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Multi-objective scheduling of electric vehicles in smart distribution system

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ABSTRACT

When preparing for the widespread adoption of Electric Vehicles (EVs), an important issue is to use a proper EVs' charging/discharging scheduling model that is able to simultaneously consider economic and environmental goals as well as technical constraints of distribution networks. This paper proposes a multi-objective operational scheduling method for charging/discharging of EVs in a smart distribution system. The proposed multi-objective framework, based on augmented ε-constraint method, aims at minimizing the total operational costs and emissions. The Vehicle to Grid (V2G) capability as well as the actual patterns of drivers are considered in order to generate the Pareto-optimal solutions. The Benders decomposition technique is used in order to solve the proposed optimization model and to convert the large scale mixed integer nonlinear problem into mixed-integer linear programming and nonlinear programming problems. The effectiveness of the proposed resources scheduling approach is tested on a 33-bus distribution test system over a 24-h period. The results show that the proposed EVs' charging/discharging method can reduce both of operation cost and air pollutant emissions.

1. Introduction

Electric Vehicles (EVs) have often been suggested as a helpful solution to reduce oil consumption and air pollutant emissions where concerns about oil security and availability and the negative environmental impact of petroleum-based transportation systems increase. Due to energy efficiency and environmental advantages over conventional vehicles, the future of EVs seems promising [1,2]. However, the integration of EVs in electric power systems poses new technical, economic, policy and regulatory challenges [3]. Heavy intermittent electrical loads due to EVs' charging/discharging may, in fact, create bottlenecks and limit the capacity supply thus, exposing the power system to severe security risks.

On the other hand, EVs can offer benefits due to their flexibility in charging and discharging time span and introduce a useful concept called "Vehicle-to-Grid" (V2G) capability [4]. V2G is defined as the option to return the stored electrical energy to the grid from the vehicle's battery. In other words, an EV can act as a controllable load as well as a distributed storage device. Being connected to the electricity network when not in use, the battery of an EV can supply power during peak load times and thus increase the reliability of the grid [5,6]. As a result, taking into account the total number of available EVs in a locality, distributed storage capacity provided by V2G can have a relevant impact on distribution system operation.

EV owners may also make money by using the stored energy in their vehicles; the battery of EV can discharge as well as charge according to the owner convenience. Moreover, V2G capability provides some valuable power system services such as regulation, spinning reserve, and peaking capacity [4]. Conversely, the power system operation and control, in which a large number of EVs appears as additional electricity demand, can be significantly changed from the present ones without EVs [7,8], also thanks to the future smart grid that can activate the V2G capability where EVs are intelligently utilized as Distributed Energy Resources (DERs). Although EVs have lots of economical and environmental advantages, they will introduce further complexity to planning and operation of smart grids. So, the integration of EVs into power system requires new methods and more computational resources [7–9].

In [10], a day-ahead energy resource scheduling model for smart grids including a large number of EVs has been proposed. The paper introduced a new demand response model provided by EVs in which the vehicle owners could offer energy reduction or shifting by changing their trip plan. In [11], a real-time load management method for coordinating the charging of multiple Plug-in Electric Vehicles (PEVs) in a smart distribution system has been proposed. The real-time control strategy is based on the minimization of total costs of generated energy and energy losses. In [12], an economic dispatch model considering the uncertainties

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Nomenclature

Acronyms

EV	Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
PEV	Plug-in Electric Vehicle
DER	Distributed Energy Resource
DG	Distributed Generator
DSO	Distribution System Operator
TSO	Transmission System Operator
ISO	Independent System Operator
PLCC	Power Line Carrier Communication
DC	Data Concentrator
MDM	Meter Data Management
DMS	Distribution Management System
EVMS	Electric Vehicle Management System
MINLP	Mixed-Integer Nonlinear Programming
MILP	Mixed-Integer Linear Programming
NLP	Nonlinear Programming

Sets

t	index of optimization periods, $t = 1, 2, \ldots, 24$
v	index of electric vehicles, $v = 1, 2, \ldots, N_v$
i	index of DGs, $i = 1, 2, \ldots, I$
ζ	index of objective functions, $\zeta = cost, emission$
k	index of Pareto-optimal solutions, $k = 1, \ldots, K$
n, m	index of buses, $n, m = 1, 2, \ldots, N$

Variable: (1) Binary variable

$u(i, t)$	on/off status (1/0) of the non-renewable DG i in period t
$X(v, t)$	binary variable of EV v related to discharge state in period t
$Y(v, t)$	binary variable of EV v related to charge state in period t

(2) Continuous variable

F^{cost}	total expected cost ($)
$F^{Emission}$	total emission (kg)
$P_{grid}(t)$	scheduled hourly power from the main grid in period t (kW)
$C_{DG}(i, t)$	hourly cost of DG i in period t ($)
$SU(i, t)$	start up cost of DG i in period t ($)
$P_{DG}(i, t)$	active output power of DG i in period t (kW)
$P_{EV}^{Dch}(v, t)$	power discharge of EV v in period t (kW)
$P_{EV}^{Ch}(v, t)$	power charge of EV v in period t (kW)
Em^{DG}	total emission of DGs (kg)
Em^{grid}	total emission of the main grid (kg)
$Loss(t)$	total power losses of distribution network during period t (kW)
$E_s(v, t)$	state of charge related to EV v in period t (kW h)
$P_{inj}(n, t)$	net injected active power to node n (p.u.)
$Q_{inj}(n, t)$	net injected reactive power to node n (p.u.)
$V(n, t)$	voltage at node n in period t (p.u.)

Parameters

D_t	total hourly demand in period t (kW)
$C_{Dch}^{v,t}$	discharge price of EV v in period t ($/kW h)
$E_{CO_2}^{grid,t}$	average emission rate of the main grid generation system in period t (kg/kW h)
$E_{CO_2}^{DG,i}$	emission rate of DG i (kg/kW h)
Ω_t	hourly electricity price of open market ($/kW h)
P_i^{min}	minimum output power limits of DG i (kW)
P_i^{max}	maximum output power limits of DG i (kW)
Sc_i	start-up cost of DG i ($)
a_i, b_i, c_i	cost coefficients of DG i
η_v^C	grid-to-vehicle charging efficiency coefficient for EV v
η_v^D	vehicle-to-grid discharging efficiency coefficient for EV v
$E_{trip}^{v,t}$	required energy for traveling of EV v in period t (kW h)
$P_{Dch,v}^{Max}$	maximum power discharge of EV v (kW)
$P_{Ch,v}^{Max}$	maximum power charge of EV v (kW)
Ψ_v^{max}	maximum level of state of charge for EV v (kW h)
Ψ_v^{min}	minimum level of state of charge for EV v (kW h)
$E_{Bat,v}^{max}$	maximum capacity of battery of EV v (kW h)
$Y_{n,m}$	element (n, m) of the admittance matrix

of EVs and wind generators has been presented. Optimal charge/discharge of EVs was carried out using probability distributions of the charge/discharge behaviors of EVs as well as Rayleigh probability distribution function for wind speed. However, the emission reduction target was not taken into account in the model. A new load management strategy for optimal charging of Plug-in Hybrid Electric Vehicles (PHEVs) to reduce peak load has been proposed in [13]. Implementing a game theory approach, PHEV's charging has been seen as a game among all users with the objective of minimizing the cost of charging for car owners'. However, the V2G capability has not taken into account in the paper.

