Sensai Analytics – Volvo Group: Data-based modelling of lithium-ion remaining useful life and residual value – Results from POV 1

Proof-of-Value-1 Project Report
Revision 1.2
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Executive Summary

Sensai Analytics and Volvo Group successfully demonstrate the use of data-based forecasting of (i) battery capacity fade, and (ii) battery residual value in arbitrage and frequency response markets.

Problem: Volvo Group sells battery electric trucks and digital services for monitoring them. Predicting the wear and remaining useful life of the batteries in these vehicles, to plan for maintenance, leasing agreements, and range estimations, remains a major challenge owing to the lack of historical performance data available. Furthermore, there are significant opportunities to reuse retired electric vehicle (EV) batteries in new applications, but lifecycle decisions can be difficult to make.

Solution: Sensai Analytics is a data-driven battery analytics startup located in Greentown Labs, Somerville, MA, & Cork, Ireland. Their core team is comprised of world-leading battery scientists and machine learning engineers from MIT, Georgia Tech, & Trinity College Dublin. Sensai is bringing to market its Li-ion battery monitoring solutions, that builds upon a unique combination of technologies that enable easier creation and scaling of machine learning models for data-driven batteries. These technologies are based on Sensai's in-house expertise in and battery analytics and second-life techno-economics, that aim to massively simplify decisions made across a battery's lifecycle and whether to refurbish, reuse or recycle?

In this proof-of-value (POV) project, Sensai Analytics demonstrated data-based approaches to useful life and residual value forecasting, and quantified their value. In short, a data-based lithium-ion capacity fade model was trained using Volvo Truck's own data, to show the effectiveness of the methods, while to provide insights into the value of reusing batteries, the project demonstrated a residual value modelling approach that quantified the value of retired Volvo Truck batteries in multiple reuse scenarios.

Value: The value of Sensai Analytics technology is shown to potentially provide a 23% boost in Electric Truck Lifetime Productivity if used to extend a vehicle's first-life by 2 years (or 25%), or 9% if used to find the optimum point for battery removal. Given the early stage of the electric truck and battery reuse markets and the developing nature of battery supply chains, however, many assumptions are required to model the value generated by Sensai Analytics and these numbers will be further evaluated in any future engagements.

1. Project Summary

Problem Statement: Volvo Trucks is engaged in a long-term plan to offer a fossil-free commercial vehicle line-up by 2040, with their first electric trucks currently entering the market. A core component of their electrified products are the lithium-ion batteries used for energy storage that account for a significant portion of the bill of materials for each vehicle. It is known that the ability of these batteries to store energy will degrade over time, reducing the driving range of the vehicles. The nature of the trucking industry, however, means each vehicle will be subjected to very different usage patterns in terms of cycling, charging, and temperature, making it extremely difficult to plan for the management of battery maintenance, replacement, and reuse across all vehicles. Furthermore, the rapid pace of electrification of the transport industry, means a significant barrier to forecasting how individual batteries will degrade over time, is simply a lack of data, with very few vehicles in the field and even less having 'aged-out' their batteries. Given that batteries are the most expensive component in the vehicle, it is imperative to manage these assets across their full life cycle, in order to extract as much value as possible.

Phase 1 scope: The creation of accurate data-based lithium-ion battery wear models for electric vehicles remains a significant challenge for the industry owing to the difficulty and expense involved in conducting accelerated aging tests that cover all possible use cases, while the use field data is difficult owing to its usual format, and the lack of adequate validation data of battery state-of-health collected in the field. In vehicles, for example, the data collected on battery usage is often in the form of histograms of time spent in different operating regions, as stored in the BMS. Sensai Analytics' have solved these problems by developing machine learning approaches that uses as model inputs, features related to histograms of the time batteries spend in different operational ranges of current, voltage, power and temperature, to learn how a battery's state-of-health changes over time. This supervised machine learning approach learns an initial model with lab data collected during accelerated aging tests, and then adapts to field data over time using online adaptation. In this phase of the POV, Sensai Analytics applied part of their technology to Volvo Trucks' lab data to prove the accuracy of their methods, and show how histograms of operational ranges are adequate for creating accurate data-based models of capacity fade, and could potentially be used to forecast battery remaining useful life using typical electric driving patterns.

Phase 2 scope: Over the coming years, a fleet of millions of lithium-ion batteries that will be deemed unsuitable for the rigorous trucking duty cycle/environment after a number of years operation, but still containing significant value for other applications, will become available to OEMs. These used batteries present a massive financial opportunity for Volvo Trucks as they can be repurposed for new applications where the duty cycling and current levels are less onerous than EV driving — potentially increasing a battery's lifetime value and postponing the eventual cost of recycling, while also providing environmental/sustainability benefits by reducing resource use. In the second phase of the POV, the residual value of different reuse applications for Volvo Truck batteries were quantified, demonstrating how the methods could be used to solve the key question of battery grading, i.e., when is the optimum end of the first-life? and whether to refurbish, reuse, or recycle?

2. Results

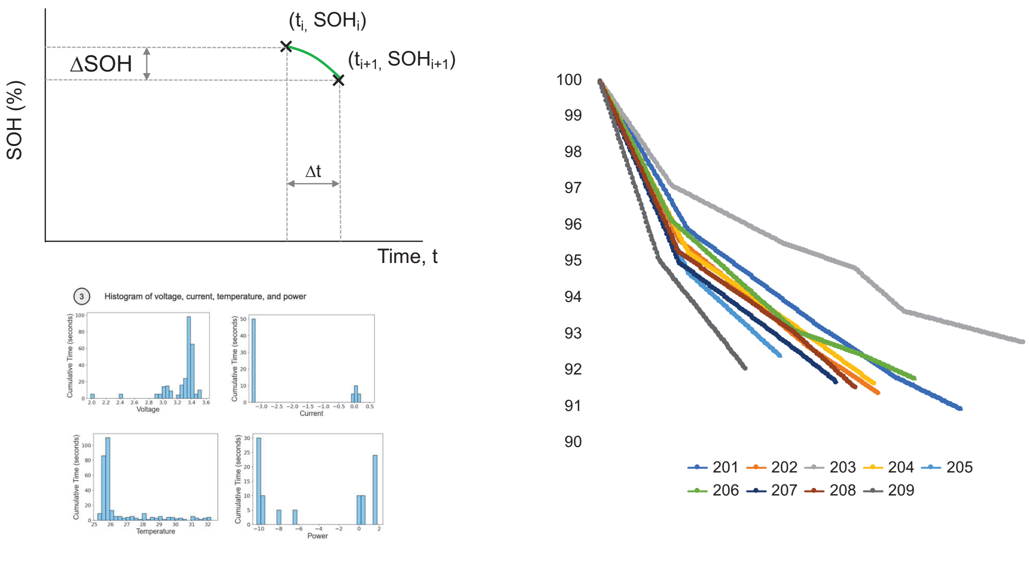
<u>Phase 1: Data-based remaining useful life (RUL) forecasting</u>

1.1 Data sharing after pre-processing and feature engineering stages.

The first step in the project was for Volvo Group to pre-process and then share data with Sensai. The data pre-process is described in detail in the document: “Sensai Analytics_Data Requirements_1April2022 .pdf”, and is only briefly summarized here.

