Research Paper

DeepBESS: an explainable deep learning framework for battery energy storage system state-of-health prediction and adaptive charging control in renewable energy microgrids

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ABSTRACT

Renewable energy microgrids can't function without Lithium-ion Battery Energy Storage Systems (BESS), which act as a buffer between load demand on the grid and intermittent renewable energy resources like photovoltaic (PV) systems. The core issues in maximizing the battery life, operational safety and economic viability in these systems include accurate prediction of State-of-Health (SoH) and adaptive charging control. This paper introduces a novel explainable deep learning framework (DeepBESS), which not only applies a Temporal Convolutional Network-Bidirectional Long Short-Term Memory (TCN-BiLSTM) hybrid network to effectively predict SoH status at multiple time horizons but also uses an XGBoost-ARIMA joint optimization module to generate an adaptive charging schedule. A Shapley Additive Explanations (SHAP) interpretability layer is integrated to illustrate SoH predictions at feature-level, and without the need for electrochemical expertise for engineering insights. It is tested on two public datasets -- the NASA Battery Dataset, and the Oxford Battery Degradation Dataset -- with a strict split on the cell level for training, validation and test sets of 70/15/15 per cent respectively. The SoH prediction Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE) of DeepBESS are 0.87% and 0.62% respectively, which is a 31.4% improvement in RMSE compared to a Vanilla Long Short-Term Memory (LSTM) baseline and 12.1% compared to the XGBoost-ARIMA standalone model. The adaptive charging controller is tested by a STM32F429ZI based embedded BESS testbed and extends simulated battery cycle life by 18.3% compared to a conventional Constant Current-Constant Voltage (CC-CV) charge controller, with an embedded real-time estimation of the battery's Health of Charge (SoH) being reached with a latency of 47 milliseconds. The dominant degradation indicators that can be identified using SHAP analysis are the voltage rate dV/dt and discharged capacity Q(t). The proposed solution is highly deployable, interpretable and accurate, and provides a full battery health management solution for next generation renewable energy microgrids. The results show that the temporal deep learning combined with explainability and adaptive control results in significant improvements in the predictive performance as well as the battery operational time.

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1. INTRODUCTION

The deployment of Battery Energy Storage Systems (BESS) as the key enabling technology to cope with the intermittency of PV and wind power and the time-varying nature of the electricity load has increased over the last years, driven by this global transition towards renewable energy [1]. BESS is the most important energy buffer in micro grids, which will absorb excess energy generation when generation is in the peak time and provide deficit demand when energy generation is low. Moreover, the previous studies have shown that hierarchical switching charging-discharging controllers enable continuous sustainability of BESS, indicating that the control strategy is a direct control to the battery life [2], [3]. The economic viability of BESS plays heavily on battery life – a failure to deliver that performance before the end of the project can cost up to 40% of its lifetime revenue in commercial microgrid projects [4].

The most important measure of battery health is State-of-Health (SoH) which is simply the ratio of the maximum charge capacity at present compared to the rated capacity (SoH = Q_max,current / Q_rated). The vast majority of operational systems have a goal of replacing most of them at SoH = 0.80. The advantages of accurate SoH trajectory prediction are: (1) scheduling maintenance well in advance of catastrophic failure; (2) selection of an adaptive charging protocol to reduce capacity fading due to stress; (3) accurate lifetime cost modeling of BESS economic optimization [5].

There are some fundamental limitations in the existing approaches on SoH estimation. Costly parameterization is needed for electrochemical models [6] and they are too complex to be computed on embedded devices. Equivalent Circuit Models (ECMs) [7] have not been able to work well for multi-mechanism degradation regimes. The classical machine learning methods such as Support Vector Regression (SVR), Gaussian Process Regression (GPR) and Random Forests do not generalize well when applied to different degradation patterns [8]. Recent deep learning techniques such as LSTM autoencoders [9] and Temporal Convolutional Networks (TCNs) [10] have demonstrated promising results, yet there are no techniques that are able to handle all three aspects: prediction accuracy, explainability and coupling with adaptive charging control. Moreover, previous studies about similar embedded monitoring systems [3], [11] have not considered the adoption of real-time explainable health diagnostics.

