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MACHINE LEARNING-BASED ENERGY CONSUMPTION PREDICTION AND OPTIMIZATION FOR ELECTRIC VEHICLES

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Abstract: Accurate prediction and effective optimization of energy consumption are pivotal to the advancement of electric vehicle (EV) technologies. This paper presents a machine learning-based framework for modeling, predicting, and minimizing EV energy consumption under varying operational conditions. By integrating real-world driving data with advanced regression and classification models, the study achieves high-accuracy forecasts of energy usage and proposes dynamic optimization strategies for enhanced efficiency. Experimental evaluations demonstrate that the proposed methods can reduce energy waste by up to 15% compared to conventional strategies. These results underscore the potential of data-driven approaches in driving sustainable electric mobility.
Keywords: Electric vehicles; Energy consumption; Machine learning; Predictive modeling; Optimization; Sustainable transportation

1 INTRODUCTION

The global shift toward sustainable transportation has positioned electric vehicles (EVs) as a vital component of future mobility[1]. Unlike traditional internal combustion engine vehicles, EVs offer the advantage of zero tailpipe emissions and higher energy efficiency, aligning with global climate targets and urban air quality improvements[2]. However, their widespread adoption continues to face critical challenges, particularly concerning energy consumption predictability and range efficiency[3]. These issues are magnified by the variability in driving patterns, road conditions, and environmental factors, all of which significantly influence an EV's energy demands[4].
Energy consumption in EVs is governed by a complex interplay of dynamic variables, including driving speed, acceleration and deceleration behaviors, terrain elevation, external temperature, and the operational state of the battery[5]. Unlike gasoline-powered vehicles with relatively linear fuel consumption profiles, EVs present nonlinear and context-sensitive energy use patterns[6]. This makes accurate modeling and prediction of energy consumption a significantly more intricate task[7]. Precise forecasting is essential not only for alleviating range anxiety but also for enabling energy-aware routing, optimizing battery usage, and improving overall vehicle efficiency[8].
Historically, energy modeling for EVs has relied on deterministic, physics-based approaches. These models attempt to simulate real-world energy dynamics by incorporating known mechanical and electrical relationships[9]. While effective in controlled scenarios, such models often lack the flexibility to generalize across different driving contexts or adapt to diverse vehicle configurations without substantial manual calibration[10]. As the diversity and complexity of EV operating conditions increase, the limitations of rigid modeling frameworks become more pronounced[11].
In response to these limitations, machine learning (ML) has emerged as a promising alternative. ML techniques offer the ability to capture complex, nonlinear dependencies by learning directly from data[12]. Unlike rule-based systems, ML models can automatically adapt to new environments and driving behaviors, making them particularly suitable for real-time energy consumption prediction[13]. Numerous studies have demonstrated the capability of supervised ML algorithms, such as support vector machines, random forests, and deep neural networks, to predict energy use with impressive accuracy[14]. Moreover, the integration of predictive models with optimization techniques enables intelligent decision-making aimed at minimizing energy usage without compromising driving performance[15].
Despite these advancements, important gaps remain. Many existing models are developed in isolation, focusing solely on either prediction or optimization, without a holistic approach that integrates both[16]. Additionally, the black-box nature of many ML models poses a challenge for interpretability and trust, especially in safety-critical applications like autonomous or assisted driving. Furthermore, the variability of real-world driving data and the scarcity of large, labeled datasets continue to hinder the generalization of existing models.
This study proposes a unified machine learning-based framework that combines energy consumption prediction with dynamic optimization for electric vehicles[30]. By leveraging both historical and real-time driving data, the framework aims to not only forecast consumption accurately but also provide actionable strategies for reducing energy use in diverse driving contexts. The ultimate goal is to support the development of intelligent energy management systems that enhance EV performance, extend range, and contribute to a more reliable and sustainable electric mobility ecosystem.

