Bi-Level Model for Operational Scheduling of a Distribution Company that Supplies Electric Vehicle Parking Lots

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Abstract

Nowadays, the presence of renewable energy resources (RERs), electric vehicle (EV) penetration, and the implementation of demand response (DR) programs are the main affecting factors in the operational scheduling of a distribution company (DISCO). By the new market participants such as parking lot (PL) owners in the DISCO, a bi-level framework can be created for modeling the distribution network. Therefore, in this paper, a new bi-level model is suggested for DISCO's operational scheduling that involves technical and environmental terms in the objective function. The maximization of the profit of the DISCO owner and the PL owner are the objective functions in each level. These purposes depend on the customers' load, the power purchased from the upstream network, the power exchanged with the PL owner (for the upper-level) and the power exchanged with the DISCO owner, as well as the EV owners (for the lower-level). Linearization of the model is carried out by applying the Karush–Kuhn–Tucker (KKT) condition and Fortuny-Amat and McCarl linearization approach. Furthermore, EVs' and RERs' uncertainties, as well as DR programs are modeled. Also, three types of risk are described including risk-seeker, risk-neutral, and risk-averse (with conditional value-at-risk (CVaR) index). For evaluation of the proposed model, it is applied to the IEEE 15-bus test system. Results show that by charging/discharging schedule of EVs and critical peak pricing program, the DISCO owner gains more profit. Also, the sensitivity analysis allows determining that the EV penetration, nominal power of RERs and customer involvement in the DR program directly affect the DISCO owner's profit.

Keywords: Distribution company; bi-level model; Karush–Kuhn–Tucker method; electric vehicle parking lot; demand response; renewable energy resources.

1. Nomenclature

Indices

b	Index of branch or bus
n	Index of EV number
w	Index of scenario
Sb	Index of slack bus
h	Index of hour

Parameters

C^{cd}	Equipment cost depreciation ($/kWh)
E^{CO_2}	Average emission rate of the upstream network generation (kg/MWh)
I^{max}	Maximum current of lines (A)
R	Large constants
P^{L}	The customers' load before DR (kW)
$P^{L,DR}$	The customers' load after DR (kW)
$P^{PV,\max}$	Maximum Output power of PV unit (kW)
$P^{Wi,\max}$	Maximum Output power of wind unit (kW)
$R^{\max}$	Charging or discharging rate (kWh)
$V^{\max}$	Maximum voltage (V)
$V^{\min}$	Minimum voltage (V)
η^{ch}	Charging efficiency (%)
η^{dch}	Discharging efficiency (%)
η^{Trans}	Transformer efficiency (%)
ρ	Probability of each scenario
α	Confidence level
β	Risk aversion parameter
π^{E}	Penalty of greenhouse gas emissions ($/kg)
π^{L}	Energy sold price to the customer before DR ($/kWh)
$\pi^{L,DR}$	Energy sold price to the customer after DR ($/kWh)
π^{G2PL}	Energy sold price to the PL owner ($/kWh)
π^{PL2EV}	Energy purchased price of the PL by EV owner ($/kWh)
π^{PL2G}	Energy purchased price of the PL by DISCO owner ($/kWh)
π^{Up2G}	Energy purchased price from the upstream network ($/kWh)

Variables

P^{ch}	Power charged of EVs (kW)
P^{dch}	Power discharged of EVs (kW)
P^{loss}	Power loss of the SDISOC (kW)
P^{Up2G}	Power purchased from the upstream network (kW)
SOE	State of energy (kWh)
X	Binary variable
μ	dual variables ($/kWh)
B	Profit of each scenario
γ	Auxiliary variable for calculating CVaR in each scenario
ξ	Value-at-risk

2. Introduction

2.1 Aims and Motivation

Due to internal combustion engine vehicles and fossil fuel power plants, transportation sector and electricity grids are two main sources of air pollution and greenhouse gas emissions. The high penetration of electric vehicles (EVs), as well as the usage of renewable energy resources (RERs) are appropriate solutions for controlling environmental problems. Charging of EVs that are parked in parking lots (PLs) for supplying the customers (vehicle to grid - V2G - applications) at the on-peak periods is one of the promising solutions.

However, the uncertainties of the RERs and EVs would make the operation and planning of distribution networks more complicated. On the other hand, performing demand response (DR) programs, would help to reduce the problems. Also, with considering the DISCO's uncertainties e.g. output power of RERs, availability of EVs and etc. the risk-based model is necessary. One of the best risk measures is conditional value-at-risk (CVaR) because of linear form [1].

This paper suggests a risk-based bi-level model with technical and environmental terms for obtaining profit's maximization of the SDISCO owner, in the presence of PL. This profit is evaluated in four cases: 1) without considering RERs and considering controlled charging (CC) of EVs ; 2) considering RERs and charging/discharging schedule (CDS) of EVs ; 3) considering RERs and CC of EVs ; 4) considering RERs and with CDS of EVs. For all cases, eight DR programs are considered. Also, uncertainties of RERs and EVs are modeled with probability distribution function (PDF). Forasmuch as, due to uncertainties, three types of objective function based on risk are defined.

2.2 Literature Review

Operation of EVs having different impacts on the DISCO. These impacts are usually divided into economic, environmental and grid impact [2]. In terms of economic impact, there are three stakeholders, i.e., the DISCO owners, the EV owners and also the PL owners [3]. Regarding environmental impact, some studies have shown that if EVs charge at the on-peak periods with the traditional power plant, EVs are not environmental-friendly. But, using RERs and CDS, the DISCO becomes greener [4]. Also, the impact of EVs on power grid are included the impact on losses [5-6], load profile [7], transformer and cable [8-9], voltage profile [10], harmonics [11-12], and stability influence [13-14].

With the dawn of smart grids and utilization of the vehicle to grid (V2G) ability of EVs, the efficiency, reliability and stability of distribution system are improved. In fact, by using V2G capability, the distribution system is obtained some benefit such as ancillary service [15], peak load shaving [16-17], emission's reduction [18] and support for the integration of RERs [19-20] and losses reduction [21].

For performing of DR programs, the suitable model of voluntary programs and mandatory programs of a price-based demand response (PBDR) and incentive-based DR (IBDR) program are presented in [22,23-24].

In [25], for evaluation of the optimal behavior of the PL as the responsive load in each PBDR and IBDR program, a new model is presented in energy and reserve markets. In [26] by considering Time of Use (TOU) program, sitting and sizing of EV's charging stations is determined. In [27], with the goal of minimizing the charging cost and maximizing EVs number for charging, a model is developed for DR program in a PL. In [28], the effect of EVs and IBDR on transmission network expansion planning is evaluated with the aim of minimizing cost. In [29], with load, RERs, EVs uncertainties, a new stochastic model is proposed for participation planning of EVs in IBDR and PBDR programs. In [30], by considering the EV owners charging behavior, dynamic electricity pricing and a PBDR program, EVs charging scheduling for reducing the peak load is modeled. The purpose of the objective function is to minimize all the EV owners cost of charging.

In [31], due to market prices and EV mobility uncertainties, the model based on CVaR index is suggested with the goal of EV aggregator's maximization profit. In [32], by modeling EVs and distributed generation as flexible recourses and considering uncertainties such as RERs generation, market price and demand, a CVaR-based model is offered for minimizing the expected regret value.

