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Machine learning-based energy management system for electric vehicles with BLDC motor integration

K. S. R. Vara Prasad, V. Usha Reddy
Department of Electrical and Electronics Engineering, S. V. U. College of Engineering, Tirupati, India

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ABSTRACT

This paper proposes a machine learning-based energy management system for electric vehicles with BLDC motor integration. Efficient energy management is essential for improving the performance, range, and reliability of electric vehicles (EVs), particularly those powered by brushless DC (BLDC) motors. Traditional energy management systems (EMS), such as rule-based and fuzzy logic controllers, often lack the adaptability required for dynamic driving conditions and optimal energy distribution. This paper presents a machine learning (ML)-based EMS framework tailored for EVs equipped with BLDC motors, aiming to enhance system responsiveness and energy efficiency. ML algorithms, including decision trees, random forests, support vector machines (SVMs), and XGBoost, are trained on diverse datasets that reflect varying load demands, driving cycles, and battery state-of-charge (SOC) levels. The proposed EMS is modeled and validated in Python programming to simulate realistic EV operating scenarios. Simulation results indicate that the ML-based EMS outperforms conventional methods by achieving up to 15% energy savings, reducing battery stress, and maintaining smoother SOC transitions. These findings highlight the potential of ML-driven strategies for creating adaptive, intelligent EMS solutions in next-generation BLDC motor-based EVs.

Corresponding Author:

K. S. R. Vara Prasad
Department of Electrical and Electronics Engineering, S. V. U. College of Engineering
Tirupati, Andhra Pradesh, India
Email: ksrvaram220@yahoo.com

1. INTRODUCTION

Electric vehicles (EVs) represent a pivotal shift toward cleaner and more sustainable transportation solutions, driven by the global imperative to reduce carbon emissions, fossil fuel dependency, and urban air pollution [1], [2]. Despite significant advancements in battery technology and power electronics, EVs still face key challenges such as limited driving range, prolonged charging times, and reduced operational efficiency under dynamic conditions. These limitations underscore the urgent need for intelligent energy management strategies that can optimize the use of onboard energy resources. At the core of this optimization lies the energy management system (EMS), which is responsible for real-time decision-making regarding energy allocation, battery usage, and powertrain control. A well-designed EMS ensures that energy stored in the battery is distributed efficiently among various components, such as the traction motor, regenerative braking system, and auxiliary loads, while also extending battery life and enhancing vehicle reliability [3], [4].

Historically, EMS strategies have relied on rule-based or heuristic algorithms due to their simplicity and ease of implementation. However, these methods often lack adaptability and fail to respond effectively to the nonlinear and dynamic nature of modern EV operations, especially in hybrid and plug-in hybrid configurations (HEVs and PHEVs) [5]-[7]. In recent years, machine learning (ML) and artificial intelligence (AI) techniques have emerged as robust alternatives for developing data-driven, adaptive EMS solutions. By leveraging historical and real-time data, ML models can predict driving behavior, battery state of charge (SoC), energy demand, and system health, thereby facilitating more accurate and responsive control strategies [8]. Supervised learning algorithms such as XGBoost [4], random forest [9], and support vector machines (SVM) have demonstrated strong performance in energy usage classification and anomaly detection under uncertain environments.

Further advancements have been achieved through deep reinforcement learning (DRL), which enables EMS frameworks to learn optimal control policies by interacting with the driving environment. DRL-based EMS approaches can simultaneously balance multiple objectives, such as energy efficiency, emissions reduction, and user comfort, without requiring explicit system models [10], [11]. Techniques like twin delayed deep deterministic policy gradient (TD3) [12], Q-learning, and actor-critic methods have shown potential in real-time powertrain control and route-aware energy management [13], [14]. A growing trend in intelligent EMS is the modeling of driver behavior and the development of personalized energy strategies. Incorporating user profiles and real-time feedback allows EMS to dynamically adjust to individual driving styles, load conditions, and route preferences, leading to enhanced efficiency and driving experience [15].

Moreover, the integration of renewable energy sources, smart grid infrastructure, and vehicle-to-grid (V2G) systems has introduced new layers of complexity and opportunity. EMSs must now coordinate with distributed energy resources (DERs), bidirectional charging stations, and demand response programs [16]-[18]. To manage this, hybrid control approaches incorporating neural networks, adaptive neuro-fuzzy inference systems (ANFIS), and metaheuristic optimization are being explored [19]-[21].

