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Electricity markets for DC distribution systems: Locational pricing trumps wholesale pricing

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ABSTRACT

DC distribution systems are a promising alternative to existing AC distribution systems. They connect customers to local energy sources without conversion, thus reducing power losses. However, the unique features of DC impose strict requirements for system operation compared to AC. Within the context of a liberalized energy market, this article demonstrates three promising market designs—an outcome of a comprehensive engineering design framework—that meet those DC requirements. They are an *integrated market* design, which incorporates all system costs into energy prices; a market design that passes *wholesale energy prices* directly to prosumers; and a *locational energy market* design that relieves congestion with nodal prices. An optimization model estimates the three market designs' performance by simulating a realistic DC distribution system, featuring a high share of electric vehicles. Results indicate that the integrated market design is optimal in theory but computationally infeasible in practice. The wholesale energy price design aiming at constraint-free energy trading requires substantial investments in flexibility. The locational energy market design yields nearly optimal operation in urban networks and is considered the best feasible market design for DC distribution systems.

1. Introduction

Converting power distribution networks to direct current (DC) can increase network capacity and reduce energy losses [1], thus providing a promising alternative to alternating current (AC) systems [2]. Both photovoltaic (PV) generation and much contemporary power consumption are DC in nature. Hence, connecting them via DC distribution systems (DCDSs) is more efficient than via AC [3]. The increase in network capacity by switching to DC is an additional benefit in an environment where transport electrification and PV generation lead to significant increases in power flows.

In DCDSs, network issues due to rapid electrification (notably electric vehicles, EVs) and PV installation have a different impact than in AC networks [4]. For example, DC substations use converters that typically have little tolerance to instant overloads, whereas AC substations based on transformers may tolerate an overload up to an hour. The conventional strategy of network reinforcement is costly and slow and still may not satisfy the increasing peak load. If enough network capacity is available over time, shifting flexible loads is a more efficient solution [5]. To stimulate prosumer participation, price-based coordination strategies have been proposed within the context of electricity markets [6], where energy prices reflect the system's technical characteristics. However, popular intervention strategies in AC networks—including those based on dynamic network capacity or reactive power control—cannot comply with DC characteristics and are therefore not applicable to a DCDS. Because DCDSs typically have lower system inertia, stricter power limits and a stronger power-voltage coupling effect [7].

The literature provides three categories of network capacity allocation strategies for distribution systems (all focused on AC). The first category is monetary incentives [8]: prices that reflect temporal [9] and locational [10] resource scarcity. The second category is direct load control [11], where a central dispatcher directly controls prosumers' power devices according to an optimal schedule. It includes controlled demand response, renewable curtailment and redispatch [12]. The third category is based on available transfer capability [13], in which the estimated available

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Acronyms

AC	alternating current
DC	direct current
DCDS	direct current distribution system
DSO	distribution system operator
EULV	European low voltage distribution test feeder
EV	electric vehicle
Flex	(local) flexibility option
IM	integrated market
LEM	locational energy market
LMO	local market operator
PV	photovoltaic
SOC	state of charge
WEP	wholesale energy price

network capacity between price zones is allocated through explicit auctions. However, the capacity of a distribution network is hard to evaluate due to a low level of aggregation and a high degree of uncertainty. This article focuses on monetary incentives, because they comply with electricity market regulations [14,15] and can incentivize prosumers to boost system efficiency. We thus investigate how local market design should be adjusted to meet a DCDS's technical requirements, thereby improving the market efficiency.

Researchers have proposed market-based coordination schemes for distribution networks as summarized in [16,17], but most of them are designed to meet today's regulations for AC networks and may not be directly implemented in DC. Ref. [12] proposes an optional local flexibility market for prosumers with an aggregator playing a key role. Ref. [18] presents five coordination schemes between transmission and distribution system operators, but no one allows prosumers to access the market without an aggregator. These aggregator-based coordination schemes may not be able to manage DC congestion precisely at a 1-min resolution. Moreover, they do not incentivize efficient allocation of network capacity (as is the case with the current regulation). By contrast, Refs. [19,20] discuss network-constrained local energy trading, whereas [19] adopts price-based control for EV charging, and [20] discusses the bidding strategies for the aggregator of prosumers. Unfortunately, prosumers cannot trade energy directly in both cases, but we argue that direct prosumer participation (without aggregators) can create better incentives and higher market efficiency. Hence, we explore market designs tailored to DC, including those beyond current market regulations.

A few authors have studied economic DCDS operation, such as the optimal operation of AC/DC microgrids under uncertain market prices and renewable generation [21,22]. Mohsenian-Rad et al. [23] presented a decentralized control framework where price incentives encourage prosumers to offer ancillary services. Asad et al. [24] proposed a fair nodal price covering the real costs of energy prosumption. However, neither pricing scheme resolves DCDS congestion. Karambelkar et al. [25] proposed an exact optimal power flow formulation, where locational marginal prices mitigate voltage deviation and line congestion. Such a pricing scheme can hardly be implemented because solving such a problem is computationally challenging. Thus, we are eager for a promising DCDS market design that meets the requirements of economic efficiency, system reliability and computational feasibility.

Our previous work identified three technically feasible DCDS market designs using a comprehensive engineering design framework: stating goals, listing options, performance tests, evaluation, and improvement [26]. The three designs are an *integrated market (IM)* design that incorporates all system costs in energy prices; a market design that passes *wholesale energy price (WEP)* directly to prosumers while counting on distribution system operators (DSOs) to resolve network issues; and a *locational energy market (LEM)* design that relieves congestion with nodal prices while letting the DSO regulate voltage. The IM optimizes DCDS operation with prosumer preferences, but the computational complexity and privacy concerns hinder its implementation. The WEP passes wholesale prices on to prosumers then requires a DSO to relieve congestion. The LEM based on linear power flow is computationally feasible but introduces a small dispatching error. These market designs are categorized as *price-based control*, *local flexibility market* and *local energy market*, respectively [16]. This article evaluates them quantitatively.

We expose each market design's potential by stress-testing its performance with large numbers of EVs. We adopt an optimization model to quantitatively evaluate the design goals of economic efficiency, system reliability and computational feasibility. In this model, prosumers operate their devices under local energy prices without knowing their effect on the market. We assume that prosumers fully share their preferences and run devices for their benefit; clearly, poor performance in this model means even worse in reality. We stress-test our market designs with a significant share of PV generation, to which we add a futuristic volume of EVs. EV charging flexibility can be a major advantage to economic DCDS operation. However, it also leads to grid overloads under wrong incentives, thereby creating peak loads orders higher than today.

