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EV-observing distribution system management considering strategic VPPs and active & reactive power markets

Mahoor Ebrahimi [a,*], Mahan Ebrahimi [b], Miadreza Shafie-khah [a], Hannu Laaksonen [a]

[a] School of Technology and Innovations, University of Vaasa, Vaasa, Finland
[b] Department of Electrical Engineering, Sharif University of Technology, Tehran, Iran

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ABSTRACT

The growing deployment of new flexible resources, renewable energy resources (RES), and Electric Vehicles (EV) in the distribution system necessitates new methods to manage the distribution system operation optimally. In this regard, our paper, by deploying the concept of Virtual Power Plants (VPPs) as the aggregation of multiple agents and local power markets that are known as important tools for future power systems presents a management framework for the distribution systems with high penetration of EVs. To this end, the interaction of the DSO and VPPs is studied based on their strategic behaviour through the local active and reactive power markets. This way, a bilevel optimization approach is proposed where the DSO aims to minimize its operational cost by setting the operation point of its own facilities and determining the hourly active and reactive power prices for VPPs considering the distribution system congestion in the upper level. At the lower level, VPPs try to minimize their cost by scheduling their assets based on the local active and reactive power prices set by the DSO. The results show how nodal pricing in local markets could improve the distribution system operation. In addition, it is indicated that Reactive Power Support (RPS) from VPP-owned EVPLs can decrease the VPPs' cost by gaining profit in the reactive power market and facilitating their participation in the active power market.

1. Introduction

1.1. Background

Active distribution networks (ADNs) have become an increasingly popular concept in the field of power systems. Unlike traditional passive distribution networks, which are designed for one-way power flow from the transmission system to consumers, ADNs allow for two-way power flow and active participation of distributed energy resources (DERs) such as renewable energy sources, energy storage systems, and electric vehicles [1]. ADNs offer several advantages, including improved system reliability, increased energy efficiency, and reduced carbon emissions [2]. By utilizing DERs, ADNs can help to mitigate power system problems such as voltage fluctuations, power quality issues, and overloading of the distribution network [3]. However, there are several challenges associated with the implementation of ADNs. One of the main challenges is the need for advanced control and communication systems to ensure the efficient and reliable operation of the network, and communication networks must be in place to facilitate the exchange of information between different components of the network [4]. Another challenge is the need for accurate modelling and forecasting of DERs, which can be difficult due to the variability and uncertainty of renewable energy sources and EV charging patterns [5]. In addition, regulatory frameworks and local market mechanisms must be developed to incentivize the deployment of DERs and ensure the cost-effective operation of the network [6].

VPPs have emerged as a promising technology to address the challenges associated with the integration of DERs in ADNs [7]. There exist some interpretations of the VPP concept. In our paper, the VPP is an aggregation of DERs that could be utilized to make contracts in the market and to offer different services to the power system operator, the explanation presented in the majority of the literature such as [8–10], and [11]. In such a definition, VPP components can connect to different points of the distribution network. This allows for the optimization of the operation of the DERs in response to the needs of the grid, and the provision of various grid services such as peak shaving, frequency regulation, and voltage support [12]. One of the key advantages of VPPs is their ability to provide a cost-effective solution for managing the integration of DERs into ADNs [13]. By aggregating the output of multiple DERs, VPPs can provide a more reliable and predictable source of energy compared to individual DERs, which can

* Corresponding author.
E-mail address: mahoor.ebrahimi@uwasa.fi (M. Ebrahimi).

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Nomenclature

Indices

i/j	DSo-owned assets located in bus i/j
k	VPP and assets owned by that VPP
t	Time

Parameters

$\Delta_i^{DG,max}$	DG ramp rate
η_{ch}/η_{dc}	Charge/discharge efficiency of EV
η_{in}/η_{out}	Charging/discharging efficiency of ESS
ρ	Power factor
$c^{RES}/c_n/d_{k,n}$	Cost of RES/DG/marginal utility of DR
$C_{ins}^{PL,ch}$	Total charging capacity of the installed EV chargers
Cap_{cl}^{EV}	Battery capacity of the EV class cl
E_k^{AGG}	Total demand of aggregator
$e_{m,1-2}^X/f_m^X$	Coefficients in the linearized model
E_t^{arr}	Added energy to EVPL due to EVs arrival
E_t^{dep}	Depleted energy from EVPL due to EVs departure
k_t^P/k_t^Q	Wholesale active/reactive energy price
$N^{EV,ent}$	Number of total arrived EVs in a day
$N_t^{EV,arr}/N_t^{EV,dep}$	Number of arrived/departed EVs at time t
$P_{L,i,t}^{Fix}/Q_{L,i,t}^{Fix}$	Inelastic active/reactive load
S^{DG}/S_k^{VPP}	DG/VPP feeder capacity
S_{ij}	Line capacity
Sh_{cl}	Share of EVs class cl from all available EVs
SOC_{cl}^{arr}	Arriving SOC of the EVs class cl
SOC_{cl}^{dep}	Departing SOC of the EVs class cl
$T_{k,start}^{AGG}/T_{k,end}^{AGG}$	Start/end time of aggregator

Variables

$\delta_{i,t}^{ESS}$	ESS charging/discharging status
$\pi_{k,t}^P/\pi_{k,t}^P$	Local active/reactive energy price
$E_{i,t}^{ESS}$	ESS residual energy
E_t^{PL}	EVPL stored energy
$P_{i,t}^{ESS,in}$	ESS Charging power
$P_{i,t}^{ESS,out}$	ESS Discharging power
$P_i/Q_i/V_i/\theta_i$	Active/reactive power injection/voltage amplitude/angle of bus i
$P_{k,t}^{AGG}/Q_{k,t}^{AGG}$	Active/reactive power the aggregator
$P_{k,t}^{DR}/Q_{k,t}^{DR}$	Active/reactive power of DR
$P_{k,t}^{DR}$	Active power of the nth segment of DR
$P_{k,t}^{VPP}/Q_{k,t}^{VPP}$	Transacted active/reactive power between VPP and the DSO
$P_{n,t}^{DG}$	Active power production of the nth segment of DG
P_t^{DG}/Q_t^{DG}	Active/reactive generated power of DGs
P_t^{DN}/Q_t^{DN}	Transacted active/reactive power between DSO and wholesale market
$P_t^{PL,ch}/P_t^{PL,dc}$	Charge/discharge power of EVPL
P_t^{RES}	RES power output

be variable and intermittent [14]. This can help to reduce the need for costly upgrades to the distribution network and the installation of additional grid infrastructure. Additionally, VPPs can provide valuable grid services such as demand response, which can help to manage the load on the grid during times of peak demand [15].

The integration of VPPs into ADN systems presents unique challenges due to the diverse parties involved, including load-serving entities, price-sensitive demand response, distributed generators, and flexible load aggregators [16]. To ensure effective collaboration, VPP agents need to provide their aggregated external characteristics to the Distribution System Operator (DSO), who then computes optimal operational decisions and issues dispatching trajectories to VPP agents [17]. However, conflicts of interest can arise when VPP agents and DSOs belong to different owners. To address this, bi-level programming models are often used to separately consider the economic objectives and operational constraints of both VPPs and ADN [9]. By encouraging the participation of VPPs through reasonable pricing strategies, DSOs can improve the overall economy of the system, leading to more efficient and sustainable grid operations.

In this regard, some studies have been conducted to design a framework that models the local market consisting of VPP and distribution system. Authors in [18] used the multi-leader–follower concept of game theory to model its bilevel interaction among VPP and ADN. The research aims to determine the annual bilateral contract's optimal prices of VPPs to form a competition inside the ADN. Ref. [19] proposed an approach for determining the optimal location and contract pricing of distributed generation (DG). The authors of [20] developed a two-layer energy management model for the smart distribution network that incorporates VPPs participating in day-ahead energy and reserve markets. The first layer focuses on maximizing profits for VPPs, while also considering constraints such as renewable and flexible energy sources and coordination with the VPP operator. The second layer aims to optimize the distribution system operator's management of the distribution network by minimizing network energy loss and voltage deviation, taking into account uncertain parameters such as load, market price, and maximum power of renewable energy sources.

Ref. [21] did the same with this difference that the distribution company and a retailer compete at the upper level. At the lower level, consumers buy energy with the aim of minimizing their own expenses. The authors in [22] proposed a robust optimization approach to aggregate an Autonomous Distribution System as a VPP and determine its time-varying feasible range of active power and ramp rates. The robust optimization model considers uncertainties such as dispatch orders from the transmission system operator (TSO) and renewable distributed generators.

1.2. Contributions

Characteristics of the previous studies about distribution system management are presented in Table 1. The classification includes local active and reactive power markets, power flow, DR, RES, EV, as well as strategic VPP, Microgrid, or aggregator. In this regard, the private ownership of the VPPs and the conflict between the objective of such private agents and the DSO has been considered in some studies. A part of reviewed papers in the literature investigated the possible role of the active power market in distribution system management neglecting the potential impact of the reactive power market framework. This has been investigated in [9] where a framework for both the local active and reactive power market has been considered in the interaction between VPPs and the DSO. However, the impact of EVs as one of the most important elements in the future energy system has not been taken into account. This paper by filling the mentioned gap proposes bilevel programming modelling the local active and reactive power market framework at the distribution level to find the optimal management strategy of the DSO considering the strategic behaviour of VPPs and the operation of both DSO-owned and VPP-owned EV parking lots. This paper proposes a thorough model for EV parking lots reflecting the arrival and departure uncertainty of EVs and different existing EV classes. In addition, both DSO-owned and VPP-owned EV parking lots,

Table 1
Previous studies about active distribution system management.

Ref	Strategic VPP/MG/Agg	LAPM	LRPM	Power flow	DR	RES	EV
[9]	✓	✓	✓	✓	✓	✓	✘
[18]	✘	✘	✘	✓	✘	✘	✘
[19]	✓	✘	✘	✓	✘	✘	✘
[20]	✓	✘	✘	✓	✘	✓	✓
[21]	✓	✘	✘	✓	✘	✓	✘
[22]	✓	✘	✘	✓	✘	✓	✘
[23]	✓	✓	✘	✓	✘	✘	✘
[24]	✓	✓	✘	✓	✘	✓	✓
[25]	✓	✓	✘	✓	✓	✓	✘
[26]	✘	✓	✘	✘	✓	✓	✘
[27]	✘	✘	✘	✓	✓	✓	✘
[28]	✘	✘	✘	✓	✓	✓	✘
[29]	✓	✓	✘	✓	✓	✓	✘
Our paper	✓	✓	✓	✓	✓	✓	✓

LAPM/LRPM: Local active/reactive power market.

owing to their power electronic infrastructure, can provide RPS. This way, the DSO can reduce its operational cost by improving the system operation condition in terms of voltage and line flow, and VPPs can gain additional profit by selling their RPS in the reactive power market. Therefore, the potential of EV parking lots to act as reactive power providers is also modelled. Moreover, the Vehicle-to-Grid (V2G) mode charging has been considered and modelled for the DSO-owned EVPLs. This way, these EVPLs can serve as energy storage for some hours if it is required by the DSO to improve the system operation. The main contributions of this paper are listed below:

- Proposing a comprehensive framework for distribution system management considering the private ownership of the VPPs where the pricing strategy of the DSO, bidding strategy of the VPPs, dispatching strategy of both the DSO and VPPs, a market scheme for active and reactive power, involved uncertainties, distribution system topology and network constraints, and different VPP-owned and DSO-owned consumers, prosumers, generators such as RES, DG, EV parking lot, flexible load, demand response as well as energy storage systems are modelled.
- Modelling and investigating the potential of EV parking lots to act as flexible load, reactive power providers, and operate in the V2G charging mode in the competitive reactive and active power market framework in the distribution system to overcome the challenges resulting from their high penetration and utilize their potential capacities to improve the system operation.

