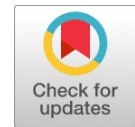# Investigation of an Autonomous Vehicle's using Artificial Neural Network (ANN)

Abel Varghese, Mahendher Marri, Sibi Chacko

Abstract: This paper presents a study of autonomous vehicles on a normal highway in UAE, using MATLAB/Simulink® 2022. There is great potential for autonomous vehicles to improve the safety and efficiency of transportation, enhance the quality of time spent in cars, and make transportation more accessible to everyone. The vehicles utilized in the study have three different speeds 40, 80, and 120 km/hr. All vehicles modelled are representative of that available in the UAE. In the model, lane following and lane-keeping assistance functions and Simulink block which are described using artificial neural networks are selected. Simulation is validated with existing published results of physical vehicle models. In the simulations, it is assumed that vehicles have minimal steering angles as the system is in an autonomous collision free environment, selected from MATLAB. Results are obtained as velocities, accelerations, and safe distance with respect to the preceding vehicle. The following results are critically analyzed and validated.

Nomenclature

C_f *– Cornering stiffness of front tires, N/rad*
C_r *– Cornering stiffness of front tires, N/rad*
l_f *– Longitudinal distance from CG to front tires, m*
l_r *– Longitudinal distance from CG to rear tires, m*
m *– Total mass of the vehicle, kg*
I_z *– Yaw moment of inertia of vehicle, mNs^2*

Keywords: Artificial Neural Networks, Ackermann, Autonomous Vehicle, Deep Neural Networks, CNN, MATLAB, YOLO.

I. INTRODUCTION

Artificial Neural Network was inspired by the human brain, where a large amount of data is stored and processed simultaneously in the form of neurons. Artificial intelligence (AI), made up of neural networks, were created because of research into cognitive ability and computer design. The most critical subset of artificial intelligence, artificial neural networks, is a statistical approach for developing prediction models. Artificial neural networks are made up of data processing units comparable to those found in the human brain. A multi-layered detector model has numerous levels, each with an input and one or more outputs since processors in one layer are coupled to processors in another[1,2].

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The fact that a variety of teaching algorithms may be employed to train this network is the reason why it is so popular. Artificial neural networks are created by simulating the human brain, with which they share two characteristics. In artificial neural networks, information is first obtained through networks. Second, information is stored using connections between artificial neurons[3]. However, it is not possible to make a perfect replica of the human brain, thus creating logical programming scripts which process the information and deploy the decision. Currently, usage/creation of autonomous systems around the globe has increased as in comparison to the past years. It was employed to make life easier, smoother, and safer. There is a huge development in the automobile industry to decrease road hazards all over the world. Fig. 1 illustrates a feed-backward neural network with one hidden layer [4]. Multiple hidden layers can be utilized based on the complexity of the problem. The information in neural networks flows in feed-forward and feed backward. To see how data is processed through the neural framework, a feed-forward artificial neural network (FFANN) is commonly utilized[5].
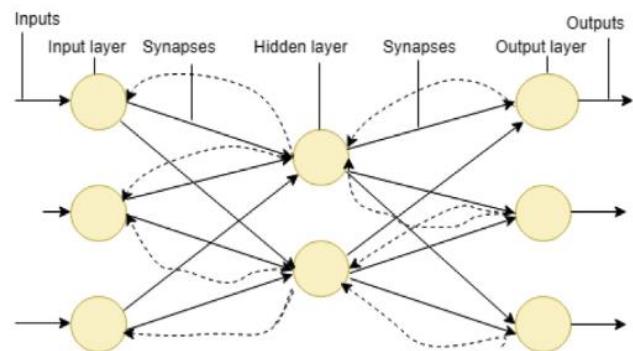

Fig. 1. A schematic of Feed-backward Neural Network with one hidden layer [4].

Many studies have been conducted to improve the learning execution of FFANNs by altering the organization's engineering and learning calculations[6]. Different questions about information depiction in neural organizations have been raised because of the neural organization's abilities to achieve practical reliance on information as cerebrum-like designs. Indeed, even complex challenges (as evidenced by readily available data) can be decoded as consistent standards. Expert knowledge about the system or data is reflected in the rules, which can be used for reasoning, decision-making, or explanatory purposes. Furthermore, systems with a human-machine interface demand that rules may be simple and easy to understand[7].

Investigation of an Autonomous Vehicle's using Artificial Neural Network (ANN)

With the rapid expansion of highways and the widespread use of automobiles, people have begun to place a greater emphasis on modern, efficient, and precise, intelligent transportation systems (ITSs). Due to viewpoint changes, when car structures and LP have similar color, multi-style plate formats, and non-uniform outdoor illumination circumstances during picture capture, the task of vehicle license plate recognition (VLPR) is rather tough from vehicle photographs. The VLPR is commonly used for speed detection, security control in restricted areas, unattended parking zones, traffic law enforcement, and electronic toll collecting, among other applications[8].
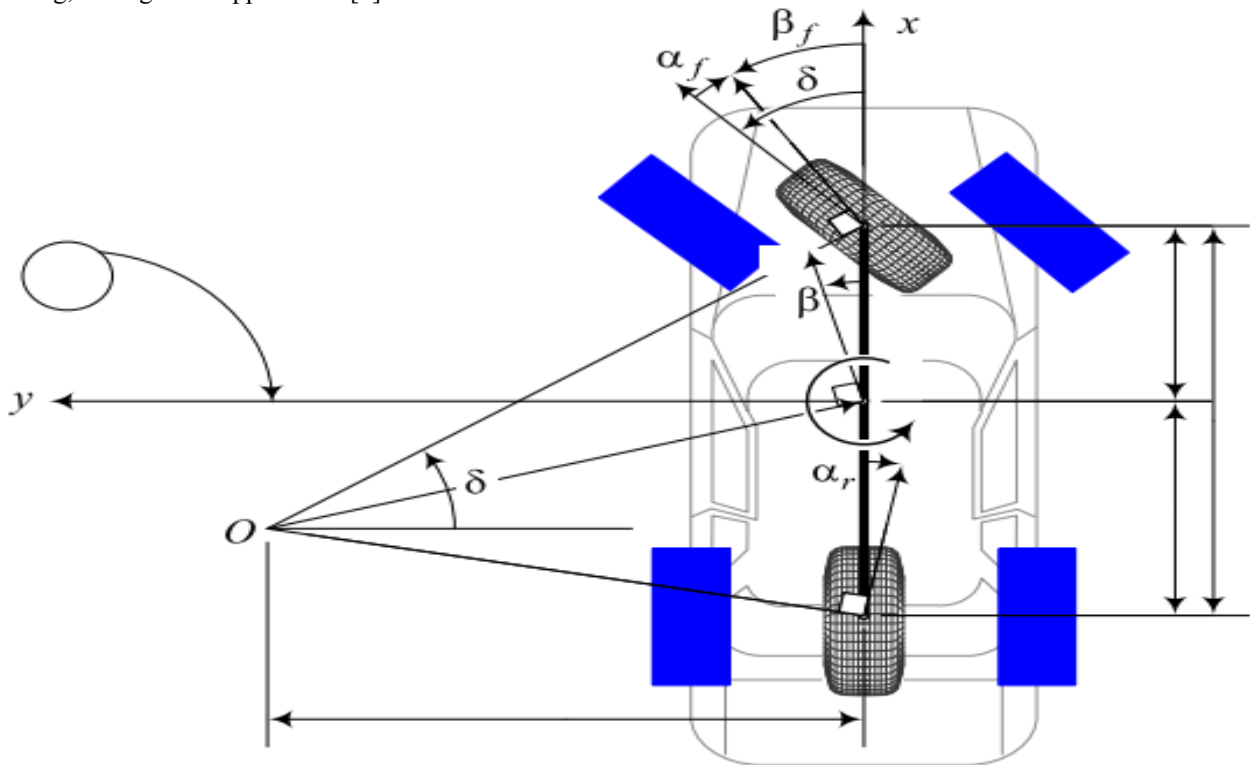

