Pourghaderi, Niloofar; Fotuhi-Firuzabad, Mahmud; Moeini-Aghtaie, Moein; Kabirifar, Milad; Lehtonen, Matti

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ORIGINAL RESEARCH

Optimal energy and flexibility self-scheduling of a technical virtual power plant under uncertainty: A two-stage adaptive robust approach

Niloofar Pourghaderi[1] | **Mahmud Fotuhi-Firuzabad**[1] | **Moein Moeini-Aghtaie**[2] | **Milad Kabirifar**[1] | **Matti Lehtonen**[3]

[1]Electrical Engineering Department, Sharif University of Technology, Tehran, Iran

[2]Department of Energy Engineering, Sharif University of Technology, Tehran, Iran

[3]Department of Electrical Engineering and Automation, Aalto University, Espoo, Finland

Correspondence
Prof. Mahmud Fotuhi-Firuzabad, Electrical Engineering Department, Sharif University of Technology, Tehran, Iran.
Email: fotuhi@sharif.edu

Abstract

This paper presents a two-stage adaptive robust optimization framework for day-ahead energy and intra-day flexibility self-scheduling of a technical virtual power plant (TVPP). The TVPP exploits diverse distributed energy resources' (DERs) flexibility capabilities in order to offer flexibility services to wholesale flexibility market as well as preserving the distribution network's operational constraints in the presence of DER uncertainties. The TVPP aims at maximizing its profit in energy and flexibility markets considering the worst-case uncertainty realization. In the proposed framework, the first stage models the TVPP's participation strategy in day-ahead energy market and determines the DERs' optimal energy dispatch. The second stage addresses the TVPP's strategy in intra-day flexibility market to determine the DERs' optimal flexibility capability provision by adjusting their energy dispatch for the worst-case realization of uncertainties. The uncertainty characteristics associated with photovoltaic units, electric vehicles, heating, ventilation and air conditioning systems, and other responsive loads as well as the transmission network's flexibility capability requests are considered using an adaptive robust approach. Adopting the duality theory, the model is formulated as a mixed-integer linear programming problem and is solved using a column-and-constraint generation algorithm. This model is implemented on a standard test system and the model effectiveness is demonstrated.

1 | INTRODUCTION

1.1 | Background and motivation

Increasing penetration of renewable energy sources (RESs) and high grow rate of electrical energy demand aggravate the uncertainty and variability in electrical energy systems [1]. Furthermore, increasing penetration of distributed energy resources (DERs) in distribution networks is the other event which would change the vision of these networks. These events can be translated to new operational challenges which should be handled by system operators and decision makers. To meet the power systems operational challenges, utilizing flexibility capabilities in power systems is taken into attention [1].

DERs can provide flexibility services due to their controllability features [2]. By appropriate aggregation and coordination of DERs, their flexibility features can be utilized to mitigate the operational challenges of distribution network as well as offering flexibility to transmission systems. These achievements can be yielded by the concept of virtual power plants (VPPs) which can aggregate and manage the flexibility of diverse small-scale DERs under their supervision [3, 4]. VPPs are categorized into commercial and technical virtual power plants (CVPPs and TVPPs, respectively); the CVPPs aggregate DERs without considering their geographical locations in the network and the impact of network constraints on the DER aggregated profile while the TVPPs consider the network operational constraints in their decision makings [5]. Therefore, the TVPPs can exploit the DERs' flexibility features to satisfy the distribution network operational constraints besides trading in wholesale market.

To efficiently manage and coordinate the DERs' flexibility capabilities, their associated uncertainties should be addressed effectively. The commonly used tools to address uncertainty sources are stochastic programming and robust optimization [6–9]. In the stochastic programming, uncertain parameters are often modelled using pre-sampling discrete scenarios by considering the probability distributions of the uncertain parameters. Using the stochastic approach, a large number of scenarios is required for accurate modelling of the uncertainty sources which cause computational complexity. Moreover, it may be difficult to identify the uncertain parameters' accurate probability distribution functions (PDFs) [6]. However, detailed probabilistic information of uncertain parameters is not required in the robust approach and it is an appropriate tool to model the uncertainty when the probability distribution of uncertain parameter is either not known or inaccurate [7]. In the robust approach, uncertain parameters can take value within the uncertainty sets and robustness of the model is determined based on uncertainty bounds and budget of uncertainties (BoUs) [8]. Constructing proper uncertainty bounds in the robust approach is usually easier than generating accurate scenarios in the stochastic programming. In addition, the robust optimization model guaranties that the solution is immunized against all the realizations of uncertainties within the uncertainty set [8, 9]. However, by using the stochastic method, the results may not be feasible for all the cases of uncertainty occurrences [8]. It should be noted that in the robust optimization approach, all the decision variables should be determined before the realization of uncertainty sources becomes known [10]. However, in the majority of the real-world problems, only a part of variables should be determined before uncertainty realizations and the others can be specified after the uncertain data become known. Therefore, authors in [10] has introduced adaptive robust optimization as an extension of the robust optimization in which two types of decisions are made; the first type of decisions should be made in the current time stage (here-and-now decision-making) and the second type of decisions can be made at a time stage in the future (wait-and-see decision-making) [8, 10]. The wait-and-see decisions can be adjusted based on the information that is not known in the current time stage, but may be learned before making decisions in the future time stage. For example, in day-ahead scheduling, the DERs' commitment statuses in each time interval are decided one day in advance as here-and-now decisions. However, the DERs' operation adjustments are determined after uncertainty realizations as wait-and-see decisions in order to cover the uncertainties. The adaptive robust optimization is less conservative than the robust optimization [10].

1.2 | Literature review

In order to exploit DERs' flexibility features, ref. [11] has modelled a distribution system operator (DSO) which schedules flexible DERs to minimize the distribution network's energy procurement cost. In [12], flexibility of responsive loads and energy storage systems (ESSs) in distribution system has been exploited to minimize system costs in the presence of renewable sources. Ref. [13] has addressed an optimization model for participation of a DER aggregator in day-ahead (DA) energy market utilizing demand flexibility. In [14], flexibility of loads and inverters of solar generation has been utilized by the DSO in DA energy market. Refs. [12] and [13] model DERs' uncertainties using stochastic approach and other mentioned references do not model uncertainty sources. In these references, DERs' flexibility features are utilized in energy scheduling of distribution network or trading in energy market. Therefore, providing flexibility products to adjust the DERs' energy dispatch and trading in flexibility market are not considered.

In [15], an aggregator manages the DERs to provide flexibility products in order to meet the flexibility requests of the DSO or the balancing responsible parties (BRPs). Ref. [16] has presented a non-linear model from an aggregator viewpoint that manages the home appliances to provide the DSO/BRP flexibility request. Moreover, flexibility-oriented scheduling of a microgrid has been presented in [17], where the microgrid agent determines the DERs' flexibility schedules while meeting the DSO's flexibility requirements. Ref. [18] has addressed a non-linear model for DA scheduling and real-time (RT) operational management of DERs in the distribution system to schedule and activate the DERs' flexibility services, respectively. In these references, trading flexibility products in the wholesale market is not considered. To address flexibility trading in wholesale flexibility market, in [2] and [4], DERs are managed to provide flexibility services as a tertiary reserve product in RT market. Moreover, authors in [19] have modelled a flexibility service provider that manages distributed battery storage units and participates in flexibility market. Refs. [20] and [21] exploit the DERs' flexibility capabilities while considering agents' preferences and hierarchical transactions in flexibility market. In [15–17] and [2], network operational constraints are not addressed. Moreover [15–17], and [19] do not consider DERs uncertainties in their models [21], considers the load and renewable generation uncertainties using a statistical approach and [2, 4, 18] and [20] address the DERs' uncertainties using stochastic approach.

Due to advantages of the robust optimization presented in Section 1.1 [22–29], have addressed uncertainty sources using robust approaches. Refs. [22–24] have utilized robust approaches to model uncertainty sources in a CVPP's energy (and reserve) scheduling problem. Ref. [22] has modelled a CVPP's participation in DA and RT energy markets while using a robust optimization approach to consider wind power and market price uncertainty. Authors in [23] have addressed a CVPP's offering strategy in the DA and RT energy markets using an adaptive robust optimization approach for modelling the wind power production uncertainty. Moreover [24], has modelled a CVPP's optimization problem to participate in DA energy and reserve markets while an adaptive robust optimization approach has been applied to address the uncertainty in available wind power generation and requests for reserve deployment. In these references, exploiting the DERs' flexibility capabilities is not addressed. Refs. [9] and [25–29] have modelled robust approaches considering the DERs' flexibility provision. In [9], flexibility services from DERs are contracted in DA time-horizon and distribution grid management is deployed considering the contracted flexibility. This reference has addressed renewable resources uncertainty in distribution grid management. However, the DER flexibility provision models and transactions with wholesale flexibility market are not regarded. Ref. [25] has proposed DA scheduling of generation and demand side resources utilizing their flexibility features to meet the gas-supply uncertainty and wind power variability. Authors in [26] have utilized home thermal flexibility to control the heating, ventilation and air conditioning systems' (HVACs) consumption while uncertainties in renewable generation and loads as well as the HVACs' consumption power limits are considered. Ref. [27] has considered ESSs' optimal energy arbitrage and flexibility provision in a residential energy storage controller, in which DERs' uncertainties are not addressed. In [28], a VPP aggregates multi-energy DERs and participates in DA energy and reserve markets while utilizing the flexibility features of quick-start devices. Uncertainties in reserve deployment requests are addressed in this reference while DERs' uncertainties are not taken into account. Ref. [29] has modelled a wind-storage system in which ESSs are addressed as flexible DERs to cover the wind power uncertainty. In this reference, utilizing diverse DERs' flexibility provision to meet different uncertainty sources associated with the DERs and flexibility requests are not addressed. Moreover, network operation constraints are not modelled. The most related literature is compared with the proposed model in Table 1. For the references which applied robust approaches to model uncertainty sources, types of flexible resources which have been used to cover uncertainties are mentioned in the table. Moreover, the papers that used adaptive robust approaches are specified in the table.

According to the table and the reviewed literature, it can be summarized that refs. [11, 14–17], and [19] do not address the DERs' uncertainty in their models. However, to avoid obtaining sub-optimal energy and flexibility schedules, it is necessary to characterize the uncertainty sources in the decision optimization problem. Therefore, ref. [21] considers the uncertainties using a statistical approach and [2, 4, 12, 13, 18] and [20] address the DERs' uncertainties using stochastic approach. As presented in Section 1.1, using the stochastic approach has some challenges such as the large number of scenarios for accurate modelling of the uncertainty sources and computational complexity, as well as difficulty to identify the uncertain parameters' PDFs. In addition, the solution of the stochastic optimization method may not be feasible for all the uncertainty realization scenarios [8]. For these reasons, utilizing the robust optimization methods for uncertainty modelling is taken into attention which solves the challenges of the stochastic method [6, 8]. Refs. [22–24] have addressed uncertainty sources in the energy (and reserve) scheduling problem using robust approaches. In these references, exploiting the DERs' flexibility capabilities is not addressed and integration of the flexibility products to the power system operation is not modelled. Due to the importance of utilizing the DERs' flexibility features to meet the power systems' requirements, Refs. [9] and [25–29] have modelled robust approaches considering the DERs' flexibility provision. In these references, coordinating flexibility capability provision of diverse DERs like conventional distributed generators (DGs), RESs, electric vehicles (EVs), HVACs and other responsive loads (RLs) and offering the flexibility capabilities to wholesale flexibility market while considering different uncertainty sources associated with the DERs are not modelled. Moreover, uncertainty of the transmission network's flexibility requests is disregarded. In this regard, the uncertainty characteristics associated with diverse DERs containing RESs, EVs, HVACs and other RLs as well as the transmission system operator's (TSO) requested flexibility capabilities should be modelled cooperatively in flexibility scheduling of DERs in the network. In addition, energy scheduling considering flexibility provision to meet the TSO's uncertain flexibility requests and preserve the distribution network operational constraints in the presence of different DERs' uncertainties should be taken into account. Therefore, by considering the proposed framework introduced in Section 1.3, an adaptive robust optimization model is utilized for exploiting flexibility capabilities of diverse DERs to meet the TSO's uncertain flexibility requests and preserve the distribution network operational constraints in presence of DERs' uncertainties.

1.3 | Aims and contributions

This paper models a TVPP that aggregates and coordinates diverse DERs' flexibility capabilities to offer flexibility services to the intra-day (ID) flexibility market as well as preserving the network operational constraints in the presence of uncertainties. Since the DERs' flexibility capabilities depend on their initial energy dispatch determined in the energy market, this paper proposes a two-stage optimization framework to model the TVPP's participation in wholesale DA energy and ID flexibility markets for optimal decision makings in both markets. The TVPP aims at maximizing its profit in markets as well as satisfying the distribution network operational constraints. In the proposed two-stage framework, the first stage models the TVPP's participation in DA energy market and determines the DERs' optimal energy dispatch. In the second stage, the TVPP's participation in the ID flexibility market is considered to determine the DERs' optimal flexibility capability provision by adjusting their output power considering the worst-case realization of uncertainties. The proposed two-stage model determines the optimal energy transactions in the first stage (here-and-now decision-making) in a way that the TVPP's flexibility transactions would be optimized when uncertainties are exposed in the second stage (wait-and-see decision-making). An adaptive robust optimization framework is proposed to address the uncertainties associated with diverse DERs and the TSO's requested flexibility capabilities. To the best of the authors' knowledge, it is the first time in the literature that an adaptive robust optimization model is utilized for exploiting flexibility capabilities of diverse DERs to meet the TSO's uncertain

TABLE 1 Comparison of the proposed model with state-of-the-art literature.