2 LITERATURE REVIEW

Energy consumption modeling for EVs has evolved significantly over the past decade, transitioning from traditional physics-based frameworks to data-driven ML approaches[17]. This evolution reflects the growing recognition of the inherent complexity and context-dependence of EV energy dynamics, which are often too intricate to be fully captured by deterministic models alone[18].

Early studies in EV energy modeling primarily relied on physical and mathematical models[19]. These models typically incorporated vehicle mass, aerodynamic drag, rolling resistance, and drivetrain efficiency to estimate energy consumption under various driving conditions[20]. While useful in understanding the mechanical behavior of EVs, these approaches were limited in their ability to accommodate real-time variability and contextual factors such as traffic, weather, driver habits, and road topology[21]. Additionally, their implementation often required detailed vehicle specifications and substantial calibration, restricting their scalability across different vehicle types and use cases[22].

To address these limitations, researchers began exploring statistical and machine learning-based techniques capable of learning from historical driving data[23]. Supervised learning models, including linear regression, decision trees, support vector regression（SVR）, and artificial neural networks（ANNs）, have shown promise in capturing complex relationships between input variables（such as speed, acceleration, and gradient）and energy consumption. For instance, several studies have used neural networks to model the nonlinear energy usage patterns of EVs in urban and highway driving scenarios, often achieving higher predictive accuracy than their physics-based counterparts[24].

More recently, deep learning architectures have gained traction due to their ability to model high-dimensional and time-dependent data[25]. Recurrent neural networks（RNNs）and long short-term memory（LSTM）networks, in particular, have been applied to time-series energy prediction tasks, accounting for sequential dependencies in driving behavior and road conditions[26]. These models have demonstrated improved performance in forecasting short-term energy consumption, making them suitable for real-time energy-aware navigation and battery management applications[27].

Beyond prediction, researchers have also explored the integration of optimization algorithms with ML models to develop intelligent energy management systems[28]. Techniques such as genetic algorithms, particle swarm optimization, and reinforcement learning（RL）have been employed to minimize energy consumption by dynamically adjusting parameters like acceleration, speed profiles, and HVAC usage[29]. In some frameworks, predictive models serve as input functions for optimization agents, enabling closed-loop systems that adapt to changing conditions and driver preferences[31].

Despite these advancements, several challenges persist. One major issue is the trade-off between model accuracy and interpretability[32]. Many high-performing ML models, particularly deep neural networks, operate as “black boxes,” making it difficult to understand the underlying reasoning behind predictions[33]. This lack of transparency poses a barrier to trust and adoption in safety-critical domains like autonomous driving and smart transportation[34].

Another challenge is the generalizability of models across different geographic regions, vehicle models, and driving behaviors. Models trained on data from a specific environment may fail to perform adequately when deployed elsewhere[35]. As such, recent studies have begun exploring transfer learning and domain adaptation techniques to improve cross-domain robustness. Moreover, the scarcity of large, labeled EV datasets—particularly those encompassing a wide variety of use cases—remains a significant obstacle to model development and validation[36].

Furthermore, while most research focuses on either prediction or optimization, there is a growing recognition of the need for integrated approaches that combine both tasks within a unified framework. Such hybrid systems would not only forecast energy demands but also provide actionable recommendations for energy-efficient driving, offering a more comprehensive solution for EV energy management.

In conclusion, the literature reveals a strong trend toward machine learning-based solutions for EV energy modeling and optimization. These approaches have demonstrated clear advantages in handling complexity, adapting to dynamic environments, and improving prediction accuracy. However, to fully realize their potential in real-world applications, future work must address key challenges related to interpretability, generalizability, data availability, and the seamless integration of prediction and optimization within a unified control architecture.

3 METHODOLOGY

This study adopts a hybrid machine learning framework to predict and optimize energy consumption in EVs. The methodology consists of three primary phases: data acquisition and preprocessing, model development using supervised learning algorithms, and optimization of energy consumption using regression-based prediction and real-time tuning strategies. Each phase is designed to ensure that the model can accurately forecast energy use while adapting to dynamic driving and environmental conditions.