The model training process creates a data-driven model that forecasts ΔSOH (%) across a period, Δt, based on histograms of the time a cell spends in different operating ranges of Voltage, Current, Temperature and Power, during that period. The first processing step is to start by dividing the complete SOH history into segments of width, Δt. Δt does not need to be constant, and is typically in the range of hours – i.e. in this project 8, 12, 24, and 100 hours were used. For each segment, Δt, the time series of V, I, T, & P are converted from raw time series into histograms of the time spent in different operating ranges, based on bins provided in the requirements document. After feature engineering, a complete labelled data point for each segment consists of: time elapsed since start of experiment, Δt, ΔSOH, and histograms of time spent in different operating regimes of current, voltage, power and temperature regimes (as outlined in Figure 1 (a)).

In this project, the data pre-processing and sharing was conducted twice, with Volvo Trucks uploading the prepared data sets to a shared project Sharepoint to provide the Sensai team with access. Data from 9 cells (Cells 201 - 209) was shared, with separate csv files provided containing the relevant features and target variables for each cell. The state-of-health data for each cell is shown in Figure 1 (b) and shows the variation between the cells which were each subjected to different cycling conditions – information on which was not shared with Sensai.



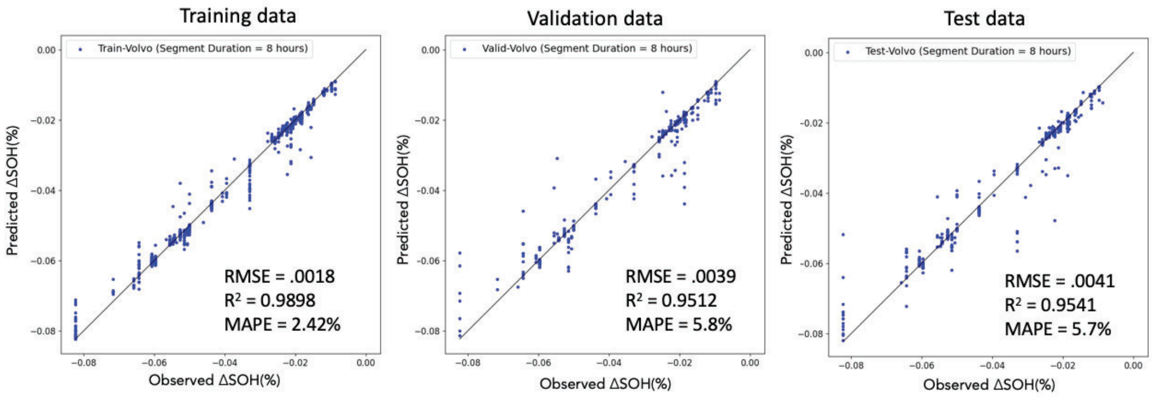
(a) (b)

Figure 1: (a) overview of a labelled data point for each segment consists of: time elapsed since start of experiment, Δt, ΔSOH, and histograms of time spent in different operating regimes of current, voltage, power and temperature regimes, and (b) the state-of-health data for each cell shared by Volvo Group.

1.2 Lithium-ion prognostics model training using lab measurements of capacity fade for Volvo Group's batteries

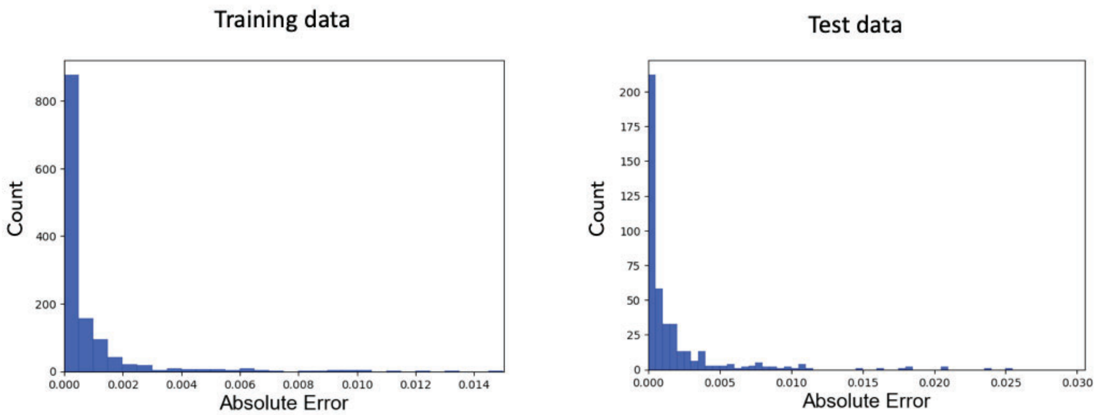
In the next step, a machine learning process was undertaken by Sensai to learn from the data provided, and create a data-based battery degradation model. The method used is not described here but an overview and technical details were provided previously in the original scope of work and data requirements document.

The first training process undertaken was a simple data split where data from all cells was divided into training, validation and testing sets in a 60% : 20% : 20% split. While this means data from the same cells will be in both the training set, and the test set, given the small amount of data available, and Sensai not knowing whether their methods would work with Volvo Truck's data (the point of this POV), this was considered a useful first step to ensure the modelling process was able to learn from the data provided. Figures 2 (a), (b), and (c) show the results, predicted versus actual ΔSOH (%), for a model trained on the training data and applied to the validation and test set. Referring just to the test set, the model showed good accuracy and a strong ability to learn from this data with RMSE, R^2, and MAPE values of 0.0041, 0.954 and 5.7% respectively. Separately, histograms of the absolute difference between the predicted and actual ΔSOH values for the training and test data are shown in Figures 3 (a) & (b) to provide an overview of their distribution.



(a) (b) (c)

Figure 2: Scatter plots of (a) the Predicted versus Actual ΔSOH (%) for a model trained on the training data and, (b) applied to the validation and, (c) test set.



(a) (b)

Figure 3: Absolute error histograms for the (a) training and, (b) testing data.

Having confirmed through this simple first step that Sensai's machine learning approach can be applied to the provided data, a more rigorous machine learning task was undertaken. In the next experiments, a data-based battery degradation model was trained using the data from 8 of the cells available and then tested against the remaining one. The purpose of these 'leave-one-out' experiments was to check how well the model learns from multiple cells and then generalizes to data not seen before, i.e. a new cell. This is a better representation of how a machine learning model would be used in practice, i.e. trained on lab data and then used the estimate the SOH and remaining useful life of the pack or modules in a new vehicle for which there is no data available.

The results of these experiments are show in Figure 4 with the error metrics for each one summarized in Table 1. In total, 9 experiments were undertaken, with each cell excluded once. The figures show that, in general, models trained on data from 8 cells, and then tested on the excluded one, model very accurately the decrease in SOH of the test cell over time, a very positive result given that all of these cells are cycled under different operating conditions (not known to Sensai) which shows the data-based approach generalizes well to different operating conditions.

It is worth noting the inaccuracy in the experiment performed with Cell 203 as test. Cell 203 is the only cell in the data set that contains data where the cell was cycled under dynamic conditions. Given the unique nature of these operating conditions, compared to the other cells, a model trained on data from the 8 other cells did not generalize well in this case. This is not surprising, and future experiments would clearly benefit from having more data from cells cycled under dynamic operating conditions.

Most promisingly, it can be seen that the models pick-up the transition from the early 'non-linear' aging process to the later 'linear' stage with good accuracy for all cells. This is important behaviour to capture when modelling the battery packs in trucks, and suggest this method might also be able to estimate/forecast the even later stage 'knee-point' in battery aging, although very large data sets would probably be required to test that appropriately.

