
Original Research Article

Research on computer aided vehicle control strategy of pure electric vehicle

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Abstract: The paper focuses on pure electric vehicle (PEV) intelligent control, systematically reviewing mainstream algorithms including MPC and reinforcement learning. It compares hierarchical/integrated control frameworks, analyzes the computational energy paradox restricting onboard deployment, and points out gaps between simulation and real vehicle tests. Hybrid MPC-RL control schemes integrating V2X perception are highlighted as a promising direction to balance stability, energy efficiency and real-time computing performance for future EV control systems.

Keywords: pure electric vehicle; vehicle control strategy; model predictive control; reinforcement learning; torque vectoring; energy management

1. Introduction

The electrification of transportation represents one of the most consequential technological transitions of the twenty-first century, driven by the imperative to decarbonize a sector responsible for approximately 24% of global energy-related carbon dioxide emissions^[1]. Pure electric vehicles (PEVs), powered exclusively by battery storage, offer the prospect of zero tailpipe emissions and reduced dependence on fossil fuels, yet their widespread adoption hinges on overcoming persistent challenges related to range anxiety, battery degradation, and charging infrastructure^[2]. Central to addressing these challenges is the development of sophisticated vehicle control strategies that can simultaneously optimize energy efficiency, ensure driving safety, and enhance ride comfort—Objectives that are often fundamentally at odds with one another.

2. Foundational framework for PEV control

2.1. Control objectives and their inherent trade-offs

The control of a pure electric vehicle can be conceptualized as a multi-objective optimization problem subject to dynamic constraints. Three primary objectives dominate the control hierarchy: Energy efficiency, vehicle stability, and ride comfort. Energy efficiency encompasses not only the immediate minimization of tractive energy consumption but also the maximization of regenerative braking recovery and the preservation of battery health over the vehicle lifetime^[3]. Vehicle stability, traditionally addressed through electronic stability control systems, must now be achieved through coordinated torque distribution across independently actuated wheels, a capability that introduces the risk of energy-inefficient interventions^[4]. Ride comfort, often treated as a secondary consideration, is increasingly recognized as a critical factor in consumer acceptance and is directly influenced by control decisions regarding acceleration, braking, and suspension response^[5].

These objectives are inherently coupled and frequently conflicting. Aggressive regenerative braking, for instance, may recover kinetic energy but can compromise braking stability and ride comfort if the control system fails to coordinate with hydraulic braking. Similarly, torque vectoring interventions designed to enhance yaw stability inevitably incur energy penalties that reduce overall efficiency^[6]. The central challenge of computer-aided vehicle control lies in navigating these trade-offs through real-time optimization that respects physical constraints and driver expectations.

2.2. Control architectures: Hierarchical and integrated approaches

PEV control mainly adopts hierarchical and integrated architectures. Hierarchical schemes are widely used in research and real vehicles: Upper layers output target yaw rate/acceleration, and bottom layers convert them into motor and brake control signals^[7]. This decomposition reduces computational complexity and facilitates modular development but introduces the risk of suboptimal coordination when conflicts arise between layers.

Integrated control architectures, by contrast, seek to solve the control problem holistically within a single optimization framework. These approaches explicitly model the coupling between longitudinal, lateral, and vertical vehicle dynamics and optimize across all objectives simultaneously^[5].

3. Model predictive control for integrated vehicle dynamics

3.1. MPC as the dominant paradigm

Model predictive control (MPC) has emerged as the predominant advanced control strategy for PEVs, with recent systematic reviews identifying it as the most widely adopted technique in energy-aware adaptive cruise control systems, accounting for approximately 42% of published approaches^[8]. The appeal of MPC lies in its inherent ability to handle multi-variable systems with coupled dynamics, incorporate physical constraints on states and actuators, and optimize over a finite prediction horizon using a model of the system's behavior. These characteristics align naturally with the demands of PEV control, where constraints on motor torque limits, battery power, and tire-road friction must be respected while optimizing competing objectives.

3.2. Longitudinal control: Adaptive cruise and energy optimization

In the longitudinal domain, MPC has been extensively applied to adaptive cruise control (ACC) systems for PEVs, where the objectives of maintaining safe inter-vehicle distance, tracking desired speed, and minimizing energy consumption must be balanced. Conventional MPC implementations employ fixed weighting coefficients in the cost function to represent these trade-offs, but such static weighting fails to accommodate the varying importance of different objectives under changing driving conditions.

