REGRESSION ANALYSIS OF LITHIUM-ION BATTERY DEGRADATION DATA

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Abstract: The focus of this research is to carry out regression analysis to discover the factors that significantly contribute to the life cycle of the lithium-ion cells using the degradation data. The research was conducted by investigating the batchwise degradation model of these cells which concludes that the degradation of the cells starts slowly and accelerates later. This was followed by creating a regression model to identify the relation between the charging policy and the average life-cycle of these cells.

Research Question/Motivation
Lithium-ion batteries are deployed in a wide range of applications due to their low and falling costs, high energy densities and long lifetimes. However, as is the case with many chemical, mechanical and electronic systems, long battery lifetime entails delayed feedback of performance, often many months to years. Accurate prediction of lifetime using early-cycle data would unlock new opportunities in battery production, use and optimization. One emerging application enabled by early prediction is high-throughput optimization of processes spanning large parameter spaces, such as multistep fast charging and formation cycling, which are otherwise intractable due to the extraordinary time required. The task of predicting lithium-ion battery lifetime is critically important given its broad utility but challenging due to nonlinear degradation with cycling and wide variability, even when controlling for operating conditions. [1]

Introduction
The data of 124 commercial lithium-ion cells charged under fast charging was used. The data was collected in 3 batches and 72 different fast charging conditions were used. All the cells were charged using one or two-stage charging. All these cells follow a C1(Q1%)-C2 charging policy where C1 and C2 are the applied rates and Q1 represents the SOC at which the current switches.

Research Methods
A batchwise degradation model was created on these cells after conducting a scaling on the discharge capacities. A point on each of these discharge curves was found where the degradation begins to accelerate, called the elbow point. Based on the data, a parametric equation of third degree was created for each of the discharge curves to study the behavior of the discharge curve better. The elbow point was used as a feature to predict the life-cycle of the cells. The main reason of using quantile regression is that the method allows for understanding relationships between variables outside the mean of the data making it useful in understanding outcomes that are non-normally distributed and that have nonlinear relationships with predictor variables.

Data Analysis
A multiple linear regression model with an R^2 value of 0.9346 was found using elbow point, C1, C2, Q1 and X1or2 (1 = one stage charging, 2 = two stage charging). A quantile regression model was also built at 5, 10, 50, 90 and 95 percentiles to compare it with the results of the multiple linear regression model. The results of the models are shown in Figure 2 and 3. Figure 2 shows the plots for the quantile regression model whereas Figure 3 shows the residual plots for the multiple linear regression model. Each black dot is the slope coefficient for the quantile indicated on the x axis. The red lines are the least squares estimate and its confidence interval. You can see how the lower and upper quartiles are well beyond the least squares estimate. It appears that the linear regression slope is not enough to describe the relationship between the variables and the response based on Figure 2.