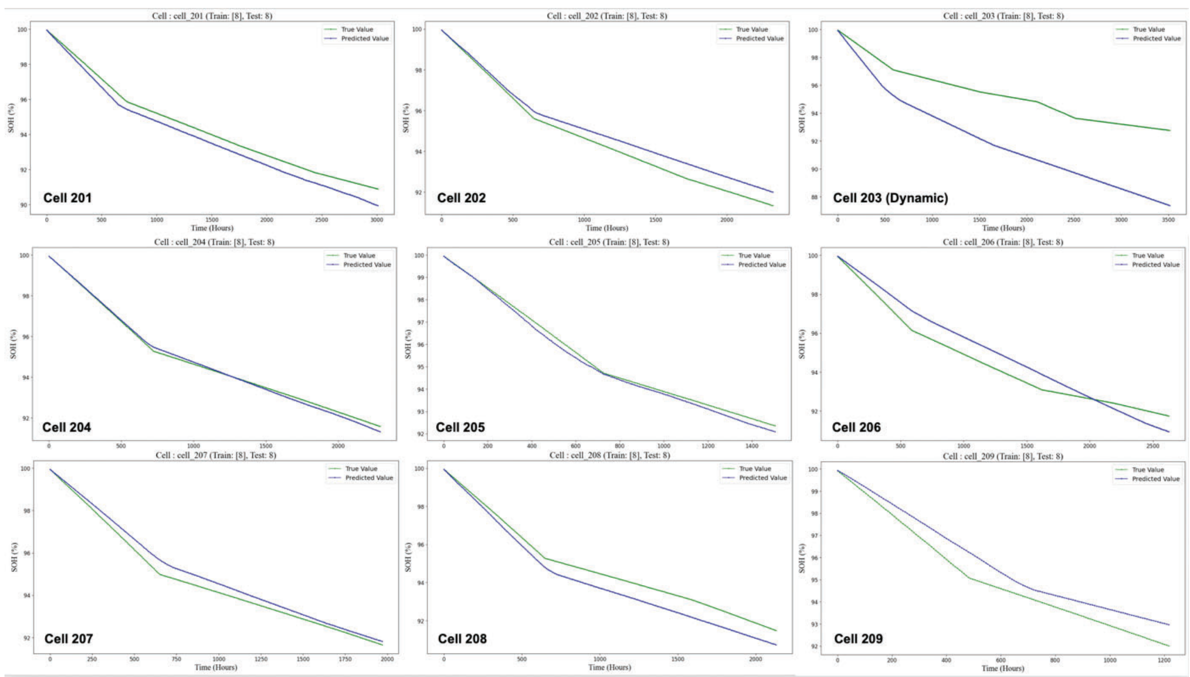


Figure 4: Plots of the actual (green) versus forecasted (blue) SOH trajectory for the 9 cells used as test cells in the 'leave-one-out' experiments.

Table 1 shows the error metrics from the nine experiments. In general, most RMSE values remained low while the majority of R^2 values are greater than 0.8. The average MAPE (excluding Cell 203) of 21% is slightly higher than would be hoped, but it is worth noting that the ground truth for these experiments is the ~100% SOH at the start, and any error compounds across the whole SOH trajectory/battery aging, as another ground truth is not used at any stage, but the trajectory forecasted from the start only.

Table 1: Error metrics for the 'leave-one-out' experiments on Volvo Group's data.

Cell Name	Type	RMSE	MAPE (%)	R^2
cell_201	Test	0.005	17.3	0.841
cell_202	Test	0.004	10.8	0.955
cell_203	Test	0.015	109	0.393
cell_204	Test	0.004	11.9	0.948
cell_205	Test	0.008	14.9	0.785
cell_206	Test	0.010	53.6	0.580
cell_207	Test	0.007	17.4	0.886
cell_208	Test	0.005	14.8	0.920
cell_209	Test	0.017	32.1	0.543
Average (excl. 203)	**-**	**0.0075**	**21**	**0.81**

1.3 Compare to larger open-source data set

Given the relatively small size of the data set available from Volvo Tucks, and Sensai's prior work with open-source data sets, it was decided to run the same experiments on data provided on the aging of NMC batteries under different cycling conditions measured and made public by Sandia National Labs. This data set contains experimental measurements on the capacity fade of lithium-ion cells under various charging and discharging regimes, temperatures and SOC windows.

The dataset from Sandia National Labs (SNL) consists of 32 commercial 18650 NMC cells cycled to 80% capacity. The experiments examine the influence of temperature, depth of discharge (DOD), and discharge current on the long-term degradation of the commercial cells. The cells were fixed at a range of temperatures from 15-35°C, charged at C-rates from 0.5-3C, and cycled between DOD limits of 0, 20, 40, 60, 80 & 100%, meaning a wide range of usage conditions were covered. Each round of cycling consisted of a capacity check, some number of cycles at the designated conditions for that cell, and another capacity check at the end. The capacity check consisted of three charge/discharge cycles from 0-100% SOC at 0.5C

The NMC dataset is one of the most comprehensive available with accelerated aging measurements from 32 cells in total, covering wide ranges of cycling, calendar, and temperature conditions and including high resolution time series data on the current, voltage, and temperature witnessed by the batteries during the experiments taken over ~18months.

Table 2: A summary of publicly available data set used.

Dataset	**Sandia National Labs**
Battery Vendor	LG Chem
Cathode	NMC
Form factor	18650 Cylindrical
Nominal capacity	3 Ah
Number of cells	32
Charge rate	0.5 – 3C
Discharge rate	0.5 C
SOC limits	0, 20, 40, 60, 80, 100%

Given this experiment was not part of the original POV scope, and Sensai have spent more time working with LFP data from Sandia National Labs, the data pre-processing was mostly conducted using the same script used in Section 1.1. This meant some of the data/cells were not easily usable and a decision was made to only work with 24 of the 32 cells available given the noise and gaps in data in the 8 other cells (this was explained in POV meeting no. 15 on December 8th 2022, and anyone who would like to see the noise and missing data should read the meeting slides from that day, that have been uploaded to Sharepoint).

This left 24 cells for this experiment, 20 which were cycled from 0-100% SOC limits, and 4 cycled from 40-60% SOC limits, with all other C-rates and temperatures outlined in Table 2 present in the data set. As in Section 1.1, the data from each cell was pre-processed into a common format to simplify the model training process. **Overall this data set results in 10x more data being available for model training & testing compared to the Volvo Group data set.**

Results

A model training process was completed as in Section 1.2, with Figures 5 (a) & (b) showing the results; the Predicted versus Actual ΔSOH, for a model trained on the training data and applied to the test set (the validation data is excluded for brevity). Referring just to the test set, the model showed good accuracy and a strong ability to learn from this data with RMSE and R^2, values of 0.0059 (absolute), and 0.907. Despite the larger amount of data available, interestingly these values are slightly worse than achieved with the Volvo Group data set, but this is not completely surprising given the greater noise, number of outliers and missing values in the Sandia National Labs data set. What this indicates to Sensai is the quality of data is vital for this approach (and all machine learning approaches) and getting good data (e.g. from Volvo Group's well controlled lab-based accelerated aging experiments) is more important than getting lots of data. Separately, histograms of the absolute difference between the predicted and actual ΔSOH values for the training and test data are shown in Figures 5 (c) & (d) to provide an overview of their distribution.

