Smart Distribution System Operational Scheduling Considering Electric Vehicle Parking Lot and Demand Response Programs

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Abstract

Electric vehicle (EV) technology with a vehicle to grid (V2G) property is used in power systems to mitigate greenhouse gas emissions, reduce peak load of the distribution system, provide ancillary service, etc. In addition, demand response (DR) programs as an effective strategy can provide an opportunity for consumers to play a significant role in the planning and operation of a smart distribution company (SDISCO) by reducing or shifting their demand, especially during the on-peak period. In this paper, the optimal operation of a SDISCO is evaluated, including renewable energy resources (RERs) along with EV parking lots (PLs). RER and PL uncertainties and a suitable charging/discharging schedule of EVs are also considered. Furthermore, price-based DR programs and incentive-based DR programs are used for operational scheduling. To achieve this aim, a techno-economic formulation is developed in which the SDISCO acts as the owner of RERs and PLs. Moreover, DR programs are prioritized by using the technique for order preference by similarity to ideal solution method. In addition, a sensitivity analysis is carried out to investigate different factors that affect the operational scheduling of the SDISCO. The proposed model is tested on the IEEE 15-bus distribution system over a 24-h period, and the results prove the effectiveness of the model.

Keywords: Operational scheduling, electric vehicle parking lots, demand response programs, smart distribution system.

Nomenclature

Indices	
b , b'	Index for branch or bus
F	Index for linear partitions in linearization
n , N	Index for EV number
S , s	Index for scenarios
Sb	Index for slack bus
t , t′	Index for time (h)
Parameters	
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)
$P^{L,DR}$	Customers' demand after DR (kW)
$P^{L,max}$	Maximum customers' demand before DR (kW)
P^{PV}	Output power of PV unit (kW)
$P^{PV\text{-}Rated}$	Rated output of PV unit (kW)
$P^{PV,max}$	Maximum output power of PV unit (kW)
P^W	Output power of wind unit (kW)
$P^{W\text{-}Rated}$	Rated 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)
Pr^{ch}	Charging tariff of EVs ($/kWh)
Pr^{dch}	Discharging tariff of EVs ($/kWh)
$t^{dep,min}$	Lower bound of the departure time
V_a, V_b	Wind speed limit
V_{ci}	Cut-in speed of wind turbine (m/s)
V_{co}	Cut-off speed of wind turbine (m/s)
V_r	Rated speed of wind turbine (m/s)
V^{Rated}	Nominal voltage (V)
V^{max}	Maximum allowable voltage (V)
V^{min}	Minimum allowable voltage (V)
$X_{b, b'}$	Reactance between branches b and b′ (Ω)
Z	Impedance (Ω)
ΔS	Upper limit in the discretization of quadratic flow terms (kVA)
η^{ch}	Charging efficiency (%)
η^{dch}	Discharging efficiency (%)
θ	Illumination intensity (w.m^2)
θ_r	Rated illumination intensity (w.m^2)
μ	Mean value
ρ^s	Probability of each scenario
σ	Standard deviation
Variables	
I,I2	Current flow (A), Squared current flow (A2)
P^{ch}	Transferred power for charging EVs (kW)
P^{dch}	Discharging power of EVs (kW)
$P^{G2L,DR}$	Power purchased from the SDISCO by customer after DR programs (kW)
P^{G2PL}	Power purchased from the SDISCO by PLs (kW)
P^{Loss}	Power loss of the SDISCO (kW)
P^{PL2G}	Power purchased from PLs by the SDISCO (kW)
$P^{PV2L,DR}$	Power purchased from PV unit by customer after DR

$Pr^{L,DR}$	Electricity price after DR (\$/kWh)
Pr^{Wh2G}	Price of purchased electricity from the wholesale market by the SDISCO (\$/kWh)
P(v)	Probability of the wind speed
$Q^{L,DR}$	Customers' reactive power after DR (kVAR)
$R_{b,b'}$	Resistance between branches b and b′ (Ω)
R^{ch}	Charging rate (kWh)
R^{dch}	Discharging rate (kWh)
SOE^{arv}	Initial SOE of EVs at the arrival time to the PLs (kWh)
S^{b}	Apparent power in bus b (kVA)
$S^{b,max}$	Maximum apparent power in bus b (kVA)
SOE^{dep}	Desired SOE of EVs at the departure time from PLs (kWh)
$SOE^{ini,min/max}$	Truncation region for the initial SOE of EVs
SOE^{max}	Maximum rate of SOE (kWh)
SOE^{min}	Minimum rate of SOE (kWh)
t^{arv}	Arrival time of EVs to the PLs
$t^{arv,max}$	Upper bound of the arrival time
$t^{arv,min}$	Lower bound of the arrival time
t^{dep}	Departure time of EVs from the PLs
$t^{dep,max}$	Upper bound of the departure time
	programs (kW)
P^{PV2PL}	Power purchased from PV unit by PLs (kW)
P^{Wh2G}	Power purchased from the wholesale market by the SDISCO (kW)
$P^{W2L,DR}$	Power purchased from wind unit by customer after DR programs (kW)
P^{W2PL}	Power purchased from wind unit by PLs (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^{ch}	Binary variable that shows the charge status of EVs (0 or 1)
X^{dch}	Binary variable that shows the discharge status of EVs (0 or 1)
Others	
m	Alternative quantity
o	Attribute quantity
SS	Distance between each alternative and the ideal solution/nonideal solution
V	Ideal-solution/nonideal solution
W	Weight of attributes
λ	Decision maker's importance factor

1. Introduction

1.1. Motivation and Aims

The penetration of electric vehicles (EVs) considering different types of charging can bring advantages and disadvantages to the owner of a smart distribution company (SDISCO). The operation of EVs can be classified into uncontrolled charging mode, controlled charging mode, and smart charging/discharging mode. If EVs are charged in an uncontrolled charging mode, improper results may occur such as increase in loss [1,2], high demand [3,4], unbalancing of the load [5,6], voltage drop [7], and decrease in the cable and transformer life [8,9]. EVs also offer a unique advantage in terms of a technology known as vehicle to grid (V2G) [10]. The V2G concept is essentially the ability of EVs to inject the electrical power to the SDISCO. Therefore, by using the controlled charging mode or smart charging/discharging mode, i.e., charging during the mid-peak or off-peak periods and discharging during the on-peak period, the performance of SDISCO is improved. This mode has many benefits for the SDISCO, such as ancillary service-spinning reserve [11-12], load leveling and peak load shaving [13-14], voltage regulation [15], and decreasing in CO_2 gas emissions [16].

Moreover, demand response (DR) programs are a key element in the sustainable development of the SDISCO, which can be enabled by the SDISCO. DR is a set of actions for reducing the consumer's demand that is implemented by changing the price of electricity or paying an incentive or receiving a penalty. These programs are implemented when interruptions occur in the conventional power plant or renewable energy resource (RER) generations. DR programs are also designed to improve the reliability of the SDISCO and reduce the electricity consumption during on-peak hours [17].

Because the number of EVs may increase in the future, the management and operation of the SDISCO at present are more complicated than that in the past. One of the important solutions in this context is an efficient use of parking lots (PLs). EV owners do not use the EVs: 93– 96% of daytime. The high numbers of EVs having V2G capability can provide a good opportunity for the operation and planning of the SDISCO, if an optimal management of charging/discharging the EVs is implemented. Furthermore, uncertainty is one of the most important and inherent features of RERs and PLs. In the presence of uncertainty in the SDISCO, the operation and planning are also uncertain. Therefore, using DR programs is considered as a tool for reducing the amount of energy not-supplied (ENS).

This paper aims at the operational scheduling of the SDISCO considering RERs and PLs and their uncertainties. To achieve this goal, a techno-economic formulation is developed to maximize the profit of the SDISCO. However, the uncertain nature of different RESs and PLs may have considerable effects on the optimal operation of the SDISCO. Therefore, uncertainties are modeled using the probability distribution function (PDF). Furthermore, the impact of several subgroups of DR programs, i.e., price-based DR (PBDR) programs, incentive-based DR (IBDR) programs, and combined PBDR and IBDR programs, on the operational scheduling of the SDISCO is also investigated. Moreover, DR programs are prioritized by using the technique for order preference by similarity to ideal solution (TOPSIS). Furthermore, the effects of controlled charging mode of EVs and the smart charging/discharging on the operation of the SDISCO are appraised. In addition, the impact of the size of wind and photovoltaic (PV) units and the number of EVs on the operation of the SDISCO is evaluated. Moreover, because the model includes different uncertainties, a stochastic programming is used to solve the objective function.

1.2. Literature Review

Among the related studies on EVs, several reviews are presented in [10, 18, 19]. In [10], different standards and codes for EVs, V2G concept and its benefits, the impact of charging strategies of EVs on distribution systems, and the comparison of an uncoordinated and coordinated strategy of charging are investigated. In [18], the EV history, the current status of EV technologies (power train configurations, development time-line of EV battery, EV battery type, charging levels, and converter topologies of EV charger), impacts of EV deployment (economic, environmental, power grid impacts), and the relationship between EVs and the smart grid are reviewed. In [19], a review is provided on plug-in EV scheduling and optimization methods for integrating EVs in the power system. This review includes the impact assessment and analytical charging strategies, scheduling objectives, conventional mathematical optimization, and meta-heuristic algorithm approach, as well as a comparison of these methods.

The US Department of Energy categorizes DR into IBDR and PBDR groups, which have several subgroups as explained in the following section [20]. In [21], an economic model for the responsive load is proposed. Price elasticity of the demand, electricity price, and the incentive and penalty values are the main factors that change in customers' demand. To select the most efficient DR program, an analytical hierarchy process is used. In [22], a flexible responsive load economic model is presented. In this report, by using the linear function of demand curve, variable elasticity is calculated. Prioritization of ten programs and twenty scenarios with different participation levels is evaluated from individual stakeholders, i.e., customer, utility, and independent system operator (ISO). In [23], the nonlinear PBDR programs are modeled. The implementation of DR programs is investigated in different networks with different participation levels of the responsive load, elasticity, and electricity price.

In [10, 18-23], a comprehensive description of EVs and DR programs is provided. In the following, we review the reports in which the effect of EVs and DR programs on the planning and operation of the SDISCO is investigated.

In [24], the behavior of EV PLs by using a model for achieving optimal strategies is evaluated in both PBDR and IBDR programs and several subgroups. The aim of the objective function is maximizing the PLs' profit considering PLs and electricity market uncertainties. The participation level of EVs in each DR program is also optimized. Results show that the type of DR programs affects the charging/discharging schedule of the EVs, traded energy with the grid, and the participation in the reserve and energy markets. In [25], a probabilistic framework is presented for the operation of distribution companies in the presence of distributed generations (DGs) and battery energy storage. In this model, the uncertainty of electricity prices and output power of DGs are also considered. In [26], operation costs and emissions are minimized by using a stochastic programming model in the presence of RERs and DR programs.

In [27], by applying an IBDR program, sitting and sizing of PLs are performed for an increasing distribution company reliability by calculating the ENS and average sustained interruption duration indices (ASIDI). By using the genetic algorithm, the objective function is solved in four scenarios with different availabilities of EVs on a 33-bus radial distribution network. In [28], by using IBDR programs and a suitable charge/discharge schedule of EVs, an operational planning model of a microgrid (MG) is presented. The proposed model aims at minimizing the total operation cost of MG. For evaluating the robustness of the presented model, the case study is carried out in two scenarios. Results indicate that the application of DR and the participation of EVs in energy or reserve market causes a reduction in the total operational cost of MG.

In [29], a mathematical model is presented to solve the static transmission network expansion planning problem considering RERs and EVs together with the IBDR program. The goal of objective function is to minimize the total cost of the system. By using the artificial bee colony algorithm and considering eight scenarios on three test systems, the mathematical model is solved, and the results indicate that the total system cost is significantly reduced. In [30], by considering wind generation and DR program, a stochastic operational scheduling of the SDISCO is proposed in the energy and reserve markets. By testing on an 83-bus distribution system, results show that the load's participation in the energy and reserve scheduling reduces the total operation costs. In [31], for the scheduling of local distribution systems with EVs and RERs, a model for minimizing the total cost of the network is presented including the cost of power supply for loads and EVs and the cost of ENS as the reliability costs. A modified bat algorithm (BA) is proposed and tested on a grid-connected MG to solve this problem.

Although many studies have used the EVs and DR programs, the simultaneous consideration of RER and EV uncertainties and the PBDR and IDBR programs in the operation of the SDISCO has not been addressed in the literature.

1.3. Contributions

In this paper, a new model is presented for the optimal operation of the SDISCO considering the V2G property of EVs, RER and EV uncertainties, and IBDR and PBDR programs. The main contributions of the paper are as follows:

1. Presenting a techno-economic model for the operational scheduling of the SDISCO by the simultaneous consideration of RER and EV uncertainties and the PBDR and IDBR programs.
2. Presenting a sensitivity analysis to investigate the different factors that may affect the operational scheduling of the SDISCO.
3. Investigating several subgroups of DR programs for the operation of the SDISCO in the presence of EVs and prioritizing the programs based on indices such as the SDISCO’s profit, network loss, and demand peak.