The remainder of this paper is structured as follows: Section 2 describes the overall structure of the problem; Section 3 presents the problem formulation including the lower-level and upper-level problem of the bilevel optimization approach; The deployed simplification methods and equivalent single-level model is explained in Section 4. The simulation results are discussed in Section 5, and the conclusions are summarized in Section 6.

2. Overall structure of the problem

To conduct a comprehensive distribution system management, it is required to model all of the effective elements involved in the distribution system. In this regard, firstly, main energy resources and loads such as distributed generation, renewable energy resources, electric vehicles, energy storage systems, flexible and static loads, and demand response should be modelled. In this regard, the ownership of such assets could be with private sectors. In some countries, besides private sectors, the DSO itself could also own such assets. Therefore, in our model, both options of assets' ownership have been considered. However, the model can be easily modified for the cases where the DSO cannot own any asset. Besides the mentioned loads and assets, the DSO should guarantee the stable operation of the network taking care of the system voltage and power flow that has been modelled in our paper.

The other effective point that can motivate the flexible resources in the distribution system to act as active agents is the local active and reactive power markets. These markets are substantial drives for active and reactive power support from flexible agents in the distribution system. In this regard, the nodal pricing scheme for both active and reactive power can shape the incentives based on the system's needs. Because the distribution system requirements for active and reactive power support in different buses are not similar. Therefore, the different local market prices could better incentivize the agents to have a response similar to the DSO's needs and desires. Moreover, single-level optimization framework cannot model the conflict between the DSO and VPP's interests. Therefore, bilevel optimization model is used where the DSO in the upper level aims to minimize the distribution system cost while guaranteeing the stable operation of the system in terms of network constraints. In addition, at the lower level, VPPs who have different ownership try to minimize their own operational costs based on the local market prices. Finally, due to the importance of the role of the electric vehicle in the future power system, their role in acting as flexible load, energy storage system (in V2G mode), and RPS have been investigated to pave the way for increasing the EV penetration by tackling their operational challenges and making benefit from their potential active and reactive power support.

The active and reactive power price determined by DSO at the distribution level is of substantial importance to the efficient operation of the distribution-level agents and consequently the DSO-owned facilities. This way, the price should be precisely determined considering every effective parameter. In this regard, VPPs play a vital role as price-maker participants in local markets. Therefore, the DSO should accurately consider the operation of VPPs for the price determination and operation of its own facilities. To this end, as the DSO and VPPs have different ownership, the local market clearing scheme is formulated as a bilevel optimization problem where at the upper level, the DSO issues the hourly active and reactive prices and at the lower level, VPPs send the active and reactive power trade feedback to the DSO. The overall framework of the distribution system management in this paper is depicted in Fig. 1 where the DSO determines sets of optimal decisions for active and reactive power prices, its bidding plan to the upstream wholesale active and reactive markets, and dispatching of its own facilities including EVPL equipped with bidirectional and unidirectional EV chargers, ESS, DG, PV, and WT to handle the active and reactive power flow constraints considering the elaborate network topology (congestion and voltage level) and minimize its cost. To this end, the DSO utilizes the VPPs' assets' data, the wholesale active and reactive power price forecast, and the weather situation forecast. VPP managers dispatch the active and reactive power based on the active and reactive power price determined by the DSO. VPPs in this paper consist of EVPLs equipped with unidirectional chargers, DG, PV, WP, price-sensitive DR aggregators, flexible loads, and inelastic loads. Modelling all the VPP facilities is conducted considering relevant uncertainties.

It should be noted that in the bilevel optimization model, the DSO at the upper level defines its decision variables while considering the VPPs' problem at the lower level. In other words, the optimization problem of the VPPs is a constraint in DSO's optimization problem. Upper and lower-level problems are described below in detail. In this paper, it is assumed that DSO participates in the wholesale market as a price-taker player where the wholesale price is obtained from the forecast. As the main focus of the paper is regarding the local market clearing process, the uncertainty of wholesale market price has been neglected. However, the uncertainty of RES has been considered via deploying a chance-constrained formulation described in the problem formulation. In addition, the uncertainty of EVs' arrival and departure is taken into account via employing an uncertainty-observed storage model for the EV parking lot where the characteristic of the storage

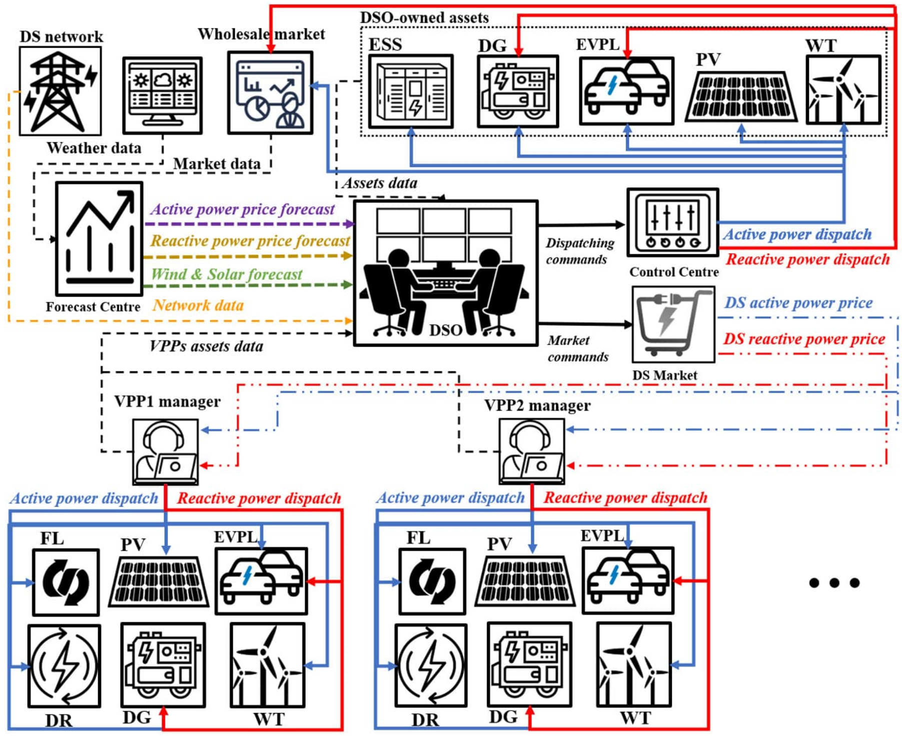

Fig. 1. Overall framework.

model is extracted from the probability distribution function of the arrival and departure pattern of EVs.

It is worth mentioning that the total demand within the distribution system is supplied by the DSO-owned resources such as RES, DG, and ESS through discharging, VPP-owned resources comprising DG, and RES, as well as the upstream grid. Under all circumstances, the value of loss of load is maintained at zero, ensuring a reliable power supply. The share of the mentioned resources for supplying the load is based on the optimization problem that models the market interaction and cost minimization involving the DSO and different VPPs. This way, it is ensured that the solution derived from our framework is the optimal power supply solution.

To summarize the market interactions, VPP agents calculate the aggregated profile of their controllable and uncontrollable assets and submit the equivalent parameters of the aggregated model to the DSO. The DSO, based on the bidding information of the market participants, sets the market prices for the VPPs, and VPPs disaggregate their dispatching plan to individual assets [9]. It is essential to emphasize that, unlike a microgrid, becoming part of a VPP is a voluntary choice for each individual asset. The main objective in establishing a VPP is aggregation, enabling increased profitability. The portion of the total VPP profit allocated to each individual asset is determined and remunerated. As a result, individual assets contribute their data to the VPP manager, enhancing market participation efficiency and profitability. Otherwise, each asset could individually participate in the market with lower profit without joining a VPP. However, it is important to note that when developing the communication infrastructure for the VPP, privacy, and cybersecurity issues related to data transactions in centralized structures must be carefully addressed.

3. Problem formulation

3.1. Upper-level problem

As mentioned in the previous section, the DSO in this paper seeks to minimize the distribution system cost by scheduling its own assets, determining its traded power with the upstream grid, and deciding on active and reactive prices in the local market. Determining the active and reactive prices empowers the DSO to have indirect control over the operation of VPPs. In this regard, the DSO's objective function is presented in (1). The first and second term in the objective function stands for the cost of active and reactive power transaction with the upstream grid. The third and fourth terms stand for the generation cost of the DSO-owned RES and DG. The last two terms are the income from selling active and reactive power to VPPs. The generation cost of the DG has been estimated with a linear formulation as represented in (2) and (3).

$$MinC_{dn} = \Delta T(\sum_{t=1}^{T} k_t^P P_t^{DN} + k_t^Q Q_t^{DN} + \sum_{i=1}^{NB}[c_i^{RES}.P_{i,t}^{RES} + F_i^{DG}(P_{i,t}^{DG})] - \sum_{k=1}^{N_{VPP}} (\pi_{k,t}^P.P_{k,t}^{VPP} + \pi_{k,t}^Q.Q_{k,t}^{VPP})) \tag{1}$$

$$F_i^{DG}(P_{i,t}^{DG}) = \sum_{n=1}^{N_i^{DG,seg}} c_{i,n}.P_{i,n,t}^{DG} \tag{2}$$

$$P_{i,t}^{DG} = \sum_{n=1}^{N_i^{DG,seg}} P_{i,n,t}^{DG} \tag{3}$$

3.1.1. Power flow equations, thermal, and voltage constraints

The DSO is responsible for supervising the active and reactive power flow in the distribution network to maintain within the allowed limits. In this regard, the linearized formulation of AC power flow for the distribution system proposed in [30] is used. It should be noted that in the mentioned linearized AC power flow, the network loss is taken into account. In addition, Eqs. (4) and (5) represent the net active and reactive power injection for all bus i and for VVP k located in bus i, accordingly. Eqs. (6) and (7) define the relation between the injected active and reactive power of each bus with the different buses' voltage magnitude and angle. Moreover, Eqs. (8) and (9) represent the constraint for voltage magnitude and branch power flow to be maintained within the allowed limits.