A significant advance has been the development of dynamic weight model predictive control (DWMPC) strategies that adapt the cost function weights based on real-time assessment of driving urgency^[9]. By integrating a fuzzy inference system that evaluates spacing error and velocity error, these approaches can dynamically adjust the velocity tracking weight, yielding a more context-sensitive control response. Simulation results under the Worldwide Harmonized Light Vehicles Test Cycle (WLTC) demonstrate that DWMPC outperforms fixed-weight MPC, achieving a 6.5% reduction in energy consumption while simultaneously reducing vehicle jerk by 42.9% and response time by 41.8%^[9]. This improvement illustrates the value of context-awareness in longitudinal control and points toward the integration of traffic state perception as a critical enabler for future systems^[10].

3.3. Coordinated longitudinal-vertical control

The coupling between longitudinal and vertical vehicle dynamics, often neglected in simpler control formulations, has attracted increasing attention as researchers recognize the interaction between braking/suspension systems and its implications for both energy recovery and ride comfort. A recent study employing the twin delayed deep deterministic policy gradient (TD3) algorithm for longitudinal-vertical coordinated control explicitly models the coupling between electro-hydraulic composite braking and suspension systems^[5]. The proposed adaptive control scheme distinguishes between general and emergency braking conditions, achieving global optimal control for regenerative braking energy recovery, braking stability, and ride comfort.

4. Reinforcement learning for adaptive torque vectoring and energy management

4.1. The promise of model-free adaptability

MPC excels at constrained multi-objective optimization yet suffers from model uncertainties and

unmodeled dynamics. As a model-free alternative, reinforcement learning (RL) generates control policies via environmental interactions, well suited for EVs with variable road friction, loads and aging components hard to model mathematically^[4].

Recent reviews of RL applications in electric vehicle control have identified torque vectoring and energy management as the two primary domains where RL-based approaches have demonstrated significant potential^[4,6]. In torque vectoring applications, RL policies can learn to balance yaw stability improvement against energy consumption penalties through experience, adapting to changing conditions without requiring manual re-tuning. In energy management, RL offers the prospect of learning optimal power-split strategies that account for driving patterns, battery state-of-health, and regenerative braking opportunities.

4.2. Deep reinforcement learning in practice

The application of deep reinforcement learning (DRL) to PEV control has progressed from proof-of-concept demonstrations to increasingly sophisticated implementations that address real-world constraints. The TD3 algorithm-based strategy for longitudinal-vertical coordinated control represents a notable example, demonstrating that DRL can effectively handle the coupled dynamics of braking and suspension systems^[5]. The TD3 approach consistently outperformed both MPC-PID and deep deterministic policy gradient (DDPG) baselines in terms of energy recovery efficiency and ride comfort metrics.

5. The simulation-to-reality gap and deployment challenges

5.1. Validation practices and their limitations

The reasons for this gap are multifaceted. Simulation environments offer the ability to evaluate control strategies under controlled and repeatable conditions, to explore extreme scenarios that would be unsafe to test on public roads, and to iterate rapidly on algorithm development. However, the fidelity of vehicle dynamics models, tire models, and actuator models employed in simulation is inherently limited, and the gap between simulated and real-world performance can be substantial. This is particularly true for RL-based approaches, where policies trained in simulation may exploit artifacts of the simulator that do not transfer to the physical system.

5.2. The computational energy paradox

Advanced PEV control faces the computational energy paradox: Elaborate optimizers and neural networks deliver better performance but raise ECU power draw. Energy saved by optimized control must cover computing overhead. Hardware limits restrict complex algorithms for mass EVs. MPC-AI hybrids balance performance and real-time execution, preferring practical near-optimal solutions over theoretical optima.

6. Conclusion and future perspectives

This review summarizes advanced control strategies for pure electric vehicles (PEVs), tracking their evolution from rule-based/PID methods to optimization and learning-based algorithms, and draws three key conclusions.

First, model predictive control (MPC) has become the mainstream PEV control method. Dynamic-weight and nonlinear MPC greatly boost adaptability for coupled multi-variable systems in longitudinal and integrated motion control under physical limits.

Second, reinforcement learning (RL) serves as a supplementary model-free scheme. It adapts to uncertain complex environments, generating untuned control policies to balance vehicle stability and energy efficiency in torque vectoring and energy management.

Future research focuses on three promising paths. Hybrid frameworks merging MPC's constraint management and RL's adaptability can balance robustness and flexibility. V2X communication and real-time traffic data will support predictive, context-aware control. Standard verification systems combining hardware-in-the-loop tests and real driving data are required to narrow the simulation-reality gap and transfer theoretical algorithms to practical, efficient EV controllers.

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