Cyber-Physical Vehicle Systems
Methodology and Applications
The automotive industry has entered a transformational period that will see an unprecedented evolution in the technological capabilities of vehicles. Significant advances in new manufacturing techniques, low-cost sensors, high processing power, and ubiquitous real-time access to information mean that vehicles are rapidly changing and growing in complexity. These new technologies—including the inevitable evolution toward autonomous vehicles—will ultimately deliver substantial benefits to drivers, passengers, and the environment. Synthesis Lectures on Advances in Automotive Technology Series is intended to introduce such new transformational technologies in the automotive industry to its readers.

**Cyber-Physical Vehicle Systems: Methodology and Applications**
Chen Lv, Yang Xing, Junzhi Zhang, and Dongpu Cao
2020

**Reinforcement Learning-Enabled Intelligent Energy Management for Hybrid Electric Vehicles**
Teng Liu
2019

**Deep Learning for Autonomous Vehicle Control: Algorithms, State-of-the-Art, and Future Prospects**
Sampo Kuutti, Saber Fallah, Richard Bowden, and Phil Barber
2019

**Narrow Tilting Vehicles: Mechanism, Dynamics, and Control**
Chen Tang and Amir Khajepour
2019

**Dynamic Stability and Control of Tripped and Untripped Vehicle Rollover**
Zhilin Jin, Bin Li, and Jungxuan Li
2019
Real-Time Road Profile Identification and Monitoring: Theory and Application
Yechen Qin, Hong Wang, Yanjun Huang, and Xiaolin Tang
2018

Noise and Torsional Vibration Analysis of Hybrid Vehicles
Xiaolin Tang, Yanjun Huang, Hong Wang, and Yechen Qin
2018

Smart Charging and Anti-Idling Systems
Yanjun Huang, Soheil Mohagheghi Fard, Milad Khazraee, Hong Wang, and Amir Khajepour
2018

Design and Advanced Robust Chassis Dynamics Control for X-by-Wire Unmanned Ground Vehicle
Jun Ni, Jibin Hu, and Changle Xiang
2018

Electrification of Heavy-Duty Construction Vehicles
Hong Wang, Yanjun Huang, Amir Khajepour, and Chuan Hu
2017

Vehicle Suspension System Technology and Design
Avesta Goodarzi and Amir Khajepour
2017
ABSTRACT
This book studies the design optimization, state estimation, and advanced control methods for cyber-physical vehicle systems (CPVS) and their applications in real-world automotive systems. First, in Chapter 1, key challenges and state-of-the-art of vehicle design and control in the context of cyber-physical systems are introduced. In Chapter 2, a cyber-physical system (CPS) based framework is proposed for high-level co-design optimization of the plant and controller parameters for CPVS, in view of vehicle’s dynamic performance, drivability, and energy along with different driving styles. System description, requirements, constraints, optimization objectives, and methodology are investigated. In Chapter 3, an Artificial-Neural-Network-based estimation method is studied for accurate state estimation of CPVS. In Chapter 4, a high-precision controller is designed for a safety-critical CPVS. The detailed control synthesis and experimental validation are presented. The application results presented throughout the book validate the feasibility and effectiveness of the proposed theoretical methods of design, estimation, control, and optimization for cyber-physical vehicle systems.

KEYWORDS
cyber-physical vehicle systems, co-design optimization, dynamic modeling, design space exploration, parameter optimization, state estimation, neural networks, controller synthesis, simulation validation, experimental testing
## Contents