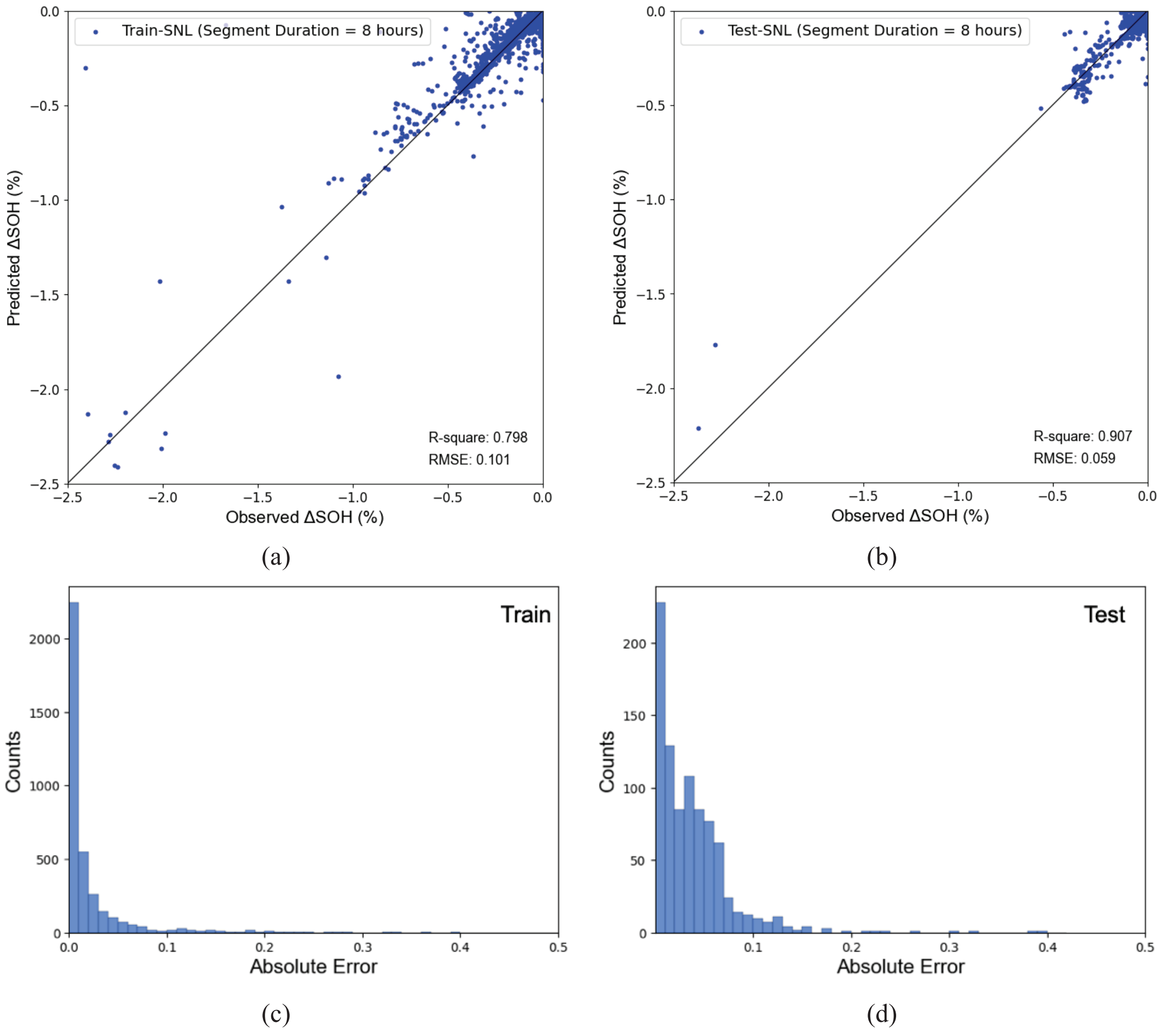
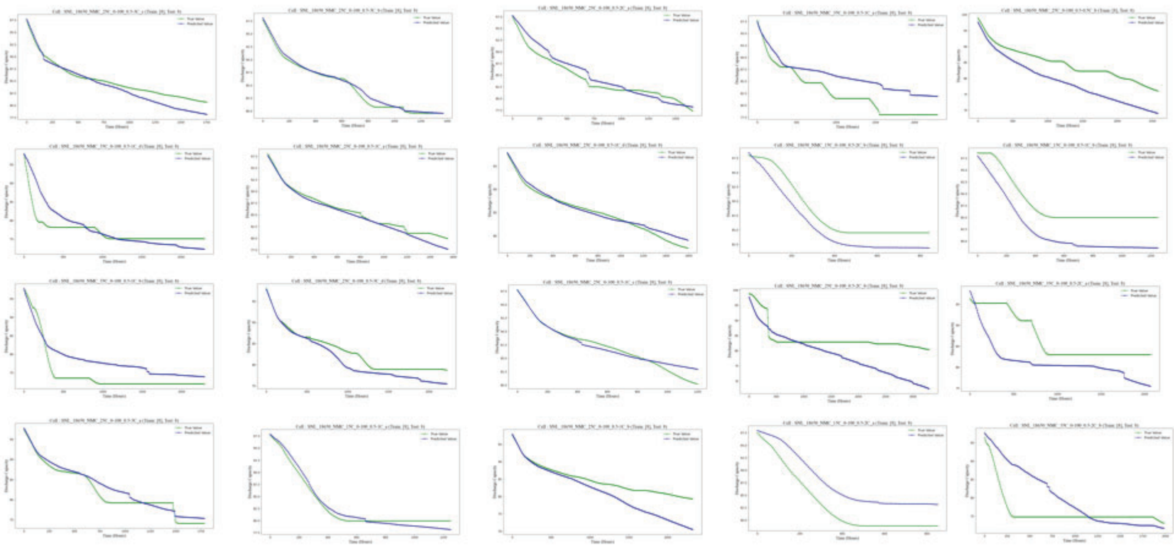
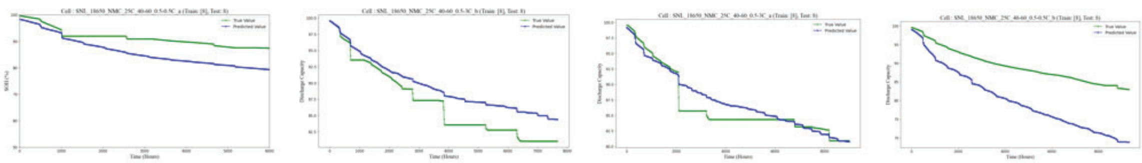


Figure 5: Scatter plots of the Predicted versus Actual ΔSOH (%) for a model trained on (a) the training data and, (b) applied the test data, and corresponding absolute error histograms for (c) the training and, (d) test data.

Twenty-four 'leave-one-out' experiments similar to those conducted in Section 1.2 were carried out on this data as well with the results plotted in Figures 6 (a) & (b). The individual plots show that, similar to Section 1.2, in general, models trained on data from 23 cells, and then tested on the excluded one, model very accurately the decrease in SOH of the test cell. There are definitely cells where it is less accurate, but this seems generally due to some of the cells having slightly unusual SOH trajectories, which likely results from the rapid turnaround of the data pre-processing which didn't allow enough time to manually go through each cell and improve the pre-processing for each. The 40-60% SOC limit cells are plotted separately in Figure 6 (b) and mostly show good agreement, with some errors compounding as is typical based on our initialization conditions.



(a)



(b)

Figure 6: Plots of the actual (green) versus forecasted (blue) SOH trajectory for the 24 cells used as test cells in the 'leave-one-out' experiments with the 0-100% cells in (a) and 40-60% in (b).

This concluded the data-based SOH estimation and forecasting section of the POV with some questions answered and other interesting ones found. A summary of the learnings from Phase 1 of the project are listed below and are likely to form the basis of any follow-on project, as described in Section 4, Next Steps.

Learnings from Phase 1; to build upon in future engagements.