References	DERs' flexibility provision	Offer to wholesale flexibility market	Offer to wholesale energy market	Adaptive robust/other robust optimization frameworks	Network operational constraints	Uncertainties associated with RESs	HVACs	RLs	EVs	TSO's requested flexibility
[12]	✓				✓	✓				
[13]	✓		✓			✓				
[15–17]	✓									
[18]	✓		✓		✓	✓				
[2]	✓	✓	✓			✓	✓		✓	
[4]	✓	✓	✓		✓	✓	✓		✓	
[19]	✓		✓		✓					
[20]	✓	✓			✓	✓	✓		✓	
[21]	✓	✓	✓		✓	✓				
[22]			✓	/ ✓		✓				
[23, 24]			✓	✓ /		✓				
[9]	✓(DGs, RLs, PVs, wind)			✓ /	✓	✓				
[25]	✓(generation units, responsive demands)			✓ /	✓	✓				
[26]	✓(HVACs)			/ ✓	✓	✓		✓		
[27]	✓(ESSs)			/ ✓						
[28]	✓(multi-energy quick-start devices)		✓	✓ /						
[29]	✓(ESSs)	✓	✓	/ ✓		✓				
Proposed model	✓(DGs, ESSs, EVs, HVACs, RLs, PVs)	✓	✓	✓ /	✓	✓	✓	✓	✓	✓

flexibility requests and preserve the distribution network operational constraints in the presence of DERs' uncertainties. The robustness of the model is controlled by adjusting BoUs. The model is formulated as a mixed integer linear programming (MILP) problem by using duality theory and is solved using a column-and-constraint generation (CCG) algorithm.

In summary, the main contribution of the presented model is to address diverse uncertainty sources in DA energy and ID flexibility self-scheduling of a TVPP by proposing a two-stage adaptive robust optimization framework, aiming at exploiting flexibility capabilities of diverse DERs to offer flexibility to meet the transmission network's uncertain flexibility requests while satisfying the distribution network operational constraints in the presence of DERs' uncertainties. In this regard, the worst-case realization of uncertainties associated with diverse DERs (including photovoltaic (PV) units, EVs, HVACs, and other RLs) as well as the TSO's requested flexibility is considered to determine the DERs' optimal flexibility capability provision by adjusting their output power in flexibility market.

2 | SYSTEM MODEL AND PROBLEM DESCRIPTION

The TVPP aggregates DERs dispersed in the distribution network including DGs, PV units, ESSs and customers owning EVs, HVACs and other RLs. The TVPP coordinates the DERs' flexibility capabilities and assists the transmission network in providing the required flexibility by offering flexibility capabilities to the wholesale flexibility market. Meanwhile, the TVPP aims at preserving the distribution network operational constraints in the presence of uncertainties. The wholesale flexibility market is considered to be operated intra-daily which is closer to RT market and is an appropriate platform for trading flexibility [30]. It is assumed that the TSO requests a portion of its required flexibility capabilities from the TVPP. The TVPP offers flexibility services to the ID flexibility market with the aim of maximizing its profit while fulfilling the TSO's flexibility requests. The TVPP's flexibility offer can be more than the TSO's flexibility request [15].

The flexibility products are considered as upward and downward flexibility capabilities [21]; upward flexibility (UF) is the capability of increasing/decreasing the DERs' production/consumption power from their initial energy dispatches, respectively. In contrast, downward flexibility (DF) is the capability of decreasing/increasing the DERs' production/consumption power, respectively. It is notified that the DERs' flexibility provision depends on their initial energy schedules determined in the energy market. Therefore, optimal energy transactions in energy market should be determined in a way that the flexibility transactions in flexibility markets would be optimized. In this regard, a two-stage optimization model is proposed to determine the TVPP's optimal schedules in energy market and obtain the optimal flexibility strategy considering the initial energy schedules. In the first stage, the TVPP participates in the DA energy market to obtain the DERs' optimal energy management as well as the TVPP's offer in the energy market. In the second stage, the TVPP participates in the ID flexibility market and determines the DERs' optimal flexibility provision and optimal flexibility offer to flexibility market while meeting the existing uncertainties. In the proposed model, the uncertainty characteristics of PV units' output power, EV owners' behaviours, outside temperature of the customers' buildings, required energy of the RLs as well as the transmission network's requested flexibility capability are taken into account by applying an adaptive robust approach. In order to model a large EV fleet, aggregated model of the EVs at each bus is considered as a virtual battery (VB) at the corresponding bus and the VBs' characteristics are determined based on the EVs' uncertain behaviours [31]. Therefore, energy capacity and available power of the VBs are calculated based on the EV owners' driving pattern and have uncertainty. The proposed two-stage model is depicted in Figure 1.

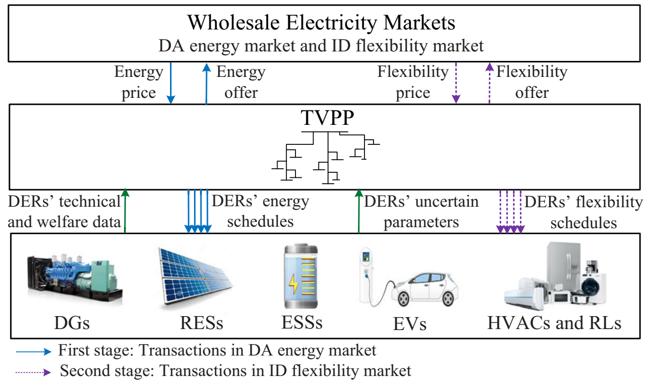

FIGURE 1 Two-stage framework of the TVPP's energy and flexibility self-scheduling.

TABLE 2 General formulation of the proposed model.

	First stage	Second stage
Objective	$\max_{\{DA\ decision\ variables\}} \begin{bmatrix}\text{TVPP's profit in} \\ \text{DA energy market}\end{bmatrix}$	$\min_{\{Uncertain\ variables\}} \max_{\{ID\ decision\ variables\}} \begin{bmatrix}\text{TVPP's profit in ID} \\ \text{flexibility market}\end{bmatrix}$
Constraints	TVPP's and DERs' constraints in DA energy market	TVPP's and DERs' constraints in ID flexibility market Uncertainty constraints

The TVPP aims to maximize its profit in energy and flexibility markets considering the DERs' and the network's associated constraints. General formulation of the model is described in Table 2 in which the TVPP's goal and associated constraints are represented for each stage. Based on the table, in the first stage the TVPP determines the DA energy management with the aim of maximizing its profit. In the second stage, the TVPP's ID flexibility management is addressed to maximize the TVPP's profit while the solution is immunized against the worst-case realization of uncertain variables; in other words, the uncertain variables are attained in the way to minimize the TVPP's profit in the ID flexibility market. It is worth noting that in the proposed two-stage model, distribution network operational constraints are considered in the first stage so that the optimal

DA energy schedules satisfy the network constraints. Moreover, in the second stage, the ID flexibility self-scheduling problem is optimized to specify the optimal power adjustment in order to preserve the network operational constraints in the presence of worst-case realization of uncertainties. Furthermore, it should be noted that in the proposed two-stage adaptive robust optimization model, the ESSs' and VBs' charging and discharging statuses which are here-and-now decisions are determined in the first stage before uncertainty realization. After the uncertain parameters are exposed, the ESSs' and VBs' operation adjustments which are wait-and-see decisions are determined in the second stage based on their predetermined statuses to cover the realized uncertainties. In other words, the ESSs' and VBs' charging and discharging statuses and their charging and discharging powers are determined in the energy scheduling problem in the first stage which are utilized as the inputs of the second stage problem. Based on the first stage results, the ESSs' and VBs' provided flexibility by adjusting their charging or discharging power is determined in the second stage. However, by adjusting the ESSs' and VBs' charging/discharging power due to flexibility provision in the second stage, their charging status may be changed to the discharging status and vice versa; this leads to the ESSs' and VBs' optimal charging/discharging dispatch and power adjustment to optimally utilize their flexibility capabilities. In the proposed model, the existing uncertainties are modelled by defining a polyhedral uncertainty set [8]. Moreover, the model conservativeness is adjusted using BoUs. The detailed mathematical formulation is presented in Section 3.

3 | MATHEMATICAL FORMULATION

3.1 | First stage

In the first stage, the TVPP participates in the DA energy market with the aim of maximizing its profit through (1),

$$\underset{\Omega_{DA}}{Max}\left\{ OF_1 = \sum_{t\in T}\left[\left[\begin{array}{l} -P_{VPP}^{t}.\pi_{E\_W}^{t} - \sum\limits_{r\in DG} c_{DG}^{r}.P_{DG}^{r,t} \\ -\sum\limits_{r\in ES} d_{ES}^{r}.\left|P_{ES}^{r,t}\right| \\ +\sum\limits_{r\in VB}\left(P_{VB\_ch}^{r,t} - P_{VB\_dch}^{r,t}\right).\pi_{E\_L}^{t} \\ +\sum\limits_{c\in C}\left(P_{FL}^{c,t} + P_{RL}^{c,t} + \sum\limits_{r\in H_C} P_{H}^{r,t}\right).\pi_{E\_L}^{t} \end{array}\right]\right]\right\} \tag{1}$$

where Ω_{DA} is the set of decision variables in DA energy scheduling which were defined in Nomenclature Section. Based on (1), the TVPP's profit is comprised of (1) cost/revenue of purchasing/selling power from/to energy market, (2) DGs' production cost, (3) ESSs' operating cost, (4) revenue obtained by selling power to VBs for EV charging or imposed cost due to purchasing the VBs' discharging power and (5) revenue attained by selling power to the customers. It should be noted that the ESSs' operational cost function is considered based on [21] and the absolute function is linearized to preserve the model linearity.

The TVPP considers active power balance at each bus of the network through (2). For the point of common coupling, the TVPP's power transactions with wholesale energy market should be taken into account. The reactive power balance at each bus of the network is considered similar to (2). Moreover, power flow Equation (3) is addressed based on the linearized form of DistFlow model which is linear with respect to the square of bus voltage amplitudes [32]. In these equations, b_1 represents the buses connected to bus b through the distribution lines.

$$\begin{aligned} &P_{VPP}^{t}\Big|_{b=PCC} + \sum_{r\in DG_b} P_{DG}^{r,t} + \sum_{r\in PV_b} \bar{P}_{PV}^{r,t} \\ &\quad - \sum_{r\in ES_b} P_{ES}^{r,t} - \sum_{b_1\in B_b} P_J^{b,b_1,t} \\ &= \sum_{c\in C_b}\left(P_{\mathrm{FL}}^{c,t} + P_{\mathrm{RL}}^{c,t} + \sum_{r\in H_c} P_H^{r,t}\right) \\ &\quad + \sum_{r\in VB_b}\left(P_{VB\_ch}^{r,t} - P_{VB\_dch}^{r,t}\right), \quad \forall b\in B, t\in T \end{aligned} \tag{2}$$

$$V^{b,t^2} - V^{b_1,t^2} - 2\left(r_J^{b,b_1,t}.P_J^{b,b_1,t} + x_J^{b,b_1,t}.Q_J^{b,b_1,t}\right) = 0, \quad \forall b\in B, b_1\in B_b, t\in T \tag{3}$$

The line power flows should be within the limits considering inequality (4) which is linearized using the pricewise linearization approach. The bus voltages should be mounted within the limits based on (5). Moreover, voltage amplitude of the slack bus is set to 1 p.u. It is worth noting that by considering the power balance at the distribution network buses and the network operational constraints in the first stage associated with the TVPP's DA energy self-scheduling problem, the optimal DA energy schedules are determined so that the network constraints are satisfied.

$$P_J^{b,b_1,t^2} + Q_J^{b,b_1,t^2} \le S_J^{b,b_1^2}, \qquad \forall b\in B, b_1\in B_b, t\in T \tag{4}$$

$$V_{\min}^{b\ \ 2} \le V^{b,t^2} \le V_{\max}^{b\ \ 2}, \qquad \forall b\in B, t\in T \tag{5}$$

The TVPP considers the DERs' technical and welfare constraints in DA energy scheduling. In order to model the DGs, their output power should be within the allowable limits through (6). Moreover, the ramp rate limits of the DGs should be taken into account based on (7). Here, constant power factors are considered for the DERs and the DERs' reactive power is obtained based on their active power.