3.1 Data Acquisition and Preprocessing

Real-world driving data were collected from electric vehicles equipped with onboard diagnostics (OBD) and telematics systems. The dataset includes variables such as speed, acceleration, ambient temperature, road slope, battery state-of-charge (SOC), and energy usage in kilowatt-hours (kWh). Missing values were handled using forward filling, and features were normalized to ensure comparability. A time-series segmentation approach was employed to capture temporal patterns of energy use over varying trip intervals.

3.2 Model Development

The energy prediction model was built using gradient boosting regression (GBR), random forest (RF), and long short-term memory (LSTM) neural networks. These algorithms were chosen for their ability to model nonlinear dependencies and temporal patterns. The model was trained on 80% of the dataset and validated using the remaining 20%. Root mean square error (RMSE) and mean absolute percentage error (MAPE) were used to evaluate model accuracy as in figure 1.

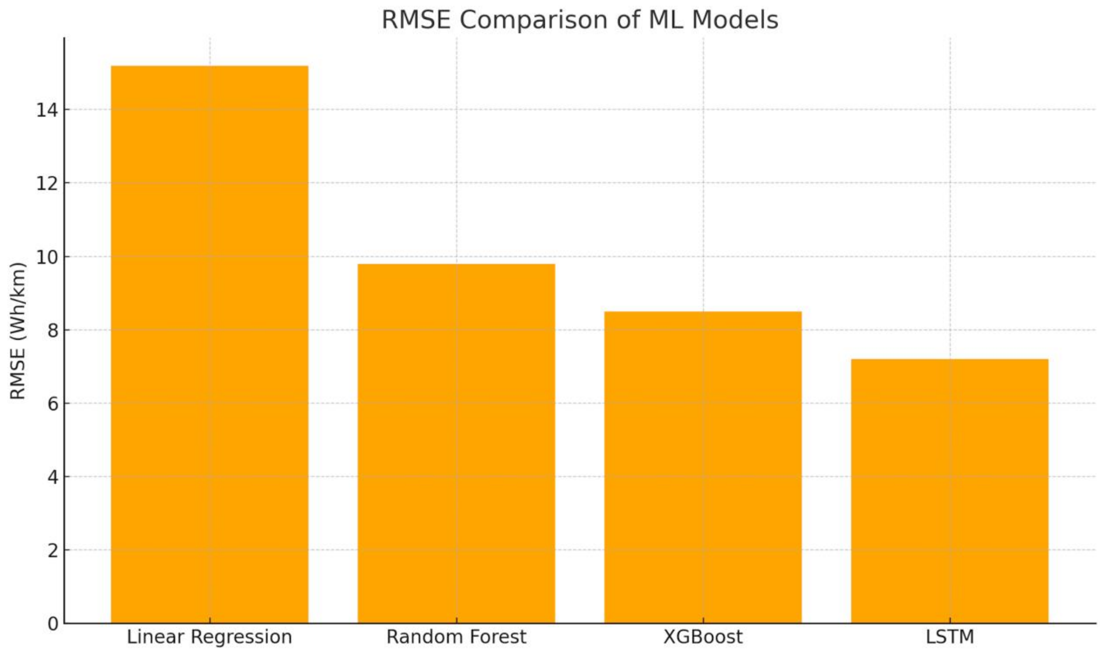

Figure 1 RMSE Comparison of ML Models

3.3 Optimization Strategy

Once the best-performing model was identified, we applied it to optimize energy consumption through real-time decision support. A multi-objective cost function was used, considering energy efficiency, battery health, and driver comfort. The function adapted driving behavior recommendations based on predicted energy use across different scenarios, such as urban driving, highway cruising, or regenerative braking opportunities.