1. The method works on this initial data set from Volvo Trucks. Although it might require some adaptation to the type of data collected in-vehicles (i.e. the histograms will require a different format).
2. The amount of dynamic data (Cell 203 only) was not enough to categorically say this method will work as well with that type of data, although Sensai has experience applying these methods to other data sets and remain confident this dynamic data won't be an issue. This would be an important point to address in any future project.
3. Feedback from the team at Volvo Truck's has made it clear that in practice, for many reasons, confidence intervals for predictions/estimations are important. These would be developed during any further project based on an adaptation of the input training data to include uncertainty estimations.
4. In addition, while a general model as produced here in useful, the best application of this technology would be to adapt it to individual battery modules within packs, with an online learning implementation where data from the field is used to update individual models over time.

Phase 2: Data-based residual value (RV) forecasting

In the second phase of this POV, a capacity fade model was be used to calculate the residual value of Volvo Truck's batteries reused as grid-tied energy storage systems in the California (CAISO), New York (NYISO) and Pennsylvania-New Jersey-Maryland (PJM) electricity markets comparing two applications; (i) price arbitrage (CAISO & NYISO) and, (ii) frequency response (PJM). The maximum residual value will be found by optimizing the daily control policy to balance short- and long-term revenue potential using degradation aware optimization that dynamically values battery degradation[1], with an overview and example results shown in Figures 7 (a) & (b).

Battery degradation: the data-based models created in Phase 1 were not used here, given differences between the inputs required to model degradation with them, and what was required to run the valuation models. More specifically; voltage is an input to the models developed in Phase 1, but not available from the simulation methods used here, where SOC is used. This would be addressed in future projects and the models directly used together.

Instead, battery degradation was modelled as a linear process (cycle life modelling) considering a cycle life of 4500 equivalent full cycles to 80% SOH for a Volvo Group NMC battery under 25^{o}C, 1C/1C charge/discharge rates. In some of the modelling, it was decided to also run a higher cycle life of 7200 equivalent full cycles to 80% SOH to represent an LFP battery.

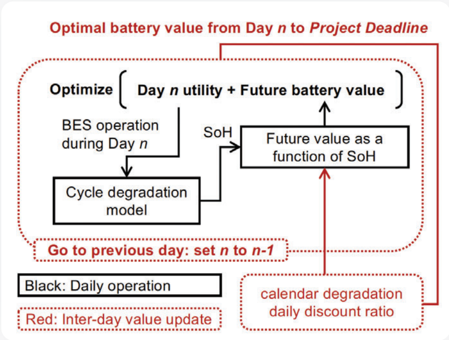
Price Arbitrage

In the CAISO and NYISO markets, batteries can be used as stand-alone stationary energy storage systems that charge by purchasing electricity when prices are low (i.e. during periods of high solar irradiance) and sell when prices are high, i.e. in the evening. These systems generally work by buying and selling power in the day-ahead electricity market, and are a vital resource in providing stability and buffer to the grid in areas with high renewables penetration, with projects actively encouraged by the grid operator. The first reuse application will consider Volvo Trucks batteries in the arbitrage market in California and New York.

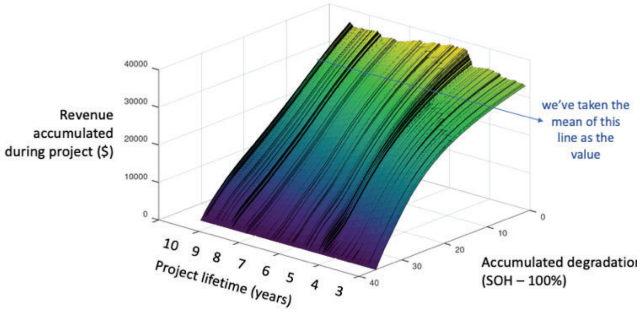
Modelling overview: 10-years of historical electricity market prices from an individual node in each market were downloaded and used (e.g. Figure 7 (c)) - with batch simulations run for different initial state-of-health conditions (in this case considered as different initial capacities), i.e., batteries were modelled with initial capacities from 100% (a new battery) to 65% (taken as the likely range of values when removed from the vehicle), and project lifetimes from 1-10 years were be considered.

The batteries modelled were assumed to have 1-hour energy storage (much lower than the typical 4-hour system) but used here given the knowledge of battery aging under 1C charge/discharge conditions, rather than typical 0.25C.

[1] B. Xu, "Dynamic Valuation of Battery Lifetime," in *IEEE Transactions on Power Systems*, (2022)



(a)



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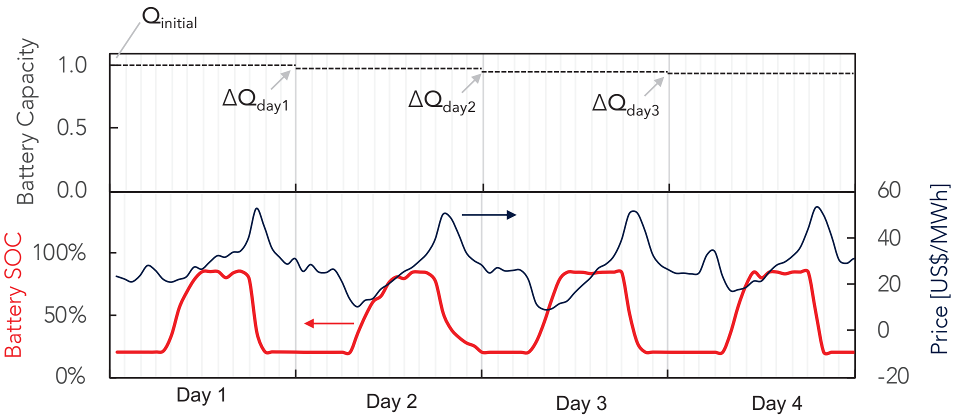


(c)

Figure 7: (a) The Battery Valuation Framework, (b) example output from the modeling process, and (c) example data used during residual value modeling.

Results

The results from the residual value modelling in CAISO are presented in Figures 8 (a) & (b). They show a new battery (100% SOH) has a value of between \$6,600 and \$7,200 /MWh/year depending on the assumed end-of-life (EoL) which decreases pretty rapidly for batteries with lower initial SOHs. In fact, in this modelled scenario, a battery with an initial SOH of 80% has a value of only \$2,000 /MWh/year. These values appear quite low and show the high dependence of the final value on the electricity price data, arbitrage opportunities, and location. In fact, having seen these results, Sensai did a literature review to see whether studies had been undertaken on battery value versus location and found a recent study[2] which showed the value of a new battery in CAISO can vary from as low as \$18,000 per year to a high of \$48,000 per year for a 4-hour system. The study looked at a 4-hour system which would not result in a 4x revenue increase versus our 1-hour system but more likely a 2-3x increase owing to charging/discharging power limits. Therefore, this analysis and literature review show the data used here results in battery residual values at the lower end of the scale, and highlights the importance of careful consideration of the input data used, or sensitivity analysis that would need to be undertaken when using these methods.

[2] R. H. Byrne, et al., "Opportunities for Energy Storage in CAISO: Day-Ahead and Real-Time Market Arbitrage," 2018 International Symposium on Power Electronics, Electrical Drives, Automation and Motion (SPEEDAM), 2018, pp. 63-68.

In light of these lower valuations, Sensai also studied battery value in the NYISO market for which they also had 10-year historical data for a particular location. In this case, values over double that of the CAISO analysis were determined as outlined in Figure 8 (c) & (d). In this case, an 80% SOH battery would have a residual value of ~$6,000 per MWh, and retain ~50% of their initial value.

