Machine Learning for Prediction of Li-Ion Battery Performance

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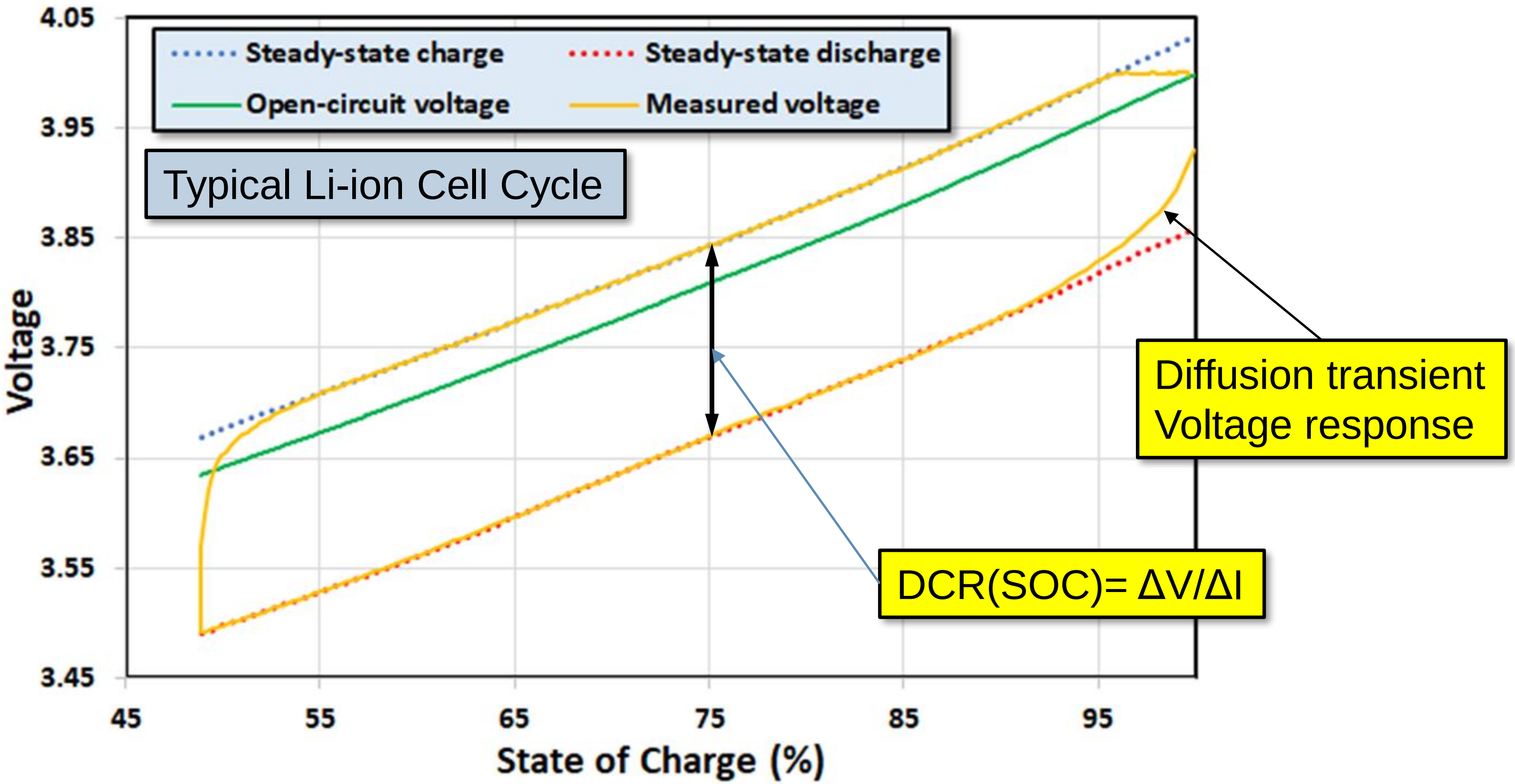
- **Life tests or operating spacecraft generate large battery datasets**
  - *The data contains far more information that we normally extract or trend*
- **Machine learning methods offer new opportunities**
  - *Automated extraction of battery parameters*
  - *Trending and visualization of parameters over large datasets*
  - *Prediction of performance for other cycling conditions or into the future*
- **Our Approach**
  - *Convert each cycle in the dataset into a simplified physics-based model based on a few fundamental parameters: OCV, DC resistance, Li ion diffusion rates, etc.*
  - *Train a neural net to recognize patterns in these parameters over the dataset*
  - *Query the neural net to obtain the parameters that best describe any operating condition of interest*
    - Trend the parameters to visualize how the cells respond or degrade
    - Convert ML-generated parameters to performance using the physics-based model

