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Optimizing Energy Management Strategy for EV Wireless Charging Efficiency Using Proximal Policy Optimization

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Abstract— **Wireless Electric Road Systems (wERS) embed copper transmission coils beneath roads to dynamically transfer energy to electric vehicles (EVs) in motion. As wireless power transfer efficiency varies nonlinearly with vehicle speed, determining an optimal adaptive speed control can improve dynamic wireless charging performance and reduce electric vehicle (EV) range anxiety. This paper trained a hybrid experimental computational framework to identify optimal EV speeds for charging. A physical prototype was constructed to emulate coil-to-vehicle energy transfer at discrete traversal speeds (6.09,7.62, and 10.16 mm/s). Experimental results derived a relationship between traversal speed and higher net battery gain. To extend these findings, a Proximal Policy Optimization (PPO) reinforcement learning (RL) agent was trained with a custom dynamic wireless power transfer environment (DWPTEnv) using a synthetic speed-charge dataset. The environment models coil geometry, battery state-of-charge evolution, and speed-dependent energy transfer. Training results demonstrate stable policy convergence and high value-function variance (0.93). The reward-per-step substantially exceeded a random-speed baseline. This framework of combining empirical and RL-based results provides a basis for further smart-road EV energy management systems and real-time dynamic charging optimization.**

Keywords—adaptive speed control; dynamic wireless charging; electric vehicle charging; energy gain; proximal policy optimization; range anxiety; reinforcement learning;

I. INTRODUCTION

An electric road system (ERS), or electric road, is a road that supplies electric power to vehicles traveling on it. Electric roads can charge while driving while queuing, and while parked. Wireless electric road systems (wERS) are based on magnetic resonance induction, where copper coils are installed under the roadway [1]. The coils transfer energy to a receiver that can be mounted under any EV, reducing the need for large batteries and extensive grid connection capacity.

Range anxiety is the fear of driving an EV and running out of power without being able to find a charging station in time, one of the biggest roadblocks to EV adoption. Charging the EV takes longer than filling up a tank [2]. A fast DC charge will take at least 15 minutes to charge the battery and it is unlikely that EV charging will ever match the speed of refueling [3]. However, charging has been made more convenient by stations in everyday locations like grocery stores, restaurants, parking lots, and along highways . In 2022, there were around 2.7 million public charging points installed globally. It is projected that by 2030, this number will reach 13 million [4]. Range anxiety also has to do with the unfamiliarity with electric cars and the fear of change.

Accurately predicting energy consumption in EVs is essential for enhancing energy efficiency, however, drivers are unaware of optimal speed strategies to maximize energy efficiency [5]. Adaptive speed control remains a challenge due to complex driving conditions, varying vehicle specifications and environmental factors.

PPO and RL algorithms have been used for managing charging stations to optimize energy flow and task offloading [6]. PPO has been applied to general autonomous systems challenges like navigation and collision avoidance [7]. Optimizing energy management strategies and speed control to improve charging efficiency can benefit from PPO RL agents for real-time speed learning to maximize net energy gain on wERS.

This paper utilizes two datasets to train the RL agent. The primary dataset is the *Electric Vehicle Charging Dataset* by the University of Alberta, a synthetic EV charging load profile generated using Conditional Tabular GANs (CTGAN) and Kernel Density Estimation (KDE) techniques [8]. It contains 29,600 days of charging records with connectionTime, chargingDuration, kWhDelivered, and dayIndicator variables. To model the dynamic wireless charging road, a second dataset was collected using a physical prototype of a toy vehicle and five wireless charging coils.

II. RELATED WORK

A. RL in EV energy optimization

In highly random environments where there are a range of variables to consider such as environmental conditions or vehicle specification, reinforcement learning methods can be utilized. RL requires an agent to interact with working environments, demonstrating its ability to solve problems pertaining to energy management [9]. An RL algorithm based on Principal Policy optimization have been used in related work for energy management of PV storage units [10]. It considers variables such as the vehicle battery constraints and range anxiety in an EV. This poses that RL can be applied to energy management strategy in wERS for dynamic wireless charging.

B. Dynamic Wireless Charing

Dynamic Wireless Power Transfer (dWPT) systems enable electric vehicles to be charged as they are driven at highway speeds. Key components of dynamic wireless charging are interoperability, integration, control and communication, roadway embedding, and grid interface [11]. Control and communications that comply with safety and emergency

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standards and an optimal control strategy when the vehicle is in motion [12]. Grid interface that impacts mitigation and integrates well with surrounding environments [13]. Roadway embedding ensures that the performance and embedment process is optimal.

