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STRATEGIC APPROACH FOR ANCILLARY SERVICES OF ELECTRIC VEHICLE BATTERY IN WEEKEND DAYS

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ABSTRACT

An exceptionally consistent development has been seen in the adjustment of electric vehicles (EVs) in the present days. More often EVs are connected to the distribution network for charging only and then utilized for transportation. Nonetheless, EV batteries can be utilized intentionally for ancillary services also for the performance improvement of the distribution system. This article proposes a particle swarm optimization (PSO) based scheduling approach applied to scheduling of EVs to enhance the performance of the electrical distribution system. This method optimizes system performance parameters such as voltage deviation of buses, power losses and network security index of different busses. The capability of the planned method is verified on a 28-bus Indian distribution system and adequate outcome are presented.

KEYWORDS

Electric vehicles, Particle swarm optimization, Power loss, Network security index, Voltage deviation index.

1. INTRODUCTION

In the current scenario, pollution is the biggest problem in worldwide. It is increasing year by year. Although the sectors like agriculture, energy sector, thermal power plant, and transportation sector are responsible for this, major impacts comes from the bulky and noisy conventional vehicles. To overcome these many issues it is important to move towards environment-friendly vehicles. In the present time, EVs is very demanding because of charging, discharging and pollution free vehicles. But when a large number of EVs connected in the network then it affects the performance of the system. So it is necessary to analyze the performance of the network when it is connected to the system. The Government of India has taken different steps and gives support for manufacture and adoption of electric vehicles in place of bulky and noisy traditional fossil fuel dependent vehicles.

It is very imperative to have a proper charging schedule for EV used both in commercial and personal transporting activity. Many of the authors suggested different scheduling technologies from a different point of view. In (Yang et.al, 2015) under uncertain demand when the EV aggregators may act as follower or leader, the author suggested non-cooperative and cooperative charging methods where the first method is related to inequality and LDDM theory and the second is based on joint optimization of the cooperation between the power system and SEVs. Whereas in (Wu et.al, 2017) author suggest a battery swapping optimized technology in charging stations, for that the EV customer has to provide proper information about the battery like number of charged battery required, type of battery, their charging rate and when to be needed, etc. In (Sun et.al, 2016) paper discrete charging of EVs and capacity limitation of the transformer are taking into consideration. Which give a big impact on

system stability, by two different successive binary programs. In the first case by considering the capacity of the transformer to achieve an aggregate load profile and secondly decrease the on-off switching of EVs. (Maigha and Crow, 2017) due to charging and discharging, the life of a battery is degraded so it is important to maximize battery life degradation. System performance depends on load demand, so if the EVs are charging in high demand hours then it gives the worst impact on network performance. During the charging of EVs, sometimes low capacity EVs also pays the same amount as high capacity EVs so it is important to decrease this unfairness between different EVs. In (Wang et.al 2017) paper by using a new scheduling approach called as physical fair quenching framework all the issues eliminates during offline and online by capture the characteristics of EVs charging in sub grid, and apply a new approach called PSTFQ was designed for avoiding the physical problems.

In the above paper, most of them only consider charging of EVs. But very few of the paper deals with charging and discharging both conditions are as follows. In (Chekired and Khoukhi, 2017) formulate electric vehicle scheduling by using cloud computing. By using communication between the smart grid and cloud platform schedule the charging and discharging of EVs and also discuss the interaction between EVs, electric vehicles power supply stations, smart grid, and cloud providers. During peak hours discharging the battery, maintaining the grid stability and the EVs on the basis of the demand-supply curve and also simultaneously minimize the waiting time to plug-in for charging and discharging. Charging of EVs creates a problem in the distribution system, resulting in transformer overloading and under-voltage problem and unfairness among EVs. Due to charging and discharging performance of network improve power loss decrease voltage profile improve (Clement-Nyns et.al 2009, Sundstrom and Binding, 2011, Sortomme et.al 2010, Tang-Nyns et.al 2019).