$$P_{i,t} = P_t^{DN} - P_{k,t}^{VPP} + P_{i,t}^{RES} + P_{i,t}^{DG} + P_{i,t}^{ESS,out} - P_{i,t}^{ESS,in} - P_{L,i,t}^{Fix} \tag{4}$$

$$Q_{i,t} = Q_t^{DN} - Q_{k,t}^{VPP} + Q_{i,t}^{DG} - Q_{L,i,t}^{Fix} \tag{5}$$

$$P_i = \sum_{j=1,i\neq j}^{N_B} P_{ij} = \sum_{j=1,i\neq j}^{N_B} (\frac{r_{ij}}{r_{ij}^2 + x_{ij}^2}(V_i - V_j) + \frac{x_{ij}}{r_{ij}^2 + x_{ij}^2}(\theta_i - \theta_j)) \tag{6}$$

$$Q_i = \sum_{j=1,i\neq j}^{N_B} Q_{i,j} = \sum_{j=1,i\neq j}^{N_B} (\frac{x_{ij}}{r_{ij}^2 + x_{ij}^2}(V_i - V_j) - \frac{r_{ij}}{r_{ij}^2 + x_{ij}^2}(\theta_i - \theta_j)) \tag{7}$$

$$P_{ij}^2 + Q_{ij}^2 \leq S_{ij}^2 \tag{8}$$

$$V_{i,min} \leq V_i \leq V_{i,max} \tag{9}$$

3.1.2. DSO-owned EV parking lot

In this paper, EVPL is modelled as energy storage where the parameters of the storage model are obtained considering the uncertain EV owners' behaviour. It is assumed that EVPL hosts several EV classes with different characteristics. Eq. (10) presents how EVPL's stored energy in each hour is calculated. The energy added to the EVPL or derived from it due to EVs' arrival and departure is obtained from the number of arriving and departing EVs in each hour. Uncertain arrival and departure of EVs in a commercial EVPL are modelled with a Truncated Normal Distribution (TND) in the related studies. This way, using the Cumulative Distribution Function (CDF) of TND, the number of arriving and departing EVs in each hour is obtained as represented in (11) and (12) where F_t^{TND} is CDF of TND. It is given that the number of EVs parking in the EVPL in a day is equal to the number of EV chargers. Such uncertainty modelling that provides a storage-based model via the CDF of arriving and departing pattern makes it a proper model for large-scale applications with a high share of EVs because of its low computational burden.

$$E_{i,t}^{PL} = E_{i,t-1}^{PL} - E_{i,t}^{dep} + E_{i,t}^{arr} + \Delta t\eta_{ch} P_{i,t}^{PL,ch} - (\Delta t/\eta_{dc}) P_{i,t}^{PL,dc} \tag{10}$$

$$N_t^{Ev,arr} = N^{EV,ent}(F_{t+0.5}^{TND,arr} - F_{t-0.5}^{TND,arr}) \tag{11}$$

$$N_t^{Ev,dep} = N^{EV,ent}(F_{t+0.5}^{TND,dep} - F_{t-0.5}^{TND,dep}) \tag{12}$$

$$N^{EV,ent} \leq N^{EV,ava} \tag{13}$$

$$F^{TND}(x) = \frac{\Phi(x,\mu,\sigma) - \Phi(a,\mu,\sigma)}{\Phi(b,\mu,\sigma) - \Phi(a,\mu,\sigma)} \tag{14}$$

$$E_{i,t}^{arr} = N_{i,t}^{Ev,arr}(\sum_{cl} Cap_{cl}^{EV} SOC_{cl}^{arr} Sh_{cl}) \tag{15}$$

$$E_{i,t}^{dep} = N_{i,t}^{Ev,dep}(\sum_{cl} Cap_{cl}^{EV} SOC_{cl}^{dep} Sh_{cl}) \tag{16}$$

EVPL's charging power should be less than the total charging capacity of the EVPL which is equal to the total charging capacity of the EV chargers as represented in (17). Moreover, EVPL's charging power in each hour is less than the summation of the nominal charging power of the parked EVs in that hour as presented in (18). Eq. (21) represents the hourly number of EVs parked in EVPL. The hourly maximum and minimum energy of EVPL is determined as shown in (22). Furthermore, (25) represents the constraint on the active and reactive power of EVPL. Finally, the output power of EVPL is equal to the summation of the charge and discharge power. However, the charge and discharge power cannot be positive at the same time as presented in (27). To prevent the non-linearity resulting from (27), the Fortuny-Amat transformation [31] is deployed according to (28) and (29).

$$0 \leq P_{i,t}^{PL,ch} \leq C_i^{PL,ins,ch} \tag{17}$$

$$0 \leq P_{i,t}^{PL,ch} \leq N_{i,t}^{EV,par}(\sum_{cl} P_{cl}^{ch,max} Sh_{cl}) \tag{18}$$

$$0 \leq P_{i,t}^{PL,dc} \leq C_i^{PL,ins,dc} \tag{19}$$

$$0 \leq P_{i,t}^{PL,dc} \leq N_t^{EV,par}(\sum_{cl} P_{cl}^{dc,max} Sh_{cl}) \tag{20}$$

$$N_{i,t}^{EV,par} = N_{i,t-1}^{EV,par} + N_{i,t}^{Ev,arr} - N_{i,t}^{Ev,dep} \tag{21}$$

$$E_{i,t}^{PL,min} \leq E_{i,t}^{PL} \leq E_{i,t}^{PL,max} \tag{22}$$

$$E_{i,t}^{PL,min} = N_{i,t}^{EV,par}(\sum_{cl} Cap_{cl}^{EV} SOC^{min} Sh_{cl}) \tag{23}$$

$$E_{i,t}^{PL,max} = N_{i,t}^{EV,par}(\sum_{cl} Cap_{cl}^{EV} SOC^{max} Sh_{cl}) \tag{24}$$

$$(P_{i,t}^{PL})^2 + (Q_{i,t}^{PL})^2 \leq (S_i^{PL})^2 \tag{25}$$

$$P_{i,t}^{PL} = P_{i,t}^{PL,ch} + P_{i,t}^{PL,dc} \tag{26}$$

$$P_{i,t}^{PL,ch} P_{i,t}^{PL,dc} = 0 \tag{27}$$

$$0 \leq P_{i,t}^{PL,ch} \leq u_t M \tag{28}$$

$$0 \leq P_{i,t}^{PL,dc} \leq (1 - u_t) M \tag{29}$$

3.1.3. DSO-owned DG and RES constraints

The power output of the DG should be within the maximum and minimum amount to satisfy the ramp rate and nominal capacity constraint as indicated in (30), (31), and (32). To take into account the uncertainty of RES generation, the chance-constrained-based formulation presented in [9] is utilized where $\Phi_a(.)$ is the CDF of the standard normal distribution. $P_{i,t}^{RES,f}$ and $\sigma_{i,t}^f$ are the mean and square difference of RES generation forecast, respectively, and η is the confidence level. The derivation of the RES chance-constrained formulation can be found in [9]. Such RES uncertainty modelling based on the chance-constrained formulation makes it an efficient approach for large-scale applications with a high share of RES owing to its low computational burden.

$$P_{i,n}^{DG,min} \leq P_{i,n,t}^{DG} \leq P_{i,n}^{DG,max} \tag{30}$$

$$\Delta_i^{DG,min} \leq P_{i,t}^{DG} - P_{i,t-1}^{DG} \leq \Delta_i^{DG,max} \tag{31}$$

$$(P_{i,t}^{DG})^2 + (Q_{i,t}^{DG})^2 \leq (S_i^{DG})^2 \tag{32}$$

$$0 \leq P_{i,t}^{RES} \leq \bar{P}_{i,t}^{RES,f} + \sigma_{i,t}^f.\Phi_a^- 1(1-\eta) \tag{33}$$

3.1.4. ESS constraints

The operation of the DSO-owned energy storage system, considering ESS dissipation (γ), serving as a flexibility provider for the distribution system is formulated according to (37) [9]. Eqs. (34) and (35) represent the charging and discharging rate limit of the battery. Moreover, the SOC limit condition of the battery is indicated in (36).

$$0 \leq P_i^{ESS,in} \leq P_i^{ESS,in,max}.\delta_{i,t}^{ESS} \tag{34}$$

$$0 \leq P_i^{ESS,out} \leq P_i^{ESS,out,max}.(1 - \delta_{i,t}^{ESS}) \tag{35}$$

$$E_i^{ESS,min} \leq E_{i,t}^{ESS} \leq E_i^{ESS,max}, \delta_{i,t}^{ESS} \in 0,1 \tag{36}$$

$$E_{i,t}^{ESS} = E_{i,0}^{ESS} + \sum_{t=1}^{j} (\gamma^{ESS})^{j,t} \eta_{in}.\Delta T.P_{i,t}^{ESS,in} - \sum_{t=1}^{j} (\gamma^{ESS})^{j,t} \eta_{out}.\Delta T.P_{i,t}^{ESS,out} \tag{37}$$

3.2. Lower-level problem

As mentioned beforehand, VPPs in this paper manage the operation of their own assets in response to the active and reactive prices determined by the DSO in the lower level of the proposed bi-level optimization approach. It is noteworthy that according to the VPP definition in the introduction section, in this paper, VPP is the aggregation of different DERs that are directly connected to the same substation in the distribution system. Therefore, in our paper, there does not exist an internal network within VPPs.

3.2.1. VPPs objective function

VPPs schedule the operation of their assets consisting of EVPLs equipped with unidirectional chargers, DG, PV, WP, price-sensitive DR aggregators, flexible loads, and inelastic loads to minimize their cost as presented in (38). The first term in the VPPs' objective function stands for the utility function of the DR aggregators that is estimated with a piecewise linear function indicated in (39) [32]. The second and third terms represents the operation cost of DG and RES, and the last two terms are the cost of trading with the DSO.

$$minC^{i}_{VPP,k} = \Delta T.\sum_{t=1}^{T} -U^{DR}_{k}(P^{DR}_{k,t}) + F^{DG}_{k}(P^{DG}_{k,t}) + c^{RES}_{k}.P^{RES}_{k,t}+ (\pi^{P}_{k,t}.P^{VPP}_{k,t} + \pi^{Q}_{k,t}.Q^{VPP}_{k,t}) \tag{38}$$

$$U^{DR}_{k}(P^{DR}_{k,t}) = \sum_{n=1}^{N^{DR,seg}_{k}} d_{k,n}.P^{DR}_{k,n,t} \tag{39}$$

3.2.2. Power balance

The active and reactive power balance constraint should be satisfied for each VPP as presented in (40) and (41).

$$P^{VPP}_{k,t} + P^{DG}_{k,t} + P^{RES}_{k,t} = P^{PL}_{k,t} + P^{DR}_{k,t} + P^{AGG}_{k,t} + P^{Fix}_{L,k,t} : \lambda^{(5)} \tag{40}$$

$$Q^{VPP}_{k,t} + Q^{DG}_{k,t} = Q^{PL}_{k,t} + Q^{DR}_{k,t} + Q^{AGG}_{k,t} + Q^{Fix}_{L,k,t} : \lambda^{(6)} \tag{41}$$