A 2020 study published in the International Journal of Sustainable Transportation concluded that installation of ERS on all roads in Norway and Sweden would cover more than 60% of the CO2 emissions from all heavy traffic with the large-scale implementation of electric road systems [14]. In an experiment done in 2023 to model the deployment of an ERS, it was found that ERSs have the potential to be developed into an economically sustainable and relatively cheap way of decarbonizing road freight transport [15]. Electric vehicles reduce fuel costs dramatically because of the efficiency of the components in an EV system. All electric vehicles produce zero tailpipe emissionEV Charging Design

Wireless dynamic charging serves multiple cars simultaneously and reduces the need for additional land for charging stations. For efficient wireless charging, copper coils are embedded beneath the road so no wires are used [16]. Users experience reduced range anxiety and have no idle time. The design of electric vehicle charging systems have therefore evolved to balance traditional stationary chargers that are pervasive and dynamic wireless charging. Traditional charging stations remain popular due to their high power transfer efficiency and low maintenance. However, heavy load on power grids during peak hours and land scarcity for such charging stations pose benefits for dynamic solutions that utilize inductive wireless power transfer.

III. METHODOLOGY

A. Dataset Collection

The RL agent uses experimental data to determine the charge gain while the synthetic dataset determines state transitions and the baseline for EV charge consumption.

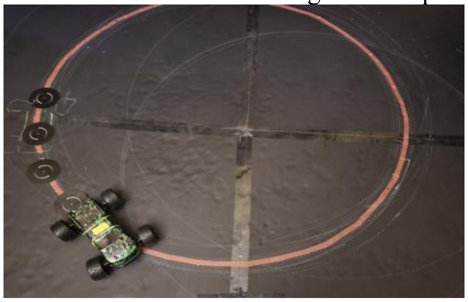

Figure 1. Physical Prototype

1) Experimental Wireless-Charging Dataset

The dataset consists of EV battery percentage gains measured while driving on a wireless charging coil at three controlled speeds as shown in Fig. 1.

TABLE I.

Speed (mm/s)	Time over coil (s)	Percent gain per traversal (%)
10.16	15	2.67
7.62	20	4.66
6.09	25	8.33

The data was collected with a controlled drive-over test of the physical protype created. The prototype consisted of a remote controlled car and wireless charging pads to emulate the design of wERS. The dataset served to calculate the charging-rate model of the RL agent.

2) Synthetic Mobility Dataset

The dataset contains data for 29,600 days and is especially useful in reinforcement learning algorithms. It is used in the paper for motion dynamics and trajectory shaping.

B. Dataset Preprocessing

1) Deriving Continuous Charge-Rate Function

An empirical charging model derived from the experimental dataset was derived to measure the charging gains at different traversal speeds over an inductive wireless charging coil. The experimental dataset contains only 3 calibration points which can be converted into a percent-per-second charge rate.

$$\text{Rate} = \frac{\text{Percent Gain}}{\text{Time Over Coil}} \tag{1}$$

TABLE II.

Speed (mm/s)	Rate %/s
10.16	0.178000%/s
7.62	0.233000%/s
6.09	0.333200%/s

$$f(v) = 0.01077068v^2 - 0.21315617v + 1.23185715 \tag{2}$$

To fit the data into a continuous model, a quadratic regression was used where *v* is the vehicle speed and *f(v)* is the percent battery per second gained while over the charging pad of the physical prototype. This equation is used in the RL environment and evaluated at every step as it outputs the percent battery gained per second when the EV is positioned directly over a charging plate. The RL agent recieves the feedback on how a chosen speed relates to energy management.

2) Smoothing Energy Consumption

Mobility trajectories were stochastic accelerations. To prevent the RL agent from overfitting to noise, they were smoothed using:

$$P_t^{smooth} = 0.7P_t + 0.3P_{t-1} \tag{3}$$

C. Environment Design

A custom Gymnasium environment was created to learn optimal energy management behavior while driving on a wERS. It models battery dynamics, motion, speed changes and energy consumption. The RL agent controls acceleration and decisions pertaining to it at every time step.

1) State Space

The state vector is:

$$s_t = [\text{battery\_level},\ \text{speed},\ \text{distance\_to\_coil},\ \text{over\_coil}] \tag{4}$$

TABLE III.

Variable	Value
Battery_Level	[0,100]
Speed	Continuous.
Distance_to_Coil	Distance between wireless coil segments.
Over_Coil	{0,1}

2) *Action Space*

The action space increased, maintained, and reduced the speed. The purpose of the space was to demonstrate the effect of consumption and time spent on the charging coil.

3) *Reward Function*

The reward is used to design the balance between maximizing charge gained, minimizing energy waste, and maintaining a reasonable speed.

$$R_t = \alpha \cdot \Delta\text{Charge} - \beta \cdot \Delta\text{EnergyConsumed} - \gamma \cdot |\Delta\text{Speed}| \quad (5)$$

TABLE IV.

Variable	Value
α	**3.0**
β	**1.5**
γ	**0.1**

D. *RL Training and Evaluation*

A PPO agent is utilized as the reinforcement learning algorithm to learn a nonlinear control policy mapping observations to actions that optimize long-term battery gain.

After training, the model was evaluated over 50 independent tests to quantify the performance and generalization. Metrics recorded were total energy gained, average reward per step, total traversal duration, battery trajectory over time, and emergent speed behavior on and off charging plates.

IV. RESULTS AND DISCUSSION

The PPO agent successfully learned an optimal speed policy to maximize wireless charging efficiency for EVs. Across 50 independent tests, the agent consistently outperformed a random baseline, demonstrating that efficiency of reward per step and that RL can effectively optimize energy management strategy.