In [33], the CVaR-based model is presented for EV aggregator in day-ahead and real-time market, because of price uncertainty. The aim of this model is minimizing the conditional expectation of electricity purchase cost. In [34], by the aim of maximization of operation revenue a risk-based model is provided in the presence of a virtual power plant (VPP). In [35], with considering smart energy hub (SEH) and the goal of profit's maximization a CVaR-based model is proposed. In [36], for finding the best feeder routing a CVaR-based model is offered because of load and price uncertainties. In [37], due to some uncertainties and with the goal of minimizing the cost of planning scheme, a CVaR-based model is proposed. In [38], for losses reduction and reliability improvement by reconfiguration of distribution company and considering uncertainties, a CVaR-based model is suggested. In [39], a decentralized energy trading algorithm is projected in view of renewables integration and risk.

In [40], due to the presence of distribution system operators and the PL owner, for the planning of distribution system, a new model is proposed. In the proposed bi-level model, the lower level maximizes the PL owner benefit's and the upper level minimizes the planning cost. In [41], profit's maximization and operation cost's minimization the distribution company and micro-grid (MG), respectively, are the aim of upper and lower level of the presented model that is solved by Karush–Kuhn–Tucker (KKT) method and dual theory. In [42], with the benefit maximizing of EVs aggregator in the upper level and minimizing operation cost of the system in the lower level, a new model is proposed which is solved by the game theoretic approach.

In [43], for EVs' charging and investment costs' minimization and in the upper level and maximizing the captured traffic flow in the lower level, bi-level programming is presented and is solved by an imperialist competitive algorithm. In [44], with the presence of the VPP and independent system operator (ISO), the model is formulated as a bi-level. The goal of lower and upper level is minimizing the total "as-bid" production cost and maximizing the profit of VPP, respectively. This model is solved by KKT conditions and dual theory. In [45], the main objective function of bi-level model in upper level and lower level are maximizing the active distribution network's profit and maximizing the social welfare in ISO point of view. In [46], by considering DR program and uncertainties of RERs, a bi-level model is explained. The main objective of the upper level is maximizing the operation benefit of VPP and the lower level is minimizing the operation cost and the load of system. In [47], by modeling the generator and load aggregator, a decentralized algorithm is designed for an energy trading market with renewables and price-responsive load aggregators. A model is presented considering the objective of maximizing the social welfare for the distribution network operators in outer level and optimal responses of the load aggregators and generators to price signals in inner level.

However, the reviewed reference does not address the impact of the PL and charging/discharging power on the operation of the DISCO. This paper suggests a bi-level model for operational scheduling of the DISCO, considering the main objective of the PL owner and the DISCO owner, RERs and the EVs uncertainties, 8 DR programs. In each level, the aim is to maximize the profit. By introducing CVaR index, the risk-based bi-level model is also defined. Finally, by applying KKT method, Fortuny-Amat McCall linearization method and stochastic programming, the model is solved.

2.3 Contributions

A novel bi-level model is proposed in this paper for considering the presence of an EV PL along with a DISCO who owns RERs and is responsible for DR programs. The CVaR-based model is also considered for taking uncertainties into account. Therefore, the novelties of the proposed model are:

1. Offering a new technical and environmental-based bi-level model for operational scheduling of the DISCO.
2. Considering the effect of three types of risk on maximizing the profits of the DISCO.
3. Evaluation of eight DR programs on all parts of objective function, in a comprehensive manner.

3. Problem formulation

Traditionally, the DISCOs operate the grid to maximize their profits from selling the energy to the various customers. On the other hand, PL owners, as the new players in the grid, try to reduce operation costs or increase their profits. Therefore, and according to Fig. 1, a bi-level model has been proposed, built upon the presence of two decision makers, i.e., the DISCO owner and the PL owner. At each level, the aim is to maximize profit.

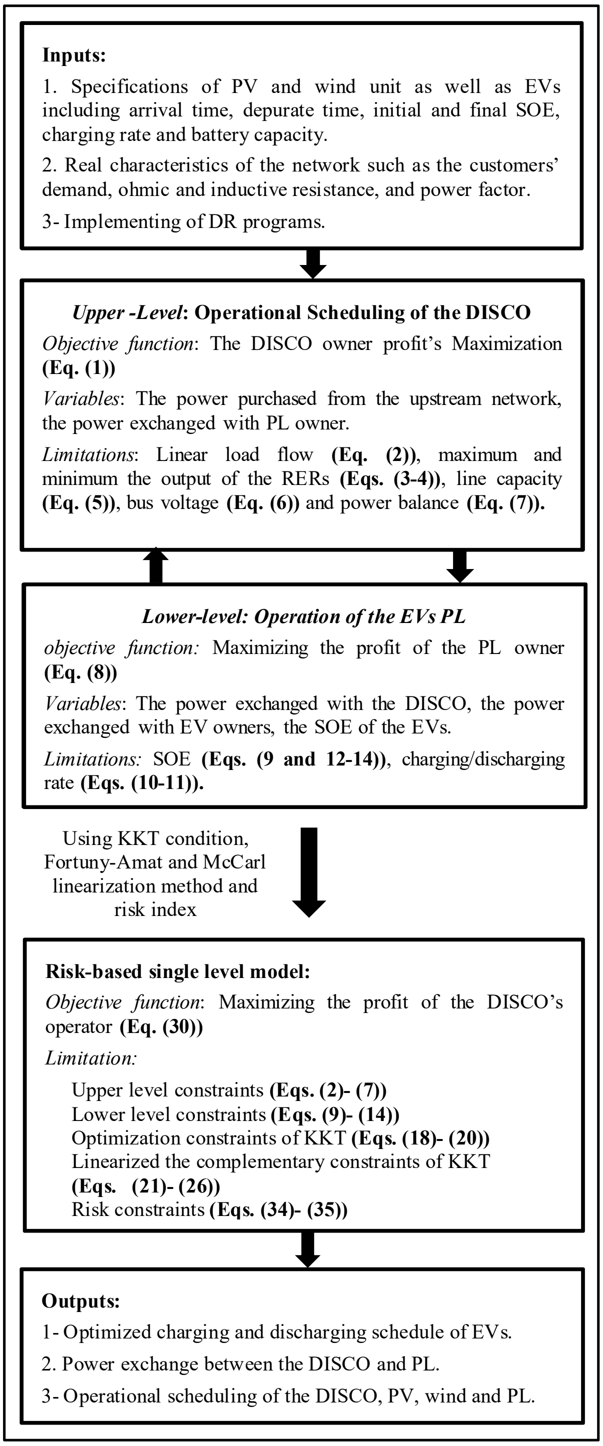

Fig.1. The proposed framework for the risk-based bi-level model

The power purchased from the upstream network and the power exchanged with the PL owner are variables in the upper-level. In the lower-level, variables are the power exchanged with the DISCO owner; the power exchanged with the EV owners and SOE of EVs.

