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Li-Ion Battery Capacity and State-of-Health Prediction through Novel Kolmogorov-Arnold Networks (KANs)

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***Abstract*—** Based on the pressing need for fast, reliable estimates of capacity and State-of-Health (SOH) in electric-vehicle lithium-ion batteries, this study set out to test whether Kolmogorov-Arnold Networks (KANs) can outperform the multilayer perceptron (MLP) models that dominate current battery-management research. Through the NASA AMES PCoE dataset—which tracks four cells (B0005, B0006, B0007 and B0018) from initial charge to end-of-life—we trained shallow and deep KAN architectures alongside depth-matched MLP baselines. Each model received 24 historic cycles and was asked to forecast the future 10 cycles. KANs performance was gauged with mean-absolute error (MAE) and root-mean-square error (RMSE). The experiments show a consistent edge for KANs. On battery B0005, the deep KAN cut capacity-forecast MAE to 0.014 and RMSE to 0.015, versus 0.023 and 0.030 for the deep MLP. Across all four cells, the deep KAN lowered capacity MAE by an average of 36 % and SOH RMSE by 30%. Shallow KANs also surpassed their MLP counterparts, though by smaller margins, confirming that the spline-based adaptive links inherent to KANs not merely by increasing depth but also in driving the improvement. Combined, these results demonstrate that KANs deliver more accurate, more data-efficient and easier-to-interpret forecasts than conventional MLPs. The specific gains—up to 0.009 absolute MAE and 0.015 absolute RMSE on individual batteries—suggest that replacing MLP blocks with KANs can immediately enhance real-time battery-management systems without inflating model size or computational cost.

***Keywords*—** Li-Ion Battery, Kolmogorov Arnold Networks (KANs), Deep Learning, Machine Learning, Time Series Forecasting.

I. INTRODUCTION

The The big push towards electric transportation has really cranked up the demand for reliable and efficient ways to store energy [1]. Leading the charge here are Lithium-ion (Li-ion) batteries, which have become the go-to technology for meeting these needs [2].

Li-ion batteries are utilized because they pack a lot of energy into a small space (high energy density), last through many charge cycles (long cycle life), and don't lose charge quickly when sitting idle (low self-discharge rate). That makes them pivotal for everything from electric vehicles (EVs) and storing renewable energy to the portable gadgets we use every day [3].

But as we rely on these batteries more and more, figuring out how healthy they are and how well they're performing has become quite critical. Getting this right helps keep things running reliably, improves safety, and cuts down on repair costs [4]. At the heart of the systems managing these batteries (called Battery Management Systems, or BMS) is the need to accurately estimate two key things: the battery's "State of Health" (SOH) and how much charge it still has left (remaining capacity) [5].

SOH is a measure of how much the battery has degraded compared to when it was brand new; it basically tells how much useful life it has left. Predicting SOH and capacity accurately means operators can plan how to use the batteries in a smart and efficient way and perform scheduling before arrival of potential problem and thus avoid sudden failures that could cost money or even be dangerous [6].

The main challenge is that even though knowing these parameters are crucial, one can't just directly measure SOH or remaining capacity while the battery is in service. The current ways around this usually involve either complicated electrochemical models or making educated guesses based on parameters that can be measured such as voltage, current, temperature, and impedance [7]. Over the past ten years, researchers have come up with variety of different methods for estimating SOH and predicting battery capacity [8]. These generally fall into two main groups: model-based and data-driven approaches.

Model-based techniques rely on detailed models of how the battery works physically or chemically. They've had some success, but they often need a lot of expert knowledge, serious computing power, and very specific details about the battery itself. This makes them hard to scale up or adapt easily to different real-world conditions [9]–[11].

