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Laplacian Kernel Ridge Regression for Novel Non-Linear Battery State-of-Health Estimation in Electric and Hybrid Vehicles

Riley Orr and Rawa Adla
Undergraduate Student and Associate Professor
Department of Electrical and Computer Engineering
Florida Polytechnic University
Lakeland, FL, USA
rorr2511@floridapoly.edu, radla@floridapoly.edu

Abstract

Due to the increase of greenhouse gases causing climate change, many industries are beginning to make changes to their designs and processes. The automotive industry has responded with (hybrid) electric vehicles (EV's) which either improve gas mileage or forgo it all together. Opting to use grid power stored by lithium-ion batteries (LIB's) chosen for the energy density, lifespan, and reliability. These LIBs are operated by a battery management system (BMS) which measures and reports battery data while maintaining operational ranges for the LIB. State-of-Health (SOH) is one key metric in BMS that represents a percentage which relates to the maximum capacity of a LIB versus it's rated value. Many different methods of SOH estimation have been developed using electrochemical models, equivalent circuit models, open-circuit voltage, and coulomb-counting, all of which struggle due to constant need for recalibration to maintain accuracy. Recent research has begun to apply machine learning (ML) to the SOH problem utilizing numerous algorithms reliant on neural networks (NN), gaussian process regression (GPR) or Support Vector Machines (SVM). This paper introduces Laplacian Kernel Ridge Regression (LKRR) as a novel solution to estimate the SOH. The research results show that the proposed method is robust, accurate, and requires lower training costs than other ML techniques for medium-sized datasets.

Keywords
State-of-Health, Electric Vehicles, Machine Learning, Artificial Intelligence, Kernel Ridge Regression

1. Introduction

Electrification is underway in many industries, namely, the automotive industry with Hybrid and Electric Vehicles (EV's). Primarily Hybrid Electric Vehicles (HEV's), but EV's are on the rise in not only the United States but the entire world (Kapustin et al. 2020). This is exemplified by the declaration at COP26 held in the United Kingdom which states that they aim to have 100% of new cars electric by 2040(n.d.). As this continues, the reliance on Lithium-Ion Batteries (LIB's) is also increasing extremely fast. LIBs are the battery of choice because of their energy density, lifespan, and discharge rate largely attributed to the high reactivity of lithium Ion batteries (Roberts et al. 2011; Scrosati et al. 2010). To control and maintain the safety and reliability of battery systems, EV's and power grid level batteries utilize battery management systems (BMS)(Tran et al. 2022). These systems are used to measure the voltage, current, and temperature of each module in a battery pack which allows the system to limit output so that it stays within operational ranges. Many modern systems also attempt to estimate state-of-charge (SOC) and state-of-health (SOH) which provide information such as the percent of a phones battery life (SOC) and the 'age' of the battery (SOH)(Mahmoudzadeh Andwari et al. 2017).

With the evident need for low-cost, accurate, SOH and SOC estimation for design of optimal BMS's, the need for accurate, interpretable, and low-cost algorithms arises.

1.1 Objectives

This research study aims to enhance the accuracy of State-of-Health (SOH) estimation while providing a robust solution that significantly improves computational speed. By demonstrating the effectiveness of Kernel Ridge Regression (KRR) in battery SOH estimation, the study will highlight both high computational speed and accuracy, making it a highly competitive approach.

