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16. Abstract

Freight traffic, particularly when it's significant in proportion, affects the performance of the road network in a more sensitive and significant way compared to other types of traffic, in the aspects of mobility, environment, and safety due to the complexity of characteristics of the resulting mixed-class traffic. Trucks need extra distance and time for deceleration and acceleration, and their interactions with conventional vehicles can present more uncertainty to the traffic due to their lengths and speeds. Therefore, a traffic bottleneck appears more easily on a road segment or intersection where freight traffic is significant. Therefore, the research insight into the control and operation of significant freight traffic is necessary. It has been shown in the research of FMRI's first-year project that the coordination of signals fails when the demand is composed of a large portion of trucks. Strategies have been developed in the FMRI second-year project to formulate multiple trucks' trajectories to pass consecutive signals individually and cooperatively considering mixed traffic conditions. The stability problem of vehicle streams has been studied in the third-year project.

With the development of artificial intelligence technologies, intelligent agents can learn from historical experiences by exploring the knowledge in their environment. Some researchers have implemented neural network-based methods to learn driving behaviors. A research question is: Other than applying active control, as we did in the previous research, is it possible for autonomous vehicles to learn from the experiences, while keeping safety and one step further, reaching the optimal performances in our concerned scenarios? Compared to automated controllers that have been widely developed, AI algorithms have seldom been studied due to their computation speed and the black-box structure that has not been widely validated in vehicle control. Aside from on the freeway, the performance under different traffic scenarios has not been analyzed. Therefore, looking for insight into the algorithm is valuable work, and a piece of exploratory research is proposed to operate vehicles (trucks) using artificial intelligence technologies. The research has developed a model to provide trajectories given initial status for trucks through a neural network-based model, and the experience for the learning is from the results of optimized models we have developed so far. The well-trained AI model lets trucks drive with trajectories that are close to optimal control trajectories and ensures collision avoidance for all the vehicles

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ARTIFICIAL INTELLIGENCE DESIGN FOR TRUCKS PASSING SIGNALIZED INTERSECTIONS ALONG A CORRIDOR WITH SIGNIFICANT FREIGHT TRAFFIC

Final Report

by

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EXCUTIVE SUMMARY

Freight traffic, particularly when it's significant in proportion, affects the performance of the road network in a more sensitive and significant way compared to other types of traffic, in the aspects of mobility, environment, and safety due to the complexity of characteristics of the resulting mixed-class traffic. Trucks need extra distance and time for deceleration and acceleration, and their interactions with conventional vehicles can present more uncertainty to the traffic due to their lengths and speeds. Therefore, a traffic bottleneck appears more easily on a road segment or intersection where freight traffic is significant. Therefore, the research insight into the control and operation of significant freight traffic is necessary. It has been shown in the research of FMRI's first-year project that the coordination of signals fails when the demand is composed of a large portion of trucks. Strategies have been developed in the FMRI second-year project to formulate multiple trucks' trajectories to pass consecutive signals individually and cooperatively considering mixed traffic conditions. The stability problem of vehicle streams has been studied in the third-year project.

With the development of artificial intelligence technologies, intelligent agents can learn from historical experiences by exploring the knowledge in their environment. Some researchers have implemented neural network-based methods to learn driving behaviors. A research question is: Other than applying active control, as we did in the previous research, is it possible for autonomous vehicles to learn from the experiences, while keeping safety and one step further, reaching the optimal performances in our concerned scenarios? Compared to automated controllers that have been widely developed, AI algorithms have seldom been studied due to their computation speed and the black-box structure that has not been widely validated in vehicle control. Aside from on the freeway, the performance under different traffic scenarios has not been analyzed. Therefore, looking for insight into the algorithm is valuable work, and a piece of exploratory research is proposed to operate vehicles (trucks) using artificial intelligence technologies. The research has developed a model to provide trajectories given initial status for trucks through a neural network-based model, and the experience for the learning is from the results of optimized models we have developed so far. The well-trained AI model lets trucks drive with trajectories that are close to optimal control trajectories and ensures collision avoidance for all the vehicles.

1. INTRODUCTION

1.1 OVERVIEW

Ensuring the safe and efficient operation of trucks has always been a curial problem, particularly when trucks make a significant portion of the traffic. When solving the problem of trucks approaching signals in an urban street, current methods are to use connected and automated vehicles (CAVs) technology while the controllers are model-based active controllers. However, more solutions are expected especially when Artificial intelligence (AI) technology becomes more mature.

