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Optimizing vehicle-to-grid scheduling and strategic placement for dynamic wireless charging of electric vehicles

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ABSTRACT

Dynamic wireless charging of electric vehicles (EVs) has become popular in intelligent transportation systems (ITS). However, both economic and smart city perspectives should be taken into account in the integration of wireless charging infrastructure for electric vehicles. Current research mainly focuses on power transfer (PT) or autonomous vehicle-to-grid (V2G) transfer. This paper presents a multilayered approach that combines optimal PT planning based on urban traffic and energy efficiency data with dynamic V2G planning. Simulation results show that the efficiency of PT placement and V2G scheduling increases and provides good results for smart city enterprises. This multilayered approach not only optimizes the efficiency of power transfer placement and V2G scheduling but also positions itself as a pivotal driver for the sustainable evolution of urban mobility. As dynamic wireless charging continues to shape the future of intelligent transportation systems, this research stands at the intersection of technological innovation, economic prudence, and urban planning, offering a blueprint for the seamless integration of EVs into the fabric of smart cities.

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1. INTRODUCTION

Wireless charging systems of electric vehicle (EV) have become important in smart cities because they integrate with internet of things (IoT) devices and enable energy management. These systems are designed to provide urban EV users with convenient and flexible electric services beyond the limits of traditional payment methods. Wireless power transfer (WPT) technology enables wireless charging of the electric vehicle from a remote location, which can be divided into a fixed system or power [1]. Wireless charging involves using permanent connections to transmit power to the EV's charging station. However, the downside is that EVs need to be parked for a long time to complete the charging process. Dynamic wireless charging systems offer great opportunities by allowing electric vehicles to be charged while driving. These systems utilize charging tracks embedded in traffic highways to facilitate power transfer while EVs are on the move. Various studies [2], [3] have proposed models for dynamic wireless charging, analyzing hardware efficiency and optimizing charging protocols during slow-moving traffic. The placement of power transfer (PT) devices in a smart city's traffic network is a crucial aspect that requires technical and economic considerations. Researchers have explored optimal locations for dynamic charging centers, addressing deployment costs and charging delays. Additionally, the interaction between EVs and the smart grid (SG) system plays a vital role in managing the city's energy needs. EVs, with vehicle-to-grid (V2G) technology, can contribute auxiliary services to the SG, including returning energy and providing supplementary services.

This study aims to bridge research gaps by proposing an integrated dynamic wireless charging system of EVs, considering facility locations and operations. The multi-layer system contributes to the development of the electricity payment system in smart cities by solving the energy transmission [4] and V2G problems of different electricity groups in the city [5].

The flowchart of a proposed system of a network is depicted in Figure 1. The street network of a clever metropolis [6], EVs [7], PTs [8], and device evaluate [9] are the four key components of the multistage framework, which are provided on this segment. The subsequent illustrations show every element's specific. A city street is modeled as a graph G (V, E), where nodes (V) represent intersections and edges (E) represent roads [10]. The travel distance (d_{ij}) between nodes is determined using the Dijkstra method for traffic routing. There are wired and wireless charging stations throughout the city [11]. While there are wired charging stations with physical chargers in the parking lot, the wireless system includes dynamic charging pads in the parking lot and permanent electrical equipment along the road. This work focuses on the design of a wireless charging system for EVs, considering the deployment of PTs in urban networks.

EVs are mobile batteries, and they function as movable energy storage units in urban settings. These vehicles, equipped with quick start and rapid response capabilities, act as dynamic power storage devices. EV batteries can receive power management signals, allowing them to provide various auxiliary services in cities, including frequency regulation [12]. The system operator issues power management signals to coordinate subordinate EVs, optimizing their charging and discharging schedules through regular control signals. This contribution of EVs aids in maintaining SG stability, particularly in frequency control, where a group of EVs significantly enhances the grid's capacity [13]. Figure 2 presents a viable track option in the city of Bhubaneswar, Odisha, India. This track has a very high volume of traffic and is one of the most common roadways of communication in the city. Power transfer devices (PTs) are the power supply units for roadway powering systems. PTs operate on WPT technology, specifically near-field electromagnetic induction [14]. They fall into two main categories: magnetic induction and electrostatic induction, each tailored to different power levels and gap separations. Deployed on city road segments, PTs enable EVs to wirelessly charge and discharge using WPT technology [15]. The collection of PTs in a city is denoted as set K, with each road segment (i, j) containing an embedded PT.

