TEACHING - LEARNING BASED OPTIMIZATION METHOD FOR PEV SCHEDULING INCORPORATING PV UNITS

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ABSTRACT

An unplanned charge or even discharge of EVs in a distribution electricity network causes some technical problems, especially while there are other sources of power such as PhotoVoltaics (PVs). This paper employs a novel Teaching and Learning Based Optimization (TLBO) approach to mitigate the corresponding serious side effects. In this work, the proposed strategy finds the optimum schedule of plug-in electric vehicles (PEVs) in order to improve the system voltage profile and reduce active power losses, while the PV units are supplying the system. To investigate the efficiency, a TLBO-based proposed method is applied to a typical standard IEEE distribution network.

I. INTRODUCTION

Widespread use of Plug-in Electric Vehicles (PEVs) in the smart distribution network is one of the approaches concerning to increase the reliability, to reduce the greenhouse gases emission, and to decrease the total cost of operation. Although these technologies have many advantages to count, the uncoordinated operation of them could create drastic bearings on network operational criteria, resulting in non-smooth voltage profile, active power loss increment, and perilous voltage stability.

S. W. Hadley et al. [1], assumed that the vehicles are plugged in at certain time and left until fully charged. A. Maitra et al, have used transportation data provided by the American National Household Travel Survey (NHTS) to develop a methodology for assessing the anticipated impacts of PEVs on distribution grids [2]. In [3], the authors, proposed a probabilistic approach based on the Monte Carlo (MC) simulation to evaluate the impacts of uncontrolled charging of PEVs on distribution networks. The impact of PEVs on the reactive power flow of the system is stated in [4]. F. L. Pieltain et al. assumed that 85% of vehicles are charged during valley hours and the remaining are charged during peak hours, irrespective of their arrival times [5]. The author in [6], have studied the application of EVs as a backup source of buildings. Singh et al. [7], proposed the coordinated PEV charging as distributed energy resources to smooth the load profile. Lin Cheng et al. [8], proposed a framework for the distribution power network voltage regulation, and collaboration of EVs with Online Load Tap Changing (OLTC) to mitigate the voltage problems caused by distribution solar generations. M. Alam et al. developed a coordinated charge/discharge pattern to optimize the use of limited PEV battery capacity in order to mitigate the PV impacts [9]. Maigha et al. 2017 [10], proposed a solution for the valley filling (system perspective) and charging cost reduction (customer perspective). A predictive control strategy has been used in [11] to schedule the optimal charging/discharging plug in electric vehicles. The authors in [12] have shown that they have the potential to solve the existing and future power quality issues by intelligently integration of PEVs in a power grid. Demand Response (DR) program along with the PEVs charging are proposed in [13] to provide a real time charging scheme.

In this paper, a proposed teaching and learning based optimization (TLBO) algorithm is implemented to determine the optimal charging and discharging of PEVs in a typical distribution electric power network integrated with PV sources. Considering distribution grid real power loss and voltage deviation as a multi-objective function, optimal amount of electric power consumption to charge or inject power to discharge EVs are assessed. It is worth noting that the behavior of the EV owners is modeled by consideration of typical residential daily activities. The present paper is organized as: problem definition is provided in section 2, TLBO algorithm is described in section 3, simulation results and case study discussion are given under section 4 and lastly the conclusion is stated in section 5.

II. PROBLEM DEFINITION

The objective of an optimal PEV scheduling problem is to minimize the active power losses and improve the voltage profile. In this case, we have two sets of formulations and constraints: one is the PEVs and PVs related constraint sets, and the other is the grid rule criteria. To calculate the grid voltage profile, and active power losses, power flow has been run throughout the system with the following specifications:

- Newton Raphson power flow algorithm
- AC power flow formulation

Maximum 10 iterations have been done for the Newton's method. The power flow equations must be satisfied based on the following formulations:

$$Q_{G,i} - Q_{D,i} = V_i \sum_{j \in N_i} V_j \ (B_{ij} cos\theta_{ij} - G_{ij} sin\theta_{ij}) \quad (1)$$

$$P_{G,i} - P_{D,i} = V_i \sum_{j \in N_i} V_j \ (G_{ij} cos\theta_{ij} + B_{ij} sin\theta_{ij}) \quad (2)$$

$P_{G,i}$ and $Q_{G,i}$ are the injected active and reactive power to bus-i, $P_{D,i}$ and $Q_{D,i}$ are active and reactive power demands from bus-i, B_{ij} and G_{ij} are transfer susceptance and conductance between buses i and j, respectively. θ_{ij} is the voltage angle difference between buses i and j.

