Voltage Regulation in Distribution Networks via Fleet Electric Vehicles Incentive Service

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***Abstract*—As environmental concerns continue to grow, promoting green sources of transportation has become a priority for many governments and researchers. Electric vehicles (EVs) have become increasingly pervasive in recent years, with both personal and commercial users embracing this mode of transportation. In the future, EV fleets owned by rental and delivery companies are expected to play a greater role in routine operations. From a grid perspective, grid voltage deviation varies depending on the loads on the distribution network, and the energy capacity of EV fleets represents a great potential source of support for the grid. When leveraging EV fleet to provide grid voltage support, it's important to optimize the EV fleet locations that can best support voltage regulation, while avoiding the risk of turning on all EVs for voltage regulation and potentially losing their mobility for other services. In this paper, we propose an incentive-based control strategy to encourage EVs in desired locations to participate in grid voltage regulation. By identifying the target nodes and allowing the remaining EVs to be used for other purposes, this incentive-based strategy aims to strike a balance between the needs of the grid and the needs of the EV fleet. Our results show that this strategy can effectively regulate grid voltage deviation and improve the performance of the grid by leveraging EV fleet.**

***Index Terms*—Electric vehicle fleet, vehicle-to-grid (V2G), distribution network, voltage regulation, EV management**

I. Introduction

Researchers, policymakers, and corporations are promoting the transition towards clean energy resources due to the growing environmental concerns and impact of climate change, resulting in an increasing presence of renewable resources and electric vehicles (EVs) in the power grid [1]. The unpredictable and intermittent nature of renewable generation, along with the ever increasing and varying energy demand, poses challenges in stable and reliable operations of the grid. Though EVs are undeniably beneficial for environmental sustainability, an insurgence in EVs may change the daily power profile of the grid. With suitable control and co-ordination strategies, EVs could be capitalized for ancillary services in the future renewable energy-centric grid. The past decade witnessed rapid adoption of EVs as the public's new mode of transportation [2]. Several EV models, including Tesla, BM Bolt, Volt, Nissan Leaf and BMW I series have achieved success stories. On the other hand, the popularity of eMobility concept has also accelerated the adoption of EVs in transportation and rental companies such as FedEx and Uber [3]. With an eye toward the future, the ubiquitous EVs owned by these companies are not only a form of green energy transportation, but also potential passive income sources which can provide services via vehicle-to-grid (V2G).

In contrast to individual private owned EVs which are constrained by user specific requirements (e.g., departure state of charge, available time frame, etc.), fleet EVs owned by companies facilitate easy control access via company managed aggregators and provide large scale dispensable energy. Additionally, companies usually have a higher motivation to provide profitable services when EVs are idle. There is, however, limited research on EV fleet control and consequent grid behavior, and whether such services are indeed profitable. In this paper, we investigate the economic benefit and the improvement in grid stability facilitated by EV fleets operating to provide voltage regulation services in the distribution network. In the study, the distribution network with renewable energy resources and EV fleet integration are modeled in OpenDSS (open source distribution system simulator) [4] to emulate realistic energy demand and daily loading patterns. The EV fleet behavior models with sufficient level of fidelity and the optimal fleet control strategy for regulation of distribution grid voltage are developed. The impact of the EV fleet on voltage stability and the grid performance is compared subsequently with that of no EV. From the perspective of the EV fleet, the incentive for providing grid services is investigated by using price signals in the control framework.

The rest of the paper is organized as follows: Section II describes the EV fleet and grid modeling, as well as the proposed incentive-based control strategy that enables the nearby EV fleet to regulate the grid voltage. In Section III, a case study is formulated based on a designed scenario, which takes into account the delivery truck V2G time, and uses the incentive control to support grid voltage regulation. Finally, Section IV concludes the paper and discusses potential future work.

II. Modeling the Integration of Electric Vehicles and the Grid

The EV fleet presents a unique benefit to the power grid, where the parked EV fleet is in idle and can be served as energy storage to support grid stability and reliability. To assess the viability of control algorithms for EV fleets, we have modeled the fleet and constructed a test network using

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openDSS for distribution network simulations. Additionally, we have designed an incentive algorithm to encourage the EV fleet to participate in grid network regulation, thus demonstrating the potential for EV fleets to provide support to the power grid.