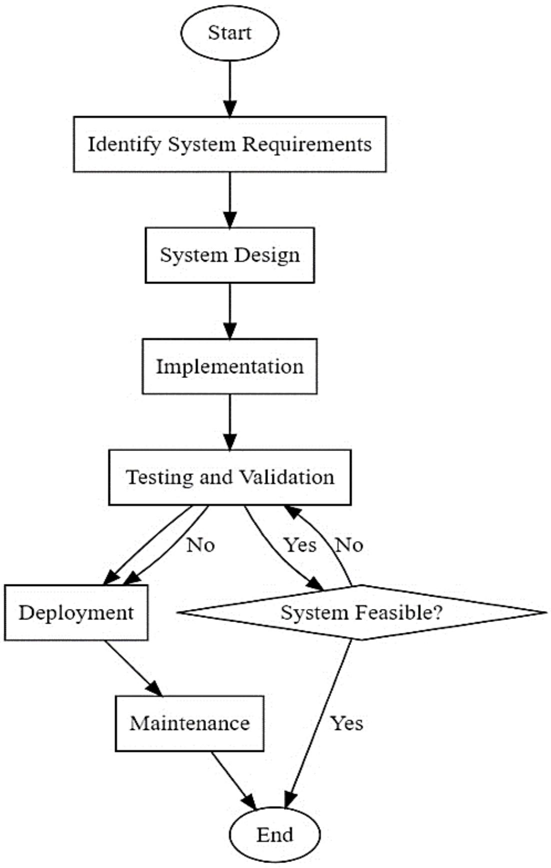


Figure 1. Flowchart of proposed system

In a smart city, the integration of intelligent transportation systems (ITS) and the SG forms a cohesive system. The SG manages EV charging, while ITS focuses on urban vehicle mobility [16]. Both systems coordinate EVs, combining mobility and charging operations through shared information. Consider a simplified, where an EV's itinerary involves strategic use of power transfer devices for joint movement and charging, optimizing battery usage. Creating a strategic plan for PT deployment based on transportation and EV conditions is critical for deployment [17]. The multi-stage strategy includes evaluation of energy demand and traffic data, followed by optimal PT placement (first stage) and dynamic V2G handover (second stage). EV users can choose between dynamic V2G transmission and normal travel, enabling reliable city planning. PT facilitates travel and payment planning in a multi-layered process as shown in Figure 1.

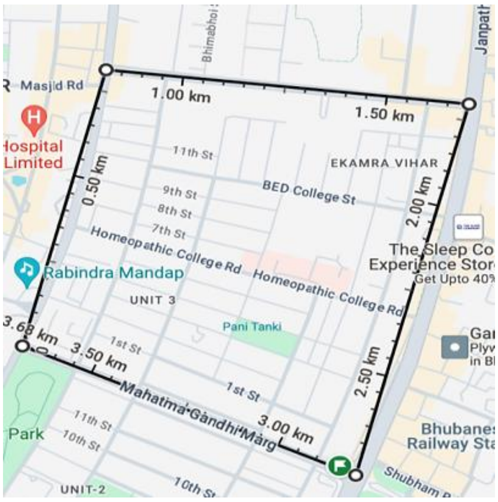


Figure 2. A 3.68 km track for viable placement of track

2. METHOD

First, the complex synchronization of a power track (PT) placement schematic is highlighted, where sophisticated traffic data analytics are combined with cutting-edge geographic information system (GIS) technological capabilities [18]. With the use of GIS technologies to handle spatial data, this complex combination results in a careful examination of municipal traffic patterns. Finding the best places to strategically position PTs-essential parts of a dynamic wireless charging infrastructure is the result [19]. With the addition of real-time and historical traffic data analytics, the GIS tools allow for a more sophisticated knowledge of high-traffic regions and the best routes for EVs. As such, a strategic placement plan that aims to optimize accessibility and coverage for dynamic wireless charging infrastructure in urban environments is informed by this scientific methodology [20]. The EV wireless charging procedure is briefly shown in Figure 3, which also provides a clear visual representation of consumption and related operations. The picture provides a clear synopsis of the complex workings of the EV wireless charging system by using a variety of scenarios to illustrate the suggested system model informatics.

