System Identification and Control for a Cruise Control System

Tan Jin Chun (32194471), Agill Kumar Saravanan (31106889)

I. EXECUTIVE SUMMARY

The cruise control system is an essential feedback mechanism present in every vehicle. For this project, the controller aims to sustain a set velocity for the vehicle, even when faced with variations in input torque or environmental disruptions like changing road inclines. Initially, the mathematical model stated below connecting the car's velocity to the torque input is established to assist in system identification.

$$m\frac{dv}{dt} = F - F_d, \qquad F = \frac{nu}{r}T \tag{1}$$

where m represents the car's mass and F is the force produced by the engine, which is linked to the input torque multiplied by the gear number-to-gear radius ratio. F_d denotes the non-linear disturbance forces that arise from varying road slopes because of the weight of the mass. For system identification, we'll operate under the assumption that the terrain is level, making F_d insignificant. The system is recognized as a 2nd order plant with one zero, displaying an average Root Mean Squared Error of 12 when comparing the real and estimated step responses. Subsequently, three controllers are devised for various scenarios: a shift in set velocity on flat terrain, an alteration in road gradient at a steady speed and modifications in both set velocity and road incline. These controllers aim to regulate speed via reference tracking and disturbance mitigation. The controllers attain accuracies of 0.0687, 0.0422, and 0.0935 respectively, suggesting an optimal reference speed of $60kmh^{-1}$ on any inclined slope.

II. SYSTEM IDENTIFICATION

(A) Identification Rationale

For system identification, we utilized a conventional prediction and optimization technique grounded in existing analytical models. This was done to discern the longitudinal dynamics of a car's velocity on flat terrain in reaction to a torque input. The optimization hinged on MATLAB's 'fminsearch' function, which uses the least squares method for RMSE (cost function) identification. Four sets of ground truth input-output pairs were used to train the model, optimizing the parameters for each prediction system model introduced.

The system identification deployed four primary models:

a) Model A: Scaled 1st order model

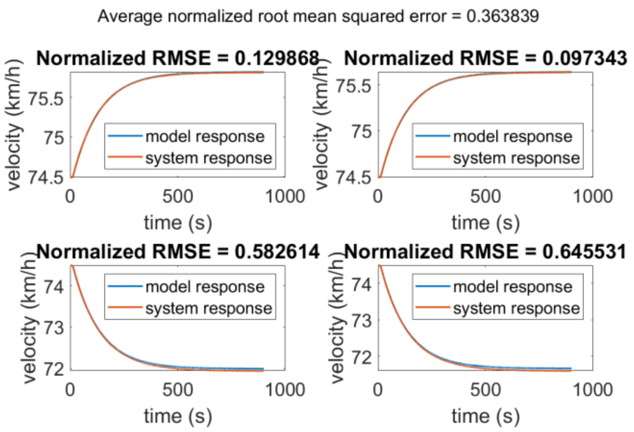

Figure 1: 1st Order Model

b) Model B: Scaled 1st order model incorporating delay.)

