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ON ADAPTIVE CONTROL OF ELECTRIC VEHICLES CONSIDERING OPERATING CONDITIONS

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ASTRACT

Electric cars drive in a lot of different conditions, which change how they work and how much energy they use all the time. The slope of the road, the weight of the vehicle, the state of charge of the battery, and the driver's demand all add uncertainty that makes traditional fixed-parameter control strategies less effective. These kinds of controllers might work well in normal situations, but they often don't work as well in real life. This makes batteries work harder and uses more energy.

This paper presents an adaptive control framework for electric vehicles that explicitly addresses varying operational conditions. A control-oriented model of the electric vehicle is developed, incorporating the essential interactions between longitudinal vehicle dynamics, the electric drivetrain, and the battery energy system. This formulation posits that the control problem is characterized by parameters that are often uncertain and subject to temporal variation, in addition to practical constraints on motor torque and battery operational limits.

The proposed method incorporates knowledge of operating conditions directly into the control strategy, enabling real-time adjustments of control parameters in response to variations in road conditions, vehicle mass, and battery status. The function of the controller is track vehicle speed and make it more energy-efficient while also limiting how much power the battery needs. It does this by changing how much torque the traction motor has. The formula also makes sure that it works with the limits of regenerative braking, which makes it safe and easy to use.

KEYWORDS

Electric vehicles, adaptive control, operating conditions, longitudinal vehicle dynamics

INTRODUCTION.

Because there are so many more electric vehicles (EVs) on the road, it is of vital importance to have advanced control strategies for them. Electric vehicles (EVs) have very different dynamic characteristics than traditional internal combustion engine vehicles [1,2]. The main differences are the electric drivetrain, power electronics, and energy storage system which are all very closely linked [3,4] . This means that the performance, energy efficiency, and durability of vehicle parts are very sensitive to changes in the operating conditions they are used including the road profile, the weight of the vehicle, the state of charge of the battery, and the driver's behavior [5,6]. Modern vehicle control systems still have a big problem making sure that electric vehicles (EVs) work well and reliably in all of these different situations [7–9].

Most electric cars still use controllers that are set once for a few "normal" conditions and then not changed [10,11] . These settings may perform well in lab tests or on standard driving cycles, but daily driving is much more unpredictable [12]. The vehicle might be subjected to hills, extra loads, and a battery whose internal resistance changes with temperature and state of charge. Different drivers also have different needs for the car [13–16].

Adaptive control is one way to deal with these problems in electric vehicles. The main idea is that the controller changes its settings in real time based on how the system is currently acting or how it is expected to act. This way, it can keep the car stable, responsive, and efficient in a wide range of driving situations [17]. Researchers have looked into a number of these kinds of methods in the last few years to make electric vehicles (EVs) smarter and more adaptable. These include fuzzy logic controllers, model-reference adaptive control, gain-scheduling, and data-driven methods [18–20]. These strategies have been shown to be more robust, track torque more accurately, and use less energy than traditional fixed controllers[21–23].

Even with all these advances, some important issues remain. Many recent studies look at how to adapt the controller but do not fully model the real operating conditions inside the control framework [24,25]. In practice, factors such as road slope, vehicle weight, and battery limits strongly influence how the controller should make decisions. On top of that, some adaptive methods depend on complicated models or heavy algorithms, which demand a lot of computing power and can be difficult to run in real time on existing vehicle control units [22].

LITERATURE REVIEW.

In recent years, research on adaptive control for electric vehicles (EVs) has moved steadily away from fixed-parameter controllers toward strategies that explicitly respond to changing operating conditions such as temperature, road gradient and traffic patterns [26]. Work in this area covers several layers of the vehicle, from powertrain and energy management to motion control and connected functions, yet there is still a noticeable lack of integrated concepts that treat these influences jointly and in real time [27,28].

Early studies on adaptive control in electrified powertrains concentrated mainly on plug-in hybrid architectures, where the controller adjusts torque split and battery usage along a driving cycle to reduce fuel or energy consumption [29]. More recent contributions extend these ideas to pure battery electric vehicles by embedding adaptation directly into the motor drive, battery management system and supervisory controller, allowing control gains and thresholds to change with state-of-charge, temperature and driver demand [30]. These developments are driven by the pronounced nonlinear behaviour of electric powertrains and the well-known sensitivity of lithium-ion batteries to their operating window [31].

A substantial part of the literature concentrates on adaptive energy and powertrain management, typically combining optimal control with on-line adaptation to driving conditions [32]. For example, one study introduces a model adaptive control scheme combined with Pontryagin's Minimum Principle, showing that it can improve motor efficiency while reducing computational burden compared to classical dynamic programming or purely adaptive optimization. In hybrid and plug-in hybrid vehicles, similar ideas appear in the form of adaptive rule-based or learning-augmented strategies that recognize the current driving pattern and update their rules in real time, achieving measurable energy savings on mixed urban-highway cycles [33,34].