The second point explores the complexities of the dynamic V2G scheduling schematic, an advanced framework that utilizes state-of-the-art communication protocols and SG technology. The effective bidirectional connection between EVs and the power grid is key to this schematic's operation. The spine of the SG is its infrastructure, which allows scheduling dynamics to be adjusted in real-time in response to changes in energy demand, the availability of renewable energy sources, and the stability of the power system [21]. Most importantly, communication protocols like MQTT and CoAP are used to set up dependable data exchange systems that make it easier for EVs and the power grid to integrate and coordinate [22]. This point accentuates the scientific prowess inherent in the orchestration of SG technologies and communication protocols, creating a responsive and adaptable framework that optimally manages the bidirectional energy flow between EVs and the power grid in dynamic wireless charging systems.

A Simulink model block diagram illustrating the WPT process is shown in Figure 4. In order to assess the model's performance, it is put through a rigorous investigation and testing process. This results in a detailed visualization of all the various parts that are involved in the wireless power transfer process. The graphical representation in Figure 5 illustrates the dynamic trends in voltage, current, and battery percentage over time, offering a comprehensive visual insight into the temporal variations of these crucial parameters. The battery percentage dips over time as the power is being used by the brushless DC (BLDC) motor of the EV. The current and voltage stay constant over the same period of time showing the stability factor of this Simulink model. The time-dependent representation in Figure 6 visually displays the variations in speed and torque of the bladeless DC motor in the EV providing a clear and detailed overview of their dynamic behavior. The speed starting at zero has a negative response in initial stages, attains a peak constant after some time. The torque starts at zero attain a specific operational torque and at half operation touch a sudden peak for a moment and returns to its operational value.

The third point describes the complex field of wireless charging technology, which is a key element of the architectural framework that maximizes the scheduling of V2G traffic and the placement of power tracks (PTs). This technology, which may be implemented via resonant or inductive approaches, is the primary means of facilitating the contactless transmission of electrical energy to EVs. Resonant wireless charging reduces energy losses during this transmission process by resonating at particular frequencies, whereas inductive wireless charging uses electromagnetic fields to transmit energy without physical touch [23], [24]. The goal of developing effective, contactless EV charging systems is central to this scientific discussion, since it guarantees the ease and adaptability that come with wireless charging.

