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ABSTRACT

Future energy markets for low voltage AC and DC distribution systems will facilitate prosumer participation in the market. To comply with market regulations and grid constraints, a tailored market design reflecting (DC) operational requirements is needed. Our previous work identified a *locational energy market* design. However, its real-life implementation faces challenges due to uncertainties in system operation, prosumer preferences, and bidding strategies. This article tests the market design under uncertain scenarios. To this end, we develop an agent-based model that simulates typical electric vehicle user preferences and bidding strategies, influenced by varying degrees of range anxiety. The market design is tested in challenging scenarios with a high share of solar panels and electric vehicles, modelled using the high-resolution Pecan Street database. Simulations indicate that the proposed market design maintains both economic efficiency and system reliability under real-life uncertainties. This in turn indicates the practical feasibility of locational energy markets in helping to integrate renewable generation sources and bidirectional power flows.

1. Introduction

Mitigating grid congestion is a key challenge in the transition to a carbon-free energy system, on account of significant renewable generation and bidirectional power flows [1–3]. Among the technologies under consideration is the use of direct current distribution systems (DCDSs) [4]. By eliminating unnecessary AC/DC conversions, DCDSs offer higher energy efficiency, greater power capacity, and enhanced control flexibility [5]. However, DCDSs have unique technical features, such as low system inertia, limited overloading capability, and a direct connection between nodal voltage and power flow [6–8]. These DC features require tailored operational strategies, particularly precise allocation mechanisms for energy and grid capacity. In a liberalised electricity market, a DCDS needs a market design that meets both market regulations and DC-specific features. Although various market mechanisms have been developed for (low voltage) AC distribution systems [9–13], they cannot guarantee the operational reliability of a DCDS in real-life operation [6].

Our previous work [5] proposed a design framework for local energy markets: identifying goals, listing options, testing, evaluating, and improving them. We investigated three unique (DC) features that require a tailored market design: low system inertia, strict power limits, and power-voltage coupling. Upon exploring the design space, we identified three fundamentally different but promising market designs, consistent with the literature [9,14]: an *integrated market*, allowing a distribution system operator (DSO) to dispatch prosumer devices with one energy price with system costs included; a market that passes *wholesale energy prices* directly to prosumers while leaving grid issues to the DSO; and a *locational energy market (LEM)* that mitigates congestion with local prices and leaves voltage regulation to the DSO. Although designed for DC, this market design can also inspire future low voltage AC markets by facilitating prosumer participation.

Our subsequent work [15] evaluated the potential of these market designs using a deterministic optimisation model. Assuming complete information and honest bidding, we simulated the markets in an urban residential area with a high share of electric vehicles (EVs). The results demonstrated the economic efficiency and system reliability of the LEM design compared to the theoretically optimal *integrated market* design. The latter aggregates prosumer flexibility for efficient system operation and offers the best possible performance. Such a direct-control-based design [16] is difficult to implement due to (1) the need for private prosumer preferences, (2) low autonomy of prosumers, and (3) computational and communication burdens. The *wholesale energy price* design requires the least prosumer preferences but demands unnecessarily high

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investments in flexibility and is therefore disqualified. Among the three candidates, the LEM design shows the highest potential for system reliability and market efficiency.

Therefore, we focus on the promising LEM design and evaluate its performance under uncertainty, considering consumer behaviour. An optimisation model as in Piao et al. [15] is unsuitable for this purpose, as real prosumers may not optimise their behaviour collectively but follow individual bidding strategies. The uncertainties of PV generation, household consumption, and the presence of many EVs exacerbate this situation, resulting in a volatile power flow that is multiple times higher than those experienced today. Such power flows can cause grid congestion and challenge the economic efficiency and system reliability of a DCDS in market operation.

This article quantitatively evaluates the LEM design's economic efficiency and system reliability in the face of uncertainty and prosumer behaviour. We used agent-based modelling (ABM) for this evaluation, because market performance depends on the collective decisions of autonomous entities [17–19]. We model adaptive bidding strategies for EVs, implement their market interactions, and analyse the market clearing results in various simulations under uncertainty. We compare the performance of the LEM design against a deterministic optimisation benchmark, and then validate the feasibility of the market outcome using a power system analysis tool, PyPSA [20]. Finally, we demonstrate the LEM's economic efficiency and system reliability under uncertainty using simulation results based on a widely-used IEEE test feeder and the high-resolution Pecan Street database [21].

This article contributes to the literature by conceptualising a practically feasible and easy-to-implement LEM design and demonstrating its economic efficiency and stability under uncertainty. We present the first comprehensive DCDS market design, based on earlier research steps: qualitative analysis of feasible market designs [5] and quantitative analysis in theory [15]. Using behavioural models, we simulate DCDS operation under uncertainty and prosumer behaviour, validating our theoretical analysis that the LEM design is efficient and reliable in real-world scenarios. This also shows that efficient DCDS operation can indeed be market-driven, as required by liberalised energy markets, thereby removing the market-side barrier to large-scale DCDS deployment.

2. Locational energy market design

Localised energy systems are identified as central in enabling the feasibility of the energy transition for distribution grids [22]. This section introduces the principle of the LEM design [15]. In Section 3, the design's market rules will be implemented in the behavioural models of the Local Market Operator (LMO), DSO, and flexible prosumers such as EVs.

Fig. 1(a) illustrates the LEM design and depicts the interaction between the LMO, DSO, and flexible prosumers, such as EVs. In this design, prosumers are required to submit price-quantity pairs for the flexible portion of their power consumption. The allocation of energy to a flexible prosumer depends on their bid and the market-clearing result determined by the LMO/DSO. For example, an EV may not receive a full charge if the owner's bid price is low. In contrast, traditional household consumption, which has low flexibility but a high willingness to pay, is always served. Inflexible prosumers are not required to place explicit energy bids, but still pay the market-clearing price.

The LEM is cleared per programme time unit (PTU, typically 15 min) in four steps, as shown in Fig. 1(b). First, the LMO/DSO predicts inflexible consumption and offers *auctioned substation capacity* (ASC) – the expected remaining substation capacity minus a reserve margin – to flexible consumers. Second, flexible prosumers schedule their consumption and bid for locally available energy. Third, the LMO/DSO allocates energy using a supply–demand matching algorithm subject to the ASC, and determines the market-clearing price based on marginal principle. If the substation reaches its capacity limit in real time, the DSO redispatches flexible consumption such as EVs during the same PTU. Such redispatch should ensure that prosumers do not experience discomfort. Detailed interactions between the LMO, DSO, and EVs are elaborated in Section 3.1.

