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AI-Driven Dynamic Wireless EV Charging System: Battery Health Prediction and Energy Optimization Using IoT Data

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Abstract: Charging is still the weakest part of owning an electric vehicle (EV). Sessions are long, public chargers are unevenly spread, and the battery tends to wear out sooner than owners expect. Most published work tackles only one of these problems: the wireless power link, the estimation of battery health, or the sensing of battery data. This paper describes the design of a dynamic wireless charging system that brings these pieces together and adds an energy-optimization step. Transmitter coils placed under the road supply power to a receiver coil on a moving vehicle by inductive coupling. An ESP32-based sensing unit records voltage, temperature, charge cycles and charging time and sends them to a cloud platform, where machine learning models are intended to estimate battery health and suggest changes to the power transfer. A web dashboard presents the results to the operator. The work reported here covers the first project stage: system architecture, component selection, preparation of a battery dataset and exploratory analysis. On a sample of ten records, battery health dropped from 95% to 87% between cycles 5 and 14 ($r = -0.98$), and higher temperature went with lower health ($r = -0.63$). The planned prediction models and the remaining hardware validation are also outlined.

Keywords: Dynamic wireless power transfer, electric vehicle, battery health prediction, Internet of Things, machine learning, energy optimization

I. INTRODUCTION

Interest in electric vehicles has grown steadily as countries try to cut transport emissions and rely less on imported fuel. Yet the experience of charging has not kept pace with the vehicles themselves. A plug-in session usually means parking for a long time, chargers are scarce outside large cities, and the battery pays a price when it is run hot, charged unevenly or cycled hard again and again.

Wireless charging removes the cable, and the dynamic form of it goes further by feeding the vehicle while it drives. Coils buried in the road transfer energy to a pickup coil under the car, so stops for charging become shorter and in principle the battery can be smaller [1], [2]. Much of the effort in this area has gone into coil geometry, alignment and transfer efficiency. The decision side, meaning when and how much power to send to a particular battery, gets far less attention. On the battery side, health and degradation are well studied [3], [4], but mostly as a software problem on logged data, with no connection to the charger that is actually supplying the energy.

We propose a system that treats these as one problem. Wireless power transfer supplies the energy, IoT sensors report the state of the battery as it charges, machine learning turns those readings into a health estimate, and the estimate is used to adjust the transfer. The contributions of this stage of the work are: (i) a layered system architecture covering power, sensing, communication, analytics and display; (ii) a hardware and software specification for a prototype; (iii) an exploratory analysis of a battery dataset showing how health relates to cycles, temperature and voltage; and (iv) a plan for the prediction models to be trained and tested in the next stage.

II. RELATED WORK

A. Dynamic Wireless Power Transfer

In dynamic wireless power transfer (DWPT), a transmitter coil in the road carries alternating current and produces a changing magnetic field. A receiver coil on the vehicle picks up that field and converts it back to electrical energy. Two mechanisms are common. Plain electromagnetic induction works over short distances, whereas resonant coupling, in

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which both coils are tuned to the same frequency, keeps efficiency up over larger gaps [5]. Surveys of roadway-powered systems point to the same open issues: misalignment between coils, losses across the air gap, and the cost of installing coils along the road [1], [2]. Current research on these issues is mostly about the power electronics and the coils, not about adapting the charging to the battery.

B. Battery Health Estimation

Estimating state of charge and state of health is a central task of a battery management system [3]. Model-based approaches, such as Kalman filtering on an equivalent-circuit model, track internal states from voltage and current [6]. Data-driven approaches learn the pattern directly from measurements; Severson *et al.* showed that features from early cycles can predict how long a cell will last [4]. These methods improve safety and allow early warning of failure, but they run offline or inside the vehicle and have no link to a wireless charging infrastructure.

C. IoT-Based Battery Monitoring

Sensor-to-cloud frameworks have been reported that read voltage and temperature, store them online and raise an alert when a threshold is crossed. They give a useful live picture, but they stop at monitoring: there is no predictive model, and nothing in them changes how the battery is charged.

D. Research Gap

Table I summarizes the three strands. Each covers part of the problem, and none of them combines contactless in-motion charging, health prediction, real-time monitoring and energy optimization. That combination is what this work sets out to build.

