Design and Comparison of a Lateral and Longitudinal Controller for an Autonomous Vehicle

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Abstract

Autonomous vehicles are the future which can ensure safety and optimized use of infrastructure the world has. One of the key research areas in this domain is the development of controllers for the motion of the vehicle. The paper aims to design and compare the lateral and longitudinal controllers in a single model, designed in MATLAB. With the set of real-time input variables, the controller will generate a path, based on vehicle's present position, orientation relative to the point ahead of the vehicles intended path and the required orientation along the path at a specific position. The model was able to simulate the various driving conditions and the scope of future work is also discussed. Such a model will be helpful for those who wants a base development project which can act as a reference to build the model, for further research and development.

Keywords
MATLAB, PI Controller, Stanley Controller, and Simulation.

1. Introduction
One of the rapid accelerations in the automotive industry is the research and development of autonomous vehicle (AV) which tend to a) reduce the severity of accidents, b) increase mobility for people with disabilities and the elderly, c) reduce pollution and d) use the infrastructure to the full potential. The concept of AV has started to be in passenger cars in the name of advanced driver assistance system (ADAS) for the past few years (Van et al., 2021). Humans experience distraction, fatigue and emotions while driving which causes 94% accidents as reported by the National Highway Traffic Safety Administration (NHTSA).

The Society of Automotive Engineers international standards define autonomous vehicle from Level 0 to Level 5. In Level 0 the driver takes full control while in Level 5 the vehicle takes full control. Currently, most vehicles on roads are equipped with Level 1 or Level 2 autonomy due to the fact that the sensor for AV posts a lot of limitations and high costs. The features that are now available includes emergency braking, lane keeping assist, blind spot monitoring and adaptive cruise control. The Figure 1 show a system level topology of an autonomous BEV model, having longitudinal control which consists of a drive cycle, controller, battery, power converter, traction motor and vehicle body. Since this is a closed loop system, feedback is necessary to the controller which forms the output characteristics of the vehicle. The drive cycle gives the velocity with respect to the time as input to the controller. An example of a such a drive cycle called the Modified Indian Drive Cycle is depicted by Figure 2. The controller is responsible for calculating the commands that shall be send to the motor according to the input drive cycle and the current state of the vehicle which it receives via the feedback loop from vehicle dynamics.

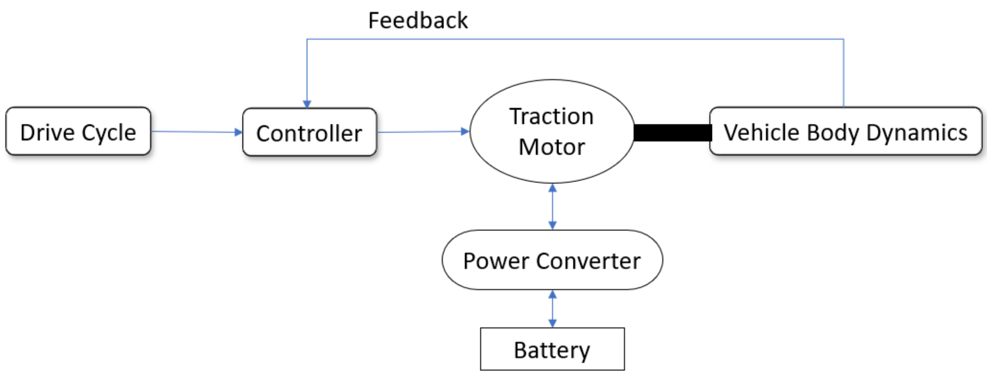


Figure 1. A system level topology of an Autonomous BEV model

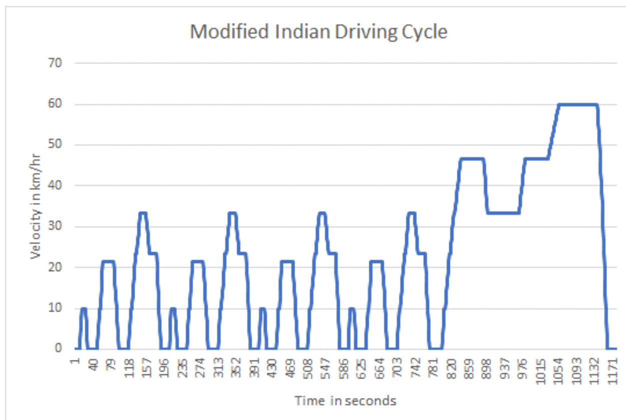


Figure 2. The Modified Indian Driving Cycle

1.1 Objectives

In this work we try to design and model a controller for the lateral and longitudinal control of an AV in Simulink, MATLAB. The models generally used for simulations have only one form of control in which the longitudinal control is more in common. Here we incorporated both lateral and longitudinal control of the vehicle into a single model so that its way simpler to use this as base development project for future works wherein one can test the effectiveness of the control algorithm. Here we have elected a battery electric vehicle (BEV) as the vehicle to be controller since most of the ADAS systems are implemented in BEVs.