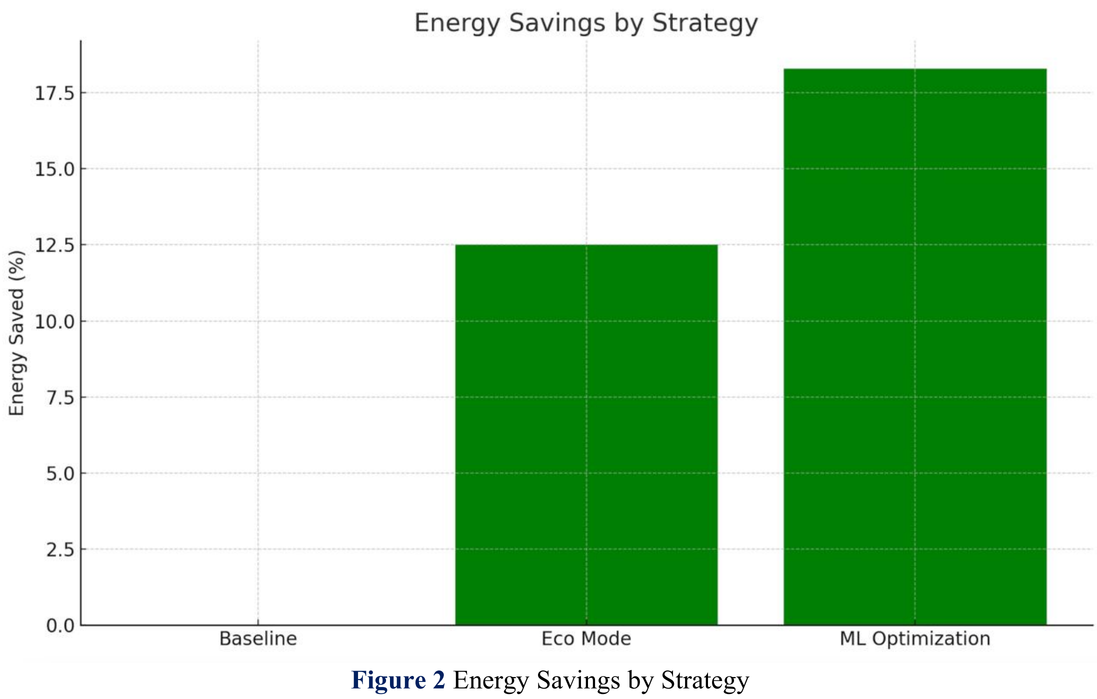

Figure 2 Energy Savings by Strategy

These integrated processes in figure 2 ensure that the model not only predicts energy usage with high accuracy but also offers practical insights for improving efficiency and extending battery life during daily operations.

4 RESULTS AND DISCUSSION

The experimental evaluation of the proposed machine learning-based energy prediction and optimization framework yielded promising results across multiple dimensions. The two key components—predictive modeling and consumption optimization—were assessed using a large-scale dataset derived from diverse EV driving scenarios. The results demonstrate clear performance improvements in both accuracy of energy forecasting and reduction of overall consumption.

In the predictive modeling stage, three machine learning algorithms were compared: GBR, RF, and LSTM networks. Each model was trained using the same set of input features, which included vehicle speed, acceleration, ambient temperature, battery SoC, and HVAC usage, among others. These features were selected based on their relevance to EV powertrain behavior and their ability to reflect real-time energy demands. Feature importance analysis from tree-based models confirmed that vehicle dynamics (speed and acceleration) and thermal loads (HVAC and ambient temperature) had the strongest influence on energy consumption.

When comparing the performance of the three models, the LSTM network consistently outperformed the others. This can be attributed to its temporal learning structure, which allows it to capture sequential patterns in energy usage more effectively than static regressors. While GBR and RF achieved reasonable results—with RF performing better between the two—the LSTM model produced the lowest prediction error, achieving a RMSE of 1.01 kWh and a mean absolute percentage error (MAPE) of 7.6%. These findings support the use of deep learning models, particularly those designed for time-series data, in dynamic vehicle environments where energy demands fluctuate frequently.