3.2.3. VPP-owned EV parking lots

Equipping EVPLs with bidirectional EV chargers is very costly for private sectors, and in most cases, the investment cost of bidirectional chargers outweighs the profit resulting from the discharging capability of the bidirectional chargers. Therefore, in this paper, it is assumed that VPP-owned EVPLs are just equipped with unidirectional chargers. As a result, the discharge power of VPP-owned EVPLs is zero, and the output power of VPP-owned EVPLs is equal to EVPL's charge power as shown in (42). Except for the mentioned point, the VPP-owned EVPLs constraints are similar to DSO-owned EVPLs, as represented in (43)–(47). It is noteworthy that $E^{arr}_{k,t}$, $E^{dep}_{k,t}$, $E^{PL,min}_{k,t}$, and $E^{PL,max}_{k,t}$ are obtained similar to the DSO-owned EVPL equations.

$$P^{PL}_{k,t} = P^{PL,ch}_{k,t} \tag{42}$$

$$E^{PL}_{k,t} = E^{PL}_{k,t-1} - E^{dep}_{k,t} + E^{arr}_{k,t} + \Delta t\eta_{ch} P^{PL,ch}_{k,t} : \lambda^{(8)} \tag{43}$$

$$0 \leq P^{PL,ch}_{k,t} \leq C^{PL,ins}_{k} \tag{44}$$

$$0 \leq P^{PL,ch}_{k,t} \leq N^{EV,par}_{k,t}(\sum_{cl} P^{ch,max}_{cl} Sh_{cl}) : \mu^{(9-)}, \mu^{(9+)} \tag{45}$$

$$E^{PL,min}_{k,t} \leq E^{PL}_{k,t} \leq E^{PL,max}_{k,t} : \mu^{(8-)}, \mu^{(8+)} \tag{46}$$

$$(P^{PL}_{k,t})^2 + (Q^{PL}_{k,t})^2 \leq (S^{PL}_{k})^2 \tag{47}$$

3.2.4. DG, RES

The operation of VPP-owned DGs and RES is similar to the DSO-owned ones as indicated in (48)–(52).

$$P^{DG}_{k,t} = \sum_{n=1}^{N^{DG,seg}_{k}} P^{DG}_{k,n,t} : \lambda^{(1)} \tag{48}$$

$$P^{DG}_{k,n,t} \geq P^{DG,min}_{k,n}, P^{DG}_{k,n,t} \leq P^{DG,max}_{k,n} : \mu^{(1-)}, \mu^{(1+)} \tag{49}$$

$$\Delta^{DG,min}_{k} \leq P^{DG}_{k,t} - P^{DG}_{k,t-1} \leq \Delta^{DG,max}_{k,n} : \mu^{(7-)}, \mu^{(7+)} \tag{50}$$

$$(P^{DG}_{k,t})^2 + (Q^{DG}_{k,t})^2 \leq (S^{DG}_{k})^2 \tag{51}$$

$$0 \leq P^{RES}_{k,t} \leq \bar{P}^{RES,f}_{k,t} + \sigma^{f}_{k,t}.\Phi^{-}_{a}1(1-\eta) : \mu^{(4)} \tag{52}$$

3.2.5. DR aggregator

The operation of the DR aggregator is formulated in (53)–(55) where $\rho_{DR,N}$ is the constant power factor of DR.

$$P^{DR}_{k,n,t} \geq P^{DR,min}_{k,n}, P^{DR}_{k,n,t} \leq P^{DR,max}_{k,n} : \mu^{(3-)}, \mu^{(3+)} \tag{53}$$

$$P^{DR}_{k,t} = \sum_{n=1}^{N^{DR,seg}_{k}} P^{DR}_{k,n,t} : \lambda^{(2)} \tag{54}$$

$$\zeta_{DR,N} = tan(arccos(\rho_{DR,N})) = \frac{Q^{DR}_{k,t}}{P^{DR}_{k,t}} : \lambda^{(3)} \tag{55}$$

3.2.6. Flexible load aggregator

Other flexible loads of VPPs are modelled as indicated in (56)–(59).

$$P^{AGG}_{k,t} \geq P^{AGG,min}_{k}, P^{AGG}_{k,t} \leq P^{AGG,max}_{k} \tag{56}$$

$$(T^{AGG}_{start,k} \leq t \leq T^{AGG}_{end,k}) : \mu^{(5-)}, \mu^{(5+)} \tag{57}$$

$$E^{AGG}_{k} = \Delta T.\sum_{t=T^{AGG}_{start,k}}^{T^{AGG}_{end,k}} P^{AGG}_{k,t} : \lambda^{(7)} \tag{58}$$

$$\zeta_{AGG,N} = tan(arccos(\rho_{AGG,N})) = \frac{Q^{AGG}_{k,t}}{P^{AGG}_{k,t}} : \lambda^{(4)} \tag{59}$$

3.2.7. VPP power exchange

VPPs are limited for trading active and reactive power with the DSO due to the limitation of the connecting line (60).

$$(P^{VPP}_{k,t})^2 + (Q^{VPP}_{k,t})^2 \leq (S^{VPP}_{k})^2 \tag{60}$$

4. Model simplification

4.1. Linearization of quadratic constraints

The quadratic constraints in the lower level of the problem add non-linearity to the problem which may lead to non-convexity when transforming the bilevel model to the equivalent single-level model. Therefore, the linearization approach presented in [33] is deployed. In this approach, the surrounding of the feasible region of quadratic constraints that is a circle is approximated with a polygon with the desired number of line segments. Therefore, a set of linear constraints stands for the quadratic constraint as presented in (61)–(63).

$$\begin{bmatrix} e^{PL}_{1,1} & e^{PL}_{1,2} \\ \vdots & \vdots \\ e^{PL}_{N_{seg},1} & e^{PL}_{N_{seg},2} \end{bmatrix} \begin{bmatrix} P^{PL}_{k,t} \\ Q^{PL}_{k,t} \end{bmatrix} \leq S^{PL}_{k} \begin{bmatrix} f^{PL}_{1} \\ \vdots \\ f^{PL}_{N_{seg}} \end{bmatrix} : \mu^{(10)} \tag{61}$$

$$\begin{bmatrix} e^{VPP}_{1,1} & e^{VPP}_{1,2} \\ \vdots & \vdots \\ e^{VPP}_{N_{seg},2} & e^{VPP}_{N_{seg},2} \end{bmatrix} \begin{bmatrix} P^{VPP}_{k,t} \\ Q^{VPP}_{k,t} \end{bmatrix} \leq S^{VPP} \begin{bmatrix} f^{VPP}_{1} \\ \vdots \\ f^{VPP}_{N_{seg}} \end{bmatrix} : \mu^{(6)} \tag{62}$$

$$\begin{bmatrix} e^{DG}_{1,1} & e^{DG}_{1,2} \\ \vdots & \vdots \\ e^{DG}_{N_{seg},2} & e^{DG}_{N_{seg},2} \end{bmatrix} \begin{bmatrix} P^{DG}_{t} \\ Q^{DG}_{t} \end{bmatrix} \leq S^{DG} \begin{bmatrix} f^{DG}_{1} \\ \vdots \\ f^{DG}_{N_{seg}} \end{bmatrix} : \mu^{(2)} \tag{63}$$

4.2. Equivalent single-level model of problem

To solve the bilevel optimization problem it is required to convert the problem to a single-level problem. As the lower-level problem is a linear and convex optimization, the process of transforming the bilevel to single-level optimization is done by writing the KKT optimality condition of the lower-level problem as indicated in (64)–(65)

$$\frac{\partial L}{\partial P^{VPP}_{k,t}} = \Delta T.\pi^{P}_{k,t} - \lambda^{(5)}_{k,t} + \sum_{m=1}^{N_{seg}} \mu^{(6)}_{k,m,t}.e^{VPP}_{m,1} \tag{64a}$$

$$\frac{\partial L}{\partial P^{PL,ch}_{k,t}} = \Delta T.\pi^{P}_{k,t} - \Delta T.\lambda^{(8)}_{k,t}.\eta_{ch} + \sum_{m=1}^{N_{seg}} \mu^{(10)}_{k,m,t}.e^{PL}_{m,1} + \mu^{(9+)}_{k,t} - \mu^{(9-)}_{k,t} + \lambda^{(5)}_{k,t} \tag{64b}$$

$$\frac{\partial L}{\partial P^{DG}_{k,t}} = \lambda^{(1)}_{k,t} - \lambda^{(5)}_{k,t} + \sum_{m=1}^{N_{seg}} \mu^{(2)}_{k,m,t}.e^{DG}_{m,1} - \mu^{(7-)}_{k,t} + \mu^{(7+)}_{k,t} + \mu^{(7-)}_{k,t+1} - \mu^{(7+)}_{k,t+1} \tag{64c}$$

$$\frac{\partial L}{\partial P^{DG}_{k,n,t}} = \Delta T.c_{k,n} - \lambda^{(1)}_{k,t} - \mu^{(1-)}_{k,n,t} + \mu^{(1+)}_{k,n,t} \tag{64d}$$

$$\frac{\partial L}{\partial P^{RES}_{k,t}} = \Delta T.c^{(RES)}_{k} - \lambda^{(5)}_{k,t} - \mu^{(4-)}_{k,t} + \mu^{(4+)}_{k,t} \tag{64e}$$

$$\frac{\partial L}{\partial P^{DR}_{k,t}} = \lambda^{(2)}_{k,t} + \lambda^{(3)}_{k,t}\zeta_{DR,N} + \lambda^{(5)}_{k,t} \tag{64f}$$

$$\frac{\partial L}{\partial P^{DR}_{k,n,t}} = -\Delta T.d_{k,n} - \lambda^{(2)}_{k,t} - \mu^{(3-)}_{k,n,t} + \mu^{(3+)}_{k,n,t} \tag{64g}$$

$$\frac{\partial L}{\partial P^{AGG}_{k,t}} = \lambda^{(4)}_{k,t}\zeta_{AGG,N} + \lambda^{(5)}_{k,t} - \lambda^{(7)}_{k}.\Delta T - \mu^{(5-)}_{k,t} + \mu^{(5+)}_{k,t} \tag{64h}$$

$$\frac{\partial L}{\partial Q^{VPP}_{k,t}} = \Delta T.\pi^{Q}_{k,t} - \lambda^{(6)}_{k,t} + \sum_{m=1}^{N_{seg}} \mu^{(6)}_{k,m,t}.e^{VPP}_{m,2} \tag{64i}$$

$$\frac{\partial L}{\partial Q^{PL}_{k,t}} = \Delta T.\pi^{Q}_{k,t} + \sum_{m=1}^{N_{seg}} \mu^{(10)}_{k,m,t}.e^{PL}_{m,2} + \lambda^{(6)}_{k,t} \tag{64j}$$

$$\frac{\partial L}{\partial Q^{DG}_{k,t}} = -\lambda^{(6)}_{k,t} + \sum_{m=1}^{N_{seg}} \mu^{(2)}_{k,m,t}.e^{DG}_{m,2} \tag{64k}$$

$$\frac{\partial L}{\partial Q^{DR}_{k,t}} = -\lambda^{(3)}_{k,t} + \lambda^{(6)}_{k,t} \tag{64l}$$