A planning method for optimal utilization of the power system infrastructure during off-peak times for charging PHEVs has been proposed in [14]. The proposed planning model has focused on environmental and economic issues with the purpose to integrate large number of PHEVs into the electric grid, considering the most relevant planning uncertainties. In [15], the role of EVs in the demand side management and the grid balancing for the UK electricity network has been assessed. Results showed that electric vehicle owners would benefit from flexible charging and selling tariffs, with the majority of revenue derived from V2G participation in balancing markets. In order to handle the power challenges in presence of EVs, a multi-objective Distributed Generators (DGs) allocation method has been proposed in [16]. The method improved the voltage profile and minimized distribution power losses considering time-dependent load of a parking lot of EVs.

In [17], a method for planning the charging of EVs including grid constraints has been presented. The method establishes an individual charging plan for each vehicle and avoids distribution network congestion while satisfying the requirements of the individual vehicle owners. New methodology for estimating the electric energy and power consumption by light-duty EVs have been proposed in [18]. It has been assumed that a certain percentage of PEVs has been operated as pure electric vehicles in charge mode; however, this percentage was totally dependent on travel patterns and can change from day to day. In [19], a unit commitment model with V2G using the particle swarm optimization in order to reduce costs and emissions in smart grids has been presented. A heuristic method for minimizing the EV charging cost in response to time-of-use price in a regulated market has been presented in [20]. The results demonstrated that peak demand can be reduced by using the proposed control strategy for EVs. In [21], an analytical method which is able to model the electric load behavior of multitudes of EVs has been presented. A simplified stochastic model has been established based on non-homogeneous semi-Markov processes for the grid connectivity of electric vehicles over a 24-h period.

In this paper, a multi-objective approach for electric vehicle scheduling in a smart distribution grid is presented in which the environmental and economic issues as well as various driving patterns of EVs owners are taken into account. The innovative contributions of the proposed method are highlighted as follows:

- To include a novel conceptual model for an electric vehicle management system that can be applied to real cases.
- To consider various types of EV owners' driving patterns in the charging/discharging scheduling method.
- To evaluate the emission reduction target in the EVs charging/discharging scheduling in a smart distribution grid.

The rest of the paper is organized as follows: Section 2 describes the electric vehicle management system conceptual model. In Section 3, the resource scheduling is formulated. Some simulation results are described in Section 4 and finally the concluding remarks are presented in Section 5.

2. Proposed system architecture

In the proposed model, the Distribution System Operator (DSO) is responsible for resources scheduling in the distribution network. The interactions between DSO and its upstream regulator (Independent/Transmission System Operator (ISO/TSO)) as well as its downstream actors and components are shown in Fig. 1 [22–25].

2.1. Advanced metering infrastructure

The smart metering system architecture of a real pilot project is considered for the proposed distribution network configuration [26] as shown in Fig. 2. It consists of:

- *Smart meters* with Power Line Carrier Communication (PLCC), installed at the customer premises. They may be single phase or three phase smart meters. Also, the smart meter of medium and large customers could directly be connected to the utility by using General Packet Radio Service (GPRS). Moreover, the electric parameters of each feeder in the secondary part of the main substation (63/20 kV) as well as those in distribution substation transformers (20/0.4 kV) are measured by smart meters. So, the distribution losses of each line in Medium Voltage (MV) and Low Voltage (LV) network can be easily calculated.
- *Data Concentrators* (*DC*) installed in proximity of 20 kV/400 V substation distribution transformers in order to manage all smart meters measured data from each installation at LV network. Data concentrators integrate PLCC that exchange information with smart meters and communicate with central meter data management systems.

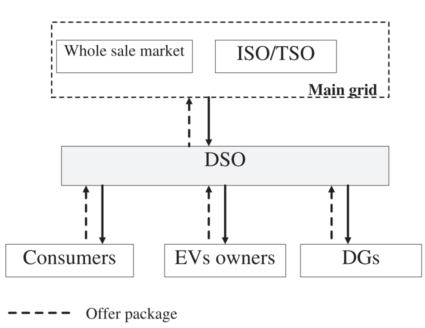

Fig. 1. Interactions between DSO and participants.

- *Meter data management system* mainly Meter Data Management & Repository (MDM/R) systems in which the received unprocessed data from all meters or sensors are collected and processed in order to deliver the required data to DSO and application systems.
- *Electric vehicle charging point* available at each home or workplace recognized as the charging plug that is an electricity plug equipped with PLCC modem that sends the EV data to a smart meter. In this case, we propose an identification chip to install in EVs: when an EV connects to an electricity plug, this chip sends a signal to a smart meter. As soon as the smart meter recognizes an EV connection, it sends its charging and discharging data to the MDM/R.

2.2. Electric vehicles management system

EVs should be integrated with other distributed resources of distribution network. An application system that is responsible for EVs integration and coordination with other distribution application systems should be, thus, defined within the Distribution Management System (DMS). A new application system, named Electric Vehicles Management System (EVMS), is presented in this paper that can be viewed as a sub-system or module within the DMS. It is responsible for EVs charging/discharging scheduling and management in the smart distribution network.

The EVMS acquires EV owners' information from MDM system or from the Customer Information System (CIS) and, also receives EVs charging/discharging measured data from MDM system. Geographical Information System (GIS) provides geospatial information on the network topology and parameters and provides EVs resource geospatial information through CIS.

EVMS is responsible for maintaining a relational database of EVs resources, their attributes, and their historical behavior/patterns before charging/discharging events. Customers can agree and sign-up to participate in one or more charging/discharging events.

Customer enrollment business processes are carried out by using a cell phone application or an internet portal. Each EV owner who is willing to participate in charging/discharging programs could fill out the form and insert the required information. The information flow of EVMS is shown in Fig. 3.

3. Energy resources scheduling formulation

This section presents the mathematical formulation of the proposed EVs scheduling methodology including the multi-objective optimization and decomposition technique. The assumptions considered in the proposed method are also discussed as follows.

The hourly electricity prices for electricity, as well as average emission rate of the main grid's power plants through the next 24-h period are available. The DSO is responsible for EVs charging/discharging management as well as energy scheduling in the distribution system [27].

