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Intelligent Electric Vehicles: AI-Based Battery, Energy, and Control Systems

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Abstract – Electric vehicles (EVs) are becoming software-intensive systems in which battery management, energy distribution, motion control and charging all generate large volumes of data. Artificial intelligence (AI) offers ways to turn this data into better decisions, but its adoption is limited by safety, data and validation concerns. This paper reviews how machine learning, deep learning and reinforcement learning are applied across four EV functions: battery state estimation, energy management, motion control and smart charging. It compares learning-based methods with rule-based and optimization-based baselines, and uses recent benchmark and simulation results to show that learning works best when it augments, rather than replaces, proven model-based controllers. The role of open simulation tools and the Functional Mock-up Interface in training and validating AI controllers is also discussed. Finally, open challenges such as data quality, the simulation-to-reality gap, explainability and functional safety are summarized, together with directions for future work.

Keywords – Electric vehicles, artificial intelligence, reinforcement learning, battery management system, energy management, smart charging, vehicle simulation

I. INTRODUCTION

The transition from combustion engines to electric propulsion has changed what a vehicle is. A modern EV carries hundreds of sensors, a battery pack that must be monitored cell by cell, power electronics, and increasingly an automated driving stack. Each of these produces data that can be used to improve efficiency, safety and user experience. Artificial intelligence, and in particular deep learning [1] and reinforcement learning (RL) [2], provides tools to learn from this data where hand-crafted models are difficult to build or tune.

AI is already visible in several EV functions. Data-driven models can predict battery lifetime from early-cycle measurements [3], RL agents can decide how to split power in hybrid powertrains [4], and learned policies can correct the output of a conventional controller during path following [5]. At the same time, EVs are safety-critical machines. A learned component that behaves unpredictably in an unseen situation is not acceptable, so the question is not only what AI can do but how it can be trained, validated and combined with established engineering methods.The objective of this paper is to give a structured review of AI in EVs for a reader new to the field.

Section II summarizes EV subsystems and the main AI paradigms. Sections III to VI review battery management, energy management, motion control and charging. Section VII discusses simulation tools that make safe AI development possible, and Section VIII lists open challenges. Section IX concludes the paper.

II. BACKGROUND

1 Main Subsystems of an Electric Vehicle

An EV can be viewed as four interacting subsystems. The energy storage subsystem consists of the battery, and in some vehicles a fuel cell, together with converters. The drivetrain contains the electric machines, inverters and transmission. The chassis and steering subsystem determines how torque becomes motion. Finally, the control and software layer coordinates all of them. Because thermal, electrical and mechanical effects interact, for example battery temperature limits the power available to the motors, improvements in one subsystem often depend on information from another. This coupling is the main reason data-driven methods are attractive.

2. AI Paradigms Used in Vehicles

Three paradigms dominate current work. Supervised learning maps labelled inputs to outputs and is used for estimation tasks such as battery state or driver intent. Deep networks extend this to raw signals, and recurrent models such as long short-term

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memory (LSTM) networks [6] handle time series. Unsupervised learning finds structure in unlabelled data, for example clustering driving patterns. Reinforcement learning learns a decision policy by interacting with an environment and maximizing a cumulative reward [2]. Deep RL combines neural networks with this idea and has achieved strong results in control tasks [7]. The basic Q-learning update is

$$Q(s,a) \leftarrow Q(s,a) + \alpha[\, r + \gamma \max Q(s', a') - Q(s,a) \,] \quad (1)$$

where s is the state, a the action, r the reward, α the learning rate and γ the discount factor. In an EV setting, the state may contain speed, battery state of charge (SoC) and temperature, the action may be a power split, and the reward may penalize energy use and constraint violations.

III. AI IN BATTERY MANAGEMENT

The battery is the most expensive and most safety-relevant component of an EV, so battery management systems (BMS) were among the first places where learning methods were tested.