<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preface</td>
<td></td>
<td>ix</td>
</tr>
<tr>
<td>1</td>
<td>Introductions</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>Co-Design Optimization for Cyber-Physical Vehicle System</td>
<td>5</td>
</tr>
<tr>
<td>2.1</td>
<td>Problem Formulation</td>
<td>5</td>
</tr>
<tr>
<td>2.1.1</td>
<td>Hierarchical Optimization Methodology</td>
<td>5</td>
</tr>
<tr>
<td>2.1.2</td>
<td>System Description</td>
<td>5</td>
</tr>
<tr>
<td>2.1.3</td>
<td>Driving Event</td>
<td>7</td>
</tr>
<tr>
<td>2.1.4</td>
<td>Driving Style Recognition</td>
<td>7</td>
</tr>
<tr>
<td>2.1.5</td>
<td>Requirements for the Design and Optimization of CPVS</td>
<td>9</td>
</tr>
<tr>
<td>2.1.6</td>
<td>Constraints for Vehicle Design and Optimization</td>
<td>10</td>
</tr>
<tr>
<td>2.2</td>
<td>System Modeling and Validation</td>
<td>11</td>
</tr>
<tr>
<td>2.2.1</td>
<td>Electric Powertrain system</td>
<td>11</td>
</tr>
<tr>
<td>2.2.2</td>
<td>Blended Brake System</td>
<td>12</td>
</tr>
<tr>
<td>2.2.3</td>
<td>Dynamic Model of the Vehicle and Tyre</td>
<td>12</td>
</tr>
<tr>
<td>2.2.4</td>
<td>Experimental Validation</td>
<td>13</td>
</tr>
<tr>
<td>2.3</td>
<td>Controller Design for Different Driving Styles</td>
<td>13</td>
</tr>
<tr>
<td>2.3.1</td>
<td>High-Level Controller Architecture</td>
<td>13</td>
</tr>
<tr>
<td>2.3.2</td>
<td>Low-Level Controller for Different Driving Styles</td>
<td>14</td>
</tr>
<tr>
<td>2.4</td>
<td>Driving-Style-Based Performance Exploration and Parameter Optimization</td>
<td>16</td>
</tr>
<tr>
<td>2.4.1</td>
<td>Design Space Exploration</td>
<td>16</td>
</tr>
<tr>
<td>2.4.2</td>
<td>Performance Exploration Methodology</td>
<td>16</td>
</tr>
<tr>
<td>2.4.3</td>
<td>Driving-Style-Oriented Multi-Objective Optimization</td>
<td>16</td>
</tr>
<tr>
<td>2.5</td>
<td>Optimization Results and Analysis</td>
<td>18</td>
</tr>
<tr>
<td>2.5.1</td>
<td>Optimization Results for the Aggressive Driving Style</td>
<td>19</td>
</tr>
<tr>
<td>2.5.2</td>
<td>Optimization Results of the Moderate Driving Style</td>
<td>19</td>
</tr>
<tr>
<td>2.5.3</td>
<td>Optimization Results of the Conservative Driving Style</td>
<td>21</td>
</tr>
<tr>
<td>2.5.4</td>
<td>Comparison and Discussion</td>
<td>21</td>
</tr>
<tr>
<td>Section</td>
<td>Title</td>
<td>Page</td>
</tr>
<tr>
<td>---------</td>
<td>----------------------------------------------------------------------</td>
<td>------</td>
</tr>
<tr>
<td>3</td>
<td>State Estimation of Cyber-Physical Vehicle Systems</td>
<td>23</td>
</tr>
<tr>
<td>3.1</td>
<td>Multilayer Artificial Neural Networks Architecture</td>
<td>25</td>
</tr>
<tr>
<td>3.1.1</td>
<td>System Architecture</td>
<td>25</td>
</tr>
<tr>
<td>3.1.2</td>
<td>Multilayer Feed-Forward Neural Network</td>
<td>25</td>
</tr>
<tr>
<td>3.2</td>
<td>Standard Backpropagation Algorithm</td>
<td>27</td>
</tr>
<tr>
<td>3.3</td>
<td>Levenberg–Marquardt Backpropagation</td>
<td>30</td>
</tr>
<tr>
<td>3.4</td>
<td>Experimental Testing and Data Collection</td>
<td>33</td>
</tr>
<tr>
<td>3.4.1</td>
<td>Testing Vehicle and Scenario</td>
<td>33</td>
</tr>
<tr>
<td>3.4.2</td>
<td>Data Collection and Processing</td>
<td>35</td>
</tr>
<tr>
<td>3.4.3</td>
<td>Feature Selection and Model Training</td>
<td>35</td>
</tr>
<tr>
<td>3.5</td>
<td>Experiment Results and Discussions</td>
<td>38</td>
</tr>
<tr>
<td>3.5.1</td>
<td>Results of the ANN-Based Braking Pressure Estimation</td>
<td>38</td>
</tr>
<tr>
<td>3.5.2</td>
<td>Importance Analysis of the Selected Features</td>
<td>40</td>
</tr>
<tr>
<td>3.5.3</td>
<td>Comparison of Estimation Results with Different Learning Methods</td>
<td>40</td>
</tr>
<tr>
<td>4</td>
<td>Controller Design of Cyber-Physical Vehicle Systems</td>
<td>43</td>
</tr>
<tr>
<td>4.1</td>
<td>Description of the Newly Proposed BBW System</td>
<td>45</td>
</tr>
<tr>
<td>4.2</td>
<td>Control Algorithm Design for Hydraulic Pump-Based Pressure Modulation</td>
<td>47</td>
</tr>
<tr>
<td>4.3</td>
<td>Control Algorithm Design for Closed-Loop Pressure-Difference-Limiting Modulation</td>
<td>49</td>
</tr>
<tr>
<td>4.3.1</td>
<td>Linear Modulation of On/Off Valve</td>
<td>49</td>
</tr>
<tr>
<td>4.3.2</td>
<td>Closed-Loop Pressure-Difference-Limiting Control</td>
<td>53</td>
</tr>
<tr>
<td>4.4</td>
<td>Hardware-in-the-Loop Test Results</td>
<td>54</td>
</tr>
<tr>
<td>4.4.1</td>
<td>Comparison of HPBPM and CLPDL Control</td>
<td>56</td>
</tr>
<tr>
<td>4.4.2</td>
<td>Brake Blending Algorithm Based on CLPDL Modulation</td>
<td>59</td>
</tr>
<tr>
<td>5</td>
<td>Conclusions</td>
<td>61</td>
</tr>
<tr>
<td></td>
<td>References</td>
<td>63</td>
</tr>
<tr>
<td></td>
<td>Authors' Biographies</td>
<td>73</td>
</tr>
</tbody>
</table>
Preface

