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Towards a transactive energy system for integration of distributed energy resources: home energy management, distributed optimal power flow, and peer-to-peer energy trading

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Abstract

This paper reviews approaches for facilitating the integration of small-scale *distributed energy resources* (DER) into low- and medium-voltage networks, in the context of the emerging *transactive energy* (TE) concept. We focus on three general categories: (i) *uncoordinated approaches* that only consider energy management of an individual user; (ii) *coordinated approaches* that orchestrate the response of several users by casting the energy management problem as an optimization problem; and (iii) *peer-to-peer* energy trading that aims to better utilize the DER by establishing decentralized energy markets. A second separate, but important, consideration is that DER integration methods can be implemented with diverse levels of network awareness, given their capability to address system or consumer interests. This paper systematically classifies the existing literature on DER integration approaches according to these categories. In doing so, a review of the methods in each category is presented, and differences between the categories are identified and explained through a comparative analysis. In addition, case studies examine technical implementation considerations but leave market aspects aside. The analysis contained in this paper gives researchers and practitioners in DER integration the information needed to select a tailored approach to their specific power network and system integration problems.

Keywords: Transactive energy, virtual power plants, distributed optimization, peer-to-peer energy trading, behind-the-meter distributed energy resources, prosumers, smart grids.

1. Introduction

Power systems are experiencing a transition in paradigm due to the rapid and increasing penetration of "behind-the-meter" *distributed energy resources* (DER) connected at low- and medium-voltage levels, including *photovoltaic* (PV) systems, *electric vehicles* (EV), *battery storage* (BS) systems and flexible loads. To give some context, according to the International Energy Agency (IEA), the installed capacity of rooftop PV systems has grown from 8 GW in 2007 to over 400 GW in 2017 [1]. A similar trend is observed in the United States, where the installed capacity of residential PV systems has increased from 5 GW in 2015 to almost 12 GW in 2018 [2]. Australia is another country with a similar trend; for example, the number of households with rooftop solar passed two million in 2018, meaning that one in five households now have a solar PV system on their roof [3]. The Australian Energy Market Operator (AEMO) projects an increase in the installed capacity of behind-the-meter PV-battery systems from approximately 8 GW in 2018 to nearly 21 GW in 2030 [4]. In this way, technological, computational, and communication advances have facilitated the massive and widespread integration of DER into power systems. As a result, new opportunities and challenges arise for all stakeholders, including retailers, policymakers, industry, commercial, and residential users [5].

Given this context, the concept of *transactive energy* (TE) has emerged as a central element to the vision of the future grid [6, 7]. TE refers to economic and control mechanisms that allow the dynamic balance of supply and demand across the entire electrical infrastructure, using value as a key operational parameter [8]. A successful transition to this emerging concept will therefore require harnessing the inherent flexibility of the demand side to enable future energy balance and ancillary services from the distribution level. For this reason, one of the most important requirements for the emerging TE concept is the efficient integration of DER into power systems, both from a technical and economic perspective. This, in turn, motivates the study of methods and approaches that aim to facilitate the efficient integration of DER.

The potential benefits of efficient integration of behind-the-meter DER are substantial [4, 5, 9–11]. End-users, such as small residential, commercial and industrial users, are empowered by the inherent flexibility of DER as they can manage their electricity usage and production capabilities in response to price and dispatch signals. In this way, DER owners may reduce their electricity cost by managing their demand, reduce their reliance on the grid, maximize the value of their DER, provide back-up supply or arbitrage their retail tariff [12]. In addition, DER flexibility can be seen as a valuable system resource that may provide opportunities to alleviate costly network investment. In Australia, for example, the Australian Energy Networks Association (ENA) and the

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Nomenclature

Sets

$\boldsymbol{x}_a$ Set of all the variables of agent a.

$\boldsymbol{y}$ Set of all network variables.

$\mathcal{A}$ Set of users.

$\mathcal{A}_{\mathrm{b}}$ Set of buyers, $\mathcal{A}_{\mathrm{b}} \subseteq \mathcal{A}$.

$\mathcal{A}_{\mathrm{s}}$ Set of sellers, $\mathcal{A}_{\mathrm{s}} \subseteq \mathcal{A}$.

$\mathcal{E}$ Set of branches in the LV network.

$\mathcal{N}$ Set of buses in the electricity network.

$\mathcal{T}$ Set of time-slots, $t \in \mathcal{T}$.

Ω Set of trades ω in a P2P market.

Ω_b/Ω_s Set of trades of buyer b ($\Omega_b \subseteq \Omega$)/seller s ($\Omega_s \subseteq \Omega$).

Variables

α_ω Transaction price of trade ω.

α_b/α_s Bid price of a buyer b/seller s.

$\hat{p}_i$ Duplicate variable of p_i at bus i.

$\mu_{a,\mathrm{batt}}^{\mathrm{ch/dis},t}$ Binary value of charging/discharging state of user a's battery during time-slot t.

$\mu_{a,\mathrm{batt}}^{\mathrm{ch/dis},t}$ Charging/discharging energy of user a's battery during time-slot t.

$\mu_{a,\mathrm{batt}}^{t}$ Binary value of 'on' or 'off' state of user a's battery during time-slot t.

Φ_{nl}^{ij} PTDF of line (n, l) with power variations at bus i and j.

π_ω Amount of power to exchange of trade ω.

π_b/π_s Amount of power to purchase by buyer b/to sell by seller s.

Ψ_{nl} Injection shift factor of line (n, l).

o_b/o_s Order bid of a buyer b/seller s.

$e_{a,\mathrm{batt}}^{\mathrm{SoC},t}$ Battery state of charge by user a's battery during time-step t.

k Iteration number.

p_i/q_i Net active/reactive power injection at bus i.

r/ζ Primal/dual residuals.

S_{ij} Apparent power flowing in line (i, j).

v_i Complex voltage at bus i.

$x_{a,+/-}^{t}$ Energy imported from/exported to grid during time-slot t.

$x_{a,\mathrm{net}}^{t}$ Net electricity required by user a during time-slot t.

$x_{a,\mathrm{batt}}^{t}$ Energy dispatch by user a's battery during time-slot t.

$x_{a,\mathrm{pv}}^{t}$ Electrical energy generated by the PV system during time-slot t.

Parameters

Δ^t Time-step resolution.

$\eta_{a,\mathrm{batt}}^{\mathrm{ch/dis}}$ Charging/discharging efficiency of user a's battery.

η_a^{inv} Inverter efficiengy of user a's PV system.

$\gamma_{a,\mathrm{batt}}^{\mathrm{ch,max/min}}$ Maximum/minimum charge power of user a's battery.

$\gamma_{a,\mathrm{batt}}^{\mathrm{dis,max/min}}$ Maximum/minimum discharge power of user a's battery.

$\overline{p}_i/\underline{p}_i$ Maximum/minimum active power injection at bus i.

$\overline{q}_i/\underline{q}_i$ Maximum/minimum reactive power injection at bus i.

$\overline{v}_i/\underline{v}_i$ Maximum/minimum voltage at bus i.

ρ ADMM penalty parameter.

$\tau_{a,\mathrm{batt}}$ Scheduling interval of user a's battery.

N Total number of buses.

N_a Total number of users.

$u(\cdot)_{b/s}$ Utility function of buyer b/seller s.

$v(\cdot)_{b/s}$ Valuation function of buyer b/seller s.

$C(\cdot)$ Cost function.

$c_{0/1/2}$ Coefficient of the constant/linear/quadratic term of aggregator cost function.

$e_{a,\mathrm{batt}}^{\mathrm{SoC,max/min}}$ Maximum/minimum state of energy of user a's battery.

Abbreviations

ADMM Alternating direction method of multipliers.

DER Distributed energy resources.

DLT Distributed ledger technologies.

FiT Feed-in tariff.

HEMS Home energy management system.

LSF Loss sensitivity factors.

LV Low voltage.

NPS Network permission structure.

OE Operating envelopes.

OPF Optimal power flow.

P2P Peer-to-peer.

PTDF Power transfer distribution factors.

PV Photovoltaic.

SoC State of charge.

ToU Time-of-use

VPP Virtual power plant.

VSC Voltage sensitivity coefficients.

Commonwealth Scientific and Industrial Research Organisation (CSIRO) estimate that $16 billion in network infrastructure investment can be avoided by the orchestration of DER by 2050 [9]. DER flexibility can also facilitate the uptake of variable renewable energy sources. DER can provide demand shifting, load and resource balancing, and become an integral part of a reliable system [5]. The potential benefits of DER have also been recognized by the Australian Energy Market Commission (AEMC), who indicates that DER can be used to provide ancillary services, such as *frequency control ancillary services* (FCAS) to the market operator [12]. For example, batteries connected at the distribution level can be used to provide a lowering FCAS service, which involves the batteries to charge to absorb power from the grid.

As a consequence of the breadth of potential benefits of DER, different approaches for integrating them into power systems have been developed. In particular, in this paper, we concentrate on DER connected behind-the-meter in residential, small commercial, and small industrial buildings. It is our intention, then, to review exemplar DER integration approaches so that we can systematically investigate the implications that each one brings to the distribution networks and the end-users. For this purpose, we define three general categories for DER integration:

- *Uncoordinated approaches* that consider self-interested users with local energy management systems;
- *Coordinated approaches* that consider aggregation schemes for the coordination of a large number of DER spread across an electrical distribution network; and
- *Peer-to-peer approaches* that consider decentralized energy trading between users in a local market.

In this context, the DER integration process can be viewed bottom up, starting with *uncoordinated* approaches by considering prosumers[1] as self-interested users, who are equipped with local and automated *home energy management systems* (HEMS) that aim to minimize the electricity cost and maximize comfort.[2] Since each automated HEMS operates in the sole benefit of its owner, this approach may not require a sophisticated *information and communication technology* (ICT) infrastructure. Hence, from a practical point of view, this DER integration approach might be considered suitable when the DER penetration level in the distribution network is low, as the impact on the network is likely negligible.

However, the increasing penetration of DER into power systems introduces new challenges for the electricity system. Power systems have physical and technical limits that restrict the number of DER that they can host [13, 14]. Moreover, PV-battery systems operated passively and in the sole benefit of their owners, may not alleviate the network issues caused by high PV penetration, such as overvoltage and transformer capacity issues [15]. Consequently, passive and uncoordinated DER operation provides little benefit to the network, and can in some settings exacerbate the existing problems or may even create new ones [5].

A possible *uncoordinated* solution to overcome these drawbacks is to define *operating envelopes* that establish the limits within which DER must operate in order to satisfy the network technical constraints [5]. In practice, a future *distribution system operator* (DSO) is expected to be in charge of calculating and publishing the operating envelopes [12, 16]. In such a setting, users still aim to maximize their economic benefit through energy management, but they are now aware of the network constraints.

Now, the aggregation of a large number of DER has been proposed to facilitate the efficient integration of DER and to exploit the demand-side flexibility [12]. A typical aggregation scheme comprises an *aggregator* and a set of users, each with DER controlled by an automated HEMS. In this *coordination* approach, an aggregator interacts with each HEMS to orchestrate the DER operation. Furthermore, an aggregation scheme can be seen as a *virtual power plant* (VPP), which might behave like a single dispatchable resource to provide network support and system frequency control services.[3]

The VPP concept is being tested in many countries around the world. One example is the Australian prototype of a 5MW VPP consisting of up to 1000 residential energy storage systems installed behind-the-meter, and capable of dispatching up to 12 MWh of stored energy [17]. The US is also making headway in creating VPP. It is expected to deploy a 20MW VPP in 2022 by combining the output from 5000 residential PV-battery systems [18]. Similarly, a project in Japan anticipates aggregating more than 10000 assets to a VPP between 2020 and 2021 [19]. Other VPP trial projects have also been deployed in Germany, Austria, Belgium, Denmark and Finland [20] (see Appendix A for more VPP trial examples).

In this context, the problem of DER coordination as a VPP can be cast as a single optimization problem that aligns the objectives of individual users with the objective of the aggregator. Electricity network constraints can be introduced into the DER coordination problem, resulting in a model akin to the *optimal power flow* (OPF) problem used in the wholesale market, but the number of market agents (users) is significantly larger than in the conventional OPF problem. The OPF problem with DER consists of finding the lowest cost of dispatching power from generators and DER to satisfy the electricity demand at all buses, in a way that is governed by physical laws, such as Ohm's Law and Kirchhoff's Law, and other technical restrictions, for example, distribution lines' capacity.

In addition to these aggregation schemes, which we classified as coordinated approaches, *peer-to-peer* (P2P) energy trading has emerged as viable approach for efficiently managing the uptake of DER [10, 21]. P2P schemes are based on the concept of decentralized energy trading between peers. Indeed, some companies[4] are exploring the benefits of P2P energy trading through trial projects in many parts of the world, including Australia, Japan, the US, the UK, Netherlands, Thailand and Colombia [21–23]

[1]A prosumer is an end-user who both produces and consumes energy.

[2]HEMS is a generic term used for all small users, including residential, commercial and small industrial users connected to a low-voltage network.

[3]We do not explicitly consider network services provided by an aggregator in this work.

[4]Examples of companies offering P2P energy services include LO3 Energy (https://lo3energy.com), Energylocals (https://energylocals.com.au/), Vandebron (https://vandebron.nl/), Piclo (https://piclo.energy/), Powerpeers (https://www.powerpeers.nl/), Enosi (https://enosi.io/), Dajie (https://www.dajie.eu/) and PowerLedger (https://powerledger.io/).

(see Appendix A for more P2P trial examples). The deployment of this decentralized marketplace is possible due to the emerging technologies, such as blockchain and other *distributed ledger technologies* (DLT). The use of DLT in many industry sectors is still in its exploration phase; for example, at a fundamental level, a debate is taking place between the implementation of public/permissionless or private/permissioned DLT [24]. In the context of P2P energy trading, these technologies enable secure virtual P2P transactions without the presence of any intermediary by an automated execution of smart contracts and the creation of a cryptocurrency [25, 26]. Then, these new P2P market schemes allow, among other things, the local balance of supply and demand, the efficient integration of DER, as well as providing value to the participating users.

Against this background, this paper presents a review of DER integration approaches that have been developed in the transition to the emerging TE concept. In doing so, we provide a self-contained description of the key elements to consider in the TE context. In addition, we compare practical implications of exemplar DER integration approaches that have been proposed in the literature. Thus, the main contribution of this paper is to review DER integration approaches and provide a comparative analysis to highlight the technical implications of adopting exemplar methods, but leaving market aspects aside.

In more detail, the contributions of the paper are:

- We introduce a general transactive energy framework that captures the essential elements and requirements, which provides a common basis from which to systematically compare and contrast DER integration approaches.
- We classify the proposed DER integration methods based on the three categories: uncoordinated, coordinated and P2P approaches.
- Using this framework, we present a brief review, accompanied by self-contained descriptions of suitable methods for DER integration.
- In order to highlight the technical implications of adopting each approach, we simulate the five canonical DER integration models and evaluate their performance using a generic low voltage network as a case study.

The outline of this paper is presented in Fig. 1. This paper is organized as follows. Section 2 reviews the TE framework considered in this work, defines a set of relevant requirements and introduces the DER integration approaches evaluated in this paper. A formal and general description of the TE problem with models of users and electricity network is given in Section 3. Sections 4, 5, and 6 present a brief review and a detailed formulation for uncoordinated, coordinated and P2P approaches, respectively. Section 7 presents a case study to analyse and compare the implications of each approach. Section 8 concludes the paper.

2. Transactive energy

TE is a market-based approach that can establish the appropriate conditions to coordinate the production and consumption of energy across the network among all users and entities. Unlike typical hierarchical structures, a TE framework integrates many participants via two-way exchange of information and economic incentive signals that are standardized in the form of a market protocol [27]. Indeed, TE frameworks have been proposed to include fundamental requirements, as well as market and control features [7, 28, 29].

Recently, research studies have shown an increased interest in the TE concept. The work in [30] studies the performance of a double-auction-based TE system. Another study [31] evaluates the concept of local energy markets considering a TE system. Moreover, previous research has studied TE frameworks to facilitate the integration of DER into power systems, adopting multiagent systems [32], simulation-based valuation methods [33], modelling and assessment frameworks [34] and management schemes

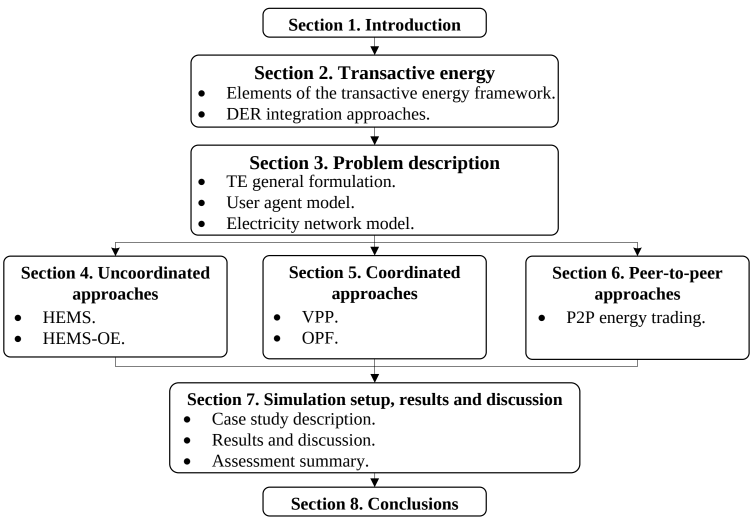


Fig. 1: Outline of the paper.

