Using Optimized Long Short-Term Memory for Time Series Forecasting of Electric Vehicles Battery Charging

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Abstract – The last decade has seen a significant rise in the adoption and development of Electric Vehicles (EVs), driven by environmental concerns, technological advancements, and governmental support. Batteries, central to EVs, have witnessed groundbreaking innovations in terms of energy density, charging speeds, and longevity. Expanding charging infrastructure and the automotive industry's investment in EV research have made them more mainstream. Effective Battery Management (BM), which includes monitoring essential parameters and thermal management, is critical for the longevity and reliability of EVs. Accurate charge prediction, in particular, aids in trip planning, reduces range anxiety and facilitates cost-effective charging coordinated with dynamic electricity pricing. Traditional models like linear regression and Autor-Rgressive Integrated Moving Average (ARIMA) have been standard for EV battery charge prediction. However, these often struggle with the dynamic nature of EV charging data. Even models like the vanilla Long Short-Term Memory (LSTM), which are adept at recognizing long-term patterns, require meticulous hyperparameter tuning. This work introduces the DWT-DE-LSTM model, which utilizes the Discrete Wavelet Transform (DWT) to dissect battery charging data at different resolutions and a Differential Evolution (DE) strategy for model optimization. Tests using the Panasonic 18650PF Li-ion Battery Dataset revealed the superior efficacy of the DWT-DE-LSTM model, emphasizing its suitability for real-world battery charge prediction.

Keywords – EV, Charge Prediction, LSTM, Differential Evolution, Battery Management, Energy.

I. INTRODUCTION

The last decade has witnessed a meteoric rise in the adoption and development of Electric Vehicles (EVs), marking a change in basic assumptions in global transportation. As concerns over environmental sustainability, climate change, and depleting fossil fuel reserves intensify, EVs present a promising alternative, embodying the vision of a cleaner and greener future. Governments worldwide, recognizing EVs' environmental and economic potential, have implemented various incentives, from tax breaks to purchase subsidies, accelerating their adoption rates. Technological advancements have further catalyzed this growth [1]. Batteries, the heart of EVs, have seen tremendous innovations, leading to enhanced energy densities, faster charging, and extended lifespans. Simultaneously, the proliferation of charging infrastructure has made EVs more accessible and convenient for the average consumer. Moreover, the automotive industry, traditionally reliant on internal combustion engines, is transforming, with major players investing heavily in EV research, development, and production [2]. This collective momentum towards EVs, driven by policy, technology, and market dynamics, signifies not just a trend but a comprehensive movement toward sustainable transportation.

Battery Management (BM) plays a pivotal role in the efficient operation of EVs. Proper BM ensures optimal charging and discharging cycles, safeguards against overcharging or deep discharging, and monitors critical parameters like voltage, current, and temperature [3]. These parameters are crucial as they impact the battery's health and, by extension, the vehicle's reliability [4]. Moreover, thermal management within the battery system is vital to prevent overheating, which can lead to reduced battery life or, in extreme cases, pose safety risks. Amidst these complexities, charge prediction emerges as a critical component. Accurate forecasting of the battery's charge level aids drivers in planning their trips, reduces range anxiety, and ensures that the battery operates within its optimal limits [5].

Furthermore, with the growth of smart grids and dynamic electricity pricing, precise charge prediction can facilitate cost-effective charging by enabling EVs to draw power during off-peak hours [6]. Effective BM, underscored by accurate charge prediction, is foundational to the promise of EVs as a sustainable and reliable mode of transportation.

The EV battery charge prediction landscape has been characterized by traditional models, such as linear regression, support vector machines, and more straightforward time series forecasting techniques like ARIMA [7]. While these models have shown promise in scenarios with consistent charging patterns, they often falter when confronted with the non-linear and dynamic nature of real-world EV charging data. Another widely adopted model is the vanilla LSTM, which can capture long-term dependencies in sequential data but requires fine-tuned hyperparameters for optimal performance [8]. One of the significant challenges with these models is their inability to simultaneously process information across different time scales, missing both granular short-term variations and overarching long-term trends. Additionally, selecting hyperparameters in models like LSTMs can be complex, often requiring exhaustive trial-and-error methods [9]. To address the above limitations, this work proposed the DWT-DE-LSTM model. This innovative approach harnesses the strength of the Discrete Wavelet Transform (DWT) to break down battery charging data into varying resolutions, offering a clear snapshot of short-term fluctuations and long-term patterns.