EV owners that are willing to participate in charging/discharging program should submit their trip and parked time to EVMS for the next 24-h using their internet or cell phone portal. EV owners receive an incentive price for their vehicles' discharging. This incentive price is calculated based on the difference between electricity prices in the charging and discharging periods. Also, an additional incentive may be considered for EV owners due to their share in emission reduction. The EV owners have, therefore, enough motivation to participate in the charging/discharging scheduling program that is managed by DSO.

On the other hand, DSO benefits from proper charging/discharging scheduling of EVs: charging EVs in periods with low electricity prices and discharging their stored energy in periods with high

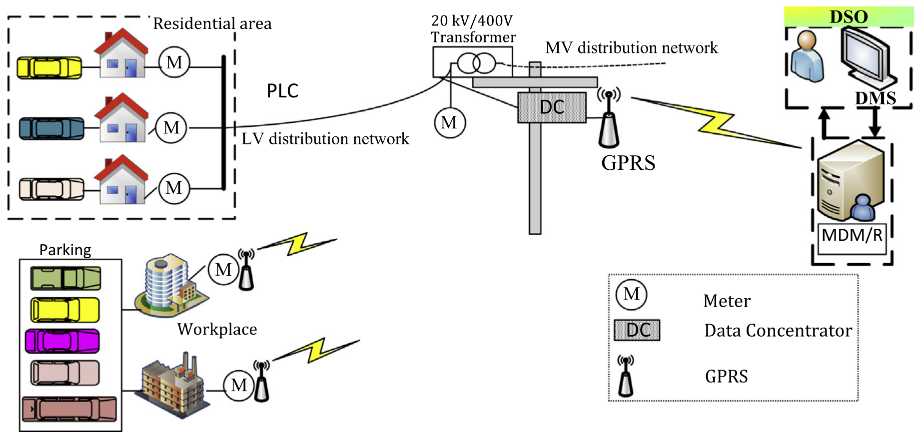

Fig. 2. Advanced metering architecture.

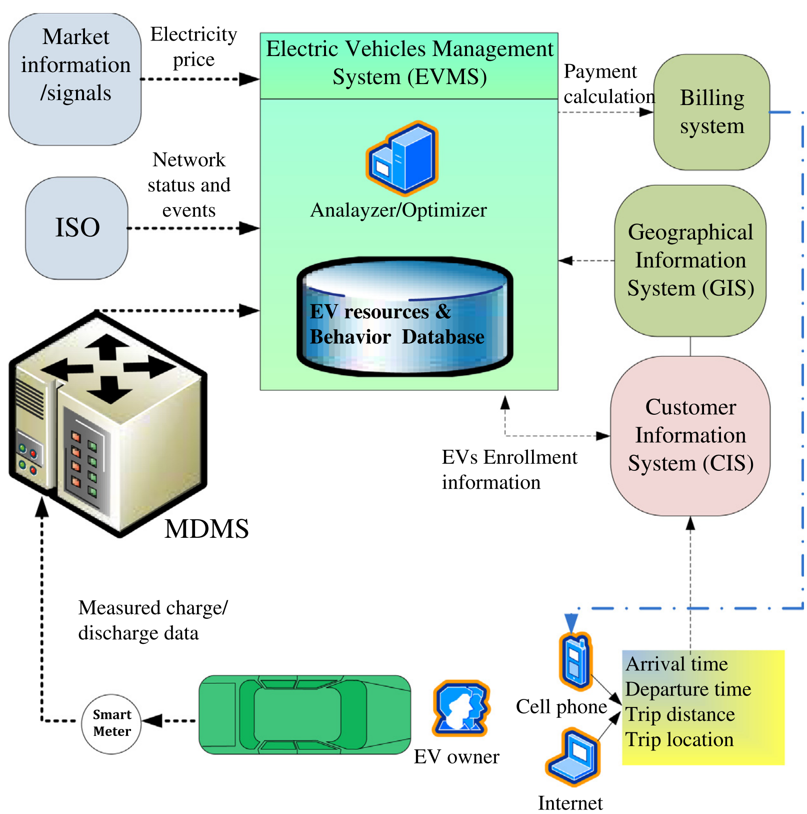

Fig. 3. Electric vehicle management system diagram.

electricity prices reduce the total operational costs of the system. Moreover, by taking into account the emission rate of power produced in the electric industry, the proper charging and discharging of EVs could reduce the air pollutant emission.

However, the stochastic behavior of EVs' owners in the presence of incentives is not considered in this study and it is assumed that the EVs owners carry out charge/discharge in a scheduled time. The stochastic character of consumers that may not accept incentives and will be able to use their EVs when this is necessary and the consequent uncertainties related to the charge/discharge procedure will be considered by the authors in a future work.

In order to use the proposed method for a real distribution system, some technical and regulatory requirements should be taken into account. First, the distribution system should be equipped with AMI system to measure the charge/discharge amount of each EV [28]. Moreover, AMI system can detect the EV connection point while it plugs into the charging point socket in all places in the distribution network. EVs need to have an identification chip in order to be recognized while connected to the electricity network. A two-way communication link between EV owners and EVMS is required for enrollment in charge/discharge programs as well as for communication of the charging cost and incentives for EV owners. The available customer portal for billing and energy management programs may simultaneously be used for this purpose. Regarding to the regulatory requirement, the value of incentives for EVs owners due to their voluntary participation in V2G program should be clearly determined. Also, an incentive price for the carbon emission reduction is required.

3.1. Objective function and constraints

The proposed EVs scheduling model has two objective functions: cost (F^{cost}) and emission ($F^{Emission}$). The multi-objective function of the proposed model is presented as follows:

$$Minimize\{F^{cost}, F^{Emission}\} \tag{1}$$

3.1.1. Cost function

The total operation cost of the distribution network where is integrated with large number of EVs represents the cost objective function of the multi-objective model that should be minimized. The cost objective function is given as follows:

$$F^{Cost} = \sum_{t=1}^{T}\left[P_{grid}(t)\times\Omega_t + \sum_{i=1}^{I}(C_{DG}(i,t)+SU(i,t)) + \sum_{v=1}^{N_v}P_{EV}^{Dch}(v,t)\times C_{Dch}^{v,t}\right] \tag{2}$$

where $P_{grid}(t)$ and Ω_t are the scheduled purchased power from the main grid and the hourly electricity price in period t; I is the number of DGs; $C_{DG}(i, t)$ and $SU(i, t)$ represent the hourly fuel and startup costs of DG i in period t, respectively; N_v is the total number of EVs; $P_{EV}^{Dch}(v,t)$ and $C_{Dch}^{v,t}$ are power discharge and discharge price of EV v in period t; In this study, the duration period t is considered equal to 1 h. As a result, the charge/discharge scheduling period length is same as one in generation scheduling.