Inflexible consumption prediction. Small, inflexible prosumers typically cannot predict their PV generation or schedule household consumption accurately. The LEM design requires the LMO/DSO to predict the following information for the next PTU as a reference: aggregate PV generation, aggregate residential consumption, and the real-time wholesale energy price.

Flexible consumption scheduling and bidding. Flexible prosumers submit energy bids in price-quantity pairs, similar to many existing energy markets [23]—one PTU in advance. Market-based scheduling reduces operational uncertainty by efficiently allocating energy and ASC in advance. In the PTU, the DSO retains the right to redispatch flexible devices to prevent DC substation overload. The LEM design requires a certain level of prosumer intelligence in scheduling, prediction, and bidding. Inflexible prosumers are not required to place bids, but their prosumption is billed by the same market clearing price.

Constrained supply–demand matching. The LEM is designed to manage short periods of grid congestion caused by flexible consumption. Both wholesale and local market participants contribute to the supply and demand in an LEM. The LMO/DSO estimates the substation capacity reserved for inflexible prosumption and auctions energy and the remaining capacity, namely ASC, to flexible prosumers. The auction uses a grid-constrained supply–demand matching algorithm that maximises economic welfare. Our earlier simulations of a residential area [15] indicated that the DC substation converter is likely the only bottleneck. Distribution cables, when used for bipolar DC, have significantly higher capacity than for AC distribution, suggesting that urban residential DCDSs would only need to shift flexible consumption by a few hours to maintain reliable system operation.

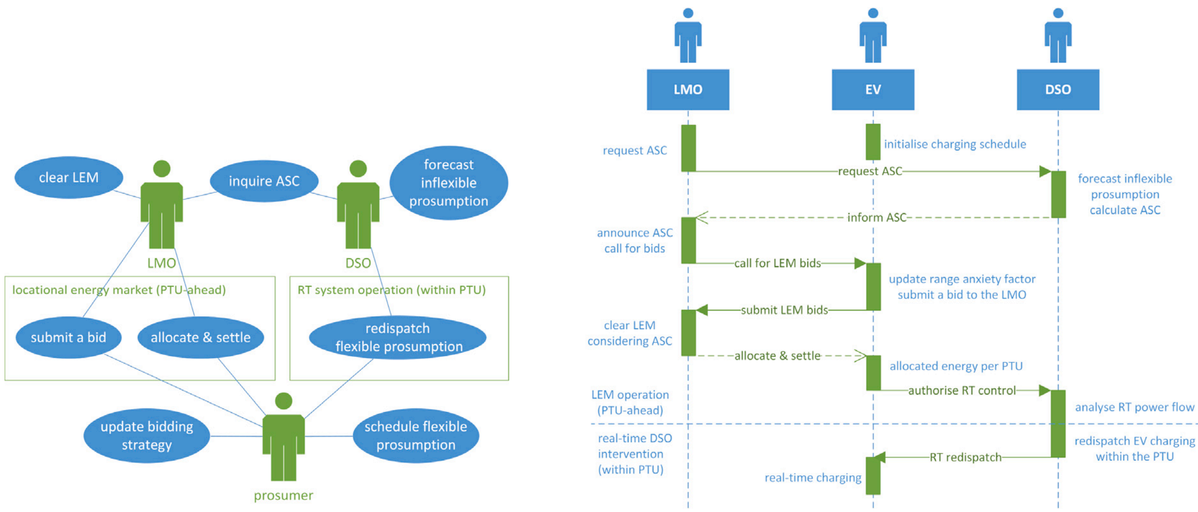
Real-time intervention. The LEM design requires the DSO to predict volatile prosumption; errors in this prediction may result in DC substation congestion or voltage instability [24]. The DSO can redispatch flexible consumption within the current PTU, similar to Olivella-Rosell et al. [25]. The DSO may ramp up or down flexible devices while guaranteeing that prosumers receive the agreed amount of energy at the agreed price. The DSO may have a legal mandate to do so, as in the German Energy Industry Act (§14a EnWG).

3. Model conceptualisation

This section presents an ABM developed to evaluate how prosumers' adaptive bidding strategies impact the LEM design under uncertainty. Section 4 discusses a realistic case study using this ABM. Given that much of the flexibility in a future DCDS will stem from EV charging, the ABM is designed to estimate the impact of EV charging on market efficiency and DCDS reliability under uncertainty [26]. EVs are assumed to be the sole source of flexibility, while household consumption and PV generation are considered inflexible. For comparison, we use the deterministic optimisation model presented in Piao et al. [15] as the best possible market performance in the hypothetical situation when complete information is available.

3.1. An agent-based model for the LEM design

The LEM design allows EV owners to schedule charging for the next PTU via the LMO. Since EV charging preferences and bidding strategies significantly influence market outcomes, we develop an ABM to simulate these effects. The model captures two typical types of EV charging behaviour: urgent and wait-and-see (cost-minimising). For each upcoming PTU, EV agents update their charging strategy and submit energy bids (demand and willingness to pay) to the LMO. The latter then clears the market subject to the ASC to maximise economic



(a) a use case diagram. RT: real time. (b) a sequence diagram.

Fig. 1. The LEM design explained.

welfare. After market clearing, each EV agent adapts its charging strategy and makes an energy bid for the next PTU.

The sequence of LEM operations is illustrated in Fig. 1(b). One PTU ahead, the LMO instructs the DSO to estimate the ASC. Our model conservatively predicts inflexible consumption and thereby the ASC based on historical load profiles. More accurate predictions can be made using techniques like statistical, physical, or machine learning-based methods. The LMO then announces the ASC and invites EVs to submit price-quantity pairs for the next PTU. Once the LMO receives all EV bids, it matches supply and demand subject to the ASC, allocates energy and settles transactions at the market clearing price. In that PTU, the DSO may intervene in EV charging to ensure the DCDS's operational security while delivering the promised energy.

3.1.1. Local market operator agent

An LMO agent facilitates prosumer bidding and performs market clearing. Its clearing algorithm efficiently allocates energy and substation capacity among local prosumers (Algorithm 1) by matches the lowest bids with the highest offers. The outputs are the market clearing price, the traded quantity, and the buyer-seller information. The local energy price typically matches the wholesale energy price, as long as the DC substation converter is not congested.

An example of the clearing algorithm is the following. Suppose the ASC is 50 and the wholesale price is €5. Suppose the bids are $\{b_1 = (10, €\,3), b_2 = (15, €\,5)\}$ and the asks are $\{a_1 = (2, €\,1), a_2 = (16, €\,2), a_3 = (7, €\,3)\}$. Further suppose that the agent of a_2 is in the wholesale market, while all other agents are in the local market only.