The influence of operating conditions has become a central theme in recent work. Experimental analyses demonstrate that low ambient temperatures, can cut the achievable range to roughly half of what is observed at moderate conditions, highlighting the importance of adaptive thermal and energy management strategies [35]. Other authors bring road information directly into the control loop, using road gradient and road type to adapt power split, torque demand and battery usage along hilly or mixed routes with the aim of extending component life and reducing total energy consumption [36,37].

Adaptive control has also become closely linked with connected and automated driving. Eco-cruising strategies for connected EVs, for instance, exploit information about road geometry, traffic signals and preceding vehicles to shape the vehicle's speed profile, with simulations and experiments showing appreciable reductions in energy use compared with typical human driving [38,39] . At the same time, large-scale observational studies reveal that conventional adaptive cruise control, when designed without energy efficiency as an explicit target, can slightly increase EV consumption, which motivates new adaptive cruise algorithms that incorporate energy objectives from the outset[40–42].

More recently, researchers have started to rely heavily on artificial intelligence and IoT connectivity to realize richer forms of adaptive behaviour [35–37] . Neural-network-based controllers for electric drives, for example, have been shown to deliver accurate torque control under variable loads and road conditions, illustrating how learning-based approaches can capture nonlinearities and uncertainties that are difficult to model explicitly [34]. At the same time, AI-IoT frameworks have been proposed in which EVs exchange data about their environment and traffic state through cloud platforms, enabling cooperative control strategies that aim at improving fleet-level energy efficiency and sustainability rather than focusing on a single vehicle.

Despite this progress, the existing body of work still exhibits several important gaps. Many studies focus on a single subsystem-such as the motor drive (electric machine), the battery or the cruise controller-without embedding it into a unified vehicle-level architecture that simultaneously adapts propulsion, regenerative braking and thermal management [43] . In addition, a large proportion of reported results are based on standardized driving cycles or relatively short test routes, and there are fewer studies that rely on long-term real-world measurements collected in diverse climates, for example in regions with both very hot summers and cold winters [44,45].

ELECTRIC VEHICLE SYSTEM DESCRIPTION.

The longitudinal dynamics, energy storage system, and electric drivetrain of an electric vehicle significantly influence its performance. Rapid electric actuators and energy limitations imposed by batteries influence electric vehicle dynamics, unlike traditional vehicles where engine dynamics govern system behavior. The creation of adaptive control techniques that perform effectively under diverse operating situations necessitates an accurate yet manageable system description.

The primary components include a traction electric motor (electric machine), a power electronic inverter, a battery pack equipped with a battery management system (BMS) and a mechanical powertrain featuring a fixed gear ratio and differential. The vehicle control system receives commands from the driver and converts them into torque requests. The electric machine subsequently transmits these demands to the wheels.

The battery is the only part that provides power on board, and it only works within a certain range of voltage, current, and temperature. The battery's state of charge (SOC) level and temperature affect how much traction and regenerative braking power it has. So, the control system has to keep changing how it works to make sure safety and efficiency.The vehicle's forward motion is controlled by the balance between the traction force at the wheels and the forces that push against it. Newton's second law can be used to explain the vehicle motion:

$$m\,dv/dt = F_{trac} - F_{res} \quad (1)$$

Where m is the vehicle mass, v is the longitudinal vehicle speed, F_{trac} is the traction force at the wheels, and F_{res} is the total resistive force.

The total resistance force includes aerodynamic drag, rolling resistance and gravitational force:

$$F_{res} = \frac{1}{2}\rho A C_d v^2 + mgC_r\cos(\theta) + mg\sin(\theta) \quad (2)$$

Where ρ is the density of air, A is the vehicle frontal area, C_d is the aerodynamic drag coefficient, C_r is the rolling resistance coefficient, *g* is gravitational acceleration and θ is the road slope angle.

The traction force generated at the wheels is related to the electric machine torque through the drivetrain:

$$F_{trac}=\frac{(T_m i_g \eta_g)}{R_w} \tag{3}$$

The electric machine is assumed to operate in torque control mode, which is typical for electric vehicle applications. Electrical dynamics are significantly faster than mechanical dynamics and are therefore neglected for control-oriented modeling. The electric machine torque is limited by the torque-speed characteristic of the machine:

$$T_m \leq T_{max}(\omega_m) \tag{4}$$

The motor angular speed is related to vehicle speed by:

$$\omega_m=\frac{(v\, i_g)}{R_w} \tag{5}$$

To describe the energy behavior of the battery while maintaining computational simplicity, a first-order equivalent circuit model is adopted. The battery terminal voltage is expressed as:

$$V_b=V_{oc}(SOC)-R_b(SOC,T_b)I_b \tag{6}$$

Where V_{oc} is the open-circuit voltage, R_b is the internal resistance, I_b is the battery current, and T_b is the battery temperature.