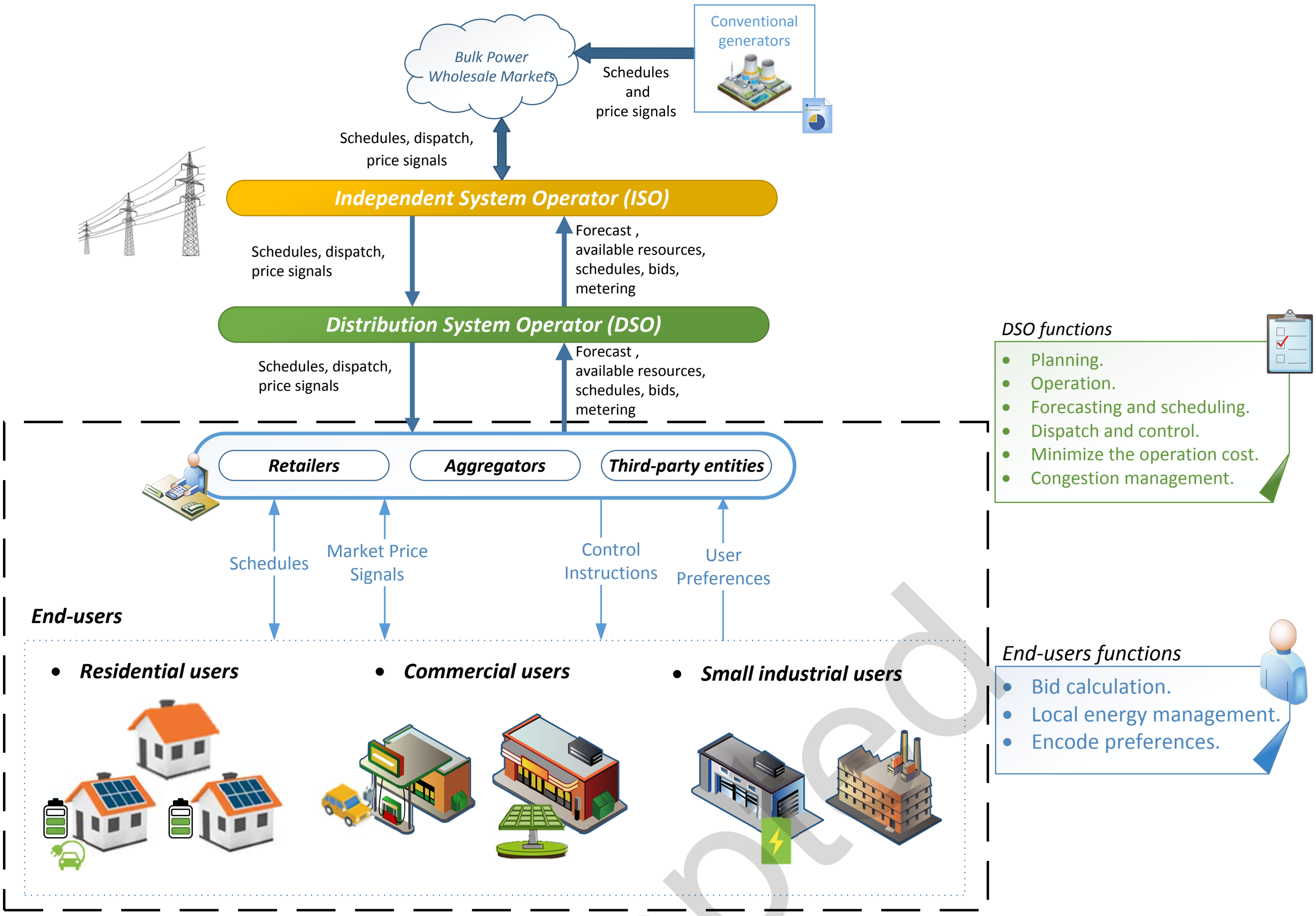


Fig. 2: A transactive energy framework (the dashed line is the scope of this paper). This general framework can be adapted based on the organizational structure of a particular power system. The ISO includes the transmission system operator and/or the market operator for a given power system, depending on how that system is organized.

[35]. Nonetheless, there has been limited work on evaluating and comparing different approaches considering the emerging TE framework.

Existing reviews that examine TE mainly provide conceptual overviews. Reviews of the state-of-art of transactive energy are presented in [28, 35, 36], introducing concepts and elements that have been considered in research studies and demonstration projects. Similarly, the authors in [37] present a comprehensive survey of TE studies and projects, which are classified based on the grid level of application considering control and management features. Other works [26, 38] expand the review of TE framework by discussing functional structures, DLT and the concept of local energy markets. However, these studies do not evaluate and compare the performance and technical implications of TE approaches.

In light of this shortcoming, in this paper, we extend and synthesize the existing TE reviews by providing a systematic comparison of DER integration approaches. We adopt exemplar methods to evaluate the DER integration performance and assess their practical implications. The adopted TE framework is illustrated in Fig. 2, in which entities and users can interact and participate in the market through the underlying communication, control, operation and negotiation layers. The dashed line in Fig. 2 points out the scope of this paper.

2.1. *Elements of the transactive energy framework*

There are common system characteristics and a set of requirements to be considered in the TE context. In this section, the underlying key elements are described and analyzed. Specifically, the four fundamental elements of consideration are:

1. Users and entities, including a network operator.
2. Electricity network, including physical and technical constraints.
3. Regulatory and financial environment.
4. Computational and communication requirements.

The descriptions below are given in general terms, and they are not tailored to a specific model. Detailed description and specific problem formulations are put forward later in this paper.

2.1.1. Users and entities

This paper focuses on the role of users and entities at the distribution level since its operation under a TE architecture remains speculative and it is the first layer to suffer the consequences of high DER penetration. Hence, DER integration challenges should be addressed properly at this level in advance before they escalate upstream to other levels. Specifically, we distinguish three main classes, each with different roles: (i) *users*, (ii) *interface entities* (e.g. aggregators, retailers, etc.), and (iii) a *DSO*, as described below.

The first class is related to the nature of *users* (small-loads), including residential, commercial and small industrial electricity end-users. As discussed above, demand-side participation has become a central and relevant element of power systems [39]. In our model, users are considered as self-interested with heterogeneous preferences, which determine their electricity use patterns. These preferences and behaviors are not necessarily aligned with the operating requirements of the system. Hence, in a TE system, the objectives of the system can be achieved through control and price signals that promote and coordinate the active users' participation.

The second class comprises *interface entities* that facilitate the interaction between users and the TE upper levels. This interface entity may take the form of an aggregator, a retailer, or a utility company, among others. The main goal of this interface entity is to create a large-scale scheme that allows the coordination, scheduling or control of DER via the direct and active interaction with end-users, and to enable the opportunity to provide energy services back to the electricity system. In doing so, new demand-side aggregation schemes and business models may be deployed, including demand response programs and local energy markets [10, 40–42]. These programs empower users while bringing new operational capabilities to the electricity system. It is crucial that these programs do not impose large additional system-wide costs in the system, as they should facilitate the economic and operational DER integration. Extra charges may limit the scope of a TE system. Another essential point to consider is that the interface entity directly interacts with users (agents). For this reason, privacy and prerogative of residential and industrial users should be preserved.

The third class encompasses a DSO, whose main role is to provide users with safe and reliable access to electricity in a cost-efficient way. As such, the DSO is responsible for resolving operational problems, such as grid congestion and voltage violations. The DSO has a model of the physical network itself, which can be used to simulate power flows, and analyze voltages and currents on the network. These simulations then can be used to define network operating envelopes within which DER should operate. Additionally, the DSO may be interested in operating the system in a way that optimizes a particular objective taking into consideration any variable operating costs. Examples include minimization of operating costs of diesel generators, minimization of substation transformer degradation, or loss minimization.

2.1.2. Electricity network

Users are physically connected through an electricity grid, which puts operating and technical limits that must be respected all times. The capacity of network components (e.g. conductors and transformers) is not infinite. Therefore, network constraints represent hard technical limits that restrict the ability of DER to deliver services. There are also constraints that describe the physical system, e.g. power flows. Indeed, high DER penetration without control and coordination might lead to network problems that include overvoltage, reverse power flows with congestion problems and phase unbalance [43–45].

To this end, crude solutions have been introduced to alleviate the network problems that arise due to the increasing DER penetration. One evident solution is to upgrade and increase the network capacity; however, this typically requires costly grid investment, which increases the cost of delivery of energy and services for all users. Another temporary solution is to restrict further DER installation at locations that may face the risk of network problems; but this may reduce the DER value for the users to self-consumption alone, preventing them to harness other value streams. This indicates a need for exploring more dynamic and efficient techniques to improve these ad-hoc solutions to more active network management solutions. Such sophisticated systems will facilitate the efficient DER integration and preserve users' prerogative.

Importantly, in this paper we adopt terminology that distinguishes whether a method considers the electricity network or not, in the following sense: a method is *network-aware* when the electricity network constraints are included in the formulation of the problem. In contrast, a method is *network-oblivious* when a solution ignores the technical and operating constraints associated with the electricity network. The electricity network model used in this paper is presented in Section 3.3.

2.1.3. Regulatory and financial environment

The current regulatory and financial environment in the electricity industry is based on centralized and hierarchical structures that were developed many years ago. This traditional environment was designed with large power stations and passive users in mind. But, with the emergence of active users, the traditional regulatory environment needs to evolve to accommodate them. Significant changes to the regulatory and financial environment may be needed over the long-term as the prevalence of DER increases [5, 9, 12].

In the emerging TE concept, the capability to orchestrate DER will be fundamental to harness the full potential of behind-the-meter DER. Coordination capability also empowers users since they might become involved in new services and business models, for example, they will be able to participate in local energy markets. [4].

Within this context, we detail three fundamental principles that have to be considered in the emerging regulatory and financial environment.[5] First, users are key to DER integration. Regulatory and financial environments need to empower user participation in

[5] It is worth noting that the principles to consider in the emerging regulatory and financial environment are not restricted to the three fundamental principles described only. We attempt to outline some desirable principles that are relevant to the DER integration approaches reviewed in this paper.

a fair, simple and transparent manner [9]. In this way, users with DER may be able to receive incentives for providing network services while those without DER have to be treated fairly. Likewise, it is important to clearly explain to the users potential benefits for all stakeholders and the electricity system, that can be achieved with an efficient DER integration [12]. Otherwise, users may refuse to engage, which will have negative consequences for everyone.

Second, the emerging environments need to have the flexibility to incorporate new programs and business models to leverage active demand-side participation while delivering outcomes that benefit both users' and network's interests. These new programs should be *consumer-centric* to facilitate the large-scale DER integration. Examples of these programs include demand response programs and local energy markets [9, 10]. In these programs, price and incentive signals can be used to promote efficient procurement of services provided by DER that that produce reductions in users' electricity bills and grid-related costs. In other words, the inherent DER flexibility creates the opportunity to unlock more effective network utilization, making electricity more affordable for the users [9].

Third, regulatory *permissions* and *proscriptions* frameworks may be required in order to mitigate network issues in LV networks related to the great penetration of DER. On one hand, in a *permission* framework, users may need to ask for permission to deliver services (send power) to the network. On the other hand, in a *proscription* framework, users must obey the operation settings established by the network operator.

The principles described above are only some prominent principles required to facilitate DER integration. Also, they are relevant to the DER integration approaches reviewed later in this paper. The emerging TE concept will require more changes in the regulatory and financial environment.

2.1.4. Computation and communication requirements

Electric power systems are based on the traditional centralized dispatch architecture, in which large generators supply all the electricity demand. This traditional model was not designed to consider many of the emerging trends, such as the increasing uptake of DER, decentralized power supply from the demand-side, and the advent of innovations in information and communication technologies. Therefore, the transition to a TE system requires a more decentralized approach to system balancing, with a communication network and computing capabilities. Furthermore, new monitoring equipment and advanced communication infrastructure is likely to be needed to allow active management of the electricity network to meet the technical and operational needs, as well as to provide greater network visibility to the system operators.

Given this context, the dispatch will need to be done in a distributed fashion. To successfully do so, users and entities require a two-way communication network with adequate latency and bandwidth. This communication network allows for dynamic interaction between autonomous agents, acting on behalf of the users and the intermediary entities.

However, the communication and computation burden can become unwieldy in large-scale systems [46–49]. Hence, distributed and decentralized approaches could be considered to alleviate these barriers, as is detailed in Section 5.

Now, five canonical approaches are introduced below; while Sections 4, 5 and 6 provide concrete details of each DER integration approach.

2.2. DER integration approaches

Building on the TE system description above, we now provide a brief review of some prominent approaches from the literature of DER integration. In doing so, we start by noting some key divisions in the way a DER integration approach is formulated, and also their capability to address system or consumer interests as well as the level of their network awareness. First, DER integration approaches can be broadly classified into three categories: (i) *uncoordinated*, (ii) *coordinated*, and (iii) *peer-to-peer*. Specifically, uncoordinated approaches only consider energy management of an individual user, coordinated approaches orchestrate the response of several DER by casting the energy management problem as an optimization problem, and peer-to-peer frameworks aim to better utilize DER by establishing a decentralized local energy market.

Second, the approaches can be widely classed along a network-focus spectrum, whose extreme points are *network-aware* and *network-oblivious*. In an electricity network context, the former refers to approaches that consider network constraints in the formulation, while the latter refers to approaches that are network-agnostic. Apart from these extreme classes, some approaches might consider approximate or ad-hoc network constraints that provide a certain level of network awareness. Similarly, DER integration approaches can also be classed along a customer-focus spectrum from *customer-oriented* to *system-oriented*. In more detail, customer-oriented approaches are mainly focused on the individual interests of each user, whereas system-oriented approaches aim to maximize social welfare, including the interests of all users and the system. Fig. 3 can be used as a guide map, which uses the classes defined above and outlines the differences between the focal points of each DER integration approach studied in this paper.

Before explaining the specific methods in more detail, we now provide a brief introduction and review the five canonical DER integration approaches.[6]

[6]Note that there exist a plethora of DER integration methods. They may differ substantially from each other in terms of the three classes established, or along the spectra defined, or in terms of the TE elements of consideration described above. Hence, to avoid unnecessarily over-complicating this paper, we only formulate and assess exemplar approaches that allow us to focus on the evaluation of the technical implications of their deployment. An extensive review of all the methods is beyond the scope of this paper.

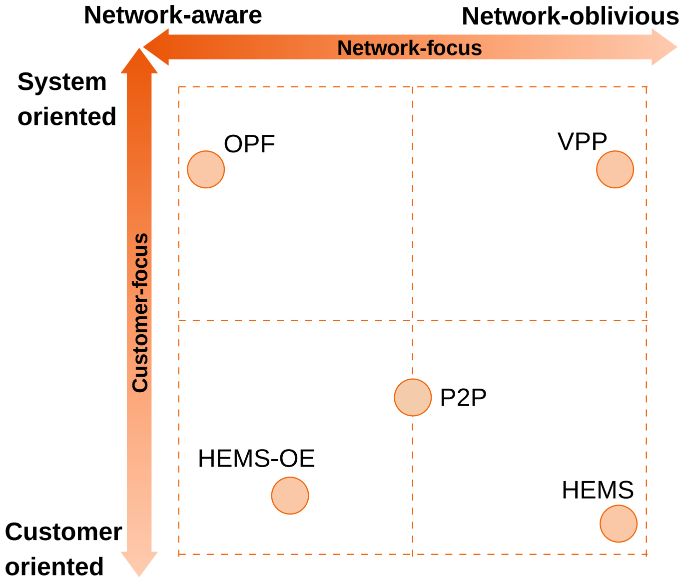


Fig. 3: Map of DER integration approaches based on the levels of network and customer awareness.

Uncoordinated approaches

The pathway to unlock the DER potential starts by implementing *uncoordinated approaches* that consider individual users with DER, whose operation depends on the sole benefit of the DER owners without any aggregation or coordination. We consider two commonly used uncoordinated approaches:

- *Home energy management system* (HEMS): Users are equipped with a HEMS that aims to minimize user's electricity cost by optimizing local generation, storage and consumption of electrical energy to reduce their electricity bills. In order to offer economic benefits to the users, this approach also considers different tariff schemes (e.g. feed-in tariff and time-of-use tariff). Additionally. this approach is network-oblivious in the sense that the users are not aware of the technical and operating constraints of the electricity network. Hence, even though this uncoordinated approach may bring economic benefits to the users, it can also lead to network problems such as overvoltage and overloading, especially in networks with high DER penetration [13, 44].

- *Home energy management system* with *operating envelopes* (HEMS-OE): Under this approach, the users still aim to minimize their electricity expenditure, but there are *operating envelopes* that impose restrictions on the operation of the DER. In practice, the DSO calculates and publishes the operating envelopes to prevent the DER from adversely affecting the operation of the network [5, 12]. In addition, the DSO might require a certain level of network state visibility to adequately build the operating envelopes [12, 16].

Coordinated approaches

Moving from uncoordinated to more community-based or cooperative models, the following *coordinated approaches* have the potential to orchestrate the DER operation for the joint benefit of the users and the intermediary entity (aggregator or DSO). This can be done through a dynamic interaction using control and price signals to change the users' consumption and generation patterns. Participation in this scheme may be financially attractive for end-users as incentives are provided, typically in the form of a payment, discount, or a monetary transfer. In particular, we consider the following coordinated approaches:

- *Virtual power plants* (VPP): A VPP is an aggregation of a large number of DER scattered around the system but not necessarily connected to the same feeder or distribution system. DER in a VPP are coordinated to exploit their inherent flexibility [50]. By definition, a VPP does not consider network constraints and the aggregated DER are not necessarily connected to the same network. The VPP concept shares some important characteristics with the concept of microgrids since both consider the aggregation and coordination of DER.[7] However, previous studies have identified three key distinctions between a microgrid and a VPP. First, a microgrid covers a static set of DER in an enclosed area, whereas a VPP is not limited by geography and encompasses a wide variety of DER. Second, a microgrid can operate in an isolated mode while a VPP cannot. Third, a microgrid faces regulatory obstacles, whereas a VPP can be easily incorporated into the existing regulatory framework. Other similitudes and differences between VPP and microgrid can be found in [52–54].

[7]CIGRÉ Working group C6.22 (WG6.22) defined microgrids in [51] as electricity distribution systems containing DER that operates in a coordinated manner either connected to the grid or in an isolated mode. Moreover, WG6.22 described three main types of microgrids: (i) customer microgrids, (ii) utility microgrids, and (iii) virtual microgrids. While the main difference between customer and utility microgrids are primarily based on regulatory and business model aspects, the main difference between virtual microgrids and the other microgrid types is that the former cover DER at multiple sites in large geographic areas. Given these definitions, a VPP can be classified as a virtual microgrid.

Table 1: List of relevant references for each DER integration approach.

Approach	References
HEMS	[55–69]
HEMS-OE	[16, 43, 45, 70–76]
VPP	[40, 50, 77–93]
OPF	[94–111]
P2P	[21, 112–143]

- *Optimal power flow* (OPF): Since it is imperative to consider network constraints in DER orchestration, an ideal approach is to employ the traditional OPF approach, but incorporate a larger number of market agents (users). The aim of the resulting OPF problem is to determine the optimal DER dispatch subject to technical, operating and network constraints.

