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Original Scientific Article

Opportunistic Wireless Charging for Urban EVs and Grid Effects

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Abstract—**The study evaluates the grid-side implications of on-route, opportunistic wireless charging for electric vehicles (EV), where EVs are charged during routine traffic dwell, relative to a conventional depot plug-in regime that concentrates charging after service. Using a city scale microscopic traffic–power simulation over a six-hour period with a mixed EV fleet, study analysis integrates vehicle activity, station utilization, and feeder-level indicators. The findings show that the distribution of uniform energy across operating hours leads to a significant reduction in instantaneous loading, increases the utilization of available distribution capacity and reduces load peaks. Conversely, compressing charging into a terminal window alone results in the generation of a high magnitude wave. The key findings illustrate that temporal regulation of charging is a important factor in achieving grid compatibility, and opportunistic wireless top-ups represent a viable mechanism for aligning urban EV charging with distribution grid operating envelopes. It further motivates field trials coupling control policies with observed traffic and feeder limits.**

Keywords - electric vehicle charging, wireless power transfer, opportunistic charging, city-scale SUMO scenario.

I. INTRODUCTION

Electric vehicles (EVs) are rapidly transitioning from a niche to a mainstream transportation technology, promising significant environmental benefits by reducing exhaust emissions and fuel consumption. However, they are also driving a shift in energy demand from gasoline to the electric grid. As EV adoption accelerates globally, electricity grids and distribution systems face new challenges and opportunities in meeting the charging needs of millions of vehicles [1,2]. Evidence shows that, unmanaged, highly coincident residential charging amplifies evening peaks and stresses low-voltage assets, whereas smart-managed charging materially mitigates both transmission and distribution level impacts [3,4].

When the impact of EVs on the day is examined, the aggregate electricity demand from EV charging is still modest today, which is approximately 0.7% of global final electricity consumption in 2024 [5], but is set to rise quickly this decade, with multiple scenarios anticipating EVs accounting for several percent of total demand by the mid-2030s. This may shift the integration challenge from energy volumes to when and where charging occurs on the power system [6]. From a statistical point of view, electric car sales, which were 9% in global 2021 and 5% in 2020, exceeded 10 million in 2022 [7] and according to the IEA report [5], global electric vehicle sales, which were previously 13.5 million in 2023, exceeded 17 million in 2024. By the end of 2024, the proportion of electric vehicles in traffic is 4.5% for cars and 4.9% for buses worldwide, while this proportion is projected to reach 15% for cars and 11% for buses by 2030. In this scenario, the energy issue, which does not pose a serious problem for the grid, could become a problem in the coming years with the increase in population and vehicle sales.

As EVs become integral to daily life, their charging needs pose new challenges for drivers

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and city infrastructure. To meet the rising energy demand of EVs sustainably, many studies and pilot programs focus on smart charging, which schedules and modulates charging in response to grid conditions or prices [8,9]. While the smart charging methods optimize planned charging sessions, a complementary concept has emerged as opportunistic or opportunity charging during short stops in a vehicle's normal routine [10]. This process refers to giving an EV brief but high-power charging bursts whenever the vehicle is stopped for a short duration, rather than only relying on long, dedicated charging sessions. In other words, the vehicle consumes energy whenever it has a few seconds or minutes of idle time, thereby helping to keep the battery fully charged. This concept is already being implemented wirelessly in some contexts via inductive charging pads [11].

One underutilized opportunity for opportunistic charging is the time vehicles spend waiting at red traffic lights. A 2021 traffic signal performance analysis [12] revealed that 40-45% of vehicles in busy cities wait at red signals during peak hours. When the time spent waiting at a red light, which is approximately 15-20 seconds per vehicle, is also factored in, the cumulative impact is substantial. These eye-opening figures highlight that wasted time can be used as an energy opportunity by integrating wireless chargers at traffic light intersections.

