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Aggregators as digital intermediaries to local electricity markets

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ABSTRACT

This paper considers how a novel digitally enabled mechanism to aggregate distributed energy resources (DERs) can support significant challenges to decarbonise the energy system, support the energy market in terms of demand and energy cost, and organise a large number of distributed assets. In this study, we present the potential for accelerating the energy transition by incentivising prosumers, i.e. households who are both consumers and producers of electricity, to offer flexibility to the energy system. At local community level, this is achieved though integration of DERs including micro-scale renewable and vehicle-to-grid technologies. Individual participation of such assets in local electricity markets is currently an untapped business and poses a technological challenge of managing many small providers in the UK's large-scale energy systems; it also poses a challenge in terms of the complexity of satisfying market demand and producing benefits to the providers.

The preferences and descriptions of DERs are articulated using an agent-based model that feeds into a visual analytics based environment. We adopt the concept of a single entity performing digital aggregation of distinct DERs in a power market, to reveal the capacity for dynamic organisation of DERs, and recommend particular configurations of DERs satisfying alternative portfolio optimisation strategies. Our work includes analysis of aggregator participation in 'new' distributed electricity markets for the aggregated DER capacity, quantification of the effects of non-participant prosumers and aggregator decision-making strategies to reduce uncertainties regarding electric vehicle charging. It also provides insights on how degrees of transparency can support effective policy formulation for the domestic electricity market.

Introduction

The UK Government has set an ambitious agenda for building world-class digital infrastructure to unlock a data-driven economy for the UK. The growth of renewables is becoming increasingly important as the UK is committed to bring all greenhouse gas emissions to net zero by 2050 (Skidmore 2019). Increasing penetrations of small-scale low carbon technologies is enabling resilience driven aspirations of decentralised power system control and operation. Straightforward translation of Peer-to-Peer (P2P) business models is unlikely to succeed in the energy supply sector in the nearest future. Individuals will not be sufficiently motivated to 'actively' trade energy in real-time even if the current regulatory environment facilitated it, because the scale at which they can operate individually is insufficient to attract market interest. But digital intermediation offers the potential to achieve this in a latent delegated way due to the aggregation potential enabled by digital technologies and by incentive mechanisms related to smart contracts (Guzman et al. 2020). The potential of P2P energy trading via energy platforms is complementary to digital aggregation.

Flexibility is becoming an increasingly important characteristic for power systems that are currently in the process of substantial transformation toward massive inclusion of renewable energy resources. From the perspective of such transition and the growing demand for flexibility, digital aggregators are envisioned as important intermediaries that will provide small prosumers with access to multiple electricity markets. This will be achieved by bundling small-scale DERs (prosumer-owned assets) that may consume, store and/or act as micro-generators. For such assets, flexibility is referred to as an ability to provide upward or downward shifts in electricity generation/demand for their local grids. This intermediation is considered critical since such prosumers would not be able (or likely be unwilling) to perform as independent flexibility providers in future power networks partly driven by scale but also their ability to deal with the fiscal and counter party risk this brings.

We aim to assess the potential of such digital intermediaries to provide flexibility to distribution networks and efficiently trade energy by assessing risks and uncertainties, as well as optimising aggregator's multi-market portfolio. In the following sections we provide a literature review on multi-agent systems, prosumer contract types and probabilistic methods for network congestion analysis; discuss agent characterisation as a process of prosumer stereotyping to identify what loads are typical of the local community and what uncertainties one needs to address to manage these loads within an aggregator's portfolio; present power network heuristics used for quantification of congestion caused by DERs on the network, contingent on prosumer behaviour.

Literature review

To date, only ad-hoc assemblies of different approaches and models have been identified across pilot projects and emerging P2P trading of DER flexibility. The challenge for digital aggregation is to create portfolios of DERs that help to manage network constraints and can be viable in the energy market. Given that prosumers and their DERs have variable traits, we examine how a multi-agent architecture for grid decentralisation might be formulated and consider alternative contract types to facilitate energy trading of DERs. In order to demonstrate how aggregated DERs contribute to network constraints we cover probabilistic methods for network congestion analysis at the distributed system operator (DSO) level.