A. Electric Fleet Modeling

To model the EV fleet, we first established a representation for a single EV. Based on the current range of EV designs and battery configurations, most EVs have a range of 200 to 400 miles and a voltage of 400 V to 800 V. As the focus of this paper is on grid voltage regulation and promoting an efficient and accurate strategy to enable EV service, we have synthesized the battery performance close to market EVs. Below is a table of synthesized parameters for EVs:

TABLE I
SYNTHESIZED EV PARAMETERS

Parameter	Value
Cell capacity	90 Ah
Cell voltage range	2.7 V to 4.15 V
Cell internal resistance	1.4 mΩ
Cells per module	5
Modules per pack	32
Pack voltage range	432 V to 664 V

We took into account the primary purpose of EVs in our simulation setup. To achieve this, we defined a single EV behavior and accounted for critical elements such as V2G available time, maximum and minimum state of charge (SOC), and battery power availability to enable optimal grid management. Our modeling of the single EV's SOC and power capabilities relied on synthetic data, including the battery's SOC-open circuit voltage (OCV) characteristics [5], maximum current limit, and internal resistance, which were based on a typical electric vehicle.

In the simulation setup, sensor inaccuracy is not in the scope of this study, therefore, we have used the Coulomb counting method [6] for SOC calculation.

$$SOC_t = SOC_{t-1} + \frac{1}{Q} \cdot \int_{t-1}^{t} i(\tau) d\tau \tag{1}$$

where Q denotes the battery capacity.

The SOC maximum and minimum boundaries shown in (2) pose a constraint for V2G services that the grid manager should take into consideration. $SOC_{k,i}$ denotes the k^{th} vehicle at node i. The SOC_{V2Gmax} represents the upper limit to which the V2G can charge. The SOC_{V2Gmin}, on the other hand, represents the lower limit beyond which the V2G service should stop. The SOC_{V2Gmin} can have different thresholds based on different scenarios, such as whether the vehicle needs to reserve capacity for its future drive, or if there is a safe cut-off limit to avoid over-discharging the battery. It's important to note that the battery management system may lock the battery from operating in the next drive cycle due to violations of current, voltage, temperature, and/or SOC limits. Therefore, the V2G service should avoid violating these limits to prevent the battery from locking.

$$SOC_{V2Gmin} \leq SOC_{k,i} \leq SOC_{V2Gmax} \tag{2}$$

The power prediction model in this work utilizes the power prediction methods presented in Ref. [5] for a single EV. In this paper, the charge power is denoted with negative values, representing grid supplying power to the EV, while discharge power is denoted with positive values, indicating grid receiving power from the EV. The power estimation is calculated using voltage-limited power prediction, as shown in (3) and (4), and current-limited power prediction, as shown in (5) and (6). The overall power prediction takes the maximum of both calculations in the charge direction and the minimum in the discharge direction, as shown in (7).

$$P_{min,v}^{chg} = V_{max} \cdot \frac{V_{OCV} - V_{max}}{R^{chg}} \tag{3}$$

$$P_{max,v}^{dchg} = V_{min} \cdot \frac{V_{OCV} - V_{min}}{R^{dchg}} \tag{4}$$

$$P_{min,I}^{chg} = (V_{OCV} - I_{min} \cdot R^{chg}) \cdot I_{min} \tag{5}$$

$$P_{max,I}^{dchg} = (V_{OCV} - I_{max} \cdot R^{dchg}) \cdot I_{max} \tag{6}$$

$$\begin{aligned} P_{min}^{chg} &= \min\{P_{min,v}^{chg}, P_{min,I}^{chg}\} \\ P_{max}^{dchg} &= \max\{P_{max,v}^{dchg}, P_{max,I}^{dchg}\} \end{aligned} \tag{7}$$

where V_{max} represents the maximum operating voltage of a cell, while V_{min} represents the minimum operating voltage. V_{OCV} denotes the open circuit voltage of the cell. I_{max} and I_{min}, respectively, represent the maximum current in the discharge and charge directions. Finally, R^{chg} and R^{dchg} represent the battery's internal resistance in the charge and discharge directions, respectively, which vary according to the corresponding pulse duration.