Data-driven methods, on the other hand, use machine learning (ML) such as Artificial Neural Networks (ANNs) [12], Recurrent Neural Networks (RNNs) [13], LSTMs [14], and GRUs [15]. These algorithms have proved over time that they can be flexible, make accurate predictions, and learn general patterns from past data. However, these ML models often have complex setups with multitude of parameters, meaning they require plethora of computational power for training and making quick predictions [16]. Plus, traditional neural networks often act like "black boxes" – it's hard to tell why they make a certain prediction [17]. This lack of transparency makes it tough to rely on them completely, especially in safety-focused applications such as managing batteries in cars, where regulations are strict.

To tackle these issues, the latest innovations in deep learning aren't just trying to make predictions more accurate; they're also working on making the models easier to understand (more interpretable) and more efficient to run [18].

One exciting new development is Kolmogorov-Arnold Networks (KANs). This is a fresh take on neural networks, inspired by a mathematical concept called the Kolmogorov-Arnold representation theorem, and it's showing a lot of promise as an alternative to the usual ML algorithms [19]. Unlike standard networks that use fixed math functions (activation functions) and simple weighted connections, KANs use adaptable, curve-based (spline-based) functions right on the connections between neurons. This means each connection can learn and adjust its own specific function based on the data it sees .

This built-in adaptability helps KANs get really good results on intricate prediction tasks, often using far fewer adjustable parameters than traditional networks. As a result, KANs inherently offer better interpretability through the adaptive representation of data relationships via learned spline functions, providing intuitive insights into the underlying dynamics and patterns.

The rest of paper is organized as follows: Section 2 provides the problem formulation of time series forecasting and how KANs are used for this scenario. Section 3 details dataset description and complete data analysis for various battery parameters. Section 4 is dedicated to defining experimental setup that was utilized to achieve the desired results. Section 5 provides results for SoH and capacity both in graphical form and tabular form for MAE and RMSE. The discussion is concluded in Section 6.

II. PROBLEM FORMULATION

A. Problem Definition

The accurate estimation of the State of Health (SOH) and residual capacity of a Li-ion battery is essentially a time-series forecasting task. Mathematically, the prediction of battery SOH values over a future interval can be represented as follows:

Given a sequence of battery SOH observations:

$$\mathrm{Y} = [\mathrm{y_t}, \mathrm{y_{t+1}}, \mathrm{y_{t+2}}, \dots, \mathrm{y_{t+T}}] \in \mathrm{R}^{\mathrm{T+1}} \qquad (1)$$

based solely on historical observations up to cycle $t-1$:

$$\mathrm{X} = [\mathrm{x_{t-c}}, \mathrm{x_{t-c+1}}, \dots, \mathrm{x_{t-2}}, \mathrm{x_{t-1}}] \in \mathrm{R}^{\mathrm{c}} \qquad (2)$$

where t represents the starting prediction cycle, T indicates the prediction horizon length, c represents the context length (length of historical data).

The forecasting problem is defined by the predictive mapping:

$$\mathrm{Y} = \mathrm{f(X)} + \varepsilon \qquad (3)$$

where ε represents a minimal prediction error, typically assumed as Gaussian noise.

B. Kolmogorov-Arnold Representation Theorem

The foundation of Kolmogorov-Arnold Networks (KANs) relies on the Kolmogorov-Arnold theorem, which states any continuous multivariate function $\boldsymbol{f}: \mathbb{R}^{\boldsymbol{n}} \to \mathbb{R}$: can be expressed as a composition of univariate continuous functions:

$$\boldsymbol{f}(x_1, x_2, \dots, x_n) = \sum_{i=1}^{2n+1} \Phi_i \left(\sum_{j=1}^{n} \varphi_{i,j}(x_j) \right) \qquad (4)$$

where: $\Phi_i: \mathbb{R} \to \mathbb{R}$ is outer functions $\varphi_{i,j}: [0,1] \to \mathbb{R}$ is inner functions and n is the input dimensionality.