The fuel cost of a generator can be expressed mainly as a function of its real power output and can be modeled by a quadratic polynomial [29]. The operational cost of a distributed generation unit (like a diesel generator) with a quadratic cost function $C_{DG}(i, t)$ is given by [22]:

$$C_{DG}(i,t) = a_i\times u(i,t) + b_i\times P_{DG}(i,t) + c_i\times P_{DG}^2(i,t) \tag{3}$$

where a_i, b_i and c_i represents the cost coefficient of DGs; $P_{DG}(i, t)$ and $u(i, t)$ are the active output power and the binary variable which shows the on or off state of DG i in period t, respectively.

To implement a linear programming approach, the nonlinear cost function of DG is approximated by a linear function that for practical purpose is indistinguishable from the nonlinear model. This method is detailed in [30].

3.1.2. Emission function

The distribution loads are supplied by both of DGs installed in distribution network and conventional power plants connected to the main grid as well as EVs discharging energy. The CO_2 emissions of DGs (Em^{DG}) are calculated as follows:

$$Em^{DG} = \sum_{t=1}^{T}\sum_{i=1}^{I}E_{CO_2}^{DG,i}\times P_{DG}(i,t) \tag{4}$$

where $E_{CO_2}^{DG,i}$ is CO_2 emission rate of the DG i.

The average CO_2 emission of the main grid's power plants (Em^{grid}) due to generating electricity for supplying the distribution system demand is calculated as follows:

$$Em^{grid} = \sum_{t=1}^{T}E_{CO_2}^{grid,t}\times P_{grid}(t) \tag{5}$$

where $E_{CO_2}^{grid,t}$ is the average CO_2 emission rate of the main grid's power plants at hour t.

The objective function of total emission during the planning period is calculated as follows:

$$F^{Emission} = Em^{grid} + Em^{DG} \tag{6}$$

The constraints of this model are described below:

3.1.3. Constraints

Load balance

$$P_{grid}(t) + \sum_{i=1}^{I}P_{DG}(i,t) + \sum_{v=1}^{N_v}P_{EV}^{Dch}(v,t) = D_t + \sum_{v=1}^{N_v}P_{EV}^{Ch}(v,t) + Loss(t) \quad \forall t\in\{1,\ldots,T\} \tag{7}$$

where $P_{EV}^{Dch}(v,t)$ and $P_{EV}^{Ch}(v,t)$ are, respectively, power discharge and charge of vehicle v in period t; D_t represents the total hourly active demand in period t; $Loss(t)$ represent the total power losses of the distribution network in period t.

EVs constraints. In each period of scheduling, the EV charge and discharge are not simultaneous:

$$X(v,t) + Y(v,t) \leqslant 1 \quad \forall t\in\{1,\ldots,T\}; \quad \forall v\in\{1,\ldots,N_v\}; \quad X,Y\in\{0,1\} \tag{8}$$

where $X(v, t)$ and $Y(v, t)$ are, respectively, the binary variables of EV v related to power discharge and charge states in period t.

The battery energy balance for each vehicle should be considered. The state of charge variable ($E_s(v, t)$) represents the stored energy in the battery of vehicle v at the end of period t. The energy consumption for traveling in period t $\left(E_{trip}^{v,t}\right)$ has to be considered jointly with the energy remained from the previous period and the charge/discharge in the period [10].

$$E_s(v,t) = E_s(v,t-1) + \eta_v^C\times P_{EV}^{Ch}(v,t) - E_{trip}^{v,t} - \frac{1}{\eta_v^D}\times P_{EV}^{Dch}(v,t) \quad \forall t\in\{1,\ldots,T\}; \quad \forall v\in\{1,\ldots,N_v\} \tag{9}$$

where η_v^C and η_v^D represent, respectively, the grid-to-vehicle charging and vehicle-to-grid discharging efficiency coefficients of EV v.

The discharge and charge limit for each EV considering the battery discharge rate is given as follows [7]:

$$P_{EV}^{Dch}(v,t) \leqslant P_{Dch,v}^{Max}\times X(v,t) \quad \forall t\in\{1,\ldots,T\}; \quad \forall v\in\{1,\ldots,N_v\} \tag{10}$$

$$P_{EV}^{Ch}(v,t) \leqslant P_{Ch,v}^{Max}\times Y(v,t) \quad \forall t\in\{1,\ldots,T\}; \quad \forall v\in\{1,\ldots,N_v\} \tag{11}$$

where $P_{Dch,v}^{Max}$ and $P_{Ch,v}^{Max}$ are the maximum power discharge and charge of EV v.

Depletion of EV battery up to a certain minimum level $\left(\Psi_v^{min}\right)$ and charging up to a maximum level (Ψ_v^{max}) are ensured by Eqs. 12, 13 to prevent loss of battery life [8].

$$E_s(v,t) \leqslant \Psi_v^{max} \quad \forall t\in\{1,\ldots,T\}; \quad \forall v\in\{1,\ldots,N_v\} \tag{12}$$

$$E_s(v,t) \geqslant \Psi_v^{min} \quad \forall t\in\{1,\ldots,T\}; \quad \forall v\in\{1,\ldots,N_v\} \tag{13}$$

where Ψ_v^{min} and Ψ_v^{max} is defined based on the battery capacity limit for each EV that are calculated as follows:

$$\Psi_v^{max} = \phi_v^{max}\times E_{Bat,v}^{max} \quad \forall v\in\{1,\ldots,N_v\} \tag{14}$$

$$\Psi_v^{min} = \phi_v^{min}\times E_{Bat,v}^{max} \quad \forall v\in\{1,\ldots,N_v\} \tag{15}$$

where $E_{Bat,v}^{max}$ represents the maximum capacity of battery of EV v; ϕ_v^{max} and ϕ_v^{min} are, respectively, the maximum and minimum percentage of battery capacity considering battery life.

The vehicle battery discharge and charge limits considering, respectively, the battery state of charge and the battery capacity and the previous period stored energy are given as follows [9]:

$$\frac{1}{\eta_v^D}\times P_{EV}^{Dch}(v,t) \leqslant E_s(v,t-1) \quad \forall t\in\{1,\ldots,T\}; \quad \forall v\in\{1,\ldots,N_v\} \tag{16}$$

$$\eta_v^C\times P_{EV}^{Ch}(v,t) \leqslant \Psi_v^{max} - E_s(v,t-1) \quad \forall t\in\{1,\ldots,T\}; \quad \forall v\in\{1,\ldots,N_v\} \tag{17}$$

The required stored energy in EVs' battery in order to travel the specific distance in each trip is given as follows [9]:

$$E_s\left(v, t_{last}^q\right) \geqslant E_{trip,q}^{v,t} \quad \forall t \in \{1, \ldots, T\};$$
$$\forall v \in \{1, \ldots, N_v\}; \quad D_{trip} \subset t \tag{18}$$

where t_{last}^q represents the last period when the EV is connected to the grid before start qth trip in period $t_{last}^q + 1$; $E_{trip,q}^{v,t}$ is the required energy of EV v for trip q in period t.