Furthermore, the Differential Evolution (DE) strategy aids in fine-tuning the model's parameters, ensuring its precision. Together, these components aim to produce a more accurate and reliable battery charge prediction, addressing the gaps left by previous models. Employing the Panasonic 18650PF Li-ion Battery Dataset for experiments, the proposed model was benchmarked against other established models. Our results underscored the superior performance of the DWT-DE-LSTM, reinforcing its potential as a robust solution for battery charge prediction in real-world applications [10].

The research work is organized as follows: Section 2 presents the literature review, Section 3 presents the methodologies and the proposed work, Section 4 presents the experimental analysis, and Section 5 presents the conclusion of future work.

II. LITERATURE REVIEW

Recent advancements in the Electric Vehicle (EV) charging prediction domain have highlighted diverse methodologies, each shedding light on distinct aspects of this complex problem. [11] introduced a Deep Learning (DL)--based LSTM recurrent neural network predictor model. The unique aspect of this model is the integration of the Empirical Mode Decomposition (EMD) for data decomposition and the Arithmetic Optimization Algorithm (AOA) for parameter tuning. On the EV charging dataset from Georgia Tech, Atlanta, USA, the proposed model surpassed previous methods, achieving an impressive 97.14% prediction accuracy.

Similarly, [12] developed a model based on the LSTM neural network to forecast fast-charging power demand. Real-world datasets from Jeju Island, South Korea, served as their testbed, wherein their proposed model was deemed superior in aggregating fast-charging power demand. [13] brought forth a mixed LSTM neural network, which, unlike traditional LSTMs, segmented various feature types and processed them distinctly within its mixed neural network architecture. Benchmarked against numerous innovative Machine Learning (ML) and DL models using the EV charging data from the city of Dundee, UK, this method exhibited exceptional predictive accuracy.

On the other hand, [14] combined the prowess of XGBoost and LSTM for their charging load forecasting model. Unique feature engineering, phase space reconstruction, and the LSTM model's training underscored this method, which, upon validation, proved valuable for high permeability EV load forecasting. [15] innovated with an LSTM-RNN model, integrating extended input and constrained output. By introducing an additional slow time-varying information window and constraining the output variation, they achieved enhanced SOC estimation performance on $LiFePO_4$ battery datasets.

In [16-18] deployed a DL approach called Sequence to Sequence (Seq2Seq) for time-series forecasting of monthly commercial EV charging. Against other time series and ML models, their Seq2Seq method demonstrated superior multi-step prediction capabilities on Utah and Los Angeles datasets.

Given the multitude of methods presented in these studies, each with its strengths and distinctions, it becomes evident that while significant strides have been made, there remains scope for a model that seamlessly integrates various strengths while addressing the existing gaps. The DWT-DE-LSTM model seeks to fill this void, offering an evolved approach to battery charge prediction, which is integral for the burgeoning EV industry [19-20].

III. METHODOLOGIES

DWT for Time Series Decomposition

The Discrete Wavelet Transform (DWT) offers a method for multi-scale analysis of time series data. Distinct from the Fourier Transforms that highlight frequency aspects, wavelets can concurrently depict data in the time and frequency realms. This combined representation positions DWT as apt for time series data that exhibits changing patterns. DWT's appeal in this study is attributed to its capability to emphasize distinct time series features, dividing data into approximations and intricate specifics. This stratified view helps discern patterns that might be overlooked in a single-scale analysis. Leveraging models like LSTM for prediction benefits, as data highlighting complex patterns across multiple scales can enhance forecast accuracy [21-23]. LSTM's structure is geared towards modeling extended dependencies, and when paired with data refined by DWT, the combined effect promises improved forecasting outcomes in **Fig 1**.

