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Longitudinal Vehicle Dynamics Parameter Identification for Effective Control System Design

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SUMMARY

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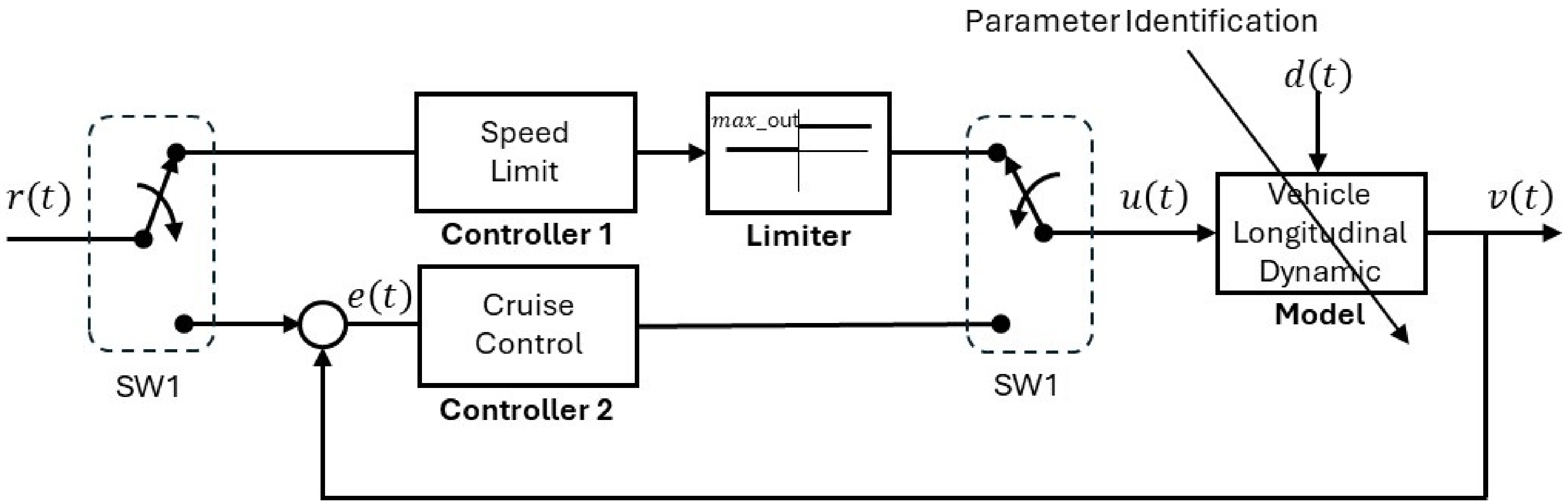
1. INTRODUCTION

Speed limiter and cruise control are longitudinal control features for a road vehicle. A **speed limiter** (or governor) is an electronic system that caps a vehicle's maximum speed by monitoring its velocity and automatically reducing engine power. In contrast, **cruise control** maintains a constant driver-selected speed using an automatic throttle control. This technology not only relieves driver fatigue during long trips but also improves fuel efficiency, promotes smoother traffic flow, and enhances safety by keeping a safe following distance

