A multi-objective scheduling method for EV fleet scheduling

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Contents

ABSTRACT

The number of increasing of grid-connected electric vehicles (EVs) has led to emerging new opportunities and threats in electrical distribution systems (DS). Developing realistic model of EV interaction with the DS and optimally manage these interactions in distribution system operators (DSOs) intentions, are the most important. In this paper, a comprehensive model describing the electric vehicle integration to an smart distributed system(SDS) is presented by considering the real-world data from EV manufacturers and DSOs. a novel energy management strategy (EMS) based on the multi-objective optimization problem (MOOP) is developed to fulfill the operational objectives of DSO and EV owner, including peak load shaving, loss minimization, and EV owner profit maximization. In this regard, an innovative dimension reduction approach is presented, to make it feasible to apply the heuristic optimization methods to a MOOP with a large number of decision variables.The improved electromagnetism like algorithm (IEMA) is employed to perform the multi-objective energy scheduling for a large-scale EV fleet.The method is applied to the modified IEEE-33 bus test system.

Keywords

Smart grid,Electric vehicle,Vehicle-grid(V2G), grid-Vehicle(G2V),Multi-objective-optimization(MOO).

1.INTRODUCTION

Air pollution is major challenge facing human societies in the current century and combustion of fuel by engine vehicles are one of the major sources of these problems The transportation sector accounts for about 25% of the total world energy consumption.Particularly the light-duty vehicles used for passenger transportation, by allocating about 45% of the total transportation energy to itself, consumes more energy than any other transportation modes ,therefore it has a significant role in exacerbating the above mentioned challenge.The idea of replacing the internal combustion engine vehicles with EVs has been in the center of attention as an effective solution to the environmental concerns, because of their benefits such of less environmental pollution the possibility of direct charging by renewable energy sources and high-energy efficiency.The battery capacity of EVs is significantly increased, in a way that as compared to the primary EVs with a low battery capacity (about 4 kWh), currently EVs with a high battery capacity (up to100 kWh) are available. These two factors (increase in number and capacity) causes a significant increase in the charging demand of EVs. Having in mind that EVs can directly charge through the low-voltage outlets of residential houses (120 and 240-volt sockets), this additional charge is mainly imposed on distribution network infrastructure.

Investigations show that a typical vehicle is in park mode at 95 percent of the daytime. On the other hand, vehicles in the same geographic area generally have similar displacement behavior, which can lead to the establishment of synergy between them. These two features help to the formation of large battery capacity that can be used to implement a variety of ancillary services by defining the appropriate vehicle to grid (V2G) and grid to vehicle (G2V) programs. The essential requirement for developing an optimal EV scheduling is to have a proper understanding of the EVs impacts on the DS.The main goal of modeling is to determine the three important parameters of the time, location, and amount of charge exchanged between EVs and DS.

2.COMPREHENSIVE MODELING OF EVISDS

2.1.Number of EVs connected to each bus

The number of vehicles connected to the DS depends on the number of total houses connected to the network (Nh) and the number of vehicles per household. The parameter of the vehicle per household (Cvph) varies across different cities.The penetration level of EVs (PEL) in the grid, only the specific percent of available vehicles are of an electrical type.
Then, the total number of EVs connected to each system bus (NEV) can be calculated as follows:

$$NEV = Nh * Cvph * PEL \tag{1}$$

Therefore, information about the number of households connected to each medium voltage or low voltage bus (Nh,i), is available. Hence, the number of EVs connected to the ith bus of the DS (NEV,i) is:

$$NEV, i = Nh, i * Cvph * PEL \tag{2}$$

2.2. Type of EVs connected to network

Each EV have different battery capacity, charge/discharge Characteristic curve, and environmental protection agency (EPA) range. EPA range (EPAR) is the maximum distance that an EV can travel only on battery power with one full charge based on the US environmental protection agency (EPA) criteria.Moreover, the sales market share of each manufacturer is different. Therefore, in order to reach a realistic EVISDS model, not only the specific battery characteristics of each manufacturer should be considered but also the market share of each manufacturer should be taken into account.It is noteworthy that almost information of all manufacturers (30 different manufacturers) is considered to form the appropriate PDF. However, for the sake of brevity, only the first ten manufacturer's information is presented in Table 1.

Class	Model Name	Sales number	C_m (kWh)	EPAR (mi)	Charge rate (kW)
1	Tesla Model S	30,200	100	315	10
2	Chevrolet Volt	24,739	18.4	85	3.6
3	Tesla Model X	19,600	75	237	17
4	Ford Fusion Energi	15,938	7	21	3.3
5	Nissan LEAF	14,006	40	151	6.6
6	Ford C-MAX Energi	7,957	8	20	3.3
7	BMW i3	7,625	33	114	7.7
8	Audi A3 Plug In	4,280	9	16	3.3
9	BMW X5	5,995	9	14	3.5
10	VW e-Golf	3,937	36	125	7.2

Table 1: U.S. EV sales by the model in 2016 and their technical specifications (top 10 manufacturer).