This book studies the design optimization, state estimation, and advanced control methods for Cyber-Physical Vehicle Systems (CPVS) and their applications in real-world automotive systems.

In Chapter 1, key challenges and state-of-the-art of vehicle design and control in the context of cyber-physical systems are introduced. In Chapter 2, a Cyber-Physical System (CPS)-based framework for co-design optimization of an automated electric vehicle with different driving styles was proposed. The multi-objective optimization problem was formulated. The driving style recognition algorithm was developed using unsupervised machine learning and validated via vehicle testing. The system modelling and experimental verification were carried out. Vehicle control algorithms were synthesized for three typical driving styles with different protocol selections. The performance exploration methodology and algorithms were proposed. Test results show that the overall performances of the vehicle were significantly improved by the proposed co-design optimization approach. Future work will be focused on real vehicle application of the proposed methods and CPS design methodology improvement.

In Chapter 3, a novel probabilistic estimation method of brake pressure is developed for a safety critical CPVS based on multilayer Artificial Neural Network (ANN) with Levenberg-Marquardt Backpropagation Training (LMBP) training algorithm. The high-level architecture of the proposed multilayer ANN for brake pressure estimation is illustrated at first. Then, an efficient algorithm of LMBP method is developed for model training. The real vehicle testing is carried out on a chassis dynamometer under New European Drive Cycle (NEDC) driving cycles. The experimental results show that the developed model can accurately estimate the brake pressure, and its performance is advantageous over other learning-based methods with respect to estimation accuracy, demonstrating the feasibility and effectiveness of the proposed algorithm.

