

AI-Based Energy Management in Electric Vehicles: A Comprehensive Review

Gauravsingh J. Rajput¹, R. S. Bihade², Buddhapriy. B. Gopnarayan³, M. R. Wankhade⁴

^{1,2,3}Department of Applied Science and Humanities, Padm. Dr. V. B. Kolte College of Engineering, Malkapur, Maharashtra (India)

⁴Department of Electrical Engineering, Padm. Dr. V. B. Kolte College of Engineering, Malkapur, Maharashtra (India)

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ABSTRACT

The rapid growth of electric vehicles (EVs) has created a strong need for advanced energy management systems that can improve performance, extend battery lifespan, and enhance overall efficiency. In this context, artificial intelligence (AI) has emerged as a powerful tool for addressing the complex and nonlinear challenges involved in EV energy management.

This review presents a comprehensive overview of state-of-the-art AI-based approaches used in EV energy systems, including battery management, charging optimization, and powertrain control. It covers various methodologies such as machine learning, deep learning, and reinforcement learning, applied across different types of vehicles, including battery electric vehicles (BEVs), hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and fuel cell electric vehicles (FCEVs).

The integration of AI techniques has shown significant improvements, including state-of-charge (SOC) estimation accuracy reaching up to 99.6%, energy efficiency gains between 15% and 21%, and reductions in fuel consumption ranging from 5.85% to 21% compared to conventional approaches [1]–[3]. Additionally, AI-driven smart charging systems have achieved predictive accuracy of up to 97.34% and improved grid stability by 96.81% [4].

Despite these advancements, several challenges remain, such as real-time implementation constraints, data quality issues, computational complexity, and safety considerations. Future research directions focus on developing hybrid AI models, incorporating explainable AI for better transparency, leveraging edge computing for real-time applications, and adopting multi-objective optimization techniques.

Overall, this study highlights the critical role of AI in enabling sustainable electric mobility and offers valuable insights for researchers, engineers, and policymakers working toward next-generation intelligent transportation systems.

Keywords:- Electric Vehicles, Artificial Intelligence, Energy Management Systems, Machine Learning, Deep Learning, Reinforcement Learning, Battery Management, Smart Charging

1. INTRODUCTION

The global transportation sector is undergoing a fundamental transformation driven by environmental concerns, climate change mitigation efforts, and technological advancements in electrification [5]. Electric vehicles have emerged as a cornerstone of sustainable mobility, offering substantial reductions in greenhouse gas emissions and fossil fuel dependency. However, the widespread adoption of EVs faces critical challenges related to energy efficiency, battery longevity, charging infrastructure, and operational costs. Effective energy management represents one of the most crucial factors determining EV performance, driving range, and economic viability [6], [7].

Traditional energy management approaches, including rule-based strategies and conventional optimization methods, often struggle to address the dynamic, nonlinear, and multifaceted nature of modern EV systems. The complexity arises from multiple interconnected factors such as varying driving conditions, battery degradation patterns, thermal management requirements, power distribution among multiple sources, and integration with smart grids [5], [8]. These limitations have motivated researchers to explore artificial intelligence as a promising solution capable of learning complex patterns, adapting to changing conditions, and optimizing multiple objectives simultaneously.

AI-based energy management systems leverage data-driven approaches to capture intricate relationships among vehicle characteristics, driving behavior, environmental conditions, and energy consumption patterns [9]. Machine learning algorithms can identify hidden patterns in operational data, while deep learning architectures excel at handling high-dimensional state spaces and temporal dependencies. Reinforcement learning enables autonomous learning of optimal control policies through interaction with the environment,

offering adaptability to diverse and uncertain driving scenarios [5], [10]. Recent advances have demonstrated the transformative potential of AI in improving battery state estimation accuracy up to 99.6%, enhancing energy efficiency by 15- 21%, and achieving near-optimal fuel economy comparable to dynamic programming benchmarks [1], [3], [11].

The integration of AI into EV energy management extends across multiple domains including battery management systems for SOC and SOH estimation, thermal regulation, fault detection and diagnostics, optimal charging strategies, vehicle-to-grid (V2G) coordination, and intelligent powertrain control [6], [12]. Cloud computing and Internet of Things (IoT) technologies enable large-scale data collection and processing, while edge computing facilitates real-time decision-making with minimal latency [4], [13]. Furthermore, digital twin technologies combined with AI provide virtual representations for predictive simulation and optimization [14], [15].