2.3.Charging level of EV

The charge level of an electric vehicle depends on its park location.Typically three methods are popular :

1. Slow charge or charge level 1: charge rate of about 3 kW (single phase 230 V with the current of 16 amps AC).
2. Moderate charge or level 2: Charge rate up to 19 kW (single-phase/ 400 V with 80 amps AC current). 3. Fast charge or level
3. Charge rate up to 100 kW (three-phase 600 V AC or 300–600 V DC with a current of 150–400 amps).

2.4. EV availability in workplace

EV in the park mode can be divided into two categories in terms of participation in V2G/G2V programs.

The first category is the EVs that have the ability to exchange energy with the network at the park time and therefore effectively participate in V2G/G2V programs. These EVs are often parked in office or commercial buildings or parking lots that are equipped with suitable charge facilities.

The second category is EVs that do not have access to charging equipment, so there is no possibility for them to participate in V2G/G2V program.The available times for EVs charge/discharge are shown schematically in Fig. 1. Therefore, not all EVs will be able to participate in the V2G/G2V programs during the work times.

$$\psi_w = \frac{N_{EV,w}}{N_{EV}} \tag{3}$$

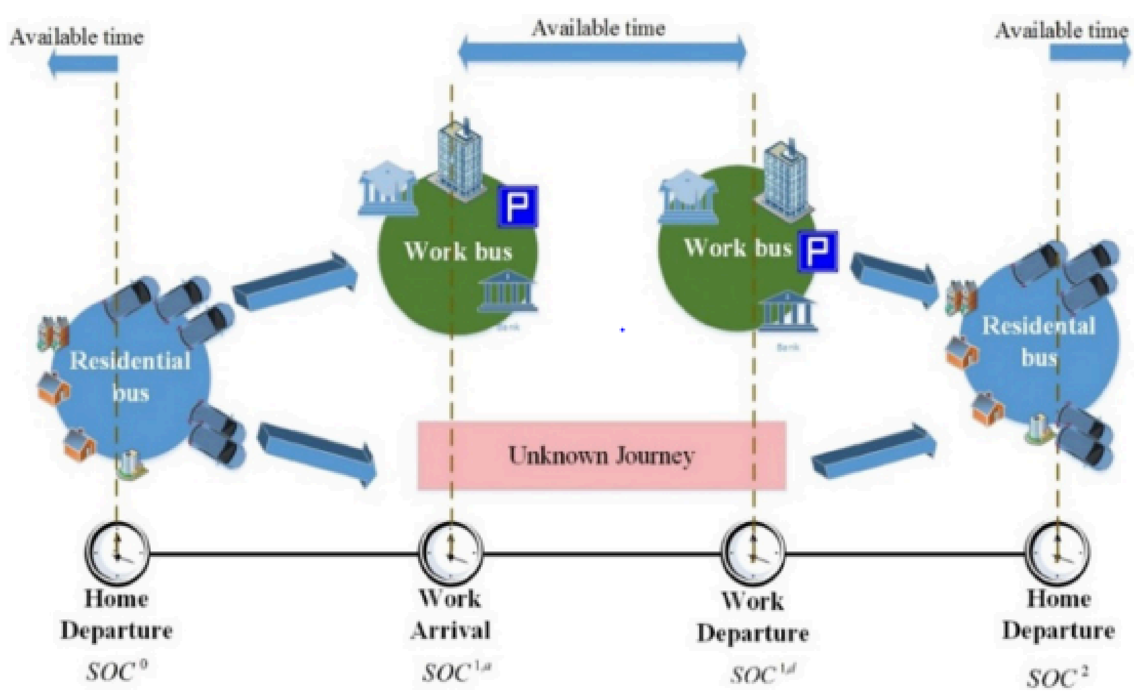

Fig. 1. Two different groups of EVs in terms of controllability throughout the day.

2.5.Traffic effect

The behavior of EV With respect to Traffic effect can be analyzed from two different perspectives, travel delay, and charge consumption. In the case of travel delay, it may affect the arrival/departure time of EVs to system buses.In the case of traffic impact on the EV consumption, it should be noted that comprehensive tests are carried out on EVs to determine their EPA range.These tests are formed based on standard driving cycles that are developed by official organizations (such as EPA) to model real-world driving patterns.