Line 1 of Algorithm 1 sets a dummy bid–ask quantity at 50 units, and line 2 sorts the bids and asks respectively by price, bids ascending (lowest first) and asks descending (highest first). This gives: $\{b_1, b_2\}$ and $\{a_3, a_2, a_1\}$ respectively.

In the first iteration of the loop of the algorithm (lines 3–10), since there is both a bid and an ask existing in the market, we match the lowest bid (b_1) with the highest ask (a_3). There is a residual bid quantity of 3 units. The clearing price is therefore the bid price (€3) and the clearing quantity is 3.

In the second iteration of the loop, again there is both a bid and an ask in the market. We match b_2 with a_2. There is a residual ask quantity of 1, and the clearing price is the ask price (€2). Moreover, the ASC is reduced by the traded amount, namely 15 units, since a wholesale market player was involved.

There is now no bid remaining, so the market is cleared at the asking price of a_1, namely €1.

3.1.2. Electric vehicle agent

The charging behaviour of EV agents is realistically modelled based on literature. Daina et al. [27] identify three key decision factors for EV owners: target energy level (EV driving range), effective charging time, and charging costs. Their research shows that (1) 80%–90% of EV drivers prefer a higher state of charge upon departure; (2) 90% prefer not to delay departure; and (3) 60% accept flexible charging schedules, while the remaining 40% prefer immediate charging. We model EV charging preferences based on arrival and departure times (with no delay considered), the energy required for a full charge, and a default willingness to pay for a unit of energy.

In particular, we implement a *range anxiety factor* [28,29] to distinguish EV owners' charging preferences. As defined by Eqs. (Eq. (1)) and (Eq. (2)), a range anxiety factor is the ratio of energy to be charged to the maximum energy that can be charged by departure. Lower anxiety means that the EV owner is willing to postpone charging to the periods with the lowest energy prices, as long as her EV can be fully charged by departure. The wait-and-see strategy is an adaptive charging strategy based on this range anxiety factor, which increases if the planned charging cannot be achieved. Higher anxiety means an EV owner is willing to bid higher prices to see her bid accepted; a unit range anxiety factor means she prefers immediate full-power charging regardless of the energy price. We implement the behaviour of EV agents according to Algorithm 2. During peak hours, one EV is not completely charged by departure and must go to an external fast charging station and pay a penalty for inconvenience and higher energy costs.

We introduce a *range anxiety factor*[28,29] to differentiate the charging preferences of EV owners. As defined by Eqs. (Eq. (1)) and (Eq. (2)), it is the ratio of energy to be charged to the maximum energy that can be charged by departure: lower anxiety suggests that the EV owner is willing to delay charging to lower energy price hours. The wait-and-see strategy adopts this range anxiety factor that increases if the planned charging cannot be guaranteed. Higher anxiety indicates a higher willingness to pay to see the bid accepted; a unit range anxiety is a preference for immediate full-power charging regardless of energy price. The behaviour of an EV agent is implemented in Algorithm 2. During peak hours, an EV may not be fully charged upon departure and must use fast charging stations outside this DCDS, incurring penalties for inconvenience and higher energy costs.

Algorithm 1 LMO market clearing algorithm

Require: local power supply in bids, and local flexible power demand in asks
Require: ASC, based on the predicted inflexible local power prosumption
add dummy bid–ask representing wholesale market supply–demand limited by ASC
sort all bids and all asks by price
while both bid and ask exist **do**
  match the lowest bid and the highest ask
  update residual bid and ask, traded quantity and buyer-seller information
  market-clearing price ← price of the residual bid and ask
  if either the buyer or the seller is the wholesale market **then**
    decrease the ASC by the traded amount
  end if
end while
return market-clearing price, quantity, and buyer-seller information

Algorithm 2 Range anxiety based energy bidding strategy for EV $e \in \mathcal{E}$

Require: charging arrival and departure time t_a^e, t_d^e, initial & target SOC r_a^e, r_d^e
Require: energy capacity, charging efficiency and power rating of the battery of EV e: c^e, η^e, $\underline{p}^e$
Require: expected wholesale energy prices $\lambda_t^w,\ t \in [t_a^e, t_d^e)$
$t \leftarrow t_a^e$
while $t < t_d^e$ and $r_t^e < r_d^e$ **do**
  calculate unit anxiety charging strategy $(b^e_{t,u=1}, p^e_{t,u=1})$: full-power charging until reaching the target SOC r_d^e
  calculate zero anxiety charging strategy $(b^e_{t,u=0}, p^e_{t,u=0})$: a greedy algorithm seeking the lowest bidding price
  update range anxiety factor u_t^e according to Equation (1)

$$u_t^e = \frac{(r_d^e - r_t^e)\ c^e}{\eta^e(-\underline{p}^e)(t_d^e - t)} \quad \forall t \in [t_a^e, t_d^e), \forall e \in \mathcal{E} \tag{1}$$

  update bidding price b_t^e according to Equation (2)

$$b_t^e = u_t^e b^e_{t,u=1} + (1 - u_t^e) b^e_{t,u=1} \quad \forall t \in [t_a^e, t_d^e), \forall e \in \mathcal{E} \tag{2}$$

  update bidding quantity p_t^e: $p_t^e \leftarrow p^e_{t,u=1}$ if *urgent*, or $p_t^e \leftarrow p^e_{t,u=0}$ if *wait-and-see*
  submit a bid $(b_t^e,\ p_t^e)$ to the LMO
  receive the energy allocation q_t^e from the LMO
  update SOC: $r^e_{t+1} \leftarrow r^e_{t+1} + \frac{\eta^e q_t^e}{c^e}$
  $t \leftarrow t + 1$
end while
return submitted energy bids $(b_t^e, p_t^e), t \in [t_a^e, t_d^e)$

3.2. The benchmark: A deterministic optimisation model

This deterministic model [15] serves as a benchmark for the LEM model, representing the best possible market performance under ideal conditions. It is a deterministic optimisation model with complete information: the LMO/DSO is fully aware of the preference and availability of each EV. The objective function minimises the DCDS's operational costs (as detailed in Equation 1 of Piao et al. [15]), subject to the DC substation's capacity (Equations 2–4, 23, 24) and the availability of EVs (Equations 11–16). The inputs of the model are inflexible household consumption, PV generation, wholesale energy prices, and EV charging preferences. The outputs include EV charging schedule (market clearing results), the total system cost (economic efficiency), and the power flow (system reliability). As voltage deviations have limited impact on the power flow of a bipolar DCDS, we employ a linearised power flow model to improve solution speed, subsequently verifying the solution feasibility using PyPSA [20].

