A Review on Model Predictive Control and Deep Reinforcement Learning Approaches for Energy-Efficient Eco-Driving in Battery Electric Vehicles

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Abstract:

Energy-efficient driving methods have become important with the emerging concern for sustainable mobility and rapid acceptance of battery electric vehicles. Eco-driving, being a very broad topic, can be optimized using Model Predictive Control (MPC) and Deep Reinforcement Learning (DRL) as two promising options. An MPC builds a structured framework that predicts the vehicle's future states and optimizes control over a finite time horizon so as to maximize the control of speed, acceleration, and regenerative braking under varying traffic and road conditions. Recent literature has established MPC as a valid tool to incorporate real-time information into predictive eco-driving; for example, V2V, V2I, and SPaT information. On the other hand, DRL learns from data to build adaptive control policies in dynamic traffic scenarios, tackling challenges of uncertainties, complex interactions, and long-term objectives. Combining MPC and DRL yields a good combination of short-term precision and long-term adaptability, forming a hybrid framework capable of addressing real-world barriers such as delays in communication, computational constraints, and the unpredictability of traffic. This paper presents a survey of recent developments in the application of MPC- and DRL-based eco-driving systems targeting BEVs, comparing their approaches, potential, and limitations. It also discusses their applications in predictive cruise control, cooperative driving, and multi-agent traffic systems. Finally, the paper identifies gaps in the research and points out the research agenda into large-scale validation, generalization across disparate driving scenarios, and on robustness under uncertainty toward energy-efficient public transport and sustainable EV mobility.

Keywords: *Model Predictive Control, Deep Reinforcement Learning, Eco-Driving, Battery Electric Vehicles, Energy Management, Sustainable.*

I. INTRODUCTION

The evolutionary trajectory of transportation sustainability is recognized worldwide as a solution to the problems of energy shortage, air pollution, and climate change [1]. The emissions from traditional internal combustion engine (ICE) vehicles have driven the demand for cleaner and more energy-efficient alternatives. Battery electric vehicles came forth as a much needed option, providing zero tailpipe emissions, minimizing fossil fuel use, and making use of renewable energy. Nevertheless, the limited driving range and the energy hungry nature of BEVs are primary concerns that present obstacles in adoption. Thus, optimizing energy efficiency using intelligent eco-driving strategies is quite necessary in extracting the best performance from a vehicle and helping with the sustainability goals of green mobility [2].

Eco-driving encompasses driving behaviors and control strategies wherein energy consumption is optimized and unnecessary acceleration, braking, and idling are avoided while employing regenerative braking and predictive route planning. For BEVs, eco-driving offers benefits such as improving range, battery longevity, and lower operational costs. The arrival of recent-generation EMS has allowed for decision-making and control in real-time with respect to changing traffic scenarios, driver behavior, and road environment [3]. To this end, research in developing control has heavily focused on Model Predictive Control and Deep Reinforcement Learning [4]. Model Predictive Control (MPC) is a general framework for optimization that predicts future vehicle dynamics and selects the best control inputs over a certain finite horizon. Constraints can be incorporated in MPC, which makes it very useful for eco-driving [5]. Predictive cruise control, adaptive energy management, and cooperative driving strategies could be fields where MPC reduces energy consumption but maintains safety and comfort of the vehicle. They face the issues related to computational demand and robustness under uncertain and dynamic driving environments.DRL complements MPC by being a data-driven approach to adaptive and long-term decision-making. By interacting with the environment, DRL agents learn optimal driving policies with respect to energy efficiency, safety, and comfort. Recent studies have applied DRL to complex urban traffic, signalized intersections, and mixed traffic flow scenarios for eco-driving, demonstrating significant simulated energy savings [6].

Moreover, hierarchical and multi-agent DRL designs have extended the eco-driving approaches to cooperative vehicular systems to further augment traffic efficiency. Outstanding issues include high sample complexity, limited generalization with respect to routes, and dependence on simulation-based training [7].

The merging of MPC and DRL sets forth a hybrid paradigm wherein the prediction potential of MPC meshes with the adaptability of DRL. It operates on the short-horizon optimization and long-term energy management that opens up avenues for resilience against uncertainties during actual driving [8]. Besides, developments in connected and automated vehicle (CAV) technologies, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications, and intelligent horizons usher in new possibilities for predictive eco-driving and help to build cooperative and sustainable transportation ecosystems. Figure 1: The EMS structure for connected HEVs/PHEVs.