2.6. Road type

Information regarding the various manufacturers says that an EV consumes more charge on the highway comparing to the city road.The reason behind this is that EV power losses, including aerodynamic, tire, and drivetrain losses increase with the increment of its speed.The coefficient of EV consumption increment resulting from driving on the highway (ECI_{hw}) can be calculated by the following equation.

$$ECI_{hw} = (1 + Rc + \emptyset) \tag{4}$$

$$\emptyset = (1 \;\; Rand <= Phw\;)\; otherwise\; (0 \; if\; Rand > Phw) \tag{5}$$

where Rc is road coefficient which determines the ratio of EV consumption in highway comparing to city road. $\emptyset$ is a binary stochastic coefficient that determines whether the parameter ECIhw is applied to a specific EV or not. The value of Phw indicates how many percents of the roads in the study area are of highway type, which considered to be 0.1.

2.7. EV SOC calculation

Value of SOC at each time step depends on the amount of SOC in the previous time step, and the amount of energy exchanged between EV and network at the current interval. When the vehicle is parked at home or work, it may be in G2V (load) or V2G (generator) mode, which is determined by the central energy management strategy.SOC calculation can be formulated as follows:

$$SOC(t) = SOC(t-1) + (K_I/C_m) * (K_C * \eta_{ch} * P_{charge} - (1 - K_c) * \eta dis^{-1} P_{discharge}) * \Delta(t) * 100 \quad (6)$$

$$K_I = \begin{cases} 1 & \text{Active mode} \\ 0 & \text{Idele mode} \end{cases}, \quad K_C = \begin{cases} 1 & \text{Charge mode: G2V} \\ 0 & \text{Discharge mode: V2G} \end{cases} + \quad (7)$$

where KC defines the EV energy exchange mode. Parameter KI specifies whether the EV is in active mode or idle mode. P_{charge} and $P_{discharge}$, are the charging and discharging rate of EV in kW. Δ(t) is the specific time range in hour, which determines the duration of each time step (in this paper is 0.25 h equal to 15 min) and Cm is the rated battery capacity in kWh. Furthermore, ηch and ηdis represent the charge and discharge vehicle-to-grid efficiency coefficients.

The assumption of two trips per day for an EV is a reasonable assumption as shown in different surveys. Therefore Considering that an EV travels half of the daily mileage to reach its destination (workplace), the amount of SOC after arriving at the destination can be calculated as follows:

$$SOC^{0,d} = SOC^{0} - ECI_{hw} * (d/(2 * EPAR)) * 100\% \quad (8)$$

where, SOC^{0} and $SOC^{0,d}$ are the state of charge of EV at home departure and work arrival times.

If a car has an energy exchange with the network at the workplace, its SOC when leaving the workplace ($SOC^{1,d}$). Then again, by considering half way journey to home, EV SOC when returns to home (SOC^{2}) can be calculated as follows:

$$SOC^{2} = SOC^{1,d} - ECI_{hw} * (d/(2 * EPAR)) * 100\% \quad (9)$$

3.Formulation of optimization problem

3.1. Mathematic formulation of MOOEVS problem

They have considered the three main objective peak load shaving, active power loss minimization and EV charge cost minimization (owner revenue maximization).The parametric form of the overall objective function is as follows:

$$minF(\overline{x}) = min(f1(\overline{x}), f2(\overline{x}), f3(\overline{x})) \tag{10}$$

$$\text{Subject to: } g(\overline{x}) = 0 \ \ and\ h(\overline{x}) <= 0 \tag{11}$$

3.1.1. Peak load shaving

Peak load increasing in DS can lead to a series of problems such as overloading of the distribution feeders and power transformers, which consequently jeopardize the system reliability by imposing the unwanted blackouts. Therefore, peak load minimization is one of the main objectives of DSOs, which can be modeled mathematically as follows:

$$minE = \sum_{t=1}^{T} (P_{load,t} - P_{target,t}) \tag{12}$$

where $P_{load,t}$ is the peak power and $P_{target,t}$ is the target peak power at time step t. T is the number of total time steps. E is the difference between these two values.

3.1.2. Active power loss minimization

Total active power loss in the network is the sum of the wasted power in each transmission line, which can be minimized by:

$$min \sum_{t=1}^{T} \{ \sum_{l=1}^{lines} \eta * I_{l,t}^{2} \} \tag{13}$$

where $\eta\ and\ I_l$ are the resistance and current of l^{th} line respectively.

3.1.3. EV charge cost

Charging cost depends on three factors that includes charging cost, discharging revenue and battery degradation cost.

Charge/discharge cost: The EV have ability of two-way power exchange between the EV and grid, and taking into account the price of electricity at charging (C_{charge}) and discharging times ($C_{discharge}$), EV energy exchange can be scheduled in such a way that the EV owner revenue is maximized.