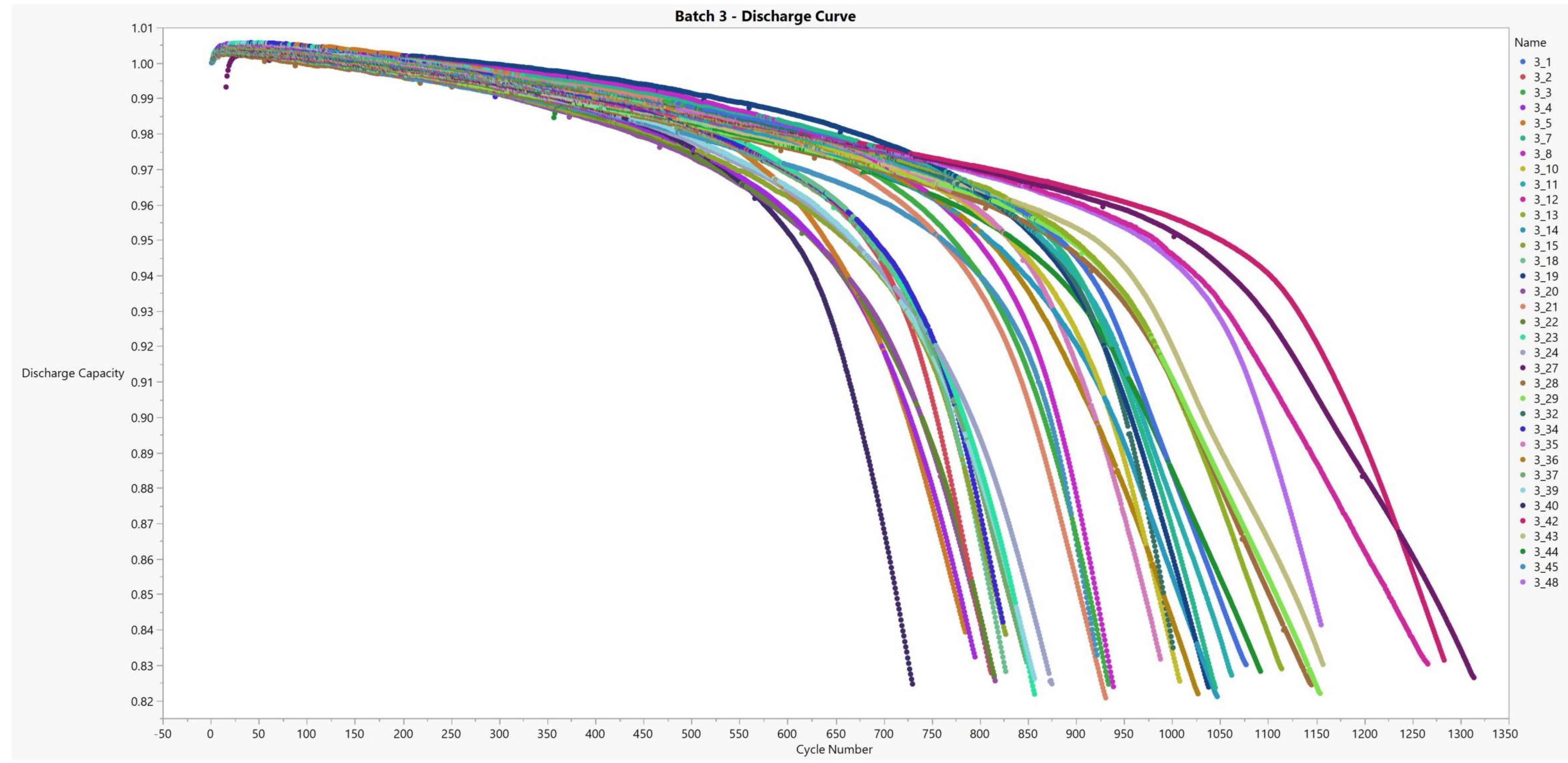

Figure 1: Discharge Curve (Batch 3)

		Quantile Regression				
Characteristic	**Linear Regression**	**5th**	**10th**	**50th**	**90th**	**95th**
Intercept	1329.838	216.44870	303.29650	525.95584	2635.42600	3059.57400
Elbow Point	2.186	2.11515	2.48803	2.67633	2.44818	2.44339
C1	-42.633	9.89451	4.98840	-7.63988	-38.69422	-32.97197
Q1	-85.454	-44.52409	-96.32932	-128.18337	-120.29580	-112.30640
C2	-84.488	-9.12593	-21.32199	-25.96251	-67.18808	-56.65509
Charging type	-258.929	-41.70022	-63.72632	-125.94095	-949.58930	-1195.22600

