Towards a Fair, Smart and Scalable Framework for Community Energy

Introduction

Renewables are shifting control of energy generation from centralised to distributed production. Rather than large fossil-fuel companies controlling the energy market, distributed energy resources (DERs) move power to the 'grid-edge' with local 'prosumers' (producers and consumers) using near zero-marginal cost clean energy to reduce bills, increase their energy independence and contribute to grid flexibility.

The AI revolution is driving this transformation of the energy sector. Machine learning tools are used to intelligently manage these DERs, enabling new 'prosumers' to maximise the benefits of their low-carbon assets. By integrating many prosumers together into Virtual Power Plants (VPPs), intermittent and variable generation can be managed, providing much-needed grid flexibility. This reduces the need for dirty 'peakers' during periods of maximum demand helping to drive the decarbonisation of the grid.

There is immense potential to empower local communities through community-based VPPs (cVPPs). These systems enable local ownership of renewable assets and reinvest profits from surplus energy and grid services back into the community. These practical benefits can help maintain vital popular support for energy transition whilst accelerating the drive towards net zero.

Despite some community energy projects successfully creating their own cVPPs, the sector currently lacks a unified framework for scalable, smart community energy systems. Existing technologies often fail to prioritise user trust, data privacy, or democratic control over profits. Developing such a technological framework could play a transformative role in revitalising fragmented communities that have for too long felt powerless against the structural forces that control their lives.

Literature Review

The Local Energy Oxfordshire (LEO) project recently conducted ‘Smart Fair Neighbourhood Trials’ to explore barriers to community energy adoption[1]. These trials demonstrated the feasibility of shifting from a top-down to a bottom-up energy model, with households and communities playing active roles. Benefits include enhanced community trust, reductions in fuel poverty[2] and the attraction of local investment.

[1] Local Energy Oxfordshire (2023)
[2] Savelli, I. and Morstyn, T. (2023)

To achieve this transition via "FutureFit" homes that generate, store, and sell clean energy, communities must develop a shared understanding of the benefits of community electrification. This can only happen if the community project is intrinsically fair, ethical and explainable. The ML models used for optimisation must be transparent in explaining how data is used and instructions are generated to enable grid flexibility.

To understand the potential for explainable, ethical AI with low-carbon technology, I first reviewed how machine learning is currently being used in smart grids and energy markets to improve efficiency, manage energy use and maximise revenue.

A common tool is Multi-Agent Reinforcement Learning.[3] The goal of reinforcement learning is to learn a policy which maps states (e.g. high electricity prices, low renewable generation) to actions (e.g. release battery-stored energy) to maximise long-term expected reward. Recent advances involve factoring this state-to-action function that is learnt by households[4]. This enables model training to be centralised but decentralises execution amongst individual agents (households) allowing for efficient deployment at scale. Convolutional neural network architectures can also be used to enhance feature extraction from time series data when learning the state-to-action function (deep RL). While these methods address scalability and data privacy, they remain ‘black boxes’ that lack explainability.

Explainable AI (XAI) is needed to build user trust. These emerging energy communities have to fairly allocate the benefits of collectively owned DERs and will not trust an AI unless they understand how shared resources have been distributed. One promising approach involves a computationally scalable method for approximating the shapley value in an asset-sharing community[5]. The shapley value is a solution concept in cooperative game theory which provides a fair way to allocate the profit from a cooperative game. K-means clustering of individual user's smart meter profiles was used to create different classes of demand profile (e.g. remote workers and 'night owls'), the researchers developed an efficient method to calculate the benefits of shared renewable assets which accurately accounts for the varying energy demands of users. These Shapely values can be used as the basis of XAI techniques like SHAP (SHapley Additive exPlanations)[6] enabling end users to understand why ML models make their decisions, enhancing trust.

