Boosting Integration Capacity of Electric Vehicles: A Robust Security Constrained Decision Making

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***Abstract*— Global electric vehicles (EVs) fleet is expanding at a rapid pace. Considering the uncertain driving pattern of EVs, they are dynamic consumers of electricity and their integration can give rise to operational problems and jeopardize the security of the power system. Under such circumstances, the implementation of demand-side response (DSR) programs is more likely to be an effective solution for reducing the risks of load curtailment or security problems. This study proposes a voltage stability constrained DSR-coordinated planning model for increasing the penetration level of EVs in a distribution system consisting of photovoltaics (PVs), wind turbines (WTs) and responsive loads. The uncertainties of PV/WT generation, the driving pattern of EVs, and load demand are modeled by an improved form of information gap decision theory (IGDT), hereafter called weighted IGDT (WIGDT). Due to the fact that the proposed model is nonlinear and non-convex, a linearization technique is adopted and the proposed model is formulated as a mixed-integer linear programming (MILP), solved using the general algebraic modeling system (GAMS) software. The standard 33-bus distribution test system and a real-world smart distribution network, based in the Isle of Wight in the UK, are used to evaluate the performance of the model.**

***Index Terms*—Electric vehicles (EVs), renewable energy resource (RES), planning, demand-side response (DSR), uncertainty.**

NOMENCLATURE

Indices

i	Index of system buses
t	Index of hour
y	Index of years

Sets

ψ_b	Set of system buses
ψ_t	Set of hour
ψ_y	Set of planning years

Parameters

$(G/B)_{ij}$	Conductance/susceptance of line between buses i and j [pu]
$(P/Q)_{\max/min}$	Maximum/minimum active/reactive power injected from upstream network [MW/MVAr]
$(P/Q)^{L}_{i,d,t}$	Active/reactive load demand at cop [MW/MVAr]
$\eta^{(ch/dch)_{PL}}_{i,y,t}$	Charging/discharging efficiency of EVs
$\eta^{TR_{PL}}_{i,y,t}$	Transmission efficiency of EVs [KW/KM]
$\gamma^{max/min}_{i}$	Maximum/minimum flexibility of responsive loads
$(\hat{P/Q})^{L}_{i,d,t}$	Active/reactive load demand at LLP [MW/MVAr]
$\kappa^{(PV/WT/PL)}_{i,y}$	Investment cost of PV/WT/PL [$]
Υ	Loading margin
Cap^{PL}_{y}	Annual capacity of parking lot [number of EV]
D^{PL}_{y}	Rate of annual increase in the number of EVs [%]
$D^{EV}_{\max/min}$	Maximum/minimum traveling distance of an EV [KM]
$N^{DR}_{\max}$	Maximum available responsive loads
$N^{PL}_{\max}$	Maximum PLs that could be installed in the network
$N^{WT/PV}_{\max}$	Wind/PV profile
$P^{(Ch/dch)_{EV}}_{\max}$	Maximum charging/discharging rate of an EV [KW]
P^{EV}_{CH2TR}	Percentage of EVs that consumed their charged power through transmission mode [%]
$S^{\max}_{ij}$	Maximum apparent power through the branches [MVA]
$SOC^{EV}_{\max/min}$	Maximum state of charge of an EV [KWh]
$V_{\max/min}$	Maximum/minimum voltage magnitude [pu]

Variables

$\chi^{(PV/WT/PL)}_{i,y}$	Binary variable indicating installation status of PV/WT/PL [1/0: Installed/otherwise]
$\gamma^{DR}_{i,y,t}$	DSR index
$\hat{V}_{i,y,t}$	Voltage magnitude at LLP [pu]
$\hat{\theta}_{j,y,t}$	Voltage angle at LLP[pu]
$(\hat{P/Q})^{UN}_{i,y,t}$	Active/reactive power injected from upstream network at LLP [MW/MVAr]
$\theta_{j,y,t}$	Voltage angle at COP [pu]
$D^{E}_{i,y}$	Annual load growth [%]
$N^{(G2V/V2G/TR)}_{i,y,t}$	Number of EVs in G2V/V2G/transmission state [number of EV]
$P^{(Ch/DCh)_{PL}}_{i,y,t}$	Charged/dischaged active power of PL [MW]
$SOC^{PL}_{i,y,t}$	State of charge of PL [MWh]
$V_{i,y,t}$	Voltage magnitude at COP [pu]

I. Introduction

A. Electric Mobility Outlook

THE UK Industrial Strategy sets four Grand Challenges out to put the country at the forefront of the industries of the future in the areas of artificial intelligence and big data, clean growth, e-mobility and aging [1]. According to this strategy, an ambitious mission is developed to put the UK at the forefront of the design and manufacturing of zero-emission vehicles, with all new cars and vans zero emission by 2040. Furthermore, the recent Global Electric Vehicle (EV) Outlook 2019 report, highlights the rapidly growing path of e-mobility. According to this report, the global electric car fleet in 2018 shows a significant increase with respect to that of 2017, with an increase of almost 5.1 million vehicles. The EVs consumed an estimated 58 terawatt-hours of electricity in 2018, worldwide, similar to the total electricity demand of Switzerland in 2017 [2].

B. Motivation and Research Question

Worldwide growth in the integration of renewable energy resources (RESs) into the power generation mix, brought a great challenge to the operation of the power systems. Although RESs are an environmentally friendly form of generation and have several positive aspects, their intermittency can bring about several challenges to the power system such as voltage instability. In a such situation, EVs in parallel with demand-side response (DSR) would be able to play an active or even a proactive role in increasing the flexibility of power systems. Therefore, long-term planning and expansion scenarios as well as short-term policies and market frameworks, are required to ensure a coordinated and adaptable integration of all components.

This work tries to design a coordinated decision-making framework that boosts the integration capacity of the power networks while considering voltage stability-as the security measure-and generation adequacy in a long-term horizon. In brief, the objective of this work is to provide an answer to a key research question for power systems engineering as follows:

“With the rapid growth of e-mobility, how, can we integrate millions of EVs into the distribution system? And what is the optimal coordinated integration strategy?”

C. Literature Survey

Several research works have been conducted for defining the optimal integration capacity of EVs in the distribution networks. In [3], a two-stage optimization problem is introduced for optimal allocation of parking lots (PLs), and RESs from the owner of parking lots point of view, using a mixed integer non-linear programming (MINLP) model. This model has been solved by a mixed genetic algorithm and particle swarm optimization. A multi-objective optimization problem is introduced in [4], for optimal allocation of PLs, from PL owner’s viewpoint, while the voltage profile is considered as another objective function. Prebeg *et al* [5] benefited from EVs as storage, and these technologies are adopted to increase the penetration level of RESs. The effect of charging/discharging pattern of EVs on the operation cost of the distribution system as well as the system load profile is investigated in [6], while the optimal location for parking lots is optimally selected. Different bidirectional control strategies are proposed in [7] for optimal active/reactive power management of distribution system equipped with EVs, which can provide the grid with active and reactive power support.