In order to overcome these basic shortcomings, this paper introduces "DeepBESS". The main results of this work are: (1) a hybrid predictor based on TCN and BiLSTM, which extracts multi-scale features from a set of signals and models long-range dependencies with the bidirectional architecture of the BiLSTM, leading to an RMSE of 0.87%; (2) a joint optimizer of XGBoost and ARIMA that provided near-term predictions of SoH degradation and generation/load scheduling windows to select cycle-stress-minimizing protocols; (3) an explainability layer based on SHAP, which decomposes feature attributions for guiding field engineers in identifying the dominant degradation drivers; and (4) embedded testbed validation on a STM32F429ZI based BESS controller, resulting in a cycle life extension of 18.3% with a real-time evaluation latency of 47 ms.

2. RELATED WORK

2.1 Battery State Estimation Methods

Traditional Coulomb counting is an integration of charge and discharge current to obtain the capacity estimation, but it has the problem of a drift in capacity estimation after long-term use [6]. The Kalman filter based methods [7] solve the problem of drift, but need to know the ECM parameters, which can be hard to obtain for degraded cells in the field. The design of controller strategies for battery storage in renewable energy systems, such as those presented in [3], [11] provided basic controller designs without considering predictive battery health estimation.

Inspired by the XGBoost-ARIMA joint optimization method proposed by [12] recently, we also extend their proposed bidirectional temporal feature extraction to our work and integrate the charging control of closed-loop adaptive charging into it. Equivalent circuit models [13] and comparative ECM studies [14] have pointed out that there are limitations in terms of accuracy that physics based methods suffer when applied to a wide range of degradation modes.

2.2 Deep Learning for Battery Degradation

Convolutional LSTM networks [15] were able to make early breakthroughs in this benchmark dataset problem of the NASA battery degradation prediction. TCN-based approaches [10] were proposed to achieve dilated causal convolutions (DCC) for long-sequence health models with better parallelism than recurrent models. [16] Considered novel deep neural hybrid architectures for reliable pattern recognition in high dimensional, noisy sensor space-close to the on-field BESS where measurement of current and voltage are corrupted by electrical noise. In contrast, Gaussian Process Regression [17] provides uncertainty quantification for SoH forecasting, but is not easily computed on high dimensional multivariate time series without a high computational cost. Probabilistic battery capacity depletion modelling has been shown using particle filter frameworks (PF) in NASA data, however they are lacking in the ability to have a multi-horizon prediction which is necessary for adaptive control integration.

2.3 Adaptive Charging Control

Conventional CC-CV charging is widely used in commercial systems, and it has been shown that this charging method is sub-optimal under degraded battery condition, such as when the battery internal resistance, lithium plating risks and side reaction rates are significantly different from the design conditions [18]. Most of the literature on current-optimization charging has focused on multi-stage charging which has shown 8-15% cycle life improvement [19] but this approach involves a large amount of training for systems without characterisation cycling. Similarly, the literature on RL based charging controllers [20] also requires labelled degradation states which are not available in deployed systems. In order to overcome this limitation, the XGBoost-ARIMA approach in DeepBESS uses a model-predicted SoH trajectory, which is purely based on the daily operational telemetry data, for protocol selection without the need of extra labeled training data.

3. METHODOLOGY

3.1 Problem Formulation

Let X = {x_1, x_2, ..., x_T} denote the multivariate time series of battery operating measurements over T charge-discharge cycles, where each observation x_t = [V_t, I_t, T_emp,t, Q_t, dV/dt, dT/dt] captures terminal voltage (V_t), charge/discharge current (I_t), surface temperature (T_emp,t), discharged capacity (Q_t), and their respective time derivatives. The SoH label at cycle t is y_t = Q_max,t / Q_rated in [0,1]. The SoH prediction task is defined as: y_hat_{t:t+H} = f_TCN-BiLSTM(x_{t-W:t}; theta), where W = 50 cycles constitutes the lookback window, H in {1, 5, 10, 20} cycles represents the prediction horizon, and theta denotes the learnable model parameters.