KANs implement adaptive spline-based univariate activation functions to approximate these inner and outer functions. Let each spline function $\varphi_{i,j}(x)$ be represented by B-splines defined as:

$$\varphi_{i,j}(x_j) = \sum_{m=1}^{G+k-1} w_{i,j,m} B_{m,k}(x_j) \qquad (5)$$

where $B_{m,k}(x_j)$ are B-spline basis functions. $w_{i,j,m}$ are trainable spline coefficients and k denotes spline order. G is the number of intervals (with $G+1$ knots). The B-spline basis functions $B_{m,k}(x)$ are defined recursively via the Cox–de Boor formula:

for $k = 1$:

$$B_{\{m,1\}(x_j)} = \begin{cases} 1, if\ x_j \in [t_m, t_{m+1}) \\ 0, otherwise \end{cases} \qquad (6)$$

for $k > 1$:

$$\begin{aligned} &\mathrm{B_{m,k}(x_j)} \\ &= \frac{\mathrm{x_j - t_m}}{\mathrm{t_{m+k-1} - t_m}} \mathrm{B_{m,k-1}(x_j)} \\ &+ \frac{\mathrm{t_{m+k} - x_j}}{\mathrm{t_{m+k} - t_{m+1}}} \mathrm{B_{m+1,k-1}(x_j)} \end{aligned} \qquad (7)$$

A deep KAN model multiple hidden layers is utilized to improve predictive capabilities. The general output of a deep KAN architecture consisting of LLL layers is formulated as:

$$\boldsymbol{Y} = \Phi^{(L)} \left(\Phi^{(L-1)} \left(\dots \Phi^{(1)}(X) \right) \right) \qquad (8)$$

Each hidden KAN layer is defined by the following transformation:

$$\Phi^{(l)}\left(z^{(l-1)}\right) = \left[\sum_{i=1}^{n_{l-1}} \varphi_{i,1}^{(l)}\left(z_i^{(l-1)}\right), \ldots, \sum_{i=1}^{n_{l-1}} \varphi_{i,n_l}^{(l)}\left(z_i^{(l-1)}\right)\right] \quad (9)$$

Where $\boldsymbol{z}^{(0)} = X$ is input layer data and $\boldsymbol{z}^{(l)}$ is the output of the l-th KAN hidden layer, n_l is the number of nodes in the l-th hidden layer. The Fig. 1 shows the implementation of forecasting task through KAN network.

C. Training and Optimization Process

The KAN parameters $(w_{i,j,m})$ are optimized by minimizing the Mean Squared Error (MSE) between predicted and actual SOH values, formulated as:

$$\text{MSE} = \frac{1}{M}\sum_{i=1}^{M}(y_i - \hat{y}_i)^2 \quad (10)$$

where y_i are the actual observed values, $\hat{y}_i$ are SOH values predicted by the KAN, M denotes total data samples.

$$w_{i,j,m}^{(\text{new})} = w_{i,j,m}^{(\text{old})} - \eta\frac{\partial \text{MSE}}{\partial w_{i,j,m}} \quad (11)$$

where η is learning rate.

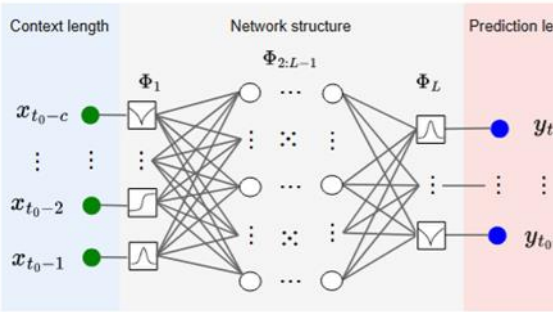

Figure1. Implementation of forecasting task in KAN based network

III. Dataset And Preprocessing

[1] Dataset Description

This study utilizes a comprehensive dataset provided by NASA's Ames Prognostics Centre of Excellence (PCoE) [20]. This dataset is widely recognized and extensively used in battery health prognosis research. It consists of detailed records from four Li-ion battery cells labelled B0005, B0006, B0007, and B0018. Each battery was subjected to various operational cycles, including charging, discharging, and impedance measurements under controlled environmental conditions.