2. Literature Review

Efforts made to estimate the state-of-charge and similarly the state of health primarily come in three categories, open-circuit voltage models which simply plug into a table, equivalent models based on the underlying characteristics like the electrochemistry or an equivalent circuit, and the center of much recent attention is machine learning/artificial intelligence to tackle the problem. Each having their own issues hybrid models utilizing two or more have become the note some recent research at the cost of added complexity(Xu et al. 2020).Many of these methods have been primarily focused on the State-Of-Charge (SOC) which in simple terms is percentage of charge left, similar to what is shown on a cellphone. Where the Depth-Of-Discharge (DOD) provides the percentage that has been depleted thus far. State-of-Health (SOH) is a little different in that rather than compare the current capacity to the rated capacity, the measure compares the battery at 100% capacity now to the battery at its rated capacity(Dini et al. 2024). Keeping this in mind as a battery degrades the more accurate representation of SOC would be shown by the equation 2.3. Equations 2.1 and 2.2 are calculated from the C_{left} or the capacity left in the battery at the present time; C_{rated} which is the rated capacity or the capacity of a brand-new battery; and C_{max} which is the maximum capacity or fully charged capacity of the battery at a given time. It should also be noted that the relationship between SOC and SOH is also the same as the maximum SOC of the battery at a given time.

$$SOC = \frac{C_{left}}{C_{rated}} \cdot 100\% = 100\% - DOD \; \#(2.1)$$

$$SOH = \frac{C_{max}}{C_{rated}} \cdot 100\% \; \#(2.2)$$

$$SOC = SOH - DOD \; \#(2.3)$$

One of the first and most intuitive methods to attempt at estimating this is known as Coulomb-counting or the ampere-hour method. This operates on the principle that capacity is the amount of charge stored in a battery which can be found by the integral of current with respect to time (Ng et al. 2009; Movassagh et al. 2021; Xiong et al. 2020).Then, the DOD is given by equation 2.4 where I_b is the measured current through the battery

$$DOD = \int I_b dt \; \#(2.4)$$

At the same time, Open-Circuit Voltage methods are another common method of estimation which relies on one of three methods to estimate SOC from the open circuit voltage of the battery. These are tables, sigmoid functions, or polynomial functions (Dini et al. 2024). Both, coulomb-counting and open-circuit voltage run into errors resulting from degradation and a need for constant recalibration.

Alternative algorithms to estimate state-of-charge (SOC) and state-of-health (SOH) have been designed using empirical models based on electrochemistry or equivalent circuits to represent the behavior of a battery. From an Electrochemical standpoint the primary equations are the Sheperd model and the Nernst equation(Lihua Liu et al. 2020; Marcicki et al. 2013; Moussa et al. 2022). As for equivalent circuits, for batteries and other electrochemical devices the equivalent circuit is generally a simple RC circuit which allows for low-cost matrix math(Lai et al. 2018). In most systems, SOC estimation is prioritized for multiple reasons. First, it addresses a more immediate problem, it is required for the EV system to provide information to driver whether the target destination within the available range or not based on the current SOC. on the other hand, SOH is a metric more suited to determine whether a battery replacement is needed as it shows how the battery has degraded over time(Yu et al. 2015). Secondly, the solution is more straightforward for SOC than SOH because there is more data available for SOC and updated regularly. whereas, SOH is more long-term related to the batteries life-cycle therefore less data is generally available for the SOH (Tao et al. 2024).

Recently, due to the increased complexity of measuring SOH, machine-learning (ML) and artificial intelligence (AI) are commonly used for this task(Dini et al. 2024). This is a broad field with many different algorithms used having pros and cons suited for different datasets depending on the amount of data, the datatypes, the number of inputs, training times and costs, the type of relationships for which the method tends to be accurate, tendency to over/underfit and overall accuracy and robustness.

Neural Networks (NN) are a now broad topic in the field of artificial intelligence with numerous algorithms associated. In general, a NN consists of an input layer, an output layer, and one or more hidden layers each of which have one or more nodes or neurons (Abiodun et al. 2018). Modeled after the way the human brain operates NN connects these neurons with weights for both the path, and the node itself(Islam et al. 2019). This can be modified via different activation functions and optimization algorithms(Dongare et al. 2012). Some popular NN's for SOH applications are Back-Propagation NN (BPNN), Long Short-Term Memory (LSTM), Radial Basis Function NN (RBFNN), Extreme Learning Machine (ELM), Deep Neural Network (DNN), Nonlinear Autoregressive with eXogenous inputs (NARX), and Convolutional Neural Networks (CNN)(Ren et al. 2023).

