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Voltage Fluctuation Smoothing in Distribution Systems with RES Considering Degradation and Charging Plan of EV Batteries

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Abstract – Recently, the use of renewable energy sources (RES) and electric vehicles (EVs) has been rapidly increased worldwide. As a result of the highly fluctuating nature of RES, the charging and discharging rates of EVs significantly have to be increased, and so the lifespan of EV batteries decreases. In this paper, an optimization-based method is proposed to smooth voltage fluctuations due to various RES types by optimally controlling the charging and discharging power of EVs and the reactive power of the RES inverters. To extend the lifespan of the EV battery, EV power fluctuations and their minimum preset state of charge (SOC) are considered in the proposed optimization model. For this purpose, a new multi-objective function is formulated, including 1) voltage fluctuations, 2) EV power fluctuations, and 3) the deviation of SOC of EVs from their minimum desired level. The use of the hull moving average (HMA) is proposed to mitigate voltage fluctuations, which eliminates the lag problem of the widely used moving average methods. The gravitational search algorithm (GSA) is utilized to accurately solve the optimization model. The simulation results demonstrate the effectiveness of the proposed method to smooth voltage fluctuations while considering degradation and charging plan of EV batteries.

Index terms– Voltage fluctuation; RES; Electric vehicles; distribution system; GSA; vehicle to grid (V2G)

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1. Introduction

In recent years, the integration of various renewable energy sources (RES) into power systems has significantly increased across the world. Indeed, rapid deployment of RES results in substantial energy security, climate change alleviation, and financial benefits [1–3]. RES are clean and quiet energy sources, and they are commercially available in flexible and modular structures. The costs of these promising sources of electricity are dramatically declining and so they became preferable alternatives compared with other conventional energy sources. Photovoltaic (PV) and wind turbine generation system (WTGS) are the preferable types of RES worldwide due to their flexibility and the rapid development of their technologies [4]. Typically, large-scale PV and WTGS units are integrated into transmission systems while small-scale PV and WTGS units are connected to low-voltage and medium-voltage distribution networks [5,6].

Several studies have been directed to investigate the fluctuating nature of different RES types and define efficient ways to mitigate their negative consequences [7,8]. To cope with this issue, several techniques have been developed in the literature to mitigate such fluctuations by employing the reactive power capability of the RES inverter during rapid power transients [9,10]. However, these techniques are constrained by the rating of the RES inverter and they could reduce the lifetime of the RES inverter [11–13]. Other techniques for fluctuation mitigation are based on employing various components in distribution systems, such as storage systems [14–22], distributed generation [23,24], capacitors [25,26], and dump loads [7].

Recently, the use of electric vehicles (EVs) has been dramatically increased worldwide [27,28]. The number of operating electric vehicles was about one million in 2015, as reported by the international energy agency [29]. In 2020, several countries, which are called electric vehicle initiative group, follow a strategy to increase the number of such vehicles to 20 million [30]. EVs are electric cars in which batteries are used as a power source to be charged during their parking

time via the utility [31–33]. Indeed, the batteries of EVs can be employed to reduce the undesired fluctuations caused by RES. The authors of [34] proposed a method to reduce voltage fluctuations by controlling the charging/discharging power of EVs and injecting the highest allowed reactive power of the PV inverter. In [35], to reduce the operational problems with PV, a control algorithm was proposed based on the charging and discharging control schemes of the EVs. EVs were treated as coordinated loads to prevent voltage violations with PV [36]. In [37], two methods were proposed for mitigating voltage rise with PV and EVs. The main advantage of these two methods is that the reactive power of the PV inverter and the power of EVs are optimized in a simultaneous manner. The minimum capacity of the storage device to alleviate the power fluctuations of PV has been modeled in [38]. In [39], the energy storage systems with RES are controlled based on a dynamic approach to minimize the operation cost of the system. An adaptive approach for controlling EVs and reconfiguring distribution systems has been introduced in [40]. The authors of [41] have studied the planning and operation problems of parking lots of plug-in EVs. In [42], the use of the simple moving average (SMA) method has been proposed to smooth the power fluctuations of PV. The SMA method has been employed in [43] for smoothing the PV power fluctuations in the presence of a DG unit and a battery device. In [44], a battery device is utilized to track a smoothed profile generated by the SMA method for mitigating power fluctuations of PV. In [45], the exponential moving average (EMA) method has been employed to reduce the fluctuations of PV power.