Multi-agent systems

Multi-agent energy systems are used to provide autonomous distributed control of energy assets in a smart grid with the digital aggregator or virtual power plant operator serving as an intermediary between low-voltage (LV) networks and various energy markets. Local autonomy and cooperation capabilities of the multi-agent architecture offer prospects for scheduling and negotiation, to address challenging issues of: integration, heterogeneity, high flexibility, high robustness, reliability, and scalability (Ouelhadj et al. 2005). Social abilities of agents such as negotiation and their decision making in the environments of limited information have been investigated and reviewed by many researchers (Hutchinson et al. 2010; Howell et al. 2017) to develop novel control algorithms for power systems, experiencing the growing penetration of renewable energy sources such as photovoltaic (PV) panels, wind power and EVs.

In multi-agent systems, stakeholders, such as suppliers, consumers and prosumers, implement a generic bidding strategy that can be governed by local policies (Deissenroth et al. 2017). Each energy agent is characterised by its preferences and goals, and constrained by many factors such as device characteristics or limitations of the LV network. The ensuing behaviour of agents pursuing their goals allows market-based coordination of supply and demand.

Facilitation of P2P energy trading and smart contracts

A perspective paper by Morstyn et al. (2018) envisioned federated power plants facilitated by P2P energy platforms to incentivise coordination between prosumers via smart contracts. This approach enables operation of prosumers as an autonomous entity bidding in the markets and acting as a trading coalition without an aggregation agent/virtual power plant operator. Such P2P electricity markets conceptually allow prosumers to directly share their electricity. The concept was also reviewed in (Sousa et al. 2019) distinguishing between full P2P markets and community-based markets where loads are aggregated via a dedicated community manager (CM). The paper also covered a hybrid approach with energy collectives represented by CM operating in a P2P ecosystem. In (Zhang et al. 2018) a P2P platform called Elecbay was proposed to enable trading via competitive energy trading where prosumers are not aggregated with each other. However, this was subject to the assumption that prosumers willingly contribute to maintaining the local energy balance. A general form of smart contracts for P2P markets was proposed in (Thomas et al. 2019).

Contract types

A digital aggregator can operate one of two broad types of control over each agent's DERs: direct coordination (full control) or incentive signals (dependent control).

Direct coordination. This type of contract suggests bidirectional aggregator-to-agents communication. This will allow direct coordination of DERs as described by Morstyn et al. (2018), where DERs are dispatched to the markets considering their operational parameters and DER owners' preferences. Such an approach may be most efficient for the markets that require services like frequency regulation, i.e. response at fast timescale. A review of vehicle to Grid (V2G) implementation by Kempton and Tomić (2005) estimated that electric vehicle (EV) fleets are specifically competitive for spinning reserves and frequency regulation markets, while not very competitive for baseload and peak power markets.

Disadvantages of direct control include privacy and security concerns, as well as potential unwillingness of DER owners to become subscribers on such terms. Also, there is a concern for the impracticality of centralised direct controls for large numbers of prosumers. A number of papers discussed distributed optimisation strategies to address these issues. For example, shadow pricing methods for congestion management were proposed by Biegel et al. (2012), involving the implementation of Lagrange multipliers for distributed flow optimisation. These methods can be applied, if network constraints can be represented as affine functions[1]. Further, in the work by Kraning (2014), strategies based on proximal message passing were proposed for dynamic network energy management, assuming that all objective functions are convex closed proper (CCP) functions.

Incentive signals. An alternative contract type proposes price/incentive signals from an aggregator to DER owners via unidirectional communication and indirect control (Heussen et al. 2012). The prosumers are responsible for their consumption and/or generation decisions based on the incentive signals and their own preferences.

This can be implemented as time-of-use pricing, where an aggregator sends prosumers time-varying incentive signals. Consumer responsiveness to time-varying prices was investigated by Schofield et al. (2014). Such contracts may be implemented as, for example, day-ahead dynamic pricing, assuming forecast information is available to an aggregator. This can be further enhanced with location-based incentives: clustering of distributed generation, congestion information, level of renewables penetration. The risk of dynamic pricing is the potential of creating new demand peaks as prosumers may start behaving in a similar manner shifting their consumption to the low price periods which may reduce system stability (Morstyn et al. 2018).