Peer-to-peer approaches

The high DER penetration also opens up a possibility for new business models. Ultimately, the concept of *decentralized frameworks* has emerged, which consists of a local P2P energy trading with bilateral energy transactions between users. Specifically, we consider the following P2P framework:

- *Peer-to-peer* (P2P): Users take the role of buyers or sellers in a local energy market to trade electricity among them. The energy surplus of the sellers can be seen as an opportunity to trade with those users who are willing to buy in the local market. Nevertheless, decentralized P2P markets may lead to network issues when network constraints are not explicitly accounted for in the trading.

Given the approaches described above, Table 1 contains a list of relevant references related to each approach, while examples of DER integration trials around the world are presented in Appendix A.

3. Problem description

The adopted TE model comprises N_a agents, $\mathcal{A} := \{0, 1, 2, \ldots, N_a\}$. Agent 0 is an independent entity (e.g. an aggregator, a retailer, third-party, etc.), while each $a \neq 0$ is a user agent. User agents may interact with the upper layers in the TE system through the intervention of the interface entities, as mentioned earlier. Let's define a time horizon $\mathcal{T} := \{t^0, t^0 + \Delta^t, ..., t^0 + (T-1)\Delta^t\}$ consisting of T time-slots.

3.1. TE general formulation

The DER coordination problem can be written in the general form:

$$\text{minimize } F(\boldsymbol{x}), \quad \boldsymbol{x} \in \mathcal{X}, \tag{1}$$

where $\mathcal{X}$ is the feasible energy allocation set defined by the constraints of each autonomous entity that interacts with the DSO, and the constraints of the physical network. The choice of the objective function $F(\boldsymbol{x})$ is governed by the nature of the framework and the design properties. Examples of applications under this context include direct load control, demand response programs, incentive mechanisms, local energy exchange market models, to name a few.

This model is general and flexible enough to integrate different types of users and entities, from energy market operators to intermediary entities, such as aggregators, retailers, virtual power plants, microgrids, etc. Therefore, $F(\boldsymbol{x})$ can include objectives from the users and the intermediary entities.

The work in this paper focuses on the comparison of DER integration approaches that have been proposed as steps towards the deployment of the TE concept.[8] In this context, the main challenge is to coordinate energy flows within distribution network constraints through the interaction between autonomous agents acting on behalf of the users and the intermediary entities. Therefore, formal definitions of the user agents' and electricity network models are required, before introducing the detailed formulation of each DER integration approach implemented in this paper.

3.2. User agent model

In this work, we assume that all users are capable of predicting their levels of demand and generation for electrical energy for a particular time-slot t. For sake of compactness, the electrical load of a user is not divided into tasks.[9] Specifically, we consider PV systems and residential battery storage systems in our study. Fig. 4 depicts the schematic connection between the user agent and the grid.

[8] The comparative analysis presented in this paper only focuses on technical implications, leaving market aspects aside.

[9] Interested readers in tasks or device type classification are referred to [46, 144].

To capture the response to preferences and prices, the user agent model described below is an optimization-based model for a local energy management agent. It can be used for managing energy consumption of each individual user, but it can also be included in aggregation approaches, as discussed in Section 5.

The net electric energy required by agent $a \neq 0$ is denoted by

$$\boldsymbol{x}_{a,\text{net}} = \left[x_{a,\text{net}}^{t}, \ldots, x_{a,\text{net}}^{t+T-\Delta^t}\right] \in \mathcal{X}_{a,\text{net}}, \tag{2}$$

where $x_{a,\text{net}}$ is the net electric energy required by agent $a \neq 0$ during time-slot t and $\mathcal{X}_{a,\text{net}}$ is the feasible set defined by

$$x_{a,\text{net}}^{t} = x_{a,+}^{t} - x_{a,-}^{t}, \tag{3}$$

$$P_a^{\min}\Delta^t \leq x_{a,\text{net}}^{t} \leq P_a^{\max}\Delta^t, \quad t \in \mathcal{T}, \tag{4}$$

where $P_a^{\max}$ and $P_a^{\min}$ are the maximum and minimum power that can be absorbed and injected into the grid, respectively. $x_{a,+}^{t}$ ($x_{a,-}^{t}$) is the energy that agent a imports from (exports to) the grid at time-slot t. The amounts of energy $x_{a,+}^{t}$ and $x_{a,-}^{t}$ depend on the *base load*, the energy dispatch from *PV systems* and *battery storage*. Let $x_{a,\text{load}}^{t}$ be the base load at time t, which includes must-run devices and uncontrollable loads that have no flexibility in its timing or magnitude. The electrical energy generated by the PV system during time-slot t is denoted by $x_{a,\text{pv}}^{t}$. The energy dispatch from a battery storage system is governed by the following constraints, $\forall t \in \mathcal{T}$:

$$x_{a,\text{batt}}^{t} = x_{a,\text{batt}}^{\text{dis},t} - x_{a,\text{batt}}^{\text{ch},t}, \tag{5a}$$

$$\mu_{a,\text{batt}}^{\text{ch},t}\left(\gamma_{a,\text{batt}}^{\text{ch,min}}\Delta^t\right) \leq x_{a,\text{batt}}^{\text{ch},t} \leq \mu_{a,\text{batt}}^{\text{dis,t}}\left(\gamma_{a,\text{batt}}^{\text{ch,max}}\Delta^t\right), \tag{5b}$$

$$\mu_{a,\text{batt}}^{\text{dis},t}\left(\gamma_{a,\text{batt}}^{\text{dis,min}}\Delta^t\right) \leq x_{a,\text{batt}}^{\text{dis},t} \leq \mu_{a,\text{batt}}^{\text{dis,t}}\left(\gamma_{a,\text{batt}}^{\text{dis,max}}\Delta^t\right), \tag{5c}$$

$$\mu_{a,\text{batt}}^{t} = \mu_{a,\text{batt}}^{\text{dis},t} + \mu_{a,\text{batt}}^{\text{ch},t}, \tag{5d}$$

$$e_{a,\text{batt}}^{\text{SoC},t} = e_{a,\text{batt}}^{\text{SoC},t-\Delta^t} + \eta_a^{\text{ch}} x_{a,\text{batt}}^{\text{ch}} - \frac{x_{a,\text{batt}}^{\text{dis}}}{\eta_a^{\text{dis}}}, \tag{5e}$$

$$e_{a,\text{batt}}^{\text{SoC,min}} \leq e_{a,\text{batt}}^{\text{SoC},t} \leq e_{a,\text{batt}}^{\text{SoC,max}}, \tag{5f}$$

$$e_{a,\text{batt}}^{\text{SoC},\tau_{a,\text{batt}}^{\text{start}}-\Delta^t} = e_{a,\text{batt}}^{\text{SoC,ini}}, \tag{5g}$$

$$e_{a,\text{batt}}^{\text{SoC},\tau_{a,\text{batt}}^{\text{end}}} \geq e_{a,\text{batt}}^{\text{SoC,final}}, \tag{5h}$$

where $x_{a,\text{batt}}$ in the defining constraint (5a) takes negative values when the battery is charging, and $x_{a,\text{batt}}$ takes positive values when the battery is discharging. The state of charge during time-slot t is defined by $e_{a,\text{batt}}^{\text{SoC},t}$. The charging powers of the battery vary within the upper and lower limits $\gamma_{a,\text{batt}}^{\text{ch,max}}$ and $\gamma_{a,\text{batt}}^{\text{ch,min}}$. $\mu_{a,\text{batt}}^{\text{ch},t} \in \{0, 1\}$ is a binary variable that represents the charging mode at time t, and $x_{a,\text{batt}}^{\text{ch},t}$ is the charging power. Analogously, in (5c), the maximum and minimum discharging powers of the battery are $\gamma_{a,\text{batt}}^{\text{dis,max}}$ and $\gamma_{a,\text{batt}}^{\text{dis,min}}$, respectively. $\mu_{a,\text{batt}}^{\text{dis},t} \in \{0, 1\}$ is a binary variable, and $x_{a,\text{batt}}^{\text{dis},t}$ is the discharging power. Initial and final state of energy of agent a's battery are given by $e_{a,\text{batt}}^{\text{SoC,ini}}$ and $e_{a,\text{batt}}^{\text{SoC,final}}$, respectively. Constraints (5e) – (5h) model the stage of energy of the battery. Constraint (5f) ensures that the state of energy is within the minimum, $e_{a,\text{batt}}^{\text{SoC,min}}$, and the maximum, $e_{a,\text{batt}}^{\text{SoC,max}}$, states of energy. Also, $\tau_{a,\text{batt}}^{\text{start}}$ and $\tau_{a,\text{batt}}^{\text{end}}$ are the start and end times of the desired scheduling interval. Then, constraint (5g) ensures that the state of energy $e_{a,\text{batt}}^{\text{SoC},\tau_{a,\text{batt}}^{\text{start}}-\Delta^t}$ at $\tau_{a,\text{batt}}^{\text{start}} - \Delta^t$ is equal to $e_{a,\text{batt}}^{\text{SoC,ini}}$, which is the initial state of energy. Last, constraint (5h) ensures that the battery is charged to at least $e_{a,\text{batt}}^{\text{SoC,final}}$ at $\tau_{a,\text{batt}}^{\text{end}}$. We assume charging efficiency η_a^{ch}, and discharging efficiency η_a^{dis}.

Now, we can formally define the energy imported, $x_{a,+}^{t}$, and exported, $x_{a,-}^{t}$, by agent a during time-slot $t \in \mathcal{T}$, as follows:

$$x_{a,+}^{t} = x_{a,\text{load}}^{t} - \eta_a^{\text{inv}}\left(x_{a,\text{batt}}^{\text{dem},t} - x_{a,\text{batt}}^{\text{ch},t} + \left(1 - \kappa_{a,\text{pv}}^{t}\right)x_{a,\text{pv}}^{t}\right), \tag{6}$$

$$x_{a,-}^{t} = \eta_a^{\text{inv}}\left(x_{a,\text{load}}^{\text{exp},t} + \kappa_{a,\text{pv}}^{t} x_{a,\text{pv}}^{t}\right), \tag{7}$$

$$x_{a,\text{batt}}^{\text{dis},t} = x_{a,\text{batt}}^{\text{dem},t} + x_{a,\text{batt}}^{\text{grid},t}, \tag{8}$$

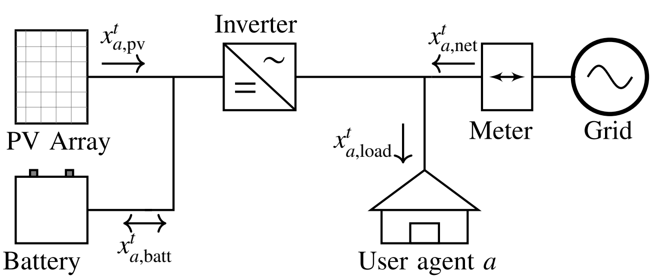


Fig. 4: User agent - grid connection.

where η_a^{inv} is the efficiency of the inverter, $\kappa_a^{\text{pv},t} \in [0, 1]$ is a variable that captures the proportion of the PV energy that is exported to the grid, and $x_{a,\text{batt}}^{\text{dem},t}$ ($x_{a,\text{batt}}^{\text{grid},t}$) is the energy exported from the battery to cover the agent's demand (to the grid) at time-slot t.

Finally, the set of all the variables of agent $a \neq 0$ can be defined by

$$\boldsymbol{x}_a \in \mathcal{X}_a. \tag{9}$$

3.3. Electricity network model

Users are physically connected to an electricity grid that places technical and operating limits on the DER integration models. Power flows in a LV network are governed by physical laws, such as Ohm's Law and Kirchhoff's Law, and other technical restrictions, which become constraints in the DER coordination problem. We consider the branch flow formulation, first proposed in [145], to model a distribution network. This is represented as a tree graph $\mathcal{G}(\mathcal{N}, \mathcal{E})$, consisting of a set of distribution lines $\mathcal{E}$ connecting a set of buses $\mathcal{N}$ indexed by $i = 0, 1, \ldots, N$, where the root of the radial network is denoted by 0, and it is considered as the slack bus.

Given a graph $\mathcal{G}$, there is a unique path between any two buses in $\mathcal{G}$. Let the pair (i, j) denote a line that connects the pair of buses $i, j \in \mathcal{N}$, where j is closer to the feeder 0. We call j the unique ancestor of i, denote by $\varsigma(i)$, and call i the child of j. Denote the child set of j as $\delta(j) := \{i : (i, j) \in \mathcal{E}\}$. Thus, a link (i, j) can be denoted as $(i, \varsigma(i))$.

For each bus $i \in \mathcal{N}$, let $V_i = |V_i| e^{\mathbf{i}\theta_i}$ be its complex voltage, and $v_i := |V_i|^2$ be its magnitude squared. We assume the complex voltage V_0 at the feeder root node is given and fixed. Let $s_i = p_i + \mathbf{i}q_i$ be its complex power required at bus i. For each line $(i, \varsigma(i)) \in \mathcal{E}$, let $Z_{ij} = R_{ij} + \mathbf{i}X_{ij}$ be its impedance, and let I_{ij} be the complex current flowing from bus i to $\varsigma(i)$, and $\ell_{ij} = |I_{ij}|^2$ be its magnitude squared. Let $S_{ij} = P_{ij} + \mathbf{i}Q_{ij}$ be the complex power flowing from buses i to $\varsigma(i)$.

Following Ohm's Law, Kirchhoff's Law and other operating constraints, an equivalent AC power flow model in a radial distribution network can be defined by the branch flow model as follows:

$$p_i = P_{ij} - \sum_{k \in \delta(j)} P_{jk} + R_{jk}\ell_{jk}, \qquad i \in \mathcal{N}, \tag{10a}$$

$$q_i = Q_{ij} - \sum_{k \in \delta(j)} Q_{jk} + X_{jk}\ell_{jk}, \qquad i \in \mathcal{N}, \tag{10b}$$

$$v_i = v_{\varsigma(i)} + 2(R_{ij}P_{ij} + X_{ij}Q_{ij}) - (R_{ij}^2 + X_{ij}^2)\ell_{ij}, \qquad (i, j) \in \mathcal{E}, \tag{10c}$$

$$\ell_{ij}v_i = P_{ij}^2 + Q_{ij}^2, \qquad (i, j) \in \mathcal{E}, \tag{10d}$$

In addition to (10), there are operating constraints for each bus $i \in \mathcal{N}$ and for each line $(i, j) \in \mathcal{E}$ that must be satisfied. These constraints are:

- Voltage magnitude constraints, for each bus $i \in \mathcal{N}$

$$\underline{v}_i \leq v_i \leq \overline{v}_i, \tag{11}$$

  where $\underline{v}_i$ and $\overline{v}_i$ are the minimum and maximum voltage limit at bus i, respectively. Note that at bus 0, $\underline{v}_0 = \overline{v}_0$, as the voltage magnitude at the root bus is assumed to be fixed.

- Power injection constraints, for each bus $i \in \mathcal{N}$

$$\underline{p}_i \leq p_i \leq \overline{p}_i, \tag{12}$$

$$\underline{q}_i \leq q_i \leq \overline{q}_i, \tag{13}$$

  where active power p_i can vary within $[\underline{p}_i, \overline{p}_i]$, and reactive power can vary within $[\underline{q}_i, \overline{q}_i]$.

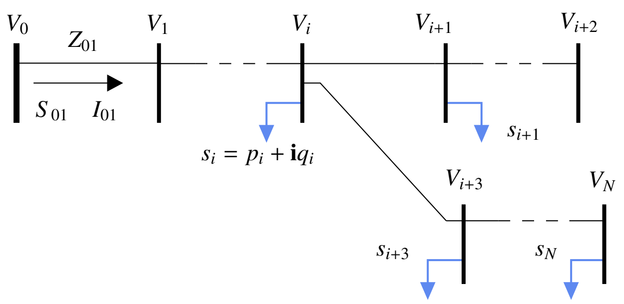


Fig. 5: Diagram of a distribution network.

- The complex power flow of each line $(i, j) \in \mathcal{E}$, in both directions, is limited by a higher bound that imposes the following constraints:

$$P_{ij}^2 + Q_{ij}^2 \leq \overline{S}_{ij}^2, \qquad (i, j) \in \mathcal{E}, \tag{14}$$

$$\left(P_{ij} - \ell_{ij} R_{ij}\right)^2 + \left(Q_{ij} - \ell_{ij} X_{ij}\right)^2 \leq \overline{S}_{ij}^2, \qquad (i, j) \in \mathcal{E}, \tag{15}$$

  where $\overline{S}_{ij}^2$ is the maximum complex power of line (i, j).

Now, the set of network problem variables can be defined as

$$\boldsymbol{y} := \left\{\{P_{ij}, Q_{ij}, \ell_{ij}\}_{(i,j)\in\mathcal{E}}, \{v_i, p_i, q_i\}_{i\in\mathcal{N}}\right\}_{t\in\mathcal{T}} \in \mathcal{Y}. \tag{16}$$

Finally, it is worth noting that every agent $a \in \mathcal{A}$ is connected to a unique bus i, that is, $\mathcal{A} \subseteq \mathcal{N}$.

Given this context, Sections 4, 5 and 6 provide a detailed formulation of the underlying problem for each DER integration approach adopted in this paper. In addition, we also incorporate a high-level review of various methods that have been proposed to carry out each approach. In doing so, we use the three broad categories presented in Section 2.2: (i) uncoordinated approaches, (ii) coordinated approaches, and (iii) P2P approaches.[10]

4. Uncoordinated approaches

Uncoordinated approaches represent the first step on the pathway of the DER integration process. In these uncoordinated approaches, individual users are equipped with automated HEMS that aim to minimize their electricity cost.

4.1. Home energy management system (HEMS)

In power systems, users have historically been passive, paying a fixed tariff for their energy consumption. In order to harness the inherent flexibility of behind-the-meter DER, new tariff structures have been introduced in the system to reward the contribution and to incentivize flexible consumer behavior. Examples of this include *feed-in-tariffs* (FiT) and *time-of-use* (ToU) tariffs. The former offer economic incentives to end-users for their power injection, while the latter is a variation of the price over time that could result in shifting the demand away from peak periods.

In this approach, users are equipped with a HEMS for optimally scheduling DER to minimize the electricity cost while maintaining acceptable comfort levels. There is a plethora of studies on energy management techniques to schedule DER. The authors in [55] reviewed energy management systems considering their modelling and complexity. Additionally, the work in [56] provides a techno-economic study of HEMS considering forecast and computation limitations.