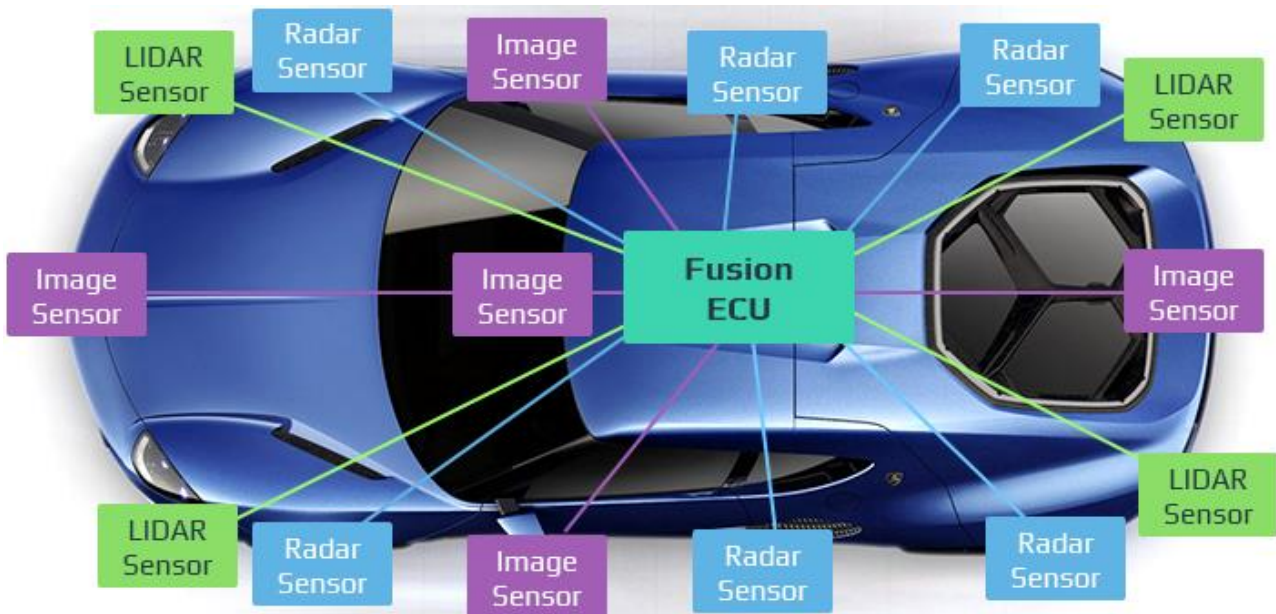**Fig. 2. Mathematical illustration of bicycle model [14].**

Fig. 3. Position of vision, radar, and LIDAR sensor on autonomous vehicles [21].

S. Khoshjavan et al[9]. implemented the ANN (Artificial Neural Network) to find the effect of various parameters consisting of coal composition to estimate the coal Hard grove Grindability Index (HGI) index values. ANN training and testing results showed a square correlation coefficient of 0.962 and 0.82, respectively. A supervised back-propagation neural network was used with the Levenberg Marquardt approximation. This approximation makes training faster and more accurate with lower error possibilities. Li et al[10].

proposed two various methods for autonomous navigation considering different types of road scenarios. The sensing systems are based on the fusion of Light Detection and Ranging (LIDAR) and vision data.

These methods mainly focused on detecting drivable areas for an autonomous vehicle. Demonstrated algorithms can easily navigate the vehicle on un-marked (no lanes/one-way) and marked roads. Trepagnier et al [11]. developed a vehicle using multi-processing units and Laser Detection and Ranging (LADAR) on unknown terrain. The developed vehicle tested in a DARPA Grand Challenge competition, where a vehicle must drive autonomously on a desert track length is 132 miles. Vehicle actuators customed by Electronic Mobility Controls (EMC), and it is a primary control system. Azouaoui and Chopra [12] investigated Intelligent Autonomous Vehicles (IAV) to avoid obstacles in real-time and various pattern classifiers are being used in obstacle environments. Vehicle motions/directions are constrained to three actions: Right Turn, Forward, and Left Turn.

In obstacle detection, three ultrasonic sensors are employed in the vehicle. Neural networks performed better than known conventional systems; however, to analyze complex maps, a parallel computing configuration is utilized. Performance of accuracy will be increased by using the Field Programmable Gate Array (FPGA), which brings us closer to human recognition, obstacle avoidance, and decision making. Many maritime [13] vessels have crashed and groundings have occurred, while approaching to a port where traffic congestion is high. As part of the port's vessel traffic services, automatic guiding systems are needed to deal with the challenges of surface ships maneuvering in confined seas.

II. MATHEMATICAL MODEL

A. Vehicle Dynamics and Kinematics Model

A schematic of the location and dynamic rotation of the vehicle is shown in Fig. 2 bicycle model of a four-wheel vehicle [14]. In general, driving systems like steering wheels, accelerators, and brakes of manual cars are controlled by human drivers. Whereas autonomous cars are controlled by a set of sensors and computers.

Table. 1. The Parameters of this 3-DOF car Model [15].