The Simplified Physics-Based Model

- **Referred to as a Reduced-Order model (ROM)**
  - *Can be as simple or complex as needed*
- **Our ROM assumes cell performance governed by OCV, DCR, and Li diffusion as functions of state of charge**

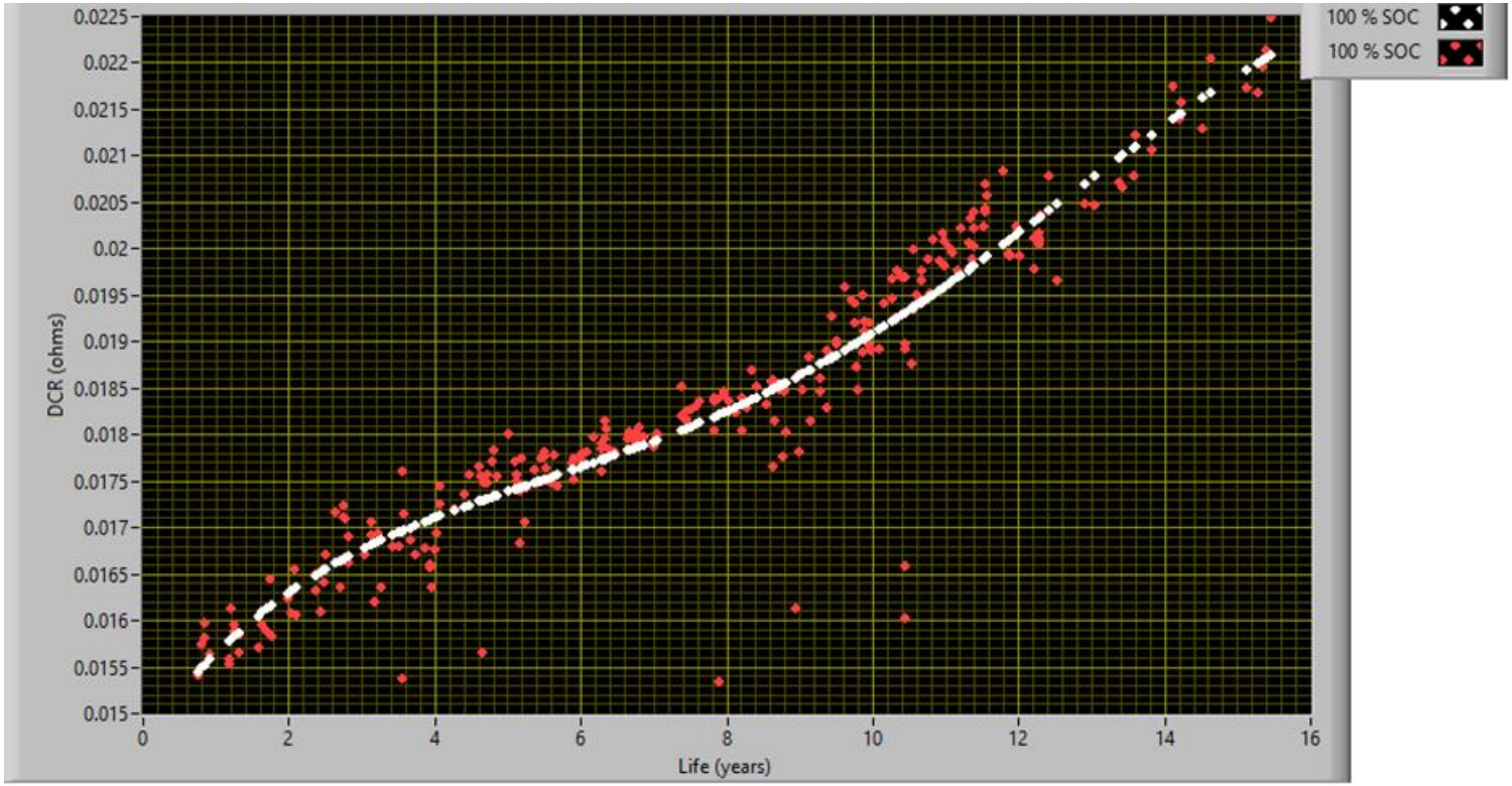


The Life-Test Database and Neural Net Training

- **Accelerated geosynchronous life test, 60% maximum DOD**
  - *15-years of cell cycling, 5,132 GEO cycles, 4GB of data in 140 data files*
- **Each cycle is fit to the Reduced Order model (~12 hr for 5,132 GEO cycles**
  - *OCV, DCR, and diffusion parameters represented as polynomial functions of SOC*
- **The ROM parameters from each cycle are used as input to train a neural net**
  - *The neural net learns the cell response patterns over the entire database*
  - *Various patterns are related to cell age, DOD, temperature, or any other variables that change during the life test*
  - *5,132 GEO cycles typically result in a neural net containing 600-700 discrete patterns (composite ROMs)*
- **The patterns in the trained neural net can be examined by queries for the pattern that matches any desired cell age, DOD, temperature, etc.**
- **The results of many queries map the information in the neural net and allow it to be visualized for any way a cell is operated**