In a carbon-free integration planning model, the work presented in [8] utilized the vehicle-to-grid (V2G) option in an integrated transport and energy infrastructure, with the aim of demand supply in islanded microgrids. A systematic analysis is proposed in [9] for clustering EV users, and optimal control strategies are devised for commercial and public parking lots using water-filling algorithm. The work presented by Liu [10] *et al* indicates that increasing the number and capacity of EVs, as an energy service provider, can raise the penetration of renewable generation, while the charging satisfaction, an index reflecting the charging convenience of EV users, can also be increased. The EVs can be used for dealing with intermittency of weather-dependent generation units. To compensate for the variability of wind and solar power generation, a robust control strategy is proposed in [11] for V2G and grid-to-vehicle (G2V) functionalities. To manage the power flow of transmission systems under the large-scale penetration of EVs and RESs, reference [12] equipped the system with on-load tap changers as well as phase-shifting transformers which can improve the capability of dealing with fluctuation of RESs.

Regarding the intermittency of renewable units, it is important to consider the uncertainty of RESs on long/short-term horizon. In [13], a stochastic non-linear programming model is introduced for dealing with the uncertainty of Photovoltaic (PV) generation, and reducing the operation cost of distribution system under the penetration of small-scale PLs. Meanwhile, renewable generation is not the only source of the uncertainty, and system load demand and driving patterns of EVs are other forms of the uncertainties that should be considered. In [14] and [15], a two-stage optimization framework is presented for long-term planning and short-term operation of EVs with consideration for demand uncertainty. To deal with uncertainty of EVs’ driving pattern, Monte-Carlo simulation and non-parametric Bootstrap techniques are used in [16] and [17], respectively. A probability density function is generated for an EV fleet in [18] using three driving pattern parameters, namely, (a) arrival time, (b) departure time, and (c) trip distance, while Kernel density has been used as a probability density function estimation. Finally, in an optimal parking lot allocation problem, the point estimate method, which suffers from several drawbacks such as computation time and low accuracy, has been adopted for dealing with the EV driving pattern [19].

As an active demand consumer or energy provider, EVs can have positive or negative impacts on the power system. The effect of EVs charging/discharging schedule on different aspects of power systems such as resilience [20], reliability [21], and power loss reduction [22], has been examined in the literature. Voltage stability, is another important aspect which is investigated in long/short-term studies of the power systems under the penetration of new energy resources [23]. In [24], the impact of EVs penetration on voltage quality and harmonic distortion is investigated. Also, [25] has explored the effect of EVs on the low voltage network using a robust approach. Accordingly, the implementation of different methodologies is of utmost importance to improve the voltage stability of the system.

D. Research Gap

Table I presents a taxonomy of existing approaches and reviews the previous researches in the area to clearly highlight the novel aspects of this work. Although the concept of EV integration has been widely investigated, there are a number of important aspects that have not been considered, namely:

I. Decisive operational and security constraints that can significantly affect the optimal allocation of EV fleets have not been taken into account.
II. Voltage stability constraints, one of the most important limitations in power system expansion planning studies, have not been considered as the limit of the integration planning of PLs.
III. The majority of the previous literature has utilized probabilistic or stochastic approaches for dealing with uncertainty. Nevertheless, these methodologies, need a sizable amount of information about the uncertain parameter and considerably increase the computation time.
IV. The driving pattern of EVs has not been considered in the state of charge of the battery of EVs, or it has been taken into account as the parameter instead of an uncertain variable. It should be noted also that the available data such as arrival time, departure time, and trip distribution are more likely to experience sudden changes and there is not an accurate probabilistic distribution function to model their characteristics.

E. Contributions

Given above considerations, this paper proposes a voltage stability constrained DSR-coordinated planning model for increasing the penetration level of EVs in a distribution system. The studied distribution system consists of PVs and wind turbine (WT) generations as well as responsive loads, taking into account multiple uncertainties of EVs' driving pattern, PV/WT generation, and system demand. The optimal allocation strategy selects the best candidate buses for installation of PLs, WTs, and PV, while the optimal capacity of EV fleets in terms of MW and number of EVs as well as optimal capacity of WTs and PVs is defined. The well-known uncertainty modeling technique, Information Gap Decision Theory (IGDT) [27] is adopted to model the aforementioned uncertainties. The proposed DSR-coordinated planning model is an MINLP problem which considers various operational and physical constraints. However, it is generally a tough task to obtain global optimal solutions from such a typically NP-hard problem. Accordingly, a linearization technique is adopted to facilitate the problem solving and achieve the global optimal solution.

In brief, the main contributions of this paper can be summarized as follows:

- The increasing penetration level of EVs in the distribution networks is analysed by a DSR coordinated framework;
- The optimal buses for DSR program, as well as optimal location and capacity of PLs, WTs, and PVs is selected in a long-term planning horizon subject to the voltage stability constraints;
- The uncertainties of driving pattern of EVs, PV/WT generation, and system load is modeled using the IGDT-based framework;
- The effect of different integration scenarios on voltage stability margin is investigated.
- A weighting factor is introduced for IGDT technique (called WIGDT) for modeling multiple uncertainties.
- The role of responsive loads in improving the robustness of system is evaluated.

F. Paper Organization

The remainder of the paper is organized as follows. Section II provides the model formulation. The test system and framework description is presented in Section III. Simulation results are given in Section IV. Finally, Section V concludes the paper.

II. Model Formulation

In this section, the mathematical model for the proposed MILP model is introduced. The objective function, as well as general equality and inequality constraints for the model are introduced; then, the mathematical description of the IGDT technique for dealing with different uncertainties is presented.