The aforementioned methods mitigate the voltage fluctuations by controlling the charging and discharging rate of the EV batteries. As a result of the highly fluctuating nature of RES generation, the power of EVs highly fluctuates, and thus the lifespan of the EV batteries is significantly decreased. In other words, the voltage fluctuations will be solved at the expense of the EV power

fluctuations. It is a fact that decreasing the charging and discharging rate of the battery maintains the battery health [46–49]. Another factor that can increase the lifespan of the battery is maintaining a healthy state of charge (SOC). The use of the SMA and EMA methods in the literature can mitigate the voltage fluctuations due to RES, but they result in high fluctuations of EV power, and so decay the lifespan of its battery.

In this paper, an optimization-based method is proposed to mitigate the voltage fluctuations due to PV and WTGS by optimally controlling the charging/discharging power of EVs and the reactive power of the PV and WTGS inverters. Based on the literature, the battery degradation of EV is affected by several factors. The two following factors are considered in this paper: 1) the charging/discharging rate of EV batteries, and 2) the SOC of the EV batteries during V2G operation. To extend the lifespan of the EV batteries, the fluctuations of EV charging power and their minimum SOC during V2G operation and at departure time are considered in the proposed optimization model. For this purpose, the objective function of the optimization problem is formulated to minimize: 1) voltage fluctuations, 2) EV power fluctuations, and 3) the deviation of SOC of EVs from their desired level. In this formulation, we propose the use of the hull moving average (HMA) to mitigate voltage and SMA to mitigate EV power fluctuations. Unlike SMA, HMA eliminates the lag problem and mitigates the fluctuations at the same time. The third term in the objective function guarantees the charging goal of the EVs while considering their individual parking time schedule and their current SOC status. To accurately solve the optimization model, the efficacious gravitational search algorithm (GSA) is utilized. The proposed method is applied to the 33-bus and 90-bus distribution systems with PV, WTGS, and EVs. The proposed method is a helpful tool that enables system operators to make the trade-off between decreasing the voltage fluctuations and decreasing the EV power fluctuations while meeting the EV charging goal.

2. Problem Description

2.1 RES impacts

The variability of the irradiance and wind speed due to weather conditions can cause high fluctuations in the output power of PV and WTGS, respectively. These fluctuations in the output powers make RES intermittent and unreliable sources when connected to the distribution systems. Therefore, as the penetration of RES in the distribution system increases, the power fluctuations can have serious impacts on power quality and reliability. One of these impacts is voltage fluctuation at the entire distribution system, and especially at the point of common connection (PCC) of PV or WTGS. The voltage fluctuations may lead to the disconnecting of PV and WTGS from the distribution system [50], which can result in a shortage in the power system.

Figure 1. Active power output of a PV system (partly cloudy day).

Figures 1 and 2 are used as examples of the power generation of PV and WTGS, respectively, in which they have a time resolution of 1 minute. The PV data were extracted from a set of measurement data of a PV generator. The complete set of data were collected in 2013, from February 25 to March 12 and from June 17 to July 2 [51]. While the data of WTGS were extracted from the data sets of Nevada Power Clark Station [52]. To illustrate the voltage fluctuations problem, Figure 3 demonstrates the voltage profile at PCC of the PV system which is calculated

by time-series power flow analysis. It can be seen from the figure that the voltage is significantly fluctuated due to the high variation in the output power of PV. In this context, mitigating of these fluctuations is necessary to prevent their negative impacts on the distribution system.

Figure 2. Active power output of a WTGS.

Figure 3. Voltage magnitude at PCC of the PV system.

2.2 Impact of EV Batteries

Deployment of EVs will encourage the cooperation among the power generation, power transmission, and power supply. EVs are expected to be widely used in the future. Therefore, the stress and fluctuations in the distribution system will be increased. On the contrary, EVs can be

useful for power dispatching to efficiently manage load, as long as the charging/discharging behavior of EVs can be scheduled effectively.

To mitigate the voltage fluctuations, EVs can be utilized for this purpose during their parking at the charging station. However, in this case, the fluctuations of the charging/discharging power of EVs can be increased to compensate the fluctuations from RES. These frequent changes between charging mode and discharging mode may have a complex set of effects on EVs batteries performance and lifespan. Therefore, the fluctuations in the charging/discharging power of EVs should be considered and mitigated. Mitigating these fluctuations decreases the charging/discharging rate which increases the lifespan of EV batteries [46]. Moreover, EV batteries should be operated at high SOC levels during V2G operation to optimize their lifespan as described and modeled in [53,54]. Furthermore, it is important to consider the charging plan of EVs which is preset by their owners.