Battery degradation cost: It occurs due to the loss of battery capacity of vehicle. It increases significantly with the participation of EV in V2G program, therefore, the extra cost that is imposed.

$$min \sum_{t=1}^{T} [(P_{charge}(t) * C_{charge}(t)) - (P_{discharge}(t) * C_{discharge}(t)) \\ C_{deg} * (E_{trans})] * \Delta(t) \quad (14)$$

where the term $C_{deg} * (E_{trans})$ represent the method that returns battery degradation cost in per-unit based on the transferred energy in V2G program (E_{trans}).

3.1.4. Problem constraints

The minimization of objective function is subjected to several equality and inequality constraints.

The power drawn from the power transformers (S_T) must be less than its nominal capacity (S_T^{Rated}) . Furthermore, the current of each line should be less than it's nominal thermal loading limit (I_l^{Max})

$$S_T \leq S_T^{Rated} \tag{15}$$

$$\left|I_l\right| \leq I_l^{Max} \tag{16}$$

Constraint (17) and (18) limits the maximum charging and discharging power of EV, respectively. Constraint (19) defines that no power is exchanged between the grid and EV when EV is not parked

$$P_{charge} \leq min(P_{charge}^{Max}, P_{plug}^{Max}) \tag{17}$$

$$P_{discharge} \leq min(P_{discharge}^{Max}, P_{plug}^{Max}) \tag{18}$$

$$P_{EV}(t) = 0 \quad \text{if:EV not parked} \tag{19}$$

Where P_{charge}^{Max} and $P_{discharge}^{Max}$ are maximum charge and discharge power of EV and P_{plug}^{Max} is maximum power rate when Ev plugged to it.

4.Improved multi-objective EMA

In a single-objective problem, the charge of each particle is calculated according to the corresponding objective function, while in a multi-objective problem, the average value of all objectives is allocated as a particle charge. In a single-objective EMA, all particles move toward each other based on their charge quantity, however in developed IEMA, an extra movement is considered toward the best-fitted solution stored in external memory. An external repository is a place where all non-dominated solutions are stored.The competition is more intense for it to remain in the external memory. After finding the solution vectors, a Pareto-optimal method based on the dominance concept is applied to the developed problem to attain appropriate solutions

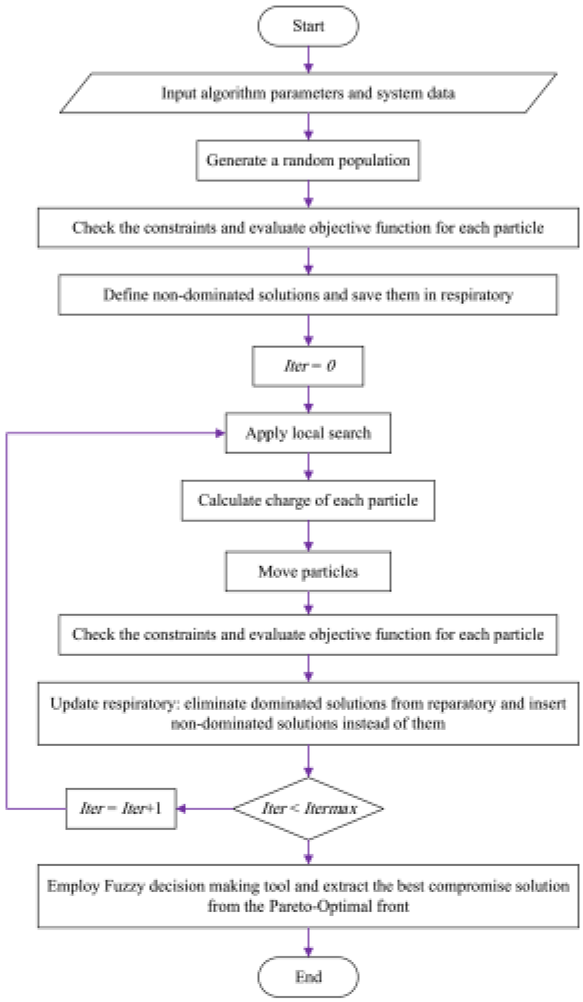

Fig-2. Optimization steps of applied multi-objective IEMA.

After a Pareto front was created, the next step is to choose a solution as the best compromise solution. The fitness of the chosen solution for all objective functions must be evaluated; however, in practice, it is not possible due to the different range of objective functions.In the EMA method, the local search parameter (LSP) is responsible for making a balance between intensification and diversification characteristics of the algorithm. In conventional EMA, the value of LSP is constant over the entire optimization procedure, which in turn increases the risk of trapping algorithm in the local minimums.

By approaching to the final iterations the amount of LSP will decrease, which means that the search space is narrowed around the previously found optimum results to perform a fine-tuning role and improve the intensification characteristic of the algorithm.

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