Parameter	Value
m	1300
C_f	53000
C_r	42000
I_z	1343.1
l_f	1.24
l_r	1.62

A front-wheel-steering car's kinematic center of rotation is on a line perpendicular to the rear wheels – in line with the extended line of the rear axle. The kinematic rotation center is located at the intersection of perpendicular lines to the wheels that, in an ideal situation, will always intersect at a location. The kinematic rotation center is the theoretical location where the vehicle will turn, although this will only happen at low velocities around zero. When driving at low speeds, the kinematic condition between a front-wheel-steering vehicle's inner and outer wheels that allows them to turn without slipping on the ground (slip-free) is expressed by (Ackerman condition),

$$\cot \delta_o - \cot \delta_i = \frac{w}{l} \tag{1}$$

Where, δ_o and δ_i Inner and outer steering directions. W is the path, and l is the wheelbases (distance from front wheel center to rear-wheel center).

$$R = \sqrt{a_2^2 + l^2 \cot^2 \delta} \tag{2}$$

Where R is the distance from the kinematic center to the vehicle's center of mass, C and a_2 are the distance between point C to the rear axle. δ is the average value of the steering angle. Estimation of vehicle steering direction can be done by applying the bicycle method shown in Fig. 2.

$$\cot \delta = \frac{\cot \delta_o + \cot \delta_i}{2} \tag{3}$$

Kinematics of the vehicle is divided into two categories: Forward and Inverse.
Forward kinematics

$$v_x = \frac{r}{2}(\omega_f \cos \varphi_f + \omega_r \cos \varphi_r) \tag{4}$$

$$v_y = \frac{r}{2}(\omega_f \sin \varphi_f + \omega_r \sin \varphi_r) \tag{5}$$

Inverse kinematics

$$\varphi_f = a \tan \left[\frac{\omega(L_f + L_r)}{v_x} \right] \tag{6}$$

$$\omega_f = \frac{v_x}{r \cos \varphi_f} \tag{7}$$

$$\omega_r = \frac{v_x}{r} \tag{8}$$

Where r is the radius of the wheel (m), ω_f and ω_r are the angular velocities (rad/s) of the front and rear wheel, respectively, L_f and L_r are the distance from the center of point, C to the front wheel and rear wheel (m), v_x, v_y are the linear velocities (m/s).
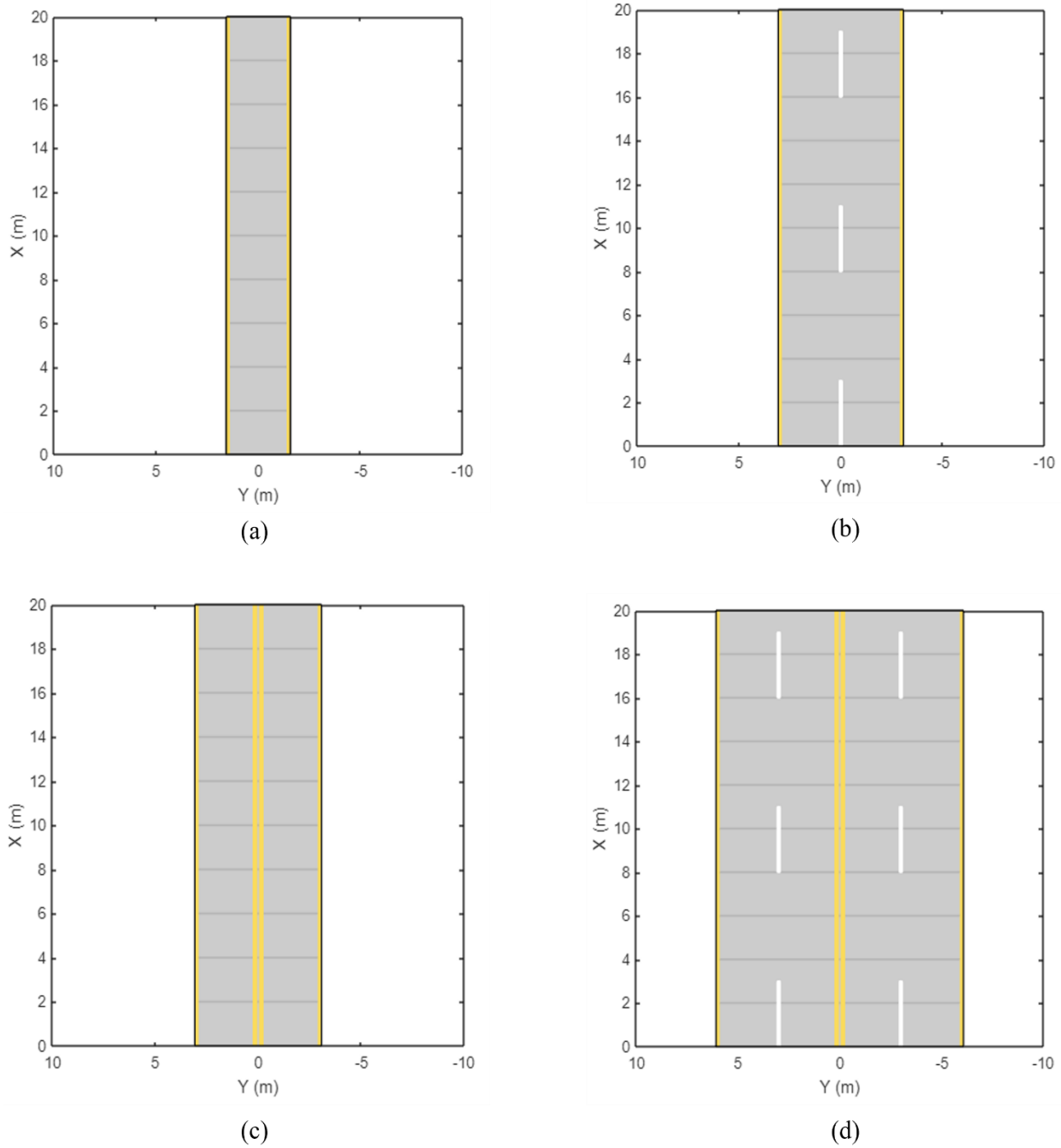
(a)

(b)

(c)

(d)

Fig. 4. Virtual roads developed in MATLAB using driving scenarios application, (a) one-way road (lane), (b) two-lane road not restricted to change lane, (c) two-lane road with restriction to shift to another lane, and (d) Double Lane Road not restricted to lane shift. Double yellow defines the division of two independent lanes.