This article contributes to the literature with the first quantitative assessment of market designs tailored to a DCDS. Following a comprehensive design framework, we analyze the performance of three market designs in Ref. [26] quantitatively using an optimization model. Realistic simulations suggest that converter congestion is the primary concern of the DCDS operation, especially in the presence of volatile energy prosumption and large numbers of EVs. By contrast, constraints regarding nodal voltage and cable capacity are not a limiting factor in an urban DCDS and can presumably be removed from its market design. Our studies on DCDS markets also shed light on new market designs for low-voltage AC distribution systems, where increasing numbers of prosumer devices are interfaced with converters.

2. Three potential DCDS market designs

In exploring the design space for DCDS electricity markets, our previous article [26] identified the three market designs mentioned in Section 1. This section briefly summarizes these market designs, as seen in Table 1. First, all the designs have a complete market architecture: all tradeable commodities, including network capacity and voltage regulation services, are rewarded. Second, all have a complete linkage to wholesale electricity markets. Third, they all apply uniform pricing, namely no distinction between energy sell and buy prices. We changed the name of the *locational flexibility market* design to *wholesale energy price (WEP)* design since the latter better describes its key feature.

2.1. Integrated market (IM) design

The IM design based on direct control rewards power generation but also the provision of network capacity and voltage regulation services, all in a single integrated commodity. Assuming complete information, this market performs security-constrained economic dispatch with a non-linear power flow model, which accurately measures voltage drops and losses. An independent local market operator (LMO) collects information from the DSO and the prosumers, who submit complex bids including energy needs,

Table 1
Comparison of three DCDS market designs, adapted from Ref. [26].

design	IM	WEP	LEM
linkage	all sub-markets	voltage−network	energy−network
commodity	integrated product	energy and locational Flex	locational energy
flexibility	paid implicitly	paid explicitly	paid implicitly
advantages	theoretically optimal; no need for Flex battery	no institutional changes; easy to implement	fast market clearing; close to optimal in urban grids
challenges	computational complexity	congestion and voltage regulation	no incentive for voltage regulation; up to 5% less accurate

constraints, preferences and costs. Then the LMO allocates energy and other resources to maximize the economic welfare of local prosumers. With sufficient flexibility, the IM design yields an optimal system operation in theory, unlike the next two designs. Prosumers are remunerated for their marginal contribution to the total economic welfare. This remuneration creates a time-dependent locational energy price, which also covers the congestion and voltage regulation payments. In practice, the IM design will face computational challenges because of the complex market clearing algorithms.

2.2. Wholesale energy price (WEP) design

The second design allows prosumers to trade energy directly at wholesale prices but counts on the DSO to regulate network operation. The DSO can introduce a *local flexibility market* to purchase flexibility form prosumers. Previous studies typically define flexibility payments based on a prosumer's actual energy delivery, thereby creating a distorted incentive of *pay-for-not-doing*. By contrast, this design defines *Flex*, an option to adjust a flexible prosumer's power devices, as an explicit, standard commodity that a prosumer sells to the DSO.

In daily operation, prosumers schedule power devices themselves based on wholesale prices, whereas the DSO estimates the DCDS's load factor based on historical data and forecasts. Then the DSO announces the Flex demand and invites prosumers to submit Flex offers. Finally, the DSO takes the lowest-price Flex offers and dispatches them in real-time for network regulation. If all prosumers participate in this Flex market, we will reach the same level of economic efficiency as in the IM design. Because a DSO would look for the same least-cost solution considering the grid constraints. The only difference is that a DSO would pay EV owners to relieve the congestion they themselves created. As a result, EV charging costs would be lower than in the IM design, but they would be borne by the DSO and would presumably be transferred back to prosumers as socialized system costs.

The WEP design explicitly treats system services as commodities, thereby creating new business models for energy storage and demand response. The proposed Flex market acknowledges the local value of Flex [27] and attracts Flex investments where network congestion and voltage deviations occur. However, a Flex market is not likely to yield an optimal system operation because it provides perverse incentives to flexible loads: it rewards some schedules that worsen congestion. Meanwhile, its product pricing and standardization are challenging, because flexible devices typically have different operational costs and constraints.

2.3. Locational energy market (LEM) design

In the third design, an LMO allocates energy optimally within network capacity limits under the nodal pricing principle. The LEM design adopts a linear power flow model in energy trading, which explicitly links the energy and network capacity markets. LEM is cleared to minimize generation costs and the transactions are settled at locational energy prices. Apart from energy trading, the DSO provides voltage regulation services using flexible devices such as batteries. The LEM design is in line with the current business model for DSOs, who provide system services and passes the costs along to customers. This design is less optimal than the IM, but it is computationally less challenging and can ensure system reliability with less prosumer information.

3. Optimization model

This section estimates the theoretical potential of each DCDS market design with an optimization model, where we assume complete information availability. We do not include a WEP model but use historical price series instead. Our focus is to develop and test local energy market designs that can resolve DC network issues. As EV charging only represents a fraction of wholesale energy demand today, we assume that local market clearing with EVs does not affect the wholesale energy price (WEP). This is a limitation of our work: future work should investigate the interaction between the wholesale and local energy markets.

We study an urban residential DCDS with sufficient capacity to meet the household load today, but is challenged by a high share of EVs and PV panels in future. This scenario is suitable because flexible loads such as EV charging might 1) create an order of magnitude higher load than today and 2) cause severe network problems. Market designs for DCDSs should be fit for such a scenario. Our model assumes that both household consumption and PV generation are inflexible and may not be curtailed, and that EVs are the only flexible prosumers. The simulation starts at noon and lasts 24 hours to cover the time horizon of overnight EV charging. It adopts a 1-min resolution to highlight the consequences of even brief congestion of the DC substation converter. Unlike AC transformers, DC converters typically cannot sustain brief overloads and require more precise system operation.

Below we show how to model the three market designs as an optimization problem.

3.1. Integrated market (IM) model

The IM market design has, by definition, only one market which rewards the provision of energy, network capacity and voltage regulation services. Voltage and network constraints are integrated into the optimization problem and are therefore considered simultaneously with energy dispatch. The allocation mechanism is a one-step deterministic optimization problem and is settled at a 1-min resolution with DC smart meters. This model serves as a reference for the WEP and LEM models that follow in the subsequent subsections.

