

# ENABLING ELECTRIC VEHICLE ADOPTION



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## IDENTIFYING CHARGING STATION MALFUNCTIONS

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## Problem Statement

### Motivation



**Charging Station Ownership:** Public charging stations used by GM Electric Vehicle (EV) drivers are owned and operated by third party providers called Charging Point Operators (CPOs).



**Limited Station Visibility:** GM is reliant on the CPOs for all maintenance, and CPOs are limited to reactive and often delayed repairs. Additionally, GM lacks awareness of real-time station status.



**High Failure Incidence:** GM suspects high failure incidence across EV charging stations, bringing negative implications for driver experience.

### Objective

**Develop a modeling methodology to evaluate charging station health by promptly identifying charging stations that have failed or are exhibiting deficiencies**

### Scope

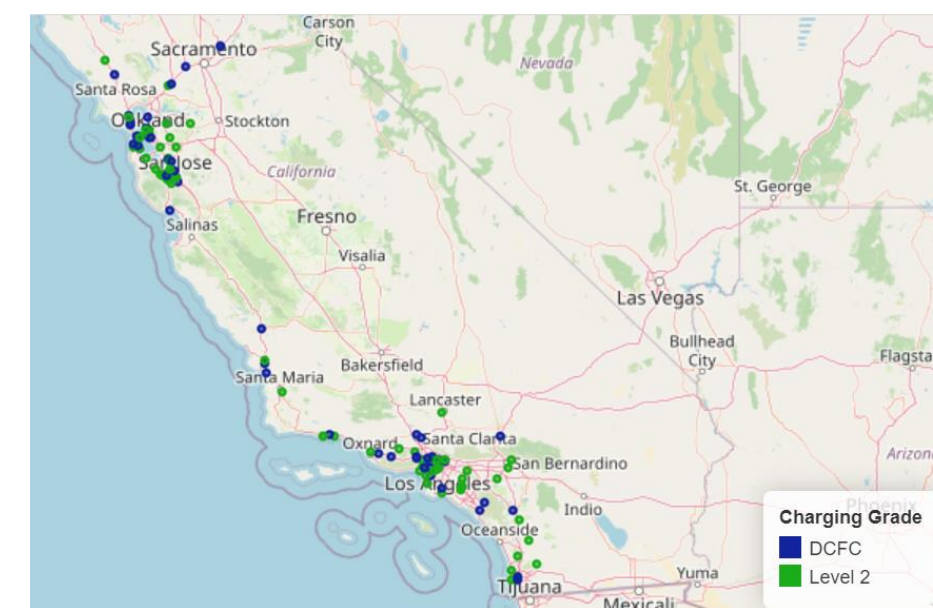
We focused our study on data from 121 EV charging stations in California. This includes 49 Direct Current Fast Charge (DCFC) and 72 Level 2 stations from various CPOs.

### Station Failure Prevalence

**28%**  
Reported failure incidence by CARB study

**<5%**  
Reported downtime by CPOs

The prevalence of failures at charging stations is widely disputed. Our project was GM's first attempt to **understand the magnitude of this issue.**



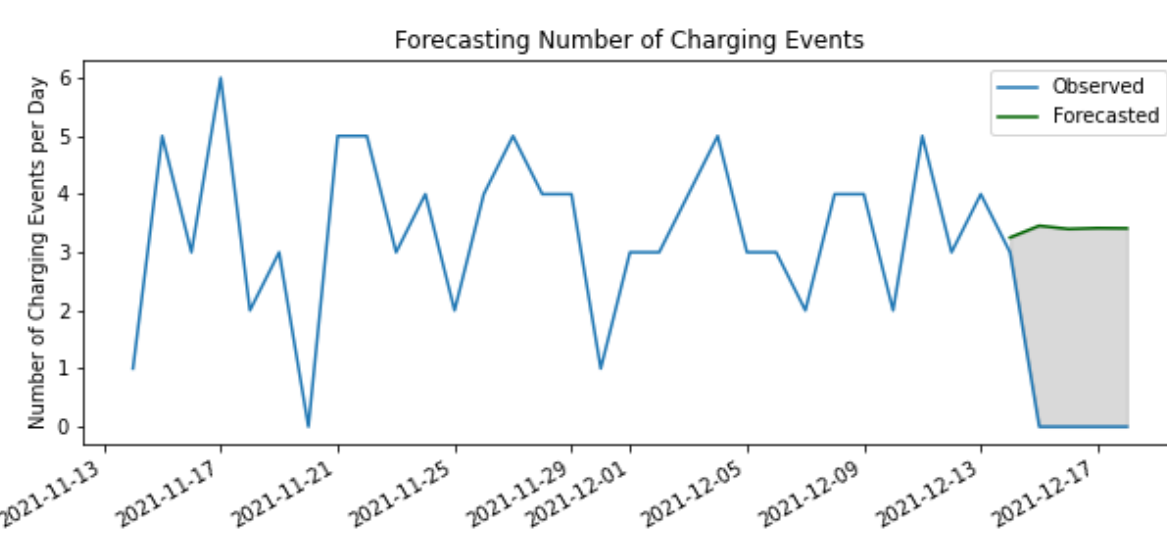
## Analytical Approach

We developed a unique modeling approach for each of three distinct charging failure types:

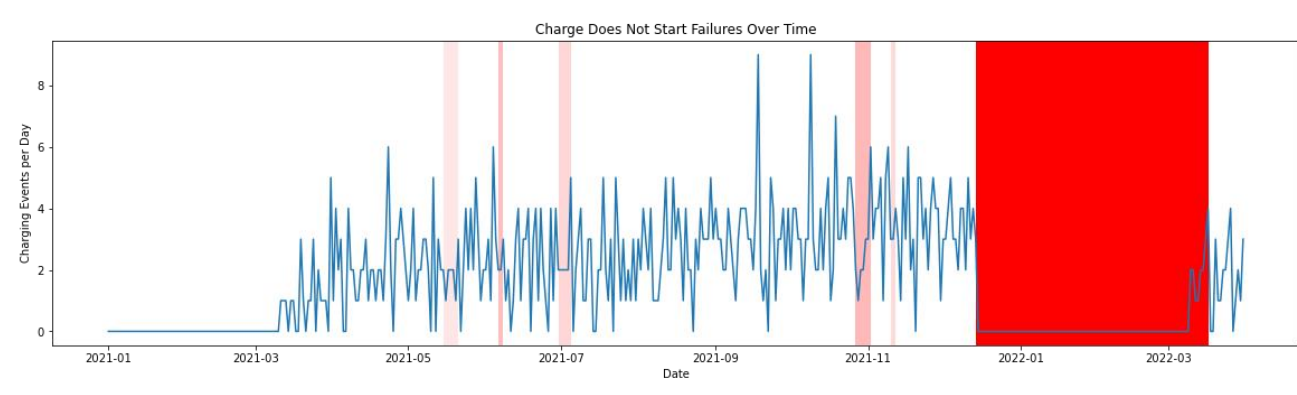
### Charge Does Not Start



We used ARIMA models to **forecast the number of charging events** and **residual analysis** to flag days where our forecast consistently exceeded the observed values



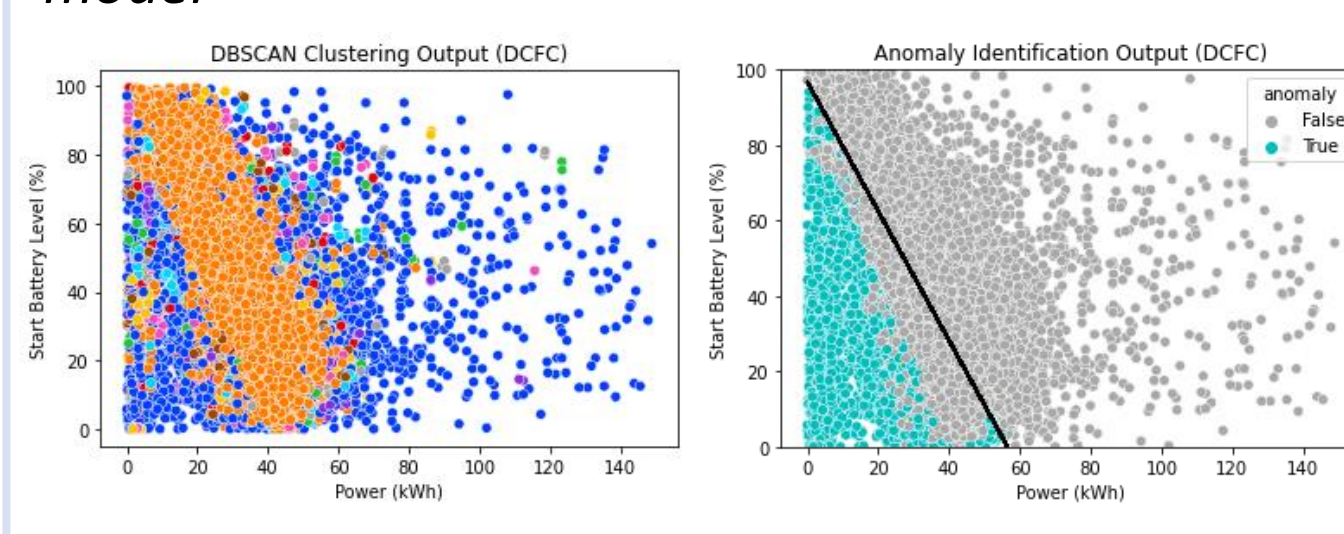
Using this forecasting approach, we **identified time ranges where there was a significant decrease in number of charges** as an indication of charge not starting



