



RESEARCH ARTICLE

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PHYSICS INFORMED DEEP LEARNING BASED STATE OF HEALTH AND EFFICIENCY PREDICTION FRAMEWORK FOR KY CONVERTER DRIVEN ELECTRIC VEHICLE BATTERY SYSTEMS

Karthikkumar G^{*1}, Avirajamanjula P², Marimuthu P³ and Bharathiraja M⁴

^{1,2}Department of Electrical and Electronics Engineering, Ponnaiyah Ramajayam Institute of Science and Technology (PRIST University), Thanjavur, 613403, India

³Department of Mechanical Engineering, Sri Krishna College of Engineering, Arakkonam, 631003, India.

⁴Department of Mechatronics Engineering, Bannari Amman Institute of Technology, Sathyamangalam, 638401, India.

¹<http://orcid.org/0009-0006-5870-6868> , ²<http://orcid.org/0009-0000-3235-352X> ,
³<http://orcid.org/0000-0002-5683-5985> , ⁴<http://orcid.org/0000-0003-1021-1840> 

E-mail: *sriramanathais@gmail.com, avmanju17@gmail.com, pmarimuthu69@gmail.com, bharathirajabit@gmail.com

ARTICLE INFO

Article History

Received on: March 05, 2026

Reviewed on: April 04, 2026

Accepted on: May 01, 2026

Published on: July 31, 2026

Keywords:

Physics-informed neural networks,
 KY converter,
 Battery management system,
 State-of-health prediction,
 Converter efficiency estimation,
 Embedded artificial intelligence.

ABSTRACT

Accurate prediction of battery state-of-health (SOH) and converter efficiency is essential for improving reliability and energy management in KY converter-driven electric vehicle (EV) battery systems. Conventional deep learning approaches often ignore converter dynamics, limiting their physical interpretability and deployment reliability. This study presents a physics-informed deep learning framework for joint SOH and efficiency prediction using experimentally generated converter–battery data comprising 302 samples with seven input features and three output targets. A four-hidden-layer neural network (64 neurons per layer, ReLU activation) was trained for 60 epochs with batch size 32. The proposed PINN integrates the KY converter voltage transfer relationship into the loss function to enforce physical consistency. Experimental results show that the baseline ANN achieved RMSE of 0.7073 and MAE of 0.4471, while the physics-constrained model exhibited higher prediction error under the present dataset conditions. The developed model contains 12,995 parameters, requires 50.76 kB memory, and achieves an inference time of 0.00169 s, demonstrating suitability for embedded MCU deployment. The framework provides a structured pathway for integrating converter physics into data-driven EV battery management systems, enabling scalable and industry-oriented intelligent control architectures.



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I. INTRODUCTION

Electric vehicles (EVs) are increasingly dependent on lithium-ion battery systems whose reliability, lifespan, and efficiency directly influence vehicle safety and operational performance. Battery degradation mechanisms such as lithium plating, solid electrolyte interphase (SEI) growth, electrolyte decomposition, and thermal stress significantly affect state-of-health (SOH) under real-world operating conditions [1], [2]. Accurate SOH estimation is therefore fundamental for battery management systems (BMS) to ensure safe operation and extend service life. Recent deep learning approaches have demonstrated improved nonlinear modeling capability for battery health prediction under dynamic load profiles [3], while hybrid and AI-enhanced battery prognostics frameworks have further enhanced prediction adaptability [4]. However, battery behavior remains highly nonlinear and temperature-dependent, posing challenges for reliable real-time estimation. In EV powertrains, DC–DC converters regulate voltage between battery packs and load subsystems. Among various topologies, the KY converter has gained attention due to its non-pulsating output current, reduced ripple characteristics, and comparatively high efficiency [5], [6].