In Chapter 4, a typical safety-critical CPVS, i.e., the Brake-By Wire (BBW) system, was introduced. Compared to the existing BBW system, the newly developed system enjoys the advantage of a simple structure and low cost because only conventional valves and sensors are added to the usual hydraulic layouts. Two pressure modulation methods, namely, the Hydraulic Pump-Based Pressure Modulation (HPBPM) and Closed-Loop Pressure-Difference-Limiting (CLPDL) modulation, were proposed to improve the modulation precision of hydraulic brake
pressure and reduce valve’s operation noise as well. Experiments were conducted in a hardware-
in-the-loop test rig to demonstrate the performance of the proposed control methods.

Chen Lv, Yang Xing, Junzhi Zhang, and Dongpu Cao
December 2019
Intelligent vehicles have been gaining increasing attention from both academia and industrial sectors [1]. The field of intelligent vehicles exhibits a multidisciplinary nature, involving transportation, automotive engineering, information, energy, and security [2–5]. Intelligent vehicles have increased their capabilities in highly and even fully automated driving. However, unresolved problems do exist due to strong uncertainties and complex human-vehicle interactions.

Highly automated vehicles are likely to be on public roads within a few years. Before transitioning to fully autonomous driving, driver behavior should be better understood and integrated to enhance vehicle performance and traffic efficiency [6–9]. To address these challenges, researchers have explored advanced driver assistance systems (ADAS), and human-machine interface (HMI) from a variety of points of view [10, 11]. However, since the dynamic relationships between driver and vehicle are highly complex, satisfactory driver-vehicle interactions should go beyond the present ADAS and HMI systems. Human-vehicle interactions have already been considered in a high-level closed loop, where driving style, driving feel, and vehicle performance are considered [12]. Driving style plays a very important role in vehicle energy efficiency and ride comfort, thus significantly impacting controller synthesis [12–14]. For instance, control objectives and control protocols should be adaptively adjusted according to different driving styles. Based on the findings reported in [13], a better understanding of driving styles could help improve ADAS performance and further reduce vehicle’s fuel consumption through driver feedback. In [14], an enhanced intelligent driver model was developed, and then it was used to investigate the impact of different driving strategies on traffic capacity. In [15], an adaptive cruise control strategy considering the characteristics of different driving styles was developed, and the proposed strategy could automatically adapt to different traffic situations. Nevertheless, advanced control and optimization of vehicle systems with characterized driving styles are still open challenges and worthwhile exploring.

In the meantime, the ever-growing attention to the environment and energy conservation requires automobiles to be cleaner and more efficient [16–18]. In this study, an electric vehicle (EV) is chosen as the platform to conduct our research in cyber-physical vehicle systems. Based on existing studies, small changes in driving style can cause unnecessary energy waste and suboptimal performance of an EV [19, 20]. Moreover, regenerative braking capability of EVs can be enhanced by prior knowledge of driving style. Hence, an optimal energy management strategy can be obtained with knowledge about the entire driving cycle, environment, and driver behaviors. Therefore, the information of operating scenarios, driver behaviors, and driver-vehicle...
2 1. INTRODUCTIONS

A Cyber-Physical System (CPS) is a distributed, networked system that fuses computational processes (cyber world) with the physical world. An intelligent electric vehicle is a typical example of Cyber-Physical Vehicle System (CPVS). In details, an automated electric vehicle involves the following subsystems: the controller, representing the “Cyber” world, the physical vehicle plant, the driver, the “Human,” and the environment. These different parts, which are highly coupled, decide the vehicle’s behavior and final performance, as Fig. 1.1 shows. The main drawback of the conventional implementations in vehicle design and control is the lack of global optimality in the selection of architecture, parameters, and variables [25]. For instance, by using the conventional design method, 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. In this context, the emerging co-design method provides the capability to extend system design space and further enhance the performance of CPS [24–28]. In [24], a platform-based design method utilizing contracts to do the high-level abstraction of the components in a CPS was proposed, and it is able to offer support to the overall design process. In [26], co-design optimization of a cyber physical vehicle system, which considers task time, actuator characteristics, energy consumption, and processor workload, was investigated. In [27], a CPS-based control framework was developed for vehicle systems to min-

Figure 1.1: Schematic diagram of the CPVS.

interactions are crucial and should be integrated to enhance the energy efficiency of automated electric vehicles.
imize the car-following fuel consumption and ensure inter-vehicle safety. Besides the cyber and the physical worlds, we also need to take “Human” of an automated vehicle into consideration. Thus, the interactive impacts between the vehicle plant, control variables, multi-performance, and driver styles should be well understood [29–31].

