# Leveraging MATLAB-Simulink in Building Battery State-of-Health Estimation Pipelines for Electric Vehicles

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# Artificial Intelligence Team Overview

Team

- About 25 full-time employees
- Average experience 12 years

Projects

- Autonomous Driving: Trajectory Planning, Decision Making
- Vehicle AI: Smart Controls, Diagnostics & Prognostics

# Motivation

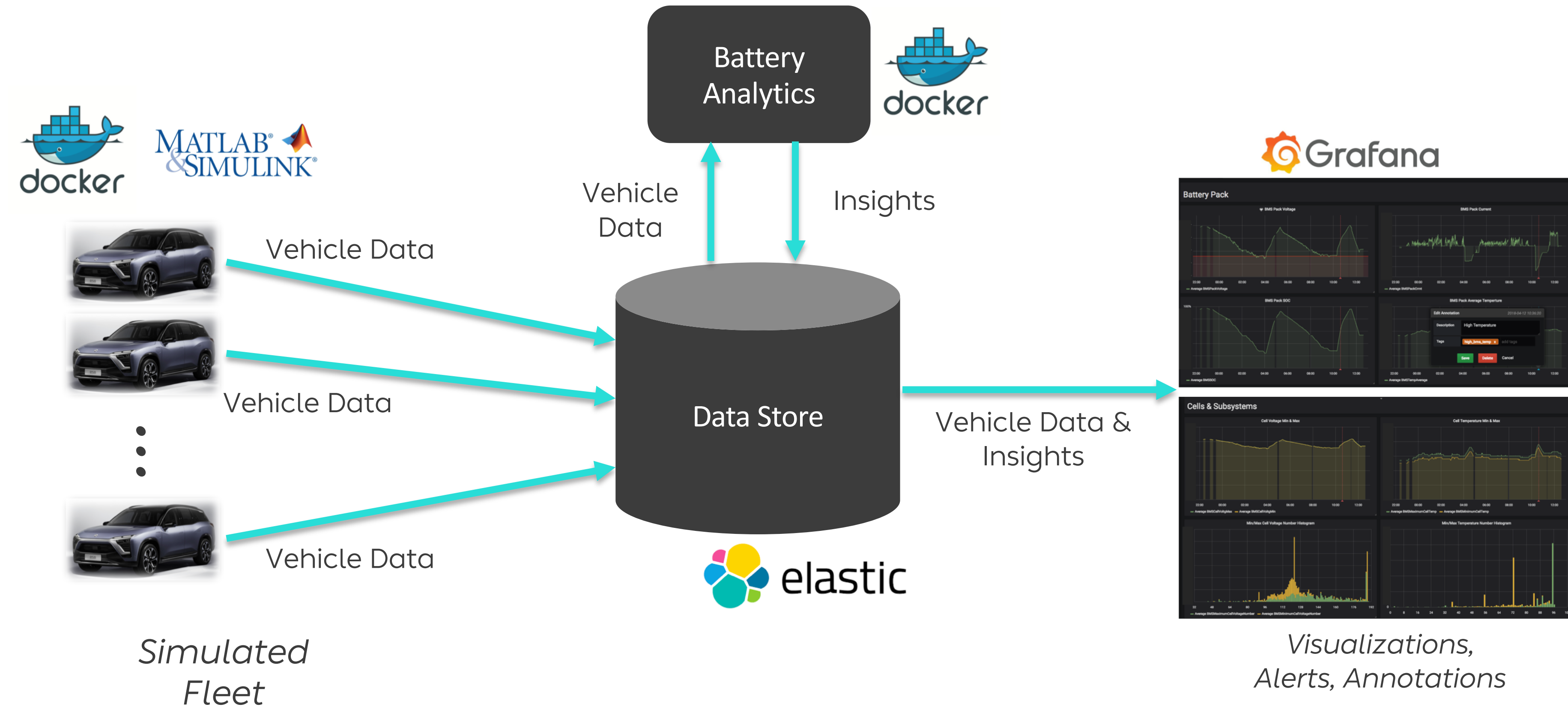
- In electric vehicles, understanding battery State-of-Health (SOH) is critical
  - Powertrain performance
  - Range estimation
  - Fleet management
  - Service operations

# Challenges

- In the product design phase, battery data is available only under laboratory and limited driving conditions
  - No existing fleet
  - Limited in-vehicle data collection
  - Data for only specific driving conditions
- However, to build an analytics stack focused on monitoring battery SOH and predicting battery life, we need lots of data