1.4. Paper Organization

The rest of the paper is organized as follows. A brief review of the EV and RER uncertainties is described in section 2. PBDR and IBDR programs are explained in section 3. Problem formulation is presented in section 4. Numerical results are discussed in Section 5. Finally, conclusions are reported in Section 6.

2. EV and RER Uncertainties

In this section, the modeling of PLs based on the specifications of EVs is carried out. Moreover, the modeling of RERs, i.e., wind and PV generation, considering their intermittent nature is performed.

2.1. EV uncertainty

The uncertainties of each EV owner involve the initial state of energy (SOE), duration of the presence of EVs in PLs, charge/discharge rate, battery capacity of EVs, and the desired final SOE. Many reports have studied the uncertainty of EVs; hence, appropriate PDFs have been suggested to have a maximum overlap with real data. On this basis, the behavior of EVs is modeled as a *truncated Gaussian distribution* [32].

Thus, the behavior of each EV is modeled by Eqs. (1) - (3).

$$SOE_n^{ini} = f_{TG}\left(X;\mu_{SOE};\sigma_{SOE}^2;\left(SOE_n^{ini,\min};SOE_n^{ini,\max}\right)\right) \quad \forall n \tag{1}$$

$$t_n^{arv} = f_{TG}\left(X;\mu_{arv};\sigma_{arv}^2;\left(t_n^{arv,\min};t_n^{arv,\max}\right)\right) \quad \forall n \tag{2}$$

$$t_n^{dep} = f_{TG}\left(X;\mu_{dep};\sigma_{dep}^2;\left(\max(t_n^{dep,\min},t_n^{arv});t_n^{dep,\max}\right)\right) \quad \forall n \tag{3}$$

2.2. RER uncertainty

There are two sources of uncertainty of RERs, i.e., the output power generation of wind and PV units. The stochastic wind speed and illumination intensity are the main factors that affect the wind and PV output. The modeling of these uncertainties is presented as follows.

2.2.1. Uncertainty of Wind Power Generation

Because of the intermittent nature of the wind speed, many experiments prove that the stochastic wind speed in many regions roughly pursues the *Weibull* PDF [33-34]. Eq. (4) shows the *Weibull* PDF where $c > 0$ and $k > 0$ denote the scale and the shape factors, respectively. The wind speed probability can be computed by Eq. (5). On the basis of the recognized PDF of the wind speed, the relationship between the output power of a wind generating unit and the wind speed is formulated by Eq. (6) [35]. Eq. (6) shows that electricity can be generated when there is minimum wind speed, and electricity generation continues until the rated wind speed is reached. At the rated wind speed, the electricity produced is equal to the rated power of wind generation unit. If the wind speed is less than the minimum or more than the maximum limit, the power generated by the wind turbine is zero.

$$f(v) = \frac{K}{c^K} v^{(K-1)} e^{-(\frac{v}{c})^K} \qquad 0 \le v \le \infty \tag{4}$$

$$P(v) = \int_{v_a}^{v_b} f(v)dv \tag{5}$$

$$P^w = \begin{cases} 0 & 0 \le \mathrm{V} \le \mathrm{V_{ci}}, V_{co} \le V \\ P^{W-Rated} \times \dfrac{V - V_{ci}}{V_r - V_{ci}} & \mathrm{V_{ci}} \le V < V_r \\ P^{W-Rated} & \mathrm{V_r} \le \mathrm{V} \le \mathrm{V_{co}} \end{cases} \tag{6}$$

2.2.2. Uncertainty of PV Units

The output of a PV unit is predominantly affected by the illumination intensity. Because the illumination intensity is an uncertain variable, the output of the PV unit is also uncertain. In [35], it is shown that the distribution of solar irradiance is characterized by the *Weibull PDF* shown in Eq. (7). On this basis, electricity is generated when there is minimum illumination intensity and continues until the rated illumination intensity is reached. If the illumination intensity is higher than the rated illumination intensity, the electricity generated is equal to the rated power of PV.

$$P^{PV} = \begin{cases} P^{PV-Rated} \times \dfrac{\theta}{\theta_r} & 0 \le \theta \le \theta_r \\ P^{PV-Rated} & \theta_r \le \theta \end{cases} \tag{7}$$

2.3. Simulation of uncertainties

The stochastic programming is used for modeling and solving problems that involve various uncertainties. In stochastic programming, each uncertain parameter is considered a random variable. The random variables are usually described by a set of scenarios. These scenarios are obtained by the PDFs. For the uncertainty simulation, scenario generation and scenario reduction steps are needed. First, after collecting historical data, the output is gained by (1), (2), (3), (6), and (7). Then, by using a scenario tree technique, the different output states are described. By using the interval method, the initial output of the scenario set is achieved. Because most practical optimization problems are very large when all possible scenarios are considered, the number of scenarios should be reduced. Therefore, it is necessary to construct a scenario reduction method for deleting similar scenarios to save the computational cost. The basic concept of scenario reduction is to choose a reference scenario and then compare this scenario with other scenarios to remove the closest scenario. Here, the *Kantorovich distance* (K-distance) is utilized to calculate the distance between different scenarios under the objective function of the minimum K-distance between the initial scenario and the reduced scenario. The scenario with the minimum K-distance is deleted. The probability of a deleted scenario should be added to the reference scenario. Then, the final simulation scenarios and the probability of all scenarios can be calculated. The scenario reduction model is described in [34, 36].

3. Modeling of IBDR and PBDR programs

On the basis of Eq. (8), the price elasticity of demand is defined as the demand sensitivity with respect to the price.

$$E = \frac{Pr^0}{P^0} \cdot \frac{\partial P}{\partial Pr} \tag{8}$$

If the electricity price varies at different periods or there is an incentive for demand reduction during the on-peak period, the responsive load reacts as follows.

1. One part of demand of the responsive load (such as lighting demand) has a single-period sensitivity, because it cannot be transferred to other periods, and it can be only *on* or *off* during the same period. This part of demand is called the single-period elastic load. The elasticity of such demand that is not sensitive to the electricity prices at other periods is called *self-elasticity* [21]. The value of self-elasticity based on Eq. (9) is negative.

$$E(t,t) = \frac{Pr^0(t)}{P^0(t)} \cdot \frac{P(t) - P^0(t)}{Pr(t) - Pr^0(t)} \le 0 \tag{9}$$

2. Another part of demand of the responsive load has a multiperiod sensitivity, because it can be transferred from one period to another period. This part of demand is called the multiperiod elastic load. The elasticity of this part of demand, which is sensitive to the electricity prices at different periods, is called the *cross-elasticity* [21]. The value of cross-elasticity as presented in Eq. (10) is positive.

$$E(t,t') = \frac{Pr^{0}(t')}{P^{0}(t)} \cdot \frac{P(t)-P^{0}(t)}{Pr(t')-Pr^{0}(t')} \geq 0 \tag{10}$$

Fig. 1 shows that the DR programs are divided into two main categories, i.e., PBDR programs and IBDR programs.

All the PBDR programs are voluntary programs such as the time of use (TOU), real-time pricing (RTP), and critical peak pricing (CPP); however, the IBDR programs include voluntary programs (emergency DR program (EDRP) and direct load control (DLC)), mandatory programs (interruptible/curtailable programs (I/C) and capacity market program (CAP)), and market-clearing programs (demand bidding (DB) and ancillary services (A/S) market). A detailed description of DR programs can be found in [21–23]. Therefore, for the load economic model, we have Eq. (11) [21]:

$$P(t) = P^{0}(t) \times \left\{ 1 + \sum_{t' \varepsilon T} \frac{Pr(t') - Pr^{0}(t') + A(t') + PEN(t')}{Pr^{0}(t')} \times E(t,t') \right\} \tag{11}$$

According to Eq. (11), it is clear how the consumption of customers will change to yield the maximum profit. The SDISCO is responsible for implementing DR programs. Despite many benefits of DR, there is an additional cost as presented in Eq. (12).

$$C^{DR} = \left(A(t) \times \left(P^{0}(t) - P(t)\right)\right) - \left(PEN(t) \times \left(P^{con}(t) - \left(P^{0}(t) - P(t)\right)\right)\right) \tag{12}$$

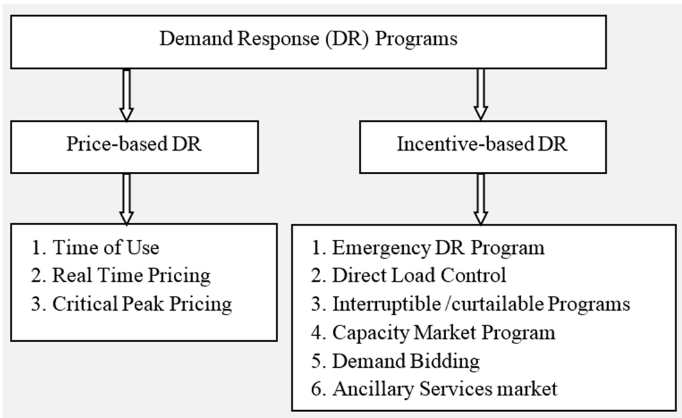

Fig. 1. Main and lateral categories of DR programs

4. Problem Formulation

In this paper, the objective function is to maximize the SDISCO profit in terms of income and cost. EV owners are one of the main players related to the operation of the SDISCO. EV owners expect to pay a lower cost for charging EVs or departure with the desired SOE from the PLs. The SDISCO because of the V2G capability of EVs, the management of charging/discharging schedule of EVs, and the implementation of DR programs is interested in achieving the objectives, i.e., reducing losses, improving voltage profile, increasing reliability index, and avoiding feeder and transformer congestions.

4.1. Objective function

For customer orientation and satisfaction, the SDISCO should provide the needed energy for the customers and charging the EVs. This energy is purchased from the wholesale market. The SDISCO can also use the RER generation. In this paper, it is assumed that the SDISCO also owns the EV PLs and renewable energy units. Indeed, by encouraging the EV owners, paying proper incentives, and considering the V2G capability, a part of the needed energy for the customers during the on-peak period can be supplied. In addition to paying this incentive to the EV owners, the

SDISCO must pay a battery depreciation cost to the EV owners because of the participation in V2G modes. The SDISCO also implements the DR programs for using their benefits.

According to the abovementioned data, the objective function is composed of the following terms:

1. The income from selling the energy to EV owners,
2. The income from selling the energy to the customers,
3. The cost of energy purchased from the wholesale market,
4. The cost of energy purchased from EV owners for supplying it to the customers,
5. The cost of battery depreciation,
6. The cost of implementation of DR programs.

Term 1 is the income from selling the energy to EV owners for charging the EVs. The income is presented in Eq. (13).

$$F_1 = \sum_{s=1}^{Ns} \rho_s \sum_{n=1}^{N} \sum_{t=1}^{24} P_{n,t,s}^{ch} \times \mathrm{Pr}_{\mathrm{t}}^{\mathrm{ch}} \times \Delta\mathrm{t} = \sum_{s=1}^{Ns} \rho_s \sum_{n=1}^{N} \sum_{t=1}^{24} \left(P_{n,t,s}^{G2PL} + P_{n,t,s}^{W2PL} + P_{n,t,s}^{PV2PL} \right) \times \mathrm{Pr}_{\mathrm{t}}^{\mathrm{ch}} \times \Delta\mathrm{t} \tag{13}$$

Term 2 is the income from selling the energy to residential, industrial, and commercial loads. This income is formulated in Eq. (14).

$$F_2 = \sum_{b=2}^{Nb} \sum_{t=1}^{24} \mathrm{P}_{\mathrm{b,t}}^{\mathrm{L,DR}} \times \mathrm{Pr}_{\mathrm{t}}^{\mathrm{L,DR}} \times \Delta\mathrm{t} = \sum_{b=2}^{Nb} \sum_{t=1}^{24} \left(P_{b,t}^{G2L,DR} + P_{b,t}^{PV2L,DR} + P_{b,t}^{W2L,DR} \right) \times \mathrm{Pr}_{\mathrm{t}}^{\mathrm{L,DR}} \times \Delta\mathrm{t} \tag{14}$$

Term 3 is the cost of energy purchased from the wholesale market to supply various loads and charge the EVs. This cost is expressed in Eq. (15).

$$\mathrm{F}_3 = \sum_{\mathrm{Sb}=1}^{\mathrm{NSb}} \sum_{\mathrm{t}=1}^{24} P_{Sb,t}^{Wh2G} \times \mathrm{Pr}_{\mathrm{t}}^{\mathrm{Wh2G}} \times \Delta\mathrm{t} \tag{15}$$

Term 4 is the cost of the EV owner’s bid to the energy market that results from the discharge of the EV batteries during the on-peak period. This cost paid to EV owners is given by Eq. (16).