Recent literature reviews [22]-[24] highlight the evolution of EMS from static, rule-based systems to hybrid, AI-enabled architectures that integrate real-time optimization, predictive modeling, and edge computing. The advent of edge AI enables low-latency, decentralized EMS operation, offering faster response times and improved data privacy [25]-[27]. Despite this progress, several research gaps persist: i) data sparsity and heterogeneity across EV platforms, ii) high computational complexity of advanced ML/DRL algorithms, iii) limited interpretability of black-box models in safety-critical systems, and iv) lack of standardization and regulatory compliance in EMS design.

To address these challenges, this paper proposes a comparative EMS framework leveraging decision tree, SVM, and XGBoost classifiers trained on real-time EV operational data. The framework enhances energy efficiency, supports predictive load management, and facilitates fault diagnosis in electric traction systems. Additionally, the study integrates BLDC motor health monitoring, battery state of health (SoH) estimation, and load forecasting, offering a comprehensive AI-driven solution for next-generation EMS in EVs.

2. ENERGY MANAGEMENT SYSTEM (EMS) IN ELECTRIC VEHICLES (EVS)

2.1. Overview of EMS in EV powertrains

An EV powertrain comprises several key subsystems: the battery, inverter, electric motor, and a controller that governs the energy flow. The EMS functions as the supervisory control unit responsible for intelligently distributing power among these components during different phases of operation, such as acceleration, cruising, braking, and charging. In this study, the EMS is designed to predict and manage power distribution strategies using both rule-based logic and machine learning (ML) models. The objective is to optimize energy efficiency, maintain battery health, and prolong vehicle range under varying driving conditions.

Table 1 outlines the typical battery specifications used in the dataset simulation and model training. These values are based on a representative lithium-ion battery pack suitable for mid-range EVs. Table 2 presents key motor parameters critical for the EMS model, particularly in capturing features like speed, acceleration, and load. A 48 V, 3 kW BLDC motor is considered the propulsion unit, driving the vehicle load under EMS supervision.

Table 1. Battery parameters used in simulation

Parameter	Value	Description
Battery type	Li-ion (NMC)	Nickel manganese cobalt oxide
Nominal voltage	350 V	Average voltage under standard operation
Capacity	100 Ah	Maximum charge storage
Total energy	35 kWh	$E_{total} = V_{nom} \times Q$
Usable energy	31.5 kWh	~90% of total energy for safe operation
SOC range	10–100%	Operational window for EMS

Table 2. BLDC motor parameters

Parameter	Value
Rated voltage	48 V
Rated power	3 kW
Rated speed	3000 RPM
Peak torque	10–15 Nm
Back EMF constant K_e	0.08 V/rad/s
Stator resistance	0.15–0.25 Ω
Cooling mechanism	Natural/Fan
Control strategy	FOC or 6-Step

2.2. Rule-based EMS logic

In the first approach, a conventional rule-based EMS is defined using simple conditional logic based on state of charge (SOC) and load. The logic can be represented by the following decision boundaries:

- If SOC > 0.8 and load < 2000 W: use battery
- If SOC < 0.3: enable regenerative braking
- Else: use an optimized energy mix

This approach is deterministic and computationally efficient, but lacks adaptability to dynamic driving patterns or unseen scenarios.

2.3. Energy flow and management phases in EV

The EMS interacts with the EV subsystems across three major operational phases:

- Discharge phase: Battery powers the motor through the inverter, as presented in (1).

$$P_{motor} = V_{battery} \times I_{drawn} \tag{1}$$

- Regenerative braking phase: Motor acts as a generator to recover energy, as presented in (2).

$$E_{regen} = \int_{t_1}^{t_2} V(t).I(t)dt \tag{2}$$

- Charging phase: Battery is recharged via an external power source. A simplified block diagram of the EV energy flow is shown in Figure 1, where energy paths are monitored and governed by the EMS logic.

While rule-based EMS offers ease of implementation, it cannot adapt or optimize under uncertain or variable operating conditions. This limitation motivates the integration of data-driven EMS models, such as machine learning classifiers, which can dynamically learn patterns from input features like battery SOC, load (power demand), speed, and acceleration. These features are scaled and fed into ML models that classify the optimal power distribution strategy from the training data, offering improved precision and adaptability compared to static rule sets.