Solution: Scalable simulation-based data generation deployed in the cloud

# Cloud-based Architecture



# Outline

| | |
|---|---|
| **Vehicle Simulation** | Li-ion Cell Models<br>Powertrain<br>Vehicle Dynamics<br>Driving Conditions |
| **Battery Analytics** | SOH Estimation<br>SOH Prediction |
| **Cloud Deployment** | Code Generation<br>Simulation as a Service<br>Batch Simulations<br>Analytics<br>Dashboards |

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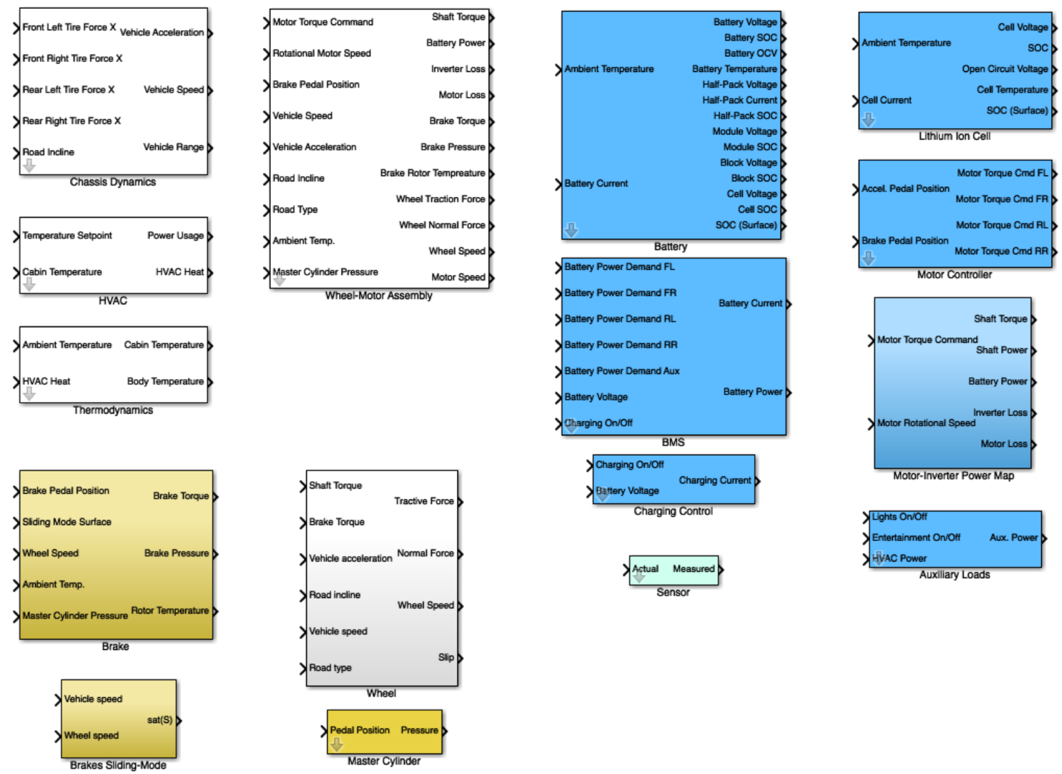
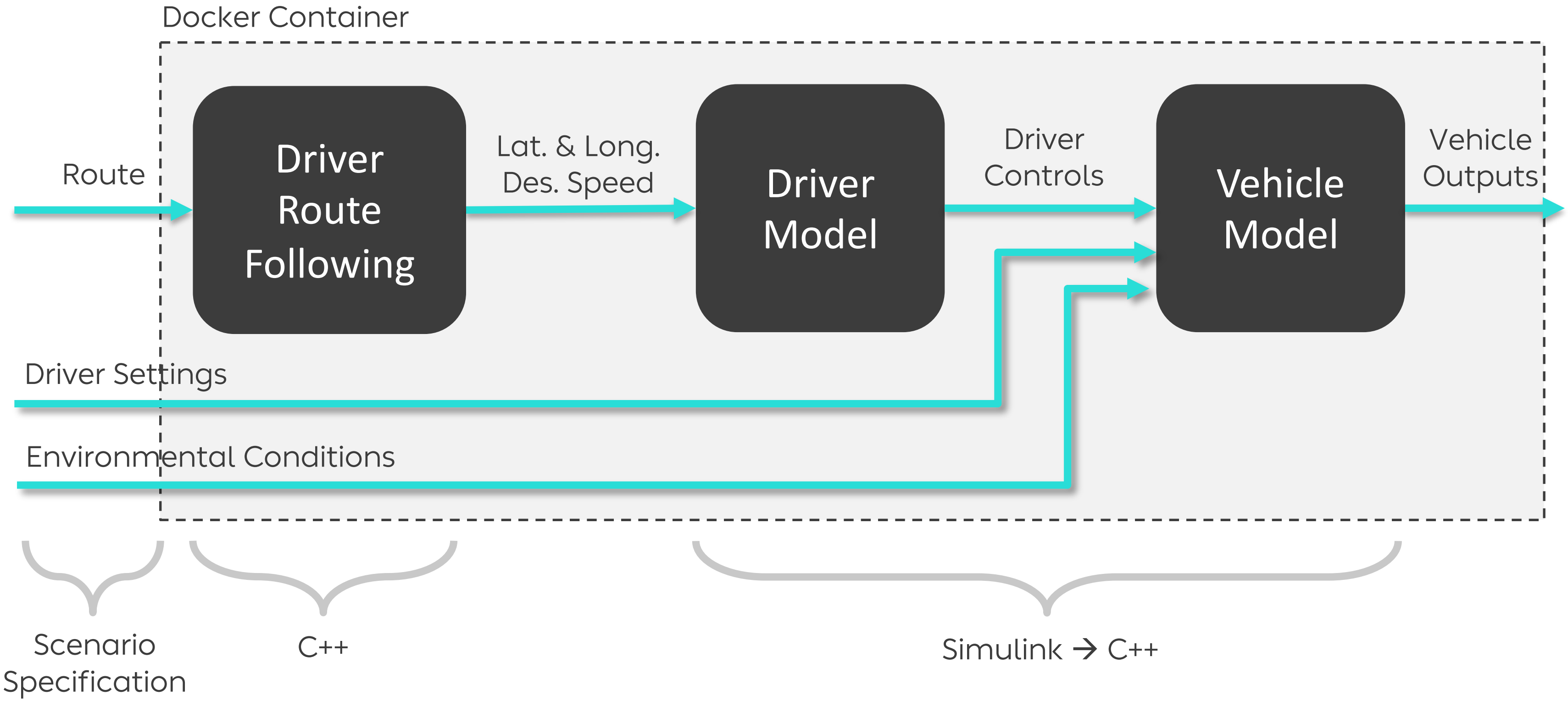
# Vehicle Simulation Summary