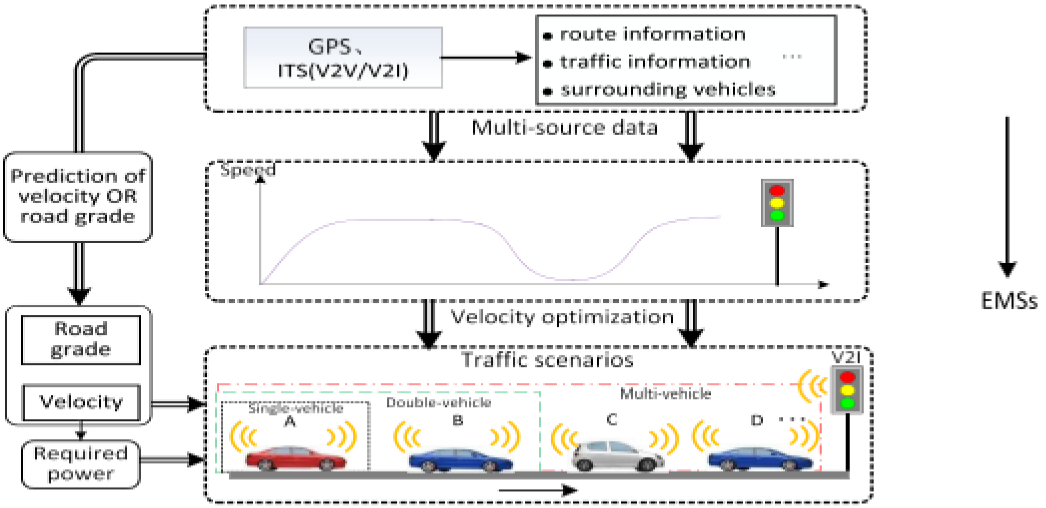

Figure 1: The EMS structure for connected HEVs/PHEVs.

This study is an attempt to analyze recent advances in MPC and DRL-based eco-driving methods for BEVs. It draws together various methodologies, showcases contributions, and brings out limitations to existing research. The paper ends with a set of open issues to be addressed and research priorities for developing a robust, scalable, and intelligent eco-driving framework serving as a potential bridge in the transition to energy-efficient and sustainable electric mobility.

A. Evolution of Hybrid Electric Vehicles (HEVs)

Hybrid electric automotive evolution began with Ferdinand Porsche's design of the Lohner-Porsche Mixte in 1901: the first hybrid car that combined an internal combustion engine with wheel-mounted electric motors. After this early innovation, interest waned in the past, as petroleum became cheap and available aplenty [11]. During the 1970s, the oil crisis put the limelight once again on fuel-efficient alternatives and zoomed research on hybrid powertrains. Enter 1997, when Toyota thrust the industry into an era with the introduction of the first mass-produced HEV: the Prius-which became a global synonym for fuel economy and reduced emissions [12]. The 2000s witnessed an explosion of growth with improvements in nickel-metal hydride and lithium-ion batteries, regenerative braking, and power electronics. By the 2010s, glimmered plug-in HEVs that took hybrid technology to the next step, further extending electric-only driving and fossil-fuel dependency reduction. With the integration of intelligent control algorithms, predictive energy management, and eco-driving strategies, performance enhancements followed [13]. The present-day HEV occupies the ever-evolving artificial intelligence, connectivity to lambda of renewable energy services and coupling into the fully electric and sustainable transport systems.

II. WORKING PRINCIPLES OF ENERGY MANAGEMENT SYSTEMS (EMS)

Energy Management System (EMS) typically serves as the brain of the vehicle and thus acts by achieving optimal coordination between ICE, electric motor, and energy storage systems in the case of a hybrid electric vehicle (HEV) or plug-in hybrid electric vehicle (PHEV) [14]. However, EMS tends to balance power demand and supply while attempting to save fuel, reduce pollutant emissions, and satisfy some other aspects of vehicle performance. It must decide when the ICE should operate, when the electric motor should assist, and when to draw energy from or store energy into the battery [15]. Keeping the battery charge within Automotive SOC limits prolongs battery life by preventing either too much use or discharge of the battery. Regenerative braking is also under the control of the EMS system, which allows the recovery of kinetic energy during deceleration and conversion of this kinetic energy into usable electrical energy, hence improving fuel economy [16].