$$0 \le P_{DG}^{r,t} \le P_{DG\_\max}^{r}, \qquad \forall r\in DG,\ t\in T \tag{6}$$

$$-R_{DG\_dn}^{r} \le P_{DG}^{r,t+1} - P_{DG}^{r,t} \le R_{DG\_up}^{r}, \qquad \forall r\in DG,\ t\in T \tag{7}$$

To model the PVs, it is considered that these generating units produce their maximum available capacity in energy market, that is, $\bar{P}_{PV}^{r,t}$. Modelling the HVACs, their power consumption limits are considered in (8). Moreover, the customers' desired temperature range should be satisfied through (9). Relation between the HVAC systems' output power and the customer building's temperature is considered in (10) [33].

$$0 \le P_{H}^{r,t} \le P_{H\_\max}^{r}, \qquad \forall r \in H,\, t \in T \tag{8}$$

$$\theta_{C\_\min}^{c} \le \theta_{C}^{c,t} \le \theta_{C\_\max}^{c}, \qquad \forall c \in C,\, t \in T \tag{9}$$

$$K_{C}^{c}\left(\theta_{C}^{c,t} - \theta_{C}^{c,t-1}\right)\Big/\Delta t = \left(1\Big/R_{C}^{c}\right)\left(\bar{\theta}_{O}^{t} - \theta_{C}^{c,t-1}\right) - \sum_{r \in H_c} P_{H}^{r,t}, \qquad \forall c \in C,\, t \in T \tag{10}$$

The customers' RLs are modelled by considering their power consumption limits in (11). Moreover, the required energy of the RLs should be provided according to (12).

$$0 \le P_{RL}^{c,t} \le P_{RL\_\max}^{c}, \qquad \forall c \in C,\, t \in T \tag{11}$$

$$\sum_{t \in T} P_{RL}^{c,t}.\Delta t \ge \bar{E}_{RL\_req}^{c}, \qquad \forall c \in C,\, t \in T \tag{12}$$

In order to model the EVs, the aggregated model of the customers' EVs at each bus is considered as a VB at the corresponding bus. In this regard, the VBs' available power and their energy capacity are calculated based on the EV owners' driving patterns and change over the time intervals; the maximum charging and discharging powers of each VB at each time interval are equal to the sum of these parameters associated with the EVs which are plugged in at the corresponding bus at the proposed time interval. The VBs' minimum and maximum state of charge (SoC) are calculated similarly. Moreover, $S_{VB\_arr}^{r,t}$ is defined as the amount of increase in the VBs' SoC at each time interval due to arrival of the EVs at the proposed time interval. In addition, $S_{VB\_dep}^{r,t}$ is introduced as the amount of decrease in the VBs' SoC at each time interval due to the EVs' departure [31]. Constraint (13) ensures that the VBs' charging and discharging operations do not occur at the same time by using binary variables $x_{VB\_ch}^{r,t}$ and $x_{VB\_dch}^{r,t}$ in the VBs' energy management model. The VBs' charging and discharging powers should be mounted within the allowable ranges as presented in (14) and (15), respectively. Based on these constraints, either the charging power or the discharging power has a positive value and the other variable is zero. The VBs' SoC is calculated based on (16). SoC of the VBs should be within the limits at each time considering (17). Moreover, the VBs' SoC at the last time interval of the scheduling horizon is considered to be equal to the SoC at the beginning time interval [31].

$$x_{VB\_ch}^{r,t} + x_{VB\_dch}^{r,t} \le 1, \qquad \forall r \in VB,\, t \in T \tag{13}$$

$$0 \le P_{VB\_ch}^{r,t} \le \bar{P}_{ch\_\max}^{r,t}.x_{VB\_ch}^{r,t}, \qquad \forall r \in VB,\, t \in T \tag{14}$$

$$0 \le P_{VB\_dch}^{r,t} \le \bar{P}_{dch\_\max}^{r,t}.x_{VB\_dch}^{r,t}, \qquad \forall r \in VB,\, t \in T \tag{15}$$

$$S_{VB}^{r,t} = S_{VB}^{r,t-1} + \left(P_{VB\_ch}^{r,t} - P_{VB\_dch}^{r,t}\right).\Delta t + \bar{S}_{VB\_arr}^{r,t} - \bar{S}_{VB\_dep}^{r,t}, \qquad \forall r \in VB,\, t \in T \tag{16}$$

$$\bar{S}_{VB\_\min}^{r,t} \le S_{VB}^{r,t} \le \bar{S}_{VB\_\max}^{r,t}, \qquad \forall r \in VB,\, t \in T \tag{17}$$

To model the ESSs, their simultaneous charging and discharging operations are prevented through (18). The ESSs' charging and discharging powers are limited based on (19) and (20), respectively. Equation (21) is considered to calculate the ESSs' SoC, where $P_{ESS}^{r,t}$ is defined as the ESSs' charging minus discharging powers. The ESSs' SoC limits are addressed in (22). Furthermore, the ESSs' ramp rate limits are addressed in (23).

$$x_{ES\_ch}^{r,t} + x_{ES\_dch}^{r,t} \le 1, \qquad \forall r \in ES,\, t \in T \tag{18}$$

$$0 \le P_{ES\_ch}^{r,t} \le P_{ch\_\max}^{r,t}.x_{ES\_ch}^{r,t}, \qquad \forall r \in ES,\, t \in T \tag{19}$$

$$0 \le P_{ES\_dch}^{r,t} \le P_{dch\_\max}^{r,t}.x_{ES\_dch}^{r,t}, \qquad \forall r \in ES,\, t \in T \tag{20}$$

$$S_{ES}^{r,t} = S_{ES}^{r,t-1} + P_{ES}^{r,t}.\Delta t, \qquad \forall r \in ES,\, t \in T \tag{21}$$

$$S_{ES\_\min}^{r,t} \le S_{ES}^{r,t} \le S_{ES\_\max}^{r,t}, \qquad \forall r \in ES,\, t \in T \tag{22}$$

$$-R_{ES\_dn}^{r} \le P_{ES}^{r,t+1} - P_{ES}^{r,t} \le R_{ES\_up}^{r}, \qquad \forall r \in ES,\, t \in T \tag{23}$$

It is worth noting that in the first stage, the TVPP's energy management is determined for the forecasted amounts of the uncertain variables. The DERs' energy dispatch and the TVPP's energy offer to market are determined in this stage and are the inputs for the TVPP's ID flexibility self-scheduling problem in the second stage. The TVPP determines optimal flexibility management of DERs and optimal offering strategy in the ID flexibility market by considering the existing uncertainties.

3.2 | Second stage

In the second stage, the TVPP aims at maximizing its profit in the ID flexibility market. In this stage, the worst-case uncertainty realizations are identified which minimize the TVPP's profit. The objective of the second stage problem is presented in (24),

$$\underset{\Omega_{Unc}}{\mathrm{Min}}\ \underset{\Omega_{ID}}{\mathrm{Max}} \left\{ OF_2 = \sum_{t\in T} \left[\begin{array}{l} U^t_{VPP}\,\pi^t_{U\_W} + D^t_{VPP}\,\pi^t_{D\_W} \\ -\sum\limits_{r\in DG} c^r_{DG}.U^{r,t}_{DG} + \sum\limits_{r\in DG} c^r_{DG}.D^{r,t}_{DG} \\ -\sum\limits_{r\in ES} d^r_{ES}.\left(\left|P^{r,t}_{ES} - U^{r,t}_{ES}\right| - \left|P^{r,t}_{ES}\right|\right) \\ -\sum\limits_{r\in ES} d^r_{ES}.\left(\left|P^{r,t}_{ES} + D^{r,t}_{ES}\right| - \left|P^{r,t}_{ES}\right|\right) \\ -\left(\sum\limits_{c\in C}\left(U^{c,t}_{RL} + \sum\limits_{r\in H_c} U^{r,t}_{H}\right) + \sum\limits_{r\in VB} U^{r,t}_{VB}\right).\pi^t_{U\_L} \\ -\left(\sum\limits_{c\in C}\left(D^{c,t}_{RL} + \sum\limits_{r\in H_c} D^{r,t}_{H}\right) + \sum\limits_{r\in VB} D^{r,t}_{VB}\right).\pi^t_{D\_L} \end{array} \right] \right\} \tag{24}$$

where Ω_{ID} is the set of variables in ID flexibility self-scheduling problem and Ω_{Unc} is the set of uncertain variables which are introduced in Nomenclature. The TVPP's profit in this stage comprises of (1) revenue obtained by offering upward and downward flexibility capabilities to the wholesale flexibility market, (2) imposed cost to DGs due to power production increase by offering upward flexibility or revenue obtained due to decrease in the DGs' costs through providing downward flexibility, (3) changes in the ESSs' operating cost due to flexibility provision, (4) cost of purchasing upward and downward flexibility from the customers and VBs. In the following, the constraints that the TVPP considers in the ID flexibility scheduling model are presented in which associated dual variables are represented in front of the colons.

The TVPP's upward and downward flexibility capabilities offered to the wholesale flexibility market should fulfil the transmission network's flexibility requests based on (25) and (26).

$$U^t_{VPP} \geq \tilde{U}^t_{Tr} \ :\ \mu^t_{U\_VPP}, \qquad \forall t \in T \tag{25}$$

$$D^t_{VPP} \geq \tilde{D}^t_{Tr} \ :\ \mu^t_{D\_VPP}, \qquad \forall t \in T \tag{26}$$

The TVPP's flexibility self-scheduling problem is optimized by considering the power balance and the network operational constraints in the presence of worst-case uncertainty realizations. In this regard, Equations (27) and (28) respectively represent the upward and downward flexibility power balance at the network buses by adjusting the TVPP's and the DERs' active powers. Since the power balance in the energy scheduling is satisfied in (2), considering the flexibility balance in (27) and (28), which satisfy the balance in power adjustment by providing flexibility products, guarantees that the power balance in flexibility market is preserved [21]. The TVPP's offered flexibility to market is considered in the equations for the point of common coupling.

$$\begin{aligned} &\sum_{r\in DG_b} U^{r,t}_{DG} + \sum_{r\in ES_b} U^{r,t}_{ES} + \sum_{c\in C_b}\left(U^{c,t}_{RL} + \sum_{r\in H_c} U^{r,t}_{H}\right) + \sum_{r\in VB_b} U^{r,t}_{VB} \\ &- \sum_{b_1\in B_b} U^{b,b_1,t}_{J} - \left.U^t_{VPP}\right|_{b=PCC} = 0 \ :\ \lambda^{b,t}_{U\_VPP}, \qquad \forall b\in B, t\in T \end{aligned} \tag{27}$$

$$\begin{aligned} &\sum_{r\in DG_b} D^{r,t}_{DG} + \sum_{r\in PV_b} D^{r,t}_{PV} + \sum_{r\in ES_b} D^{r,t}_{ES} + \sum_{c\in C_b}\left(D^{c,t}_{RL} + \sum_{r\in H_c} D^{r,t}_{H}\right) \\ &+ \sum_{r\in VB_b} D^{r,t}_{VB} + \sum_{b_1\in B_b} D^{b,b_1,t}_{J} - \left.D^t_{VPP}\right|_{b=PCC} = 0 \ :\ \lambda^{b,t}_{D\_VPP}, \\ &\forall b\in B, t\in T \end{aligned} \tag{28}$$

Moreover, the reactive power balance at the network buses should be preserved while trading flexibility by considering (29) and (30), where index Q represents the reactive flexibility provision.

$$\begin{aligned} &\sum_{r\in DG_b} U^{r,t}_{Q\_DG} + \sum_{r\in ES_b} U^{r,t}_{Q\_ES} + \sum_{c\in C_b}\left(U^{c,t}_{Q\_RL} + \sum_{r\in H_c} U^{r,t}_{Q\_H}\right) \\ &+ \sum_{r\in VB_b} U^{r,t}_{Q\_VB} - \sum_{b_1\in B_b} U^{b,b_1,t}_{Q\_J} - \left.U^t_{Q\_VPP}\right|_{b=PCC} = 0 \ : \\ &\rho^{b,t}_{U\_VPP}, \qquad \forall b\in B, t\in T \end{aligned} \tag{29}$$

$$\begin{aligned} &\sum_{r\in DG_b} D^{r,t}_{Q\_DG} + \sum_{r\in PV_b} D^{r,t}_{Q\_PV} + \sum_{r\in ES_b} D^{r,t}_{Q\_ES} \\ &+ \sum_{c\in C_b}\left(D^{c,t}_{Q\_RL} + \sum_{r\in H_c} D^{r,t}_{Q\_H}\right) + \sum_{r\in VB_b} D^{r,t}_{Q\_VB} \\ &+ \sum_{b_1\in B_b} D^{b,b_1,t}_{Q\_J} - \left.D^t_{Q\_VPP}\right|_{b=PCC} = 0 \ :\ \rho^{b,t}_{D\_VPP}, \ \forall b\in B, t\in T \end{aligned} \tag{30}$$

The network operational constraints while utilizing the DERs' flexibility provision are addressed in (31)–(38). Constraints (31)–(34) address the power flow equations considering upward and downward flexibility trading.