3. Proposed Method

3.1 Description

A new method is proposed for mitigation of the voltage fluctuations in the distribution system due to the intermittency of RES (e.g., PV and WTGS). This method is based on utilizing the reactive power injection/absorption capability of the interface inverters of RES and the application of EVs as energy storage (in which they are parked at the charging station up to 95% of the time [55]) to mitigate the voltage fluctuations at PCC. Furthermore, the fluctuations of the charging/discharging power of EVs are considered in the proposed method to extend the lifespan of the EV batteries. The minimum SOC required by the consumers at the departure time is also incorporated and considered in the proposed method to meet the consumer needs.

Figure 4. Schematic diagram of the proposed method.

Figure 4 shows the schematic diagram of the proposed method. The proposed optimization method can be executed in the distribution management system (DMS), as shown in the figure. DMS comprises many functions (e.g., smart-grid simulator, state estimator) to manage and supervise the distribution system, and it helps system administrators as a decision support system during normal and critical conditions. The controllers of PV, WTGS, and aggregators send communication signals through the distribution system. These signals consist of wind power generation ($P_{g,i}$), the reserve reactive power of wind inverter ($Q_{inv,i}^{max}$), power generation of PV ($P_{g,j}$), the reserve reactive power of the PV inverter ($Q_{inv,j}^{max}$), the total available energy of EV batteries that can be used for mitigation of the voltage fluctuations at the charging stations i and j ($E_{av,i}$ and $E_{av,j}$), and the total energy required by EV batteries at charging stations i and j to reach their desired SOC ($E_{req,i}$ and $E_{req,j}$). Based on these signals, the optimization solver in the DMS cooperatively manages the controllable devices. The interface inverters of RES and charging stations of EVs are considered as controllable devices in which the control variables are the reactive power injection/absorption of the interface inverters ($Q_{inv,i}$ and $Q_{inv,j}$) and the charging/discharging active power of the charging stations ($P_{cs,i}$ and $P_{cs,j}$). These variables are

simultaneously calculated to mitigate the voltage fluctuations and appropriate orders are generated. DMS dispatches these orders over the distribution system (i.e., optimal reactive power injected/absorbed by the interface inverters and active power charging/discharging of the charging stations). The aggregators divide the total active power of the charging stations decided by the optimization solver among the batteries of EVs based on their charging plan. The active power charging/discharging of each EV battery depends on its SOC and departure time.

3.2 Optimization Problem Formulation

In this work, the voltage magnitude deviations at PCC from their HMAs, the deviation of active powers of EVs from their SMAs, and the deviation of the total energy of charging stations from the total required energy of EVs to reach their desired SOC are considered as an objective function to be minimized in the optimization model as follows:

$$\begin{aligned} \text{Minimize } F_t = & \alpha \sum_{i=1}^{Ndg} (HMA(V_{i,t}) - V_{i,t})^2 + \beta \sum_{j=1}^{Ncs} (SMA(P_{cs,j,t}) - P_{cs,j,t})^2 \\ & + \gamma \sum_{j=1}^{Ncs} (E_{req,j,t} \pm P_{cs,j,t} \times t) \end{aligned} \quad (1)$$

in which

$$\alpha + \beta + \gamma = 1 \quad (2)$$

$$SMA(P_{cs,j,t}) = \frac{P_{cs}(t-1) + P_{cs}(t-2) + \dots + P_{cs}(t-(n-1))}{n} = \frac{1}{n} \sum_{i=1}^{n-1} P_{cs}(t-i) \quad (3)$$

$$HMA(V_{i,t}) = \sqrt{n} WMA \left[2 \left(\frac{n}{2} \right) WMA(V_{i,t}) - n WMA(V_{i,t}) \right] \quad (4)$$

$$WMA(V_{i,t}) = \frac{nV(t-1) + (n-1)V(t-2) + \dots + 2V(t-(n-2)) + V(t-(n-1))}{n + (n-1) + \dots + 2 + 1} \quad (5)$$

where α , β , and γ are weighting factors; Ndg and Ncs are the numbers of buses connected with DG and the number of charging stations, respectively; $HMA(V_{i,t})$ and $SMA(P_{cs,j,t})$ are the hull moving

average of the voltage at bus i and the simple moving average of charging station active power at bus j at time instant t , respectively; $V_{i,t}$ and $P_{cs,j,t}$ are the voltage magnitude at bus i and the active power of the charging station at bus j at time instant t , respectively; $E_{req,j,t}$ is the total energy required by EV batteries at the charging stations j to reach their desired SOC; n is the number of related data points used in SMA/HMA smoothing; $WMA(V_{i,t})$ is the weighted moving average of the voltage at bus i for time instant t . Note that in (4) if $\sqrt{n}$ or $n/2$ is not an integer number, the number should be rounded to the nearest integer number. It is important to note that each objective function term in (1) is normalized via dividing it by its base value. The proposed combination of these three sub-objectives ensures an effective mitigation of the voltage fluctuations while optimizing EV power fluctuations and EV charging goals.