Issues with all NN are that in small to medium datasets (<10k samples) they have a strong tendency to overfitting due to the unique ability to model extremely complex equations so the quality and quantity of the data is incredibly important to the performance of any resulting NN models(Livingstone et al. 1997). This compounded by the long training and prediction time due to the computational intensiveness of NN and lack of interpretability make the family of ML algorithms less attractive of a solution (Ray 2019). One exception to the previous statement is ELM's this is because the solution is a single feedforward algorithm which is both extremely quick and precise but with these benefits the tradeoff is similar extremes in overfitting to the data leaving a fragile solution which often does not generalize to new samples which is why many of the works which utilize it aim to use ELM to improve other models in computation speeds or to improve on ELM generalization with a novel corrective measure(Lin Chen et al. 2021; Hung-Yi Chen et al. 2017).

To improve on the downsides of NN, other methods have recently become popular for use in SOH prediction. These are Support Vector Regression (SVR) and Gaussian Process Regression (GPR)(Zheng Chen et al. 2018; Ozcan et al., 2016). The promise behind the two methods is that in small to medium datasets, they can still produce accurate and robust predictions which outperform NN based methods while having reduced computational complexity which is shown by the tendency to use small private datasets or datasets of only 3-4 batteries from NASA compared to NN papers which generally compile data from many different datasets(Ren et al. 2023). SVR is a generalization of Support Vector Machines (SVM) which is a linear classification algorithm to do regression that has the ability to use one of many 'kernels' which map non-linear, multivariable data to a linear mapping that the SVR algorithm can use(Zhengyu Liu et al. 2020; Li et al. 2020). The kernel which is most commonly used with SVR is the Radial Basis Function (RBF) this because it is unique in mapping many different non-linear functions accurately even with small datasets which works by essentially returning the Euclidean distance of any given input to some constant point(Buhmann, 2000). GPR instead assumes that in a continuous domain such as time that the input variables and resulting output follow a multi-variable normal (gaussian) distribution and conducts the regression as a sum of gaussian processes which has proven to be quite accurate(Lyu et al. 2020).

This work proposes the use of Kernel Ridge Regression (KRR), which, like SVR in that it is a linear regression model capable of utilizing kernels to map non-linear data.One such popular kernel is the Radial Basis Function RBF kernel. One attractive kernel is the Laplacian Kernel (LK) which cannot be used with SVR because it does not meet the Mercer condition a requirement for SVR(Jenssen et al. 2004; Steinwart et al. 2012; Vapnik, 1997). However, KRR does not have this limitation because Ridge Regression is a least-squares model with a penalty term that balances coefficients and improves performance (McDonald 2009a). This allows KRR to be faster and more precise than SVR at medium sized datasets (1k-10k samples) and might be considered as a simplified version of SVR(Rezaei et al. 2023). The additional benefit is the use of the LK as it is similar to the RBF kernel but instead of the exponent of Euclidean distance squared LK is the exponent of Manhattan distance which is the distance as described on a grid rather than the hypotenuse (Sharma et al. 2016).

Overall, the Laplacian Kernel Ridge Regression (LKRR) provides higher performance with high computational speeds which makes a novel, competitive solution compared to other models and algorithms. The rest of this paper will describe the techniques used to implement the LKRR algorithm as well as evaluate its performance against other methods.

3. Methods

The LKRR method utilized in this paper is implemented as follows. The time series data is split into cycles, specifically focused on charging cycles as they are much more consistent primarily discussed in Data Collection, but the aim is to not have use data from the highly variable discharge cycles. From the charge cycles the health indicators were calculated as described in Table 1 do make a new dataset with each of the following health indicators which are stored per cycle per battery.