$$\begin{aligned} P^{b,b_1,t}_{U\_J} &= P^{b,b_1,t}_{J} - U^{b,b_1,t}_{J},\ Q^{b,b_1,t}_{U\_J} \\ &= Q^{b,b_1,t}_{J} - U^{b,b_1,t}_{Q\_J} \ :\ \alpha^{b,b_1,t}_{U\_VPP}, \beta^{b,b_1,t}_{U\_VPP}, \\ &\forall b\in B, b_1\in B_b, t\in T \end{aligned} \tag{31}$$

$$V_U^{b,t^2} - V_U^{b_1,t^2} - 2\left(r_J^{b,b_1,t}.P_{U_J}^{b,b_1,t} + x_J^{b,b_1,t}.Q_{U_J}^{b,b_1,t}\right) = 0 : \eta_{U_{VPP}}^{b,b_1,t},$$
$$\forall b \in B, b_1 \in B_b, t \in T \quad (32)$$

$$P_{D\_J}^{b,b_1,t} = P_J^{b,b_1,t} + D_J^{b,b_1,t}, Q_{D\_J}^{b,b_1,t}$$
$$= Q_J^{b,b_1,t} + D_{Q\_J}^{b,b_1,t} : \alpha_{D\_VPP}^{b,b_1,t}, \beta_{D\_VPP}^{b,b_1,t}, \quad (33)$$
$$\forall b \in B, b_1 \in B_b, t \in T$$

$$V_D^{b,t^2} - V_D^{b_1,t^2} - 2\left(r_J^{b,b_1,t}.P_{D\_J}^{b,b_1,t} + x_J^{b,b_1,t}.Q_{D\_J}^{b,b_1,t}\right) = 0 : \eta_{D\_VPP}^{b,b_1,t},$$
$$\forall b \in B, b_1 \in B_b, t \in T \quad (34)$$

The line power flows should be within the limits according to (35) and (36). Moreover, the bus voltage limits are considered through (37) and (38).

$$P_{U\_J}^{b,b_1,t^2} + Q_{U\_J}^{b,b_1,t^2} \le S_J^{b,b_1^2} : \delta_{U\_VPP}^{b,b_1,t}, \quad \forall b \in B, b_1 \in B_b, t \in T \quad (35)$$

$$P_{D\_J}^{b,b_1,t^2} + Q_{D\_J}^{b,b_1,t^2} \le S_J^{b,b_1^2} : \delta_{D\_VPP}^{b,b_1,t}, \quad \forall b \in B, b_1 \in B_b, t \in T \quad (36)$$

$$V_{\min}^{b^2} \le V_U^{b,t^2} \le V_{\max}^{b^2} : \omega_{U\_VPP}^{b,t}, \varpi_{U\_VPP}^{b,t}, \quad \forall b \in B, t \in T \quad (37)$$

$$V_{\min}^{b^2} \le V_D^{b,t^2} \le V_{\max}^{b^2} : \omega_{D\_VPP}^{b,t}, \varpi_{D\_VPP}^{b,t}, \quad \forall b \in B, t \in T \quad (38)$$

The TVPP considers the DERs' technical and welfare constraints in the ID flexibility scheduling. To model the DGs output power, upward and downward flexibility capabilities of the DGs are limited based on (39) and (40), respectively. Moreover, ramp rate limits of the DGs are addressed in (41) and (42).

$$0 \le U_{DG}^{r,t} \le P_{DG\_\max}^{r} - P_{DG}^{r,t} : \mu_{U\_DG}^{r,t}, \quad \forall r \in DG, t \in T \quad (39)$$

$$0 \le D_{DG}^{r,t} \le P_{DG}^{r,t} : \mu_{D\_DG}^{r,t}, \quad \forall r \in DG, t \in T \quad (40)$$

$$0 \le U_{DG}^{r,t} \le R_{DG\_up}^{r} : \sigma_{U\_DG}^{r,t}, \quad \forall r \in DG, t \in T \quad (41)$$

$$0 \le D_{DG}^{r,t} \le R_{DG\_dn}^{r} : \sigma_{D\_DG}^{r,t}, \quad \forall r \in DG, t \in T \quad (42)$$

The PV units can provide downward flexibility capability by curtailing their production power as presented in (43).

$$0 \le D_{PV}^{r,t} \le \tilde{P}_{PV}^{r,t} : \mu_{D\_PV}^{r,t}, \quad \forall r \in PV, t \in T \quad (43)$$

The HVACs' upward and downward flexibility capabilities are limited considering (44) and (45), respectively.

$$0 \le U_H^{r,t} \le P_H^{r,t} : \mu_{U\_H}^{r,t}, \quad \forall r \in H, t \in T \quad (44)$$

$$0 \le D_H^{r,t} \le P_{H\_\max}^{r} - P_H^{r,t} : \mu_{D\_H}^{r,t}, \quad \forall r \in H, t \in T \quad (45)$$

Utilizing the HVACs' upward and downward flexibility, the customer buildings' temperature should remain within the desired limits considering (46) and (47), respectively.

$$\theta_{C\_\min}^{c,t} \le \theta_{C\_U}^{c,t} \le \theta_{C\_\max}^{c,t} : \upsilon_{U\_H}^{c,t}, \vartheta_{U\_H}^{c,t}, \quad \forall c \in C, t \in T \quad (46)$$

$$\theta_{C\_\min}^{c,t} \le \theta_{C\_D}^{c,t} \le \theta_{C\_\max}^{c,t} : \upsilon_{D\_H}^{c,t}, \vartheta_{D\_H}^{c,t}, \quad \forall c \in C, t \in T \quad (47)$$

The relations between the buildings' temperature and the HVACs' power consumption when providing upward and downward flexibility are presented in (48) and (49), respectively.

$$K_C^c\left(\theta_{C\_U}^{c,t} - \theta_C^{c,t-1}\right)\Big/\Delta t = \left(1\Big/R_C^c\right)\left(\tilde{\theta}_O^t - \theta_C^{c,t-1}\right)$$
$$- \sum_{r \in H_c}\left(P_H^{r,t} - U_H^{r,t}\right) : \eta_{U\_H}^{c,t}, \quad \forall c \in C, t \in T \quad (48)$$

$$K_C^c\left(\theta_{C\_D}^{c,t} - \theta_C^{c,t-1}\right)\Big/\Delta t = \left(1\Big/R_C^c\right)\left(\tilde{\theta}_O^t - \theta_C^{c,t-1}\right)$$
$$- \sum_{r \in H_c}\left(P_H^{r,t} + D_H^{r,t}\right) : \eta_{D\_H}^{c,t}, \quad \forall c \in C, t \in T \quad (49)$$

In order to model the RLs' flexibility capability provision, their upward and downward flexibility should be within the limits shown in (50) and (51), respectively. Moreover, the RLs should consume their required energy while providing flexibility which is addressed in (52).

$$0 \le U_{RL}^{c,t} \le P_{RL}^{c,t} : \mu_{U\_RL}^{c,t}, \quad \forall c \in C, t \in T \quad (50)$$

$$0 \le D_{RL}^{c,t} \le P_{RL\_\max}^{c} - P_{RL}^{c,t} : \mu_{D\_RL}^{c,t}, \quad \forall c \in C, t \in T \quad (51)$$

$$\sum_{t \in T}\left(P_{RL}^{c,t} - U_{RL}^{c,t}\right).\Delta t \ge \tilde{E}_{RL\_req}^{c} : \nu_{U\_RL}^{c,t}, \quad \forall c \in C, t \in T \quad (52)$$

To model the VBs, the limits associated with their upward and downward flexibility provision are addressed in (53) and (54), respectively. It is worth noting that for utilizing the VBs' flexibility, their charging and discharging powers which have been determined in the first stage are considered as input parameters in the second stage. In these constraints, either the charging power or the discharging power has a positive value and the other one is equal to zero. It should be noted that if in the first stage, a VB is managed to be in the charging mode, then in the second stage, it can provide upward flexibility by reducing its charging power. By providing upward flexibility, the VB's charging power is reduced until it becomes equal to zero; thereafter, by providing more upward flexibility, the VB enters the discharging mode and produces upward flexibility up to the maximum allowable discharging power. In addition, in this case, the ESS can provide downward flexibility by increasing its charging power up to the maximum allowable charging power. In the same way, if a VB is managed to be operated in the discharging mode in the first stage, it can provide upward flexibility by increasing the discharging power up to the maximum allowable discharging power. Moreover, the VB can provide downward flexibility by decreasing its discharging power. In this way, the VB's discharging power is reduced until it becomes equal to zero; then, the VB enters the charging mode and produces downward flexibility until the maximum allowable charging power. The VBs' SoC when providing upward and downward flexibility is presented in (55) and (56), respectively. The VBs' SoC should be within the associated limits based on (57) and (58).

$$0 \le U_{VB}^{r,t} \le P_{VB\_ch}^{r,t} - P_{VB\_dch}^{r,t} + \tilde{P}_{dch\_\max}^{r,t} : \mu_{U\_VB}^{r,t}, \quad \forall r \in VB, t \in T \tag{53}$$

$$0 \le D_{VB}^{r,t} \le -P_{VB\_ch}^{r,t} + P_{VB\_dch}^{r,t} + \tilde{P}_{ch\_\max}^{r,t} : \mu_{D\_VB}^{r,t}, \quad \forall r \in VB, t \in T \tag{54}$$

$$S_{VB\_U}^{r,t} = S_{VB}^{r,t-1} + \left(P_{VB\_ch}^{r,t} - P_{VB\_dch}^{r,t} - U_{VB}^{r,t}\right).\Delta t + \tilde{S}_{VB\_arr}^{r,t} - \tilde{S}_{VB\_dep}^{r,t} : \eta_{U\_VB}^{r,t}, \quad \forall r \in VB, t \in T \tag{55}$$

$$S_{VB\_D}^{r,t} = S_{VB}^{r,t-1} + \left(P_{VB\_ch}^{r,t} - P_{VB\_dch}^{r,t} + D_{VB}^{r,t}\right).\Delta t + \tilde{S}_{VB\_arr}^{r,t} - \tilde{S}_{VB\_dep}^{r,t} : \eta_{D\_VB}^{r,t}, \quad \forall r \in VB, t \in T \tag{56}$$

$$\tilde{S}_{VB\_\min}^{r,t} \le S_{VB\_U}^{r,t} \le \tilde{S}_{VB\_\max}^{r,t} : \upsilon_{U\_VB}^{r,t}, \vartheta_{U\_VB}^{r,t}, \quad \forall r \in VB, t \in T \tag{57}$$

$$\tilde{S}_{VB\_\min}^{r,t} \le S_{VB\_D}^{r,t} \le \tilde{S}_{VB\_\max}^{r,t} : \upsilon_{D\_VB}^{r,t}, \vartheta_{D\_VB}^{r,t}, \quad \forall r \in VB, t \in T \tag{58}$$

Similar to the VBs, the ESSs' flexibility provision is modelled considering (53), (54), (57) and (58) in which the ESS's maximum charging and discharging powers as well as their minimum and maximum allowable SoC are determined parameters. Moreover, the ESSs' SoC is calculated based on (59) and (60).

$$S_{ES\_U}^{r,t} = S_{ES}^{r,t-1} + \left(P_{ES}^{r,t} - U_{ES}^{r,t}\right).\Delta t : \eta_{U\_ES}^{r,t}, \quad \forall r \in ES, t \in T \tag{59}$$

$$S_{ES\_D}^{r,t} = S_{ES}^{r,t-1} + \left(P_{ES}^{r,t} + D_{ES}^{r,t}\right).\Delta t : \eta_{D\_ES}^{r,t}, \quad \forall r \in ES, t \in T \tag{60}$$

The ESSs' ramp rate limits are presented in (61) and (62).

$$0 \le U_{ES}^{r,t} \le R_{ES\_up}^{r} : \sigma_{U\_ES}^{r,t}, \quad \forall r \in ES, t \in T \tag{61}$$

$$0 \le D_{ES}^{r,t} \le R_{ES\_dn}^{r} : \sigma_{D\_ES}^{r,t}, \quad \forall r \in ES, t \in T \tag{62}$$

The TVPP's ID flexibility self-scheduling problem is solved under the worst-case uncertainty realization. The proposed adaptive robust optimization model characterizes the uncertainties through a polyhedral uncertainty set. The polyhedral uncertainty set states the variation range of uncertain variables and controls the robustness of the model by means of BoUs [8]. In the polyhedral uncertainty set, the worst-case realization of uncertainties corresponds to one of the extreme points of the polyhedron representing the uncertainty set [24]. Therefore, the polyhedral uncertainty set can be equivalently defined as the set of extremes of the polyhedron. In this way, the uncertainty set Ψ is defined in (63) in which binary variables ζ and ξ are used to model the extreme points. It is noted that at each time interval, either ζ or ξ can take value. Moreover, sum of ζ and ξ should be lower than the BoU representing the level of conservativeness of the model.