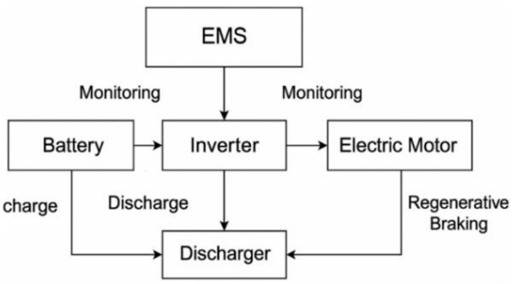

Figure 1. EV energy flow

3. MACHINE LEARNING-BASED ENERGY MANAGEMENT SYSTEM (EMS)

To overcome the limitations of conventional EMS strategies (rule-based and fuzzy logic), this study explores a machine learning (ML)-driven EMS for EVs. The objective is to learn optimal power distribution strategies from operational data to enhance battery life, improve energy efficiency, and support dynamic driving conditions. The ML-EMS system is trained and evaluated using labeled datasets of EV operational parameters, such as speed, acceleration, current, voltage, and SOC, to classify or predict power flow control actions during different drive cycles. Figure 2 illustrates the complete workflow of the proposed energy management system for EVs, comparing conventional rule-based logic with machine learning-based approaches, from data preprocessing to model evaluation and deployment.

3.1. Dataset construction and feature mapping

Table 3 presents the mapping of critical electrical and vehicular parameters used as features in the supervised machine learning models. These inputs are directly derived from the sensor and simulation data of the EV system. The target label for classification includes EMS operation modes such as: discharge (motor load), regenerative braking (energy recovery), idle (no significant energy flow), and charging (external power source). The (3)-(6) are used to derive computed features:

– Electrical power as presented in (3).

$$P_{elec} = \frac{V*I}{1000}\ KW \tag{3}$$

– State of charge estimation based on coulomb counting as presented in (4).

$$SOC(t) = SOC(t_0) - \frac{1}{c_{nom}} \int_{t_0}^{t} I(\tau)d\tau \tag{4}$$

– Motor torque estimation as presented in (5).

$$\tau = \frac{60*P_{elec}}{2\pi*N} \tag{5}$$

Where: P_{elec}: Electrical power (W), N: Motor speed in RPM.

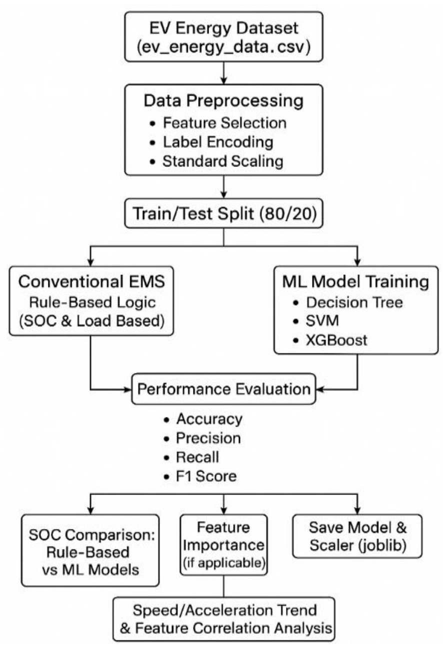

Figure 2. Block diagram of an ML-based energy management system for electric vehicles

Table 3. Feature mapping for ML-EMS

Feature name	Description	Units
Voltage	Terminal voltage of the battery	Volts (V)
Current	Instantaneous battery current	Amperes (A)
Power	Instantaneous electrical power (V × I/1000)	kW
Speed	Rotational speed of BLDC motor	RPM
SOC	Battery state of charge	%
Torque	Torque demanded from the motor	Nm
Acceleration	Rate of change of vehicle speed	m/s²

3.2. Model development and supervised learning approach

In this study, the development of intelligent EMS logic for EVs is formulated as a supervised multi-class classification problem. The objective is to predict the EMS operation mode—such as charging, discharging, regenerative braking, or idle, based on real-time features derived from the powertrain. These features include:

- State of charge (SOC) – (%)
- Battery voltage (V) and current (A)
- Motor speed (RPM) and torque (Nm)
- Acceleration (m/s²) and vehicle speed (km/h)
- Throttle position (%) and braking intensity
- Load power demand (Kw)

The corresponding output label (target) denotes the EMS mode, which is predicted based on the above features using the following machine learning models:

i) Decision tree (DT) classifier

The decision tree classifier is a hierarchical model that recursively partitions the feature space into decision regions based on threshold splits, as shown in Figure 3. It is constructed using criteria such as Gini impurity or entropy to maximize class purity at each node, as presented in (6).

$$\textit{At each split: } Gini(D) = 1 - \sum_{i=1}^{k} p_i^2 \tag{6}$$

Where p_i is the proportion of class i in subset D.