- Electrical
  - Cell models and battery configuration
  - Cell/battery health degradation
  - Motor and inverter efficiency and losses
  - Torque/current limits
  - Regenerative braking
  - Charging
  - HVAC
  - Thermal management
- Mechanical
  - Drag
  - Road type
  - Brakes
  - Driver model
- Sensors
  - Speed, brake pressures, voltages, currents, etc.
- Fault injection via parameter changes

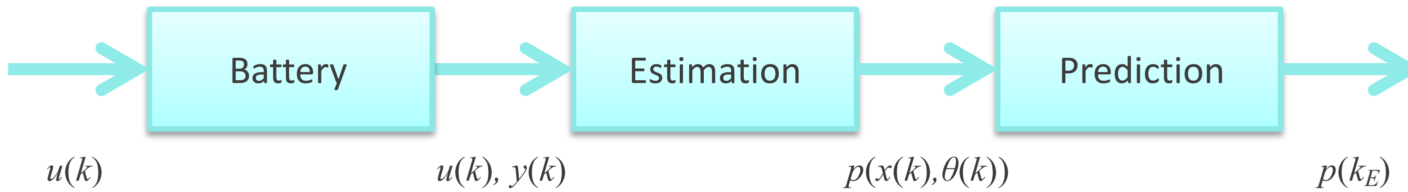


# Simulation Architecture



# Battery Analytics

# Prognostics Architecture




System gets input and produces output

Estimation module estimates the states and parameters, given system inputs and outputs

- Must handle sensor noise
- Must handle process noise

For some event E, e.g., end-of-discharge or end-of-life, prediction module predicts $k_E$

- Must handle state-parameter uncertainty at time of prediction
- Must handle future process noise trajectories
- Must handle future input trajectories (battery loads)