TABLE I. EXISTING WORK AND WHAT IT LACKS

Existing work	What it offers	What is missing
Wireless charging systems	Contactless charging, including while moving	No AI/ML prediction and no IoT monitoring
Battery prediction systems	Early detection of failure, safer operation	No wireless charging integration, no IoT communication; software only
IoT monitoring systems	Live tracking, cloud storage, threshold alerts	No predictive model and no energy optimization

III. PROPOSED SYSTEM

A. Architecture

The design rests on four parts that work together: wireless power transfer, IoT-based monitoring, AI/ML prediction and cloud analytics. The power path starts at a supply (grid AC or solar panels) that drives the transmitter coil. The receiver coil in the vehicle feeds a rectifier and regulator, which turn the induced AC into DC at a level that is safe for the battery. In parallel, a voltage sensor and a temperature sensor watch the battery, and an ESP32 microcontroller collects their readings and sends them to the cloud. A prediction module analyses the stored data, and a dashboard shows the outcome. Fig. 1 gives the overall picture.



Fig. 1. Proposed dynamic wireless power transfer system with AI/ML and IoT.



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B. *Operating Sequence*

One charging pass goes through nine steps. (1) The transmitter is powered from the grid or from solar panels. (2) The transmitter coil produces an oscillating magnetic field across the air gap. (3) The receiver coil in the moving vehicle captures that field and, through induction, converts it to electrical energy. (4) A rectifier and voltage regulator condition the power before it enters the battery. (5) Sensors follow voltage, temperature, charging time and the number of completed cycles throughout. (6) The ESP32 packages the readings and sends them over Wi-Fi to cloud services such as ThingSpeak and Blynk. (7) Machine learning models examine the uploaded data for patterns and anomalies. (8) The models estimate present battery health and project how it is likely to decline. (9) Based on that estimate, the system adjusts the energy-transfer parameters to reduce losses and avoid conditions that speed up wear.

IV. HARDWARE AND SOFTWARE

Table II lists the hardware planned for the prototype and the job each part does. The architecture diagram also contains a current sensor, whose reading appears on the dashboard.

TABLE II. HARDWARE COMPONENTS

Component	Role in the system
Arduino Nano	Coordinates the core control operations
ESP32	Wireless communication and cloud data transmission
Transmitter coil	Produces the oscillating magnetic field for energy transfer
Receiver coil	Captures the transmitted energy on the vehicle
Voltage sensor	Measures voltage across the battery terminals
Temperature sensor	Tracks heat around the battery while charging
Relay module	Switches and regulates power flow in the circuit
Rectifier circuit	Converts AC to DC suitable for battery charging
Battery	Receives and stores the transferred energy
LCD display	Shows battery status and system feedback to the user

On the software side, the ESP32 and Arduino code is written in the Arduino IDE. Data analysis and model development use Python in Jupyter Notebook and Google Colab. ThingSpeak and Blynk handle live cloud monitoring, Firebase stores structured records, and Power BI or Tableau is used for visual analysis of the dataset.

V. METHODOLOGY

A. *Data Collection and Preparation*

Battery data comes from the voltage and temperature sensors and the IoT modules that forward readings to the cloud. The dataset is a structured CSV file with six columns: timestamp, voltage, temperature, charging time, charging cycles and battery health. Records were checked for inconsistencies and cleaned before analysis. The dataset serves three purposes in the project: finding behavioral patterns, training the prediction models, and feeding the visualizations.

B. *Exploratory Data Analysis*

Exploratory data analysis (EDA) was carried out to see how the recorded parameters relate to battery health. Line plots, bar charts and scatter plots were produced in Python and are discussed in Section VII. The analysis was also used to decide which variables are worth giving to the models.

C. *Machine Learning Design*

The model will take four inputs: voltage readings during charging, temperature around the battery, the cumulative number of charge cycles, and the charging duration of each session. It will produce three outputs: a battery health percentage (the estimated remaining capacity), an efficiency score describing how well the battery accepts power, and a degradation trend that projects the decline over future cycles. Four algorithms are being considered (Table III). Linear regression is the baseline. Random forests [7] and decision trees can handle non-linear relations between the inputs, and a long short-term memory (LSTM) network [8] is included for the time-series nature of the data. The models will be compared on held-out data using mean absolute error, root mean squared error and R-squared; these evaluations belong to the next stage and no results are claimed here.

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TABLE III. CANDIDATE PREDICTION ALGORITHMS

Algorithm	Intended role
Linear regression	Baseline model for battery health estimation
Decision tree	Identifies patterns in the battery dataset; easy to interpret
Random forest	Ensemble of trees, expected to improve accuracy over a single tree
LSTM	Handles sequences of readings to capture long-term degradation

VI. IOT INTEGRATION AND DASHBOARD

The ESP32 is the link between the sensors and the cloud. It sends battery readings at regular intervals, so the system can be watched from anywhere without physical access, and it allows alerts to be raised when a parameter leaves its safe range. ThingSpeak is used for time-series logging and graphs, Blynk for a mobile view, and Firebase for structured storage and retrieval.

