Algorithm design for mixed-integer black-box optimization problems with uncertainty

Thomaser, A.M.

Chapter 3

Engineering Problems

Vehicle dynamics control systems (VDCSs) have become a cornerstone in the automotive industry. These systems use advanced control algorithms that, in conjunction with a range of sensors and actuators, dynamically modulate the vehicle's response, taking into account different driving conditions [104]. Therefore, VDCSs significantly improve both the safety and driving dynamics of modern vehicles providing enhanced driving pleasure.

The basis for modern VDCSs was laid by the development of the Antilock Braking System (ABS) [75] and the Electronic Stability Control (ESC) [78]. The introduction of these two systems in road vehicles has been shown to significantly improve braking performance and reduce the number of traffic accidents and fatalities by mitigating skidding and loss of control [25, 33, 34, 81].

The behavior of VDCSs depends on the precise calibration of system parameters designed to achieve optimal performance. Recent advances in simulation technology, coupled with the exponential growth in computational resources, have paved the way for the virtual pre-design of these parameters. To facilitate this virtual pre-design process, objective characteristic values (CVs) are required for assessing the performance of system parameters. These CVs are integral to the formulation of an objective function for determining the optimal parameters using an optimization algorithm.

In Sections 3.1 and 3.2, two such objective functions are defined mathematically for two different VDCSs. Furthermore, a brief overview of vehicle dynamics simulation and modeling is given (Section 3.3). Finally, a dataset created for benchmarking and algorithm design throughout this thesis is described (Section 3.4).

3.1 Antilock Braking System

The ABS is designed to prevent wheels from locking and to maximize the brake forces exerted by the tires during braking by adjusting brake pressure to keep brake slip within an optimal range. This reduces the braking distance. Moreover, the driver maintains control and can steer the vehicle even in an emergency braking situation. The brake slip s is the amount by which the wheel's circumferential speed v_{wheel} is behind the vehicle's linear speed (road speed) v_{vehicle} [75]:

$$s = \frac{v_{\text{vehicle}} - v_{\text{wheel}}}{v_{\text{vehicle}}} \cdot 100\%. \tag{3.1}$$

The longitudinal brake force that can be transmitted is proportional to the coefficient of friction μ_{x}. Figure 3.1 illustrates the relationship between the coefficient of friction and brake slip during straight-line braking with ABS for various road conditions. The ranges in which the ABS keeps the brake slip are shaded blue. The curves for dry, wet and ice demonstrate that ABS can significantly reduce braking distances compared to scenarios where the wheels lock up ($s = 100\%$). Snow leads to a unique situation where a wedge of snow accumulates in front of locked wheels, aiding in deceleration. In this case, the benefit of ABS lies in preserving steerability.

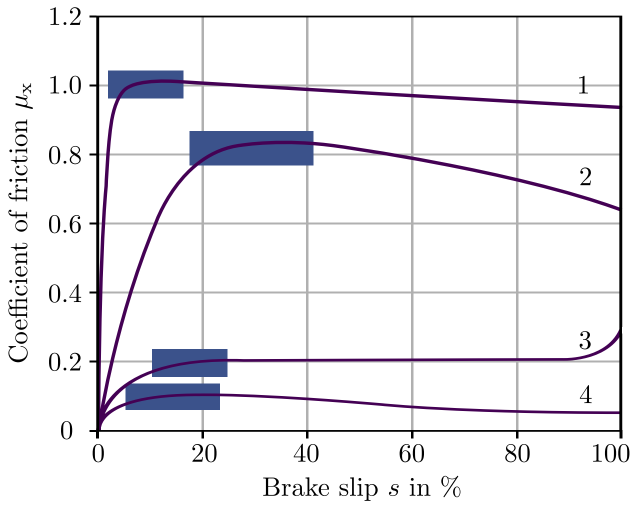

Figure 3.1: Relationship between the coefficient of friction μ_{x} and brake slip s during straight-line braking for various road conditions (1: dry, 2: wet, 3: snow, 4: ice). ABS keeps the brake slip in the shaded blue ranges. Figure is adapted from [75].