In the current battery management system, the current and power prediction supports the vehicle's driving in a dynamic environment. However, in the V2G service, minimizing the battery aging effect is essential and should not deviate from the EV's main purpose. Using short-term power prediction is not an optimal choice, as it potentially adds strong power cycles on the battery for a longer V2G time period, which generates heat and increases the chance of operating at higher temperatures. Limiting the current at a moderate level to minimize aging is more appropriate in the V2G service. Therefore, we have reduced I_{lim} for V2G based on the allowed SOC swing and the projected V2G service duration as shown in (8).

$$I_{min,max} = \frac{I_{c-rate} \cdot (SOC_{V2Gmax} - SOC_{V2Gmin})}{T_{V2G}} \tag{8}$$

where I_{crate} denotes the C-rate current, and T_{V2G} denotes the projected V2G support time duration. There are many incentive programs to promote V2G, and in our case study, it is assumed that the EV will be available for the entire period during its V2G time.

B. Grid Modeling of IEEE 34-Bus Distribution Network

The V2G performance and its capability to regulate the voltage are validated on the IEEE 34-bus distribution test network [7], [8]. The 34-bus network is the model of a feeder located in Arizona, which has an operating voltage of 24.9 kV, and multiple in-line regulators and shunt capacitors. The total connected load in the network is 2.04 MW and the network loading is unbalanced in nature.

The test network with the distributed energy resources are modeled and simulated using OpenDSS. Increasing photovoltaic (PV) hosting capacity can alleviate the distribution network load during daytime, as discussed in [9]. Considering the trend of increasing renewable penetration, the test network is modified by adding three phase PV units as in [10]. The PVSystem model built in OpenDSS is utilized where the combination of PV panel and inverter is described with sufficient level of fidelity. The power produced by the PV plant is dependent on a number of factors including the irradiance and ambient temperature which are provided as inputs. During periods of high demand with no/low PV generation, the voltage at extreme buses may fall beyond the desirable limits. Therefore, in our study we consider the point of common coupling (PCC) of EV fleet with the grid at the buses farthest from the substation. In our study, we assume that the EV charging station exists at Bus 890 as shown in Fig. 1, which is often observed to suffer from under-voltage due to its distance from the substation, both with and without PV. The EV fleet modeled in Section II-A is further defined as a lumped storage in the distribution network modeling domain. The storage model available in OpenDSS is used by characterizing the power rating and storage capacity according to the EV fleet aggregated at the PCC.

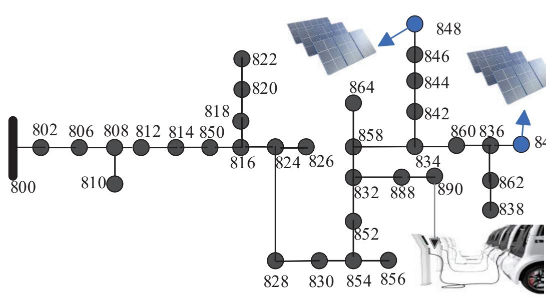

Fig. 1. IEEE 34-bus distribution network with PV and EV penetration

C. Incentive Based EV Fleet Control

Various load profiles and distribution sources are incorporated in the grid modeling, including PV and EV fleets at different locations, to examine grid voltage deviations. Node voltage deviations can vary depending on the configuration of the distribution network. To regulate voltage more effectively, it is better to enable EV fleets close to the nodes that need voltage regulation, allowing voltage to be directly injected to support regulation. While other EV fleet locations can provide support, the further they are from the node, the less effective their voltage regulation support will be. Even if all EVs close to that node are available for grid services, it may not be financially beneficial for the fleet company to engage all available EVs for grid services due to reasons such as the need for flexibility or other more financially attractive services. To address this, an incentive-based control algorithm is proposed to encourage more EVs close to the node requiring voltage regulation to participate, as shown in Algorithm 1.

The algorithm uses ΔV_i to represent the node voltage deviation, which is the difference between the voltage at time t and the reference voltage V_{ref}. The maximum acceptable deviation from the reference voltage is denoted by ΔV_{thd} and set to 5% of V_{ref} in our study. The reactive power demand at node i is denoted by $Q_{demand,i}$.