4. Experiment design

The experiments we undertake aim to quantitatively assess the LEM design's economic efficiency and system reliability under uncertainty. We are particularly interested in how the design handles congestion and voltage issues that could reduce the reliability of an urban DCDS. Therefore, we require the following realistic scenario. The grid represents a low voltage DC distribution system for load-intensive urban residential areas. The DCDS serves rooftop PV panels and household loads that are either inflexible or price-elastic. High-resolution prosumption data from pilot projects should be used to capture the instant effects of fluctuating prosumption. Besides, we also simulate a futuristic number of EVs in the residential area. Finally, we incorporate historical wholesale energy prices to model the conditions under which local prosumers trade energy collectively.

4.1. Data sources

As low voltage DCDSs are not yet widely deployed or standardised, we lack a reference example for such systems. Instead, we use the widely-adopted IEEE European Low Voltage Distribution Test Feeder [30] to represent a typical residential distribution system with household consumers, simplifying the original 906-node network to a 41-node model of its main branches. The 400 V 3-phase AC network is upgraded to bipolar, ±350 V DC. We simulate local prosumption fluctuations using 1-min resolution measurements from the Pecan Street database (2018) [21], covering 52 full weeks of a year. This data set includes high-resolution consumption data from 25 real households in Austin, featuring inflexible consumption and PV panels. Since the Pecan Street data do not represent a futuristic density of EVs, we simulate this aspect by incorporating 25 synthetic driving profiles from Verzijlbergh et al. [31]. The uncertainty in wholesale energy prices is modelled using the ERCOT day-ahead energy price [32].

4.2. Scenarios

The simulations aim to test the LEM design under conditions of high prosumption uncertainty and assess its ability to coordinate EV charging. We consider three scenarios with one, two and four EVs per household. Two common types of EV owner behaviour are modelled: (1) urgent charging, where EVs charge at maximum power upon arrival, and (2) wait-and-see charging, where EVs seek to minimise charging costs while adapting their range anxiety-based bidding strategy.

Other scenario parameters are kept constant. The DC substation converter has a capacity of 150 kW, and the cable power rating is doubled compared to Table A.4, as we switch from unipolar to bipolar DC. To account for potential errors introduced by power flow linearisation up to 5%, we set such a reserve margin on the ASC, namely 95% of the DC substation capacity minus a conservative estimate of expected inflexible prosumption. This estimate is based on the maximum inflexible prosumption for each PTU on the same day of the week within ±1 month.

4.3. Performance criteria

Table 1 outlines the criteria used to quantify the market design's goals of economic efficiency and system reliability. For economic efficiency, the energy import cost refers to the cost of energy the LMO purchases from the wholesale market on behalf of local prosumers. The substation congestion cost reflects the differences between wholesale and local energy prices; this cost is paid by local prosumers for the

Table 1
Criteria for local electricity market design, based on Piao et al. [5].

Category	Goal	Criteria
Economic efficiency	Efficient production Cost recovery Efficient allocation	Energy import cost ($) Substation congestion cost ($) EV energy charged (MWh)
System reliability	Sufficient network capacity Voltage regulation	Max. Substation loading (≤100%) Max. cable loading (≤100%) Max. voltage deviation (within ±5%)

Table 2
Deterministic optimisation benchmark with zero, one, two and four EVs per household in 2018.

Number of EVs per household	Zero	One	Two	Four
Energy import cost ($)	6982	8596	10 237	14 031
Substation congestion cost ($)	0	0	115	2242
Total system cost ($)	6982	8596	10 352	16 273
EV energy demand (MWh)	0.00	60.52	121.03	242.06
Max. substation loading[a] (%)	73.60	95.90	118.49	121.99
Max. cable loading[a] (%)	52.57	68.50	94.14	112.26
Max. voltage deviation (%)	1.16	1.52	1.96	2.42
wt. avg. PV generation energy price (¢/kWh)	5.60	5.60	5.61	5.94
wt. avg. inflexible load energy price (¢/kWh)	4.68	4.68	4.69	4.86
wt. avg. EV charging energy price (¢/kWh)	–	2.65	2.75	3.74

[a] Loading before the DSO redispatches EV charging to resolve congestion. In real time, peak loads are shaved by the DSO within the PTU; hence, substation and cable loading is always kept below 100%.

eventually grid expansion and maintenance. In scenarios where not all EV charging demand can be met locally, we impose an additional fast-charging cost of 1 $/kWh, a penalty for inconvenience and for the higher energy costs at commercial fast charging stations outside the DCDS. The system reliability is evaluated based on three criteria: maximum substation load factor, maximum cable load factor, and maximum voltage deviation. To further assess the impact of the LEM design on different types of prosumers, we calculated the weighted average ('wt. avg.') energy price for PV generation, inflexible loads, and EV charging at home.

5. Simulation results

Benchmark scenarios with zero to four EVs per household

We introduce four benchmark cases to estimate the theoretical potential of a market design with complete information availability (Table 2). These cases assume that local prosumption, wholesale energy prices, and EV availability are fully known, and that EV owners are entirely cooperative. EV charging demand represents only a fraction of total energy consumption, but the uncertainty of EV charging becomes the primary source of substation congestion, as shown in Fig. A.4(a,d,g).

With optimal scheduling, the benchmark cases demonstrate the lowest possible energy import costs, ranging from $6982 to $14,031. The cost of substation congestion remains negligible with up to two EVs per household. In the extreme scenario of four EVs per household, this cost is still limited to $2242. Clearly, such an optimal outcome is unlikely under real-world uncertainty. The total system cost (defined as the sum of energy import cost, substation congestion cost, and any EV fast charging cost if applicable) is driven primarily by energy import costs and increases proportionately with the number of EVs.

Simulations suggest that cable congestion and voltage issues are not significant constraints in an urban DCDS with short cable lengths [15]. Even with four EVs per household, no cable congestion or voltage problems were observed. Scenarios with two and four EVs show a risk of instantaneous overloading of the DC substation and some cables; however, these risks are mitigated by the DSO's redispatch in EV charging. Whereas congestion slightly increased the weighted average EV charging price (2.65–3.74 ¢/kWh), inflexible consumers did not experience much higher prices. EV charging occurs mainly during low-price periods around midnight, when inflexible consumption and PV generation are minimal. In most cases, the local energy price is linked to the wholesale price, according to which prosumers can effectively schedule their energy use.