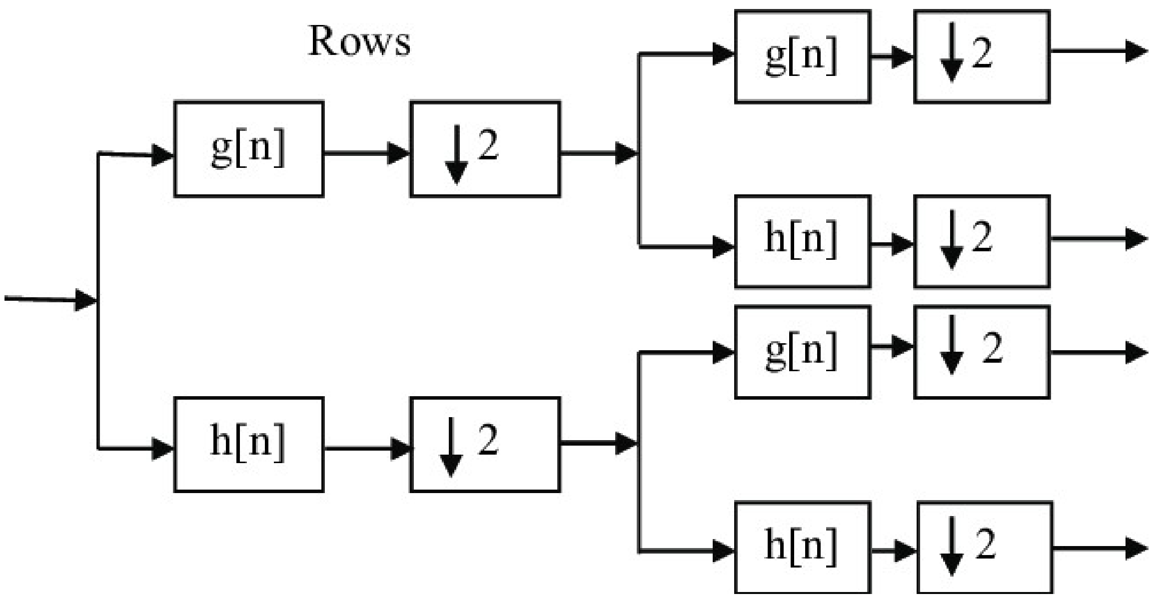

Fig 1. DWT Decomposition

To provide a concrete visualization of the DWT process, consider **Fig 1.** In **Fig 1**, the signal, represented as $x[n]$, undergoes multiple stages of decomposition using two filters: a low-pass filter (denoted by $h[n]$) and a high-pass filter (denoted by $g[n]$). At each level of decomposition, the signal is split into approximation (low-frequency) and detail (high-frequency) coefficients. These coefficients provide multi-resolution representations of the original signal, enabling detailed insights into its characteristics at varying scales.

DWT for Decomposing EV Battery Charging Time Series Data

When this work uses this on data like EV battery charging, DWT helps us see patterns in the overall charging process and the short-term changes. Using DWT on the EV battery charging data means figuring out specific wavelet coefficient values [24-25]. These values give us information about the charging data at distinct levels. This work gets these values by comparing our charging data to standard wavelet function patterns.

The mathematical embodiment of the wavelet coefficient can be delineated as EQU (1)

$$W(\alpha,\beta) = k^{-\frac{\alpha}{2}} \sum_{n=0}^{N} \Phi\left(\frac{n-\beta\cdot k^{\alpha}}{k^{\alpha}}\right) \cdot x(n) \tag{1}$$

where:

- $W(\alpha,\beta)$ is the wavelet coefficient at a given scale α and translation β.
- Φ represents the chosen wavelet function.
- $x(n)$ is the time series entry of the EV battery charging rate at time instance n.

- N is the total number of time points in the data.
- The multiplier $k^{-\frac{\alpha}{2}}$ acts as a normalization component, ensuring the wavelet holds consistent energy across varying scales.

By breaking down the EV battery charging data using DWT, this work obtains a series of coefficients that narrate the charging behavior across multiple resolutions. This granular understanding is instrumental for subsequent LSTM predictive modelling phases.