Based on what has been stated, the proposed model is expressed as follows:

$$
\begin{aligned}
& \mathit{Maximize} \\
& OF_1 \times \Delta h + \sum_{w=1}^{Nw} \rho_w \times OF_2 \times \Delta h \\
& = \left(\begin{array}{l}
\sum_{b=2}^{Nb} \sum_{h=1}^{24} P_{b,h}^{L,DR} \times \pi_h^{L,DR} \\
-\sum_{Sb=1}^{NSb} \sum_{h=1}^{24} P_{Sb,h}^{Up2G} \times \pi_h^{Up2G} \\
+\sum_{Sb=1}^{NSb} \sum_{h=1}^{24} \left(\begin{array}{l} 0.5 \times \pi_h^{E} \times E_h^{CO_2} \times (P_{sb,h}^{Up2G \ \ without \ \ RERs/V2G/DR} \\ -P_{sb,h}^{Up2G \ \ with \ \ RERs/V2G/DR}) \end{array} \right) \\
-\sum_{b=2}^{Nb} \sum_{h=1}^{24} \left(\begin{array}{l} INC_h \left(P_{b,h}^{L} - P_{b,h}^{L,DR} \right) \\ -PEN_h \left(P_{b,h}^{con} - P_{b,h}^{L} + P_{b,h}^{L,DR} \right) \end{array} \right)
\end{array} \right) \times \Delta h \\
& + \sum_{w=1}^{Ns} \rho_w \left(\sum_{n=1}^{N} \sum_{h=1}^{24} P_{n,h,w}^{ch} \times \pi_h^{G2PL} - \sum_{n=1}^{N} \sum_{h=1}^{24} P_{n,h,w}^{dch} \times \pi_h^{PL2G} \right) \times \Delta h
\end{aligned} \tag{1}
$$

subject to:

$$\mathit{Linear\ Power\ Flow} \tag{2}$$

$$0 \le P_{b,h,w}^{W} \le P^{W,\max} \tag{3}$$

$$0 \le P_{b,h,w}^{PV} \le P^{PV,\max} \tag{4}$$

$$0 \le I_{b,h,w} \le I_b^{\max} \tag{5}$$

$$V^{\min} \le V_{b,h,w} \le V^{\max} \tag{6}$$

$$P_{Sb,h}^{Up2G} \times \eta^{Trans} + P_{b,h,w}^{Wi} + P_{b,h,w}^{PV} + \sum_{\mathrm{N}} P_{n,h,w}^{dch} = P_{b,h}^{\mathrm{L,DR}} + P_{h,w}^{Loss} + \sum_{\mathrm{N}} P_{n,h,w}^{ch} \tag{7}$$

where:

$$
\begin{aligned}
& \mathit{Maximize} \\
& \sum_{w=1}^{Nw} \rho_w \times OF_3 \times \Delta h \\
& = \sum_{w=1}^{Nw} \rho_w \left(\begin{array}{l}
\sum_{n=1}^{N} \sum_{h=1}^{24} P_{n,h,w}^{ch} \times \pi_h^{PL2EV} + \sum_{n=1}^{N} \sum_{h=1}^{24} P_{n,h,w}^{dch} \times \pi_h^{PL2G} \\
-\sum_{n=1}^{N} \sum_{h=1}^{24} P_{n,h,w}^{ch} \times \pi_h^{G2PL} - \sum_{n=1}^{N} \sum_{h=1}^{24} 0.5 \times P_{n,h,w}^{dch} \times \pi_h^{PL2G} \\
-\sum_{n=1}^{N} \sum_{h=1}^{24} P_{n,h,w}^{dch} \times C^{cd}
\end{array} \right) \times \Delta h
\end{aligned} \tag{8}
$$

S.t:

$$SOE_{n,h,w}^{\min} \le SOE_{n,h,w} \le SOE_{n,h,w}^{\max} \qquad \forall \mathrm{n,h,w} \qquad \mu_{n,h,w}^{1}, \mu_{n,h,w}^{2} \tag{9}$$

$$0 \le P_{n,h,w}^{ch} \le R_n^{\max} \qquad \forall \mathrm{n,h,w} \qquad \mu_{n,h,w}^{3}, \mu_{n,h,w}^{4} \tag{10}$$

$$0 \le P_{n,h,w}^{dch} \le R_n^{\max} \qquad \forall \mathrm{n,h,w} \qquad \mu_{n,h,w}^{5}, \mu_{n,h,w}^{6} \tag{11}$$

$$SOE_{\mathrm{n},h,w} = SOE_{\mathrm{n,h\text{-}1,s}} + \left(P_{n,h,w}^{ch} \times \eta^{ch} \times \Delta h \right) - \left(\frac{P_{n,h,w}^{dch}}{\eta^{dch}} \times \Delta h \right) \qquad \forall \mathrm{n,h} \succ \mathrm{h}^{\mathrm{arv}}, \mathrm{w} \quad \mu_{n,h,w}^{7} \tag{12}$$

$$SOE_{n,h,w} = SOE^{arv}_{n,h,w} + \left(P^{ch}_{n,h,w} \times \eta^{ch} \times \Delta h\right) - \left(\frac{P^{dch}_{n,h,w}}{\eta^{dch}} \times \Delta h\right) \qquad \forall n,h^{arv},w \qquad \mu^{8}_{n,h,w} \tag{13}$$

$$SOE_{n,h,w} = SOE^{dep}_{n,h,w} \qquad \forall n,h^{dep},w \qquad \mu^{9}_{n,h,w} \tag{14}$$

For upper-level Eqs. (1) - (7) is defined. Eq. (1) is the objective function. The first and fifth terms denote the income of the selling energy to the PL and the customer, respectively. The second term is the cost of the energy purchased from the upstream network for supplying the customers' load, EVs charging and losses. Surely generating energy in the upstream network because of conventional power plants produces CO_2 emission. Due to this emission, the upstream network, pay the penalty to the environmental community. So the upstream network encourages the DISCO owner to supply the customers' load by the RERs generation or capability of V2G of EVs, especially at the on-peak periods. It is assumed that the upstream network for the lower power consumption of the DISCO, 50% of unpaid penalty is paid to the DISCO owner as income. This income is expressed in the third term. The fourth term explains the performing DR programs' cost. This term is fully explained in [48], where *INC*, *PEN* are the price of incentive and penalty of DR programs, respectively. Finally, the sixth term denotes the energy purchased cost from the PL owner. The constraints of this level are linear power flow [49], RERs generation, bus voltage, line current and power balance as Eqs. (2) – (7), respectively. Based on Eqs. (3) and (4), the power produced by RERs i.e. output power of PV unit (P^{PV}) and output power of wind unit (P^{wi}) should be between zero and the maximum value. Also, based on Eqs. (5) and (6), line current and bus voltage must be limited between minimum and the maximum value. These values for bus voltage are ±5% of nominal voltage. Eq. (7) shows the power balance constraint i.e. equality of power production with power consumption.

In addition, Eqs. (8) – (14) introduces the lower-level. Eq. (8) is the objective function. The benefits resulted from selling energy to EV owners and the DISCO owner are explained in first and second terms, respectively. The third term is the cost of the purchasing energy from the DISCO owner (for charging of EVs). Also, to persuade the EV owners to attended in V2G mode, a part of the income from the energy sold to the DISCO owner must be paid to them. It is supposed that, the PL owner is paid 50% of this income to the EV owners. This is given by the fourth term. Finally, the fifth term denotes the cost of battery depreciation for many time discharging. The SOE of each EVs, the amount of charging/discharging power are the constraints of this level. Based on Eqs (9) - (14), at the arrival time of the EVs to the PL, the PL owners receives the initial and desired SOE, the rated capacity of battery and departure time from the EV owners. With these specifications, the energy needed for each EV is calculated that is the difference between initial and desired SOE. So, according to the departure time as well as the charging/discharging rate, determines the time and charging/discharging power of the EVs. It is noted that, the SOE is limited between 0.15 and 0.9 capacity of battery in each time. Also, the minimum and maximum charging/discharging power are zero and 10 kWh. In this Eqs., SOE^{min}, SOE^{max}, SOE^{arv} and SOE^{dep} are minimum and maximum rate of SOE, initial/desired SOE of EVs at the arrival time (h^{arv}) /departure time (h^{dep}) to/from the PL, respectively. Also, μ^1 to μ^9 are the dual variables for decision variables in upper and lower level.