In model-based approaches, require a dynamic model of the battery

# Lithium Ion Chemistry

**Discharge**

Positive electrode is cathode, negative electrode is anode

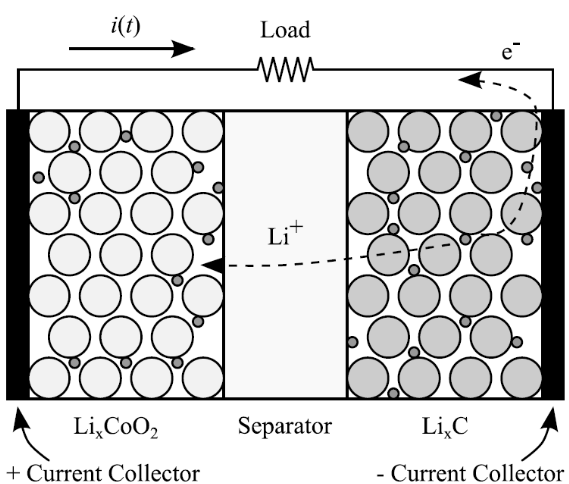
Reduction at pos. electrode:

$Li_{1-n}CoO_2 + nLi^+ + ne^- \rightarrow LiCoO_2$

Oxidation at neg. electrode:

$Li_nC \rightarrow nLi^+ + ne^- + C$

Current flows + to −, electrons flow − to +, lithium ions flow − to +




**Charge**

Positive electrode is anode, negative electrode is cathode

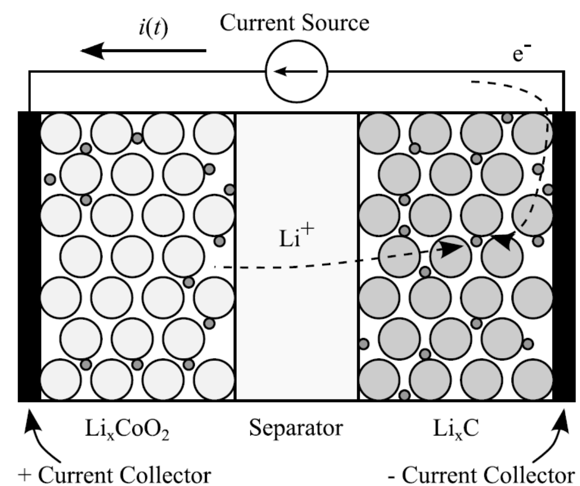
Oxidation at pos. electrode:

$LiCoO_2 \rightarrow Li_{1-n}CoO_2 + nLi^+ + ne^-$

Reduction at neg. electrode:

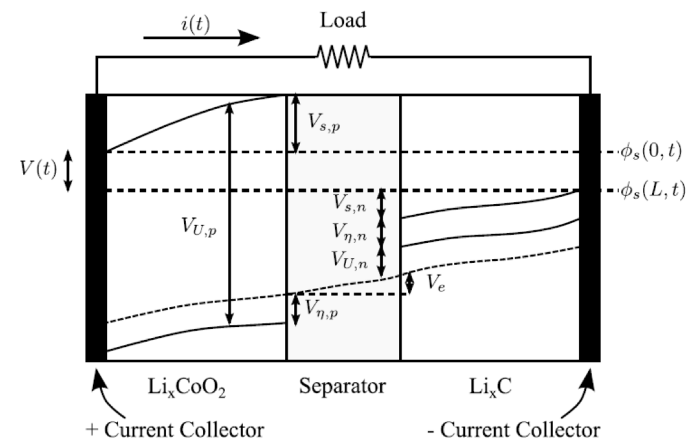
$nLi^+ + ne^- + C \rightarrow Li_nC$

Current flows − to +, electrons flow + to −, lithium ions flow + to −



# Cell Discharge Modeling

- Lumped-parameter, ordinary differential equations
- Capture voltage contributions from different sources
  - Equilibrium potential →Nernst equation with Redlich-Kister expansion
  - Concentration overpotential → split electrodes into surface and bulk control volumes
  - Surface overpotential → Butler-Volmer equation applied at surface layers
  - Ohmic overpotential → Constant lumped resistance accounting for current collector resistances, electrolyte resistance, solid-phase ohmic resistances



# Battery Aging Modeling

Aging results in two major qualitative effects on dynamics:

- Loss of capacity (due to diffusion stress, irreversible parasitic side reactions)
- Increase in internal resistance (due to solid electrolyte interface layer growth)

Capture with changes in three age-related parameters:

- qmax (max available charge)
- Ro (Ohmic resistance)
- D (diffusion rate parameter)

Given a discharge cycle, can estimate age-related parameters and determine how they change over time

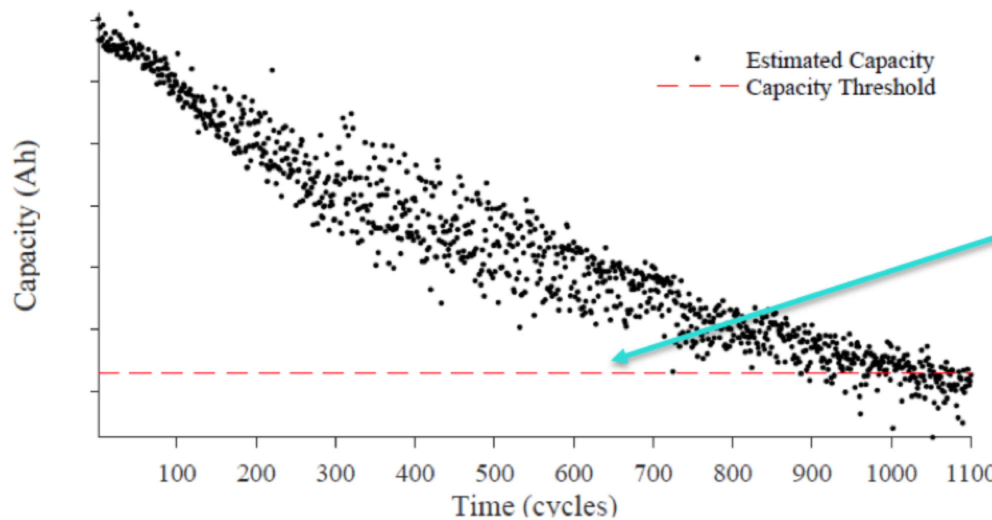
- Assume rate of change of age parameters is of form w*|iapplied|
- w is aging rate parameter, iapplied is applied current

Models developed and validated in MATLAB

# Defining EOL

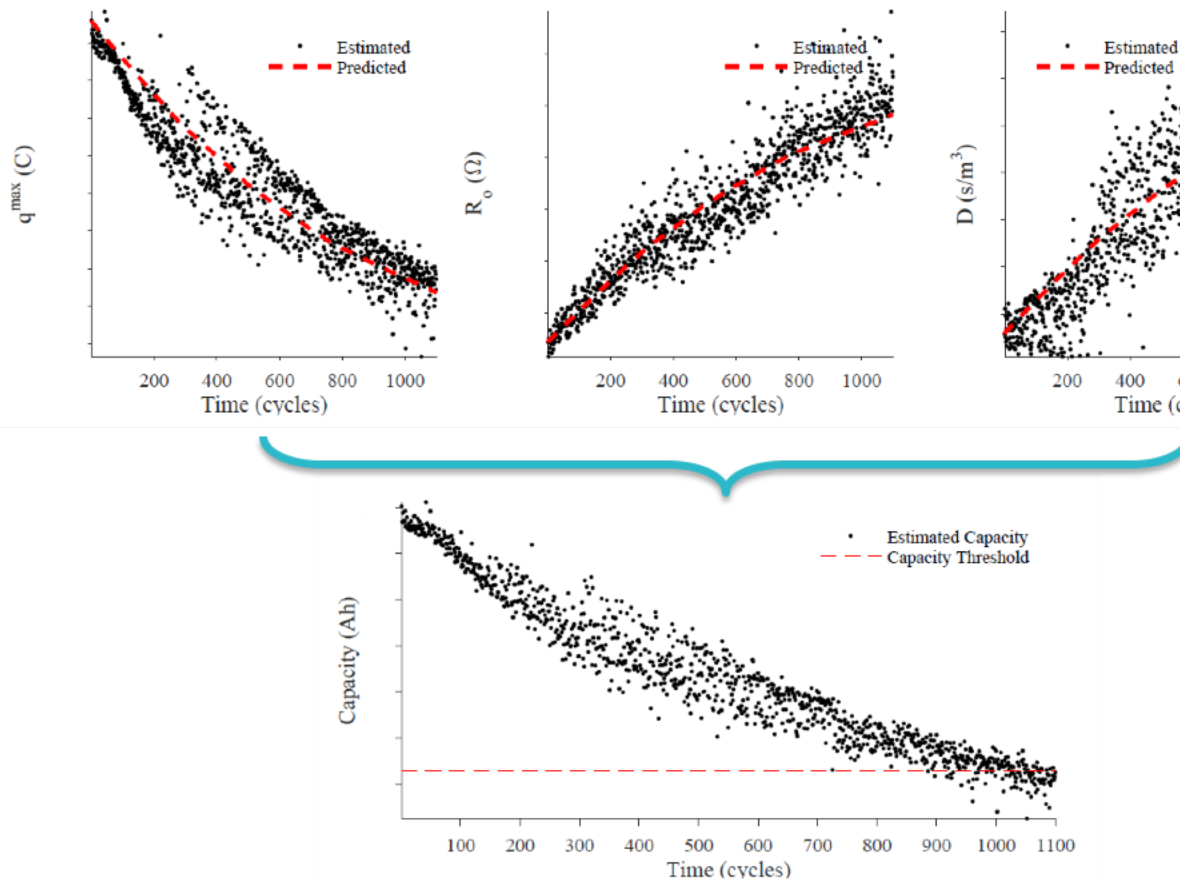
Capacity is measured in Ah for a given discharge cycle