What the Trained Neural Net Contains

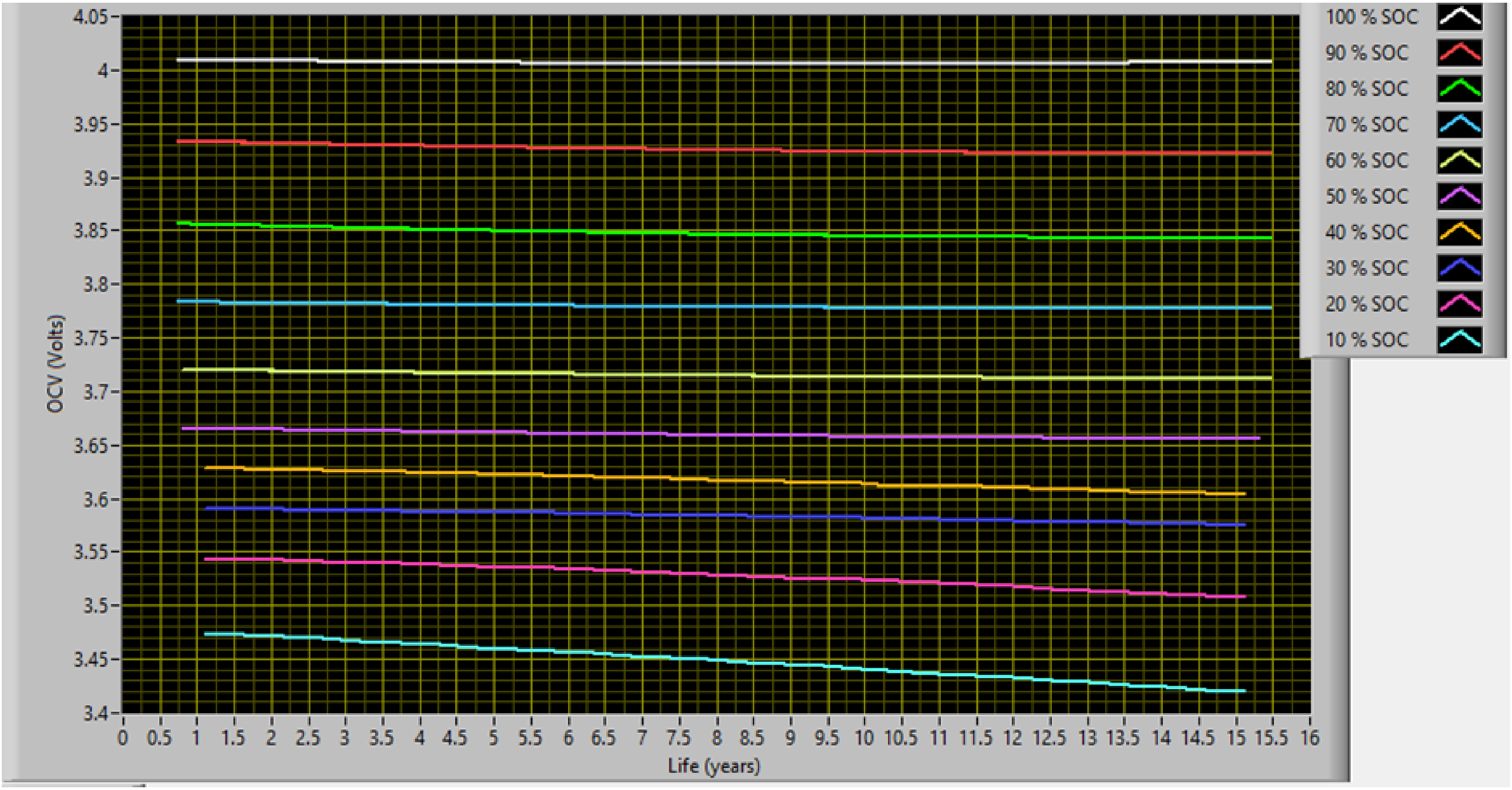
- **A sufficiently large number of queries can examine all the information in the trained neural net**
  - *For example, OCV or DCR trends over the age of a cell*



DC resistance at 100% SOC as a function of cell age, the points are from the raw queries to the neural net, the line is an automated fit to the data