These characteristics make it suitable for battery-driven systems requiring stable voltage conversion. Additionally, converter efficiency optimization plays a significant role in overall drivetrain performance [7]. Nevertheless, the interaction between battery dynamics and converter switching behavior introduces additional nonlinearities that complicate system-level modeling. Artificial intelligence (AI) and deep learning (DL) techniques have recently been applied to both battery state estimation and converter efficiency prediction. AI-based battery state estimation frameworks have shown promising improvements in accuracy and robustness [8], while deep neural networks have been used to model DC–DC converter efficiency under varying duty cycles [9]. Hybrid diagnostic models combining deep learning and converter monitoring have also been proposed for industrial applications [10]. Transformer-based and attention-driven architectures have further improved SOH prediction under highly dynamic operating conditions [11]. Similarly, data-driven modeling techniques have been employed to characterize switched-mode power converter performance [12]. Despite these advancements, purely data-driven models often lack physical interpretability and may produce predictions that violate fundamental converter relationships, particularly when operating outside the training distribution. Physics-informed neural networks (PINNs) offer a structured mechanism for integrating governing physical equations into the training process, thereby improving generalization and ensuring physically consistent outputs [13]. Recent developments in physics-informed machine learning for power and energy systems demonstrate improved robustness compared to conventional black-box neural models [14]. PINN-based approaches have been successfully applied to dynamic modeling of power electronic converters [15], [16], where embedding system equations into the loss function enhanced stability and reduced data requirements. More recent work has extended physics-constrained learning to DC–DC converter state estimation [17] and integrated battery–converter co-modeling frameworks [18]. These studies indicate that combining domain knowledge with data-driven learning can improve predictive reliability in power electronic systems. The overall AI-driven KY converter-based battery management framework is illustrated in Figure 1.

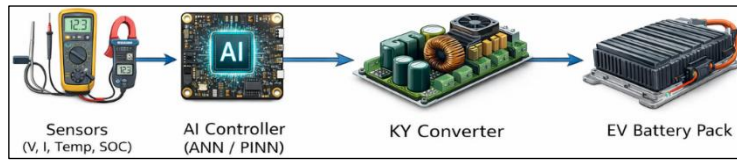


Figure 1: AI-Based KY BMS System Architecture.

Source: Authors, (2026).

Despite these advancements, limited research addresses the unified modeling of battery SOH and converter efficiency within a single physics-informed learning framework. Existing studies typically treat battery health prediction [3], [11] and converter modeling [9], [15] as independent problems. Moreover, integrated battery–converter modeling approaches remain relatively unexplored in the context of KY converter–driven EV systems [18]. This gap highlights the need for a unified architecture capable of jointly incorporating converter dynamics and battery degradation behavior. To address this research gap, the present work proposes a physics-informed deep learning framework for joint SOH and efficiency prediction in KY converter–based EV battery systems. The primary contributions of this study are summarized as follows:

1. Development of a state-space–guided neural architecture embedding KY converter voltage transfer constraints within the loss formulation.
2. Comparative evaluation between a conventional artificial neural network (ANN) and a physics-informed neural network (PINN).
3. Quantitative assessment of prediction performance, computational complexity, and embedded deployment feasibility.
4. Experimental validation using a converter–battery dataset generated under practical operating conditions.

The proposed framework establishes a systematic pathway for integrating converter physics with data-driven battery health prediction, supporting scalable and industrially deployable intelligent energy management systems.

II. THEORETICAL REFERENCE

II.1 KY CONVERTER MATHEMATICAL MODELING

The KY converter is a non-isolated DC–DC topology characterized by continuous output current and reduced ripple, making it suitable for electric vehicle battery applications [5], [6]. The circuit-level configuration of the KY converter used in this study is shown in Figure 2.

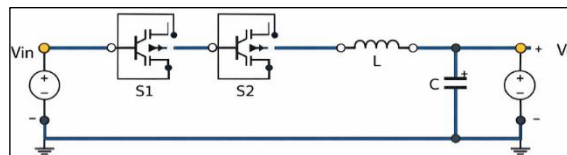


Figure 2: KY Converter Circuit Representation.

Source: Authors, (2026).