In general, there are two common energy management scheduling approaches used in the literature: mathematical optimization and heuristic methods. The solution techniques depend on a range of factors, including modelling, input data assumptions, forecast uncertainties, and computational cost. Thus, several methods have been proposed for solving the HEMS problem. These methods include:

- *Mixed-integer linear programming* (MILP): HEMS problem can be cast as a MILP problem. A MILP formulation requires a linear objective function subject to linear constraints with continuous and integer variables. If the problem considers uncertainty related to electrical demand and PV output, a stochastic MILP formulation can be implemented [57–61]. Stochastic MILP can handle stochasticity by using a scenario-based approach [146]. Nonetheless, the scheduling problem becomes computationally challenging as the number of scenarios increases, thereby the computational time increases.

- *Particle swarm optimization* (PSO): It is a population-based stochastic optimization technique, which is inspired by social behavior of groups of organizations. PSO can provide feasible solutions within a reasonable amount of computation time. However, the computational complexity and the accuracy of a PSO problem with stochastic variables depend on the scenario reduction method [62, 63], the same issue as in stochastic MILP.

- *Dynamic programming* (DP): Stochastic variables and non-linear constraints can be handled using DP. Then, the HEMS problem can be thought of as a sequential decision making process under uncertainty. However, the dimension of state and action spaces lead to an exponential increase in the computational complexity [66–69]. To overcome this drawback, *approximate dynamic programming* (ADP) can be applied [64, 65].

In this work, we use a mixed-integer linear programming (MILP) solution technique to solve the HEMS problem. We adopt the system topology presented in Fig. 4, which consists of a user agent with a PV system and a battery storage system. Observe that the grid is myopic to the DER management, thus the user agent privacy is preserved. Specifically, the goal of the HEMS is to

[10] Observe that in order to provide a self-contained paper, we consider prominent DER integration approaches and models to capture their technical implications, which are presented and discussed later in Section 7.

minimize the electricity cost across a decision horizon, given the import and export tariffs, such as FiT, flat and ToU tariffs. Then, the optimization problem of a local HEMS for each user is given by:

$$\begin{aligned} \underset{x_a \in X_a}{\text{minimize}} \quad & \sum_{t \in \mathcal{T}} \sigma^{\text{ft/tou}^t} x^t_{a,+} - \sigma^{\text{fit}} x^t_{a,-}, \\ \text{subject to} \quad & \\ & \text{power balance constraints, and} \\ & \text{DER operational constraints,} \\ & \forall t \in \mathcal{T}, \end{aligned} \tag{17}$$

where $\sigma^{\text{ft/tou}^t}$ and σ^{fit}, are, respectively, the flat/ToU and the FiT tariff. The solution of (17) is the optimal schedule of the user's demand. The net demand exchanged with the grid is given by $x^t_{a,\text{net}} = p^t_i \Delta^t$. Note that there is no consideration of the state of the local network in this decision.

4.2. Home energy management system with operating envelopes (HEMS-OE)

Since electricity networks have a limited hosting capacity, high DER penetration without coordination may lead to network issues [15, 43, 45, 70–72, 147]. A conventional, but high cost option is grid reinforcement, which requires replacing or adding new conductors to the network [73]. Although grid reinforcement is an effective method for solving the overvoltage issues, it is not cost-efficient [43].

As an alternative, an uncoordinated and short-term solution is to impose system network *operating envelopes* to prevent the violation of network constraints; this requires network state estimation not typically used in low-voltage grids [5, 12]. In this work, the network *operating envelopes* are associated with the maximum amount of active power that DER can inject into the grid (i.e. active power curtailment schemes) [16, 74–76]. Thus, the voltage and capacity issues can be prevented by modulating the amount of active power injected.

To define the maximum limit that users can inject (i.e. operating envelopes related to maximum power injection constraint), the relationship between power injections and voltage changes is analysed through the Jacobian matrix [148]

$$J = \begin{bmatrix} \frac{\partial P}{\partial |V|} & \frac{\partial P}{\partial \theta} \\ \frac{\partial Q}{\partial |V|} & \frac{\partial Q}{\partial \theta} \end{bmatrix}, \tag{18}$$

where P and Q represent the active and reactive bus injections or withdraws, and θ and V represent the voltage angles and magnitudes. Using the inverse of the Jacobian, the changes in the voltage levels (ΔV_i) can be defined as a function of the changes in the active and reactive power (ΔP_i, ΔQ_i). Hence, the voltage changes at a specific operating point is defined by:

$$\Delta V_i = \left(\frac{\partial V_i}{\partial P_i}\right) \Delta P_i + \left(\frac{\partial V_i}{\partial Q_i}\right) \Delta Q_i. \tag{19}$$

In light of the above, the curtailment strategy used in this paper for the HEMS-OE approach relies on the identification of the maximum amount of active power that users can export while the network limits are respected. Thus, network envelopes can be incorporated into the HEMS optimization problem. Specifically, the maximum limit of power injected can be defined by modifying the limits (4).

Note that this approach requires network visibility and communication channels to calculate and publish operating envelopes. Thus, the HEMS-OE approach requires ICT or exploits the benefits of the *Internet of Things* (IoT) concept [149].

5. Coordinated approaches

This section contains the problem formulation related to aggregation schemes that coordinate demand-side DER. We adopt a typical framework comprising an aggregator and small-scale users as outlined in Fig. 6. In this setting, the role of the aggregator is to coordinate DER via interaction with individual HEMS, that is with automated agents acting on users' behalf.

This paper considers VPP and OPF approaches for DER coordination, formally described below.

5.1. Virtual power plant (VPP)

The VPP concept broadly refers to the integration, through advanced information and communication technologies, of a cluster of individual DER to deliver multiple services that have typically been provided by conventional power plants [50]. A typical VPP comprises an aggregator that coordinates, schedules or controls participating DER to work in the best interests of the system and the users, in the absence of network constraints [77–79]. An *aggregator* does this by providing either control instructions or price signals for price-responsive loads or agents. A VPP enables users to gain economic benefits resulting from the network services provided to the system by the aggregator.

Indeed, the VPP concept has been considered for demand-side programs applications [20, 50, 52, 53], such as: (i) *direct load control* (DLC) programs, and (ii) *demand response* (DR) programs. In DLC programs, users receive an incentive for allowing a degree of control over certain devices through a contract with the conditions of load control policy. In contrast, in DR programs, the

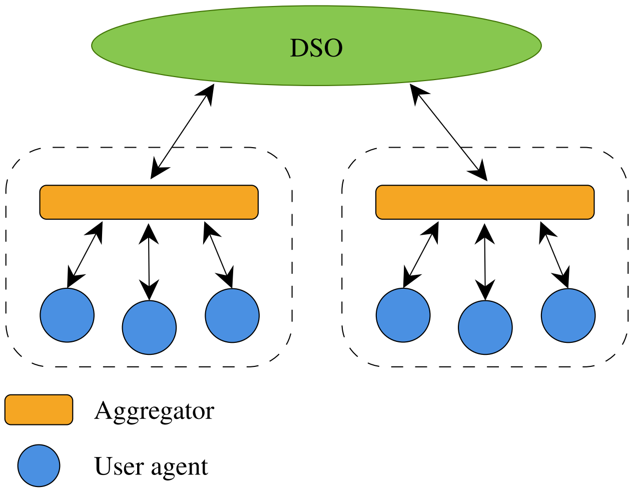


Fig. 6: Interaction between an aggregator and user agents through two-way communication channels.

aggregator uses price signals to incentivize users to adjust their utilization patterns, and to coordinate the DER operation. Many diverse methodologies for generating price signals have been proposed in the literature [40, 80–82], including optimization-based shadow prices or Lagrange multipliers [83, 84, 87, 92, 97], mechanism design and non-cooperative games [85, 86, 93], statistical scoring rules [150–152], and combinations of these [46].

5.1.1. Aggregator model

Formally, an aggregator is an independent entity that coordinates DER and it serves as an interface for user agents to interact with the upper layers in the TE system. Let define the aggregator cost function $C^t : \mathbb{R}_+ \to \mathbb{R}_+$, which represents the cost of importing energy from the grid during time-slot t. Specifically, $C^t(x_0^t)$ is the cost of drawing energy x_0^t from the grid during time-slot t. The amount of energy imported from the grid can be restricted, that is $\boldsymbol{x}_0 := \left\{x_0^t\right\}_{t\in\mathcal{T}} \in \mathcal{X}_0 := \left\{x_0^t \in \mathbb{R}_+ \mid 0 \le x_0^t \le P_{\mathrm{G}}^{\max}\Delta^t, t \in \mathcal{T}\right\}$. Assuming that the marginal energy producer has a quadratic cost function, which is a reasonable approximation for conventional fossil-fuel generation, including coal- and gas-fired power plants, we adopt a quadratic cost function, $C^t(x_0^t)$, to represent the aggregator cost associated with the purchase of electricity in the wholesale market. Then, the aggregator cost function can be approximated by

$$C^t(x_0^t) = c_2(x_0^t)^2 + c_1 x_0^t + c_0, \tag{20}$$

where c_0, c_1, and c_2 are parameters which are related to the variations in the prices in the wholesale market. This quadratic cost function can be used to represent the participation of the aggregator in the wholesale market, where aggregators face costs for balancing and regulation services, or where aggregators can offer network services.[11]

An alternative model to the quadratic cost function is to represent the cost function as single- or multiple-segment linear cost functions, similar to the piece-wise linear supply functions used in many wholesale electricity markets.

5.1.2. Aggregation problem

If it has the private information and preferences of the user agents, the objective of the aggregator is to minimize the total electricity cost, and thereby efficiently coordinate DER, by solving the following problem:

$$\underset{\boldsymbol{x}_a\in\mathcal{X}_a,\boldsymbol{x}_0\in\mathcal{X}_0}{\text{minimize}} \quad \sum_{t\in\mathcal{T}}\left(C^t(x_0^t) + \sum_{a\in\mathcal{A}\backslash 0} g_a(\boldsymbol{x}_a)\right), \tag{21a}$$

$$\text{subject to} \quad \sum_{a\in\mathcal{A}\backslash 0} x_{a,\mathrm{net}}^t = x_0^t, \qquad t\in\mathcal{T}, \tag{21b}$$

where x_0^t is the total demand during time-slot t. The function of user agents $g_a(\cdot)$ can be adapted to integrate some properties in the model, such as user satisfaction and comfort [92], local exchange models [118], end-users preferences [117], etc. In this work, the user agent functions $g_a(\cdot)$ take the form on the objective function (17), so the objective is also to minimize the electricity cost of user agents. Observe that (21) does not consider network constraints.

The feasible sets $\mathcal{X}_a$ are disjoint since the user agent model includes binary variables to represent device operation points. Consequently, the model (21) is a mixed-integer quadratic programming (MIQP) problem. When solved centrally, this NP-hard problem can be intractable, especially for large-scale aggregation schemes. Adopting a piece-wise linear function with multiple

[11] The quadratic cost function in (20) is assumed to be a general approximation of efficient markets. Observe that the prices in the wholesale market are also influenced by the congestion on the transmission network. In this paper, we neglect this component.

segments to model the cost function $C^t(\cdot)$ results in mixed-integer linear programming (MILP) problem with additional binary variables (associated with the piece-wise linear segments). Consequently, this large-scale aggregation problem would most likely exhibit slow computation, when it is solved centrally.

Additionally, under a centralized model, the aggregation scheme problem (21) needs to collect the agents' private information in $\mathcal{X}_a$. Indeed, collecting this private information in a large-scale aggregation scheme requires a substantial communication overhead, not to mention privacy concerns and the possible presence of agents that strategize over the information they reveal.

In response to these challenges, distributed techniques have been proposed as a way to efficiently implement large-scale aggregation schemes [95] in a distributed fashion. Thus, the aggregation problem can be decomposed into a set of subproblems, coordinated through the interaction between aggregator and electricity user agents. Compared to centralized techniques, distributed methods are superior in terms of scalability, privacy preservation, and robustness. Then, the underlying DER coordination problem can be solved in a distributed fashion to alleviate computational complexity, communication overhead and privacy concerns.

Indeed, several distributed techniques and tools have been studied and proposed to tackle the barriers of large-scale DER coordination. Previous works decompose the problem in terms of the devices to solve the problem in a distributed manner [86–90]. However, it is required to decompose the problem at the user level to preserve users' prerogative and privacy [91, 92].

Given these observations, problem (21) can be decomposed at the user level by using the Lagrangian relaxation to relax the coupling constraints (21b). Specifically, the partial Lagrangian of (21) is given by [46, 92]

$$L_{\mathrm{VPP}}(\boldsymbol{x}, \boldsymbol{\xi}) \coloneqq \sum_{t\in\mathcal{T}} \left(C^t(x_0^t) + \sum_{a\in\mathcal{A}\setminus 0} g_a(\boldsymbol{x}_a) + \xi^t \left(\sum_{a\in\mathcal{A}\setminus 0} x_{a,\mathrm{net}}^t - x_0^t \right) \right), \tag{22}$$

where $\boldsymbol{\xi} \coloneqq \left[\xi^{t_0}, \ldots, \xi^{t_0+(T-1)\Delta^t}\right]$ is the vector of Lagrange multipliers. The Lagrange dual function can be decomposed into individual agent subproblems that can be solved in parallel. Thus, the dual function is

$$D(\boldsymbol{\xi}) = \underset{\boldsymbol{x}_a\in\mathcal{X}_a, \boldsymbol{x}_0\in\mathcal{X},}{\text{minimize}} \; L_{\mathrm{VPP}}(\boldsymbol{x}, \boldsymbol{\xi}), \tag{23}$$

which can also be defined by

$$D(\boldsymbol{\xi}) = D_0(\boldsymbol{\xi}) + \sum_{a\in\mathcal{A}\setminus 0} D_a(\boldsymbol{\xi}), \tag{24}$$

where the aggregator solves

$$D_0(\boldsymbol{\xi}) = \inf_{\boldsymbol{x}_0\in\mathcal{X}_0} \left\{ \sum_{t\in\mathcal{T}} \left(C^t\left(x_0^t\right) - \xi^t x_0^t \right) \right\}, \tag{25}$$

while each user agent solves

$$D_a(\boldsymbol{\xi}) = \underset{\boldsymbol{x}_a\in\mathcal{X}_a}{\text{minimize}} \sum_{t\in\mathcal{T}} \left(\xi^t x_{a,\mathrm{net}}^t \right). \tag{26}$$

In this way, the VPP problem can be solved in a distributed manner as in [92].

5.2. *Optimal power flow (OPF)*

In power systems, centralized approaches have typically been deployed to solve the economic dispatch problem and optimal power flow problem [94]. The conventional OPF problem aims to minimize the total cost of power generation, minimize power losses in the network, or maximize social welfare. Indeed, this centralized approach has been used in many systems and market arrangements. Therefore, a standard approach for coordinating DER subject to network constraints is to solve the OPF problem.

Specifically, the OPF problem with DER aims to minimize the cost of energy and system operation for all agents, and thereby efficiently coordinating DER. Formally, let (10) – (15) define a feasible set $\mathcal{Y}$ for the network variables $\boldsymbol{y} \in \mathcal{Y}$, let (20) be expressed by $f(\boldsymbol{y})$, and let the user agent functions $g_a(\cdot)$ take the form on the objective function in (17). Then, the coordination of DER under network constrains can be achieved by solving the following problem:

$$\begin{aligned} \underset{\boldsymbol{y}\in\mathcal{Y}, \boldsymbol{x}_a\in\mathcal{X}_a}{\text{minimize}} \quad & \sum_{t\in\mathcal{T}} \left(f(\boldsymbol{y}) + \sum_{a\in\mathcal{A}\setminus 0} g_a(\boldsymbol{x}_a) \right) \\ \text{subject to} \quad & \\ & \text{power flow constraints,} \\ & \text{power balance constraints, and} \\ & \text{DER operational constraints,} \\ & \forall t \in \mathcal{T}. \end{aligned} \tag{27}$$

This extension of problem (21) to the OPF with DER problem (27) belongs to the class of mixed-integer nonlinear programming (MINLP) problems which is even more challenging to solve centrally, even to local optimality. Approximations and convex relaxations of the AC OPF model can make the problem less challenging to solve, but they do not guarantee all network constraints are met [95]. For instance, voltage magnitude and reactive power constraints are ignored in the commonly used DC OPF approximation. Particularly, the DC OPF neglects power losses, reactive power flows, and assumes small angle differences between connected buses [153].

Given this context, distributed algorithms have been considered for implementing a distributed AC OPF. For example, the work in [96, 97] uses decomposition techniques and distributed algorithms to solve a large-scale optimization problem by decomposing it into smaller subproblems.

5.3. Distributed OPF with DER

The existing work on distributed OPF is extensive and several distributed optimization techniques have been applied to date. In general, distributed OPF can be classified into five categories:[12]

- Dual-decomposition-based methods;
- Optimality conditions decomposition (OCD) methods;
- Consensus + Innovate (C+I);
- Gradient dynamics;
- Dynamic programming with message passing.

Note that the OPF problem (27) is not separable in terms of user agents since the variables corresponding to the agents' power consumption are in both $\mathcal{Y}$ (i.e. component of a power balance equation within the network feasible set) and $\mathcal{X}_a$ (i.e. component of the power balance equation within the prosumer feasible set). However, we can bestow a separable structure by creating copies of the associated power consumption variables and then enforce *consensus* between these coupling variables. That is, one copy for the aggregator and another for user agents [98]. Specifically, to enable a decomposable structure for the problem, we create two copies of powers injected, p_i, at each bus i where agent a is located, as shown in Fig. 7. In doing so, we introduce the following coupling constraints:

$$\hat{p}_i = p_i, \quad \{\forall a \in \mathcal{A} \setminus 0 | \mathcal{A} \subseteq \mathcal{N}\},\ t \in \mathcal{T}, \tag{28}$$

where the term $\hat{p}_i \in \mathcal{Y}$ is a copy for the network problem, and the term p_i is a copy for the agent problem. Consequently, the OPF problem becomes

$$\underset{y \in \mathcal{Y}, \boldsymbol{x}_a \in \mathcal{X}_a}{\text{minimize}} \quad \sum_{t \in \mathcal{T}} \left(f(\boldsymbol{y}) + \sum_{a \in \mathcal{A} \setminus 0} g_a(\boldsymbol{x}_a) \right) \tag{29a}$$

$$\text{subject to} \quad (28). \tag{29b}$$

Now, problem (29) is of the general form

$$\underset{y \in \mathcal{Y}, \boldsymbol{x}_a \in \mathcal{X}_a}{\text{minimize}} \quad f(\boldsymbol{y}) + g(\boldsymbol{x}_a) \tag{30a}$$

$$\text{subject to} \quad \boldsymbol{A}\boldsymbol{y} + \boldsymbol{B}\boldsymbol{x}_a = \boldsymbol{c}, \tag{30b}$$

where $g(\boldsymbol{x}_a) = \sum_{a \in \mathcal{A} \setminus 0} g_a(\boldsymbol{x}_a)$, constraints (30b) are defined by (28), $\mathcal{Y}$ is the feasible set defined by constraints (10) – (15) and $\mathcal{X}_a$ is the feasible set defined by constraints (2) – (8).

