Optimal Charging Strategy of Electric Vehicles in Unbalanced Three-Phase Distribution Network

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Abstract

Background: The increasing penetration of Electric Vehicles (EV) could lead to significant impact on the power systems, particularly for existing distribution networks. Methods: These impacts contain phase unbalance, excessive voltage deviations and overloading of equipment, which arise when a large numbers of Electric Vehicles are simultaneously charged. Results: In the current research, an optimal charging strategy is designed to control charging rates of Electric Vehicles in unbalanced three-phase distribution networks. A technique according to the Particle Swarm Optimization (PSO) is designed in order to reduce the charging cost of vehicles, with considering certain constraints. The constraint set involves transformer and line restrictions, unbalance of phase and voltage range. Conclusion: The proposed charging strategy is investigated on a real distribution network. Findings shows that high penetration of Electric Vehicles can be sustained in the existing distribution networks, demonstrating the effectiveness of the proposed method.

Keywords: Charging Strategy, Electric Vehicle, Particle Swarm Optimization, Smart Grids, Unbalanced Distribution Network

1. Introduction

Electrification of transportation sectors have been received increasing consideration in recent times. Therefore, the utilization of Electrical Vehicles (EVs) will increase over the coming years. As an alternative of fossil fuel, EVs store the needed energy from electrical distribution networks for transportsations. Uncoordinated charging of large EVs could lead to undesirable circumstances including phase unbalance, overloads, voltage limit violations and a growth in power losses. With increasing penetration of EVs in the current distribution networks, these issues must be avoided. To face the problem related to large penetration of EVs in distribution networks, optimal charging strategies are addressed in the papers.

In a method according to the linear programming is proposed to evaluate optimal charging ratio for each EV aiming at maximizing the power that can be transferred to the vehicles when operating over the network restricts. The authors' of propose a price-based scheme to control charging of EVs. More in details, it determines the optimal price signals subject to the cost minimizing charging schedule of the EV owners, who are responding to a mixture of price signals and distribution use of network charges. Reference aims to coordinate three actors: The owner of EV, the Fleet and the distribution system operators, taking into account every EV owner's

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driving requirement, the charging cost of EV and thermal constraints of connections as well as transformers under market environment. In\(^5\), a distribution locational marginal pricing scheme is proposed to relieve congestion induced via the EVs’ charging in coming distribution networks. In the presented approach, the operator of distribution process specifies DLMPs via the using the public welfare optimization of the electric distribution network which takes into account EV aggregators as expense takers in the local DSO market. The authors’ of\(^6\) proposed a real-time charging strategy for EVs in unbalanced distribution networks. However, the proposed method optimizes for single time steps, separately. Reference\(^4\) proposed a method to transfer EV’s charging to off-peak times considering the current and anticipated restrictions of the distribution network in a finite charging horizon. In\(^2\) an economic procedure for EVs’ charging that properly determines possible charging capability in a manner that makes assure the stability of network. In\(^7\) a EVs’ charging strategy based on game theoretic approach to minimize charging cost of EVs’ owner.

Most of the approaches discussed in the literature supposed to balanced networks. Nevertheless, most of EVs’ charging would be happened on unbalanced distribution networks; therefore issues related to unbalance networks conditions were being neglected. Moreover, in the some cases, they tried to optimize network according to the operators’ view, which can limit the incentive of EV owners to participate in the program. In the current research, an optimal charging strategy is proposed to control charging rates of Electric Vehicles in unbalanced three-phase distribution networks. A technique according to the PSO is employed, as far as reduce the charging expense of vehicles, regarding performance and applicable condition. The proposed charging strategy reduces the overall energy costs, while satisfying operational constraints leading to a more realistic model.

The current article is organized as below. Part 2 outlines the methodology. The solution algorithm is discussed in part 3. The findings and discussion are presented in part 4. Ultimately, part 5 outlines the main conclusions.

## 2. Methodology

This section provides optimal charging strategy of EVs in the unbalanced three-phase distribution networks. The complete mathematical formulation of the proposed method, involving the objective and constraints function, is presented in the following subsections.

### 2.1 Assumptions

The following realistic assumptions described in this subsection are based on Australian Victoria EV trial as part of a pilot load control work. It is assumed that EVs’ charging rates are controlled centrally by the network operator through Advanced Metering Infrastructure as a main part of smart grids technology. This is shown schematically in Figure 1. Moreover, certain the network knowledge characteristics is necessary, i.e. topology of network, line impedances/admittances, loads and nominal voltages.

![Figure 1](image)

**Figure 1.** Schematic of EVs’ centralized control.

### 2.2 Objective Function

The purpose of the developed method is to reduce total charging expense of vehicles for a 24-h horizon. The least charging expense can be considered as EV owners’ concentrated objective, as it incentives them to permit network operator centrally controls their charging rates. The objective function is given as:

\[
\text{Min Cost} = \sum_{\forall \text{nodes}} \sum_{\text{phases}} P_{\text{ach}} \cdot (0.6 \cdot (7/0)) + \sum_{\forall \text{nodes}} \sum_{\text{phases}} P_{\text{bcch}} \cdot (0.6 \cdot (7/0)) + \sum_{\forall \text{nodes}} \sum_{\text{phases}} P_{\text{ccch}} \cdot (0.6 \cdot (7/0))
\]  

Where, \(P_{\text{a}}\), \(P_{\text{b}}\), and \(P_{\text{c}}\) are EVs’ charging rate at phase \(a\), \(b\), and \(c\) of node \(i\) during time step \(t\), respectively. Cost of electricity at time step \(t\) is denoted by \(p_t\).