In the present study, a simulation model with parameters tuned for realism is built using Simulation of Urban Mobility (SUMO) [13] to investigate the feasibility and grid impact of charging electric vehicles via wireless power transfer (WPT). The simulation is based on a detailed urban traffic scenario modeled from Monaco, a representative medium-sized city network. The Monaco traffic scenario, known as MoST [14], provides an accurate road topology of the city and includes real-world features like buildings, bus routes, and, importantly, 12 signalized intersections whose traffic lights operate with timing programs identical to the real city. Traffic demand in the model was generated using actual demographic and traffic data, including EV shares expected in 2030, and the scenario was validated by comparing simulation outputs to real traffic counts.

II. Materials and Method

The scenario used in this study is designed to model urban mobility, providing a multimodal traffic simulation environment that allows detailed analysis of vehicular traffic, public transport, pedestrian flows and cycling in an urban environment, that is built upon the SUMO. While the original scenario [14] includes a diverse fleet, this study modified the vehicle composition by replacing a percentage of conventional vehicles with pre-calibrated EV types for realistically analyzing energy-related metrics. The power system model is therefore not a grid simulation but rather a vehicle-centric energy consumption model, which utilizes SUMO battery device and the physics-based powertrain models (MMPEVEM [14]) to accurately model consumption, efficiency, and battery capacity. Furthermore, to enable opportunistic charging, wireless charging stations have been placed on bus stops and at traffic signal intersections. The result is an integration framework that has the potential to combine the dynamic traffic situation of the vehicle with the energy model. Finally, simulation generates detailed time series data, which is then processed using Python scripts to collect and calculate final energy demand profiles and infrastructure utilization metrics.

A. Vehicle Fleet and Energy Consumption Model

The realism of the simulation is based on detailed modeling of the vehicle fleet and the

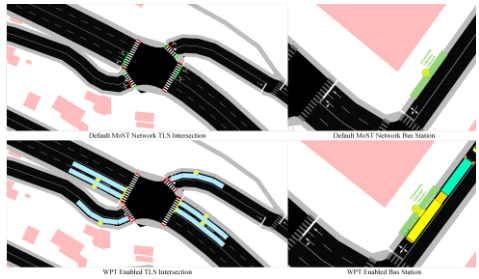


Figure 1. WPT enabled SUMO network.

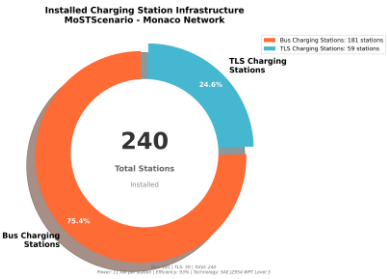


Figure 2. Installed charging stations.

physics governing their energy use, where each vehicle acts as an independent agent whose behavior and energy consumption are dynamically calculated. To create a realistic urban environment, the scenario simulates a heterogeneous fleet where electric vehicles enter congestion and interact with conventional traffic by defining specific vehicle type distributions in Table I. The energy consumption for each electric vehicle is dynamically calculated by SUMO's physics-based model using the detailed parameters in the definitions [15,16]. In addition, to achieve the expected distribution of vehicles by 2030 [5], the vehicle types listed in the table have been distributed in a way that meets the expected occurrence rate projections. Each of these EV cars has been configured with a 5% spawn rate, totaling 15%, and EV bus has been configured with an 11% occurrence rate.

TABLE I. EV PHYSICAL AND DYNAMIC PARAMETERS.