3.1.1. Objective and decision variables

This model minimizes local prosumers' energy net import costs.

$$\min_{p_t^w, p_t^e} C = \sum_{t \in \mathcal{T}} \lambda_t^w p_t^w \Delta t \tag{1}$$

The decision variable is the EV charging power p_t^e, whereas the power imported from the wholesale market p_t^w is a dependent variable. The objective function (1) is subject to the constraints regarding the network (2)–(10) and EVs (11)–(16). If Flex batteries are present—although unnecessary for the IM design—the function is further subject to the Flex battery constraints (18)–(22). Table A1 presents the list of indices, variables and parameters used in the optimization model.

3.1.2. Network constraints

Substation converter power limit

$$-\overline{p^w} \le p_t^w \le \overline{p^w} \quad \forall t \tag{2}$$

where $\overline{p^w}$ is the available substation converter capacity.

Nodal power injection

$$p_t^{n=1} = p_t^w \quad \forall t \tag{3}$$

$$p_t^n = \sum_{g \in \mathscr{G}^n} p_t^g + \sum_{l \in \mathscr{L}^n} p_t^l + \sum_{e \in \mathscr{E}^n} p_t^e + \sum_{f \in \mathscr{F}^n} p_t^f \quad \forall t, \forall n \ne 1 \tag{4}$$

where $\mathscr{G}^n, \mathscr{L}^n, \mathscr{E}^n, \mathscr{F}^n$ are the sets of generators, loads, EVs and Flex batteries at node n. This equation indicates that a node's net generation equals the sum of the power flowing out of this node.

Nodal power expression (non-linear)

$$p_t^n = i_t^n v_t^n \quad \forall t, \forall n \tag{5}$$

Nodal voltage limit

$$v_t^{n=1} = v_{ref} \quad \forall t \tag{6}$$

$$0 < \underline{v} \le v_t^n \le \overline{v} \quad \forall t, \forall n \ne 1 \tag{7}$$

Nodal current balance

$$i_t^n = \sum_{m|(n,m) \in \mathscr{A}} f_t^{(n,m)} - \sum_{m|(m,n) \in \mathscr{A}} f_t^{(m,n)} \quad \forall t, \forall n \tag{8}$$

Line current flow

$$\omega^{(m,n)} f_t^{(m,n)} = \left(v_t^m - v_t^n\right) \quad \forall t, \forall (m,n) \in \mathscr{A} \tag{9}$$

Line current limit

$$-\overline{f^a} \le f_t^a \le \overline{f^a} \quad \forall t, \forall a \tag{10}$$

3.1.3. EV charging constraints

EV charging power

$$p_t^e = 0 \quad \forall t \in \left[0, t_a^e\right) \vee \left[t_d^e, T\right], \forall e \tag{11}$$

$$\underline{p^e} \le p_t^e \le 0 \quad \forall t \in \left[t_a^e, t_d^e\right), \forall e \tag{12}$$

EV State-of-Charge (SOC) update

$$\left(r_{t+1}^e - r_t^e\right) c^e = -\eta^e p_t^e \Delta t \quad \forall t \ne T, \forall e \tag{13}$$

EV SOC limit

$$0 \le r_t^e \le 1 \quad \forall t, \forall e \tag{14}$$

$$r_{t_a^e}^e = r_a^e \quad \forall e \tag{15}$$

$$r_{t_d^e}^e \ge r_d^e \quad \forall e \tag{16}$$

3.2. Wholesale energy price (WEP) design model

Prosumers directly face WEPs in this market design. EVs, the only flexible prosumers in this model, are charged to minimize energy purchase costs. If the market clearing results violate a DCDS's technical constraints, namely equations (2), (7) and (10), the DSO resolves such problems outside the energy market with Flex batteries. Since the WEP design requires such batteries, it yields higher capital costs than the IM. With this model, we attempt to indicate the order of magnitude of the cost increase.

3.2.1. Objective and decision variables

The objective function is shown in (17). The first term describes the total energy net import costs (considering energy losses), whereas the second term represents the Flex battery depreciation costs. Hence, the optimization model may dispatch batteries for system service provision but also for energy arbitrage—when energy price differences can cover battery depreciation costs.

$$\min_{p_t^w, p_t^f} C = \sum_{t \in \mathscr{T}} \lambda_t^w p_t^w \Delta t + \sum_{t \in \mathscr{T}} \sum_{f \in \mathscr{F}} \lambda^f p_t^{f,dis} \Delta t \tag{17}$$

The decision variable is the Flex battery power p_t^f, whereas the power imported from the wholesale market p_t^w is a dependent variable. The constraints are from the network (2)–(10), EVs (11)–(16) and Flex batteries (18)–(22).

3.2.2. Flex battery constraints

Flex batteries are unnecessary in the IM and LEM design but are crucial to the WEP design.

Flex battery charging power

$$\underline{p^f} \le p_t^f \le \overline{p^f} \quad \forall t, \forall f \tag{18}$$

$$p_t^f = \eta^{f+} p_t^{f+} - \eta^{f-} p_t^{f-} \quad \forall t, \forall f \tag{19}$$

Flex battery SOC update

$$\left(r_{t+1}^f - r_t^f\right) c^f = -p_t^f \Delta t \quad \forall t \ne T, \forall f \tag{20}$$

Flex battery SOC limit

$$0 \le r_t^f \le 1 \quad \forall t, \forall f \tag{21}$$

$$r_{t=1}^f = r_{t=T}^f = r_i^f \quad \forall f \tag{22}$$

3.3. Locational energy market (LEM) model

Compared to the IM model, the LEM model leaves out voltage drops and energy losses, namely constraints (5)–(7). Instead, the DSO uses Flex batteries to meet constraint (7) in real time. Consequently, The LEM typically results in a power dispatching error up to 5% in our simulation, so we also introduce such an amount of reserve margin when allocating the network capacity.

The objective function of the LEM is the same as the IM, namely equation (1). The optimization problem is subject to EV constraints

(11)–(16) and the following network constraints. Compared to the IM, constraints (2)–(4) remain the same, but constraints (5)–(10) for non-linear power flow modeling are removed. Constraints (8) and (10), expressed in current in the IM, are replaced by (23) and (24), expressed in power in the LEM model.

Nodal power balance

$$p_t^n = \sum_{m|(n,m)\in\mathscr{A}} p_t^{(n,m)} - \sum_{m|(m,n)\in\mathscr{A}} p_t^{(m,n)} \quad \forall t, \forall n \tag{23}$$

Line power limit

$$-\overline{p^a} \leq p_t^a \leq \overline{p^a} \quad \forall t, \forall a \tag{24}$$

3.4. Implementation and verification

The optimization model is formulated mathematically using Pyomo [28]. The IM and WEP models present a non-linear programming problem solved by IPOPT. By contrast, the LEM model presents a linear programming problem solved by Gurobi. We check whether a market design leads to a technically feasible DCDS operation by simulating its cable power flow and nodal voltage deviation. We adopt PyPSA [29], a power system simulation tool, for this purpose: the EV dispatch plans as our model output are passed to PyPSA as inputs.