Differential Evolution Optimized LSTM for Battery Charging Forecasting (DE-LSTM)

After transforming the EV battery charging data using the Discrete Wavelet Transform (DWT), the next challenge is to predict the charging patterns optimally. Here, Long Short-Term Memory (LSTM) networks, known for their prowess in modeling sequential data, are employed. However, the hyperparameters of an LSTM can dramatically affect its performance. To ensure that the LSTM is tuned optimally for this task, DE-a robust optimization strategy is used. By combining the adaptive search capabilities of DE with the sequential modeling strengths of LSTM, the aim is to achieve precise forecasting of battery charging patterns.

Differential Evolution (DE)

DE is a renowned global optimization method that handles complex problems like non-differentiable, nonlinear, and multi-modal optimization tasks. Originating from the genetic algorithms' paradigm, DE's distinctiveness arises from using different vectors for perturbation, resulting in novel candidate solutions. In DE, an initial population represented by x_i where i spans 1 to NP, undergoes a series of operations. For mutation, each member x_i undergoes perturbation using three randomly chosen members: x_{r1}, x_{r2}, x_{r3}. The mutation generates a new mutant vector, v_i, as EQU (2)

$$v_i = x_{r1} + F \times (x_{r2} - x_{r3}) \tag{2}$$

where F is a predefined scaling factor.

Crossover is then employed to mix components from v_i and x_i based on a pivotal parameter, the crossover rate CR. For each component, EQU (3)

$$u_{ij} = \begin{cases} v_{ij} & \text{if rand } (j) \leq CR \text{ or } j = \text{ random dimension in } [1, D] \\ x_{ij} & \text{otherwise} \end{cases} \tag{3}$$

where CR is a probability, typically within [0,1], determining the likelihood of adopting components from v_i. The selection phase then evaluates u_i against x_i using a chosen objective function. Superior or equal performing u_i replaces x_i for the next iteration. Through mutation, crossover, and selection, DE continuously refines its population, striking a balance between exploration and exploitation. This makes DE ideal for tuning hyperparameters in advanced forecasting models, such as LSTM, especially for intricate tasks like predicting EV battery charging patterns.

Long Short-Term Memory (LSTM) Networks

LSTM networks are a specialized subset of Recurrent Neural Networks (RNN) designed to address long-term dependencies in sequence data. What sets LSTMs apart from standard RNNs are their unique internal structures called "cells," which govern the storage and management of information. In the case of the LSTM cell are the state variables, the cell state C_t, and the hidden state h_t . However, what enables LSTMs to regulate the flow of information are three critical gates:

Forget Gate (f_t) : Using the sigmoid function, this gate decides what portion of the previous information in the cell state should be thrown away or kept. Mathematically, EQU (4) is defined as:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{4}$$

where W_f is the weight matrix for the forget gate, h_{t-1} represents the previous hidden state, x_t is the current input, and b_f is the biased term for the forget gate.

Input Gate (i_t) : This gate defines which new information gets stored in the cell state. It consists of two parts: EQU (5)

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{5}$$

which decides which values to update, and EQU (6)

$$\tilde{C}_t = \tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right) \tag{6}$$

which creates a vector of new candidate values.

Output Gate (o_t) : Determines the next hidden state h_t. The output is based on the cell state, but in a filtered form, EQU (7) and EQU (8)

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = o_t \times \tanh(C_t) \tag{8}$$

With these gates in place, the cell state C_t gets updated as EQU (9)

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \tag{9}$$

These mechanics enable the LSTM to learn patterns over long durations, making it particularly adept for time series forecasting tasks.