Parameter	**Vehicle Type Distributions**			
	Electric Bus	***BMW i3***	***VW ID3***	***VW ID4***
Battery Capacity (kWh)	200	39	58	77
Auxiliary Power Draw (kW)	8.0	0.36	0.36	0.36
Propulsion Efficiency	93%	82%	82%	82%
Recupera-tion Efficiency	78%	82%	82%	82%
Air Drag Coefficient	0.60	0.29	0.26	0.28
Roll Drag Coefficient	0.009	0.007	0.007	0.0075
Vehicle Mass (kg)	14000	1417	1794	2124

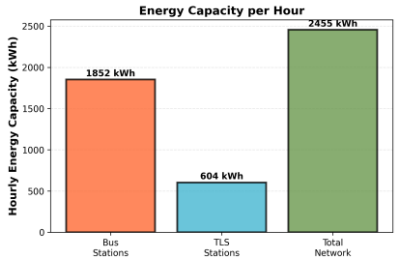


Figure 3. Energy capacity per hour.

B. *Built-in Charging Station Model*

The WPT infrastructure is modeled as a network consisting of charging zones defined as bus station chargers and traffic light system (TLS) chargers. Since the MoST scenario in its original version did not have wireless charging stations, an example showing the changes made to the network is provided in Fig. 1. Charging stations with the same size and coordinates as bus stops have been defined at existing bus station locations. For TLS charging stations, wireless charging pads were positioned in front of traffic lights. This configuration enabled the simultaneous charging of multiple vehicles, with each vehicle charging sequentially as the preceding vehicle came to a halt, and the activation was synchronized with the vehicles' stop-signal.

The energy transfer for each station is defined by a constant power model, which is inspired by a WPT standard [17] that supports up to 11kW power above 90% efficiency. The rate of energy delivery to the vehicle's battery, P_{batt} is a function of the charger's nominal grid power, that is $P_{nominal}$, and its end-to-end grid to battery efficiency, η. This relationship is governed by the Eq. (1):

$$P_{batt} = P_{nominal} \cdot \eta \,. \tag{1}$$

For this simulation, all charging stations are parameterized with a nominal power of 11 kW and an efficiency (η) of 93%, based on the SAE J2954 standard. This results in a constant power influx of 10.23 kW to the vehicle's battery model during any active charging session. Total installed charging stations with their types and numbers in the SUMO network is illustrated in Fig. 2, and their hourly charging capacity is stated in Fig. 3.

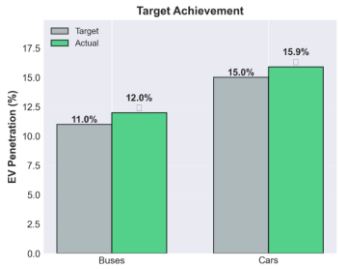


Figure 4. EV target achievement.

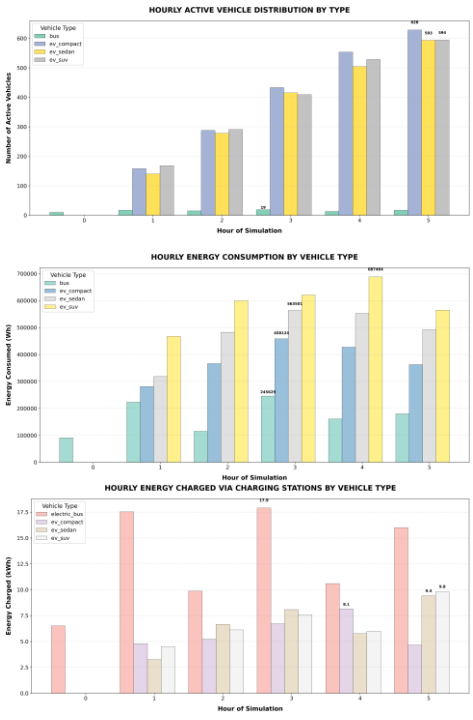


Figure 5. Hourly vehicle analysis.