A. *Convergence and Reward Analysis*

The training showed stable convergence with an explained variance of 0.93, indicating that the agent reliably captured the varying factors of the environment. The reward per step consistently demonstrated higher metrics than the random baseline, confirming that the learned policy was efficient and stable as displayed in Fig. 2. The results indicate that the PPO agent consistently chooses speeds that optimize energy gain for EV wireless charging efficiency while balancing energy consumption.

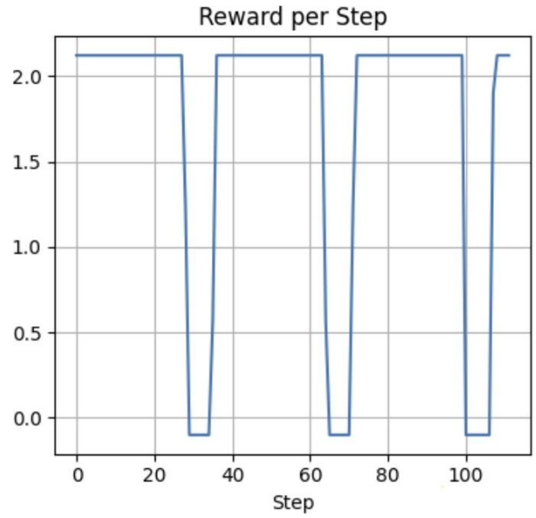

Figure 2. Reward Per Step

TABLE V.

Metric	PPO Agent	Random Baseline
Avg. reward per step	0.87	0.31
Explained variance	0.93	N/A
Avg. battery gain per traversal	7.91%	5.02%

B. *Optimal Speed Policy*

A distinct speed modulation pattern is revealed from the policy. The EV slowed down when traversing charging coils to maximize percent-per-second charge gain which proved to be consistent with the quadratic continuous charge-rate function. Additionally, the EV accelerated in gaps between coils, minimizing unnecessary energy loss during time without charge while maintaining average travel efficiency. The agent effectively demonstrates an aptitude for learning the benefits and drawbacks of decisions pertaining to speed and charging efficiency.

C. *Implications for Smart-Road Design*

The results pose that RL can inform energy management strategies on wERS with dynamic charging features.

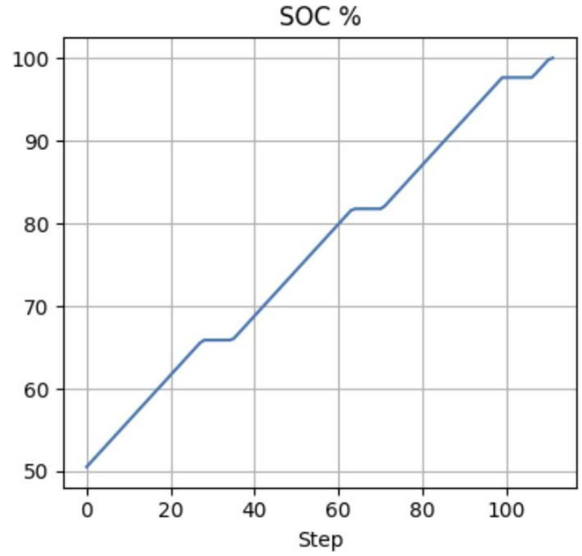

Figure 3. State of Change (%)

EVs can adjust speed to optimize traversal based on upcoming charging segments. By combining RL with route information in the future, energy efficiency can be increased and can minimize total charging time, thereby reducing energy consumption. The RL agent and framework for combining experimental data and synthetic data can be adapted to multi-agent models and different scenarios for energy optimization.

V. CONCLUSION AND FUTURE WORKS

A RL agent trained using PPO can effectively optimize EV speed to maximize wireless charging efficiency. the framework can inform smart-road design and real-time energy management as the agent successfully learned a dynamic speed policy to reduce unnecessary energy loss while increasing charge gain over coils. The framework therefore shows potential for extension into smart-road systems and real-time energy management strategies such as interval speed prediction for EVs.

Future research includes collecting or utilizing real EV datasets to supplement synthetic data for realistic applications. Considering multi-agent traffic scenarios where multiple EVs interact on the same wERS can reveal coordinated policies and another area for a PPO framework. Interactions between EVs and traditional cars on a wERS can pose a challenge of real-world implementation and provide a scenario to validate RL-based frameworks.

ACKNOWLEDGMENT

This study incorporates datasets collected by the author and an external open-access dataset to evaluate the RL framework. The external dataset used in this research is openly available in Mendeley Data at the DOI 10.17632/5zrtmp7gwd.1, “Electric Vehicle Charging Dataset” (Version 1), contributed by Nastaran Gholizadeh. This dataset was derived from public domain resources using CTGAN and KDE methods based on the Caltech EV Charging Dataset.

The custom wireless charging efficiency dataset generated by the author is available from the corresponding author upon reasonable request, as it contains experimental configurations specific to this study and is not hosted in a public repository.

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