To further advance the existing CPS methods as well as their applications in vehicle engineering, the following topics will be explored for CPVS in this book: (1) a novel co-design optimization methodology for CPVS; (2) dynamic estimation of hybrid states for online monitoring of CPVS; and (3) advanced control synthesis for CPVS for improving multiple performance.
Co-Design Optimization for Cyber-Physical Vehicle System

2.1 PROBLEM FORMULATION

In this section, the co-design of a typical CPVS, i.e., an automated electric vehicle, with different driving styles is formulated as a multi-objective optimization problem. The goal is to find optimal assignments for design variables to maximize performances while satisfying a number of constraints. To ensure the problem to be solved within a reasonable complexity, the following assumptions are made: (1) the vehicle operates in normal conditions, and vehicle stability could be guaranteed by stability control functions; (2) only longitudinal motion control is considered in this study; and (3) the sizing of the electric powertrain is fixed, i.e., the parameters of the battery and the electric motor are constant to bound the exploration space.

2.1.1 HIERARCHICAL OPTIMIZATION METHODOLOGY

The optimization problem is formulated as a constrained multi-objective one where both vehicle and controller parameters need to be chosen. In this book, the Platform-Based Design (PBD) is adopted as the co-design methodology [21].

As Fig. 2.1 shows, PBD is a meet-in-the-middle approach that favors re-usability. At the top layer, there are high-level requirements and constraints. The bottom layer is defined by a design platform, i.e., a library of components characterized by their behaviors and performance. In this study, the bottom layer contains the models of the vehicle, electric powertrain, brakes, and driver-style-based controller. The models are parametrized to capture families of the system, components and controllers. The design problem is to select a set of components and their parameters so that the constraints are satisfied with the objective functions optimized. The selection process is called mapping, indicated as the middle-layer 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 parameters, controller protocols, and variables for the intelligent electric vehicle is then made possible.

2.1.2 SYSTEM DESCRIPTION

(1) Physical plant: For the structure of the studied automated electric vehicle, a central electric motor is installed at the front axle of the vehicle. During acceleration, the motor, which is
2. CO-DESIGN OPTIMIZATION FOR CYBER-PHYSICAL VEHICLE SYSTEM

Figure 2.1: Platform-based design optimization of CPVS.

Figure 2.2: Longitudinal motion control architecture of the intelligent vehicle.

powered by the battery, provides propulsion through the transmission system to the wheels. During deceleration, the regenerative braking torque generated by the motor is blended with the friction braking modulated by the hydraulic modulator.

(2) Control architecture: The high-level strategy for the longitudinal motion control of the automated EV is designed to track a reference acceleration, generated via the pre-defined acceleration profile, as shown in Fig. 2.2. The reference acceleration profile is a 3D look-up table defined by the reference vehicle speed $v_{ref}$, the ego-vehicle speed $v$, and the reference acceleration $a_{ref}$. 
2.1.3 DRIVING EVENT

A driving event is a driving maneuver, such as acceleration, deceleration, turning, and lane change, which can be used to identify driving styles [28]. As mentioned previously, this study mainly focuses on longitudinal motion control, hence the adopted driving events are defined as [29] follows.

1. Event 1: 0–50 km/h acceleration. In this event, the car is accelerated from 0–50 km/h. The vehicle acceleration, jerk, and the time taken in this process are typical performance indices. This event is used to optimize and evaluate the dynamic performance and ride comfort under different driving styles.