2. Literature Review

Cheng (2011) in his work states that the five main pillars which constitute the action of an AV are a) perception, b) localization and mapping, c) path planning, d) decision making and e) vehicle control. Different sensor like LiDAR, RADAR and camera continuously scans and monitor the environment in perception. In Localization and mapping, with the data from perception, an algorithm calculates the local and global position of the vehicle under motion and maps the environment. In path planning with data available so far, the viable routes the vehicle can take is generated and in decision making the optimal route is selected analyzing the environment and the current state of the vehicle. Then the vehicle control will generate appropriate command to control the vehicle to follow the selected path. This process is a high frequency closed loop process which enables the AV to handle high-speed motion and dynamic environment.

3. Methods

The paper focuses on building a model that has both the lateral and longitudinal control of the autonomous vehicle. The primary task was to identify the problem that existed in the automotive industry and where the technology is heading so that the effort and time spent on solving the problem shall appeal to the masses and make the technology to be made easy to deal with. For this extensive reading of articles, online sources and even by communicating with experts in the field at the university. The data collected during this time helped to set aside any kind of ambiguity and confusion related to the project. It also improved the project execution and its future scope. With the project problem identified and stated, the next phase was to set the outcomes of the project. The objectives were given a rough draft and was compared with the literature survey that was done. On comparison, the objectives were refined and stated without giving any chance of confusion. The entire process to be completed was planned and scheduled in accordance with the process sequence. The time scheduled for completion of the project was 4 months and the project was completed as per the schedule previously prepared.

The initial data for the modelling was calculated with simple calculations with the vehicle parameters and the decided drive cycle. The maximum and average torque of the motor, the average and peak power, the average and peak currents, and the battery capacity. All these calculated parameters were compared with the vehicle under consideration for the simulation and found that the specifications match perfectly. The specification of the vehicle was noted and summarized. After that the model build was started. With collected data a base model idea was first generated, and some tests were carried out on each individual subsystems to check for the working and correctness of the model according to our input parameters.

The subsystems were then clubbed together to make the base model. Some sample simulations were run to check it's working, and the data was compared to the idea generated and the collected data. Some modifications were made to the model when deviation was found out to be present. The preliminary results at this stage were captured. The model simulations were carried out with proper inputs, and it was refined for the final simulations. There was constant checking of the results and corrections done to the model. Then the final simulations were carried out once the simulation and data captured looked close to our output goals. The final results were captured and documented.

4. Development of the Model

Add data collection here. (10 font) already stated, there were models within which just the longitudinal control was available. Such a draft model was selected, whose input is a drive cycle, and the output shows how much the velocity of the vehicle matches with the input drive cycle. The model consisted of the longitudinal controller, a battery, a motor, a differential, and vehicle dynamics block in 1 degree of freedom (DOF). The draft model is shown in Figure 3.

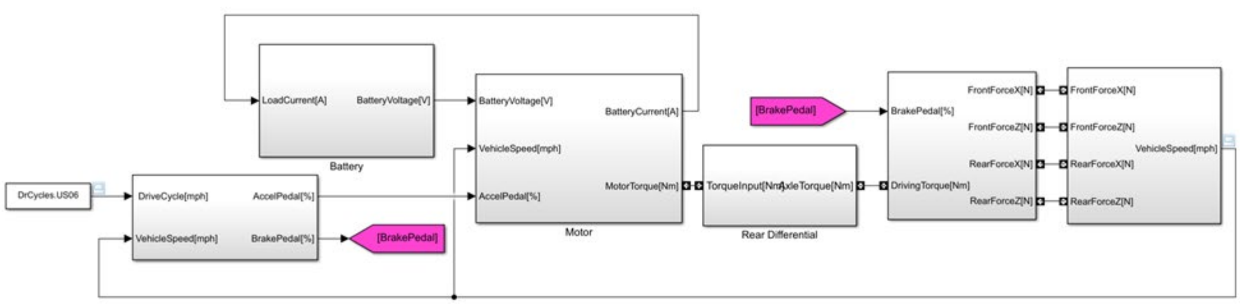


Figure 3. The Draft model of the vehicle

Since the draft model uses 1 DOF Vehicle body with two axles, we can only simulate the forward and reverse motion of the vehicle. In order to include the lateral dynamics as well, changes were made to the draft model. The developed model can simulate both lateral and longitudinal dynamics of the vehicle and are having a couple of subsystems which are important in the working of the model as well as during simulation. They are:

4.1 PI Longitudinal Controller subsystem

The model includes a proportional integral derivative (PID) controller that is configured in PI format which is tuned via the frequency response-based tuner as shown in Figure 4. The time domain parameter is set to continuous. Saturation blocks are given to the signals flowing out of the PI controller to make sure that the values of such signals fall in between the upper and the lower limits we have defined. To define the input output relation in algebraic format, transfer functions are used.