A dashboard prototype has been built for the operator (Fig. 2). It shows live voltage and temperature streams, the cycle count, a gauge for predicted battery health, a grid that marks which road coils are active, an energy-optimization panel with a recommended power level and charging mode, a predictive-maintenance panel, and a table of connected vehicles. The figures displayed in this prototype are placeholder values used to design the interface and are not measurements from the hardware.

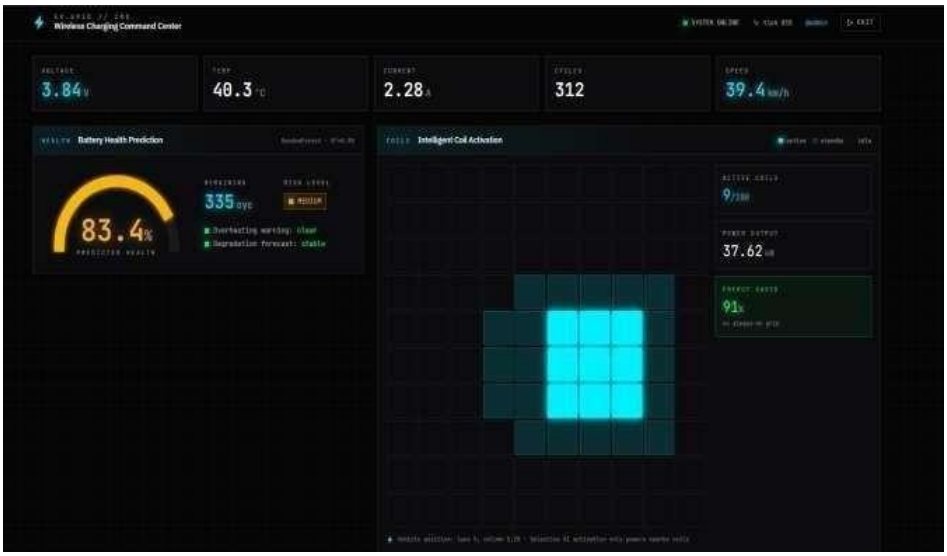


Fig. 2. Dashboard prototype of the wireless charging command center.

VII. PRELIMINARY RESULTS AND DISCUSSION

The exploratory analysis used a small sample of ten records covering charge cycles 5 to 14. Because the sample is so small, the figures below indicate direction only and should not be read as general conclusions.

Battery health fell from 95% at cycle 5 to 87% at cycle 14, with one small recovery at cycle 8 (Fig. 3). The correlation between cycle count and health in this sample is r = -0.98, so the decline is almost linear over this range. Temperature in the same records varied between 27 and 33 degrees Celsius. Health and temperature are negatively correlated (r = -0.63): the cycles with the highest temperatures, 11 to 13, are also among the lowest-health points.

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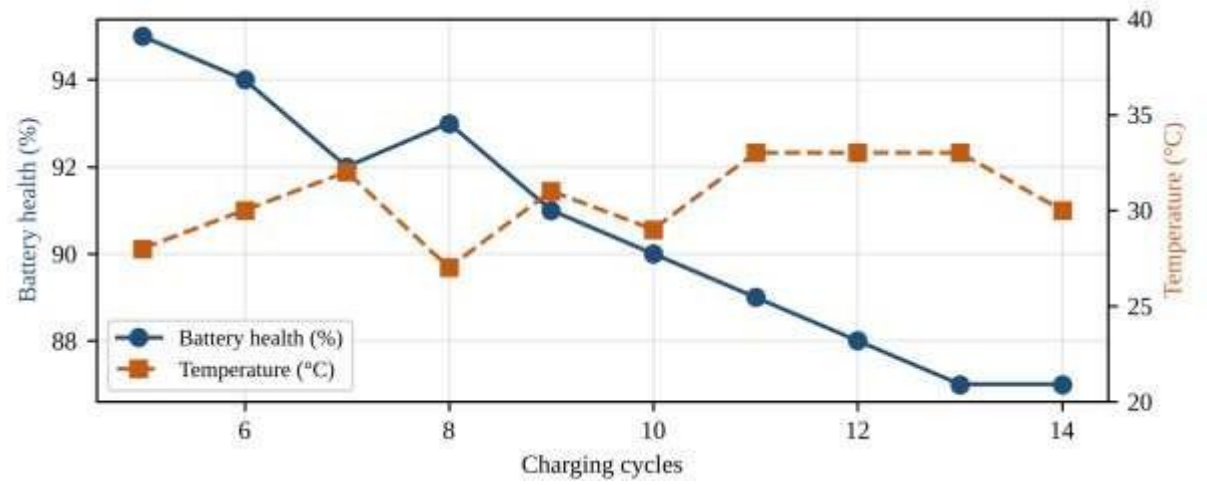


Fig. 3. Battery health and temperature against charging cycles.