The dataset was generated under carefully controlled laboratory conditions, wherein each battery underwent repeated charge-discharge cycles until the capacity degraded below a predefined threshold (typically 70% of the initial capacity), marking the battery's end-of-life (EoL). The dataset encapsulates critical parameters including terminal voltage, current, battery temperature, discharge capacity, and internal resistance measurements. These features collectively facilitate a robust analysis and prediction of battery health dynamics.

[1] Dataset Proprocessing

Before proceeding with predictive modeling, meticulous preprocessing steps are necessary to ensure data quality and reliability. Initially, raw data provided in MATLAB (.mat) format was converted to comma-separated values (CSV) files using custom Python scripts. Each CSV file corresponds to individual battery cells, simplifying subsequent analysis in Python-based analytical frameworks.

Post-conversion, the data were examined thoroughly for consistency. Columns representing discharge cycles were extracted since the discharge phase predominantly characterizes battery degradation. Additional features, specifically cycle number, ambient temperature, terminal voltage, current, battery temperature, and discharge capacity, were also checked for further analysis.

[1] Exploratory Data Analysis

The exploratory data analysis stage aimed to uncover critical insights about the dataset's characteristics and underlying patterns related to battery degradation. Initially, descriptive statistics were calculated to understand the distribution and variability of key battery parameters such as voltage, current, temperature, and capacity.

Density plots for these features were generated to visualize their distributions and to identify any deviations or anomalies. The voltage distribution prominently exhibited peaks around fully charged (approximately 4.2 volts) and nearly depleted states, reflecting typical Li-ion discharge behavior. Current distribution revealed operational modes dominated by relatively low-load conditions, while temperature remained consistently between 20°C to 26°C across cycles, indicative of stable laboratory conditions. Discharge capacity distributions illustrated clear initial capacity variations among batteries, reinforcing the necessity of individual battery-level modeling. A figure presenting density plots for voltage, current, capacity, and temperature would be crucial to include. Density plots for various battery parameters are shown in Fig.2.

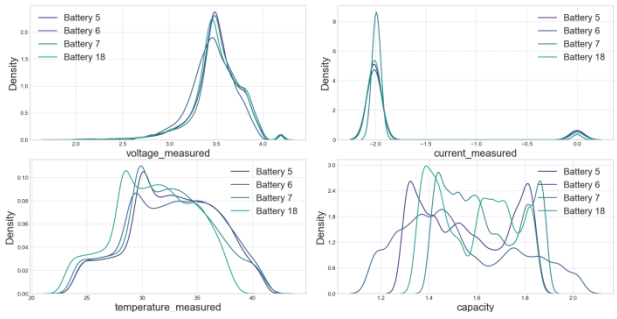

Figure 2. Density Plots for current, voltage temperature and capacity

Battery capacity degradation was thoroughly examined through plots of discharge capacity against cycle number, and they are plotted in terms of number of cycles. All batteries demonstrated a pronounced degradation trend, consistent with the known non-linear capacity fade characteristic of Li-ion

batteries. Capacity degradation plots provide visual confirmation of the batteries' declining performance and offer foundational data for predictive modeling. Therefore, inclusion of capacity degradation plots is recommended.

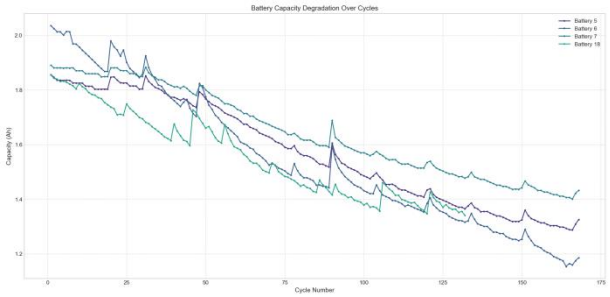

Figure 3. Battery Capacity Degradation

Additionally, the SOH, defined as the ratio of current to initial battery capacity, was calculated and analyzed over successive cycles. This metric similarly showed a downward trajectory (Fig.3), confirming capacity fade and health deterioration over operational lifespan. SOH plots provide a clear, intuitive representation of health degradation.