- Captures rule-based heuristics that are common in classical EMS systems.
- Interpretable structure allows tracing back decision logic (e.g., “If SOC < 20% and torque demand is high, enter idle or power-saving mode”).
- Low computational cost enables real-time embedded deployment in onboard EV control units.

ii) Support vector machine (SVM)

The support vector machine is a discriminative classifier that finds an optimal hyperplane with maximum margin separating different classes in a transformed feature space. A radial basis function (RBF) kernel is used to handle non-linear separability. Given training vectors $x_i \in R^n$, labels $y_i \in \{1,...,K\}$, SVM solves, as presented in (7).

$$min \frac{1}{2} \|w\|^2 + C\xi_i \ s.t. \ y_i(w^T \emptyset(x_i) + b) \geq 1 - \xi_i \tag{7}$$

Where $\phi(x_i)$ is the kernel mapping.

- Robust to outliers and generalizes well on high-dimensional, nonlinear EMS feature sets as shown in Figure 4.
- Particularly effective in scenarios with overlapping class distributions (e.g., partial braking with low regenerative output vs low-load discharging).
- Suitable for real-time classification with pre-trained, kernel-optimized models.

iii) XGBoost classifier

XGBoost (extreme gradient boosting) is an ensemble-based classifier that builds sequential weak learners (decision trees) to minimize a regularized loss function using gradient descent optimization. It excels in both accuracy and computational efficiency. The model predicts, as presented in (8).

$$\widehat{y_i} = \sum_{m=1}^{M} f_m(x_i), \quad f_m \in F \tag{8}$$

Where each f_m is a regression tree and F is the functional space. The loss function includes a regularization term, as presented in (9) and (10).

$$L = \sum_i l(y_i, \hat{y}_i) + \sum_m \Omega(f_m) \tag{9}$$

$$\Omega(f) = \gamma T + \frac{1}{2} \lambda \|w\|^2 \tag{10}$$

- Automatically captures complex feature interactions and non-linear dependencies among SOC, speed, and power demand as shown in Figure 5.
- Handles feature sparsity, noise, and missing data without preprocessing penalties.
- Ideal for large-scale, high-dimensional EMS datasets and supports incremental updates (online learning).