1. State of Charge Estimation

SoC cannot be measured directly and is usually inferred from voltage, current and temperature. Model-based observers such as the extended Kalman filter remain a standard approach [8]. Their accuracy depends on an equivalent-circuit model whose parameters change with temperature and aging. Neural networks, especially LSTM models [6], learn the mapping from measurement history to SoC without an explicit cell model and can adapt to nonlinear behavior. In practice, hybrid schemes that use a network to correct a filter combine the physical consistency of the observer with the flexibility of learning.

2. State of Health and Remaining Useful Life

Predicting how fast a cell will degrade is valuable for warranty, second-life use and charging strategy. Severson et al. showed that features extracted from early charge and discharge cycles can be used with regularized regression to predict cycle life before capacity visibly fades [3]. Machine learning has also been applied to impedance spectra to identify degradation patterns [9]. These studies show that small, well-chosen features can be as useful as very deep models, which matters because labelled aging data are slow and costly to collect.

3. Thermal Management

Thermal limits restrict charging and discharging power. Learning-based predictors of cell temperature allow the thermal controller to act before limits are reached, and they reduce the number of temperature sensors needed. The main concern is generalization: a model trained on one cell chemistry or pack design may not transfer to another without retraining.

IV. AI FOR ENERGY MANAGEMENT

1. Reinforcement Learning for Power Split

In hybrid and multi-source vehicles, an energy management strategy (EMS) decides how much power each source supplies. Classical solutions use rules or optimization such as dynamic programming, which needs the whole drive cycle in advance. RL removes this requirement because the policy is learned from experience and then executed online. Surveys report that RL-based EMS can approach the efficiency of offline optimal solutions while remaining implementable in real time [4]. Examples include Q-learning combined with neuro-dynamic programming for plug-in hybrids [10] and deep RL methods that use cumulative trip information to improve decisions [11]. A typical reward combines fuel or energy use with a penalty on deviation from a target SoC:

$$r_t = -(\, \Delta E_t + \lambda\, (SoC_t - SoC_ref)^2 \,) \quad (2)$$

where ΔE is the energy used in the step and λ weights the SoC penalty. Choosing λ is itself a design problem, because it trades efficiency against battery protection.

2. Evidence from an Open Benchmark

A useful reference point is the IEEE VTS Motor Vehicle Challenge 2023, in which student teams designed energy management and torque vectoring strategies for a vehicle with a fuel cell, a battery and three motors [12]. According to the summary in [5], fifteen teams submitted twenty-one strategies that were scored on energy use, constraint violations, battery degradation and velocity loss, with weights and test cycles hidden from the participants. The winning solution was rule-based [13], while some optimization-based methods, such as model predictive control, ranked low. The organizers suggest that calibrating an optimizer is hard when the exact cost function is unknown. Some teams also explored neural network approaches, but technical details were not released, so no firm conclusion about learned strategies can be drawn from this event [5].

Table I: Energy Management Approaches in the Benchmark [5]

Approach	Strength	Weakness
Rule-based	Simple, robust, fast	No optimality guarantee
Optimization	Explicit constraints	Needs tuning and model

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Data-driven	Adaptive, flexible	Unclear training, safety

This result does not mean learning is unsuitable. It suggests that robustness across unseen conditions is as important as peak performance, and that learned strategies should be tested on the same range of cycles as rule-based baselines before conclusions are drawn.

V. AI FOR MOTION CONTROL AND AUTOMATED DRIVING

1. Residual Reinforcement Learning

Training a controller from scratch with RL is slow and unsafe in early training because the agent acts randomly. Residual RL avoids this by keeping a conventional controller in the loop and training the agent to output only a bounded correction [14]. The commanded action is

$$a^{cmd} = a^{B} + a^{RL} \quad (3)$$

where a^{B} is the action of the baseline controller and a^{RL} is the learned residual. Because the baseline already stabilizes the vehicle, learning only has to improve performance, and sample efficiency increases.