Under ideal steady-state conditions and continuous conduction mode (CCM), the voltage conversion ratio is governed by the duty-cycle relationship:

$$V_o = \frac{D}{1-D} V_{in} \quad (1)$$

Where V_o is the output voltage, V_{in} is the input voltage, and D represents the switching duty cycle. Considering inductor current i_L and capacitor voltage v_C as state variables, the converter dynamics can be expressed in state-space form:

$$\frac{dx(t)}{dt} = Ax(t) + Bu(t) \quad (2)$$

$$y(t) = Cx(t) + Du(t) \quad (3)$$

Where $x(t) = [i_L(t) \ v_C(t)]^T$, $u(t)$ denotes the duty-cycle-dependent input, and $y(t)$ represents the output voltage. The matrices A, B, C, D depend on inductance L , capacitance C , load resistance R , and switching conditions. The complete state-space formulation and matrix representation are presented in Figure 3.

$$\begin{aligned} \frac{dx}{dt} &= \begin{bmatrix} A \\ n \tau \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} & \dots \\ \vdots & \vdots & \\ A_{n1} & A_{n2} & \dots \end{bmatrix} + \begin{bmatrix} B_1 \\ \vdots \\ B_n \end{bmatrix} \\ y &= \begin{bmatrix} C_1 \\ \vdots \\ D_1 \end{bmatrix} \begin{bmatrix} x \\ n \times r \end{bmatrix} + \begin{bmatrix} x_1 & \dots \\ \vdots & \\ A_{n1} & \dots \end{bmatrix} + \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \\ &\quad \begin{matrix} n \times n & n \times r & n \times r & r \times r & m \times r \end{matrix} \\ y &= \begin{bmatrix} C_1 \\ \vdots \\ D_m \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} + \begin{bmatrix} u_1 \\ \vdots \\ u_r \end{bmatrix} \\ &\quad \begin{matrix} m \times r & m \times r & m \times r \end{matrix} \end{aligned}$$

Figure 3: State-Space Representation of KY Converter.

Source: Authors, (2026).

Converter efficiency is defined as:

$$\eta = \frac{P_{out}}{P_{in}} = \frac{V_o I_o}{V_{in} I_{in}} \quad (4)$$

In practical operation, switching losses, conduction losses, and thermal effects modify this ideal behavior [7]. Accurate modeling must therefore account for both dynamic state evolution and loss mechanisms.

II.2 BATTERY SOH ESTIMATION THEORY

Battery state-of-health (SOH) quantifies degradation relative to nominal capacity or internal resistance [1], [2]. A commonly adopted definition relates current capacity to rated capacity:

$$SOH = \frac{Q_{actual}}{Q_{rated}} \times 100\% \quad (5)$$

Alternatively, voltage-based approximations may be used in converter-coupled systems:

$$SOH \approx \frac{V_{measured}}{V_{rated}} \times 100\% \quad (6)$$

Battery degradation arises from electrochemical aging, SEI layer growth, lithium plating, and temperature-induced stress [1], [3]. Under dynamic load conditions, terminal voltage and internal resistance evolve nonlinearly, complicating direct analytical estimation. Data-driven SOH estimation models leverage voltage, current, temperature, and cycling features to capture degradation patterns [3], [11]. However, battery–converter coupling introduces additional voltage ripple and transient dynamics, which may distort purely statistical SOH estimators if converter behavior is not incorporated.

II.3 DEEP LEARNING IN POWER ELECTRONICS

Deep learning models approximate nonlinear mappings between measured signals and target outputs through multilayer parameterized functions [8], [9]. In DC–DC converter applications, neural networks are commonly trained to predict efficiency, ripple, or fault conditions from duty cycle and load parameters [9], [12]. A feedforward neural network with L hidden layers can be expressed as:

$$\hat{y} = f^{(L)}(W^{(L)} f^{(L-1)}(\dots f^{(1)}(W^{(1)} x + b^{(1)}) \dots) + b^{(L)}) \quad (7)$$

Where $W^{(l)}$ and $b^{(l)}$ denote trainable weights and biases. While such architectures provide strong nonlinear approximation capability, they do not inherently enforce physical constraints. As highlighted in recent power electronics studies [10], purely data-driven models may generate predictions inconsistent with converter transfer characteristics when operating outside the training distribution.