One of the most widespread techniques used to solve the distributed OPF problem is the *alternating direction method of multipliers* (ADMM) because of its simplicity [99]. Using this technique, a large-scale problem, such as the OPF with DER, can

[12] See [154] for a review of different decomposition approaches for the DC OPF and [95] for a comprehensive review of distributed methods, for the offline solution of OPF problems as well as online algorithms for real-time solutions.

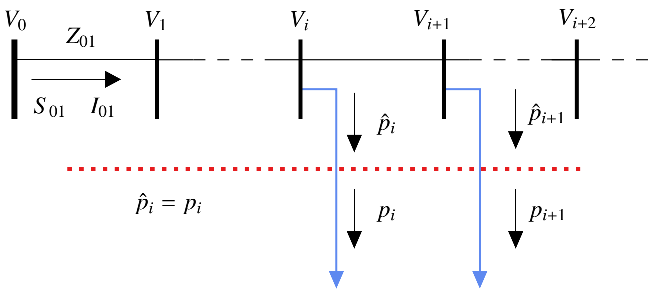


Fig. 7: Illustration of coupling constraints in distributed OPF.

be decomposed into local subproblems, which can be solved in parallel by the agents. The solutions to local subproblems are coordinated by an interface entity (e.g. aggregator) to find a solution to a large global problem.

First, we obtain the augmented Lagrangian of (30), defined as

$$L(\boldsymbol{y}, z, \boldsymbol{\lambda}_a) \coloneqq f(\boldsymbol{y}) + g(\boldsymbol{x}_a) + \boldsymbol{\lambda}_a^\top (A\boldsymbol{y} + B\boldsymbol{x}_a - \boldsymbol{c}) + \frac{\rho}{2} \|A\boldsymbol{y} + B\boldsymbol{x}_a - \boldsymbol{c}\|^2 , \tag{31}$$

where ρ is a penalty parameter and $\boldsymbol{\lambda}_a \coloneqq \left\{\{\lambda_a\}_{a\in\mathcal{A}\setminus 0}\right\}_{t\in\mathcal{T}}$ are the dual variables associated with the coupling constraints (28). Then, we can decompose the problem into the general form of ADMM as follows:

$$\boldsymbol{y}^{k+1} \coloneqq \arg\min_{\boldsymbol{y}\in\mathcal{Y}} L(\boldsymbol{y}, \boldsymbol{x}_a^k, \boldsymbol{\lambda}_a^k), \tag{32a}$$

$$\boldsymbol{x}_a^{k+1} \coloneqq \arg\min_{\boldsymbol{x}_a\in\mathcal{X}_a} L(\boldsymbol{y}^{k+1}, \boldsymbol{x}_a, \boldsymbol{\lambda}_a^k), \tag{32b}$$

$$\boldsymbol{\lambda}_a^{k+1} \coloneqq \boldsymbol{\lambda}_a^k + \rho(A\boldsymbol{y}^{k+1} + B\boldsymbol{x}_a^{k+1} - \boldsymbol{c}). \tag{32c}$$

At each iteration k, ADMM generates a new iterate and the convergence is monitored using the primal and dual residuals:

$$\boldsymbol{r}^{k+1} = A\boldsymbol{y}^{k+1} + B\boldsymbol{x}_a^{k+1} - \boldsymbol{c}, \tag{33a}$$

$$\boldsymbol{\xi}^{k+1} = \rho A^\top B(\boldsymbol{x}_a^k - \boldsymbol{x}_a^{k+1}). \tag{33b}$$

Specifically, the augmented Lagrangian function for the OPF is given by

$$L_{\text{OPF}}(\hat{p}_i, p_i, \lambda_a) \coloneqq \left(\frac{\rho}{2}(\hat{p}_i - p_i)^2 + \lambda_a(\hat{p}_i - p_i)\right), \tag{34}$$

where ρ is a penalty parameter and λ_a is the dual variable associated with each coupling constraint. Then, the aggregator solves

$$\boldsymbol{y}^{k+1} = \arg\min_{\boldsymbol{y}\in\mathcal{Y}} f(\boldsymbol{y}) + \sum_{a\in\mathcal{A}\setminus 0} \left(g_a(\boldsymbol{x}_a) + \sum_{t\in\mathcal{T}} L_{\text{OPF}}\left(\hat{p}_i, p_i^k, \lambda_a^k\right) \right), \tag{35}$$

each user agent solves the subproblem

$$\boldsymbol{x}_a^{k+1} = \arg\min_{\boldsymbol{x}_a\in\mathcal{X}_a} g_a(\boldsymbol{x}_a) + \sum_{t\in\mathcal{T}} L_{\text{OPF}}(\hat{p}_i, p_i^k, \lambda_a^k), \quad \forall a \in \mathcal{A} \setminus 0, \tag{36}$$

and finally the aggregator updates $\boldsymbol{\lambda}_a^k$ as

$$\lambda_a^{k+1} = \lambda_a^k + \rho\left(p_i^{k+1} - \hat{p}_i^{k+1}\right), \quad \forall a \in \mathcal{A} \setminus 0,\ t \in \mathcal{T}. \tag{37}$$

As in [102], we use primal and dual residuals to define a stopping criteria. The primal and dual residuals are, respectively:

$$\boldsymbol{r}^k = (\hat{p}_i^k - p_i^k)^\top, \tag{38a}$$

$$\boldsymbol{\zeta}^k = (p_i^k - p_i^{k-1})^\top, \tag{38b}$$

where (38a) represent violation of the constraint (28) at the current solution, and (38b) represents the violation of the Karush-Kuhn-Tucker (KKT) stationarity constraints at the current iteration. The termination criteria are then given by

$$\|\boldsymbol{r}^k\|_2 \leq \epsilon^{\text{pri}} \quad \text{and} \quad \|\boldsymbol{\zeta}^k\|_2 \leq \epsilon^{\text{dual}}, \tag{39}$$

where ϵ^{pri} and ϵ^{dual} are feasibility tolerances determined by the following equations [99]:

$$\epsilon^{\text{pri}} = \sqrt{N_a}\epsilon^{\text{abs}} + \epsilon^{\text{rel}}\max\{\|\hat{\boldsymbol{p}}^k\|_2, \|\boldsymbol{p}^k\|_2\}, \tag{40a}$$

$$\epsilon^{\text{dual}} = \sqrt{N_a}\epsilon^{\text{abs}} + \epsilon^{\text{rel}}\|\boldsymbol{\lambda}_a^k\|_2, \tag{40b}$$

where $\hat{\boldsymbol{p}}$ and $\boldsymbol{p}$ are vectors composed by all variables $\hat{p}_i$; $\{\epsilon^{\text{abs}}, \epsilon^{\text{rel}}\} \in \mathbb{R}_+$. Small values for these tolerances guarantee more accurate results by requiring the residuals to be smaller. However, this requires a higher number of iterations, which directly impacts the total computation time.

Since agents' problems are decoupled, the subproblems can be solved in parallel. The set of user agent variables is then $\boldsymbol{x}_a$, and the feasible set for the variables of each agent $\mathcal{X}_a$. Consequently, we maintain privacy for each agent, sharing only its resulting net power profile with the aggregator who updates the multipliers.

The distributed OPF based on the ADMM technique is described in Algorithm 1.

Algorithm 1 Distributed OPF algorithm

```
Initialization: Aggregator sets k, ρ, ε^abs, ε^rel
while ||r^k||_2 ≥ ε^pri  and  ||ζ^k||_2 ≥ ε^dual do
    Aggregator computes y^{k+1} using (35).
    Locally each agent computes x_a^{k+1} using (36) in parallel.
    Aggregator updates λ_a^{k+1} using (37).
end while
```

5.4. Economic mechanisms and market designs

Observe that users may act as self-interest agents that use rational and strategic behaviors in order to achieve their individual goals, such as lowering their electricity cost. In this context, the DER coordination problem can be associated with game theory, and particularly *algorithmic mechanism design* [155]. In order to efficiently allocate a set of resources among agents, a mechanism design can be considered to create rules for allocating the resources to agents that value them the most as well as establishing payment schemes. When the allocation rules and the payment scheme lead to *truthful* actions, it can be said that the mechanism is efficient.

Nonetheless, the coordination process considers the exchange of messages between the aggregator and the self-interested users, who can misinform the solution of the local subproblems in order to maximize their individual welfare, for example reducing their electricity expenditure [156]. Given that the information received by the aggregator might be manipulated by the users, the outcome of the DER coordination problem may not be optimal, which in this context would be the maximization of the social welfare when users truly report their local information.

One alternative to hinder this gaming behaviour is to implement an economic mechanism that encourages the agents to *faithfully* perform their established computation and *truthfully* report the outcome of the local subproblems. However, designing an efficient mechanism with these properties is computationally difficult, because of the additional technical constraints that are inherent to DER aggregation schemes [91]. These include discrete operating points of DER, computation and communication limits, and the fact that preferences over power usage profiles are combinatorial.[13] Moreover, in general, other mechanism design considerations, such as keep the mechanism's budget balanced, or ensuring it is individually rational for every agent to participate in the mechanism, conflict with the goal of truthfulness, making market design a challenging analytic task in its own right, even in simple settings.

Since this paper is focused on the technical implications of adopting DER integration approaches but leave market aspects aside, the implementation of mechanism design is not considered in this paper and it is proposed for future research. Interested readers are referred to [46, 85, 93, 157–162] for implementations of mechanism design principles and a deeper discussion of the points made here.

6. Peer-to-peer approaches

Local energy trading between users is a new concept of growing importance in the energy sector. Specifically, P2P trading is based on a decentralized scheme, in which users (or their automated agents) can trade energy among themselves with a limited or no intervention of a third party. Market designs focused on P2P structures offer more flexibility and trading options to the users, while their autonomy and privacy are preserved. Thus, when compared to centralized schemes, P2P markets are more consumer oriented [142, 143]. The work in [21, 112–116, 163] reviews and discusses different P2P structures and trading mechanisms that have been proposed for P2P trading so far.

In general, existing P2P energy trading research can be classified according to the technical approach adopted in the market mechanism. As such, four technical approaches commonly used in P2P studies are:

- *Distributed methods*: P2P energy trading can be cast as an optimization problem, which can be divided into subproblems through decomposition techniques [117–119]. Furthermore, consensus methods have been proposed to include price and product differentiation properties [120], and a primal-dual gradient method has been considered to fully decentralized the market structure [121].

- *Game theory-based methods*: Game theory can be used to analyse and design a P2P system through the model of noncooperative and cooperative games. In this way, the users' behavior and their active interaction in the market can be integrated in pricing and incentive schemes [122–125, 128, 129].

- *Matching theory-based methods*: Matching theory encompasses a theoretical framework for matching between agents in two-sided sets. A decentralized matching mechanism using bilateral contract networks has been proposed for P2P. As such, bilateral contracts have theoretical virtues that bring desirable properties to the market, such as, *stability* and *competitive equilibrium* [126, 130–132].

[13] In this context, power usage profiles are combinatorial in the sense that users can choose different scheduled combinations to complete discrete tasks; and these combinations have user's preferences over them.

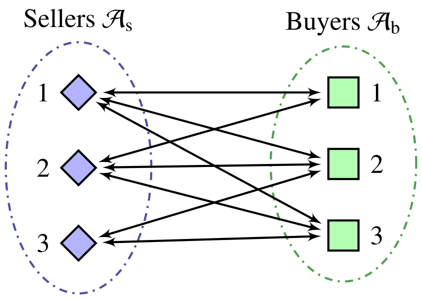


Fig. 8: Bipartite graph between sellers and buyers using many-to-many agent matching.

- *Auction-based methods*: User agents negotiate and express their interest to trade through *bids* submitted based on agents' preferences and market information. The allocation of the resources and the corresponding payments between agents is defined by a *clearing policy*, which depends on a matching mechanism [164]. Then, the outcome of a matching process determines which agents trade, the amount to exchange, and the payments associated with each transaction [127, 133–138].

Since our interest is to evaluate the technical implications of P2P energy trading and to compare it with others DER integration approaches, in this paper we adopt the methodology proposed in [127]. This methodology uses an auction-based method to clear the market and includes a *network permission structure* (NPS) to incorporate network constraints into the trading mechanism. In this way, this methodology captures the economic benefits associated with P2P energy trading while respecting the network constraints.

Specifically, we adopt a *continuous double auction* (CDA) for P2P energy trading. In this setting, bidding agents (*buyers* and *sellers*) negotiate directly the exchange of resources between themselves, as is illustrated in Fig. 8. Each buyer is free to attempt to trade with any seller. That is, each buyer can match with many sellers and vice versa. The exchange process depends on the buyers' desired quantity to purchase and a maximum capacity of units that sellers have to trade.

A CDA belongs to the class of many-to-many double-sided auctions, in which multiple buyers and sellers compete in the market. Then, a bid represents the maximum price at which a buyer is willing to buy, and an ask is a minimum price at which a seller is willing to sell. The arrival of all bids and asks are queued in an *order book* in which the orders are ranked according to prices and arrival time. Specifically, matching occurs if a buyer quotes a higher price than a seller who is recorded in the order book. Then, the market clears continuously as long as the market stays open. Observe that market agents in a CDA only trade at profit, therefore trades in a CDA coincide with a Pareto efficient allocation. This auction mechanism has been found to be a highly efficient method [165], and is widely used in stock markets around the world, such as NASDAQ and the New York stock exchange. Additionally, previous studies of local energy markets have considered a CDA for bilateral trading [115, 136, 166–171].

6.1. P2P trading formulation using a CDA

We now introduce concepts from this auction protocol, a CDA, to formulate the P2P energy trading model. The set of all agents $\mathcal{A}$ is composed of the union of two finite and disjointed sets: a set of buyers $\mathcal{A}_b$ indexed by $b = 1, 2, \ldots, N_b$, and a set of sellers $\mathcal{A}_s$ indexed by $s = 1, 2, \ldots, N_s$. That is, $\mathcal{A} = \mathcal{A}_b \cup \mathcal{A}_s$. Each buyer b has a valuation function $v_b : \mathbb{R}_+ \to \mathbb{R}_+$, where $v_b(x_b)$ is the value to b for a level of demand for electrical energy, $x_b \in \mathbb{R}_+$, in the P2P market. Equivalently, each seller s has a valuation function $v_s : \mathbb{R}_+ \to \mathbb{R}_+$, where $v_s(x_s)$ is the value to s for a level of generation for electrical energy, $x_s \in \mathbb{R}_+$, in the P2P market.

Formally, we define the concepts of a *bid* and an *ask*. A bid $o_b = \langle b, \alpha_b, \pi_b, t\rangle$ is an offer from a buyer b to purchase a quantity $\pi_b \in \mathbb{R}_+$ at a maximum unit price of $\alpha_b \in \mathbb{R}_+$ in the market. Similarly, an ask $o_s = \langle s, \alpha_s, \pi_s, t\rangle$ is an offer from a seller s to sell a quantity $\pi_s \in \mathbb{R}_+$ at a minimum unit price of $\alpha_s \in \mathbb{R}_+$ in the market. Market agents use the information available in the market and their preferences to determine the amount and price to trade in the market.

Agents make offers at any time during the *trading period*. Once this time has elapsed, the market is closed and no more offers are accepted. Bids and asks are queued and published in the order book. The current best (uncleared) bid in the order book is called the *outstanding bid* o_b^*. The current best (uncleared) ask in the queue is called the *outstanding ask* o_s^*.

Additionally, there are two relevant elements related to a CDA: (i) agents' bidding strategies, and (ii) the matching clearing process, as described below.

Agents' bidding strategies

The strategic behavior of agents plays an important role in the output of the market. Since the information in the order book and transaction prices are public, agents can adopt bidding strategies to maximize the economic benefits from the market. Indeed, agents are capable of communicating and interacting with other agents, as well as make decisions and react to the perceived environment [172]. A CDA marketplace with *zero intelligence* (ZI) can sustain high market efficiency [165]. Building on this strategy, the authors in [173] proposed *zero intelligence plus* (ZIP) traders, which possess the following attributes: (i) to adapt responding appropriately to dynamic state of the market, (ii) capability to learn from the market, and (iii) make predictions of future trends.

Specifically, we introduce the concept of *limit prices*, which are the maximum (minimum) bid (ask) a buyer (seller) is willing to offer. The difference between the limit prices and the submitted offer (bid or ask) prices are determined by the *profit margin* that each agent can adjust in order to remain competitive in the market.

Algorithm 2 Matching process in a CDA with ZIP traders

while market is open **do**
  randomly select a new ZIP trader
  if buyer **then**
    new $o_b = \langle b, \alpha_b, \pi_b, t \rangle$
  else
    new $o_s = \langle s, \alpha_s, \pi_s, t \rangle$
  end if
  allocate a new order in the *order book*.
▹ Evaluate matching process with best bid and ask.
  if $o^*_b(\alpha_b) \geq o^*_s(\alpha_s)$ **then**
    clear orders o^*_b and o^*_s at a price α_ω and amount π_ω.
    if $o^*_b(t) < o^*_s(t)$ **then**
      $\alpha_\omega = o^*_b(\alpha_b)$
    else
      $\alpha_\omega = o^*_s(\alpha_s)$
    end if
  end if
▹ Update order book and adjust the bidding strategies.
end while

Matching clearing process

A CDA is a continuous matching marketplace. A transaction $\omega \in \Omega$ occurs whenever there is a matching between a bid and an ask, as is shown in Algorithm 2. In more detail, there is a matching when a new bid overlaps the outstanding ask or when a new ask overlaps the outstanding bid. The *transaction price* is equal to the earlier one of o^*_b and o^*_s. Thus, a transaction ω is a four-tuple $\langle b, s, \alpha_\omega, \pi_\omega \rangle$, which is the underlying matching between a seller $\omega(s) = o^*_s(s)$ and a buyer $\omega(b) = o^*_b(b)$ that are willing to exchange π_ω units at a price α_ω. Formally, let Ω be the set of trades in the P2P market. The set of underlying trades $\Omega_b \subseteq \Omega$, in which a buyer b is involved is given by $\Omega_b := \{\omega \in \Omega | \omega(b) = b\}$. Similarly, the set of underlying trades $\Omega_s \subseteq \Omega$, in which a seller s is involved is given by $\Omega_s := \{\omega \in \Omega | \omega(s) = s\}$.

