

Cyber-Physical System Based Optimization Framework for Intelligent Powertrain Control

Chen Lv
 Cranfield University

Hong Wang
 University of Waterloo

Bolin Zhao
 Eindhoven University of Technology

Dongpu Cao and Wang Huaji
 Cranfield University

Junzhi Zhang, Yutong Li, and Ye Yuan
 Tsinghua University

ABSTRACT

The interactions between automatic controls, physics, and driver is an important step towards highly automated driving. This study investigates the dynamical interactions between human-selected driving modes, vehicle controller and physical plant parameters, to determine how to optimally adapt powertrain control to different human-like driving requirements. A cyber-physical system (CPS) based framework is proposed for co-design optimization of the physical plant parameters and controller variables for an electric powertrain, in view of vehicle's dynamic performance, ride comfort, and energy efficiency under different driving modes. System structure, performance requirements and constraints, optimization goals and methodology are investigated. Intelligent powertrain control algorithms are synthesized for three driving modes, namely sport, eco, and normal modes, with appropriate protocol selections. The performance exploration methodology is presented. Simulation-based parameter optimizations are carried out according to the objective functions. Simulation results show that an electric powertrain with intelligent controller can perform its tasks well under sport, eco, and normal driving modes. The vehicle further improves overall performance in vehicle dynamics, ride comfort, and energy efficiency. The results validate the feasibility and effectiveness of the proposed CPS-based optimization framework, and demonstrate its advantages over a baseline benchmark.

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INTRODUCTION

The ever-growing attention to the environment and energy conservation requires automobiles to be cleaner and more energy efficient. Technologies such as powertrain electrification and alternative fuels are being actively researched and developed. Among these solutions, various types of electrified vehicles with alternative power sources, including battery electric vehicles (BEVs), hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and fuel cell electric vehicles (FCEVs), are very promising due to their higher efficiency and lower or even zero emissions [1], [2], [3], [4], [5]. Moreover, regenerative braking systems (RBS) can recover the vehicle's kinetic energy during deceleration, further reducing fuel consumption [6], [7], [8], [9].

A Cyber-Physical System is a distributed, networked system that fuses computational processes (cyber world) with the physical world. An electrical vehicle is a typical example of CPS [10]. In details, an electric powertrain involves the following subsystems: the controller, representing the "Cyber" world, the physical plant, the driver, the "Human", and the environment. These different parts, which are highly coupled, decide the vehicle and powertrain's behavior and performance [11].

Recent study shows that human driver behaviors, including driving modes, driving styles, and driver-vehicle interactions, exert crucial impacts on the performances of electrified powertrains. In [12], the effect of driving styles on a conventional vehicle and an electrical one was compared. The results showed important influence

of driving styles in all vehicle platforms. For instance, high-acceleration events have a particularly negative effect on HEVs. Besides, the regenerative braking performance of an electrified powertrain is strongly related to the driver torque request, actuated by the accelerator and brake pedals [13]. The energy efficiency of BEVs can be improved over 20% through regenerative braking. Therefore, small changes in driving mode can cause unnecessary energy waste and sub-optimal vehicle performance [14]. And information of driving scenarios, driver modes, and driver-vehicle interactions is crucial and should be integrated to enhance electric powertrain performance.

The main drawback of the conventional implementations in powertrain design and control is the lack of global optimality in the selection of architecture, parameters, and variables [15]. By using the conventional design flow, which deals with different subsystems independently, even if the controller is very well designed, the improvement of vehicle performance could be limited, since the physical architecture and parameters are not optimized in sync with the controller, and the system potential is not fully explored. Optimal co-design of the physical architecture and controller parameters with human operation consideration provides the ability to extend system design space and improve the overall CPS performances [16]-[19]. However, in addition to the cyber and the physical worlds, we need to include the “Human” side of a vehicle. To do so, the interactions between the physical plant, controller parameters, vehicle performance, and driving mode have to be well understood.

In this paper, we propose a CPS based framework for the optimal co-design of the physical plant parameters and controller variables for an electric powertrain with different driving mode considerations, while taking into account the trade-off between vehicle dynamic performance, ride comfort, and energy efficiency.

The paper is organized as follows: The co-design optimization problem is illustrated in Section II. A cyber-physical optimization framework is proposed and presented in Section III. System models and driving-mode-oriented controller synthesis are described in Section IV. Then, the performance exploration methodology is proposed in Section V. Section VI reports simulation-based design optimization results, followed by conclusions in Section VII.