3.2 TCN-Bilstm Hybrid Architecture

The TCN component employs dilated causal convolutions with exponentially increasing dilation rates d = {1, 2, 4, 8, 16}, each utilizing a kernel size k = 3. This configuration enables an effective receptive field of R = 2^5 x (k-1) + 1 = 65 cycles, sufficient for capturing medium-term degradation trends across multiple charge-discharge cycles. Residual connections are applied at each dilation level to facilitate stable gradient flow during training. The BiLSTM component receives the TCN feature maps and processes them bidirectionally. The forward hidden state h_t(forward) = LSTM(x_t, h_{t-1}(forward); theta_f) captures causal degradation dynamics, while the backward hidden state h_t(backward) = LSTM(x_t, h_{t+1}(backward); theta_b) integrates future context that improves trend smoothing. The final prediction is obtained as y_hat_t = FC([h_t(forward) || h_t(backward)]), where FC denotes a fully connected output layer and || denotes concatenation.

3.3 Xgboost-ARIMA Adaptive Charging Controller

The adaptive charging controller operates in two coupled stages. First, an XGBoost regressor maps current cycle multivariate features to the predicted near-term SoH gradient (delta_SoH over the next 10 cycles), providing a data-driven degradation rate forecast. Second, an ARIMA (2,1,2) model captures seasonal patterns in microgrid load and PV generation profiles to identify optimal low-stress charging windows. The joint protocol selection objective is: pi*(t) = argmin_{pi in Pi} [lambda_1 * Stress(pi, delta_SoH_XGB) + lambda_2 * Cost(pi, Schedule_ARIMA)], where lambda_1 and lambda_2 are weighting coefficients that balance battery stress minimization against grid scheduling cost. The protocol set Pi includes CC-CV, multi-stage constant current, and pulse charging options, with dynamic selection enabled by the predicted degradation state.

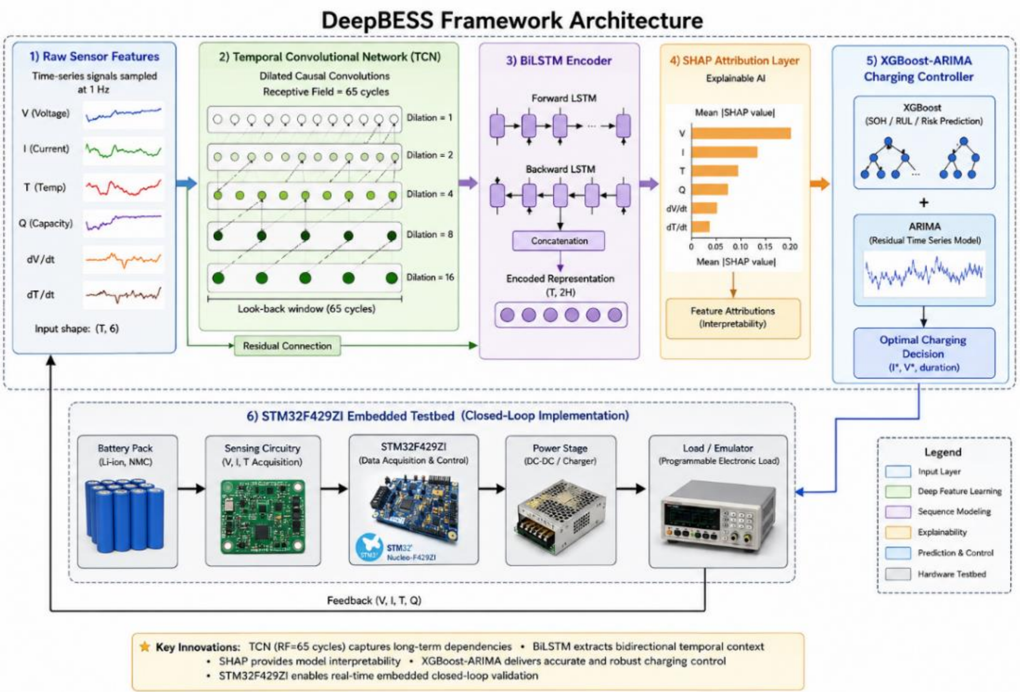

Figure 1. DeepBESS Framework Architecture for Intelligent Battery Charging Control