The applications of CAVs or automated vehicles (AVs) in a traffic system have been studied in the last few years. CAVs can react, communicate, or make cooperative decisions regarding the environment such as surrounding vehicles and traffic facilities with the help of vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) communication technologies. Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC) take advantage of the V2V communications so that vehicles can drive at a harmonized speed with short headways, addressing some issues that may occur for HVs such as mobility, fuel efficiency and, safety issues (Wang et al., 2018). When only considering the longitudinal direction, the design of a CACC system is usually based on a vehicle dynamics control strategy. Staring from ACC, vehicle dynamics are modeled by an optimal control framework to maintain speed while reducing emissions. When it comes to CACC, constant longitudinal spacing or headway should also be maintained (Dey et al., 2015) (Xiao et al., 2023). Among all the objectives, the mobility of the traffic, fuel efficiency, and the stability of the traffic are the major concerns (Wang et al., 2018).

In some studies, the platoon of CAVs is usually cooperatively considered. For example, a mixed-integer linear programming (MILP) based model is used to optimize vehicle trajectories as well as the traffic signal at isolated signalized intersections. The trajectories are generated by optimal control, car-following models, and lane choice models (Xiao et al., 2021; Yu et al., 2018). A Predictive Cruise Control method is used to control vehicles when traveling through multiple consecutive intersections to save fuel and CO2 emissions (Asadi and Vahidi, 2010). A nonlinear-programming-based method to control a CAV platoon is designed to pass multiple intersections to maximize throughput and comfort (Liu et al., 2019).

A comprehensive survey by (Rios-Torres and Malikopoulos, 2016) reviewed various approaches to coordinate CAVs at intersections, on-ramps. The methods include both centralized and decentralized techniques, using either heuristic rules or optimization and control algorithms to minimize travel time, fuel consumption, or other metrics. According to a comprehensive survey by (Gholamhosseinian and Seitz, 2022), various strategies for cooperative intersection management has been reviewed including reservation-based approaches, auction-based approaches, and decentralized approaches. Coordination at both signal and non-signal is studied considering a fully cooperative intersection management (CIM) that contributes to both traffic safety and efficiency (Chen and Englund, 2015). The way to model interaction include space and time discretization and trajectory Modeling.

Truck trajectory generation problem has become a widely studied topic so that vehicle drives following a trajectory in difference conditions for the purpose of mobility, safety, and fuel-efficiency etc.

Artificial intelligence-based model can provide trajectories or car following strategies for vehicles regardless of domain knowledge (Naveed et al., 2021). For example LSTM model is developed to predict surrounding vehicle trajectories incorporating the spatial-temporal attention mechanisms (Lin et al., 2021). Imitation learning or inverse reinforcement learning is applied to help with decision making process in AVs (Gao et al., 2018).

The longitudinal control strategies have been developed to improve the mobility to mitigate the stop-and-go waves and other adverse traffic effects on freeways (Li et al., 2021) . Although longitudinal control strategies in the freeway environment have been well studied, the existence of traffic signals in an urban area makes longitudinal control strategies of AV significantly different from those in the freeway environment. Many previous studies concerned the strategies for vehicles approaching an isolated intersection (Kuderer et al., 2015; Tohfeh and Fakharian, 2015; Zhang et al., 2018) .

This research proposes a neural network-based model for the longitudinal trajectories of automated trucks, as an enhancement to or an alternative approach for traditional active control. The information is learned from expert experiences to ensure safety and optimal performance. The expert trajectories are generated from optimal control models that optimize travel time or emission respectively. The output is a well-trained model that generates trajectories for trucks that with small errors compared to trajectories generated by optimal control. Since no real-world data are available, the expert demonstrations data used for training the model is generated from the simulation and the proposed method is also tested in numerical cases.

2. METHODOLOGY

The longitudinal control for CAVs follows a step: the optimal control is applied to generate the expert trajectories for vehicles in scenarios as show in Figure 1. AI technique Neural Network is utilized to learn the expert trajectories and produce new trajectories based on initial status of vehicles.