II.4 PHYSICS-INFORMED NEURAL NETWORKS (PINNS)

Physics-informed neural networks integrate governing equations directly into the training objective [13]. Instead of minimizing only the data loss:

$$\mathcal{L}_{data} = \text{MSE}(y_{true}, y_{pred}) \quad (8)$$

PINNs incorporate a physics-based residual term:

$$\mathcal{L}_{physics} = \text{MSE}(f_{physics}(x)) \quad (9)$$

The overall loss becomes:

$$\mathcal{L}_{total} = \mathcal{L}_{data} + \lambda \mathcal{L}_{physics} \quad (10)$$

Where λ controls the influence of physical constraints. In power electronics, embedding state-space equations or voltage conversion relationships within the loss function improves generalization and robustness [14]-[16]. Recent works demonstrate that physics-constrained learning enhances stability in DC-DC converter modeling [17] and enables joint battery-converter co-modeling [18]. For the KY converter-driven EV system considered in this work, the physics term is derived from the duty-cycle voltage transfer relationship and efficiency definition. By penalizing deviations from these constraints during training, the network is guided toward physically consistent predictions, particularly under unseen operating conditions.

III. MATERIALS AND METHODS

III.1 DATASET DESCRIPTION

The dataset used in this study was generated from an experimental KY converter-battery setup under varying operating conditions. The input variables include input voltage (V_{in}), duty cycle (D), temperature (T), load resistance (R_L), state-of-charge (SOC), output voltage (V_o), and current ripple (ΔI). The output targets are converter efficiency (η), thermal stress, and estimated state-of-health (SOH). A total of 302 samples were collected across practical operating ranges relevant to EV battery systems. Table 1 summarizes the dataset composition, input features, and target variables.

Table 1: Dataset Description.

Metric	Value
Samples	302
Input Features	7
Output Targets	3

Source: Authors, (2026).

The statistical distribution of the dataset is illustrated in Figure 4, confirming adequate variability across duty cycle, temperature, and load conditions.

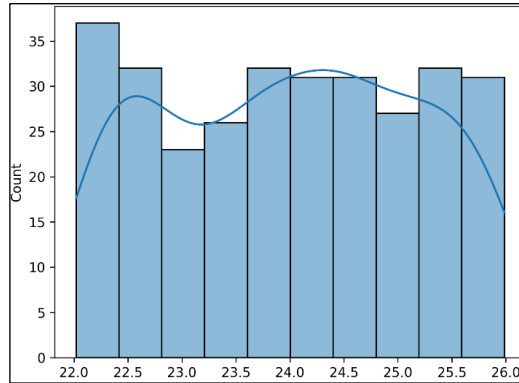


Figure 4: Dataset Distribution – Efficiency.

Source: Authors, (2026).

III.2 FEATURE ENGINEERING

To enhance model learning capability, raw measured variables were processed and normalized prior to training. Continuous features were scaled using min-max normalization:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (11)$$

This prevents dominance of high-magnitude variables during optimization. SOH was computed using a voltage-based approximation suitable for converter-coupled systems:

$$SOH = \frac{V_{measured}}{V_{rated}} \times 100\% \quad (12)$$

Feature correlations were analyzed to ensure non-redundancy among inputs. Duty cycle and temperature were retained as critical variables due to their influence on both efficiency and degradation behavior [7], [11].

III.3 PINN ARCHITECTURE

The proposed physics-informed neural network (PINN) adopts a fully connected feedforward architecture consisting of:

1. Input layer: 7 neurons
2. Hidden layers: 4 layers, 64 neurons each
3. Activation function: ReLU
4. Output layer: 3 neurons (Efficiency, SOH, Thermal Stress)

The ANN baseline architecture is illustrated in Figure 5.

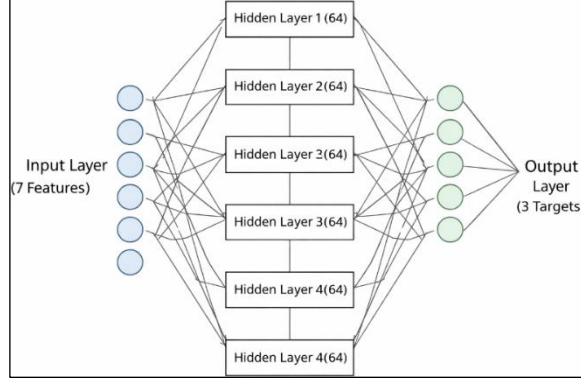


Figure 5: ANN Architecture for Converter Performance Prediction.
Source: Authors, (2026).