B.   MATLAB setup

MATLAB is used for modeling neural networks and vehicle dynamics. Training the neural network involves different architecture for a specific type of signal as input/output. Convolutional Neural Network (CNN) is used for image classification and regression, for object detection You Only Look Once (YOLO), and for sequence to label and sequence to sequence Long Short-Term Memory Network (LSTM). Each architect reads and stores information in various formats. In developing neural networks, it is mandatory to download/add plugins to train the neural network.
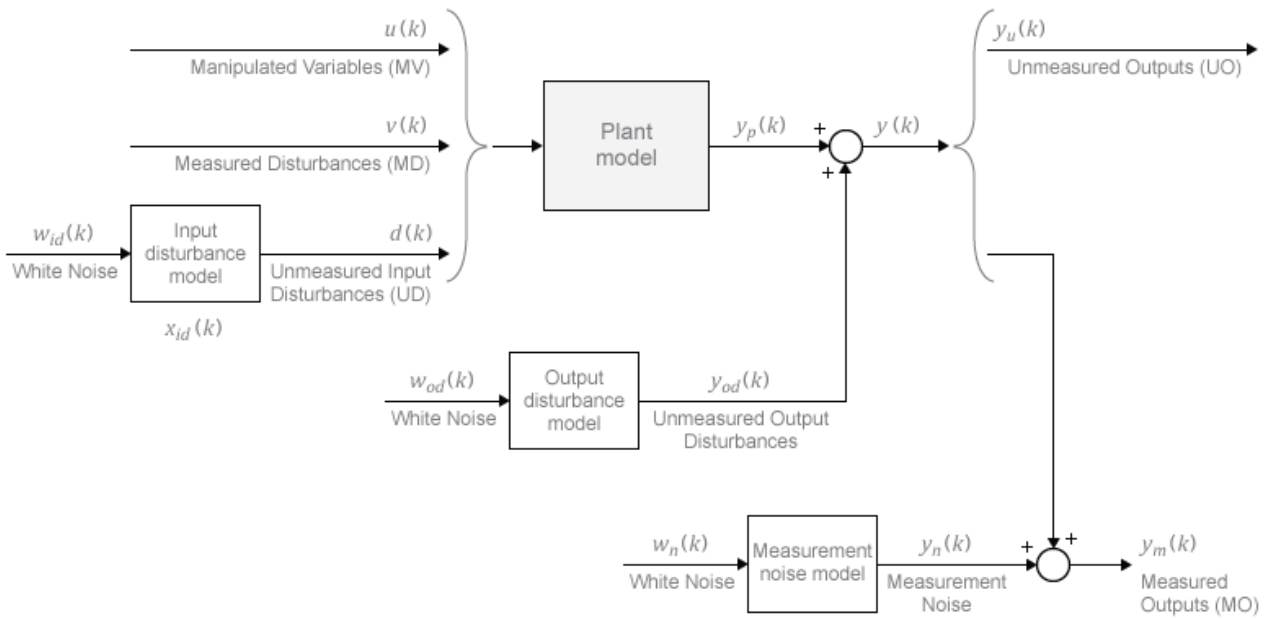
Fig. 5. Model Predictive Controller (MPC) model [22].

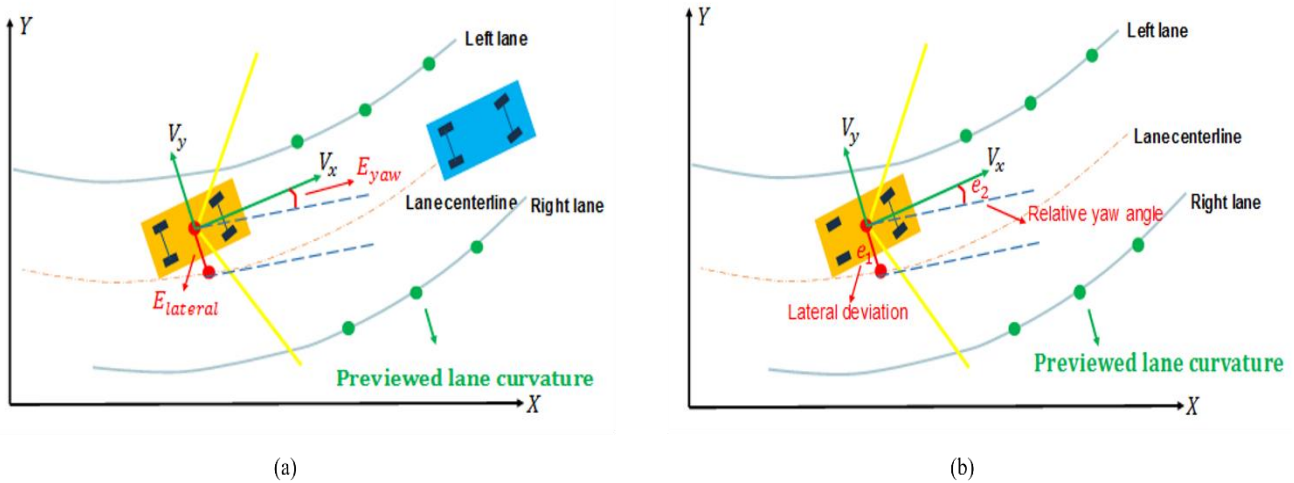(a)   (b)

Fig. 6. Mathematical model, (a) lane following assistance with collision detection [24], and (b) lane-keeping assistance [23].

Convolutional Neural Networks (CNNs) comprise three types of layers (or building blocks): convolution, pooling, and fully connected layers. The first two layers, convolution and pooling extract, features, while the third, a fully linked layer, transfer those features into the final output, such as classification. A convolution layer is an essential part of CNN, which is made up of a stack of mathematical operations like convolution, a specific sort of linear operation. Because a feature can appear anywhere in a digital image, pixel values are stored in a two-dimensional (2D) grid. An array of numbers, and a small grid of parameters called a kernel, an optimizable feature extractor, is applied at each image position. CNNs are highly efficient for image processing. Extracted features can evolve hierarchically and progressively more complicated as one layer feeds its output into the next layer. Training in adjusting parameters like kernels to reduce the disparity between outputs and ground truth labels using optimization algorithms like backpropagation and gradient descent, among others[16]. Video surveillance and sophisticated driver assistance systems use object detection as a crucial component (ADAS). Object detection methods discover and classify items in photos or videos using machine learning, deep learning, or computer vision techniques. Deep neural networks, which can extract more abundant characteristics and combine multi-scale features for identification, are primarily used to improve object detection algorithms[5,17].
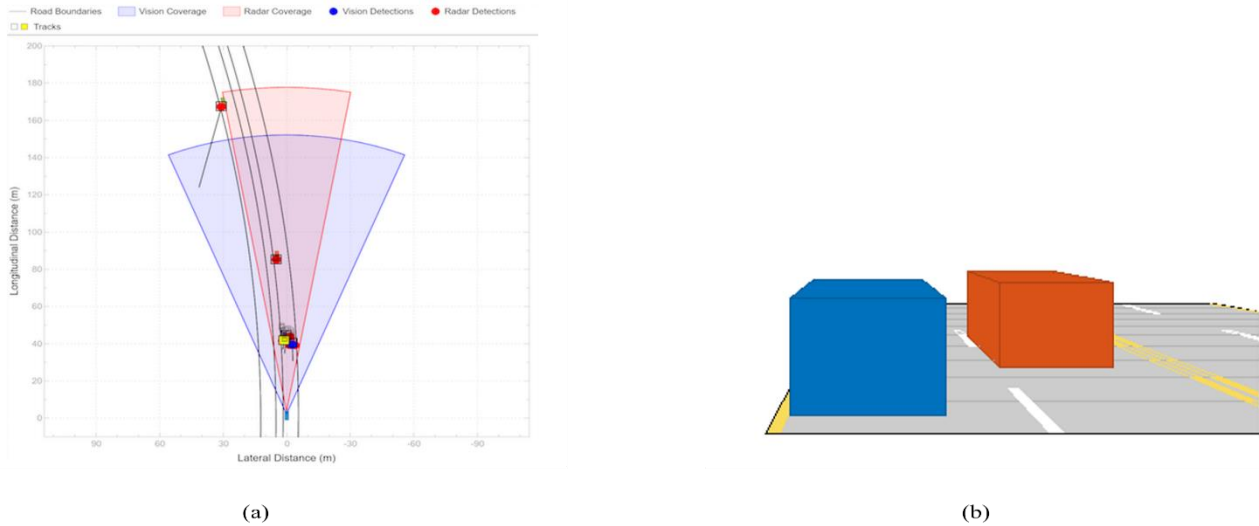
(a) (b)

Fig. 7. (a) Birdseye view [26], and (b) Car chase view (blue and orange block represent the Ego vehicle and lead vehicle, respectively).