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Above paper considers network power loss, voltage magnitude and switching time of the battery in distribution system for charging and discharging scheduling of EVs. But in this paper we consider power loss, voltage deviation index and network security index are considered simultaneously. This article proposes a PSO build approach to give out optimal scheduling of EVs connected to distribution system employing deal with different objectives. Battery modeling is also incorporated in charging and discharging of EVs for multi-objective purposes. In this paper we only consider weekend day scheduling of EVs because in weekend days most of the offices, shops and industries are closed. Due to this availability of EVs for ancillary services is more and thus it can contribute more in network performance. The remaining paper is organized as follows in section 2 Problem formulation of the proposed methodology is presented. In section 3 methodology, section 4 result and discussion and conclusion is incorporated in section 5.

Nomenclature

vd_i = voltage deviation of bus-i	V_m = minimum voltage of the bus
$E_{bat}(t)$ = energy of battery at time t	W_i = weight function,
$E_{bat}(t-1)$ = energy of battery at time t-1	$p_{bat}^{initial}$ = initial battery capacity
V_i and V_j are voltage at bus-i and j,	Δt = difference between two consecutive time
$\Delta E_{bat}(t)$ = change battery energy between two consecutive time,	G_{ij} = conductance of line,
θ_i and θ_j are the voltage angle at bus i and j respectively,	SOC_{old} = previous value of soc
SOC_{new} = updated value of state of charge of battery,	$(P_{loss})_{avg}$ = average power loss during 24 hrs,
$(VDI)_{avg}$ = average voltage deviation during 24 hrs,	$E_{bat,act}$ = actual energy capacity of battery
$(NSI)_{avg}$ = average network security index during 24 hrs,	nEV = number of EVs,
n_c, n_d is the efficiency of battery during charging and discharging hours respectively	

2. Problem formulation

2.1 Objective function

This study aims to maximize the performance of the distribution networks on the viewpoint of reduction of average power loss, minimization of average voltage deviation and improvement of network security level. Voltage deviation of the network is realized with a voltage deviation index as presented below.

2.1.1 Active Power loss

The majority of the distribution systems are radial in nature. Due to high resistance to reactance ratio in the network active power losses are more. Therefore, for better performance, it is necessary to calculate and decrease so that the system efficiency get improves. Power loss can be calculated as

$$P_{loss} = \{V_j^2(t) + V_i^2(t) - 2 \times V_i(t)V_j \times \cos(\theta_i(t) - \theta_j(t))\} \times G_{ij} \quad (1)$$

The average power loss can be written as

$$(P_{loss})_{avg} = \frac{\sum_{t=1}^{nT} \sum_{i=1}^{N-1} P_{lossi}}{(N-1)nT} \quad (2)$$

2.1.2. Network security index

The network security index evaluation helps to determine the level of hazard for power flow in the line before going to extremes. If the line surpasses its accessible exchange limit, that is overburden then congestion occurs because each line has a certain accessible exchange limit. Line loading is the ratio of power flow (MVA) through the line and power capacity (MVA) for line-i.

$$LL_i = \frac{L_{MVA,i}}{L_{MVA_{max},i}} \quad (3)$$

The average value of network security index (NSI) is calculated by adding the loading of every line for each time interval of network and written as

$$(NSI)_{avg} = \frac{\sum_{t=1}^{nT} \sum_{i=1}^{N-1} LL_i}{(N-1)(nT)} \quad (4)$$

More outage occurs when the value of NSI is more, so the lower value of NSI is augmented.

2.1.3 Voltage deviation index

Voltage deviation index assessment help to calculate voltage variation of busses in the distribution and transmission system as well in different loading condition. This deviation is calculated as the difference between the voltages of the bus concerning the reference voltage of bus-i.

$$vd_i = |V_{nominal} - V_m(i)| \quad (5)$$

Where $V_{nominal}$ is the nominal voltage of buses in p.u.

The average value of the voltage deviation index can be calculated for the whole network represented as

$$(VDI)_{avg} = \frac{\sum_{t=1}^{nT} \sum_{i=1}^{N-1} vd_i}{(N-1)(nT)} \quad (6)$$

Lower the value of VDI indicates network would turn out to be more secure.

2.2 Battery modeling

The EVs can inject or absorbed active power during ancillary services. In this process EVs battery can be considered as controllable burden or generators. These controllable devices can store energy in the term of charging state and feedback into the system for the time of discharging state. The EVs battery dispatch optimization issues depends on repeated assessment of a solution vector of battery power or battery energy.