2. Event 2: 50–0 km/h deceleration. In this event, the car is decelerated from 50 km/h to 0. The deceleration and the time taken in this process are typical performance indices. The energy recovered during the braking process can be used to evaluate energy efficiency. This event is used to optimize and check vehicle’s dynamic performance and energy efficiency under different driving styles.

3. Event 3: driving cycle. Although the energy consumption of the vehicle can be evaluated in the above two events, the time duration of an acceleration or deceleration procedure is relatively short, making it difficult to evaluate energy consumption at the vehicle level. Thus, the ECE driving cycle is adopted for measuring energy efficiency under different driving styles. The ECE driving cycle, which is a series of data points representing the vehicle speed vs. time, exhibits the typical driving conditions of a car in urban areas [17]. It is usually adopted to carry out road testing for studying the fuel economy of a passenger car.

2.1.4 DRIVING STYLE RECOGNITION

To identify driving style for control synthesis and system optimization, a driving style recognition (DSR) algorithm is developed using unsupervised machine learning with partially labeled data. The data set is collected in the road tests with a Sedan-Type vehicle, and it is comprised of 9 real life cycles covering over 500 km. The data can be overall classified into three groups according to the driver feedback as aggressive, conservative, and moderate. These three driving styles are firstly defined as [29–34] as follows.

1. Aggressive: Aggressive drivers exhibit frequent changes in throttle and brake pedal positions [32]. They drive with sharp and abrupt accelerations and decelerations, aiming at vehicle dynamic performance. This kind of behavior would result in higher fuel consumption and increased likelihood of accidents [29].

2. Conservative: Conservative drivers often exhibit mild operational behaviors with small amplitudes and low-frequency actions on a steering wheel, accelerator, and brake pedal [33]. They value energy efficiency and ride comfort, and avoid abrupt variations of vehicle state.
(3) Moderate: Moderate drivers are positioned between the above two. They would like to balance multiple performances, such as vehicle dynamic performance, ride comfort, and energy efficiency [29].

The unlabeled data set is pre-processed for driving events detection and statistics extraction. A total amount of six signals is used: throttle pedal position, brake light switch, longitudinal and lateral accelerations, steering wheel angle and vehicle speed. Five statistics are extracted per event: maximum, minimum, mean, standard deviation, and root mean square. The reduced set of signals is clustered using Gaussian Mixture Models (GMM), which generates the DSR classification algorithm to be implemented onboard. The performance of the DSR algorithm is validated against the subjective labels and further tested with a new set of data from a new real-life route with changeable road type, as shown in Fig. 2.3. This new data set is collected by a Sport Utility Vehicle (SUV)-type vehicle with a different driver.

Table 2.1 shows the results of the SUV driving data using the developed DSR algorithm. So as to quantitatively evaluate the performance of the algorithm, the driving cycles are classified per events using the aggressiveness index. The aggressiveness index is transformed from the classification into an equivalent index, assigning an increasing value from 0–1 to the different events based on the level of aggressiveness [34]. To provide further information about the robustness of each classification, the number of events identified is included in brackets and italics. According to the results, the conservative cycle is classified as the least aggressive one, particularly by acceleration and brake events analysis. The moderate cycle is situated between the aggressive and conservative ones. While the aggressive cycle is identified as the sportiest one, but it has a similar braking level with the moderate one, agreeing with driver’s feedback.
Table 2.1: Driving style recognition results in SUV cycles

<table>
<thead>
<tr>
<th></th>
<th>Aggressive Cycle</th>
<th>Moderate Cycle</th>
<th>Conservative Cycle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acceleration</td>
<td>0.55 (149)</td>
<td>0.43 (113)</td>
<td>0.34 (106)</td>
</tr>
<tr>
<td>Brake</td>
<td>0.58 (33)</td>
<td>0.56 (25)</td>
<td>0.36 (22)</td>
</tr>
<tr>
<td>Cruise</td>
<td>0.83 (149)</td>
<td>0.69 (126)</td>
<td>0.70 (124)</td>
</tr>
<tr>
<td>Turn</td>
<td>0.41 (6)</td>
<td>0.29 (7)</td>
<td>0.29 (7)</td>
</tr>
</tbody>
</table>

Finally, the consistency and robustness of the algorithm are verified using the test data set. The test shows consistency in the identification and aligns with drivers' perception. The above testing results validate the suitability of this approach for DSR, its onboard implement capability and robustness to vehicle and driver characteristics. More detailed algorithms with experimental results can be found in [34].