A recurrent neural network with a long short-term memory is a form of recurrent neural network (RNN). Because LSTMs can learn long-term connections between time steps of input, they are commonly employed to learn, process, and classify sequential data. Sentiment analysis, language modeling, speech recognition, and video analysis are typical LSTM applications. For training such features, LSTM, which can sustain a long-term memory, is functional [18-20]. Types of sensors are required for autonomous vehicles: visual cameras, Light Detection and Ranging (LIDAR), Radio Detection and Ranging (RADAR), Ultrasonics sensors, odometer, and Global Positioning System (GPS). Fig.3 shows the setup of all these sensors on the vehicle[21]. A model predictive controller estimates the controller state and predicts future plant outputs using linear plant, disturbance, and noise models, as shown in Fig.5. The controller solves a quadratic programming optimization problem using the projected plant outputs[22].
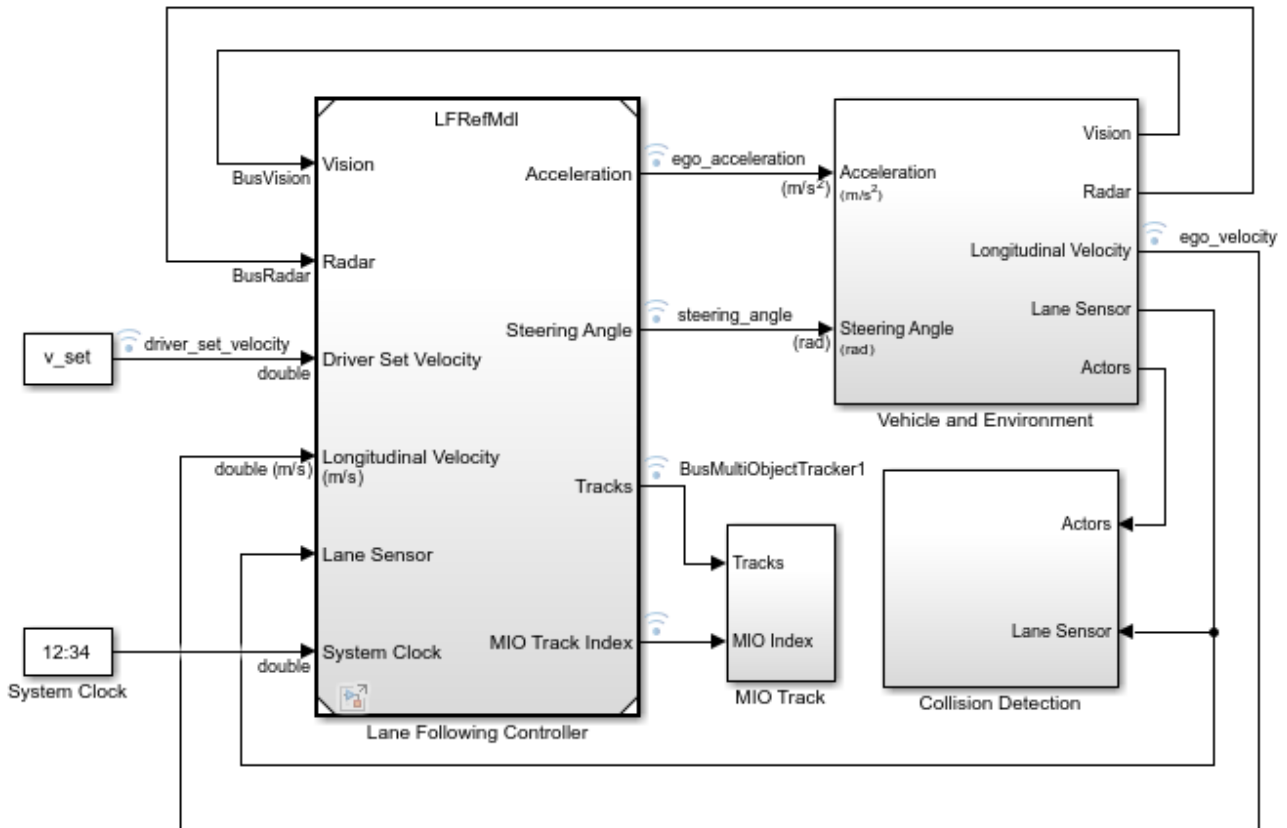

Fig. 8. Simulink setup for lane following and collision detection [23].

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Adopted pre-loaded MATLAB/Simulink example to demonstrate the lane following and lane-keeping assistance model shown in Fig. 6[23,24] and 8[23]. The existing model is configuring to current study assumptions. For example, the ego vehicle has a constant value, and speed will be altered by measuring the lead vehicle distance, steering angle, lateral deviation, and yaw rate functions. Roads are designed in MATLAB using the driving scenario toolbox, and dimensions of the roads and bank angle is taken from[25] in Fig. 4. Fig. 7 represents the (a) Birdseye view [26] and (b) car chase for the current designed road. Speeds of ego as per United Arab Emirates Roads 40, 80, and 120 km/hr. Table. 1 consists of the vehicle dynamics parameter, which is used in simulation to match the physical properties of the vehicle. Section 3 describes the outcomes of this research.