Table 1. Investigated Health Indicators and the associated calculation

Health Indicator	**Calculation**
Previous SOH	SOH(cycle-1)
Sample Energy	$\int V * I dt$
Constant-Current Charging Time	max(t) where I(t) = 1.5A
Maximum Temperature	max(temperature)
Nominal to Threshold Voltage Time	t(V=4.2V) – t(V=3.8V)
Average Incremental Capacity	mean($\frac{I*dt}{dV}$)
Maximum Voltage Change	max(dV)

The Health Indicators (HI) from Table 1 are compared using grey correlational analysis because of its ability to give correlation for non-linear relationships(Tosun, 2006). Highest 3 performing parameters are then used as input features for the Laplacian Kernel Ridge Regression (LKRR) through the Sci-Kit Learn Library(Pedregosa et al., 2011). Grey Correlational coefficients are calculated via the following equations for a dataset with column X_0 as the ideal set and column or columns X_K where both columns are the same length. The Grey Relational Coefficient (GRC) is(Ju-Long, 1982) is calculated via equation 3.1. This works summing the minimum and maximum difference in SOH and the health indicator that is being evaluated, this is then divided by the sum of the current difference between SOH and the health indicator with the maximum difference. The resulting value, especially the average across the entire dataset, gives a strong indication to how well the dataset's are correlated where a higher value shows a stronger relation.

$$\gamma_{0k}(j) = \frac{|x_0(j) - x_k(j)| + \rho|x_0(j) - x_k(j)|}{|x_0(j) - x_k(j)| + \rho|x_0(j) - x_k(j)|} \#(3.1)$$

From this analysis the GRC for different indicators are calculated and the comparison results are presented in Table 2 as the basis to decide what Health Indicators are used in the model as input features.

Table 2. Grey Relational Coefficient

Feature	**Grey Relational Coefficient**
Previous SOH	0.98396302
Constant Current Charging Time	0.785264299
Sample Energy	0.783669334
Maximum temperature	0.778816864
Nominal to Threshold Voltage Time	0.735747666
Cycle	0.641666402
Maximum change in Voltage	0.590575114
Average Incremental Capacity	0.514613874

This shows that of the HI chosen the highest performing were previous SOH, Constant Current Charging Time, and Sample Energy, therefore this will be used for Laplacian Kernel Ridge Regression modeling.

Ridge regression is derived from a least squares regression model. In simple terms, it introduces a parameter α multiplied by the Euclidian distance of the weight vector to the origin. The purpose of this is to encourage solutions with smaller weights that reduce the tendency to overfit(McDonald 2009b). The equation which the regression looks to minimize is given in equation 3.2(Pedregosa et al., 2011). The equation is the squared Euclidean distance from prediction to actual plus α times squared Euclidean distance from the weight vector to the origin which prioritizes solutions with smaller weights.

$$||y - Xw||_2^2 + \alpha||w||_2^2 \ \#(3.2)$$

Reducing the tendency to overfit is crucial in making a robust model to prove more accurate for general systems such as the slight differences which will apply to every battery. This algorithm is a linear regression however which is where the Laplacian Kernel comes into consideration. Similar to but lower in computational cost to the radial basis function kernel, it maps the input features so that the ridge regression may be applied. Equation 3.3 which governs this kernel is shown(Pedregosa et al. 2011; Fadel et al. 2016). It maps the input vector x to instead be the Manhattan distance instead of Euclidean distance, this is the distance in a grid-like format rather than the shortest path. This is then the exponent to the -γ of this distance which is useful for mapping non-linear relationships in a method less computationally expensive than the similar radial basis function.

$$K(x, y) = exp\ exp\ \left(-\gamma||x - y||_1\right) \ \#(3.3)$$

The proposed model is the minimized ridge function of the Laplacian mapped input features which is using equation 3.3 to map the X in equation 3.2 to a form which is linear and can be regressed properly using the linear method of equation 3.2. The input features for the proposed model is just as important as the algorithm itself. The health indicators proposed for LKRR is discussed in the following data collection section explaining how and why they are derived from the dataset.