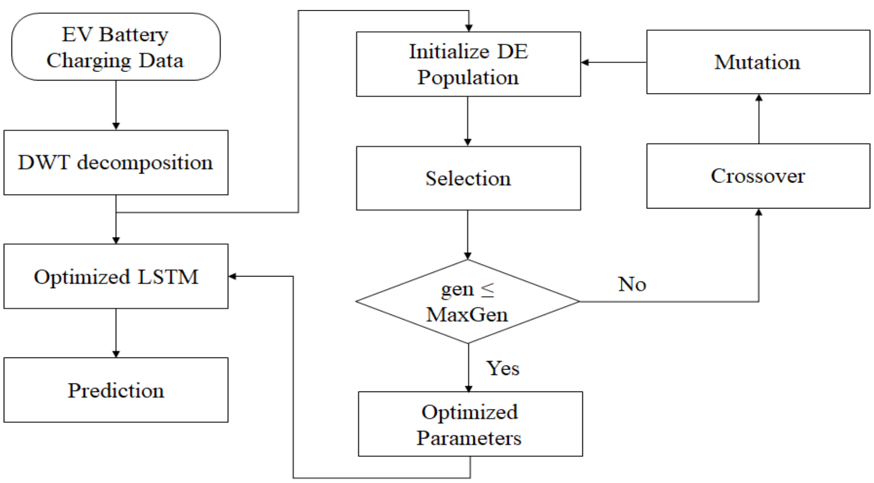

Fig 2. Flow Diagram of the Proposed Model

DE Optimized LSTM (DE-LSTM)

DE-LSTM synergizes the global optimization capabilities of DE with the sequence modeling proficiency of LSTM. Here's how the integrated approach functions:

- **Initialization**: Begin with an initial population of potential LSTM configurations. Each individual in the population represents a unique set of LSTM hyperparameters.
- **Fitness Evaluation**: For each individual (or configuration) in the population, an LSTM model is trained on the DWT-transformed EV battery charging data. The performance of the model, measured by a metric Mean Absolute Error (MAE) on a validation set, determines the fitness of that individual.
- **Evolutionary Optimization**:
  - **Mutation**: For each individual, a mutant LSTM configuration is generated by perturbing it using different vectors of other randomly selected configurations, adhering to the DE mutation strategy.
  - **Crossover**: Components of the mutant configuration and the original are mixed based on the crossover rate (CR) to produce a trial configuration.
  - **Selection**: The trial configuration's LSTM model is trained and evaluated. If its performance surpasses or matches the original individual's LSTM, it replaces the original in the next generation.
- **Termination**: The process iteratively refines the population of LSTM configurations until a stopping criterion (like a set number of generations or convergence to a performance threshold) is met.

The result of DE-LSTM is an LSTM architecture that has been fine-tuned specifically for the forecasting task. By dynamically adjusting its hyperparameters based on the evolutionary intelligence of DE, the LSTM can offer more accurate and reliable predictions of EV battery charging patterns. **Algorithm 1** presents the steps involved in the process of DE-optimized LSTM, and the same is presented pictorially in **Fig 2.**

Algorithm 1: DE-LSTM for EV Battery Charging Prediction
Input:

- DWT-transformed EV battery charging time series data: D_{train} (training data), D_{val} (validation data), D_{test} (testing data).
- DE parameters: Population size N_{pop}, Crossover rate CR, Scaling factor F, Maximum generations MaxGen.

Output:

- Predicted EV battery charging patterns on D_{test} using the LSTM model trained with the best configuration obtained from DE optimization.

Procedure:

Initialization:

Randomly generate an initial population of N_{pop} LSTM configurations.
Set gen $= 1$ (current generation).

While gen ≤ MaxGen:

For each ind in the population:

Mutation:

Randomly select three distinct individuals: ind_1, ind_2 , $ind_3$from the population.
Generate a mutant configuration mutant by perturbing and using difference vectors from ind_1, ind_2 , $ind_3$and scaling by factor F.

Crossover:

For each hyperparameter h in ind:
Generate a random number of rand.
If rand $< CR$, set h of the trial (trial individual) to h of mutant.
Else, set h of $trial$ to h of ind.

Selection:

Train LSTM using in-configuration on D_{train} and evaluate on D_{val} to get performance per $f1$.
Train LSTM using trial configuration on D_{train} and evaluate on D_{val} to get performance per f 2.
If per $f2$ is better than or equal to per $f1$:
Replace ind with the trial in the population.
Increment gen by 1.

Post-Evolution:

Select the best individual bestConfig from the final population based on the highest performance on D_{val} .
Train an LSTM using bestConfig on the combined dataset ($D_{train} + D_{val}$).

Forecasting:

Use the trained LSTM model with bestConfig to make predictions on D_{test} .
Return the predictions for EV battery charging patterns.