- But, EOD is dependent on the load, so capacity measurement will be different depending on how battery is used
- Only meaningful to measure capacity w/r/t reference conditions
- For given age parameters, can use model to simulate a reference discharge and compute corresponding capacity




EOL defined as 50% capacity as measured at reference conditions.

# State of Health Estimation



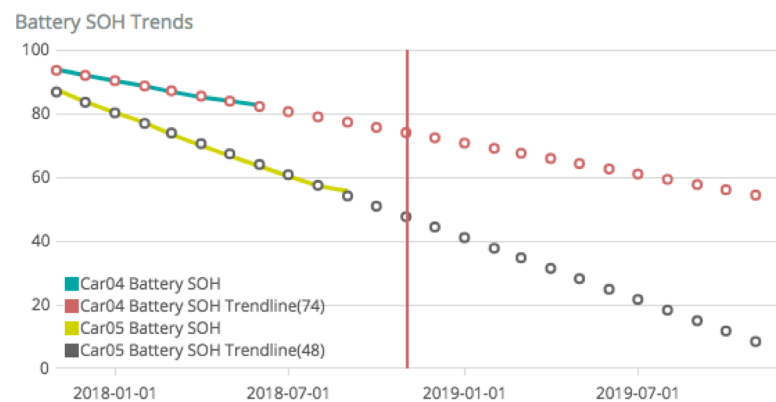
# Battery Analytics

Health Estimation

- For each trip, take pack voltage, current, and temperature
- Estimate battery state of charge (SOC) using unscented Kalman filter (UKF)
- Estimate current values of aging parameters over the trip
- Map aging parameters to current battery capacity/state of health (SOH)

State of Health Prediction

- Obtain SOH estimates for all previous trips
- Determine expected future battery loads
- Fit aging model (e.g., linear regression)
- Predict time/miles at which SOH will fall below 80%