$$\frac{\partial L}{\partial Q^{AGG}_{k,t}} = -\lambda^{(4)}_{k,t} + \lambda^{(6)}_{k,t} \tag{64m}$$

$$\frac{\partial L}{\partial E^{PL}_{k,t}} = \lambda^{(8)}_{k,t} - \lambda^{(8)}_{k,t+1} - \mu^{(8-)}_{k,t} + \mu^{(8+)}_{k,t} \tag{64n}$$

$$P^{DR}_{k,t} + P^{AGG}_{k,t} + P^{Fix}_{L,k,t} + P^{PL,ch}_{k,t} - P^{VPP}_{k,t} - P^{DG}_{k,t} - P^{RES}_{k,t} = 0 \tag{65a}$$

$$Q^{DR}_{k,t} + Q^{AGG}_{k,t} + Q^{Fix}_{L,k,t} + Q^{PL}_{k,t} - Q^{VPP}_{k,t} - Q^{DG}_{k,t} = 0 \tag{65b}$$

$$P^{DG}_{k,t} - \sum_{n=1}^{N_k^{DG,seg}} P^{DG}_{k,n,t} = 0 \tag{65c}$$

$$P^{DR}_{k,t} - \sum_{n=1}^{N_k^{DR,seg}} P^{DR}_{k,n,t} = 0 \tag{65d}$$

$$\zeta_{DR,N}.P^{DR}_{k,t} - Q^{DR}_{k,t} = 0 \tag{65e}$$

$$zeta_{AGG,N}.P^{AGG}_{k,t} - Q^{AGG}_{k,t} = 0 \tag{65f}$$

$$E^{AGG}_{k} - \Delta T.\sum_{t=T^{AGG}_{start,k}}^{T^{AGG}_{end,k}} P^{AGG}_{k,t} = 0 \tag{65g}$$

$$SOE^{PL,min}_{k,t} - E^{PL}_{k,t} \le 0 \tag{66a}$$

$$E^{PL}_{k,t} - SOE^{PL,max}_{k,t} \le 0 \tag{66b}$$

$$-\ P^{PL}_{k,t} \le 0 \tag{66c}$$

$$P^{PL}_{k,t} - P^{ch,PL,max}_{k,t} \le 0 \tag{66d}$$

$$P^{DG,min}_{k,n} - P^{DG}_{k,n,t} \le 0 \tag{66e}$$

$$P^{DG}_{k,n,t} - P^{DG,max}_{k,n} \le 0 \tag{66f}$$

$$\Delta^{DG,min}_{k} - P^{DG}_{k,t} - P^{DG}_{k,t-1} \le 0 \tag{66g}$$

$$P^{DG}_{k,t} - P^{DG}_{k,t-1} - \Delta^{DG,max}_{k,n} \le 0 \tag{66h}$$

$$-\ P^{RES}_{k,t} \le 0 \tag{66i}$$

$$P^{RES}_{k,t} - \bar{P}^{RES}_{k,t} + \sigma^{f}_{k,t}.\Phi^{-}_{a}1(1-\eta) \le 0 \tag{66j}$$

$$P^{DR,min}_{k,n} - P^{DR}_{k,n,t} \le 0 \tag{66k}$$

$$P^{DR}_{k,n,t} - P^{DR,max}_{k,n} \le 0 \tag{66l}$$

$$P^{AGG,min}_{k} - P^{AGG}_{k,t} \le 0 \tag{66m}$$

$$P^{AGG}_{k,t} - P^{AGG,max}_{k} \le 0 \tag{66n}$$

$$e^{DG}_{m,1}.P^{DG}_{k,m,t} + e^{DG}_{m,2}.Q^{DG}_{k,m,t} - S^{DG}_{k,N}.f^{DG}_{m} \le 0 \tag{66o}$$

$$e^{VPP}_{m,1}.P^{VPP}_{k,m,t} + e^{VPP}_{m,2}.Q^{VPP}_{k,m,t} - S^{VPP}_{k,N}.f^{VPP}_{m} \le 0 \tag{66p}$$

$$\mu^{(8-)}_{k,t}.(SOE^{PL,min}_{k,t} - E^{PL}_{k,t}) = 0 \tag{67a}$$

$$\mu^{(8+)}_{k,t}.(E^{PL}_{k,t} - SOE^{PL,max}_{k,t}) = 0 \tag{67b}$$

$$\mu^{(9-)}_{k,t}.P^{PL}_{k,t} = 0 \tag{67c}$$

$$\mu^{(9+)}_{k,t}.(P^{PL}_{k,t} - P^{ch,PL,max}_{k,t}) = 0 \tag{67d}$$

$$\mu^{(1-)}_{k,n,t}.(P^{DG,min}_{k,n} - P^{DG}_{k,n,t}) = 0 \tag{67e}$$

$$\mu^{(1+)}_{k,n,t}.(P^{DG}_{k,n,t} - P^{DG,max}_{k,n}) = 0 \tag{67f}$$

$$\mu^{(7-)}_{k,t}.(\Delta^{DG,min}_{k} - P^{DG}_{k,t} + P^{DG}_{k,t-1}) = 0 \tag{67g}$$

$$\mu^{(7+)}_{k,t}.(P^{DG}_{k,t} - P^{DG}_{k,t-1} - \Delta^{DG,max}_{k,n}) = 0 \tag{67h}$$

$$\mu^{(4-)}_{k,t}.(-P^{RES}_{k,t}) = 0 \tag{67i}$$

$$\mu^{(4+)}_{k,t}.(P^{RES}_{k,t} - \bar{P}^{RES}_{k,t} + \sigma^{f}_{k,t}.\Phi^{-}_{a}1(1-\eta)) = 0 \tag{67j}$$

$$\mu^{(3-)}_{k,n,t}.(P^{DR,min}_{k,n} - P^{DR}_{k,n,t}) = 0 \tag{67k}$$

$$\mu^{(3+)}_{k,n,t}.(P^{DR}_{k,n,t} - P^{DR,max}_{k,n}) = 0 \tag{67l}$$

$$\mu^{(5-)}_{k,t}.(P^{AGG,min}_{k} - P^{AGG}_{k,t}) = 0 \tag{67m}$$

$$\mu^{(5+)}_{k,t}.(P^{AGG}_{k,t} - P^{AGG,max}_{k}) = 0 \tag{67n}$$

$$\mu^{(2)}_{k,m,t}.(e^{DG}_{m,1}.P^{DG}_{k,m,t} + e^{DG}_{m,2}.Q^{DG}_{k,m,t} - S^{DG}_{k,N}.f^{DG}_{m}) = 0 \tag{67o}$$

$$\mu^{(6)}_{k,m,t}.(e^{VPP}_{m,1}.P^{VPP}_{k,m,t} + e^{VPP}_{m,2}.Q^{VPP}_{k,m,t} - S^{VPP}_{k,N}.f^{VPP}_{m}) = 0 \tag{67p}$$

$$\mu^{(10)}_{k,m,t}.(e^{PL}_{m,1}.P^{PL}_{k,m,t} + e^{PL}_{m,2}.Q^{PL}_{k,m,t} - S^{PL}_{k,N}.f^{PL}_{m}) = 0 \tag{67q}$$

$$\mu^{(1-)}_{k,n,t}, \mu^{(1+)}_{k,n,t}, \mu^{(2)}_{k,m,t}, \mu^{(3-)}_{k,n,t}, \mu^{(3+)}_{k,n,t}, \mu^{(4-)}_{k,t}, \mu^{(4+)}_{k,t}, \mu^{(5-)}_{k,t}, \mu^{(5+)}_{k,t}, \mu^{(6)}_{k,m,t}, \mu^{(7-)}_{k,t}, \mu^{(7+)}_{k,t}, \mu^{(8-)}_{k,t}, \mu^{(8+)}_{k,t}, \mu^{(9-)}_{k,t}, \mu^{(9+)}_{k,t}, \mu^{(10)}_{k,m,t} \ge 0 \tag{68}$$

It is worth mentioning that $\lambda^{(1-8)}$ are the Lagrange multiplier of the equality constraints (48), (54), (55), (59), (40), (41), (58), and (43), respectively. Moreover, $\mu^{(1-10)}$ are corresponding to inequality constraints (49), (63), (53), (52), (57), (62), (50), (46), (45), and (61). Therefore, (38)–(60) are replaced with the constraints resulting from the KKT condition presented in (64)–(68) and a single-level optimization is shaped to be solved.

4.3. Removing the non-linearity resulted from bilinear terms in constraints

To discard the non-linearity of bilinear terms in (67) and (27), the Fortuny-Amat transformation presented in [31] is deployed.

4.4. Bilinear terms in objective function

The objective function of the equivalent single-level problem consists of bilinear terms ($k^P_t P^{DN}_t$ and $k^Q_t Q^{DN}_t$) in which two variables of the problem are multiplied. Indeed, P^{DN}_t and Q^{DN}_t are the parameters of the upper-level problem and decision variables of the lower-level problem. However, when transforming the bilevel optimization to the single-level optimization, it is a decision variable of the equivalent single-level problem. Therefore, via the strong duality theorem, the dual objective function of the lower-level problem is used instead of the bilinear terms as represented in (69).

$$\Delta T.\sum_{t=1}^{T}(\pi^{P}_{k,t}.P^{VPP}_{k,t} + \pi^{Q}_{k,t}.Q^{VPP}_{k,t}) = \Delta T.\sum_{t=1}^{T}$$