4. Data Collection

For this proposed model, the data inputs are integral to its performance both in criteria and in the quality and quantity of data. For determining the SOH of batteries, the NASA Ames Prognostic Data Repository was chosen to conduct this study and analysis. This data is available publicly and it was used for multiple research studies(Saha et al. 2007). This dataset is collected from multiple 18650 lithium-ion battery cells discharged to different voltages via different load conditions and then recharged in many cycles until there is a 30% fade in capacity. In this case like most charging cycles, it is made up of a constant current period until threshold voltage is reached then constant voltage until fully charged(Cope et al. 1999).

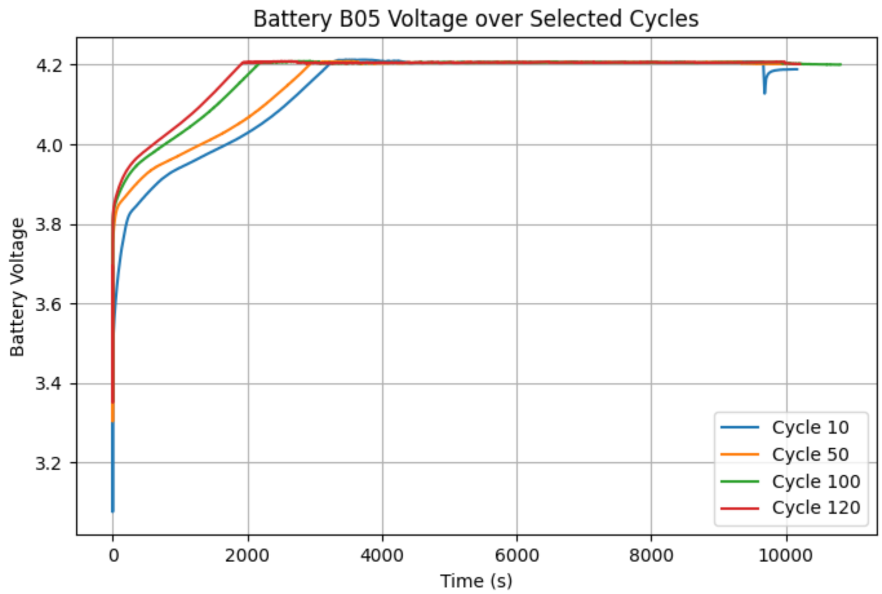

Figure 1. Voltage-Time curves of selected charge cycles.

Figure 1 shows charging cycles 10, 50, 100, and 120. With each of them there is a sharp rise in voltage until a plateau at 4.2V which is the threshold voltage. The period prior to the threshold is the constant current (CC) period of charging and a previously explored health indicator(Zhengyu Liu et al. 2020). This is important as in real-world applications the discharge and load are often dynamic and unpredictable whereas charging is more consistent. Therefore, for SOH estimation it should be thought to use the much more predictable charging period for battery health indicators. However, the period of constant voltage (CV) is not as clear in its differences as the cycle converges and are distinguished by the time at which CV begins shown in figure 2.