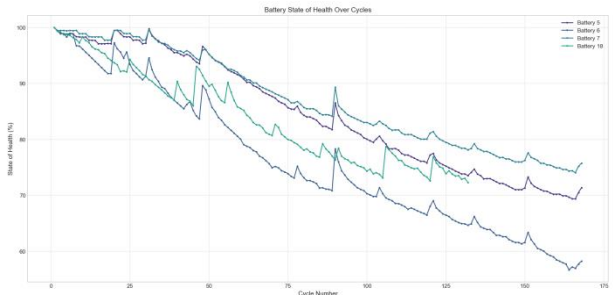

Figure 4. Batteries SoH

The temporal evolution of mean battery temperature across cycles was analyzed to investigate trends in thermal behavior during battery aging. Although temperature variations were generally minor due to controlled laboratory conditions, noticeable increments towards the batteries' end-of-life suggested increased internal resistance and chemical inefficiencies as batteries aged and they can be seen Fig.4. Including temperature evolution graphs would offer insightful context on how temperature correlates with battery aging.

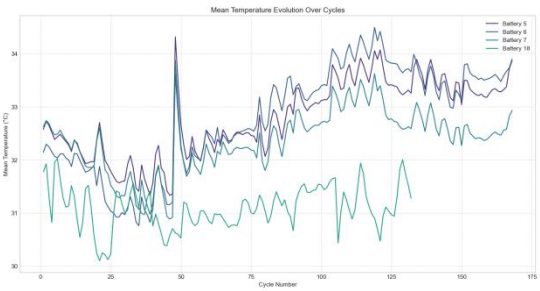

Figure5. Temperature evolution over cycles

Lastly, Pearson correlation analysis was conducted among features, particularly highlighting relationships between capacity, cycle number, RUL, voltage, current, and temperature. The analysis revealed strong negative correlations between cycle number and capacity, and between cycle number and RUL, validating the logical relationships assumed in predictive modeling and is shown in Fig.4.

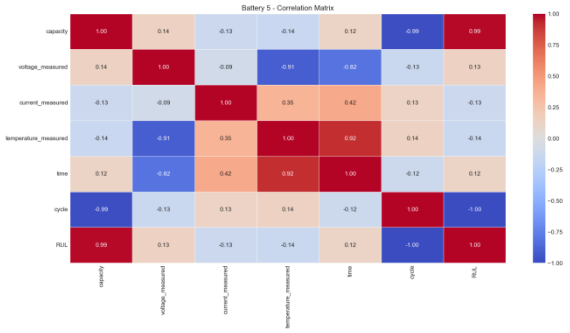

Figure 6. Features Correlation among battery parameters

IV. EXPERIMENTAL SETUP

In order to verify the accuracy of the model in predicting the capacity and SoH of Li-ion battery, each battery is treated separately owing to different battery characteristics and values of parameters. The battery 5, 6, 7 has 166 valid cycles while battery 18 has 132 cycles.

The main aim is to investigate the comparison between Multi-layer Perceptron (MLP) with KAN architectures for predicting the health of Li-Ion battery. Basic MLP architecture is taken for comparison as KANs are direct replacement of MLPs and they can be used as plug in replacement of the MLPs. This is the reason why MLP is selected for comparison rather than sophisticated ML algorithms such as LSTM and transformers. We take the input length of 24 cycles and predict 10 cycles in the future. This is evident in the example of where context length or input length is 24 cycles while prediction length is 10 cycles.