The following constraints are considered in the model:

$$P_{g,m,t} + P_{DG,m,t} - P_{L,m,t} \pm P_{cs,m,t} - V_{m,t} \sum_{n=1}^{NB} V_{n,t} \begin{bmatrix} G_{mn} \cos(\delta_{mn,t}) + \\ B_{mn} \sin(\delta_{mn,t}) \end{bmatrix} = 0 \quad \forall m, t \quad (6)$$

$$Q_{g,m,t} \pm Q_{inv,m,t} - Q_{L,m,t} - V_{m,t} \sum_{n=1}^{NB} V_{n,t} \begin{bmatrix} G_{mn} \sin(\delta_{mn,t}) - \\ B_{mn} \cos(\delta_{mn,t}) \end{bmatrix} = 0 \quad \forall m, t \quad (7)$$

$$P_{cs,m,t}^{min} \leq P_{cs,m,t} \leq P_{cs,m,t}^{max} \quad (8)$$

$$Q_{inv,m,t}^{min} \leq Q_{inv,m,t} \leq Q_{inv,m,t}^{max} \quad (9)$$

$$V_m^{min} \leq V_{m,t} \leq V_m^{max} \quad (10)$$

where $P_{g,m,t}$ and $Q_{g,m,t}$ are the active and reactive power generated at m th bus for time instant t , respectively; $P_{DG,m,t}$ and $Q_{DG,m,t}$ are the active and reactive power of DG for m th bus at time instant t ; $P_{L,m,t}$ and $Q_{L,m,t}$ are the active and reactive power demand at m th bus for time instant t ; B_{mn} and G_{mn} are the susceptance and conductance between bus m and bus n , respectively; δ_{mn} is the difference voltage angles at bus m and bus n ; NB is the number of buses; $P_{cs,m,t}^{min}$ and $P_{cs,m,t}^{max}$ are

minimum and maximum active power of m th charging station at time instant t , respectively. These values are computed by knowing the total available and required energies at that charging station. $Q_{inv,m,t}^{min}$ and $Q_{inv,m,t}^{max}$ are the minimum and maximum reactive power of the inverter m at time instant t , respectively; V_m^{min} and V_m^{max} are the minimum and maximum voltage limits at bus m , respectively. The control variables of the optimization model are the reactive power of the interface inverters (Q_{inv}) and the active power of the charging stations (P_{cs}). These variables are simultaneously calculated to mitigate the voltage fluctuations. It is important to note that the converters of the charging stations are assumed to work at unity power factor, so they cannot inject/absorb reactive power.

To illustrate the difference between SMA and HMA, they are applied to smooth the output voltage shown in Figure 3. The time series data are represented by the voltage at PCC of PV, in which the data points consist of sequential values of voltage through a time period. 24-hours data have been used with a time resolution of 1 minute in which the total values obtained are 1440.

The SMA and HMA of the studied voltage profile (Figure 3) are illustrated in Figure 5. The number of related data points used in SMA/HMA smoothing is 35. In this figure, the actual voltage is compared with the smoothed voltage during the period from 10 h to 15 h. As a result, it can be noted that the lag between the actual and smoothed values is very high in the case of SMA, and this increases the stress on the EV batteries and the inverters of RES to mitigate the fluctuations. Furthermore, this high mismatch between the actual voltage and the smoothed voltage by SMA can mislead system operator and planners to effectively mitigate these fluctuations. On the other hand, the HMA reduces the lag from the actual voltage as compared to SMA. The HMA employs WMA and frustrates the effect of the smoothing (and resulting lag) by using the square root of the number of relevant data points instead of the actual number of the data points. Therefore, in this

work, HMA is used in the optimization model for mitigating the voltage fluctuations, thanks to the unique feature for lag reducing. SMA is used to mitigate the fluctuations of charging/discharging power of EVs due to its high smoothing feature and so it can reduce the changes in charging /discharging rate, which in turn reduces the stress on EV batteries.

Figure 5. Actual voltage and smoothed voltage using SMA and HMA.

3.3 Modeling of EV battery

At time instant t , the SOC of the EV battery updates according to the charging/discharging as follows,

$$SOC_{i,t} = SOC_{i,t-1} + \eta_{ch,i} P_{ch,i,t} \Delta t X - \eta_{dc,i} P_{dc,i,t} \Delta t Y \quad (11)$$

where $SOC_{i,t}$ is the state of charge of i th EV at time instant t ; $\eta_{ch,i}$ and $\eta_{dc,i}$ are the charging and discharging efficiencies of i th EV; $P_{ch,i,t}$ and $P_{dc,i,t}$ are the charging and discharging powers of i th EV at time instant t , respectively. X and Y are binary variables ($X, Y \in \{0, 1\}$), in which $X \cdot Y = 0$ because the charging and discharging of the EV battery cannot be performed at the same time.

