Flynn, "Efficient methods for approximating the shapley value for asset sharing in energy communities," *Applied Energy*, vol. 331, p. 120328, 2023.

[7] L. Diestelmeier, "Citizen energy communities as a vehicle for a just energy transition in the EU-challenges for the transposition," *Oil, Gas & Energy Law Intelligence*, vol. 2021, no. 1, 2021.

[8] National Energy Action (NEA), "What is fuel poverty," https://www.nea.org.uk/, 2024.

[9] S. Krumdieck, *Transition Engineering: Building a Sustainable Future*. CRC Press, 2020. [Online]. Available: https://books.google.fr/books?id=f9frxQEACAAJ

[10] W. Tushar, T. K. Saha, C. Yuen, P. Liddell, R. Bean, and H. V. Poor, "Peer-to-peer energy trading with sustainable user participation: A game theoretic approach," *IEEE Access*, vol. 6, pp. 62 932–62 943, 2018.