Probabilistic methods for network congestion analysis

Probabilistic approaches to assessing network congestion are presented on 3-phase LV network models for the north of England (Navarro, Ochoa, and Randles 2013; Navarro-Espinosa and Ocho 2016). The impacts of low carbon technologies are assessed using Monte-Carlo methods to carry out power flow studies from 0 to

[1] Affine function is the composition of a linear function followed by a translation, i.e. $(x + b) \circ (ax)$.

100% penetration of EV, PV and heat pumps (HP). While probabilities of voltage and current violations are presented, the flexibility required to address these violations is not considered. In Esmat, Usaola, and Moreno (2018) a flexibility market is presented, which includes day-ahead and real-time procurement of flexibility using scenario based probabilistic methods to estimate the likelihood of congestion. The DSO is assumed to carry out demand shifting of flexible assets, known as the payback effect, however, in practise it is more likely that the aggregator would optimise the shifting of demand. Furthermore, arbitrary levels of demand flexibility are assumed (e.g. 10%), and individual agent behaviour or 3-phase LV networks are not modelled. Other than using Monte-Carlo or scenario based approaches, methods of forecasting LV network congestion and subsequent dispatch of flexibility are rare in the literature. State of the art load forecasting methods are widely applied to aggregated national demand, such as in Nagbe, Cugliari, and Jacques 2018; Shah et al. 2019, however methods of forecasting individual customer demand such as employed in (Stephen et al. 2014; Stephen, Telford, and Galloway 2020) will be required to more accurately forecast congestion on LV feeders.

Methodology

An integrated digital platform was created to identify the opportunities of including diverse distributed energy resources at scale. The digital aggregator platform provides a link between:

a. The aggregator, which has contracts with multiple agents including owners of electric vehicles, PV panels, heat pumps and batteries at domestic scale;
b. The network, on which the agents are physically located, operated and monitored by the DSO.

The stages of the aggregator portfolio optimisation implement direct control of DERs and are as follows:

1. Aggregator multi-agent system is used to optimise asset/agent portfolio. Agent positions are then passed to the network heuristic model.
2. Network heuristic carries out load flow to check for thermal and voltage constraints.
    a. If no constraints: aggregator can submit offering to the national markets (e.g. wholesale day-ahead, intraday, balancing mechanism or ancillary services);
    b. If constraints: network heuristic carries out sensitivity analysis to determine agents most effective at solving constraints. Agent adjustments passed back to aggregator.
3. The aggregator can then optimise these adjustments based on agent pricing, repeating steps 1 and 2, if necessary.
4. Multi-market optimisation is carried out by the aggregator based on maximising profits or other objectives such as prioritising environmental improvement (e.g. decarbonisation) or community benefit (e.g. affordable inclusion).

In the following sections we discuss how the agents are characterised, introduce the variety of DERs in their possession, and provide a description of network congestion heuristic implemented for a low voltage (LV) network (modelled in OpenDSS, an electric power distribution system simulator).

Agent characterisation

Agent characterisation is the process of profiling and stereotyping the participators in a local grid. The purpose of characterisation is to create a distinctive representation of prosumers and their assets that would be suitable for distributed convex optimisation algorithms such as alternating directions method of multipliers (ADMM) (Morstyn, Hredzak, and Agelidis 2018). The algorithms allow the construction of prosumer energy consumption reference profiles to reveal the different types of asset availability during delivery time periods (that is to say the time periods when the prosumer is required to increase or decrease their power consumption). Each agent that represents a DER owner is further characterised by flexible and inflexible components of the power drawn from the grid; with some DER owners having an EV, an energy battery storage system, a renewable energy source (e.g. PV) or a combination of such assets.

Three alternative scenarios of EV charging behaviour were considered, i.e. when an EV is parked and plugged in at a residential area, or charging at a public charging station located on the same LV network within the community, or charging off-grid. These scenarios are used to create information on the capability of providing flexibility at different parts of the LV network. EV related uncertainties such as vehicle location and on/off grid status are modelled with discrete-time Markov chains using time-varying transition matrices to characterise EV state (e.g. parked at different locations or moving) and quantify probabilities of the non-delivery of energy assets associated with EV usage.