The outcome of the CDA gives a set of transactions Ω. Formally, the individual payoff of a buyer and a seller are defined by utility functions u_b and u_s as follows:

$$u_b(x_b) \triangleq \begin{cases} v_b(x_b) - \sum_{\omega \in \Omega_b} \alpha_\omega \pi_\omega, & \text{if } \Omega_b \notin \varnothing; \\ 0, & \text{otherwise.} \end{cases} \tag{41}$$

$$u_s(x_s) \triangleq \begin{cases} \sum_{\omega \in \Omega_s} \alpha_\omega \pi_\omega - v_s(x_s), & \text{if } \Omega_s \notin \varnothing; \\ 0, & \text{otherwise.} \end{cases} \tag{42}$$

Then, if a buyer b is unmatched in the market, $u_b = 0$. Equivalently, if a seller s is unmatched, then $u_s = 0$.

Given this P2P trading mechanism, a CDA promotes DER coordination using prices and bids in the P2P market.

6.2. Network permission structure (NPS)

Despite the importance of considering network constraints in P2P markets, only a few studies include network envelopes and analyse the impact on the trading [121, 131, 139–141]. In this work, we implemented the methodology presented in [127]. Specifically, this methodology aims to estimate the changes in voltages and power flows due to changes in the energy exported and imported by the users involved in the trades. In this way, the impact of the bilateral transactions can be estimated through sensitivity coefficients, which can also be used to allocate the external cost associated with the exchange of electricity. In particular, this technique incorporate three factors in a market mechanism: (i) *voltage sensitivity coefficients*, (ii) *power transfer distribution factors*, and (iii) *loss sensitivity factors*; they are described below.

Voltage sensitivity coefficients (VSC)

The voltage changes in the network due to power changes can be determined using the VSC. Since the trades in a P2P market considers the exchange of active power, the variations in the voltages as a function of the active power is given by [174]:

$$\Delta |V_i| = \frac{\Delta P_n}{|V_i|} \mathrm{Re}\left(V_i^* \frac{\partial V_i}{\partial P_n} \right). \tag{43}$$

where V_i (V^*) denotes the complex (conjugate) voltage in the bus $i \in \mathcal{N}/0$, and P_n denotes the power injection or absorption in the bus n.

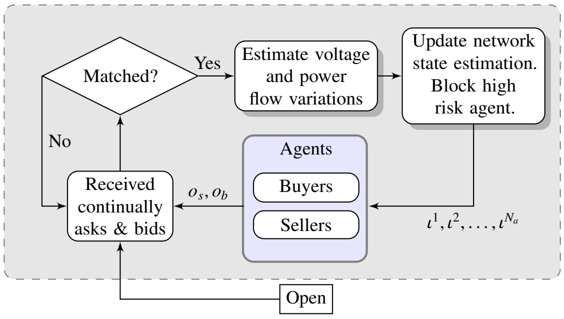


Fig. 9: Outline of a P2P trading with the NPS.

Power transfer distribution factors (PTDF)

Using a similar approach, the changes in the active power flowing through the branches can be determined based on the changes in the injection (seller) and withdraw (buyer) of active power for each bilateral transaction. As such, the PTDF for a line (n, l) considering the exchange of a seller at bus i and a buyer at bus j can be defined as follows [94]:

$$\Phi_{nl}^{ij} = \Psi_{nl}^{i} - \Psi_{nl}^{j} = \frac{\Delta P_{nl}^{i}}{\Delta P_i} - \frac{\Delta P_{nl}^{j}}{\Delta P_j}, \tag{44}$$

where Ψ_{nl}^{i} and Ψ_{nl}^{j} are the line flow sensitivities in branch (n, l) with respect to injections at bus i and j, respectively.

Loss sensitivity factors (LSF)

Now, LSF can be used to calculate the active power losses in the system due to injections and withdraws of active power. The LSF is defined as follows [175]:

$$\frac{\partial P_{\text{loss}}}{\partial P_n} = 2\text{Re}\left[\mathbf{V}^{*^\top} G \frac{\partial \mathbf{V}}{\partial P_n}\right], \tag{45}$$

where G is the conductance matrix and $\mathbf{V}$ denotes the concatenation of voltage values in all buses in the network.

Now, using the definitions and formulations above, the outline of the NPS is presented in Fig. 9. Once the market is open, the bids and asks are queued in the order book. Every time a bilateral transaction is settled, voltage values, power flows and losses are estimated using the three factors described above: (i) VSC, (ii) PTDF and (iii) LSF. VSC can be used to avoid voltage issues in the network, whereas PTDF can be used to respect capacity limits. Then, only the transactions that obey the network constraints are permitted. Also, PTDF and LSF can be used to allocate external costs among the traders. These external costs can be associated with a utilization fee or grid-related operating costs.

Then, the NPS is a mechanism that resolves the services trading in the market, considering the network limits. If the limits of the network are reached, then the NPS will ensure that an individual DER is aware of this and it is prevented from sending power to the network.

With this P2P trading formulation in mind, we now define two P2P market models that will be evaluated in Section 7:

- *Balanced P2P*: The matching between sellers and buyers can be used to promote local balancing between demand and generation in a LV network. In particular, the DSO might use a market rule that limits users to only export the energy traded in the P2P market. Assuming that local balancing is a sufficient condition to operate within the network limits, this balanced P2P model can be implemented without explicitly considering the network constraints. In other words, this model uses a CDA to match agents, but do not consider the NPS.

- *P2P-NPS*: In this model, the market mechanism incorporates the NPS described above to explicitly consider the network constraints.

7. Simulation setup, results and discussion

In this section, our interest is to examine the five DER integration approaches described above in one consistent problem setting as shown in Fig. 10. First, we describe the case studies and the simulation parameters considered in the study. Second, we evaluate practical considerations of implementing these approaches given the network operating constraints of a LV network. Third, we also compare the economic benefits that each DER integration approach brings to users for this particular setting. Fourth, we present a comparative analysis based on the elements presented earlier in Section 2.1. Finally, we provide a summary of advantages and drawbacks of each approach.

Before describing the case study and presenting the results, observe that we consider two P2P cases based on the models described earlier in Section 6. The first case is a balanced P2P market (P2P case in Fig. 10). Assuming that local balancing is a sufficient condition to obey the operating limits, the network constraints are neglected in this model. Then, in this balanced P2P,

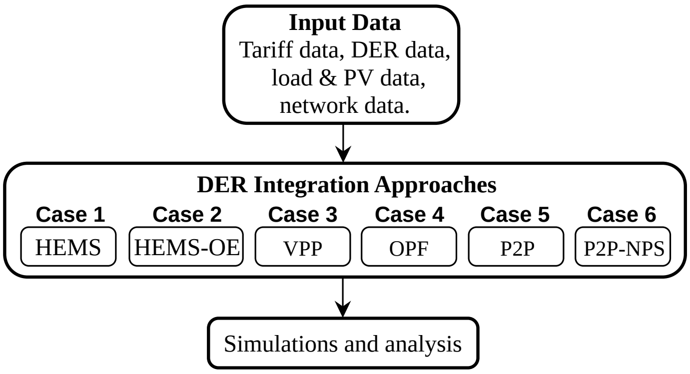


Fig. 10: Simulation framework.

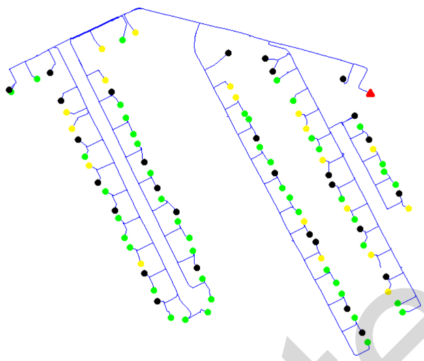


Fig. 11: Low-voltage feeder with 30 consumers (black dots), 20 users with only PV (yellow dots) and 50 users with PV and battery (green dots). The red triangle represents the location of the transformer.

users only export the amount that they were able to match in the CDA. The second case (P2P-NPS case in Fig. 10) also uses the CDA for matching asks and bids, but includes the NPS described in Section 6.2. Since the P2P-NPS explicitly takes into account the network constraints, users may export more power than the amount traded in the P2P market as long as the voltage and power flows remain within the limits. Note that if in this case the power injected into the grid exceeds the local demand, the power flows upstream to the MV network.

7.1. Case study description

Our study considers a LV network with high DER penetration, as illustrated in Fig. 11. The network comprises one feeder and 100 single-phase users. Specifically, there are 30 consumers, 20 users equipped with PV systems, and 50 users with PV systems and battery storage devices. The PV systems considered in the study have an installed capacity of 5.0 kWp, and the battery capacity is 9.8 kWh/5 kW. In our simulations, $e_{a,\text{batt}}^{\text{SoC,max}}$ is set to 9.8 kWh, whereas $e_{a,\text{batt}}^{\text{SoC,min}}$ is set to 1 kWh. The maximum charging and discharging powers $\gamma_{a,\text{batt}}^{\text{ch,max}}$ and $\gamma_{a,\text{batt}}^{\text{dis,max}}$ are set to 5 kW. Moreover, the initial and final state of energy in the batteries $e_{a,\text{batt}}^{\text{SoC,ini}}$ and $e_{a,\text{batt}}^{\text{SoC,final}}$ are set to 3 kWh. Also, the battery efficiencies $\eta_{a,\text{batt}}^{\text{dis}}$ and $\eta_{a,\text{batt}}^{\text{ch}}$ are set to 0.9. We assume an inverter efficiency η_a^{inv} of 1.

Demand and solar PV generation profiles are taken from the Ausgrid (a distribution network service provider in New South Wales, Australia) *Solar Home Electricity Data* [176]. This dataset comprises half-hourly resolution electricity demand and solar PV data. For the VPP and OPF cases, the coefficients of the quadratic cost function (20) are $c_2 = 0.005$ \$/kWh^2, $c_1 = c_0 = 0$. Finally, the minimum and maximum voltage levels allowed for this feeder are 0.94 pu and 1.10 pu, respectively [177].

Specifically, we evaluate two scenarios to capture the effect of the retail import tariffs in the DER integration approaches. The first scenario uses a flat tariff while the second scenario considers a ToU tariff. Also, an export tariff (FiT) is used in both scenarios. The import and export tariffs used in this study are shown in Fig. 12.

For each scenario, all cases use the same input data. The simulation results of each case include voltage profiles, power flows, and income and expenses for users. These results are used to present a comparative analysis and to discuss the operating implications of each approach. Once more, it is worth pointing out that:

- the HEMS, VPP and P2P approaches are network oblivious, and
- the HEMS-OE, OPF and P2P-NPS approaches include electricity network constraints in their models, as described in the previous sections.

In order to set the operating envelopes for the HEMS-OE approach, we assessed the variations in the voltage levels due to changes in the amount of power injected into the network by each user, as shown in Fig. 13. Observe that each line is the voltage

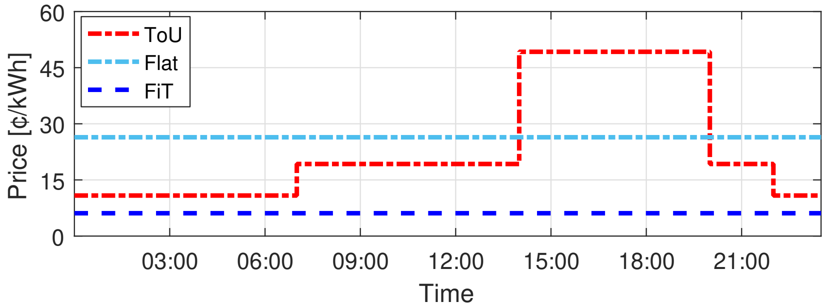


Fig. 12: Feed-in-tariff (FiT), flat and time-of-use (ToU) tariffs.

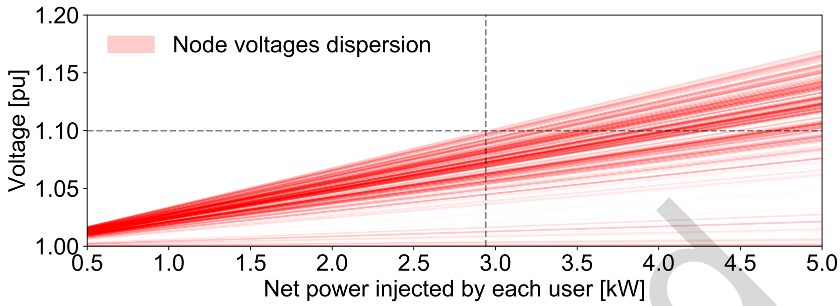


Fig. 13: Voltage variations at the point of connection of each user due to changes in the net power injected by the users. Each line represents the voltage at each user bus.

variation at each user bus. We assume that each user injects the same amount of power. Then, we can estimate the voltage values based on the net power injected. For example, the voltages are between 1.00 pu and 1.10 pu when all users inject less than 3.0 kW. Using this sensitivity analysis, we implemented an active power curtailment strategy. Specifically, given the maximum voltage limit of 1.10 pu, we set the maximum power that users can export to the grid to 3 kW, considering that a minimum load would be always present in this system.

We use OpenDSS software to simulate the power flows for each case. We consider one day simulation with time-step resolution $\Delta^t = 0.5$ h, i.e. $\mathcal{T} = \{1, ..., 48\}$. The comparison presented in this paper is mainly focused on evaluating the voltage levels and the transformer capacity since these are the most common issues with high DER penetration [178]. Furthermore, we also assess economic benefits that users can achieve with each of these approaches.

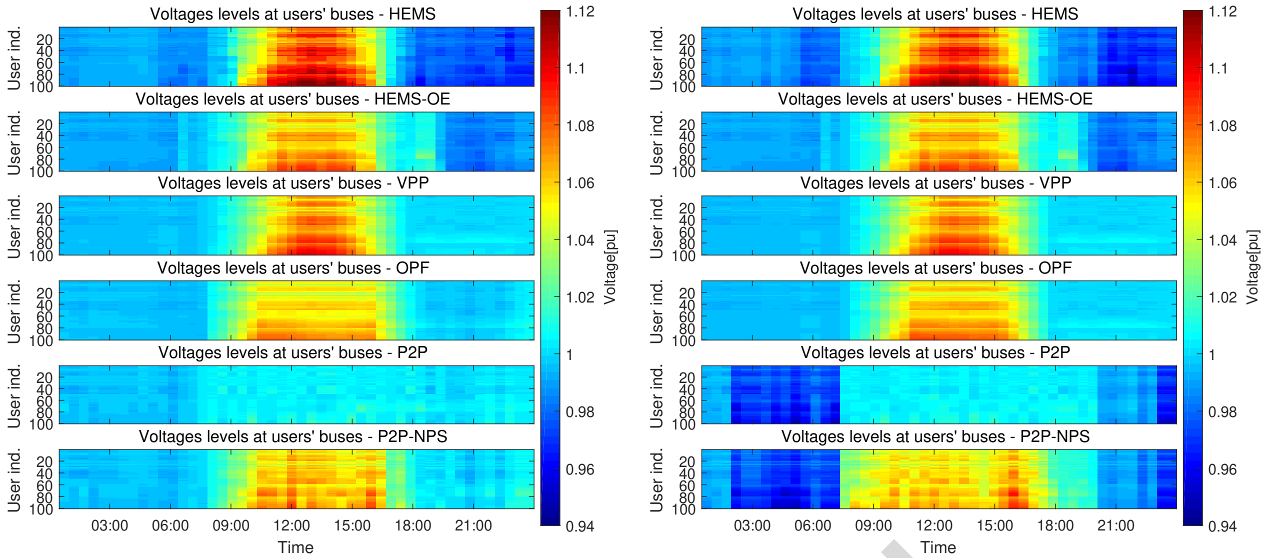
7.2. Results and discussion

Fig. 14a and Fig. 14b show the voltage levels at users' buses over one day using flat and ToU tariffs, respectively. Overall, all the cases exhibit voltage fluctuations across the day, except for the P2P case where the users only export the energy traded in the P2P market. The voltages increased around midday due to the power injected into the grid by the users. In fact, the HEMS approach presents overvoltage issues as the voltages exceed the maximum voltage limit 1.1 pu (dark red section) in both scenarios, which means this approach would not be feasible for this particular network with high DER penetration. In contrast, HEMS-OE, OPF , P2P and P2P-NPS approaches do not violate voltage limits. The voltages in the VPP case do not exceed the limits, but voltages are just under the maximum at midday.

Furthermore, it is clear from Fig. 14 that VPP and OPF approaches reflect smooth and moderate voltage variations throughout the day. Conversely, the HEMS, HEMS-OE, P2P and P2P-NPS cases exhibit sharp and sudden changes around 07:00 and 20:00 due to large fluctuations in the load and generation profiles. These changes are more evident with the ToU tariff as users change their consumption patterns to minimize their electricity expenditure considering the different price levels in the ToU tariff. Similarly, the sharp variations in the P2P and P2P-NPS cases result from the agents' strategies to trade, which drives the agents' behavior.