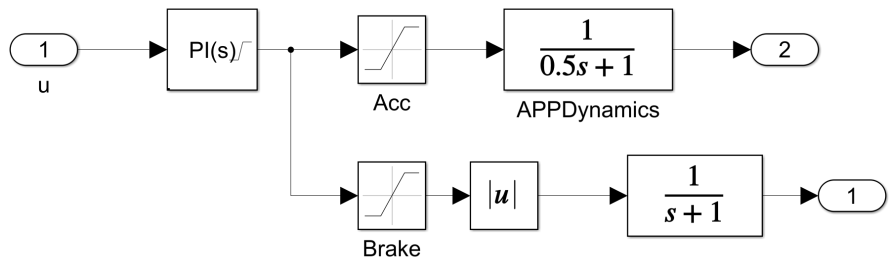


Figure 4. The PI Longitudinal Controller Subsystem

4.2 Motor subsystem

The motor subsystem in Figure 5 has a mapped motor block operating in torque control mode. The torque speed envelope of the motor either from the manufacturer or after testing in the lab is imported into the block. The block accepts motor speed and torque in rad/sec and Nm, so the velocity signal is converted first to rotational speed after taking into consideration the wheel radius and gear ratio of the differential. One of the branches goes to the motor block while the other signal is fed to a one-dimensional (1D) lookup table which uses linear point slope interpolation, to give the corresponding torque output which is mapped according to the motor. The battery voltage also forms an input to the block and the outputs are motor torque and battery current. The motor used for this simulation has a nominal power of 7 kW, rated speed of 2600 RPM, rated current of 150A and rated voltage of 48 V.

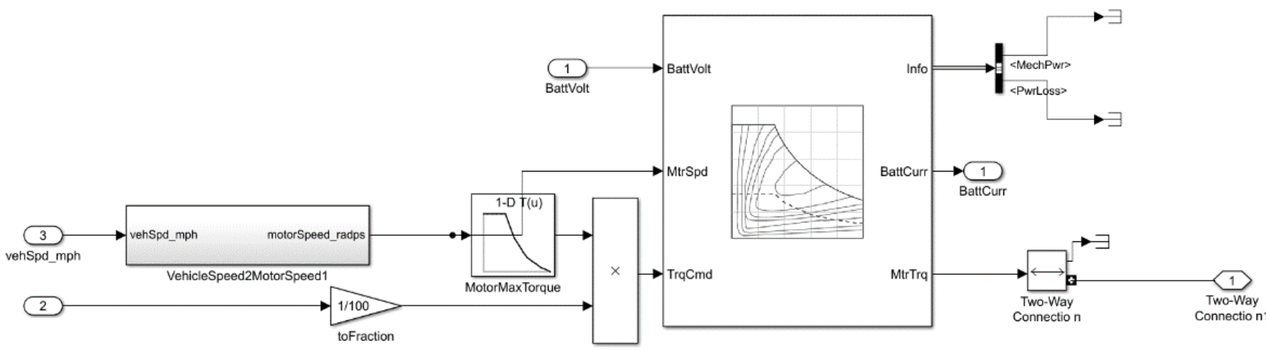


Figure 5. The Motor Subsystem

4.3 Battery subsystem

The battery subsystem shown in Figure 6 consists of a datasheet battery block from Powertrains Blocksets. A lithium-ion battery model is implemented in it, based off discharge characteristics at various temperatures. The nominal voltage of the battery is 48.1 V. The battery temperature and the current the motor requests is given as input to the battery block. The output of the block, the battery voltage connects to the motor input. The state of charge (SOC) of the battery is constantly monitored and if it falls below 5%, the simulation is stopped (Figure 6).

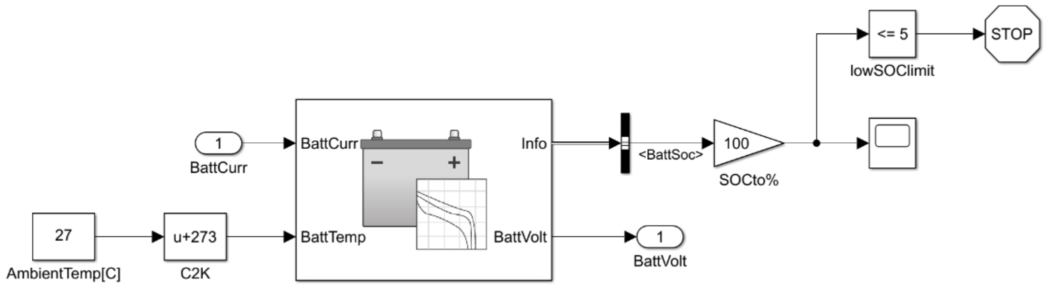


Figure 6. The Battery Subsystem

4.4 Differential subsystem

The Figure 7 shows the differential subsystem. Here, we have used an open differential having a gear ratio of 3.11. The viscous and damping coefficients of the axles as well as the carrier are defined. In the axle complains, the torsional stiffness and torsional damping is provided (Figure 7).

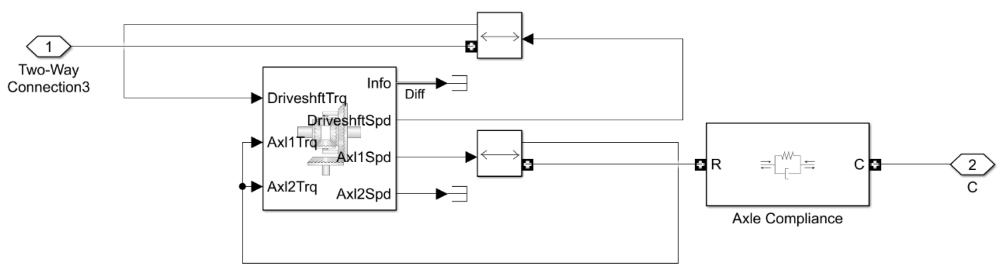


Figure 7. The Differential Subsystem

4.5 Front wheels subsystem

The longitudinal wheels with disc brakes are provided to model the front wheels. The front wheels only have the steering and braking capabilities hence the input axle torque is grounded as shown in Figure 8. Here we use the Tire Magic Formula to model the wheels having a radius of 0.265 m. The Magic Formula coefficients are specified based on the type of road that we plan to run the simulation on (Figure 8).