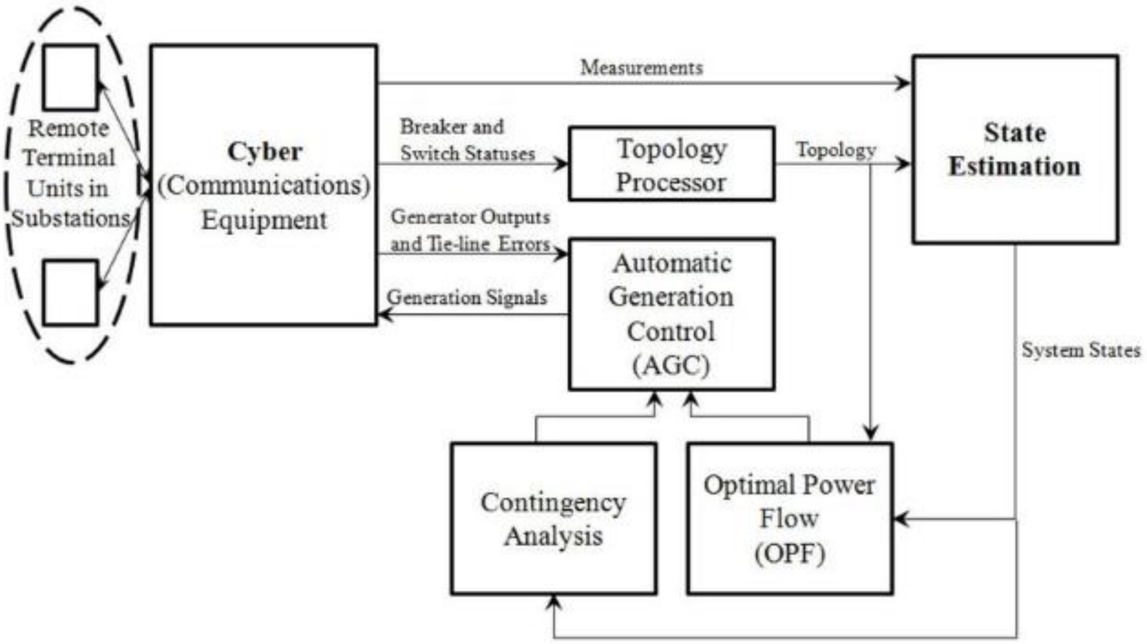

Figure 2: A schematic diagram of an Energy Management System (EMS)

The figure 2 represents the functioning of an Energy Management System (EMS) in modern power grids, showing how data is collected, processed, and used for control and optimization. At the field level, Remote Terminal Units (RTUs) in substations measure electrical parameters such as bus voltages, line flows, generator outputs, and breaker or switch statuses. These measurements are transmitted via the Cyber (communications) equipment, which acts as the communication backbone between substations and the control center, carrying both measurement data upstream and generation control signals downstream. The Topology Processor then interprets breaker and switch statuses to determine the real-time connectivity of the grid, providing the network model to the State Estimation (SE) function. SE fuses raw measurements with the topology to compute the most accurate snapshot of the system states (bus voltages and angles), filtering out bad or noisy data. These system states feed into higher-level applications: the Automatic Generation Control (AGC), Optimal Power Flow (OPF), and Contingency Analysis (CA).
AGC maintains system frequency and scheduled tie-line exchanges by adjusting generator outputs in real time, sending control signals back through the cyber layer. OPF uses the estimated system states to optimize generator dispatch economically while ensuring operational limits like line capacity and voltage are respected. Meanwhile, Contingency Analysis evaluates the system's resilience under potential failures (e.g., a line or generator outage), helping operators or automated systems ensure reliability. These applications are interdependent—OPF provides economic setpoints, CA verifies their security, and AGC makes fine real-time adjustments to track them while stabilizing the system. Overall, the EMS continuously cycles through data acquisition, state estimation, optimization, security analysis, and control, ensuring that the grid operates reliably, economically, and securely.