PROBLEM DESCRIPTION

In this study, the goal is to formulate the CPS-based intelligent powertrain control under different driving modes for an electric vehicle as a multi-objective optimization problem. Optimal assignments for design variables to maximize performances while satisfying a number of constraints are expected to be found. To ensure that the problem is of a reasonable complexity, only longitudinal vehicle control in normal driving situations is considered, and the sizing of the powertrain system is fixed, i.e., the parameters of the energy source (battery) and the power source (electric motor) are constant to bound the exploration space.

Intelligent Electric Powertrain System

Electric Powertrain System

Figure 1 shows the overall structure of the electrified powertrain system considered in this study. For the physical structure, a central electric motor is installed at the front axle of the vehicle. During acceleration, the electric motor, powered by the battery, provides propulsion through the transmission system to the wheels. During deceleration, the regenerative braking torque generated by the motor is synchronized with the friction brake torque modulated by the hydraulic modulator, in a cooperative regenerative braking function.

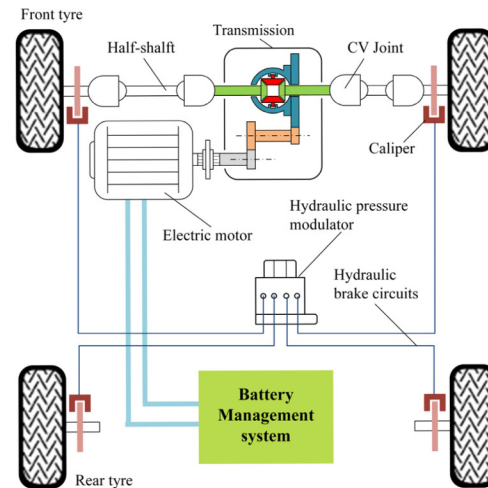


Figure 1. Structure of the electric powertrain physical plant.

Intelligent Powertrain Control Architecture

The high-level powertrain control strategy is designed to output a suitable torque to propel the vehicle, satisfying the longitudinal motion requirement of the vehicle. The output torque demand is generally determined by driver's operation maneuver. Specifically, as Figure 2 shows, in this study, the intelligent powertrain controller is synthesized considering different driving modes, i.e. the requested output torque of the powertrain is not only decided by the driver's operation, but also differentiated by the driving modes. In the implementation phase, the driving mode can be either selected through a human-machine interface (HMI), or identified by smart sensing of driver's intentions or preferences using machine learning approaches. In this work, we assume that the driving mode selection is available via HMI.

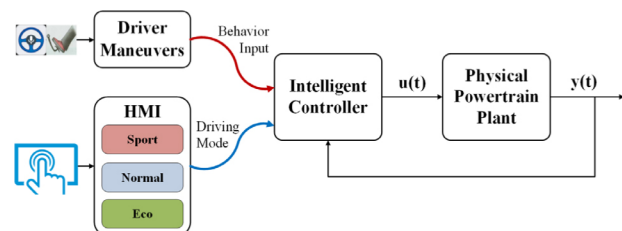


Figure 2. Structure of the electric powertrain physical plant.

Driving Mode

Oriented by the driving-mode-aware intelligent powertrain control described above, three driving modes are considered in this work and defined as follows.

1. Sport: The Sport driving mode exhibits sharp and abrupt accelerations and deceleration, aiming at vehicle dynamic performance. This mode results in higher fuel consumption and increased likelihood of accidents as well.
2. Eco: The driving mode of Eco exhibits a high efficient energy conversion of the powertrain with small amplitudes and low frequency actions on both longitudinal and lateral dynamics. This Eco mode values primarily energy efficiency, avoiding abrupt variation of powertrain torque demand.
3. Normal: The Normal driving mode is in between. It does not aim at absolute vehicle performance, but would like to balance multiple performances, such as vehicle dynamic performance, energy consumption, and ride comfort.

Driving Scenario

In this paper, as mentioned above, we focus on vehicle longitudinal motion control, whereas the lateral motion and dynamics related to the steering wheel operation are not involved. Hence, the following driving scenarios are of importance in our derivations.