A standard maneuver for assessing a vehicle's braking performance is the emergency straight-line full-stop braking maneuver with ABS fully engaged [63]. A braking maneuver is defined, consisting of the following three phases (Figure 3.2):

(1) Acceleration of the vehicle to a maximum velocity of 103.5 km/h,
(2) Coasting the vehicle in neutral without accelerating or braking to 103 km/h,
(3) Braking of the vehicle with maximum deceleration until the vehicle stops.

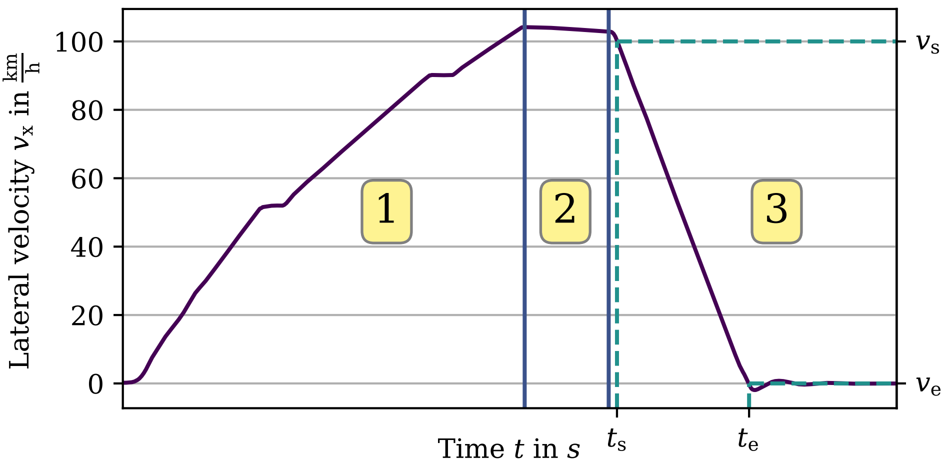

Figure 3.2: Illustration of the lateral velocity v_x of a vehicle over the three defined phases (1: acceleration, 2: coasting, 3: braking) of an emergency straight-line full-stop braking maneuver for calculating the braking distance from the start velocity $v_s = 100$ km/h at start time t_s to the end velocity $v_e = 0$ km/h at end time t_e.

The braking distance y is a CV for the ABS performance and is defined as the integral of the vehicle's longitudinal velocity v_x over time from the start velocity $v_s = 100$ km/h at time t_s to the end velocity $v_e = 0$ km/h at time t_e:

$$y = \int_{t_s}^{t_e} v_x(t)\, dt. \tag{3.2}$$

The objective is to find an optimal parameter configuration $\mathbf{x}^*$ for the d ABS parameters within the feasible input space $\mathbf{x} \in \mathbb{D}^d \subset \mathbb{R}^d$ that minimize the braking distance $y(\mathbf{x})$, as defined in Equation (3.2):

$$\mathbf{x}^* = \arg\min_{\mathbf{x} \in \mathbb{D}^d} y(\mathbf{x}). \tag{3.3}$$

3.2 Active Rollover Protection

At the limit of driving dynamics, the imminent risk of a vehicle rollover is characterized by one or more wheels lifting off the ground. High lateral force build-up can cause vehicles to rollover. In general, rollovers can be either tripped or untripped [104]. Tripped rollovers occur due to the influence of an external lateral force applied to the vehicle. For example, when the vehicle hits a curb. Untripped rollovers, on the other hand, occur as a result of sharp steering, such as when cornering at high speed or making a quick lane change. The resulting lateral forces on the tires cause the vehicle to roll over. In these scenarios, the Active Rollover Protection (ARP) as part of the ESC can intervene to prevent a vehicle rollover by stabilizing the vehicle through selective wheel braking and a reduction of engine torque.