The algorithm considers an incentive factor α that the grid operator sets to regulate grid voltage. This factor is a function of the location of EVs with respect to the nodes needing voltage regulation and the power demand. It can represent a reward or electricity discount to encourage or discourage EV fleet participation, similar to the price design in game theory used in [11]. The grid operator controls the EV fleet engagement at each node through this incentive factor. At each node, the grid operator checks the voltage deviation between the node and reference voltage. If the deviation is greater than a certain threshold, the incentive-based control will be enabled. Since node locations, load distribution, and distributed energy resources locations vary across different distribution networks, in this study we target all nodes that have voltage deviation to spread the voltage regulation support across several nodes. If the power demand is high, the grid operator will check the closest EV nodes and assess their aggregated power capability based on available time and predicted power. If the grid operator deems it is necessary to use all EVs at one node, the incentive factor will be set to 1. Equation (9) describes how we assess the incentive factor.

$$\alpha_i = \begin{cases} 1 & \text{if } Q_{demand,i} > \sum_{j=1}^{n} P_{pred,EV,j} \\ \frac{Q_{demand,i}}{\sum_{j=1}^{n} P_{pred,EV,j}} & \text{otherwise} \end{cases} \tag{9}$$

where the index j denotes one of the n identified EV locations that support voltage regulation at node i, while $P_{pred,EV,j}$ represents the predicted power of the EVs located at node j. The total predicted power from all identified EV locations is obtained by summing $P_{pred,EV,j}$ over all n locations.

Modeling the incentive factor and EV participation will require some market insight. Our approach will model the incentive factor with a linear relationship between EV numbers, where the number of participating EVs ($N_{EV\_con,j}$) close by node i is calculated by (10).

$$N_{EV\_con,j} = \alpha_i \cdot N_{EV,j} \tag{10}$$

where α represents the ratio of participating EVs to the total number of EVs ($N_{EV,j}$).

Algorithm 1 Incentive-based Vehicle-to-Grid Regulation

$dt \leftarrow 1$ hr ▷ time step set to 1 hr
for each time step **do**
  for each node **do**
    Compute delta voltage $\Delta V_i = V_{t,i} - V_{ref}$
    if $\Delta V_i \notin \Delta V_{thd}$ where $\Delta V_{thd} = 5\% V_{ref}$ **then**
      Enable incentive-based control for node i
      Compute reactive power demand $Q_{demand,i}$
      Identify nearest EV fleet sites close to node i
      Check EV discharge power availability
      Compute α based on linear relationship of (9)
      Set α for EV fleet at node i
    else
      Set α_i to 0 for this node location
    end if
  end for
end for

III. Simulation and Results

The overall framework for model implementation includes two components: the grid modeling module for evaluating the network behavior, and the EV fleet modeling and control module. In the grid domain, the distribution network is simulated to identify the buses with voltage violations and determine the reactive power compensation to alleviate the under voltage. The second module implements the proposed incentive control strategy that utilizes nearby EV fleets to regulate the voltage at the buses in the network.

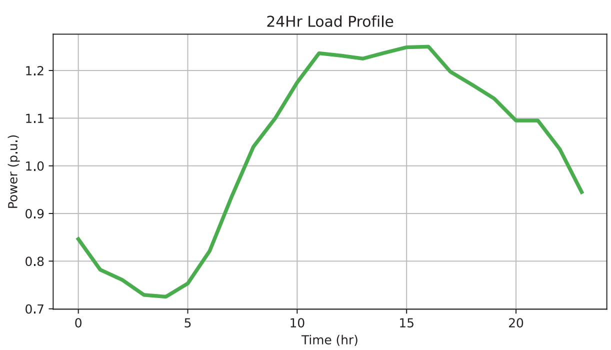

Fig. 2. A typical load profile for the IEEE 34-bus system

A. EV Fleet Schedule

The voltage regulation support envisions a future where more EV fleets are available, and the V2G technology can be used as another source of profit for EV owners. In this study, delivery trucks were considered as an option of the EV fleet. By analyzing fixed delivery routes, vehicle metrics like SOC swing and drive period can be predicted. Previous studies, such as the work in [12] on repeated commuting driving cycle, can help determine V2G availability during "off-delivery" time.