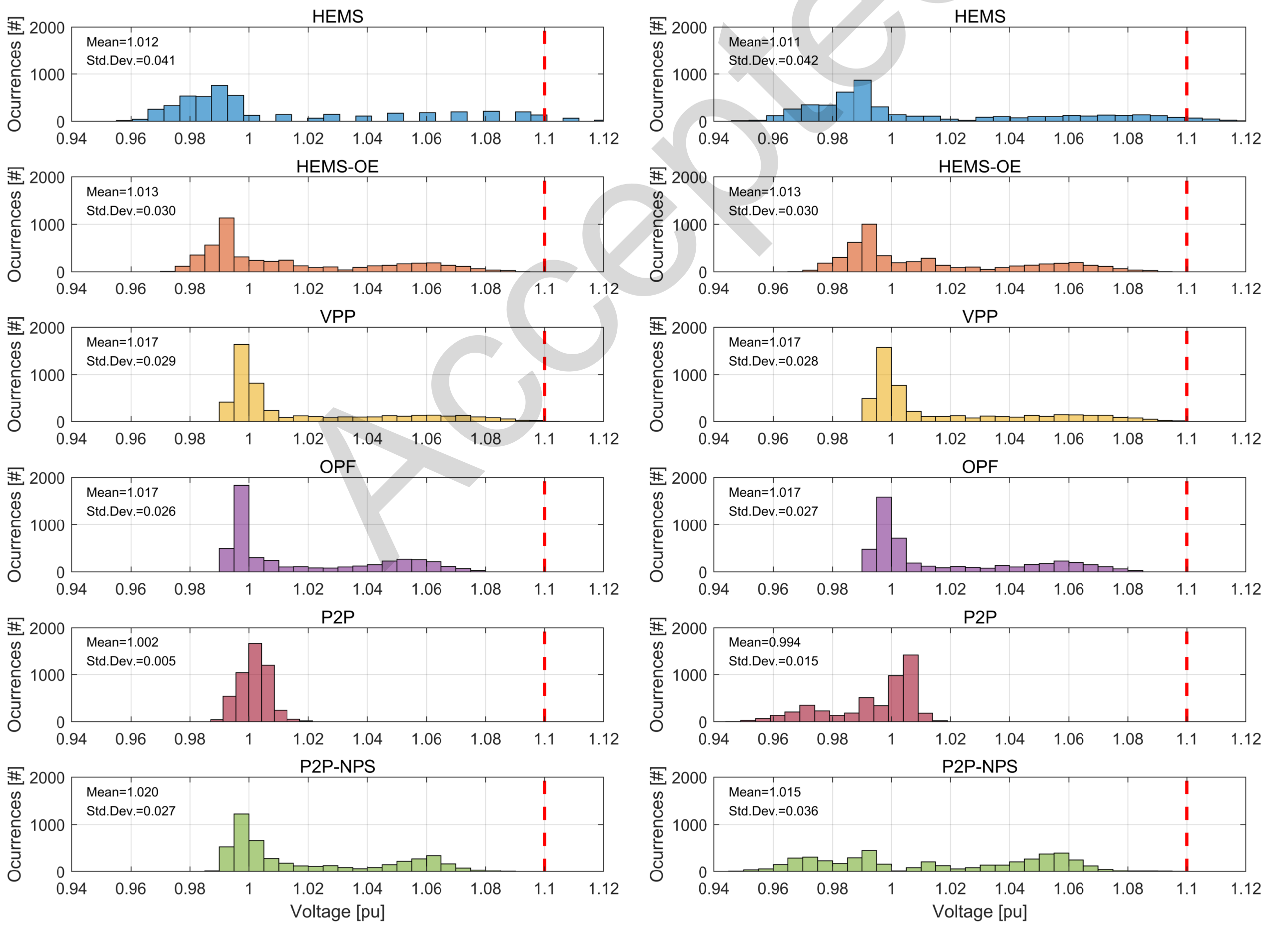
Finally, a close observation of Fig. 14b reveals that HEMS, P2P and P2P-NPS cases operate at certain times (around 21:00 for HEMS and 5:00 for P2P and P2P-NPS) with voltage values close to the minimum limit. This stems from the fact that users are charging their battery at that time. In other words, users in the HEMS case aim to charge batteries at night due to cheaper import tariff, whereas in the P2P and P2P-NPS cases, users are preparing for trading periods. This situation is different with the flat tariff as the maximum limit price to trade is the same throughout the day. Consequently, the minimum voltage values in the P2P and P2P-NPS cases are just under 1 pu when using a flat tariff.

The analysis of the voltage profiles is complemented with the information presented in Fig. 15, which illustrates the histograms of voltages during one day for both scenarios. Note that occurrences are counted for each user node and for each time-slot t. The charts in Fig. 15 also exhibit the mean and standard deviation from each histogram. It is evident that apart from the HEMS case, the voltages for all cases remain within their limits. Specifically, the voltages for the HEMS case vary between 0.945 pu and 1.123 pu,



(a) Flat tariff. (b) ToU tariff.

Fig. 14: Voltage levels at users' buses for different DER integration approaches.



(a) Flat tariff. (b) ToU tariff.

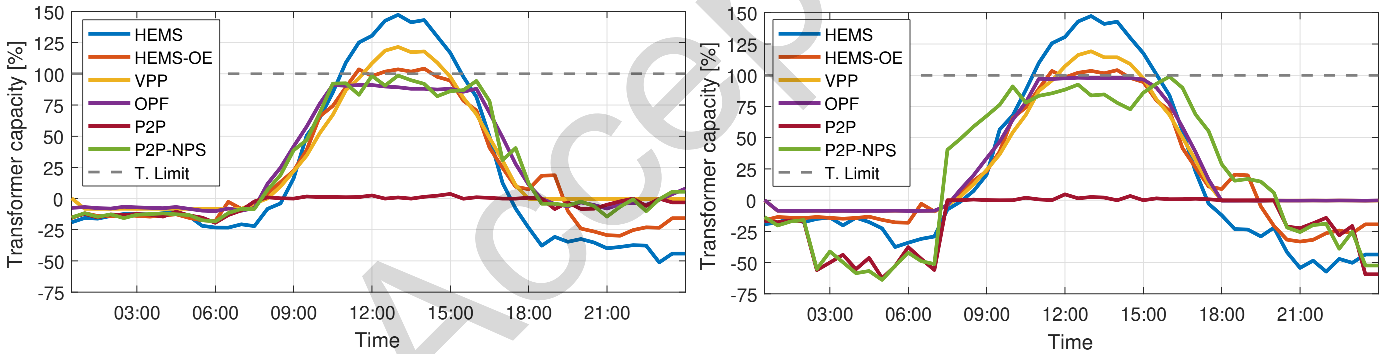
Fig. 15: Histogram voltage profiles at users' buses for different DER integration approaches.

with an average voltage of 1.01 pu and standard deviation of 0.04. For the HEMS-OE case, the voltages remain within the limits due to the operating envelopes implemented. In this case, the average voltage was 1.013 pu with a standard deviation of 0.030.

Observe in Fig. 15 that both coordination approaches (VPP and OPF) result in the same average voltage of 1.017 pu, with the standard deviations of 0.029 and 0.026 for VPP and OPF, respectively. Although these results might suggest that the VPP approach does not lead to voltages issues, note that these findings cannot be generalized to all contexts and networks. A direct comparison between VPP and OPF shows that the maximum voltage in the OPF case was 1.085 pu, whereas the maximum voltage in the VPP case was 1.099 pu. Then, with higher DER penetration levels, the limit may be exceeded in the VPP case as the main driver for the coordination it is the aggregator's cost function along with the user utility functions, and the network constraints are not explicitly considered.

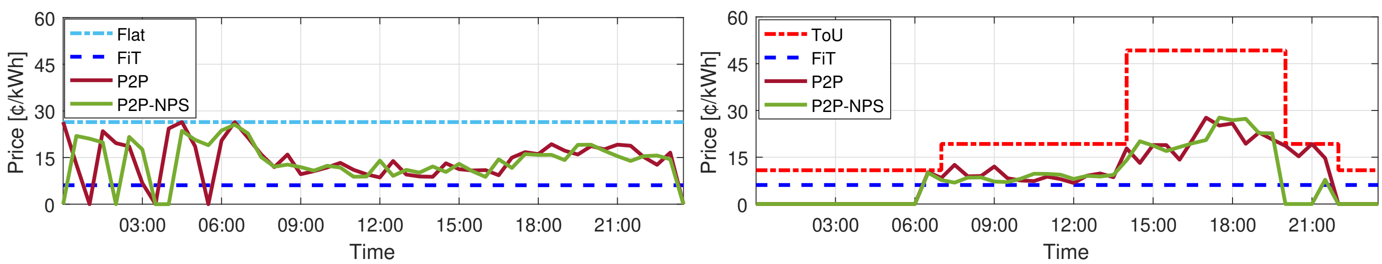
Regarding the P2P case using a flat tariff, the average voltage was 1.002 with a standard deviation of 0.005. Similarly, for the P2P case using the ToU tariff, the average voltage was 0.994 pu with a standard deviation of 0.015. These low standard deviations indicate that the voltage values are close to the mean. This is expected, because the market rule promotes balancing between generation and demand. For the P2P-NPS case, the use of a flat tariff results in an average voltage of 1.020 pu with a standard deviation of 0.027. With a ToU tariff, the frequency of occurrences in the P2P-NPS case is evenly spread between the allowed operating range. This is more due to changes in the consumption patterns motivated by the bidding process and the range of the price levels in the ToU tariff.

Plots in Fig. 16 show the comparison of the transformer power flows for the six cases relative to the transformer's capacity limit. Positive values denote the amount of power going upstream (i.e. reverse power flow) as a percentage of the transformer capacity, while the negative values denote the amount of power going downstream. From these curves, we identified the time-slots when the transformer capacity limit is exceeded. It is clear that HEMS and VPP cases exhibit capacity issues (from 10:00 to 15:30 for the HEMS case and from 11:00 to 15:00 for the VPP case) as the reverse power flow exceeds the capacity limit in both scenarios. Hence, these approaches are not feasible in this particular network setting. Interestingly, even though the HEMS-OE case includes network envelopes that restrict the amount of power injected, the maximum capacity limit is slightly exceeded at certain times around midday in both scenarios. This is because the operating envelopes implemented are only based on the voltage constraints, ignoring the transformer capacity limits. In the P2P case, the power flowing through the transformer reached a plateau around 8:00 and then changes again around 20:00. This is because P2P case promotes local balancing, which in turn allows respecting the transformer capacity limits. Indeed, local balancing result in a reduction of the transformer utilization as the power flowing through



(a) Flat tariff. (b) ToU tariff.

Fig. 16: Transformer loading capacity for different DER integration approaches.



(a) Flat tariff. (b) ToU tariff.

Fig. 17: Tariffs and average transaction prices in the P2P market, with (P2P-NPS) and without (P2P) a network permission structure.

the transformer between 8:00 and 20:00 is minimal. OPF and P2P-NPS cases reached operating points close to the limit, but they remained within bounds throughout the day. Thus, given that $T = 48$, the number of time-slots the transformer rated power was exceeded is 10, 5, 6 for HEMS, HEMS-OE and VPP, respectively. For the OPF, P2P and P2P-NPS cases, the transformer rated power was never exceeded. These numbers remain the same in both scenarios.

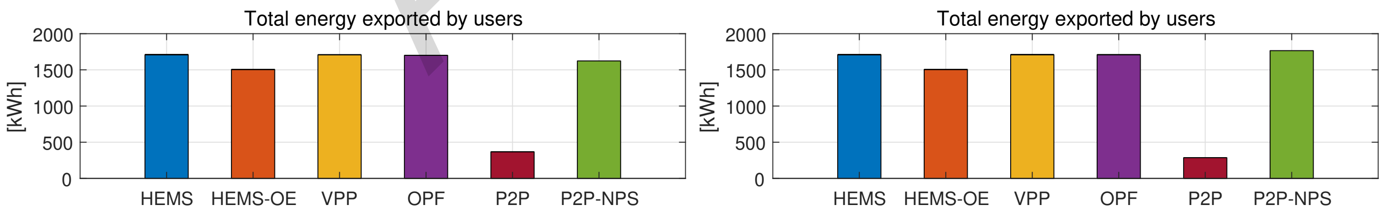
In addition, it is evident from Fig. 16 that all cases show similar transformer power flow trends. That is, in all cases the demand peaks during the morning and evening, while generation peaks at midday. Additionally, the flat part in the morning and evening for the VPP and OPF cases can be explained by the quadratic cost function of the aggregator. That is, fluctuations are penalized under a quadratic price, which flattens the demand profile.

In Fig. 17, we compare the *average transaction prices* (ATP) in the P2P market shown relative to FiT, flat and ToU tariffs. As was mentioned in Section 6, the tariffs are used in the bidding strategy as budget constraints, which forbids the trader from buying or selling at a loss. Consequently, the ATP are within the respective tariffs, bringing economic benefits to both buyers and sellers. It is worth noting that these prices only apply to the users who participate and match their orders in the market. The users who do not match their orders, their costs and revenues depend on the respective tariff. It can be seen from Fig. 17a that the use of a flat tariff results in an extended trading period. Specifically, there are bilateral transactions throughout the day as the limit prices (export and import tariffs) remain the same. In contrast, the scenario with a ToU tariff (Fig. 17b) shows that the users trade between 06:00 and 20:00 when they can achieve better economic benefits. After 20:00, the users may not be willing to trade as they prefer to charge batteries at low rates, or to meet their own demand.

We analyze and compare the energy exported by the users in each approach in Figs. 18 and 19. The total amount of energy exported to the LV network from the users in each approach is illustrated in Fig. 18, showing that the greatest amount occurs in the P2P-NPS case using the ToU tariff. Interestingly, apart from the HEMS-OE and P2P cases, all cases exported around 1700 kWh in both scenarios. But, OPF and P2P-NPS are the only approaches that do not violate network constraints. In other words, the coordination of DER allows allocating a similar amount of energy exported in a way that the network constraints are respected. It is also clear that although the operating envelopes in HEMS-OE ensure that the network constraints are respected, the implementation of operating envelopes without any coordination result in energy spilled. It is evident from Fig. 18 that the P2P is the case with the highest amount of energy spilled. This is because users only exported the amount of energy traded in the P2P market.

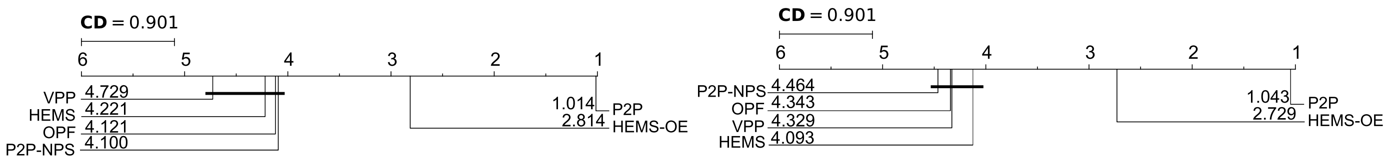
To complement our analysis, Fig. 19 shows a *critical difference* (CD) diagram proposed in [179], to visually compare the performance of each approach regarding the energy exported by end-users using average ranks. For each prosumer, we rank the approaches from 1 to 6 (i.e. 1 for the approach with the lowest energy exported, and 6 for the highest) and then we calculate the average of each approach's ranks across all end-users. In Fig. 19, those approaches that are not joined by the black line can be regarded as statistically different. The black line displays the CD of 0.901. It is evident that P2P and HEMS-OE ranks are statistically significantly lower than the other methods, whose ranks do not differ more than the CD between them in both scenarios. This demonstrates that the HEMS-OE approach and the balanced P2P don't seize the full DER potential.

Fig. 20 illustrates the incomes and expenses that each approach brings to the users. This information is summarized in Table 2. Notably, the P2P-NPS case reflects the highest net balance in both scenarios since this approach offers the highest incomes and the lowest expenses. This is due to the fact that, in some instances, the incomes and expenses are related to the transaction prices in the P2P market, which vary between the import and export tariffs as shown in Fig. 17. This further corroborates the economic benefit that users can achieve since ZIP traders in a P2P market do not buy or sell at a loss. In other words, no buyer would pay more than the tariff of a retailer (flat/ToU), and no seller would sell their energy cheaper than the export tariff (FiT). However, the monetary



(a) Flat tariff. (b) ToU tariff.

Fig. 18: Comparison of the amount of energy exported by users in each approach.

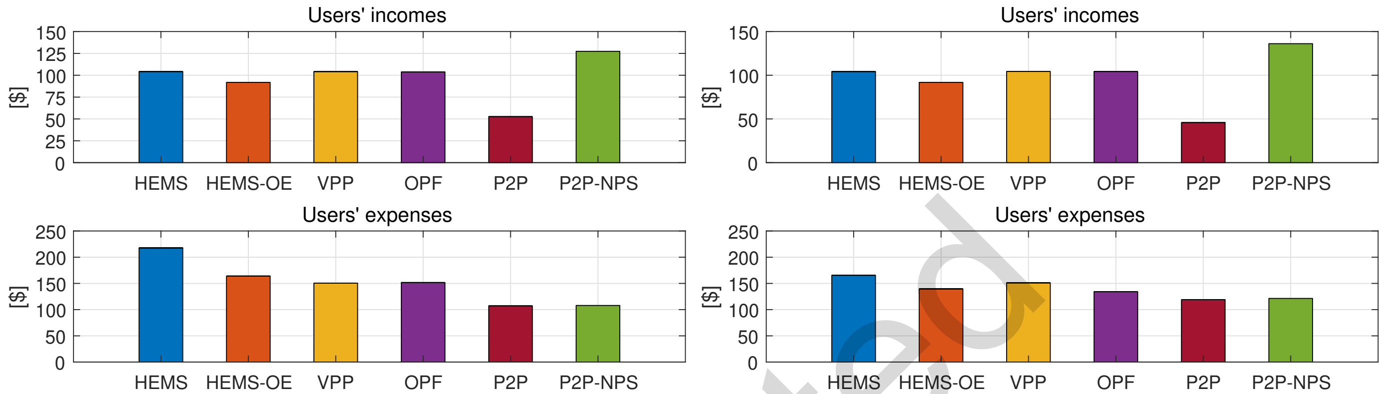


(a) Flat tariff. (b) ToU tariff.

Fig. 19: Critical difference diagram with CD = 0.901 for energy exported by users.

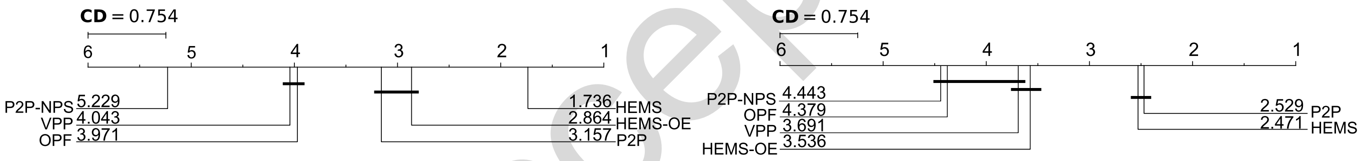
Table 2: Net balance, expenses and incomes.