Research Focus

My research aims to develop a scalable ML framework for expanding cVPPs[7] with three core principles:

[3] Keren, S. Essayeh, C. and Morstyn, T. (2024)
[4] Charbonnier, F. Peng, B. et al. (2025)
[5] Cremers, S. Robu, V. Zhang, P. Norbu, S. Flynn, D. (2023)
[6] Machlev, R. Heistrene, L. Perl, M. Levy, K.Y. Belikov, J. Mannor, S. Levron, Y. (2022)
[7] Xie, H. Ahmad, T. Zhang, D. Goh, H. H. Wu, T. (2024)

1. **Explainability**: Users must easily understand the decisions made by ML models.
2. **Fairness**: Shared costs and benefits of renewable assets (e.g., batteries, solar panels) must be allocated equitably.
3. **Control**: Communities should own their data, democratically decide profit reinvestment, and be able to adapt the framework to their specific needs.

I am particularly interested in exploring blockchain technology as a tool for user privacy[8] and participatory democracy[9], enabling transparent governance models, such as liquid democracy. Inspired by concepts like Democratic Confederalism[10], cVPPs could even physically centre around a community hub[11] where the local energy convener could base their operations.[12]

I want to understand whether direct democratic control of renewable assets in local energy communities via this explainable AI framework would encourage uptake of distributed energy resources. I'd always be evaluating the extent to which this fairAI framework could make the energy transition just, politically sustainable and economically viable and would aim to adapt my proposal co-creatively with community energy groups throughout the process.

Research Approach

To develop this explainable AI framework, I would take an interdisciplinary research approach where I develop the technical skills required whilst simultaneously conducting social research to ensure that the framework is scalable whilst remaining explainable, fair and controlled by community groups.

Technical Research:
I will develop my understanding of current ML techniques. This would include deep multi-agent renforcement learning to optimise home energy management and short-term forecasting to predict behaviour (including under demand flexibility incentives). By accessing high-quality synthetic smart meter profiles from OpenSynth and partnering with Community Energy England, I will acquire relevant datasets to train and test my novel ML models.

I will also integrate explainable AI techniques, addressing the ‘black box’ nature of the ML models used. Building on literature reviews, I will implement these methods to consolidate understanding. I'd then aim to integrate (a potentially blockchain-based)[13] system to give local energy communities transparent and direct democratic control over the priorities of their intelligently controlled cVPP.

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[8] Bird, B. Bokkisam, H. R. Savelli, I. Morstyn, T. Cuffe, P. (2023)
[9] Varoufakis, Y. (2023)
[10] Öcalan, A. (2011)
[11] Greenfield, A. (2021)
[12] Local Energy Oxfordshire (2023)
[13] Bird, B. Bokkisam, H. R. Savelli, I. Morstyn, T. Cuffe, P. (2023)

Social Research:
To ensure the system I'd develop adheres to it's core values of explainability, fairness and control, I'd work closely with community energy organisations to co-create a scalable, economically viable system that leverages the practical experience developed by community energy experts. Community Energy England has a vast database of community energy organisations and could act as a key hub to enable this social research. I'd initially conduct interviews with key experts to develop a specification and then run focus groups, surveys and field trials with users and build a system iteratively to ensure the framework aligns with real-world challenges.

Conclusion and Impact

The 2024 Community Energy England State of the Sector report[14] identifies several barriers to community energy growth, including skills shortages, limited development funding, and challenges in identifying viable business models. My research aims to address these barriers by developing a scalable, explainable, and fair ML framework for community energy systems.

By collaborating with sector partners to leverage their expertise, this framework will adapt to the diverse needs of communities while empowering them to lead the energy transition. A democratic system for managing renewable assets will foster community engagement, build trust, and enable connectedness, ensuring the transition to net zero benefits local economies and addresses community priorities.

Ultimately, this research seeks to drive the growth of the community energy sector and create a future where distributed energy systems not only support decarbonisation but also empower individuals and communities to take ownership of their energy futures.

[14] Community Energy England (2024)

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