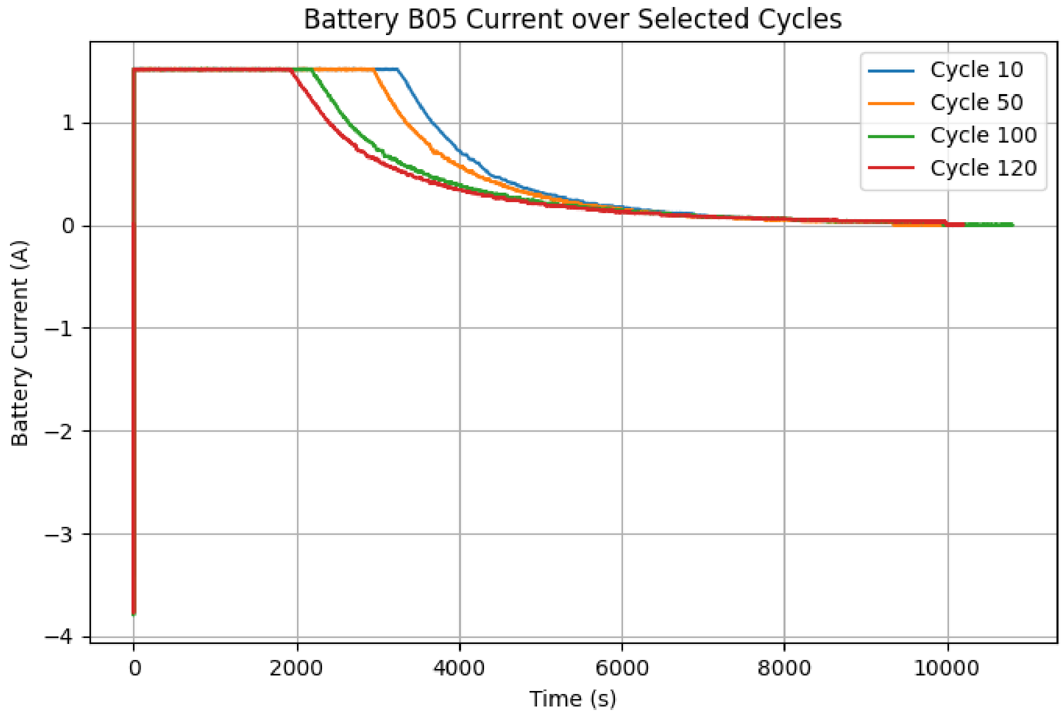

Figure 2. Current-Time curves of selected charging cycles.

From the charging cycle data, health indicators (HI) are calculated. The chosen indicators are based in the literature of similar models namely SVR and GPR. This is the previous SOH because as a dynamic system the SOH is simply a change from the previous SOH cycle over cycle shown in Figure 3. It is important to note that this change is not a linear change and thus related to more than just the number of cycles. The health indicators explored are Sample Energy, Constant-Current Charging Time, Maximum Temperature, Nominal to Threshold Voltage Time , Average Incremental Capacity, and Maximum Voltage Change. To get this information from the public dataset, it was first extracted from the MATLAB files into more useable CSV files. This was then cleaned and all calculations to get the appropriate data was done utilizing the pandas library(team 2024). Table 1 describes each of these HI and how they are calculated.

5. Results and Discussion

5.1 Numerical Results

As a regression algorithm there is only a single training stage which is made up of a single matrix calculation to solve for the minimum of equation 3.2 with the inputs of the previous SOH, Constant Current Charging Time, and Sample Energy after mapping through the Laplacian kernel detailed in equation 3.3. All numerical results are saved in Comma Separated Value files for ease of use across any software which one may use for modeling or data analysis. The input features were organized in a .csv file which followed the format shown in Table 4.

Table 3. Input feature data structure

Index	**Cycle**	**Energy**	**SOH**	**CCCT**	**Previous SOH**
1	2	19448.42	0.923164	3230.344	0.928244
2	3	19426.66	0.917675	3227.312	0.923164
3	4	19374.24	0.917631	3217.812	0.917675
4	5	19357.76	0.917323	3216.812	0.917631

5.2 Graphical Results

After LKRR was trained, it was then used to predict battery 5 of the dataset and plotted alongside the error using Python.