Useful for Visualizing Trends in the Database

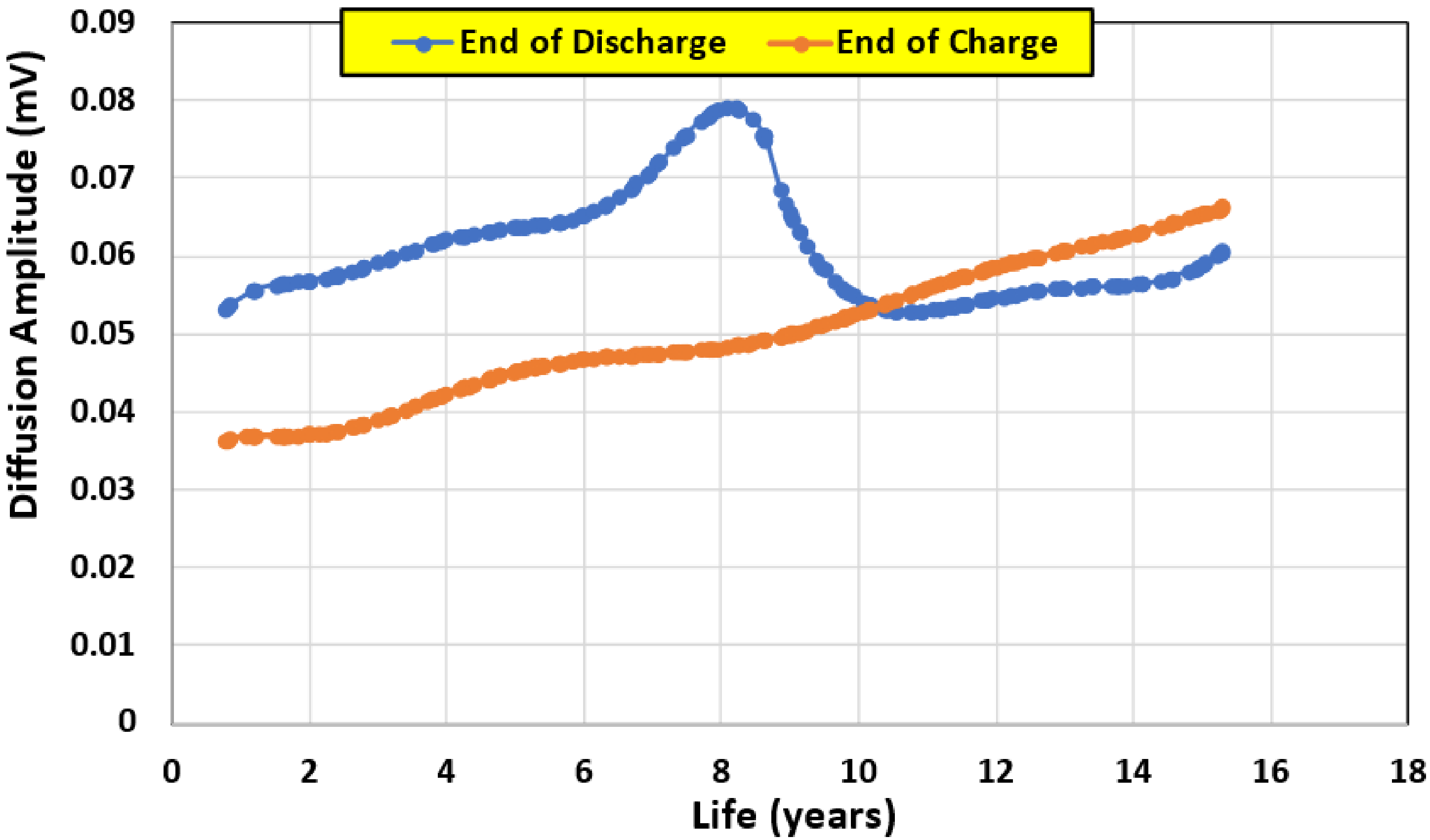
OCV as a function of life and state of charge



Decrease in OCV with increasing age at low state of charge is because the cell is slowly losing capacity as it ages