1. Scenario 1: 0-50km/h acceleration. In this scenario, the car is accelerated from 0 to 50 km/h. With the intelligent powertrain controller, the motor torque will be generated based on different control strategies and parameter selections corresponding to different driving modes. The vehicle acceleration, jerk, and the time taken in this process are used to evaluate the dynamic performance and ride comfort under different driving modes.
2. Scenario 2: 50-0 km/h deceleration. In this scenario, the car is decelerated from 50 km/h to 0. For an electric car, the total brake demand is distributed to the regenerative and frictional brakes. Different deceleration demands will be generated by the intelligent powertrain controller under different driving modes. The deceleration and the time taken in this process are typical performance indices. The overall energy recovered during the braking process can be used to evaluate energy consumption. This scenario will be used to verify vehicle's performance and energy efficiency during optimization.
3. Scenario 3: standard driving cycle. The standard ECE driving cycle is adopted for measuring energy efficiency since this driving cycle is close to the behavior of a vehicle in an urban area and covers an extended operation time period. This scenario will be used to check vehicle's energy efficiency during optimization.

Vehicle Performance

The performances for vehicle design and control involve safety, dynamical performance, energy efficiency, and ride comfort. Driving mode consideration implies the introduction of trade-offs between multiple performances that are the objective functions in our optimization problem under different driving modes.

1. Dynamic performance: Dynamic performance is the fundamental and the most important indicator of a car. Maximum speed and acceleration time are proxies for dynamic performance. Dynamic performance depends on driver behavior as well as on the parameters of the physical plant and the controller. In this paper, we select the acceleration time and the deceleration time as two indicators for the dynamic performance.
2. Energy efficiency: The energy efficiency of a vehicle can be represented by the fuel or energy consumed during a certain trip. Powertrain performance as well as driving mode have great effects on energy consumption. For electrified vehicles, energy consumption can be significantly enhanced through regenerative braking. Thus, in this paper, we set the regenerated braking energy as one of the optimization goals in the trade-off problem.
3. Ride comfort: During accelerations and decelerations, torsional oscillations may occur in the powertrain due to fast torque transitions, resulting in unexpected jerks at the vehicle level and deteriorated drivability. To cope with this problem, an active damping controller is usually required [20]. Thus, we would like to co-optimize related plant parameters and controller variables to improve comfort level under different driving modes.

Basic Requirements and Limitations

During vehicle design, control, and optimization, there are some basic requirements and limitations of the physical systems that need to be taken into account.

1. Maximum vehicle speed: The maximum speed of the vehicle is determined by the highest rotational speed of the electric motor, the radius of tire, and the gear ratio.
2. Minimum gradeability: Gradeability is defined as the highest grade a vehicle can ascend maintaining a particular speed. It is an important requirement in vehicle design.
3. Minimum brake intensity: In order to guarantee stability during braking, a vehicle needs to have enough braking force, represented by the brake intensity z , as required by regulation ECE-R13 [21].
4. Powertrain limitation: Once the sizing of the power source is given, then the output torque of the powertrain is bounded by the outer characteristics profile of the electric drive.

CYBER-PHYSICAL OPTIMIZATION FRAMEWORK

The optimization problem is a constrained multi-objective optimization problem where both vehicle and controller parameters need to be optimally chosen. In this paper, we adopt as co-design methodology Platform-Based Design (PBD) [10]. As Figure 3 shows, PBD is a meet-in-the-middle approach that favors re-usability. At the top layer are high-level requirements and constraints, which are characterized by driving modes, driver maneuvers, and driving scenarios. The bottom layer is defined by a design platform, i.e., a library of components characterized by their behaviors and performance. The bottom layer contains the models of the electric powertrain, the brakes, and the driver-mode-aware control. The models are parameterized to capture families of vehicles, powertrains,

brakes and controllers. The design problem is to select a set of components and their parameters so that the constraints are satisfied and the objective functions optimized. The selection process is called mapping, indicated as the meeting point in the diagram, since the obligations captured in the requirements and constraints are discharged by particular components or combinations thereof. Co-design of the physical plant parameters, controller protocols and variables, for the intelligent electric powertrain is then made possible.