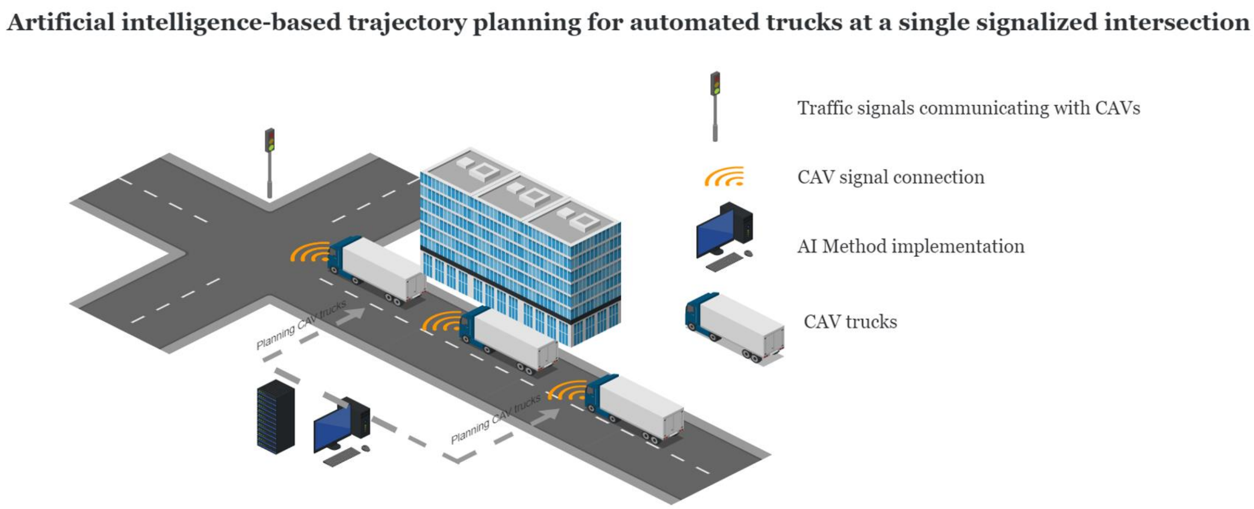

Figure 1 Schematic concept: AV equipped with AI.

2.1 ARTIFICIAL INTELLIGENT DESIGN FOR VEHICLE TRAJECTORIES

The proposed approach integrates optimal control, AI, and traffic flow modeling to develop an intelligent system for managing vehicle traffic. Figure 2 illustrates the framework of methodology, which consists of three main components:

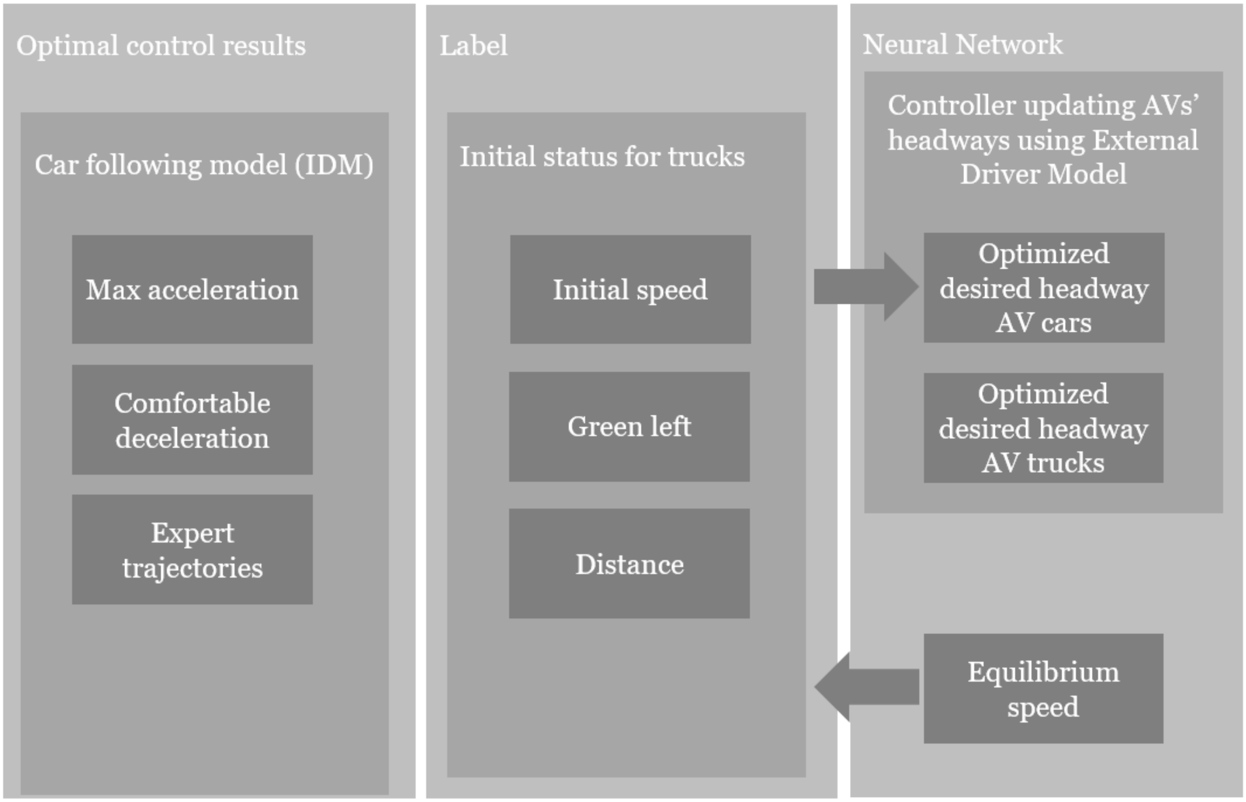

Figure 2 Flow chart of the research scope and methodology

1. Optimal Control Results This component utilizes a car-following optimal control model. It incorporates:
    - Maximum acceleration: Defining the upper limit of vehicle acceleration
    - Comfortable deceleration: Ensuring passenger comfort during braking
    - Expert trajectories: Pre-computed optimal paths for vehicles
2. Label Generation This stage prepares the input data for the neural network. It considers the initial status for trucks, including:
    - Initial speed: The velocity of the truck at the start of the scenario
    - Green left: The remaining time of the green signal phase
    - Distance: The initial position of the truck relative to the intersection
3. Neural Network The core of the system is a neural network that acts as a controller for updating the headways of Autonomous Vehicles (AVs). It processes the following:
    - Inputs: Initial status for trucks (from the Label component)
    - Outputs: New trajectories

For expert trajectory generation, optimal control method is formulated. When an individual vehicle is traveling within one block between two intersections, its state including position and speed is known. The problem is decomposed into different scenarios and is then scaled towards multiple vehicles along consecutive intersections. The constraints from the longitudinal position and feasible arrival moments of a vehicle with the presence of signals are mathematically described.

The system writes with a linear time-invariant system (LTI):

$$x_{n,i}(t) = Ax_{n,i}(t) + Bu_{n,i}(t) \tag{1}$$

$$\mathrm{A} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \mathrm{B} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \tag{2}$$

where the control variable $u_{n,i}$ is the acceleration of the vehicle. The cost function to ensure optimal performances is defined as follows considering the comfort and terminal performances:

$$J_{n,i} = \min \int_{t=0}^{T_{n,i}} L\left(x_{n,i}(t), u_{n,i}(t)\right) dt + \Phi\left(T_{n,i}, x_{n,i}(T_{n,i})\right) \tag{3}$$

where the ending time or the control horizon $T_{n,i}$ is a variable which is determined systematically. It is then discussed in 3.2, based on different scenarios. The running cost is set as an instantaneous cost showing the penalties concerning comfort. It is expressed as the quadratic term of acceleration.

$$L = \frac{1}{2} {u_{n,i}}^2 \tag{4}$$

The terminal cost gives penalties so that the final states can approach desired values (terminal speed and terminal distance).

$$\Phi = w_1\left({x_{n,i}}^{(1)}(T_{n,i}) - {l^*}_{n,i}\right)^2 + w_2\left({x_{n,i}}^{(2)}(T_{n,i}) - {v^*}_{n,i}\right)^2 \tag{5}$$

Again, $T_{k,i}$ will be determined systematically. Weighing factors w_1 and w_2 show the penalty for the state deviation from the terminal speed and the terminal distance at the end of the horizon.