Uncertainty set (63) addresses the uncertainties in the PV units' output power, ambient temperature, required energy of the RLs, the VBs' characteristics and the TSO's flexibility requests, respectively. The proposed uncertainty

$$\Psi = \Big\{ \tilde{P}_{PV}^{r,t} = \bar{P}_{PV}^{r,t} + \widehat{P}_{PV}^{r,t}\left(\zeta_{PV}^{r,t} - \xi_{PV}^{r,t}\right),$$

$$\zeta_{PV}^{r,t} + \xi_{PV}^{r,t} = 1, \quad \forall r \in PV, t \in T$$

$$\tilde{\theta}_{O}^{t} = \bar{\theta}_{O}^{t} + \widehat{\theta}_{O}^{t}\left(\zeta_{O}^{t} - \xi_{O}^{t}\right), \zeta_{O}^{t} + \xi_{O}^{t} = 1, \quad \forall t \in T$$

$$\tilde{E}_{RL\_req}^{c} = \bar{E}_{RL\_req}^{c} + \widehat{E}_{RL\_req}^{c}\left(\zeta_{RL\_req}^{c} - \xi_{RL\_req}^{c}\right),$$

$$\zeta_{RL\_req}^{c} + \xi_{RL\_req}^{c} = 1, \quad \forall c \in C$$

$$\tilde{P}_{ch\_\max}^{r,t} = \bar{P}_{ch\_\max}^{r,t} + \widehat{P}_{ch\_\max}^{r,t}\left(\zeta_{VB}^{r,t} - \xi_{VB}^{r,t}\right), \quad \forall r \in VB, t \in T$$

$$\tilde{P}_{dch\_\max}^{r,t} = \bar{P}_{dch\_\max}^{r,t} + \widehat{P}_{dch\_\max}^{r,t}\left(\zeta_{VB}^{r,t} - \xi_{VB}^{r,t}\right), \quad \forall r \in VB, t \in T$$

$$\tilde{S}_{VB\_\max}^{r,t} = \bar{S}_{VB\_\max}^{r,t} + \widehat{S}_{VB\_\max}^{r,t}\left(\zeta_{VB}^{r,t} - \xi_{VB}^{r,t}\right), \quad \forall r \in VB, t \in T$$

$$\tilde{S}^{r,t}_{VB\_\min} = \bar{S}^{r,t}_{VB\_\min} + \widehat{S}^{r,t}_{VB\_\min}\left(\zeta^{r,t}_{VB} - \xi^{r,t}_{VB}\right),$$
$$\zeta^{r,t}_{VB} + \xi^{r,t}_{VB} = 1, \qquad \forall r \in VB,\ t \in T$$
$$\tilde{S}^{r,t}_{VB\_arr} = \bar{S}^{r,t}_{VB\_arr} + \widehat{S}^{r,t}_{VB\_arr}\left(\zeta^{r,t}_{VB\_arr} - \xi^{r,t}_{VB\_arr}\right), \forall r \in VB,\ t \in T$$
$$\zeta^{r,t}_{VB\_arr} + \xi^{r,t}_{VB\_arr} = 1, \qquad \forall r \in VB,\ t \in T$$
$$\tilde{S}^{r,t}_{VB\_dep} = \bar{S}^{r,t}_{VB\_dep} + \widehat{S}^{r,t}_{VB\_dep}\left(\zeta^{r,t}_{VB\_dep} - \xi^{r,t}_{VB\_dep}\right), \quad \forall r \in VB,\ t \in T$$
$$\zeta^{r,t}_{VB\_dep} + \xi^{r,t}_{VB\_dep} = 1, \quad \forall r \in VB,\ t \in T$$
$$\tilde{U}^{t}_{Tr} = \bar{U}^{t}_{Tr} + \widehat{U}^{t}_{Tr}\left(\zeta^{t}_{U\_Tr} - \xi^{t}_{U\_Tr}\right), \zeta^{t}_{U\_Tr} + \xi^{t}_{U\_Tr} = 1, \quad \forall t \in T$$
$$\tilde{D}^{t}_{Tr} = \bar{D}^{t}_{Tr} + \widehat{D}^{t}_{Tr}\left(\zeta^{t}_{D\_Tr} - \xi^{t}_{D\_Tr}\right), \zeta^{t}_{D\_Tr} + \xi^{t}_{D\_Tr} = 1, \quad \forall t \in T$$
$$\sum_{t\in T}\sum_{r\in PV}\left(\zeta^{r,t}_{PV} + \xi^{r,t}_{PV}\right) \le \Gamma_{PV}, \sum_{t\in T}\left(\zeta^{t}_{O} + \xi^{t}_{O}\right) \le \Gamma_{H}$$
$$\sum_{c\in C}\left(\zeta^{c}_{RL\_req} + \xi^{c}_{RL\_req}\right) \le \Gamma_{RL}, \sum_{t\in T}\left(\zeta^{t}_{U\_Tr} + \xi^{t}_{U\_Tr}\right) + \left(\zeta^{t}_{D\_Tr} + \xi^{t}_{D\_Tr}\right) \le \Gamma_{Tr}$$
$$\sum_{t\in T}\sum_{r\in VB}\left(\zeta^{r,t}_{VB} + \xi^{r,t}_{VB}\right) + \left(\zeta^{r,t}_{VB\_arr} + \xi^{r,t}_{VB\_arr}\right) + \left(\zeta^{r,t}_{VB\_dep} + \xi^{r,t}_{VB\_dep}\right) \le \Gamma_{VB} \Big\} \tag{63}$$

set states that the uncertain variables can take value at one of the extremes of the bound around the forecasted amount. Moreover, in the three lowermost lines of the set, the associated BoUs are presented. It is worth noting that since the uncertainty in the EVs' arrival/departure time to/from the associated VBs causes the changes in the VBs' maximum charging and discharging powers and minimum and maximum SoC in the same direction, binary variables for these uncertain variables are considered to be equivalent.

It is worth noting that the correlations of uncertain variables can be modelled by defining a correlated uncertainty set [34, 35]. In this context, statistical analyses can be carried out to identify the possible correlations of uncertain variables based on the historical data. Correlations can be considered as spatial and temporal correlations as well as the cross correlations between different uncertain variables. In order to model the correlations of uncertain variables, their correlations can be incorporated into the uncertainty set. Covariance is a typical parameter that characterizes the correlation of uncertain variables. By considering covariance matrix in constructing the polyhedral uncertainty set (63), a correlated uncertainty set is achieved. Considering the correlated uncertainty set in the proposed adaptive robust optimization model, the correlations of uncertain variables would be taken into account. Since in the proposed model, different uncertainty sources are addressed, extensive statistical analyses are required to identify the correlations of these uncertain variables to construct a precise covariance matrix. Moreover, it is required to investigate precise and reliable historical data to identify the correlations which is challenging for some of the uncertain variables like RLs' required energy and TSO's requested flexibility due to the subject novelty and limited data.

4 | SOLUTION METHOD

In order to solve the proposed two-stage adaptive robust optimization problem, it is divided into a master problem and a sub-problem which are solved iteratively using a CCG approach. The objective of the master problem is presented in (64),

$$\underset{\Omega_{MP}}{Max}\left\{OF_1 + \varphi\right\} \tag{64}$$

where OF_1 is the first stage objective function and φ is an auxiliary variable. Ω_{MP} contains the first stage variables (Ω_{DA}), the auxiliary variable (φ), as well as the second stage variables (Ω_{ID}) for the iteration $i_1 = 1, \dots, i$. Objective (64) is satisfied subject to (65)–(67).

$$\text{Constraints (2)–(23)} \tag{65}$$

$$\varphi \le \sum_{t\in T}\left[\begin{array}{l} U^{t,i_1}_{VPP}\,\pi^{t}_{U\_W} + D^{t,i_1}_{VPP}\,\pi^{t}_{D\_W} \\ -\sum_{r\in DG} c^{r}_{DG}.U^{r,t,i_1}_{DG} + \sum_{r\in DG} c^{r}_{DG}.D^{r,t,i_1}_{DG} \\ -\sum_{r\in ES} d^{r}_{ES}.\left(\left|P^{r,t,i_1}_{ES} - U^{r,t,i_1}_{ES}\right| - \left|P^{r,t,i_1}_{ES}\right|\right) \\ -\sum_{r\in ES} d^{r}_{ES}.\left(\left|P^{r,t,i_1}_{ES} + D^{r,t,i_1}_{ES}\right| - \left|P^{r,t,i_1}_{ES}\right|\right) \\ -\left(\sum_{c\in C}\left(U^{c,t,i_1}_{RL} + \sum_{r\in H_c} U^{r,t,i_1}_{H}\right) + \sum_{r\in VB} U^{r,t,i_1}_{VB}\right).\pi^{t}_{U\_L} \\ -\left(\sum_{c\in C}\left(D^{c,t,i_1}_{RL} + \sum_{r\in H_c} D^{r,t,i_1}_{H}\right) + \sum_{r\in VB} D^{r,t,i_1}_{VB}\right).\pi^{t}_{D\_L} \end{array}\right],$$
$$\forall i_1 = 1, \dots, i \tag{66}$$

$$\text{Constraints (25)–(62) considered for iteration } i_1 = 1, \dots, i. \tag{67}$$

It should be noted that in the master problem, uncertain variables are considered as known parameters for each iteration and are taken from the sub-problem.

The objective and constraints of the sub-problem are presented in (68)–(70), where OF_2 is the second stage objective function. The DA energy management variables are taken from the master problem and are input parameters for the sub-problem.

$$\underset{\Omega_{Unc}}{\text{Min}}\ \underset{\Omega_{ID}}{\text{Max}}\ \left\{OF_2\right\} \tag{68}$$

$$\text{Constraints (25)–(62)} \tag{69}$$

$$\text{Constraints in (63)} \tag{70}$$

The sub-problem is a min-max optimization problem which cannot be solved by off-the-shelf solvers. In this regard, since the inner problem (maximization of the TVPP's profit) is linear, it is substituted by the associated dual problem and is recast to a minimization problem. Therefore, a single minimization problem is obtained. The objective function of the dual problem suffers non-linearity due to multiplication of uncertain variables and dual variables in terms of $\tilde{P}^{r,t}_{PV}.\mu^{r,t}_{D\_PV}$, $\tilde{\theta}^{t}_{O}.(\eta^{c,t}_{U\_H}+\eta^{c,t}_{D\_H})/R^{c}_{C}$, $\tilde{E}^{\,c}_{RL\_req}.\ \nu^{c,t}_{U\_RL}$, $\tilde{P}^{r,t}_{dch\_\max}.\mu^{r,t}_{U\_VB}$, $\tilde{P}^{r,t}_{ch\_\max}.\mu^{r,t}_{D\_VB}$, $\tilde{S}^{r,t}_{VB\_\max}.(\vartheta^{r,t}_{U\_VB}+\vartheta^{r,t}_{D\_VB})$, $\tilde{S}^{r,t}_{VB\_\min}.(\upsilon^{r,t}_{U\_VB}+\upsilon^{r,t}_{U\_VB})$, $\tilde{S}^{r,t}_{VB\_arr}.(\eta^{r,t}_{U\_VB}+\eta^{r,t}_{D\_VB})$, $\tilde{S}^{r,t}_{VB\_dep}.(\eta^{r,t}_{U\_VB}+\eta^{r,t}_{D\_VB})$, $\tilde{U}^{t}_{Tr}.\mu^{t}_{U\_VPP}$ and $\tilde{D}^{t}_{Tr}.\mu^{t}_{D\_VPP}$. These non-linear terms are linearized by defining new variables and utilizing large numbers [8]; in the following, the linearization procedure of the first non-linear term of the objective function (i.e. $\tilde{P}^{r,t}_{PV}.\mu^{r,t}_{D\_PV}$) is addressed by rewriting the term as (71).

$$\begin{aligned}\tilde{P}^{r,t}_{PV}.\mu^{r,t}_{D\_PV} &= \left(\bar{P}^{r,t}_{PV}+\widehat{P}^{r,t}_{PV}\left(\zeta^{r,t}_{PV}-\xi^{r,t}_{PV}\right)\right).\mu^{r,t}_{D\_PV}\\ &= \bar{P}^{r,t}_{PV}.\mu^{r,t}_{D\_PV}+\widehat{P}^{r,t}_{PV}\left(\zeta^{r,t}_{PV}-\xi^{r,t}_{PV}\right).\mu^{r,t}_{D\_PV},\\ &\qquad \forall r\in PV,\ t\in T\end{aligned} \tag{71}$$

The terms $\zeta^{r,t}_{PV}.\mu^{r,t}_{D\_PV}$ and $\xi^{r,t}_{PV}.\mu^{r,t}_{D\_PV}$ in (71) are defined as new variables, namely $\mu^{+r,t}_{D\_PV}$ and $\mu^{-r,t}_{D\_PV}$, respectively. Therefore, the non-linear part of the equality (71) is linearized as (72)–(74). M_{μ} is a sufficiently large number.

$$\widehat{P}^{r,t}_{PV}.\left(\zeta^{r,t}_{PV}-\xi^{r,t}_{PV}\right).\mu^{r,t}_{D\_PV}=\widehat{P}^{r,t}_{PV}.\left(\mu^{+r,t}_{D\_PV}-\mu^{-r,t}_{D\_PV}\right),\quad \forall r\in PV,\ t\in T \tag{72}$$

$$\left|\mu^{+r,t}_{D\_PV}\right|\le M_{\mu}.\zeta^{r,t}_{PV},\quad \left|\mu^{+r,t}_{D\_PV}-\mu^{r,t}_{D\_PV}\right|\le M_{\mu}.\left(1-\zeta^{r,t}_{PV}\right),\quad \forall r\in PV,\ t\in T \tag{73}$$

$$\left|\mu^{-r,t}_{D\_PV}\right|\le M_{\mu}\xi^{r,t}_{PV},\quad \left|\mu^{-r,t}_{D\_PV}-\mu^{r,t}_{D\_PV}\right|\le M_{\mu}\left(1-\xi^{r,t}_{PV}\right),\quad \forall r\in PV,\ t\in T \tag{74}$$

Other non-linear terms are linearized in the same way. Therefore, the resulting problem is a linear programming problem and solved iteratively based on the CCG algorithm. In this regard, the lower bound ($-\infty$), the upper bound ($+\infty$) as well as the convergence tolerance (ε) are set. By solving the master problem, the upper bound is updated to be equal to the master problem objective function ($OF_1+\varphi$). After that based on the master problem results, the sub-problem is solved and the lower bound is updated to be equal to max{lower bound, OF_1+OF_2}. Afterward, the master problem is solved to update the upper bound again and this iterative solution will be continued until the upper and lower bounds converge to ε. Details around the steps of the CCG algorithm and updating the lower and upper bounds have been presented in [24].