DG constraints. The distributed generation units have a maximum and minimum generating capacity beyond which it is not feasible to generate due to technical reasons. Generating limits are specified as upper and lower limits for the real and reactive power outputs.

$$P_{DG}(i,t) \leqslant P_i^{max} \cdot u(i,t) \quad \forall t \in \{1, \ldots, T\}; \quad \forall i \in \{1, \ldots, I\} \tag{19}$$

$$P_{DG}(i,t) \geqslant P_i^{min} \cdot u(i,t) \quad \forall t \in \{1, \ldots, T\}; \quad \forall i \in \{1, \ldots, I\} \tag{20}$$

where P_i^{min} and P_i^{max} are the minimum and maximum limits of ith DG output power; $u(i, t)$ represents the on/off state of DG.

The startup cost ($SU(i, t)$) of DG units is calculated as follows:

$$SU(i,t) = Sc_i \times (u(i,t) - u(i,t-1)) \tag{21}$$

$$SU(i,t) \geqslant 0 \tag{22}$$

where Sc_i is the start up cost of ith DG.

Power flow constraints

$$P_{inj}(n,t) = \sum_{m=1}^{N} |V(n,t)||V(m,t)||Y_{n,m}| \cos(\delta(m,t) - \delta(n,t) + \theta_{n,m}) \quad \forall n,t \tag{23}$$

$$Q_{inj}(n,t) = -\sum_{m=1}^{N} |V(n,t)||V(m,t)||Y_{n,m}| \sin(\delta(m,t) - \delta(n,t) + \theta_{n,m}) \quad \forall n,t \tag{24}$$

where N is the total number of buses; n and m are index for buses; $|V(n, t)|$ is voltage amplitude at node n; $\delta(n, t)$ is voltage angle at node n; $|Y_{n,m}|$ is element (n, m) of the admittance matrix; $\theta_{n,m}$ is the angle of $Y_{n,m}$; $P_{inj}(n, t)$ and $Q_{inj}(n, t)$ are the net injected active and reactive power to node n, respectively.

The other network operation constraints are as follows:

$$|S(n,m,t)| \leqslant S_{n,m}^{max} \quad \forall t \in \{1, \ldots, T\}; \quad \forall n,m \in \{1, \ldots, N\} \tag{25}$$

$$V_n^{min} \leqslant V(n,t) \leqslant V_n^{max} \quad \forall t \in \{1, \ldots, T\}; \quad \forall n \in \{1, \ldots, N\} \tag{26}$$

$$P_{grid}(t) \leqslant P_{sub}^{max} \quad \forall t \in \{1, \ldots, T\} \tag{27}$$

where $|S(n, m, t)|$ is the apparent power flow from node n to m; $S_{n,m}^{max}$ is the capacity of the line/cable between node n and node m; V_n^{max} and V_n^{min} are the maximum and minimum voltage magnitude at node n, respectively; P_{sub}^{max} is the maximum power drawn from the main substation.

3.2. Multi-objective augmented ε-constraint method

In order to deal with the trade-off between reducing the cost and the amount of air pollutants emission produced by conventional generators, the augmented ε-constraint method is used in the proposed method [31,32].

In this method, only the range of emission objective function ($F^{Emission}$) is calculated, since F^{cost} is the main objective function. Then, the range of the objective function $F^{Emission}$ is divided to k equal intervals. Therefore, there are in total $(k+1)$ grid points for $F^{Emission}$. Thus, $(k+1)$ optimization sub-problems must be solved where some of these sub-problems may have infeasible solution space. The problem has the following form:

$$\min \left(F^{cost} - \delta \times \left(\frac{S_2}{r_2}\right)\right) \tag{28}$$

$$\text{subject to}: F^{Emission} + S_2 = \varepsilon_2^k, \quad S_2 \in R^+$$

where

$$\varepsilon_2^k = F_{max}^{Emission} - \left(\frac{F_{max}^{Emission} - F_{min}^{Emission}}{q_2}\right) \times k, \quad k = 0, 1, \ldots, q_2 \tag{29}$$

where δ is a scaling factor; S_2 is a slack variable; $F_{max}^{Emission}$ and $F_{min}^{Emission}$ represent the maximum and minimum values of the emission objective function, based on the payoff table, respectively; ε_2^k is the k th range of $F^{Emission}$; r_2 is the range of the total air pollutants emission $\left(F_{max}^{Emission} - F_{min}^{Emission}\right)$, and q_2 is the number of equal part.

It should be noted that S_2 is a slack variable which is defined to prevent inefficient solutions by the original ε-constraint method [31]. $\delta \times \left(\frac{S_2}{r_2}\right)$ is considered in Eq. (28) (instead of S_2) in order to prevent any scaling problem. In fact, δ is a scaling factor selected in order to make the slack variable S_2 comparable with the cost objective function [32].

In solving each of the sub-problems all the constraints of the model should be also considered. By solving each optimization sub-problem, one Pareto-optimal solution is obtained. With a higher number of grid points, a denser efficient set is obtained but with a higher computational time. A trade-off between the density of the efficient set and time consuming is always necessary. In this paper, the number of intervals for the objective function $F^{Emission}$ is considered to be equal to 10.

3.3. Best compromise solution

When the Pareto-optimal solution is obtained, one of the solutions is chosen as the best compromise solution. Fuzzy set is introduced here to handle the problem [33]. Here a linear membership function $\left(\mu_\zeta^k\right)$ is described for each of the objective functions, i.e. F^{Cost} and $F^{Emission}$:

$$\mu_\zeta^k = \begin{cases} 1, & F_\zeta^k \leqslant F_\zeta^{min} \\ \left[\dfrac{F_\zeta^{max} - F_\zeta^k}{F_\zeta^{max} - F_\zeta^{min}}\right], & F_\zeta^{min} \leqslant F_\zeta^k \leqslant F_\zeta^{max} \\ 0, & F_\zeta^k \geqslant F_\zeta^{max} \end{cases} \tag{30}$$

where F_ζ^k and μ_ζ^k represent, respectively, the value of the ζth objective function in the kth Pareto-optimal solution and its membership function. For each of k solution, the membership function can be normalized as follows:

$$\mu^k = \frac{\sum_{\zeta=1}^{p} \omega_\zeta \mu_\zeta^k}{\sum_{k=1}^{K} \sum_{\zeta=1}^{p} \omega_\zeta \mu_\zeta^k} \tag{31}$$

where ω_ζ is the weight value of the ζth objective function in the multi-objective mathematical programming problem also, K is the number of Pareto-optimal solutions. The weight values ω_ζ can be selected by the operator based on the importance of economic issue and environmental allowance. The solution with the maximum membership function μ^k is the most preferred compromise solution based on the implemented weight factors and so is selected as the best Pareto-optimal solution.