$$F_4 = \sum_{s=1}^{Ns} \rho_s \sum_{n=1}^{N} \sum_{t=1}^{24} P_{n,t,s}^{dch} \times \mathrm{Pr}_{\mathrm{t}}^{\mathrm{dch}} \times \Delta\mathrm{t} = \sum_{s=1}^{Ns} \rho_s \sum_{n=1}^{N} \sum_{t=1}^{24} P_{n,t,s}^{PL2G} \times \mathrm{Pr}_{\mathrm{t}}^{\mathrm{dch}} \times \Delta\mathrm{t} \tag{16}$$

Term 5 is the cost of battery depreciation. In general, the depth of discharge affects the life of EV battery [37, 38]. This term is computed using the amount of power exchange between EVs and the SDISCO. This cost paid to the EV owners is presented in Eq. (17).

$$\mathrm{F}_5 = \sum_{\mathrm{s}=1}^{\mathrm{Ns}} \rho_{\mathrm{s}} \sum_{\mathrm{n}=1}^{\mathrm{N}} \sum_{\mathrm{t}=1}^{24} P_{n,t,s}^{dch} \times \mathrm{C}^{\mathrm{cd}} \times \Delta\mathrm{t} \tag{17}$$

Term 6 is the cost of implementation of DR programs. As previously mentioned, by implementation of the DR, the SDISCO will also incur costs because of the type of DR programs. This cost can be calculated by Eq. (18).

$$\mathrm{F}_6 = \sum_{\mathrm{b}=2}^{\mathrm{Nb}} \sum_{\mathrm{t}=1}^{24} \left(\mathrm{A}_{\mathrm{t}} \left(\mathrm{P}_{\mathrm{b,t}}^{\mathrm{L}} - \mathrm{P}_{\mathrm{b,t}}^{\mathrm{L,DR}} \right) - \mathrm{PEN}_{\mathrm{t}} \left(\mathrm{P}_{\mathrm{b,t}}^{\mathrm{con}} - \mathrm{P}_{\mathrm{b,t}}^{\mathrm{L}} + \mathrm{P}_{\mathrm{b,t}}^{\mathrm{L,DR}} \right) \right) \times \Delta\mathrm{t} \tag{18}$$

It can be noted that the time interval in this paper is 1 h (Δt=1). After a description of the income and cost, the objective function is as presented in Eq. (19).

$$MAX\ \ OF = F_1 + F_2 - F_3 - F_4 - F_5 - F_6 \tag{19}$$

It should be noted that the energy purchased from the wholesale market is used for meeting the customers' demand and charging the EVs. The SDISCO also purchases the energy from the wholesale network that leads to lower losses. Therefore, the presented model for the operational scheduling of the SDISCO is a techno-economic model.

4.2. Constraints

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

1) RER generation

Based on Eqs. (20) - (21), wind and solar generation units are limited to the forecasted power generation in each hour according to the wind speed and solar radiation, respectively.

$$0 \le P_{b,t,s}^{W} \le P^{W,\max} \tag{20}$$

$$0 \le P_{b,t,s}^{PV} \le P^{PV,\max} \tag{21}$$

2) Bus Voltage and Line Thermal Capacity

Because of the line thermal capacity, the power flow of each branch must be less than the maximum permissible power. The voltage of each bus should be also between the minimum and maximum range of the voltage. Therefore, Eqs. (22) - (23) are used.

$$S_{b,t,s} \le S^{b,\max} \tag{22}$$

$$V^{\min} = 0.95 \le V_{b,t,s} \le V^{\max} = 1.05 \tag{23}$$

3) 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, a linear power flow is considered based on [32]. This power flow is used only in radial distribution networks. Therefore, a term is considered as a block to avoid nonlinearities. Note that the EVs in the PLs act as a source during the on-peak period and as a load during the off-peak or mid-peak periods. The active and reactive power balance in this power flow is shown in Eqs. (24) and (25), respectively:

$$\begin{aligned} & P_{Sb,t}^{Wh2G} + P_{b,t,s}^{\mathrm{PV}} + P_{b,t,s}^{\mathrm{W}} + \sum_{\mathrm{N}} P_{n,t,s}^{dch} - \sum_{\mathrm{N}} P_{n,t,s}^{ch} - \sum_{b'} \left[\left(P_{b,b',t,s}^{+} - P_{b,b',t,s}^{-} \right) + R_{b,b'} I2_{b,b',t,s} \right] \\ & + \sum_{b'} \left(P_{b',b,t,s}^{+} - P_{b',b,t,s}^{-} \right) - P_{b,t}^{\mathrm{L,DR}} = 0 \qquad \forall \mathrm{t,s} \end{aligned} \tag{24}$$

$$Q_{Sb,t,s}^{Wh2G} - \sum_{b'} \left[\left(Q_{b,b',t,s}^{+} - Q_{b,b',t,s}^{-} \right) + X_{b,b'} I2_{b,b',t,s} \right] + \sum_{b'} \left(Q_{b',b,t,s}^{+} - Q_{b',b,t,s}^{-} \right) - Q_{b,t}^{\mathrm{L,DR}} = 0 \qquad \forall \mathrm{t,s} \tag{25}$$

Note that $I2$ refers to an auxiliary variable linearly representing 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 nonzero at a time. This condition is again implicitly enforced by optimality. Moreover, Eqs. (26) and (27) limit these variables by the maximum apparent power for completeness.

$$0 \le \left(P_{b,b',t,s}^{+} + P_{b,b',t,s}^{-} \right) \le V^{Rated} \times I^{\max,b\,b'} \tag{26}$$

$$0 \le \left(Q^{+}_{b,b',t,s} + Q^{-}_{b,b',t,s}\right) \le V^{Rated} \times I^{\max,b,b'} \tag{27}$$

Eq. (28) is presented for balancing the voltage between two nodes. It should be noted that *V2* in Eq. (28) is an auxiliary variable that represents the squared voltage relation.

$$V2_{b,t,s} - V2_{b',t,s} - Z^{2}_{b,b'} I2_{b,b',t,s} - 2R_{b,b'}\left(P^{+}_{b,b',t,s} - P^{-}_{b,b',t,s}\right) - 2X_{b,b'}\left(Q^{+}_{b,b',t,s} - Q^{-}_{b,b',t,s}\right) = 0 \tag{28}$$

Eq. (29) is used for linearizing the active and reactive power flows that appear in the apparent power expression.

$$V2^{Rated}_{b} I2_{b,b',t,s} = \sum_{f}\left[(2f-1)\Delta S_{b,b'} \Delta P_{b,b',f,t,s}\right] + \sum_{f}\left[(2f-1)\Delta S_{b,b'} \Delta Q_{b,b',f,t,s}\right] \tag{29}$$

For piecewise linearization, Eqs. (30) - (34) are presented. The number of blocks required to linearize the quadratic curve is set to five according to [39], which maintains the right balance between accuracy and computational requirements. Further descriptions, justifications, and derivations of the network model used in this paper can be found in [40-41].

$$P^{+}_{b,b',t,s} + P^{-}_{b,b',t,s} = \sum_{f} \Delta P_{b,b',f,t,s} \tag{30}$$

$$Q^{+}_{b,b',t,s} + Q^{-}_{b,b',t,s} = \sum_{f} \Delta Q_{b,b',f,t,s} \tag{31}$$

$$0 \le \Delta P_{b,b',f,t,s} \le \Delta S_{b,b'} \tag{32}$$

$$0 \le \Delta Q_{b,b',f,t,s} \le \Delta S_{b,b'} \tag{33}$$

$$\Delta S_{b,b'} = \frac{V^{Rated} \times I^{\max,b,b'}}{F} \tag{34}$$

4) Power Balance

According to this constraint, the total power generated is equal to the total power consumed. This constraint is shown in Eq. (35).

$$P^{Wh2G}_{Sb,t} + P^{W}_{b,t,s} + P^{PV}_{b,t,s} + \sum_{\mathrm{N}} P^{dch}_{n,t,s} = P^{\mathrm{L,DR}}_{b,t} + P^{Loss}_{t,s} + \sum_{\mathrm{N}} P^{ch}_{n,t,s} \tag{35}$$

5) DR constraint

DR programs are generally considered in the reduction of power during the on-peak period. Hence, at another time, a new peak load may occur because of the implementation of DR. Therefore, in this paper, with Eq. (36), the unexpected peak load is avoided.

$$P^{L,DR}_{b,t} \le P^{L,\max}_{b} \tag{36}$$

6) EV constraint

Eq. (37) indicates that the charge and discharge of EVs are not simultaneous. According to Eq. (38), the total SOE of the EVs cannot exceed the minimum and maximum SOE of each EV. Also, according to Eqs. (39) - (40), the SOE of EVs at each hour appertains many factors including the remaining SOE of the EVs from the previous hour, the amount of power exchanged with the SDISCO and the PLs, the charge/discharge efficiency, and the initial SOE of EVs [31, 38]. The amount of power purchased by each EV from the PLs is limited to its maximum value. Further, the amount of power that each EV can sell to the PL is also limited to a maximum value. These two constraints are shown in Eqs. (41) and (42), respectively. Finally, according to Eq. (43), the management of charging/discharging the EVs should be accurate in such a way that at the departure time, the SOE of EVs reaches the desired value.

$$X^{ch}_{n,t,s} + X^{dch}_{n,t,s} \le 1 \qquad \forall n,t,s \qquad (37)$$

$$SOE^{\min}_{n,t,s} \le SOE_{n,t,s} \le SOE^{\max}_{n,t,s} \qquad \forall n,t,s \qquad (38)$$

$$SOE_{n,t,s} = SOE_{n,t-1,s} + \left(P^{ch}_{n,t,s} \times \Delta t \times \eta^{ch}\right) - \left(\frac{P^{dch}_{n,t,s} \times \Delta t}{\eta^{dch}}\right) \qquad \forall n,t \succ t^{arv},s \qquad (39)$$

$$SOE_{n,t,s} = \mathrm{SOE}^{\mathrm{arv}}_{\mathrm{n,t,s}} + \left(P^{ch}_{n,t,s} \times \Delta t \times \eta^{ch}\right) - \left(\frac{P^{dch}_{n,t,s} \times \Delta t}{\eta^{dch}}\right) \qquad \forall n,t^{arv},s \qquad (40)$$

$$0 \le P^{ch}_{n,t,s} \le X^{ch}_{n,t,s} \times R^{ch}_{n} \qquad \forall n,t,s \qquad (41)$$

$$0 \le P^{dch}_{n,t,s} \le X^{dch}_{n,t,s} \times R^{dch}_{n} \qquad \forall n,t,s \qquad (42)$$

$$SOE_{n,t,s} = \mathrm{SOE}^{\mathrm{dep}}_{\mathrm{n,t,s}} \qquad \forall n,t^{dep},s \qquad (43)$$

4.3. The problem-solving process

In this paper, a stochastic programming is used for solving the objective function. In fact, stochastic programming is used for modeling and solving the problems that involve different uncertainties. Uncertainties in the application of stochastic parameters are considered as random variables. These variables are usually expressed by a set of scenarios. As noted, these scenarios are obtained using the PDFs (in this paper, *truncated Gaussian distribution* and *Weibull distribution*). On the basis of the customers' demand, duration of the presence of EVs in PLs, wind and PV unit output, power purchased from the wholesale market by the SDISCO, and DR implementation, the framework of the proposed model and the flowchart of the stochastic operational scheduling of the SDISCO are shown in Fig. 2 and Fig. 3, respectively.

The decision variables in the proposed model are binary and integer variables. The presence of such variables leads to the mixed-integer problem. In addition, because of the linear objective function and constraints, the model is linear. Therefore, by considering all the relations, the proposed optimization model is a mixed-integer linear programming (MILP) problem. Therefore, in this paper, the simulation is carried out through CPLEX solver of GAMS. A scenario tree of all uncertainties is generated by the Monte Carlo method. The simulation is implemented in a laptop with Core i7 up to 3.5 GHz CPU, 12 GB RAM (DDR4), and 4 MB Cash.