Can Find Previously Unknown Trends in the Data

Diffusion resistance amplitude as a function of life at maximum 60% DOD

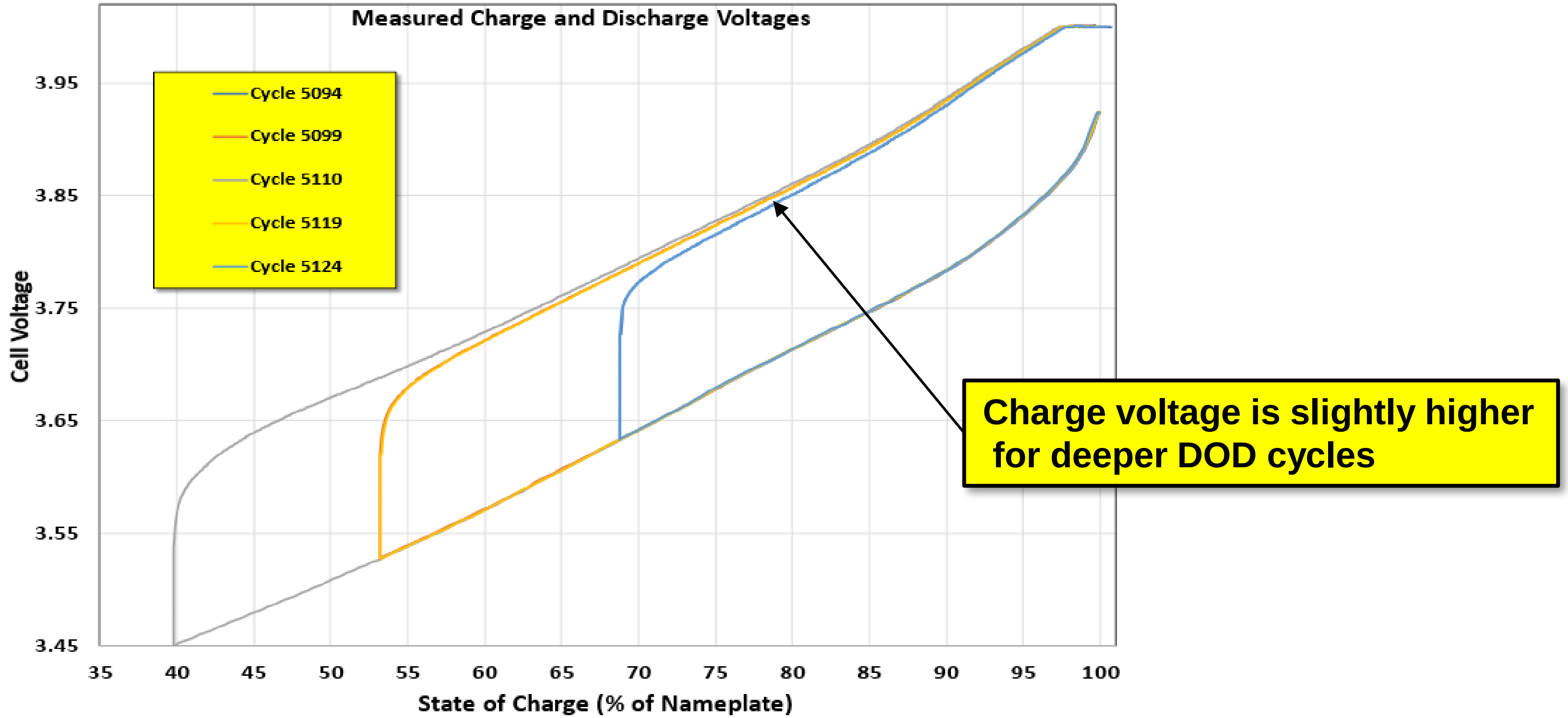


- *The diffusion resistance at 60% DOD drops after ~9 years of cycling*
- *After this drop, the cell degradation rate roughly doubles. Why?*