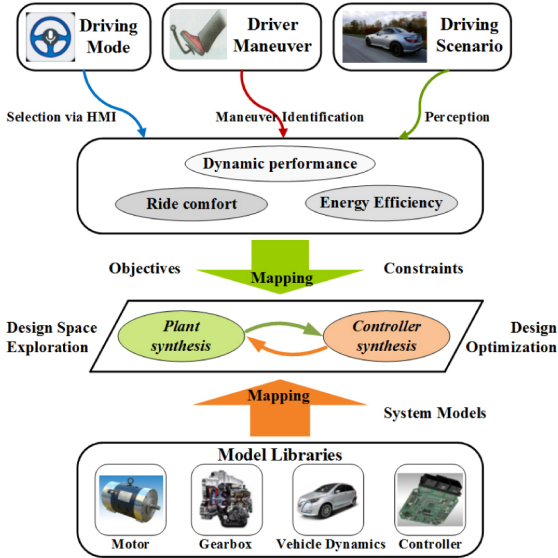


Figure 3. PBD-based optimization framework for electrified powertrain.

SYSTEM MODELLING AND FORMULATION

The following model and formulation is able to support interactive performance exploration and optimization between components at different layers within a unifying framework.

System Modelling

Electric Powertrain Model

Oriented by controller synthesis and optimization, the powertrain is simplified to a two-inertia model, as presented in Figure 4. One inertia corresponds to the electric motor, and the other corresponds to the contribution by the wheels. The gearbox, consisting of the transmission, final drive, differential, and inner and outer constant-velocity (CV) joints, is located close to the motor inertia.

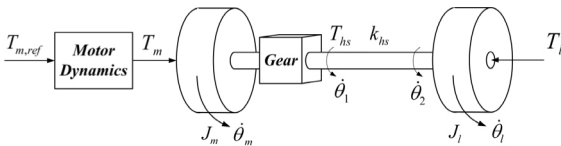


Figure 4. Structure of the simplified powertrain system model.

Assuming that the half shafts are of the same length, the motor output torque is considered to be equally distributed over the left and right half shafts. The motor torque is modelled as a first-order reaction, as shown in equation (1). The transmitted torque via the gearbox can be represented by equation (2). The model for the half-shaft torque can be given by equation (3).

$$T_{m,ref} = T_m + \tau_m \dot{T}_m \quad (1)$$

$$J_m \ddot{\theta}_m = T_m - 2T_{hs} / i_g \quad (2)$$

$$T_{hs} = k_{hs} (\theta_m / i_g - \theta_w) + c_{hs} (\dot{\theta}_m / i_g - \dot{\theta}_w) \quad (3)$$

where, τ_m is the small time constant, T_{hs} is the half-shaft torque, J_m is the motor inertia, and θ_m and θ_w are the angular positions of electric motor and load, respectively. Furthermore, k_{hs} and c_{hs} are the stiffness coefficient and damping coefficient of the half shaft, respectively.

The energy source, i.e. the battery, is built as an open-circuit voltage-resistance model based on the data of the lithium-ion battery utilized in a commercial electric vehicle. In this paper, look-up tables are compiled on the basis of the state of charge (SOC) and temperature data for the battery, modeling its charging-discharging internal resistance. The model's input is the power required by the electric motor, and its outputs include the SOC, the voltage at the output port, the current, and the temperature of the battery. The detailed model with parameters can be found in [6].

Regenerative Brake Model

In this paper, the brake force distribution (BFD) ratio β is set to a fixed value, which can be obtained by the parameters of the brake devices. The front and rear brake demand can be calculated as follows.

$$T_b = 2T_{b,fw} + 2T_{b,rw} \quad (4)$$

$$T_{b,fw} = \frac{\beta}{2} \cdot T_{b,dmd} \quad (5)$$

$$T_{b,rw} = \frac{1-\beta}{2} \cdot T_{b,dmd} \quad (6)$$

where T_b is the actual braking torque provided by the blended brakes, $T_{b,dmd}$ is the demanded braking torque of the vehicle, and $T_{b,fw}$ and $T_{b,rw}$ are the brake torque of one front wheel and one rear wheel, respectively.

Vehicle Longitudinal Model

Because we focus on the longitudinal motion of the vehicle, the vehicle model adopts the longitudinal dynamics model:

$$m\dot{v} = \frac{2T_{hs}}{r} - \frac{T_b}{r} - fmg - \frac{1}{2}C_D A \rho v^2 \quad (7)$$

where m is the vehicle mass, v is the vehicle speed, r is the nominal radius of tire, C_D is the coefficient of air resistance, A is the frontal area, and ρ is the air density.