Standardized maneuvers are employed to assess the driving behavior and the effectiveness of controller interventions, such as from the ARP. The Sine with dwell (SWD) [64] is one such maneuver. During the SWD maneuver, the vehicle initially drives at a constant speed of 80 ± 2 km/h in a straight line. A steering machine then imposes a sinusoidal steering input at a frequency of 0.7 Hz, incorporating a dwell period of 500 ms at the peak of the second half-wave. The amplitude of the steering wheel angle is set to a predetermined multiple of the characteristic steering wheel angle $\delta_{0.3\mathrm{g}}$, which is ascertained from previous slowly increasing steer tests. These preliminary tests are designed to establish the vehicle's characteristic steering response at a lateral acceleration of 0.3g, providing a baseline for the SWD maneuver.

The induced steering angle causes a pronounced oversteer response in the vehicle, which can be critical to rollover, especially in vehicles with a high center of gravity. To ensure stability, several criteria must be satisfied. At no point should two wheels simultaneously lift more than 5 cm off the ground [19]. Additionally, the yaw rate should decrease to a specified fraction of its peak value within a certain time frame after the steering angle reverses direction [64]. Besides these stability criteria, an agility criterion is specified: the lateral displacement of the vehicle's center of gravity from its original path during straight-ahead driving must surpass a defined threshold [64].

Dourson [27] demonstrated through simulations that the parameters of ARP, which maximize the velocity of the vehicle one second after the SWD maneuver, also meet the specified stability and agility criteria. However, it should be noted that the used simulation model had limitations that prevented the modeling of a road edge contact and tire separation.

3.3 Vehicle Dynamics Modeling and Simulation

Various vehicle models with different complexity levels have been developed to simulate vehicle dynamics accurately. These vehicle models range from single-track to twin-track and extend to sophisticated multibody system models, each with their respective stages of expansion [90, 114]. With a higher model complexity, the required computing resources increase. Consequently, the choice of a vehicle model is guided by the principle that it should be sufficiently but not excessively detailed for the respective application.

A twin-track model implemented in MATLAB/Simulink [123] is employed for the simulation of a full vehicle with VDCSs, such as ABS or ARP. A twin-track model provides a balance between computational efficiency and the necessary level of complexity. The mechanical vehicle is modeled as a five-body system (one car body plus four wheels) with 16 degrees of freedom. The key components of the model are equations of motion, tires, drivetrain, aerodynamics, suspension, steering and braking. The control system is represented by sensors, logic and actuators. The simulation of the interaction between these modeled components enables the simulation of a closed control loop.

The primary phenomena that affect vehicle dynamics occur between the tire and the road surface. Thus, the tire model is an essential simulation component. The employed MF-Tyre/MF-Swift tire model [119] has been developed based on Pacejka's Magic Formula [97]. This tire model can simulate the steady-state and transient behaviors of a tire under various slip conditions. In addition, curved regular grid (CRG) tracks [133] are utilized for the road surface representation. A CRG track provides detailed three-dimensional road profiles with high precision along a predefined reference line while optimizing memory usage.

The described vehicle dynamics simulation is integrated into an overarching workflow. This workflow is designed to connect seamlessly with user input or an optimization algorithm. The vehicle dynamics control system parameters can be automatically adjusted and the simulation can be started. Once a vehicle dynamics simulation is completed, the results are post-processed to calculate the CVs. These CVs are then used to determine the objective function value. Moreover, simulation runs are parallelized and executed asynchronously. Consequently, several simulation instances can run independently without waiting for each other.

3.4 ABS Benchmark Dataset

The vehicle dynamics simulation described in Section 3.3 is computationally expensive. Benchmarking and designing optimization algorithms typically require multiple optimization runs for statistical analysis. Thus, the real-world problems are not practical for extensive experimentation. To replace the computationally expensive simulation, a dataset is created using the workflow described in Section 3.3.

For the creation of this dataset, two ABS parameters with significant influence on the ABS control behavior, denoted as x_1 and x_2, are considered. The range of each parameter is defined by a lower bound lb and upper bound ub: $x_1 \in [-5, 6]$ and $x_2 \in [-5, 4]$. For both x_1 and x_2, only a discrete set of values D_i with a resolution of 0.1 is permitted, resulting in 111 distinct possibilities for x_1 and 91 for x_2. The two-dimensional input space $\mathbb{D}^2 = \times_{i=1}^{2} D_i$ is defined by the Cartesian product. The total number of possible combinations for x_1 and x_2 is 10 101.