Can Point to New Physics*

**Physics not included in our Reduced Order Model*

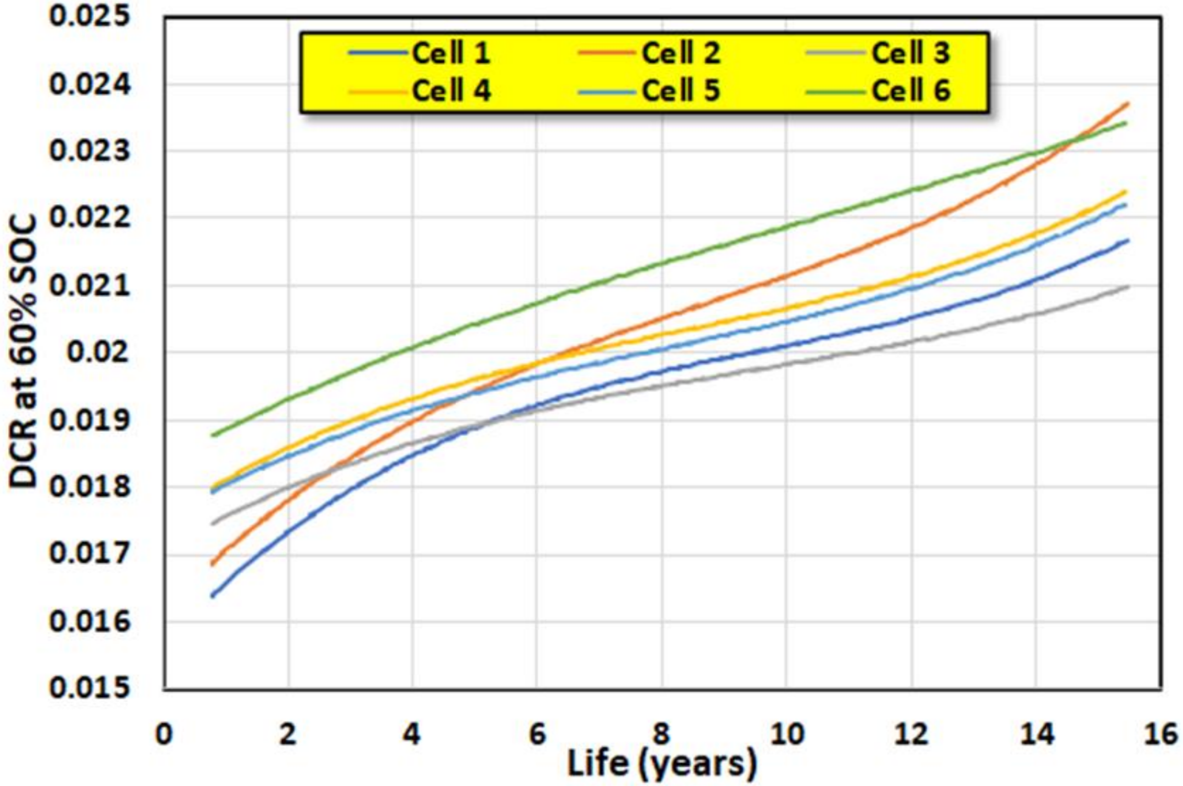
- **The neural net predicted a slightly different OCV, depending on how deeply the cell was discharged**
- **Examination of actual data showed this was real**



- ***Effect was traced to a SOC offset between the average SOC in the cathode, and the SOC at the current collector***
- ***The diffusion effect could be included in an improved ROM, but was empirically "learned" by the neural net***