Based on the above recognition and classification algorithms, the features of aggressive, conservative, and moderate driving styles can be extracted, and online recognition of a driver's driving style can be realized using the well-trained model as well. Meanwhile, according to the above features obtained, the three dimensional human-like acceleration profiles are developed for each driving style, as illustrated in Fig. 2.4.

2.1.5 REQUIREMENTS FOR THE DESIGN AND OPTIMIZATION OF CPVS

The requirements for vehicle design and control involve dynamical performance, energy efficiency, and ride comfort. Driving style consideration implies the introduction of multiple trade-offs between performances that are set as the objective functions in our optimization problem, under different driving styles, operating conditions, and driving tasks.
2. CO-DESIGN OPTIMIZATION FOR CYBER-PHYSICAL VEHICLE SYSTEM

(1) Dynamic performance: Dynamic performance is considered as the fundamental and the most important indicator of a car \[29\]. Maximum speed and acceleration time are proxies for dynamic performance. In this study, we select the 0–50 km/h acceleration time \( t_{\text{acc}} \) and the 50–0 km/h deceleration time \( t_{\text{brk}} \) as two indicators for the dynamic performance to capture driver’s behavior and select suitable value for the gear ratio \( i_g \).

(2) Ride comfort: The comfort level of a vehicle, also known as drivability, can be assessed by vehicle’s jerk \( j \), which is the second derivative of the vehicle’s longitudinal velocity \( v \) \[17\]:

\[
j = \ddot{v}.
\]

During acceleration, torsional oscillations may occur in the drivetrain due to fast torque transitions, resulting in unexpected jerks at vehicle level and deteriorated drivability. To cope with this problem, an active damping controller is usually required \[36\]. Although aggressive drivers may enjoy fierce acceleration and jerk, for those who prefer conservative or moderate driving style, ride comfort is a very important performance. In this study, jerk is used to capture the comfort level of the vehicle.

(3) Energy efficiency: The energy efficiency of a vehicle can be represented by the energy consumed during a certain trip. Typically, energy consumption can be reduced by optimizing the powertrain energy management \[29\]. For electrified vehicles, it can be further enhanced through regenerative braking. Thus, in this study, the regenerated braking energy defined in Equation (2.2) is set as one of the optimization goals in the trade-off problem \[18\]:

\[
E_{\text{reg}} = \eta_{\text{gen}} \int T_{\text{m,reg}} \omega_m dt.
\]  

2.1.6 CONSTRAINTS FOR VEHICLE DESIGN AND OPTIMIZATION

Constraints in the optimization problem involve indicators that are set to stay within specific bounds to limit the search space.

(1) Maximum vehicle speed: The constraint on vehicle speed is posed as:

\[
v_{\text{max}} = \frac{r \pi n_{\text{max}}}{(30 i_g)} \geq (100/3.6) \text{ m/s},
\]

where \( v_{\text{max}} \) is the maximum speed of the vehicle, \( n_{\text{max}} \) is the highest rotational speed of the electric motor, \( r \) is the nominal radius of tire, and \( i_g \) is the gear ratio.

(2) Minimum gradeability: Gradeability is defined as the highest grade that a vehicle can achieve with a maintained speed. Once the motor parameters are given, this performance is
determined by the gear ratio, as Equation (2.4) shows [35]:

\[ \eta_l g T_{m,max} = m g r (f \cos \alpha_{max} + \sin \alpha_{max}) \]  
\[ i_{max} = \tan \alpha_{max} \geq 30\% \]  

where \( T_{m,max} \) is motor’s peak torque, \( m \) is the total mass of the vehicle, \( \eta_l \) is the efficiency of the transmission system, \( f \) is the friction drag coefficient, and \( \alpha \) is the grade angle.