Further, beyond internal vehicle dynamics and decision-making, advanced EMS has an integration with external sources of information for predictive and adaptive decision-making. Using GPS, road-gradient data, ITS, V2V communication, and V2I communication, the EMS may forecast traffic conditions, anticipate power requirements, and adjust its control strategies in real-time [17]. For example, when approaching a traffic signal, the EMS may start the hybrid engine in electric mode and prevent wasting fuel while idling. While going uphill, it gives priority to ICE power and preserves battery charge. These external inputs for hybrid EMS development uplift the efficiency, reliability, and sustainability levels of hybrid vehicles and truly form a hybrid EMS as a predictive intelligent control system rather than a reactive system [18].

In a typical single-vehicle EMS, the power split would be optimized initially between the engine and electric motor, according to various objective functions depending on operating conditions, such as fuel consumption, battery life, and emissions. Predictive models, eco-driving techniques, and route or terrain preview data all allow decisions to be exercised online, as seen in Figure 3. Eco-driving methods, such as keeping a steady speed, anticipating traffic lights through V2I data, working on route planning, applying mild acceleration control, and maximizing regenerative braking, can all contribute toward destroying fuel consumption and extending battery life and overall energy efficiency [19]

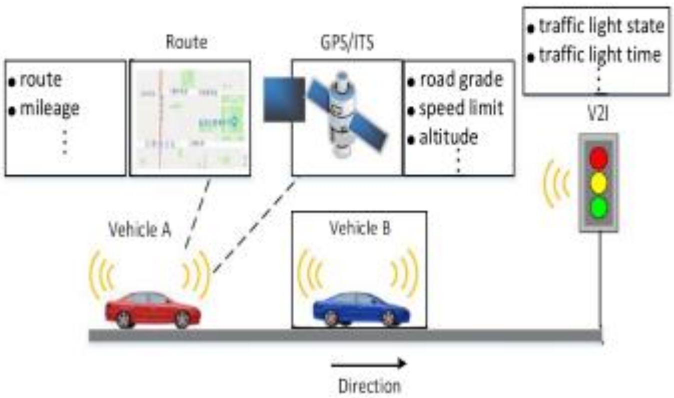

Figure 3: The scenario of the single-vehicle energy management.

Predictive control in single-vehicle EMS further enhances this by predicting future driving conditions like road slope, velocity, and traffic flow, allowing for optimum power distribution between the engine and motor in advance. Equipped with GPS and Intelligent Transportation Systems (ITS), predictive EMS modernizes the operating points dynamically for best fuel consumption, emission reductions, and efficient battery use, with smoothness retained [20] Going beyond the single-car systems, double-vehicle energy management techniques are designed for car-following scenarios where the following vehicle adapts to the leader's speed, braking intention, and road conditions through V2V communications as a cooperating agent for efficient regenerative braking, reduced friction braking, safety, and energy efficiency, as depicted in Figure 4 [21]