Based on the research in [13], package delivery for the EV fleet primarily occurs in the morning from 6 am to 12 pm and in the early afternoon. To optimize the use of the EV fleet, two groups were established: package delivery and idle. During the day, $2/3$ of the EVs perform delivery tasks, with a 50% swing in SOC through driving, leaving them available for V2G services during the rest of the day. The V2G operation for the package delivery group starts at an SOC of 40% and stops at 15%. For the idle group, constituting the remaining $1/3$ of the fleet, the V2G operation is available throughout the day, starting at an SOC of 90% and stopping at 15%. When connecting to the grid for V2G services, it is assumed that the EVs have already completed their primary tasks. The idle group assumes no delivery tasks throughout the day, while the delivery group starts with a low SOC, leaving the remaining capacity available for V2G services. To minimize battery aging, a cut-off SOC of 15% is chosen for V2G services, as the battery internal resistance increases significantly at lower SOC.

B. Test Cases

Two case studies are considered in our simulations. The first case study involves EV penetration in the original 34-bus network without any solar PVs, while the latter case considers the integration of both solar PVs and EV fleet into the network. In both these cases, the EVs are located near bus 890, and a time varying load profile shown in Fig. 2 is used for model simulation. The load curve represents the variation of per unit load multiplier, which is multiplied with the specific load at different nodes to obtain the time-series load profile for each node. The EV fleet comprises of 150 EVs, with 100 EVs in the delivery group as mentioned in Section III-A. The remaining EVs are assumed to be idle. It is identified in both cases, bus 890 is the worst performing node in terms of voltage. Hence, the voltage at this bus is represented in Fig. 3 and Fig. 4 for the two cases to illustrate the voltage regulation provided by the EV fleet. As seen in Figs. 3 and 4 that, the voltage falls during the period of heavy loading. This drop in voltage is less for the case with solar PVs (Fig. 4), since the PVs inject power into the network during the daytime peak load hours. It is observed that the EV fleet integration enhances the voltage profile considerably in both cases.

Figure 5 demonstrates the implementation of incentive control to address the power demand from the grid in the load-only scenario. As the grid's demand for power increases, more EVs are needed to provide the necessary power. This prompts an increase in the incentive factor to encourage further participation, as shown in Fig. 5a. Fig. 5b displays the SOC of select EVs, with higher power-predicting EVs being discharged first. The plot shows that all vehicles will be discharged to their lower SOC limit. The current limit for EVs for V2G is based on the expected V2G time, and the discharge rate is mild, which has less impact on battery aging. Later in the day, the delivery group EVs are utilized to discharge and provide the required power. Fig. 5c shows the actual power demand and the power supplied by the participating EVs, indicating that as more EVs participate, the grid's power demand can be fulfilled.

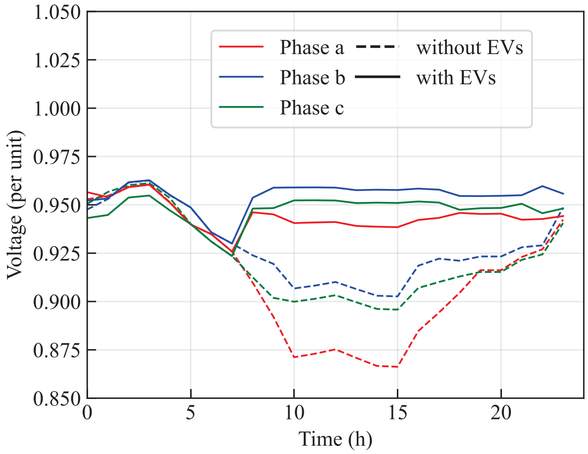

Fig. 3. Voltage regulation by the EV fleet at bus 890 in the network without solar PVs

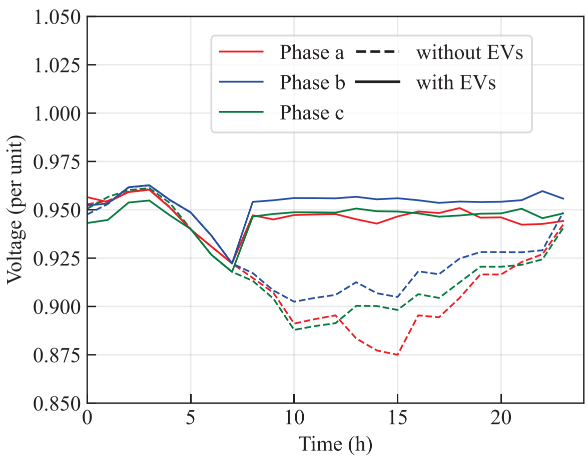

Fig. 4. Voltage regulation by the EV fleet at bus 890 in the network with solar PVs

