Operational scheduling of a smart distribution system considering electric vehicles parking lot: a bi-level approach

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Abstract

In this paper, a new bi-level framework is presented for operational scheduling of a smart distribution company (SDISCO) with electric vehicle (EV) parking lot (PL) and renewable energy sources (RES), i.e., wind and photovoltaic (PV) units. In the proposed bi-level model, maximization of the profit of SDISCO is obtained in the upper-level (leader) problem by minimizing the cost of power purchased from the wholesale market due to the EV PL unique capability, i.e., PL-to-grid. The lower-level (follower) problem aims to maximize the profit of the PL owner. This model is converted to a non-linear single-level problem by using Karush–Kuhn–Tucker (KKT) conditions. Fortuny-Amat and McCarl method is used for linearization based on auxiliary binary variables and sufficiently large constants. Moreover, uncertainties such as duration of the presence of EVs in PL, the initial state of the charge (SOC) of EVs and output power generation of wind and PV units are simultaneously considered through a set of scenarios. The SDISCO's profit is investigated in four modes: 1) without RES and with the controlled charging of EVs; 2) without RES and with smart charging/discharging of EVs; 3) with RES and with the controlled charging of EVs; 4) with RES and with smart charging/discharging of EVs. In all these modes, a price-based demand response (DR) program is considered, as well as incentive-based DR, and combined price-based DR and incentive-based DR. The presented model is tested on the IEEE 15-bus distribution system over a 24-h period. The results show that SDISCO gains more profit by using a suitable charging/discharging schedule and employing a critical peak pricing (CPP) program. Furthermore, by comparing this bi-level model with the centralized model, the effectiveness of the bi-level model is demonstrated. Also, sensitivity analyses on the number of EVs, size of RES and the percentage of customer participation in the DR program are evaluated on the optimal operation of the SDISCO.

Keywords: Operational scheduling; bi-level model; electric vehicles; demand response; uncertainty.

Nomenclature

Indices

b , b'	Index for branch or bus	t^{dep}	Departure time of EVs from the PL
F	Index for linear partitions in linearization	V^{Rated}	Nominal Voltage (V)
n , N	Index for EV number	V^{max}	Maximum allowable voltage (V)
S , s	Index for scenarios	V^{min}	Minimum allowable voltage (V)
Sb	Index for slack bus	$X_{b,b'}$	Reactance between branch b , b' (Ω)
t , t'	Index for time (hour)	Z	Impedance (Ω)
Parameters		ΔS	Upper limit in the discretization of quadratic flow terms (kVA)

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$A(t)$	Incentive of DR programs at t-th hour ($/kWh)
C^{cd}	Cost of equipment depreciation ($/kWh)
$E(t,t)$	Self-elasticity
$E(t,t')$	Cross-elasticity
$I^{max, b, b'}$	Maximum current of branch b, b′ (A)
$P(t)$	Customers' demand at t-th hour after DR (kW)
$P^0(t)$	Initial demand at t-th hour (kW)
P^{con}	Contracted power in DR programs (kW)
P^L	Customers' demand before DR (kW)
$P^{L,DR}$	Customers' demand after DR (kW)
P^{max}	Charging or Discharging rate (kWh)
P^{PV}	Output power of PV unit (kW)
$P^{PV,max}$	Maximum Output power of PV unit (kW)
P^W	Output power of wind unit (kW)
$P^{W,max}$	Maximum Output power of wind unit (kW)
$PEN(t)$	Penalty of DR programs at t-th hour ($/kWh)
$Pr^0(t)$	Initial electricity price at t-th hour ($/kWh)
$Pr(t)$	Electricity price at t-th hour after DR ($/kWh)
$\rho^{L,DR}$	Electricity price after DR ($/kWh)
ρ^{ch}	Charging tariff of EVs ($/kWh)
ρ^{PL2EV}	Price of power purchased of PL by EVs ($/kWh)
ρ^{dch}	Discharging tariff of EVs ($/kWh)
ρ^{Wh2G}	Price of buying electricity from the wholesale market by SDISCO ($/kWh)
$Q^{L,DR}$	Customers' reactive power after DR (kVAR)
$R_{b, b'}$	Resistance between branch b , b′ (Ω)
SOC^{arv}	Initial SOC of EVs at the arrival time to the PL (kWh)
η^{ch}	Charging efficiency (%)
η^{dch}	Discharging efficiency (%)
SOC^{dep}	Desired SOC of EVs at the departure time from PL (kWh)
SOC^{max}	Maximum rate of SOC (kWh)
SOC^{min}	Minimum rate of SOC (kWh)
t^{arv}	Arrival time of EVs to the PL
π_s	Probability of each scenario
Variables	
I,I2	Current flow (A), Squared current flow (A2)
P^{ch}	Transferred power for EVs charging (kW)
P^{dch}	Discharging power of EVs (kW)
P^{Loss}	Power loss of SDISCO (kW)
P^{Wh2G}	Power purchased from wholesale market by SDISCO (kW)
P^+	Active power flows in downstream directions (kW)
P^-	Active power flows in upstream directions (kW)
Q^{Wh2G}	SDISCO's reactive power (kVAR)
Q^+	Reactive power flows in downstream directions (kVAR)
Q^-	Reactive power flows in upstream directions (kVAR)
V,V2	Voltage (V), Squared voltage (V2)
X	Binary variable for linearization of the complementary conditions
λ	dual variable ($/kWh)
Others	
C	Greater than or equal to zero constraint
L	Lagrangian function
M	Sufficiently large constants

1. Introduction

1.1. Motivation

Among various energy consumers in the world, the transportation sector is one of the largest users of fossil fuels and the largest contributor to greenhouse gas emissions and pollutants. According to the report of the international energy agency (IEA), the transportation sector consumed 45% of the worlds' oil in 1973, and this value was reached to 62.3% in 2011. In terms of greenhouse gas emissions, the transportation sector accounts for more than 20% of the carbon dioxide [1]. On the other word, the global demands for fossil fuels due to the continuous growth of human activities are incrementing which leads to an increase in greenhouse gas emissions and pollutants. With regard to benefits, e.g., reducing the fuel consumption and greenhouse gas emissions and improving the energy efficiency, electric vehicles (EVs) have recently gained much attention and will be widely used in the transportation system in the future [2]. For example, 62% of the total fleet in the United States of America is estimated to be hybrid EVs in 2050 [3].

The power system has limited storage capacity, therefore vehicle-to-grid (V2G) concept, that has emerged with the EVs, has attracted the attention of many operators and planners, and it has created new hopes for providing the storage requirements of the power system. It is noted a large number of EVs that is imposed on smart distribution company (SDISCO) in the future, resulting in high energy consumption demands. In this situation, coordination of PLs in the operation modes consist of PL-to-Grid (PL2G) and Grid-to-PL (G2PL) is a challenging issue of the SDISCO. In the PL-to-Grid mode, the PL's power is injected into the SDISCO, that is resulting from discharging the EVs. In the Grid-to-PL mode, the power is drawn from the SDISCO by PL for charging the EVs. Also, the high penetrations of EVs to SDISCO increase the production of the traditional power plant. So, the fossil fuel consumption and greenhouse gas emission increase. Therefore, the use of renewable energy sources (RES) is also inevitable alongside traditional power plants for supplying this part of the energy. Studies show that EV owners do not use the vehicles more than 93% to 96% of day-time [4-5]. Thus, it is clear that by increasing the penetration of EVs in the transportation sector, the battery storage capacity of these vehicles while they are parked can be used for improving the performance of SDISCO.

Moreover, demand response (DR) is one of the most cost-effective and efficient methods for smoothing the load profile. By participating in DR programs, customers are able to change their energy consumption in response to energy price changes and get incentives in return.

This paper aims at the operational scheduling of SDISCO considering RES and PL along with their uncertainty. Since the PL owner is private, a new bi-level model is developed. In the upper-level, maximization of the profit of SDISCO has performed, while in the lower-level, maximization of the profit of PL owner has conducted. However, the uncertain nature of RESs and PL may have a considerable effect on the optimal operation of SDISCO. So, uncertainties are modeled by the probability distribution function (PDF). Furthermore, the effect of charging methods, i.e., controlled charging, smart charging/discharging, and also a price-based and an incentive-based DR program are considered on the operational scheduling of SDISCO. In addition, the effect of the size of wind and photovoltaic (PV) units and the number of EVs are evaluated on the operations of SDISCO. Since the model involves uncertainties, stochastic programming is used for solving the objective function. In fact, this paper aims at answering the following questions:

- What is the appropriate model with the aim of maximization of the SDISCO's profit considering the presence of the new decision maker, i.e., the private owner of PL?
- What is the optimal operational scheduling of the SDISCO, PV and wind units, and PL?
- How to prioritize different DR programs based on some indices such as profit of SDISCO and network losses?
- What are the main effecting factors on the optimal operational scheduling of SDISCO?

1.2. Literature survey

With the increasing penetration of EVs and RES on the distribution company, operation and planning of this system are facing new challenges. Distribution Company must supply the demand at acceptable voltage magnitudes and feeder loading levels. So, a reasonable operation strategy is provided by SDISCO in the presence of RES and EVs and purchasing power from the wholesale market while maintaining the system security. In fact, SDISCO buys the energy from the wholesale market for inconstant prices and sells to the customers for flat or dynamic tariffs.

Many studies focused on the impact of EVs on the distribution company such as losses [6-7], distribution company equipment [8-9], voltage profile [10-12], and the increase of power demand [13-14]. In [6], with penetration of EVs to the network, the energy losses increase 40%. In [7], a model for minimizing the losses is proposed. The result shows that the energy losses of the system are 1.4%, 2.4% and 2.1% in without EVs situation, uncoordinated charging mode and coordinated charging mode, respectively. In [8], the impact of EV charging is analyzed on the distribution transformer. Also, the result shows that with smart charging scenarios, the negative effects on the transformer lifetime are mitigated. In [9], the load capability of cable in the presence of EVs is evaluated. The cable loading is limited to 15% and 25% penetration of EVs by fast charging and normal charging, respectively. In [10], with a model for minimizing the purchasing energy for charging the EVs and losses, the voltage profile and total cost are evaluated. The result shows that the voltage drop of the system is 7.64%, 17.15% and 10% in without EVs situation, uncoordinated charging mode and coordinated charging mode, respectively. In [12], with the aim of maximizing the delivered charging power of EVs, the voltage drop and total cost are improved. In [13], it is shown that with penetration of one million EVs, the peak load increases only up to 1.5%. Also, if all conventional cars are replaced by EVs, the peak load increases up to 200%. In [14], the increasing load due to the uncoordinated charging of EVs and the negative effect on the system reliability is investigated. Also, the adverse effect of EVs is addressed by the implementation of time-of-use programs. In fact, EVs are charged in off-peak and mid-peak periods.

Also, the allocation of optimal capacity and the location of PL are addressed in [15-19]. In [15], the allocation of PL in the distribution system is studied to achieve several aims such as the reliability improvement, power losses reduction, and increasing V2G revenue. In [16], minimizing the overall energy cost of the distribution system for optimal allocation and sizing of PL is performed by using an artificial bee colony and firefly algorithm considering charging/discharging scheduling. In [17], with the aim of maximizing the distribution system profit and by using the probabilistic approaches and presenting a simple scheduling model for the optimal charge/discharge of EV, the allocation of PL is investigated. Subsequent to [17], in [18], another approach is presented that solves the allocation of PL by genetic algorithm. The objective function of this approach is the maximization of the distribution system profit with considering the welfare of the EV owners. In [19], siting and sizing of charging station are carried out with two-stage optimization model. In this model, in the first stage, the power system, and in the second stage the transportation network are optimized.

In [20], for optimal scheduling of EV charging, dynamic optimal power flow is solved. Moreover, according to the result of some studies such as [21-22], EV charging only with traditional power plants creates inappropriate environmental impact. Thus, it is inevitable to use RES along with traditional power plants. Therefore, interactions of EVs are investigated with solar photovoltaic [23-24], wind turbine [25-26] and both of them [27-28]. On the other hand, uncertainty is one of the important and inherent characteristics of RES. On this basis, operation and planning of the distribution systems confront with the uncertainty. Therefore, it is essential to employ DR programs as means to manage the energy not supplied by these resources. Studies [29-31] evaluate different DR strategies in power systems.

For showing the difference between the current paper and previous related studies, Table 1 is presented. In [32], a mixed-integer second-order cone programming (MISOCP) model is proposed for solving the optimal operation problem of radial distribution networks with energy storage. For accuracy of the proposed MISOCP model, a Mixed-Integer Linear Programming (MILP) formulation is also suggested. In [33], a probabilistic framework is presented for the operation of the distribution system in the presence of distributed generations (DGs) and battery energy storage. In this model, the uncertainty of electricity prices and output power of DGs is also considered.

In [34], a multi-objective bi-level optimal operation model is presented for the distribution system with grid-connected microgrid. The aim of the upper level is the power loss reduction and voltage profile improvement, while the lower-level minimizes the operation cost of micro-grid. For solving this model, a combination method is used based on a self-adaptive genetic algorithm and non-linear programming.

In [35-36], the operation of active distribution grids in which distribution company (DISCO) and MGs cooperate with each other is modeled by the bi-level approach. Maximization of the DISCO profit and minimization of the MGs cost in upper and lower level is achieved, respectively. For solving the problem is used Karush–Kuhn–Tucker conditions and dual theory.