III. RESULTS

In the scenario, the simulation start time step is set to 14400 and the end time step to 36000. Here, when the simulation origin is taken as 0, it can be said that the simulation corresponds to the real-life period between 4:00 AM and 10:00 AM, which covers 6 hours long period. The simulation took 6647 seconds with real-time factor 3.24, and 37902 vehicles inserted during the simulation. Looking at the distribution of vehicles in Fig. 4, it can be said that the statistical distributions determined in the methodology section have approximately the expected percentage distribution. While a total share of 15% was expected for distribution EV cars, the result was 15.9%, and the expected 11% share for EV buses was 12%, which is around the expectation by 2030. When examining hourly analyses on a vehicle basis, the hourly distribution of active EVs can be observed in Fig. 5 with their peak numbers. The labels namely represent EV buses, compact EVs (BMW i3), EV sedans (VW ID3), and EV SUVs (VW ID4), respectively as listed in Table I. Despite their relatively small fleet size, EV buses exhibit a disproportionately high charging demand due to their larger battery capacities and higher daily energy turnover. In contrast, passenger EVs that consist of particularly sedans and compacts, display more moderate yet stable charging levels across the simulation period. EV SUVs follow a similar charging pattern but with slightly higher hourly demand, reflecting the increased mass and aerodynamic drag typical of this segment.

During the simulation period, since passenger electric vehicles and electric buses served different primary purposes, the relatively few EV bus measurements generally yielded high results. The main reasons for this can be listed as follows:

- Each EV is an agent with its own ID and own measurements, since same buses operates in the city, per vehicle metrics are more stacked on EV buses.
- There are map boundaries, so passenger vehicles can generally only be observed for a very short time, while buses can be observed for longer periods because they travel on city routes.
- Bus stops have much longer dwell times compared to waiting times at traffic lights. Therefore, buses have many more opportunities to charge.

The effect of this fundamental difference can also be seen in Fig. 6, as energy transferred from charging stations. Additionally, the top 10 stations that charge the highest number of vehicles are shown in the figure with the number of charging events. The stations with the highest frequencies are TLS stations, that located in the waiting areas at traffic lights. However, not all TLS stations in general, but rather TLS stations

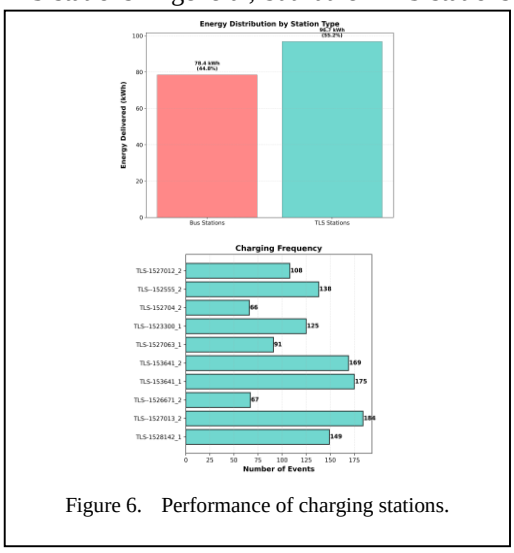


Figure 6. Performance of charging stations.

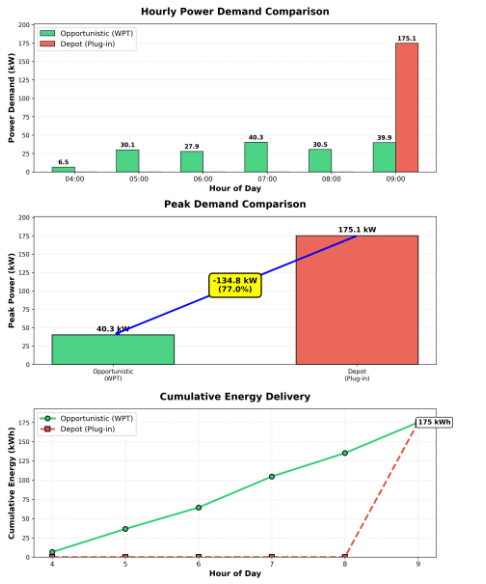


Figure 7. Grid Impact of oppurtunistic and depot charging scenarios.

in high-traffic areas playing an active role in wireless charging activities. In addition to this, the high frequency of bus stops not included in this ranking due to their low rate, but while vehicles generally visit TLS only once, bus stop visits are repeated much more frequently due to buses' circular activities, yet their vehicle numbers are not much as EV car types, resulting in low frequency on bus stop visits.

