

Design

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Project Title:

Remote DCFC Reliability and
Downtime Detection Tool

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Task Manager:

Jaskaren Virk
Transportation Engineer (Electrical)
Jaskaren.Virk@dot.ca.gov

DRISI Division Chief:

Prakash Sah, PE
Prakash.Sah@dot.ca.gov

Remote DCFC Reliability and Downtime Detection Tool

New anomaly detection models are being developed to detect Direct Current Fast Charging (DCFC) electric vehicle (EV) charger failures that standard monitoring systems can miss.

WHAT IS THE NEED?

The California Department of Transportation (Caltrans) operates a growing network of public EV charging stations across California. Keeping these chargers consistently available and working is essential for building public trust and supporting the state's EV adoption goals.

Current monitoring systems rely mainly on backend data, like network connectivity or payment processing, which often miss problems that directly affect users, such as blocked access, damaged cables, or unresponsive units. Remote locations mean that physical site visits can be inconvenient, costly, and delayed.

This research project is developing a tool to fill that gap. By analyzing charger usage data, the tool will help detect real-time failures that users experience, even when backend systems show the charger as operational. Remote detection can allow for more rapid repairs when needed.

WHAT ARE WE DOING?

This project aims to enhance Caltrans' EV charging infrastructure reliability by developing an anomaly detection tool that identifies failures not captured by standard network monitoring, such as blocked access, damaged connectors, or other on-site issues. The tool leverages real-world charger usage patterns and consists of two complementary models: a probability-based model for detecting statistically unusual gaps in usage and a Long Short-Term Memory (LSTM) neural network for identifying more complex temporal anomalies. Initial work focused on historical ZEV 30-30 data due to early delays in accessing live Caltrans charger data, allowing for early model validation while resolving data access challenges.

The project has completed or is progressing through three



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key research tasks. Model conceptualization involved reviewing literature and evaluating relevant anomaly detection techniques. Data collection and processing included preparing historical datasets, incorporating new Caltrans data, and performing time-series transformations and descriptive analyses to guide model design. The naive probability model and LSTM model have been built and validated, with a technical report submitted to Caltrans detailing datasets, model architecture, and validation results.

As the project transitions toward integration testing and field validation, challenges have arisen in engaging Caltrans' maintenance staff. To address this, alternative validation strategies are being developed using publicly available live charger status information from networks and Google Maps as proxies. A limited three-month dataset will be scraped to construct utilization-over-time feeds, and student testers will verify charger availability at select sites. Preliminary tests have confirmed this approach is feasible, providing a practical path forward if direct field support from Caltrans is not available by year-end.

WHAT IS OUR GOAL?

The project's goal is to deliver a robust, scalable tool that enables Caltrans to detect real-world EV charger failures more quickly and accurately. By supplementing existing monitoring protocols, this tool can support proactive maintenance, improve reliability reporting, and ultimately enhance the EV charging experience for the public.

WHAT IS THE BENEFIT?

This tool provides Caltrans with a new method for identifying EV charger reliability issues by analyzing actual usage patterns. It is capable of detecting "silent failures," such as chargers that appear online but go unused due to blocked access or malfunctioning equipment.

By uncovering these issues, the tool can help reduce charger downtime through faster failure detection,

support compliance with state reliability reporting requirements, increase public confidence in EV charging infrastructure, and prioritize maintenance efforts based on real-world usage data.

WHAT IS THE PROGRESS TO DATE?

The project has continued advancing through the first three technical tasks, moving from model design and early testing toward validation and refinement. The research team completed a comparative literature review of anomaly detection methods—including statistical, machine learning, and deep learning approaches—to determine the most suitable techniques for identifying EV charging disruptions. This work established the foundation for the modeling framework.

Due to initial delays in accessing current Caltrans data, development began using historical data from the ZEV 30-30 initiative. These data were cleaned, transformed into hourly time series, and analyzed to understand temporal and spatial usage patterns. As access to newer Caltrans datasets improved, we began incorporating them into the modeling workflow to enhance model performance and robustness.

Two anomaly detection models have now been developed:

1. A naïve probability-based model that flags unusually long gaps in usage
2. An LSTM-based model designed to detect more complex temporal disruptions.

Both models were initially validated using ZEV 30-30 data and are now being further calibrated and tested with newer Caltrans datasets. Because we have faced challenges establishing contact with Caltrans charging equipment maintenance staff and remain uncertain whether on-site testing support will be available, we are advancing alternative validation strategies. These include scraping a limited sample (approximately three months) of publicly available live charger status data to generate utilization-over-time feeds, as well

as leveraging historical Caltrans charger data with documented maintenance closures to calibrate and stress-test the models under known disruption events. These efforts ensure continued progress toward robust validation while maintaining the project schedule.