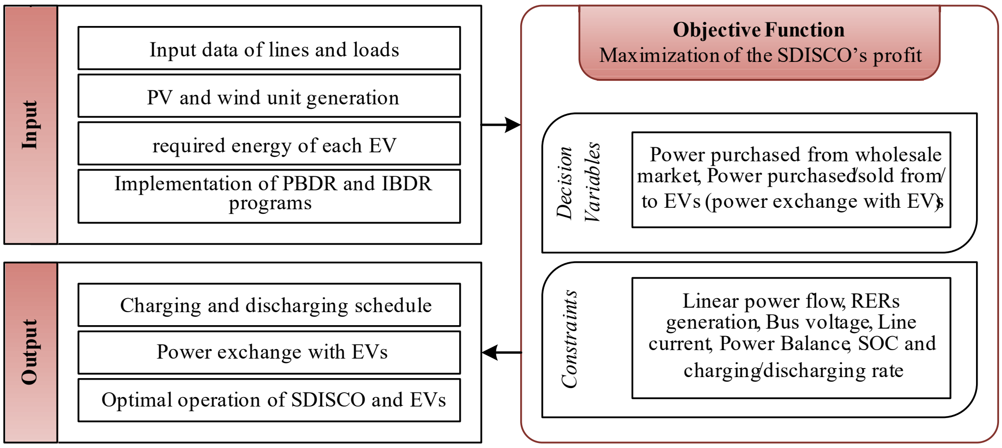

Fig. 2. Framework of the proposed model

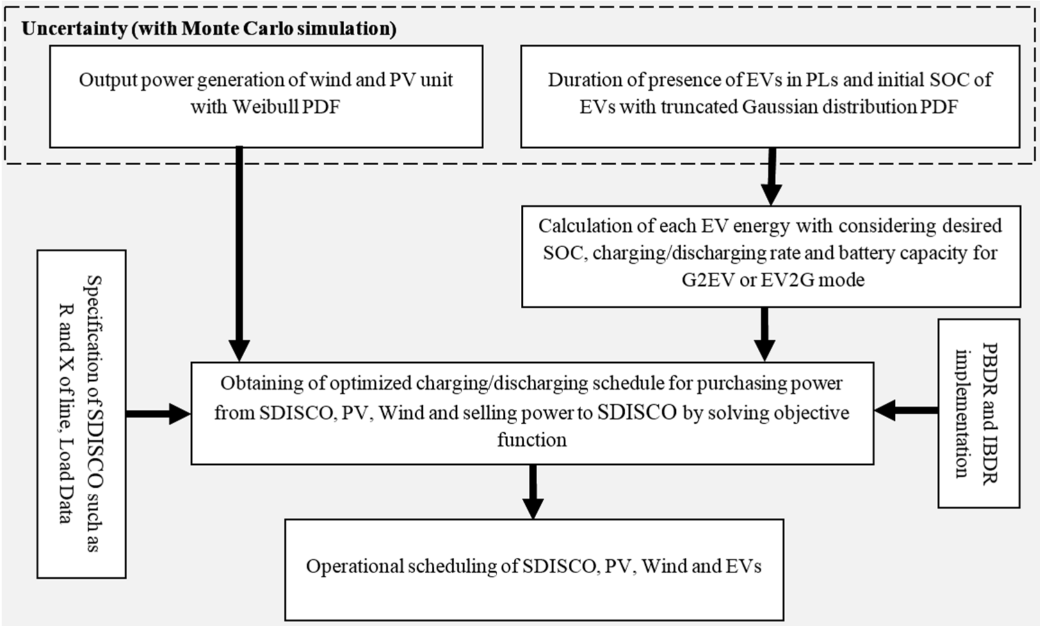

Fig. 3. Flowchart of the stochastic operational scheduling of the SDISCO

5. Numerical Studies and Discussion

The proposed methodology is tested on the standard IEEE 15-bus distribution system over a 24-h period. The data of this test system are shown in Fig. 4 [42]. A wind turbine and a PV system are installed on bus 12 with a rated power of 200 *kW*. For the wind turbine, the cut-in, nominal, and cut-out speeds were 4, 14, and 25 *m/s*. The shape and scale indices for the wind generation are 2 and 6.5, respectively [35]. For PV generation, the rated illumination intensity is 1000 $w.m^{-2}$, and the shape and scale indices are 1.8 and 5.5, respectively [35]. The modified details of EVs' probability distributions are presented in Table 1 [32]. The PL is installed on bus 11. It is assumed that 100 EVs can be parked in the PL. The power factor of all loads is 0.95 lagging.

The wind and PV units are also assumed to have a fixed power factor equal to 1. Twenty-four hours are divided into the off-peak period (1-7 and 22-24), mid-peak period (8-9 and 15-18), and on-peak period (10-14 and 19-21). The charge and discharge efficiencies of EV batteries are assumed to be 90% and 95%, respectively.

The battery capacity is assumed to be 50 kWh, and the maximum charging and discharging rates of EV batteries are 10 kW per hour. Depletion of EV batteries is assumed up to 85% of the rated battery capacity for life-time optimization.

The price of degradation cost of V2G is 0.03 \$/kWh [43]. The price elasticity of the demand is considered as listed in Table 2 [21]. To study the operational scheduling, various PBDR and IBDR programs are considered, as presented in Table 3. The hourly prices of the energy market in RTP programs are extracted from [44].

Table 1. Probability distribution of EVs

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

Table 2. Self- and cross-elasticities

	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 3. Cases considered for PBDR and IBDR programs

Program	Electricity price for load, charging and discharging EVs (\$/MWh)	Incentive value (\$/MWh)	Penalty value (\$/MWh)
Base case	171.125 flat rate	0	0
TOU	85.562, 171.125, and 342.25 for off-peak, mid-peak, and on-peak periods, respectively	0	0
CPP	400 at 19, 20, and 21 h and 171.125 at other hours	0	0
RTP	As reference [30]	0	0
TOU+ CPP	85.562,171.125, and 342.25 for off-peak, mid-peak, and on-peak periods, respectively and 400 at 19,20, and 21 h	0	0
EDRP	171.125 flat rate	150	0
CAP	171.125 flat rate	150	50
TOU+ EDRP	85.562,171.125, and 342.25 for off-peak, mid-peak, and on-peak periods, respectively	150	0
TOU+ CAP	85.562,171.125, and 342.25 for off-peak, mid-peak, and on-peak periods, respectively	150	50

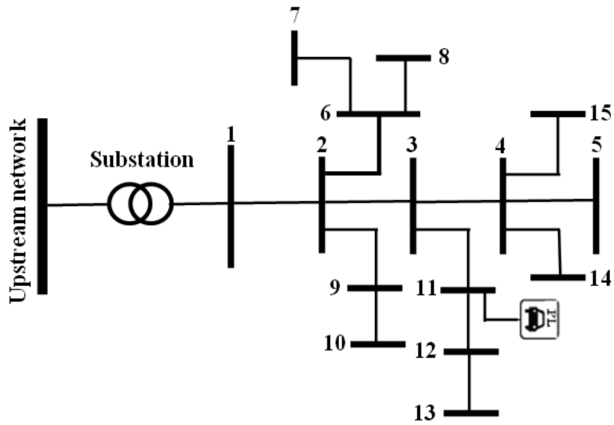

Fig. 4. The considered 15-bus distribution system

For an accurate and comprehensive study of the impacts of DR programs, RERs, and EVs on the operation of the SDISCO, the profit, peak, and loss are investigated in four cases. It is noted that the demand of the SDISCO in the presence of EVs could increase 1 MW during the off-peak and mid-peak periods because of the presence of 100 EVs with a maximum charging rate of 10 kW per hour. The same amount of power with the smart charging/discharging during the on-peak period is available for the SDISCO to meet the customers' demand.

Moreover, as shown in Table 3, nine programs are considered for a comprehensive review of the impact of DR programs. In this paper, it is assumed that the total number of signed contracts for the participating customers in DR programs is equal to 20% of the total customers' demand during the scheduling period. In the base case, the flat rate price is implemented where no DR program is adopted.

Therefore, the four cases are as follows:

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

The profit of the SDISCO and the peak and loss in the four cases are shown in Table 4. By comparing the data provided in Table 4, from different viewpoints, the following results can be obtained:

Profit point of view

1. In each program, case 4, i.e., SDISCO with EVs by smart charging/discharging with wind and PV units, results in the highest profit.
2. Among PBDR programs, RTP is the worst program in terms of profit. Because in the third and fourth cases, EVs do not participate in the smart discharging program, and the results are similar to those for the first and second cases. Furthermore, the CPP is the best program in terms of profit.
3. Among IBDR programs, the CAP is better than EPDR.
4. Among the combined programs, TOU+CAP is the best combination.

Network Loss point of view

1. In each DR program, case 2, i.e., SDISCO with EVs by controlled charging with wind and PV units, leads to the lowest loss. Because in this case, in addition to the use of RERs, EVs are charged in 1 or 2 h only, and the SDISCO purchases less power from the wholesale market.
2. Among PBDR programs, the RTP is the worst program in terms of loss.
3. Among IBDR programs, the CAP is better than EPDR.
4. Among the combined programs, TOU+CAP is the best combination.

Peak point of view

1. In each program, case 3, i.e., SDISCO with EVs by smart charging/discharging without wind and PV units, leads to the highest peak. Because, in this case, because of the lack of RERs and a very high charging/discharging the EVs, more power is purchased from the wholesale market.
2. Among PBDR programs, the TOU+CPP is the worst program in terms of peak.
3. Among IBDR programs, the CAP is better than EPDR.
4. Among the combined programs, TOU+CAP is the best combination.

As can be seen in the first program, the profits of the SDISCO, even by the controlled charging of the EVs, are negative. It is shown that the penetration of EVs in the future will challenge the distribution company. Furthermore, in 25 programs, despite the encouraging incentives for consumers to reduce their consumption, the SDISCO still faces a negative profit. Therefore, it is very cost-effective for the SDISCO to use RERs, appropriate DR programs, and a smart charging/discharging mode of EVs.

Table 4. Technical comparison of the programs

Program no.	Programs	Case	Loss (kW)	Profit ($)	Peak (kW)
1		1	644.59	-268.833	2124.29
2	Flat rate	2	554.35	596.782	1975.34
3		3	721.90	692.658	2511.07
4		4	630.32	1552.66	2360.76
5		1	635.54	842.128	2227.60
6	TOU	2	547.65	1705.71	2078.49
7		3	720.49	1293.42	2534.08
8		4	633.50	2150.32	2383.69
9		1	652.67	176.978	2390.68
10	RTP	2	560.20	1043.39	2171.92
11		3	652.67	176.978	2390.68
12		4	560.20	1043.39	2171.92
13		1	624.90	922.112	2143.56
14	CPP	2	537.98	1786.29	1994.57
15		3	705.64	1874.30	2530.45
16		4	617.86	2732.80	2380.07
17		1	631.52	1066.75	2232.46
18	TOU + CPP	2	543.74	1930.29	2083.34
19		3	717.63	1517.46	2538.97
20		4	631.20	2374.01	2388.56
21		1	602.50	210.618	2169.19
22	CAP	2	516.79	1074.04	2020.16
23		3	693.36	1165.41	2556.22
24		4	607.94	2022.05	2405.75
25		1	611.99	-198.207	2157.96
26	EDRP	2	525.99	665.457	2008.95
27		3	700.1	757.938	2544.93
28		4	613.34	1615.43	2394.50
29		1	607.68	288.223	2261.28
30	TOU + EDRP	2	522.46	1150.26	2112.12
31		3	702.84	734.252	2567.94
32		4	618.14	1930.22	2417.44
33		1	598.41	489.367	2272.50
34	TOU + CAP	2	515.86	1350.235	2123.34
35		3	697.24	933.500	2579.23
36		4	611.45	1786.30	2428.69

In the following, the prioritization of DR programs based on some indices is performed by using the TOPSIS and entropy method [21]. The TOPSIS is one of the most important techniques for solving multiattribute decision making (MADM) problems. It is based on the basic rule that the chosen alternative should be as far as possible from the negative ideal solution and as close as possible to the positive ideal solution. The negative ideal solution maximizes the cost criteria and minimizes the benefit criteria, whereas the positive solution maximizes the benefit criteria and minimizes the cost criteria. The optimal performance is, therefore, that the alternative is the farthest from the negative ideal solution and the closest to the ideal solution. The steps in the implementation of this technique are given below.

Step 1: Establishing the decision matrix

First, the decision matrix for the analysis must be created. In this paper, the decision matrix has *m* alternatives, i.e., PBDR and IBDR programs, presence or absence of RERs, controlled charging or smart charging/discharging the EVs, and *o* attributes, i.e., the SDISCO's profit, loss, and peak.

Therefore, a 32×3 matrix is formed for the analysis. It is noted that programs 1 and 25 because of the negative profits, and programs 11 and 12 because of the similarity to programs 9 and 10, respectively, are eliminated.