5.1. LEM performance with one EV per household

This scenario assumes one EV in an average household. The energy import costs, $8112 with wait-and-see charging and $8570 with urgent charging, are comparable to the benchmark. In early January, wholesale energy prices exceed EV owners' willing to pay, leading some EVs (1.40% of the total demand) to opt out of the LEM and instead use fast charging at a fixed price of 1 $/kWh, resulting in an additional fast-charging cost of up to $850. The LEM is relatively efficient with wait-and-see charging, as the total system cost is only 5.81% higher than the benchmark.

The LEM also ensures the system reliability through its implicit auction of substation capacity. Voltage deviations and grid loading remain within safe limits. With wait-and-see charging, the substation congestion cost of $223 is significantly lower than the energy import cost. The LEM offers price signals as efficient as the benchmark, encouraging prosumers to behave flexibly. The market rule increases the energy prices when residual demand exceeds the ASC and alleviates congestion by postponing less urgent EV charging.

With flexible prosumers (wait-and-see charging), the LEM design generates similarly efficient price signals as the benchmark, confirming the conclusions of Piao et al. [15]. The weighted average EV charging price of 2.14 ¢/kWh (excluding fast-charging) is much lower than the price for inflexible loads, as prosumers charge EVs during off-peak hours. However, price-insensitive prosumers (urgent charging) fail to use DC substation capacity efficiently, resulting in a congestion cost of $2550 and a higher EV charging price of 3.96 ¢/kWh. Such inflexible

Table 3
LEM performance with one, two and four EVs per household in 2018.

Number of EVs per household Charging strategy (WS = wait-and-see, U = urgent)	One WS	One U	Two WS	Two U	Four WS	Four U
Energy import cost ($)	8112	8570	9305	9903	11 783	12 515
Fast charging cost ($)	760	850	1810	1900	24 090	9250
Substation congestion cost ($)	223	2550	762	4058	2342	8466
Total system cost ($)	9095	11 970	11 877	15 861	38 215	30 231
EV energy demand (MWh)[a]	60.77	60.66	119.76	119.97	240.91	242.69
EV energy charged (MWh)	60.01	59.81	117.95	118.07	216.82	233.44
Residual EV energy demand (MWh)	0.76	0.85	1.81	1.90	24.09	9.25
Max. substation loading (%)[b]	90.66	83.33	92.50	90.56	101.53	96.95
Max. cable loading (%)	71.63	64.73	82.40	68.43	80.62	81.86
Max. voltage deviation (%)	1.50	1.50	1.67	1.49	1.75	1.66
wt. avg. PV generation energy price (¢/kWh)	5.60	5.60	5.60	5.60	5.68	5.66
wt. avg. inflexible load energy price (¢/kWh)	4.70	5.27	4.74	5.37	4.87	5.76
wt. avg. EV charging energy price (¢/kWh)[c]	2.14	3.96	2.44	4.16	3.06	4.62

[a] EV energy demand varies due to the randomness in EV driving pattern.
[b] Potential overload is mitigated by DSO redispatch within the same PTU.
[c] Price does not include fast charging costs for the residual EV energy demand.

prosumers also increase the weighted average energy cost for inflexible loads from 4.70 ¢/kWh to 5.27 ¢/kWh.

5.2. LEM performance with two EVs per household

In this scenario, the total system cost of $11,877 (with wait-and-see charging) is only 14.7% higher than the unrealistic benchmark, demonstrating the high efficiency of the LEM design. The LEM effectively coordinates flexible prosumers, as indicated by a low substation congestion cost of $762. However, the efficiency of the LEM design is highly dependent on prosumer behaviour; the total system cost can rise to $15,861 with prosumers insensitive to prices (urgent), 53.2% higher than the benchmark. The autonomy granted to prosumers by the LEM exacerbates the congestion of the substation in the evening, driving up the congestion cost to $4058. This congestion also made the weighted average EV charging price to increase to 4.16 ¢/kWh (2.44 ¢/kWh with wait-and-see) and raised the price for inflexible households to 5.37 ¢/kWh. Nonetheless, the LEM design ensured DCDS reliability under both charging strategies. No overloads of substations or cables, nor large voltage deviations, occur due to the conservative reserve margin of the ASC and the use of bipolar DC.

5.3. LEM performance with four EVs per household

This extreme scenario tests the limit of the LEM design, with the total energy demand of 100 EVs (242 MWh) nearly matching the inflexible demand (294 MWh). Even with urgent charging, 9.25 MWh of residual EV charging demand (3.81%) must be met with external fast charging, incurring an additional cost of $9250. The substation congestion cost increases to $8466 (Fig. A.3(d)), and the total cost of the system increases to 85.8% higher than the benchmark. Consequently, the LEM design is not an efficient solution for such extreme scenarios; the LMO/DSO should expand the grid capacity to accommodate higher power demand. However, the LEM still maintains DCDS reliability in this scenario. An instantaneous substation overload of 1.53% (with wait-and-see charging) can be mitigated by DSO intervention of EV charging.

Ironically, in extreme situations, the LEM design may perform even worse in economic efficiency, with the participation of flexible, self-scheduling prosumers than with inflexible ones. Although urgent charging allows the charging of as many EVs as possible (Fig. A.3(c)), wait-and-see charging encourages EVs to delay charging until periods with lower wholesale prices. However, this delay can lead to energy shortages later, preventing EVs from being fully charged by departure, even at higher bidding prices (Fig. A.3(b)). As a result, a total of 24.09 MWh EV demand (ca. 10%) must be met by additional fast charging at a cost of $24,090. The total system cost of $38,215 is even significantly higher than that of urgent charging. Hence, the LEM cannot ensure a DCDS's market efficiency in the presence of excessive uncoordinated flexibility. An improved design should coordinate local energy prosumption through additional measures such as a locational flexibility market [5,9].

6. Discussion

The empirical results indicated that a simple LEM design can enable efficient DCDS operation under uncertainty. In a common scenario with one EV per household, its total system cost $9095 is comparable to the benchmark ($8596), despite an increased substation congestion cost of $223, as shown in Table 3. A relatively simple LEM design yields a quasi-optimal DCDS operation while accommodating a reasonable degree of prosumer flexibility. The design overlooks voltage deviations and cable capacity, but these simplifications have a minimal impact on the overall efficiency and reliability of the DCDS. It even ensures a market outcome within network constraints in the extreme scenario with four EVs per household. The simple bidding format of the LEM, price–quantity pairs, preserves privacy, as prosumers only share minimum necessary information. Additionally, it enhances the scalability of the LEM design, making it faster than but almost as reliable as the optimal *integrated market* design.