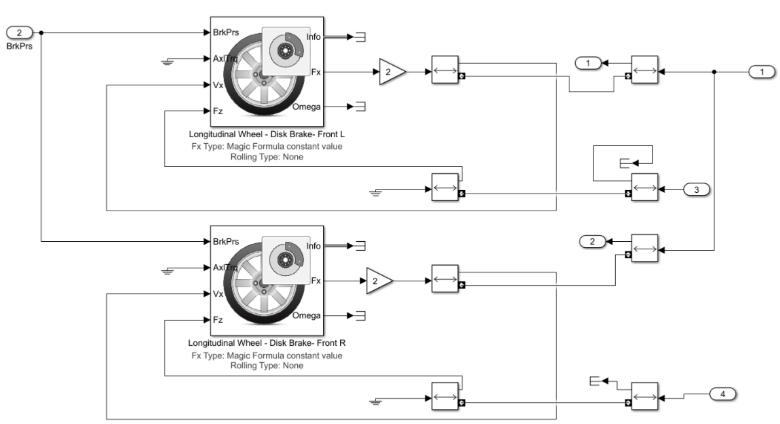


Figure 8. The front wheels subsystem

4.6 Rear wheels subsystem

For rear wheels, we use the same longitudinal wheels with disc brakes but here the axle torque input is given to the blocks (Figure 9).

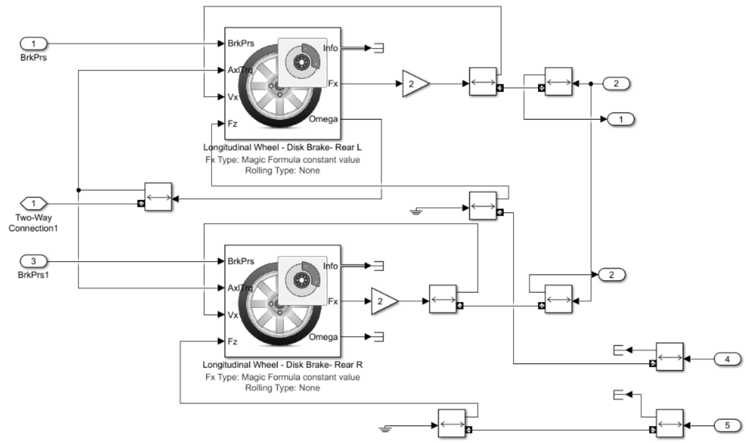


Figure 9. The rear wheels subsystem

4.7 Lateral Controller Stanley subsystem

The Lateral Controller Stanley block after getting the data of the current pose and the reference pose computes the angle at which the vehicle's wheels shall turn or steer, so that the vehicle will follow the requested path. The current velocity at which the vehicle is moving as well as the current direction of motion is also taken into consideration while calculating the steering angle in degrees (Figure 10).

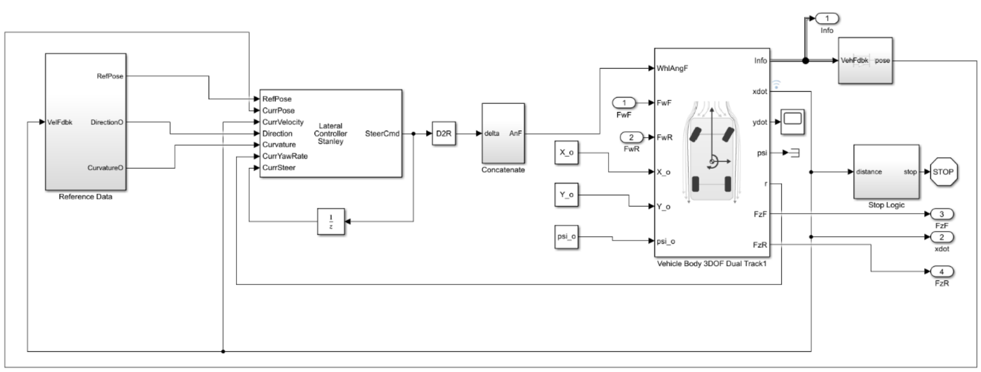


Figure 10. The Stanley controller and Vehicle body 3DOF – dual track blocks

With respect to steering angle input and reference data, the Vehicle body 3DOF dual track calculates the longitudinal and lateral velocity of the vehicle, the current yaw rate of the vehicle, and the force on the front and rear axles which is an input to the wheels subsystem. The forces that act on all the four wheels are shown in Figure 11.