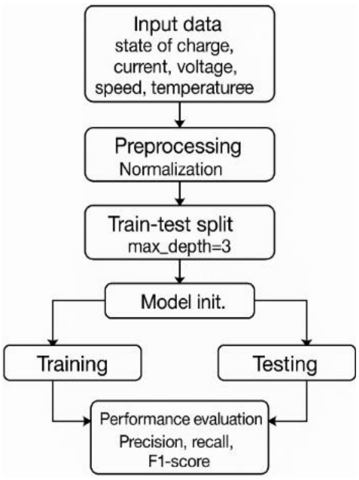

Figure 3. Decision tree flow chart

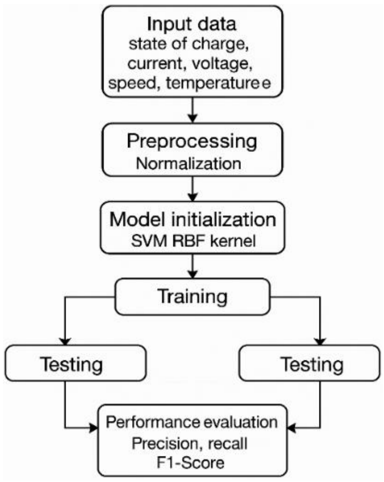

Figure 4. Support vector machine flow chart

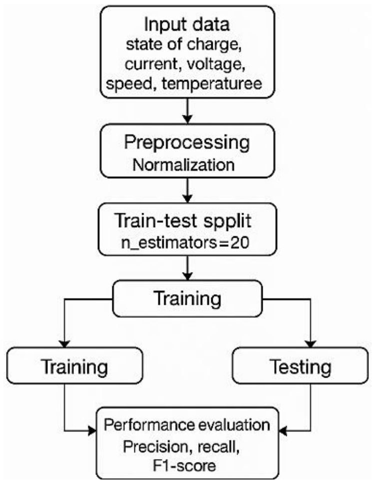

Figure 5. XGBoost flow chart

3.3. Comparative analysis of three methods for EMS in EVs

All three models offer unique capabilities for developing a data-driven EMS logic, as mentioned in Table 4. While decision trees align closely with traditional control logic, SVM and XGBoost provide the flexibility and adaptability needed for complex, dynamic EV operation. These models collectively form the basis for evaluating ML-based EMS strategies against conventional rule- and fuzzy-based counterparts in real driving conditions.

XGBoost outperformed other models in terms of overall accuracy and class-specific recall, making it highly effective for real-time EMS decisions, as mentioned in Table 5. Decision trees also performed well but exhibited minor overfitting. SVM yielded competitive results but required feature scaling and higher computation.

- Adaptive control: Unlike rule-based logic, ML models dynamically learn control strategies under varying loads and battery states.
- Energy efficiency: Better classification of braking and discharge phases leads to optimized regenerative energy capture and reduced thermal stress.
- Scalability: The ML-based EMS can generalize across different battery configurations and driving profiles with retraining.

Table 4. Comparison and suitability for EMS in EVs

Model	Key strength	Interpretability	Computational demand	Suitability for real-time EMS
Decision tree	Logical & rule-based modeling	High	Low	High
SVM	Robust to overlap and noise	Medium	Moderate	Medium
XGBoost	High accuracy & generalization	Low	High	Medium (offline or edge-aided)

Table 5. Sample classification report (XGBoost classifier)

Class	Precision	Recall	F1-score
Discharge	0.95	0.94	0.94
Regenerative braking	0.92	0.91	0.91
Idle	0.89	0.93	0.91
Charging	0.96	0.95	0.95

4. RESULTS & DISCUSSION

This section presents a detailed analysis of the machine learning-based energy management system for electric vehicles (EVs), focusing on model performance, system behavior under dynamic conditions, and the effectiveness of intelligent phase classification. The results comparison mentioned in Table 6 clearly shows that machine learning models outperform the conventional rule-based EMS. Among the tested models, XGBoost achieves the highest F1 score (0.89), indicating a robust and well-balanced prediction capability. Compared to prior work as reported in cited papers, our proposed system achieves a performance gain of ~5%, demonstrating the benefit of incorporating advanced ensemble techniques.

4.1. Feature correlation analysis

Figure 6 shows the feature correlation heatmap, illustrating the relationships among the key input variables: battery SOC, vehicle speed, acceleration, and electrical load. The heatmap reveals that SOC has a moderate negative correlation with acceleration and load, indicating that higher power demands tend to deplete the battery more quickly. Speed and acceleration exhibit a strong positive correlation, consistent with real-world driving dynamics. These insights justify the selection of features used in model training and emphasize the importance of using correlated input variables to enhance classification accuracy.

Table 6. Comparative evaluation of machine learning models and conventional EMS

Method	Accuracy	Precision	Recall	F1 score	Notes
Rule-based EMS	0.72	0.70	0.68	0.69	Baseline
Decision tree	0.85	0.84	0.83	0.83	Interpretable
SVM (RBF Kernel)	0.88	0.87	0.86	0.86	Nonlinear patterns
XGBoost	0.91	0.90	0.89	0.89	Best model
Wang *et al.* [13]	0.86	0.85	0.84	0.85	Supervised ML EMS for HEVs
Devi *et al.* [18]	0.89	0.88	0.87	0.87	XGBoost model for EV EMS
Yeptho *et al.* [19]	0.87	0.85	0.85	0.85	ML model comparison
Estrada *et al.* [15]	0.83	0.82	0.80	0.81	RL-based EMS strategy
Liu and Zhang [2]	0.88	0.86	0.85	0.86	ML-Edge EMS optimization