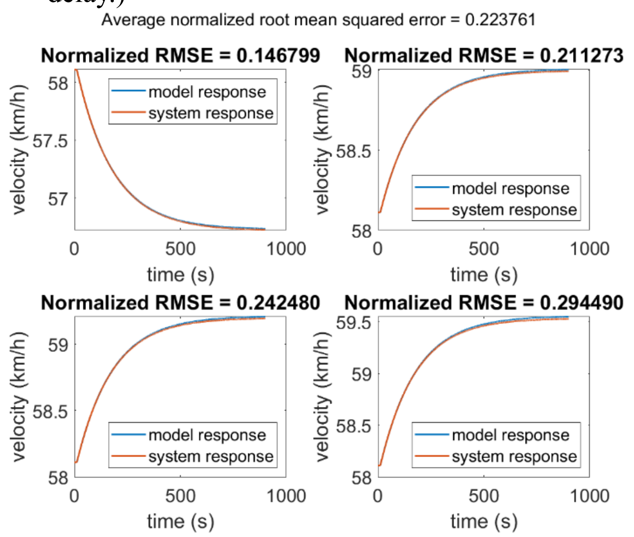

Figure 2: 1st Order with Delay Model

c) Model C: Scaled 2nd order model

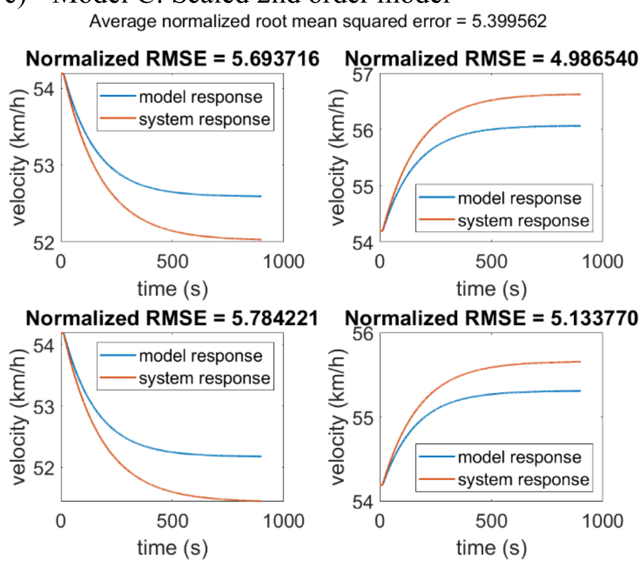

Figure 3: 2nd Order Model

d) Model D: Scaled 2nd order model, inclusive of 1 zero

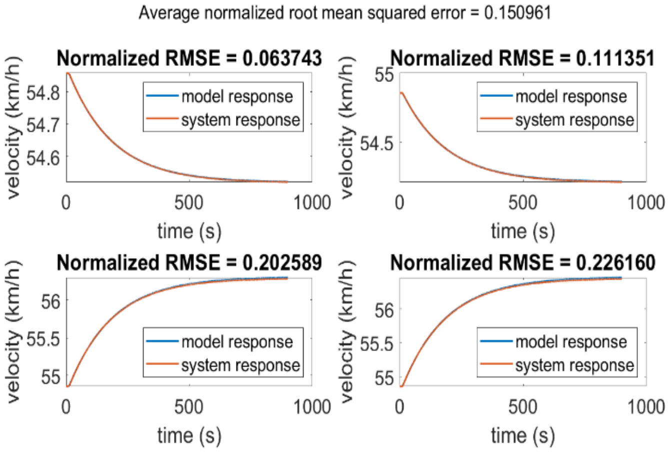

Figure 4: 2nd Order with 1 Zero Model

It's worth noting that all four selected models maintained linearity and were strictly proper. This adherence ensured the condition of system causality was met. Moreover, each model integrated a scaling factor to draw a more generalized response from the canonical model behaviour.

Initial assessments indicate that Models A, B, and D outperformed Model C in terms of performance metrics, with Model C exhibiting a notably higher RMSE. This observation aligns with the 1st order differential equation (presented in equation 1) which associates the torque applied to the car with its velocity, producing a 1st order model through its transfer function. To replicate the real-world lag between input and output, it's essential to incorporate a delay into the system. Notably, a 2nd order system with a single zero can approximate a delayed 1st order model via the Padé approximation. This explains why Model D, even as a 2nd order model, managed to achieve a low RMSE.

Given its superior performance and additional flexibility for parameter adjustment, we opted for the 2nd order system with one zero as our definitive system model. Further details about the reduced RMSE of Model D over 100 epochs are discussed in Section 2B: Identification Validation.

(B) Identification Validation

To substantiate the system modelling selection detailed in Section 2A, each model underwent testing over 100 iterations. These tests used random torque requests as inputs and the average RMSE was calculated based on the car's original system model. For each iteration, every model was retrained with fresh parameters to verify its adaptability and general applicability. The summarized average RMSE for all four models is presented below.

Model	Model RMSE Statistics over 100 iterations			
	Mean	Max	Min	Standard Deviation
A	0.5263	6.9675	0.1888	0.6952
B	0.7833	2.8745	0.1312	0.8641
C	Fail to converge after 100 iterations			
D	0.3351	0.7093	0.0974	0.1232

Table 1: RMSE statistics for each model

Upon evaluating all four models, Model D stood out with the lowest RMSE and standard deviation, indicating superior accuracy in mimicking the system. Consequently, Model D was selected for the control system design in the project's second phase. However, it's essential to acknowledge that this system identification focuses solely on car dynamics influenced by varying torque inputs on level terrain.

It overlooks non-linear disturbances such as wind resistance and variations in road inclines. The car's mass and its occupants are also not factored in. If exposed to roads with gradients, the system model might demonstrate deviations. A potential enhancement would involve training the model on varied road inclines and integrating primary linear disturbances, bolstering the identified system's resilience.