To solve the proposed bi-level model, Fortuny-Amat and McCarl linearization method and KKT conditions are applied [41, 48]. In fact, the objective function of the converting model is the upper level objective function i.e. profit maximization of the DISCO owner. In addition to the constraints of the upper and lower level levels, there are also constraints of KKT optimization, linearizing the complementary constraints of KKT in the converted model [41, 48]. Therefore, the bi-level problem is changed to linear single-level as follows:

(1) (15)

subject to:

(2) - (7) (16)

(9) – (14) (17)

$$\pi_h^{PL2EV} - \pi_h^{G2PL} - \left(\eta^{ch} \times \mu_{n,h,w}^{7} \; \Big|_{h \succ h^{arv}}\right) - \left(\eta^{ch} \times \mu_{n,h,w}^{8} \Big|_{h = h^{arv}}\right) - \left(\mu_{n,h,w}^{4} - \mu_{n,h,w}^{3}\right) = 0 \tag{18}$$

$$0.5\pi_h^{PL2G} - C^{cd} + \left(\frac{\mu_{n,h,w}^{7}}{\eta^{dch}} \; \Big|_{h \succ h^{arv}}\right) + \left(\frac{\mu_{n,h,w}^{8}}{\eta^{dch}} \; \Big|_{h = h^{arv}}\right) - \left(\mu_{n,h,w}^{6} - \mu_{n,h,w}^{5}\right) = 0 \tag{19}$$

$$\mu_{n,h,w}^{7} \Big|_{h \succ h^{arv}} - \mu_{n,h+1,w}^{2} + \mu_{n,h,w}^{8} \Big|_{h = h^{arv}} + \mu_{n,h,w}^{9} \Big|_{h = h^{dep}} - \left(\mu_{n,h,w}^{2} - \mu_{n,h,w}^{1}\right) = 0 \tag{20}$$

$$\begin{aligned} & SOE_{n,h,w} - SOE_{n,h,w}^{\min} \le Y_{n,h,w}^{1} \times R_1 \\ & \mu_{n,h,w}^{1} \le (1 - Y_{n,h,w}^{1}) \times R_2 \end{aligned} \tag{21}$$

$$\begin{aligned} & SOE_{n,h,w}^{\max} - SOE_{n,h,w} \le Y_{n,h,w}^{2} \times R_1 \\ & \mu_{n,h,w}^{2} \le (1 - Y_{n,h,w}^{2}) \times R_2 \end{aligned} \tag{22}$$

$$\begin{aligned} & P_{n,h,w}^{ch} \le Y_{n,h,w}^{3} \times R_1 \\ & \mu_{n,h,w}^{3} \le (1 - Y_{n,h,w}^{3}) \times R_2 \end{aligned} \tag{23}$$

$$\begin{aligned} & R_n^{\max} \text{-} P_{n,h,w}^{ch} \le Y_{n,h,w}^{4} \times R_1 \\ & \mu_{n,h,w}^{4} \le (1 - Y_{n,h,w}^{4}) \times R_2 \end{aligned} \tag{24}$$

$$\begin{aligned} & P_{n,h,w}^{dch} \le Y_{n,h,w}^{5} \times R_1 \\ & \mu_{n,h,w}^{5} \le (1 - Y_{n,h,w}^{5}) \times R_2 \end{aligned} \tag{25}$$

$$\begin{aligned} & R_n^{\max} - P_{n,h,w}^{dch} \le Y_{n,h,w}^{6} \times R_1 \\ & \mu_{n,h,w}^{6} \le (1 - Y_{n,h,w}^{6}) \times R_2 \end{aligned} \tag{26}$$

In this paper, due to the uncertainties of EVs and RERs, the DISCO owner is exposed to risk in which a certain level is acceptable. So for investigating the level of risk, three different strategies for risk management are introduced, which include: risk-seeker, risk-neutral, and risk-averse [37].

1. If the uncertainties are not considered, i.e., there is one scenario (S=1), the DISCO owner has exposed no risk. In this case, the objective function is solved by S=1.

2. Risk-neutral is assessed by considering the several scenarios for uncertainties. In fact, in this case, the expected value of a set of scenarios is the optimal response.
3. In risk-averse strategy, as risk-neutral, uncertainties are considered as a set of scenarios but for controlling the risk of having low profit, a coefficient should be added to objective function for measuring the risk related with profit. This coefficient denotes as risk measure. Because of the linear definition of CVaR index, this concept is used in this paper that the expression as Eqs. (27) to (29) [1]:

$$B_w = \zeta - \frac{1}{1-\alpha}\sum_{w=1}^{Nw} \rho_w \gamma_w \tag{27}$$

$$-B_w + \zeta - \gamma_w \le 0 \tag{28}$$

$$\gamma_w \ge 0 \tag{29}$$

The parameter α is considered 0.95 [50]. So, the CVaR-based model is as Eqs. (30) – (35):

$$\begin{aligned} & Maximize \\ & (1-\beta)\times\left(OF_1 + \sum_{w=1}^{Nw} \rho_w \times OF_2\right) + \beta \times \left(\zeta - \frac{1}{1-\alpha}\sum_{w=1}^{Nw}\rho_w \gamma_w\right) \end{aligned} \tag{30}$$

$$(2) - (7) \tag{31}$$

$$(9) - (14) \tag{32}$$

$$(18) - (26) \tag{33}$$

$$-OF_1 - OF_2 + \zeta - \gamma_w \le 0 \tag{34}$$

$$\gamma_w \ge 0 \tag{35}$$

4. Numerical results

To prove the usefulness of the presented bi-level model, the standard 15-bus distribution system is used. The customers' load with 0.95 lagging power factor and specification of system are shown in Fig. 2 are from [48].

For evaluation of proposed model, eight DR programs i.e. time of use (TOU), real-time pricing (RTP), critical peak pricing (CPP), TOU+CPP, Emergency DR program (EDRP), capacity market program (CAP), TOU+EDRP and TOU+CAP are considered, as individually shown in Table 1. The energy purchased price from upstream network is from [48]. Also, The RERs' specifications with 1 power factor are from [51]. For modeling the uncertainty of EVs Table 2 is presented [48]. The price elasticity of the load is taken into account as recorded in Table 3 [48]. Other required data are explained in Table 4.