A. Objective Function

The objective function used in this study minimizes the investment and operation costs of various technologies in the network.

$$\min \quad TC = \left\{ \sum_{y \in \psi_y} \left(Cost_y^{inv} + Cost_y^{op} \right) \right\} \tag{1}$$

$$\begin{aligned} Cost_y^{inv} = \Bigg\{ & \sum_{i \in \psi_{wt}} \left(\kappa_{i,y}^{WT} \times (\chi_{i,y}^{WT} - \chi_{i,y-1}^{WT}) \right) + \\ & \sum_{i \in \psi_{pv}} \left(\kappa_{i,y}^{PV} \times (\chi_{i,y}^{PV} - \chi_{i,y-1}^{PV}) \right) + \sum_{i \in \psi_{pl}} \left(\kappa_{i,y}^{PL} \times (\chi_{i,y}^{PL} - \chi_{i,y-1}^{PL}) \right) \Bigg\} \end{aligned} \tag{2}$$

$$Cost_y^{op} = 365 \sum_{t \in \psi_h} \sum_{i \in \psi_b} \left\{ \begin{array}{l} \left(\lambda_t^{WT} \times P_{i,y,t}^{WT} \right) + \left(\lambda_t^{PV} \times P_{i,y,t}^{PV} \right) \\ + \left(\lambda_t^{MP} \times (P_{i,y,t}^{PL_{dch}} - P_{i,y,t}^{PL_{ch}}) \right) \\ + \left(\lambda_t^{MP} \times (P_{i,y,t}^{DR} - P_{i,y,t}^{L}) \right) \\ + \left(\lambda_t^{MP} \times P_{i,y,t}^{UN} \right) \end{array} \right\} \tag{3}$$

The model is solved subject to the power flow constraints at current operation point (COP), loadability limit point (LLP), the network physical/operational constraints, and technical limitations of various technologies such as WT, PV, and EVs.

TABLE I: Comparison of the proposed model of this paper with the available literature.

Reference	DSR	VSC	EV Allocation: Location	EV Allocation: Capacity	EV Allocation: Sizing	RES Allocation: Location	RES Allocation: Capacity	Uncertainty: Driving Pattern	Uncertainty: Load	Uncertainty: DRR	Uncertainty Modeling Technique
[3]	x	x	✓	✓	x	✓	✓	x	x	x	—
[4]	x	x	✓	✓	x	x	x	x	x	x	—
[6]	x	x	✓	✓	✓	x	x	x	x	x	—
[10]	x	x	✓	x	✓	✓	✓	x	x	x	—
[15]	x	x	✓	x	✓	x	x	x	✓	x	Stochastic
[18]	x	x	x	x	x	x	x	✓	x	x	Probabilistic
[26]	✓	✓	x	x	x	x	x	x	x	x	—
This paper	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	WIGDT

B. Investment Constraints

In an expansion planning model, the status of installed elements in the network should not change over the planning period, mathematically expressed as follows:

$$\chi_{i,y-1}^{PV} \leqslant \chi_{i,y}^{PV} \tag{4a}$$

$$\chi_{i,y-1}^{WT} \leqslant \chi_{i,y}^{WT} \tag{4b}$$

$$\chi_{i,y-1}^{PL} \leqslant \chi_{i,y}^{PL} \tag{4c}$$

C. Power Flow Constraints at current Operation Point

The AC power flow equations are effective constraints in power system studies since they cover different operational and physical characteristics of the network. Such constraints, however, are highly non-linear and non-convex which can cause significant computation burden while the results derived from them are more likely to be locally optimal. Accordingly, this study benefited from the methodology described in [28] so as to linearize the non-linear AC power flow equation as follows.

$$P_{i,y,t}^{UN} + P_{i,y,t}^{WT} + P_{i,y,t}^{PV} + \left(P_{i,y,t}^{PL_{dch}} - P_{i,y,t}^{PL_{ch}}\right) - P_{i,d,t}^{DR} - \left((1-\chi_{i,y}^{DR})P_{i,d,t}^{L}\right) = \sum_{j\in\psi_b} P_{ij,y,t} \tag{5}$$

$$Q_{i,y,t}^{UN} + Q_{i,y,t}^{WT} - Q_{i,d,t}^{DR} - \left((1-\chi_{i,y}^{DR})Q_{i,d,t}^{L}\right) = \sum_{j\in\psi_b} Q_{ij,y,t} \tag{6}$$

$$P_{ij,y,t} = G_{ij} + 2G_{ij}\Delta V_{i,y,t} - G_{ij}\cos(\phi_{ij,y,t}) - G_{ij}(\sin(\delta_{ij,y,t}) - \sin(\phi_{ij,y,t}) + B_{ij}\sin(\phi_{ij,y,t}) + B_{ij}(\cos(\phi_{ij,y,t}) - \cos(\delta_{ij,y,t})) \tag{7}$$

$$Q_{ij,y,t} = B_{ij} + 2B_{ij}\Delta V_{i,y,t} - B_{ij}\cos(\phi_{ij,y,t}) - B_{ij}(\sin(\delta_{ij,y,t}) - \sin(\phi_{ij,y,t}) - G_{ij}\sin(\phi_{ij,y,t}) - G_{ij}(\cos(\phi_{ij,y,t}) - \cos(\delta_{ij,y,t})) \tag{8}$$

$$\theta_{i,y,t} - \theta_{j,y,t} = \phi_{ij,y,t} \tag{9}$$

$$\Delta V_{i,y,t} + \Delta V_{j,y,t} + \theta_{i,y,t} - \theta_{j,y,t} = \delta_{ij,y,t} \tag{10}$$

where, (5) and (6) are the active and reactive power balance at system buses respectively, while (7) and (8) are the active and reactive power flow through the system branches. Constraints (9) and (10) express (7) and (8). Nevertheless, in these equations, the *sine* and *cosine* functions are non-linear and there is a need to linearize them, as follows:

$$\sin x \cong \eta_1 x + \varepsilon_1 \tag{11}$$

$$\cos x \cong \Omega_1 + \Omega_2 \tag{12a}$$

$$\upsilon_1 + \upsilon_2 = 1 \quad , \forall \upsilon_1, \upsilon_2 \in \{0,1\} \tag{12b}$$

$$\Omega_1 \geqslant -\upsilon_1 K_1 \tag{12c}$$

$$\Omega_1 \leqslant \upsilon_1 K_2 \tag{12d}$$

$$\Omega_1 \geqslant (\eta_2 x + \varepsilon_2) - (1-\upsilon_1)K_3 \tag{12e}$$

$$\Omega_1 \leqslant (\eta_2 x + \eta_2) + (1-\upsilon_1)K_4 \tag{12f}$$

$$\Omega_2 \geqslant -\upsilon_2 K_5 \tag{12g}$$

$$\Omega_2 \leqslant \upsilon_2 K_6 \tag{12h}$$

$$\Omega_2 \geqslant (\eta_3 x + \varepsilon_3) - (1-\upsilon_2)K_7 \tag{12i}$$

$$\Omega_2 \leqslant (\eta_3 x + \varepsilon_3) + (1-\upsilon_2)K_8 \tag{12j}$$

where, (11) is the best approximation for the *sine* function, while the best approximation for the *cosine* function is given in (12a)-(12j). The coefficients given in these equations can be found in [28]. In addition to the aforementioned constraints, the following limitations are considered for the COP.

