Eletrônica de Potência
Open Journal of Power Electronics

Check for updates

Received September 12, 2025; accepted November 28, 2025; Date of publication January 13, 2026.
The review of this paper was arranged by Associate Editor Renata O. de Sousa and Editor-in-Chief Heverton Augusto Pereira.

*Digital Object Identifier http://doi.org/10.18618/REP.e202604*

# Demand Response Program applied for Electric Vehicle Charging in Distribution Networks

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**ABSTRACT** The growing penetration of Electric Vehicles (EVs) poses new challenges to distribution system operation, particularly regarding peak demand and asset overloading. This paper proposes an optimization model for EV charging profiles based on time-varying and location-sensitive signals derived from the electrical impedance matrix of the distribution network. Building on a previously published tariff-sensitivity framework, this study develops an EV charging optimization model that uses nodal and hourly signals to reflect the marginal impact of current injections on line congestion. The optimization minimizes the total EV charging cost while mitigating adverse grid impacts. Simulation results using the IEEE 123-bus system demonstrate reductions in losses and line loading, as well as cost savings for EV owners. By combining the proposed approach with the existing tariff-sensitivity framework, Distribution System Operators (DSOs) can better align incentives for EV owners, without compromising their charging profiles, and mitigate network issues, thereby supporting the scalable integration of EVs.

**KEYWORDS** Charging Optimization, Distribution System Operation, Demand Response Program, Electric Vehicles, Sensitivity-Based Network Tariffs.

## NOMENCLATURE

### Index

$p$ Phase index.
$k$ Bus index of the distribution system.
$\ell$ Line index of the distribution system.
$t$ Time index.

### Sets

$\Omega_p$ Set of phases of a line.
$\Omega_k$ Set of buses in the system.
$\Omega_\ell$ Set of lines in the distribution system.
$\Omega_t$ Set of time periods (analysis horizon).
$\Omega_t^{v,nc}$ Set of time periods during which the electric vehicle is unavailable for charging.

### Constants

$a_{\ell,k}$ Element of the current sensitivity matrix relating line $\ell$ and bus $k$.
$a_{\ell,k,p}$ Element of the current sensitivity matrix relating line $\ell$, bus $k$, and phase $p$.
$c_\ell^u$ Unit cost of a line.
$C_\ell$ Cost of a distribution line.
$Cap_\ell$ Capacity of a distribution line.
$I_{k,p,t}^{d,Real}$ Real part of current demand for each bus, phase, and time.
$y_{i,j}$ Admittance of line $(i,j)$.
$y_{i,j}^{sh}$ Shunt admittance of line $(i,j)$.
$z_{(i,k)}^{bus}$ Element $(i,k)$ of the $Z_{bus}$ impedance matrix.
$T^p$ Tariff during peak hours.
$T^{op}$ Tariff during off-peak hours.
$T^{p,a}$ Tariff related to current during peak hours.
$T^{op,a}$ Tariff related to current during off-peak hours.
$R_\ell$ Line resistance.
$RT^{\Delta y}$ Transformation ratio (reflection factor) from secondary to primary side for a $\Delta$–$Y$ transformer.

### Variables

$I_{k,p,t}$ Bus current for each phase and time.
$I_{\ell,p,t}^{Real}$ Real part of the bus current for all phases and times.
$I_{\ell,p,t}^{Imag}$ Imaginary part of the bus current for all phases and times.
$I_{\ell,p,t}^{abs}$ Quadratic magnitude of peak current for each line and phase.
$I_{\ell,p,t}^{Real}$ Real part of line current for each phase and time.
$I_{\ell,p,t}^{Imag}$ Imaginary part of line current for each phase and time.
$V_i$ Voltage at bus $i$.
$V_j$ Voltage at bus $j$.
$\delta_{k,p,t}$ Locational and hourly cost associated with each bus.
$\Delta I_{k,p,t}$ Sum of Electric Vehicles (EVs) charging for each bus, phase, and time.
$\Delta I_{v,k,p,t}^{EV}$ Individual EV charging current for each bus, phase, and time.
$\overline{\Delta I_v^{EV}}$ Power capacity of the Electric Vehicles (EVs).
$\delta_{\ell,p}$ Cost of the maximum loading of line $\ell$.

  

**Abbreviations**

$EV$ Electric Vehicle.
$DRP$ Demand Response Program.
$DER$ Distributed Energy Resource.