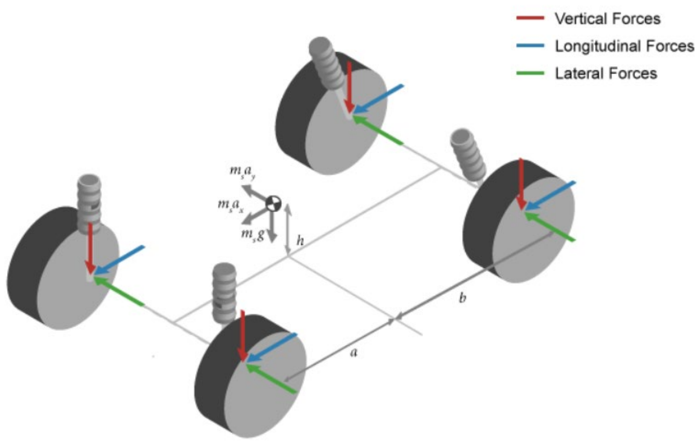


Figure 11. The forces acting on dual track model

With all these subsystems combined we form the fully developed model as shown in Figure 12. Some additional blocks are added to visualize the movement of the vehicle as well as scopes are provided to obtain the graphs.

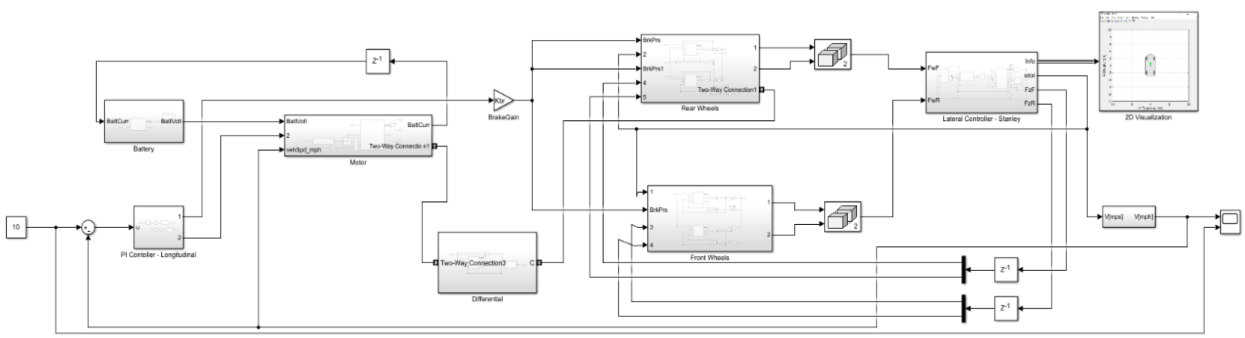


Figure 12. The developed model with Lateral and Longitudinal Control

To test the model, the roads are created in the Driving Scenario Designer app, with the vehicle at the center of the road. The road was created according to our test conditions, but we have an option to import maps from OpenDRIVE or OpenStreetMap or HERE HD Live Map. We can also add sensors and other components to the actor vehicle to simulate a fully autonomous vehicle if needed. To carry out the simulation we are using the vehicle parameters of a E-BAJA vehicle, given in table 1.

Table1. The vehicle parameters

Sl. No.	Parameter	Value	Unit
1	Vehicle mass	400	kg
2	Radius of the wheels	0.265	m
3	Coefficient of drag	0.6	-
4	Coefficient of rolling resistance	0.08	-
5	Frontal projected area	1.2	m^2

5. Results and Discussion

5.1 Simulation

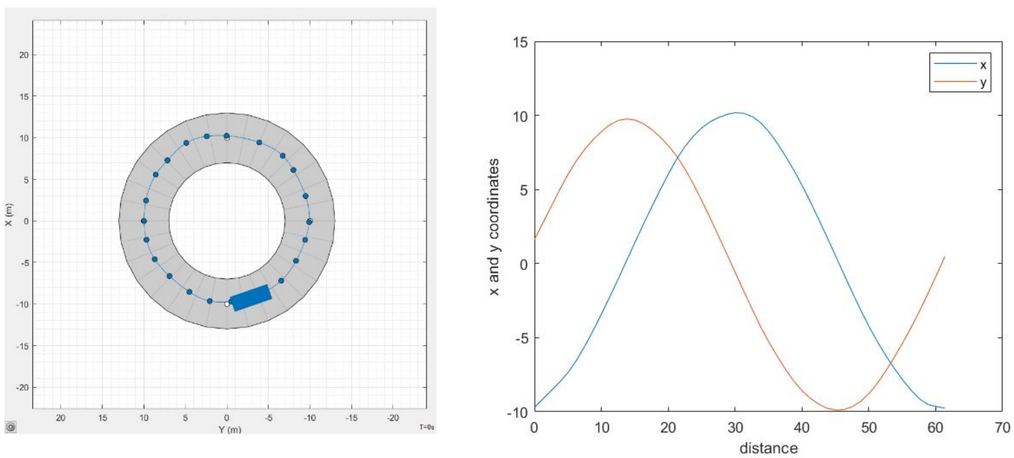
Simulations with two tests were carried out to determine the handling capability of the controllers used under steady state conditions. The tests are carried out on skid pads with large paved are. The following are the tests:

5.1.1 The constant radius test

In constant radius test, the vehicle is made to travel along a curve having a constant radius of 10 m and with each test being conducted the velocity at which the vehicle will travel is increased. The Driving Scenario Designer app is used to create the road and the road is imported into the model. The road in the app and the x & y coordinates vs distance curve of the road made are shown in Figure 13.