Figure 6 displays the simulation results of EV power for grid voltage regulation with the availability of solar PV power generation. Although the solar PV power injection does not directly affect the worst node, Fig. 6c shows that the power demand for EVs decreases slightly during daytime compared to the scenario without PV. The incentive factor for EV participation at the end of the 24-hour simulation is 68%, slightly lower than the 70% observed in the scenario without PV. Despite the small amount of solar PV generation, it covers a portion of the grid's power demand, resulting in fewer EVs required to participate in V2G services. Therefore, a reduction in the incentive factor may still guarantee sufficient power delivery. This test case demonstrates that the integration of multiple renewable sources can improve voltage regulation. By coordinating these renewables, a more efficient method for regulating grid voltage can be achieved.

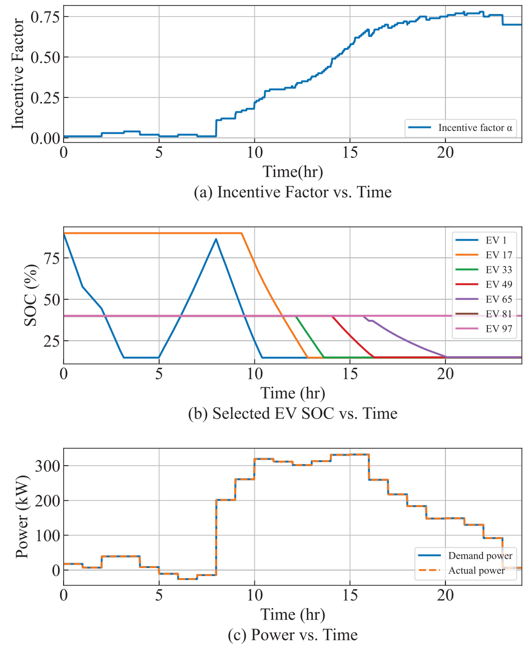

Fig. 5. EV fleet operating characteristics in the network without solar PV

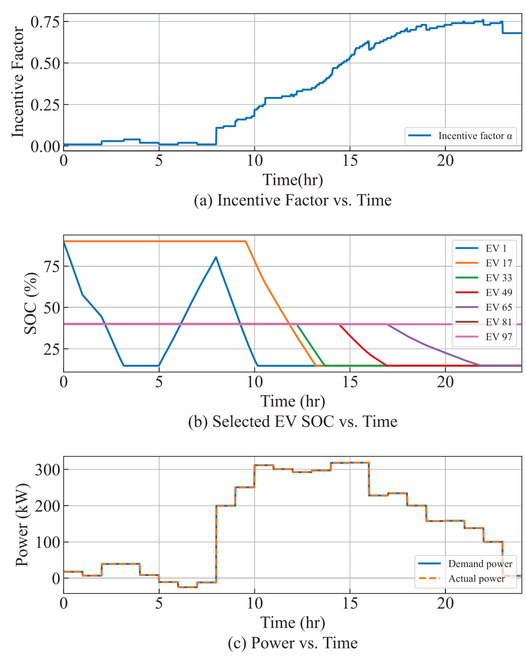

Fig. 6. EV fleet operating characteristics in the network with solar PV

IV. Conclusion

This paper proposes an incentive-based vehicle-to-grid (V2G) service for regulating grid voltage. The incentive factor encourages or discourages the EV fleet's participation in the V2G service based on the node's voltage regulation needs and predicted EV fleet power. An aggregated EV fleet model is used, and the power prediction is adjusted based on the V2G service period. The proposed incentive factor can serve as a signal to stimulate EV participation in voltage regulation, and can be implemented through dynamic tariffs. The developed incentive control is compared with a baseline without an EV fleet, and the results show that it can potentially optimize the number of EVs for voltage regulation and release unused EVs for other purposes.

Potential future work will explore (i) a more accurate model for the relationship between the incentive signal and the participated EVs, and (ii) the aging influence on the incentive signal.

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