2.2 EXPERT TRAJECTORY GENERATION SOLUTION

The desired speed is set the terminal speed at each intersection for each vehicle ${v^*}_{n,i} = v_0$. The block length between two intersections is used as terminal distance ${l^*}_{n,i} = l_i$.The problem then writes:

$$J_{n,i} = \sum_{K=1}^{T} \left({u_{n,i_{t+k-1}}}^2 \right) + w_1 \left({{x_{n,i}}^{(2)}}_T^{\ 2} - 2{{x_{n,i}}^{(2)}}_T {v_{n,i}}^* + {v_{n,i}}^{*2} \right) + w_2 \left({{x_{n,i}}^{(1)}}_T^{\ 2} - 2{{x_{n,i}}^{(1)}}_T l^* + {l_{n,i}}^{*2} \right) \tag{6}$$

s.t.

$$\left(x_{n,i}, u_{n,i}\right) \in \Omega \cap U \tag{7}$$

Ω represents the constraints from vehicle dynamics, including the limitation from maximal speed, maximal acceleration, distance, etc. U represents the physical constraints from the preceding vehicle during the period when it follows preceding vehicle $f_{n,i}$.

$$\Omega = \left\{x_{n,i_{t+1}} = A_d x_{n,i_t} + B_d u_{n,i_t}, u_{n,i_t} \in \left(u_{n,i,lb}, u_{n,i,ub}\right), x_{n,i}{}^{(1)} \in (0, l_i), x_{n,i}{}^{(2)} \in \left(v_{n,i,lb}, v_{n,i,ub}\right)\right\} \tag{8}$$

$$U = \left\{s_{n,i} \leq s_{n-1,i} + d_s + d_v, t \in (0, f_{n,i})\right\} \tag{9}$$

where d_s is a safe distance that can ensure safety and d_v is the vehicle length; $f_{n,i}$ is the duration of following, determined differently in different scenarios in upper-level control.

The linearly constrained LQ (linear quadratic) optimal control problems are converted to discrete versions and solved by quadratic programming. The objective function becomes:

$$J = \frac{1}{2} \sum_{K=1}^{T} x_{t+k}^T Q_{t+k}\, x_{t+k} + u_{t+k-1}^T R_{t+k} u_{t+k-1} + x_N^T Q_N x_N \tag{10}$$

Matrices Q, Q_N and R are diagonal matrices to ensure the positive-definiteness. They are set as

$$Q = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}, R = 1, Q_N = \begin{pmatrix} w_1 & 0 \\ 0 & w_2 \end{pmatrix} \tag{11}$$

The optimal control problem is implemented in linearly constrained LQ (linear quartic) optimal control problem on the affine subspace in a discrete time system. the parameters of original LTI system is transferred as their discrete version and the objective function is:

$$\min J_1 = \sum_{K=1}^{t_P} x_{t+k}^T Q_{t+k}\, x_{t+k} + u_{t+k-1}^T R_{t+k} u_{t+k-1} + x_N^T Q_N x_N$$

$$= \sum_{K=1}^{t_P} \frac{1}{2} \left(u_{t+k-1}{}^2 + w_1 x_{2,t+k} u_{t+k-1}\right) + w_2\left(x^2{}_{2_T} - 2x_{2_T} v^* + v^{*2}\right) + w_3\left(x^2{}_{1_T} - 2x_{1_T} L^* + L^{*2}\right)$$

matrices Q and R are diagonal matrices to ensure the positive-definiteness.
s.t.

$$(x, u) \in \Omega \cap U$$

where
$\Omega = \{(x,u) satisfying\ x_{t+1} = A_d x_t + B_d u_t\}$

$$U = \begin{cases} (d_{t+i}{}^j) x_{t+i} \leq c_i{}^j \\ u_t \in (u_{lb}, u_{ub}) \end{cases}$$

Defining y = $\left[x_{1,t+1}, \ldots, x_{1,t+t_P}, x_{2,t+1}, \ldots, x_{2,t+t_P}, u_{2,t+1}, \ldots, u_{2,t+t_P}\right]^T$

and defining a quadratic cost function in the objectivations, the problem is transferred to a quartic programming. (in appendix A)
In the quartic programming, the matrixes are formulated as follows:
Hessian matrix H=

$$\begin{bmatrix} \begin{matrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & w_3 \end{matrix} & 0 & 0 \\ 0 & \begin{matrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & w_2 \end{matrix} & \begin{matrix} \frac{1}{4}w_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \frac{1}{4}w_1 \end{matrix} \\ 0 & \begin{matrix} \frac{1}{4}w_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \frac{1}{4}w_1 \end{matrix} & \begin{matrix} \frac{1}{2} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \frac{1}{2} \end{matrix} \end{bmatrix}$$

$$\mathrm{C} = [\underbrace{0, \ldots 0, -2w_3L^*}_{p}\ \underbrace{0, \ldots 0, -2w_2v^*}_{p}\ \underbrace{0, \ldots 0}_{p}]$$