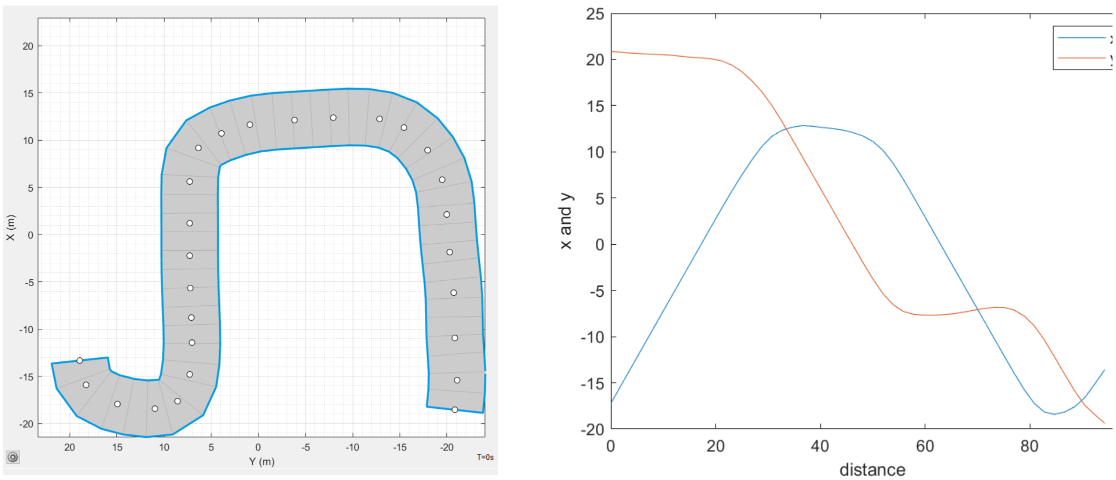
5.1.2 The constant speed test

In constant speed test, a road is designed in the Driving Scenario Designer app as shown in Figure 14 (A). The x & y coordinates vs distance plot is also plotted in Figure 14 (B). The vehicle is made to travel at constant speed (Figure 13 and Figure 14), increasing the sped up to 60kmph after the completion of each test. The simulations for both the tests are carried out at the speeds given in the Table 2.



(A) (B)

Figure 13. (A) Constant radius path in Driving Scenario Designer app and (B) the x & y coordinates vs distance plots for constant radius curve



(A) (B)

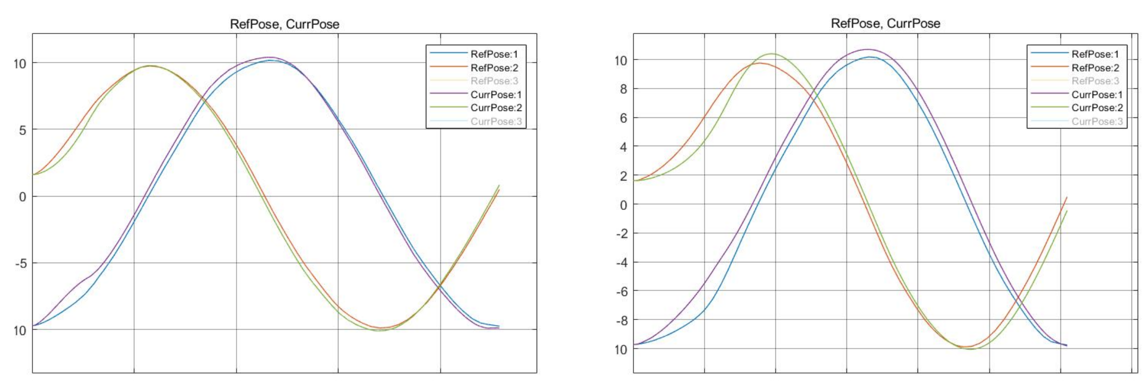
Figure 14. (A) The Constant speed test path in Driving Scenario Designer App and (B) the x & y coordinates vs distance plots for constant radius curve

Table 2. The Speeds at which Simulations are carried out

Sl. No.	Vehicle speed in kmph
1	10
2	20
3	30
4	40
5	50
6	60

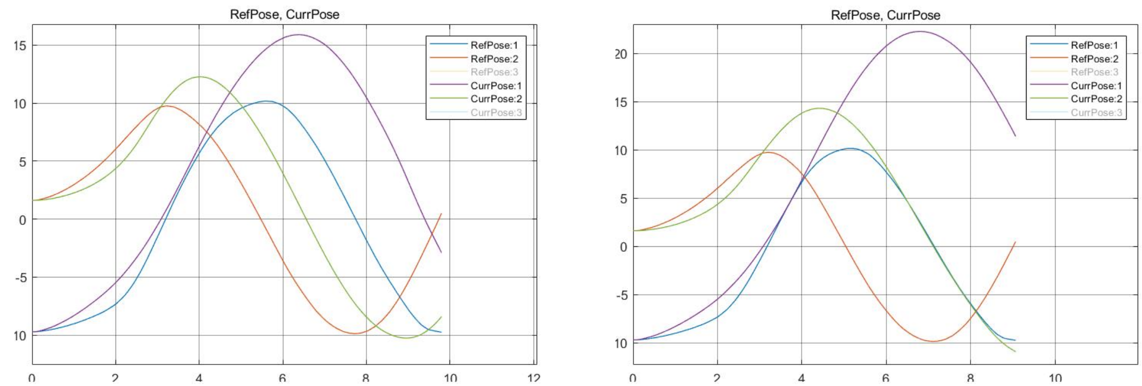
5.2 Handling characteristics under constant radius tests

The x & y coordinates vs the distance curve is plotted for different speeds, and it shows the deviation of current path from reference path. The Refpose 1 and Refpose 2 represents x & y axis coordinates of the reference path respectively while CurrPose 1 and CurrPose 2 represents x & y axis coordinates of the current path respectively (Figure 15-17).