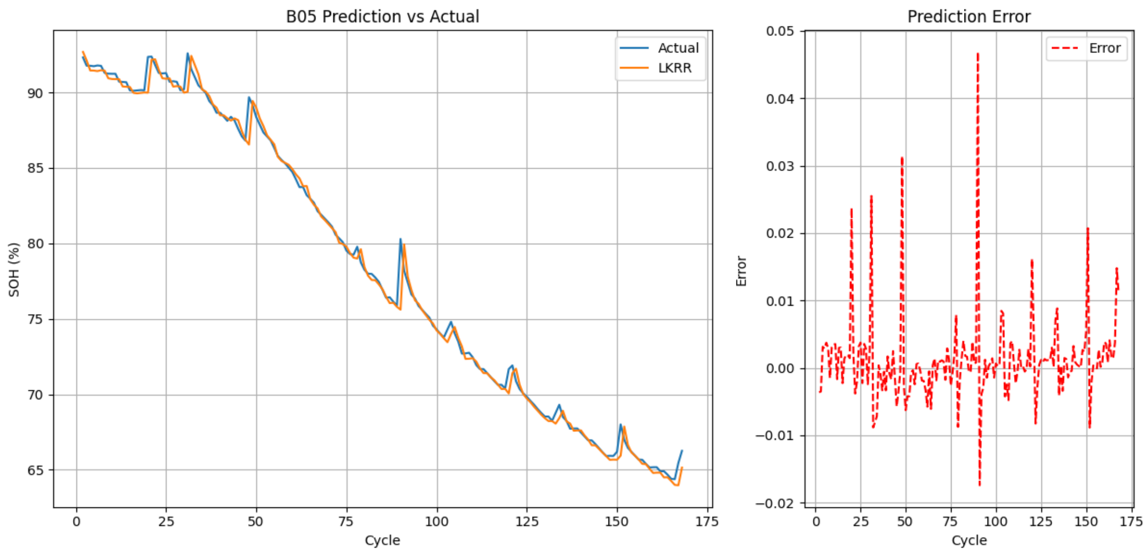

Figure 3. Battery 5 from the dataset model performance.

Battery 5 was used as a testing set to see the performance across the entire life cycle of one of the batteries in the dataset and shown in Figure 3. It provides some strong insights, namely that the error appears to peak when capacity regeneration occurs but that the overall accuracy is quite high and maintained across all 168 cycles of battery 5.

5.3 Validation

To validate the proposed model, a comparative study and evaluation of the results against various machine learning approaches for modeling and estimating SOH were conducted. As shown in Table 3, the performance of LKRR surpasses that of all other ML techniques. The results demonstrate that LKRR outperforms every other tested model in terms of computational speed, accuracy, or both

Table 4. Comparison of Different ML approaches to SOH modeling

Model	**Training Time (s)**	**RMSE**	**MAPE**
LKRR	0.40626	0.006383	0.462995%
RBFKRR	0.507938	0.006964	0.609729%
SVR (RBF)	0.029814	0.033095	4.23804%
BPNN	0.114332	0.012089	1.194684%
DNN	36.26392	0.010515	0.996792%
ELM	0.027235	0.006838	0.536083%
LSTM	26.7764	0.020243	2.528927%
GRU	31.9896	0.011967	1.308369%
GPR	1.957377	0.006920	0.518487%