## I. INTRODUCTION

The transition toward decarbonization in the transportation sector is accelerating the worldwide adoption of Electric Vehicles (EVs). While EVs represent a promising alternative to internal combustion engine vehicles, their large-scale integration into electric distribution systems poses operational challenges. If not properly managed, these may result in undesirable effects such as line overloading, voltage violations, and increased system losses [1], [2]. Uncontrolled or poorly coordinated EV charging may cause demand peaks, overloading distribution system components and increasing the need for infrastructure upgrades. This challenge becomes more critical in low- and medium-voltage networks, where limited hosting capacity and radial topologies dominate. Several studies have investigated smart charging strategies aimed at optimizing EV charging profiles to align with network limitations and electricity price signals [3], [4]. Control strategies range from centralized architectures, where an aggregator optimizes the collective behavior of a fleet of EVs, to decentralized and price-based mechanisms that allow individual users to make local decisions based on dynamic tariffs as presented in [5] and [6]. Centralized approaches are generally more effective in minimizing system-wide impacts but usually require significant communication infrastructure and user coordination. In contrast, price-responsive decentralized methods offer scalability and flexibility but may be inefficient if tariff signals do not reflect localized grid constraints [7]. In response to these limitations, recent research has focused on locational pricing mechanisms that consider the physical characteristics of the network. Nodal and hourly prices enable the derivation of sensitivity coefficients that quantify the impact of current injections or withdrawals at each node on system power flows and losses [8]. These sensitivity-based tariffs provide Distribution System Operators (DSOs) with a tool to create economic incentives that reflect technical priorities, such as congestion relief or voltage profile support. Additionally, Demand Response (DR) programs have emerged as a key strategy to enhance distribution system flexibility and actively engage consumers in energy management. In particular, price-based DR programs encourage users to adjust their consumption in response to dynamic electricity prices. When combined with smart EV charging, such programs help shift demand to off-peak periods, reduce peak loads, and optimize asset utilization [9], [10]. Recent regulatory advances, such as ANEEL's Resolution No. 964/2021 ( [11]) in Brazil, have provided a formal structure for DR participation in wholesale markets, enabling consumers to respond to market signals in real time. Integrating sensitivity-based pricing into DR programs, particularly in the context of EV charging, offers a promising pathway to simultaneously achieve economic efficiency and grid stability. Building on this foundation, the current study extends the concept of tariff sensitivity to smart charging of EVs. The proposed optimization model schedules EV charging in response to the price signal associated with network impact. These price signals internalize the marginal impact of charging actions on the grid by linking user behavior to localized stress indicators, such as line loading. The novelty of this work lies in the combination of impedance-based pricing with smart EV charging strategies. By incorporating sensitivity metrics directly into the objective function of the optimization model, the approach enables a more efficient allocation of grid resources, promoting load flattening and improved reliability without the need for heavy infrastructure expansion. Moreover, the model supports time-varying tariffs that reflect both temporal and spatial grid conditions, enhancing user responsiveness to network needs and providing a natural extension of previous work [12]. Meanwhile, $Z_{bus}$-based allocation methods have traditionally been applied for cost attribution in transmission and distribution networks, with applications in network tariff design and access pricing [12], [13]. Their adaptation to demand response and EV charging is an emerging area explored in this work. Lima and Teixeira [12] proposed a DR program that uses sensitivity-based tariff signals to manage the operation of energy storage devices in distribution systems. The model showed potential to delay infrastructure investment and reduce operational costs. To provide a clear structure, the remainder of this paper is organized as follows. Section 2 describes the mathematical model for EV charging. Section 3 presents the case study and simulation setup, followed by the results and discussion. Finally, Section 4 concludes the paper with insights into the model's potential and directions for future research.

## II. PROPOSED OPTIMIZATION MODEL

This section presents the strategic distribution of the DR program, the locational and hourly signals for system usage, and the optimization model for EV charging that supports the DR program.

### A. Demand Response Program for EV charging

One of the key challenges in implementing a DR program for EV charging is that peak currents in a line may simply shift from one time slot to another, potentially causing adverse effects on the distribution system, particularly in lines or transformers operating near their thermal limits. To address this issue, the DR program should incorporate time- and location-sensitive distribution usage signals, allowing the identification of optimal buses and time slots for load shifting within a 24-hour horizon. This targeted strategy enhances the effectiveness of the DR program while preserving EV owners' charging requirements and scheduling preferences.

To describe the proposed approach, the Demand Response (DR) program algorithm can be summarized as follows:

i. Initialization of input data, including tariffs, network parameters, baseline load curve, and the initial and final state of charge and time for each EV.
ii. Computation of the power flow solution in OpenDSS to assess the initial network conditions without EVs.
iii. Execution of an optimization process to minimize network costs, energy losses, and EV charging costs by determining the optimal charging profile for each EV under both network and EV constraints.
iv. Generation of an EV charging schedule for each vehicle.
v. Computation of a power flow using a naïve (uncoordinated) solution for comparison purposes.

In the proposed paper, the uncoordinated solution assumes that all EVs charge simultaneously. Although this is not a realistic scenario, it emphasizes the importance of the proposed model in reducing network costs through coordinated charging. Furthermore, the proposed model can be adapted to operate under different tariff structures, as it is sensitive to current variations along each line over time.

The proposed optimization problem was implemented in Python using the Pyomo library and solved with the Gurobi solver. As the model includes quadratic and convex constraints, it was formulated as a continuous quadratic programming (QP) problem and solved using Gurobi's Barrier (Interior-Point) Method. Considering the computational effort, the optimization is intended to be executed preemptively, for instance, the day before, using forecasted base load and tariff data.

### B. $Z_{bus}$ Network sensitive matrix

The $Z_{bus}$ method was originally proposed for transmission systems, as detailed in [13]. In this method, system costs are allocated according to the electrical location of current injection and extraction buses within the transmission network. Thus, tariffs reflect the costs associated with the grid infrastructure at each bus. In this work, the method is adapted for distribution systems to capture both locational and temporal cost signals.