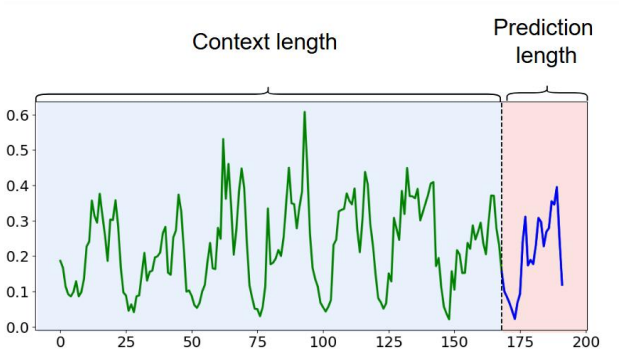

Figure 7. Prediction Length and Context Length in Time Series Forecasting

Based on the Fig. 6, $T = 10$, and $c = 24$ in equation (1) and (2). The models are compared in such a way that depths of the architecture are similar but they underlying architecture is changed so to check the impact on accuracy of forecasting and to check for parameter efficiency. Python programming language is used with Pytorch Framework for KANs implementation, and 4070 NVIDIA RTX GPU is utilized with

VRAM of 12GB. Different parameters for which these parameters are tested are given in Table I.

The models are evaluated against two commonly used metrics in machine learning and are referred to as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Mean Absolute Error (MAE) measures the average magnitude of the errors between the predicted values ($\hat{y}_i$) and the actual values (y_i) without considering their direction. MAE is calculated as follows:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|^2$$

where n denotes the total number of observations, y_i represents the true values while $\hat{y}_i$ is the predicted value for each observation.

Root Mean Squared Error (RMSE) is another widely used metric that measures the average magnitude of the error, but with an emphasis on larger errors since it squares the individual deviations before averaging. RMSE is defined by:

$$RMSE = \sqrt{MAE}$$

V. Simulation And Results

We performed forecasting for different li-ion batteries. Due to spatial constraints, results of two batteries (5, 6) capacity are shown in Fig. 8 and SoH results are also similar as it can be seen that in Fig.3 and Fig.4 that capacity and SoH shared the same waveform overall. The actual battery capacity curve is shown in black, and it is evident that KAN is following the trend better than MLP for both the batteries. KANs provide improved approximation as compared to MLP for the same type of parameters.

Furthermore, it is also to be noted that KANs are more responsive as compared to Muli-layer Perceptron in case of battery 5 where the red curve at the starting point follows the same pattern as of actual capacity. Although, there is an exception that the last point in the curve does not follow the pattern, and it is due to the fact that there is a sharp sudden rise in capacity which can be considered an anomaly situation. Apart from that, KANs provide more robustness and more variability as per the demand of the output curve. Such resilience indicates that KANs are better equipped than MLPs to handle a wide range of battery fluctuations, thereby offering a more dependable solution for deployment across diverse battery conditions.

Table II provides a comprehensive numerical comparison of various MLP and KAN architectures across all batteries for Cap (capacity) and SoH, reporting metrics of MAE and RMSE. From these results, it is evident that the deep layered KAN model delivers the strongest performance. Its notably lower MSE and RMSE values demonstrate superior precision in forecasting capacity and SoH of batteries, while its reduced MAE and MAPE confirm that it maintains this accuracy uniformly across varying battery conditions—an essential quality for reliable real-world deployment.

KANs are built upon a rigorous theoretical framework that naturally excels at capturing the intricate, nonlinear dynamics present in traffic data. This solid foundation underpins their high flexibility and precision in forecasting. Their reliable performance across a range of traffic scenarios further highlights their strong ability to generalize—an important trait for systems deployed in diverse geographic and operational settings. Additionally, our results show that KANs achieve these superior accuracy levels using significantly fewer parameters than traditional MLP architecture.