The percent of the charging/discharging power for each EV with respect to the total power of the charging station depends on the capacity of EV battery (C_i), current SOC ($SOC_{i,t}$), and the remaining time before the departure (T_i). The charging/discharging power of the individual EV i at time instant t can be mathematically formulated as follows,

$$P_{ch,i,t} = \frac{\frac{1}{T_i} (C_i - SOC_{i,t} \times C_i)}{\sum_{j=1}^N \frac{1}{T_j} (C_j - SOC_{j,t} \times C_j)} \times P_{cs,t} \quad (12)$$

$$P_{dc,i,t} = \frac{T_i (SOC_{i,t} \times C_i)}{\sum_{j=1}^N T_j (SOC_{j,t} \times C_j)} \times P_{cs,t} \quad (13)$$

By using these equations (12 and 13), the aggregator can divide the total active power of the charging station which is calculated by the optimization solver among the batteries of the EVs based on their current SOC and the remaining time before the departure.

3.4 Modeling of Stochastic Nature of EVs

Not all EVs are connected to the distribution system at the same time. The number of EVs connected to the distribution system and their SOC depends on daily return time of the user from the last trip and daily traveling distance per vehicle. These parameters should be considered because they are directly related to the driving habits of the users and their preference for charging/discharging of EVs. In this paper, users' daily return time from the last trip and the initial SOC of individual EV are assumed to be random variables with a normal probability density function (pdf) [56,57]. Therefore, the pdf of users' daily return time from the last trip (initial parking time) and initial SOC of EV battery can be mathematically written as follows,

$$f(T_r; \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(T_r - \mu)^2}{2\sigma^2}} \quad (14)$$

$$f(SOC; \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(SOC-\mu)^2}{2\sigma^2}} \quad (15)$$

where μ is the mean, indicating the location of the maximum probability density, σ is the standard deviation, and T_r is the return time. Most EV' users back to home after ending their work; therefore, the mean of daily return time is $\mu=18$ and the standard deviation is $\sigma = 5$ hours [58]. The normal distribution function for $N = 100$ EVs is shown in Figure 6. The mean and standard deviation for probability density function of the initial SOC of EV battery are $\mu=50\%$ and $\sigma = 14 \%$ [58], respectively. Figure. 7 shows the probability density of initial SOC of the EV battery, where the SOC varies from zero to the full capacity of the battery.

Figure 6. Initial parking time distribution of EVs with $\mu=18$ and $\sigma = 5$ hours for 100 EVs [57,58].

Figure 7. Probability density function of initial battery SOC with $\mu = 50\%$ and $\sigma = 14\%$ [57,58].

4. Gravitational Search Algorithm (GSA)

GSA is a population-based search algorithm and it is one of the modern stochastic search algorithms and it was developed in [59]. In GSA, each possible solution is called an agent and each agent is considered as an object. The performances of that algorithm are measured by its mass which is in proportion to its fitness values. Each object attracts the other object by the gravity force, and the global movement of all agents will be directed towards the agents with heavier masses. The heavier masses have higher fitness values, therefore, the agent with the heaviest mass describes the optimal solution. There are four particulars for each mass as follows, 1) mass passion, 2) mass inertial, 3) active gravitational mass, and 4) passive gravitational mass. The mass position is equaled by a problem solution and a fitness function is used to specify its inertial and gravitational masses [59].

Consider a system consisting of K masses, where K is the dimension of the search place. The i th agent position is described as follows,

$$X_i = [x_i^1, x_i^2, \dots, x_i^d, \dots, x_i^q] \quad \text{for } i = 1, 2, \dots, K \quad (16)$$

where q is the space dimension of the problem, x_i^d represents the position of i th agent in the d th dimension.