The state of charge dynamics are given by:

$$d(SOC)/dt=-I_b/Q_b \tag{7}$$

Where Q_b is the nominal battery capacity.

These equations show that battery operating limits vary dynamically with SOC and temperature which affects the available traction and regenerative braking power.

To design the controller the EV system can be represented in a compact nonlinear state-space form:

$$\dot{x}=f(x,u,p) \tag{8}$$

where

x = [v SOC]^T is the state vector,

u = T_m is the control input, and

p represents the operating condition parameters, including vehicle mass, road slope, and battery characteristics.

This representation emphasizes the dependence of vehicle dynamics on operating conditions and forms the basis for the adaptive control strategy developed in the subsequent section.

PROBLEM FORMULATION

The primary control objective is to regulate the traction motor torque in such a way that the vehicle longitudinal speed follows the driver's demand with minimal error. This objective must be achieved while respecting physical limitations of the electric drivetrain and battery system.

The desired vehicle speed trajectory is denoted as v_{ref} which is generated from driver accelerator and brake inputs. The speed tracking error is defined as:

$$e_v=v_{ref}-v \tag{9}$$

In addition to tracking performance, the control system aims to optimize energy usage and reduce battery stress. Excessive battery current and frequent high-power transients are known to accelerate battery aging. Therefore, the control objectives can be summarized as follows:

- Minimize vehicle speed tracking error
- Maximize energy efficiency

- Limit battery current peaks
- Ensure smooth torque response for driving comfort

Eq. (1) used in the previous section describes the vehicle dynamics which, as first approximation, assumes that several parameters such as the vehicle mass, road slope and rolling resistance coefficients are constant. However, in reality the parameters are subject to changes depending on operating conditions.

To explicitly represent these uncertainties, the system dynamics are rewritten in a parametric form:

$$dv/dt=f(v,T_m)+\Delta(v,p) \qquad (10)$$

Where $f(v,T_m)$ represents the nominal vehicle dynamics and $\Delta(v,p)$ captures the uncertaintiy and disturbances introduced by operating conditions p.

The control input of the system is the motor torque T_m, which is subject to several constraints imposed by the motor and battery characteristics. These constraints are expressed as:

$$T_{min}(\omega_m)\le T_m\le T_{max}(\omega_m) \qquad (11)$$

In addition, the battery current must remain within allowable bounds to ensure safe operation:

$$I_{min}\le I_b\le I_{max} \qquad (12)$$

During regenerative braking, negative motor torque is applied to recover energy. However, regenerative braking capability is limited by battery SOC and charging power constraints. This is expressed as:

$$T_m\ge T_{reg,min}(SOC) \qquad (13)$$

The adaptive control problem is addressed to ensure vehicle tracking while adpating to unknown and time-varying operating conditions, subject to actuator and battery constraints.

The contol law is expressed as:

$$T_m=u(v,v_{ref},x,\hat{p}) \qquad (14)$$

Where x represents the system state vector and $\hat{p}$ denotes estimated or measured operation condition parameters.

The adaptation mechanism adjusts controller parameters in real time to compensate for changes in vehicle mass, road slope and battery limitations.

For adaptive control design, the system is represented in a control-affine form:

$$dv/dt=a(v,p)+b(v)T_m \qquad (15)$$

Where $a(v,p)$ represents the uncertain nonlinear dynamics influenced by operating conditons and $b(v)$ is a known control effectiveness term.

CONCLUSION.

This paper studied the issues related to control electric vehicles at different driving conditions. Due to the fact that main vehicle parameters (mass, road slope, battery resistance, etc.) are subject to changes with operations, new control strategies are required to track the vehicle performance in real-time mode.

The research developed a control-focused model of the electric vehicle that specifies the critical relationships among longitudinal motion, the electric drivetrain, and the energy provided by the battery. This model illustrates the control challenge amidst unpredictable, temporally varying characteristics and the practical limitations of the motor and batteries. This viewpoint inherently supports the adoption of adaptive control, as it allows the controller to react dynamically to changing operating conditions rather than depending on cautious, overly conservative tuning.

Nevertheless, the scope of this work is subject to certain limitations. The adopted models favor simplicity and computational efficiency, which is appropriate for control design but does not fully capture effects such as battery aging, thermal dynamics, or high-frequency electrical behavior. In addition, the results are currently limited to problem formulation, and ,hence, simulation model and future experimental validations are required.

Future work will focus on extending the proposed approach toward real-time implementation and experimental verification using hardware-in-the-loop or vehicle-level testing. Adding battery thermal and aging models, as well as adaptation mechanisms based on learning, is a good way to improve control performance and the life of the system even more. These kinds of changes will help make next-generation electric vehicles' control systems stronger, more efficient, and smarter.

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