What these analyses show is that rather than being a tool for finding an exact residual value, in these early stages of the battery reuse market, the best application of this analytics is likely to be as a tool that analyses and compares regions/markets to find ones that provide the greater potential for second-life batteries versus other regions/markets. Therefore, resources and effort can be focused in these higher value regions. For example, the areas within California where all of Volvo's second-life batteries would be best transported to for their reuse (and partners found in those regions to build/manage projects).

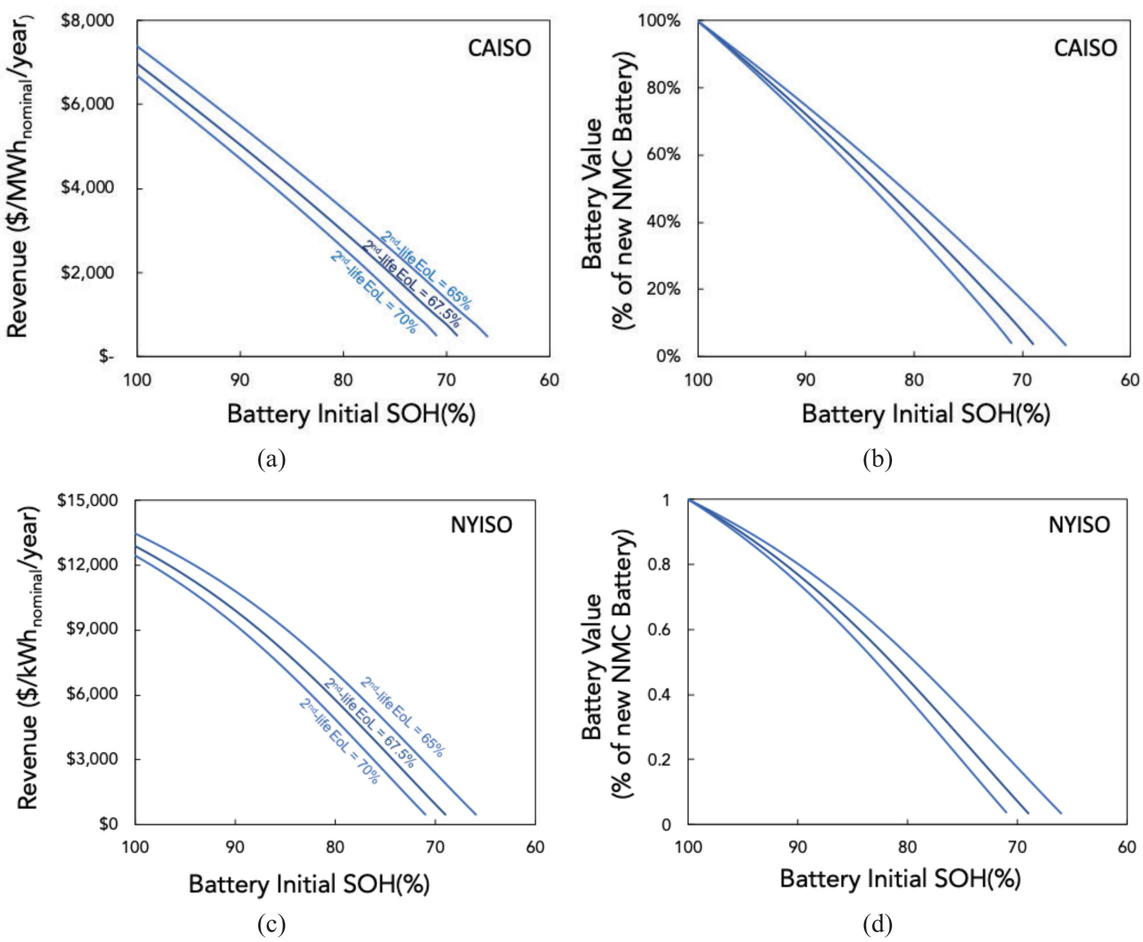


Figure 8: (a) The forecasted residual value of a 1 MWh Volvo Truck battery when reused in a Price Arbitrage application in the CAISO electricity market, (b) the value of a used NMC battery versus a new one, and in (c) and (d) the same scenarios are presented except modelled using NYISO market data.

Frequency Response

Batteries are now regularly used in electricity market to provide reliability services, i.e. batteries can be used as stand-alone stationary energy storage systems that receive power from the electricity grid, or provide power to it, when requested by the system operator, to provide stability in times when there is an excess of supply or demand. The signals from the operator might be received quite regularly or irregularly depending on where in the grid the battery is located. In general, around the world, these frequency response markets have grown quite rapidly in recent years, with generous prices given to participants. Therefore, they are known as a very valuable use of batteries and potentially second-life batteries which we will investigate here.

Modelling overview: For this mode, 5-years of historical electricity market prices from an individual node in the PJM market were downloaded and used - with batch simulations run for different initial state-of-health conditions (in this case considered as different initial capacities), i.e., batteries were modelled with initial capacities from 100% (a new battery) to 65% (taken as the likely range of values when removed from the vehicle).

The batteries modelled were assumed to provide 1 MW with 1 hour energy storage available, although hardly used as most frequency responses are required for < 20-mins.

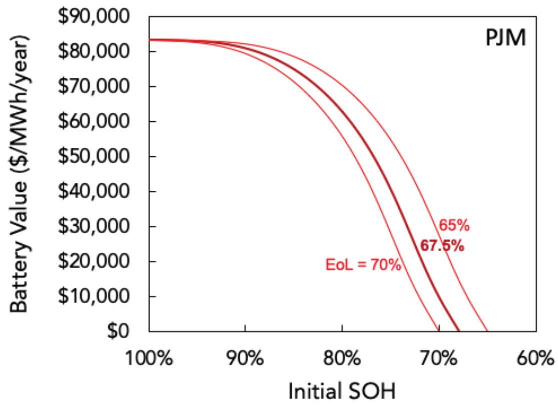
Results

The results from the residual value modelling are presented in Figures 9 (a) & (b). They show a new battery (100% SOH) has a value of ~$80,000 /MW/year depending on the assumed end-of-life (EoL) which maintains until SOH = ~90%, before dropping quite quickly. In this modelled scenario, a battery with an initial SOH of 80% retains a value of ~$60-70,000 /MW/year – much higher than the arbitrage use case.

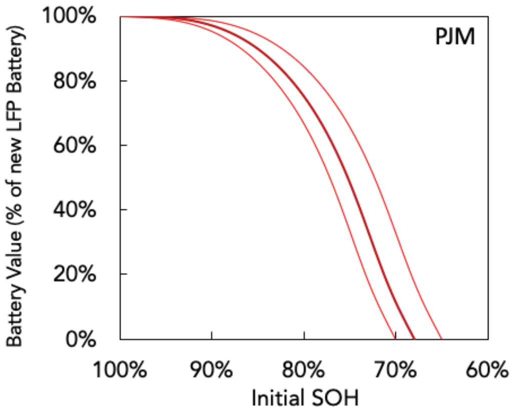
In Figures 9 (b) & (c) we see that in these scenarios, despite a shorter cycle life, NMC batteries (new and second-life) retain almost the same value as LFP batteries. It is noted that this is likely due to the oversizing of the batteries for the 5-year modelling assumption, i.e., a smaller LFP battery (less than 1 hour) would likely also last 5 years and therefore generate as much revenue as the modelled 1MW/1MWh system. This was investigated by reducing the battery energy to 800, 600, and 400 kWh (maintaining a power of 1MW) and modelling the resulting revenue as shown in Figure 9 (d). It is clear to see that a new 600 kWh system maintains the same value as a new 1 MWh system, and it is only the 400 kWh system that is not expected to last the full 5 years if cycled every day.