The stress-test scenarios involving two and four EVs per household further confirmed the LEM design's reliability under uncertainty, thanks to DSO redispatch. As introduced in Section 1, the key to reliable DCDS operation is congestion management for the DC substation, and the challenge is highly uncertain power prosumption. Since the LEM is a near real-time market, power prediction and scheduling are only needed one PTU in advance, thereby reducing uncertainty. In any scenario, no substation overload occurred. Even if uncoordinated prosumption causes substation overload, the DSO can redispatch EV charging within the same PTU.

Simulations suggest that the DC substation capacity is typically the bottleneck in a DCDS that requires congestion pricing. Consequently, a zonal market with a single price zone behind the substation is usually sufficient. First, distribution cables are often over-dimensioned to accommodate future flexible demand, avoiding the need for costly municipal construction projects. Second, the use of bipolar DC cables also contributes with a higher power capacity compared to AC cables. Therefore, one can remove the cable capacity constraints from the DCDS market design, thus establishing a uniform energy price behind the DC substation. Indeed, as the extreme case of four EVs per household was feasible, further electrification with heat pumps and home batteries is also likely to be supported in this DCDS. If substation congestion significantly increases energy prices, the DSO can quickly and cost-effectively upgrade the DC substation thanks to modular DC converters [33].

The LEM design enables a full integration of local prosumers into the wholesale market. A LMO/DSO can integrate the flexibility of the consumer more directly and efficiently than in aggregator or retailer-based market designs [12,15]. It also allows the wholesale market to directly access and dispatch local flexibility. However, such market integration may require updates to wholesale market rules. Because small prosumers typically cannot predict or schedule prosumption one day in advance, as is common in wholesale market participants. That said, new regulatory frameworks should allow LMOs/DSOs and local prosumers to participate (in)directly in the wholesale energy market, especially in intraday or real-time markets instead of day-ahead markets.

The LEM design also supports prosumer autonomy by facilitating self-scheduling. Its simple bidding format, based on price-quantity pairs, makes it easy for prosumers to understand and follow market rules. The LEM design treats all flexible technologies equally, as long as generation, consumption, and storage respond to market prices. It also ensures market fairness: prosumers who invest in flexible technologies (EVs, heat pumps, etc.) will benefit from lower energy bills, but it does not force inflexible consumers to experience a sharp increase in their energy costs (Table 3).

The LEM design is suitable for DCDSs without voltage issues and can be applied to radial, ring, or even meshed grids in an urban context. It is based on a simplified power flow model and is appropriate for urban DCDSs with relatively short cables. In rural grids, where voltage deviations can become a bottleneck of the DCDS operation, an expansion of the LEM design should include dynamic line capacity constraints that consider voltage limits. Although designed for DC, the LEM design can also inspire future low voltage AC markets by facilitating prosumer participation.

Despite its advantages, the LEM design requires a certain level of intelligence from both prosumers and the LMO/DSO to ensure optimal DCDS operation. With a simple wait-and-see strategy [29], price-sensitive EVs can schedule charging efficiently without causing much congestion; in real life, they must consider the uncertainty of energy availability and local energy prices till departure. Prosumers are incentivised to share their flexibility under the LEM design, as inflexibility may result in higher energy bills. But even with urgent charging, the DCDS operation is still reliable despite an increase in energy import costs. Meanwhile, the LMO/DSO must ensure that sufficient flexibility is available for a reliable DCDS operation and that local energy price peaks do not expose prosumers to excessive risks. If substation congestion continues to drive up local energy prices, the DSO should expand the DC substation by installing additional modular converters, easier than with AC systems.

Concerns about the LEM design arise regarding market efficiency and system reliability. Can flexible prosumers bid optimally to minimise costs while serving their demand? For example, many EVs may plan to charge simultaneously during low-price hours, but the resulting congestion may prevent it in practice. This congestion forces them to increase their bidding prices. Another consideration is that the LEM is only cleared per PTU, but intra-PTU congestion may still occur if there are considerable errors in LEM's prosumption prediction. The DSO may choose to solve it with intra-PTU redispatch.

7. Conclusion

This article demonstrates that a *locational energy market* (LEM) design can operate a direct current distribution system (DCDS) both economically and reliably under deep uncertainty. The LEM design introduced in our previous work [5,15] is the first comprehensive energy market framework for a DCDS. Its operation remains nearly as efficient as the benchmark deterministic optimisation, supported by prosumer self-scheduling and market mechanisms. Although designed for DC, the LEM design can also inspire future low voltage AC and hybrid markets by facilitating prosumer participation. Given that a DCDS typically has a single bottleneck at the DC substation converter, market efficiency can be maintained as long as the substation constraint is respected. However, efficient LEM operation does require a certain level of prosumer intelligence in self-scheduling.

We evaluated the LEM design using an agent-based model with self-scheduling EVs in a typical European DCDS. This model incorporates EV charging preferences, energy bidding strategies, and their interactions with the market. Two common charging strategies, wait-and-see and urgent charging, simulate the realistic behaviour of EV owners. We examined the impact of varying EV shares, their charging preferences, and the uncertainty of local prosumption. Our findings show that a bidding strategy based on range anxiety [29] is sufficient to achieve efficient DCDS operation, provided that grid constraints are not over-restrictive.

The LEM design performed effectively and reliably under uncertainty, with simulations based on the high-resolution 2018 Pecan Street database. The tests were carried out in scenarios with stochastic local prosumption, fluctuating wholesale energy prices, and unpredictable EV availability. With one or two EVs per household, the LEM design remained fully reliable with price-sensitive EVs adopting a wait-and-see strategy, with charging costs comparable to the benchmark. In extreme scenarios with four EVs per household, DCDS operation was still reliable, and the weighted average EV charging price was lower than that of inflexible loads, thanks to real-time interventions by a DSO. Thus, we conclude that the clear LEM design, which considers only price-quantity pairs and substation capacity constraints, is the most feasible option among the three designs proposed in the literature [5].

The assumptions underlying the LEM design require further scrutiny. First, the LEM design relies on short-term predictions of local prosumption, wholesale energy prices, and EV availability, a task that is inherently challenging due to low aggregation levels. Second, our EV preferences were modelled using 25 synthetic driving profiles, a basic range anxiety model, and a willingness-to-pay metric. Future simulations should use more advanced EV behaviour models or leverage state-of-the-art databases with comprehensive EV charging statistics. Third, our uncertainty modelling was limited to residential load, rooftop solar generation, and wholesale day-ahead energy prices. Future case studies should include other elements such as heat pumps, batteries, and smart appliances, then verify the real-life applicability of the LEM design in the context of real-time energy prices, taxes, and levies, as suggested by Stawska et al. [34].