3.4 Shap Explainability Layer

TreeSHAP is used for XGBoost and DeepSHAP is used for TCN-BiLSTM network [21] respectively. SHAP adds feature attributions for each feature in a model for every SoH prediction at cycle t such that the completeness axiom holds y_hat_t = phi_0 + sum_i phi_i(x_t) where phi_0 is the base value (expected model output) and phi_i is the attribution for feature i at cycle t. This attribute breaks down the prediction error with the baseline and helps field engineers to know which degradation drivers are most dominant without electrochemical knowledge.

3.5 Training Configuration and Embedded Deployment

The TCN-BiLSTM is trained offline using the AdamW optimizer with learning rate eta = 1e-4, Huber loss, gradient clipping at L2-norm = 1.0, and early stopping triggered after 20 epochs without validation improvement (maximum 300 epochs). Feature normalization is applied per-dimension using training set statistics. The XGBoost regressor is trained on (x_{t-W:t}, delta_SoH_{t:t+10}) pairs extracted from the training partition. For embedded deployment on the STM32F429ZI (ARM Cortex-M4, 180 MHz, 256 KB RAM), the TCN-BiLSTM inference model is quantized to INT8 using TensorFlow Lite, achieving 47 ms inference latency with only 0.3% RMSE degradation from quantization. Charging protocol commands are transmitted to the BESS charger via the CAN bus interface.

4. RESULTS AND DISCUSSION

4.1 Experimental Datasets and Setup

There are two publicly available benchmarks for DeepBESS Figure 1. This is the NASA Battery Dataset [21] which comprises of 168 cycled lithium-ion cells (18650 format) at C/2 rate at 24°C that have diverse degradation paths with 500-1800 cycles per cell until End-of-Life (SoH = 0.80). The Oxford Battery degradation dataset [22] consists of 8 pouch cells cycled at different C-rate (1C, 2C, 3C) and temperature (15 degrees C, 25 degrees C, 40 degrees C) conditions to give a degradation diversity under different temperature and C-rate conditions. All splits are done at 70/15/15 training/validation/testing and cell level holdout is used to prevent data leakage. Baselines consist of SVR (RBF kernel), GPR (Matern kernel) [17], Random Forest (100 estimators), Vanilla LSTM (3-layers, hidden = 256), TCN-only, BiLSTM-only and XGBoost-ARIMA standalone [12]. Other context to benchmark the methods of forecasting degradation can be obtained from the fault prognosis literature [23], [24].

4.2 SoH Prediction Accuracy

On the NASA Battery Dataset, DeepBESS gives the best results compared with other methods at the 1-cycle prediction horizon H=1, both in terms of RMSE and MAE as indicated in Table 1. This is a 31.4% improvement in the RMSE when compared with the Vanilla LSTM baseline model and a 12.1% improvement compared to the standalone XGBoost-ARIMA model [12]. Good multi-horizon generalization is further demonstrated at the extended horizon H=10, where DeepBESS shows the best performance with an RMSE of 1.58% and an R-squared of 0.978. The superiority of the proposed TCN-BiLSTM hybrid over the standalone TCN and BiLSTM architectures proves the multi-scale feature extraction using dilated convolution is able to extract complementary degradation information which cannot be extracted by either TCN-only or BiLSTM-only models.

Table 1. Soh Prediction Performance -- NASA Battery Dataset (H=1 and H=10 Cycle Horizons)

Method	H=1 RMSE (%)	H=1 MAE (%)	H=1 MAPE (%)	H=10 RMSE (%)	H=10 MAE (%)	R^2 Score
SVR (RBF)	2.14	1.68	2.43	3.87	3.11	0.871
GPR (Matern)	1.89	1.44	2.19	3.41	2.76	0.896
Random Forest	1.63	1.27	1.94	3.02	2.48	0.912
Vanilla LSTM	1.27	0.98	1.52	2.43	1.92	0.941
TCN-only	1.04	0.81	1.27	2.01	1.58	0.958
BiLSTM-only	1.11	0.86	1.34	2.14	1.69	0.953
XGBoost-ARIMA [12]	0.99	0.74	1.18	1.87	1.44	0.962