$$V_{\min} \leqslant V_{i,y,t} \leqslant V_{\max} \tag{13}$$

$$P_{\min}^{UN} \leqslant P_{i,y,t}^{UN} \leqslant P_{\max}^{UN} \tag{14}$$

$$Q_{\min}^{UN} \leqslant Q_{i,y,t}^{UN} \leqslant Q_{\max}^{UN} \tag{15}$$

$$\left[\sin\left(\frac{360^\circ l}{m}\right) - \sin\left(\frac{360^\circ}{m}(l-1)\right)\right] p_{ij,y,t} - \left[\cos\left(\frac{360^\circ l}{m}\right) - \cos\left(\frac{360^\circ}{m}(l-1)\right)\right] Q_{ij,y,t} - \left|S_{ij}^{\max}\right| \times \sin\left(\frac{360^\circ}{m}\right) \leqslant 0 \tag{16}$$

where, (13) is the voltage magnitude limit at the COP, whereas constraints (14) and (15) represent the limitation of active and reactive power injected from upstream network respectively. Finally, (16) shows the flow limitation through system branches, linearized based on the polygonal inner approximation [29].

D. Power Flow Constraints at Loadability Limit Point

Owing to the dramatic economical and operational losses brought about by voltage collapse, in the expansion planning studies, considering a specific level of loading margin (LM) which guarantees the voltage stability of the system in normal/contingency condition is a crucial point [23]. These constraints, however, are non-linear, and due to the fact that they should be solved with those of COP, they can cause a dramatic increase in the computation time, especially for long-term planning models. Accordingly, the voltage stability constraints for the distribution system [30] are linearized as follows:

$$\hat{P}^{UN}_{i,y,t}+P^{WT}_{i,y,t}+P^{PV}_{i,y,t}+\Big(P^{PL_{dch}}_{i,y,t}-P^{PL_{ch}}_{i,y,t}\Big)-\hat{P}^{L}_{i,d,t}=\sum_{j\in\psi_b}\hat{P}_{ij,y,t} \tag{17}$$

$$\hat{Q}^{UN}_{i,y,t}+Q^{WT}_{i,y,t}-\hat{Q}^{L}_{i,d,t}=\sum_{j\in\psi_b}\hat{Q}_{ij,y,t} \tag{18}$$

$$\hat{P}^{L}_{i,d,t}=(1+\Upsilon)\times\left(P^{DR}_{i,d,t}+\left((1-\chi^{DR}_{i,y})P^{L}_{i,d,t}\right)\right) \tag{19}$$

$$\hat{Q}^{L}_{i,d,t}=(1+\Upsilon)\times\left(Q^{DR}_{i,d,t}+\left((1-\chi^{DR}_{i,y})Q^{L}_{i,d,t}\right)\right) \tag{20}$$

$$\begin{aligned}\hat{P}_{ij,y,t}=&G_{ij}+2G_{ij}\Delta\hat{V}_{i,y,t}-G_{ij}\cos(\hat{\phi}_{ij,y,t})-G_{ij}\Big(\sin(\hat{\delta}_{ij,y,t})\\&-\sin(\hat{\phi}_{ij,y,t})+B_{ij}\sin(\hat{\phi}_{ij,y,t})+B_{ij}\Big(\cos(\hat{\phi}_{ij,y,t})-\cos(\hat{\delta}_{ij,y,t})\Big)\end{aligned} \tag{21}$$

$$\begin{aligned}\hat{Q}_{ij,y,t}=&B_{ij}+2B_{ij}\Delta\hat{V}_{i,y,t}-B_{ij}\cos(\hat{\phi}_{ij,y,t})-B_{ij}\Big(\sin(\hat{\delta}_{ij,y,t})\\&-\sin(\hat{\phi}_{ij,y,t})-G_{ij}\sin(\hat{\phi}_{ij,y,t})-G_{ij}\Big(\cos(\hat{\phi}_{ij,y,t})-\cos(\hat{\delta}_{ij,y,t})\Big)\end{aligned} \tag{22}$$

$$\hat{\theta}_{i,y,t}-\hat{\theta}_{j,y,t}=\hat{\phi}_{ij,y,t} \tag{23}$$

$$\Delta\hat{V}_{i,y,t}+\Delta\hat{V}_{j,y,t}+\hat{\theta}_{i,y,t}-\hat{\theta}_{j,y,t}=\hat{\delta}_{ij,y,t} \tag{24}$$

$$V_{\min}\leqslant\hat{V}_{i,y,t}\leqslant V_{\max} \tag{25}$$

$$P^{UN}_{\min}\leqslant\hat{P}^{UN}_{i,y,t}\leqslant P^{UN}_{\max} \tag{26}$$

$$Q^{UN}_{\min}\leqslant\hat{Q}^{UN}_{i,y,t}\leqslant Q^{UN}_{\max} \tag{27}$$

$$\begin{aligned}&\left[\sin\left(\frac{360^\circ l}{m}\right)-\sin\left(\frac{360^\circ}{m}(l-1)\right)\right]\hat{p}_{ij,y,t}\\&-\left[\cos\left(\frac{360^\circ l}{m}\right)-\cos\left(\frac{360^\circ}{m}(l-1)\right)\right]\hat{Q}_{ij,y,t}\\&-\left|S^{\max}_{ij}\right|\times\sin\left(\frac{360^\circ}{m}\right)\leqslant 0\end{aligned} \tag{28}$$

where, (17) and (18) are active and reactive power balance at LLP respectively, while the active and reactive load demand at LLP are respectively given by (19) and (20). Equations (21) and (22) are the active and reactive power flow through the system branches at LLP respectively. Constraints (25)-(28) denote the limitation of voltage, active and reactive power injected from upstream network, and apparent power flow through the system branches respectively. Note that linearization of (21) and (22) is similar to (7) and (8) respectively.