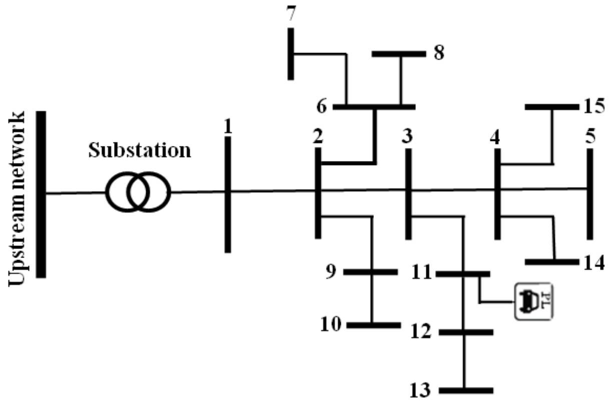

Fig. 2. The 15-bus distribution system.

Table 1. The 8 DR programs for optimal operation of the DISCO

programs	Electricity price of load, charging/discharging tariff of EVs ($/MWh) off-peak periods (1-7 and 22-24)	mid-peak periods (8-9 and 15-18)	on-peak periods (10-14 and 19-21)	Incentive value ($/MWh)	Penalty value($/MWh)
Flat (Base case)	171.125	171.125	171.125	0	0
TOU	85.562	171.125	342.25	0	0
CPP	171.125	171.125	171.125 and 400	0	0
RTP		As reference [40]		0	0
TOU+ CPP	85.562	171.125	342.25 and 400	0	0
EDRP	171.125	171.125	171.125	150	0
CAP	171.125	171.125	171.125	150	50
TOU+ EDRP	85.562	171.125	342.25	150	0
TOU+ CAP	85.562	171.125	342.25	150	50

Table 2. Uncertainties' of EVs

	Mean	Standard Deviation	Minimum	Maximum
SOE^{arv} (%)	50	25	30	60
T^{arv} (h)	8	3	7	10
T^{dep} (h)	20	3	18	24

Table 3. Elasticity of load

	On-peak	Mid-peak	Off-peak
On-peak	-0.1	0.016	0.012
Mid-peak	0.016	-0.1	0.01
Off-peak	0.012	0.01	-0.1

Table 4. Required data of EV and system

	value		Value
Charge efficiency (%)	90	Charging /discharging rates (kWh)	10
Discharge efficiency (%)	95	The price of degradation cost ($/MWh)	30
Battery capacity (kWh)	50	Nominal power of RERs (kW)	200
PL capacity	100 EVs	PL bus	11
Customer participation in DR programs (%)	20	RERs bus	12

The average of CO_2 emission because of conventional power plant generation is 985 Kg/MWh during the on-peak periods [52]. Also, the penalty for CO_2 emission considered as 0.01 $/Kg [53]. In risk-neutral and risk-averse strategies, β is 0 and 1, respectively.

In the following effects of DR programs, EVs and RERs on the DISCO are evaluated precisely. Firstly, in each of the four cases and eight DR programs, the DISCO owner's profit is calculated to determine the best program for implementing. Also the customers' load, charging/discharging power, the CO_2 emission reduction, the power purchased from the upstream network are evaluated.

In Table 5 is shown the DISCO owner's profit. Based on Table 5, we have:

- The most profit in each program is achieved in the fourth case, i.e., the presence of RERs with CDS of EVs.
- In each program and cases, when uncertainties did not consider, i.e., s=1, the DISCO gain the most profit. With considering all uncertainties and measuring risk, i.e., β=1, the DISCO owner gains the least profit.
- If EVs are penetrated to the system even by CC, in Flat rate condition, the DISCO owner is faced with negative profits. But by using DR program or RERs or CDS for EVs, the operation is profitable.
- In PBDR, IBDR and combined PBDR+IBDR programs, the DISCO owner is obtained more profit in CPP, CAP and TOU+CAP programs, respectively.
- The best program for implementation in CC and RERs + CC cases is TOU+CPP program and in CDS and RERs + CDS cases is CPP program.
- In RTP program, because of π^{PL2G} is higher than π^{Up2G}, in cases 3, 4, the objective function is very close to cases 1, 2, respectively. In fact, EVs do not participate in the V2G application.
- With comparing cases 2 and 3, in TOU program and combined programs which there is TOU program, i.e., TOU + CPP, TOU + CAP, TOU + EDRP programs, case 2 is better than case 3, but in other programs, mode case is better than case 2. In fact, with the implementation of TOU program, encouraging of the EV owners to participate in the V2G application is justified by the fact that RERs exist in the DISCO. But in other programs, even if there are no RERs, using CDS is profitable for the DISCO owner.

Table 5. The DISCO owner's profit in four Cases and eight DR programs

DRPs		Case 1	Case 2	Case 3	Case 4
flat	risk-averse	-280.78	323.01	763.41	1360.12
	risk-neutral	-268.83	605.17	753.56	1641.66
	risk-seeker	-245.99	766.76	833.11	1847.04
TOU	risk-averse	839.41	1444.56	1381.84	1982.72
	risk-neutral	852.03	1723.97	1398.17	2243.17
	risk-seeker	872.24	1882.49	1415.01	2422.79
RTP	risk-averse	188.10	787.65	189.07	789.38
	risk-neutral	188.33	1063.10	190.41	1064.68
	risk-seeker	188.49	1199.67	191.02	1202.16
CPP	risk-averse	915.10	1517.92	1913.82	2546.03
	risk-neutral	927.04	1799.59	1974.09	2840.89
	risk-seeker	949.88	1960.98	1996.13	3032.32
TOU+ CPP	risk-averse	1065.28	1670.41	1607.15	2207.75
	risk-neutral	1077.89	1949.73	1601.23	2465.91
	risk-seeker	1098.10	2108.10	1670.38	2659.42
CAP	risk-averse	210.16	812.53	1247.66	1842.87
	risk-neutral	222.10	1093.88	1271.76	2139.33
	risk-seeker	244.93	1254.88	1316.14	2324.94
EDRP	risk-averse	-201.52	400.91	837.31	1433.16
	risk-neutral	-189.59	682.43	834.52	1693.75
	risk-seeker	-166.75	843.68	914.91	1917.48
TOU+ CAP	risk-averse	498.13	1102.46	1033.60	1633.38
	risk-neutral	510.73	1379.92	1047.16	1905.47
	risk-seeker	530.93	1537.26	1086.55	2065.84
TOU+ EDRP	risk-averse	294.11	899.03	800.13	1431.53
	risk-neutral	306.72	1177.10	830.80	1706.22
	risk-seeker	326.92	1334.43	883.23	1893.96

Fig. 3 shows the outcome of DR programs on the customers' load. In accordance with Fig. 3, the initial amount of the customers' load (flat rate) is 32.170 MW. Also, the income of the energy sold to the customer in flat rate is 5505.468 $. The load shifting from the on-peak periods to other periods is observed. The customers' load and income of the energy sold based on DR programs are shown in Table 6. In CPP/CAP programs, the DISCO is achieved more/less income. Also, in TOU + CAP / RTP programs, the reduction of the customers' load is maximum/minimum. Of course, in spite of the reduction of the customers' load in all program, in RTP programs, the new peak load is created, that is not good for the DISCO owner. Based on DR programs, the highest income is achieved in CPP program with 6380.310 $.