Step 2: Normalizing the decision matrices

A decision matrix is normalized by a normalization method as presented in Eq. (44). X_{lk} is the performance of the *l-th* alternative regarding *k-th* attribute. r_{lk} represents the normalized intersection of each alternative and attribute.

$$r_{lk} = \frac{X_{lk}}{\sqrt{\sum_{l=1}^{m} X_{lk}^{2}}} \tag{44}$$

Step 3: Determining the weight by the entropy method

The weights attributed to the various criteria represent the importance of each criterion in the assessment procedure and directly affect the ranking order of alternatives. The methods for finding the weights are grouped into two classes: subjective and objective weighting methods. The objective methods, such as entropy and multiple objective programming, allow the vector weights to be obtained without any influence from the decision maker's judgments. In other words, the objective weighting methods are based only on a mathematical computation using the measurement data and information. Among the objective weighting methods, the Shannon entropy concept is a particularly useful approach for assigning weights to criteria. To calculate the weights by the entropy measure, the decision matrix has to be first normalized by adjusting the values measured on different scales to a notionally common scale. Therefore, Eq. (45) is used for calculating each weight based on the entropy method.

$$P_{lk} = \frac{X_{lk}}{\sqrt{\sum_{l=1}^{m} X_{lk}}} \qquad \mathrm{l = 1,...,m \quad k = 1,...,o} \tag{45}$$

After normalization, by Eq. (46), the entropy values are computed.

$$E = \frac{-1}{Ln(m)} \sum_{\mathrm{l=1}}^{\mathrm{m}} \mathrm{P_{lk} \times Ln(P_{lk})} \qquad 0 \le \mathrm{E} \le 1 \tag{46}$$

where m is the number of alternatives. The larger the E, the less is the information transmitted by the *kth* criterion. Then, the degree of divergence *(d_k)* of the information of each criterion can be obtained by Eq. (47):

$$d_k = 1 - E_k \tag{47}$$

A larger d_K is the most important *kth* criterion for the problem. Therefore, the weight is calculated by Eq. (48):

$$W_k = \frac{d_k}{\sum_{k=1}^{n} d_k} \tag{48}$$

This expresses the degree of importance of the *kth* criterion. Furthermore, the weights are improved, if the decision maker has a previous consideration about the importance factor of attributes. Improved weights are described in Eq. (49).

$$IW_k = \frac{\lambda_k \times W_K}{\sum_{k=1}^{n} \lambda_k \times W_K} \tag{49}$$

Step 4: Creating weighted decision matrices

The weighted normalized decision matrix is constructed by multiplying the decision matrix with its associated weights as in Eq. (50).

$$V_{lk} = W_k \times r_{lk} \tag{50}$$

Step 5: Determining ideal and nonideal solutions

In this step, the ideal and nonideal alternatives are identified. The ideal solution is the maximum value for the positive criterion and the minimum value for the negative criterion in each column. Similarly, the nonideal solution V_k^- is the minimum and the maximum values for the positive and the negative criteria, respectively, in each column. These values are calculated using Eqs. (51) and (52).

$$V_k^+ = \left(\max \ V_{lk} \left| k \in k^+ \right|, \min \ V_{lk} \left| k \in k^- \right| \right) \qquad l = 1,\ldots,m \tag{51}$$

$$V_k^- = \left(\min \ V_{lk} \left| k \in k^+ \right|, \max \ V_{lk} \left| k \in k^- \right| \right) \qquad l = 1,\ldots,m \tag{52}$$

Step 6: Calculation of Separation Measure

In this step, the Euclidean distance of each alternative and the ideal and nonideal solution is formulated by Eqs. (53) and (54), respectively.

$$SS_l^+ = \sqrt{\sum_{k=1}^{n} \left(V_{lk} - V_k^+\right)^2} \qquad l = 1,\ldots,m \tag{53}$$

$$SS_l^- = \sqrt{\sum_{k=1}^{n} \left(V_{lk} - V_k^-\right)^2} \qquad l = 1,\ldots,m \tag{54}$$

Step 7: Calculation of relative closeness to the ideal reference point

Finally, the value of relative closeness (RC) is calculated by Eq. (55). A higher C_l coefficient is the most effective program (alternative).

$$C_l = \frac{SS_l^-}{SS_l^+ + SS_l^-} \qquad l = 1,\ldots,m \tag{55}$$

The flowchart of the proposed portfolio sorting the operational scheduling programs is shown in Fig. 5.

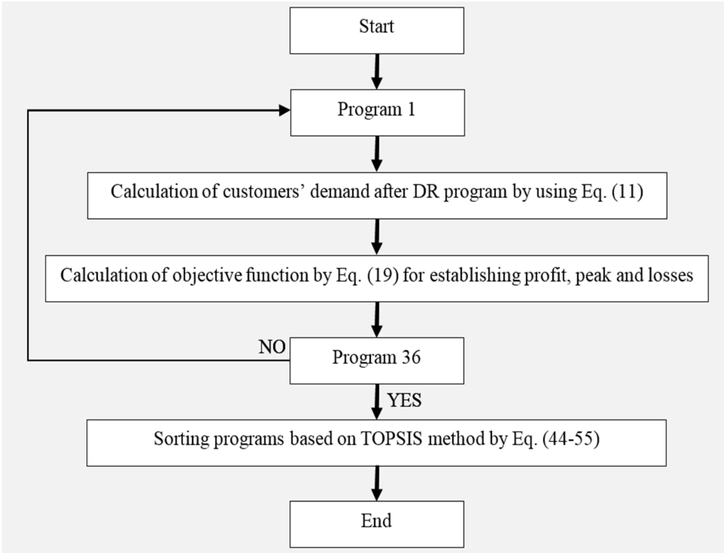

Fig. 5. Flowchart of the proposed portfolio sorting the operational scheduling programs

After establishing the decision matrix (32×3), the attributes are weighted by the entropy method. These weights are shown in Table 5. The SDISCO also modifies the weights depending on its decision. In fact, the weights of loss, profit, and peak can be modified by the following factor:

$\lambda_n = \{0.3, 0.35, 0.35\}$

The improved weights of attributes are obtained using the above factors in Eq. (49) and presented in Table 5. Now, to determine the priorities of implementing different programs, the TOPSIS method is established. Table 6 shows the results of the prioritization. As it can be seen, program 16, i.e., CPP with EVs by smart charging/discharging with wind and PV units, has the highest priority. On the contrary, program 9, i.e., RTP with EVs by controlled charging without wind and PV units, has the lowest priority.

Table 5. Weights and improved weights of attribute

Attribute	Losses	Profit	Peak
Weights	0.038	0.942	0.0190
Improved weights	0.033	0.947	0.0192

Table 6. Priority of programs

Programs	Program No.	SS_l^+	SS_l^-	C_l	Priority
Flat rate	1	-	-	-	-
	2	0.281	0.045	0.138	28
	3	0.271	0.055	0.170	26
	4	0.178	0.148	0.453	12
TOU	5	0.255	0.072	0.219	23
	6	0.162	0.164	0.504	9
	7	0.206	0.120	0.368	15
	8	0.114	0.212	0.650	3
RTP	9	0.326	8E-04	0.002	32
	10	0.233	0.093	0.286	20
	11	-	-	-	-
	12	-	-	-	-
CPP	13	0.246	0.080	0.246	22
	14	0.153	0.173	0.53	8
	15	0.144	0.183	0.559	6
	16	0.051	0.275	0.842	1
TOU + CPP	17	0.231	0.096	0.293	18
	18	0.138	0.189	0.578	5
	19	0.182	0.144	0.442	13
	20	0.090	0.236	0.724	2

CAP	21	0.323	0.004	0.012	31
	22	0.230	0.097	0.296	19
	23	0.220	0.106	0.326	16
	24	0.128	0.198	0.608	4
EDRP	25	-	-	-	-
	26	0.274	0.053	0.161	27
	27	0.264	0.063	0.191	24
	28	0.172	0.155	0.474	10
TOU + EDRP	29	0.314	0.012	0.037	30
	30	0.222	0.105	0.321	17
	31	0.266	0.060	0.184	25
	32	0.138	0.189	0.578	11
TOU + CAP	33	0.293	0.034	0.103	29
	34	0.200	0.126	0.387	14
	35	0.245	0.081	0.249	21
	36	0.153	0.173	0.530	7

In the following, the best program, i.e., program 16, is investigated more precisely. First, Table 7 shows the income and cost of each section of the objective function. It is observed that the SDISCO will gain more profit by encouraging EV owners to participate in the V2G mode.

Table 7. Amount of the revenue and cost of the objective function ($)

Income	
Selling energy to EV owners	949.253
Selling energy to customers	6380.311
Cost	
Purchasing power from the wholesale market	4052.503
Energy purchased from EV owners for meeting the customers' demand	463.076
Battery depreciation	81.183
Implementation of PBDR and IBDR programs	-
Profit	
Income –Cost	2732.802

The amount of the customers' demand with/without the implementation of the DR program is shown in Fig. 6. The figure shows that during the on-peak period, the amount of load is reduced, and this amount is transmitted to the off-peak and mid-peak periods. Thus, during these periods, the customers' demand increases slightly. As it can be seen, based on Eq. (36), any unexpected peak load is avoided. In fact, by implementing the CPP program, the reduction of power consumption of customers' demand is about 756.7 kW. The initial customers' demand was 32170.1 kW, which is reduced to 31413.4 kW.

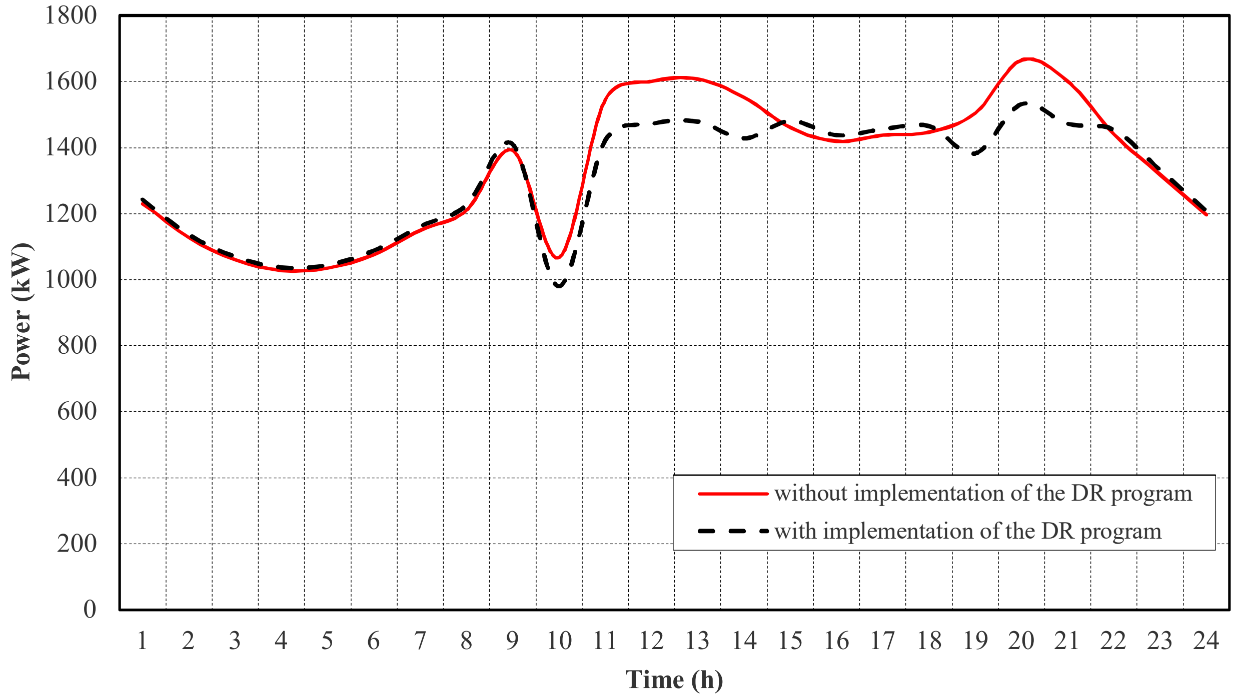

Fig. 6. Customers' demand with/without the implementation of the DR program

Fig. 7 shows the amount of power purchased from the wholesale market and customers' demand. According to Fig. 7, during the off-peak period, i.e., from 1:00 to 6:00, because of the absence of EVs and the presence of RERs, these resources provide a part of power needed for the SDISCO. From 7:00, with the arrival of EVs to the PL, the amount of power purchased from the wholesale market increases because of the charging of the EVs. However, during the first on-peak period, i.e., from 11:00 to 14:00, the amount of power purchased significantly reduces, because during this period, the SDISCO uses the RER generation and power purchased from EV owners for meeting the customers' demand. This reduction is lower at 13:00, because the energy price in this hour is lower than that in the rest of peak hours, and the SDISCO purchases power from the wholesale market. Once again, an increase in power is observed during the mid-peak period because of the charging of the EVs. This period is closer to the second on-peak period. As mentioned for the on-peak period, EVs are not charged, thus enabling them to reach their optimal SOE, i.e., 45 kWh, and the power purchased from the wholesale market dramatically increases. During the second on-peak period, i.e., from 19:00 to 21:00, because EVs are not charged and RER generation, the power purchased from the wholesale market decreases. Afterwards, because of the departure of EVs from the PL, the power purchased from the wholesale network decreases. Because some EVs are parked until around 24:00, the smart charging/discharging program shifts the charge of some EVs to 22:00. Thus, at this hour, the power purchased from the wholesale network increases. Indeed, the amount of power purchased from the wholesale network is 30879.54 kW, of which 25722.09 kW is used for meeting the customers' demand. Table 8 shows the amount of power provided by the SDISCO and RERs.