E. Annual Load Growth

In addition to various short-term uncertainties, the load growth is considered as the long-term uncertainty over the planning period, as follows:

$$P^{L}_{i,y,t}=R^{L}_{t}\times(1+D^{E}_{i,y})\times P^{L}_{i,y,t-1} \tag{29a}$$

$$Q^{L}_{i,y,t}=R^{L}_{t}\times(1+D^{E}_{i,y})\times Q^{L}_{i,y,t-1} \tag{29b}$$

F. Demand-Side Response Constraints

The DSR accounts for participation of responsive loads in energy scheduling at COP and LLP. Also, the best locations for applying the DSR program are selected via a binary-variable-based model. The following equations express the DSR model.

$$P^{DR}_{i,y,t}=P^{L}_{i,y,t}\times\gamma^{DR}_{i,y,t} \tag{30a}$$

$$Q^{DR}_{i,y,t}=Q^{L}_{i,y,t}\times\gamma^{DR}_{i,y,t} \tag{30b}$$

$$\sum_{t\in\psi_t}P^{DR}_{i,y,t}=\sum_{t\in\psi_t}P^{L}_{i,y,t} \tag{30c}$$

$$\sum_{t\in\psi_t}Q^{DR}_{i,y,t}=\sum_{t\in\psi_t}Q^{L}_{i,y,t} \tag{30d}$$

$$(1-\gamma^{Min}_{i}\times\chi^{DR}_{i,y})\leqslant\gamma^{DR}_{i,y,t}\leqslant(1-\gamma^{Max}_{i}\times\chi^{DR}_{i,y}) \tag{30e}$$

$$\sum_{i\in\psi_b}\chi^{DR}_{i,y}\leqslant N^{DR}_{\max} \tag{30f}$$

where, (30a) and (30b) denote the changes in the active and reactive demand pattern respectively. Also, according to (30c) and (30d), sum of increased and decreased demand by the responsive loads should be equal to the base load. The DSR index is limited by (30e), while constraint (30f) limits the number of responsive loads in each year.

G. Distributed generations constraints

Various factors can limit the penetration of RESs into power systems. Among those factors, economical, operational, and security constraints are decisive ones [23]. Therefore, there is need to limit the number and capacity of RESs in the network.

$$0\leqslant P^{WT}_{i,y,t}\leqslant\chi^{WT}_{i,y}\times R^{WT}_{t}\times P^{WT}_{\max} \tag{31a}$$

$$-tg(\varphi_{lead})\times P^{WT}_{i,y,t}\leqslant Q^{WT}_{i,y,t}\leqslant tg(\varphi_{lag})\times P^{WT}_{i,y,t} \tag{31b}$$

$$\sum_{i\in\psi_b}\chi^{WT}_{i,y}\leqslant N^{WT}_{\max} \tag{31c}$$

$$0 \leqslant P_{i,y,t}^{PV} \leqslant \chi_{i,y}^{PV} \times R_t^{PV} \times P_{\max}^{PV} \tag{32a}$$

$$\sum_{i \in \psi_b} \chi_{i,y}^{PV} \leqslant N_{\max}^{PV} \tag{32b}$$

where, (31a) limits the WTs' power output according to the wind profile, whereas constraint (31b) denotes the maximum and minimum reactive power of WTs. Constraint (31c) represents the limit of WTs that can be installed in the network. The same as WT, (32a) limits the maximum active power of PVs, while the number of PVs is limited by (32b).

H. Parking lots' constraints

The EVs are one of the main prosumer/producers of the smart electric grids. Therefore, suitable allocation techniques are required to calculate optimal capacity in terms of MW and number of EVs. In addition, security criteria should be considered to prevent possible stability problems. Regarding this, a linear optimal allocation model is introduced for parking lots, so as to show the effects of EV penetration on different characteristics of network in the long run.

$$\begin{aligned} SOC_{i,y,t}^{PL} = SOC_{i,y,t-1}^{PL} + \Delta t (P_{i,y,t}^{Ch_{PL}} \eta_{i,y,t}^{ch_{PL}} - \\ P_{i,y,t}^{DCh_{PL}} / \eta_{i,y,t}^{dch_{PL}} - P_{i,y,t}^{TR_{PL}}) \end{aligned} \tag{33a}$$

$$SOC_{\min}^{EV} \times Cap_y^{PL} \leqslant SOC_{i,y,t}^{PL} \leqslant SOC_{\max}^{EV} \times Cap_y^{PL} \tag{33b}$$

$$Cap_y^{PL} = D_y^{PL} \times Cap_{y-1}^{PL} \tag{33c}$$

$$P_{i,y,t}^{Ch_{PL}} \leqslant N_{i,y,t}^{G2V} \times P_{\max}^{Ch_{EV}} \tag{33d}$$

$$P_{i,y,t}^{DCh_{PL}} \leqslant N_{i,y,t}^{V2G} \times P_{\max}^{DCh_{EV}} \tag{33e}$$

$$P_{i,y,t}^{TR_{PL}} \leqslant N_{i,y,t}^{TR} \times \eta_{i,y,t}^{EV_{TR}} \times D_{\max}^{EV} \tag{33f}$$

$$P_{i,y,t}^{TR_{PL}} \geqslant N_{i,y,t}^{TR} \times \eta_{i,y,t}^{EV_{TR}} \times D_{\min}^{EV} \tag{33g}$$

$$N_{i,y,t}^{TR} \leqslant \chi_{i,y}^{PL} \times Cap_y^{PL} \tag{33h}$$

$$N_{i,y,t}^{V2G} \leqslant \chi_{i,y}^{PL} \times Cap_y^{PL} \tag{33i}$$

$$N_{i,y,t}^{G2V} \leqslant \chi_{i,y}^{PL} \times Cap_y^{PL} \tag{33j}$$

$$N_{i,y,t}^{TR} + N_{i,y,t}^{G2V} + N_{i,y,t}^{V2G} \leqslant Cap_y^{EV} \tag{33k}$$

$$\sum_{t \in \psi_t} N_{i,y,t}^{TR} \geqslant \sum_{t \in \psi_t} P_{CH2TR}^{EV} \times N_{i,y,t}^{G2V} \tag{33l}$$

$$\sum_{i \in \psi_b} \chi_{i,y}^{PL} \leqslant N_{\max}^{PL} \tag{33m}$$

where, (33a) represents the state of charge of PLs, based on the number of EVs that are in charging, discharging, and transmission states. Constraints (33b) limits the state of charge of PLs based on the annual capacity of PLs and battery size of an EV. Constraint (33c) denotes the annual growth of PL capacity. The charging and discharging active power of PLs is denoted by (33d) and (33e) respectively. According to (33f), the amount of power consumed by EVs in a day is limited regarding the maximum traveling distance of EVs, whereas constraint (33g) represents the minimum power consumed by EVs in traveling mode. The number of EVs in transmission, V2G, and G2V modes are limited by (33h)-(33j) respectively. With regard to (33k) EVs are in transmission, G2V, and V2G state, or they are parked without any power consumption. constraint (33l) denotes that a percentage of charged EVs consume their power through transmission mode. Finally, constraint (33m) limits the number of PLs that could be installed in the network.