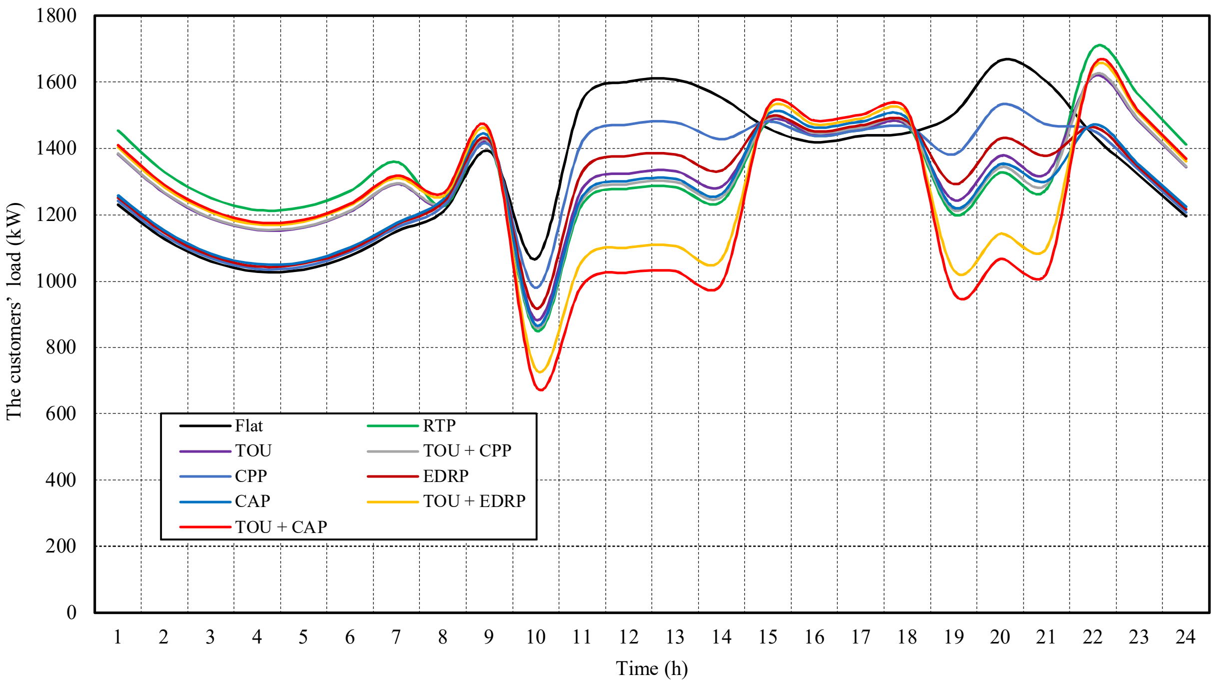

Fig. 3. Effect of the DR programs on customers' load.

Table 6. The customers' load and income of the energy sold to customer

DRPs	The customers' Load (MWh)	Income of the energy sold ($)
Flat	32.170	5505.468
RTP	31.944	5426.409
TOU	31.638	5974.142
TOU + CPP	31.445	6119.332
CPP	31.413	6380.310
EDRP	30.859	5279.741
CAP	30.412	5204.498
TOU + EDRP	30.318	5439.590
TOU + CAP	29.877	5261.406

Also, in Table 7 is reported the amount of power that transferred from the DISCO to the PL and its income and also the injecting power of the PL to the DISCO and its cost based on CDS of EVs in risk-averse type in the fourth case. As can be seen, in CAP/RTP programs, the DISCO owner achieves maximum/minimum income for the energy sold to charging EVs. Also, in CAP/ TOU+CPP programs, the DISCO owner has purchased minimum/maximum energy from EVs. Moreover, Fig. 4 is shown the power that transferred from the DISCO to the PL and vice versa, in CAP program. Based on Fig. 4, charging/discharging of EVs happens properly. Also, in 13:00, 19:00 and 20:00, since the π^{Wh2G} is closer to π^{PL2G}, the DISCO owner does not purchase energy from PL owner.

Table 7. The power charging/discharging of EVs and its income /cost in risk-averse strategy

DRPs	Charging of EVs (MWh)	Energy sold to EVs ($)	Discharging of EVs (MWh)	Energy purchased from EVs ($)
Flat	4.870	812.074	2.127	364.048
RTP	2.443	295.034	-	-
TOU	4.409	652.337	1.733	593.177
TOU + CPP	4.426	661.854	1.747	598.113
CPP	4.821	792.861	2.085	356.913
EDRP	4.825	809.537	2.089	357.533
CAP	4.884	812.641	2.113	361.685
TOU + EDRP	4.309	655.860	1.647	564.002
TOU + CAP	4.384	652.052	1.711	585.931

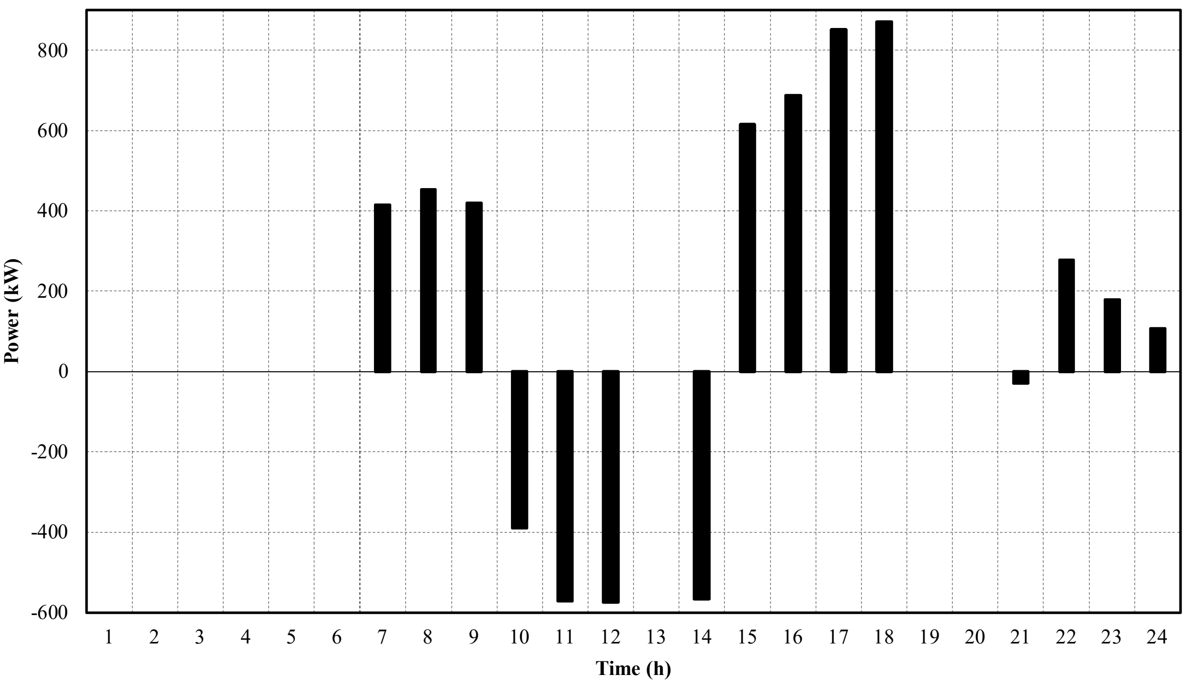

Fig. 4. The power transferred from the DISCO to the PL and vice versa in CAP program.