3.4. Computation technique

The multi-period energy resource scheduling problem formulated in the paper is a large-scale Mixed Integer Nonlinear

Programming (MINLP) optimization problem. MINLP optimization techniques require significant computer means and the execution times are not compatible with the short-term energy and reserve scheduling [10,34]. Therefore, in order to have a fast response for optimization problems with many variables, it is necessary to use alternative methodologies. In order to make the proposed model applicable for real size distribution networks with large number of EVs, and overcome the difficulties related to solving nonlinear optimization problems with binary variables, a fast and robust optimization technique known as Benders decomposition is implemented in this paper [35].

The basic idea behind this method is to decompose the problem into two simpler parts: the first part, called master problem, solves a relaxed version of the problem and get values for a subset of the variables. The second part, called sub-problem (or auxiliary problem), receives the values for the remaining variables while keeping the first ones fixed, and uses these to generate *Benders cuts* for the master problem. The master and auxiliary problems are solved iteratively until no more cuts can be generated [36]. The combination of the variables found in the last master and sub-problem iteration is the solution to the original formulation [37]. This method allows to appropriately treat the non-convexity associated with binary variables and to divide the global problem into two smaller problems which are easier to solve.

In the proposed model, the Benders technique divides the original problem into a mixed integer linear programming (MILP) master problem (Eqs. (1)–(22)) and a Nonlinear Programming (NLP) sub-problem (Eqs. (23)–(27)). Fig. 4 shows the procedure of this method. More details on Benders decomposition and its features are available in [38] and its implementation in optimal power flow problem is described in [39].

The master problem consists of 24-h multi-objective EVs scheduling problem which are solved by using the MILP solver CPLEX [40]. The sub-problem is an hourly distribution power flow with some fixed variables received from the master problem solution which is solved using NLP solver CONOPT [41]. Both the master and the sub-problem are modeled in GAMS [42] on a Pentium IV, 2.6 GHz processor with 4 GB of RAM. The computation time for the proposed multi-objective method was 14 s.

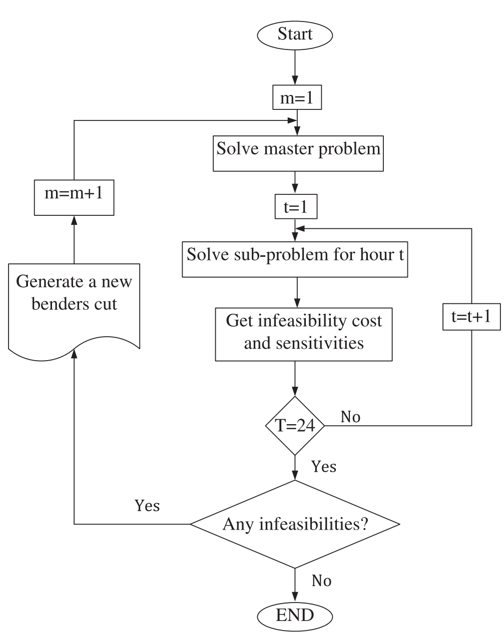

Fig. 4. Benders decomposition flowchart.

4. Case study

The proposed method was applied to a modified version of the 33-bus 22.6-kV radial distribution system given in [43] and illustrated in Fig. 5. The forecasted load profile of the test system for a 24-h period is shown in Fig. 6. Table 1 provides the hourly electricity price of open market according to [44]. Also, two diesel generator and two Fuel Cell (FC) sets are installed in bus 13, 27, 8 and 19, respectively. The fuel cells and diesel generators are assumed to have fixed power factors of 1, respectively.

The fuel cost and emission rate of diesel generator and fuel cell units are given in Table 2 [45–48]. The main grid generation system is typically composed of nuclear, hydro, gas steam, coal and gas combined cycle power plants. In this case study, it is supposed that, according to a unit commitment program at each hour, the average CO_2 emission rates of conventional power plants in the main grid for low (hours 1–6 & 23–24), medium (hours 6–20) and high (hours 19–22) load hours of the main grid are considered as 0.050, 0.562, 0.985 kg/kW h, respectively [48].

It is assumed that the test radial distribution system is for a town including residential and commercial area. The driving patterns were based on a statistical survey in a real town carried out by the authors. The information consist of trip duration of each type of customer, start and end time of their trip and average distance travel.

People using the electrical network of this town for charging their EVs is categorized as EV owners who:

(a) live and work in the town (EI1 & EI2),
(b) live in town but work out of town (EO1 & EO2),
(c) live in town and use EV only for going shopping and party (SP),
(d) plan to travel to out of town in the scheduling period (TR), and
(e) live out of town but their workplace are located in town (OU).

EI2 and EO2 refer to employees who also use their EVs in the evening or night for other purposes. In this study, we consider two typical scenarios of EV charging: (1) charging at home and (2) charging at work. The summaries of the driving pattern information are given in Tables 3 and 4.

The number of each type of EV owners and the start and end time of their connection to the grid is shown in Table 3. It is assumed that EV owners drive with a constant speed and at an average rate of 3 kW h per hour. The average trip duration for each EV owners and types of the trip are given in Table 4. It should be noted that each type of EV should store enough energy in its battery in order to cover the trip distance in the next hour.

The case study considers 3 different vehicle types, for which the technical information has been obtained from vehicle manufacturers. A typical 10 kW h battery capacity for most of EVs is selected [11]. Also, two other vehicle types that are used in this case study are Nissan Leaf with a battery capacity of 24 kW h and Citroen C-Zero with a battery with 16 kW h [49,50]. Battery chargers have some losses and therefore the energy requirement from the grid is actually greater than the stated battery capacity. Typical battery charge and discharge efficiency are assumed 90% and 95%, respectively [51]. In order to optimize EV battery life, depletion of EV battery up to 85% of the rated battery capacity is assumed.

A standard single-phase 240 V, 16 A socket (Italian standard) is assumed for charging point in home or work place. For this analysis, a fixed charging power of 4 kW is selected because this is commonly available in most single-phase residential households without having to reinforce wiring [11,52].