Fig. 4(a) groups battery performance by temperature, and the best values, 95% at 28 degrees and 94% at 30 degrees, sit in the middle of the range while the lowest, 89%, occurs at 33 degrees. Fig. 4(b) plots voltage against health. Here no clear linear relation appears (r = 0.32). This suggests that the voltage level alone says little about wear, and that features describing its variation, such as a rolling standard deviation over a charging session, may be more useful. We will test this in the next stage.

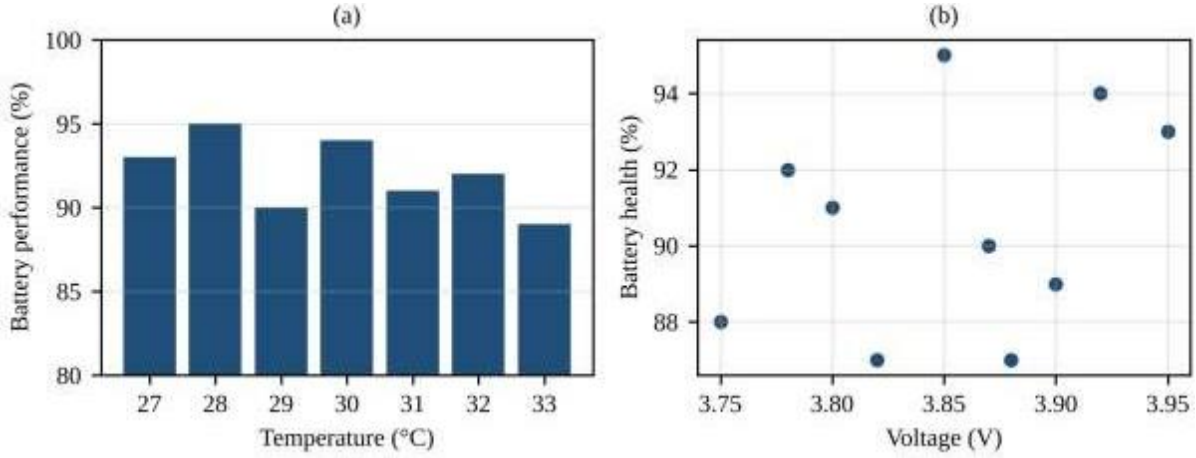


Fig. 4. (a) Battery performance against temperature; (b) battery health against voltage.

VIII. Advantages, Limitations and Future Work

Advantages. Charging while driving reduces the time a vehicle must stand at a charger and lowers the dependence on fixed charging stations. Continuous monitoring and prediction should allow the charging profile to be adjusted before the battery is stressed, which can extend its useful life. Optimizing the power sent also reduces wasted energy, and the approach supports the wider aim of cleaner and smarter transport.

Limitations. Installing coils in roads needs a large initial investment, and a smart road network must exist before the system can be used widely. Accurate alignment between the transmitter and receiver coils is still a technical challenge, and some energy is always lost across the air gap. Building and calibrating the hardware is also complex. In addition, the analysis so far rests on a small dataset, and the prediction models have not yet been trained or tested.

Future work. The next stage will build the hardware prototype and test it in the field, train and compare the models listed in Table III, and connect live sensor data to the dashboard. Longer-term directions include adaptive charging that responds to each battery, solar-powered transmitter coils embedded in the road, deep learning models for longer-horizon prediction, compatibility with autonomous vehicles, and rollout within smart-city transport plans.



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IX. CONCLUSION

This paper presented the design of a dynamic wireless charging system in which IoT sensing, machine learning and cloud analytics are combined with the power link itself. The first project stage produced the system architecture, the component list, a prepared battery dataset and an exploratory analysis. On the sample data, battery health declined steadily with the number of cycles and was lower at higher temperatures, which agrees with what is generally expected, while voltage level alone showed no clear pattern. The next stage will concentrate on building the prototype, training and evaluating the prediction models, and validating the full loop of sensing, prediction and optimization on real charging data.

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