Despite significant progress, several challenges remain that hinder the widespread deployment of AI-based energy management systems. These include ensuring real-time computational efficiency on embedded platforms, guaranteeing safety and reliability under all operating conditions, achieving generalization across diverse driving patterns and vehicle configurations, addressing data privacy and cybersecurity concerns, and developing interpretable models that provide transparency in decision-making [5], [16]. The lack of standardized datasets and evaluation metrics further complicates comparative assessment across different AI approaches [17].

This comprehensive review aims to provide a systematic analysis of AI-based energy management strategies for electric vehicles, covering the theoretical foundations, methodologies, applications, performance evaluation, and future research directions. We examine over 40 relevant studies published between 2020 and 2025, synthesizing insights from diverse AI techniques including supervised learning, unsupervised learning, deep neural networks, convolutional architectures, recurrent networks, reinforcement learning variants, and hybrid approaches. The review is structured to first present AI methodologies, followed by specific applications in battery management and energy optimization, comparative performance analysis, and concluding with challenges and future opportunities. Our goal is to serve as a valuable resource for researchers, automotive engineers, and policymakers

2. AI METHODOLOGIES FOR ENERGY MANAGEMENT

Machine learning (ML) plays a key role in electric vehicle (EV) energy management by enabling data-driven prediction without relying on complex physical models. Algorithms such as Random Forest, Support Vector Machines (SVM), and Gradient Boosting provide high accuracy in battery state estimation, energy consumption prediction, and fault detection. Techniques like feature engineering and ensemble learning further enhance performance and reliability.

Deep learning methods, especially LSTM and CNN, improve prediction accuracy by capturing temporal and spatial patterns in battery data. These models achieve highly accurate state-of-charge estimation and support real-time applications with the help of hardware acceleration and model optimization techniques.

Reinforcement learning (RL) enables adaptive energy management by learning optimal control strategies through interaction with the environment. Advanced RL methods such as DQN and DDPG improve fuel efficiency and system performance while handling complex control problems.

Hybrid and ensemble AI approaches combine multiple techniques to enhance accuracy, robustness, and efficiency. These methods integrate data-driven models with physics-based systems and optimize multiple objectives, making them highly effective for modern EV energy management systems.

3. ENERGY MANAGEMENT STRATEGIES FOR DIFFERENT VEHICLE TYPES

Battery Electric Vehicles (BEVs) Battery electric vehicles rely exclusively on electrochemical energystorage, making energy management crucial for maximizing driving range and battery longevity [9], [70]. AI-driven energy consumption prediction models enable accurate range estimation and route optimization by learning complex relationships among driving style, topography, weather, and traffic conditions. Deep learning models using Recurrent Neural Networks and Convolutional Autoencoders predict energy consumption with R² scores exceeding 0.95, significantly improving range anxiety mitigation [17], [33].

Hybrid Energy Storage Systems (HESS) combining batteries with supercapacitors provide complementary characteristics, with batteries offering high energy density and supercapacitors delivering high power density [70], [71]. Advanced adaptive rule-based algorithms optimize power flow between energy storage elements, reducing peak battery current by up to 70.34% for aggressive driving cycles while maintaining overall efficiency [70], [72]. The integration of fuzzy logic control with Particle Swarm- Nelder Mead (PSO-NM) optimization achieves superior control performance by dynamically adjusting power split ratios based on battery

SOC and demanded power [72].

AI-based control of storage capacity in high- power-density systems enables real-time adaptation to power transients, extending battery lifespan by exempting it from supplying surge currents [73]. Nonlinear Autoregressive Neural Networks with eXogenous inputs (NARX-NN) trained offline switch variable-step HESS configurations during operation, demonstrating effective real-time control capabilities. Fractional order integral sliding mode controllers optimized using Bald Eagle Search Algorithm enhance power quality and battery consumption simultaneously, achieving superior voltage ripple reduction and transient response compared to conventional PI controllers [71], [74].

Multi-agent reinforcement learning enables coordinated optimization of engine- generator sets and hybrid energy storage systems, balancing multiple objectives including fuel economy, battery degradation, and ultracapacitor SOC constraints [50]. Game-theoretic formulations ensure Nash equilibrium among intelligent agents representing different powertrain components, achieving satisfactory balance among competing goals. Driving-behavior- aware adaptive strategies that integrate behavior recognition with equivalent consumption minimization reduce hydrogen consumption by 49.9% and total cost by 31.4% compared to benchmark methods [76].