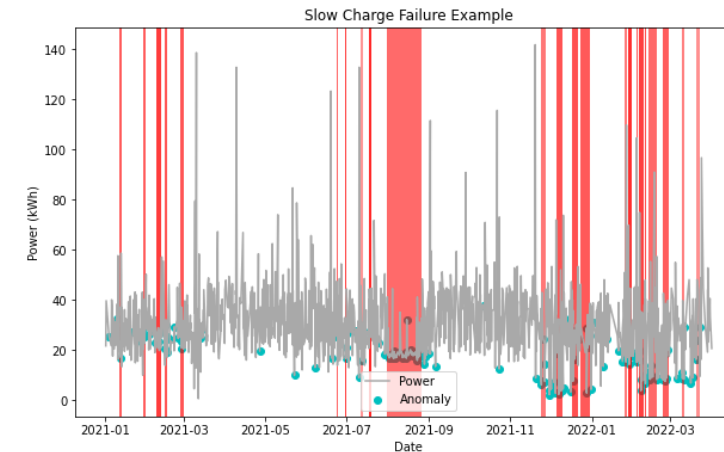
### Charge is Slow



We used DBSCAN clustering to **identify anomalous slow charging events**, considering charge power, start battery level, end battery level, and vehicle model



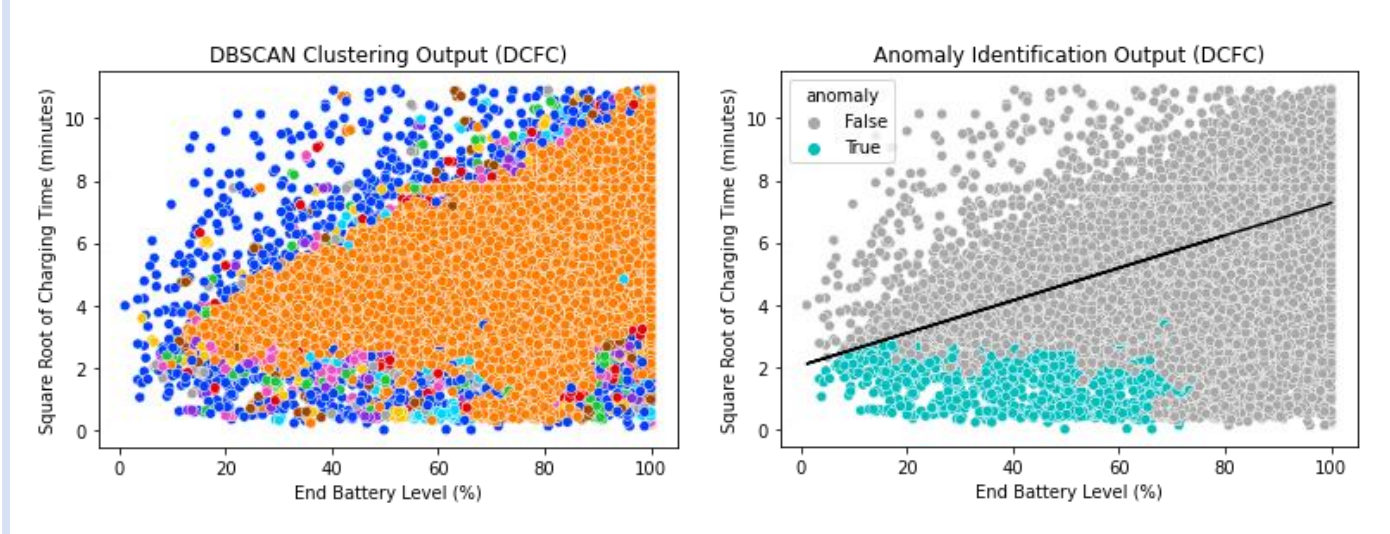
From the clustering output, we flagged slow charging events and **identified time periods of high slow charge density** at the station level