The gravitational force between agent j and agent i at the time instant t is formulated as follows,

$$F_{ij}^d(t) = G(t) \frac{M_i(t) \times M_j(t)}{S_{ij}(t) + \varepsilon} (x_j^d(t) - x_i^d(t)) \quad (17)$$

where $M_i(t)$, $M_j(t)$, and $G(t)$ are the mass of the object i , mass of the object j , and gravitational constant at time instant t , respectively; ε and $S_{ij}(t)$ are a small constant and the Euclidian distance between i and j objects, respectively. $S_{ij}(t)$ is described as follows,

$$S_{ij}(t) = \|X_i(t), X_j(t)\|_2 \quad (18)$$

The total force acting on the i th agent in d th dimension is given as follows,

$$F_i^d(t) = \sum_{j=1, j \neq i}^{d_{best}} rand_j \times F_{ij}^d(t) \quad (19)$$

where $rand_j$ and d_{best} are a random number in the range $[0,1]$ and the set of first d agents with the best fitness value and biggest mass, respectively. According to Newton's law of motion, the acceleration of the i th agent in d th dimension at time instant t can be directly computed as follows,

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} \quad (20)$$

The following position and the following velocity of the agent can be given as follows,

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \quad (21)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \quad (22)$$

where x_i^d and v_i^d are the position and velocity of an agent at time t in d th dimension, respectively.

The gravitational constant $G(t)$, described in (17), can be mathematically given as follows,

$$G(t) = G_0 e^{(-at/itermax)} \quad (23)$$

where α is a user-specified constant term; $itermax$ is the maximum number of iterations; G_0 is the initial value.

The fitness evaluation is used to calculate the masses of the objects. The masses of the agents can be updated as follows:

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^K m_j(t)} \quad (24)$$

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \quad (25)$$

where $fit_i(t)$ is the fitness value of i th at time instant t ; $best(t)$ is the best solution; $worst(t)$ is the worst solution. For minimization problem:

$$best(t) = \min_{j \in \{1, \dots, m\}} fit_j(t) \quad (26)$$

$$worst(t) = \max_{j \in \{1, \dots, m\}} fit_j(t) \quad (27)$$

5. Application of GSA to Proposed Optimization Model

In this section, the application of GSA to solve the proposed optimization model is described in the flowchart given in Figure 8. At each time instant t , the demand load, PV power, wind power and batteries status (e.g., the capacity of the battery, the state of charge, arrival time, departure time) of EVs are read. Based on the status of the batteries and the generated powers of PV and WTGS, the maximum and minimum limits of the control variables (P_{cs} , Q_{inv}) can be determined at that instant. Then, the initial population between these limits are generated based on the identified search space of GSA. Afterward, the value of the objective function given in (1) is computed for each agent. The worst value, best value, gravitational constant, acceleration, mass, velocity, and position are updated as shown in the flowchart.

Figure 8. Flowchart of the proposed method.

The previous process is repeated for the same time instant until the stopping criteria are met. Hence, the optimal values of the active power of the charging stations and the reactive power of the interface inverters for this instant are returned. The whole process is repeated to calculate the

optimal values of the entire time instants. At each time instant, the optimal active power of the charging station is checked as follows:

- If it is positive (i.e., charging mode), the charging rate of each EV is calculated using (12) and the SOC is updated using (11).
- If it is negative (i.e., discharging mode), the discharging rate of each EV is calculated using (13) and the SOC is updated using (11).

Figure 9. Daily profile of the loads.

6. Results and discussions

To demonstrate the effectiveness of the proposed method, it has been tested on two different distributions systems (IEEE 90-bus distribution system and IEEE 33-bus distribution system). The PV and WTGS are modeled to inject active power and inject/absorb reactive power at PCC. The load profile shown in Figure 9 is used for the real-time scenario, and it is assigned to all loads. The minimum and maximum voltage limits are 0.95 p.u. and 1.05 p.u., respectively [60]. Based on the standards, other limits can be used (e.g., based on EN 50160 standard, the voltage limits in Europe are 0.9 and 1.1 p.u [61]). Two models of EV batteries are considered in this paper, the Nissan leaf

lithium-ion battery with a capacity of 24 kWh and Toyota RAV4 NiMH battery with a capacity of 27.4 kWh. The number of EVs connected to each charging station is assumed to be 100 EVs. The initial parking time and initial SOC of each EV are according to Figures 6 and 7, respectively. Each EV is assumed to be parked at the charging station for 12 hours (from the initial parking time till the departure time). To ensure that the SOC of the EV battery at the departure time is enough and to optimize its lifespan, it is assumed that the EV cannot discharge to the grid (V2G) if its SOC is less than 75%. The maximum power rate of charging/discharging has been chosen 4 kW. The charger capacity has been chosen to be 4 kW because the maximum power output of a standard single-phase residential 230 V outlet is 4.6 kW [62].