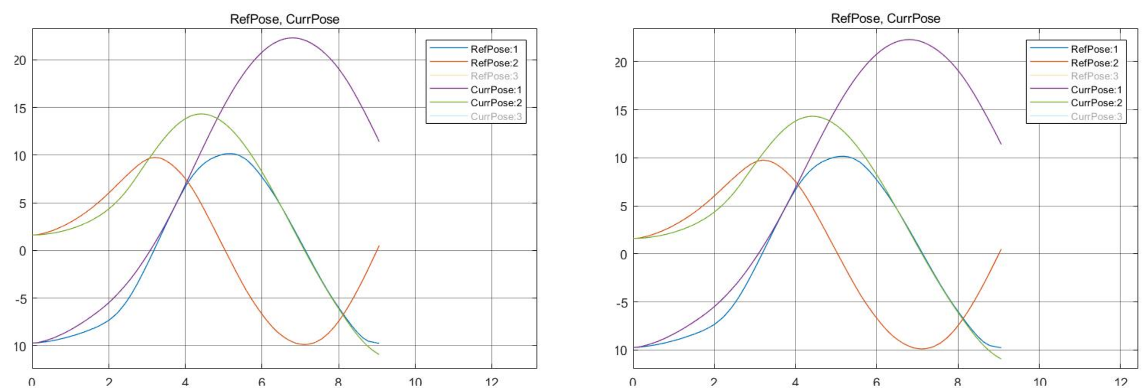
(A) (B)

Figure 15. The x & y coordinates vs distance graph of the ego vehicle at (A) 10 kmph and (B) 20 kmph



(A) (B)

Figure 16. The x & y coordinates vs distance graph of the ego vehicle at (A) 30 kmph and (B) 40 kmph



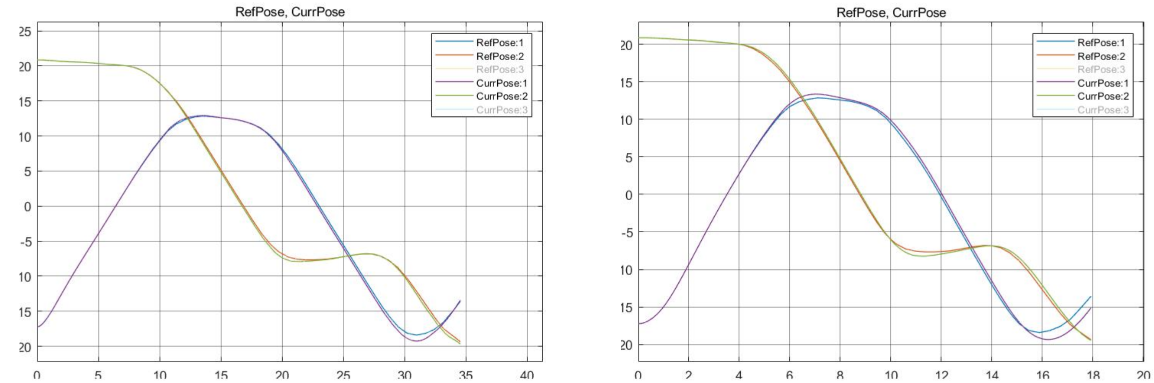
(A) (B)

Figure 17. The x & y coordinates vs distance graph of the ego vehicle at (A) 50 kmph and (B) 60 kmph

The speed at which the vehicle shall complete the path is given as a simulation data for the constant radius test. The vehicle when starting from the initial position is perpendicular to the path and one can observe this by analyzing the graph which depicts the actual and the planned path in both x and y - axes at start with a little deviation. From there the PI controller is well equipped in controlling the motion of the vehicle at lower speeds. But as speed increases the error in actual and planned path increases.

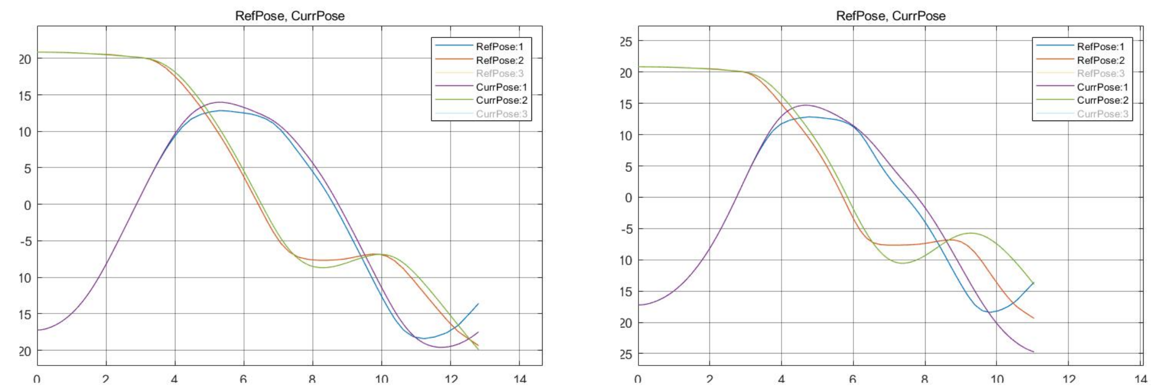
5.3 Handling characteristics under constant speed tests

For constant radius tests, the RMS error in the actual and planned path is at 0.23% in x direction and 0.21% in y direction at 10 kmph. It increases all the way to 7.57% in x direction and 2.64% in y direction at 60 kmph. The x direction RMS error is a little more as the vehicle when travelling at high speeds fails to traverse the planned path more in the x direction (Figure 18-20).