(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 [36]:

\[ z = \dot{v}/g \geq 0.1 + 0.85(\varphi - 0.2) \]  

where \( \varphi \) is the adhesion coefficient of the road.

(4) Powertrain limits: According to the assumption described above, the characteristics of the power source are given, then the limitation on motor torque can be described by:

\[ T_m \omega_m \leq P_{m,lim} \]  

where \( T_m \) is output torque of the electric motor, and \( P_{m,lim} \) is the peak power of the electric motor.

2.2 SYSTEM MODELING AND VALIDATION

2.2.1 ELECTRIC POWERTRAIN SYSTEM

The electric powertrain is comprised of an electric motor, a gearbox, a final drive, a differential, and half shafts. The motor torque is modeled as a first-order reaction, as shown in Equation (2.8). The models for the drivetrain dynamics and half-shaft torque can be given by Equations (2.9) and (2.10) [25]:

\[ T_{m,ref} = T_m + \tau_m \dot{T}_m \]  
\[ J_m \ddot{\theta}_m = T_m - 2T_{hs}/i_g \]  
\[ T_{hs} = k_{hs} (\theta_m/i_g - \theta_w) + c_{hs} (\dot{\theta}_m/i_g - \dot{\theta}_w) \]  

where \( \tau_m \) is the small time constant, \( T_{m,ref} \) is the reference torque of the electric motor, \( T_{hs} \) is the half-shaft torque, \( J_m \) is the motor inertia, and \( \theta_m \) and \( \theta_w \) are the angular positions of electric motor and load, respectively. \( k_{hs} \) and \( c_{hs} \) are the stiffness and damping coefficients of the half shaft, respectively.

In this study, the battery is built as an open-circuit voltage-resistance model. Look-up tables are compiled on the basis of the state of charge (SOC) and temperature data of the battery, modeling its charging-discharging internal resistance. The detailed model with parameters can be found in [17].
2.2.2 BLENDED BRAKE SYSTEM

The brake force distribution (BFD) should adhere to the ideal curve. To simplify the implementation and to avoid real-time modulation of brake pressure, the BFD is usually set as a fixed value, which is determined by the parameters of the installed brake devices, as shown in Fig. 2.5a. The front and rear braking demands can be calculated as follows [17]:

\[
T_b = 2T_{b,fw} + 2T_{b,rw} \quad (2.11)
\]

\[
T_{b,fw} = \beta T_{b,dmd} / 2 \quad (2.12)
\]

\[
T_{b,rw} = (1 - \beta) T_{b,dmd} / 2 \quad (2.13)
\]

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 requested braking torque of one front wheel and one rear wheel, respectively. \(\beta\) is the BFD ratio.

As shown in Fig. 2.5b, during deceleration, the overall demanded braking torque of the vehicle is supplied by the regenerative and the friction blending braking. The overall braking torque is controlled to be consistent with driver’s deceleration intention. The reference values for the regenerative and frictional braking on front axle can be given by:

\[
T_{m,reg} = \min \left( 2T_{b,fw} / i_g, T_{m,reg,lim} \right) \quad (2.14)
\]

\[
T_{b,fw,fric} = T_{b,fw} - 2T_{m,reg} / i_g \quad (2.15)
\]

where \(T_{m,reg}\) and \(T_{m,reg,lim}\) are reference torque and torque limit of the regenerative braking of the electric motor, respectively. \(T_{b,fw,fric}\) is the frictional braking torque of the front wheel.

2.2.3 DYNAMIC MODEL OF THE VEHICLE AND TYRE

A model of vehicle dynamics with seven degrees of freedom has been built. The tyre model, which is of great importance for research on acceleration and deceleration, should be able to simulate the real tyre in both adhesion and sliding. In this article, the well-known Pacejka magic formula tyre model is adopted [37]. The detailed models were described in [17].