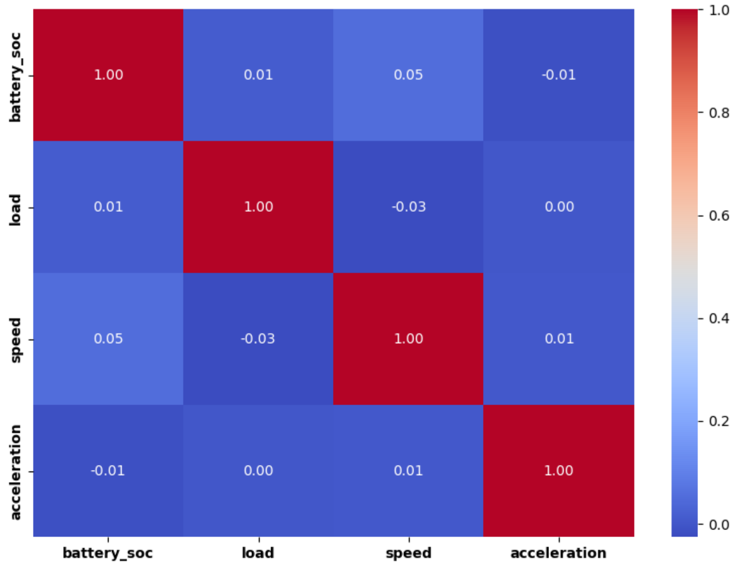

Figure 6. Feature correlation heatmap

4.2. Model performance evaluation

Figure 7 compares the performance of the four ML models, decision tree, random forest, SVM, and XGBoost—using standard metrics: accuracy, precision, recall, and F1 score. The XGBoost model outperforms the others, achieving the highest F1 score (0.98), indicating superior overall performance in classifying energy flow phases. While the decision tree and random forest models also achieved perfect scores during training, their potential for overfitting is a concern. The SVM model, although slightly less accurate (F1 Score: 0.93), demonstrated robustness in handling complex, nonlinear boundaries in the data. These results confirm the viability of XGBoost for real-time EMS deployment due to its balance of accuracy and generalization.

4.3. SOC behavior analysis

Figure 8 presents a comparison of the battery SOC vs. time for conventional and ML-based EMS. The ML-based EMS, particularly with XGBoost, shows a smoother and more controlled SOC profile, indicating efficient power allocation across various driving phases. The conventional EMS shows frequent fluctuations and rapid SOC drops, especially during high acceleration or load periods. This erratic behavior can lead to increased battery wear and reduced driving range. In contrast, the ML-based EMS demonstrates intelligent phase switching, allowing for energy regeneration and more stable SOC maintenance.