III. CONTROL SYSTEM DESIGN

(A) Design Rationale

The selected vehicle model was a second-order type with an added zero. Conventionally, cruise systems are modelled as a first-order system with a delay. However, by applying the Padé approximation, we were able to represent this first-order system with a delay as a second-order model. We adopted the Proportional-Integral-Derivative (PID) controller framework, incorporating derivative filtering and an anti-windup mechanism for the integrator. The choice was driven by the ability of this controller to achieve minimal steady-state tracking errors, filter out high-frequency signal components and keep the process output within the actuator's mechanical boundaries. Based on our analysis, the typical torque range for a cruise wheel actuator lies between 300 - 800 Nm. For the purposes of this report, we've set the torque limit at 300 Nm. The overarching objective of the cruise controller is to maintain a consistent speed amid varying speed references and road inclines, all while adhering to speed limits. The speed reference acts as the input signal, while the road slope serves as an external disturbance to the control system. As such, the system must exhibit minimal steady-state tracking errors and strong disturbance rejection capabilities. The linear time-invariant (LTI) block was defined by the subsequent transfer function,

$$C(s) = -(K_p + \frac{K_i}{s} + \frac{K_d s}{1+T_f s}), \text{ where } T_f = \frac{K_d}{NK_p}$$

The proposed cruise control system consists of five key parameters: K_p (proportional gain), K_i (integral gain), K_d (derivative gain), N (derivative filtering factor), and K_t (anti-windup gain).

For a system with a unit step input, meaning a constant velocity, a Type I system or higher can achieve a zero steady-state tracking error. The inclusion of the integral gain, K_i, ensures the elimination of this steady-state tracking error in the cruise controller. The proportional gain, K_p, determines the system's response rate, while the derivative gain, K_d, influences the system's overshoot and damping. Though higher values might enhance control, they could potentially induce system oscillations and instability. Excessive K_d values could accentuate disturbances like changes in road gradient. Consequently, a low-pass filter is integrated into the cruise controller. This filter attenuates high-frequency responses that might strain mechanical parts and reduces velocity spikes to prevent speeding infractions. The K_t parameter addresses the issue of integrator windup.

A heuristic methodology was employed to tune the PID controller's parameters. With the vehicle model—a second-order system with a zero—held constant, the PID parameters were adjusted to study the resulting system responses. The goal was to achieve a stable response characterized by a minimal normalized root-mean-square error, quick settling time, and minimal overshoot. All gain values started at zero, with individual parameters gradually increased to understand their impact on system behaviour.

Increasing the N value (an integer ranging from 5-20) reduces the bandwidth of the low-pass filter, effectively raising the value of T_f. This adjustment diminishes the high-frequency response stemming from changes in road incline or sudden shifts in reference speed. A slight increase in K_p can enhance system stability. However, substantial increases might trigger oscillations or even destabilize the system. Raising the K_i value reduces the system's settling time, expediting its response. Meanwhile, a boost in the K_d value will curb both the overshoot and oscillations during the transient phase.

The subsequent table provides a detailed breakdown of the controller parameters for each specific task.

Task	1	2	3
K_p	0.095	2.800	2.100
K_i	0.00080	0.00010	0.00002
K_d	0.2	2.6	4.3
N	20	20	20
K_t	100	95	0.000001

Table 2: Controller Parameters for each task

(B) Design Validation

For Task 1, with a constant flat slope and varying reference velocity, 100 random samples were generated with maximum and minimum reference velocities set at 110 km/h and 40 km/h, respectively. The cruise controller underwent tests for 14 combinations of reference velocity shifts, covering increments and decrements of 10, 20, 30, 40, 50, 60, and 70 km/h within the 40 km/h to 110 km/h range. It's assumed that the controller responds solely to changes in reference velocities and is unaffected by initial or final velocities.

In Task 2, where only the road slope changes while the reference velocity remains constant, 100 random samples were produced representing different road inclinations ranging from 1 to 6 degrees. The cruise controller was then evaluated against varying slope inclinations, recording system responses for ascending, descending, as well as combined ascending-descending and descending-ascending patterns.

For Task 3, which involved simultaneous changes in both slope and reference velocity, 100 random samples featuring assorted road slopes and reference velocities were generated. The cruise controller was assessed against a multitude of reference velocity shifts and various slope profiles. The 'speedList' variable was assigned either [40, 50, 60, 70, 80] or [40, 110], representing minor and major speed changes respectively.

The summarized validation outcomes for each task's test cases are presented in Table 3.

Task	NMRSE			
	Mean	Min	Max	SD (σ)
1	0.0212	0.0221	0.0201	0.0004
2	0.0382	0.0415	0.0342	0.0015
3	0.0415	0.7121	0.0019	0.0895

Table 3: RMSE Statistics Summary for Controller Design

Task 1 Validation:
The controller exhibited commendable performance, precisely tracking the reference velocity and averting substantial overshoots that could result in speeding penalties across all speed shift scenarios except for the extreme 70 km/hr alteration. Notably, the controller remained functional even with a negative reference velocity, indicative of a braking scenario. It's deduced that the system operates optimally within velocity variations from 10 to 60 km/h. However, when faced with a surge in reference velocity exceeding 70 km/h, the controller showed a 60% failure rate (59 out of 100 instances). Stability was maintained without any observed oscillations.