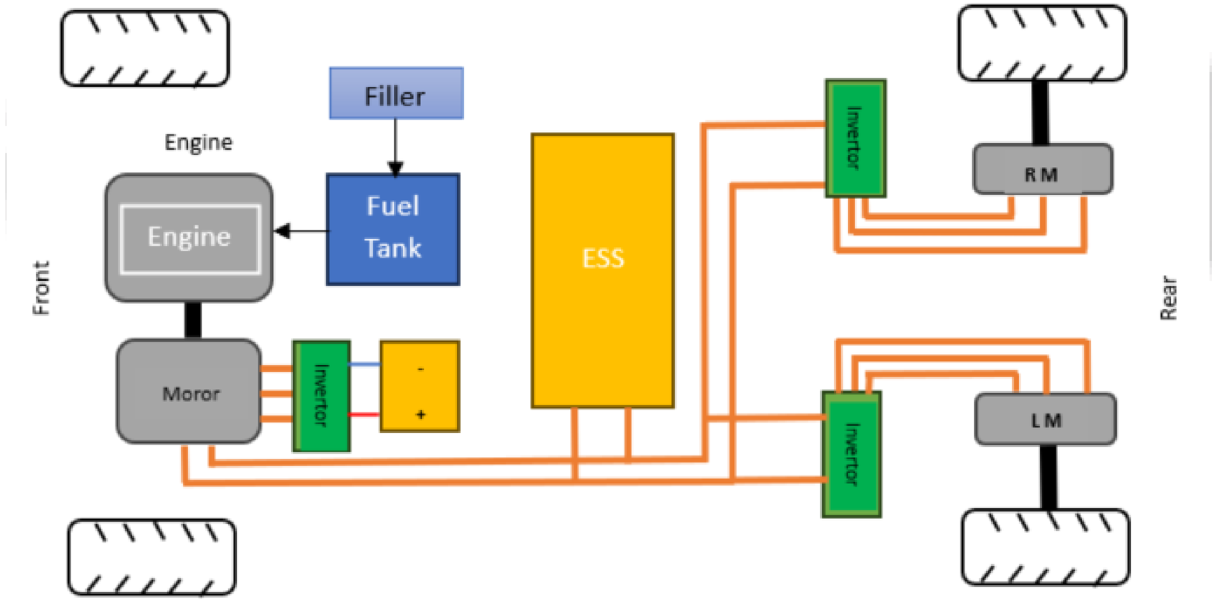

Figure 4: Double-Vehicle Energy Management Strategies

Extending this out, multi-vehicle EMS frameworks aim for coordinated energy management across vehicle platoons maintaining synchronous speeds and close distances through V2V/V2I communications. Sharing real-time information such as velocity, slope, driver intent, and battery state, these systems address aerodynamic drag, regenerative braking, load balancing between the vehicles, and sustainability on the ecosystem level, as indicated in Figure 5 [22]. Still, a great deal remains to be resolved; current EMS designs are mainly run on predetermined driving cycles and fail to respond in real-time, scarce use of external data sources; issues in terms of communication delay, controller response time, and opposing objectives between fuel consumption and emission reduction all slow down further development. Therefore, getting adaptive, robust, and intelligent energy management strategies remains a burning area to explore in the sincere pursuit of sustainable hybrid and electric vehicles [23].

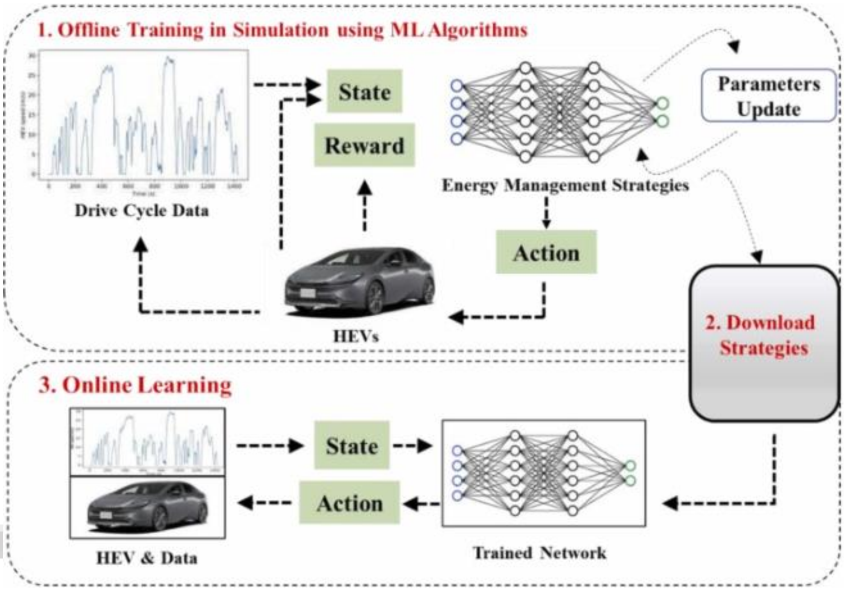

Figure 5: Multi-Vehicle Energy Management Strategies

III. DEEP REINFORCEMENT LEARNING (DRL) APPROACHES FOR ECO-DRIVING

Transfer learning and domain adaptation have been tried in the hopes of better generalization of DRL-based eco-driving policies across cities and routes, although distribution shifts in unseen traffic require fine-tuning [19]. However, hybrid DRL-model-based approaches have also been proposed, where DRL generates reference trajectories, while MPC executes final control; however, the coordination between learned- and model-based modules is limited [20]. DRL has also been applied to maximize low-level control in connected and automated vehicles by speed planning only, while classical controllers handle longitudinal and lateral dynamics, the performance of which significantly decreases due to actuator constraints and very high V2X communication latency [21]. Autonomous eco-driving within mixed traffic conditions has been examined on benchmark data such as pNEUMA, and on algorithms such as PPO and DDPG; however, these datasets lack real-world variability and sensor noise, limiting their use [22]. Multi-objective DRL with heuristic reward shaping has been introduced for achieving a trade-off between safety, efficiency, and comfort in urban eco-driving, but studies found this approach limited to the considered scenarios and not generalizable [23]. For heavy-duty vehicles such as electric buses or trucks, hierarchical DRL strategies are proposed, separating route-level planning from short-horizon control that includes regenerative braking, and real-world elements such as cargo load and road slopes are still insufficiently considered [24]. In the meanwhile, new benchmarks and simulation environments for evaluation of DRL-based eco-driving have been provided to allow for a more systematic comparison of algorithms, but the absence of standardized metrics to balance energy, comfort, and safety, combined with issues concerning reproducibility, is still a major bottleneck [25].