Nodal voltages ($V_i$) can be expressed using the elements of the impedance matrix ($z^{bus}_{(i,k)}$) and the current injection ($I_k$) at each bus as follows:

$$V_i = \sum_{k\in\Omega_k} z^{bus}_{(i,k)} I_k \tag{1}$$

The line current ($I_{(i,j)}$) flowing through line $(i,j)$ is given by:

$$I_{i,j} = (V_i - V_j) y_{(i,j)} + V_i y^{sh}_{(i,j)} \tag{2}$$

Being $y_{(i,j)}$ and $y^{sh}_{(i,j)}$, the line and shunt admitance, respectively. Thus, the line current can be formulated as the sum of contributions from the current injections at each bus $k$, as follows:

$$\begin{aligned} I_{i,j} = &\left( \sum_{k\in\Omega_k} z^{bus}_{(i,k)} I_k - \sum_{k\in\Omega_k} z^{bus}_{(j,k)} I_k \right) y_{(i,j)} \\ &+ \sum_{k\in\Omega_k} z^{bus}_{(i,k)} I_k y^{sh}_{(i,j)} \end{aligned} \tag{3}$$

When the distribution system is unbalanced, it is important to differentiate the usage of each phase. Therefore, the equation is adapted as follows:

$$I_{i,j} = \sum_{k\in\Omega_k} \left\{ \left[ z^{bus}_{(i,k)} - z^{bus}_{(j,k)} \right] y_{(i,j)} + z^{bus}_{(i,k)} y^{sh}_{(i,j)} \right\} I_k \tag{4}$$

Note that the coefficient multiplying the current element in (4) includes only network parameters. Therefore, the sensitivity coefficient ($a_{\ell,k}$) is defined, and the equation can be simplified as:

$$I_{(i,j)} = I_\ell = \sum_{k\in\Omega_k} a_{\ell,k} I_k \tag{5}$$

When the distribution system is unbalanced, it is important to differentiate the usage of each phase $p \in \Omega_p$ and bus $k \in \Omega_k$. Thus, the phase-dependent sensitivity coefficient ($a_{(\ell,k,p)}$) is introduced, and the equation is adapted as follows:

$$I_{\ell,p} = \sum_{k\in\Omega_k,\, p\in\Omega_p} a_{\ell,k,p} I_{k,p} \tag{6}$$

Developing (6),the line current for each phase and time ($I_{(\ell,p,t)}$) can be expressed by:

$$I_{\ell,p,t} = I^{\text{Real}}_{\ell,p,t} + j I^{\text{Imag}}_{\ell,p,t} \tag{7}$$

Each term of (7) can be written as:

$$I^{\text{Real}}_{\ell,p,t} = \sum_{k\in\Omega_k} \left( a^{\text{Real}}_{\ell,k,p} I^{\text{Real}}_{k,p,t} - a^{\text{Imag}}_{\ell,k,p} I^{\text{Imag}}_{k,p,t} \right) \tag{8}$$

$$I^{\text{Imag}}_{\ell,p,t} = \sum_{k\in\Omega_k} \left( a^{\text{Real}}_{\ell,k,p} I^{\text{Imag}}_{k,p,t} + a^{\text{Imag}}_{\ell,k,p} I^{\text{Real}}_{k,p,t} \right) \tag{9}$$

The squared magnitude of line current ($I^{abs}_{(\ell,p,t)}$) can be expressed by:

$$I^{\text{abs}}_{\ell,p,t} = \left( I^{\text{Real}}_{\ell,p,t} \right)^2 + \left( I^{\text{Imag}}_{\ell,p,t} \right)^2 \tag{10}$$

Since line current can be expressed as the power injection or extraction of each bus, the individual cost of each line can be optimized by considering the indirect effect of load variations on line current. In order to provide a cost sensitivity model, the line cost ($\delta_{(\ell,p)}$) considering each time and phase can be expressed by:

$$\delta_{\ell,p} = c^u_{\ell,p} \cdot \max_{t\in\Omega_t} \left( I^{\text{abs}}_{\ell,p,t} \right) \tag{11}$$

The parameter $c^u_{\ell,p}$ represents the unit cost associated with each line, expressed in $\left(\frac{R\$}{A^2}\right)$. The variable $\delta_{\ell,p}$ represents the cost associated with the maximum loading of line $\ell$.

### C. Optimization model for EV charging using DR program

The DR program is an energy management strategy in which end-users reduce or shift their consumption in response to price signals associated with grid conditions. The primary objective of the DR program in this study is to minimize peak loading in the distribution network caused by EV charging. This helps to reduce the impact on system infrastructure and defer investments in network expansion. Maintenance costs also decrease, as the network operates with reduced overloading and, consequently, lower risk of failures.

In general, load reduction is achieved through power flow management. In this work, however, line current is used as a reasonable approximation of power flow in the network. In this work, the low-voltage system is considered as an equivalent consumer with the combination of EVs and other loads to implement the DR program. EV charging in low-voltage systems is coordinated to reduce line currents and energy losses while simultaneously lowering consumers' energy bills, thereby ensuring alignment between the objectives of utilities and EV owners.