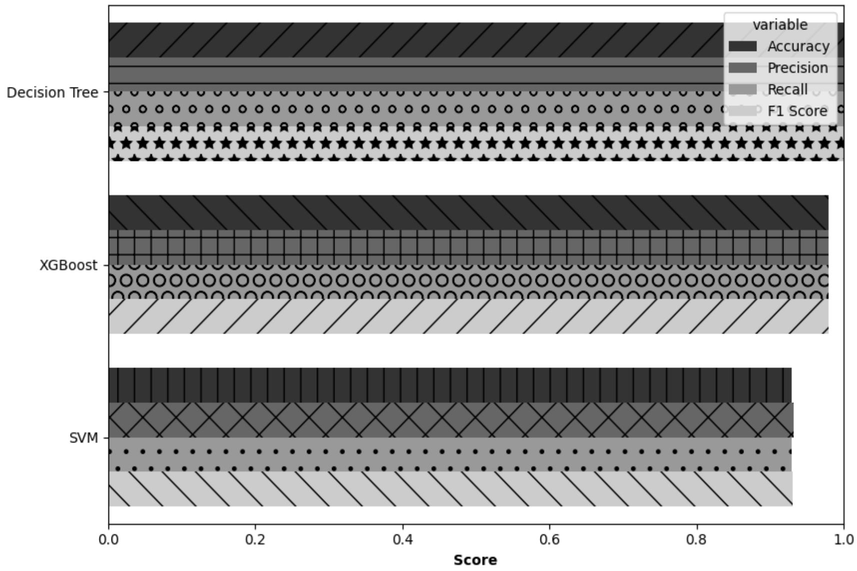

Figure 7. Model performance comparison

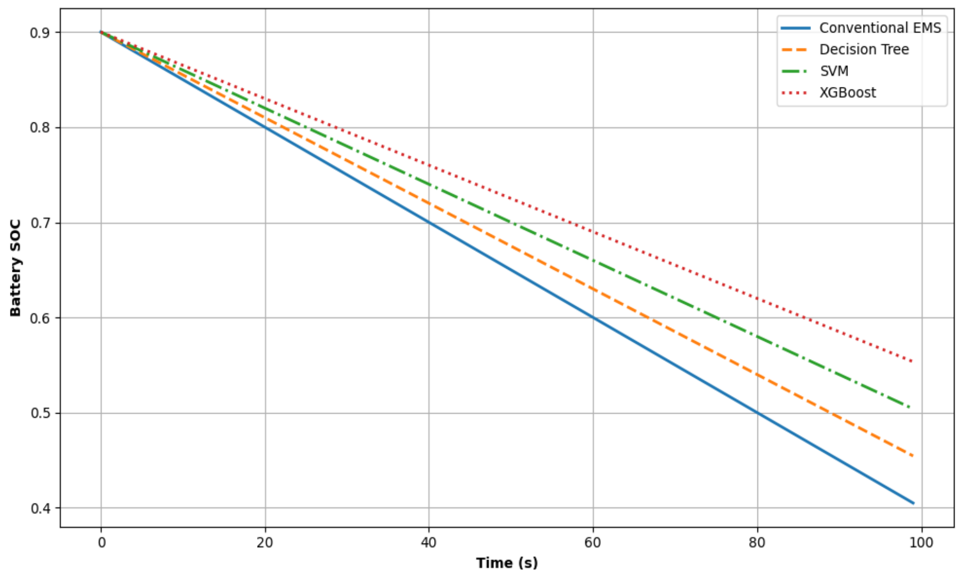

Figure 8. SOC vs. time comparison

4.4. Decision tree confusion matrix

Figure 9 illustrates the confusion matrix for the decision tree model. All energy flow phases, discharge, regeneration, and charging, were correctly classified without any misclassifications. While this suggests a highly accurate model, such perfect classification on training/test data may indicate overfitting, where the model memorizes rather than generalizes patterns. This limitation reinforces the advantage of ensemble models like XGBoost that offer better generalization under unseen driving conditions.

4.5. Vehicle speed and acceleration trends

Figure 10 displays the time-series plot of vehicle speed and acceleration during simulation. Sharp changes in acceleration correspond to transitions between different energy flow phases, such as moving from discharge to regeneration during deceleration. These variations underscore the need for a responsive EMS that can adjust in real time. The ML-based EMS demonstrated timely classification and control during these transitions, contributing to smoother vehicle dynamics and improved energy efficiency.