In this work, $P_{G,i}$ and $Q_{G,i}$ are expressed as the sum of output power injected to the bus-i:

$$P_{G,i} = \sum_{k=1}^{m} P_{EV\_k_i} + \sum_{l=1}^{f} P_{grid\_l_i} + \sum_{s=1}^{d} P_{pv\_s_i} \quad (3)$$

$$Q_{G,i} = \sum_{l=1}^{f} Q_{grid\_l_i} + \sum_{s=1}^{d} Q_{pv\_s_i} \quad (4)$$

$P_{EV_k_i}$is the active power injected by PEV-k on bus-i, $P_{grid\_l_i}$ is the active power consumed by the grid in line-l, and $P_{pv\_s_i}$ is the active power injected by PV panel-s at bus-i. The same nomenclatures are satisfied for the reactive power formulation. The grid power loss can be achieved through the following equation:

$$P_{loss,i} = Power_i^{sent} - Power_i^{Received}, \forall i \in \{1, \dots, n\} \quad (5)$$

The active power loss and the system's Total Voltage Deviation (TVD) could be calculated by:

$$P_{loss} = \sum_{k=1}^{N} g_k \left[V_i^2 + V_j^2 - 2V_iV_j cos\theta_{ij}\right] \quad (6)$$

$$TVD = \sum_{i \in N_L} |V_i - V_i^{ref}| \quad (7)$$

g_k is the bus susceptance, V_i is the bus-i voltage and V_i^{ref} is a desirable amount of voltage for each bus equal to 1 p.u.

a) Power System Constraints

Based on the system model, the grid operational constraints are discussed in this section. The amount of bus voltage must remain within a permitted range (table I). Indeed, the voltage constraint could be clarified as:

- For generation buses

$$V_{Gi-Min} \leq V_{G,i} \leq V_{Gi-Max} \quad , \quad i = 1, \dots, N_G \quad (8)$$

- For load buses

$$V_{Li-Min} \leq V_{L,i} \leq V_{Li-Max} \quad , \quad i = 1, \dots, N_L \quad (9)$$

Another power system constraint is related to the load buses. Each load bus has a limited capacity to receive the power (table I). So,

$$S_{Li} \leq S_{Li-Max} \, , \quad i = 1, \dots, N_L \quad (10)$$

b) PEVs Charger Constraints

If we consider P_{G2V} as the maximum PEV charging power; hence, P_{V2G} presents the discharging power in the vehicle to the grid status. The charging/discharging power can be formulated as the following equation.

$$P_{V2G} < P < P_{G2V} \quad (11)$$

c) Battery State of Charge (SOC) Constraints

In fact, the State of Charge (SOC) factor of PEV must be in an acceptable range depending on the size of battery. The SOC factor is calculated according to the following equation.

$$SOC(k) = SOC(k-1) - \frac{I_{batt} \times (I_{dc}(k) - I_c(k))}{C_{batt}}, \; k = 2, \dots, 24 \quad (12)$$

Where: $SOC(k)$ is the amount of SOC factor at the hour-k, $SOC(k-1)$ is the amount of SOC factor at the hour-(k-1). I_{batt} is the battery current of PEV, I_{dc} is the amount of discharge current, I_c is the value of charge current and finally C_{batt} is the battery capacity. There are some keynotes which are important in the above equation. First, the value of SOC in the present hour depends on the amount of SOC in the previous hour. The PEV is not allowed to charge or discharge in consecutive hours, because it violates the lower or upper acceptable range boundaries. Second, the values of I_{dc} and I_c are assumed to be constant in each hour. Third, the ration of current and capacity has some certain amounts related to the PEV vendor. Furthermore, the value of the SOC factor at first hour is assumed to be random. Finally, the SOC factor must be kept within an acceptable range in every hour as follows:

$$SOC_{min} < SOC(k) < SOC_{max} \, , \; k = 1, \dots, 24 \quad (13)$$

Where, SOC_{min} and SOC_{max} are minimum and maximum values of the permitted battery state of charge, respectively. As mentioned before, the charging and discharging rates are the same and could be clarified as follows:

- For charging state

$$SOC(k) = SOC(k-1) + \frac{I_{batt}}{C_{batt}} \times \frac{P}{V}, \; k = 2, \dots, 24 \quad (14)$$

- For discharging state

$$SOC(k) = SOC(k-1) - \frac{I_{batt}}{C_{batt}} \times \frac{P}{V}, \; k = 2, \dots, 24 \quad (15)$$