In [37], a bi-level model is presented for the operational decision making of a distribution company with DG and interruptible loads. The objective function of the upper-level and lower-level problem is to minimize the cost of market purchases and DG unit dispatch, and the maximization of social welfare, respectively. The problem formulated an equilibrium problem with equilibrium constraints (EPEC) and is solved by non-linear programming solver. In [38], a bi-level model is proposed for virtual power plant (VPP) operation with wind power and solar photovoltaic power. In the upper-level, the maximum VPP operation income is taken as the objective function, but in the lower-level, the aim is the minimum system net load and the minimum system operation cost.

In [39], a bi-level framework is described for EV fleet charging. The bi-level framework includes the outer-level where the genetic algorithm is used for optimization of the state of charge increments over each charging period and minimization of the maximum charging power of individual EVs. Also, in the inner-level, the aggregated battery charging power is optimized by the dynamic programming-based algorithm. In [40], the stochastic bi-level model is offered, in which the aim of the upper-level and lower-level is the maximization of the profit of active distribution network operator and maximization of the social welfare in the clearing of the market from the perspective of the independent system operator (ISO). Also, the complementary theory is used for converting the model into an MILP model. In [41], for minimizing the cost of Distribution System Operator (DSO) for installing and operating of PLs, a single-level model is offered. In this system, uncertainties of PLs, wind and PV units as well as planning and operation constraints such as network limits, network loss, urban restrictions, etc. are also considered. In [42], for PL placement in a distribution company, a single-level model is presented with the aim of maximization network reliability index. This model employs the probabilistic modeling of EV for the PL studies. In [43], a two-stage model is suggested for siting the private PL and distributed renewable resources by considering economic constraints of PL investor and distribution network constraints. Firstly, the Canadian place for installing PL is introduced to distribution network operator by PL investor based on reliability index, bus attraction index and price of land index. Then, loss reduction is performed for the distribution network operator. In [44], a multi-objective model for siting and sizing of renewable energy sources and EV charging station is proposed. The goal of the model is the minimization of power loss, total voltage fluctuations index, EVs charging and demand, while supplying depreciation costs of the battery.

In [45], the stochastic bi-level model is suggested for an EV aggregator in a competitive environment. The maximization of the profit of aggregator and minimization of the cost paid by the EV owners are the main aim of the bi-level model. Also, by using Karush–Kuhn–Tucker (KKT) and Strong duality theory the nonlinear bi-level model is converted to a linear single-level model. In [46], a new multi-objective bi-level model is proposed for the distribution network expansion planning. The minimizing of the net present value of the total planning cost and maximizing the profit of PL are the goal of the upper and lower levels, respectively. Since bi-level model is a mixed-integer nonlinear programming problem, for solving a two-stage mixed integer linear programming-embedded Immune-Genetic Algorithm is used.

In [47], a bi-level model for reduction of the peak-to-average ratio of the load of a distribution transformer in the presence of EVs is presented. The objective function in the upper level is minimizing the maximum peaks of the distribution transformer load. In the lower level, the aim is to minimize the individual household electricity bill using dynamic pricing. In [48], for congestion management of smart distribution system, a bi-level model is offered. Minimizing the total operation cost of the distribution system and maximizing the profit of each aggregator are the aims of the upper-level and lower-level, respectively. The model is solved by highly efficient commercial solver CPLEX 12.4 in MATLAB environment. In [49], a two-stage two-level model is proposed to investigate the mutual impacts of the behavior of PLs and renewable-based distribution systems. In this model, decisions taken at the first level should be considered in the optimization of the second level. The objective function at the first level is maximizing the profit of the PLs, while the second level aims at minimizing the distribution system operator's cost.

Although many works have been performed about the operation of distribution systems, a bi-level model in which by using the power exchange between SDISCO and private PL owners, the profit of both sides is maximized has not been addressed in the literature. Also, simultaneous evaluation of the effect of the RES and PL uncertainty, price-based DR and incentive-based DR programs in the operational scheduling of SDISCO has not been reported. Therefore, in this paper, by developing a new bi-level model, the optimal operational of SDISCO and private PL owners is presented.

Also, for solving the proposed model, KKT conditions and the Fortuny-Amat and McCarl linearization method have been used. These methods transform the bi-level and non-linear models into single-level and linear models that can be easily solved with optimization tools.

Table 1. A summary of previous studies

Reference	DISCO	EVs	PV	wind	DGs	price-based DR	incentive-based DR	Bi-level	Single-level	uncertainty	Solution method
[32]	*	-	*	*	-	-	-	-	*	-	GAMS - CPLEX
[33]	*	-	*	-	-	-	-	-	*	*	MCS - MATLAB
[34]	*	-	*	*	-	-	-	*	-	-	NSGA II - MATLAB
[35]	*	-	-	*	-	-	-	*	-	*	GAMS - CPLEX
[36]	*	-	-	-	*	-	-	*	-	-	GAMS - CPLEX
[37]	*	-	-	-	*	-	-	*	-	-	Not stated
[38]	-	-	*	*	-	*	*	*	-	*	GAMS - CPLEX
[39]	-	*	-	-	-	-	-	*	-	-	NSGA II - MATLAB
[40]	*	-	-	-	*	-	-	*	-	*	GAMS – CPLEX
[41]	*	*	*	*	-	-	-	-	*	*	GAMS – CPLEX
[42]	*	*	-	-	-	-	-	-	*	*	GA - MATLAB
[43]	*	*	*	*	-	-	-	-	*	-	GA,PSO-MATLAB
[44]	*	*	*	*	-	-	-	-	*	*	GA-PSO-MATLAB
[45]	-	*	-	-	-	-	-	*	-	*	GAMS – CPLEX
[46]	*	*	-	-	-	-	-	*	-	*	GAMS – MATLAB
[47]	*	*	-	-	-	-	-	*	-	*	MATLAB
[48]	*	-	-	-	-	-	-	*	-	*	CPLEX – MATLAB
[49]	*	*	*	*	-	-	-	-	-	*	GAMS – CPLEX
Current paper	*	*	*	*	-	*	*	*	-	*	GAMS – CPLEX

1.3. Contributions

The number of decision makers in SDISCO is increasing. Apart from SDISCO owners, the PL owners would also be part of the decision-making process, due to the high penetration of EVs into the network. So, this paper develops a bi-level model for operational scheduling of SDISCO in the presence of EV PL and RES. The main contributions of the paper are as follows:

1. Developing a new bi-level model in which SDISCO and PL owners maximize the profits.
2. Converting the bi-level optimization model of SDISCO and PL considering RES as well as price-based DR and incentive-based DR programs to the linear single-level model by KKT conditions.
3. Investigating different factors which may affect the operational scheduling of SDISCO in the presence of RES, PL and DR programs using sensitivity analysis.

1.4. Paper organization

The rest of the paper is organized as follows. Modeling of price-based DR and incentive-based DR programs are explained in section 2. Problem formulation of bi-level model is explained in section 3. Numerical results are discussed in section 4. Finally, conclusions are reported in section 5.

2. Modeling the price-based and incentive-based DR programs

Based on Eq. (1), the demand sensitivity respect to the price is defined as elasticity [50].

$$E = \frac{Pr^0}{P^0}.\frac{\partial P}{\partial Pr} \tag{1}$$

The customers' demand is shifted or reduced when the electricity price increases, i.e., at the on-peak periods. To encounter the price mutability, loads respond in two ways: single-period loads and multi-period loads. The load that cannot shift to other periods is a single period load. These loads should be connected or disconnected while the electricity price is changed. These loads are sensitive to a single-period and known as *self-elasticity* that the value of elasticity is negative. Because when the price increases during a period, the demand at the same period decreases and vice versa. However, the loads that adapt themselves to changing the price and to shift from on-peak period to off-peak or mid-period are known as multi-period loads. These loads are sensitive to a multi-period and known as cross-elasticity in which the value of elasticity is positive. Insomuch when prices increase over a period, demand increases at other periods. These elasticities are shown in Eq. (2) [50].

$$
\begin{aligned}
E(t,t) &= \frac{\Pr^0(t)}{P^0(t)} \cdot \frac{P(t)-P^0(t)}{\Pr(t)-\Pr^0(t)} \le 0 \\
E(t,t') &= \frac{\Pr^0(t')}{P^0(t)} \cdot \frac{P(t)-P^0(t)}{\Pr(t')-\Pr^0(t')} \ge 0
\end{aligned}
\tag{2}
$$

Based on Fig. 1, DR programs are divided into two main groups involving price-based DR programs and incentive-based DR programs. The price-based DR programs are voluntary programs; however, the incentive-based DR programs include voluntary programs, mandatory programs, and market clearing programs. So, for load economic model we will have Eq. (3) [50]:

$$
\mathrm{P(t)} = \mathrm{P^0(t)} \times \left\{ 1 + \mathrm{E(t,t)} \times \frac{\mathrm{Pr(t)} - \mathrm{Pr^0(t)} + \mathrm{A(t)} + \mathrm{PEN(t)}}{\mathrm{Pr^0(t)}} + \sum_{\mathrm{t'=1,t' \neq t}}^{24} \frac{\mathrm{Pr(t')} - \mathrm{Pr^0(t')} + \mathrm{A(t')} + \mathrm{PEN(t')}}{\mathrm{Pr^0(t')}} \times \mathrm{E(t,t')} \right\}
\tag{3}
$$

Eq. (3) calculates how much the customers' consumption will be changed to obtain the maximum profit. As regards the SDISCO that is responsible for implementing DR programs, the contribution of customers in these programs may bring some additional costs as presented in Eq. (4).

$$
\mathrm{C^{DR}} = \left(\mathrm{A(t)} \times \left(\mathrm{P^0(t)} - \mathrm{P(t)}\right)\right) - \left(\mathrm{PEN(t)} \times \left(\mathrm{P^{con}(t)} - \left(\mathrm{P^0(t)} - \mathrm{P(t)}\right)\right)\right)
\tag{4}
$$

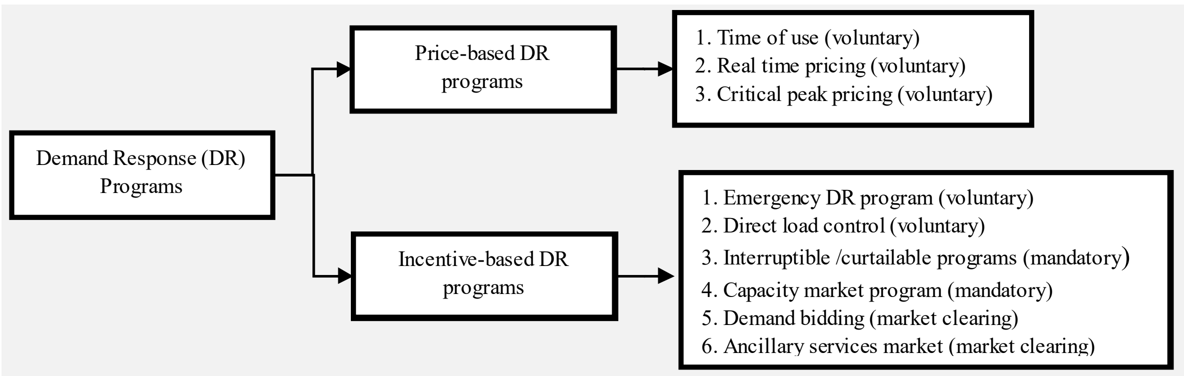

Fig.1. The category of DR programs

3. Problem Formulation

Urban PL is a suitable place for parking the EVs because of easy access, convenient spaces and long-term parking the EVs. However, it should be noted that urban PL usually has a high capacity, and a large number of EVs can be parked at the same time. It means that at any time, a large amount of energy are required to charge EVs which should be carefully monitored and controlled. EVs can be used as a load/generator and receive/inject the electrical energy from/to the SDISCO. It leads to some complexity in the optimization problem. Also, with the controlled charging and smart charging/discharging of EVs and due to V2G ability, SDISCO can solve this problem for reducing the peak load and providing ancillary services, etc. Therefore, the proper operation of SDISCO can be achieved if an energy management system is developed with the ability to control and effectively manage the process of charging/discharging of EVs. The SDISCO, PL owners as aggregators, and EV owners are the main players of the operational scheduling of SDISCO. The PL owner wants to maximize his profits. EV owners expect to pay a lower cost for charging their EVs. The SDISCO is also interested in improving the distribution system operation by reducing losses, improving voltage profile, increasing reliability index, avoiding feeder or transformer congestion, etc.

3.1. The Proposed Bi-level framework

The proposed model in this paper is related to the operational scheduling of SDISCO that is the owner of PV and wind units. Besides, in this system, there is a private PL owner. When there are two decision makers in the optimization problem in which each decision affects their desired results, a bi-level model needs to be used. Fig. 2 shows a schematic of the proposed framework. The main block of the proposed framework includes the bi-level model in which the problem of each level is shown. The objective function of the upper-level maximizes the profit of SDISCO. Maximization of PL's profit is the objective function of the lower-level considering the exchange of the energy with the SDISCO and EV owners. The operational scheduling of SDISCO, PV unit, wind unit and PL are the outputs of the framework.