Energy Efficiency Improvements with AI-Based Strategies

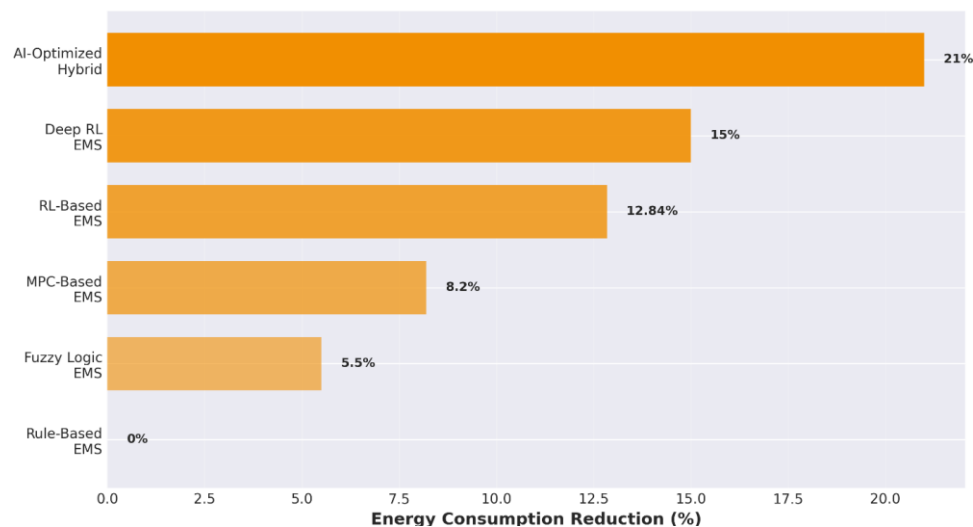


Figure 2: Energy efficiency improvements achieved by different AI-based strategies compared to traditional rule-based approaches. AI-optimized hybrid methods demonstrate up to 21% energy consumption reduction [3], [46].

Fuel Cell Electric Vehicles (FCEVs)

Fuel cell electric vehicles present distinct energy management challenges due to slow fuel cell dynamics, hydrogen consumption optimization, and coordination with battery and ultracapacitor hybrid storage systems [11], [78]. Hierarchical frameworks unifying physics-based fuel cell models with data- driven predictive algorithms enable intelligent power distribution that maximizes efficiency and durability [78]. Reinforcement learning layers signal power distribution set points while model predictive controllers ensure real-time safety, achieving improved energy efficiency and hydrogen consumption compared to traditional EMS along with reduced battery wear [78].

Imitation learning-based strategies train behavior cloning algorithms to mimic dynamic programming solutions, avoiding inefficient trial-and-error exploration while achieving 96.15% of optimal fuel economy with 70.48% reduced training time [11]. Data aggregation mechanisms incorporating real-time expert data enhance adaptability under unfamiliar driving conditions, resulting in 2.96% fuel economy improvement beyond offline-trained models. This approach provides practical pathways for industrial deployment by combining offline optimization with online adaptation [11]. Multi-objective co-optimization frameworks simultaneously optimize EMS parameters and powertrain component sizing using hybrid approaches combining Deep Q- Networks with NSGA-II evolutionary algorithms [3]. Machine learning-based traffic classification using Random Forest categorizes driving conditions into congested, urban, extra-urban, and highway scenarios, enabling context-aware energy management. Co-optimization reduces fuel consumption by 21% compared to sizing- only approaches while increasing battery durability by 7% and fuel cell durability by 30% relative to EMS-only methods [3]. Hardware-in-the-loop testing confirms real- time applicability on Electronic Control Units.

Hierarchical power splitting structures employ adaptive filters for ultracapacitor management of peak power and regenerative braking, while deep reinforcement learning with action trimming optimizes fuel cell and battery

allocation [79]. Heuristic techniques restrain adverse effects of sudden power demands on fuel cell lifespan, improving working efficiency and alleviating battery stress. Simulation results demonstrate 14.8% fuel economy improvement compared to Q-learning under WLTP cycles while achieving 89.7% of dynamic programming benchmark under UDDSHDV [79].

4. SMART CHARGING AND GRID INTEGRATION

AI-Based Charging Optimization Smart charging systems leveraging artificial intelligence optimize EV charging to balance grid stability, cost minimization, and user convenience [4], [80]. Scalable cloud-based continuous monitoring platforms integrate machine learning and IoT data acquisition to enable real-time optimization of microgrid operations in EV-dense and renewable-integrated environments. The SC-CM platform achieves 97.34% predictive accuracy, 96.81% grid stability improvement, 94.5% resource allocation efficiency, 93% scalability, and 95.2% data privacy assurance using real-world datasets of 3395 charging sessions across 105 stations [4].