5 | STUDY RESULTS

5.1 | Case study

The proposed model is implemented on the distribution test system connected to bus 5 of the Roy Billinton test system (RBTS). The distribution network contains four feeders, 44 buses and 43 lines; detailed information is adopted from [36]. The TVPP supervises the distribution network and the DERs across the network to participate in energy and flexibility markets. 3 DG units with total capacity of 2.4 MVA and ramp rate of 0.05 MW/min as well as 8 PV units with total capacity of 4 MW are dispersed in the network. Data associated with the DGs' cost function is adopted from [20]. The distribution network contains residential, commercial and office customers with total peak and average power consumption equal to 20 and 11.29 MW, respectively. The commercial buildings' HVAC systems as well as the residential customers' RLs and EVs are supervised by the TVPP to utilize their flexibility features. Data about the HVAC systems and the buildings' desired temperature are obtained from [33]. The residential customers' RLs with total peak power consumption of 0.66 MW and total required energy of 5.3 MWh during the day is considered. Moreover, residential customers' EVs with penetration level of 20% are addressed. In order to investigate the role of ESSs, a case study is defined in which 2 ESS units with total maximum charging/discharging power of 3 MW, ramp rate of 0.05 MW/min and energy capacity of 10 MWh are considered in the network. Power factors of the DGs, PVs, ESSs and EVs are considered to be 0.9 inductive and power factor of loads is regarded to be 0.95 inductive.

Forming the uncertainty set, the PVs' available power data and ambient temperature data are adopted from [33] and [37], respectively. Maximum deviation of PVs' available power and ambient temperature are respectively 9% and 8% of the forecasted amounts. Moreover, uncertainty bounds for the RLs' required energy are considered to be 10%. In order to address the EVs' uncertainty at each VB, data associated with the EV owners' travel behaviours and the EVs' battery capacities are extracted considering [33]. Different samples for the EVs' driving patterns are generated based on [38]. Accordingly, different samples for the VB's characteristics are obtained and the forecasted values and the uncertainty bounds of the VB's uncertain parameters are determined. In addition, to specify the TSO's requested flexibility and the associated uncertainty, required flexibility of the TSO is calculated considering the method presented in [21] and it is supposed that the TSO requests 20% of its required flexibility from the distribution system with uncertainty bound of 10%. It should be noted that the following assumptions are considered to construct the uncertainty set; the air temperature in all the buses of the distribution network is assumed to be identical; that is, the air temperature in the network is considered to be fully spatial correlated since it is assumed that the network region is not wide. In this context, the uncertain air temperature is not dependent on the network buses as it is shown in (63). Moreover, based on the assumption that the network region is not wide, it is considered that the solar irradiance in the network buses is identical. In addition, the VBs' maximum charging and discharging powers and their maximum and minimum allowable SOC are considered to be fully correlated since they are changed in the same way by arriving or departing the EVs to/from the VBs. In this context, binary variables associated with these uncertain variables are identical in (63) and change in the same manner. Data associated with the energy and flexibility market prices are adopted from [4]. The local energy price in the distribution network is considered to be 1.2 times the wholesale energy market price. Moreover, the TVPP procures the DERs' flexibility capability with the local flexibility prices equal to 0.7 times the wholesale flexibility market prices.

5.2 | Numerical results

Implementing the proposed model on the test system, the results are presented in the following. It should be noted that in this study, maximum BoU associated with the PV units is equal to $\Gamma_{PV\_\max} = 8 \times 24 = 192$ which expresses that all of the PV units' output power deviates from the associated forecasted amount in 24 h of the day. To compute maximum BoU of the RLs' required energy ($\Gamma_{RL\_\max}$), it should be noted that in this study the aggregated RLs at each network bus is taken into account; therefore, maximum BoU is equal to the number of buses which contain RLs, that is, 13. The VBs' maximum BoU is equal to $\Gamma_{EV\_\max} = 13 \times 24 = 312$. Moreover, maximum BoUs associated with the ambient temperature ($\Gamma_{H\_\max}$) and the TSO's requested flexibility ($\Gamma_{Tr\_\max}$) are equal to 24. In order to investigate the effect of different uncertainty sources, the TVPP's total profit as well as its individual profits in DA energy and ID flexibility markets are presented for different level of BoUs in Table 3. In column 1, the TVPP's profit is presented for the case study in which the uncertainty sources are not regarded (namely, Case I). In columns 2 to 6, the results are presented for the cases in which one of the uncertainty sources are taken into account; these results show the effect of different uncertainty sources on the TVPP's profit. Based on the presented results, uncertainties associated with EVs and PVs have more effect on the TVPP's profit. In columns 7 and 8, the TVPP's profit for 50% and 100% of the maximum BoUs is presented. As shown in the table, the TVPP's profit decreases as the BoUs is increased since the model become more conservative. Comparing the results of the worst-case realization of uncertainties (column 8) with Case I (column 1), the TVPP's total profit has reduced by 1.98%; the TVPP's profit in DA market has reduced by 0.38% and the TVPP's profit in ID market has reduced by 3.52%. The TVPP's profit in ID market is more affected by the uncertainties since the flexibility provision strategy varies to compensate the effect of uncertainties in this market.

Uncertain variables' bound is another factor that affects the TVPP's profit. To investigate the effect of uncertainty bounds, three scenarios are considered; in scenario Λ_{BC}, uncertainty bounds are equal to the amounts presented in Section 5.1. In scenarios $\Lambda_{\downarrow}$ and $\Lambda_{\uparrow}$, uncertainty bounds are assumed to be 0.5 and 1.5 times the uncertainty bounds in Λ_{BC}. The TVPP's total profit for different BoUs and three scenarios of uncertainty bounds are presented in Table 4. As shown in the table, by increasing the uncertainty bounds, the TVPP's profit decreases since the uncertain variables deviations from the forecasted values are increased. Based on the results presented in the table, in the worst case (for scenario $\Lambda_{\uparrow}$ and maximum BoUs), the TVPP's profit has reduced by 3.43% compared to Case I.

The TVPP's energy and flexibility self-scheduling for BoUs equal to 50% of the maximum BoUs and uncertainty bounds of Λ_{BC} (namely, Case II) is presented in Figure 2. In the figure, the TVPP's upward flexibility capability is demonstrated by negative sign. The energy and flexibility market prices are also demonstrated in the figure. Based on the figure, in the energy market, the TVPP purchases energy to feed the loads. In the flexibility market, the TVPP provides upward and downward flexibility by scheduling the DERs' flexibility capabilities. The TVPP provides upward flexibility capabilities mostly when the associated market price is high. Moreover, the TVPP provides considerable downward flexibility since the PV units only have capability of downward flexibility provision and the DGs' imposed cost is reduced by providing downward flexibility.

The DERs' optimal energy and flexibility schedules are presented in Figures 3a and 3b, respectively. In the figure, the DERs' generation power and their provided upward flexibility are shown by negative sign. The PV units provide considerable flexibility since it is assumed that their operational costs are not considerable and they can change their output power without imposed cost. The DGs mostly provide downward flexibility power since besides obtaining profit by providing downward flexibility, their imposed cost is reduced due to reducing their output power. The RLs provide upward flexibility in the times of peak price of upward flexibility. Moreover, the HVACs and VBs participate in providing upward and downward flexibility while their associated welfare constraints are satisfied.

The charging and discharging statuses as well as the charging and discharging powers of one of the VBs in the network are illustrated in Figure 4. As shown in the figure, the VB is either charged or discharged at each time interval in the energy market. Based on the VB's power in the energy market, the VBs' upward and downward flexibility provision by adjusting the charging or discharging power in each time interval is also addressed in the figure.

TABLE 3 TVPP's profit for different BoUs ($/day).

Column	1	2	3	4	5	6	7	8
Γ_{RL}	0	$\Gamma_{RL\_\max}$	0	0	0	0	$0.5\Gamma_{RL\_\max}$	$\Gamma_{RL\_\max}$
Γ_{H}	0	0	$\Gamma_{H\_\max}$	0	0	0	$0.5\Gamma_{H\_\max}$	$\Gamma_{H\_\max}$
Γ_{PV}	0	0	0	$\Gamma_{PV\_\max}$	0	0	$0.5\Gamma_{PV\_\max}$	$\Gamma_{PV\_\max}$
Γ_{VB}	0	0	0	0	$\Gamma_{VB\_\max}$	0	$0.5\Gamma_{VB\_\max}$	$\Gamma_{VB\_\max}$
Γ_{Tr}	0	0	0	0	0	$\Gamma_{Tr\_\max}$	$0.5\Gamma_{Tr\_\max}$	$\Gamma_{Tr\_\max}$
Profit	5515.77	5509.85	5501.75	5494.25	5492.09	5498.41	5437.76	5406.72
DA profit	3356.86	3356.58	3356.11	3357.17	3355.23	3358.16	3351.09	3344.27
ID profit	2158.92	2153.27	2145.64	2137.08	2136.86	2140.28	2086.67	2062.45

TABLE 4 TVPP's profit for different uncertainty bounds ($/day).

Γ_{RL}	$\Gamma_{RL\_\max}$	0	0	0	0	$0.5\Gamma_{RL\_\max}$	$\Gamma_{RL\_\max}$
Γ_{H}	0	$\Gamma_{H\_\max}$	0	0	0	$0.5\Gamma_{H\_\max}$	$\Gamma_{H\_\max}$
Γ_{PV}	0	0	$\Gamma_{PV\_\max}$	0	0	$0.5\Gamma_{PV\_\max}$	$\Gamma_{PV\_\max}$
Γ_{VB}	0	0	0	$\Gamma_{VB\_\max}$	0	$0.5\Gamma_{VB\_\max}$	$\Gamma_{VB\_\max}$
Γ_{Tr}	0	0	0	0	$\Gamma_{Tr\_\max}$	$0.5\Gamma_{Tr\_\max}$	$\Gamma_{Tr\_\max}$
$\Lambda_{\downarrow}$	5512.82	5510.66	5505.20	5503.83	5508.81	5488.07	5471.85
Λ_{BC}	5509.85	5501.75	5494.25	5492.09	5498.41	5437.76	5406.72
$\Lambda_{\uparrow}$	5506.87	5490.47	5483.21	5468.53	5487.34	5430.64	5326.63

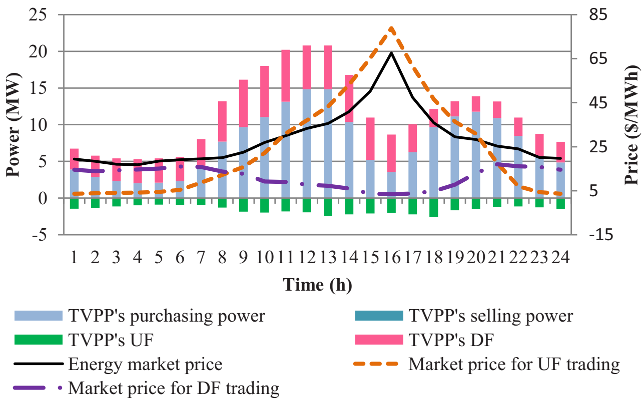

FIGURE 2 The TVPP's transaction with energy and flexibility markets.