TABLE I. MODEL CONFIGURATIONS FOR LI-ION BATTERY FORECASTING

Model	Time Horizon	Spline Details	Activation
KAN-shallow	Input/Horizon: 24/10	Grid:5, spline ordder:3	Learnable
KAN-deep	Input/Horizon: 24/10	Grid:5, spline ordder:3	Learnable
MLP-shallow	Input/Horizon: 24/10	Grid:5, spline ordder:3	ReLU
MLP-deep	Input/Horizon: 24/10	Grid:5, spline ordder:3	ReLU

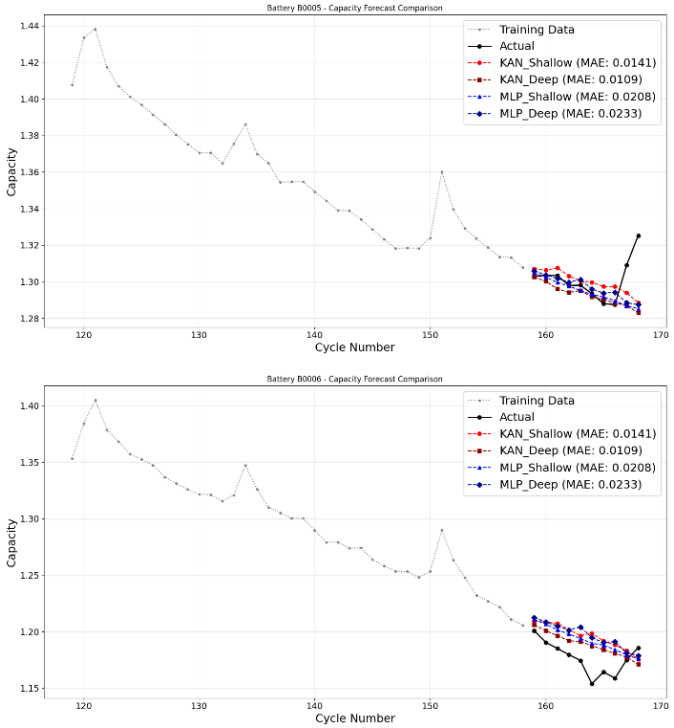

Figure 8. Battery 5 and 6 capacity forecasting results

TABLE II. CAPACITY AND SOH COMPARISON FOR BATTERIES 5, 6 AND 7 ACROSS MAE AND RMSE

Model	Battery 5				Battery 6				Battery 7			
	Cap		SoH		Cap		SoH		Cap		SoH	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
KAN-S	0.019	0.0172	0.015	0.018	0.019	0.017	0.016	0.019	0.025	0.029	0.022	0.035
KAN-D	0.014	0.015	0.021	0.024	0.014	0.015	0.013	0.021	0.019	0.026	0.020	0.031
MLP-S	0.029	0.028	0.031	0.039	0.025	0.023	0.038	0.038	0.026	0.032	0.034	0.041
MLP-D	0.023	0.030	0.033	0.037	0.022	0.027	0.034	0.036	0.025	0.030	0.031	0.039

CONCLUSION

In this paper, we proposed Kolmogorov-Arnold Networks for prediction of capacity and State-of-Health of Li-ion batteries which are one of the most critical elements of an EV. Spline-based adaptive activations are utilized in the proposed KAN architecture that model non-linearity through spline-based interpolation. This resulted in lower MAE and RMSE for NASA battery dataset comprising of four batteries as compared to traditional Multi-Layer Perceptron (MLP) and can be used as a plug-n-play type of replacement for MLP. Comparative experiments on the batteries yielded better accuracy, parameter efficiency and generalizability under varied degradation battery profiles. The results further highlighted KAN's potential for lightweight and interpretable battery management system in EV applications. The future work will be based on aggregation of KANs with other state of art methods of forecasting to achieve much better results and this aggregation can lead to KANs as a direct MLP replacement for future algorithms.

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