$$
\begin{aligned}
&(U_k^{DR}(P_{k,t}^{DR}) - F_k^{DG}(P_{k,t}^{DG}) - c_k^{RES}.P_{k,t}^{RES}) + C_{VPP,k}^{i} \\
&= \Delta T.\sum_{t=1}^{T}(\sum_{n=1}^{N_k^{DR,seg}} d_{k,n}.P_{k,n,t}^{DR} \\
&- \sum_{n=1}^{N_i^{DG,seg}} c_{i,n}.P_{i,n,t}^{DG} - c_k^{RES}.P_{k,t}^{RES}) \\
&+ \sum_{t=1}^{T} \lambda_{k,t}^{(5)} P_{L,k,t}^{Fix} + \sum_{t=1}^{T} \lambda_{k,t}^{(6)} Q_{L,k,t}^{Fix} \\
&+ \lambda_k^{(7)} E_k^{AGG} + \sum_{t=1}^{T} \lambda_{k,t}^{(8)} (E_{k,t}^{arr} - E_{k,t}^{dep}) \\
&+ \sum_{t=1}^{T} \sum_{n=1}^{N_k^{DG,seg}} \mu_{k,n,t}^{(1-)}.P_{k,n}^{DG,min} + \mu_{k,n,t}^{(1+)}.(-P_{k,n}^{DG,max}) \\
&+ \sum_{t=1}^{T} \sum_{n=1}^{N_{seg}} \mu_{k,m,t}^{(2)} (-S_{k,N}^{DG} f_m^{DG}) \\
&+ \sum_{t=1}^{T} \sum_{n=1}^{N_k^{DR,seg}} \mu_{k,n,t}^{(3-)}.P_{k,n}^{DR,min} + \mu_{k,n,t}^{(3+)}.(-P_{k,n}^{DR,max}) \\
&+ \sum_{t=1}^{T} \mu_{k,t}^{(4+)}.(-\bar{P}_{k,t}^{RES} + \sigma_{k,t}^{f}.\Phi_a^{-}1(1-\eta)) \\
&+ \sum_{t=T_{start,k}^{AGG}}^{T_{end,k}^{AGG}} \mu_{k,t}^{(5-)}.(P_k^{AGG,min}) + \mu_{k,t}^{(5+)}.(-P_k^{AGG,max}) \\
&+ \sum_{t=1}^{T} \sum_{n=1}^{N_{seg}} \mu_{k,m,t}^{(6)} (-S_{k,N}^{VPP} f_m^{VPP}) \\
&+ \sum_{t=2}^{T} \mu_{k,t}^{(7-)}.\Delta_k^{DG,min} + \mu_{k,t}^{(7+)}.(-\Delta_{k,n}^{DG,max}) \\
&+ \sum_{t=1}^{T} \mu_{k,t}^{(8-)}.SOE_{k,t}^{PL,min} + \mu_{k,t}^{(8+)}.(-SOE_{k,t}^{PL,max}) \\
&+ \sum_{t=1}^{T} \mu_{k,t}^{(9+)}.(-P_{k,t}^{ch,PL,max}) \\
&+ \sum_{t=1}^{T} \sum_{n=1}^{N_{seg}} \mu_{k,m,t}^{(10)} (-S_{k,N}^{PL} f_m^{VPP})
\end{aligned} \tag{69}
$$

By replacing (69) with the mentioned bilinear term in the objective function of the upper-level problem (1), a linear optimization problem is obtained that can be handled with mixed integer linear programming (MILP). The MILP problem is solved via Gorubi solver in Python.

5. Simulation results

5.1. Case study

We used the case study described in [9] as a basis for our research. However, a modification is made to the system by integrating EVPLs, as shown in Fig. 2. The location of the RES, DG, and VPPs is similar to the real-case distribution system used in [9]. However, the EVPLs are placed randomly in different buses of the system. This paper considers the presence of 10 classes of EVs with the characteristics including the battery capacity, arrival SOC, and maximum charging power of EVs outlined in Table 2, each with an equal share. Moreover, SOC_{cl}^{dep} of all EV classes are 0.85 and for DSO-owned EVPLs $P_{cl}^{dc,max}$ is equal to $P_{cl}^{ch,max}$. Additionally, as mentioned in the previous section, the uncertainty of the arrival and departure of EVs is modelled via TND. The parameters of the TND for arrival and departure are defined in Table 3. Furthermore, the values for the characteristics of the chance-constrained formulation of the uncertain available RES power are as follows: $\sigma_{i,t}^{f}$ is 10% of the forecasted RES power at that hour, and η is equal to 0.9. It is assumed that all EVPLs consist of 300 charging stations. Python is used for programming and Gurobi solver is utilized for solving the optimization problem, which is formulated as a Mixed-Integer Linear Programming (MILP) problem.

Table 2
EV classes and characteristics.

cl	1	2	3	4	5	6	7	8	9	10
Cap_{cl}	15	20	20	15	20	15	10	10	15	20
SOC_{cl}^{arr}	0.33	0.33	0.16	0.4	0.1	0.45	0.5	0.2	0.33	0.2
$P_{cl}^{ch,max}$	7	10	10	7	10	7	5	5	7	10

Table 3
TND characteristics of EVLPS.

	Min	Max	Average	Standard deviation
Arrival	5	17	8	3
Departure	11	24	16	3

5.2. Operation results of the DSO

As stated in previous sections, the DSO is in charge of determining the operation schedule of its assets. Fig. 3 shows the active and reactive power of DSO-owned DGs as well as the output power and state of energy of DSO-owned ESS. This way, the charging and discharging of the ESS system is managed based on the power price where charging is scheduled in the low-price hours and discharging is scheduled in high-price hours. Moreover, the operation of the DGs is managed based on the system's needs to provide active and reactive power in the bus where DGs are located. It is noteworthy that the active and reactive power of each DG is constrained by its rated capacity where the output active and reactive power generation is linked together. Furthermore, the available and scheduled power of DSO-owned RES is shown in Fig. 4(a) and (b). It is observed that, in all hours, the complete available RES generation is deployed. The output power and the containing energy of the DSO-owned EVPLs are depicted in Fig. 6(a) and (c), respectively. It is observed that, owing to the bidirectional EV chargers, EVPLs can operate the EVs in the V2G mode when required. In this way, EVPL 3, tend to deploy the V2G mode more than the others because of the system needs and lack of crucial grid limitation in bus 3. It should be noted that the discharging and charging profile that results in the containing energy of the EVPL satisfies the arrival and departure pattern of the EVs where the departed EVs are fully charged (with their desired SOC) upon their departure.

As mentioned in the previous sections, DSO, in addition to managing its flexible resources, is in charge of determining active and reactive power prices in the distribution system, as shown in Fig. 5(a) and (b). In this regard, the DSO is able to define different prices for VPPs located in different parts of the distribution system based on the nodal pricing scheme. This way, it is observed that the prices for different VPPs are different. The reason behind this price difference is that the distribution system prefers to have different amounts of active and reactive power in different parts of the system from VPPs due to the dissimilar generation and consumption profiles and grid constraints. In this regard, by determining different prices, the DSO motivates VPPs to operate according to the DSO's desired state. This way, the DSO has a sort of indirect control over VPPs' operation. The stable and reliable system operation is ensured as shown in Fig. 8 where the voltage and power flow all over the grid is within the permitted range.

5.3. Operation results of VPPs

Besides active power, VPPs also consume reactive power. However, owing to the DGs and EVPLs they can also provide positive (consumption) or negative (injection) reactive power for the system. This way,

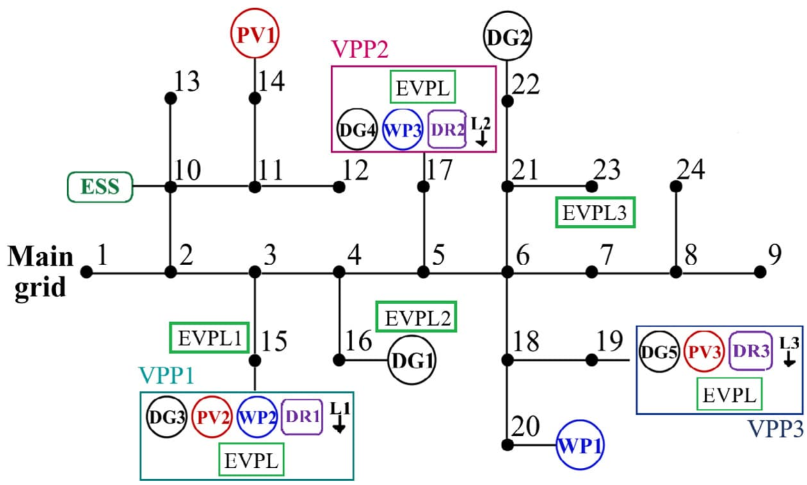

Fig. 2. Studied system.

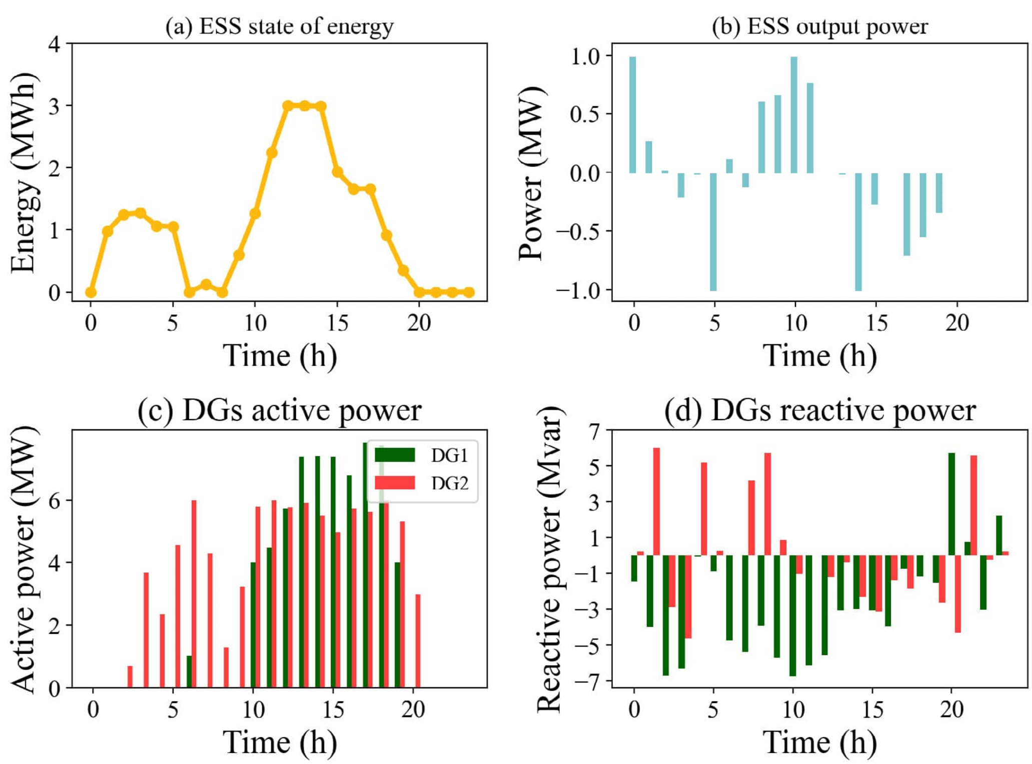

Fig. 3. Operation of DSO-owned assets.

they can benefit from this capability in the reactive market. This way, VPPs, by managing the active and reactive power of their flexible resources and loads, optimize their participation in active and reactive markets at once to have the minimum overall cost as shown in Fig. 5(c) and (d). It is worth mentioning that the limited nominal capacity of their assets links the active and reactive power management of VPPs. This way, the consumption and generation of the VPP-owned assets are scheduled according to the hourly active and reactive prices defined by the DSO. In the results, it is observed that all VPPs can deploy the whole available power of their RES without curtailment, as shown in Fig. 4(c), (d), and (e). Furthermore, the charging power and containing energy of VPP-owned EVPLs are shown in Fig. 6(b) and (d). Despite the DSO-owned EVPLS, VPP-owned EVPLs can just operate in the G2V charging mode as they are equipped with unidirectional EV chargers. The results show that the charging profile of the EVPLs is different for different VPPs as a result of the different active and reactive power prices as well as different operational limits.