Table 8. Amount of power provided by the SDISCO and RERs for meeting the customers demand (kW)

SDISCO to load	25722.09
Wind unit to load	2454.25
PV unit to load	593.47

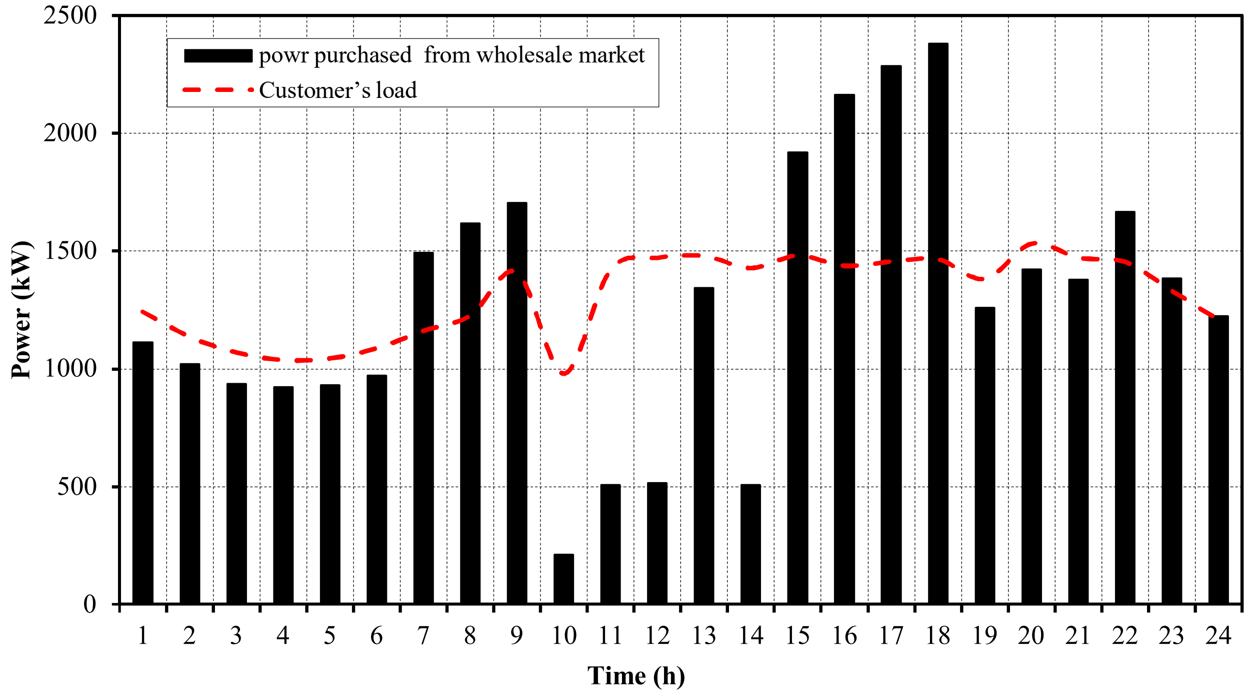

Fig. 7. Power purchased from the wholesale market and customers' demand

Figs. 8 and 9 show the smart charge/discharge scheduling of 100 EVs in PLs. The total amount of energy for charging the EVs is 5547.13 kWh, where the highest power is 1 MW at 18:00. In fact, at this time, because it is close to the second on-peak period, and after this time, there are indeed very few EVs in the PL, and there is no time for recharging the EVs; thus, all EVs are charged. Table 9 shows the amount of power provided by the SDISCO and RERs. The amount of energy transferred from the PL back to the SDISCO is about 2706.07 kWh; therefore, the highest power of this transfer is 751.48 kW at 12:00. As already stated, because the energy price of the wholesale market at 13:00 is lower than the discharging price of EVs, the SDISCO tries to use the wholesale network and RER generation at this hour for meeting the customers' demand. Because the number of EVs in the range 20:00-24:00 is low and there is no enough time for charging the EVs, the amount of power injected to the SDISCO is zero during this period.

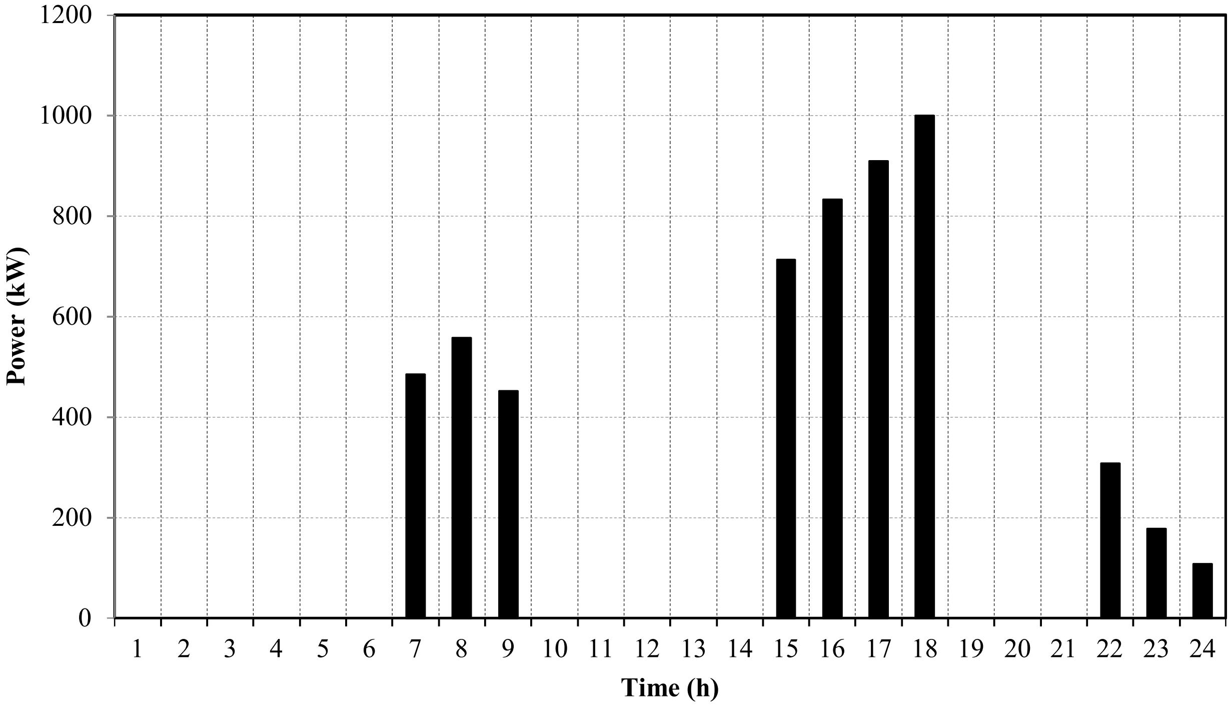

Fig. 8. The total amount of power for charging the EVs

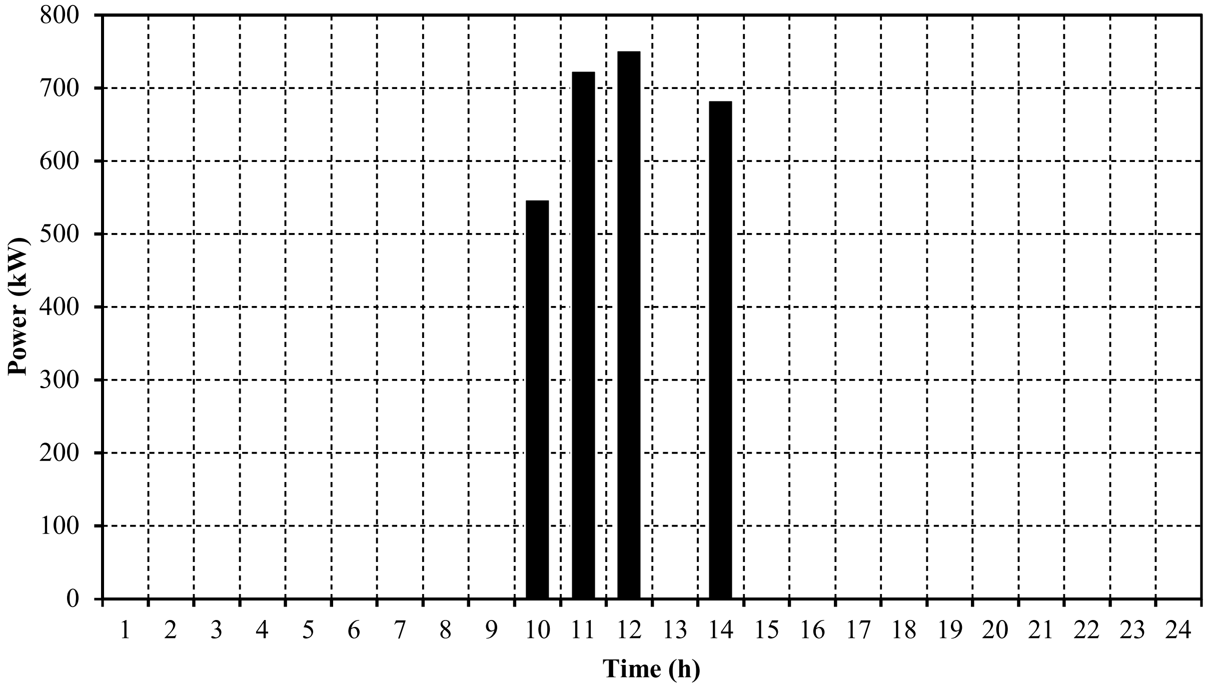

Fig. 9. Power transferred from the PLs back to the SDISCO

Table 9. Amount of power provided by the SDISCO and RERs for charging the EVs (kW)

SDISCO for charging the EVs	4672.31
Wind generation unit for charging the EVs	550.47
PV unit for charging the EVs	324.35

Typically, the SOE curve of a typical EV with an initial SOE of 29.9 kWh, arrival time of 7:00, and departure time of 20:00 is shown in Fig. 10. It is noted that the minimum and maximum charge levels of all EVs are 7.5 and 45 kWh, respectively.

As seen, after an EV enters the PL, the charging starts. The EV is then discharged during the first on-peak period. At the mid-peak period, the EV is charged to reach the desired SOE, i.e., 45 kWh. After the second on-peak period, the EV leaves the PL; thus, the smart charging/discharging program is completed at 18:00.

The network loss is also shown in Fig. 11. The total loss of the SDISCO is 617.86 kW. Loss decreases during the on-peak period and increases during the mid-peak and off-peak periods because of the discharging and charging of the EVs, respectively. Table 10 shows the contribution of each source to the loss incurred.