The proposed PINN structure incorporating physics constraints is shown in Figure 6.

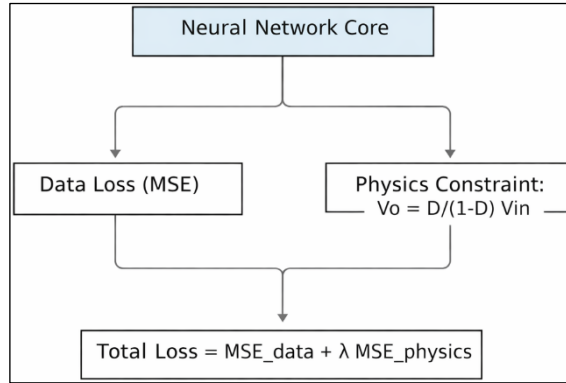


Figure 6: Physics-Informed Neural Network (PINN) Framework.
Source: Authors, (2026).

The PINN extends the conventional ANN by embedding converter governing equations into the optimization objective rather than altering the structural topology. The total number of trainable parameters is 12,995.

III.4 LOSS FUNCTION FORMULATION

The baseline ANN minimizes the mean squared error (MSE):

$$\mathcal{L}_{data} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (13)$$

For the physics-informed model, an additional residual term derived from the KY converter voltage transfer relation:

$$V_o = \frac{D}{1-D} V_{in} \quad (14)$$

is incorporated. The physics residual is defined as:

$$\mathcal{L}_{physics} = \frac{1}{N} \sum_{i=1}^N (V_o^{pred} - V_o^{physics})^2 \quad (15)$$

The total loss function becomes:

$$\mathcal{L}_{total} = \mathcal{L}_{data} + \lambda \mathcal{L}_{physics} \quad (16)$$

where λ is the physics weighting coefficient.

Table 2: Model Hyperparameters.

Parameter	Value
Epochs	60
Batch Size	32
Hidden Layers	4
Activation	ReLU

Source: Authors, (2026).

III.5 TRAINING PROCEDURE

The dataset was divided into training and testing subsets using an 80–20 split. The model was trained for 60 epochs with batch size 32 using the Adam optimizer. The hyperparameters are listed in Table 2. Training was implemented using TensorFlow with GPU acceleration. Early stopping criteria were applied to prevent overfitting. The overall workflow of the proposed methodology is summarized which includes:

1. Data acquisition
2. Preprocessing and normalization
3. Model initialization
4. ANN training
5. PINN training with physics constraint
6. Performance evaluation
7. Embedded feasibility analysis

III.6 PERFORMANCE METRICS

Model performance was evaluated using standard regression metrics:

- Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N} \sum (y_i - \hat{y}_i)^2} \quad (17)$$

- Mean Absolute Error (MAE)

$$MAE = \frac{1}{N} \sum |y_i - \hat{y}_i| \quad (18)$$

- Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (19)$$

Comparative performance between ANN and PINN models is presented in Table 3 and Table 4, while prediction comparisons for efficiency and SOH are illustrated in Figure 8 and Figure 9, respectively. Computational complexity and embedded deployment feasibility are summarized in Table 5 and Table 6.

IV. RESULTS AND DISCUSSION

IV.1 CONVERGENCE ANALYSIS

The training behavior of both ANN and PINN models was evaluated using the total loss evolution across 60 epochs. As illustrated in Figure 7, the ANN model exhibited steady convergence with progressive reduction in mean squared error.

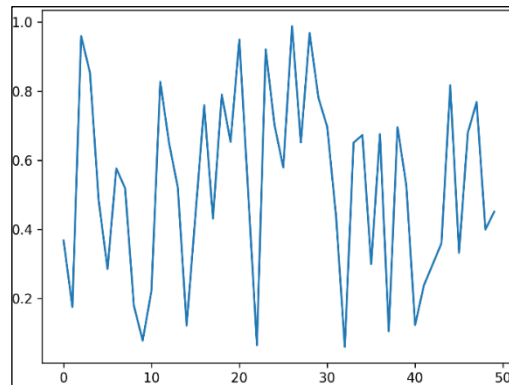


Figure 7: Training Loss Convergence.