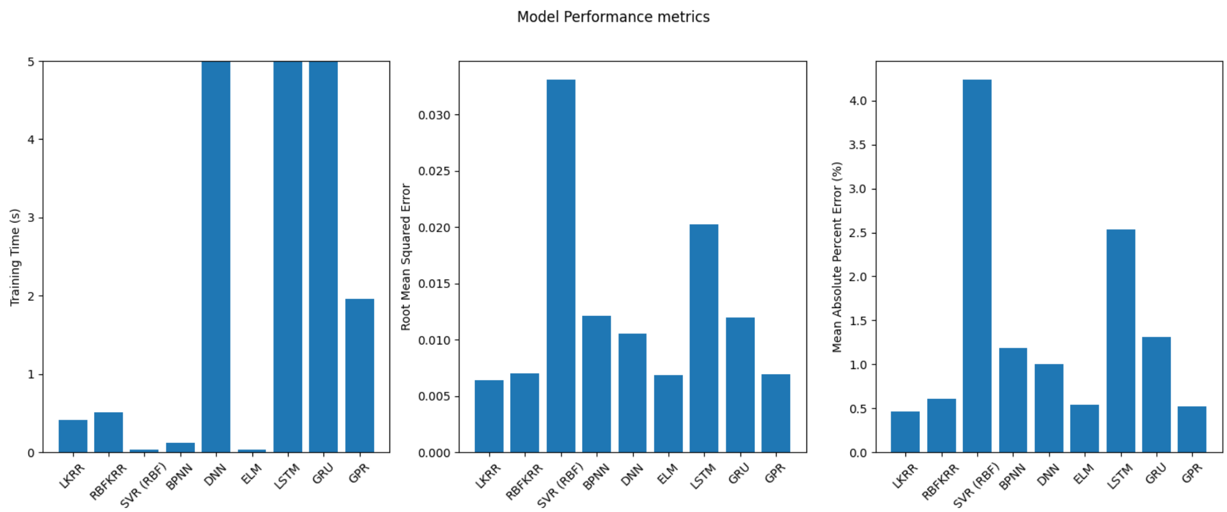

Figure 4. Model performance metrics, note that for training time, the limits were set to 5 seconds so details of the higher performing models are distinguishable**.**

The models are compared in terms of Training Time (s), which is the inverse of computational speed, Root Mean Squared Error (RMSE) but less so in terms of Mean Absolute Percent Error (MAPE) shown in Table 3. Back Propagation Neural Network (BPNN) while faster for the dataset, is not as accurate. Extreme Learning Model (ELM) and Gaussian Process Regression (GPR) prove the most competitive however GPR falls short of Laplacian Kernel Ridge Regression (LKRR) in all metrics, whereas ELM is both faster and comparable in accuracy. SVR falls short on accuracy despite bosting such low training time. LKRR proved the most accurate of models shown given the chosen input features. With the use of the RBF kernel, the Radial Basis Function Kernel Ridge Regression (RBFKRR) proved competitive however, still slower and less accurate compared to the Laplacian Kernel model as illustrated in Figure 4.

6. Conclusion

As global industries and markets become more dependent on lithium-ion batteries for energy storage and portable devices, improved battery management systems are required to keep these processes and products affordable, reliable, and safe. One of the metrics which is of the utmost importance is state-of-health as it largely determines when the battery must be replaced for a system to maintain safety and performance. Detailed in this paper, a Laplacian Kernel Ridge Regression based State-of-Health model was developed and evaluated. The results demonstrate the model efficiency, high accuracy and low-computational cost for SOH estimation in Battery Management Systems. Future work should aim to improve pre-processing via filtering techniques, and to explore real-world system implementations.For future improvements to this work, simple, efficient, filtering methods should be explored to better account for sensor errors. Further understanding of the causes of capacity regeneration may also provide a solution to find metrics that are based on the electrochemical model of LIB's.

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Biographies

Riley Orr is an undergraduate student of Electrical Engineering at Florida Polytechnic University. Currently enrolled in the 4+1 Masters of Electrical and Computer Engineering Program, regularly conducting undergraduate research at a number of institutions on a large variety of topics. With interests in sustainability he has conducted research on modeling food waste behavior patterns as well as produced electrochemical sensors for microplastics and forever chemicals utilizing advanced nanomaterials. He has been awarded with funding and grants from the US Department of Agriculture, the US Department of Energy, and the National Science Foundation as well as apprenticeship from NASA L'SPACE.

Rawa Adla, Ph.D. is an Associate Professor of Electrical and Computer Engineering at Florida Polytechnic University. She is a professional in Intelligent Transportation Systems (ITS), bringing together a strong blend of academic and industry experience in the field. Her research interests encompass ITS, autonomous vehicles, connected vehicle technologies (V2V, V2I, V2X), electric vehicles, and battery systems. Her work focuses on developing, analyzing, and testing innovative methodologies aimed at improving traffic safety, enhancing transportation system efficiency, and advancing the performance of electric vehicles and battery technologies.