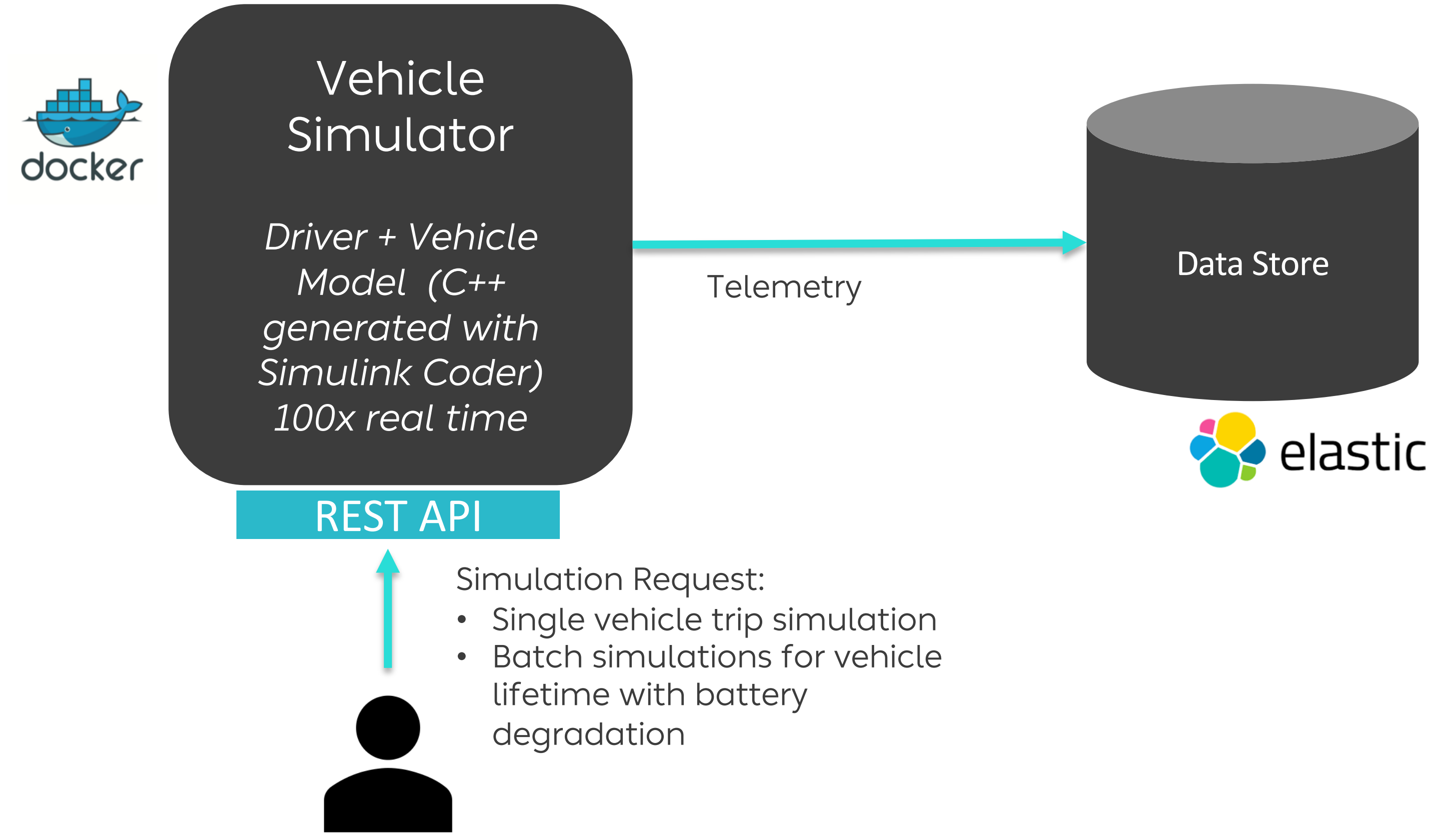



Other Metrics

- Powertrain efficiency, trip energy regenerated, etc.

# Cloud Deployment

# Simulation Deployment



# Battery Analytics Deployment

- Algorithms are implemented in Python
  - For each vehicle
    - Queries data for a trip from Elasticsearch
    - Runs analytics algorithms on the trip data
    - Pushes results back to Elasticsearch
  - Results include time-based analytics (e.g., state-of-charge) and trip summary metrics (e.g., SOH)
- Implemented as a batch job that is Dockerized