As DC distribution technology is still under development and standardisation, DCDS market design remains an emerging field, offering opportunities to propose new commodities and trading rules. Further research, with an enhanced agent-based model, should explore the influence of complex prosumer behaviours, such as irrationality, learning, scheduling, and gaming [35] on the LEM design. Lastly, this market design should be tested under various scenarios, including mixed DC–AC grids [36,37], with heterogeneous devices and ultimately validated through field tests involving real prosumers.

CRediT authorship contribution statement

Longjian Piao: Writing – original draft, Visualization, Software, Methodology, Investigation, Conceptualization. **Laurens de Vries:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition. **Mathijs de Weerdt:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Neil Yorke-Smith:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Longjian Piao reports financial support was provided by European Union. Neil Yorke-Smith reports financial support was provided by European Union. Longjian Piao reports a relationship with TenneT TSO GmbH that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Additional figures

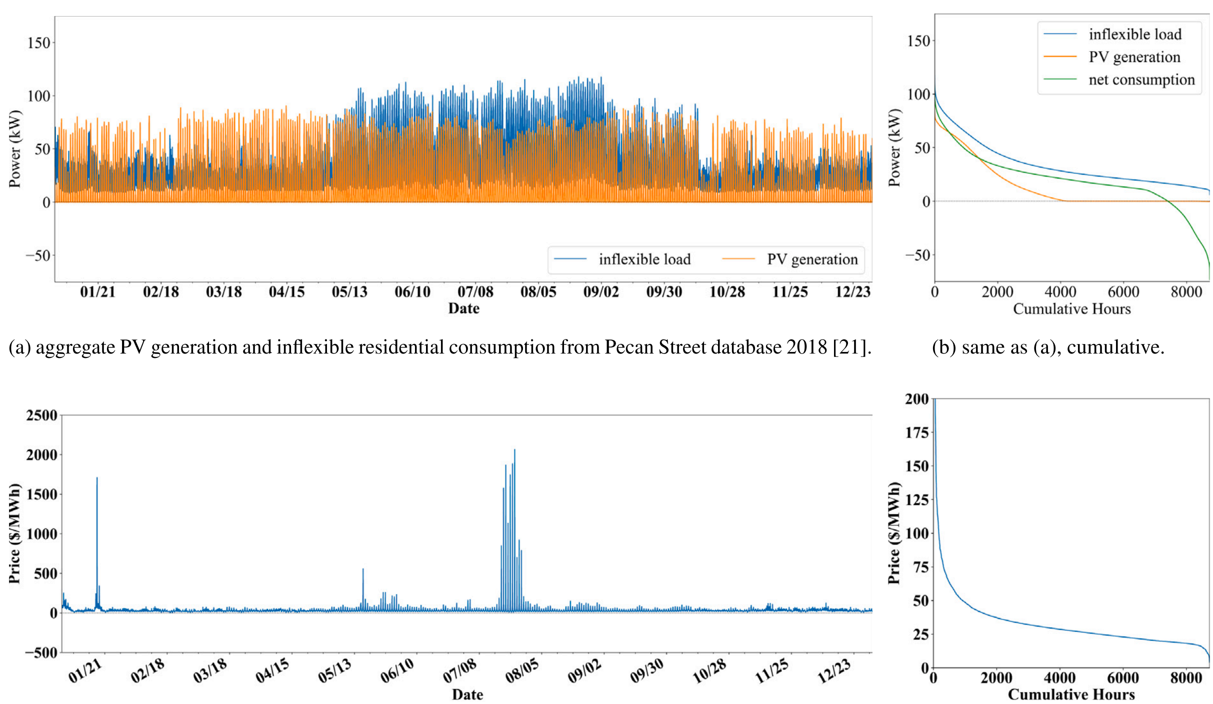
See Table A.4 and Figs. A.2–A.4.

Table A.4
IEEE EULV cable power rating under ±350VDC operation, based on [30].

Cable types	Resistance (Ω/km)	Power rating (kW)
4c_.06	0.469	110
4c_.1	0.274	150
4c_.35	0.089	210
4c_70	0.446	210

Data availability

Models related to this article can be found at DOI https://doi.org/10.4121/5627f587-e98b-4d61-a814-926fa33eef2d.



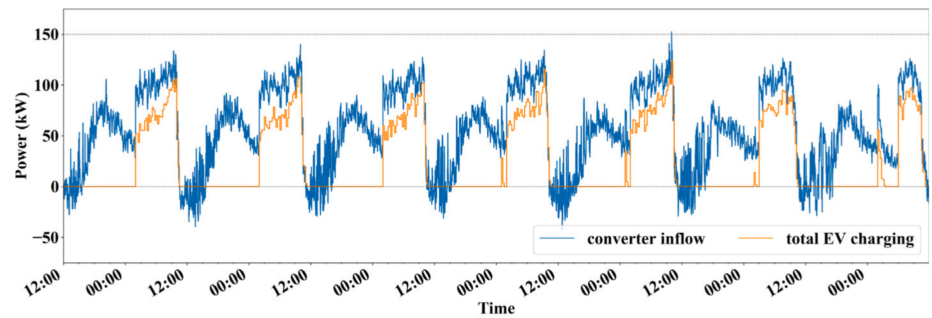
(a) aggregate PV generation and inflexible residential consumption from Pecan Street database 2018 [21].

(b) same as (a), cumulative.

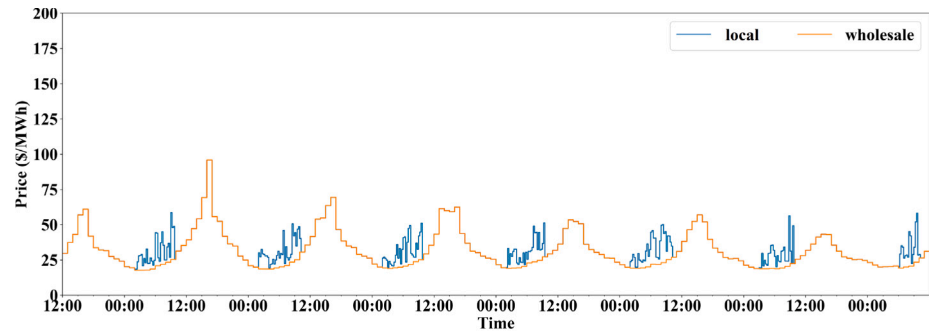
(c) ERCOT day-ahead energy price (LZ South) in 2018, from EnergyOnline [32].

(d) same as (c), cumulative.