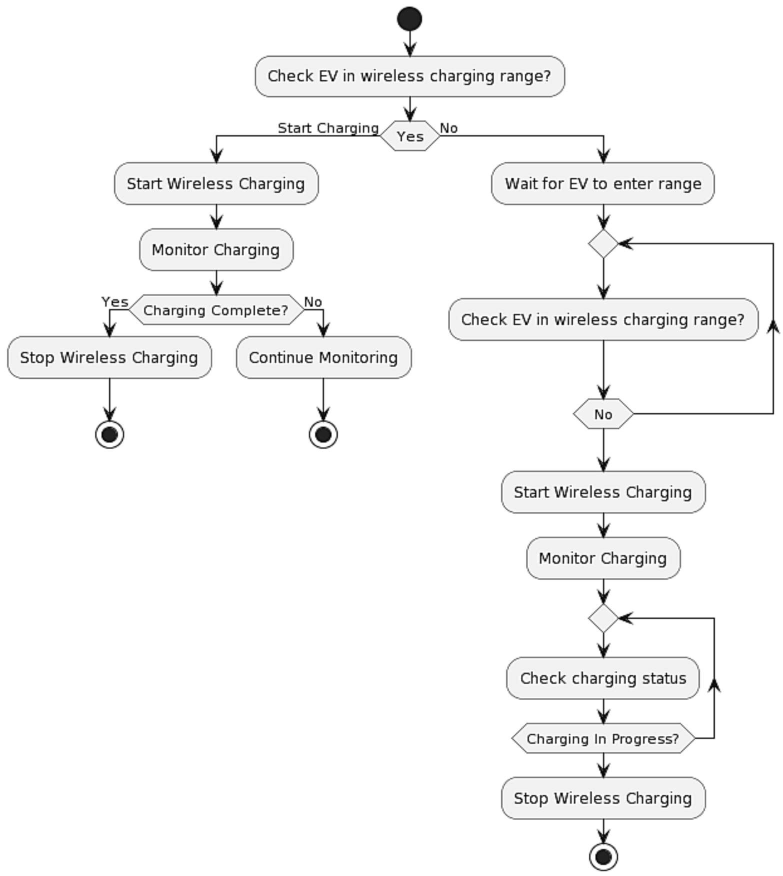


Figure 3. Flowchart for EV charging

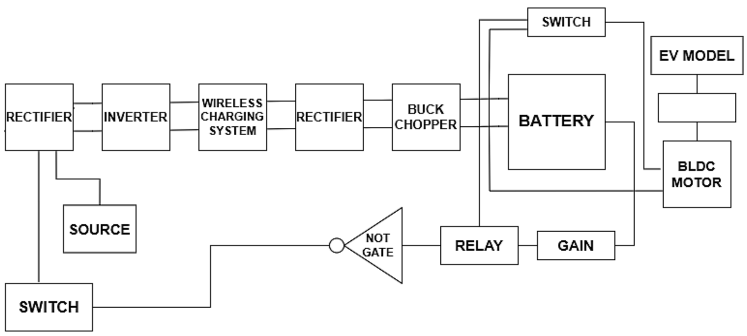
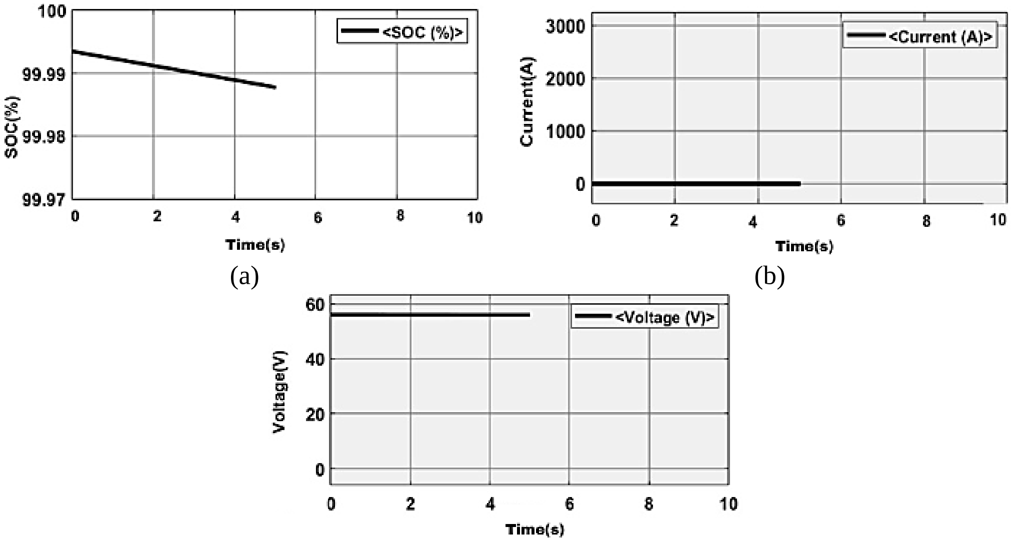


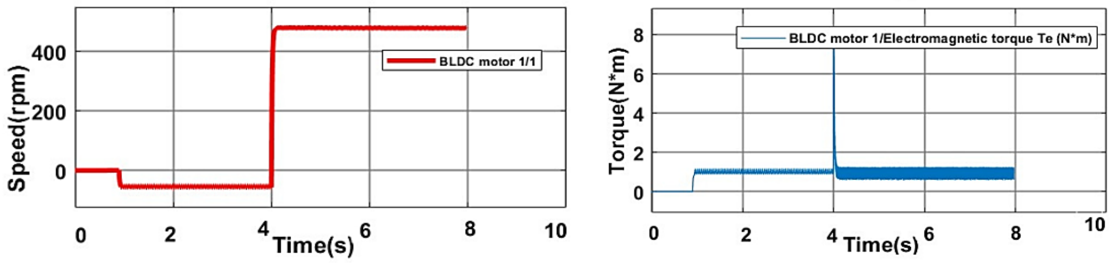
Figure 4. Block diagram of simulation of WPT power charging by Simulink