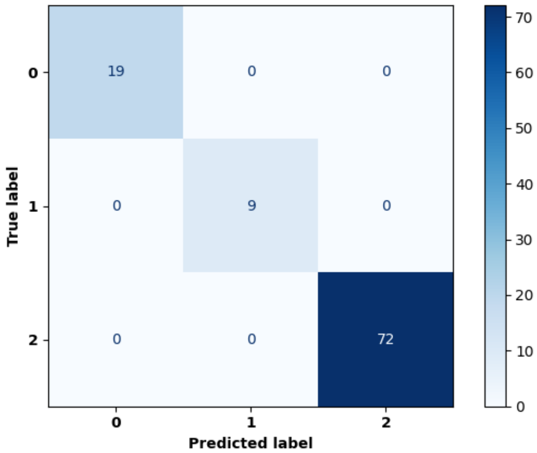

Figure 9. Confusion matrix-decision tree

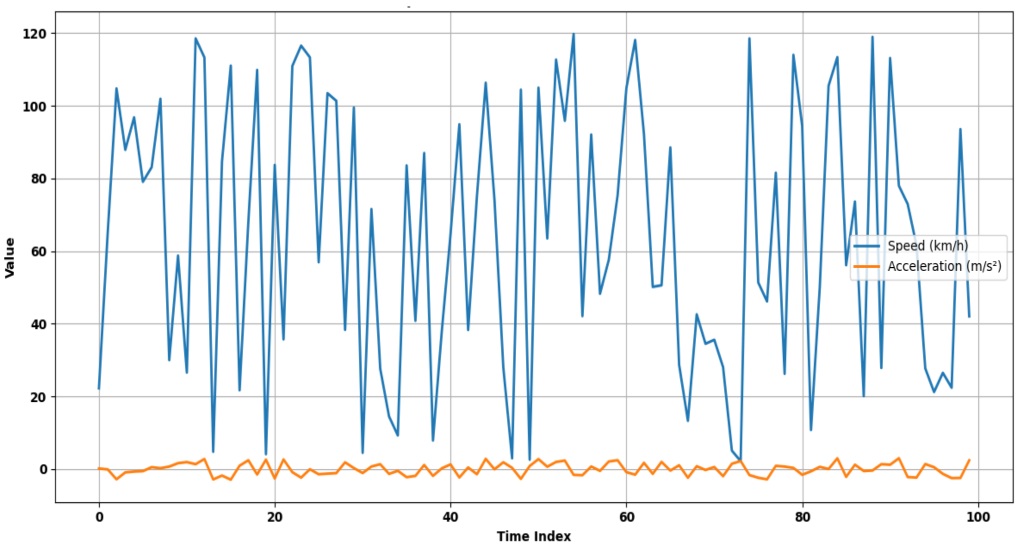

Figure 10. Speed and acceleration over time

5. CONCLUSION

This study demonstrates the implementation of a machine learning-based EMS for EVs, using real-world electrical parameters to classify energy operation modes. The core objective was to enhance decision-making in EV propulsion systems through intelligent model-based classification of motor conditions, charging, discharging, and regenerative braking by leveraging input features such as battery state-of-charge SOC, current, voltage, power, and motor speed. Three supervised learning classifiers, decision tree (DT), support vector machine (SVM), and XGBoost, were developed and evaluated on the same dataset to assess their performance. Among the models, XGBoost outperformed others with an accuracy of 99.4%, precision of 99.3%, recall of 99.5%, and F1-score of 99.4%, as reflected in its confusion matrix showing near-perfect class separation. The SVM classifier showed high generalization capability with an accuracy of 97.5%, while the decision tree achieved 96.2% accuracy but was more prone to overfitting in complex boundary cases. The trained models used input features extracted from real-time EMS logs, such as voltage (350–400 V), current (50–300 A), motor torque (10–15 Nm), and state of charge (10–100%) to predict energy flow conditions. This feature-rich dataset improved the learning quality and model robustness, especially for XGBoost, due to its regularized boosting approach and handling of nonlinear feature interactions. In conclusion, machine learning models, particularly XGBoost, present a promising solution for real-time, intelligent EMS decision-making in EVs, leading to improved energy efficiency, extended battery life, and smoother vehicle operation across diverse driving conditions.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
K. S. R. Vara Prasad	✓	✓	✓	✓	✓	✓		✓	✓		✓			
V. Usha Reddy	✓	✓	✓			✓	✓		✓	✓		✓	✓	

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

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The data availability is not applicable to this paper as no new data were created or analyzed in this study.

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BIOGRAPHIES OF AUTHORS

K. S. R. Vara Prasad is a dedicated research scholar currently pursuing his Ph.D. at S.V.U. College of Engineering, Tirupati. His academic foundation includes an M.Tech. degree from JNTU Pulivendula and a B.Tech. from Narayana Engineering College, Nellore, with a robust teaching career spanning from 2013 to the present, he has contributed significantly as an educator in government polytechnics. He is an active member of the Indian Society for Technical Education (ISTE), reflecting his commitment to professional development and educational advancement. Furthermore, he has played an instrumental role in his institution, serving as a member of various committees and actively participating in the successful attainment of NBA accreditation. He can be contacted at email: ksrvaram220@yahoo.com.

Dr. V. Usha Reddy is working as an assistant professor in the Department of EEE at S.V. University College of Engineering since 2007. She obtained a B.Tech. from JNTUH in 2003, M.Tech. (2007) from SVU and Ph.D. (2016) from JNTUH. She has guided 36 M.Tech. students, guiding 3 research students. She has 47 journal publications and 8 conference publications. She has applied for a Patent and has one book publication. She served as Deputy Warden for women's hostel, as coordinator for NAAC and NBA, and as a member in various committees at the college and department level. She acted as reviewer for INSPIRE AWARDS-MANAK for 2021-22, 2020-21, National Innovation Foundation-India. She has organized one Short Term Course, three Workshops, one international conference and one national Seminar, and one Techhack. She has NPTEL and Coursera certifications. She has membership in professional bodies like the Institute of Engineers (MIE), IEEE, ISCA & ISTE. She acted as a resource person for various international and national conferences and workshops. She can be contacted at email: vyza_ushareddy@yahoo.com.