Battery Pack
BMS Pack Voltage
22:00
00:00
02:00
04:00
06:00
08:00
10:00
12:00
Average BMSPackVoltage
BMS Pack Current
Average BMSPackCrrnt
BMS Pack SOC
100%
Average BMSSOC
BMS Pack Average Temperture
Edit Annotation
2018-04-12 10:36:20
Description
High Temperature
Tags
high_bms_temp x
add tags
Save
Delete
Cancel
Average BMSTempAverage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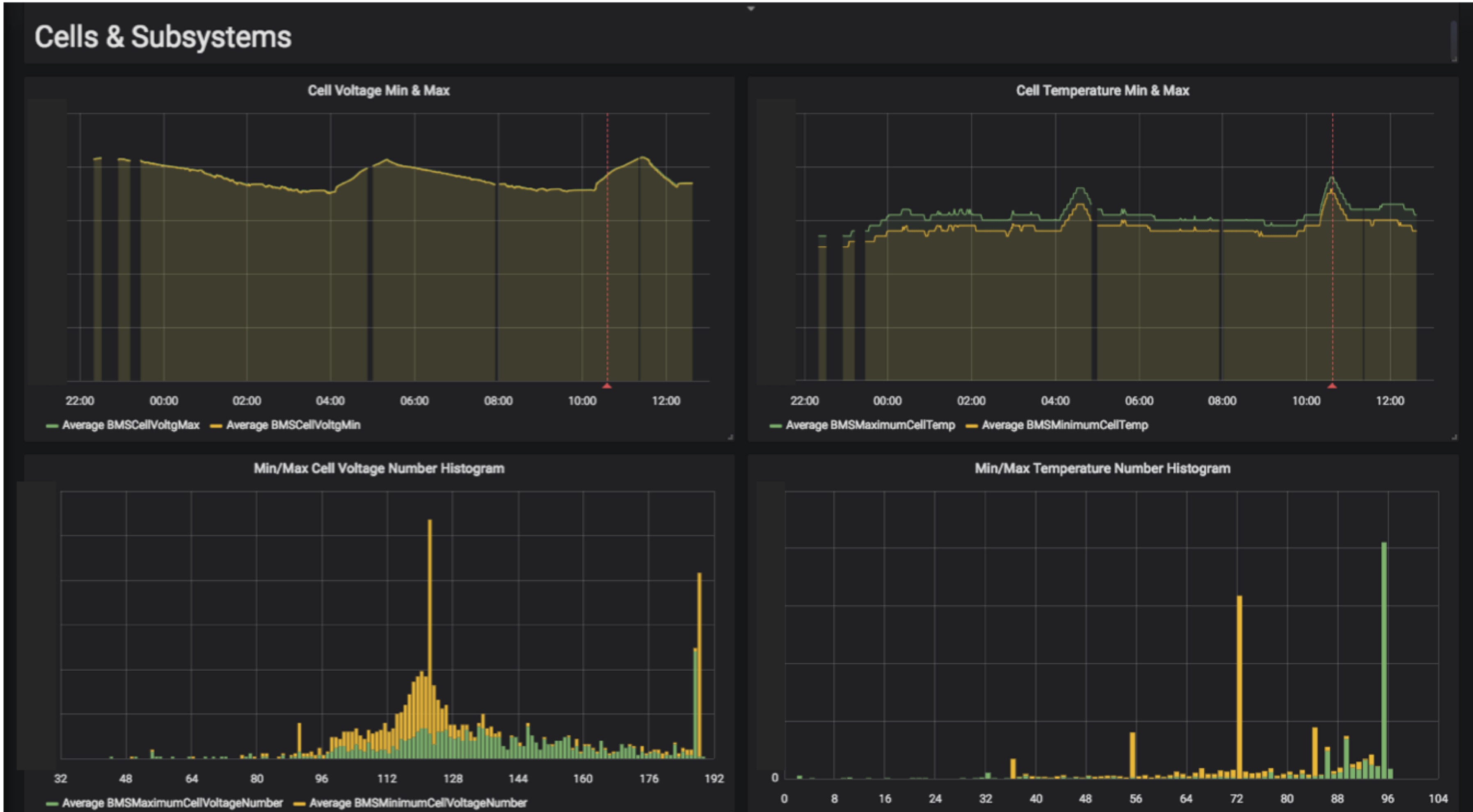
Cells & Subsystems
Cell Voltage Min & Max
22:00 00:00 02:00 04:00 06:00 08:00 10:00 12:00
Average BMSCellVoltgMax
Average BMSCellVoltgMin
Cell Temperature Min & Max
22:00 00:00 02:00 04:00 06:00 08:00 10:00 12:00
Average BMSMaximumCellTemp
Average BMSMinimumCellTemp
Min/Max Cell Voltage Number Histogram
32 48 64 80 96 112 128 144 160 176 192
Average BMSMaximumCellVoltageNumber
Average BMSMinimumCellVoltageNumber
Min/Max Temperature Number Histogram
0
0 8 16 24 32 40 48 56 64 72 80 88 96 104

# Conclusions

Summary

- Simulations executed on request basis or in batch mode
- Dashboards combining vehicle- and fleet-level metrics built from Elasticsearch data source
- Automated pipelines running on test vehicles
- Deployment to production in progress

Next Steps

- Scalability
- Validation with customer data
- Connection to service operations