5.4. Impact of the nodal pricing of local reactive and active power market

The DSO can define a unique price for VPPs all over the distribution system or determine the prices via nodal pricing where the price for active and reactive power is different for VPPs located in different buses. Table 4 presents the DSO cost in different cases for local active and reactive market pricing scheme. The lowest DSO cost is obtained when both active and reactive power prices are based on nodal pricing as depicted in Fig. 7. When just the active power price is determined based on the nodal pricing and a unique price is determined for reactive power there is 156 € increase in the DSO's cost. The DSO's cost when a unique price is determined for the active power of VPPs is 298

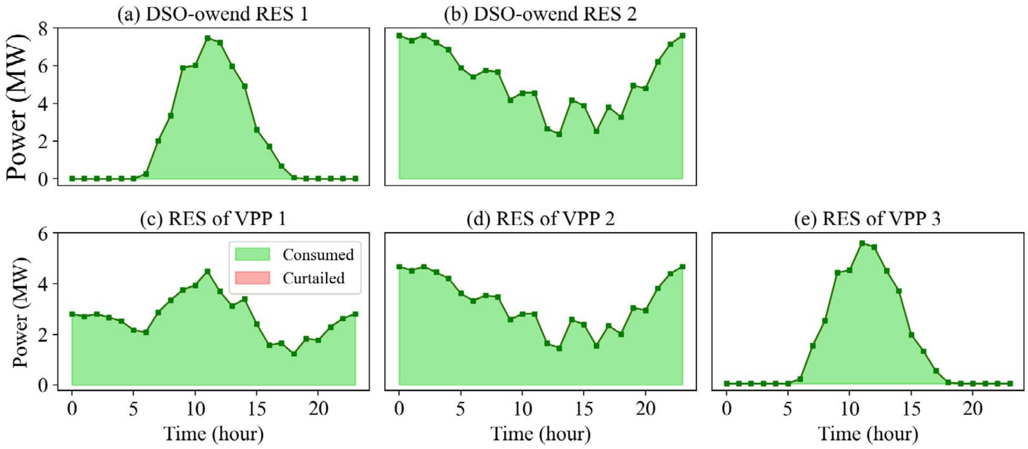

Fig. 4. RES curtailment.

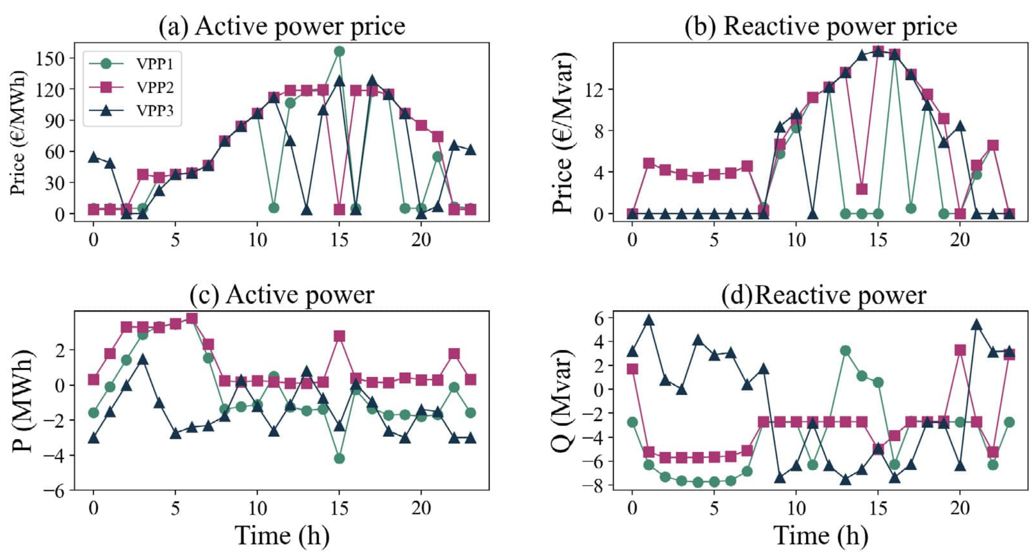

Fig. 5. Reactive and active power price for different VPPs and their consumption.

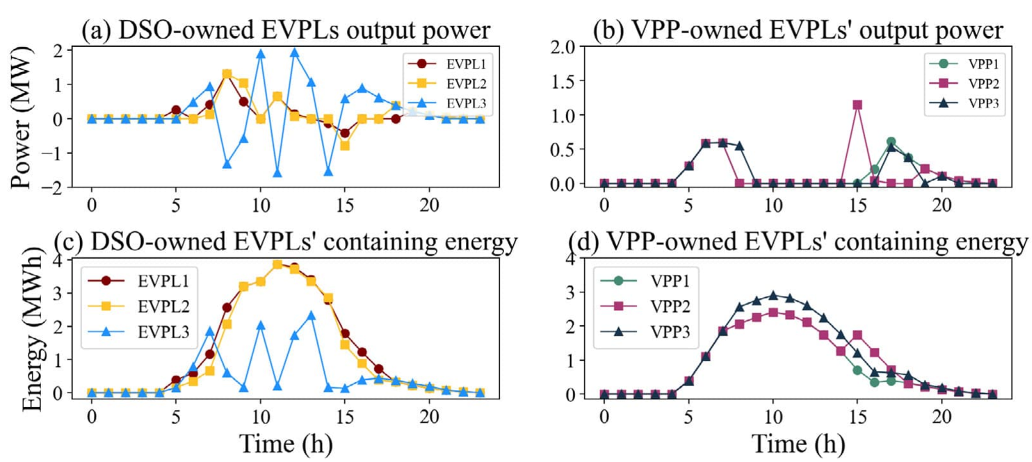

Fig. 6. The power output and containing the energy of VPP-owned EVPLs.

€ higher than case A. Finally, when none of the active and reactive power prices are determined by nodal pricing, the DSO's cost is 462 € higher than case A. The results show the effectiveness of our local market clearing via nodal pricing scheme in decreasing the cost of the distribution system. In other words, deploying the presented nodal pricing scheme for both the active and reactive power prices results in 462 € cost decrease for the DSO which is equivalent to around 4.6% profit compared to the case when nodal pricing scheme is not deployed.

Table 4
Cost of the DSO in cases A, B, C, and D (€).

Case	Nodal pricing in LAPM	Nodal pricing in LRPM	DSO cost
Case A	✓	✓	9512
Case B	✓	✘	9668
Case C	✘	✓	9810
Case D	✘	✘	9974

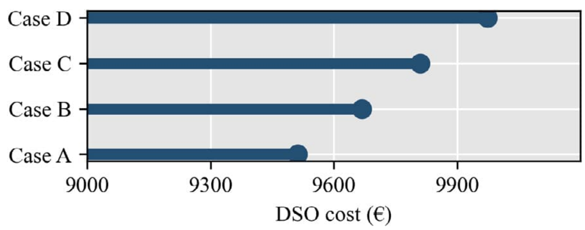

Fig. 7. Cost of the DSO in cases A, B, C, and D (€).

Table 5
Cost of the DSO in cases 1, 2, 3, and 4 (€).

Case	Reactive power	V2G charging	DSO cost
Case 1	✘	✘	9741
Case 2	✘	✓	9513
Case 3	✓	✘	9289
Case 4	✓	✓	9143

5.5. Impact of V2G charging and reactive power support from DSO-owned EVPLs

In almost all problems regarding the distribution system management, both voltage and line power constraints are established with identical limits. Nevertheless, the influence of these constraints on restricting the optimal operating point varies depending on the approach. Deploying RPS and employing V2G operation alleviate the impact of voltage and line power constraints on the optimal operating point. This is evident in the reduced overall cost of the distribution system. Deploying V2G charging from EVPLs is beneficial for the DSO according to the simulation results as presented in Table 5. It is observed that the DSO cost in case 2 where the DSO-owned EVPL can operate in V2G charging is around 2.34% less than in case 1 where the EVPL can only operate in G2V mode. Moreover, the benefit of deploying reactive power provision by EVPLs for the DSO is understood by comparing the cost of DSO for cases 1 and 3. The results show that RPS from DSO-owned EVPLs can decrease the DSO's cost by around 4.64%. It is shown that the DSO by deploying the V2G charging and RPS capability, as stated in case 4, can reduce its cost by 598 € which is equal to around 6.14% profit compared to case 1. Besides reducing the DSO's cost, RPS from EVPLs can improve the operational condition of the network in terms of voltage and branch flow. Voltage and branch flow of the system with and without RPS from DSO-owned EVPLs are shown in Figs. 8 and 9, respectively.

In order to gain a deeper comprehension of how RPS from EVPLs improves the system operation, the voltage of bus 17 (as one of the critical buses when there is a lack of RPS from DSO-owned EVPLs) has been depicted in Fig. 10(a). It is observed how RPS from EVPLs can improve the voltage of this bus by decreasing its difference with the reference voltage (equal to 1 pu). Moreover, by comparing the power flow of the line between the DS and upstream grid for the systems with and without RPS from EVPLS depicted in Fig. 10(a), it is observed that RPS via voltage improvement within the network allows for deploying a higher capacity of the line to increase the trade with the upstream grid in both directions that leads to decreasing the DS cost. This way, enhanced voltage condition alleviates constraints on determining active power consumption/generation resulting in facilitating increased trade with the upstream grid.

Table 6
Cost of VPPs in cases α, β, and γ (€).

Case	VPP1 cost	VPP2 cost	VPP3 cost
Case α	−3331	−4852	−3198
Case β	−2358	−5392	−3382
Case γ	−2842	−4562	−4128

To further investigate the role of RPS from DSO-owned EVPLs in improving the system voltage, another analysis is conducted in this section. As stated above, voltage constraint restricts the DSO from making the optimal decision for the system which leads to higher cost. Therefore, in cases where the voltage constraint is alleviated, the system could be operated with less cost. However, the overall voltage deviation within the network is increased by alleviating the voltage constraint. To evaluate the total voltage deviation within the DS, the voltage deviation (VD) index below is used that measures the summation of the absolute value of the difference between the bus voltage and reference voltage for all buses and hours as presented in Eq. (70). Our results show that with having RPS from EVPLs, when the maximum allowed voltage deviation is 0.05 (upper voltage limit equal to 1.05 and lower voltage limit equal to 0.95), the system cost is 9143 and the VD index is 16.73. However, in the case that there is no RPS from EVPLs, to have the system operation cost equal to 9143, the maximum allowed voltage deviation must be 0.0637 (upper voltage limit equal to 1.0637 and lower voltage limit equal to 0.9363) with a VD equal to 19.961. Therefore, by deploying RPS from DSO-owned EVPL's maximum allowed voltage deviation of the system could be reduced by 18%.

$$VD = \sum_{t} \sum_{bus} |V_i - 1| \tag{70}$$

5.6. Reactive power support from VPP-owned EVPLs

When EVPLs cannot provide positive and negative reactive power, the pricing strategy of the DSO differs. As a consequence, the response (scheduled active and reactive power) of VPPs varies as shown in Fig. 11. Comparing Fig. 12 and Fig. 4 shows the role of reactive power from EVPLs in improving the system operation and RES utilization. It is seen that when EVPLs can provide reactive power, there is no RES curtailment. This way, EVs that generally can make operational challenges for the DSO, improve the system operation by providing RPS. In this regard, three cases α, β, and γ are introduced to assess the benefit of reactive power provision capability for each VPP based on the VPP's cost in the cases, as outlined in Table 6. In case α, except EVPL of VPP1, none of the EVPLs in the system can provide reactive power. In case β among all EVPLs only EVPL of VPP2 can provide reactive power, and in case γ, only the EVPL of VPP3 can provide reactive power. The results show that in case α, the cost of VPP1 is lower compared to case β and case γ. Likewise, the VPP2 and VPP3 have a lower cost in the scenarios where their EVPL is the reactive power provider. However, the benefit from the reactive power capability of EVPLs is different for each VPP according to their location and the distribution system's need for the reactive power in that bus.