Table 1: Deep Reinforcement Learning (DRL) Approaches for Eco-Driving

Ref	Method / Approach	Key Findings	Results / Findings	Limitations
[19]	Transfer learning & domain adaptation for DRL eco-driving	Transfer learning improves policy generalization across cities/routes	Better generalization in unseen environments	Distribution shifts in unseen traffic still require fine-tuning
[20]	Hybrid DRL–model-based eco-driving	Combining DRL and model-based control can improve trajectory tracking	DRL generated reference trajectories; MPC executed final control	Coordination between DRL and model-based modules is brittle
[21]	Hybrid DRL for low-level CAV control	Hybrid control enhances speed planning while retaining stability	DRL + classical controllers; improved energy efficiency	Actuator constraints limit DRL exploration; V2X latency reduces performance
[22]	DRL autonomous eco-driving in mixed traffic using benchmark datasets (pNEUMA)	DRL effectively learns eco-driving behaviors from benchmark data	PPO/DDPG reduced energy consumption in simulation	Benchmark lacks real-world variability and sensor noise

[23]	Multi-objective DRL with heuristic reward shaping	Heuristic reward shaping balances safety, comfort, and efficiency	Improved urban eco-driving performance in simulation	Objective weighting scenario-dependent; lacks generality
[24]	Hierarchical DRL for electric buses and trucks	Hierarchical structure allows separation of route-level and short-horizon control	Improved energy efficiency; regenerative braking utilized	Heavy-vehicle dynamics (cargo, slopes) not fully captured in simulations
[25]	DRL benchmarks and simulation environments	Standardized simulation environments facilitate fair algorithm comparison	Enabled systematic comparison of DRL algorithms	Benchmarks lack standardized metrics combining energy, comfort, safety; reproducibility issues remain
[26]	Hybrid energy-management strategy integrating Li-ion batteries & supercapacitors with ML-assisted control	ML-assisted control improves energy capture and reduces battery stress	Simulation shows improved peak-power handling and smoother energy distribution	Large-scale on-vehicle trials and long-term reliability not reported
[27]	Comprehensive survey of battery–supercapacitor HESS	Survey highlights key design considerations, sizing, and control strategies	Comparative analysis of HESS topologies and energy/power efficiency	No new experimental results; practical validation in EVs lacking
[28]	Predictive cruise control using ANN-based energy model with supercapacitor buffer	Supercapacitors enhance energy recovery by absorbing/releasing braking pulses	Simulation shows reduced battery load fluctuations and improved fuel economy	Limited component-level characterization of supercapacitors; efficiency and thermal behavior not fully explored
[29]	Regenerative braking model for battery–supercapacitor HESS with dynamic power-sharing	Dynamic power-sharing can reduce battery degradation and increase energy recovery	Simulation indicates improvements in energy efficiency and battery cycle life	Validation largely simulation-based; limited real-vehicle testing
[30]	Optimal sizing & control for stationary hybrid energy storage systems using supercapacitors	Optimal sizing enhances energy recuperation and load handling	Experimental testbed results confirm improved energy recovery	Findings not directly generalizable to light-vehicle dynamics
[31]	Graphene-derived electrodes for high-energy supercapacitors	Improved specific energy and power density; faster charge/discharge	Electrochemical analysis shows enhanced braking energy capture	Scalability to full automotive modules and real driving integration unproven
[32]	Survey of emerging supercapacitor devices and system-level applications	Highlights materials, fabrication, energy management strategies, and system-level design considerations	Comparative analysis of supercapacitor performance, cost, and energy density	Translation from device-level improvements to full system performance not experimentally validated
[33]	Battery–supercapacitor-fed BLDC drive with HIL testing	Hybrid HESS improves real-time energy efficiency and torque response	Control strategies validated in hardware-in-the-loop simulation	Practical vehicle integration and cost implications not fully addressed
[34]	Comparison of supercapacitor and battery performance under regenerative braking	Supercapacitors achieve faster charge acceptance and improved peak-power handling	Simulation shows reduced battery stress and potential longer cycle life	Long-term cycling effects, thermal management, and repeated braking reliability unexplored
[35]	Experimental test rig evaluation of supercapacitor module	High-power pulses handled without significant degradation	Voltage, current, and thermal behavior measured under various load profiles	Vehicle integration, packaging constraints, and real-world application not addressed