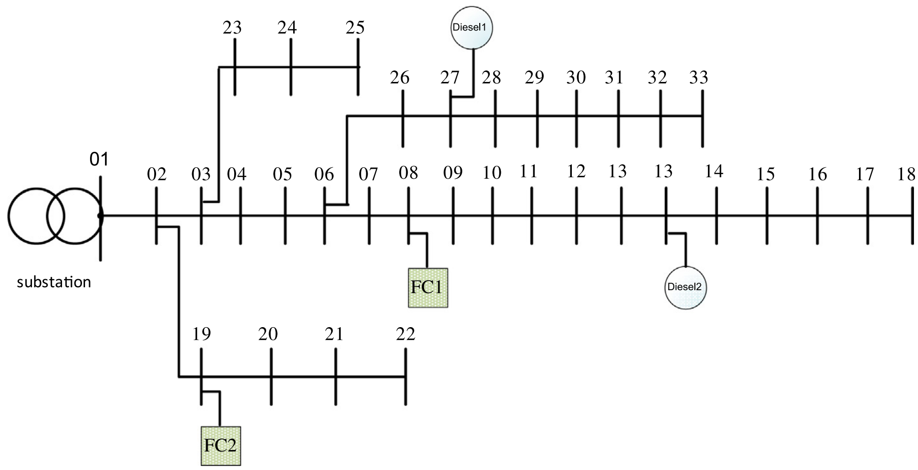

Fig. 5. 33 Bus distribution test system.

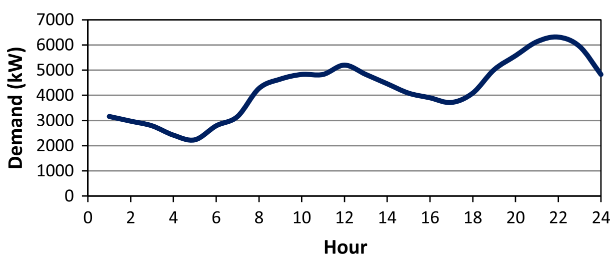

Fig. 6. Forecasted load profile of the distribution test system.

Table 1
Hourly electricity price of open market.

t	1	2	3	4	5	6
$/kW h	0.033	0.027	0.020	0.017	0.017	0.029
t	7	8	9	10	11	12
$/kW h	0.033	0.054	0.215	0.572	0.572	0.572
t	13	14	15	16	17	18
$/kW h	0.215	0.572	0.286	0.279	0.086	0.059
t	19	20	21	22	23	24
$/kW h	0.050	0.061	0.181	0.077	0.043	0.037

To analyze the effects of cost and emission reduction purposes on EVs scheduling, the proposed model is tested in 3 different cases:

- Case 1: Operation cost minimization.
- Case 2: Emission minimization.
- Case 3: Multi-objective optimization.

4.1. Case 1: Operation cost minimization

The main grid, diesel generators and fuel cells scheduled active powers in case 1 are shown in Fig. 7. Also, the charging/discharging program of EVs is illustrated in Fig. 8. Regarding the cost minimization objective, the results show that the EVs charging are carried out in the hours when the electricity prices are high. On the other hand, the EVs discharging are carried out in the hours when the electricity prices are relatively low. As shown in Fig. 7, the diesel generators have been turned on in more hours than fuel cells due to their lower operational cost.

4.2. Case 2: Emission minimization

Fig. 9 shows the main grid, diesel generators and fuel cells scheduled active powers in case 2. As shown in Fig. 9, the fuel cells have been turned on in more hours than diesel generators due to their lower emission rate. In hours 7–22, when the average emission rate of the main grid power plants is higher than the emission

Table 3
Scenario for electric vehicle location.

Type	Number	Parked time	
		Home	Workplace
EI1	200	01:00–06:00, 17:00–24:00	08:00–15:00
EI2	200	01:00–06:00, 17:00–19:00	08:00–15:00
EO1	100	01:00–05:00, 17:00–24:00	–
EO2	200	01:00–05:00, 17:00–19:00	–
SP	150	01:00–09:00, 13:00–18:00, 22:00–24:00	
OU	100	–	08:00–15:00
TR	50	01:00–06:00	

Table 4
The average trip duration.

EV owners	Trip type/trip duration (h)		
	Home to work	Work to home	Others
EI1	1	1	–
EI2	1	1	5
EO1	2	2	–
EO2	2	2	5
SP	–	–	3 & 3
OU	2	2	–
TR	–	–	10

Table 2
Cost and mission rate coefficients of generation sources.

Unit	Cost coefficient				Technical constraints		Emission
	a_i ($)	b_i ($/kW h)	c_i ($/kW h^2)	Startup ($)	P_{min} (kW)	P_{max} (kW)	CO_2 (kg/kW h)
Diesel	10	0.0133	0.002	2	50	1000	0.890
FC	45	0.375	–	3	100	1000	0.477

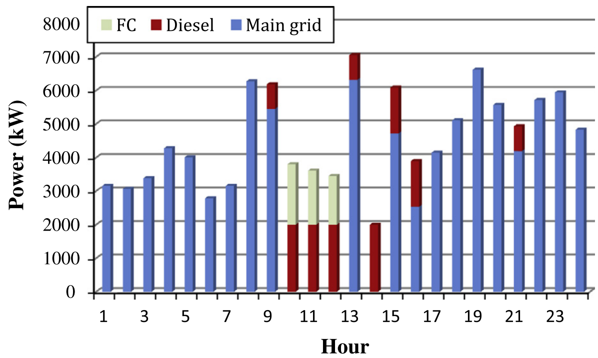

Fig. 7. Scheduled power resources in case 1.

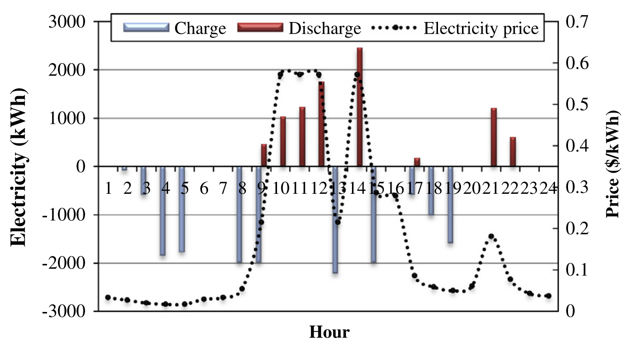

Fig. 8. EVs scheduled charging/discharging program in case 1.

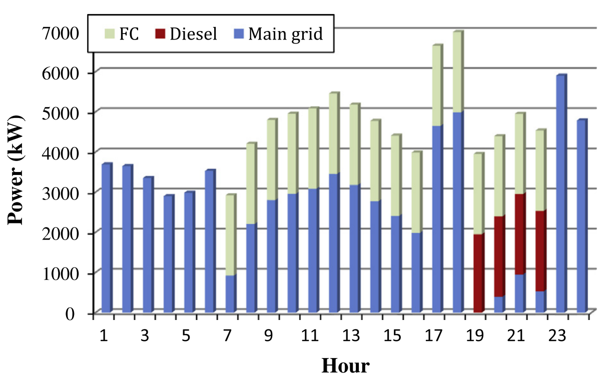

Fig. 9. Scheduled power resources in case 2.