5.7. Discussion on opportunities and obstacles

It is essential to recognize the limitations of such a centralized approach and potential obstacles to their implementation in real systems. Challenges include the unpredictable behaviour of VPP participants, ensuring secure access to their data, and the necessity of making optimal decisions promptly, especially for real-time applications. As delineated, the primary objective of this paper is just to design the local active and reactive power market fostering the engagement of VPPs in providing services geared towards enhancing the operation and economic

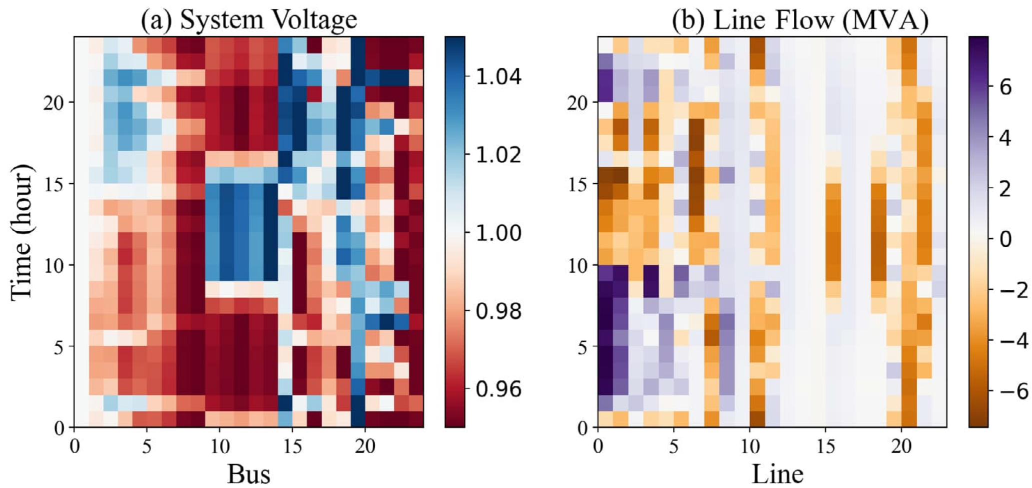

Fig. 8. Voltage and line power of the system.

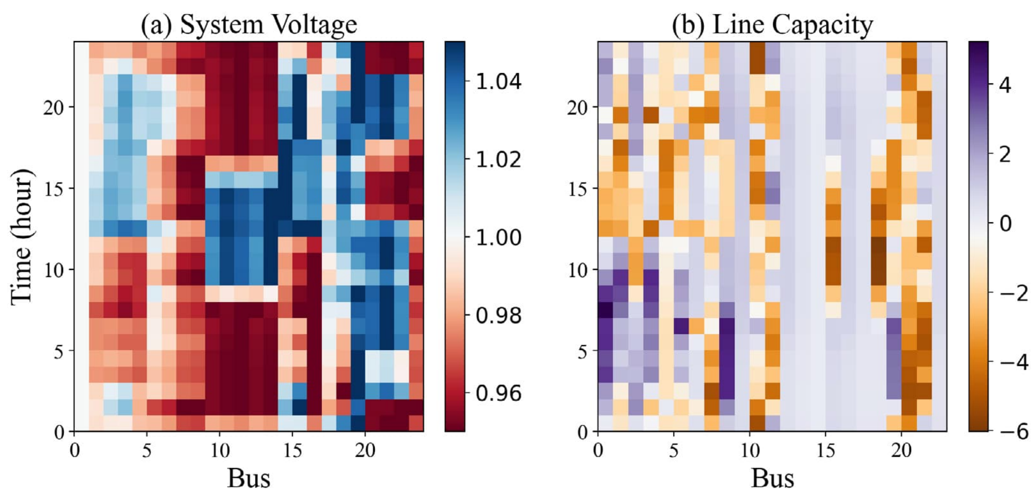

Fig. 9. Voltage and line power of the system without RPS from EVPLs.

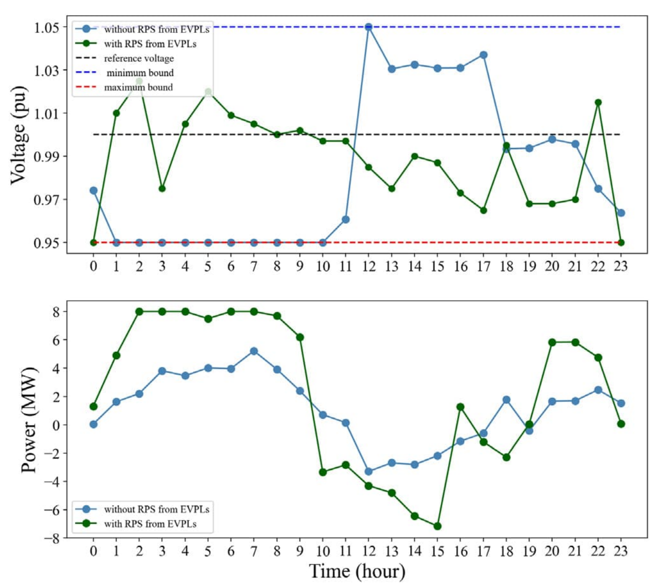

Fig. 10. (a) Voltage of bus 17 and (b) power flow between DS and upstream grid with and without RPS from EVPLs.

efficiency of ADN, focusing on the pricing mechanism within the day-ahead stage. It is imperative, however, to acknowledge that the power market constitutes a multifaceted research domain, encompassing diverse temporal scales, a variety of commodities, and communication considerations. The proposed methodology in this paper addresses the complexity of a bilevel optimization problem, involving uncertain variables, by transforming it into a deterministic MILP formulation. This transformation is achieved through the utilization of effective uncertainty modelling techniques for EVs and RES, coupled with various simplification methods. While the application of this framework is tailored for the day-ahead stage, where real-time responsiveness is not critical, it nevertheless provides fast responses, rendering it a suitable approach for large-scale systems and real-time applications. In this context, our future work will concentrate on extending the framework to couple the real-time market with the day-ahead market, encompassing services such as active and reactive power for reserve. However, the implementation of such a framework mandates a communication infrastructure ensuring the secure and efficient transmission of transaction signals during the real-time stage.

6. Conclusions

This paper proposed a bilevel optimization programming for optimal management of the distribution system based on the interaction of the DSO and the strategic VPPs through the local active and reactive power markets. The bilevel model consisting of the DSO's problem at

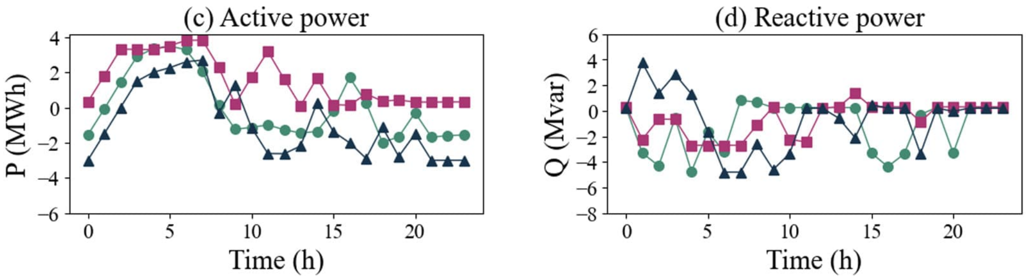

Fig. 11. Reactive and active power for different VPPs without RPS from EVPLs.

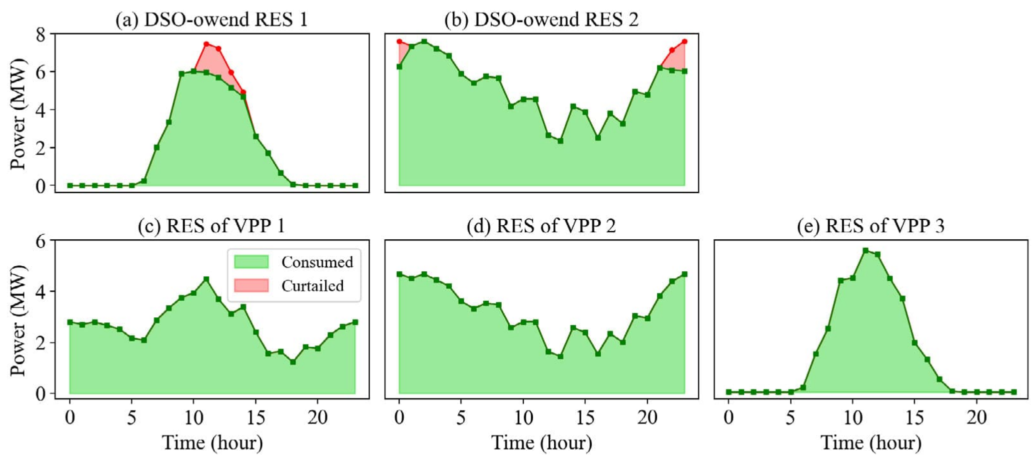

Fig. 12. RES curtailment without RPS from EVPLs.

the upper level and VPPs' problem at the lower level was transformed into a single-level optimization problem using KKT optimality conditions. Then using the strong duality theorem, piecewise linearization, and Fortuny-Amat transformation the problem was handled as a MILP problem. In this regard, it was observed that our proposed framework could ensure the optimal and stable operation of the distribution system. Our results showed that the nodal pricing scheme where the DSO defines different prices for the active and reactive power of VPPs, resulted in the lower distribution system cost. The result showed how the bidirectional EV chargers could be beneficial for the DSO to make a profit from V2G mode charging. Besides the DSO, VPPs could also benefit from the presented local market framework where their assets were scheduled based on the active and reactive prices determined by the DSO to minimize their cost strategically. In addition, the results showed that VPPs could utilize RPS from their EVPLs to reduce their cost by gaining profit in the reactive power market and facilitating their participation in the active power market via improving the local operational condition in terms of voltage and branch flow. For future work, in addition to the active and reactive power market in the day ahead stage, the role of the flexibility market will also be investigated to achieve more efficient management for the DSO.

CRediT authorship contribution statement

Mahoor Ebrahimi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mahan Ebrahimi:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis. **Miadreza Shafie-khah:** Investigation, Conceptualization, Supervision, Writing – review & editing. **Hannu Laaksonen:** Conceptualization, Supervision, Writing – review & editing.

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.

Data availability

Data will be made available on request.

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