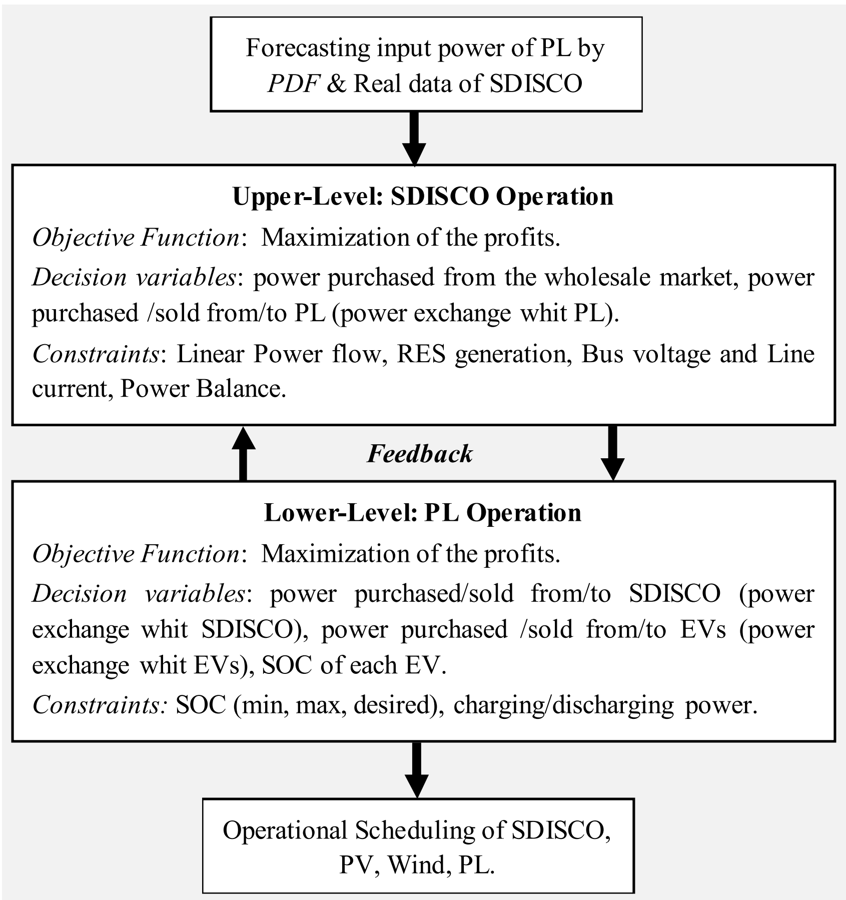

Fig.2. The proposed bi-level framework

3.2. The upper-level model

The objective function in the upper-level is a single-objective model, i.e., the maximization of SDISCO's profit. The decision variable at this level is the amount of the power purchased from the wholesale market and the power purchased/sold from/to PL (power exchange with PL). Also, power flow, RES generation, bus voltage and line current and power balance are considered as constraints.

3.2.1. Objective Function

For the customers' orientation and satisfaction, SDISCO should supply the demand including the charging of EVs. So, the objective function is composed of as follows:

1. The income from the selling the energy to PL.

This term is the income from the selling energy to the PL for charging the EVs. The income is presented in Eq. (5). It is noted that a part of the power for charging the EVs is supplied by RES generation.

$$F_1 = \sum_{s=1}^{Ns} \pi_s \sum_{n=1}^{N} \sum_{t=1}^{24} P_{n,t,s}^{ch} \times \rho_t^{ch} \times \Delta t \tag{5}$$

2. The income from the selling the energy to the customers.

This term is the income from the selling energy to residential, industrial and commercial loads. This income is formulated in Eq. (6). RES generation is also used for supplying the customers' demand.

$$F_2 = \sum_{b=2}^{Nb} \sum_{t=1}^{24} P_{b,t}^{L,DR} \times \rho_t^{L,DR} \times \Delta t \tag{6}$$

3. The cost of providing energy from the wholesale market.

SDISCO purchases energy from the wholesale market to supply various customers such as industrial, commercial and residential load and also PL for charging the EVs. This cost is expressed in Eq. (7).

$$F_3 = \sum_{Sb=1}^{NSb} \sum_{t=1}^{24} P_{Sb,t}^{Wh2G} \times \rho_t^{Wh2G} \times \Delta t \tag{7}$$

4. The cost of energy purchased from PL.

This term is the PL's bidding cost to the energy market, and it is resulted from discharging the EVs at the on-peak period. This energy is used for supplying the customers. This cost is given by Eq. (8).

$$F_4 = \sum_{s=1}^{Ns} \pi_s \sum_{n=1}^{N} \sum_{t=1}^{24} P_{n,t,s}^{dch} \times \rho_t^{dch} \times \Delta t \tag{8}$$

5. The cost of implementation of price-based and incentive-based DR programs.

As previously mentioned, with the implementation of DR programs, SDISCO incurs some costs that can be calculated by Eq. (9).

$$F_5 = \sum_{b=2}^{Nb} \sum_{t=1}^{24} \left(A_t \left(P_{b,t}^{L} - P_{b,t}^{L,DR} \right) - PEN_t \left(P_{b,t}^{con} - P_{b,t}^{L} + P_{b,t}^{L,DR} \right) \right) \times \Delta t \tag{9}$$

It is noted that the time interval in this paper is 1 hour (Δt=1). After the description of income and cost, the objective function is presented in Eq. (10).

$$MAX \quad OF_1 = (F_1 + F_2) - (F_3 + F_4 + F_5) \tag{10}$$

3.2.2. Constraints

In the following, the constraints related to the objective function are defined.

- RES generation

The wind and PV generation in each scenario must be limited to the minimum and maximum generation. Eqs. (11) - (12) describe these constraints.

$$0 \le P^{W}_{b,t,s} \le P^{W,\max} \tag{11}$$

$$0 \le P^{PV}_{b,t,s} \le P^{PV,\max} \tag{12}$$

- Bus voltage and Line current

The optimal power flow must satisfy the limitations assigned by the constraints of bus voltages and branch flows. According to Eqs. (13)-(14), the voltage of each bus and the current of each branch should be in the range. The maximum and minimum values of the voltage in each bus are 1.05 and 0.95 p.u., respectively. Also, because of the line thermal capacity, the maximum value of each branch current is limited by the conductor specifications, i.e., resistance and reactance of the branch.

$$I_{b,t,s} \le I^{b,\max} \tag{13}$$

$$V^{\min} = 0.95 \le V_{b,t,s} \le V^{\max} = 1.05 \tag{14}$$

- Linear power flow

According to this constraint, the generated total energy or power must be equal to the consumed total power or energy. In this paper, the linear power flow is adopted from [49]. This power flow model can be only used for radial distribution networks. For this purpose, the term is considered as a block to avoid nonlinearities. Note that the EVs in the PL act as a source at the on-peak period and as a load at the off-peak or mid-peak period. The active and reactive power balances in this power flow are shown in Eqs. (15) - (16):

$$P^{Wh2G}_{Sb,t} \times \eta^{Trans} + P^{\mathrm{PV}}_{b,t,s} + P^{\mathrm{W}}_{b,t,s} + \sum_{\mathrm{N}} P^{dch}_{n,t,s} - \sum_{\mathrm{N}} P^{ch}_{n,t,s} - \sum_{b'} \left[\left(P^{+}_{b,b',t,s} - P^{-}_{b,b',t,s} \right) + R_{b,b'} I2_{b,b',t,s} \right]$$
$$+ \sum_{b'} \left(P^{+}_{b',b,t,s} - P^{-}_{b',b,t,s} \right) - P^{\mathrm{L,DR}}_{b,t} = 0 \qquad \forall \mathrm{t,s} \tag{15}$$

$$Q^{Wh2G}_{Sb,t,s} - \sum_{b'} \left[\left(Q^{+}_{b,b',t,s} - Q^{-}_{b,b',t,s} \right) + X_{b,b'} I2_{b,b',t,s} \right] + \sum_{b'} \left(Q^{+}_{b',b,t,s} - Q^{-}_{b',b,t,s} \right) - Q^{\mathrm{L,DR}}_{b,t} = 0 \qquad \forall \mathrm{t,s} \tag{16}$$

Note that $I2$ refers to an auxiliary variable that linearly represents the squared current flow I^2 in a given branch. At most one of these two positive auxiliary variables, i.e., $P_{b,b,t,s}$ and $Q_{b,b,t,s}$ can be different from zero at a time. This condition is again implicitly enforced by optimality. Moreover, constraints (17)-(18) limit these variables to the maximum apparent power for the sake of completeness.

$$0 \le \left(P^{+}_{b,b',t,s} + P^{-}_{b,b',t,s} \right) \le V^{Rated} \times I^{\max,b,b'} \tag{17}$$

$$0 \le \left(Q^{+}_{b,b',t,s} + Q^{-}_{b,b',t,s} \right) \le V^{Rated} \times I^{\max b,b'} \tag{18}$$

Eq. (19) represents the balancing of the voltage between two nodes. It should be noted that $V2$ in Eq. (19) is an auxiliary variable that represents the squared voltage relations.

$$V2_{b,t,s} - V2_{b',t,s} - Z^{2}_{b,b'} I2_{b,b',t,s} - 2R_{b,b'} \left(P^{+}_{b,b',t,s} - P^{-}_{b,b',t,s} \right) - 2X_{b,b'} \left(Q^{+}_{b,b',t,s} - Q^{-}_{b,b',t,s} \right) = 0 \tag{19}$$

Eq. (20) is employed to linearize the active and reactive power flows that appear in the apparent power expression.

$$V^{Rated}_{b} 2.I2_{b,b',t,s} = \sum_{f} \left[(2f-1) \Delta S_{b,b'} \Delta P_{b,b',f,t,s} \right] + \sum_{f} \left[(2f-1) \Delta S_{b,b'} \Delta Q_{b,b',f,t,s} \right] \tag{20}$$

For piecewise linearization of the flow constraints Eqs. (21) -(25) are represented. The number of blocks required to linearize the quadratic curve is set to five according to [51], which strikes the right balance between the accuracy and computational requirements. Further descriptions, justifications, and derivations of the network model used in this paper can be found in [52].

$$P^{+}_{b,b',t,s} + P^{-}_{b,b',t,s} = \sum_{f} \Delta P_{b,b',f,t,s} \tag{21}$$

$$Q^{+}_{b,b',t,s} + Q^{-}_{b,b',t,s} = \sum_{f} \Delta Q_{b,b',f,t,s} \tag{22}$$

$$0 \le \Delta P_{b,b',f,t,s} \le \Delta S_{b,b'} \tag{23}$$

$$0 \le \Delta Q_{b,b',f,t,s} \le \Delta S_{b,b'} \tag{24}$$

$$\Delta S_{b,b'} = \frac{V^{Rated} \times I^{\max b\, b'}}{F} \tag{25}$$

- Power balance

Based on above descriptions, the power produced by the traditional power plant and RES must be equal to the power consumption by consumers. Also, PL acts as a source at the on-peak period and as a load at the off-peak or mid-peak period. Hence, the power balance is described in Eq. (26).

$$P^{Wh2G}_{Sb,t} \times \eta^{Trans} + P^{W}_{b,t,s} + P^{PV}_{b,t,s} + \sum_{\mathrm{N}} P^{dch}_{n,t,s} = P^{\mathrm{L,DR}}_{b,t} + P^{Loss}_{t,s} + \sum_{\mathrm{N}} P^{ch}_{n,t,s} \tag{26 }$$

3.3. The lower-level model

The objective function in this level is the maximization of the PL owner's profit. The decision variable is the power purchased/sold from/to SDISCO (power exchange with SDISCO), power purchased/sold from/to EV owners and SOC of EVs. Also, the SOC (minimum/maximum/desired) and charging/discharging rate are all considered as constraints.

3.3.1. Objective Function

The PL can participate in the energy markets based on the number of EVs in PL. The PL owner can gain income from the selling power to energy markets and EV owners. Also, the cost of PL involves energy purchased from the SDISCO and RES and EV owners. So, the objective function is composed of as follows:

1. The income from the selling the energy to EV owners.

EV owners need to charge their batteries, so this term denotes the income from charging the EVs while parked at the PL. This income is presented by Eq. (27).

$$F_1 = \sum_{s=1}^{Ns} \pi_s \sum_{n=1}^{N} \sum_{t=1}^{24} P^{ch}_{n,t,s} \times \rho^{PL2EV}_{t} \times \Delta\mathrm{t} \tag{27}$$

2. The income from the selling the energy to the SDISCO.

This term is the income from the PL bids to the energy market that is resulted from discharging the EVs at the on-peak period. This income is described in Eq. (28).

$$F_2 = \sum_{s=1}^{Ns} \pi_s \sum_{n=1}^{N} \sum_{t=1}^{24} P^{dch}_{n,t,s} \times \rho^{dch}_{t} \times \Delta\mathrm{t} \tag{28}$$

3. The cost of energy purchased from the SDISCO and RES by PL owner.

This cost is the energy purchased from the SDISCO and RES for charging EVs at the off-peak and mid-peak periods. This cost is given by Eq. (29).

$$F_3 = \sum_{s=1}^{Ns} \pi_s \sum_{n=1}^{N} \sum_{t=1}^{24} P^{ch}_{n,t,s} \times \rho^{ch}_{\mathrm{t}} \times \Delta\mathrm{t} \tag{29}$$

4. The cost of payment to EV owners because of participation in the V2G interaction.

For the participation of EV owners in the V2G mode, it is necessary to encourage them. So, PL owner must have a contract with EV owners. Therefore, the PL owner pays a part of income (that is obtaining from selling energy to the energy markets) to EV owners. This cost is presented in Eq. (30). Suppose that the cost of payments to EV owners, i.e., Pr^{EV2PL} is 70% of the received profit due to the selling of PL energy to SDISCO.

$$F_4 = \sum_{s=1}^{Ns} \pi_s \sum_{n=1}^{N} \sum_{t=1}^{24} 0.7 \times P_{n,t,s}^{dch} \times \rho_t^{dch} \times \Delta t \tag{30}$$

5. The cost of battery depreciation.

The depth of discharge affects the life of EVs' battery [53]. This term is computed by the amount of power exchange between EVs and SDISCO. This cost is paid to EV owners and can be formulated as Eq. (31).