IV. EXPERIMENTAL ANALYSIS

Dataset

This model utilized the Panasonic 18650PF Li-ion Battery Dataset, which records battery performance metrics under varying conditions within a controlled thermal chamber. For preprocessing, this study normalized parameters such as voltage, current, power, and temperature, ensuring they scaled between 0 and 1. This preserved the dataset's intrinsic variability and optimized the LSTM's learning. Subsequently, this work split the dataset into 70% for training, 15% for validation, and 15% for testing, ensuring a balanced representation of various battery states and conditions.

Implementation of DWT-DE-LSTM

Step 1: The battery charging time series data was first decomposed using the Discrete Wavelet Transform (DWT), allowing us to capture overarching and nuanced charging patterns.

Step 2: With the transformed data, this work ventured to train our LSTM network. However, LSTM's myriad hyperparameters can dramatically influence its effectiveness. To optimally tune these, this study employed the DE strategy.

Step 3: The DE-LSTM model underwent rigorous training on the DWT-transformed dataset. The model's hyperparameters dynamically adapted based on DE's evolutionary mechanisms, aiming for the pinnacle of forecasting accuracy.

Table 1. Hyperparameter for DE-LSTM

Hyperparameter	Value/Range
LSTM Units	50-150
Learning Rate	0.001-0.01
Batch Size	32, 64, 128
Epochs	100
DE Population	50
DE Crossover Rate	0.7-0.9
DE Scaling Factor	0.5-0.8

For the evaluation of our model's predictive capability on the Panasonic 18650PF Li-ion Battery Dataset, this model chose several standard metrics to gauge performance:

Mean Absolute Error (MAE): It measures the average magnitude of the errors between the predicted and observed values.

Root Mean Squared Error (RMSE): A popular metric for accuracy, it calculates the square root of the mean of the squared differences between predicted and actual values.

Mean Absolute Percentage Error (MAPE): This metric provides error in terms of percentage, offering a relative measure of the prediction accuracy.

R-Squared (R^2). A statistical measure indicating the proportion of the variance in the dependent variable that is predictable from the independent variable(s).

The performance of the proposed model was compared against (1) Vanilla LSTM, (2) ARIMA, and (3) Feed-forward NN.

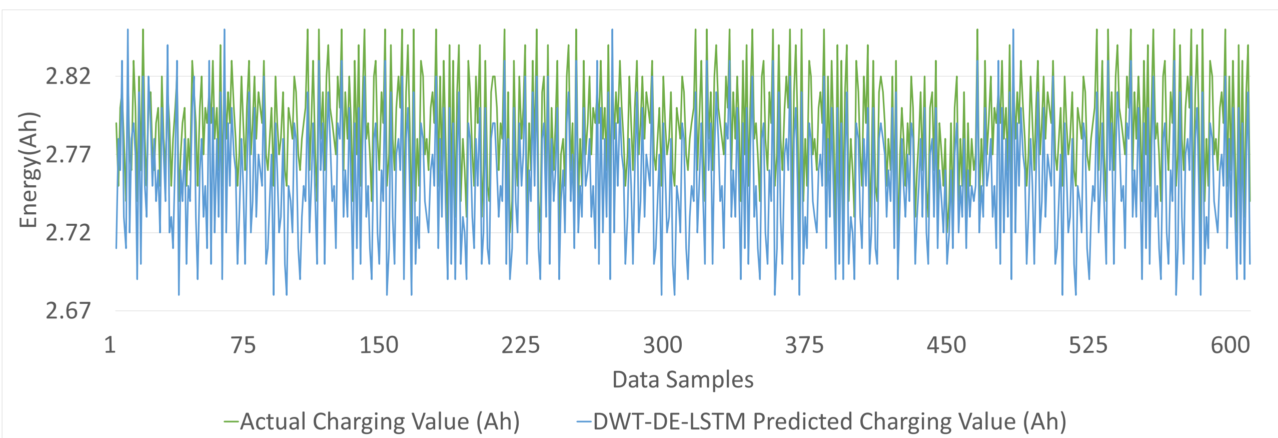

Fig 3. DWT-DE-LSTM Predicted vs Actual Charging Values Comparison

Fig 3 compares the predicted and actual energy levels of the EV battery charging. As evident from the Figure, the forecasted charging energy closely aligns with the actual energy level. Upon visual analysis of the box plots derived from multiple runs, the DWT-DE-LSTM model consistently outperformed the three baseline models across all evaluation metrics. For Mean Absolute Error (MAE), as shown in **Fig 4**, the DWT-DE-LSTM's MAE scores clustered around a narrow range of 1.18 to 1.23, indicating consistent and superior forecasting accuracy.