Table 1: Comparing results of linear and quantile regression model

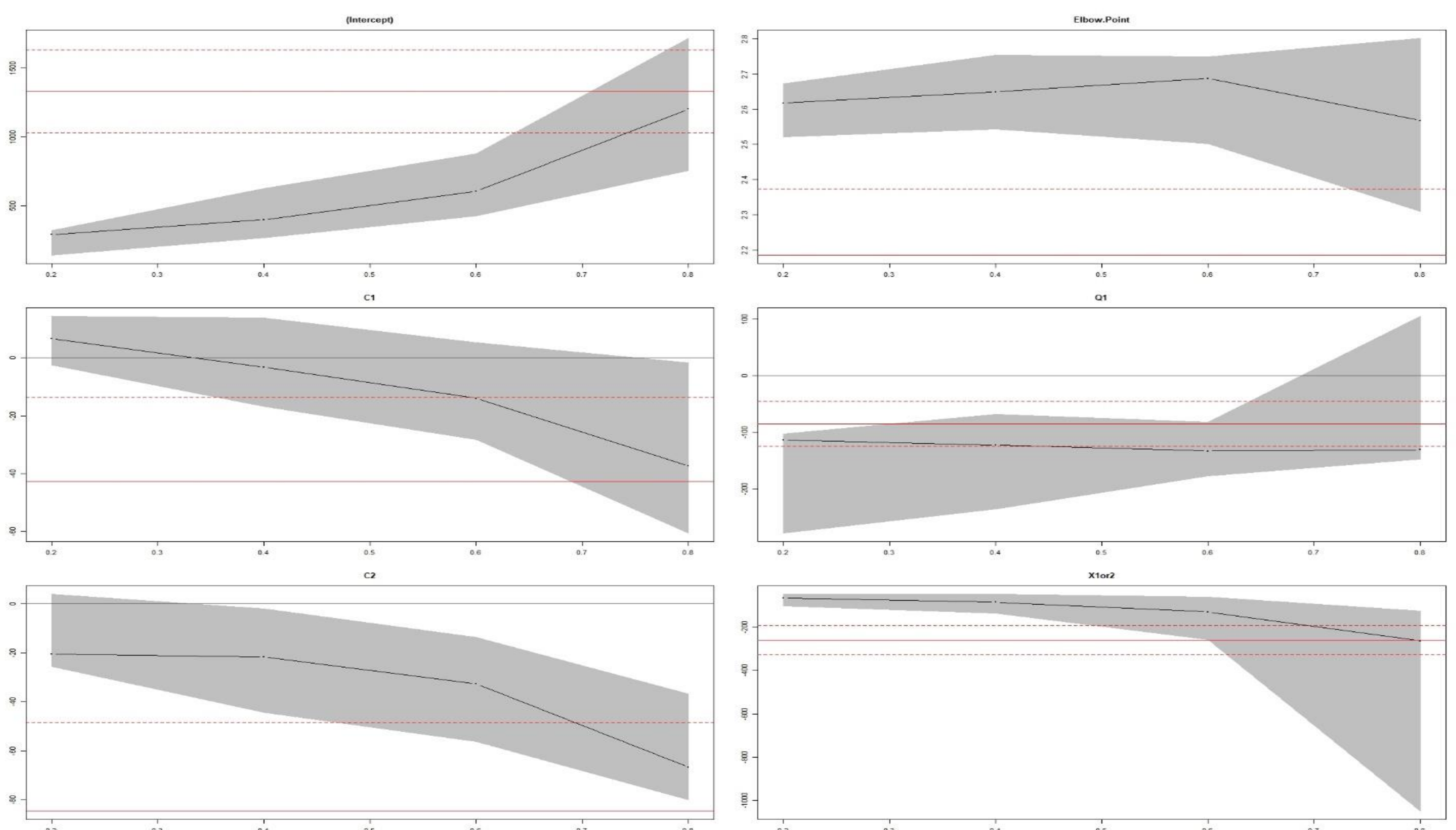

Figure 2: Quantile Regression Model Plots

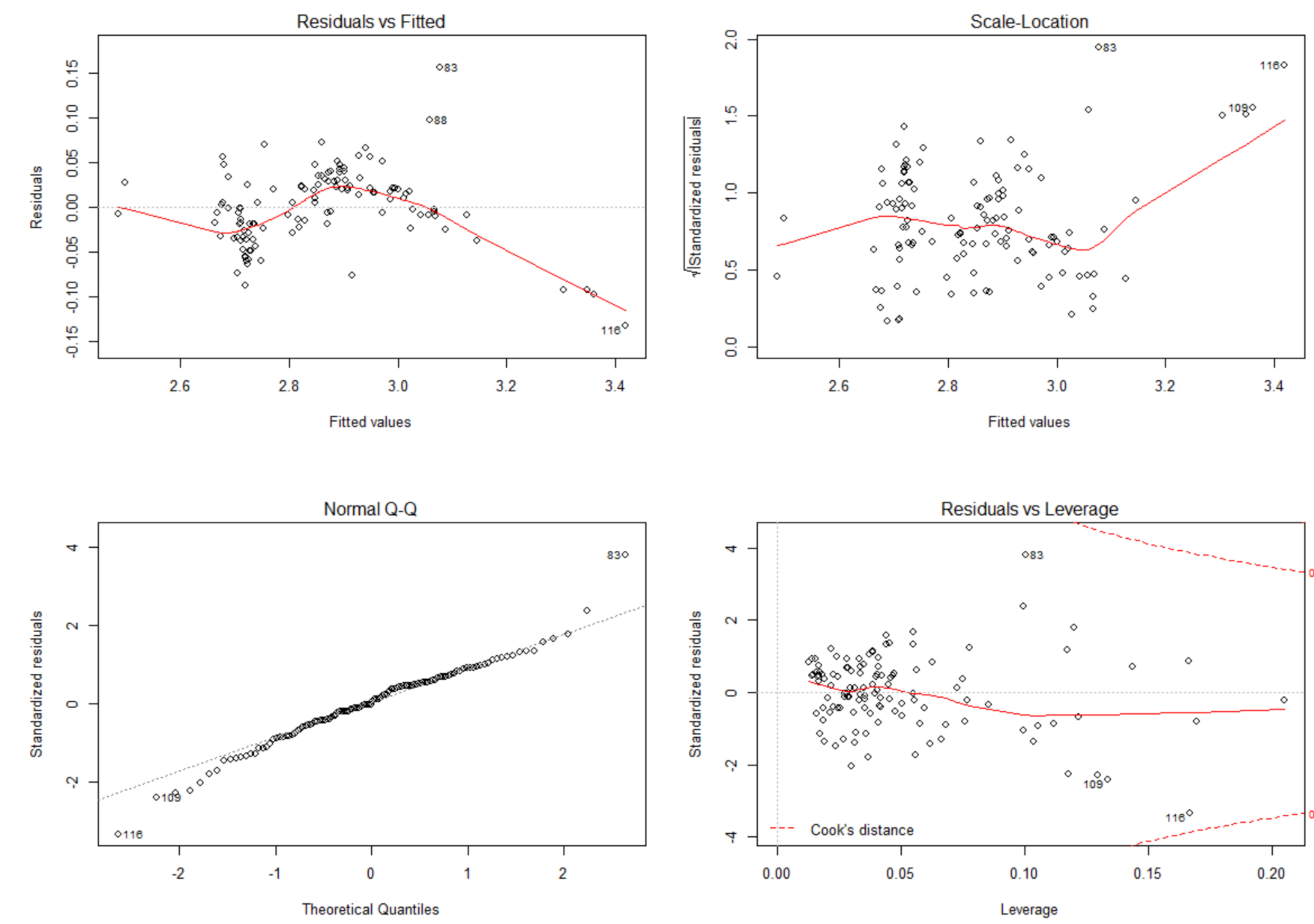

Figure 3: Residual Plots for Multiple Linear Regression Model

Obstacles faced/overcome
Initially, the batchwise degradation model faced difficulty due to the data complexity but using feature scaling and choosing the maximum discharge capacity per cycle number solved it. Finding the elbow point using the discharge data was a failure as the data collection had some issues. So instead of using the discharge curve data, the parametric equation was used in order to find the elbow point. Normality assumption was a problem which was dealt with using logarithmic transformation on the Life Cycle in the regression model.

Findings and progress thus far
The batchwise degradation model was successfully created which explains the behavior of these cells. Elbow point for each of the discharge curves was estimated. The elbow point was used as a feature to predict the life-cycle of the cells. A multiple linear regression model with an R^2 value of 0.9346 was found using elbow point, C1, C2, Q1 and X1or2 (1 = one stage charging, 2 = two stage charging).

Conclusions
Based on the regression model, it is clearly seen that the elbow point and charging policy are significant in predicting the life cycle of the cells. The quantile regression plots indicate how these variables affect the Cycle Life which highlights that linear regression might not be an optimal solution to access the relationship. On comparing the models, we can conclude that the linear regression model underestimates the variables at the 5th quantile.

References
[1] K. A. Severson, P. M. Attia, N. Jin, N. Perkins, B. Jiang, Z. Yang, M. H. Chen, M. Aykol, P. K. Herring, D. Fraggedakis, M. Z. Bazant, S. J. Harris, W. C. Chueh, R. D. Braatz, "Data-driven prediction of battery cycle life before capacity degradation", *Nature Energy 4,* 383-391 (2019)