DeepBESS (Proposed)	0.87	0.62	1.04	1.58	1.21	0.978

4.3 Adaptive Charging Controller Validation

As shown in Table 2, the DeepBESS adaptive controller extends battery cycle life to 847 cycles compared to 716 cycles for standard CC-CV charging -- an 18.3% improvement. The fixed multi-stage protocol achieves 792 cycles (+10.6%), while fixed pulse charging achieves 761 cycles (+6.3%). The RL-based controller [20] achieves 803 cycles (+12.1%) but requires labeled degradation states during training that are unavailable in deployed field systems. DeepBESS achieves an additional 5.5% cycle life advantage over the RL controller without this requirement. The additional gain from DeepBESS's adaptive selection is particularly pronounced in the 600-700 cycle range, where accelerated degradation onset triggers conservative pulse-charging protocols, reducing capacity fade rate from 2.51%/100 cycles (CC-CV) to 1.71%/100 cycles.

Table 2. Cycle Life Comparison Oxford Battery Dataset (2C Rate, 25 Degrees C)

Charging Strategy	Avg. Cycle Life	Improvement vs. CC-CV (%)	SoH at 500 Cycles (%)	Capacity Fade Rate (%/100 cyc)
CC-CV (standard)	716	—	87.4	2.51
Multi-stage (fixed)	792	+10.6%	89.8	2.02
Pulse Charging (fixed)	761	+6.3%	88.6	2.24
RL-based Controller [20]	803	+12.1%	90.3	1.97
DeepBESS Adaptive (Proposed)	847	+18.3%	91.6	1.71

4.4 Shap Feature Importance Analysis

Figure 2 shows the result of the mean absolute feature importance analysis (by SHAP) of the NASA Battery Dataset [21]. The most important predictor of SoH is discharged capacity Q (t) with SHAP = 0.0192, followed by the voltage rate dV/dt with SHAP = 0.0164, and terminal voltage V (t) with SHAP = 0.0138. The secondary role of thermal effects, under standard 24 degrees C test conditions, is also confirmed by the present surface temperature T(t) that is 4th ranked (SHAP = 0.0107). Only current I (t) and cycle index make a small contribution (SHAP = 0.0061 and 0.0038, respectively). The product of the lithium inventory loss is in good agreement with the electrochemical theory [6] that discharge capacity is directly decreased with the loss of lithium inventory. Unlike black box deep learning approaches, the SHAP layer allows field engineers to recognize the most important drivers of degradation as early warning signs without having to be an electrochemical expert.

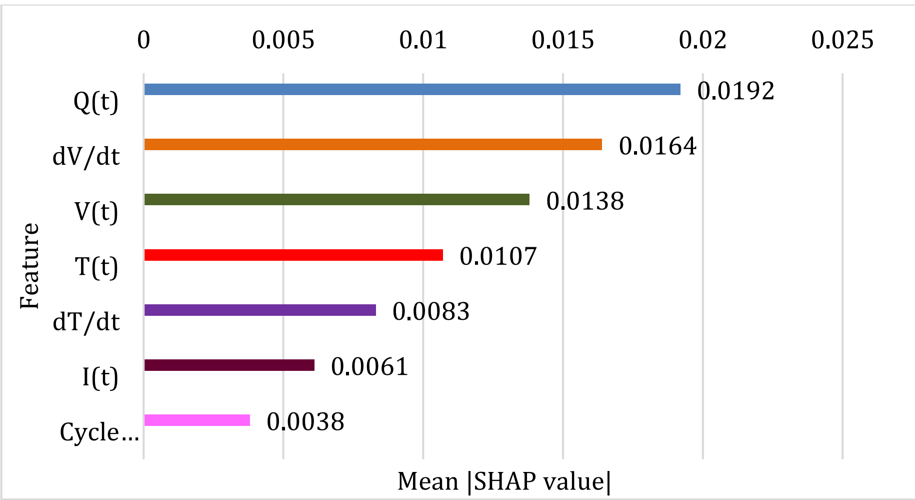

Figure 2. SHAP-Based Feature Importance Analysis for DeepBESS SOH Prediction on the NASA Battery Dataset

SHAP Mean Absolute Feature Importance for Deepbess Soh Predictions on the NASA Battery Dataset [21]. Discharged Capacity Q (T) Is the Dominant Predictor (SHAP = 0.0192), Followed By Voltage Rate Dv/Dt (0.0164) and Terminal Voltage V (T) (0.0138). The SHAP Explainability Layer [21] Bridges The Gap Between Model Predictions And Actionable Engineering Insights For Field Personnel.