$$F_5 = \sum_{s=1}^{Ns} \pi_s \sum_{n=1}^{N} \sum_{t=1}^{24} P_{n,t,s}^{dch} \times C^{cd} \times \Delta t \tag{31}$$

After the description of income and cost, the objectives function in this part is described by Eq. (32).

$$MAX \quad OF_2 = (F_1 + F_2) - (F_3 + F_4 + F_5) \tag{32}$$

3.3.2. Constraints

In this section, constraints related to the charging/discharging of EVs are expressed. Based on Eq. (33), the total SOC of the EVs cannot exceed the minimum and maximum. According to Eqs. (34) – (35), the SOC of each EV at each hour appertains many factors including the remained SOC of the EV from the previous hour, the amount of energy that exchanged with the SDISCO and PL, charge/discharge efficiency, and the initial SOC of the EV [53]. The amount of power purchased by each EV from the PL is limited to its maximum rate. Also, the amount of power that each EV can sell to the PL is limited to its maximum rate. These constraints are shown in Eqs. (36) – (37), respectively. Finally, based on Eq. (38), the management of charging/discharging of EVs should be accurate in a way that in the departure time of PL, the SOC of EVs reaches the desired SOC. Also, it is noted that the EVs' charge and discharge are not simultaneous.

$$SOC_n^{\min} \le SOC_{n,t,s} \le SOC_n^{\max} \qquad \forall n,t,s \qquad \lambda_{n,t,s}^1, \lambda_{n,t,s}^2 \tag{33}$$

$$SOC_{n,t,s} = SOC_{n,t-1,s} + \left(P_{n,t,s}^{ch} \times \Delta t \times \eta^{ch}\right) - \left(\frac{P_{n,t,s}^{dch} \times \Delta t}{\eta^{dch}}\right) \qquad \forall n, t \succ t^{arv}, s \qquad \lambda_{n,t \succ t^{arv},s}^3 \tag{34}$$

$$SOC_{n,t,s} = \mathrm{SOC}_{n,t,s}^{arv} + \left(P_{n,t,s}^{ch} \times \Delta t \times \eta^{ch}\right) - \left(\frac{P_{n,t,s}^{dch} \times \Delta t}{\eta^{dch}}\right) \qquad \forall n, t^{arv}, s \qquad \lambda_{n,t^{arv},s}^4 \tag{35}$$

$$0 \le P_{n,t,s}^{ch} \le P_n^{\max} \qquad \forall n,t,s \qquad \lambda_{n,t,s}^5, \lambda_{n,t,s}^6 \tag{36}$$

$$0 \le P_{n,t,s}^{dch} \le P_n^{\max} \qquad \forall n,t,s \qquad \lambda_{n,t,s}^7, \lambda_{n,t,s}^8 \tag{37}$$

$$SOC_{n,t,s} = \mathrm{SOC}_n^{dep} \qquad \forall n, t^{dep}, s \qquad \lambda_{n,t^{dep},s}^9 \tag{38}$$

3.4. Reformulation of bi-level as a mathematical problem with equilibrium constraints

By using two methods, a bi-level model can be converted into a single-level model. Both of these methods are equivalent and can be used instead of each other. One of these methods is using the dual of optimization model and formation of related constraints, as well as strong duality condition, which can form non-linear or linear constraints, depending on the type of model. Another method is using the KKT condition, which consists of a series of equal and new inequality constraints, which are inherently non-linear. The reason of non-linearity of this method is the presence of complementary constraints, $0 \le a \perp b \ge 0$. These series of constraints do not exist in the first method, and their existence is as strong as the dual constraint [36, 54, 55].

In the proposed model, since the lower-level is linear and convex, KKT method is used for converting the bi-level model to single-level model. In fact, by implementing the KKT method, decision-making variables in the upper-level are considered as a parameter in the lower-level. Thus, the lower-level and upper-levels is linked together.

Of course, due to the existence of complementary constraints, the model is nonlinear, which is easily linearized by Fortuny-Amat and McCarl linearization method. After the problem becomes a single-level and linear, a simple optimization problem is obtained by a series of constraints (that it is called the mathematical program with equilibrium constraints (MPEC) that can be solved by a mathematical solver).

Fig. 3 schematically shows such a problem for the proposed model. Therefore, the operational scheduling model discussed in the previous section has become a solvable single-level problem using former constraints and a series of new constraints. This new constraint has the objective function and constraints of the lower level problem.

MPEC
Operational scheduling of SDISCO *maximization of the profit of SDISCO (upper level objective function)* Subject to Upper level constraints Lower level constraints Optimization constraints of KKT Complementarily constraints of KKT

Fig. 3. The framework of the proposed model as MPEC

As stated, optimization constraints and complementary constraints KKT are necessary for obtaining the MPEC problem. The KKT conditions are explained in Appendix A.

3.5. The linear single-level model

According to descriptions in pervious section and Appendix A, the linear single-level model of bi-level model is formulated by Eq. (39).

Maximize (39)

$$\sum_{t=1}^{24}\left(\begin{array}{l}\sum_{b=2}^{Nb} P_{b,t}^{L,DR} \times \rho_t^{L,DR} - \sum_{Sb=1}^{Nsb} P_{Sb,t}^{Wh2G} \times \rho_t^{Wh2G} \\ -\sum_{b=2}^{Nb}\left(A_t\left(P_{b,t,s}^{L} - P_{b,t,s}^{L,DR}\right) - PEN_t\left(P_{b,t,s}^{con} - P_{b,t,s}^{L} + P_{b,t,s}^{L,DR}\right)\right)\end{array}\right)$$
$$+\sum_{s=1}^{Ns}\pi_s\sum_{n=1}^{N}\sum_{t=1}^{24}\left(\left(P_{n,t,s}^{ch} \times \rho_t^{ch}\right) - \left(P_{n,t,s}^{dch} \times \rho_t^{dch}\right)\right)$$

Subject to:

(11)-(26)

(33)-(38)

(A11)- (A13)

(A21) - (A26)

3.6. Centralized Model

In the centralized model, SDISCO is responsible for the operational scheduling of PLs. The objective function in this case is similar to the objective function of the upper level of the bi-level model. The only difference is that, the SDISCO pays the cost of battery depreciation to EV' owners. The centralized model is formulated by Eq. (40).

Maximize (40)

$$\sum_{t=1}^{24}\left(\begin{array}{l}\sum_{b=2}^{Nb} P_{b,t}^{L,DR}\times\rho_t^{L,DR}-\sum_{Sb=1}^{Nsb} P_{Sb,t}^{Wh2G}\times\rho_t^{Wh2G}\\ -\sum_{b=2}^{Nb}\left(A_t\left(P_{b,t,s}^{L}-P_{b,t,s}^{L,DR}\right)-PEN_t\left(P_{b,t,s}^{con}-P_{b,t,s}^{L}+P_{b,t,s}^{L,DR}\right)\right)\end{array}\right)$$

$$+\sum_{s=1}^{Ns}\pi_s\sum_{n=1}^{N}\sum_{t=1}^{24}\left(\left(P_{n,t,s}^{ch}\times\rho_t^{ch}\right)-\left(P_{n,t,s}^{dch}\times\rho_t^{dch}\right)-\left(P_{n,t,s}^{dch}\times C^{cd}\right)\right)$$

Subject to

(11)-(26)

(33)-(38)

3.7. Problem solving process

Since this problem has different uncertainties, stochastic programming is used for solving the objective function. The following five uncertainties are considered in this paper:

1. *Wind Generating Units Uncertainty*

Because of intermittent wind speed, many experiments prove that stochastic wind speed in many regions roughly pursues the *Weibull* PDF. The output of wind turbine can be obtained through the linear relationship between wind speed and wind turbine output [38].

2. *Solar Generating Sources Uncertainty*

Predominantly illumination intensity affects the output of PV. In [57], it is shown that distribution of solar irradiance is characterized by using *Weibull* PDF. The output of PV can be obtained through the linear relationship between irradiance and photovoltaic array output.

3. *Uncertainty of Arrival Time of EVs to PL*
4. *Uncertainty of Departure Time of EVs from PL*
5. *Uncertainty of Initial SOC of EVs*

Obtaining sufficient historical data for determining the exact PDF of the uncertainty in the estimation of EVs, i.e., initial SOC, duration of presence of EVs in PL (departure time minus arrival time) is very difficult. However, most studies have reasonably suggested that a truncated Gaussian distribution PDF can be employed [49].

Also, a scenario tree of all uncertainty is generated with Monte Carlo method. Then, the scenarios are reduced with the concept of Kantorovich distance (K-distance). The initial number of scenarios is 1000. Then, by using Kantorovich distance approach, the number of scenarios is reduced to 8. In fact, the main problem is solved by considering 8 scenarios.

There are the binary and integer decision variables in the linear single-level model. Therefore, with considering all the relations, the proposed model is Mixed-Integer Linear Programming (MILP) problem. So, in this paper, the simulations are carried out through CPLEX solver in GAMS.

The simulations have been implemented in a laptop with Core i7 up to 3.5 GHz CPU, 12 GB RAM (DDR4), and 4 MB Cash. The flowchart of stochastic programming-based operational scheduling of SDISCO is shown in Fig. 4.

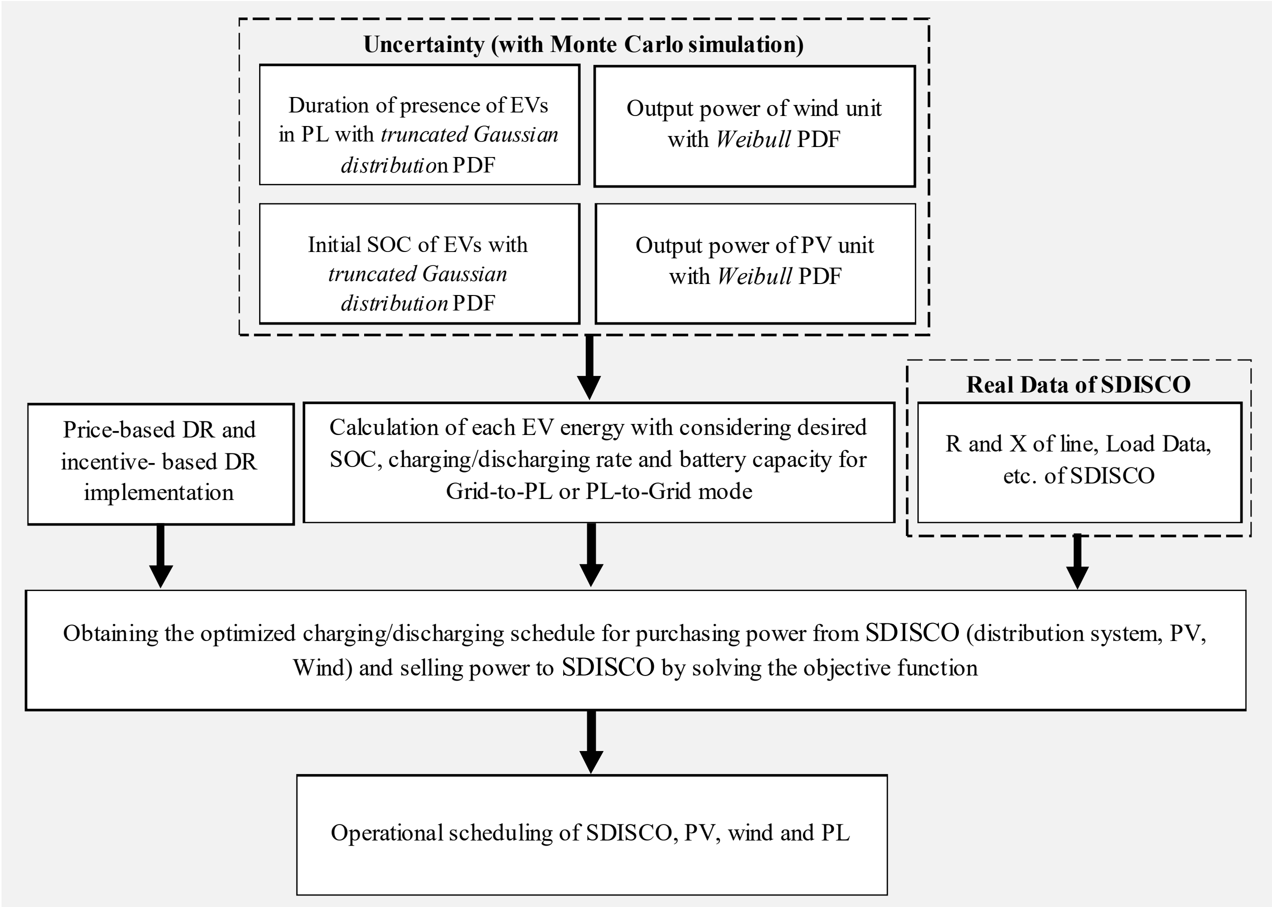

Fig. 4. Process solving of operational scheduling of SDISCO

4. Numerical results

A standard IEEE 15-bus distribution system is considered as the case study over a 24-h period. The data of this test system shown in Fig. 5 are extracted from [58]. The required specification of wind and PV units is summarized in Table 2. The modified details of EVs probability distributions are expressed in Table 3. Also, the PL is installed on bus 11. It is assumed that the capacity of PL is 100 EVs. With considering the data of Table 3, the number of EVs that enter the PL and the number of EVs that depart from the PL in eight scenarios are shown in Tables 4 and 5, respectively. Since we assumed PL capacity is 100 EVs, from 10:00 to 17:00, 100 EVs are parked in PL. Also, the amount of arrival SOC of EVs in one of the scenarios is shown in Fig 6.