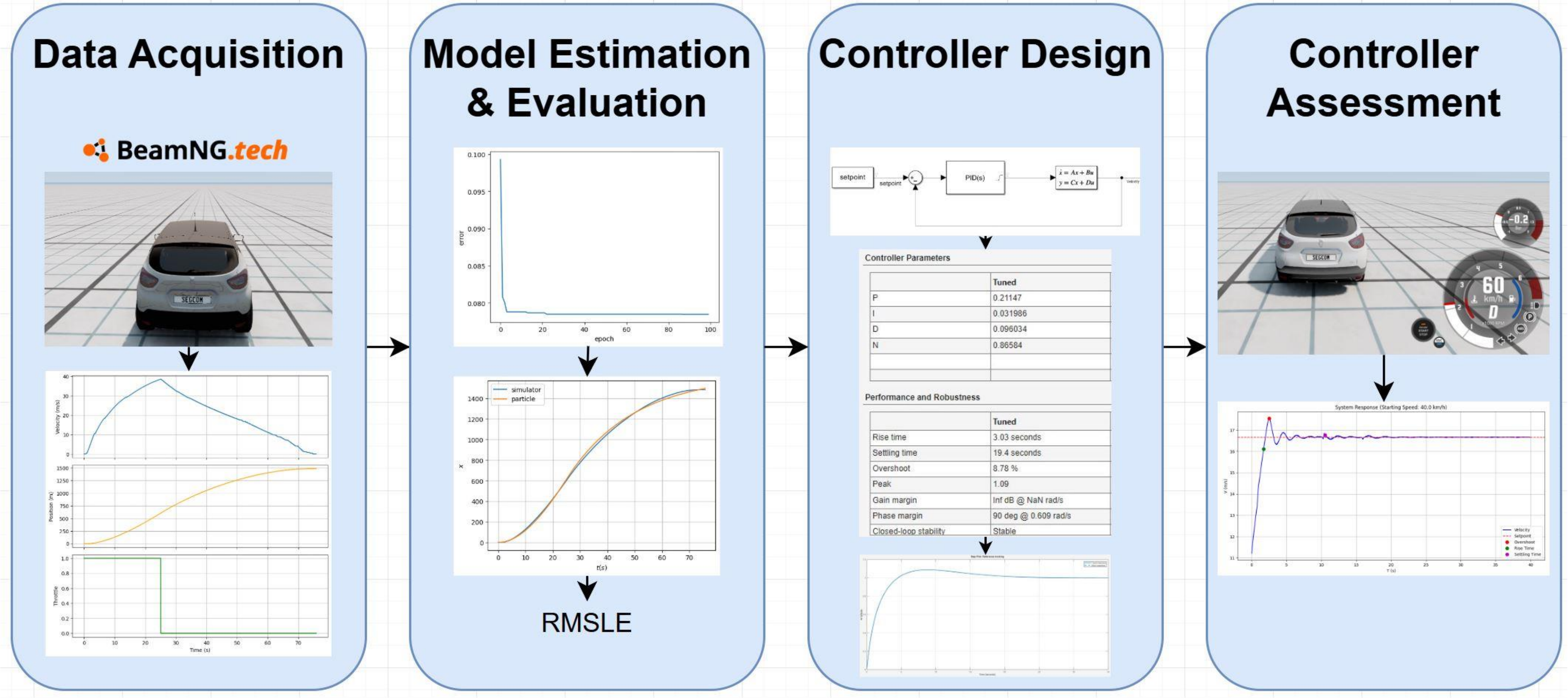
2. Objective

Since the complexity of the automotive system is growing in the control domain, the definition of accurate longitudinal dynamic models is crucial and can improve the performance, safety, and comfort.