I. Uncertainty Modeling

Despite significant results obtained by previous studies that have considered immutable forecasted values for their expansion planning, real behavior of power systems cannot be captured without consideration of their stochastic nature. Several probabilistic and non-probabilistic methodologies have been introduced for uncertainty handling since then; however, the IGDT technique benefits from various positive aspects. For instance, it does not require much information about uncertain parameter and its computation time is fairly low as opposed to Monte Carlo, scenario based, and point estimate methods [27].

The previous literature [18] have utilised the available data of arrival time, departure time, and trip distribution for dealing with uncertainty of EV behavior. However, such parameters are more likely to experience the sudden changes, while there is not a specific probabilistic distribution function that could be used for modeling the EV behavior. Due to the influence of human preference in the distance that could be travelled by an EV, it is difficult to simulate the EV behavior based on the available data. In this regard, instead of dealing with such a highly changeable/probabilistic parameter, this study utilised the IGDT method to model the driving pattern of EVs. This methodology increases the robustness of the system in face of uncertainty in the EVs' driving behavior without too much knowledge about the probabilistic distribution function of such data.

IGDT is a powerful methodology which can be used for handling the uncertainty without availability of probability distribution function of uncertain parameter(s). The decision maker in this technique, can adopt two strategies, namely, risk-averse and risk-taking. The risk-averse strategy minimizes the risk of operation, while the tendency of risk-taking strategy is to maximize the profit, which is derived by taking more risks. In this study, the risk-averse strategy is taken to minimize the operation risk caused by multiple uncertainties. In the previous literature, an uncertainty radius is selected for all uncertain variables . However, uncertainty of various variables, such as RESs and system demand, are independent and even they are in conflict with each other. Regarding this, in this work, for each uncertain variable a specific uncertainty radius is taken. Then, weighting factors are defined for each one, and the total uncertainty radius is maximized based on the weighting factors.

The proposed WIGDT method is a bi-level optimization method in which the model is first solved considering predicted values for uncertain parameters in a deterministic environment. After that, optimal values for the objective function and investment decisions are obtained, called base case values; then, the second level is solved with consideration for uncertainty and the inputs provided by the first level. The following optimization problem is solved for the first level.

$$TC_{bc} = \min_{DV} \left\{ \sum_{y \in \psi_y} \left(Cost_y^{inv} + Cost_y^{op} \right) \right\} \tag{34a}$$

$$P^L_{i,y,t} = \bar{P}^L_{i,y,t}, P^{PV/WT}_{i,y,t} = \bar{P}^{PV/WT}_{i,y,t}, P^{TR_{PL}}_{i,y,t} = \bar{P}^{TR_{PL}}_{i,y,t}$$

$$Subjectto : (2) - (33) \tag{34b}$$

where, TC_{bc} is the total investment and operation cost in base case in which the WT's output, PV's output, system load demand, and traveling distance are equal to their predicted values. Based on the proposed WIGDT technique, to minimize the negative effect of risk on the operation decisions, the operation cost of network should be increased. Consequently, in the second level of WIGDT, the investment decisions are fixed at the values obtained in the base case and the effect of uncertainties on operation decisions is calculated. Therefore, the decision variables $\chi^{PV}_{i,y}$, $\chi^{WT}_{i,y}$, $\chi^{PL}_{i,y}$, and $\chi^{DR}_{i,y}$ are fixed in their values obtained in the first level. Generally, the risk-averse strategy is solved as follows:

$$\max_{DV} \ \{ w_{res}\alpha_{res} + w_{ld}\alpha_{ld} + w_{ev}\alpha_{ev} \} \tag{35a}$$

$$Subjectto : (2) - (33) \tag{35b}$$

$$P^L_{i,y,t} = \bar{P}^L_{i,y,t} \times (1 + \alpha_{ld}) \tag{35c}$$

$$Q^L_{i,y,t} = \bar{Q}^L_{i,y,t} \times (1 + \alpha_{ld}) \tag{35d}$$

$$P^{PV}_{i,y,t} = \bar{P}^{PV}_{i,y,t} \times (1 - \alpha_{res}) \tag{35e}$$

$$P^{WT}_{i,y,t} = \bar{P}^{WT}_{i,y,t} \times (1 - \alpha_{res}) \tag{35f}$$

$$P^{TR_{PL}}_{i,y,t} = \bar{P}^{TR_{PL}}_{i,y,t} \times (1 - \alpha_{ev}) \tag{35g}$$

$$\max \sum_{y \in \psi_y} Cost_y^{op} \leqslant (1 + \beta^r) \times Cost_y^{op_{bc}} \tag{35h}$$

$$\alpha_{res}, \alpha_{ld}, \alpha_{ev} \geqslant 0 \tag{35i}$$

$$0 \leqslant \beta^r \leqslant 1 \tag{35j}$$

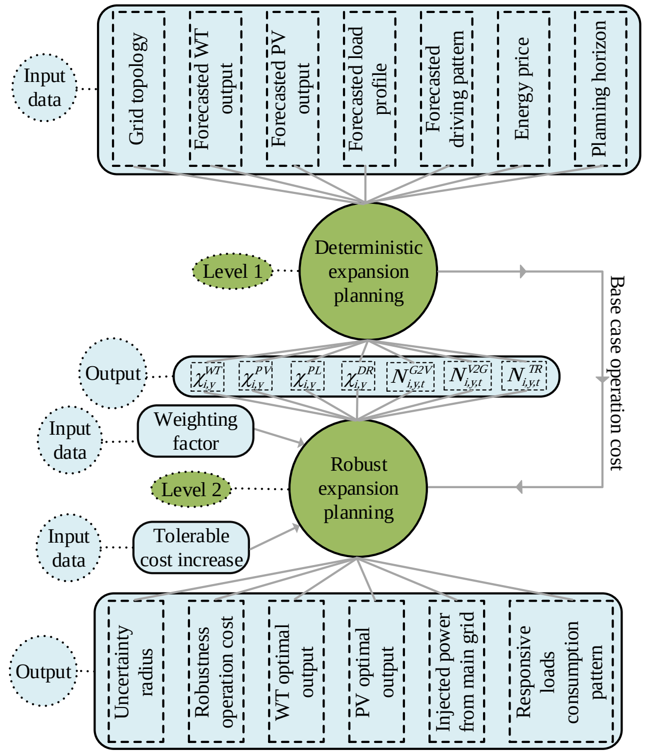

Fig. 1: Illustrative framework of the proposed model.