The power factor of customers' demand is 0.95 lagging. Also, the wind and PV units are assumed to have a fixed power factor equal to 1. The charge and discharge efficiencies of EVs are assumed 90% and 95%, respectively. The battery capacity is 50 kWh, and the rate of charging/discharging is 10 kW per hour. The maximum and minimum SOC are 7.5 and 45 kWh, respectively. The price of degradation cost of V2G is 0.03 $/kWh [59]. The price elasticity of the demand is considered as listed in Table 6. In order to study the operational scheduling, various price-based DR and incentive-based DR programs are considered, as presented in Table 7. The hourly prices of the energy market in RTP program are extracted from [60].

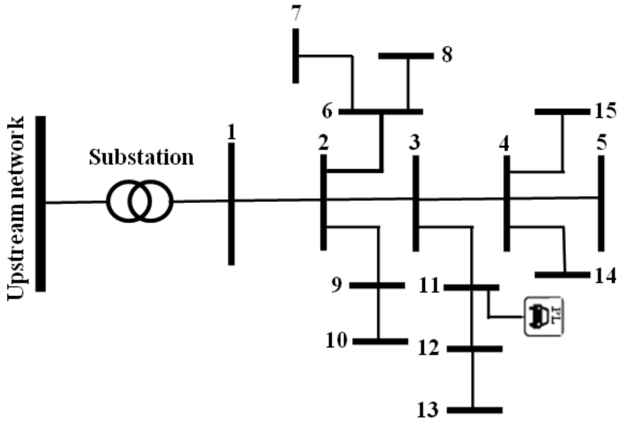

Fig. 5. The 15-bus distribution system

Table 2. Considered data for PV and wind unit [57]

Wind unit						
Size (kW)	bus	shape index	scale index	cut-in speed (m/s)	nominal speed (m/s)	cut-out speed (m/s)
200	12	2	6.5	4	14	25
PV unit						
Size (kW)	bus	shape index	scale index	rated illumination intensity (w.m^2)		
200	12	1.8	5.5	1000		

Table 3. The modified probability distribution of EVs [49]

	Mean	Standard Deviation	Min	Max
Initial SOC (%)	50	25	30	60
Arrival Time (h)	8	3	7	10
Departure Time (h)	20	3	18	24

Table 4. The number of entered EVs in arrival time in 8 scenarios

Time (h)	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8
7	43	58	50	53	45	53	54	46
8	19	11	12	11	16	11	15	12
9	14	6	12	7	9	10	10	17
10	24	25	26	29	30	26	21	25

Table 5. The number of departed EVs in departure time in 8 scenarios

Time (h)	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8
18	38	34	27	41	28	34	32	26
19	9	16	16	14	16	10	19	11
20	14	13	15	12	11	14	4	12
21	15	7	14	8	16	12	16	13
22	9	12	12	11	8	14	13	17
23	4	9	5	7	11	8	9	7
24	11	9	11	7	10	8	7	14

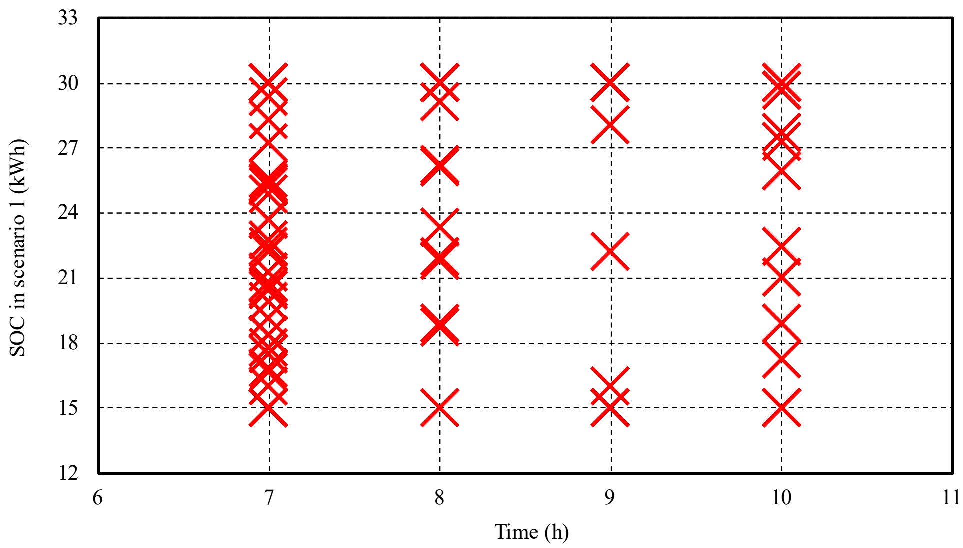

Fig. 6. The SOC of 100 EVs in scenario 1

Table 6. Self and cross elasticities [50]

	On-peak	Mid-peak	Off-peak
On-peak (10-14 and 19-21)	-0.1	0.016	0.012
Mid-peak (8-9 and 15-18)	0.016	-0.1	0.01
Off-peak (1-7 and 22-24)	0.012	0.01	-0.1

Table 7. Considered cases for price-based and incentive-based DR for operational scheduling of SDISCO

Program	Electricity Price for load, charging/discharging EVs ($/MWh)	Incentive value ($/MWh)	Penalty value ($/MWh)
Base case	171.125flat rate	0	0
TOU	85.562,171.125, 342.25at off-peak, mid-peak and on-peak, respectively	0	0
CPP	400 at 19,20,21 h and 171.125at other hours	0	0
RTP	As reference [56]	0	0
TOU+ CPP	85.562,171.125, 342.25at off-peak, mid-peak and on-peak, respectively and 400 at 19,20,21 h	0	0
EDRP	171.125flat rate	150	0
CAP	171.125flat rate	150	50
TOU+ EDRP	85.562,171.125, 342.25at off-peak, mid-peak and on-peak, respectively	150	0
TOU+ CAP	85.562,171.125, 342.25at off-peak, mid-peak and on-peak. respectively	150	50

From the SDISCO's point of view, profit, network losses and peak load are the main indices in the operational scheduling. For investigation of the network operation in the presence of RES and EVs, four modes are considered as follows:

1. SDISCO considering EVs with controlled charging, without wind and PV units,
2. SDISCO considering EVs with controlled charging, with wind and PV units,
3. SDISCO considering EVs with smart charging/discharging, without wind and PV units,
4. SDISCO considering EVs with smart charging/discharging, with wind and PV units.

Moreover, based on Table 6, eight programs have been considered for the comprehensive review of the impact of DR programs. In this paper, it is assumed that the total signed contracts for the participation of customers in DR programs are equal to 20% of the total customers' demand during the scheduling period. In the base case, flat rate prices are implemented where no DR program is adopted.

The results of the operational scheduling in 36 programs are listed in Table 8. Also, the result of comparing this data is shown in Table 9. As can be seen in the first program, the profits of SDISCO even by controlled charging of EVs are negative. Also, in the twenty-fifth program, despite the encouraging incentive for consumers to reduce their consumption, the SDISCO still faces a negative profit. Therefore, it is very cost-effective for SDISCO to use RES, appropriate DR programs and smart charging/discharging mode of EVs.

Table 8. Technical comparison of the programs

Program no.	Programs	Mode	Losses (KW)	Profit ($)	Peak (MW)
1		1	644.585	-268.833	2.124
2	Flat rate	2	554.352	596.782	1.975
3		3	721.052	768.345	2.508
4		4	627.111	1607.79	2.350
5		1	635.544	842.128	2.228
6	TOU	2	547.645	1705.71	2.078
7		3	716.553	1353.08	2.523
8		4	629.590	2211.62	2.369
9		1	652.672	176.979	2.391
10	RTP	2	560.204	1043.39	2.172
11		3	652.672	176.979	2.391
12		4	560.204	1043.39	2.172
13		1	624.901	922.111	2.144
14	CPP	2	537.979	1786.29	1.995
15		3	701.695	1920.29	2.517
16		4	614.403	2782.55	2.371
17		1	631.516	1066.75	2.232
18	TOU + CPP	2	543.742	1930.23	2.083
19		3	714.244	1580.06	2.526
20		4	627.320	2435.36	2.377
21		1	602.499	210.618	2.169
22	CAP	2	516.786	1074.04	2.020
23		3	689.856	1217.12	2.547
24		4	606.925	2097.33	2.404
25		1	611.989	-198.207	2.158
26	EDRP	2	525.995	665.457	2.009
27		3	696.570	809.107	2.538
28		4	610.610	1676.30	2.388
29		1	607.683	288.224	2.261
30	TOU + EDRP	2	522.463	1150.26	2.112
31		3	701.404	811.542	2.568
32		4	616.549	1666.58	2.417
33		1	598.414	489.368	2.273
34	TOU + CAP	2	515.864	1350.24	2.123
35		3	697.240	1014.68	2.579
36		4	607.641	1849.19	2.417

Table 9. Results of comparing 36 programs

	Profit point of view		**Losses point of view**		**Peak point of view**	
	worst	The best	worst	The best	worst	The best
Mode 1	✓	-	-	-	-	-
Mode 2	-	-	-	✓	-	✓
Mode 3	-	-	✓	-	✓	-
Mode 4	-	✓	-	-	-	-
price-based DR	RTP	CPP	RTP	CPP	TOU + CPP	CPP
incentive-based DR	EPDR	CAP	EPDR	CAP	CAP	EPDR
price-based DR + incentive-based DR	TOU + EPDR	TOU + CAP	TOU + EPDR	TOU + CAP	TOU + CAP	TOU + EPDR

In the following, by using a technique for order preference by similarity to ideal solution (TOPSIS) [50], the best program is determined. In this method, first, the decision matrix is established. In this paper, the decision matrix includes *m* alternatives, i.e., price-based and incentive-based DR programs, the presence or absence of RES and the controlled charging or smart charging/discharging of EVs and *k* attribute, i.e., SDISCO's Profit, losses, and peak. Then, the decision matrices must be normalized. By computing weighting based on entropy method, a weighted decision matrix is obtained. After that, ideal alternatives and anti-ideal alternatives have to be identified. Next, a Euclidean distance of each alternative and the ideal and anti-ideal solution is computed.

Finally, the value of relative closeness is calculated. After implementation of TOPSIS, the result of the prioritization is shown in Fig. 7. As it can be seen the program 16 (i.e., CPP with EVs with smart charging/discharging, with wind and PV units) has the highest priority and program 9 (i.e., RTP with EVs with controlled charging, without wind and PV units) has the lowest priority. It is noted that programs 1 and 25 due to the negative profits, and programs 11 and 12 because of the similarity to programs 9 and 10 are eliminated.

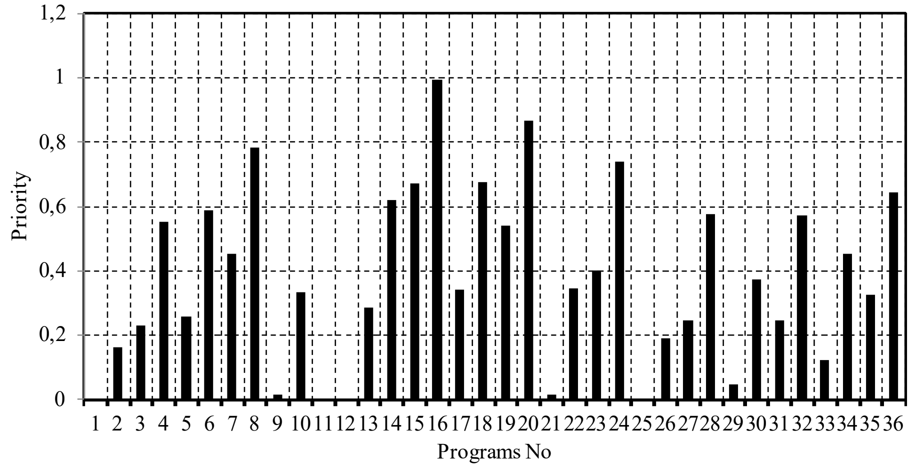

Fig.7. Priority of 36 programs based on TOPSIS method

For more precisely of the bi-level model, the best program, i.e., program 16, is evaluated from different points of view. Also, it is compared with the centralized model in which the SDISCO is responsible for PL. In the centralized model, SDISCO is paid the total cost of power purchased from EVs and the cost of battery depreciation to EV owners. It is noted that the computation time for the proposed bi-level and centralized models in CCP program are 454.27 and 43.12 seconds. The income of SDISCO in two models is shown in Table 10. As can be seen, in bi-level model, the income of SDISCO is about 50 dollars more than the centralized model.

Table 10. The amount of the income and cost in bi-level and centralized models ($)

Income	**Bi-level Model**	**Centralized Model**
Selling of energy to EV owners	934.752	949.253
Selling of energy to customers	6380.311	6380.311
Cost		
Providing power from the wholesale market	4081.835	4052.503
Energy purchased from EV owners for supplying customers' demand	450.678	463.076
Battery depreciation	0	81.183
Implementation of price-based DR and incentive-based DR programs	0	0
Profit		
Income minus Cost	2782.550	2732.802

The amount of the customers' demand with/without implementation of the DR program in each model is equal and shown in Fig. 8. Based on Fig. 8, at the on-peak periods, the amount of load is reduced, and this amount is transmitted to the off-peak and mid-peak periods. So, customers' demand somewhat increases. As it can be seen, the unexpected peak load is avoided. In fact, by the implementation of CPP program, reduction of power consumption of customer's demand is about 756.7 kW. The initial customers' demand was 32170.1 kW, which is reduced to 31413.4 kW.