The optimization model is presented as follows. The objective function (12) seeks to minimize the sum of the costs associated with line current peaks, energy losses during peak and off-peak times, and the additional energy bill for consumers:

$$\begin{aligned}\min_{\Delta I^{EV}_{v,k,p,t}} \; & \sum_{\ell,p} \delta_{\ell,p} + \sum_{\ell,p,t\in\Omega_t^p} T^{p,a} R_\ell I^{abs}_{\ell,p,t} + \sum_{\ell,p,t\in\Omega_t^{op}} T^{op,a} R_\ell I^{abs}_{\ell,p,t} \\ & + \sum_{k,p,t\in\Omega_t^p} T^{p,a} \Delta I^{EV}_{v,k,p,t} + \sum_{k,p,t\in\Omega_t^{op}} T^{op,a} \Delta I^{EV}_{v,k,p,t}\end{aligned} \tag{12}$$

Subject to:

$$I^{abs}_{\ell,p,t} = (I^{Real}_{\ell,p,t})^2 + (I^{Imag}_{\ell,p,t})^2 \tag{13}$$

$$I^{Real}_{k,p,t} = I^{(d),Real}_{k,p,t} + \Delta I_{k,p,t} \tag{14}$$

$$I^{Real}_{\ell,p,t} = \sum_{k\in\Omega_k} \left( a^{Real}_{\ell,k,p} I^{Real}_{k,p,t} - a^{Imag}_{\ell,k,p} I^{Imag}_{k,p,t} \right) \tag{15}$$

$$I^{Imag}_{\ell,p,t} = \sum_{k\in\Omega_k} \left( a^{Imag}_{\ell,k,p} I^{Real}_{k,p,t} + a^{Real}_{\ell,k,p} I^{Imag}_{k,p,t} \right) \tag{16}$$

$$I^{abs}_{\ell,p,t} \le Cap^2_\ell \tag{17}$$

$$\Delta I_{k,p,t} = \sum_{v\in\Omega_v^{k,p}} \frac{\Delta I^{EV}_{v,k,p,t}}{RT^{\Delta y}} \tag{18}$$

$$\Delta I^{inicial}_v + \sum_{v\in\Omega_v^{EV}} \Delta I^{EV}_{v,k,p,t} \ge \Delta I^{final}_v \tag{19}$$

$$\Delta I^{EV}_{v,k,p,t} = 0 \quad \forall t \in \Omega_t^{v,n,c} \tag{20}$$

$$0 \le \Delta I^{EV}_{v,k,p,t} \le \overline{\Delta I^{EV}_v}, \quad \forall v \in \Omega_v^{k,p}, t \in \Omega_t^c \tag{21}$$

$$\delta_{\ell,p} \ge c^u_{\ell,p} \cdot I^{abs}_{\ell,p,t} \tag{22}$$

Where $\ell \in \Omega_\ell$, $p \in \Omega_p$, $t \in \Omega_t$, $k \in \Omega_k$, and $v \in \Omega_v$.

The optimization variable $\Delta I^{EV}_{v,k,p,t}$ represents the variation in charging current for each electric vehicle $v$ connected at phase $p$ of node $k$ and time $t$. This formulation allows the model to explicitly determine individual EV charging profiles while capturing their combined impact on the distribution network. The aggregated current variations at the medium-voltage level, $\Delta I_{k,p,t}$, are subsequently derived from the sum of these individual EV contributions, ensuring that the optimization process remains consistent with the system representation and the network constraints defined in the medium-voltage domain.

Constraint (13) computes the squared magnitude of peak current for each line and phase across the time horizon, which is then minimized in the objective function. Constraint (14) defines the active current for each bus, phase, and time, composed of the base demand $I^{(d),\text{Real}}_{(k,p,t)}$ plus the decision variable $\Delta I_{(k,p,t)}$, which reflects the EVs charging in each bus, phase, and time. The base demand ($I^{(d),\text{Real}}_{(k,p,t)}$) serves as the baseline for defining the DR program. This current is computed using OpenDSS [14], which simulates power flow in distribution systems, and the resulting current demand is extracted for use in the proposed model.

Constraint (15) calculates the real part of line current using the sensitivity matrix $a_{\ell,k,p}$, as presented in Section II.B. Even though the model does not alter the reactive current at the buses, the reactive line current must be computed because it is influenced by the real bus current. Constraint (16) computes the reactive line current for all lines, phases, and time periods, in the same way as in (15). Constraint (17) ensures that the squared peak current for each time and each line remains below its power capacity, thereby avoiding additional utility expenses for system expansion.

The model treats the DR program as a load-shifting mechanism, reducing costs for both utilities and EV owners. Thus, $\Delta I_{(k,p,t)}$, computed in (18), can be interpreted as the reflection from the secondary to the primary of the sum of EVs charging ($\Delta I^{EV}_{(v,k,p,t)}$), in each bus, time, and phase.

Constraint (19) ensures that EVs reach their pre-determined state of charge, as defined by the consumer, considering the initial battery level. Constraint (20) establishes the time interval in which the EV is not charging. Constraint (21) bounds $\Delta I^{EV}_{(v,k,p,t)}$ to the maximum value of $\overline{\Delta I^{EV}_v}$, which represents the power capacity of the EV.

Finally, constraint (22) computes the cost associated with line current peak. This cost depends on the peak line current and the unitary cost associated with each line. The allocation of the benefits associated with the DR program is out of the scope of this paper, but it could be done for all participants of the DR program proportionally to their flexibility and the gains provided to the network compared with the non-coordinated solution. Additionally, the proposed model can be combined with the framework presented in [12], creating incentives across different time periods and regions to expand EV adoption.