During charging hours battery of EVs takes power from the network in a lightly loaded condition.

$$E_{bat}(t) = E_{bat}(t-1) + (p_{bat}^{initial} \times (\Delta t \times n_c)) \quad (7)$$

$$\Delta E_{bat}(t) = (p_{bat}^{initial} \times (\Delta t \times n_c)) \quad (8)$$

During discharging hours EVs fed back power into the network when the demand is high. So, energy of battery during discharging condition reduces that can be written as

$$E_{bat}(t) = E_{bat}(t-1) - (p_{bat}^{initial} \times (\Delta t / n_d)) \quad (9)$$

$$\Delta E_{bat}(t) = (-p_{bat}^{initial} \times (\Delta t / n_d)) \quad (10)$$

SOC of the battery is calculated as

$$SOC_{new} = SOC_{old} + \left(\frac{\Delta E_{bat}(t)}{E_{bat,act}} \right) \quad (11)$$

$$SOC_{JLL} \leq SOC_J \leq SOC_{JUL} \quad (21)$$

3. METHODOLOGY

3.1 Optimization problem

Optimal planning of discharging and charging of EVS connected to the distribution system is a challenging problem with several objective functions and constraints. The study of this problem is to produce the best result with minimization of $(P_{loss})_{avg}$, minimization of $(NSI)_{avg}$, and minimization of $(VDI)_{avg}$. Minimization of $(P_{loss})_{avg}$, $(NSI)_{avg}$ and $(VDI)_{avg}$ are the function of charging and discharging of EVs and is represented by

$$f_1 \{P_{X_{jt}}\} = (P_{loss})_{avg} \quad (12)$$

$$f_2 \{P_{X_{jt}}\} = (NSI)_{avg} \quad (13)$$

$$f_3 \{P_{X_{jt}}\} = (VDI)_{avg} \quad (14)$$

So overall objective can be written as

$$\min f = W_1 \times f_1 + W_2 \times f_2 + W_3 \times f_3 \quad (15)$$

$$\text{Where, } \sum_{i=1}^3 W_i = 1 \quad (16)$$

For charging condition of EVs power taken from the system can be represented as

$$P_{X_{jt}} = \sum_{i=1}^{nT} \sum_{j=1}^{nEV} \{ (-1 \times p_j) \times x_i \times n_c \} \quad (17)$$

For discharging condition of EVs power return back to the network can be written as

$$P_{X_{jt}} = \sum_{i=1}^{nT} \sum_{j=1}^{nEV} \{ (-1 \times p_j) \times x_i \times (1/n_d) \} \quad (18)$$

Where, $x_i = 1$ for charging, -1 for discharging and, 0 for floating or not connected of EVs to the system.

Some equality and inequality constraints are used in this methodology. Which are as follows

Equality constraints

Total system power input is equal to total power loss and total power demand is represented as:

$$PG_{ss} + P_{X_{jt}} - P_L - \sum_{i=1}^N P_{Di} = 0 \quad (19)$$

$$QG_{ss} - \sum_{i=1}^N Q_{Di} - Q_L = 0 \quad (20)$$

Inequality constraints

1. SOC limiting constraints for battery-J

2. Voltage constraints at bus-i

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad (22)$$

3. Line capability limits of line connected between bus-i and bus-j

$$S_{ij} \leq S_{ij}^{\max} \quad (23)$$

$S_{ij}^{\max}$, S_{ij} are the maximum and actual power of line in MVA.

3.2 Particle swarm optimization

PSO is a population-based stochastic algorithm. (Kennedy et. al 1995) was developed and used in research to solve optimization problems. In PSO singular particle alters its position as indicated by its own understanding, what's more, the experience of fittest neighboring particle. In this optimization technique, a swarm of a particle is given as the best solution. First is the finest arrangement it has accomplished so far which is called P_{best} . The second one is the best arrangement establish so far in the entire swarm and it is called G_{best} . In each escape, particles change their position and velocity and attempt to meet in an additionally encouraging area of the solution. Each particle 'i' is related with two vectors i.e. velocity vector and position vector. The velocity and the position of every particle are instated by arbitrary vectors inside the relating ranges. P_{best}^i is the

3.3 Application of PSO

In this paper this optimization technique is used for optimal discharging and charging scheduling of EVs battery and improvement of objective function. The process of utilization of this approach is explained in given flow chart. This flow chart give out the step to find a potential solution utilizing PSO in EV scheduling problem.