III. RESULTS AND DISCUSSION

A three-set of ego vehicle velocity simulated in MATLAB/Simulink with combined collision-free lane, and other vehicle detection. The simulation consists of three parameters that evaluate the ego vehicles and lead vehicle velocity along with the distance between each other. A set velocity was also assigned to follow the ego vehicle without colliding with the lead vehicle, as shown in Fig. 9. Fig. 7 (a) illustrates the Birdseye view assigned road scenario in the simulation. As shown in fig. 9, the lead vehicle exerted a noise at the beginning of the simulation.
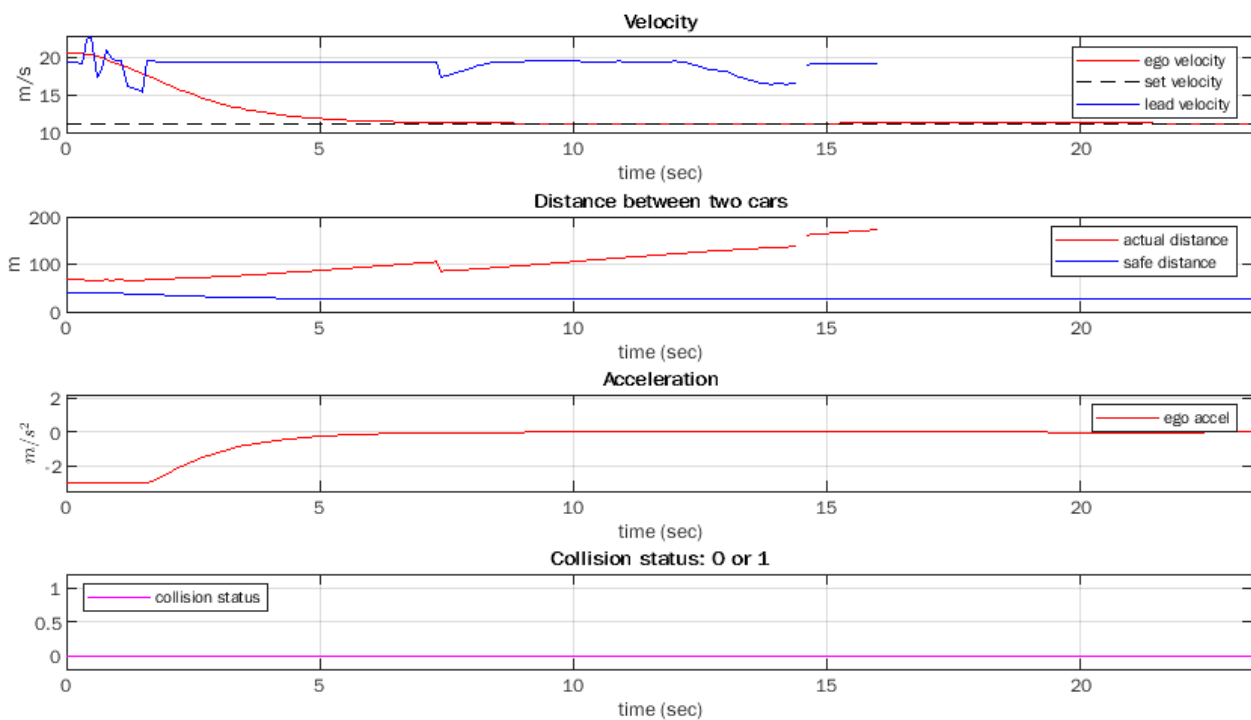

Fig. 9. Ego vehicle velocity with lead vehicle distance and collision detection for a velocity of 40 km/hr.

On the other hand, the ego vehicle exponentially reached the set velocity of 12 m/s from 20 m/s and maintained a steady state until the end of the simulation. However, the ego vehicle failed to maintain a safe distance. Acceleration of the ego vehicle increased exponentially, achieving a steady state. Similarly, an ego vehicle velocity of 80 km/hour results are plotted under similar conditions. The velocity of the ego vehicle is identical to 40 km/hour till 8 seconds of simulation. Later, it dropped the speed to avoid the collision with the leading vehicle in Fig. 10. Again, the velocity increased overtime to reach the set velocity shown in Fig. 10. The distance between both vehicles is much closer than in previous results; however, it failed to maintain a safe distance during the remaining simulation time.

A sinusoidal velocity pattern of the ego vehicle was observed for a speed of 120 km/hour under the same conditions. It reached approximately zero velocity while the vehicle was passing the bank of the road. Overshoot of acceleration appeared for increased velocity, as shown in Fig. 11. At the road bank, the acceleration dropped and increased tremendously over time. However, there is no collision vehicle noted for three velocities.
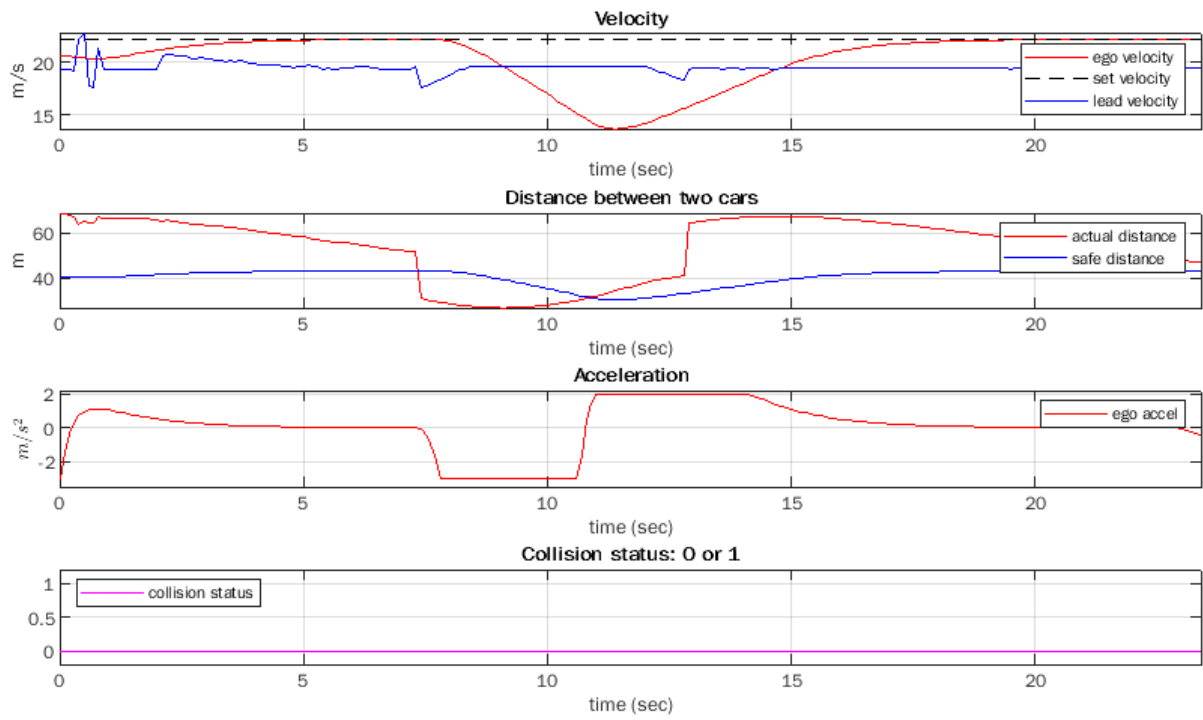
Fig. 10. Ego Vehicle Velocity with Lead Vehicle Distance and Collision Detection for a Velocity of 80 km/hr.
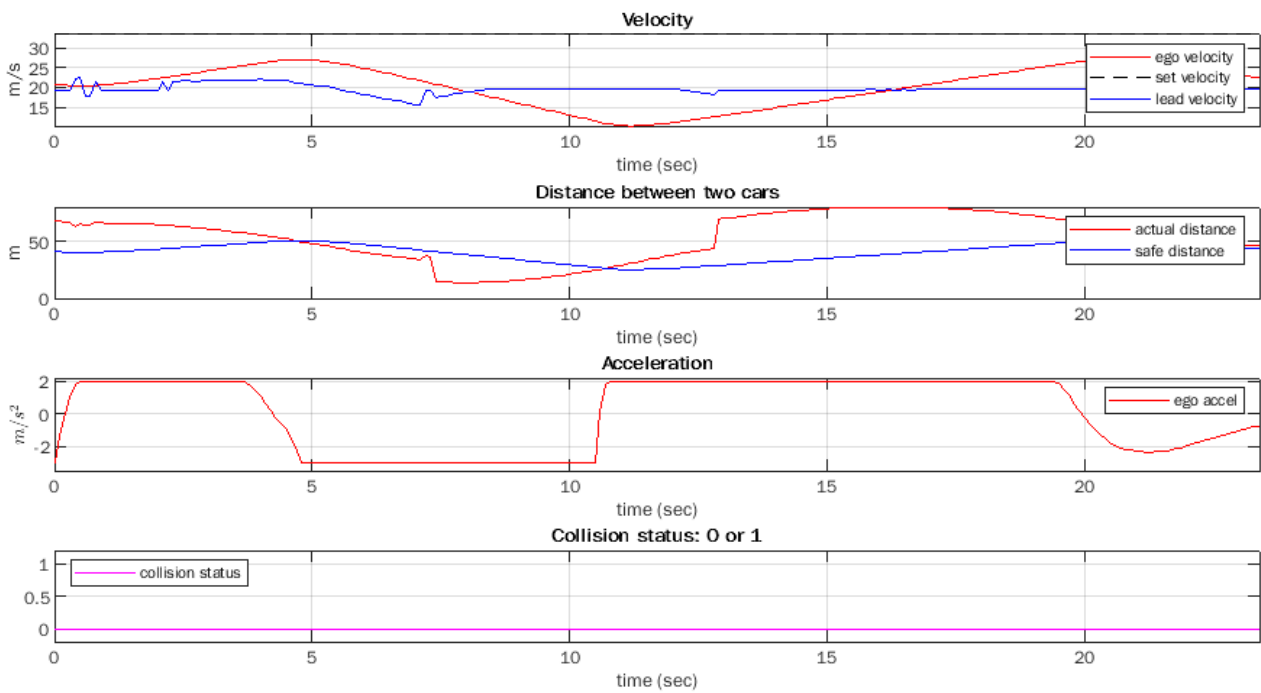