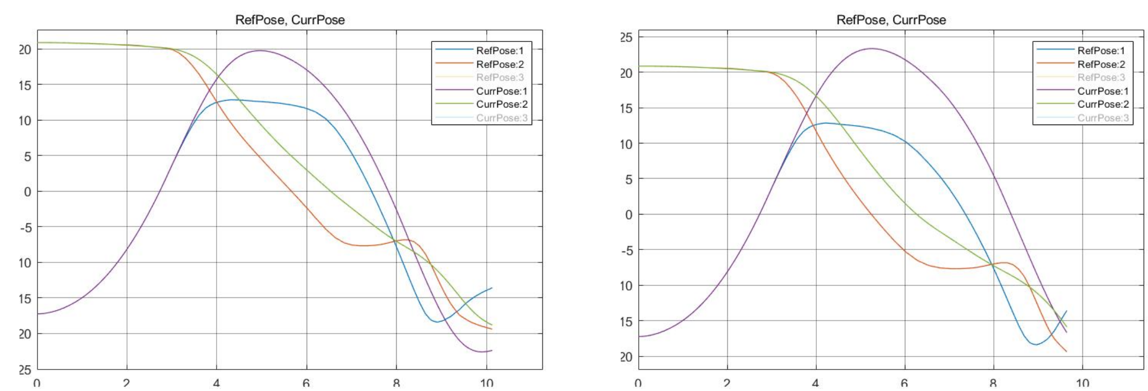
(A) (B)

Figure 18. The x & y coordinates vs distance graph of the ego vehicle at (A) 10 kmph and (B) 20 kmph



(A) (B)

Figure 19. The x & y coordinates vs distance graph of the ego vehicle at (A) 30 kmph and (B) 40 kmph

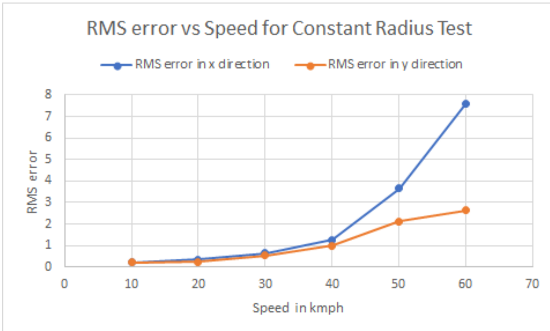


(A) (B)

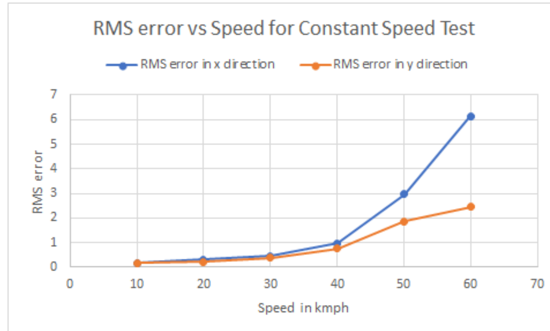
Figure 20. The x & y coordinates vs distance graph of the ego vehicle at (A) 50 kmph and (B) 60 kmph

5.4 Validation

Since at starting, the vehicle coordinates and planned path are coinciding, there is little to zero error unlike the Constant Radius Test. The trend of increased deviation at higher speeds continues here. The RMS error in the actual and planned path is at 0.17% in x direction and 0.15% in y direction at 10 kmph. It increases all the way to 6.14% in x direction and 2.46% in y direction at 60 kmph (Figure 21).



(A)



(B)

Figure 21. The RMS error vs Speed graphs for (A) Constant Radius and (B) Constant Speed Tests

6. Conclusion

The model with both longitudinal and lateral control of the vehicle was successfully modelled, and the simulations were carried out. The two major test that was performed was the Constant Radius and Constant Speed tests. For each of the tests, definite path was defined at six different velocities. The developed model in MATLAB-Simulink is capable enough to simulate the lateral and longitudinal control of the vehicle. The model is designed, keeping a four-wheeler in mind and the vehicle parameters were chosen according to it. The PI controller employed in this model is able to control the longitudinal motion of the vehicle under all conditions.

The Stanley controller used to control the lateral movement of the ego vehicle is very effective at low speeds. But as the speed increases the lateral acceleration increases and the RMS error increases. At speeds above 30 kmph the error in current coordinates and reference coordinate sis way too much. The simulation tells us that the controller is capable of making vehicle follow the planned path and if we implement a logic which can reduce speeds at turns, the model is well suited to use for future simulations and research.

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