Simultaneous using of DR programs, RERs and smart charging/discharging schedule will definitely reduce carbon dioxide (CO_2) emissions. Accordingly, Table 8 shows the amount of CO_2 emissions reduction. In fact, in Table 8, the difference between the fourth case of each program in risk-averse model and the first case of flat program is reported. It is noted that this reduction of CO_2 emission is calculated at the on-peak periods (10:00-14:00 and 19:00-21:00). TOU + CAP/ RTP, lead to the highest/lowest level of CO_2 emission reduction, respectively. The income of CO_2 emission reduction is also reported in Table 8.

Table 8. The amount of CO_2 emission reduction in risk-averse strategy

DR program	Reduction of CO_2 emission (Kg)	Income due to reduction of CO_2 emission ($)
Flat	3790.260	19.226
TOU	5322.322	26.989
RTP	3655.535	18.564
TOU + CPP	5542.072	28.093
CPP	4717.682	23.935
EDRP	5428.417	27.544
CAP	6032.202	30.609
TOU + EDRP	7003.002	35.455
TOU + CAP	7563.755	38.253

Table 9 is shown the purchasing power from the upstream network and its cost in β=1 and fourth case. Based on Table 9, in each program with higher rates of the customers' load, this amount is also greater. Also, the purchasing power from the upstream network is less than the sum of EVs charging and the customers' load, due to using of RERs and discharging power of EVs. Also, in RTP/ TOU + CAP programs, the DISCO owner is paid more/less cost to the upstream network by purchasing energy.

Table 9. The purchasing power from the upstream network and its cost in risk-averse strategy

DRPs	The power purchased from the upstream network (MWh)	Cost of the power purchased from the upstream network ($)
Flat	31.717	4612.597
RTP	32.130	4944.702
TOU	31.165	4077.561
TOU + CPP	31.124	4003.416
CPP	30.903	4294.159
EDRP	30.425	4070.664
CAP	29.891	3887.363
TOU + EDRP	29.835	3540.096
TOU + CAP	29.370	3356.111

Table 10 shows the contribution of each of sources i.e. DISCO owner, RERs units and discharging power to the charging of EVs (G2EVs, W2EVs, PV2EVs) and supplying the customers' load (G2load, wind2load, PV2load). The highest amount of both PV/wind unit participation in feeding the customers' load is in RTP program. Also, for charging of EVs, the EDRP/CAP programs are the highest amount of PV/wind unit participation. As can be seen, wind unit has a larger share than PV unit. The highest amount of energy for EVs' charging, through the DISCO happens in the Flat program. For this reason, in this program, EVs have the highest participation rates for feeding the customers' load. As a result, the DISCO owner also purchases the lowest energy from the upstream network.

Table 10. The sharing of each sources' power for charging of EVs and supplying the customers' load (MWh), in risk-averse strategy

DRPs	G2load	W2load	PV2load	Pdch2load	G2EVs	W2EVs	PV2EVs
Flat	27.68	1.990	0.416	2.085	3.364	1.038	0.467
TOU	27.39	2.103	0.429	1.709	3.034	0.914	0.459
RTP	28.31	2.709	0.860	0	2.017	0.358	0.067
TOU + CPP	27.21	2.081	0.435	1.715	3.051	0.910	0.463
CPP	26.91	2.018	0.431	2.057	3.342	1.013	0.466
EDRP	26.15	2.255	0.394	2.053	3.528	0.782	0.515
CAP	25.87	2.038	0.413	2.084	3.373	1.004	0.475
TOU + EDRP	26.01	2.138	0.485	1.688	3.105	0.861	0.417
TOU +CAP	25.64	2.102	0.452	1.679	3.013	0.906	0.446

The DISCO owner's profit is shown in Table 11, in the fourth case and 3 types of risk in CPP programs, i.e., the best program for implementation. The DISCO owner is obtained, less profit with considering risk. In fact, in risk-seeker and risk-averse condition, the DISCO owner is achieved minimum and maximum of profit, respectively. In the risk-seeker type, more energy is sold to EVs. Therefore, more energy is available for the DISCO owner because of V2G capability. Therefore, the purchasing power from the upstream network for feeding the customer is reduced. Also air pollution decreases. As a result, the DISCO owner has gained the most benefit.

Fig. 5 shows, the operational scheduling of the DISCO, discharging power as well as RERs unit for supplying the customer, losses and charging of EVs, in CPP program and β=1. As can be seen, discharging of EVs only occurs at the first on-peak periods. Also, at 13:00 discharging of EVs do not happen, according to the reason that is said in the previous section.

Table 11. The DISCO owner's profit in fourth modes with implementation of the CPP program in three types of risk ($)

Income		CPP
	Risk-averse	792.861
The energy sold to PL	Risk-neutral	949.252
	Risk-seeker	976.626
	Risk-averse	6380.310
The energy sold to the customer	Risk-neutral	6380.310
	Risk-seeker	6380.310
	Risk-averse	23.935
Environmental encourages	Risk-neutral	26.908
	Risk-seeker	28.930
Cost		
	Risk-averse	4294.159
The power purchased from the upstream network	Risk-neutral	4052.503
	Risk-seeker	3877.787
	Risk-averse	356.913
The discharging energy	Risk-neutral	463.075
	Risk-seeker	475.758
	Risk-averse	-
Implementation of PBDR and IBDR programs	Risk-neutral	-
	Risk-seeker	-
	Risk-averse	2546.034
Profit	Risk-neutral	2840.893
	Risk-seeker	3032.322

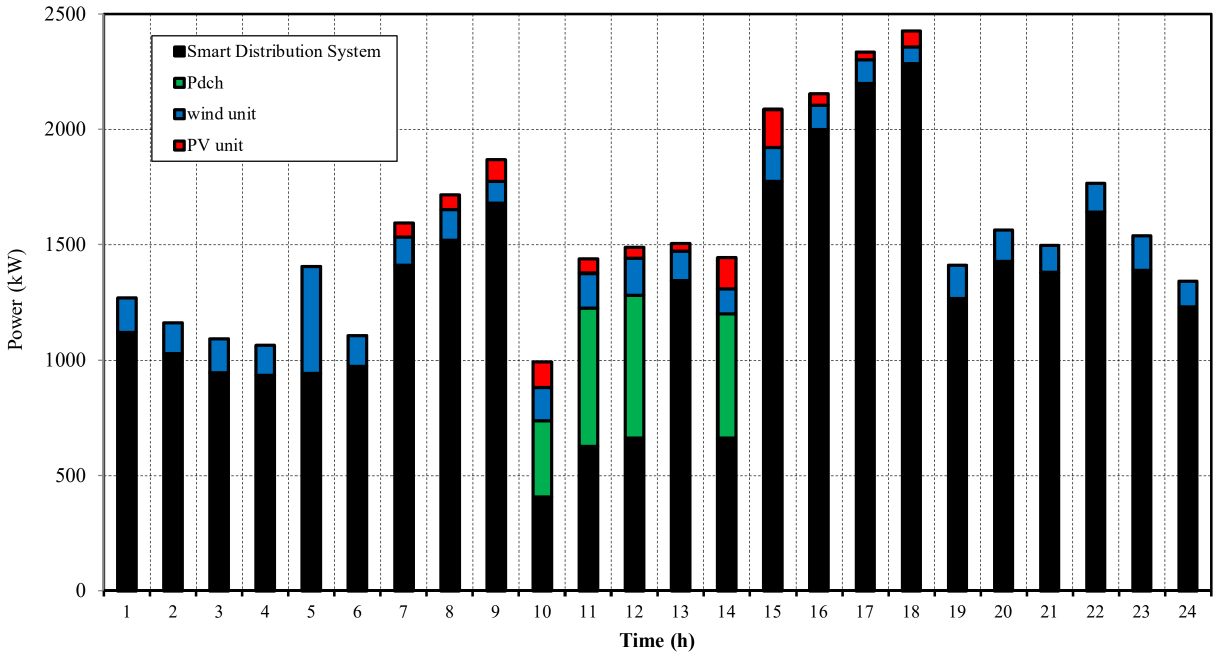

Fig. 5. The share of each resource for supplying the customer, losses and charging of EVs, in CPP program and risk-averse strategy.