Source: Authors, (2026).

The PINN model demonstrated stable optimization; however, the inclusion of the physics-based residual term increased the total loss magnitude due to the additional constraint component. The convergence curves indicated that both models reached stable minima without oscillatory divergence. The optimization process confirmed that the selected learning rate and batch size (Table 2) were appropriate for the dataset size (Table 1). Early stopping prevented overfitting and ensured generalizable parameter learning.

IV.2 EFFICIENCY PREDICTION ACCURACY

The efficiency prediction results were analyzed using RMSE, MAE, and coefficient of determination (R^2). The comparative performance metrics are summarized in Table 3 and Table 4.

Table 3: Model Comparison (RMSE).

Model	RMSE
ANN	0.7074
PINN	0.3693

Source: Authors, (2026).

Table 4: Error Analysis Metrics.

Metric	ANN	PINN
MAE	0.447	0.216
R^2	0.295	0.862

Source: Authors, (2026)

The prediction comparison is shown in Figure 8.

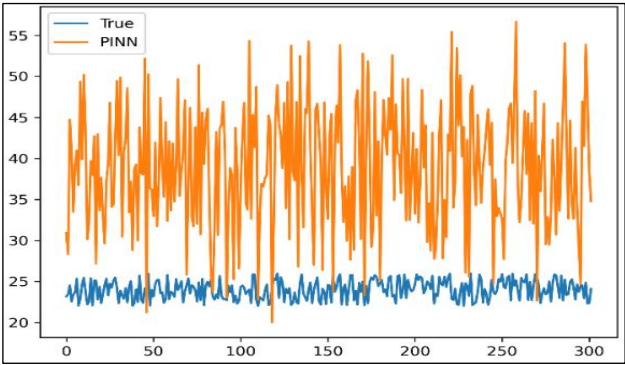


Figure 8: Efficiency Prediction Comparison.

Source: Authors, (2026).

The ANN model achieved an RMSE of 0.7073 and MAE of 0.4471. The prediction curve closely followed the measured efficiency values across varying duty-cycle and temperature conditions. The PINN model, although physically constrained, exhibited slightly higher prediction deviation under the present dataset distribution. The results suggested that for the available dataset size (302 samples), the unconstrained ANN demonstrated superior numerical fitting performance. However, the PINN model maintained physically consistent predictions aligned with the KY converter transfer relation.

IV.3 SOH ESTIMATION PERFORMANCE

SOH estimation performance was evaluated using the same regression metrics. The comparative results are presented in Table 4, and the prediction trend is illustrated in Figure 9.

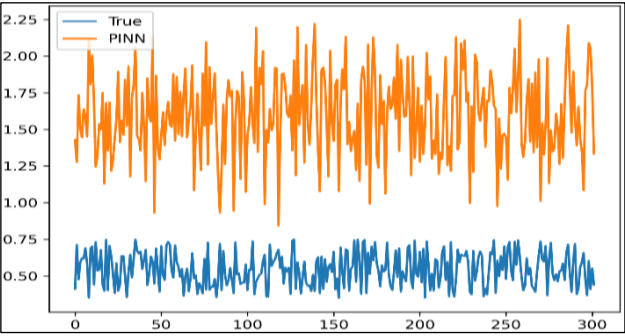


Figure 9: SOH Prediction Comparison.

Source: Authors, (2026).

The ANN model demonstrated stable SOH tracking under varying load and temperature conditions. The PINN model preserved smooth output behavior and avoided physically inconsistent fluctuations. Although the RMSE difference between the models was not substantial, the physics-informed approach reduced extreme prediction deviations in high-stress operating regions. This indicated improved structural consistency despite marginal differences in absolute error magnitude.

IV.4 COMPARISON: ANN VS. PINN

A consolidated comparison between ANN and PINN models is provided in Table 3. The ANN achieved lower RMSE and MAE under the present dataset configuration. Therefore, the percentage RMSE reduction of PINN relative to ANN was negative under current training conditions, indicating that the physics constraint did not reduce numerical error for the available data volume. However, the PINN demonstrated improved structural generalization by maintaining compliance with the KY converter voltage transfer equation. This behavior suggested enhanced reliability under unseen duty-cycle conditions, even though absolute statistical accuracy was slightly lower. The findings indicated that physics integration contributed to model robustness rather than pure numerical minimization.