4. Experiment design

Having developed the mathematical model, we use it in a simulation experiment. The purpose of the simulation is to stress-test three market designs with a large share of EVs that cause DC substation overloads. We combine a well-described IEEE reference network with three typical scenarios describing household consumption, PV generation and EV availability. Contrary to the 15-min resolution used in AC markets, we adopt a 1-min resolution to evaluate the impact of instant congestion on a DC network. Each design is assessed in terms of economic efficiency, reliability and computational complexity.

4.1. IEEE-EULV distribution test feeder

The simulated DCDS is based on the IEEE European Low Voltage Distribution Test Feeder (EULV) [30]. In our case, the low-voltage AC network is replaced by a unipolar 350 V DC system. The old AC transformer is replaced by a DC substation converter with a rated capacity of 100 kW, whereas the AC cables are used for DC distribution with only a few adaptions. We assume the DC substation to be lossless because the efficiency of DC converters is up to 99%. The cable rating is set according to Table A2. We simplified the feeder to a 41-node one (Fig. 1) while preserving its basic topology.

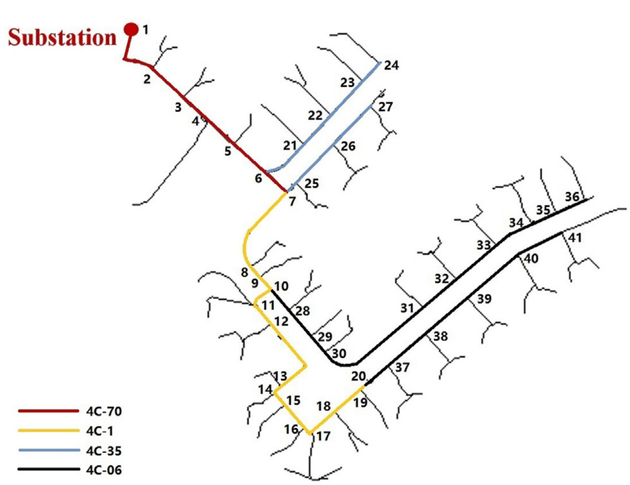

Fig. 1. Simplified 41-node IEEE-EULV feeder, adapted from Ref. [30].

4.2. Prosumers

We model inflexible household consumption and PV generation with time-series power profiles, with a resolution of 1 min. The IEEE-EULV feeder [30] provides 55 household load profiles with a 1-min resolution for 24 hours, which constitute the DCDS's inflexible baseload up to 54.5 kW. The PV systems can generate up to 100 kW peak power, allowing the DCDS to be energy self-sufficient on an average summer day. The generation profiles of 32 PV panels, also in a 1-min resolution, are based on the measurements from the UK [31]. Independent of PV ownership, 25 households own EVs. We assume that all EVs have a battery capacity of 24 kWh and should be fully charged overnight; their energy needs are based on the driving patterns from [32,33]. The maximum EV charging power is 7 kW, and we consider EV charging efficiency to be 95% in a DCDS—higher than with AC thanks to the removal of AC-DC conversion. The EV charging flexibility, represented by the minimal energy need, charging period and charging location (as shown in Table A3), is the primary flexibility source of the studied DCDS. Both PV panels and EVs are located randomly.

Flex batteries are necessary in some market designs for system service provision. The WEP design explicitly requires Flex batteries, because EV charging is self-scheduled and is unavailable for network intervention. For the LEM design, Flex batteries are only needed in the case of large voltage deviations. By contrast, the IM design does not strictly need such batteries, because all EVs provide flexibility that the DSO can use to meet a DCDS's technical constraints. We place seven identical Li-Ion batteries, each with a maximum power of 20 kW and 15-min full load time, at the two longest branches of the IEEE-EULV feeder. Their charging and discharging energy efficiency are set to 95%. These batteries' final SOC is set the same as its initial value, namely 50% in our case.

4.3. Scenarios

We aim to create realistic power profiles of a DCDS with houses, PVs, EVs, and Flex batteries. Hence, we propose three typical but challenging scenarios to describe the local PV generation and the WEPs (affected by offshore wind generation). The DC characteristics [26] requires that DCDS markets should be cleared more frequently than AC energy markets (typically with a 15-min resolution). Due to the paucity of per-minute, high-resolution load data, we can only perform a 24-hour optimization of hardware and operational costs at that resolution.

1 *S1: Sunny-Windy*: A windy summer day when local PV panels and offshore wind farms generate much power, resulting in negative WEPs at noon.
2 *S2: Sunny*: A calm summer day when local PV panels generate much power. The excess generation creates reverse power flow and voltage swells. The WEP curve is flat except in the evening.
3 *S3: Windy*: A windy winter day with low PV generation and low WEPs at dawn. EV demand for cheap wholesale energy will cause substation congestion and voltage sags.

Fig. 2 illustrates the input data. The inflexible load is the same in the three scenarios. In scenario S3, PV generation is especially low and so is the WEP due to much offshore wind generation. The WEPs are taken from the European power exchange EPEX-SPOT [34].