Speed Limit & Cruise Control



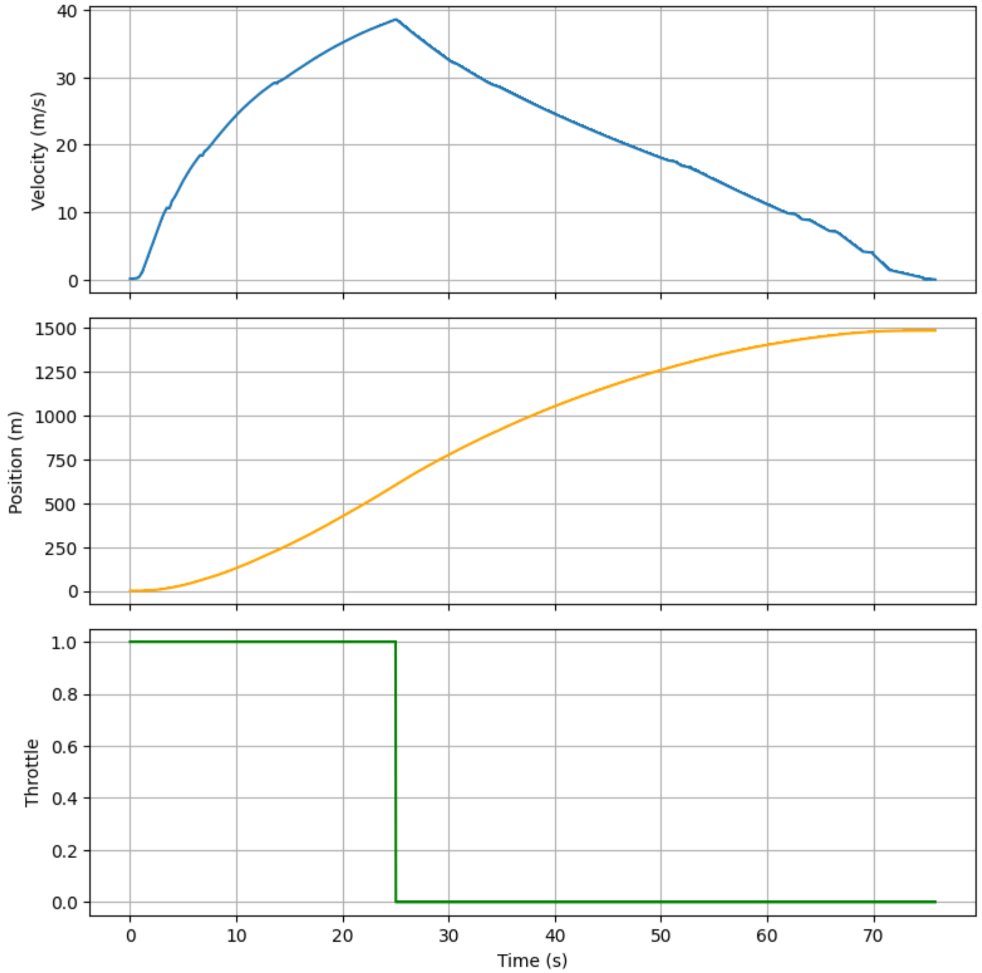
3. METHODOLOGY



4. DATA ACQUISITION

Simulations using BeamNG.tech.

- ✓ Flat surface;
- ✓ Full acceleration followed by free deceleration;
- ✓ Extracted data: position, velocity, and throttle.



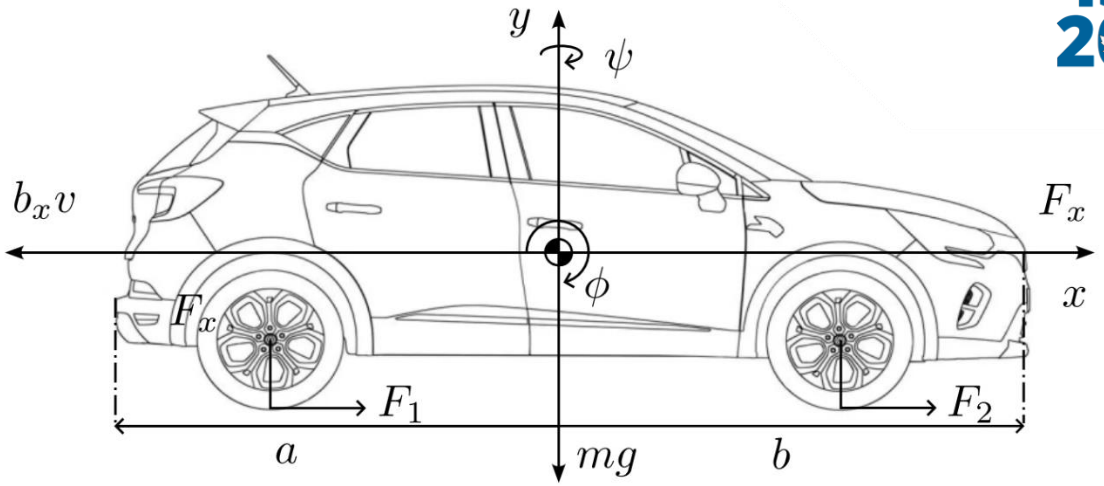
5. Model Estimation

Modeling based on Newton-Euler equations:

- Variables: mass (m), force (F_x), friction (b_x);

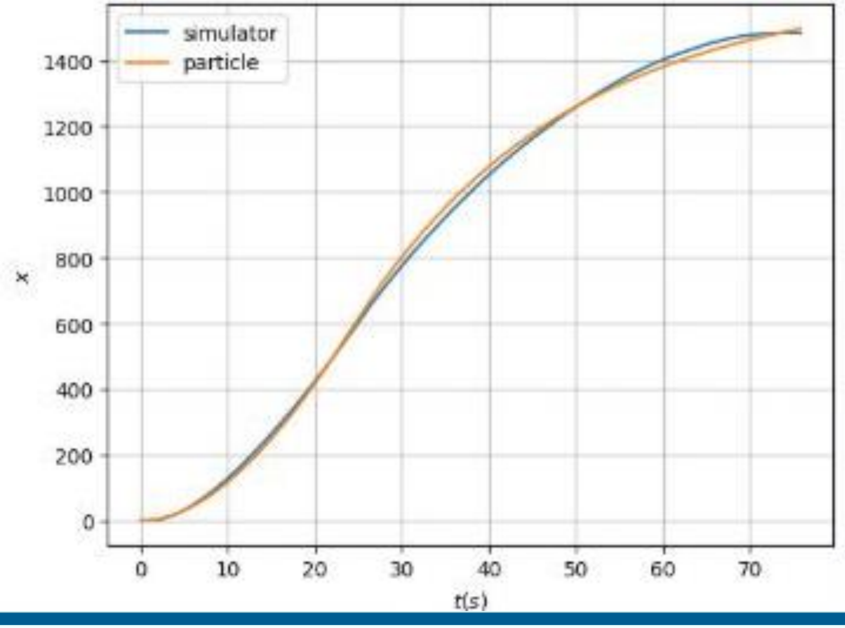
Second-order model equations:

- position (x_0) and velocity (x_1).