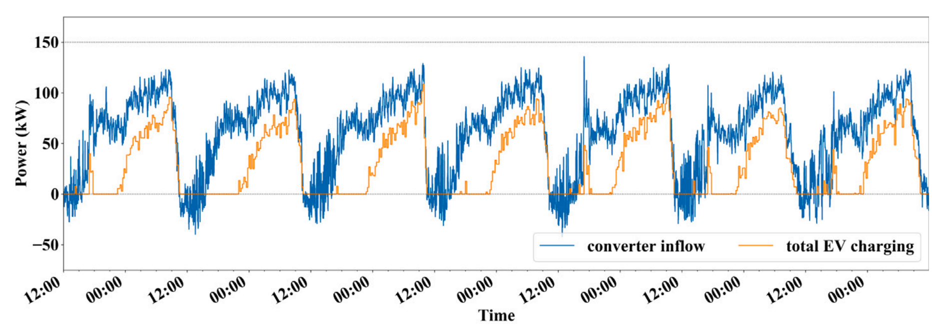
Fig. A.2. Aggregate inflexible prosumption and wholesale day-ahead energy price in the simulation. Prices above 200 $/MWh are not shown in (d).



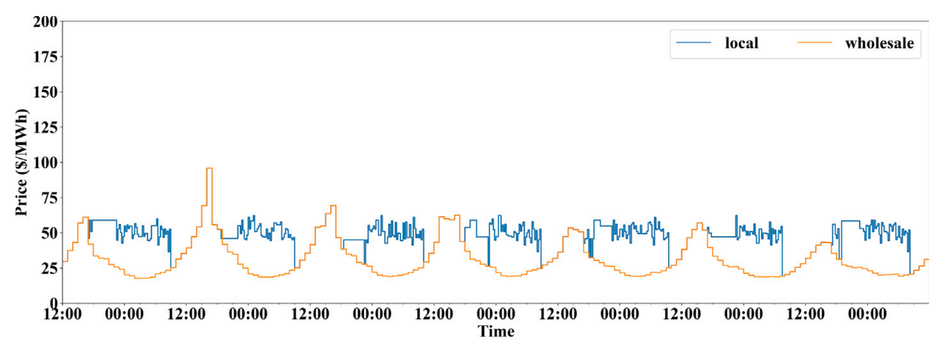
(a) wait-and-see: DC substation power versus aggregate EV charging power



(b) wait-and-see: local energy price

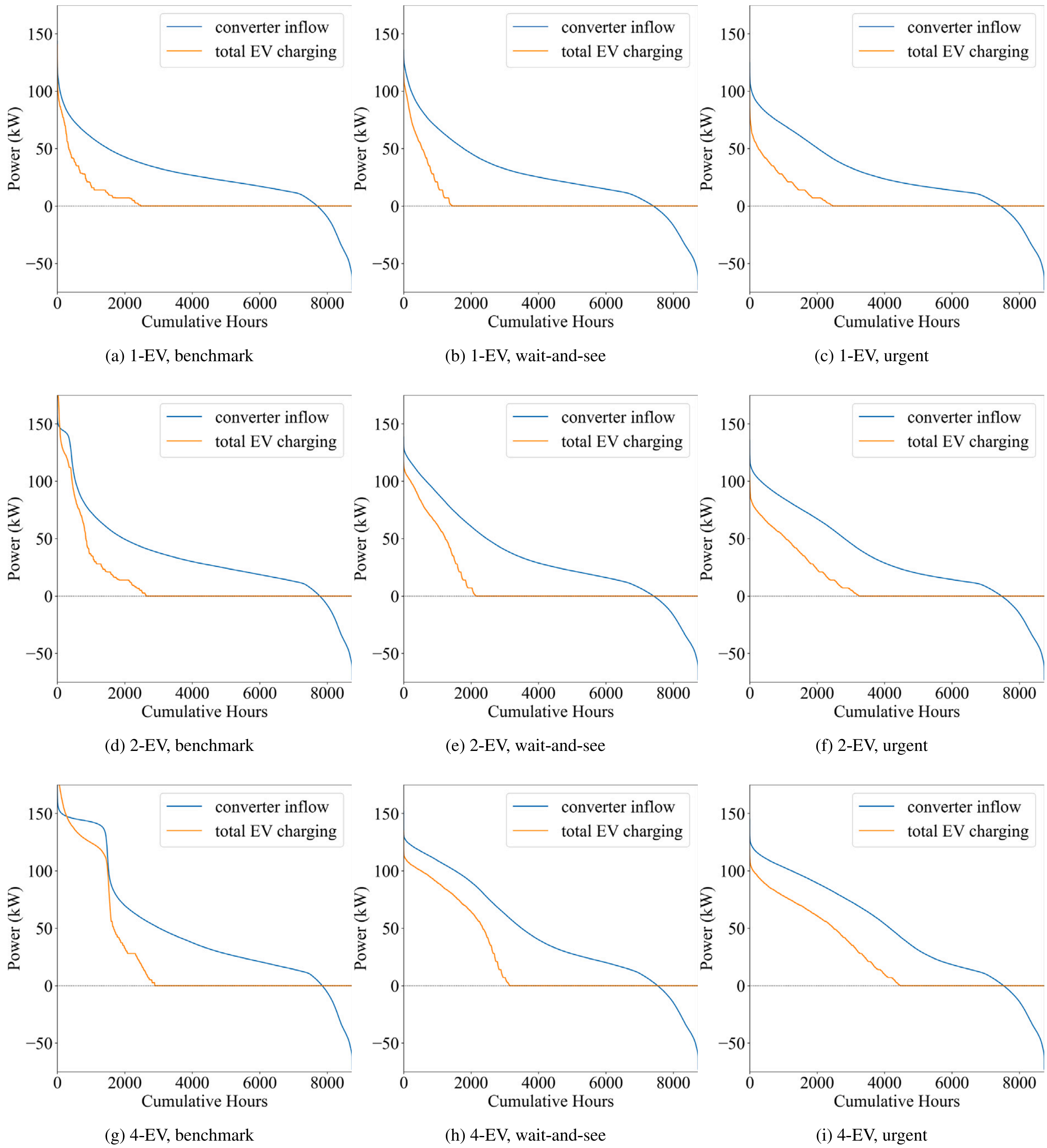


(c) urgent: DC substation power versus aggregate EV charging power



(d) urgent: local energy price

Fig. A.3. LEM simulation with 4 EVs per household: DC substation power, aggregate EV charging power, local energy price between 10–17 June.



(a) 1-EV, benchmark
(b) 1-EV, wait-and-see
(c) 1-EV, urgent
(d) 2-EV, benchmark
(e) 2-EV, wait-and-see
(f) 2-EV, urgent
(g) 4-EV, benchmark
(h) 4-EV, wait-and-see
(i) 4-EV, urgent

Fig. A.4. LEM simulation: DC substation converter power flow versus EV charging load.

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