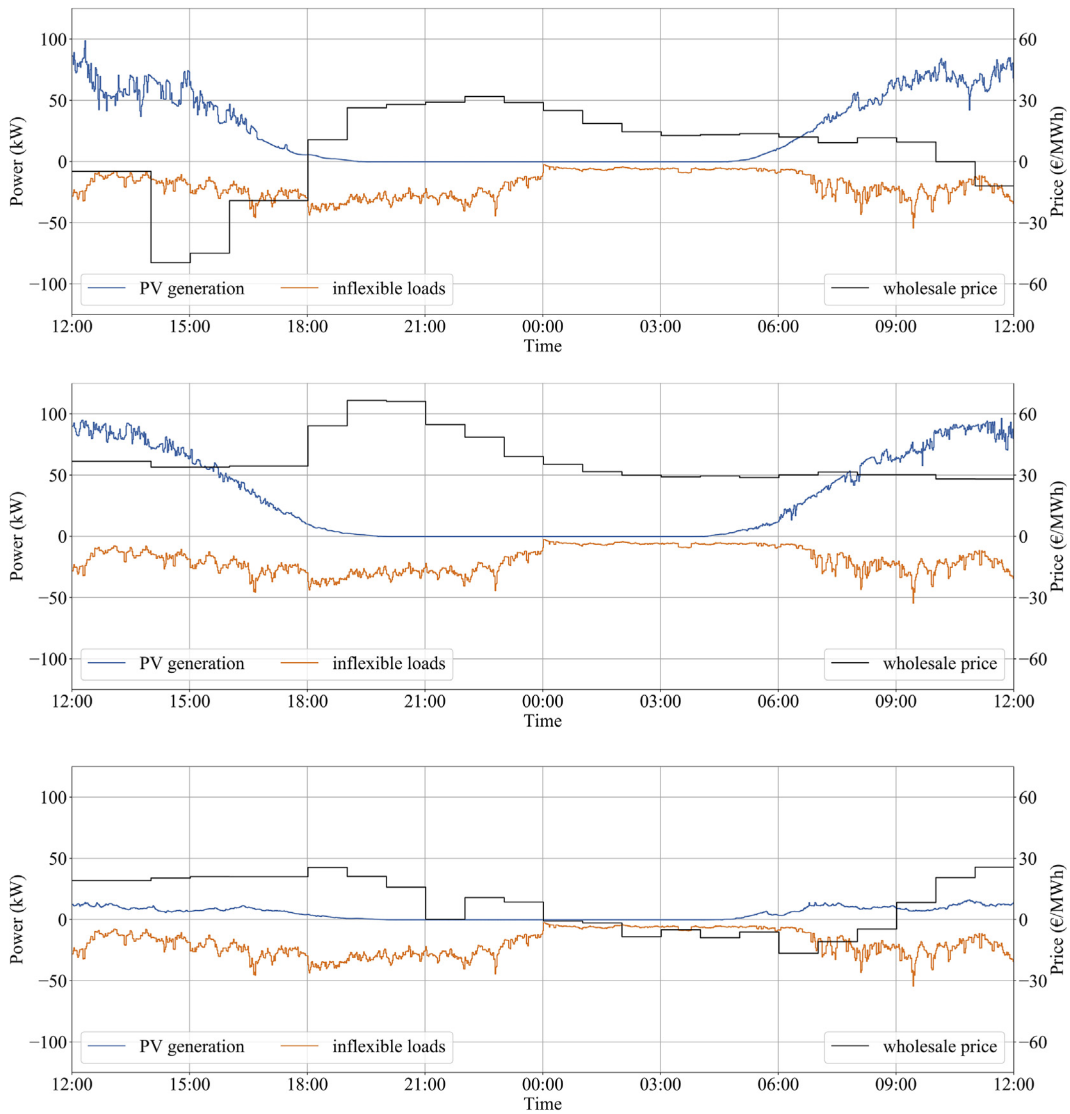

Fig. 2. Simulation scenarios: local PV generation, household consumption and WEP. (a) S1: Sunny-Windy (upper). (b) S2: Sunny (middle). (c) S3: Windy (lower).

4.4. *Performance criteria*

Table 2 lists the market design goals [35,36] and our performance indicators. We do not focus on long-term cost minimization except for cases that require additional investments in batteries.

5. Simulation results

This section compares the performance of the three market designs in the three scenarios. We evaluate to what degree each market design helps lower the overall system costs within the boundary of a DCDS.

The simulation results, summarized in Table 3, indicate that 1) all three market designs can guarantee reliable DCDS operation; 2) the choice of market design has little impact on total operational costs; and 3) this choice largely affects long-term costs due to battery investments. The IM design is theoretically optimal but computationally challenging. The WEP design requires substantial flexibility investments and is therefore disqualified. By contrast, the LEM with linear power flow modeling is promising, because it balances economic efficiency and computational feasibility.

5.1. *Economic efficiency*

5.1.1. *Total operational costs*

The total operational costs include energy net import costs and Li-Ion battery depreciation costs (estimated for 0.05 €/kWh). The WEP is the only design that needs Flex batteries: in Scenario 3, battery depreciation adds an extra €1.12 to the total operational costs, making the WEP the most expensive design. Below we elaborate on the energy net import costs. Typically, energy import costs are marginally higher with the WEP design than with the IM and LEM design, as shown in Table 3. This is perhaps counterintuitive, as in the WEP design, individual EVs minimize their wholesale energy costs. However, this leads to an expected overload of the converter. The DSO remediates this situation by discharging Flex batteries during peak hours and charging them at valley hours. Consequently, the actual wholesale energy import is not as well optimized as in the other designs, as seen in Fig. 3(c). An exception is the WEP design in Scenario 1, in which the daily energy net import cost (€6.59) is lower than the others (€8.03 and €8.04).

Table 2
Selected criteria for local electricity market design, adapted from Ref. [26].

category	goal	criterion
economic efficiency	efficient prosumption	total operational costs
	long-term cost efficiency	min. battery investment
system reliability	sufficient network capacity	max. substation & cable loading
	voltage safety	max. voltage deviation
implementability	computational feasibility	solver time

Table 3
Performance of three market designs in three scenarios, verified by PyPSA.

scenario	S1: Sunny-Windy			S2: Sunny			S3: Windy		
design	IM	WEP	LEM	IM	WEP	LEM	IM	WEP	LEM
total operational costs (€)	8.03	7.46	8.04	0.03	0.27	0.06	1.79	2.95	1.80
… due to energy import (€)	8.03	6.59	8.04	0.03	0.05	0.06	1.79	1.83	1.80
… due to battery depreciation (€)	0.00	0.88	0.00	0.00	0.22	0.00	0.00	1.12	0.00
min. battery investment[a] (k€)	0.00	25.66	0.00	0.00	19.44	0.00	0.00	68.76	0.00
max. substation loading (%)	72.92	73.16	74.67	79.55	100.00	98.35	100.00	100.00	98.50
max. cable loading (%)	70.50	97.88	95.70	75.76	97.14	96.05	97.85	97.79	96.46
max. voltage deviation (%)	3.08	4.12	3.48	3.19	4.31	4.44	4.96	5.04	4.84
solver time (sec)	933	2530	0.94	173	459	1.08	1660	2010	1.06

[a] Li-Ion battery investment & maintenance costs based on a net present value of 824 €/kW (with 0.25 h full load time) [37].

5.1.2. Minimal battery investment

The IM and LEM designs do not require Flex batteries in our scenarios, but the WEP design has a high demand for Flex batteries, because it triggers simultaneous EV charging during low-price hours. Such a need for Flex batteries can be avoided with a market design that gives locational incentives. As depicted in Fig. 4(b), the usage of the seven identical batteries depends on their location, thus avoiding cable congestion and energy losses. In our simulations, the most congestion happens on the cable between N7 and N8, whereas voltage deviations mostly occur at the furthest nodes. Hence, the DSO would potentially pay more to the batteries at such critical locations.