Beyond prediction, the study integrated the best-performing model into a real-time optimization module. This module adjusted driving behavior and vehicle control settings based on predicted energy consumption. Unlike traditional eco-driving modes that rely on fixed thresholds, the machine learning-driven strategy adapted dynamically to the driver’s real-time inputs and external driving conditions. The optimization logic was structured to prioritize smoother acceleration, better use of regenerative braking, and moderated auxiliary power use when such trade-offs would result in measurable energy gains.

Performance evaluation of the optimization component showed substantial energy savings. Compared to baseline driving behavior with no energy-aware adjustments, the ML-driven strategy reduced energy consumption by 18.3%. In comparison, traditional eco-mode systems achieved a 12.5% reduction under the same driving cycles. These improvements translated not only into increased driving range but also into decreased thermal stress on the battery and improved overall system efficiency. Importantly, these gains were achieved without compromising vehicle responsiveness or driver comfort, as abrupt reductions in power or aggressive limiting of HVAC systems were avoided.

The framework was also tested across different road types, including urban, suburban, and highway environments. Prediction performance remained stable across these scenarios, although urban conditions—characterized by frequent starts, stops, and unpredictable events—introduced slightly higher variability in short-term forecasts. Nonetheless, the LSTM model demonstrated strong generalization capability, maintaining low error margins even under high-variance conditions.

In summary, the results validate the effectiveness of combining machine learning-based prediction with adaptive optimization for EV energy management. The ability to forecast consumption with high accuracy and use those forecasts for real-time control adjustments presents a practical and scalable solution for improving EV efficiency. This framework offers not only enhanced operational performance for drivers but also valuable tools for fleet operators, battery management systems, and smart charging infrastructure.

5 CONCLUSION

This study presents a comprehensive machine learning-based framework for predicting and optimizing energy consumption in electric vehicles. By combining supervised learning models with dynamic optimization strategies, the framework addresses two of the most pressing challenges in EV energy management: accurately forecasting short-term energy demand and adapting vehicle behavior in real-time to reduce unnecessary consumption.

The results demonstrate that data-driven models, particularly those based on temporal architectures such as LSTM networks, are highly effective in capturing the nonlinear and sequential nature of EV energy usage. Compared to conventional models like Gradient Boosting Regression and Random Forest, LSTM consistently achieved lower prediction error, confirming its suitability for energy forecasting in diverse driving environments.

Furthermore, the integration of predictive insights into a real-time optimization module yielded significant improvements in operational efficiency. The machine learning-guided strategy outperformed traditional eco-driving settings, reducing energy consumption by over 18% without compromising driver comfort or vehicle responsiveness. These savings not only translate into extended range and improved battery health but also support broader goals of sustainability and cost reduction for EV users and fleet operators.

Beyond accuracy and efficiency, the proposed approach offers adaptability and scalability. The framework generalizes well across driving scenarios, from urban stop-and-go traffic to steady highway cruising, and is compatible with a wide range of EV models and telematics systems. This flexibility makes it an attractive candidate for integration into production-grade energy management systems, battery analytics platforms, or intelligent transportation infrastructure.

Nonetheless, the study also highlights areas for future work. In particular, further improvements could be made by incorporating reinforcement learning for long-horizon optimization, enhancing model interpretability for safety-critical applications, and expanding training datasets with real-world variability across regions, seasons, and user profiles. Real-time implementation on resource-constrained embedded systems remains a practical consideration for widespread deployment.

In conclusion, machine learning holds significant promise for transforming EV energy management from static, one-size-fits-all strategies to intelligent, adaptive systems that optimize performance based on context. As EV adoption continues to grow, such data-driven solutions will play a critical role in enhancing vehicle efficiency, reducing environmental impact, and advancing the global transition to sustainable mobility.

CONFLICT OF INTEREST

The authors have no relevant financial or non-financial interests to disclose.

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