III. Test Systems and Framework Description

A. Framework Description

The framework of the proposed model is given in Fig. 1. As can be seen in this figure, the model is solved in two levels. In the first level, a voltage stability constrained DSR-coordinated planning model is solved and the optimal investment decisions are obtained for various technologies. The output of this level consists of the optimal location of WTs, PVs, PLs, the location of responsive loads, and the number of EVs. The investment decisions, and the optimal operation cost are transferred to the second level. In the second level, the value of operation cost is increased to a tolerable value which is defined by the decision maker and called robustness cost; then, the total uncertainty radius, based on the weighting factors, is maximized and optimal operation decisions are obtained in an uncertain environment.

B. Test Systems and Data

To validate the effectiveness of the proposed model, standard 33-bus distribution test system (Case A) and the real-world smart distribution network of the Isle of Wight in the UK (Case B) are utilized. In the reminder of this paper, the former is called Case A and the latter is named Case B.

To demonstrate the role of new components in the system, the Case A's demand is increased by 30%. The data of WTs, PVs, and PLs is given in Table II. The annualized investment cost is obtained assuming 20 years of lifetime for components and discount rate of 7%. Table III provides the data for EVs. The planning horizon of 6 years is considered for this study. The other parameters for solving the proposed optimization problem is given in Table IV.

TABLE II: The WTs, PVs, and PLs investment and operation costs.

Parameter	Value	Unit
WT investment cost	2.6	m$/MW
WT Operation cost	17	$/MWh
PV investment cost	2.5	m$/MW
PV Operation cost	5	$/MWh
PL investment cost	304	$/EV

TABLE III: The EV data.

Parameter	Value (unit)	Parameter	Value(unit)	Parameter	Value(unit)
$SOC^{EV}_{\min}$	25(KW)	$\eta^{ch_{PL}}_{i,y,t}$	90(%)	$P^{DCh_{EV}}_{\max}$	12.5(KW)
$SOC^{EV}_{\max}$	1(KW)	$\eta^{dch_{PL}}_{i,y,t}$	93(%)	$D^{EV}_{\max}$	40(KM)
Cap^{PL}_{y}	200(EV)	$\eta^{EV_{TR}}_{i,y,t}$	1/6(KW/KM)	$D^{EV}_{\min}$	15(KM)
D^{PL}_{y}	100(EV)	$P^{Ch_{EV}}_{\max}$	12.5(KW)	P^{EV}_{CH2TR}	20(%)

C. Features and Assumptions

The proposed MILP model is tested on first and second test studies, in general algebraic modeling system (GAMS) using CPLEX solver. The following assumptions have been made for solving the model.

- For the EVs, the model is solved from system operator viewpoint. The concept of vehicle for grid [20] enables the EVs to act as the active energy service provider.
- The weighting factors can be chosen by the decision maker.
- The voltage stability margin should be satisfied in the planing horizon.

IV. Case Study and Discussion

In this section, the simulation results for the proposed model are calculated and discussed.

A. Case A: 33-bus distribution test system

In the base case, total cost of operation and investment is $6.1m. Optimal locations for installing WTs, PVs, and PLs are given in Table V. Also, the responsive buses' participation in DSR program is illustrated in Fig. 2. It is evident that the buses that are at the end of branches are more likely to participate in DSR program. Finally, Table VI summarizes number of EVs in different states at the installed PLs. It can be seen that a considerable number of EVs (almost 47 millions) consumed or delivered energy.

To evaluate the effect of voltage stability constraints on the proposed model, a sensitivity analysis is performed, in which

TABLE IV: Parameters and characteristics of the model.

Parameter	Value (unit)	Parameter	Value(unit)	Parameter	Value(unit)
γ^{Min}_{i}	20(%)	$D^{E}_{i,y}$	7(%)	$N^{DR}_{\max}$	4
γ^{Max}_{i}	20(%)	Υ	0.03	$N^{PL}_{\max}$	2
β^{r}	15(%)	$N^{WT}_{\max}$	1	$N^{PV}_{\max}$	1

TABLE V: Optimal location of various technologies over the planning horizon.

Technology	Bus number	Technology	Bus number
WT	$30/y_1$ [1]	PL	$31/y_1$
PV	$4/y_1$	PL	$33/y_1$

1Year of investment.

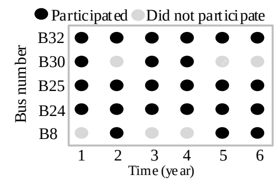

Fig. 2: DSR pattern of responsive loads.

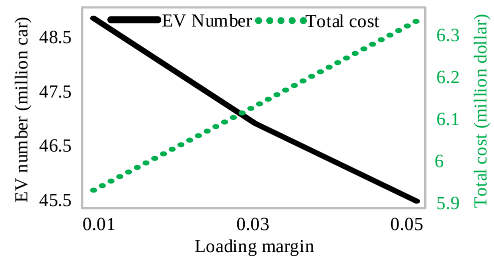

Fig. 3: Effect of LM on PLs' capacity and total cost.

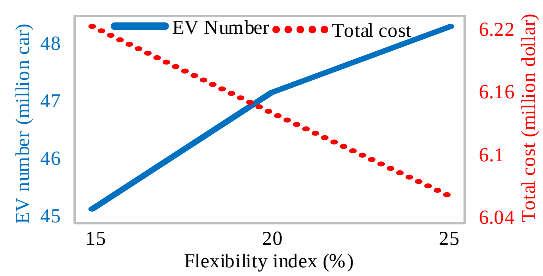

Fig. 4: Variation of PLs' capacity and total cost versus DSR index.

the value of LM (i.e. Υ) is increased from 0.01 to 0.05 and the cumulative capacity of PLs, and total operation and investment cost is illustrated in Fig. 3. It is evident that increasing the LM reduces the number of EVs, while it rises the total cost; which means that security improvement requires more budget, whereas the PLs' capacity can be affected by this measure.

Besides, these values can be affected by the DSR index. Regarding this, optimal sizes of PLs as well as operation and investment cost for different values of DSR index are obtained and shown in Fig. 4. According to this figure, increasing the DSR index reduces the total investment and operation cost, whereas it increases the penetration of EVs to the network. Therefore, it can be concluded that LM and DSR index are decisive factors in long term planning of distribution systems under penetration of EVs.

Finally, effect of different uncertainties on the injected power from main grid is evaluated in Fig. 5, which shows that the system operator needs to inject more power from upstream network so as to increase the robustness of the network. However, this can raise the total operation cost which depends on the tolerable value of robustness (i.e. β^{r}). In previous studies, Ref. [27] for instance, increasing the robustness cost has been considered as the main solution for increasing the robustness.