### 2.3 Constraints

The objective function must be minimized regarding to the certain constraints. The below equations show the voltage at phase \(a\), \(b\), and \(c\) of node \(i\) during time step \(t\) should be preserved over the rated voltage ranges indicated for the network:
The maximum and minimum allowed network voltage levels are $V_{\text{min}}$ and $V_{\text{max}}$, where assumed to be 0.9 pu and 1.1 pu, respectively.

The large variations in charging rates are undesirable for battery technologies. Therefore, the following Equations are used to limit EVs' rate of changes:

$$P_{\text{a,EV}}(t - 1, i) - \Delta \leq P_{\text{a,EV}}(t, i) \leq P_{\text{a,EV}}(t - 1, i) + \Delta$$

$$P_{\text{b,EV}}(t - 1, i) - \Delta \leq P_{\text{b,EV}}(t, i) \leq P_{\text{b,EV}}(t - 1, i) + \Delta$$

$$P_{\text{c,EV}}(t - 1, i) - \Delta \leq P_{\text{c,EV}}(t, i) \leq P_{\text{c,EV}}(t - 1, i) + \Delta$$

Where, $P_{\text{a,EV}}$, $P_{\text{b,EV}}$, and $P_{\text{c,EV}}$ are EVs' power demand at phase $a$, $b$, and $c$ of node $i$ during time step $t$, respectively. Moreover, $\Delta$ is a specified limit, in kW, by which the EVs' power demand change.

Batteries further have minimum and maximum possible power demand, i.e. $P_{\text{EV, min}}$ and $P_{\text{EV, max}}$, that should be respected:

$$P_{\text{EV, min}} \leq P_{\text{a,EV}}(t, i) \leq P_{\text{EV, max}}$$

$$P_{\text{EV, min}} \leq P_{\text{b,EV}}(t, i) \leq P_{\text{EV, max}}$$

$$P_{\text{EV, min}} \leq P_{\text{c,EV}}(t, i) \leq P_{\text{EV, max}}$$

The mathematical relations between charging rates and power demands of EVs are as follows:

$$P_{\text{a,EV}}(t, i) = \eta P_{\text{a, ch}}(t, i)$$

$$P_{\text{b,EV}}(t, i) = \eta P_{\text{b, ch}}(t, i)$$

$$P_{\text{c,EV}}(t, i) = \eta P_{\text{c, ch}}(t, i)$$

Where, $\eta$ is charging efficiency of batteries that considered loss of energy due to AC/DC conversion.

Each EV has a target of reaching to a specified energy level which expressed as follows:

$$W_{\text{a,EV}} = \sum_{t=1}^{24} P_{\text{a,EV}}(t, i) \Delta T$$

$$W_{\text{b,EV}} = \sum_{t=1}^{24} P_{\text{b,EV}}(t, i) \Delta T$$

$$W_{\text{c,EV}} = \sum_{t=1}^{24} P_{\text{c,EV}}(t, i) \Delta T$$

Where, $W_{\text{a,EV}}$, $W_{\text{b,EV}}$, and $W_{\text{c,EV}}$ are EVs' energy level at phase $a$, $b$, and $c$ of node $i$ during time step $t$, respectively.

The mathematical relation between energy level and state of charge of EVs are as follows:

$$\text{SOC}_{\text{a}} = \text{SOC}_{\text{a,0}} + \frac{W_{\text{a,EV}}}{C_{\text{a}}}$$

$$\text{SOC}_{\text{b}} = \text{SOC}_{\text{b,0}} + \frac{W_{\text{b,EV}}}{C_{\text{b}}}$$

$$\text{SOC}_{\text{c}} = \text{SOC}_{\text{c,0}} + \frac{W_{\text{c,EV}}}{C_{\text{c}}}$$

Where, $\text{SOC}_{\text{a}}$, $\text{SOC}_{\text{b}}$, and $\text{SOC}_{\text{c}}$ are batteries' state of charge at phase $a$, $b$, and $c$ of node $i$ during time step $t$, respectively. Moreover, $C_{\text{a}}$, $C_{\text{b}}$, and $C_{\text{c}}$ are batteries' capacity.

The thermal loading of transformer and line should be respect to protect this equipment which summarized as follows:

$$L_{\text{TX}} \leq L_{\text{TX, max}}$$

$$L_{\text{MC}} \leq L_{\text{MC, max}}$$

as, $L_{\text{TX}}$ and $L_{\text{MC}}$ present thermal loading, in kVA, for transformer and line, respectively and $L_{\text{TX, max}}$ and $L_{\text{MC, max}}$ represent their maximum loading.