Fig. 11. Ego Vehicle Velocity with Lead Vehicle Distance and Collision Detection for a Velocity of 120 km/hr.

On the other hand, lateral deviation, yaw angle, and steering angle were recorded for 40, 80, and 120 km/hr. For 40 km/hour, the lateral deviation is low and achieved a steady state in 5 seconds of the simulation period. In contrast, steering of a vehicle requires continuous adjustments until the moment the vehicle reaches to set condition. There is a slight rotation required to maintain in the center of the lane during the bank.
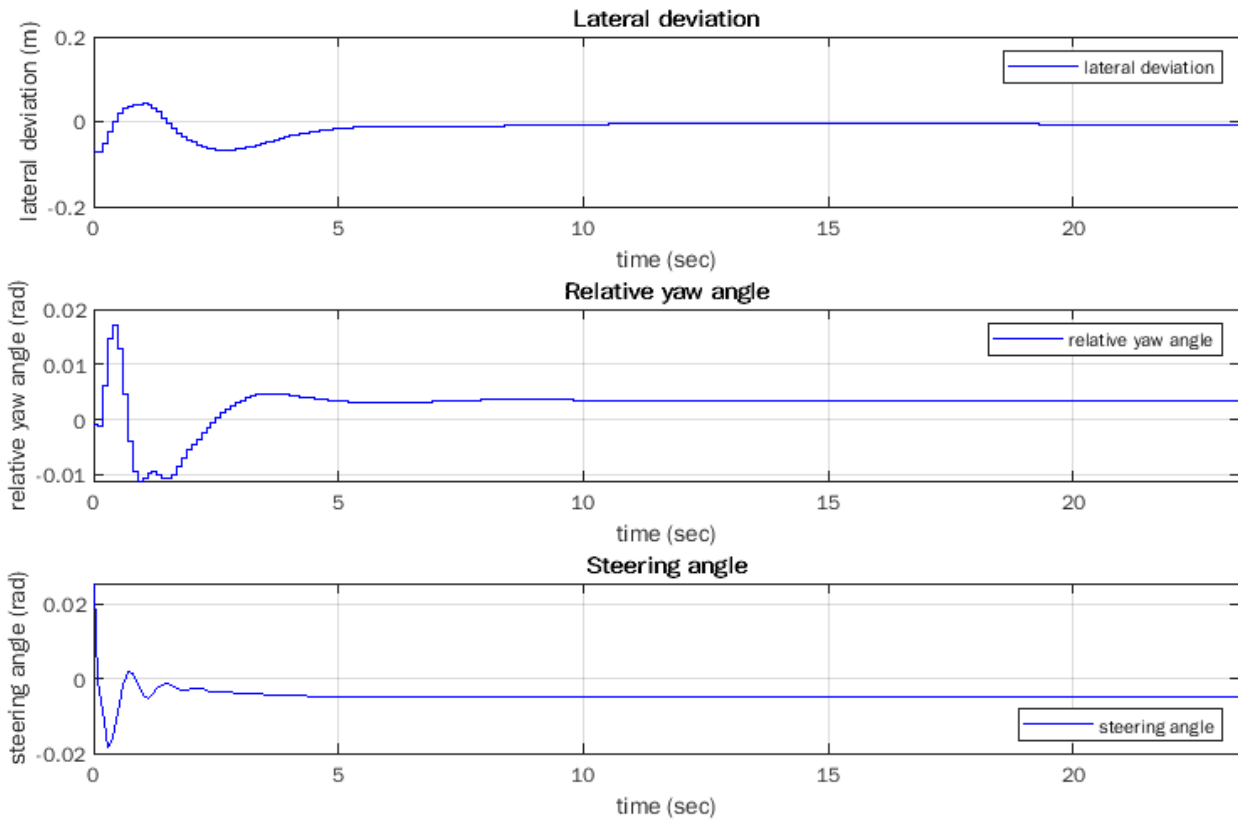
Fig. 12. Lateral Deviation, Relative yaw, and Steering Angle Keep the Ego Vehicle in the Center of the Driving Lane for a Velocity of 40 km/hr.

Fig. 13. Lateral Deviation, Relative Yaw, and Steering Angle Keep the Ego Vehicle in the Center of the Driving Lane for a Velocity of 80 km/hr.