5.2. System reliability

5.2.1. Substation & cable loading

As indicated in Table 3, all the market designs can efficiently manage DC substation congestion. The IM design coordinates EV charging best because it has complete information and can fully exploit network capacity. Cables next to the converter and the branching points are sometimes heavily loaded but never overloaded. The WEP design triggers simultaneous EV charging during the lowest-price hours, creating severe congestion at the DC substation that must be resolved by Flex batteries. We verified the feasibility of the LEM design with PyPSA. As introduced earlier, the LEM typically introduces a power dispatching error up to 5%, but this did not affect the system operation because we reserved a 5% margin for the network capacity.

5.2.2. Voltage deviation

Voltage deviation is not a limiting factor in our simulation. The IEEE-EULV feeder represents a small, densely-loaded urban residential network, in which voltage deviation plays a smaller role than network congestion. The IM and WEP designs yield lower voltage deviations and energy losses than the LEM design. Even for the LEM design, the largest observed voltage deviation of 5.04% is well within the safety range of 10%. However, Flex batteries may be needed in rural areas where voltage deviation is high.

5.3. Computational feasibility

The LEM is solved in around 1 s, much shorter than the IM and WEP designs (173–2532 s), because it formulates a linear problem that can be solved quickly. With some input data, the non-linear solver IPOPT even cannot converge to a local optimum. The computational complexity will become a challenge for the IM design, as it should be cleared at a high frequency. The same is true for the WEP design, but a DSO could settle for a less optimal solution—of course, at a higher cost to prosumers.

6. Discussion

6.1. IM design

The IM design is only optimal under the unrealistic assumption of complete prosumer information. It uses system flexibility and network capacity most efficiently and therefore eliminates the need for Flex investments. Its non-linear power flow modeling can reduce energy losses by integrating more local generation, as indicated in Fig. 3(b). Although the WEP is the lowest between 05:00–06:00, the IM still charges EVs with PV power during 08:00–09:30, thereby importing 12% less energy than in the LEM design. Since the reduced energy losses offset the slight increase in energy import costs, the IM design always has a narrow win with respect to total operational costs.

In practice, however, the IM design faces privacy concerns, computational challenges and complexity in market rules. First, the IM design is highly dependent on the availability and credibility of prosumer preferences. Prosumers may be unwilling to share private data with the LMO. Moreover, they might be unable to forecast or schedule their energy prosumption precisely with the presence of uncertainty. Second, the IM design with non-linear modeling requires a slower, non-linear solver. In our simulation, its solving time is 2–3 orders higher than the linear LEM design, and it cannot guarantee an optimal solution in all cases. Third, in practice, an LMO should coordinate not only EVs but also heat pumps, storage systems and other flexible devices. Each of these has unique and complex constraints, which further limits the IM design's scalability. Such a centralized market may be suitable for DC microgrids

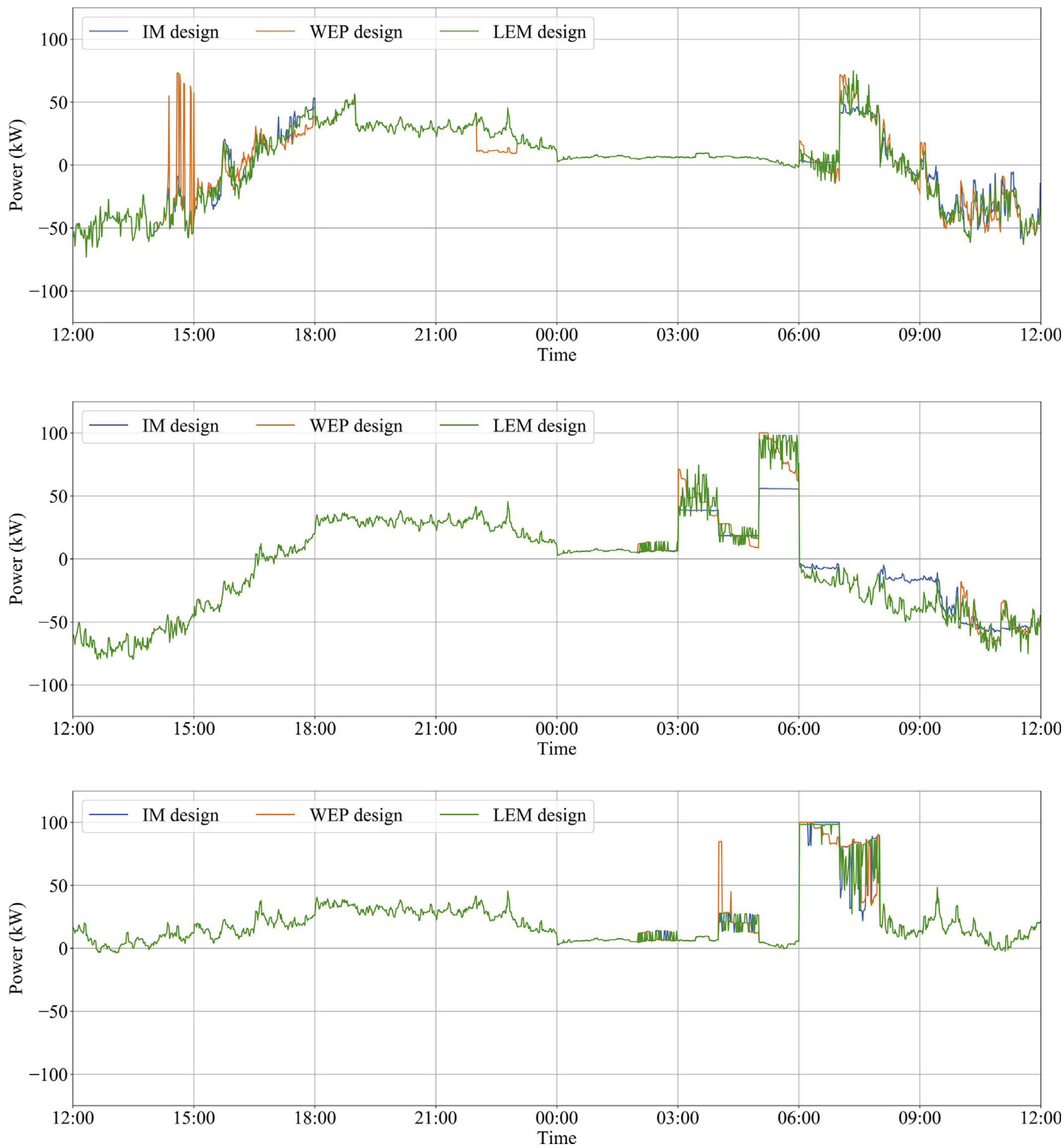

Fig. 3. Market design comparison: power imported from the wholesale energy market via the DC substation, verified by PyPSA. (a) S1 Sunny-Windy: power consumption always stays within the substation capacity (upper). (b) S2 Sunny: EV charging is high when WEP is low (03:00-04:00, 05:00-06:00) (middle). (c) S3 Windy: EV charging is high when WEP is low (06:00-08:00). In each scenario, the imported power of the three market designs are similar except the hours with low WEPs (lower).

with the required communication infrastructure in place, but not for general DCDS applications.