Optimization goal: minimize RMSLE between model output and real data (acquired from the simulator).

$$RMSLE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\log(y_i + 1) - \log(\hat{y}_i + 1))^2}$$



5. Model Estimation

ESTIMATED PARAMETERS AND RMSLE OF EACH METHOD

Method	m (kg)	b (N.s/m)	F (N)	Average Time (s)	RMSLE
GA	**1396.05**	47.71	3548.18	6.15	**0.10121**
PSO	1369.88	54.77	3617.10	5.93	**0.10121**
BFGS	1349.93	46.82	3000.09	1.15	0.13940
CG	1351.14	46.87	3000.01	0.77	0.13992
COBYLA	1349.25	46.78	3000.77	0.17	0.13898
Dogleg	1350.00	50.00	3000.00	0.12	0.15731
L-BFGS-B	1352.40	40.00	3007.38	0.31	0.12913
Nelder-Mead	1300.00	51.97	3432.57	0.45	0.10236
Newton-CG	1350.98	42.39	3001.29	185.86	0.13432
Powell	1318.80	44.42	3286.34	1.47	0.10287
SLSQP	1350.49	46.82	2999.83	0.18	0.13961
TNC	1350.00	50.00	3000.01	**0.09**	0.15731
Trust-constr	1349.87	46.14	3000.12	1.17	0.13820
Trust-exact	1349.91	49.33	3000.01	14.92	0.15175
Trust-krylov	1349.96	49.33	2999.98	11.42	0.15178
Trust-ncg	1350.07	49.34	3000.06	4.29	0.15182

PARAMETERS AND RMSLE OBTAINED BY EACH METHOD, CONSIDERING THE VEHICLE MASS

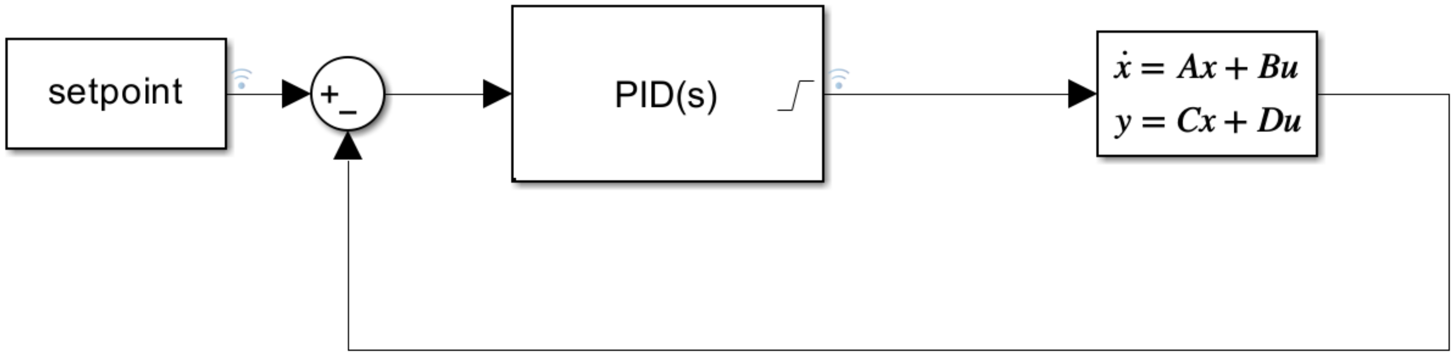
Method	b (N.s/m)	F (N)	Average Time (s)	RMSLE
GA	47.38	3525.95	6.10	0.10123
PSO	55.45	3662.29	6.16	0.10123
BFGS	47.59	3000.07	0.73	0.15466
CG	37.19	3000.69	0.50	0.13759
COBYLA	47.41	3001.99	0.14	0.18996
Dogleg	50.00	3000.00	**0.07**	0.16920
L-BFGS-B	47.41	3001.24	0.70	0.15335
Nelder-Mead	47.41	3533.34	0.59	**0.10118**
Newton-CG	49.99	3000.00	4.42	0.16907
Powell	52.10	3479.68	0.27	0.10619
SLSQP	40.00	3001.78	0.12	0.13890
TNC	50.00	3000.00	0.16	0.16920
Trust-constr	47.41	3503.58	1.39	0.10152
Trust-exact	48.09	3000.09	11.35	0.15496
Trust-krylov	48.09	3000.14	9.82	0.15495
Trust-ncg	48.09	3000.29	4.69	0.15492

6. Controller Design

PID controller design with anti-windup;

Goals:

- Rise time < 10 s;
- Settling time < 30 s;
- Overshoot < 10 %.