Generally, an optimal parameter configuration is only optimal for one vehicle setting. Five different vehicle settings are considered, with each setting consisting of a vehicle load and a tire (Table 3.1).

Table 3.1: Explanation of the vehicle settings.

Name	Tires	Vehicle Load
y_1	High performance	Partially loaded
y_2	Medium performance	Partially loaded
y_3	Under performance	Partially loaded
y_4	High performance	Fully loaded
y_5	High performance	Little loaded

The braking distance (Equation 3.2) is sensitive to slight variations in environmental conditions, vehicle characteristics and the functionality of ABS. In order to reduce the resulting variation in braking distance, the performance of a parameter configuration is averaged across the braking distances obtained from ten individual simulation runs.

Moreover, to accommodate algorithms designed for continuous input spaces, the problem is treated as quasi-continuous: for any input $\mathbf{x} \in \mathbb{R}^2$ within the specified bounds, the ABS performance is approximated by rounding x_1 and x_2 to the nearest valid points within the discrete input space $\mathbb{D}^2 = \times_{i=1}^{2} D_i$. In summary, the objective is to find a parameter setting $\mathbf{x}$ that minimizes the mean braking distance $y_i(\mathbf{x})$ for a vehicle setting i across 10 simulations:

$$\mathbf{x}^* = \underset{\mathbf{x}\in\mathbb{D}^2}{\arg\min}\ \frac{1}{10}\sum_{k=1}^{10} y_i(\mathbf{x}). \tag{3.4}$$

By exhaustively simulating every combination of the two ABS parameters (a brute-force approach), the relationship between x_1, x_2 and the braking distance can be mapped for each setting considered.

Figure 3.3 shows the resulting mean braking distances across 10 simulations y_i (Equation 3.4) for each of the 10 101 possible combinations of the two ABS parameters x_1 and x_2 for the five vehicle settings (Table 3.1). All braking distances of a particular vehicle setting i are specified as the distance in meters to the corresponding optimum.

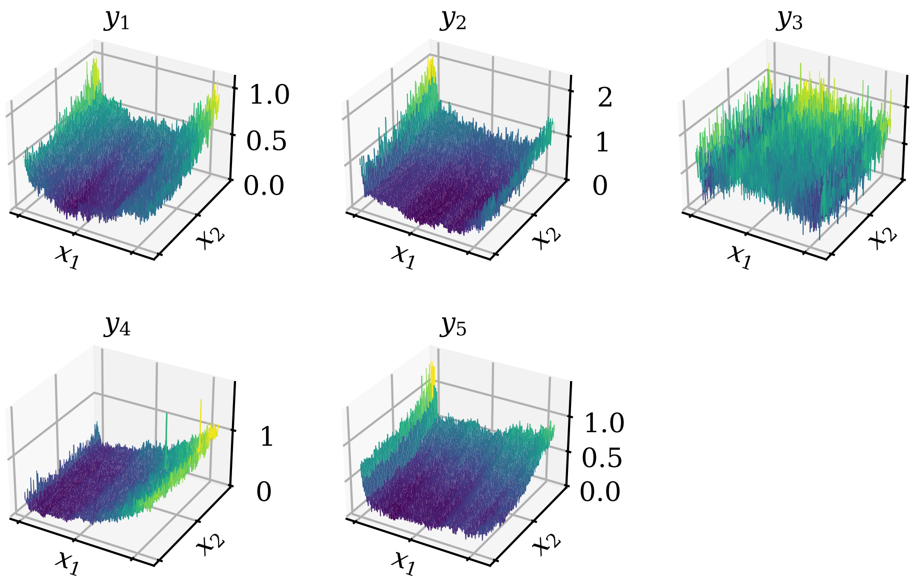

Figure 3.3: The resulting mean braking distances across 10 simulations y_i (Equation 3.4) for each of the 10 101 possible combinations of the two ABS parameters x_1 and x_2 for the five vehicle settings i (Table 3.1). The braking distances are specified as the distance in meters to the corresponding optimum $y_{i,\text{opt}}$. The objective is minimization, thus dark blue-purple indicates better solutions and yellow worse.