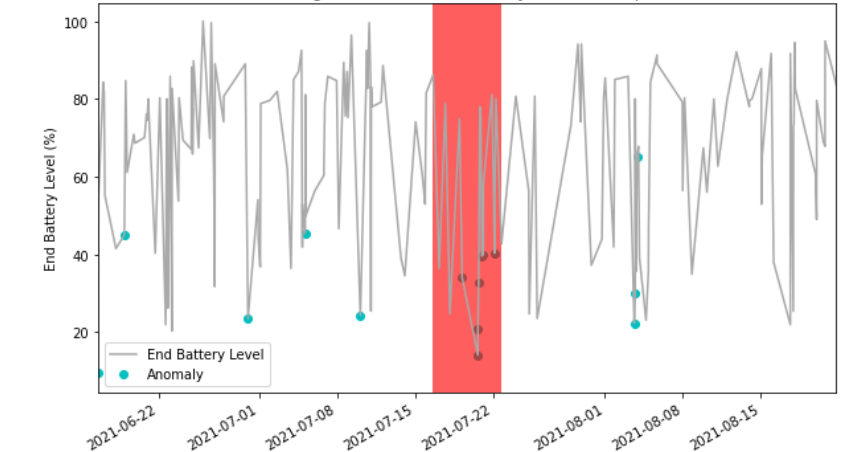
### Charge Terminates Prematurely



We used DBSCAN clustering to **identify anomalous charging events with low end battery levels and short charging durations**



From the clustering output, we flagged anomalous charging events and **identified time periods of high anomalous charge density** at the station level



For all three failure types, we **calculated a measure of confidence for each failure identified.** This confidence is based on the deviation of the anomalies from "normal behavior," scaled by the maximum possible deviation. We adjusted confidence based on the length of the failure and the concentration of anomalies within the failure window.

## Results and Impact

### Results

**24.0%**

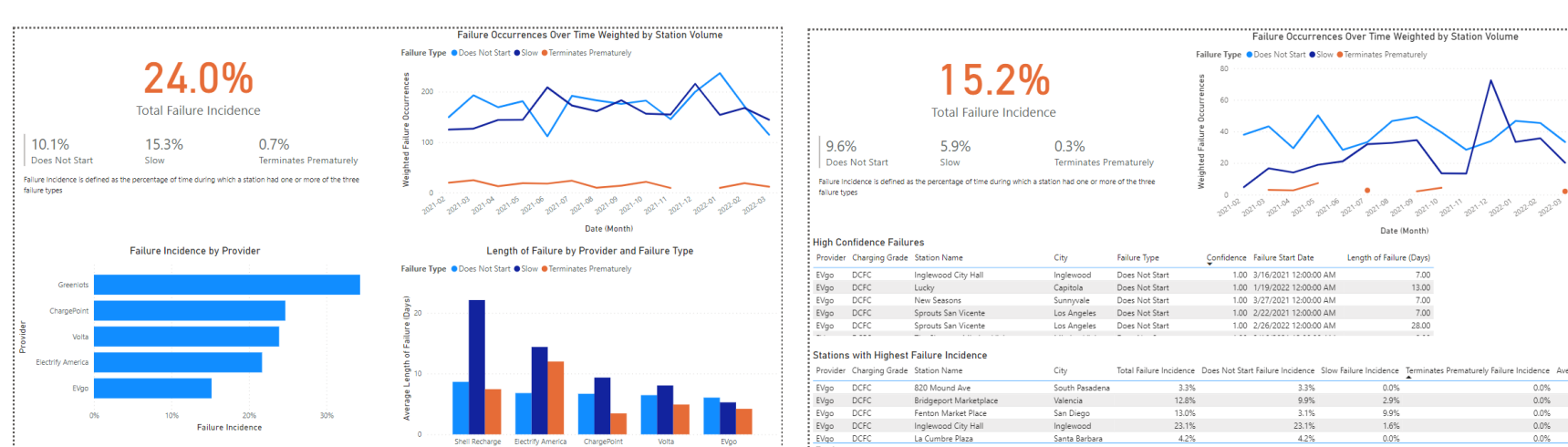
Failure Incidence Among All Failure Types

**10.1%**  
Does Not Start

**15.3%**  
Slow

**0.7%**  
Terminates Prematurely

Delivered dashboard showing summary statistics and actionable insights by CPO provider:



### Impact



**Facilitates Relationships and Data Sharing with CPOs:** Improved visibility into CPO performance enables GM to have better informed partnerships with CPOs.



**Improves Driver Experience:** Direct notification of potential charging station failures eliminates driver frustration.



**Accelerates EV Adoption:** Higher reliability and uptime of charging stations promotes EV adoption, enabling GM's all-electric, zero-emissions future.

### Future Work



Incorporate additional charging stations



Apply models to real-time with driver notifications



Leverage station visitation data