## III. CASE STUDY AND SIMULATION RESULTS

### A. Database

To validate the proposed model and its effectiveness, three case studies are carried out using the IEEE 123-bus test system, shown in Figure 1. The case studies consider the integration of 15, 45, and 90 EVs connected to the secondary buses of the system. Each case is also illustrated in Figure 1.In Cases 2 and 3, each bus accommodates five EVs, representing network conditions with a higher density of charging stations and, therefore, increased local demand. This approach allowed us to associate the increased load either with a higher number of EVs or with fast-charging behavior. To evaluate the impact of the EV charging on the distribution network, results are presented in three situations: (i) without EVs connected to the system; and (ii) the uncoordinated charging scenario, in which EVs charge simultaneously; and (iii) coordinated charging, applying the proposed model.The assumption of simultaneous charging start times was intentionally adopted to represent a worst-case scenario, where charging demand is highly concentrated. This allows the model's effectiveness in mitigating network impacts to be more clearly demonstrated.

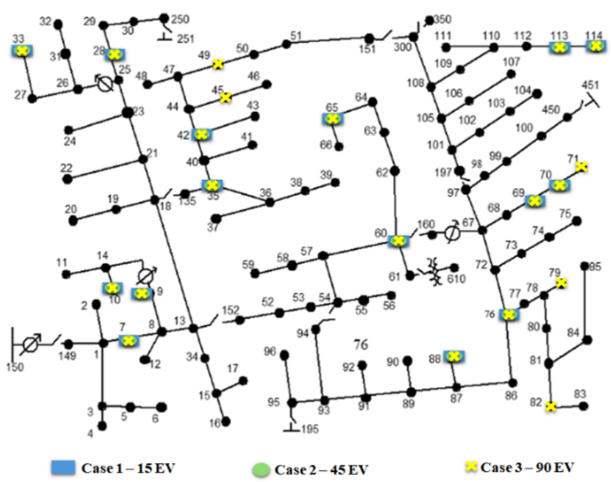


FIGURE 1. Topology of the IEEE 123-bus system.

The base load used in the studies is the same for all buses, with loads defined by a base power of 20 kW for active power and 10 kVAr for reactive power. The adopted load shape, representing daily demand variation, is illustrated in Figure 2. These data were used to configure the base case for the power flow solution from OpenDSS.

The proposed model considers EV charging in the low-voltage system and its impact on the medium-voltage level. Because of this, the bus and phase in medium voltage where the EV is connected should be indicated, as well as its capacity (in kW and A) and the accumulated energy (kWh and Ah), initial and final state of charge, charging start time, and charging end time. The capacity and energy data used are based on the BYD Dolphin Mini model, with specifications available in [15]. The start and end times of charging

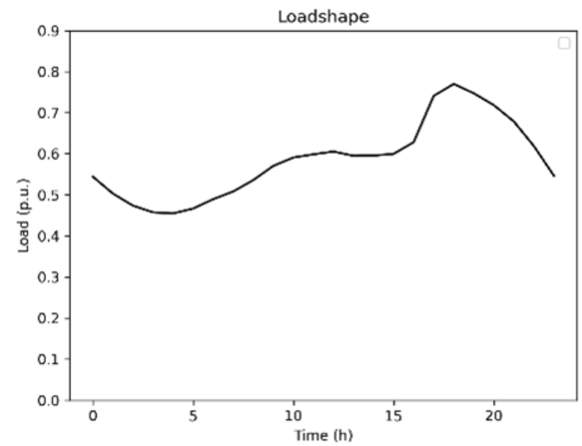


FIGURE 2. Load shape over time.

represent the availability period of each EV for participation in the DR program. Table 1 presents the input data used in the model, including sample information for a representative EV considered in the coordinated charging process.

The charging period between 17h and 23h was intentionally selected to represent the peak load hours of the distribution network. This configuration enables the evaluation of the proposed model under the most critical operating conditions, where network congestions are more likely to occur. The complete information for all EVs, as well as the information of the peak and off-peak tariff can be seen in [16]. The transformation from $R\$/kWh$ to $R\$/Ah$ was performed based on the nominal voltage of the system.

In addition to the EV data, the line cost is also an important component to be considered in the DR program. For brevity, Table 2 presents statistical information of the line parameters used in the proposed model. All data required for the simulations are available in [16].

### B. Case studies simulations

Figure 3 and Figure 4 present the uncoordinated and coordinated charging profiles for all EVs, respectively. As observed, the larger the number of EVs in the network, the greater the load variation. In general, the coordinated charging pattern accelerates charging for some EVs at the beginning of the process and reduces the charging intensity toward the end. For other EVs, the charging intensity is lower at the beginning and higher at the end of the process. The currents shown in Figures 3 and 4 represents the variation in the current on the secondary side (medium-voltage level). Therefore, its magnitude appears smaller than the actual low-voltage current, which varies approximately from 15 A to 75 A. In each case, the same number of EVs is connected per bus; however, the number of buses and EVs per bus increases in Case 3, resulting in higher overall demand and different network conditions.