Finally, a sensitivity analysis is done for investigating of the affecting factors on optimal operation of the DISCO, with the changing EVs' number, the nominal power of RERs units, as well as the percentage of customer contribution in DR program in the best DR program i.e. CPP, in 10 modes as follow:

- 200 kW of RERs units, 20% of the customer participation, 150 EVs
- 200 kW of RERs units, 30% of the customer participation, 150 EVs
- 200 kW of RERs units, 20% of the customer participation, 200 EVs
- 200 kW of RERs units, 30% of the customer participation, 200 EVs
- 500 kW of RERs units, 20% of the customer participation, 150 EVs
- 500 kW of RERs units, 30% of the customer participation, 150 EVs
- 500 kW of RERs units, 20% of the customer participation, 200 EVs
- 500 kW of RERs units, 30% of the customer participation, 200 EVs
- 500 kW of PV unit and 200 KW of wind unit, 20% of the customer participation, 200 EVs
- 200 kW of PV unit and 500 KW of wind unit, 20% of the customer participation, 200 EVs

The DISCO owner's profit, the purchasing power from the upstream network (P_s), the charging power (P_{ch}) and also the discharging power (P_{dch}), according to this sensitivity analysis are reported in Table 12.

Table 12. Sensitivity analysis in CPP program in risk-averse strategy

Mode NO.	DISCO owner's profit ($)	P_s (MWh)	P_{ch} (MWh)	P_{dch} (MWh)
Base case	2546.034	30.903	4.821	2.085
1	3218.216	32.595	7.873	3.688
2	3267.765	32.270	7.889	3.701
3	3608.987	33.664	9.771	4.285
4	3599.726	33.260	9.593	4.132
5	4133.964	26.810	7.432	3.310
6	4124.026	26.365	7.199	3.111
7	4339.259	27.088	8.413	3.124
8	4327.679	26.756	8.103	2.899
9	3813.010	32.250	9.219	3.813
10	4137.655	28.942	9.028	3.649

Based on Table 12, the following results are obtained:

- By increasing the potential of DR programs (from 20% to 30), the DISCO owner purchases less energy from the upstream network, therefore the profit of the DISCO owner increase. (To compare, e.g., modes 1 and 2, modes 3 and 4, etc.).
- By raising the size of RERs in the same situation, the profit of the DISCO owner increase, due to lower energy purchasing from the upstream network and V2G capability. (Compare for example modes 1 and 5 or modes 4 and 8).
- With more energy sold to EVs by increasing EVs' number, the profit of the DISCO owner increases. (Compare for example modes 1 and 3 or modes 5 and 7).
- By comparing mode 9 and 10, effecting of wind unit is better than the PV unit on the DISCO owner's profit because of lower energy purchasing from the upstream network and V2G capability.

4.1. Discussion

Although the results are case sensitive that can be changed by varying the test system or charging/discharging price as well as incentive and penalty price of IBDR programs, the most significant outcomes are as follow:

1. By performing of the CPP program and using RERs and CDS of EVs and three types of risk, the DISCO owner gained more profit. So that in the risk-averse model, this increase in the profit compared to the base case (flat rate) is about 87.19%. It is noted that selling more energy to the customer and EVs is the main effecting factor for achieving more profit.

2. In the risk-seeker type, the CDS of EVs by the DISCO owner was performed in a non-conservative way. In fact, as more energy was sold to EVs, more energy was available for the DISCO owner at the on-peak periods. So, the DISCO owner purchased less power from the upstream network. As a result, the DISCO owner gained a higher benefit in each program.
3. The best program from selling energy to the customer point of view is CPP. So, the income of the sold energy compared to the base case (Flat rate) was increased about 15.89% in spite of 2.3% reduction of the sold energy.
4. The best program from the purchasing power from the upstream network point of view is TOU + CAP. So that in this program this amount compared to the base case decreased about 7.39%.
5. From the sold energy to EVs point of view, CAP is the best program. This amount compared to the base case (flat rate) due to the same price of sold energy to EVs was equal.
6. From the CO_2 emission reduction point of view, the TOU + CAP is the best program. So that this reduction compared to the base case (Flat rate) was about 100%. In fact, the largest decrease in the customers' load occurs in CAP+TOU due to the biggest reduction of demand at the on-peak periods. So, the traditional power plant generated less energy.
7. CDS was conveniently implemented, so that charging of EVs happened at the mid-peak or off-peak periods. Also, discharging power was used for supplying the customers' load at the on-peak periods. Of course, in 13:00, 19:00 and 20:00, since the π^{Up2G} is closer to π^{PL2G}, the DISCO owner does not purchase energy from PL owner.
8. With the performing of the TOU program and combined programs, i.e., TOU+CPP, TOU+CAP, TOU+EDRP, encouraging the EV owners to participate in the V2G application was justified by the fact that RERs exist in the DISCO. But in other programs, even if there are not RERs, using CDS is profitable for the DISCO owner.
9. Based on a sensitivity analysis, by larger nominal power of RERs and increasing EVs number, the DISCO had a higher profit. So that with a 100% increase in EVs number (fixing the nominal power of RERs) the DISCO owner's profit increased about 42%. Also, if the nominal power of RERs raised 150%, the DISCO owner's profit was increased about 70%.
10. The effect of the wind unit was better than the effect of the PV unit on the DISCO owner's profit (if the EVs number and the customer participation was the same). So that with 150% increases only in the nominal power of the wind unit, the DISCO owner's profit increased about 62.5%. Also, if the nominal power of PV raised 150% the DISCO owner's profit increased about 49.7%.

5. Conclusions

In this paper, a new technical and environmental-based bi-level model was introduced due to the presence of the DISCO owner and the PL owner. The objective function in each level was to maximize the profit. The KKT conditions and Fortuny-Amat and McCarl linearization approach were applied to linearize the proposed model. RERs and EV uncertainty, as well as eight DR programs, were considered for investigating their effect on the profit of the DISCO owner in three types of risk. Also for the risk-based model, the CVaR concept was used. Based on the case study, the π^{Up2G}, π^{PL2G}, π^{G2PL}, EV numbers and nominal power of RERs were an important effect on CDS of EVs and benefit of DISCO owner. The greatest profit of DISCO owner in each DR programs was achieved in risk-seeker type where the uncertainties were not considered. The results proved the advantages of the presented model. Also for continuing work, the following examples are offered: Calculation of the optimal price of the energy sold/purchased to/from PL owner by presenting a non-linear bi-level model; Obtaining the optimal price of incentive and penalty of IBDR programs.

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