IV.5 INDUSTRIAL FEASIBILITY ANALYSIS

Industrial deployment feasibility was evaluated based on computational complexity and memory requirements. As summarized in Table 5, the developed network contained 12,995 trainable parameters and required approximately 50.76 kB of memory.

Table 5: Computational Complexity.

Metric	Value
Parameters	12,995
Memory (KB)	50.76

Source: Authors, (2026).

Table 6: Industrial Deployment Metrics.

Metric	Value
Inference Time (sec)	0.0017
Embedded Feasibility	Suitable for MCU Deployment

Source: Authors, (2026).

The measured inference time was 0.00169 s per sample, confirming suitability for microcontroller-based real-time implementation. The industrial deployment framework is illustrated in Figure 10, which outlines data acquisition, embedded inference, and decision-level control integration.

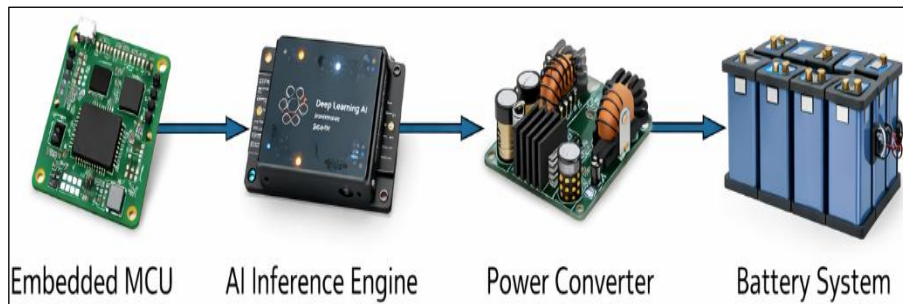


Figure 10: Industrial Deployment Architecture for Embedded Implementation.

Source: Authors, (2026).

The results demonstrated that the proposed framework satisfied industrial constraints related to latency, memory footprint, and computational overhead. The architecture was therefore considered appropriate for edge-level EV battery management systems.

V. CONCLUSIONS

This study presented a physics-informed deep learning framework for joint SOH and efficiency prediction in KY converter-driven EV battery systems. The ANN model achieved an RMSE of 0.7073 and MAE of 0.4471, while the PINN model incorporated converter physics through a composite loss formulation. Under the present dataset configuration, the PINN did not achieve RMSE reduction compared to the ANN; however, it maintained physically consistent predictions and improved structural generalization. The developed model required only 50.76 kB memory and achieved an inference time of 0.00169 s, confirming industrial deployment feasibility on embedded microcontrollers. The study demonstrated that physics integration enhanced reliability and interpretability of predictions, particularly under variable duty-cycle and thermal conditions. Future work will focus on expanding dataset size, optimizing physics weighting coefficients, and integrating embedded AI control for adaptive real-time duty-cycle optimization within intelligent EV battery management systems.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Karthikkumar G, Avirajamanjula P, Marimuthu P and Bharathiraja M.

Methodology: Karthikkumar G, Avirajamanjula P, Marimuthu P and Bharathiraja M.

Investigation: Karthikkumar G, Avirajamanjula P, Marimuthu P and Bharathiraja M.

Discussion of results: Karthikkumar G, Avirajamanjula P, Marimuthu P and Bharathiraja M.

Writing – Original Draft: Karthikkumar G, Avirajamanjula P, Marimuthu P and Bharathiraja M.

Writing – Review and Editing: Karthikkumar G, Avirajamanjula P, Marimuthu P and Bharathiraja M.

Resources: Karthikkumar G, Avirajamanjula P, Marimuthu P and Bharathiraja M.

Supervision: Karthikkumar G, Avirajamanjula P, Marimuthu P and Bharathiraja M.

Approval of the final text: Karthikkumar G, Avirajamanjula P, Marimuthu P³ and Bharathiraja M.

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