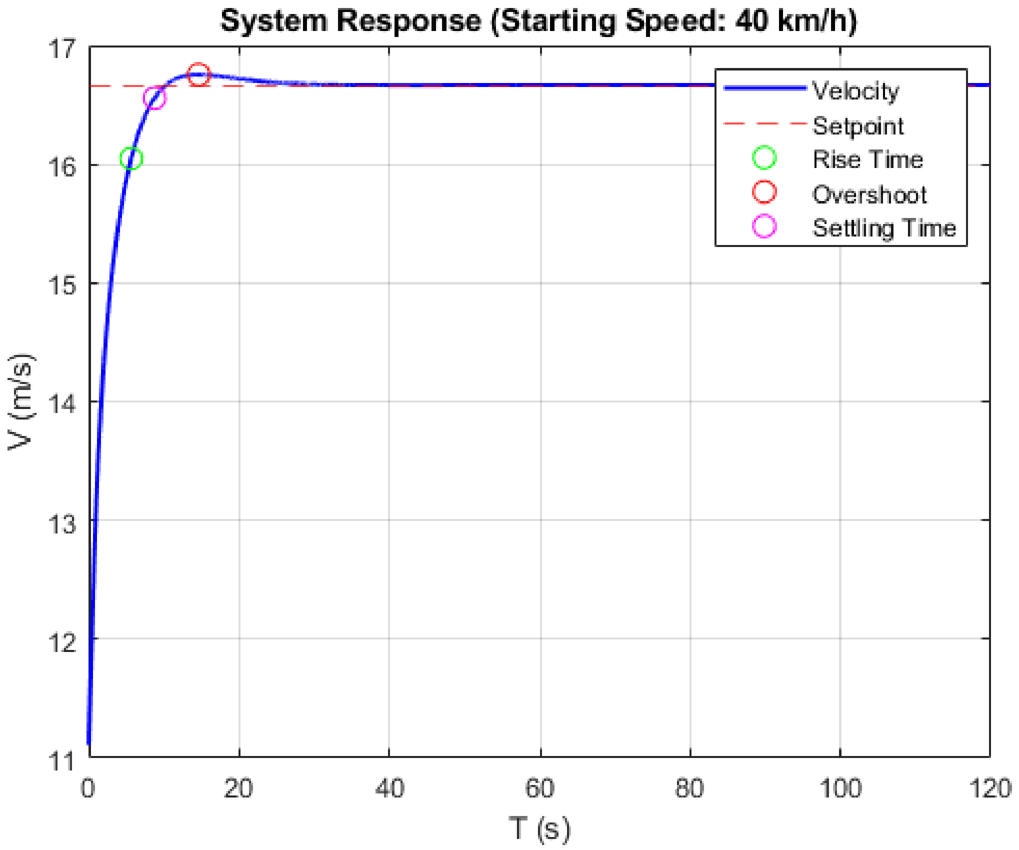


Controller Parameters and Performance Metrics obtained in PID Tuner

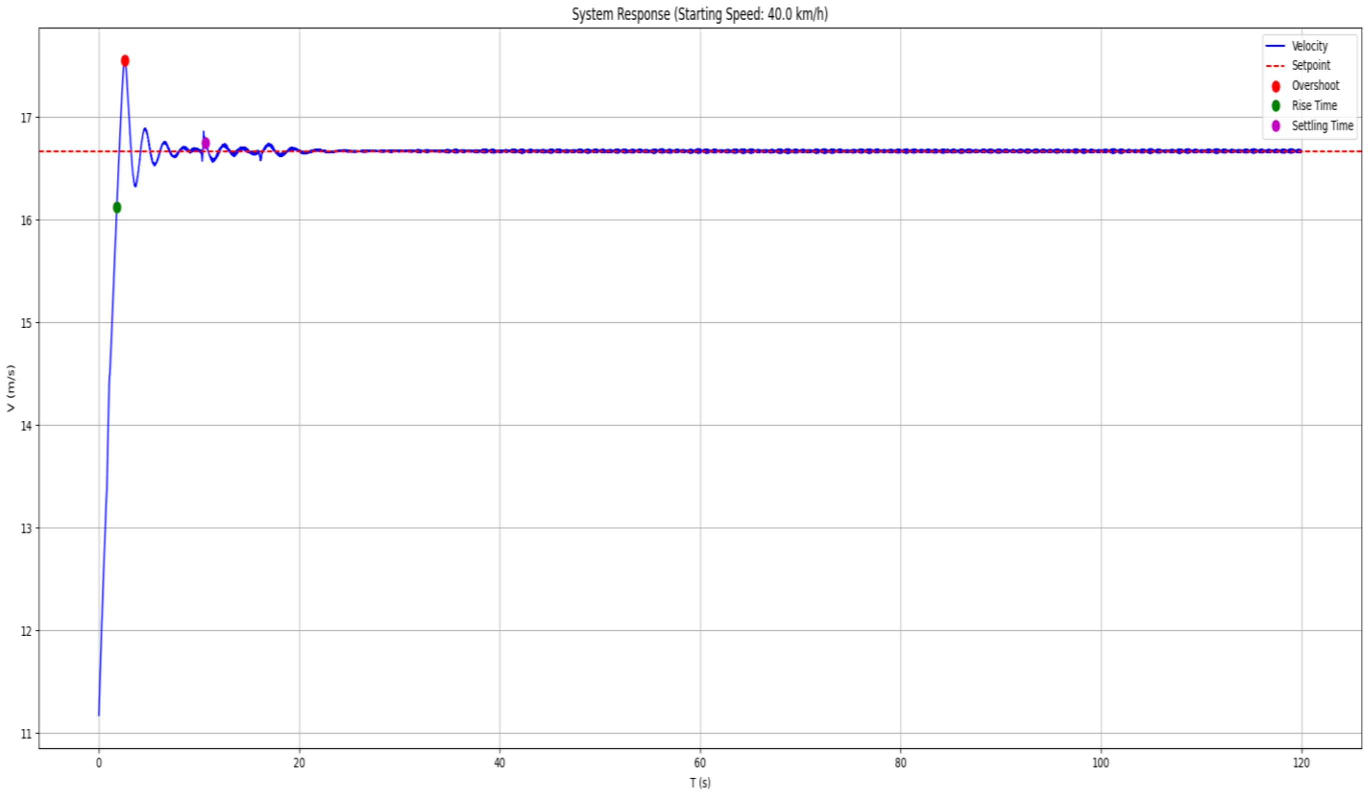
Controller Paramenters	Values
P	0.21147
I	0.031986
D	0.096034
N	0.86584
Performance and Robustness	**Values**
Rise time	3.03 sec
Setling time	19.4 sec
Overshoot	8.78 %

7. Controller Assessment

Cruise Control System with Vehicle Model



Cruise Control System with Simulated Vehicle (BeamNG)



7. Controller Assessment

Performance Metrics of the Cruise Control System in the Tested Scenarios

Vehicle	Starting Speed	Rise Time / Fall Time	Overshoot / Undershoot	Settling Time
Model	40 km/h	5.6600 s	1.56 %	8.7500 s
Model	50 km/h	6.5500 s	0.78 %	10.4000 s
Model	60 km/h	0.0000 s	0.01 %	18.8400 s
Model	70 km/h	6.4200 s	1.42 %	9.7900 s
Model	80 km/h	10.5800 s	0.28 %	25.2900 s
Simulator	40 km/h	1.6190 s	15.92 %	10.6371 s
Simulator	50 km/h	0.9230 s	31.92 %	16.5302 s
Simulator	60 km/h	0.0000 s	1.14 %	12.4617 s
Simulator	70 km/h	1.3330 s	12.76 %	13.4850 s
Simulator	80 km/h	3.4960 s	6.56 %	6.8850 s

8. CONCLUSION

Validated model effective for longitudinal control;

GA and PSO promising, especially for higher-dimensional problems.

Future Work:

- ✓ Hybrid and adaptive methods.
- ✓ Scalability to more complex models.
- ✓ Integration with AI for real-time parameter estimation
- ✓ Application in other ADAS features like ACC, AEB, FCW, etc

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REAL VEHICLES FOR TESTS

Renault CAPTUR, Jeep Renegade, and DAF Truck

Q&A