For comparing these models, the amount of power purchased from the wholesale market and the customers' demand are shown in Fig. 9. Like [61], increasing the total load at the mid-peak and off-peak periods and reducing at the on-peak periods occur with smart charging/discharging of EVs. Also, like [62] the peak electricity consumption of SDISCO occurs during the early evening periods, i.e., 17:00 and 18:00.

Table 11 indicates the detailed analyses of power purchased from the wholesale market. Indeed, the amount of power purchased from the wholesale network in bi-level and centralized model is 30863.8 and 30879.54 kW, respectively, that 25831.17 and 25722.09 kW are used for feeding the customers' demand. Table 12 indicates the amount of power provided by the SDISCO and RES in two models.

Also, Fig. 10 shows the difference of power purchased from the wholesale market in the bi-level and the centralized models. As can be seen, in charging time (mid-peak and off-peak) and discharging time (on-peak time), lower and higher power is respectively purchased by SDISCO in the bi-level model compared to the centralized model. In fact, in the bi-level model, 15.74 kW less than the centralized model is purchased.

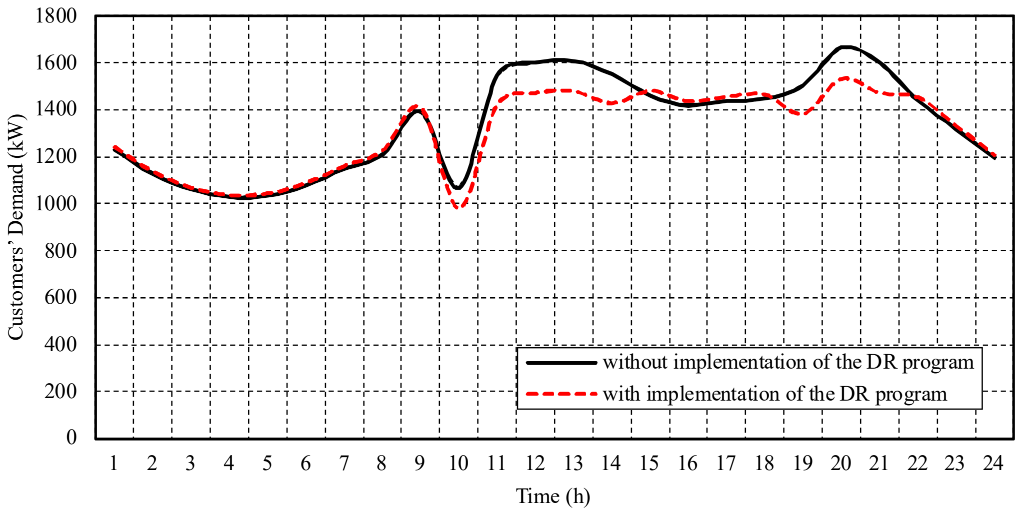

Fig. 8. Customers' demand with/without implementation of the DR program in two models

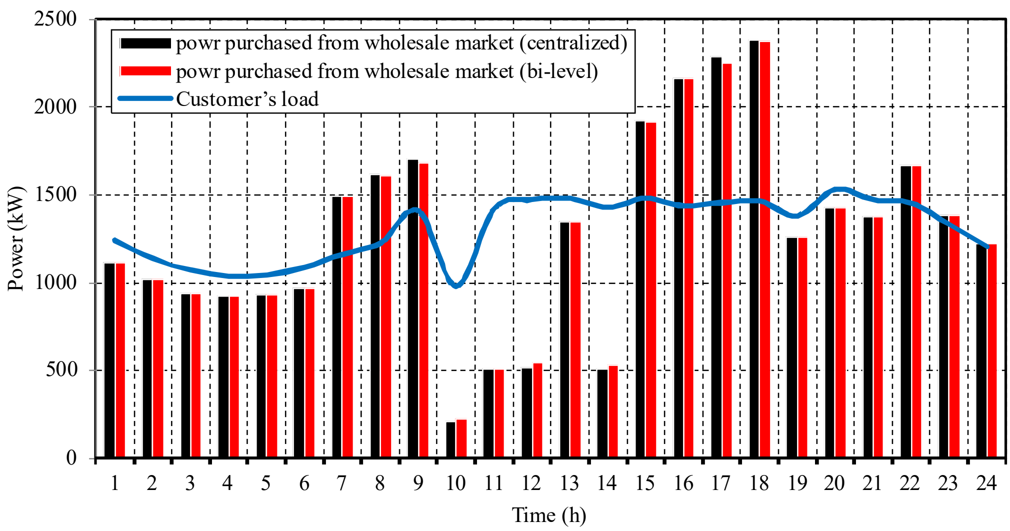

Fig. 9. Power purchased from the wholesale market in two models and customers' demand

Table 11. Result of power purchased from the wholesale market

Hour	Results	Cause
1-6	Power purchased is about the amount of load. A part of load is supplied by RES.	The absence of EVs
7-9	Power purchased is increased. A part of load is supplied by RES.	The presence of EVs (charging time)
10-12	Power purchased is severely decreased. A part of load is supplied by RES and PL-to-Grid programs.	The presence of EVs (discharging time)
13	Power purchased is about the amount of load. A part of load is supplied by RES.	The energy price in this hour is lower than the (10-12) hours
14	Power purchased is severely decreased. A part of load is supplied by RES and PL-to-Grid programs.	The presence of EVs (discharging time)
15-18	Power purchased is dramatically increased. A part of load is supplied by RES.	Discharging in previous period for participation in PL-to-Grid mode
19-21	Power purchased is decreased. A part of load is supplied by RES and PL-to-Grid programs.	The presence of EVs (discharging time)
22	Power purchased is increased. A part of load is supplied by RES.	Discharging in previous period for participation in PL-to-Grid mode
23-24	Power purchased is about the amount of load. A part of load is supplied by RES.	The absence of EVs

Table 12. The amount of power provided by the SDISCO and RES for supplying customers' demand and Relative quantities

	Bi-level model (kW)	**Centralized model (kW)**	**Relative quantities (%)**
SDISCO to load	25831.17	25722.09	0.424
Wind unit to load	2362.67	2454.25	-3.731
PV unit to Load	651.92	593.47	9.848

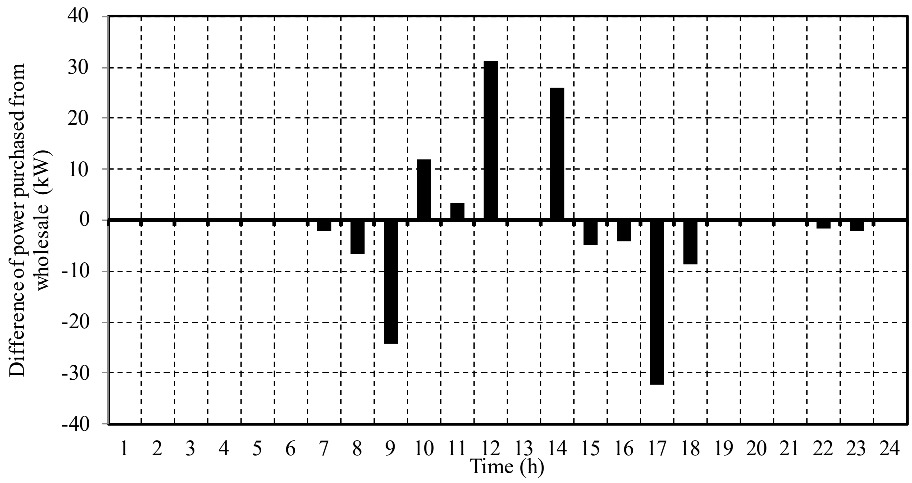

Fig. 10. Difference of power purchased from the wholesale market in the bi-level model and the centralized model

Fig. 11 shows the smart charging scheduling of 100 EVs in PL in two models. Based on Fig. 11, the total amount of power for charging of EVs in the bi-level and centralized models is 5462.39 and 5547.13 kW, respectively. The highest amount in the bi-level and centralized models is 991.67 and 1000 kW, respectively. Because in the centralized model, SDISCO has also the responsibility of the PL operation, SDISCO tries to selling more energy for gaining more profit. But in the bi-level model, the private PL owner's decision affects the charging and discharging of EVs, so less power is purchased from the SDISCO. This peak of charging EVs occurs at 18:00, unlike [63] where the peak (because of only charging of EVs) happens at 7:00.

Also, Fig. 12 shows the smart discharging scheduling of EVs. Based on Fig. 12, the total amount of power for discharging of EVs in the bi-level and centralized models is 2633.61 and 2706.07 kW, respectively. Since in the bi-level model, less power is purchased for charging the EVs, less discharging power is available for selling to SDISCO.

The highest amount in the bi-level and centralized models is 734.63 and 751.48 kW at 12:00, respectively. Since the energy price of the wholesale market at 13:00 is lower than the one in on-peak periods and due to the limitation of discharging power of EVs, the SDISCO tries to purchase the discharging power in other time of on-peak periods when the energy price of the wholesale is very high. In fact, at 13:00, SDISCO uses the network and RES generation for supplying customers' demand. Table 13 shows the amount of power provided by the SDISCO and RES.

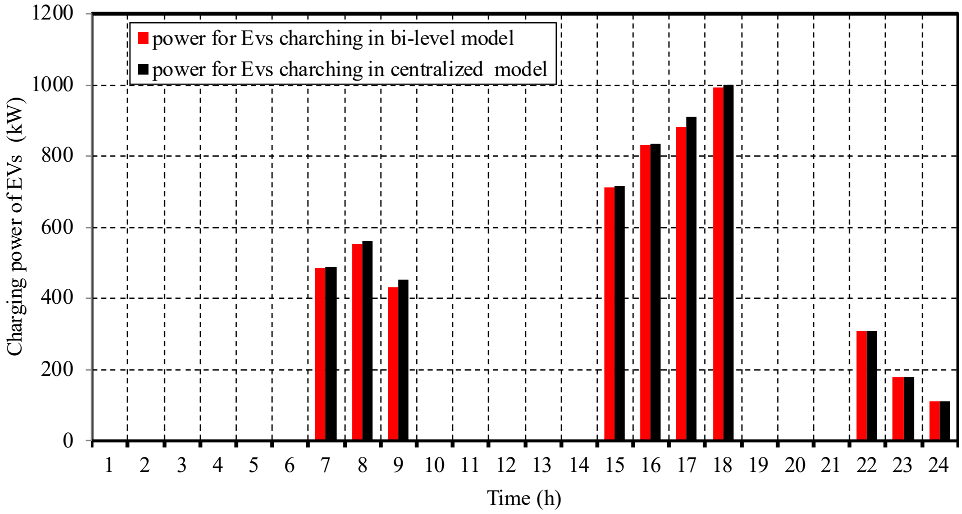

Fig. 11. Charging power of EVs in two models

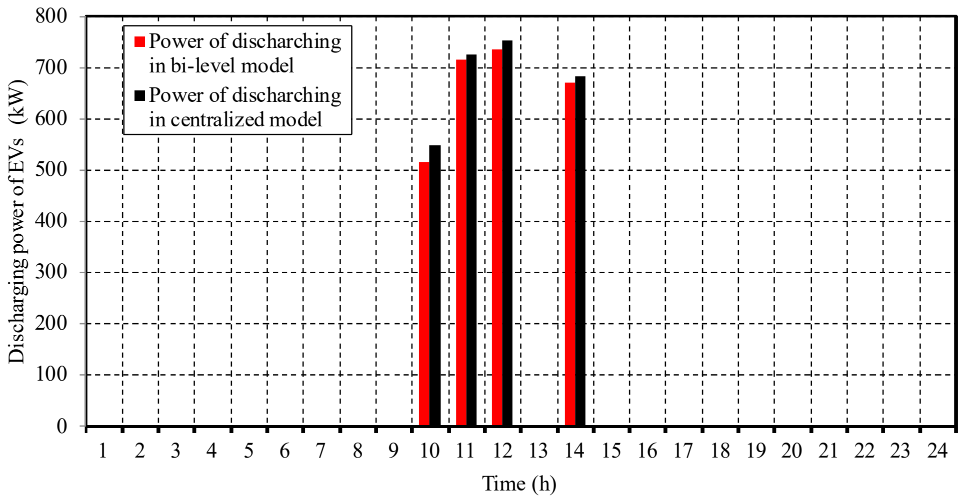

Fig. 12. Discharging power of EVs (back to SDISCO) in two models

Table 13. Power charging of EVs by the SDISCO and RES in two models and relative quantities

	Bi-level model (kW)	Centralized model (kW)	Relative quantities (%)
Power charging of EVs by SDISCO	4592.23	4672.31	-1.713
Power charging of EVs by wind unit	616.07	550.47	11.917
Power charging of EVs by PV unit	254.09	324.35	-21.661

The SDISCO losses in two models are also shown in Fig. 13. The total losses of SDISCO are 614.40 and 617.86 kW, in the bi-level and centralized models, respectively. Because of charging/discharging of EVs, increasing/decreasing losses happens, respectively. Table 14 shows the contribution of each source for supplying of losses. In the bi-level model, less power is sold to PL for charging of EVs, so SDISCO purchases less power from the wholesale market. Therefore, the network losses are reduced.