With regard to the grid effect, the hourly power consumption of these charging events, as observed throughout the simulation, was calculated by combining metrics obtained separately from each charging station. These collected charging data were examined in different sub-areas to simulate a 'what if' scenario. This what if scenario essentially examines the differences in grid effects between a scenario where opportunistic charging events, which are frequently performed throughout the simulation, occur simultaneously at the end of the 9th hour, for instance, when vehicles and operating buses are plugged in for charging after use rather than during the 4-9 a.m. hours. By shifting all opportunistic charging events, typically distributed across the operating window between 4:00 and 10:00 a.m., to occur simultaneously at the end of the 9th hour, Fig. 7 represents a depot-style plug-in regime in which vehicles and buses are charged in bulk after service completion rather than incrementally during operation. The resulting comparison plots illustrate how the same total energy demand can lead to significantly different load profiles and grid outcomes, depending solely on the temporal density of charging activity. In a distributed opportunistic charging configuration, the energy distribution exhibits a flattened curve, maintaining moderate demand levels and maintaining high load factor efficiency through continuous wireless charging. However, when cumulative demand is synchronized into a single post-operational event, the power profile collapses to a sharp peak, more than halving the instantaneous load while decreasing grid usage efficiency.

IV. CONCLUSION

The study evaluated the operational and grid-level impacts of differentiated EV charging behaviors by comparing opportunistic wireless power transfer with traditional depot-based plug-in charging in a representative six-hour city-scale simulation. The results go beyond theory and demonstrate what the system can achieve in practice when idle traffic times are converted into microcharging opportunities. By integrating WPT with routine signalized stops, the net grid demand of EVs can be gently regulated in real time. Today at modest power levels, and, as dynamic transfer capacities grow beyond common 11 kW baselines, with increased energy recovery during trips. One of the key advantages is behavioral neutrality, that is, drivers do nothing new, yet the fleet harvests many small charges that add up over a journey.

At the grid level, the opportunistic WPT scenario proved substantially more grid-compatible than its depot-based counterpart. By distributing identical total energy across multiple hours, the opportunistic WPT setup reduced peak demand, improved the load factor, and lowered the peak-to-average power ratio. The what if scenario underlies mechanism, where all distributed charging events were hypothetically concentrated into a single terminal hour, grid stress increased dramatically while overall energy delivery remained constant. This confirms that temporal synchronization, rather than the magnitude of charging, is the dominant determinant of grid load volatility. Consequently, distributed or opportunistic charging strategies act as passive grid balancing tools, smoothing demand and aligning EV energy use with the grid's natural operating

envelope. Thereupon, the findings suggest that the temporal distribution of energy transfer can become a design parameter for sustainable electric transportation systems. By enabling frequent, low-power energy transfers, opportunistic wireless charging provides grid efficiency and operational flexibility compared to the traditional storage-centric model. In addition, the high charging demands created instantly by charging stations at certain locations are spread in smaller pieces to many different areas within the city, creating a more balanced pattern. The reduction in grid usage and peak power infrastructure confirms that the system is expected to be scalable, as hourly energy capacity utilization is significantly higher than demand in traffic corridors. Since EV fleet size is only a small percentage of the total vehicle fleet, such as 15%, a policy prioritizing EV fleet growth and higher compliance with WPT standards, along with a planning shift toward phased, data-driven deployment along high-traffic corridors where vehicles and infrastructure are adapted to wireless charging standards, can maximize grid synchronization and capital efficiency, forming an integral component of smart energy ecosystems and next-generation urban mobility. In light of the results, suitability of future charging infrastructure can be evaluated using the methods employed in this framework and applying them to different larger-scale experiments at city level.

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