[36]	Nanosheet-based graphitic electrodes for regenerative supercapacitors	High specific energy, fast charge/discharge, and stable cycling	Electrochemical tests show improved capacitance and cycle stability	Full-module scaling, automotive reliability, and long-term durability uncertain
[37]	Energy management and sizing for supercapacitor-based HESS in DC traction	Optimization strategies improve energy recovery and load balancing	Simulation shows better hybrid storage ratios and converter selection	Translation to passenger vehicles requires further investigation
[38]	Green-synthesized Ni–Fe LDH nanosheet electrodes for regenerative supercapacitors	Eco-friendly synthesis with high capacitance	Electrochemical tests show good rate capability and cycle stability	Module-level balancing, ESR control, and large-scale reliability not fully resolved
[39]	Broad review of regenerative braking and HESS	Summarizes materials, control strategies, energy recovery mechanisms	Highlights improved battery life, energy recuperation, system flexibility	Experimental validation and practical solutions for cost/packaging gaps absent
[40]	Emerging high-energy-density supercapacitor products	Potential for regenerative braking in hybrid/pure EVs	Evaluates energy density, power capabilities, and efficiency	Reliant on manufacturer data; peer-reviewed validation needed for adoption
[41]	Advanced HESS control strategies and converter topologies	Optimized energy flow and improved energy recovery (up to 40%)	Simulation and bench testing confirm efficiency improvements	Real-world performance, scalability, and economic feasibility not fully addressed

The hybrid energy management strategy for Li-ion batteries and supercapacitors using another machine-learning paradigms-based control structure was proposed in order to capture maximum regenerative energy from braking events while minimizing battery stress for life extension. From simulations, the advantageous capability of peak power handling with smooth sharing of energy to the energy storage devices was noted, but large-scale testing and long-term reliability trials are not available yet [26]. An elaborate review of battery–supercapacitor HESS has addressed issues on sizing, control strategies, power electronics, and regenerative braking integration, with comparison and contrasted HESS topologies under different driving profiles that could highlight their potential benefits, but real EV evaluation remains scarce [27]. Predictive cruise control strategies with buffers in the form of supercapacitors have demonstrated improved energy recovery, reduced battery load variations, and hence thereby better fuel economy, emphasizing the need for correct energy estimations. Yet, the few characterizations of supercapacitors that include efficiency losses and thermal behavior hinder a great deal of their applicability [28].

Models for regenerative braking for battery supercapacitor HESS promise life optimization for the battery and maximization of energy recuperation by means of dynamic power transfer, but most of the validation is still simulation-based and with very little road testing in real vehicles [29]. Optimal sizing and control methods that have been tested on stationary systems indicate improved recuperation, but generalizing to light vehicle dynamics is still left incomplete [30]. High-energy electrode materials such as graphene derivatives enable better charge-discharge rates and higher energy densities but are unvalidated in terms of being incorporated into complete automotive level modules, let alone in scaled-up real-life testing scenarios [31]. Recent reviews into new supercapacitor technologies are also highlighting some issues such as thermal management, long-term durability, and system-level integration; with little experimental rehabilitation from material-level advancement [32]. The HILS test of hybrid supercapacitor-battery systems verified the energy recovery efficiencies and improvements in torque responses, but the large vehicle integration and cost feasibility remain unanswered [33].

Compared with regenerative braking, supercapacitors quickly accept charge and realize instantaneous peak power, thus reducing the aging of the batteries and improving their cycle life. Nevertheless, thermal management and long-term cycling performance are not adequately studied [34]. Experimental test rigs have shown that supercapacitors can take very high-power pulses with negligible degradation, but packaging constraints and real-world implementations are not entirely addressed [35]. Nanosheet-based electrodes may present exciting possibilities for integration due to their high specific energy and stability, but whether they can hold durability under automotive conditions remains unknown [36]. Whereas optimization studies of energy management and sizing strategies for supercapacitor-based HESS in traction applications increase load balancing, more investigation must be conducted for passenger vehicles [37].