6.1 IEEE 90-bus system

The IEEE 90-bus distribution system has been considered to test the proposed method. This system consists of 90 buses and 89 branches with the radial structure as shown in Figure 9. The total active and reactive power loads are 19.45 MA and 9.72 Mvar, respectively. The line and bus data are taken from [63]. 25% PV penetration with respect to the total load is connected to bus 28, and 25% wind power penetration with respect to the total load is connected to bus 42. Also, an EVs charging station is assumed at bus 28 and bus 35, as shown in Figure 10. The typical active power output of a PV system on a partly cloudy day and active power output of a WTGS are shown in Figures 1 and 2, respectively.

Figure 10. Single line diagram of the 90-bus distribution system.

The voltage profiles at PCC (bus 28 and bus 42) in the base case are shown in Figure 11. In this case, the inverters of PV and WTGS are assumed to operate at unity power factor without considering the EVs. It can be seen from these figures that the voltages at PCC are significantly fluctuating due to the intermittent nature of RES and they violate the lower limits in many periods.

(a)

(b)

Figure 11. Voltage profiles at PCC of the base case for the 90-bus distribution system: a) voltage profile at PCC of PV (bus 28); b) voltage profile at PCC of WTGS (bus 42).

To mitigate the voltage fluctuations and keep the voltages within limits, the reactive power of RES inverters and the active power of EV charging stations have been optimized by applying the proposed method in which the voltage magnitude deviations at PCC from their HMAs, the deviation of the charging stations' active powers from their SMAs, and the deviation of the total energy of charging stations from the total required energy of EVs to reach their desired SOC are

considered in the objective function. Figure 12 shows the voltage profiles at PCC of PV and WTGS. Compared with the base case described in Figure 11, the voltages are kept within the acceptable limits and the voltage fluctuations are significantly enhanced. The voltage profiles at all buses of the 90-bus distribution system are shown in Figure 13.

(a)

(b)

Figure 12. Voltage profiles at PCC using the proposed method for the 90-bus distribution system: a) voltage profile at PCC of PV (bus 28); b) voltage profile at PCC of WTGS (bus 42).

Figure 13. Voltage profiles at all buses using the proposed method for the 90-bus distribution system.

The charging/discharging power of the EV charging stations are shown in Figure 14. It can be seen from the figure that the fluctuations of the active power of the charging stations are low which increases the lifespan of EV batteries. The SOC of all EVs at the charging stations updated using (11), (12), and (13) are given in Figure 15. The fixed horizontal lines represent the initial SOC of EVs when they arrive at the grid. From the figure, we can note that the SOC of each EV at the departure time (after 12 hours from EV connection to the grid) is greater than the desired level which has been settled previously by the consumer (it was assumed to be 75%).

To demonstrate the effectiveness of the proposed method, it is compared with the conventional method in which only the first part of the objective function (i.e., voltage fluctuations) is considered as an objective function of the optimization model. For this purpose, the fluctuation factor is used to compare these methods and its formula is given in [37].

Figure 14. Active power of EV charging stations using the proposed method for the 90-bus distribution system: a) charging/discharging power of the charging station at bus 28; b) charging/discharging power of the charging station at bus 35.

The fluctuation factor of the active power of the charging stations at different locations are compared in Table 1. It can be seen from the table that the fluctuation factors of the charging station' active powers are significantly decreased by applying the proposed method compared with the conventional method. By applying the proposed method, the fluctuation factor of the charging station active power is reduced from 52.68 to 11.95 at bus 28 and it is reduced from

Figure 15. SOC of EVs using the proposed method for the 90-bus distribution system: a) SOC of EVs connected to charging station at bus 28; b) SOC of EVs connected to charging station at bus 35.

47.25 to 20.31 at bus 35. Therefore, the conventional method over smooths the voltages which means that the voltages are smoothed below the desirable. This over smoothing will be on the expenses of the charging station active powers. As a result of voltage over-smoothing, there is more stress on the EVs and the inverters of RES which will eventually decrease their lifespan. Figure 16 shows the excessive fluctuations of the active power of the charging stations in this case (conventional method) compared to Figure 14 (proposed method). Because of these high fluctuations, the performance and lifespan of EV batteries will be decreased. These results

demonstrate that the proposed method is an efficient tool which can be used for mitigating the voltage fluctuations without increasing the stress on either the EVs nor inverters of RES.

Table 1. Fluctuation factors with applying the conventional and proposed methods to the 90-bus distribution system

Item	Fluctuation factors of charging station' powers(kW)	
	Bus 28	Bus 35
Conventional method	52.68	47.25
Proposed method	11.95	20.31

(a)

(b)

Figure 16. Active power of EV charging stations for the 90-bus distribution system (conventional method): a) charging/ discharging power of the charging station at bus 28; b) charging/discharging power of the charging station at bus 35.