In contrast, ARIMA demonstrated the highest error rates, with its MAE values gravitating around the 1.68 to 1.73 mark. The Vanilla LSTM and Feed-forward NN also displayed higher errors than the proposed model, with their MAEs spanning 1.53 to 1.58 and 1.59 to 1.62, respectively. When examining the RMSE box plots (**Fig 5**), DWT-DE-LSTM again exhibited robust performance with values tightly grouped between 1.44 and 1.48. ARIMA had the highest error spread, ranging from 1.92 to 1.96. The Vanilla LSTM and Feed-Forward NN trailed behind the proposed model, displaying RMSE values between 1.78 to 1.82 and 1.74 to 1.78, respectively.

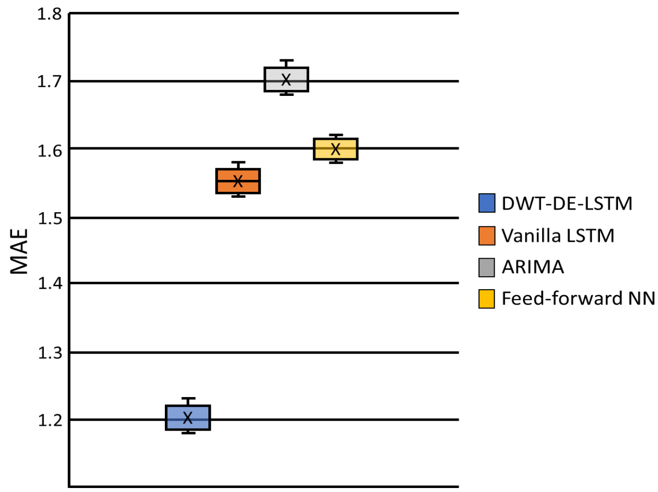

Fig 4. Mean Absolute Error (MAE)

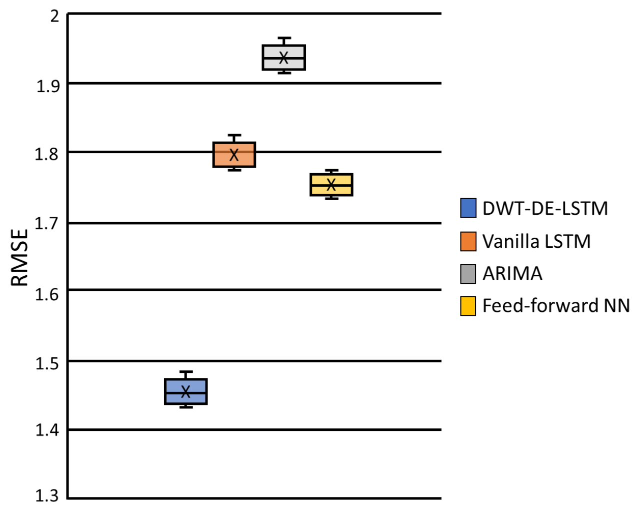

Fig 5. Root Mean Squared Error (RMSE)