TABLE VI: Cumulative capacity of parking lots (10^3EV).

State	y_1		y_2		y_3		y_4		y_5		y_6		Total
	B31	33	B31	33	B31	33	B31	33	B31	33	B31	33	
Charging/discharging	876.0	876.0	1,621.7	1,646.9	2,358.3	2,763.4	3,581.0	3,811.3	4818.0	4,380.3	5,621.0	5,857.9	38,211.9
Transmission	876.0	876.0	1,006.3	981.1	1,145.7	739.1	798.9	568.7	438.0	656.7	511.0	270.8	8,868.4

TABLE VII: Optimal location of WTs, PVs, and PLs for different values of LM in the Case B.

LM	WT Bus number	PV Bus number	PL Bus number
0.01	734/y_1 [1]	642/y_1	454/y_1
	953/y_1	834/y_1	826/y_1
0.03	862/y_1	849/y_1	454/y_1
	956/y_1	966/y_1	716/y_1
0.05	642/y_1	429/y_1	725/y_1
	730/y_1	513/y_1	839/y_1

1-Year of investment.

Nonetheless, in this study, another solution is investigated in which the effect of DSR index on the uncertainty radius is examined. Accordingly, effect of DSR index and tolerable value of robustness on total uncertainty radius is illustrated in Fig. 6. In this figure, it is evident that responsive loads can act as an alternative solution for improving robustness. Instead of increasing the robustness budget, more participation from responsive loads can improve other characteristics of network along with boosting the robustness.

B. Case B: Isle of Wight in the UK

The proposed model is also tested on the real-world distribution network of the Isle of Wight in the UK[1]. The number of candidate WTs and PVs to be installed in the network is assumed to be two for each RESs, with the capacity of 2 MW. The optimal location of different technologies is summarized in Table VII. This table implies the fact that optimal location for installing different RESs is varied based on the value of security margin. The values of operation cost in base case and risk averse strategy are \$1.920m and \$1.988m, respectively. The optimal value of uncertainty radius equals 0.66, which is considerably high, showing that robustness of the system is acceptable. Therefore, injecting power from the main grid is a valid option for increasing the resistance of system in face of uncertainty.

C. Computation Efficiency

The computational efficiency of the proposed MILP model is compared to that of MINLP for both test cases A and B in Table VIII. This table demonstrates the advantages of the proposed MILP voltage stability constrained DSR-coordinated planning model, from computational time and solution viewpoints. The computational time of the proposed MILP model is almost half of the MINLP one, while it achieved a global optimal solution.

[1]Isle Of Wight Renewable Energy Resource Investigation, https://www.iow.gov.uk/documentlibrary/download/grid-connection-study

V. Conclusions

In this study, a voltage stability constrained DSR-coordinated planning model is proposed for long-term planning of PLs, WT, and PVs. To deal with various uncertainties, an improved version of the IGDT technique is adopted and uncertainties of PV/WT power generation, EV driving pattern, and system demand are taken into consideration. Besides, the model is linearized to achieve a globally optimal solution for the problem. The proposed model increases the robustness of the system in face of uncertainties. The results obtained from the simulation of the model demonstrate the importance of security measures and highlight the role of responsive loads in long-term planning models. Generally, the main conclusions of this paper are:

- Voltage stability constraints are an important factor in long-term planning of distribution systems under penetration of various technologies such as EVs.
- The DSR index could be considered as a decisive factor in increasing the penetration of EVs to the system.
- There is a need to consider various short-term uncertainties in long-term studies.
- Robustness budget is an important factor in boosting the resistance of the system in face of uncertainties.
- Responsive loads can increase the robustness without cost implication.

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CRediT authorship contribution statement

Vahid Vahidinasab: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Writing - Original Draft, Writing - Review Editing, Visualization, Supervision, Project administration. **Saman Nikkhah:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing - Original Draft, Visualization. **Adib Allahham:** Writing - Review Editing. **Damian Giaouris:** Writing - Review Editing, Funding acquisition.

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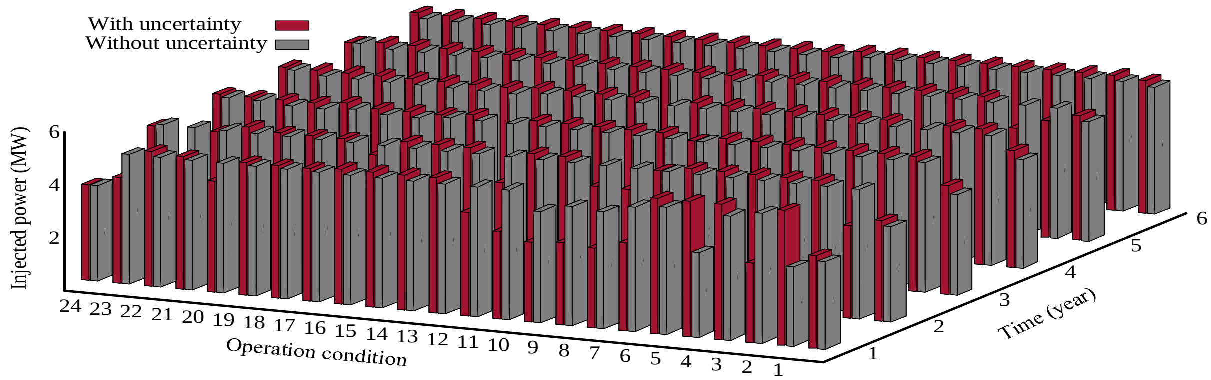

Fig. 5: Injected power from main grid in different cases.

TABLE VIII: The computational statistics of the proposed model.

	Computational Time (Min.)		Objective function (m$)	
	Case A	Case B	Case A	Case B
MINLP	357	553	6.2	2.3
MILP	159	243	6.1	1.9

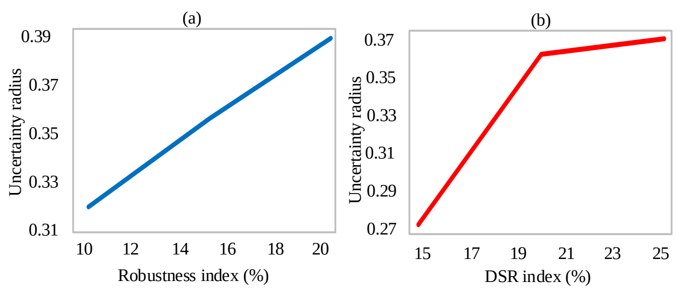

Fig. 6: Variation of uncertainty radius versus (a) robustness index, (b) DSR index.

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