6.2. WEP design

The WEP design creates new business models for flexible technologies by paying them explicitly for system service. The DSO directly purchases such flexibility for congestion management and voltage control, thus providing incentives for Flex investments at critical locations.

Nevertheless, this concept of *prosumers trade energy and the DSO solves the rest* is an expensive solution. First, the WEP design gives prosumers a wrong incentive in the short term. Directly passing WEPs to prosumers invites all EVs to charge simultaneously when the WEP is low. Such uncoordinated charging has created a peak load of 175 kW in total, much more than a 100 kW DC substation can supply. This load is even higher than the one under flat tariff charging, in which EV charging is distributed over time. Second, to serve the above peak load, the DSO must contract prosumer batteries worth €68760, and it has to pay prosumers extra for Flex activation. This causes the WEP market design and other flexibility market designs—which directly pass WEP to prosumers—to be economically inefficient. These costs, later passed on to prosumers as a system cost, can be simply avoided by a better market design. At best, the WEP design is suitable for the transition phase from a mostly inflexible to slightly flexible DCDS, but there is a risk of institutional lock-in.

The other concerns are market liquidity and competitiveness that come with limited market players. With IM and LEM, all 112 prosumers participate in locational energy trading. However, if the number of Flex providers is minimal, as in our WEP simulation, these providers may exercise market power, thus reducing the overall market efficiency. To make this design work, the DSO must contract with most of the flexible prosumers in the DCDS.

Flex-based market designs also face challenges of product pricing and standardization. Flexible devices have different

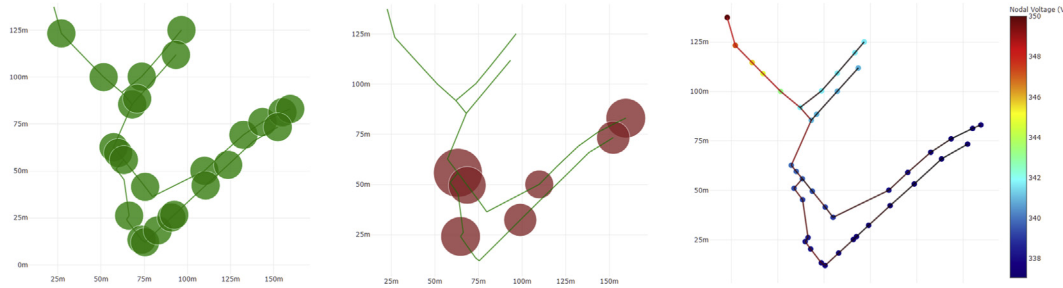

Fig. 4. S3-Windy, WEP design: a visualization of prosumer power distribution, cable loading and nodal voltage at 06:01 (+1). (a) EV charging load (left). (b) Flex battery power output (middle). (c) Cable power flow and nodal voltage (right).

operational costs and constraints in terms of power, energy and temporal flexibility. Only by standardizing these Flex contracts can we guarantee the liquidity of a neighborhood-level DCDS market.

6.3. LEM design

As a solution to IM's computational challenges, the LEM uses a linearized network model to optimize local prosumption within the network capacity constraints. LEM is fast and reliable because a linear solver can find a globally optimal solution quickly. Its power flow model is up to 5% less accurate than in the IM design, so the LMO should apply a reserve margin of 5% on the converter capacity to avoid overloading. However, the resulting loss of economic efficiency is negligible—up to €0.03 per day.

Explicit voltage regulation is not necessary for urban grids with short distribution cables. As shown in our EULV case, the maximal voltage deviation was only 4.84%. However, since the LEM does not consider nodal voltage, they may exceed the norms. In such cases, the DSO can invest in small Flex batteries for voltage regulation.

The LEM design still requires much prosumer information as in the IM design and faces the same implementation challenges. In practice, it will be substantially less accurate. However, the advantages of high economic efficiency and computational feasibility still make LEM stand out as the most attractive market design.

7. Conclusion

This article presents the first quantitative assessment of market designs tailored to DC distribution systems (DCDSs), taken from a previous study of its design options [26]. The *integrated market* (IM) design incorporates all system costs into energy prices. The *wholesale energy price* (WEP) design passes wholesale prices directly to local prosumers while counting on the distribution system operator to resolve congestion. The *locational energy market* (LEM) design relieves congestion with nodal prices, whereas a system operator regulates voltage.

We systematically analyzed how DC technical characteristics may influence local energy market design: volatile energy prosumption challenges the DC substation converter. We built an optimization model to evaluate three market designs quantitatively, with a 1-min resolution that describes volatile prosumption. Recognizing that the total demand and demand flexibility may increase significantly in the future, we included a high share of electric vehicles to test the robustness of the market designs. Simulations on a realistic urban DCDS have demonstrated that all the three market designs can manage network congestion and voltage deviation, even in extreme situations with a large share of electric vehicles. Specifically:

- Network congestion is the main challenge to distribution-level market design, because flexible prosumption will all be scheduled at low-price hours. We developed a LEM design that preserves system reliability, computational feasibility but is also as efficient as the theoretically optimal IM design.
- Voltage deviation and cable power capacity are not limiting factors of the DCDS market design, at least in urban distribution networks. The adoption of bipolar DC grids can further eliminate these limits. We suggest future DCDS market designs to focus on DC substation congestion management because of its limited tolerance for overloads.
- Simply passing wholesale prices to local prosumers, like in the WEP design, may cause severe congestion and require substantial network or flexibility investments. Local electricity markets, especially local flexibility markets (under heated discussion in the literature), should include congestion costs into energy bills, so that prosumers are not encouraged to aggravate congestion.
- Our findings from the DCDS market design are also relevant to markets designed for future AC distribution grids. The latter typically use converter-based substations and serve converter-interfaced devices, such as solar panels, electric vehicles and home batteries. Such AC grids also share DC features such as strict converter capacity limits.