	HEMS	HEMS-OE	VPP	OPF	P2P	P2P-NPS
Flat tariff						
	HEMS	**HEMS-OE**	**VPP**	**OPF**	**P2P**	**P2P-NPS**
Income [$]	104.29	91.85	104.24	103.77	52.71	127.38
Expenses [$]	-217.83	-164.02	-150.59	-151.66	-107.31	-107.95
Net balance [$]	-113.54	-72.17	-46.35	-47.89	-54.6	19.43
ToU tariff						
	HEMS	**HEMS-OE**	**VPP**	**OPF**	**P2P**	**P2P-NPS**
Income [$]	104.29	91.85	104.35	104.3	45.9	136.13
Expenses [$]	-165.63	-139.61	-151.1	-134.23	-119.12	-121.39
Net balance [$]	-61.34	-47.76	-46.75	-29.93	-73.22	14.74



(a) Flat tariff. (b) ToU tariff.

Fig. 20: Income and expenses for users.



(a) Flat tariff. (b) ToU tariff.

Fig. 21: Comparison of the net balance for users in each approach using a critical difference diagram with CD = 0.754.

benefits that users can obtain by participating in P2P trading are reduced when the P2P market includes the balancing market rule. In other words, if users only export the energy matched in the P2P market, the potential economic benefits of a P2P trading are reduced, even if they trade between the retail and FiT tariff. Thus, it is evident that P2P has the lowest incomes followed by HEMS-OE, whereas the HEMS, VPP and OPF cases presented similar incomes. Also, the expenses in the VPP and OPF cases reach similar amounts with the flat tariff, which is less than the expenses for the HEMS and HEMS-OE cases. It is worth mentioning that the economic benefits in VPP and OPF case can be improved with an additional market-based price response as proposed in [93].

Finally, Fig. 21 presents a comparison of all approaches against each other using a CD diagram and the average ranks for the net balance of the users. Interestingly, P2P-NPS ranks highest with the average rank equal to 5.229 and 4.443 for flat and ToU tariff, respectively. It can be seen that the average rank in P2P-NPS is significantly different with respect to other approaches using a flat tariff. This is due to the monetary benefits that the users achieve in the P2P trading. However, P2P-NPS is not ranked significantly higher than OPF and VPP in the scenario with ToU, as shown in Fig. 21b. This is because with ToU, the trading period is shorter since the bidding strategy aims to trade more at higher rates (see Fig. 17). From Fig. 21, we can also conclude that the VPP and OPF ranks are not significantly different in both scenarios. While HEMS has the lowest rank using a flat tariff, P2P and HEMS have lower ranks for the ToU scenario, which are significantly different from the ranks of the other approaches. This comparison demonstrates that P2P-NPS, OPF and VPP bring better economic opportunities than the uncoordinated approaches and a balanced P2P.

7.3. Assessment summary

We now present a summary of our assessment, based on the simulation results and the information presented in Table 3, which provides a comparison of the key elements of consideration described in Section 2.

Table 3: Comparison based on the key elements presented in Section 2.1

	HEMS	HEMS-OE	VPP	OPF	P2P	P2P-NPS
Agents						
User agents	✓	✓	✓	✓	✓	✓
Aggregator			✓	✓		
DSO		✓		✓	✓	✓
Electricity network		✓		✓		✓
Regul. and financ. envs.						
Permissions			✓	✓		✓
Proscriptions		✓		✓	✓	
Comm. and Comp.						
Two-way channels			✓	✓	✓	✓
Local comp.	✓	✓	✓	✓	✓	✓

In summary, our simulation results suggest that for a low-voltage network with high DER penetration, the OPF and P2P-NPS models are the only DER integration approaches that offer economic benefits to the users while respecting the operating and technical constraints imposed by the electricity network. Our analysis on the voltage levels and transformer capacity indicates that the feasible approaches that do not violate network constraints are the OPF, P2P and P2P-NPS approaches. On the other hand, the transformer capacity limits were exceeded in the HEMS, HEMS-OE and VPP approaches. The HEMS case also resulted in overvoltage issues. It is worth noting that these findings cannot be extrapolated to all contexts and networks. For instance, the LV network considered in our study did not suffer line congestion issues within the feeder. Weaker LV networks may impose more restrictive operating conditions that would affect the performance of the approaches studied in this paper, especially those that do not consider the network constraints.

Furthermore, it was shown that OPF, P2P-NPS and VPP offer more economic benefits in comparison with the uncoordinated approaches, HEMS and HEMS-OE, and the balanced P2P. It is also worth mentioning that the static operating envelopes in the HEMS-OE approach blocked the potential value of DER, and their ability to mitigate network issues was limited. These results suggest that further research is needed in dynamically setting operating envelopes using active network management systems to harness the full potential of DER while ensuring network constraints are satisfied. Instead of using static operating envelopes, distribution network constraints can take the form of dynamic operating envelopes, which involve gradual input of more information as the operating network conditions change. These dynamic operating envelopes define the limits within which DER must operate to obey network constraints. Network visibility capabilities are required to collect real-time data, and then establish the operating limits. Dynamic operating envelopes also requires a communication infrastructure that allows continuing delivery of operating envelopes [4, 5, 12].

Comparing the results of P2P and P2P-NPS cases, it can be seen that the local balancing rule established in the P2P case leads to a highly restrictive scenario. From the CD diagrams in Fig. 19 and Fig. 21, we can conclude that the users' incomes and energy exported in the P2P and P2P-NPS are significantly different. These findings suggest that alternative market rules need to be explored for P2P energy trading.

With reference to Table 3, we can conclude that user participation is crucial for all approaches. As explained in Section 2.1.1, the role of the interface entity (e.g. an aggregator) is also important for the coordination schemes such as VPP and OPF. In addition, a DSO is essential for the implementation of the approaches that incorporate technical and operating restrictions. Indeed, network constraints were not considered in the HEMS, P2P and VPP approaches, whereas HEMS-OE and P2P-NPS approaches partially integrated and considered the network limits. In constrast, the OPF is the only approach that solves the underlying problem subject to hard technical and operating constraints of the electricity network.

Regarding the regulatory and financial environment, we evaluated the approaches based on the permissions and proscriptions concepts defined in Section 2.1.3. In more detail, HEMS can be considered as the status quo scenario, in which the tariff structures are some of the drivers of the HEMS performance. When operating envelopes are included, that is in HEMS-OE, DER operation is proscripted by the DSO. Similarly, the market rule in the P2P case may limit the amount of energy to export to the grid, as shown above. On the other hand, VPP and P2P-NPS approaches request permission from either the aggregator (in the VPP case) or the DSO (in the P2P cases) in order to coordinate DER or to allow bilateral trading. In the OPF case, permissions and proscriptions are required as network constraints must be respected and the aggregator also interacts with the user agents to orchestrate DER. It is also worth mentioning that the financial flows in the VPP, OPF, P2P and P2P-NPS may depend on the allocation, pricing schemes, or market mechanisms implemented in each approach, rather than only depending on the tariff structures as in the HEMS and HEMS-OE cases.

Regarding the communication and computation requirements, VPP, OPF, P2P and P2P-NPS need two-way communication channels in order to interact among user agents and other entities. All approaches require local computation capabilities, but the total computation time for each approach are different amongst each other. Specifically, HEMS and HEMS-OE perform all the computation locally, with typical computation times between 0.2–1 seconds for one HEMS instance using Raspberry Pis [49]. Both the VPP and the OPF solved in a distributed manner require successive iterations until the distributed algorithm converges. The computation time of each iteration is determined by the complexity of the sub-problems of each user agent. Since the VPP does

Table 4: Overview of advantages and drawbacks of the five DER integration approaches studied in this paper.

DER approaches	*Overview main properties*	*Positive aspects*	*Challenges and drawbacks*
HEMS	Uncoordinated; Individual energy management; Network oblivious.	Suited to networks with low DER penetration and without communication structure.	Network constraints are ignored; therefore, network issues may occur; Reward schemes are limited to tariffs.
HEMS-OE	Uncoordinated; Individual energy management DSO delivers operating envelopes.	It is a short-term solution to address the initial network issues due to DER penetration.	Encoding operating envelopes through a good and accurate network state estimation; It limits the DER potential.
VPP	Coordinated; Distributed optimization; Network oblivious.	It promotes coordinated DER operation to achieve global objectives. It is suited to networks with low and medium DER penetration.	Coordination approach is network unaware; therefore, network issues may occur.
OPF	Coordinated; Distributed optimization; Network aware.	DER orchestration subject to network constraints; Distributed methods facilitate the computation and communication processes while users' privacy is guaranteed. It is suited to scenarios with high DER penetration.	Its implementation may require a redesign of the tariff structures; Hard to incorporate into the existing market framework.
P2P	Decentralized; Allocation and pricing rules, using a CDA; Network aware model using sensitivity coefficients.	P2P market frameworks allow the coordination of DER in a decentralized manner through new business models like bilateral trading. Users may achieve better economic benefits. It is suited to scenarios with high DER penetration.	Full match of all orders; Suboptimal outcomes; Accurate assessment of network state; Local balancing may be too restrictive; A decision horizon should be considered.

not account for network constraints, it is faster than the OPF. Lastly, the market clearing process market in a P2P market is done continuously and depends on the bids and asks submitted by the agents. This iterative process requires local computation of each agent to solve the HEMS problem and to adjust their offers based on the bidding strategy deployed. When deploying the VPP, OPF or P2P approaches, calculations can be done on a rolling-horizon basis. Our results [49] show that the HEMS computation times on small single-board computers like Raspberry Pis are sufficiently fast to allow market clearing times of 10 minutes, or even shorter, irrespective of the relatively high number of iterations required for the OPF and VPP optimization problems to converge.

In addition to that, communication requirements may further increase the total computation time for the cases above. Using a 4G network, each iteration would require additional 100 ms due to the latency in the communication network [180], while the latency in a 3G network can be as high as 500 ms. It is expected, however, that faster networks such as 5G with a much lower latency and higher bandwidth, and the emergence of the concept of *Internet of Things* (IoT) will provide ubiquitous connectivity to support wide-area aggregation of a massive number of DER [49, 149].

Finally, Table 4 summarizes the advantages and drawbacks of the five DER integration approaches assessed in this work.

The scope of this study was limited in terms of the diverse power system, network control and economic aspects that can be evaluated in the context of the emerging TE concept. Further work might explore the deployment of active network management systems for allocating hosting capacity or providing firm network capacity. Research is also needed to evaluate potential long-term arrangements between users in the TE system that may help to coordinate DER, resulting in new business models. Additionally, more work is required to develop system services that may increase the potential value-stack delivered to the users, including entering in network support agreements, offering firm frequency response and participating in markets for both energy and frequency control ancillary services [4, 11]. Finally, one particular appealing line of investigation is to extend this study by exploring the effect of DER integration approaches in network losses.

8. Conclusions

In this work, we have presented a self-contained comparison of DER integration approaches that have been considered in the transition towards the TE concept. In doing so, a careful description of key and suitable elements of the TE framework is presented and DER approaches are appraised based on the levels of network and customer focus. Then, a detailed formulation of each approach is developed.

We have evaluated and compared the technical implications of exemplar DER integration approaches to a network with high DER penetration using a LV distribution feeder as a case study. Our analysis shows that with a very high penetration of behind-the-meter DER, it is necessary to explicitly take into account network constraints. This can be done in a coordinated fashion using the OPF approach, or through a P2P market with a network permission structure. Additionally, our study shows that DER coordination can be achieved by solving an optimization problem, as in the VPP and OPF model, or using prices and bids in a P2P market.

The scope of this study was limited to technical issues associated with DER integration. Economic aspects are equally important, but were beyond the scope of this study. The technical aspects identified in the comparison study are however largely independent of the applicable regulatory and market structure, so it is safe to assume that the conclusions drawn can be generalized to systems with a different economic mechanism for DER aggregation.

Appendix A.

Example of DER integration trials are presented in Table A1. Interested readers are referred to [20, 21, 25, 37, 181–186] for more details and examples.

Table A1: Example of DER integration trials.

Trial name	Project partners	Location	DER integration approach	Size / Scale	Duration
Advanced VPP grid integration	SA Power Network, Tesla and the Commonwealth Scientific and Industrial Research Organisation (CSIRO)	Australia	VPP	Unknown	2020
AMS VPP	Advance Microgrid Solutions (AMS) and Macquarie Capital	US	VPP	Up to 62 MW	2014-2019
AutoGrid-ENERES VPP	AutoGrid and ENERES	Japan	VPP	More than 10000 assets	2020-2021
Conjoule	Innogy Innovation Hub and Tokyo Electric Power	Germany	P2P	Unknown	2017-ongoing
Consort Project	Australian National University, University of Tasmania, University of Sydney, Reposit and TasNetworks	Australia	OPF	Up to 40 battery systems	2016-2019
Couperus Smart Grid project	Stedin Netbeheer, Itho Daalderdorp, SWY, Eneco Trade, TNO and IBM	Netherlands	VPP	300 residential users with flexible loads	2012- 2014
EMPOWER	Schneider Electric, Smart Innovation Østfold AS-SmartIO, eSmart Systems AS, University of St. Gallen, Universitat Politècnica de Catalunya, Malta Intelligent Energy Management Agency and NewEn Projects GmbH	Germany, Malta, Norway, Spain and Switzerland	P2P	Multiple trials across Europe	2015-2018
Evolve	SwitchedIn, Reposit, Australian National University (ANU), ZepBen and utility companies in Queensland and New South Wales, Australia	Australia	HEMS-OE	Multiple trials across 3 national states	2019-ongoing
GMP Project	Green Mountain Power (GMP) and Tesla	US	VPP	2000 small scale-users	2018-ongoing
Indra Monash Smart Energy City project	Monash University, Indra and the Australian Renewable Energy Agency (ARENA).	Australia	OPF	3.5 MW of controllable loads, 1 MW of solar generation, two 22 kW EV chargers, and 1 MWh of battery storage.	2019-ongoing
NemoGrid	University of Applied Sciences and Arts of Southern Switzerland, Center for Solar Energy and Hydrogen Research BadenWürtemberg, University of Technology Chemnitz, Sustainable Innovation, Slock.it, Ngenic, Sonnen GmbH, Gemeinde Wüstenrot and Hive Power	Switzerland, Swedem and Germany	P2P	Unknown	2017-ongoing
Nice grid	Enedis, Netseenergy energy company, Dad'kin, Réseau de Transport d'Électricité (RTE), Watteco,Association pur la Recherche et le Developpement des Methodes et Processus Industriels (ARMINES), Saft, Alstom Grid France and Électricité de France (EDF)	France	VPP	1500 small-scale users	2012-2015
NRGCoin	Vrije Universiteit Brussel, Enervalis and Scanergy	Belgium	P2P	62 residential users	2014
Olympic Peninsula Project	Pacific Northwest National Laboratory and US Government	US	VPP	112 homes with flexible loads	2007
P2P BSES Rajdhani Power Limited	Power Ledger and BSES Rajdhani Power Ltd	India	P2P	Up to 6 MW	
P2P-SmartTest	University of Oulu (UOULU), University of Bath (UBAH), Cardiff University (CU), National Renewable Energy Centre (CENER), Centre Tecnolňgic de Telecomunicacions de Catalunya (CTTC), Inycom (INY), Katholieke Universiteit Leuven (KUL), Regenera (REGE) and Endesa (ENDE)	Finland, UK, Spain, Belgium	P2P	Multiple trials across Europe	2015-2016
Piclo Flex	Piclo, UK Power Networks, Scottish & Southern Electricity Networks, Western power distribution and SP energy networks	UK	OPF	Unknown	2017-ongoing
Piclo Match	Piclo, Good energy, ERG and essent.	UK	P2P	Unknown	2017-ongoing
PowerMatching City	Energy research Centre of the Netherlands (ECN), KEMA, Humiq and Essent New Energy	Netherlands	VPP	25 residential users with flexible loads and PV systems	2008-2014
SCE's Grid Management System	Southern California Edison (SCE)	US	OPF	Unknown	2015-ongoing
Simply VPP	Simpy energy, SA Power Network, Greensync and the Australian Renewable Energy Agency (ARENA)	Australia	VPP	More than 1000 PV-systems	2020

Table A1 (*continued*)

Trial name	Project partners	Location	DER integration approach	Size / Scale	Duration
Solar Enablement Initiative	Energy Queensland and the University of Queensland (UQ)	Australia	HEMS-OE	Unknown	2019
South Australia Testa VPP	South Australia (SA) Government and Tesla	Australia	VPP	Up to 50000 PV-battery systems	2019-2022
SunRun VPP	Sunrun and ISO New England	US	VPP	5000 PV-battery systems	2019-2022
Sustainable open Innovation Initiative	Kyocera, the Kansai Electric Power Co., ENERES Co., KDDI Corporation and Tokyo Electric Power Company (TEPCO) Group	Japan	VPP	Unknown	2018-2019
TeMix	TeMix Inc.	US	P2P	Unknown	2012-2015
The Brooklyn Microgrid	LO3 Energy, Siemens and Consolidated Edison Inc.	US	P2P	Residential microgrid	2015-ongoing
The Energy Collective	Technical University of Denmark, Royal Melbourne Institute of Technology, The Free Energy Companies, University College Dublin, The University of California in Berkeley, Radius Elnet, and University of Aalborg	Denmark	P2P	20 residential users	2016-ongoing
Transactive Energy Colombia	Royal Academy of Engineering, Newton Fund, Empresas Publicas Medellin (EPM), University College London (UCL), Universidad EIA and ERCO	Colombia	P2P	16 small-scale users	2019-ongoing
Transmission & Distribution Interface 2.0	UK Power Networks and National Grid Electricity System Operator	UK	OPF	Unknown	2017-2019
Vibeco (Virtual Buildings Ecosystem)	Finnish government and Siemens	Finland	VPP	Unknown	2019-ongoing
VPP Demonstrations	AEMO, third party aggregators and VPP	Australia	VPP	3-5 participants	2019-ongoing
VPP Powerclub South Australia	Power Ledger and Powerclub	Australia	VPP	Hundred of users with PV-battery systems	2019-ongoing

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