**TABLE 1. Data from each EV.**

| Cap (kW) | Cap (A) | $T^p$ (R$/kWh) | $T^p$ (R$/Ah) | $T^{op}$ (R$/kWh) | $T^{op}$ (R$/Ah) | Initial Charge (%) | Final Charge (%) | Initial Time (h) | Final Time (h) |
|---|---|---|---|---|---|---|---|---|---|
| 6.6 | 17.32 | 1.95892 | 0.746448 | 0.64767 | 0.246795 | 20% | 90% | 17 | 23 |

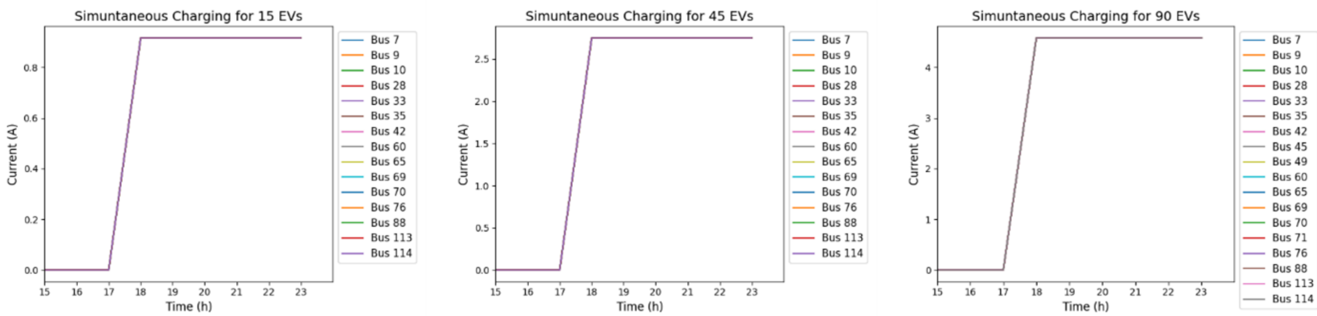


**FIGURE 3. Uncoordinated charging for 15, 45 and 90 EVs.**

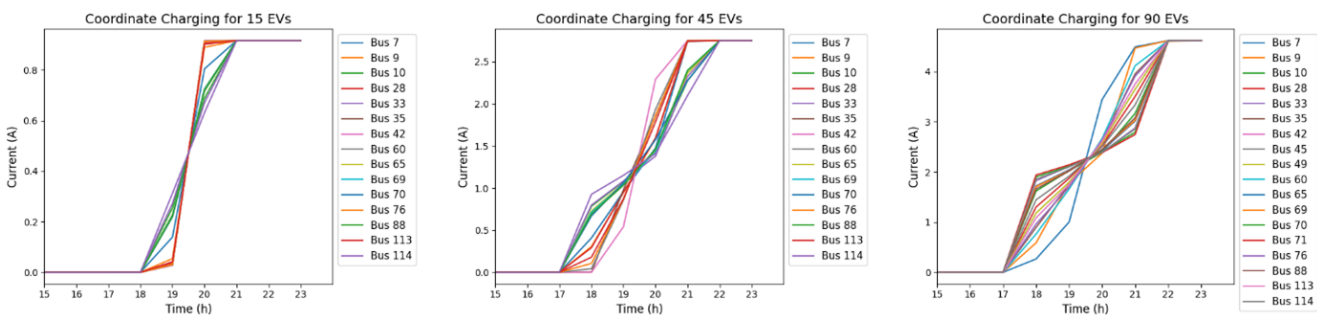


**FIGURE 4. Coordinated charging for 15, 45 and 90 EVs.**

**TABLE 2. Statistical information of the line parameters.**

| Statistic | Line Capacity (A) | Current Base (A) | Unitary cost (R$/A$^2$) |
|---|---|---|---|
| Minimum | 0.00 | 0.00 | 10.00 |
| Mean | 52.17 | 41.73 | 20.51 |
| Maximum | 350.68 | 280.54 | 30.00 |

In order to evaluate the impact on distribution systems for the three case studies, in Figure 5 and Figure 6, are presented the line currents for simultaneous charging (uncoordinated) and coordinated charging, respectively. As shown, line capacity limits are violated in the uncoordinated case. These lines are located at the beginning of the system, close to the substation. In contrast, in the coordinated case, the optimization model guarantees that all line currents remain within their capacity limits. To illustrate the voltage impact, Figure 7 and Figure 8 show the bus voltages for uncoordinated and coordinated charging. These results show that under coordinated charging, voltage drops are less pronounced, indicating more stable system operation.

Finally, to present the overall network impact, Figure 9 illustrates the sum of line currents for the base case (without EVs), uncoordinated charging, and coordinated charging with 15, 45, and 90 EVs. Results indicate that as the number of EVs in the network increases, the hosting capacity effect becomes more pronounced, particularly during peak periods. In addition to the technical results, financial outcomes were also obtained, including charging costs and loss costs for the three scenarios (coordinated and uncoordinated charging, with 15, 45, and 90 EVs). Table 3 summarizes the results. For all case studies, coordinated charging produced better results, especially for 45 EVs, with charging cost savings of $49.54\%$and a cost of losses reducing by $3\%$ . It is important to highlight that all costs and gains were computed for 1 day of analysis.

Although the IEEE 123-bus test system presents relatively short line lengths compared to typical Brazilian distribution networks, the proposed model can be readily adapted to larger and more complex systems. In particular, in Brazilian networks with longer feeders and a higher penetration of photovoltaic generation, the coordinated EV charging strategy can help alleviate medium-voltage stress by aligning the charging periods with local PV production.