(a) (b)

(c)

Figure 5. Li-ion battery: (a) change in SOC, (b) change in current, and (c) change in voltage



(a) (b)

Figure 6. In BLDC motor: (a) change in speed and (b) change in torque

The realm of optimization algorithms is explored in this point, which is an advanced aspect of the control of a dynamic wireless charging system [25]. This scientific endeavor constantly improves the system's performance by utilizing cutting-edge machine learning algorithms and optimization methodologies. These algorithms respond dynamically to changes in traffic patterns, energy consumption, and environmental circumstances by operating within the framework of adaptability [26], [27]. The integration of machine learning allows the system to learn from data and experiences, enabling it to autonomously optimize power track (PT) placement and V2G scheduling [28], [29]. This scientific method guarantees a system that adapts to the complex dynamics of urban surroundings on its own, which adds to sustainability and cost-effectiveness.

The use of optimization algorithms is evidence of the scientific rigor that went into building a flexible and responsive infrastructure [30], [31]. By means of ongoing learning and improvement, these algorithms surpass traditional programming models, enabling a self-adjusting system that corresponds with the dynamic subtleties present in urban environments [32], [33]. Thus, this point summarizes a high-level scientific endeavor by highlighting the revolutionary potential of optimization and machine learning in the orchestration of dynamic wireless charging systems.

3. RESULTS AND DISCUSSION

In this section, it is explained the results of the research and at the same time is given the comprehensive discussion. Results can be presented in figures, graphs, tables, and other forms that make the reader understands easily. The discussion can be made in several sub-sections. A simple but representative model is offered by the simulation code for V2G scheduling and ideal placement for EV dynamic wireless charging. This simulation simulates a city setting by randomly generating EV and charging station sites within a 100×100 grid as shown in Figure 7. EVs have beginning battery levels ranging from 30% to 70%, and charging is either planned or not. The charging state and rates are used to dynamically update the battery levels. The costs per kWh related with charging demand are computed using EV states and rates. The simulation results are tabulated in Table 1. To simulate the spread of infrastructure, a new charging station is introduced at random in the simulation. The code does not specifically optimize the location of the wireless charging station, but it does make it easier to visualize the simulated scenario with line plots showing the EV states over time, battery level trajectories for individual EVs, and scatter plots for EV and station locations.

The results of the Python simulation code for charging and discharging EVs were informative and provided insight into the dynamic energy interactions that occur inside the system. The cyclical nature of charging and discharging processes is effectively illustrated by the graphical representation in Figure 8, which also highlights the subtle energy transfer over time. The simulation accurately depicts how responsive the EVs are to the infrastructure for charging, with distinct peaks signifying spikes in demand and valleys signifying periods of discharge or reduced energy use. Informed decision-making about the management of energy resources is aided by this visual representation, which offers a thorough understanding of the interactions between the simulated EVs and the charging stations. The simulation also provides a way to assess the efficacy and efficiency of the infrastructure for charging by illustrating instances of possible overload or underutilization. To sum up, the simulation is an invaluable resource for researching the nuances of EV charging and discharging dynamics, enabling the development of robust and sustainable electric car energy systems optimization solutions.