It is worth noting that considering the uncertainties reduces the flexibility provision capabilities in the network which causes the TVPP's profit reduction. Comparing the results of Case I and Case II, in Case II the PVs' available power is reduced which causes reduction in the PVs' downward flexibility provision. Moreover, the RLs' required energy is increased and the time intervals that the EVs are available (i.e. the VBs' capacity) are reduced. Furthermore, the ambient temperature is changed in the way that the obtained profit would be decreased. In addition, the TSO's requested flexibility is increased which causes the TVPP's profit reduction. The DERs' optimal schedules have changed in the presence of uncertainties. Figures 5a and b demonstrate the VBs' SoC in Case I and Case II, respectively. As shown in the figure, presence of uncertainties causes that the VBs' maximum/minimum SoC decreases/increases which limits the VB's flexibility capability. Moreover, the ambient temperature changes in the way that the HVACs' upward and downward flexibility capabilities have reduced in the time intervals when the associated prices are high and the flexibility capabilities have increased in the times of low prices according to Figure 6.

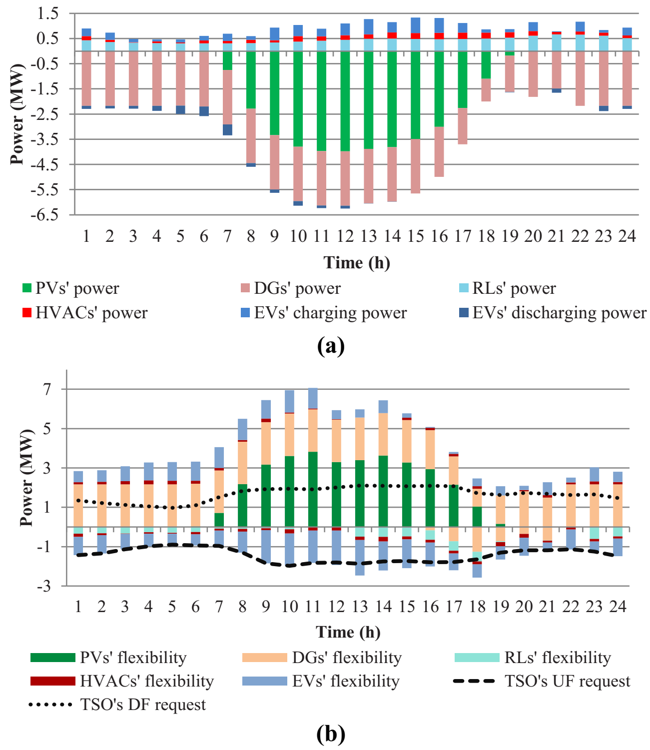

FIGURE 3 DERs' schedules in (a) DA energy market (b) ID flexibility market.

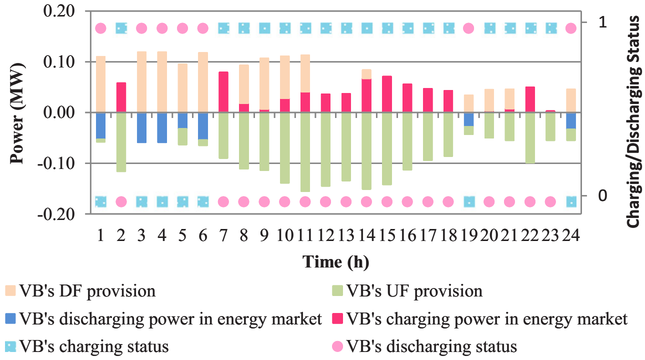

FIGURE 4 A VB's charging and discharging status and its energy and flexibility schedules.

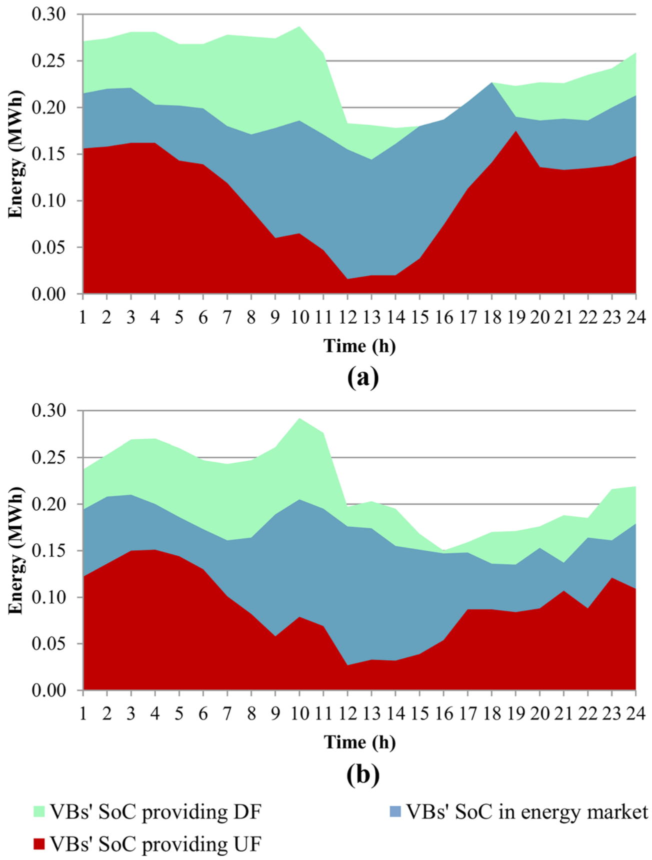

FIGURE 5 Aggregated VBs' SoC in (a) Case I (b) Case II.

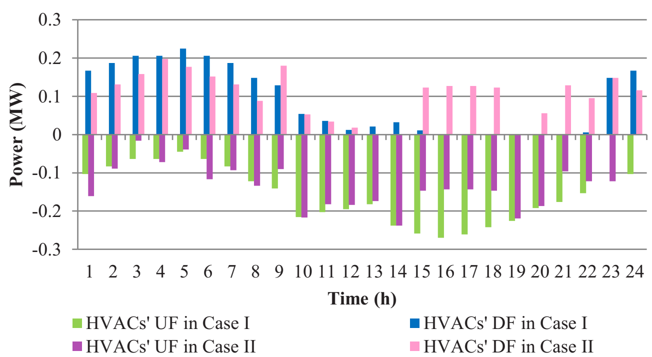

FIGURE 6 Aggregated HVACs' flexibility in Case I and Case II.

TABLE 5 TVPP's profit for different BoUs considering ESSs ($/day).

Γ_{RL}	0	$0.5\Gamma_{RL\_max}$	Γ_{RL_max}
Γ_{H}	0	$0.5\Gamma_{H\_max}$	Γ_{H_max}
Γ_{PV}	0	$0.5\Gamma_{PV\_max}$	Γ_{PV_max}
Γ_{VB}	0	$0.5\Gamma_{VB\_max}$	Γ_{VB_max}
Γ_{Tr}	0	$0.5\Gamma_{Tr\_max}$	Γ_{Tr_max}
Profit	8150.08	8096.11	8074.97
DA profit	3358.66	3351.23	3351.01
ID profit	4791.42	4744.88	4723.96

It should be noted that the distribution network operational constraints are satisfied while participating in energy and flexibility markets for all the uncertainty realizations. In the worst-case uncertainty realization, maximum power flow of lines is 84.01% in energy scheduling while it is 82.84% and 94.15% due to upward and downward flexibility transactions, respectively. Moreover, the bus voltages are between 0.95 and 1.05 p.u. in energy and flexibility transactions which are in the allowable range.

Investigating the role of ESSs in the network, a case study is considered that the system contains ESSs. In this case, the TVPP's profits in energy and flexibility markets for different level of BoUs are presented in Table 5. According to the table, utilizing the ESSs increases the TVPP's profit significantly because of the ESSs' low operating cost and high flexibility capabilities. Employing the ESSs mostly affects the TVPP's profit in ID flexibility market by providing noticeable flexibility capabilities. Moreover, by comparing the results of the worst-case realization of uncertainties with the case that the uncertainties are disregarded, the TVPP's profit has reduced by 0.92%. Therefore, by utilizing the ESSs, the profit reduction due to existing uncertainties reduced by 53.54% which emphasizes the role of ESSs in mitigating the effects of uncertainties.

In order to compare the adaptive robust optimization model with the stochastic approach, a case study is introduced (namely, Case III) in which the uncertain parameters are modelled using stochastic scenario-based optimization model. In the stochastic approach, a finite number of scenarios is generated by considering the uncertain parameters' PDFs. Defining the accurate PDFs of these parameters is more difficult than defining their uncertainty bounds for constructing uncertainty set in the robust optimization approach. In the proposed stochastic approach, the historical data associated with the PV units' output power, air temperature and EVs' driving pattern are extracted from the references presented in Section 5.1. Moreover, in order to model the uncertainty of the RLs' required energy and the TSO's flexibility request, normal PDFs with mean and standard deviation consistent with ones presented in Section 5.1 are taken into account. To generate adequate scenarios for modelling the uncertain parameters, Monte Carlo simulation is used. The Monte Carlo simulation parameters are the PDFs of the uncertain parameters' prediction errors, which are obtained from the historical data. In order to include the prediction error, the uncertain parameter in each scenario is considered to be equal to the parameter's forecasted value plus a positive or negative error which is generated randomly according to the associated PDF. The generated scenarios in the energy and flexibility self-scheduling problem cause the problem to present a large number of parameters and variables. Therefore, it is essential to deploy a scenario reduction technique to make a compromise between the computation efficiency and the model accuracy. Here, similar to [39], SCENRED scenario reduction is used which is a tool in General Algebraic Modelling System (GAMS) and includes different reduction techniques. After scenario reduction, a smaller number of scenarios with new probabilities are obtained and sum of the preserved scenarios' probabilities is equal to one [39]. Modelling the uncertain parameters based on the proposed approach, 2500 scenarios are generated using Monte Carlo simulation and 15 final scenarios are chosen using the reduction technique.

By solving the problem for each scenario and considering the associated scenario's probability, optimal energy and flexibility schedules of the TVPP and the DERs are determined. In this case, the TVPP's profit is obtained equal to 5495.17$/day which is greater than the TVPP's profit in Case II. The reason is that Case II is solved for the worst-case uncertainty realizations (for BoUs equal to 50% of the maximum BoUs); however, Case III is solved for several probable scenarios and the TVPP's expected profit is obtained considering the scenarios' occurrence probability. It is worth noting that in the adaptive robust optimization approach, the model conservativeness can be determined using BoUs and by selecting lower BOUs, the TVPP's profit would be increased while the model conservativeness is reduced. Moreover, the adaptive robust optimization approach guarantees that the solution is feasible for all the uncertainty occurrence cases in the uncertainty set; however, in the stochastic approach since the optimization problem is solved for a number of scenarios and the expected results are obtained, the solution may not be feasible for some uncertainty occurrence scenarios. In this context, for the obtained solution in Case III, the flow limit of the line which connects bus 26 and bus 29 (see the network schematic in ref. [20]) is not satisfied in time interval 10 for the uncertainty scenario in which the PV power production is relatively low (equal to 3.4 MW) and the TSO's requested flexibility is relatively high (equal to 1.98 MW). In addition, the computational time in the stochastic approach is more than the adaptive robust optimization approach; the computational time to solve the problem in Case III is 9.2 min while it is 71 s in Case II.

In order to compare the results of the stochastic approach and the adaptive robust optimization approach by focusing on the worst-case performance, an out-of-sample assessment is carried out based on the method presented in [24]. The out-of-sample assessment is executed for the generated 2500 scenarios. By implementing the out-of-sample assessment for the solution provided by the proposed stochastic model, the average profit of the stochastic model is obtained equal to 5482.12$/day which is higher than the profit obtained in the out-of-sample assessment of the adaptive robust optimization approach which is equal to 5443.87$/day. However, the economic gain of the stochastic approach in comparison with the adaptive robust optimization approach comes at the expense of more computational time as well as the fact that the obtained solution in the stochastic approach may not be feasible for some of the scenarios in the associated uncertainty scenario set. By increasing the number of scenarios in the stochastic model, the average of infeasibility level is reduced [24]. However, further increasing the scenarios would lead to computational complexity and solution time increase. Therefore, a tradeoff between the model accuracy/feasibility and the computational time should be considered.

Moreover, to highlight the merit of the adaptive robust approach in comparison with the robust approach, Case IV is introduced in which the uncertainty sources are modelled using the robust optimization approach addressed in [34]. In this model, all the decision variables should be determined before the uncertainty realizations become known and the model conservativeness in this approach is more than the adaptive robust optimization approach. In contrast to the adaptive robust optimization approach in which two types of "here-and-now" and "wait-and-see" variables are defined using a two-stage model, the adopted robust optimization approach addresses a single-stage optimization approach in which the energy and flexibility self-scheduling problem is optimized for the worst-case uncertainty realizations. The case study parameters in Case IV are equal to those introduced in Section 5.1. By using the robust optimization approach, the TVPP's profit for BoUs equal to 50% of the maximum BoUs and uncertainty bounds of Λ_{BC} is equal to 5349.01$/day which is 1.63 %/day lower than the TVPP's profit in Case II. Therefore, for the same level of BoUs and uncertainty bounds, the adaptive robust optimization approach is more economic, because this approach optimizes the energy schedules using the predicted values and then adjusts the energy schedules by providing flexibility to meet the worst-case uncertainty realizations, while in the robust approach, all the variables should be determined before the realization of uncertain data and therefore, their schedules deviate from the optimal economic value.