In general, it can be seen that frequency response is a potentially attractive market for second-life batteries, but these markets cannot be considered to be growing, given the demand for frequency response is much smaller in an electricity grid versus the potential to implement arbitrage. In fact, in the US, the use of energy storage for arbitrage is now growing a lot faster than use in frequency response markets, and there remains doubt about how much capacity for frequency response applications there will be in a few years just as second-life batteries become available at scale.

This concluded the data-based residual value forecasting section of the POV with some questions answered and other ones found. A summary of the learnings from Phase 2 of the project are listed below and are likely to form the basis of any follow-on project, as described in Section 4, Next Steps.



(a)



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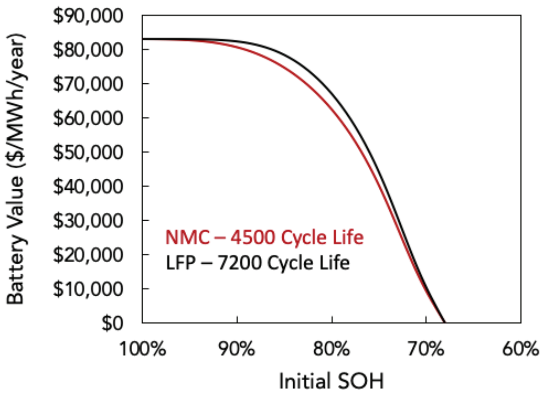

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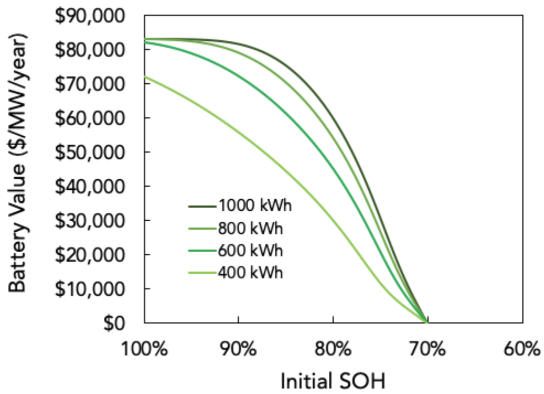


(d)

Figure 9: (a) The forecasted residual value of a 1 MWh Volvo Truck battery when reused in a Frequency Response application in the PJM electricity market, (b) the value of a used NMC battery versus a new LFP one, (c) a direct comparison between the NMC and LFP residual values, and (d) the impact of energy on the residual value of an LFP battery (1MW power).

Learnings from Phase 2; to build upon in future engagements.

- Modelled residual value is highly dependent on location and reuse-case: it is probably best to focus on expected early use cases in markets where Volvo's electric trucks are already on the road. The best use of these analytics is probably to compare regions, rather than derive an exact residual value, e.g. are there regions in the EU where a battery is 2x more valuable than others?
- The methods are useful for comparing technologies, e.g. the value of a new LFP battery system versus second-life NMC battery system.
- The residual value numbers are highly dependent on the electricity prices used, which are historical. Many battery purchasers will have their own assumptions on the future volatility and growth in electricity prices for their locations and use cases, and may want to adjust the electricity prices used in the modelling to fit their assumptions.
- Given the relatively easier cycling conditions in most reuse cases, where batteries are not cycled with the same dynamics as in a truck, the data-based degradation model is not as critical to early development as thought. While the most accurate residual values would be derived using data-based model like the one created in Phase 1, the improvements are likely to be minimal and not critical for decision-making on battery reuse, at least not until the market has scaled significantly, and the data-based modelling is working very well on a per vehicle or battery pack basis.

3. Potential Value

In the final phase of the POV, a number of different scenarios and battery lives are compared using financial models to quantify the benefit of Sensai Analytics' technology to Volvo Trucks.

A) Nearer-term value: Extending battery 1st-life through Li-ion battery aging digital services

A comparison is made between the lifetime value of batteries (present value of future revenues) where knowledge of the current SOH and an ability to forecast how it degrades versus different driving and charging behaviours is used to implement strategies to extend first-life, i.e. proactively extending 1st-life by managing charging behaviour, or providing dynamic pricing to encourage better behaviour. In a simple analysis, we model the scenario where the expected lifetime of a leased Class 8 Heavy Duty Truck is extended from 6 years to 8 years. In Table 3 below, we summarize the financial benefit of this to the lessor (e.g. Volvo Group). By assuming a simple monthly lease price of $4,000, the Lifetime Productivity of Vehicle 1 is $270,479 (including the estimated residual value for an 80% SOH battery pack sold into a CAISO arbitrage reuse case). Now assuming the lease is extended by 2 years, through the implementation of a strategy enabled by the analytics described in this project, the Lifetime Productivity of the Vehicle becomes $332,115, an increase of $61,636 or 23%. This translates to increased revenue of $7.76mn for 126 VNR all-electric trucks in California.

Table 3: Lifetime Productivity of two Vehicles considering extended lease financial modeling.

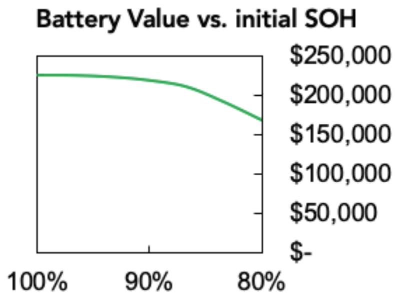
Year	1	2	3	4	5	6	7	8
Discount Factor (r = 6%)	1.000	0.940	0.884	0.831	0.781	0.734	0.690	0.648
Truck/Battery 1								
Lease revenue ($4000/month)	$48,000	$45,120	$42,413	$39,868	$37,476	$35,227		
Year-end SOH (%)	96.7%	93.3%	90.0%	86.7%	83.3%	80.0%		
Battery resale ($)	-	-	-	-	-	$22,375		
					Lifetime Productivity of Vehicle (present value)	**$270,479**		
Truck/Battery 2								
Lease revenue ($4000/month)	$48,000	$45,120	$42,413	$39,868	$37,476	$35,227	$33,114	$31,127
Year-end SOH (%)	97.5%	95.0%	92.5%	90.0%	87.5%	85.0%	82.5%	80.0%
Battery resale ($)	-	-	-	-	-	-	-	$19,770
							Lifetime Productivity of Vehicle	**$332,115**

B) Medium-term value: Increasing residual value

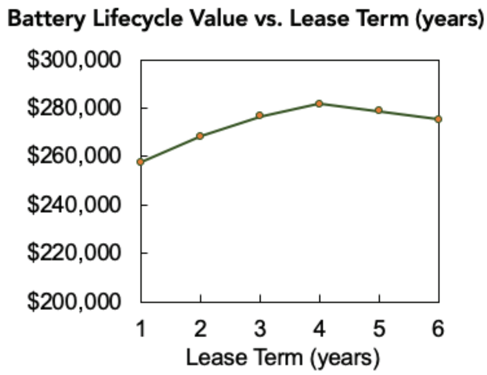
In the second case, a medium-term application of these analytics is considered, where the knowledge of residual value enables the optimum time for a battery replacement to be found, to maximize the Lifetime Productivity of a vehicle. In this case, we use the results from the frequency response modelling to calculate the residual value of the vehicle battery at the end of a vehicle lease term which we consider might run from 1 – 6 years (Table 4). The residual values are the present value of a 565 kWh battery used in a frequency response market for 5 years. The lease revenue we model is less than in A) above, at $2,780 per month, while the discount rate we consider is 8%. These values were chosen as they are required to demonstrate the optimum point of removal, and other values would often lead to analytics results that showed the best plan is to leave the battery in the vehicle for all 6 years. Nevertheless, the point of this exercise is to show that as certainty grows around battery residual values and leasing terms for Heavy Duty Electric Trucks, modelling the full financial lifecycle of the battery will be important to ensure optimum decisions are being made on battery life.