Ultsch et al. provided a framework to train such agents on simulation models exported as functional mock-up units and connected through the Gymnasium interface [15], [16]. In the use case summarized in [5], the baseline was a geometric path following controller and the residual agent learned corrections to steering and torque. The authors report that rewards saturated after fewer than 50,000 training steps and that, on an unseen path, the residual agent reduced tracking errors by between 11 and 65 percent while keeping control actions smooth [5]. These are simulation results and should be read as such, but they illustrate why hybrid control is attractive.

2. Learning-Based Path Following and Cooperation

Pure RL has also been applied to path following, including for vehicles with variable drivetrain delay [17], and to cooperative control of several vehicles using multi-agent RL [18].

Such work shows that learned policies can handle effects that are difficult to model, such as delays, but it also underlines the need for careful simulation and testing before road use.

3. Perception and Simulators

For perception and planning in automated driving, open simulators such as CARLA provide sensors, traffic and weather, allowing agents to be trained and compared under repeatable conditions [19]. Physics-based vehicle models complement them by providing realistic powertrain and energy behavior, which is important for EVs because range and efficiency depend on it.

VI. SMART CHARGING

Charging connects the vehicle to the grid, so its scheduling affects both the user and the power system. Demand is uncertain because arrival times, energy needs and electricity prices vary. Wan et al. proposed a model-free deep RL method that schedules charging in real time without needing a model of these uncertainties [21]. Forecasting models for arrival time and energy demand can also feed optimization-based schedulers. For vehicle-to-grid use, any learned scheduler must account for the additional battery aging caused by extra cycling, which links this topic back to the degradation models in Section III.

VII. SIMULATION TOOLS FOR AI DEVELOPMENT

Simulation is the safe place to train and test AI controllers. Proprietary simulation platforms and toolboxes are widely used, but their licenses and closed models can limit academic work. Open or source-available alternatives help here. The VDCWorkbench library, written in Modelica, combines vehicle dynamics, electric powertrain, battery and fuel cell models, and exports them through the Functional Mock-up Interface (FMI) so that they can be used from Python or MATLAB [5]. Its authors also report its use as the engine of the benchmark described in Section IV and as a teaching tool in a university course [5].

Two practical lessons follow for AI work. First, standardized interfaces such as FMI and Gymnasium make it possible to reuse the same model for classical control design and for RL training [15], [16]. Second, models of different fidelity should be available, because fast models speed up training while detailed models are needed for validation. The library described in [5] is stated to focus on low-to-medium fidelity and does not provide full multi-body dynamics, which is a reminder that no single model suits every stage.

VIII. CHALLENGES AND FUTURE DIRECTIONS

- Data Quality and Availability: Battery aging data take months to collect, and public datasets cover limited

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- chemistries. Methods that work with few labelled samples, and transfer between cell types, are needed.
- Simulation-to-Reality Gap: Policies trained in simulation may fail on the real vehicle if the model misses effects such as sensor noise or actuator delay. Domain randomization and validation on test vehicles are common countermeasures [20].
- Safety and Certification: Automotive software must follow functional safety processes such as ISO 26262 [22]. Learned components are hard to verify, so architectures that keep a certified controller as a fallback, or that bound the learned action as in residual RL, are more likely to be accepted.
- Explainability: Engineers and regulators need to understand why a policy chose an action. Combining simple rules with learned corrections, and logging the baseline and learned contributions separately, supports this.
- Compute and Deployment: Embedded vehicle computers have limited memory and strict timing. Model compression and standardized export formats for embedded targets are important for moving research results into vehicles.

IX. CONCLUSION

This paper reviewed the use of AI in EVs across battery management, energy management, motion control and charging. The literature shows clear benefits from learning where models are hard to obtain, particularly in battery lifetime prediction and in power management. Benchmark evidence indicates that well-designed rule-based strategies remain competitive, and recent simulation work suggests that learning is most effective as a bounded correction to a proven controller. Open simulation tools and standard interfaces make this kind of development reproducible. Future progress will depend on better data, smaller simulation-to-reality gaps and methods that satisfy functional safety requirements

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