6.2 IEEE 33-bus system

To assess the efficiency of the proposed method for dealing with different distribution systems which have different configurations, the IEEE 33-bus distribution system is considered here. This system consists of one main feeder with four laterals, 33 buses, and 32 branches as shown in Figure 17. The total peak active and reactive loads are 3.715 MW and 2.3 Mvar, respectively. The total active and reactive losses of the system in the nominal case are 0.203 MW and 0.135 Mvar, respectively. The line and bus data of that system are available in [63]. 25% PV penetration with respect to the total load is connected to bus 18, and 25% wind power penetration with respect to the total load is connected to bus 33. Also, two EV charging stations are assumed to be connected at bus 18 and bus 33, as shown in Figure 17.

Figure 17. Single line diagram of the 33-bus distribution system.

The voltage profiles of the base case at PCC (bus 18 and bus 33) are shown in Figure 18. It is clear from the figure that the voltages at PCC are significantly fluctuated due to the intermittent nature of RES as well as they violate the lower limits. By applying the proposed method, the voltages are kept within limits and the voltage fluctuations are greatly decreased. The voltage

profiles at PCC and at all busses of the 33-bus distribution system are given in Figures 19 and 20, respectively. The charging/discharging power of the charging stations and the SOC of EVs at different charging stations when applying the proposed method are illustrated in Figures 21 and 22, respectively. As shown in Figure 22, all EVs have been reached to SOC higher than 75% at the departure time.

(a)

(b)

Figure 18. Voltage magnitude at PCC for the 33-bus distribution system: a) voltage magnitude at PCC of PV (bus 18); b) voltage magnitude at PCC of WTGS (bus 33).

(a)

(b)

Figure 19. Voltage profiles at PCC for the 33-bus distribution system: a) voltage profile at PCC of PV (bus 18); b) voltage profile at PCC of WTGS (bus 33).

Figure 20. Voltage profiles at all buses using the proposed method for the 33-bus distribution system.

Table 2 shows the comparison of the fluctuation factors of the charging stations' active power for the proposed method and the conventional method. The conventional method considers the deviation of the voltages from their HMVs at PCC only in the objective function and neglects the two other terms. In the case of the conventional method, the charging/discharging power of EVs is highly fluctuating to mitigate the voltage fluctuations below the desirable level (over-smoothing problem) as shown in Figure 23.

(a)

(b)

Figure 21. Active power of EV charging stations using the proposed method for the 33-bus distribution system: a) charging/discharging power of the charging station at bus 18; b) charging/discharging power of the charging station at bus 33.

On the other hand, the fluctuation factors of the charging stations' active power are greatly reduced in the case of the proposed method compared with the conventional method. For instance, by applying the proposed method, the fluctuation factor of the charging stations' active power is reduced from 37.48 to 12.44 at bus 18 and it is reduced from 47.33 to 10.75 at bus 33. The previous results demonstrate the effectiveness of the proposed method in mitigating the voltage fluctuations and considering the fluctuations of the charging/discharging power of EVs.

(a)

(b)

Figure 22. SOC of EVs using the proposed method for the 33-bus distribution system: a) SOC of EVs connected to charging station at bus 18; b) SOC of EVs connected to charging station at bus 33.

Table 2. Fluctuation factors with applying the conventional and proposed methods to the 33-bus distribution system

Item	Fluctuation factors of charging station' powers(kW)	
	Bus 18	Bus 33
Conventional method	37.48	47.33
Proposed method	12.44	10.75

(a)

Figure 23. Active power of EV charging stations for the 33-bus distribution system (conventional method): a) charging/discharging power of the charging station at bus 18; b) charging/discharging power of the charging station at bus 33.

7. Conclusions

In this paper, an efficient method has been proposed to smooth voltage fluctuations in distribution systems with WTGS and PV. The proposed method is based on optimally controlling the charging and discharging power of EVs and the reactive power of the RES inverters in a simultaneous manner. The merit of the proposed method is that it considers the EV power fluctuations to increase the lifespan of their battles, also, the minimum allowed SOC of EVs is considered. Furthermore, we have proposed the use of HMA to mitigate voltage fluctuations to avoid the lag problem of SMA, while SMA is used to smooth EV power fluctuations. The GSA has been utilized to efficiently solve the optimization model. Two different distribution test systems have been simulated to demonstrate the effectiveness of the proposed method. The results reveal the proposed method can effectively smooth voltage fluctuations while optimizing the charging/discharging rate of EVs, thereby extending the lifespan of their batteries. Furthermore, the individual charging plans of all EVs are satisfied considering their stochastic behavior. The

future work will be directed to consider various energy storage and voltage control devices in the optimization problem.

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