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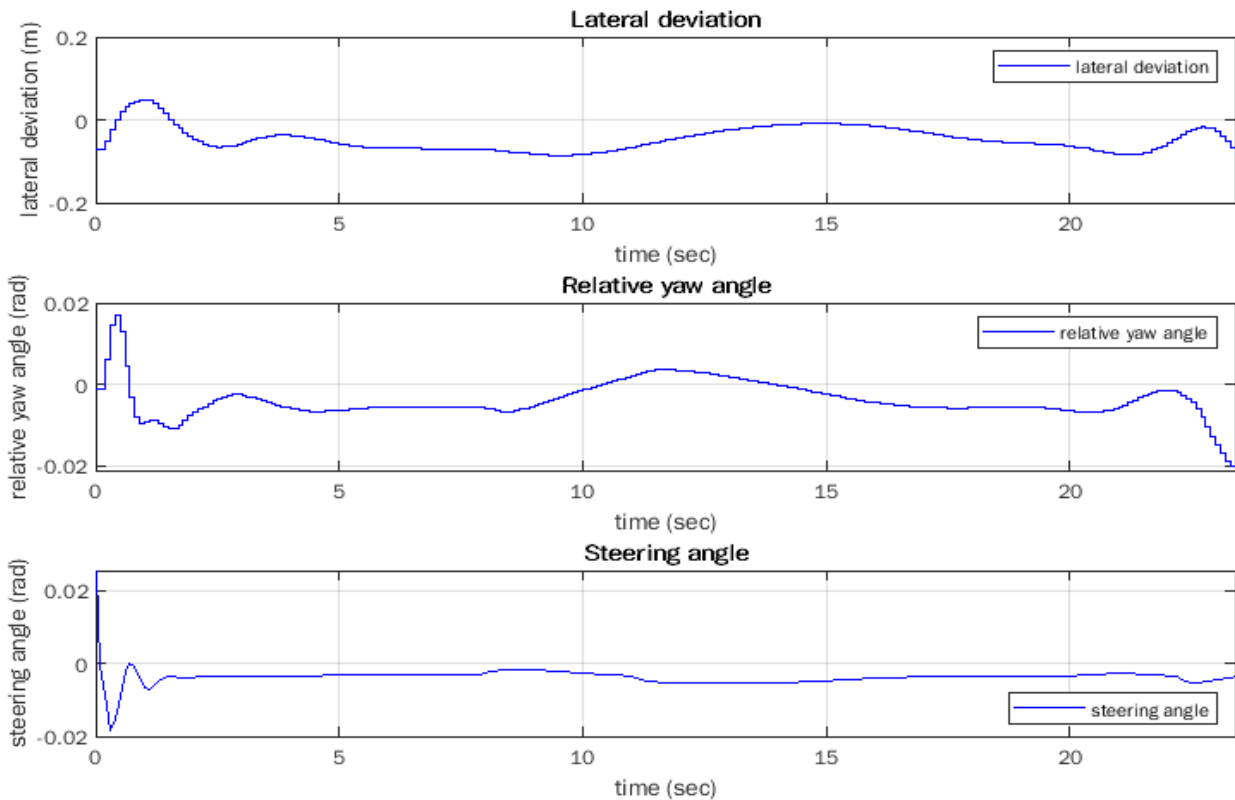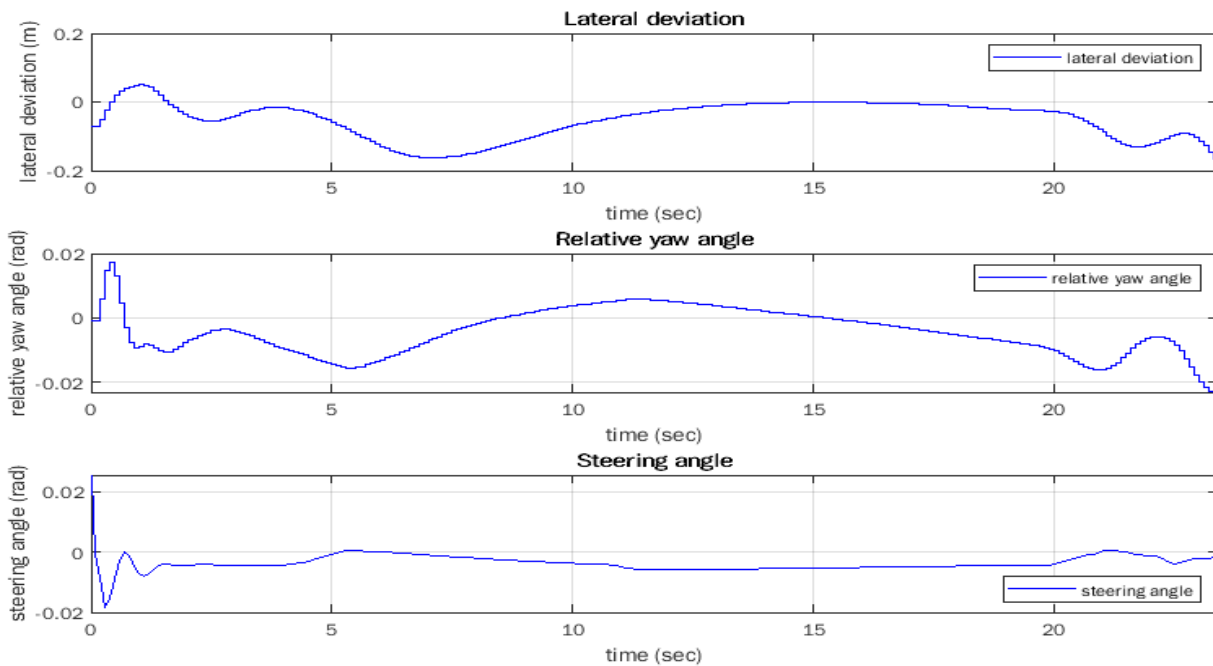**Fig. 14. Lateral Deviation, Relative Yaw, and Steering Angle Keep the Ego Vehicle in the Center of the Driving Lane for a Velocity of 120 km/hr.**

Additionally, the comparison of 80 and 120 km/hour lateral deviation of both velocities follow a similar pattern to each other. However, it's hard to maintain the vehicle trajectory to the center of the lane for 120 km/hour, as shown in Fig. 12-13. Likewise, there is an offset of yaw rate and steering angle for 80 and 120 km/hour.

IV. CONCLUSION

In this paper, a virtually developed autonomous car simulated using MATLAB/Simulink. Simulation comprises of lane assistance and collision-free trajectory with sensors for four-wheel vehicle parameters. The following are the outcomes of the simulation.

1. The ego vehicle followed the trajectory with minimal lateral deviation.
2. Sensors detected the lead vehicles, right and left vehicles, moving in the same direction.
3. Acceleration and velocity of ego vehicle achieved similar results as in real life to decrease the speed passing curve road or bank road.

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Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material/ Data Access Statement	Not relevant.
Authors Contributions	All authors having equal contribution for this article.

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