A= $\begin{bmatrix} 0 & \cdots & 0 & 1 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & 0 & \cdots & 1 & 0 & \cdots & 0 \\ 0 & \cdots & 0 & -1 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & 0 & \cdots & -1 & 0 & \cdots & 0 \\ 0 & \cdots & 0 & 0 & \cdots & 0 & 1 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 1 \\ 0 & \cdots & 0 & 0 & \cdots & 0 & -1 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & -1 \end{bmatrix}$ and B= $\begin{bmatrix} \left.\begin{matrix} x_{2,ub} \\ \vdots \\ x_{2,ub} \end{matrix}\right\} p \\ \left.\begin{matrix} x_{2,lb} \\ \vdots \\ x_{2,lb} \end{matrix}\right\} p \\ \left.\begin{matrix} u_{ub} \\ \vdots \\ u_{ub} \end{matrix}\right\} p \\ \left.\begin{matrix} u_{lb} \\ \vdots \\ u_{lb} \end{matrix}\right\} p \end{bmatrix}$

Aeq= $\begin{bmatrix} 1 & 0 & \ldots & 0 & 0 & 0 & \ldots & 0 & 0 & 0 & \ldots & 0 \\ 0 & 0 & \ldots & 0 & 1 & 0 & \ldots & 0 & 0 & 0 & \ldots & 0 \\ 0 & 0 & \ldots & 0 & 0 & 0 & \ldots & 0 & 1 & 0 & \ldots & 0 \\ -a_{11} & 1 & \ldots & 0 & -a_{12} & 0 & \ldots & 0 & -b_1 & 0 & \ldots & 0 \\ 0 & -a_{11} & 1 & 0 & 0 & -a_{12} & 0 & 0 & 0 & -b_1 & 0 & 0 \\ \vdots & 0 & -a_{11} & 1 & \vdots & 0 & -a_{12} & 0 & \vdots & 0 & -b_1 & 0 \\ 0 & \ldots & 0 & 0 & 0 & \ldots & 0 & 0 & 0 & \ldots & 0 & 0 \\ -a_{21} & 0 & \ldots & 0 & -a_{22} & 1 & \ldots & 0 & -b_2 & 0 & \ldots & 0 \\ 0 & -a_{21} & 0 & 0 & 0 & -a_{22} & 1 & 0 & 0 & -b_2 & 0 & 0 \\ \vdots & 0 & -a_{21} & 0 & \vdots & 0 & -a_{22} & 1 & \vdots & 0 & -b_2 & 0 \\ 0 & \ldots & 0 & 0 & 0 & \ldots & 0 & 0 & 0 & \ldots & 0 & 0 \end{bmatrix}$ and Beq= $\begin{bmatrix} initial\_s \\ initial\_v \\ initial\_u \\ \left.\begin{matrix} 0 \\ \vdots \\ 0 \end{matrix}\right\} p \\ \left.\begin{matrix} 0 \\ \vdots \\ 0 \end{matrix}\right\} p \end{bmatrix}$

The model predictive control problem can be implemented in linearly constrained LQ (linear quartic) problem on the affine subspace in a discrete time system. the parameters of original LTI system is transferred as their discrete version and the objective function is:

$$\min J_2 = \sum_{K=1}^{t_P} x_{t+k}^T Q_{t+k} x_{t+k} + u_{t+k-1}^T R_{t+k} u_{t+k-1}$$

Where $Q_{t+k} = \begin{bmatrix} \alpha_{1,t+k} & 0 \\ 0 & \alpha_{2,t+k} \end{bmatrix}$ and $R_{t+k} = \beta_{t+k}$

$$= \sum_{K=1}^{t_P} \alpha_{1,t+k}(\mathrm{s}_{t+k} - s^*{}_{t+k})^2 + \alpha_{2,t+k}\,\Delta \mathrm{v}_{t+k}{}^2 + \beta_{t+k} u_{t+k-1}{}^2$$

s.t.`

$$(x, u) \in \Omega \cap U$$

where

$\Omega = \{(x, u) satisfying\ x_{t+1} = A_d x_t + B_d u_t\}$

$$\begin{cases} \left(d_{t+i}{}^j\right) x_{t+i} \leq c_i{}^j \\ u_t \in (u_{lb}, u_{ub}) \end{cases}$$