Determine Causes for Cell-to-Cell Variability

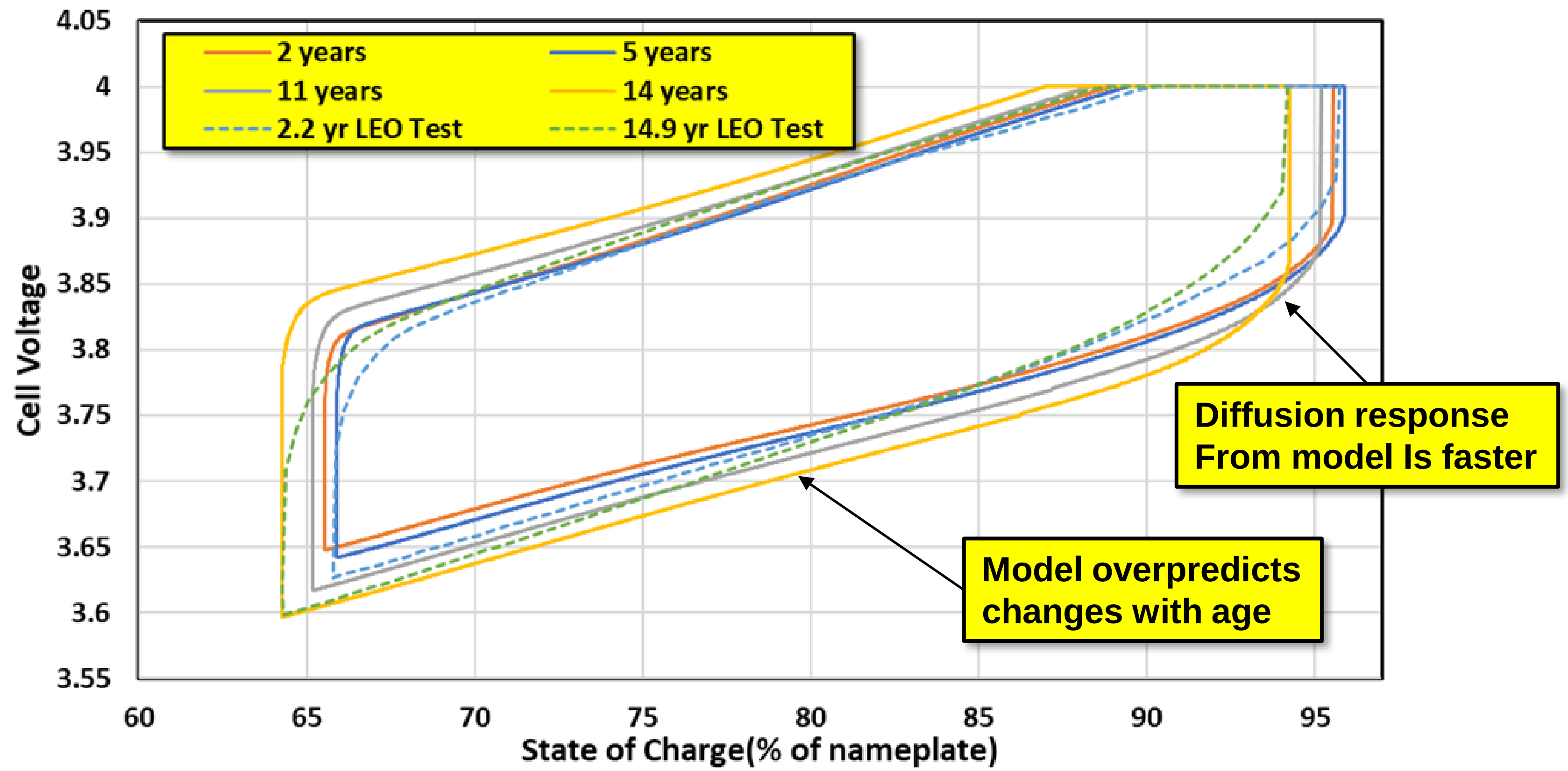
DCR for six "identical" cells operating in a pack



- *Cells can be seen to start with different performance at BOL*
- *Cell parameters are often seen to change differently as they age*
- *Can obtain statistical for cell performance or ageing in batteries*

Predict cell performance where there is no data

- **We used a neural net trained on a GEO database to predict cell performance at 2, 5, 11, and 14 years in a 30% DOD LEO life test**



- ***Compared to actual LEO life test data on a similar cell at 2.2 and 14.9 yrs***
- ***Charge and discharge voltages agree to within ~ 20mV***
- ***Systematic differences in age-related degradation are present***

Conclusions

- **Demonstrated that machine learning is useful for quick visualization of the cell responses and changes in a very large database**
  - *We can identify performance trends with the physical parameters in our ROM*
  - *We can find trends in the data that are not obvious*
  - *We can obtain evidence for additional physics that the neural net detected*
- **Trained ML models for better predicting cell and battery performance**
  - *Predicting performance where we have no life test data*
  - *Can include cell statistical variability in battery modeling*
  - *Explore the limits of extrapolating to future battery performance*
- **The Future**
  - *A model for a cell that uses multiple neural nets to model degradation in various operating environments (such as LEO vs. GEO, other temperatures, etc.)*
  - *On demand web-based neural net models for predicting the performance over life for a range of COTS or other cells*
  - *Battery digital twins*