Where P is the base active power of the battery, and V is the base voltage of the battery.

d) PV Active Power Constraints

Based on the PV power generation curve, it is possible to find the maximum active power throughout a day. The restriction inequality is mentioned below:

$$0 < P_{PV} < P_{PV,max} \quad (16)$$

e) Objective Model

Finally, in this paper, it is aimed to optimize the active power loss of the system and to obtain a quite-smooth voltage profile through coordination of PEVs and PVs. In order to involve the PEVs/PVs scheduling problem with metaheuristic techniques, the optimization cost function (grid total losses calculated through the power flow) needs to be defined. The multi-objective function of the coordination problem would be:

$$F = \omega_1 \sum_{i=1}^{N} \sum_{j=1}^{N} g_{ij} \Big[V_i(S_{pv_i}, S_{ev_i})^2 + V_j \left(S_{pv_j}, S_{ev_j}\right)^2 - 2V_i \left(S_{pv_i}, S_{ev_i}\right) V_j \left(S_{pv_j}, S_{ev_j}\right) cos(\theta_{ij}) \Big] + \omega_2 \sum_{k=1}^{N} | V_i \left(S_{pv_i}, S_{ev_i}\right) - V_i^{ref} | \quad (17)$$

$V_i\left(S_{pv_i}, S_{ev_i}\right)$ represents the voltage of bus-i, which is influenced by installed PV and plugged in EV on the same bus. ω_1 and ω_2 are assigned based on the expected effect of optimization result on smoothing voltage deviation curve or grid loss reduction (same as the sensitivity coefficient for the grid loss and voltage profile).

III. TLBO OPTIMIZATION METHOD

The idea of this algorithm resembles a class situation where a teacher (teacher has the best grade among the students) improves average grade of the class and shares his/her information with the other students. Also, students learn from mutual relations between each other [14-16]. In TLBO, the population is considered as a bunch of students, the grade mark resembles the "fitness", and teacher is known as the best solution. The Teaching/Learning process of TLBO has two main phases: Teaching phase and Learning phase.

a) Teaching Phase

The process of teaching phase is formulated as the following mathematical equation. Primarily, the difference between the teacher and the existing mean grade of the class in every dimension is calculated as DM_i with the following equation.

$$DM_i = rand\,(T_i - T_F M_i) \quad (18)$$

M_i is the mean value (mean grade of the class) of each solution in every dimension. Also, T_i expresses the teacher's grade in i-th iteration. T_F is the teaching factor and assigns the learning process speed. This tuning parameter is expected to be varied between 1 and 2 (normal or fast learning) denotes as:

$$T_F = round\,(1 + rand(0,1)) \quad (19)$$

Knowledge of learners is improved by adding the DM_i as:

$$St_i^{new} = St_i^{old} + DM_i \quad (20)$$

St_i^{new} and St_i^{old} denote the i-th solution particles imitating leaner before and after gaining knowledge. The better knowledge from new learners is accepted to replace the worse old learner.

b) Learning Phase

In addition to learning from a teacher, students also can improve their grades by interaction with each other. They work in pairs to compare the results and share knowledge. The process of learning is mentioned as following equations:

$$St_i^{new} = \begin{cases} St_i^{old} + rand(St_i - St_j) & if\ f(St_i) < f(St_j) \\ St_i^{old} + rand(St_j - St_i) & if\ f(St_j) < f(St_i) \end{cases} \quad (21)$$

In summary, the TLBO algorithm implementation phases are fulfilled in the following steps:

1) Initialize population

repeat

2) Calculating the mean of the population members
3) Choosing the best member of the population
4) Teaching phase

T(Teacher) or the best member of the population

$St_i^{new} = St_i + r(M_{new} - T_F M)$

5) Better results (St_i^{new}) will be substituted by old results
6) Learning phase

For each St_i finding another random result St_j

If St_i is better, then $St_i^{new} = St_i + r(St_i - St_j)$

If St_j is better, then $St_i^{new} = St_i + r(St_j - St_i)$

7) Better results (St_i^{new}) are substituted by old results

until requirements are met

TLBO has the least control and tuning parameters among the other metaheuristic algorithms such as Imperialistic Competition Algorithm (ICA), Tabu Search (TS) and Genetic Algorithm (GA). In the TLBO the mentioned parameters are restricted to $MaxIT$ (maximum iteration) = 300, $nPop$ (number of population) = 100 and the TF (teaching factor).