Task 2 Validation:
Overall, the cruise controller capably navigated various road inclines, with a notable exception during uphill terrains where a 1% failure likelihood was detected. Velocity notably plummeted when ascending and then sharply reverted to the target, occasionally exceeding it. Such brief speeding instances were the primary system vulnerability. However, in situations involving depressions, elevations, or downhill routes, the controller exhibited minimal steady-state tracking errors and swift response dynamics. Oscillations remained absent.

Task 3 Validation:
The controller's proficiency was evident, although challenges arose in scenarios with substantial reference velocity shifts. Echoing Task 2, the uphill ascent still posed an elevated error. Yet, most speeding penalties were avoided. Conversely, during downhill routes, the system struggled to promptly align with the new desired velocity, occasionally incurring brief speeding violations. The peak failure risk, amounting to 8%, was detected during descending phases, especially when paired with a marked velocity transition.

(C) Recommendation for Use
Gleaning insights from simulation outcomes, it's advised that any vehicular speed adjustments be capped at 60 km/h regardless of road gradient, as underlined by the preceding evaluations. Surpassing this advised reference velocity shift threshold may compromise the cruise controller's efficacy and potentially breach speed regulations. In terrains featuring pronounced inclines, minor speed adjustments are preferable. This caters to the controller's torque request limits and the extended duration required to synchronize the vehicle's pace with the updated reference, thereby minimizing abrupt speed spikes. As highlighted in the validation data, more modest velocity shifts typically correlate with reduced vehicular speed oscillations.

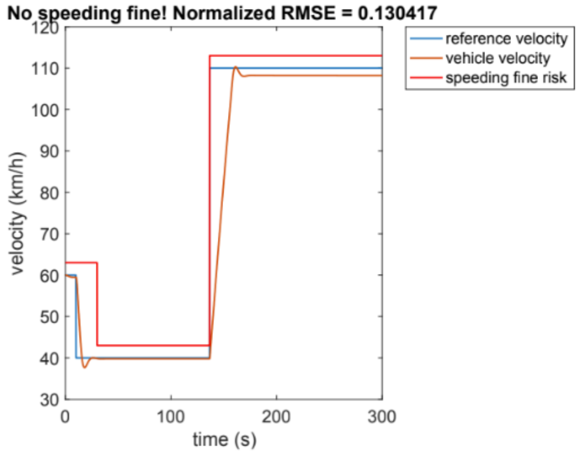

Figure 5: Vehicle model response for task 1 recommended test when compared to system response and speed fine status

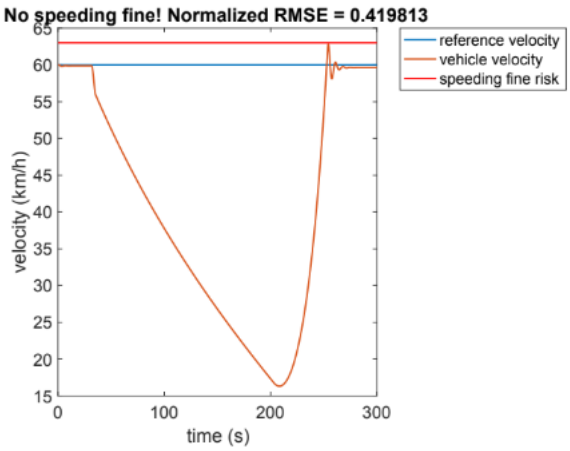

Figure 6: Vehicle model response for task 2 recommended test when compared to system response and speed fine status

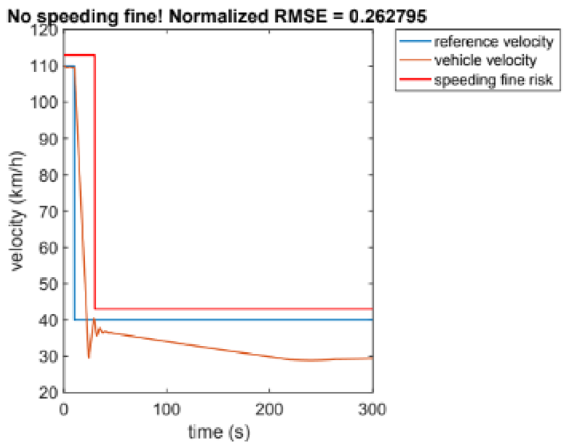

Figure 7: Vehicle model response for task 3 recommended test when compared to system response and speed fine status