In Figure 10 (a), the battery residual value versus initial SOH is shown and starts at $260,000 for a new battery, decreasing to $170,000 for one with an initial SOH of 80%. Figure 10 (b) is a summary plot of the Lifetime Productivity (or Battery Lifecycle Value), using the values in the last column of Table 4. We can see that a vehicle which is leased for 1 year and then the battery sold, for $224,295 when SOH = 96.7%, will have a Lifetime Productivity Value of $257,628. The maximum Lifetime Productivity Value found, $281,681, is for a lease term of four years, and is 9% higher than the lowest value. Leaving the battery in the vehicle for longer than 4 years results in lower lifetime productivity values as the battery residual value starts to drop much more quickly as its SOH drops below 90% (Figure 10 (a)).

While these results are highly dependent on the assumptions made (but required given the early stages we are at in the electric truck and battery reuse markets), they show the importance of this kind of analytical approach in maximizing the value of vehicles and batteries across their lifecycles.



(a)



(b)

Figure 10: (a) Battery residual value versus initial SOH, and (b) the Lifetime Productivity of a vehicle/battery combination versus lease term.

Table 4: Lifetime Productivity of a Vehicle considering different leasing periods and battery residua values.

Year	1	2	3	4	5	6			
Discount Factor (8%)	1.0	0.92	0.846	0.78	0.716	0.66			
Lease Term	Annual Lease Revenue						Year-end SOH (%)	Battery Resale	**Battery Lifecycle Value**
1	$33,333						96.7%	$224,295	**$257,628**
2	$33,333	$30,667					93.3%	$204,522	**$268,522**
3	$33,333	$30,667	$28,213				90.0%	$184,565	**$276,778**
4	$33,333	$30,667	$28,213	$25,956			86.7%	$163,512	**$281,681**
5	$33,333	$30,667	$28,213	$25,956	$23,880		83.3%	$136,903	**$278,953**
6	$33,333	$30,667	$28,213	$25,956	$23,880	$21,969	80.00%	$111,316	**$275,334**

4. Summary & Next Steps

In summary, Sensai Analytics and Volvo Group successfully demonstrated the use of data-based forecasting of (i) battery capacity fade, and (ii) battery residual value in arbitrage and frequency response markets. The models achieved reasonable accuracy with learnings from both phases of the project indicating areas where either the modelling processes should be further tested, or adapted to better fit the needs of Volvo Group. These learnings have been discussed in length during the weekly project meetings and potential tasks for a second POV project are briefly described here, based on these discussions.

1. Data-based remaining useful life forecasting – online learning

Based on the learnings from this POV, the outline of a potential structure/pipeline for an online learning process for data-based remaining useful life forecasting of individual battery modules is presented in Figure 11. In Brief, four stages are shown which include (i) training a model offline using lab-measured data of battery capacity fade, which would be called the 'global model', (ii) use this global model to estimate and forecast the SOH degradation for in-vehicle modules, with the actual SOH returned by the vehicles compared to the forecast. In (iii), after the in-vehicle modules have degraded to ~95 SOH, a fine-tuning or re-training process is undertaken where data from the in-vehicle modules is used to fine-tune a copy of the 'global model' to create a 'local model', i.e. a model per module is created and re-trained with a smart weighting of the original lab-data and in-vehicle data from that module. In (iv), these new local models are put into production and used to forecast the RUL of individual modules in vehicles.
Of course, this is a simplified overview of how online machine learning could be used to create data-based models to solve the problems of Volvo Group, a consideration of many parts are excluded for now (e.g. combining all the in-vehicle data to fine-tune the original global model so it also adapts to the field data). Some of the most important components of this approach have been discussed at length in meetings and are described below. The testing of these would form the basis of a scope of work for a follow-on project.

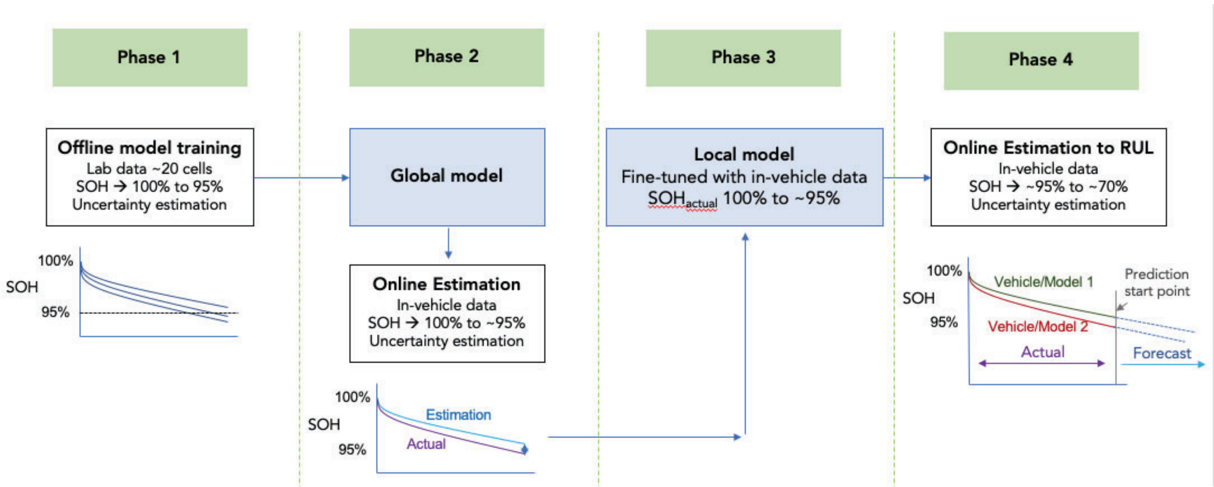


Figure 11: A simplified overview of an online machine learning pipeline for data-based RUL forecasting that combines lab and field data.

Important components to be tested in future engagements:

1. Dynamic data: further testing of these methods with dynamic data, similar to what will be recorded in vehicles, is required.
2. Confidence intervals: as described earlier, providing confidence intervals for predictions/forecasts are important and required.

3. Initialization: to date, all modelling has been done from initial SOH values of 100%, but in practice some electric trucks are already in the field, and in order to apply these methods to these vehicles it will need to be shown that modeling from an initial SOH < 100% also works.
4. Fine-tuning (creating local models): requires the testing of different model architectures available to Sensai, to find which is best suited to fine-tuning for this application, and what data-weighting process to use.
5. Finally, the feature engineering (i.e. histogram structure) would need to be adapted to match the data being collected in vehicles. Sensai have already run extensive experiments on the type and structure of histograms required for their methods to work, and have seen a wide range of possibilities, and don't see there being an issue matching one to Volvo Group's actual BMS data.

2. Data-based residual value forecasting

For any future engagement, Sensai would propose tackling the main learnings from the residual value phase of this project:

1. Adapt the approach to the best use of these analytics, i.e. comparing different regions/markets, to help focus sales efforts.
2. Continue with the approach that enables value comparison with new batteries.
3. Many battery purchasers will have their own assumptions on the future volatility and growth in electricity prices for their locations and use cases, enable easy adjustment of the electricity prices used in the modelling to fit their assumptions (this is more a UI problem for future sales tools but is noted here).