### 2.4 Unbalanced Load Flow

3-phase unbalanced power flow investigation is needed to determine network voltage and thermal loading levels. In the current research, DIgSILENT software is utilized to perform unbalanced power flow analysis which is the most powerful power system analysis package. To this end, firstly the EVs’ charging is determined by solving the optimization problem which explained in the next section through MATLAB software. Afterwards, these data i.e. EVs’ charging are imported to DIgSILENT software with DPL interface and the load flow analysis is carried out. Then, the output data of load flow are exported to MATLAB for more analysis. This exchange of data between MATLAB and DIgSILENT is continued until optimal results are obtained.
3. Solution Algorithm

In this section the solution algorithm of proposed problem is presented. The PSO technique is used in the current research to solve the problem of (1)-(21). By iterations of the evolution procedure initial from a first amount set, an optimal result is attained while producing new particle’s parameters according to the former best results for the swarm and that particle so far. More in details, the \( j \)th particle firstly begins from a stochastic position \( x_{j}^{0} \) with a velocity \( v_{j}^{0} \). It iteratively travels to another place \( x_{j}^{k} \) when Gradual updating its velocity \( v_{j}^{k} \) according to its own best experience \( p_{best}j \) and the swarm’s best knowledge \( g_{best}j \). This can be mathematically explained as follows:

\[
v_{j}^{(k+1)} = wv_{j}^{k} + c_{1}r_{1}(p_{best}j - x_{j}^{(k)}) + c_{2}r_{2}(g_{best}j - x_{j}^{(k)}) \tag{22}
\]

\[
w = \frac{w_{max} - w_{min}}{k_{max}} \cdot k \tag{23}
\]

\[
x_{j}^{(k+1)} = x_{j}^{(k)} + v_{j}^{(k+1)} \quad j = 1, 2, ..., n \tag{24}
\]

Where, \( w, c_{1}, c_{2}, r_{1}, \) and \( r_{2} \) are parameters of the PSO. Using a trial and error method the values of \( w_{max}, w_{min}, c_{1}, \) and \( c_{2} \) are set to be 0.9, 0.4, 2 and 2, respectively, as \( k \) increased from 1 to \( k_{max} = 100 \). Moreover, \( r_{1} \) and \( r_{2} \) are randomly selected between 0 and 1.

Figure 2 shows the PSO flowchart for the optimal charging strategy of EVs. The initial position of particles, i.e. EVs’ SOC and charging strategy including charging rates and charging times, are randomly assigned. Then, it is check that the EVs’ SOC and charging strategy are in contradiction with each other. If it is true, the charging strategies are modified considering EVs’ SOC. The charging strategies are imported to DIgSILENT software and load flow analysis results are exported to MATLAB software. If the load flow analysis is converged, the PSO objective function is evaluated. Otherwise, the PSO objective function is set to be infinite. If the PSO algorithm not satisfies convergence criteria, the values of \( x_{j}^{(k)}, v_{j}^{(k)}, p_{best}j, \) and \( g_{best}j \) are updated for the next iteration.

4. Results and Discussion

4.1 Data

The investigated network is according to real distribution in an inhabited area of Dublin, Ireland. The single line diagram of this network is presented in Figure 3. The technical data of the network and residential load demand are borrowed from. Meanwhile, the capacity of main transformer is assumed to be 400 kVA while the maximum current of main lines is 424 A.
Each EV is a single phase load which supplied through connected point of residential customers. It is assumed that charging rates of EVs are same and 4 kW until 95% maximum capacity and 1.5 kW until full capacity. Moreover, the capacity of EV batteries is 20 kWh with 90% efficiency.

As shown in Figure 3, half of residential customers are randomly allocated an EV which led to 67 EVs with maximum demand of 268 kW. The initial state of charge of EVs is randomly generated and shown in Figure 4. Moreover, the share of EVs between phases of network and their total energy demand are illustrated in Figure 5. (Table 1).

4.2 Simulations

The proposed strategy, as presented in Section 3, is employed for a 24-h time period. The convergence process of proposed algorithm is shown in Figure 5. As can be seen, the optimal results are obtained in iteration 6 with less than 1 minute. The charging strategies of EVs are illustrated in Figures 6 to 9.
As can be seen in Figures 6 to 9, EVs’ charging time and rate are different values. Therefore, with optimal distribution of EVs’ charging demand over 24-h time period, the network load becomes smoother and also EVs’ charging cost reduce.

Number of EVs versus start times of charging and number of EVs versus charging durations for optimal results are shown in Figures 10 and 11, respectively. As can be seen, start times charging are mainly occur in off-peak periods. Meanwhile, the charging durations is between 2 hour and 5 hour. It should be mentioned that average charging duration is 5.34 hours.

5. Conclusions

The upcoming integration of large EVs into distribution networks will cause significant challenges for operators. The strategy presented in this paper reassures the operators that distribution networks can be operated with large EVs in a manner that the risk of network overloading or voltage violation is alleviated. Moreover, due to incorporating unbalanced 3 phase load flow investigation, the proposed strategy is more appropriate in realistic applications.

The results show that minimizing the total cost of EVs is accessible while network constraints are respected which is an advantage to EV owners and operators.

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