For DER owners who use EVs or have a stand-alone battery storage system (Figure 1), a linear state-of-charge model was used to construct constraints for optimisation algorithms. The battery state-of-charge was kept within the desired limits preferred by energy distributers to ensure that the power balance is maintained at all times and the partial flows in the power network are feasible.

In order for the model to reflect a realistic generation of energy by residential PV panels under different weather conditions, we have used historic data provided by UK Power Networks which is freely distributed from the London Datastore (Greater London Authority 2020).

In addition to household-specific energy, larger consumers from the local community such as retail supermarkets (refrigeration loads) and public buildings (thermostatically controlled loads from social housing, schools, etc.) are also considered as part of a larger selection of prosumers. Refrigeration systems are a major source of power consumption by large commercial retail supermarkets and such systems are capable of providing flexibility through dynamic control of the system's pressure (Postnikov et al. 2019), thus enabling exploitation of thermal inertia in hundreds of refrigeration display cases.

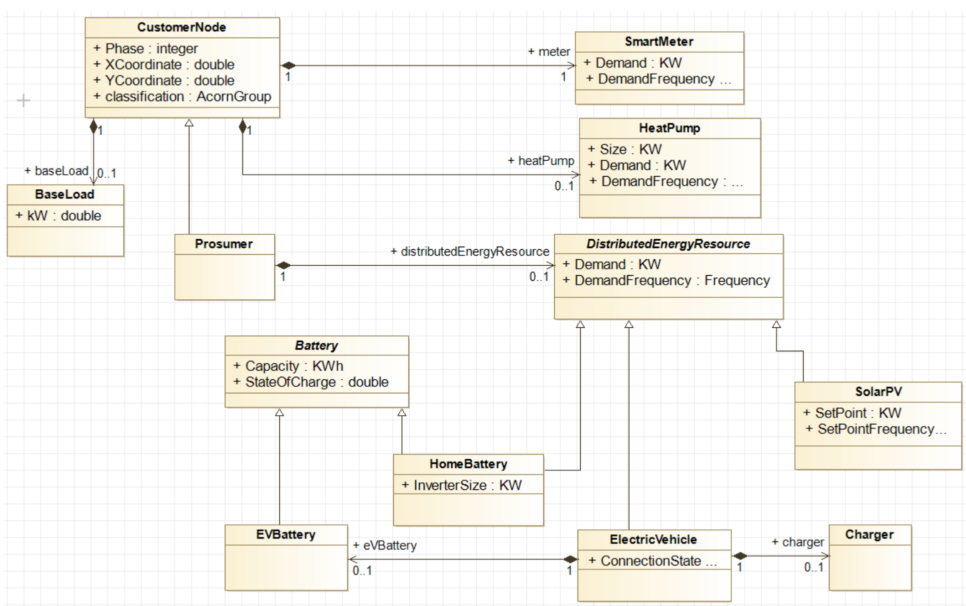

Figure 1. An example of UML[2] representation of DERs offered by prosumers (heat pumps and base load are assumed to be inflexible).

Following the agent characterisation, we constructed a multi-agent representation of participators in a local grid. In subsequent simulations, we calculated 48-hour period power profiles of DERs located within the same LV distribution network, and quantify the probabilities of non-delivery by analysing EV charging data to obtain confidence intervals for flexibility for each 30-minute time slot of the day. Then the agent positions were

[2] Unified Modeling Language.

passed to the network heuristics to determine whether thermal or voltage constraints would be violated for the current positions. In case of the network constraints violation, the algorithm carried out sensitivity analysis to recommend adjustments to agents' positions.

Network congestion heuristic

The aim of the probabilistic network congestion heuristic is to estimate the probability of network constraints (thermal or voltage violations) and subsequent agent adjustments by the DSO to remove these constraints. LV networks for the north of England (as used in (Navarro-Espinosa and Ocho 2016)) are modelled using power flow software to determine network voltage and current violations for a given set of sampled customer data, including PV generation and demands (smart meter data, EVs and heat pumps). The network heuristic determines the sensitivities of each agent (flexible customer) to any constraints, and makes adjustments to the agents based on their impact on the constraints. These probabilities were to be provided for:

- A generalised day. e.g. a summer weekend;
- A given forecast, e.g. based on day-ahead or intra-day measurements of demand;
- Different feeders, and networks, from a range of representative feeders;
- A range of PV, EV, HP and 'Agent' penetrations and clusters.