IV. PEV/PV TLBO SCHEDULING

The system under study consists of PVs, EVs, and residential loads, which PEVs and PVs are connected to the grid without coordinated schedule. This power grid is the IEEE 16-bus standard network supplying 28.7 MW active power and 17.3 MVAR reactive power loads. A typical residential load profile, shown in Fig. 1, is taken into consideration in this work. A typical active power generation curve by solar panels has been considered. In this curve the solar panel generates its maximum power at 12 noon. During hours 1 AM to 4 AM and 20 PM to 24 PM the unit generation output is near zero. In this study the maximum active power generation by the PVs is considered 2.3 MW

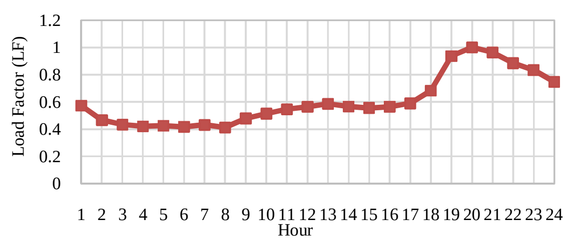

Fig. 1 Typical residential load profile

The EVs' plug-in pattern, illustrated in Fig. 2, consists of departure rush hour in the morning, arrival rush hour in the afternoon, daily shopping and other activities for a typical residential customer.

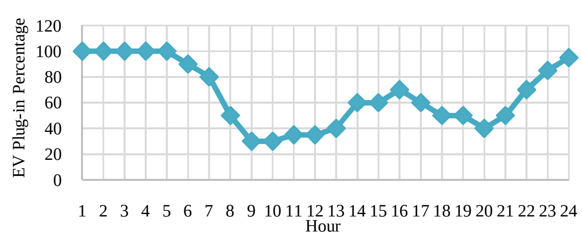

Fig. 2 Typical plug-in EVs daily pattern

a) Power Flow Specifications

The grid bus information and its limitations have been summarized in Table I.

TABLE I. The grid bus data

Bus	Pd	Qd	Vmax	Vmin
1	0	0	1.06	0.94
2	0	0	1.06	0.94
3	0	0	1.06	0.94
4	2	1.6	1.06	0.94
5	3	1.5	1.06	0.94
6	2	0.8	1.06	0.94
7	1.5	1.2	1.06	0.94
8	4	2.7	1.06	0.94
9	5	3.0	1.06	0.94
10	1	0.9	1.06	0.94
11	0.6	0.1	1.06	0.94
12	4.5	2.0	1.06	0.94
13	1	0.9	1.06	0.94
14	1	0.7	1.06	0.94
15	1	0.9	1.06	0.94
16	2.1	1.0	1.06	0.94

Increasing the connected PEVs to the grid results in the bus voltage drop and raise of the grid active power losses. On the other hand, increasing the number of installed PVs in a specified bus, leads to both over-voltage and increased active power loss of the grid.

PEV and PV Scheduling Results

In this case, 4500 EVs have been connected to bus-7, bus-12, and bus-16. It is assumed that PEVs are aggregated in three EV sets. Indeed, three set of 1500-EVs are connected to bus-7, bus-12, and bus-16. Also, three PV packs are installed in buses 7, 12, and 16. Each PV pack generates 2.25 MW (consists of 15 solar panel of 150 KW). The practical constraints about battery SOC and charging/discharge power are defined as:

$$5 < SOC\,(KWh) < 16.5$$
$$-3.7 < P(KW) < 3.7$$

The active power loss and voltage deviation of the system for 24 hours duration are shown in Fig. 3 and Fig. 4, respectively. Also, the scheduling of the PEVs is illustrated in Fig. 5. The batteries have been charged during the day hours when solar panels generate the maximum power and discharged during the peak hours. As shown in Fig. 6, The Battery SOC limit) is satisfied; while the behavior of PEV sets do not look similar. That is because of nonlinearity of the grid equations. The grid topology and the point of connection have considerable impacts on the PEV schedule. The grid peak load when the PEVs are scheduled through the proposed method is shown in Fig. 7. As a result, a better flat load curved is obtained.