These eco-friendly synthesized nanosheet electrodes for use in regenerative braking applications have shown strong capacitance and cycling stability, but module balancing and large-scale reliability continue to be areas of concern [38]. General reviews on regenerative braking systems point out an extension of battery life and energy recuperation as the major benefits; however, packaging, costing, and thermal management issues are also highlighted [39]. In principle, high-energy-density supercapacitors were envisioned to be efficient gadgets of energy conversion in hybrid and electric vehicles. Still, independent verification beyond that available from the manufacturer is necessary [40]. Lastly, energy recovery enhancements of up to 40% have been reported through the use of advanced control strategies and converter topologies, but remaining open discussions concern the scalability, economic feasibility, and real-life implementation of these approaches [41].

IV. ARTIFICIAL INTELLIGENCE IN ELECTRIC VEHICLES FOR MOBILITY OPTIMIZATION

Human translation: For demand-side management inside microgrids via Generative AI and LLMs, focus has been laid upon EV charging synchronization. But whether it works in the big urban situation is still untested [42]. A hybrid approach involving LLMs and Graph Neural Networks (GNNs) reportedly outperforms traditional methods for EV charging optimization but has to be tested against real-time dynamic grid conditions [43]. Privacy-preserving predictive approaches, such as Federated Learning Transformer Networks (FLTN), have been put forth to predict EV charge location with high accuracy without risking user data, but whether this method can generalize despite changes in geographies has yet to be ascertained [44]. AI and ML were applied in scenarios of V2X to conduct proactive handover and resource allocation for conserving energy and with quality of service considerations. However, these methods have still to be extensively tested in different network environments [45]. Another generative AI approach has been used for energy optimization and vehicle design enhancements; yet many findings were limited because they relied quite heavily on statistical methods without much real-world validation [46]. Optimization frameworks based on AI for solar PV and battery energy storage systems promise smart EV charging for high-density residential places, whereas scaling that up for a larger urban deployment remains unaddressed [47].

Deep neural networks have been applied to scheduling EV ride-hailing fleet charging toward the objectives of cost and emission reduction, while lingering issues remain as to their applicability to fleets of different sizes and usage pattern [48]. AI-based methods of optimizing an EV charging network have been proposed for better efficiency and user experience based on real-time analytics, but the actual practical incorporation of such designs into real-time infrastructure poses major challenges [49]. Ambient-level studies describe the role of AI in future EV technology, in particular its integration with IoT and big data for advanced energy management systems, but many of such studies lack empirical validation [50]. And then, hybrid AI-based frameworks using reinforcement learning and grid-aware scheduling have been proposed for fine optimization of residential EV charging systems in real time, but have not yet been optimally challenged for robustness under diversifying grid conditions [51].

V. CONCLUSION AND FUTURE WORK

This review discusses a range of energy-efficient eco-driving approaches for battery electric vehicles (BEVs), which combine MPC, DRL, and hybrid energy storage methods. The survey has found that MPC can perform short-term predictive optimization by modeling vehicle dynamics, gradients of the road, and traffic information within a constraint-based setting. It works well and with varying degrees of success for predictive cruise control, adaptive energy management, and cooperative driving, yet its real-world application is problematic due to computational difficulties and the uncertainties of real-world environments. DRL, on the other hand, provides adaptability in complex and dynamic traffic situations via learning-based policy optimization. Although it has proven very useful in mixed traffic and urban scenarios, its training complexity, dependence on simulated environments, and limited scope to generalize to various real-world settings constitute some of the challenges still existing. Hybrid combinations of MPC and DRL use the strength of either, giving short-term accuracy and long-term adaptability. Back to the same analogy, hybrid energy storage systems that combine supercapacitors and batteries hold potential to optimize braking efficiency, reduce aging of batteries, and prolong system life. Recent advances in AI, including generative AI, federated learning, and graph neural networks, extend the possibilities for optimal EV charging, fleet management, and mobility services.The future must witness the development of robust, generalizable, and cheaper eco-driving frameworks that integrate MPC, DRL, and sophisticated HESS solutions. With future improvements, such implementations will go a long way toward energy-efficient and sustainable electric driving.

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