The model inputs were sampled distributions of PV generation, EV, smart meter and heat pump demand, examples of which are shown in Figure 2. These distributions are specific to a half-hour, season, weekday/weekend and in the case of smart meter (SM), data are specific to each customer.

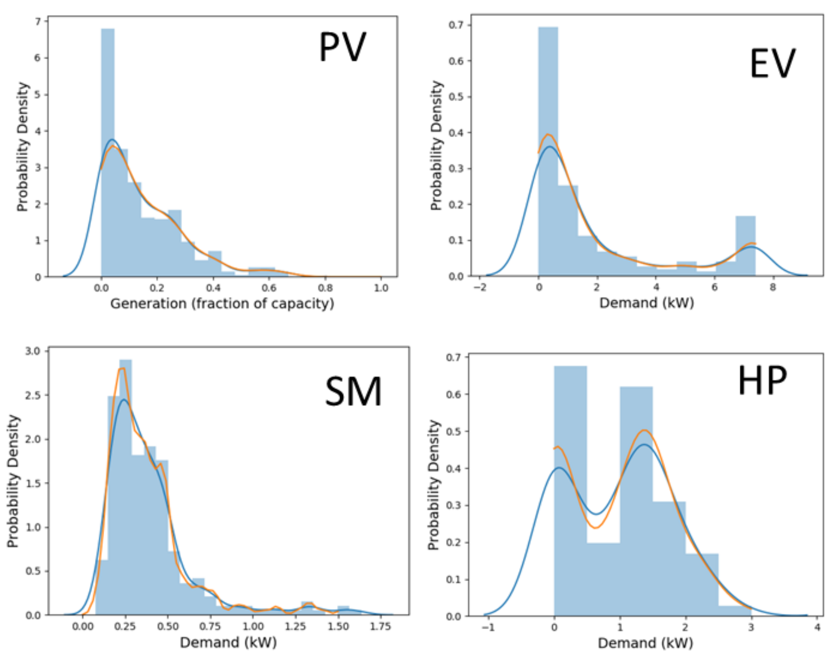

Figure 2. Examples of probability distributions of PV generation, and demand from EV, smart meter (SM) and heat pump (HP), produced from historic metered data from London Datastore (Greater London Authority 2020) using Kernal density estimation. Distributions are for a winter weekday at half-hours 20, 36, 38 and 36 for PV, EV, SM and HP respectively.

Findings and discussion

The model outputs the probabilities of agent adjustments, which can be for individual agents or for aggregated agents as shown in Figure 3. The P95 and P5 represent 95th and 5th percentiles of the aggregated adjustments required by the DSO to relieve constraints for the sampled half hours. In the example shown in Figure , with high EV and HP penetration, the P5 ranges from 1-10 kW of downward adjustment during settlement periods 35-40 (i.e. between 19:30 and 20:00). There is a high risk to the aggregator of committing agents during this peak demand window, particularly any upward flexibility, as it is likely that the DSO will require downward flexibility. In the highest 5% of cases (as shown by the P95), the total downward agent adjustments required by the DSO at 19:00 are above 55 kW. Therefore, a risk averse aggregator could reserve at least 55 kW of their downward flexibility for the DSO at this time, rather than offering it to other national markets.