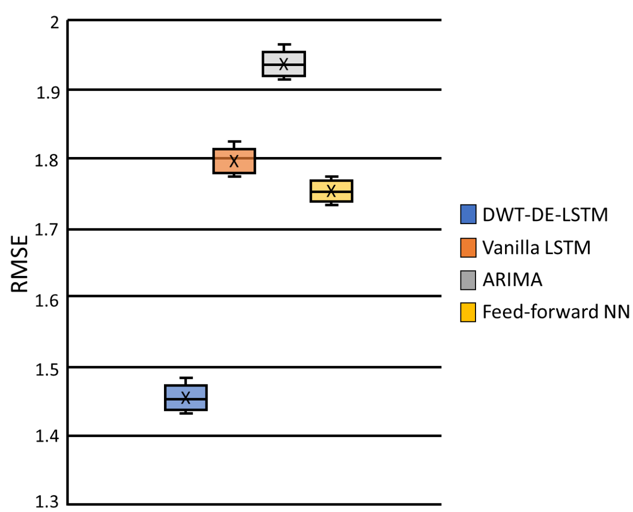

Fig 6. Mean Absolute Percentage Error (MAPE)

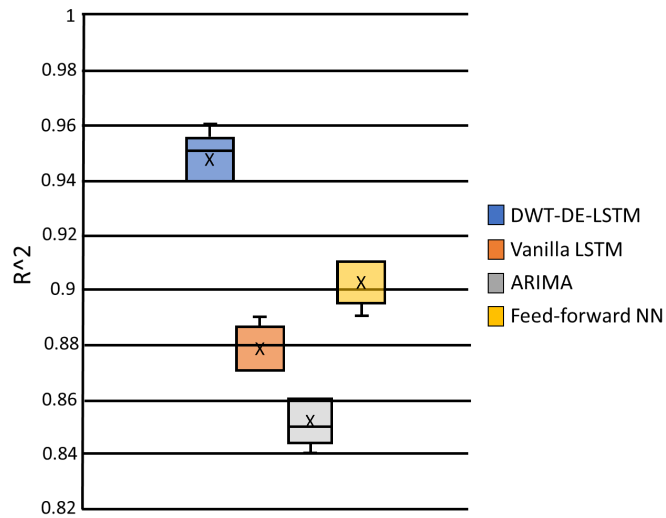

Fig 7. R-squared (R^2)

As shown in **Fig 6** for the MAPE metric, a lower percentage indicates better accuracy. The DWT-DE-LSTM model's predictions were closest to the actual values, with MAPEs hovering around 2.7% to 2.9%. In comparison, ARIMA's predictions strayed the most, evidenced by its higher MAPE range of 5.0% to 5.2%. The Vanilla LSTM and Feed-forward NN also registered higher errors than the DWT-DE-LSTM, with MAPEs of 4.4% to 4.6% and 4.2% to 4.4%, respectively. R^2 values (**Fig 7**) provide insight into the model's goodness-of-fit, with values closer to 1 being desirable. The box plots revealed that the DWT-DE-LSTM consistently achieved R^2 values around 0.94 to 0.96, highlighting its superior fit to the data. On the other hand, ARIMA had the most petite fit with values spanning 0.84 to 0.86. While Vanilla LSTM and Feed-forward NN offered better fits than ARIMA with their R^2 values clustering in the 0.87 to 0.89 and 0.89 to 0.91 regions, the proposed model still outshined them.

V. CONCLUSION AND FUTURE WORK

As the Electric Vehicles (EVs) industry continues its upward trajectory, the significance of efficient Battery Management Systems (BMS) becomes increasingly apparent. With this sector's rapid growth and evolution, there is a heightened need to address the intricacies of battery dynamics. Traditional models have often struggled to encapsulate the complex patterns of battery charging. This underscores the pressing requirement for more sophisticated prediction methodologies. Considering this, the research presented the DWT-DE-LSTM model, which ingeniously combines the Discrete Wavelet Transform's (DWT's) detailed time-frequency analysis, the prowess of Differential Evolution's (DE's) optimization techniques, and the LSTM's adeptness at sequence prediction. The Panasonic 18650PF Li-ion Battery Dataset served as a testing ground, and when set against well-regarded models such as Vanilla LSTM, ARIMA, and Feed-forward NN, the DWT-DE-LSTM model consistently displayed superior performance.

Looking ahead, there's immense potential to refine and adapt this model. Potential avenues include adapting the model to different battery technologies, integrating real-time data feeds for more dynamic predictions, and exploring its compatibility with emerging EV technologies.

Data Availability
No data was used to support this study.

Conflicts of Interests
The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests
There are no competing interests.

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