The following aspects limit our results. First, the use of a deterministic optimization model assumes complete information. Uncertainty regarding short-term wholesale energy market prices and local power prosumption is not included. Second, we did not include a wholesale energy price model in our local energy market design, whereas future work should investigate the interaction between wholesale and local energy markets. Third, we assumed that prosumers would be willing to share all their data, which may not be the practice. Fourth, flexibility was represented in the simulation by a set of identical electric vehicles. However, other flexible devices, such as batteries and heat pumps, will play an important role in practice. Finally, our data is limited to a 24-hour cycle of household consumers, limiting the simulation's representativeness. Our stress-test analysis demonstrats that the DCDS market designs perform well under extreme conditions.

Future studies should evaluate the LEM design in more realistic situations, in which the market operator is uncertain about future electricity demand, local generation [38] and WEPs. Prosumers are not always willing to share private data such as preferences, but DCDS networks are sensitive to even brief overloads. Consequently, uncertainties may arise regarding network congestion and future power prices. Agent-based simulations [39,40] are suitable to study realistic settings, where we include the previously mentioned uncertainties, prosumers' privacy concerns and their bidding strategies. Furthermore, the market designs should also be tested in more realistic power networks with diverse flexible devices, under the influence of aggregators and taxes. Third, these market designs will need to meet a more comprehensive set of criteria, including incentive compatibility, risk-hedging and prosumer involvement.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Table A1
Indices, variables and parameters of the optimization model.

name	description
T	(subscript) dispatch interval in set $\mathscr{T} = \{1,\dots,T\}$
L	(superscript) inelastic load in set $\mathscr{L} = \{1,\dots,L\}$
G	(superscript) PV array in set $\mathscr{G} = \{1,\dots,G\}$
E	(superscript) EV in set $\mathscr{E} = \{1,\dots,E\}$
F	(superscript) Flex batteries in set $\mathscr{F} = \{1,\dots,F\}$
N	(superscript) power node of the DCDS in set $\mathscr{N} = \{1,\dots,N\}$
A	(superscript) sparse index set for lines in set $\mathscr{A} = \{1,\dots,A\} \subset \mathscr{N} \times \mathscr{N}$
W	(superscript) real-time wholesale energy market
Δt	length of each dispatch interval
p_t^e	power output of EV e charging at time t, $p_t^e \in [\underline{p^e}, 0]$
p_t^f	power output of Flex f at time t (positive for discharge), $p_t^f \in [-\overline{p^f}, \overline{p^f}]$
p_t^{f+}	power discharged from Flex f at time t (considering losses), $p_t^{f+} \in [0, \overline{p^f}]$
p_t^{f-}	power charged to Flex f at time t (considering losses), $p_t^{f-} \in [0, \overline{p^f}]$
p_t^w	power imported from the wholesale market at time t, $p_t^w \in [-\overline{p^w}, \overline{p^w}]$
p_t^n	net power injection (generation) at node n at time t
i_t^n	net current injection (generation) at node n at time t
r_t^e	state of charge (SOC) of EV e at time t, $r_t^e \in [0,1]$
r_t^f	SOC of Flex battery f at time t, $r_t^f \in [0,1]$
v_t^n	voltage at node n at time t, $v_t^n \in [\underline{v}, \overline{v}]$
f_t^a	current flow of line $a \in \mathscr{A}$ at time t, $f_t^a \in [-\overline{f^a}, \overline{f^a}]$
p_t^a	reference power flow of line $a \in \mathscr{A}$ at time t, $p_t^a \in [-\overline{p^a}, \overline{p^a}]$
ω^a	line resistance of line $a \in \mathscr{A}$
η^{f+}	energy efficiency of Flex f discharging
η^{f-}	energy efficiency of Flex f charging
η^e	energy efficiency of EV e charging
c^e	energy capacity of EV e
c^f	energy capacity of Flex f
r_a^e	initial SOC of EV e upon arrival
r_d^e	target SOC of EV e upon departure
t_a^e	time of arrival of EV e
t_d^e	time of departure of EV e, $1 \le t_a^e < t_d^e \le T$
r_i^f	initial SOC of Flex f
λ_t^w	real-time wholesale energy price at time t
λ^f	depreciation cost of Flex battery s per amount of discharged energy
p_t^l	power consumption (negative generation) of inelastic load l at time t
p_t^g	power production of inflexible PV generator g at time t

Table A2
Cable ratings, based on IEEE EULV feeder [30].

line	resistance (Ω/km)	power (kW)
4c_.06	0.469	55
4c_.1	0.274	75
4c_.35	0.089	105
4c_70	0.446	105

Note: IEEE-EULV feeder did not provide cable ratings and previous publications have no consensus about the power rating of cables. We chose the above ratings for our simulations while acknowledging that the choice may affect the judgement of line congestion.

Table A3
EV charging profile, based on Verzijlbergh (2013) [33].

name	arrival	departure	distance (km)	arrival SOC	location
EV1	13:12	10:11	3.1	97.4%	N9
EV2	18:34	09:26	35.2	70.7%	N18
EV3	15:21	09:31	14.5	87.9%	N41
EV4	14:26	08:41	7.8	93.5%	N5
EV5	18:54	11:21	16.8	86.0%	N33
EV6	15:27	09:13	10.9	90.9%	N29
EV7	16:05	09:16	24.8	79.3%	N27
EV8	15:02	10:27	5.7	95.3%	N8
EV9	18:33	09:06	50.8	57.7%	N38
EV10	18:58	11:07	21.7	81.9%	N20
EV11	19:11	11:31	28.2	76.5%	N34
EV12	19:25	09:26	109.2	9.0%	N35
EV13	18:26	13:21	11.8	90.2%	N21
EV14	18:45	09:16	58.8	51.0%	N31
EV15	17:17	09:07	31.0	74.2%	N17
EV16	19:22	15:04	3.2	97.3%	N7
EV17	18:25	09:13	40.1	66.6%	N19
EV18	18:59	09:11	77.0	35.8%	N2
EV19	18:46	10:11	45.2	62.3%	N13
EV20	19:22	09:04	65.9	45.1%	N10
EV21	17:58	07:38	4.3	96.4%	N36
EV22	22:17	08:38	4.5	96.3%	N16
EV23	16:01	09:08	19.5	83.8%	N24
EV24	19:24	09:09	91.8	23.5%	N39
EV25	19:48	15:09	7.9	93.4%	N35

Note: An EV's SOC upon arrival is estimated by the driven distance and an average power consumption of 0.2 kWh/km. The 24 kWh EV batteries are fully charged upon departure.

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