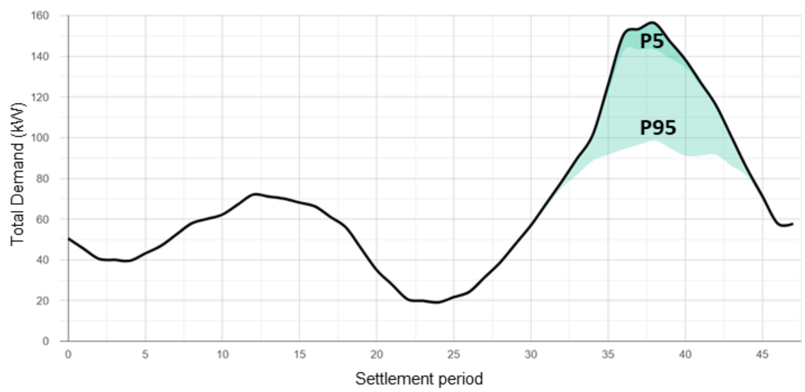

Figure 3. Probability of total agent adjustments (kW), for a typical winter day based on simulation of 90 winter days. For 100% PV and EV penetration case.

This approach does not require agents to inform the aggregator about their activity on a half hourly basis. Instead, the aggregator calculates a probability from historic data (e.g. charging EV data for a larger network, as shown in Figure 4) of how many agents are expected to be plugged in and what their state of charge will be for any given half hour of the day. The aggregator does not need to know exactly what each agent will do, but does need to know within a certain part of LV network how much flexibility all agents will be able to provide with some degree of certainty. The level of flexibility the aggregator is willing to offer based on the certainty of being available (e.g. P95, P99) is then combined with and compared to the level of risk the DSO takes in deciding how much flexibility to request.

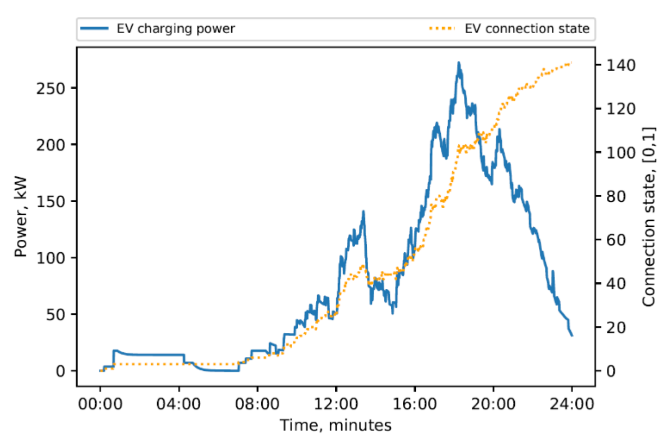

Figure 4. Electric Nation EV charging data (power and connection state) aggregated over more than 140 prosumers.

The platform proposed in this work combines several layers of the operational environment: from physical power flow resolved with OpenDSS, an electric power Distribution System Simulator, to high-level multi-market optimisation of DERs located on the LV network. To the authors' knowledge, no other research has approached the problem from these several areas of expertise, combining the aforementioned world views (DSO, prosumers, aggregator) into a single platform. However, direct control approach adopted by the authors at this stage of the project has proven to have its limits of applicability and is likely to reveal security and privacy concerns in the long term. Specifically, recent research shows that competing aggregators are capable of deviating from state-of-the-art algorithms to reduce their energy costs (Perez-Diaz et al. 2019).

Conclusion and outline for future work

In this paper, a novel integrated approach to the delivery of micro-scale energy resources to electricity markets was proposed. A probability-based heuristic was implemented on a high fidelity representation of LV network to assess and adjust agents' power consumption profiles, with particular attention paid to the adoption of household-level PV sources and the uncertainties related to EV charging. The potential of flexibility in UK local communities provides both opportunities for new markets to emerge from DER trading and challenges associated with growing EV usage and high penetration of renewable sources.

Future work will include the assessment digital ledger technologies (e.g. blockchain) to facilitate P2P energy trading between prosumers within the virtual power plant platform. The authors also seek to investigate how higher adoption of smart home technologies and household-scale energy management systems will affect the future design of the digital intermediation optimisation algorithms. Considering the limitations of direct control strategies, including those that are distributed in terms of agent communications and objective function processing, the authors will seek to implement time-of-use pricing within the proposed platform to proactively engage prosumers in making local consumption and generation decisions. Finally, the authors are interested in considering a broader selection of loads that would be more representative of community, with particular focus on retail refrigeration systems in local supermarkets as perspective providers of flexibility to support coordinated EV charging in commercial parking areas.

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