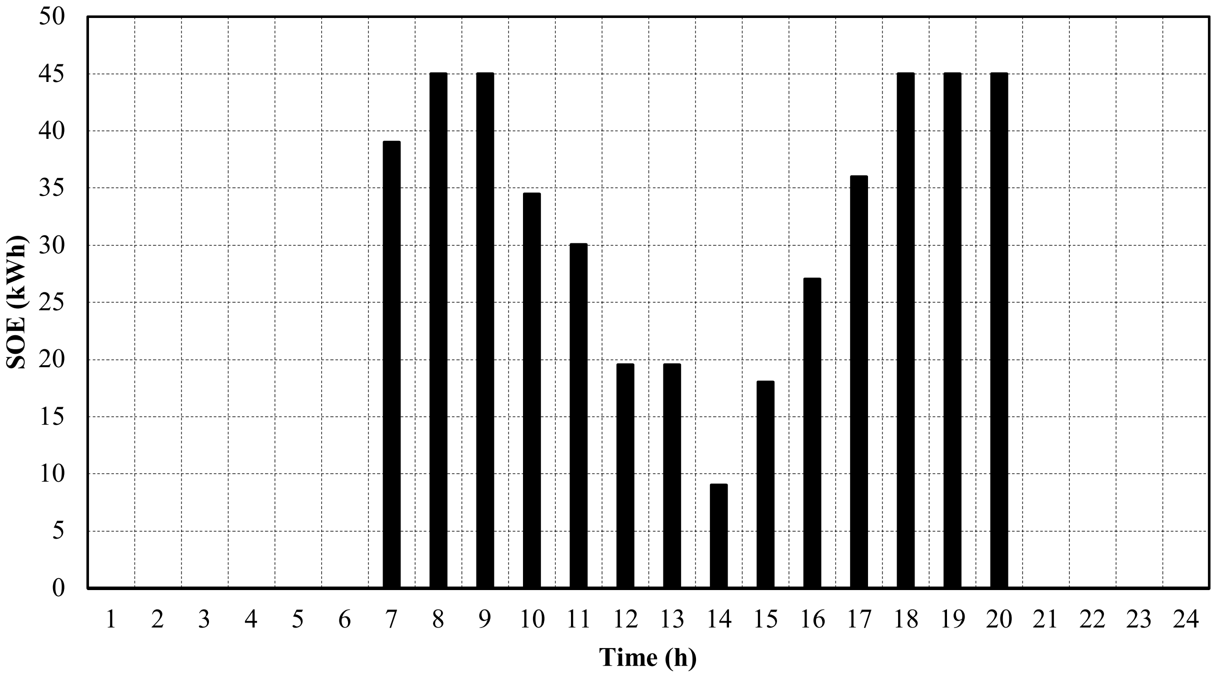

Fig. 10. SOE curve of a typical EV

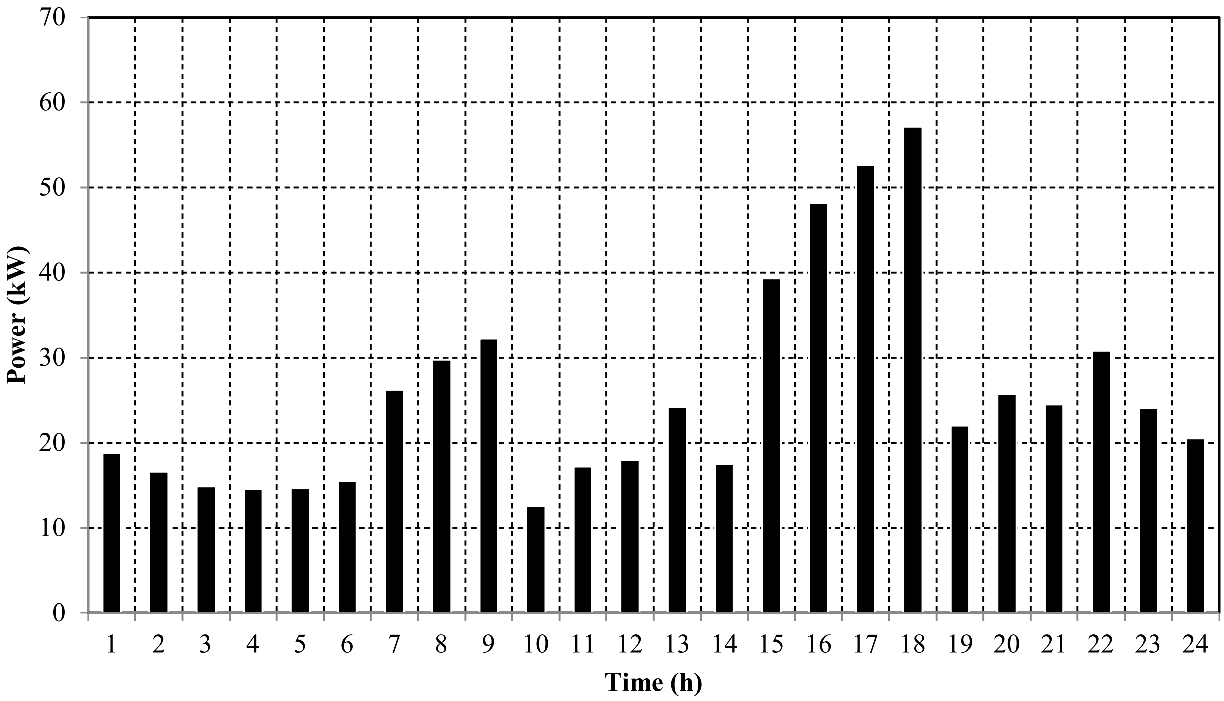

Fig. 11. Network loss

Table 10. Amount of power provided by the SDISCO and RERs for the loss incurred (kW)

SDISCO for the loss incurred	485.137
Wind generation for the loss incurred	63.429
PV unit for the loss incurred	10.845
Discharging power of EVs for the loss incurred	58.449

Fig. 12 illustrates the operational scheduling of RERs and SDISCO. From Fig. 12 and its comparison with the customers' demand (i.e., Fig. 7), during the time of charging the EVs, the overall load of the SDISCO increases, and the amount of power purchased from the wholesale market is high. Furthermore, during the on-peak period, the power purchased from the wholesale market significantly reduces because of the power injection of EVs to the network for supplying customers' demand. Moreover, the power generation of a wind unit has a larger contribution in supplying customers' demand and charging the EVs than the PV generation.

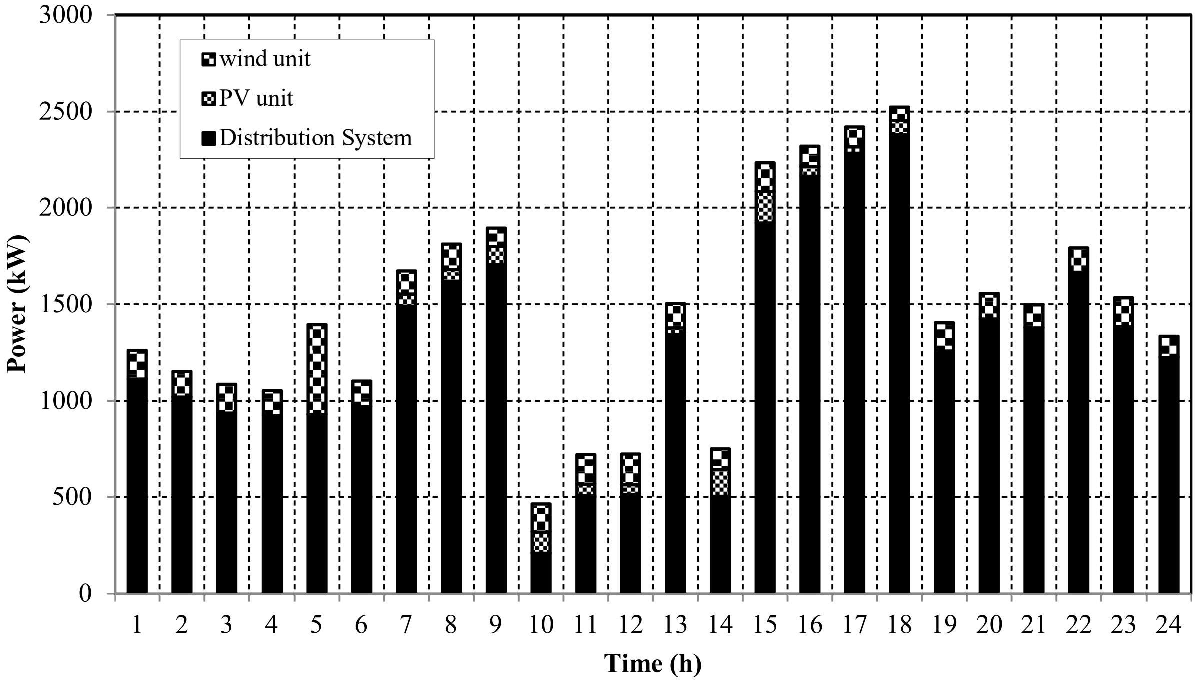

Fig. 12. Operational scheduling of the distribution system, i.e., wind and PV units, during the 24-h period

For investigating the impact of the number of scenarios on the value of objective function and the solution time, these values are calculated with different scenarios. The initial number of scenario is 1000. Then, by using the Kantorovich distance approach, the number of scenarios is reduced to 8. In fact, the main problem is solved with 8 scenarios. As previously stated, with the increase in the number of scenarios, the number of variables in the model increases, the problem becomes more complicated, and the solution time increases. The results are shown in Fig 13. Fig 13 shows that there is a little difference between the amount of the objective function (about 1.8% reduction at the worst condition, i.e., 16 scenarios), while the problem solution time dramatically changes. These results prove the usefulness of scenario reduction for solving this problem.

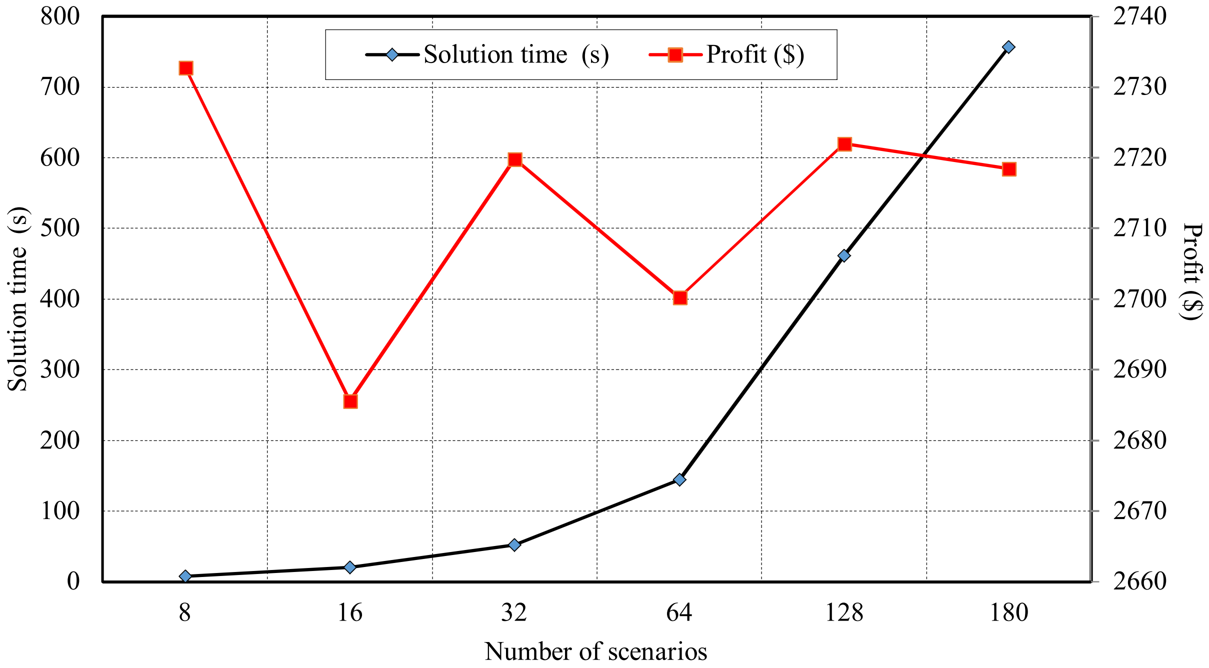

Fig 13. Impact of the number of scenarios on the objective function and solution time

One of the most important characteristics of EVs is the initial SOE. Therefore, in Table 11, we show the results of changes in the mean value of initial SOE and its impact on the profit, network loss, and peak. A change in this value does not affect the peak, because the peak network occurs at 18:00, when all EVs are charged because of their participation in the first discharge schedule, i.e., 10:00-14:00. Furthermore, with a higher mean value of SOE, EVs require less energy for obtaining the desired SOE. Therefore, the SDISCO purchases less energy from the wholesale market, and consequently, the profit increases and the network loss decreases.

Table 11. Sensitivity analysis of changing the mean value of initial SOE

Mean Value of SOE	Peak (kW)	Loss (kW)	Profit ($)
35%	2380.07	621.39	2662.47
40%	2380.07	620.42	2686.06
45%	2380.07	619.24	2710.33
50%	2380.07	617.86	2732.80
55%	2380.07	616.65	2753.70

To evaluate the EVs' participation in the DR programs, we model two cases:

- Case A: Implementation of DR programs for customers and EVs (i.e., EVs also participate in DR programs).
- Case B: Implementation of DR programs only for customers. (i.e., EVs do not participate in DR programs).

In case A, the price of selling energy to the customers and EVs is based on the DR programs. The price of purchase energy from the EVs is also equal to this price. However, in case B, only the selling energy to the customers is based on the energy price of DR programs. In this case, the prices of selling energy to EVs and purchasing energy from EVs are flat rate. The SDISCO's profit, network loss, and peak are calculated in cases A and B, with EVs by smart charging/discharging with wind and PV units.

Table 12 shows that there is only a change in the peak value in the RTP program. In case A, the price of purchasing energy from EVs is higher than that from the wholesale market. Hence, the SDISCO prefers that EVs do not participate in the smart discharging schedule.

For this reason, the SDISCO purchases less energy from the wholesale market for charging the EVs; therefore, the peak decreases. However, in case B, the price of purchasing energy from EVs is much lower than that from the wholesale market. Therefore, the SDISCO prefers that EVs participate in the smart charging/discharging schedule. Hence, the SDISCO purchases more energy from the wholesale market; thus, the peak increases.

Table 12. Comparison of peak in cases A and B

Case A			Case B		
Load	EV	Peak (kW)	Load	EV	Peak (kW)
Flat	Flat	2360.76	Flat	Flat	2360.76
TOU	TOU	2383.69	TOU	Flat	2383.68
CPP	CPP	2380.07	CPP	Flat	2380.27
RTP	RTP	2171.92	RTP	Flat	2380.64
TOU+ CPP	TOU+ CPP	2388.56	TOU+ CPP	Flat	2388.56
EDRP	EDRP	2394.50	EDRP	Flat	2394.50
CAP	CAP	2405.75	CAP	Flat	2405.75
TOU+ EDRP	TOU+ EDRP	2417.44	TOU+ EDRP	Flat	2417.43
TOU+ CAP	TOU+ CAP	2428.69	TOU+ CAP	Flat	2428.69

Table 13 shows that there is a change in the profit value in the PBDR and PBDR+IBDR programs. As mentioned above, in case B, the price of purchasing energy from EVs is much lower than that from the wholesale market; thus, the SDISCO prefers that EVs participate in the smart charging/discharging schedule. Subsequently, the SDISCO gains more profit, because it sells more energy to EVs and purchases less energy from the wholesale market during the on-peak period due to the V2G capability. Furthermore, in the PBDR program, because the price is unchanged, the SDISCO's profit is not changed.