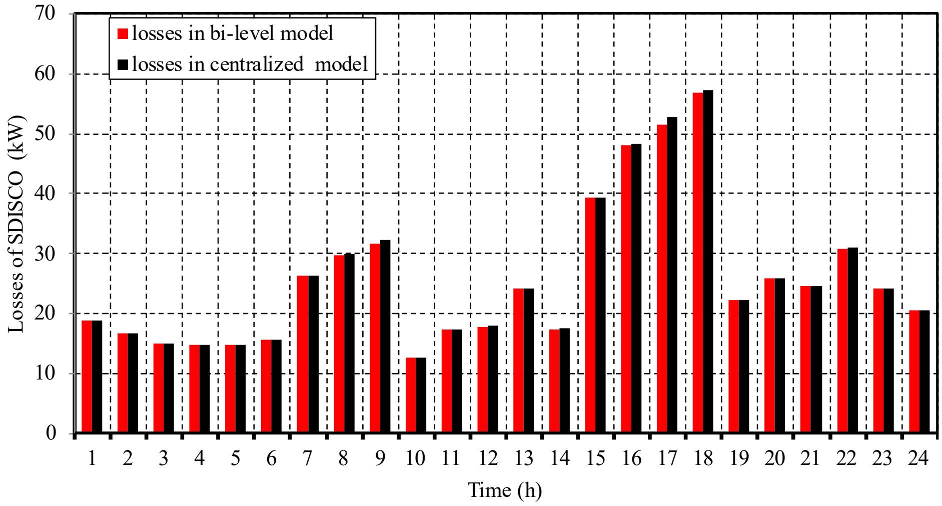

Fig. 13. Losses of SDISCO in two models

Table 14. Network losses in the bi-level and centralized models and Relative quantities

	Bi-level model (kW)	Centralized model (kW)	Relative quantities (%)
SDISCO for supplying losses	440.4	485.137	-9.221
Wind unit for supplying losses	89.41	63.429	40.960
PV unit for supplying losses	22.67	10.845	109.036
Discharging power of EVs for supplying losses	61.93	58.449	5.955

Also, Fig. 14 illustrates the operational scheduling of RES and SDISCO in the bi-level model. According to Fig. 14 and its comparison with the customers' demand (i.e., Fig. 8), it can be seen that at the time of charging the EVs, the overall load of the SDISCO increases, and the amount of power purchased from the wholesale network is higher. Also, at the on-peak periods, the purchasing of power from the wholesale network is significantly reduced, due to the power injection of EVs into the SDISCO for supplying customers' demand. Also, the generation of a wind unit has a larger share in supplying customers' demand and charging of EVs in comparison to PV generation.

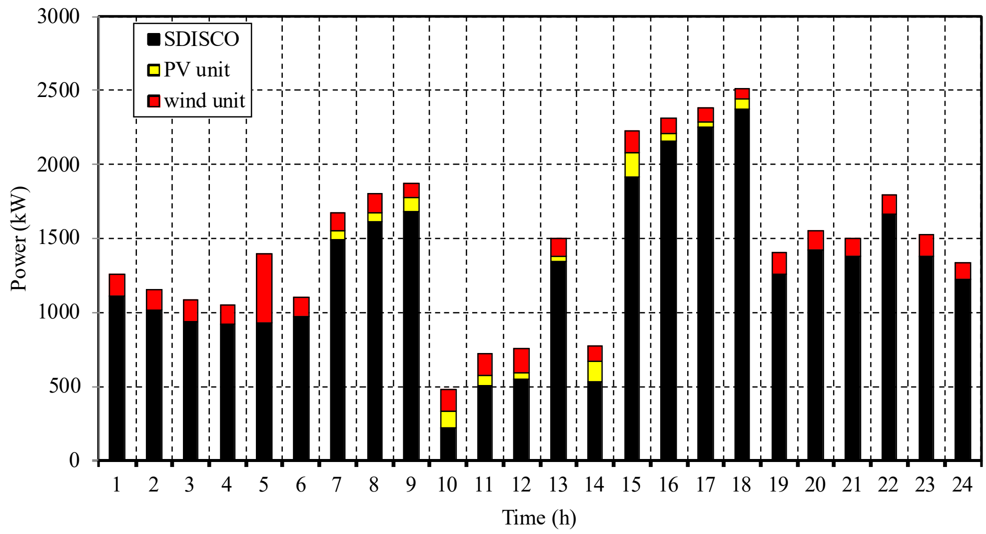

Fig. 14. Operational scheduling of SDISCO, wind and PV unit during the 24-hour period

Finally, the impact of uncertainty on the operational scheduling of SDISCO in the bi-level model considering CPP program is evaluated. If the probabilistic behavior of parameters (i.e., uncertainties) is not considered, the objective function of the model is deterministic. In this situation, there is only one scenario with probability 1.

So, for investigation of the effect of uncertainties on operational scheduling, the deterministic bi-level model with one scenario is compared with the stochastic bi-level model with a set of scenarios, i.e., the above-presented results. Table 15 shows the result of deterministic and stochastic models. By comparing these two models and considering that the amount of the customers' demand is constant in two models, it is clear that the PV and wind units have a larger contribution in the deterministic model, in supplying the customers' demand, charging the EVs as well as network losses. Also, EVs participate more in PL-to-Grid programs, and SDISCO buys less energy from the wholesale market in the deterministic model. Therefore, in the deterministic model, SDISCO gains more profit.

Table 15. The result of stochastic and deterministic models

Description	Stochastic bi-level model	Deterministic bi-level model
SDISCO for supplying load (kW)	25831.17	25340.09
Wind unit for supplying load (kW)	2362.67	2455.81
PV unit for supplying Load (kW)	651.92	880.97
Power charging of EVs by SDISCO (kW)	4952.23	4810.13
Power charging of EVs by Wind unit (kW)	616.07	668.46
Power charging of EVs by PV unit (kW)	254.09	325.22
SDISCO for supplying losses (kW)	440.4	394.14
Wind unit for supplying losses (kW)	89.41	116.25
PV unit for supplying losses (kW)	22.67	73.70
Discharging power of EVs for supplying losses (kW)	61.93	36.82
Total discharging power of EVs (kW)	2633.61	2777.38
Selling the energy to EV owners ($)	934.75	976.07
Selling the energy to load ($)	6380.31	6380.31
Providing power from wholesale market ($)	4081.83	3880.70
Energy purchased from EV owners for supplying customer ($)	450.68	475.28
Profit of SDISCO ($)	2782.55	3000.4

4.1. Sensitivity Analysis

Sensitivity analysis is performed by changing the number of EVs, the rated power generation of PV and wind units and participating customers in DR programs to investigate their impacts on the operational scheduling of SDISCO. Table 16 shows the results of this analysis. The results of this sensitivity are as follows:

- In each case, the bi-level model has a better result than the centralized model.
- With the increase of all factors, the profit of SDISCO in two models increases.
- By increasing the participation of consumers in the DR program, the energy purchased from the wholesale market is reduced. In this situation, if the rated power of RES is low, the EVs more participate in a smart charging/discharging schedule, and SDISCO gains more profit. But, if the rated power of RES is high, the SDISCO prefers to use these resources to supply the customer and charging the EVs, therefore less charging/discharging schedule occurs, and SDISCO achieves less profit.
- By increasing the rated power of the RES, power purchased from the wholesale market dramatically decreases and SDISCO gains more profit. Therefore, it seems to be necessary using RES (in spite of the uncertainty) alongside traditional power plants.
- By comparing the first and second cases, the losses increase by increasing the number of EVs due to the high power consumption which is purchased from the wholesale market. While, by comparing third and fourth cases, the network losses are reduced because of the high rated power of PV and wind units. In fact, the SDISCO uses RES and V2G program instead of the wholesale market to supply the customers, especially at the on-peak period. As a result, SDISCO buys less energy from the wholesale market. Fig. 15 illustrates this issue. Based on Fig. 15, the SDISCO at the first on-peak period (except at 13:00) does not buy the energy from the wholesale market.

Table 16. Sensitivity analysis of two models

EVs no.	Energy purchased from wholesale market (kWh)		Loss (kW)		Profit ($)		Charging power of EVs (kW)		Discharging power of EVs (kW)	
	Bi-level	Centralized	Bi-level	Centralized	Bi-level	Centralized	Bi-level	Centralized	Bi-level	Centralized
Case 1: participating customers in DR programs: 20% , Rated power of PV and wind: 200 kW										
50	29363.18	29367.70	530.09	530.70	2179.325	2144.838	2768.62	2795.59	1339.54	1362.60
100	30863.80	30879.54	614.41	617.86	2782.550	2732.802	5462.40	5547.13	2633.62	2706.07
150	32586.63	32593.75	738.34	740.33	3311.110	3203.046	8278.60	8313.99	4034.08	4064.35
Case 2: participating customers in DR programs: 30% , Rated power of PV and wind: 200 kW										
50	28980.73	28984.13	524.04	524.51	2228.871	2192.727	2775.39	2795.59	1345.32	1362.60
100	30497.40	30497.40	613.09	613.10	2861.194	2780.012	5547.13	5547.13	2706.06	2706.07
150	32180.84	32210.03	727.64	735.56	3314.173	3248.136	8156.48	8303.21	3929.67	4055.12
Case 3: participating customers in DR programs: 20% , Rated power of PV and wind: 1 MW										
50	14132.26	14132.73	1424.65	1424.72	5045.140	5018.267	2273.70	2276.52	916.38	918.80
100	15163.17	15165.67	1101.115	1101.48	5431.491	5390.460	4082.79	4097.52	1454.06	1466.65
150	17181.70	17182.87	941.13	941.92	5514.045	5462.596	5843.87	5846.49	1952.39	1954.62
Case 4: participating customers in DR programs: 30% , Rated power of PV and wind: 1 MW										
50	13854.15	13855.33	1531.99	1532.13	5018.307	4994.070	2218.02	2225.26	868.78	874.97
100	14833.27	14836.76	1161.51	1161.99	5387.285	5350.936	3993.75	4014.44	1377.93	1395.61
150	16838.72	16842.12	994.63	995.56	5469.593	5419.423	5712.11	5729.25	1839.73	1854.38

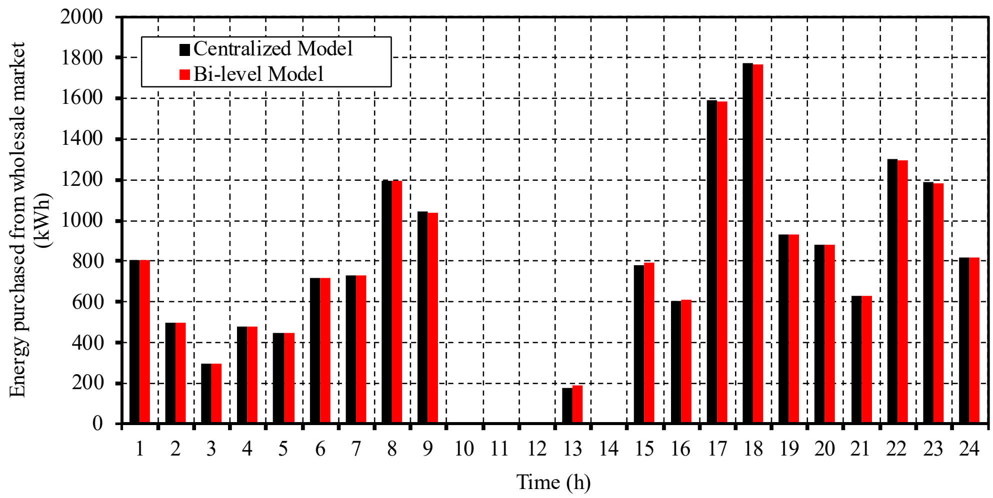

Fig. 15. Energy purchased from the wholesale market in two models in case 4 with 150 EVs

For investigation of the effect of battery capacity on the profit of SDISCO, this profit is evaluated in case 3 with changing the battery capacity. Table 17 shows that with low capacity battery, the profit is reduced.

Table 17. Profit of SDISCO in case 3 of sensitivity analyses with changing battery capacity

EVs No.	Model	Profit ($)			
		50 kWh	48 kWh	32 kWh	24 kWh
50	Bi-level	5045.140	5025.729	4874.648	4787.990
	Centralized	5018.267	5001.458	4855.409	4773.881
100	Bi-level	5431.491	5387.333	5217.003	5078.100
	Centralized	5390.460	5370.321	5191.087	5064.097
150	Bi-level	5514.045	5453.545	5318.705	5123.030
	Centralized	5462.596	5435.971	5270.744	5097.424

Finally, a sensitivity analysis is carried out by changing the payment to EV owners. Table 18 shows the profit of SDISCO in the bi-level model. Based on Table 18, when the payment to EV owners decreases, PL owner sells more energy to SDISCO. So, SDISCO buys less energy from the wholesale market, and consequently, SDISCO earns more profit.

Table 18. Profit of SDISCO in case 1 of sensitivity analyses with 100 EVs

The cost of payment to EV owners	Profit ($)
50%	2873.989
60%	2829.525
70%	2782.550
80%	2741.321

5. Conclusions

In this paper, a new bi-level model with the cooperation of SDISCO and PL owner for operational scheduling of SDISCO was developed. In this model, the objective function of the upper-level problem was maximizing the profit of SDISCO, and the objective function of the lower-level problems was maximizing the profit of PL owner. For solving the model, KKT conditions and a method based on auxiliary binary variables and sufficiently large constants was used. RES and EVs uncertainty, several groups of price-based DR and incentive-based DR programs and also system constraints such as nodal voltage, linear power flow, and charging/discharging schedule of EVs were simultaneously considered. Also, the impacts of size of RESs and number of EVs on the performance of the SDISCO were investigated. The following remarks were obtained:

- In each model, with mode 4 of CPP program, the SDISCO achieved most profit.
- Because of the penetration of EVs, the SDISCO's demand increased by 16.97% and 17.24% in the bi-level and centralized models, respectively.
- In the bi-level and centralized models, 8.10% and 8.41% of customers' demand was supplied by PL-to-Grid capability, respectively.
- Since the price of the wholesale market at 13:00 was lower than the other times of on-peak periods, discharging the EVs could happen in none of both models.
- Wind unit had a larger share in supplying customers' demand and charging of EVs in comparison to PV unit.
- In the deterministic bi-level model, since more power for charging the EVs were purchased, more power was sold to SDISCO
- The numerical study verified the effectiveness of the bi-level model. In this model, SDISCO obtained more profit. Also, the results from the technical points of view, i.e., losses and peak, in the bi-level model were more appropriate.
- With a larger size of RES and higher number of EVs, the SDISCO had a higher performance (in terms of profit, losses and peak), so that even at the on-peak period, SDISCO did not buy energy from the wholesale market.