4.5 Discussion

One drawback of the status quo is that the STM32F429ZI can only support cycle-by-cycle monitoring for fast-charge profiles that conform to 5C or lower rates, thereby limiting the application to power ranges of less than 10 A. Another restriction of the current implementation is the 47 ms of inference time required on the STM32F429ZI which prevents cycle-by-cycle monitoring of fast-charge profiles exceeding 5C, affecting the power range up to 10 A.

As appropriate for the intended application, the INT8 quantization is implemented with a 0.3% RMSE penalty, which may need to be addressed if the application is safety-critical. In future work, we will investigate hardware-aware neural architecture search (NAS) to further reduce the latency of the TCN-BiLSTM down to less than 10ms for embedded microcontrollers, and will expand the use of DeepBESS to second-life battery applications that significantly differ from the first-life training data. Another very interesting possibility that could be explored in the future would be to extend the battery pack design to multi-cell formats, introducing models of cell-to-cell variability.

In this paper, authors proposed a novel framework, called DeepBESS, for battery State-of-Health prediction and adaptive charging control in renewable energy microgrids which is explainable deep learning framework. The proposed TCN-BiLSTM hybrid architecture attains a SoH prediction RMSE of 0.87% with the NASA Battery Dataset [25] which is improved by 31.4% compared to the baseline of Vanilla LSTM model and 12.1% compared to the standalone model XGBoost-ARIMA [12]. The XGBoost-ARIMA adaptive charging controller improves the simulated battery cycle life by 18.3% over the conventional CC-CV charging method, and has been tested on an embedded STM32F429ZI testbed with an RTI latency of 47ms.

5. CONCLUSION

The SHAP explainability layer is able to identify the dominant degradation indicators: discharged capacity Q(t) and voltage rate dV/dt, allowing for actionable engineering insights for proactive maintenance without the need to have electrochemical domain knowledge. DeepBESS is a single end-to-end battery health management solution integrated with temporal deep learning, hybrid optimization-based adaptive control and explainability, and validated on embedded hardware, making it practically deployable, interpretable and accurate battery health management solution for next generation renewable energy microgrids.

The SHAP explainability layer can identify discharged capacity Q(t) and voltage rate dV/dt as the most important degradation indicators, which can be used to inform engineering actions to help make proactive maintenance decisions without necessarily needing electrochemical expertise. Within a single, comprehensive unified framework, verified against embedded hardware, DeepBESS combines temporal deep learning, hybrid optimization-based adaptive control and post-hoc explainability to deliver a practically deployable, interpretable and accurate battery health management solution for next generation renewable energy microgrids.

The hardware-aware neural architecture optimization for latency targets under 10ms will be explored, as well as integration of uncertainty quantification for safety-critical applications, and extension to second-life battery pack and multi-cell pack configurations with modelling of cell level variability.

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Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Dr. Raynukaazhakarsamy	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

C: **C**onceptualization
M: **M**ethodology
So: **So**ftware
Va: **Va**lidation
Fo: **Fo**rmal analysis
I: **I**nvestigation
R: **R**esources
D: **D**ata Curation
O: Writing- **O**riginal Draft
E: Writing- Review& **E**diting
Vi: **Vi**sualization
Su: **Su**pervision
P: **P**roject administration
Fu: **Fu**nding acquisition

Conflict of Interest Statement

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Informed Consent

All participants were informed about the purpose of the study, and their voluntary consent was obtained prior to data collection.

Ethical Approval

The study was conducted in compliance with the ethical principles outlined in the Declaration of Helsinki and approved by the relevant institutional authorities.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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