Table 13. Comparison of profit in cases A and B

Case A			Case B		
Load	EV	Profit ($)	Load	EV	Profit ($)
Flat	Flat	1552.660	Flat	Flat	1552.66
TOU	TOU	2150.319	TOU	Flat	2665.024
CPP	CPP	2732.802	CPP	Flat	2738.827
RTP	RTP	1043.391	RTP	Flat	2218.943
TOU+ CPP	TOU+ CPP	2374.001	TOU+ CPP	Flat	2888.705
EDRP	EDRP	1615.433	EDRP	Flat	1615.433
CAP	CAP	2022.049	CAP	Flat	2022.049
TOU+ EDRP	TOU+ EDRP	1589.808	TOU+ EDRP	Flat	2104.473
TOU+ CAP	TOU+ CAP	1786.293	TOU+ CAP	Flat	2292.755

From the aforementioned data, and according to Table 14, significant changes in the amount of loss occur only in the RTP program. In the rest of the programs, the amount of change in loss is negligible.

Table 14. Comparison of loss in cases A and B

Case A			Case B		
Load	EV	Loss (kW)	Load	EV	Loss (kW)
Flat	Flat	630.32	Flat	Flat	630.32
TOU	TOU	633.50	TOU	Flat	634.64
CPP	CPP	620.38	CPP	Flat	620.38
RTP	RTP	560.20	RTP	Flat	645.22
TOU+ CPP	TOU+ CPP	631.20	TOU+ CPP	Flat	632.35
EDRP	EDRP	613.34	EDRP	Flat	613.34
CAP	CAP	607.94	CAP	Flat	607.94
TOU+ EDRP	TOU+ EDRP	618.14	TOU+ EDRP	Flat	619.56
TOU+ CAP	TOU+ CAP	611.45	TOU+ CAP	Flat	613.32

5.1. Sensitivity Analysis

A sensitivity analysis is carried out to investigate the effects of different factors on the operational scheduling of the SDISCO in four cases.

The sensitivity analysis includes the change in the number of EVs, the rated power of PV and wind units, and participating customers in DR programs. Table 15 shows the results of this analysis, and from the table, the following results are obtained:

- In each case, with the increase in the number of EVs, the power purchased from the wholesale market increases. By comparing the first and second cases with the third and fourth cases, respectively, an increase in the participation of customers in DR programs reduces the power purchased. With the increase in in the rated power of RERs, the power purchased from the wholesale market significantly reduces. Therefore, the use of RERs is more appropriate than the implementation of DR programs.
- By comparing the first and second cases, the amount of network loss increases with the increase in the number of EVs due to the high power consumption, which is purchased from the wholesale market. However, by comparing the third and fourth cases, the network loss decreases, because of the high rated power of PV and wind units. In fact, the SDISCO uses RERs and V2G mode, instead of the wholesale market, to supply the customers' demand, especially during the on-peak period. As a result, the SDISCO purchases less power from the wholesale market. Fig. 14 shows that the SDISCO during the first on-peak period (except at 13:00) does not purchase power from the wholesale market.
- With the increase in all factors, the profit of the SDISCO also increases.
- Because in cases 1 and 2, the rated power of RERs is less than that in cases 3 and 4, charging and discharging the EVs in cases 1 and 2 is more than that in cases 3 and 4. Typically, according to Fig. 15, the first EV in case 3 is charged 4 times and discharged 3 times, while this EV in case 1 is charged 5 times and discharged 4 times. This difference in charging/discharging with different charging/discharging rates causes a difference in the power charging/discharging values. In fact, by using RERs with a high rated capacity, the SDISCO tries to use these resources to supply the customers and EVs, to pay less cost for the V2G mode.

Table 15. Sensitivity analysis

No. of EV	Power purchased from the wholesale market (kW)	Loss (kW)	Profit ($)	Charging power of EVs (kW)	Discharging power of EVs (kW)	Peak (kW)	Solution time (s)
Case 1: participating customers in DR programs: 20%, Rated power of PV and wind: 200 kW							
50	29367.70	530.70	2144.838	2795.59	1362.60	1853.57	5.891
100	30879.54	617.86	2732.802	5547.13	2706.07	2380.07	7.453
150	32593.75	740.33	3203.046	8313.99	4064.35	2795.70	8.687
Case 2: participating customers in DR programs: 30%, Rated power of PV and wind: 200 kW							
50	28984.13	524.51	2192.727	2795.59	1362.60	1863.16	5.562
100	30497.40	613.10	2780.012	5547.13	2706.07	2389.72	7.563
150	32210.03	735.56	3248.136	8303.21	4055.12	2805.42	8.688
Case 3: participating customers in DR programs: 20%, Rated power of PV and wind: 1 MW							
50	14132.73	1424.72	5018.267	2276.52	918.80	1251.04	5.657
100	15165.67	1101.48	5390.460	4097.52	1466.65	1795.62	7.329
150	17182.87	941.92	5462.596	5846.49	1954.62	1763.01	8.219
Case 4: participating customers in DR programs: 30%, Rated power of PV and wind: 1 MW							
50	13855.33	1532.13	4994.070	2225.26	874.97	1260.55	5.656
100	14836.76	1161.99	5350.936	4014.44	1395.61	1803.02	7.109
150	16842.12	995.56	5419.423	5729.25	1854.38	1772.58	8.000

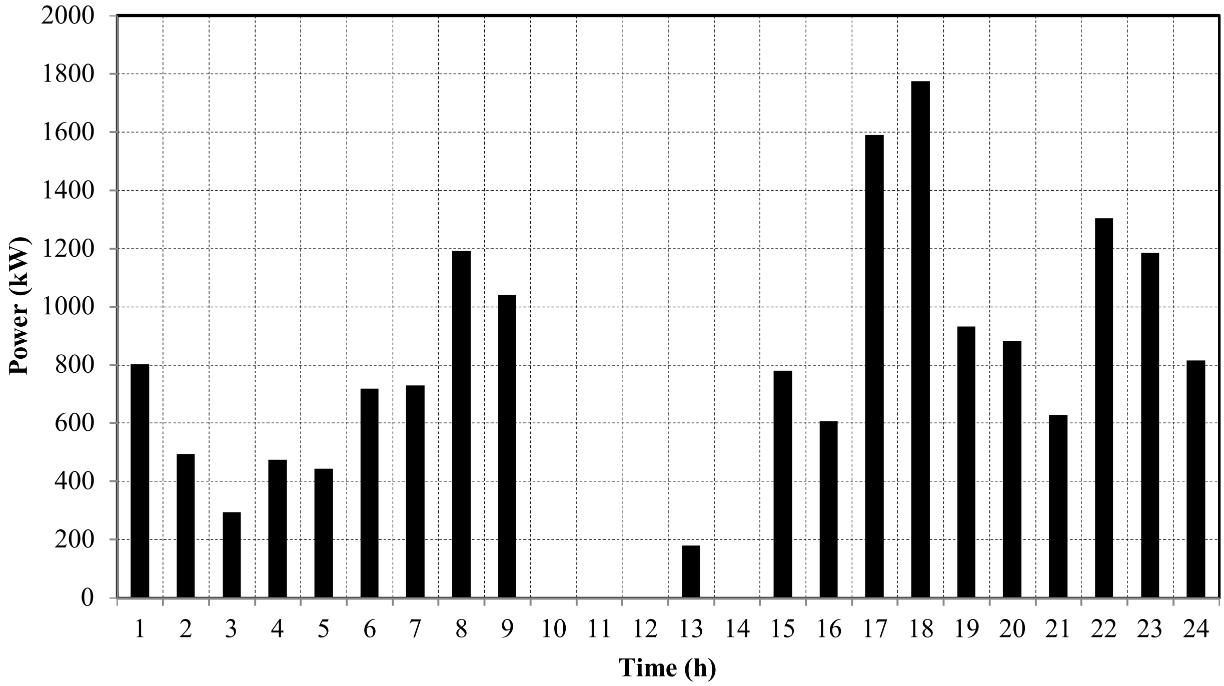

Fig. 14. Power purchased from the wholesale market in case 4 with 150 EVs

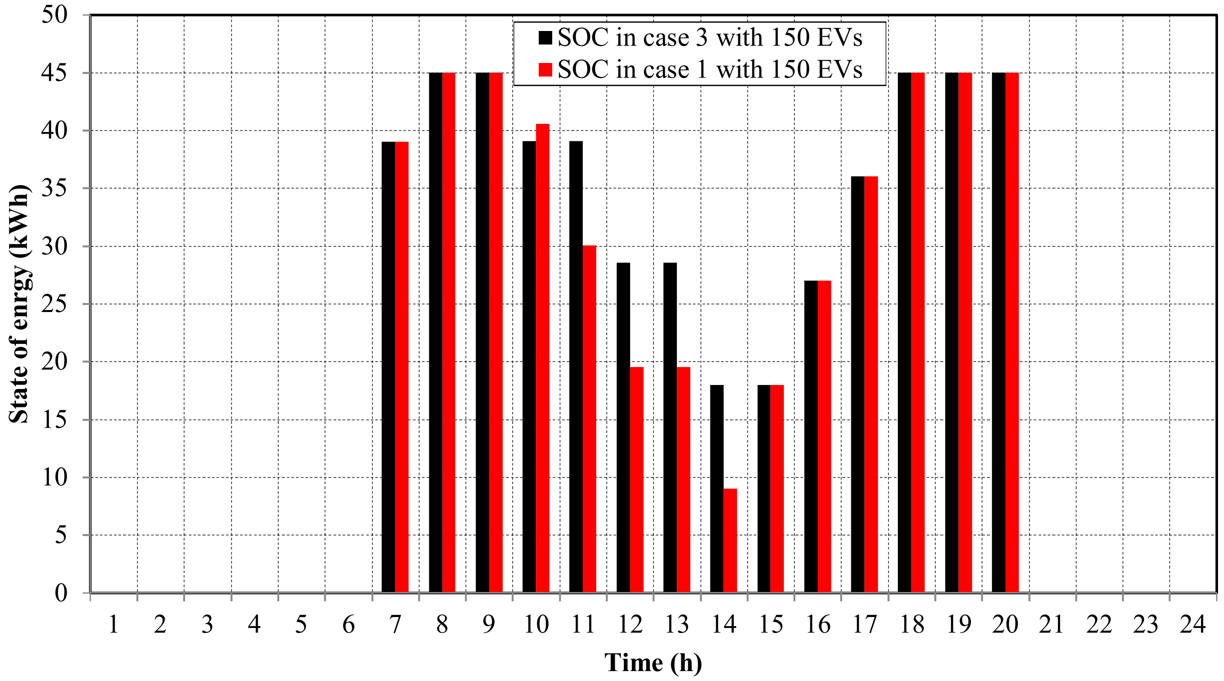

Fig. 15. Comparison of SOE in case 1 and case 3 with 200- and 1000-kW rated power of RERs

6. Conclusions

In this paper, a techno-economic model was developed for the operational scheduling of the SDISCO. The simultaneous consideration of RER and EV uncertainties was modeled, including several groups of PBDR and IDBR programs and system constraints such as nodal voltage, linear power flow, and EV charging/discharging schedule. The impacts of RES size and EV number on the performance of the SDISCO were investigated.

The following results were obtained from the numerical studies.

1. PBDR programs were better than IBDR programs in terms of priority. Hence, on the eight top priority programs, seven programs belonged to PBDR programs.
2. By using a suitable charging/discharging schedule of EVs, EVs' charging was carried out during the off-peak or mid-peak periods. Moreover, EVs' discharging occurred during the on-peak period. This discharging could not occur at 13:00, because at this time, the price of the EVs' discharging power was higher than that of the wholesale market; therefore, the SDISCO preferred to provide power from the wholesale market.
3. By the implementation of the smart charging/discharging schedule of EVs and CPP programs, the SDISCO achieved more profit than other programs.
4. Scenario reduction was useful for solving the problem, because there is a slight deviation between the amounts of the objective function with different scenarios, while the problem solution time dramatically decreases.
5. If the electricity price of charging/discharging the EVs were of flat rate, i.e., EVs did not participate in the DR programs and customers participated in the PBDR and PBDR+IBDR programs, the SDISCO gained more profit because of selling more energy to EVs and purchasing less power from the wholesale market during the on-peak period due to V2G capability.
6. With a larger size of RERs and more number of EVs, the SDISCO had a higher performance (in terms of profit, network loss, and peak); therefore, even during the on-peak period, the SDISCO did not purchase electricity from the wholesale market.

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