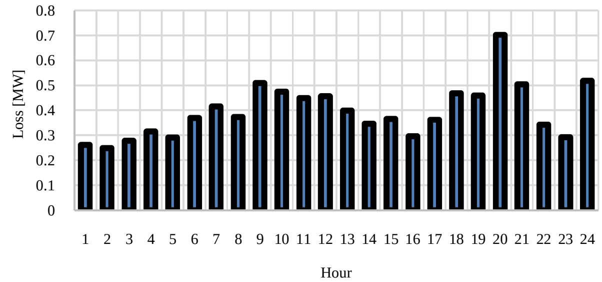

Fig. 3 Grid active loss for 24 hours

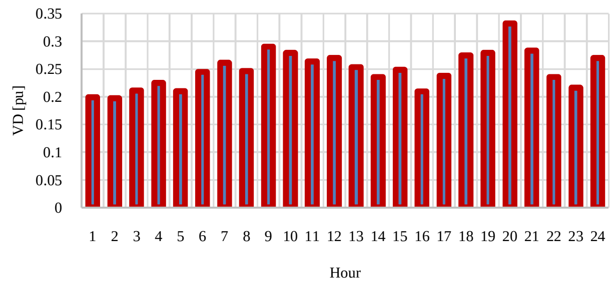

Fig. 4 Total voltage deviations in the 24-hour interval

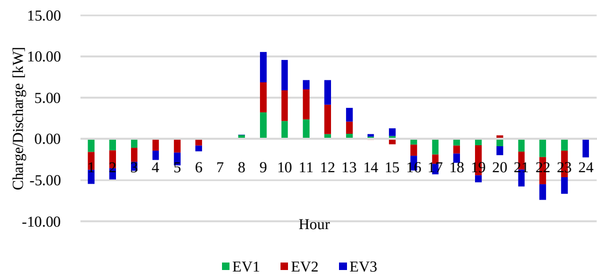

Fig. 5 Aggregated PEVs charge/discharge plan in 24-hour duration

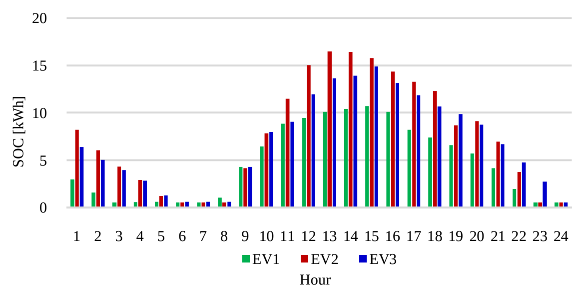

Fig. 6 Aggregated Battery SOC plan in 24-hour duration

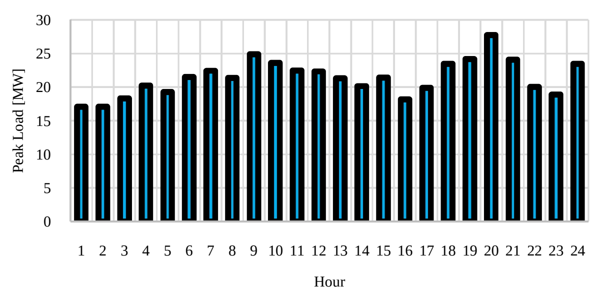

Fig. 7 Grid peak load in 24-hour period

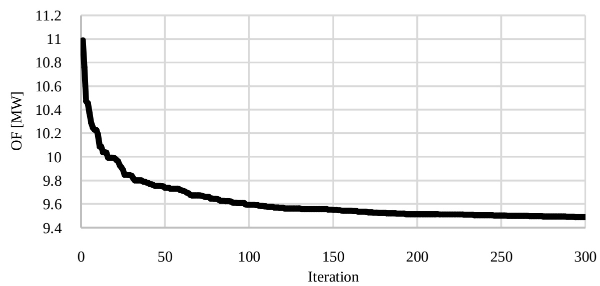

Fig. 8 Optimization convergence after 300 iterations

The convergence curve, illustrated in Fig. 8, shows the power loss reduction. Also, the peak load graph showed a significant valley filling pattern. The PEVs and PVs have shown considerable cooperation to mitigate the mentioned grid drawbacks, which indicates the powerful performance of the proposed method in problem solving.

V. CONCLUSION

Integration a large number of plug in EVs to the grid, results in the bus voltage deviation and active power loss raise tremendously. Further, we face overvoltage and increased grid loss by increasing the number of installed PVs on the grid. Therefore, a TLBO based optimization method is proposed to deal with this problem in order to control the charge or discharge of the plugged-in EVs in cooperation of PVs in the distribution electric power network. By looking at the TLBO simulation results, PEVs have been charged during the day hours and discharged at the peak hours. Discharging PEVs at peak hours causes less active power losses in the grid. By discharging PEVs at these hours some part of load demands are provided locally through the PEVs. Therefore, there is no need to increase power flow from the upper network. Finally, TLBO optimization method proved successful function to alleviate the PEVs penetration impact in cooperation of PV generation units.

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