## IV. CONCLUSIONS

This paper presented an optimization model for Electric Vehicle (EV) charging based on time- and location-sensitive tariff signals derived from the distribution network impedance

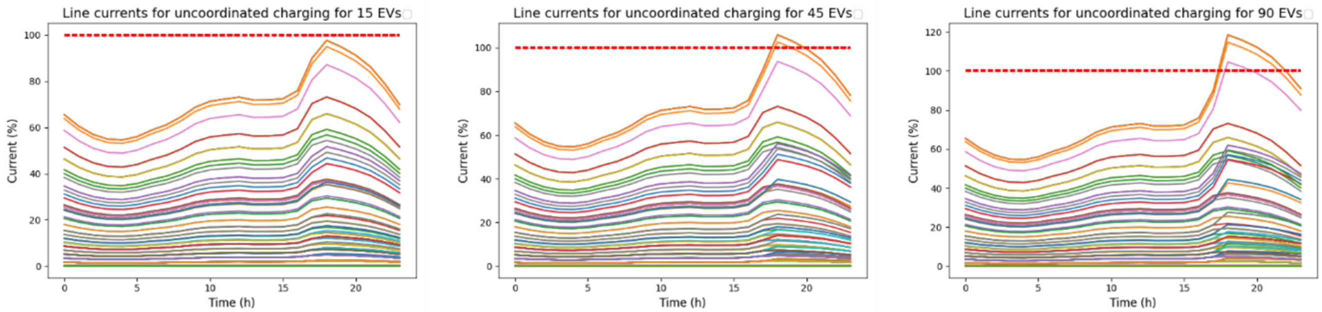


**FIGURE 5. Line currents for uncoordinated charging for 15, 45 and 90 EVs.**

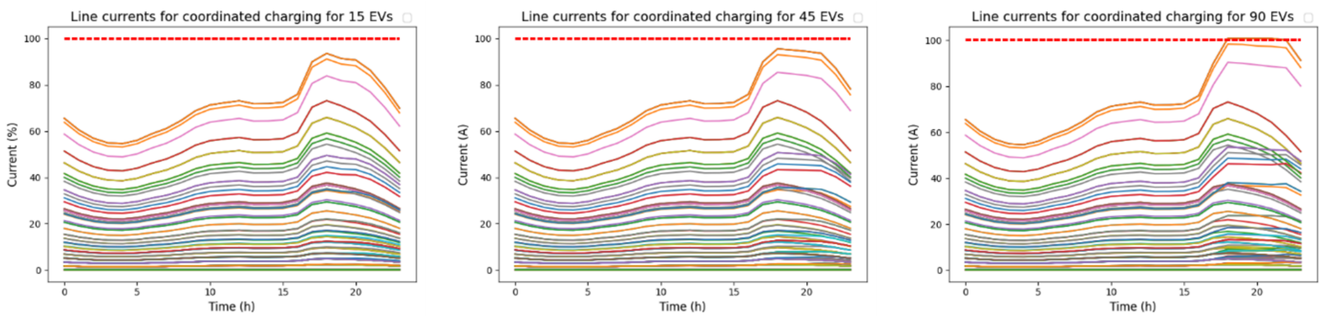


**FIGURE 6. Line currents for coordinated charging for 15, 45 and 90 EVs.**

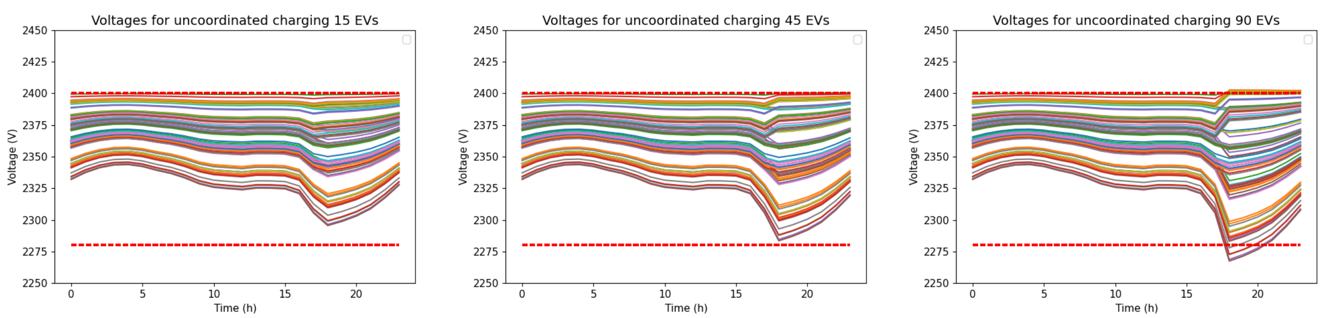


**FIGURE 7. Voltages for uncoordinated charging for 15, 45 and 90 EVs.**

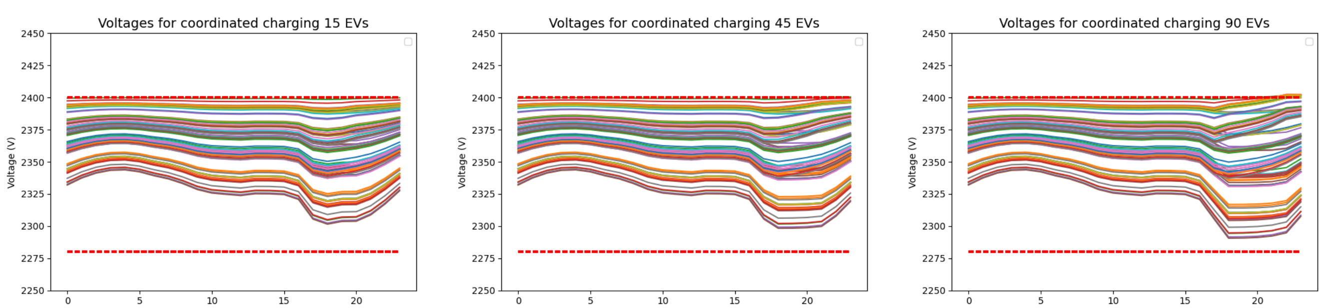


**FIGURE 8. Voltages for coordinated charging for 15, 45 and 90 EVs.**

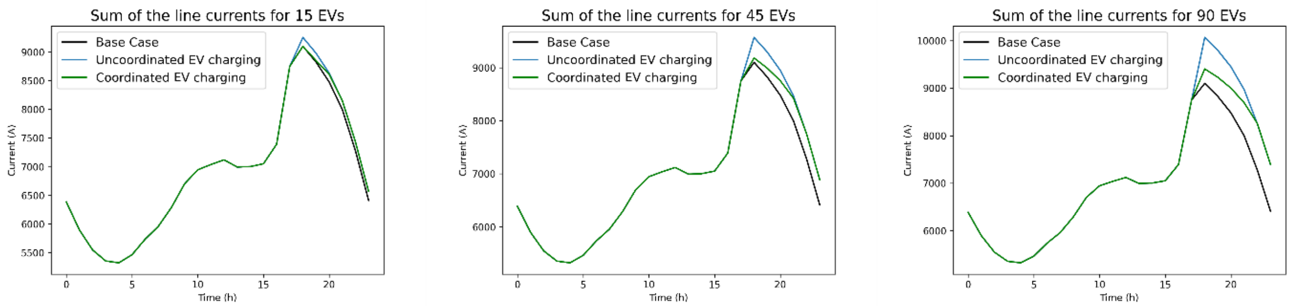


**FIGURE 9. Sum of line currents for 15, 45 and 90 EVs.**

**TABLE 3. Charging and Energy losses cost.**

| Cases / Costs | Case 1 (15 EVs) | | | Case 2 (45 EVs) | | | Case 3 (90 EVs) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coordinated | Simultaneous | Gain (%) | Coordinated | Simultaneous | Gain (%) | Coordinated | Simultaneous | Gain (%) |
| Charging (R$) | 14.73 | 34.10 | 56.8% | 51.62 | 102.30 | 49.54% | 111.03 | 204.60 | 45.73% |
| Energy Losses (R$) | 676.33 | 684.44 | 1% | 690.86 | 713.61 | 3% | 717.24 | 763.76 | 6% |

matrix. By incorporating sensitivity metrics into a demand response (DR) program, the proposed framework effectively aligns EV owners' charging needs with the operational requirements of the grid.

Simulation results using the IEEE 123-bus system demonstrated that the proposed approach reduces peak line currents, keeps all lines within capacity limits, and mitigates voltage deviations. Beyond these technical improvements, coordinated charging also provides economic benefits, including up to $45.73\%$ savings in charging costs and a $6\%$ reduction in loss-related costs compared to the uncoordinated charging scenario with 45 EVs. These results highlight the potential of sensitivity-based pricing mechanisms to enhance distribution system efficiency while ensuring fairness and scalability in EV integration.