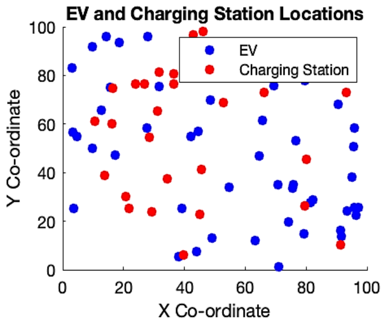


Figure 7. A city modeled graph for placement of charging location

Table 1. Simulation results

EV locations		EV station locations		EV states	Battery levels	Charging costs
10.8017	49.5067	90.4355	33.6533	1	34.4667	0
51.6997	70.6407	3.3179	18.7713	0	54.75	1.5
14.3156	24.3573	53.2426	32.1927	0	44.4667	1.6
55.9371	78.5070	71.6497	40.3857	1	40.3333	0
0.4580	7.4090	17.9302	54.8566	1	42.2667	0
76.6682	39.3883	72.5182	22.9886	0	37.3	0.6
84.8709	0.3394	90.8102	55.2175	0	70	0
91.6821	22.0677	23.1792	39.6290	0	71.3333	2
98.6968	0.1301	95.4103	54.2813	0	65.1	0
50.5133	18.9180	12.7037	23.2240	0	62.2667	0
27.1422	14.2484	74.6148	15.4829	0	40.3333	2
10.0751	26.8076	74.8509	54.3299	1	45.6333	0.7
50.7849	17.4892	82.6450	57.3464	0	38.8667	0.8
58.5609	13.8649	19.6205	30.3852	0	32.5	1
76.2887	59.8886	65.1997	6.6160	1	44.5333	0
8.2963	90.1058	72.6630	9.4489	1	60.3833	1.1
66.1596	93.9380	27.9039	67.5375	0	56.5	0.9
51.6979	22.1184	61.7851	7.0214	0	53.4	0.7
17.1048	48.2671	51.5766	83.7841	1	50.2	1.1
93.8558	37.6011	36.6833	73.9480	0	42.6667	0
59.0483	52.3780	85.0679	55.8565	1	51.1667	0.7
44.0635	26.4873	85.5772	67.0797	1	63.2	1.1
94.1919	6.8357	86.1596	71.1735	1	62.1	0.6
65.5914	43.6327	80.6467	60.1399	0	56.0333	0
45.1946	17.3853	19.3202	61.6421	0	60.8333	0
83.9697	2.6107	98.5246	60.8759	1	59.2667	1.4
53.2624	95.4678	82.8096	50.7435	1	39.25	0
55.3887	43.0597	40.2952	51.0040	0	52	0
68.0066	96.1559	5.2224	68.3308	1	46.2	1.2

Figure 8 illustrates the electric vehicle (EV) charging and discharging status in the context of vehicle-to-grid (V2G) scheduling. The pie charts represent three different scenarios: Figure 8(a) represents EVs that are exclusively in driving mode (100% driving, 0% charging); Figure 8(b) represents a balanced state where 64% are charging and 36% are driving; and Figure 8(c) represents the majority of EVs that are charging (97%) while a small percentage (3%) are driving. These distributions are crucial for efficient V2G scheduling, ensuring optimal utilization of EV batteries for grid stabilization while considering user mobility demands.

Analytical findings were obtained by simulating the hourly charging profile of EVs in a grid. The visual depiction in Figure 9 demonstrates how the requirement for charging varies throughout the day. Peak times and lulls in EV charging activity were clearly visible thanks to the excellent visualization of the whole hourly charging demand the capacity of the grid or the charging station was exceeded, warnings were produced properly, providing a proactive way to spot any operational issues. Overall, the simulation helps with informed decision-making in the design and optimization of electric car charging systems by capturing the complex dynamics of EV charging and acting as a useful tool for evaluating the reliability and effectiveness of the grid infrastructure.