Also for the future work the following suggestions are proposed:

- Presenting a three-level model in which the third-level belongs to the EVs owner. The objective function of the third-level can be the maximization of the benefit of EV owners or the minimization of the EV owners' cost.
- Modeling the behavior of the EV PL in the reserve market.
- In the proposed bi-level model, two or more private PLs can be considered. Then, the cooperative behavior of the PLs and the SDISCO can be studied.

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Appendix A) KKT conditions

To use KKT method, Firstly, constraints of the lower-level are rewritten as greater than or equal to zero as Eqs. (A1) – (A9):

$$C^1 = SOC_{n,t,s} - SOC_n^{\min} \geq 0 \qquad \forall n,t,s \qquad \lambda^1_{\mathrm{n,t,s}} \tag{A1}$$

$$C^2 = SOC_n^{\max} - SOC_{n,t,s} \geq 0 \qquad \forall n,t,s \qquad \lambda^2_{\mathrm{n,t,s}} \tag{A2}$$

$$SOC_{n,t,s} - SOC_{n,t-1,s} - \left(P^{ch}_{n,t,s} \times \Delta t \times \eta^{ch}\right) + \left(\frac{P^{dch}_{n,t,s} \times \Delta t}{\eta^{dch}}\right) = 0 \qquad \forall n,t \succ t^{arv},s \qquad \lambda^3_{\mathrm{n,t\succ t^{arv},s}} \tag{A3}$$

$$SOC_{n,t,s} - \mathrm{SOC}^{\mathrm{arv}}_{\mathrm{n,t,s}} - \left(P^{ch}_{n,t,s} \times \Delta t \times \eta^{ch}\right) + \left(\frac{P^{dch}_{n,t,s} \times \Delta t}{\eta^{dch}}\right) = 0 \qquad \forall n,t^{arv},s \qquad \lambda^4_{\mathrm{n,t^{arv},s}} \tag{A4}$$

$$C^3 = P^{ch}_{n,t,s} \geq 0 \qquad \forall n,t,s \qquad \lambda^5_{\mathrm{n,t,s}} \tag{A5}$$

$$C^4 = P_n^{\max} - P^{ch}_{n,t,s} \geq 0 \qquad \forall n,t,s \qquad \lambda^6_{\mathrm{n,t,s}} \tag{A6}$$

$$C^5 = P^{dch}_{n,t,s} \geq 0 \qquad \forall n,t,s \qquad \lambda^7_{\mathrm{n,t,s}} \tag{A7}$$

$$C^6 = P_n^{\max} - P^{dch}_{n,t,s} \geq 0 \qquad \forall n,t,s \qquad \lambda^8_{\mathrm{n,t,s}} \tag{A8}$$

$$SOC_{n,t,s} - \mathrm{SOC}^{\mathrm{dep}}_{\mathrm{n}} = 0 \qquad \forall n,t^{dep},s \qquad \lambda^9_{\mathrm{n,t^{dep},s}} \tag{A9}$$

So, the Lagrangian function is described by Eq. (A10):

$$\begin{aligned}
L = {} & \sum_{s=1}^{Ns} \pi_s \left(\begin{array}{l} \sum_{n=1}^{N}\sum_{t=1}^{24} P^{ch}_{n,t,s} \times \rho_t^{PL2EV} + \sum_{n=1}^{N}\sum_{t=1}^{24} P^{dch}_{n,t,s} \times \rho_t^{dch} - \sum_{n=1}^{N}\sum_{t=1}^{24} P^{ch}_{n,t,s} \times \rho_t^{ch} \\ - \sum_{n=1}^{N}\sum_{t=1}^{24} 0.7 \times P^{dch}_{n,t,s} \times \rho_t^{dch} - \sum_{n=1}^{N}\sum_{t=1}^{24} P^{dch}_{n,t,s} \times C^{cd} \end{array} \right) \\
& + \left(SOC_{n,t,s} - SOC_n^{\min}\right) \lambda^1_{n,t,s} + \left(SOC_n^{\max} - SOC_{n,t,s}\right) \lambda^2_{n,t,s} \\
& + \left(\mathrm{SOC_{n,t,s}} - SOC_{n,t-1,s} - \left(P^{ch}_{n,t,s} \times \eta^{ch}\right) + \left(\frac{P^{dch}_{n,t,s}}{\eta^{dch}}\right) \right) \lambda^3_{\mathrm{n,t,s}} \\
& + \left(SOC_{\mathrm{n,t,s}} - \mathrm{SOC}^{\mathrm{arv}}_{\mathrm{n,t,s}} - \left(P^{ch}_{n,t,s} \times \eta^{ch}\right) + \left(\frac{P^{dch}_{n,t,s}}{\eta^{dch}}\right) \right) \lambda^4_{\mathrm{n,t^{arv},s}} \\
& + \left(P^{ch}_{n,t,s}\right) \lambda^5_{n,t,s} + \left(P_n^{\max} - P^{ch}_{n,t,s}\right) \lambda^6_{n,t,s} + \left(P^{dch}_{n,t,s}\right) \lambda^7_{n,t,s} \\
& + \left(P_n^{\max} - P^{dch}_{n,t,s}\right) \lambda^8_{n,t,s} + \left(SOC_{\mathrm{n,t,s}} - \mathrm{SOC}^{\mathrm{dep}}_{\mathrm{n}}\right) \lambda^9_{n,t^{dep},s}
\end{aligned} \tag{A10}$$

KKT conditions including three sets of equations are illustrated in Eqs. (A11) – (A13):

Stationarity:

$$\frac{\partial L}{\partial P^{ch}_{n,t,s}} = \rho_t^{PL2EV} - \rho_t^{ch} - \left(\eta^{ch} \times \lambda^3_{\mathrm{n,t,s}} \big|_{\mathrm{t\succ t^{arv}}}\right) - \left(\eta_{ch} \times \lambda^4_{\mathrm{n,t^{arv},s}} \big|_{t=t^{arv}}\right) - \left(\lambda^6_{\mathrm{n,t,s}} - \lambda^5_{\mathrm{n,t,s}}\right) = 0 \tag{A11}$$

$$\frac{\partial L}{P^{dch}_{n,t,s}} = 0.3\rho_t^{dch} - C^{cd} + \left(\frac{\lambda^3_{\mathrm{n,t,s}}}{\eta^{dch}} \Big|_{\mathrm{t\succ t^{arv}}}\right) + \left(\frac{\lambda^4_{\mathrm{n,t^{arv},s}}}{\eta^{dch}} \Big|_{\mathrm{t=t^{arv}}}\right) - \left(\lambda^8_{\mathrm{n,t,s}} - \lambda^7_{\mathrm{n,t,s}}\right) = 0 \tag{A12}$$

$$\frac{\partial L}{SOC_{n,t,s}} = \lambda^3_{\mathrm{n,t,s}}\big|_{\mathrm{t\succ t^{arv}}} - \lambda^3_{\mathrm{n,t+1,s}} + \lambda^4_{\mathrm{n,t^{arv},s}}\big|_{\mathrm{t=t^{arv}}} + \lambda^9_{\mathrm{n,t^{dep},s}}\big|_{\mathrm{t=t^{dep}}} - \left(\lambda^2_{\mathrm{n,t,s}} - \lambda^1_{\mathrm{n,t,s}}\right) = 0 \tag{A13}$$

For constraints that are greater than or equal to zero, the complementary constraints are Eqs. (A14) -(A19).

$$0 \leq SOC_{n,t,s} - \mathrm{SOC}_{\mathrm{n}}^{\min} \perp \lambda_{\mathrm{n,t,s}}^{1} \geq 0 \tag{A14}$$

$$0 \leq SOC_{n}^{\max} - SOC_{n,t,s} \perp \lambda_{\mathrm{n,t,s}}^{2} \geq 0 \tag{A15}$$

$$0 \leq P_{n,t,s}^{ch} \perp \lambda_{\mathrm{n,t,s}}^{5} \geq 0 \tag{A16}$$

$$0 \leq P_{n}^{\max} - P_{n,t,s}^{ch} \perp \lambda_{\mathrm{n,t,s}}^{6} \geq 0 \tag{A17}$$

$$0 \leq P_{n,t,s}^{dch} \perp \lambda_{\mathrm{n,t,s}}^{7} \geq 0 \tag{A18}$$

$$0 \leq P_{n}^{\max} - P_{n,t,s}^{dch} \perp \lambda_{\mathrm{n,t,s}}^{8} \geq 0 \tag{A19}$$

As can be seen, the MPEC problem is non-linear problem because of complementary constraints. The existence of non-linear constraints creates the non-convex environment and non-linear solver that sticks at the local optima and cannot guarantee the finding of global optima, while the response of the linear model is global optima. So in these non-linear problems, a method is used based on auxiliary binary variables and sufficiently large constants, i.e., Fortuny-Amat and McCarl linearization method. So, linearization of $0 \leq a \perp b \geq 0$ is Eq. (A20) [56]:

$$\begin{aligned} & 0 \leq a \perp b \geq 0 \\ & 0 \leq a \leq X \times M \\ & 0 \leq b \leq (1 - X) \times M \\ & X \, \varepsilon \left[0,1 \right] \end{aligned} \tag{A20}$$

Therefore, for the linearization of complementary constraints, Eqs. (A21) – (A26) are achieved.

$$\begin{aligned} & 0 \leq SOC_{n,t,s} - \mathrm{SOC}_{\mathrm{n}}^{\min} \leq X_{n,t,s}^{1} \times M^{1} \\ & 0 \leq \lambda_{n,t,s}^{1} \leq (1 - X_{n,t,s}^{1}) \times M^{2} \end{aligned} \tag{A21}$$

$$\begin{aligned} & 0 \leq SOC_{n}^{\max} - SOC_{n,t,s} \leq X_{n,t,s}^{2} \times M^{1} \\ & 0 \leq \lambda_{n,t,s}^{2} \leq (1 - X_{n,t,s}^{2}) \times M^{2} \end{aligned} \tag{A22}$$

$$\begin{aligned} & 0 \leq P_{n,t,s}^{ch} \leq X_{n,t,s}^{3} \times M^{1} \\ & 0 \leq \lambda_{n,t,s}^{5} \leq (1 - X_{n,t,s}^{3}) \times M^{2} \end{aligned} \tag{A23}$$

$$\begin{aligned} & 0 \leq P_{n}^{\max} - P_{n,t,s}^{ch} \leq X_{n,t,s}^{4} \times M^{1} \\ & 0 \leq \lambda_{n,t,s}^{6} \leq (1 - X_{n,t,s}^{4}) \times M^{2} \end{aligned} \tag{A24}$$

$$\begin{aligned} & 0 \leq P_{n,t,s}^{dch} \leq X_{n,t,s}^{5} \times M^{1} \\ & 0 \leq \lambda_{n,t,s}^{7} \leq (1 - X_{n,t,s}^{5}) \times M^{2} \end{aligned} \tag{A25}$$

$$\begin{aligned} & 0 \leq P_{n}^{\max} - P_{n,t,s}^{dch} \leq X_{n,t,s}^{6} \times M^{1} \\ & 0 \leq \lambda_{n,t,s}^{8} \leq (1 - X_{n,t,s}^{6}) \times M^{2} \end{aligned} \tag{A26}$$

Also, Fig.16 is provided for showing the correlations between equations of the model.

Bi-Level Model

Upper Level

Objective Function: Maximization of the SDISCO's profit (Eq. (10))

1. The income from the selling of energy to PL (Eq. (5))
2. The income from the selling of energy to the customer (Eq. (6))
3. The cost of providing energy from the wholesale market (Eq. (7))
4. The cost of energy purchased from PL (Eq. (8))
5. The cost of implementation of price-based DR and incentive-based DR programs (Eq. (9))

Constraint of SDISCO:

1. RES generation (Eq. (11-12))
2. Bus voltage and Line current (Eq. (13-14))
3. Linear power flow (Eq. (15-25))
4. Power balance (Eq. (26))

Lower Level

Objective Function: Maximization of the EVs PL's profit (Eq. (32))

1. The income from the selling of energy to EV owners (Eq. (27))
2. The income from the selling of energy to the SDISCO (Eq. (28))
3. The cost of energy purchased from the SDISCO and RES by PL owner (Eq. (29))
4. The cost of payment to EV owners because of participation in a V2G interaction (Eq. (30))
5. The cost of battery depreciation (Eq. (31))

Constraint of EVs PL:

1. Charging/discharging of EVs (Eq. (33-38))

↓

Single Level Model (MILP)

Objective Function: Maximization of the SDISCO's profit (Eq. (10))

Constraint

1. Constraint of SDISCO (Eq. (11-26))
2. Constraint of EVs PL (Eq. (33-38))
3. Constraints of KKT (Eq. (A (11) –A (13))
4. Complementarily constraints (Eq. A (21) -(A26))

Fig.16. Correlations between equations of the proposed model