The main contribution of this study lies in combining impedance-based tariff signals with the optimization of EV charging schedules, thereby offering a practical methodology for Distribution System Operators (DSOs) to manage increasing EV penetration without costly infrastructure expansion.

Only peak and off-peak tariffs were considered in this work, following the Brazilian standard structure. However, since the proposed model operates on an hourly basis, incorporating dynamic time-varying prices, such as those adopted in other countries, would simply require adjusting the input data to reflect time-dependent tariffs.

The uncoordinated charging case was intentionally defined to represent a worst-case scenario, allowing a clearer comparison with the benefits achieved by the coordinated charging strategy. As future work, we intend to include, in addition to the baseline case, a scenario in which each EV has its own dynamic charging profile obtained by minimizing only the individual consumer's energy cost under EV-specific constraints, without considering the overall network cost and constraints.

Future research directions include extending the model to multi-day horizons, integrating distributed renewable generation and energy storage systems, and assessing regulatory mechanisms to enable large-scale implementation of sensitivity-based DR programs in real-world distribution networks.

## AUTHOR'S CONTRIBUTIONS

**D.A.LIMA:** Conceptualization, Formal Analysis, Methodology, Supervision, Validation, Writing – Original Draft, Writing – Review & Editing. **L.S.ALMEIDA:** Data Curation, Software, Writing – Review & Editing. **R.S.D.TEIXEIRA:** Conceptualization, Investigation, Validation.

## PLAGIARISM POLICY

This article was submitted to the similarity system provided by Crossref and powered by iThenticate – Similarity Check.

## DATA AVAILABILITY

The data used in this research is available in the body of the document.

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