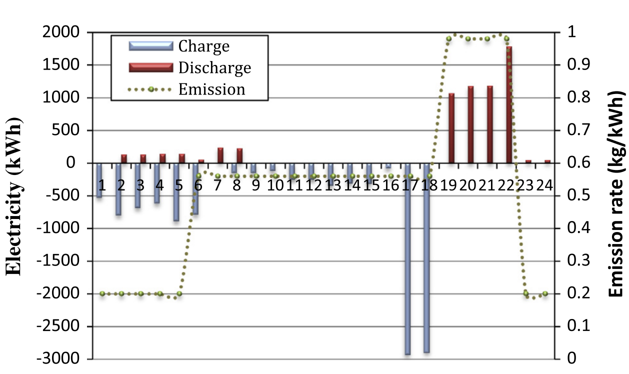

Fig. 10. EVs scheduled charging/discharging program in case 2.

Table 5
Comparison between cost and emissions in cases 1 and 2.

	Operation cost ($)	Emissions (kg)
Case 1	13,253	63,083
Case 2	24,954	50,271

rate of fuel cells, they have been kept turn on at their maximum power.

The charging/discharging program of EVs in case 2 is illustrated in Fig. 10. Regarding the emission minimization objective, the results show that the EVs are scheduled to be charged at hours with lower emission rate and, on the other hand, to be discharged in the hours when the emission rate of the bulk power generation is high.

A comparison between total operation cost and emission amount in the cases 1 and 2 has been made and the results have been shown in Table 5. As shown, if the air pollutant emissions reduction is considered as an objective of the distribution energy resources scheduling, the total operation cost significantly increases.

4.3. Multi-objective optimization

In this case, the resources scheduling are carried out considering both cost and emission as objective functions. The augmented ε-constraint method is implemented to optimize the two objectives.

The Pareto-optimal set obtained from the augmented ε-constraint method is shown in Fig. 11. The membership functions are used to evaluate each solution of the Pareto-optimal set. Then the best compromise solution, that has the maximum value of the membership function, can be obtained. It should be mentioned that in this paper it has been assumed that $w_1 = w_2 = 0.5$ as the same importance is considered for the economic and emission objectives in the multi-objective problem. Table 6 represents the above procedure in tabular form. As shown, the Pareto-solution No. 8 has been selected as the best compromise solution.

The best compromise solution results for resources scheduling are illustrated in Figs. 12 and 13. The results show that the charging is carried out during hours 3–5, 8–9, 13, 15, 17 and 18 when the electricity price is low. Moreover, during hours 19–22 at which the average emission rates of the main grid generation are high, the discharging is carried out to reduce the imported power from the main grid.

In order to evaluate the effect of V2G capability on both the cost and emission objectives in the proposed multi-objective method, the energy resources scheduling has been also carried out without using discharging capability of EVs. Total cost and emission results of the energy resource scheduling with and without considering V2G capability for the best compromise solutions are shown in Table 7. The result evidence that both EVs owners and DSO can benefit from the use of V2G capability of EV: the total operational

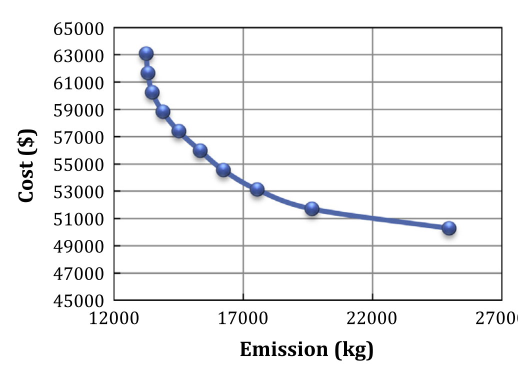

Fig. 11. Pareto-optimal front of the multi-objective method.

Table 6
Fuzzy based procedure used to determine the best compromise solution.

Pareto points (k)	Cost ($)	Emission (ton)	μ^k
1	13,253	63.08	0.079
2	13,314	61.66	0.088
3	13,483	60.24	0.095
4	13,896	58.81	0.102
5	14,510	57.39	0.106
6	15,340	55.96	0.110
7	16,234	54.54	0.113
8	17,541	53.11	0.114
9	19,658	51.69	0.108
10	24,954	50.27	0.084
The best compromise solution	17,541	53.11	0.114

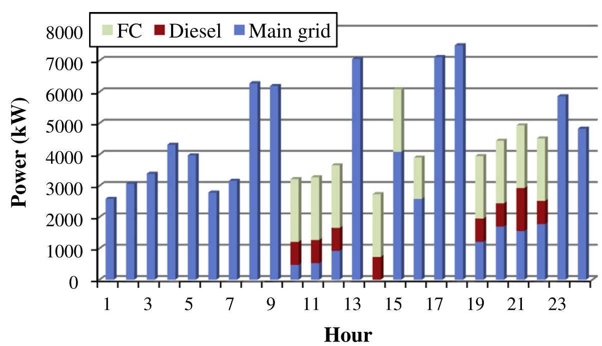

Fig. 12. Scheduled power resources in case 3.

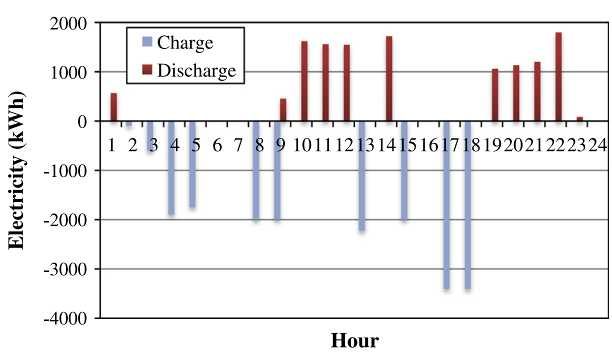

Fig. 13. EVs scheduled charging/discharging program in case 3.

Table 7
Total cost and emission of the best compromise solutions with and without considering V2G capability.

	Cost ($)	Emission (ton)	EV owners revenue ($)
Without V2G	19,993	56.05	–
With V2G	17,541	53.11	1064

cost of system and the air pollutant emission are reduced and the EVs' owners earn revenues from discharging their EVs stored energy.

5. Conclusion

In this paper, a multi-objective resource scheduling of a smart distribution system including large number of EVs has been proposed. Also, a conceptual model for EVs management system was presented. The optimization model includes the constraints associated with the EVs and distribution network. The generalized Benders decomposition method was used to solve this large-scale multi-period problem. This method shows good convergence properties for this application. The effects of cost and emission objectives were analyzed in three different cases. Simulation results evidenced that the inclusion of the emission objective function has modified the charging/discharging programs in order to reduce the total air pollutant emission.

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