A contingency-based case study (namely, Case V) is investigated in which the TVPP considers the contingency occurrences in its self-scheduling problem. In this model, the cost of load curtailment by considering the value of lost load equal to $1000/MWh are addressed in the first stage objective function (1) associated with the TVPP's energy self-scheduling problem. Moreover, the cost associated with not serving the TSO's requested flexibility is considered in the second stage objective function (24) based on the penalty equal to $1000/MW. In this case study, contingencies are considered as $N-1$ failure of distribution lines. The lines' failure rate, repair time and switching time are considered to be equal to 0.006 occs/year/km, 5 h and 1 h, respectively [40]. By occurring contingencies, islands may be created in the network due to the line outages. It is assumed that the DGs and RESs in the islands can feed a part/the whole of the loads in the islands. Moreover, by occurring line outages, appropriate switching actions are done to feed the islands' loads as much as possible and utilize the flexibility capabilities of the flexible DERs in the islands through an alternate path until the fault is removed [40]. By considering the optimal

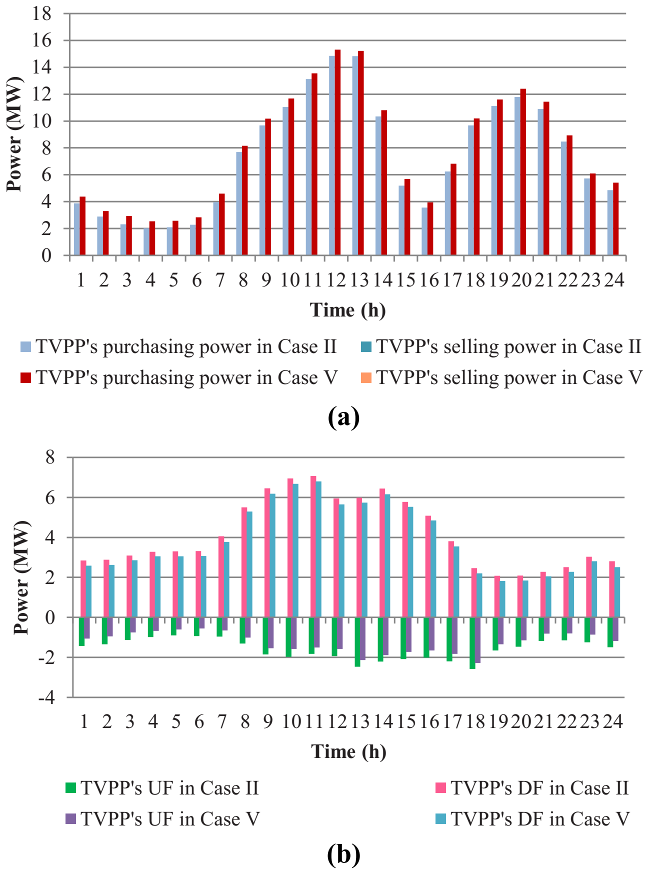

FIGURE 7 The TVPP's transaction with (a) energy and (b) flexibility markets in Case II and Case V.

energy and flexibility schedules in each contingency and taking the probability of the associated contingency into account, the TVPP's optimal strategy in markets and the DERs' optimal energy and flexibility schedules are determined. In this case study, the TVPP's optimal energy and flexibility transactions with market for BoUs equal to 50% of the maximum BoUs and uncertainty bounds of Λ_{BC} are presented in Figure 7. In comparison with Case II, the TVPP's purchasing power in wholesale energy market has increased in Case V to feed the loads in the distribution network and reduce the load curtailments during contingency occurrences. Moreover, the TVPP's flexibility provision in wholesale flexibility market has decreased in Case V since the contingency occurrences cause that some flexibility capabilities would not be available for offering to market. The TVPP's objective is obtained equal to 5408.61\$/day in this case. However, in Case II in which the TVPP does not consider the imposed costs due to contingency occurrences in its objective function, if occurrence of contingencies are addressed and the TVPP's imposed costs due to contingency occurrences are subtracted from the TVPP's profit [40], its profit has reduced to 5246.05\$/day which is 3 %/day lower than Case V. Therefore, it can be concluded that modelling the contingency occurrences in the TVPP's decision making is profitable by minimizing the imposed costs due to contingency occurrences.

6 | CONCLUSION

This paper proposed a two-stage adaptive robust optimization framework to address the uncertainties associated with the DERs and the transmission network's flexibility requests in energy and flexibility self-scheduling of a TVPP. A max-min-max optimization problem was presented and converted to an MILP problem solved by a CCG algorithm. The model was implemented on the RBTS-Bus 5 distribution network and the results were presented and discussed. In this regard, the TVPP's optimal energy and flexibility offers to market as well as the DERs' optimal energy and flexibility schedules were presented. Moreover, effect of different uncertainty sources and different level of conservativeness on the TVPP's profit was addressed. It was shown that the PVs' and EVs' uncertainties have more effect on the TVPP's profit. Furthermore, it was demonstrated that by increasing uncertainty bounds and BoUs, the model conservativeness has increased which cause the TVPP's profit reduction. Effect of existing uncertainties on the DERs' scheduling was also demonstrated. In addition, it was shown that the distribution network operational constraints are satisfied in the presence of uncertainties. Moreover, the ESSs' attractive role in uncertainty mitigation and flexibility provision was approved. In addition, the proposed model was compared with the stochastic and robust optimization models by investigating case studies. A contingency-based case study was also addressed to consider the contingency occurrences in the TVPP's self-scheduling problem. In future works, the market prices uncertainty can be incorporated in the model. Moreover, modelling explicit correlations of uncertainty sources can be taken into account by incorporating covariance matrices into the uncertainty set.

NOMENCLATURE

Indices and Sets

r	Index of DERs.
c, C	Index and set of customers, respectively.
b, b_1, B	Indices and set of network buses, respectively.
DG, PV, H, RL, VB, ES	Sets of DGs, PVs, HVACs, RLs, VBs and ESSs.
$DG_b, PV_b, VB_b, ES_b, C_b$	Sets of DGs, PVs, VBs, ESSs and customers at bus b.
H_c	Sets of HVACs belong to customer c.
B_b	Set of network buses connected to bus b.
J	Set of network lines.
t, T	Index and set of time intervals, respectively.

Parameters

$P_{FL}^{c,t}$	Customers' fixed load.
$P_{PV}^{r,t}$	PVs' production power.

$E_{RL\_req}^{c}$ RLs' required energy.
$S_{VB\_arr}^{r,t}$ Increase in VBs' SoC due to EVs' arrival.
$S_{VB\_dep}^{r,t}$ Decrease in VBs' SoC due to EVs' departure.
$S_{ES\_0}^{r,t}$ Initial SoC of ESSs.
$R_{DG\_up}^{r}, R_{DG\_dn}^{r}$ Upward and downward ramp rate of DGs.
$R_{ES\_up}^{r}, R_{ES\_dn}^{r}$ Upward and downward ramp rate of ESSs.
θ_{O}^{t} Ambient temperature.
R_{C}^{c}, K_{C}^{c} Equivalent resistance of customer buildings and heat capacity of space.
$c_{DG}^{r,t}$ DGs' marginal operation cost.
$a_{ES}^{r,t}$ ESSs' cost function coefficient.
U_{Tr}^{t}, D_{Tr}^{t} TSO's requested upward and downward flexibility capabilities.
$\Gamma_{PV}, \Gamma_{H}, \Gamma_{RL}, \Gamma_{VB}, \Gamma_{Tr}$ BoU associated with PVs, HVACs, RLs, VBs and TSO's requested flexibility.
$\pi_{E\_W}^{t}, \pi_{E\_L}^{t}$ Wholesale energy market price and distribution network local energy price.
$\pi_{U\_W}^{t}, \pi_{D\_W}^{t}$ Wholesale flexibility market prices for upward and downward flexibility procurement.
$\pi_{U\_L}^{t}, \pi_{D\_L}^{t}$ Distribution network local flexibility prices for upward and downward flexibility procurement.
$r_{J}^{b,b_1,t}, x_{J}^{b,b_1,t}$ Resistance and reactance of network lines.
S_{J}^{b,b_1} Maximum flow of network lines.
Δt Duration of time intervals.
$(.)_{\min}, (.)_{\max}$ Minimum and maximum amount of variables.
$\overline{(.)}, \widehat{(.)}$ Forecasted amount of uncertain variables and associated uncertainty bound.

First stage variables (Ω_{DA})

P_{VPP}^{t} TVPP's power trading with energy market (positive/negative value for purchasing/selling power from/to market).
$P_{DG}^{r,t}$ DGs' output power.
$P_{H}^{r,t}, P_{RL}^{c,t}$ HVACs' and RLs' consumption power.
$\theta_{C}^{c,t}$ Customer buildings' temperature.
$x_{VB\_ch}^{r,t}, x_{VB\_dch}^{r,t}$/ $x_{ES\_ch}^{r,t}, x_{ES\_dch}^{r,t}$ Binary variables representing the VBs'/ESSs' charging and discharging statuses.
$P_{VB\_ch}^{r,t}, P_{VB\_dch}^{r,t}$/ $P_{ES\_ch}^{r,t}, P_{ES\_dch}^{r,t}$ VBs'/ESSs' charging and discharging powers.
$P_{ES}^{r,t}$ ESSs' power (positive/negative value indicates charging/discharging status).
$S_{VB}^{r,t}/S_{ES}^{r,t}$ SoC of VBs/ESSs.
$P_{J}^{b,b_1,t}, Q_{J}^{b,b_1,t}$ Active and reactive power flow of lines.
$V^{b,t}$ Voltage amplitude of network buses.

Second stage variables (Ω_{ID})

U_{VPP}^{t}, D_{VPP}^{t} TVPP's upward and downward flexibility capability offered to market.
$U_{DG}^{r,t}, D_{DG}^{r,t}$/ $U_{H}^{r,t}, D_{H}^{r,t}$/ $U_{RL}^{c,t}, D_{RL}^{c,t}$/ $U_{VB}^{r,t}, D_{VB}^{r,t}$/ $U_{ES}^{r,t}, D_{ES}^{r,t}$ DGs'/HVACs'/RLs'/VBs'/ESSs' upward and downward flexibility capability provision.
$D_{PV}^{r,t}$ PVs' downward flexibility capability provision.
$S_{VB\_U}^{r,t}, S_{VB\_D}^{r,t}$/ $S_{ES\_U}^{r,t}, S_{ES\_D}^{r,t}$ VBs'/ESSs' SoC after upward and downward flexibility provision.
$\theta_{C\_U}^{c,t}, \theta_{C\_D}^{c,t}$ Buildings' temperature after upward and downward flexibility provision.
$U_{J}^{b,b_1,t}, D_{J}^{b,b_1,t}$ Change in the lines' active power flow due to upward and downward flexibility transactions.
$P_{U\_J}^{b,b_1,t}, Q_{U\_J}^{b,b_1,t}$ Active and reactive power flow of lines due to upward flexibility transactions.
$P_{D\_J}^{b,b_1,t}, Q_{D\_J}^{b,b_1,t}$ Active and reactive power flow of lines due to downward flexibility transactions.
$V_{U}^{b,t}, V_{D}^{b,t}$ Voltage amplitude of buses due to upward and downward flexibility transactions.

Uncertain variables in the second stage (Ω_{Unc})

$\tilde{P}_{PV}^{r,t}$ PVs' output power.
$\tilde{\theta}_{O}^{t}$ Ambient temperature.
$\tilde{E}_{RL\_req}^{c}$ RLs' required energy.
$\tilde{P}_{ch\_\max}^{r,t}, \tilde{P}_{dch\_\max}^{r,t}$ VBs' maximum charging and discharging powers.
$\tilde{S}_{VB\_\min}^{r,t}, \tilde{S}_{VB\_\max}^{r,t}$ VBs' minimum and maximum SoC.
$\tilde{S}_{VB\_arr}^{r,t}$ Increase in VBs' SoC due to EVs' arrival.
$\tilde{S}_{VB\_dep}^{r,t}$ Decrease in VBs' SoC due to EVs' departure.
$\tilde{U}_{Tr}^{t}, \tilde{D}_{Tr}^{t}$ TSO's requested upward and downward flexibility capabilities.

AUTHOR CONTRIBUTIONS

Niloofar Pourghaderi: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing—original draft; Mahmud Fotuhi-Firuzabad: Conceptualization, Methodology, Supervision, Writing—review and editing; Moein Moeini-Aghtaie: Conceptualization, Methodology, Supervision, Validation, Writing—review and editing; Milad Kabirifar: Formal analysis, Validation, Visualization, Writing—review & editing; Matti Lehtonen: Validation, Writing—review and editing.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Niloofar Pourghaderi https://orcid.org/0000-0001-6759-1931
Mahmud Fotuhi-Firuzabad https://orcid.org/0000-0002-5507-9938
Moein Moeini-Aghtaie https://orcid.org/0000-0002-7656-6807
Milad Kabirifar https://orcid.org/0000-0002-8151-8199
Matti Lehtonen https://orcid.org/0000-0002-9979-7333

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