Figure 1: Flow chart of the purposed methodology

4. RESULT AND DISCUSSION

To assess and highlight EVs scheduling approach for charging and discharging, we perform a broad simulation on a 28-bus Indian distribution system. 11 KV and 1 MVA are taken as a base value for the

system. This distribution system is considered radial in nature and Bus-1 is treated as substation as shown in Fig. 2. Required line capacity and network data are taken from (Kayal and Chanda, 2015). We use MATLAB to play out our simulation and Newton Raphson power flow algorithm is utilized to calculate power flow in line and bus voltage of this test network. In this distribution system at 5 different residential load point, different number of EVs are connected, which have followed simultaneous charging and discharging pattern. In this simulation, a number of iteration and the number of a particle are taken 10000 and 100 respectively which can give the best optimal solution. In this simulation analysis, considering different time zone availability of EVs for the use of ancillary services and charging. In weekend day i.e. Saturday and Sundays from 12 AM to 4 PM and from 10 PM to 12 AM are considered for optimized charging and discharging of EV battery according to its SOC level. In the remaining time, the EV battery is used for transportation

Figure 2: 28-bus single line diagram of Indian distribution network with EVs (S/S: substation, CB: circuit breaker, RCL: reclosure, R: residential load, C: commercial load, I: industrial load)

In the above Fig.2, 5 different charging station is considered at 5 different residential load point. It is assumed that number of EVs connected at bus-25, bus-22, bus-19, bus-10, and bus-13 are 3, 1, 2, 2 and 1 respectively. So, overall 9 EVs are connected at 5 different load points. The parameters of battery are specified Table 1. It is assumed that initial SOC level of battery when connected to the network is 0.4.

Table 1: Specification of EV battery (Wang et.al 2018)	
parameter	Value
Energy capacity	24kWh
Power capacity	6.6kW
State of charge	0.2 – 0.95
Charging efficiency	90%
Discharging efficiency	95%

Figure 3: Load demand curve of weekend days (RD: residential demand, CD: commercial demand, ID: industrial demand)

Figure 4: Comparison of voltage variation between the scenario of without and with ancillary services of EVs in weekend days

Figure 5: Variation of SOC level between the scenario of without and with ancillary services of EVs in week days

Table 2: Comparison of network's performance between the cases of without and with ancillary services of EVs in week days			
	Avg. network power loss (MW)	Avg. VDI (p.u.)	Avg. NSI (p.u.)
Charging	0.0323	0.0476	0.3537
Ancillary	0.0322	0.0476	0.3358

Table 3: Optimum charging and discharging pattern of EVs for ancillary services												
Hour	01	02	03	04	05	06	07	08	09	10	11	12
	0	0	0	1	1	0	0	0	-1	0	0	0
Hour	13	14	15	16	17	18	19	20	21	22	23	24
	-1	1	1	0	0	0	0	0	0	0	0	0

In Fig. 3 load demand during the weekend day of the network is shown. In the load demand curve RD stands for residential load, CD stands for commercial load and ID stands for industrial load demand during 24hrs. The minimum voltage magnitude graph obtained during the weekend day for charging only and charging and discharging both are presented in Fig. 4. SOC of EVs battery during different time intervals is furnished in Fig. 5. Obtained average power loss, average voltage deviation and average network security index of the network during charging and ancillary services are mentioned in Table 2. Table 3 shows the optimal battery charging and discharging optimal pattern. The study reveals that voltage drop at peak demand hours has decreased after connecting EVs. It also shows that maximum line loading improves by 5.051% after penetration of EVs units. Power loss and voltage deviation of system are decrease by 0.3059 and 0.4201% respectively.

5. CONCLUSION

This article proposes a method of scheduling of electric vehicles connected to a distribution network. The main aim of this paper is to manage of power transfer between vehicle to power network and vice-versa so that during high demand hours EVs supply power to the network and in light load condition EVs should be charged. An effective optimization model has been implemented to find out optimal scheduling and best performance of the distribution networks with various operational constraints. The performance improvement of the network has been observed with the

obtained scheduling arrangement. The effectiveness of the proposed model is thus justified to obtain most preferred scheduling of EVs in weekend days and can be further extended to the week days.

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