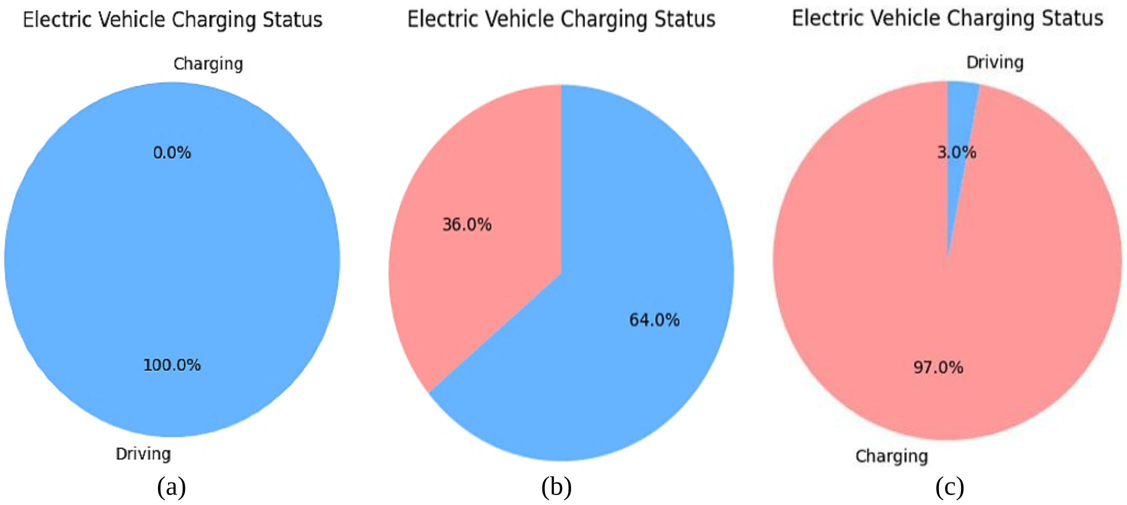


Figure 8. Pictograph: (a) driving mode, (b) balanced state, and (c) EV charging discharging majority

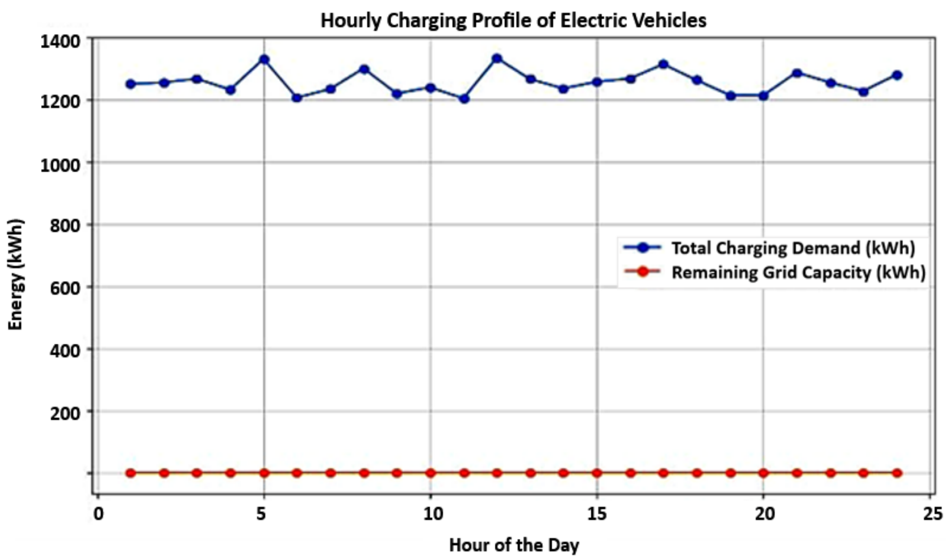


Figure 9. Hourly charging profile of EVs

4. CONCLUSION

This study adds to the body of knowledge by providing a thorough and multi-layered framework for optimizing vehicle-to-grid (V2G) scheduling and placing power tracks (PTs) strategically in relation to dynamic wireless charging of EVs. Proposed method integrates economic concerns and smart city viewpoints, acknowledging the growing popularity of dynamic wireless charging in intelligent transportation systems (ITS) beyond traditional research bounds. The study deviates from the prevailing emphasis on discrete elements of autonomous V2G transfer or power transfer (PT). Rather, it takes a comprehensive strategy, fusing dynamic V2G planning with optimum PT planning based on urban traffic and energy efficiency data. The simulation findings provide significant gains in V2G scheduling and PT placement efficiency, demonstrating the efficacy of this multilayered technique. These results validate the possible advantages of our methodology for smart city firms' undertakings, in line with the overall objective of augmenting the sustainability and intelligence of urban transport systems.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Ayush Kumar		✓	✓	✓	✓	✓		✓	✓	✓	✓			
Surender Reddy Salkuti	✓			✓		✓	✓			✓		✓	✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no competing interests.

ETHICAL APPROVAL

This article does not contain any studies with human participants or animal studies performed by any of the authors.

DATA AVAILABILITY

The datasets used and/or analyzed during the current study available from the corresponding author [SRS], on reasonable requests.

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