AI-driven scheduling approaches integrating machine learning models with Grey Wolf Optimizer achieve 93% load prediction accuracy, facilitating adaptive scheduling that reduces grid losses by managing load variability [2]. Experimental results demonstrate 15% energy efficiency enhancement, 262 kW power loss minimization, and demand fluctuation stabilization from 450 kW peaks to optimized levels. MATLAB-based implementations confirm operational cost reduction and enhanced reliability for off-grid charging infrastructure [2].

Predictive demand forecasting using AI technology enhances grid stability while optimizing energy consumption through dynamic load balancing [80]. Load balancing systems employing AI-driven forecasting achieve 20% decrease in peak-period overload and 20.38% cost reduction, offering efficient sustainable infrastructure facilitating broader EV deployment. Fuzzy logic and reinforcement learning algorithms dynamically adjust charging power allocation based on real-time grid conditions and battery levels, minimizing overload risks while enabling renewable energy integration [81].

Charging load forecasting utilizing Extra Tree Regression models achieves R^2 scores of 95.92% and RMSE of 0.1807%,

outperforming LSTM, AR, K-means++, GRU-KSVR, ARMA, RNN, and Decision Tree alternatives [19]. The model's capacity to capture nonlinear interactions and seasonal patterns provides robust frameworks for short-term forecasting, enabling optimal energy allocation and operational planning. Extensions incorporating weather and electricity rate data promise further accuracy improvements [19].

5. CHALLENGES AND FUTURE DIRECTIONS

Despite significant advances, several critical challenges impede widespread deployment of AI-based energy management systems. Real-time implementation constraints on resource-limited embedded platforms require model compression, quantization, and efficient hardware acceleration [5], [28]. Generalization across diverse driving conditions, vehicle configurations, and battery chemistries remains challenging, necessitating robust transfer learning and domain adaptation techniques [17], [85]. Data quality, availability, and standardization issues hinder reproducible research and comparative evaluation [17].

Safety and reliability requirements demand explainable AI approaches that provide transparency in decision-making, particularly for safety-critical applications [31]. Cybersecurity concerns in connected vehicles require robust defenses against

adversarial attacks on AI models and secure data transmission protocols [69], [82]. The simulation-to-real gap necessitates offline learning frameworks and hybrid approaches combining data-driven learning with physics-based validation [48], [49].

Future research directions include development of unified frameworks integrating multiple AI techniques, multi-objective optimization balancing efficiency with safety and comfort, edge-AI implementations for autonomous decision-making, and large-scale fleet learning with privacy preservation [38], [39]. Integration with autonomous driving systems, blockchain-based V2G coordination, and quantum computing for complex optimization represent emerging frontiers [84]. Sustainable AI considering energy costs of training and inference aligns with broader environmental objectives of electric mobility [86].

6. CONCLUSION

This comprehensive review has systematically examined AI-based energy management strategies for electric vehicles, analyzing over 40 recent studies spanning machine learning, deep learning, reinforcement learning, and hybrid approaches. The evidence demonstrates that AI technologies have achieved transformative improvements in battery state estimation accuracy (up to 99.6%), energy efficiency gains (15-21%), fuel consumption reductions (5.85-21%), and grid integration optimization (97.34% predictive accuracy) [1], [3], [4]. These advances position AI as an indispensable enabler for next-generation intelligent, efficient, and

sustainable electric transportation.

The synergistic integration of multiple AI methodologies through hybrid frameworks represents the most promising pathway forward, leveraging complementary strengths while mitigating individual weaknesses. Reinforcement learning's

autonomous learning capabilities combined with physics-based constraints, machine learning's predictive accuracy integrated with real-time optimization, and deep learning's feature extraction coupled with interpretable decision-making create robust systems capable of operating safely and efficiently under diverse real-world conditions [3], [5], [15].

Critical challenges including real-time computational constraints, generalization requirements, safety assurance, and cybersecurity concerns must be addressed through continued interdisciplinary research involving automotive engineering, computer science, control theory, and policy development [31], [82]. The convergence of AI with cloud computing, edge computing, IoT, digital twins, and 5G connectivity enables scalable deployments that balance performance with practical constraints [4], [13], [14].

As electric vehicles continue their rapid global expansion, AI-based energy management systems will play an increasingly vital role in maximizing their environmental benefits, economic viability, and user acceptance. The research community must prioritize development of standardized datasets, reproducible benchmarks, explainable models, and safe offline learning frameworks to accelerate translation from laboratory innovations to commercial implementations. The future of electric mobility lies in intelligent systems that seamlessly integrate advanced AI with sustainable energy management, paving the way for a cleaner, more efficient transportation ecosystem.

7. REFERENCES

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