Defining a new variable in quartic programming, y =

$[s_{t+1}, \dots, s_{t+t_P}, s^*{}_{t+1}, \dots, s^*{}_{t+tp}, \Delta v_{t+1}, \dots, \Delta v_{t+t_P}, u_{t+1}, \dots, u_{t+t_P}]^T$

In the quartic programming, the matrixes are formulated as follows:

Hessian matrix H=

$$\begin{bmatrix}
\begin{matrix} \alpha_{1,t+1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \alpha_{1,t+k} \end{matrix} & \begin{matrix} -\alpha_{1,t+1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & -\alpha_{1,t+1} \end{matrix} & \begin{matrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{matrix} & \begin{matrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{matrix} \\
\begin{matrix} -\alpha_{1,t+1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & -\alpha_{1,t+1} \end{matrix} & \begin{matrix} \alpha_{1,t+1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \alpha_{1,t+k} \end{matrix} & \begin{matrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{matrix} & \begin{matrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{matrix} \\
\begin{matrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{matrix} & \begin{matrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{matrix} & \begin{matrix} \alpha_{2,t+1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \alpha_{2,t+k} \end{matrix} & \begin{matrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{matrix} \\
\begin{matrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{matrix} & \begin{matrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{matrix} & \begin{matrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{matrix} & \begin{matrix} \beta_{t+1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \beta_{t+k} \end{matrix}
\end{bmatrix}$$

$$\mathrm{C} = [\underbrace{0, \dots 0{,}0}_{p}\ \underbrace{0, \dots 0{,}0}_{p}\ \underbrace{0, \dots 0}_{p}\ \underbrace{0, \dots 0}_{p}]$$

$$
A=\begin{bmatrix}
1 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0\\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots\\
0 & \cdots & 1 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0\\
-1 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0\\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots\\
0 & \cdots & -1 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0\\
0 & \cdots & 0 & 1 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0\\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots\\
0 & \cdots & 0 & 0 & \cdots & 1 & 0 & \cdots & 0 & 0 & \cdots & 0\\
0 & \cdots & 0 & -1 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0\\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots\\
0 & \cdots & 0 & 0 & \cdots & -1 & 0 & \cdots & 0 & 0 & \cdots & 0\\
0 & \cdots & 0 & 0 & \cdots & 0 & 1 & \cdots & 0 & 0 & \cdots & 0\\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots\\
0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 1 & 0 & \cdots & 0\\
0 & \cdots & 0 & 0 & \cdots & 0 & -1 & \cdots & 0 & 0 & \cdots & 0\\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots\\
0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & -1 & 0 & \cdots & 0\\
0 & \cdots & 0 & 0 & \cdots & 0 & 1 & \cdots & 0 & 1 & \cdots & 0\\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots\\
0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 1 & 0 & \cdots & 1\\
0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & -1 & \cdots & 0\\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots\\
0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & -1
\end{bmatrix}
\quad \text{and} \quad
B=\begin{bmatrix}
\left.\begin{matrix} s_{ub}\\ \vdots\\ s_{ub}\end{matrix}\right\}p\\
\left.\begin{matrix} s_{lb}\\ \vdots\\ s_{lb}\end{matrix}\right\}p\\
\left.\begin{matrix} {s_{ub}}^*\\ \vdots\\ {s_{ub}}^*\end{matrix}\right\}p\\
\left.\begin{matrix} {s_{lb}}^*\\ \vdots\\ {s_{lb}}^*\end{matrix}\right\}p\\
\left.\begin{matrix} \Delta v_{ub}\\ \vdots\\ \Delta v_{ub}\end{matrix}\right\}p\\
\left.\begin{matrix} \Delta v_{lb}\\ \vdots\\ \Delta v_{lb}\end{matrix}\right\}p\\
\left.\begin{matrix} u_{ub}\\ \vdots\\ u_{ub}\end{matrix}\right\}p\\
\left.\begin{matrix} u_{lb}\\ \vdots\\ u_{lb}\end{matrix}\right\}p
\end{bmatrix}
$$

$$
Aeq=\begin{bmatrix}
1 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0\\
0 & 0 & \dots & 0 & 1 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0\\
0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 1 & 0 & \dots & 0 & 0 & 0 & \dots & 0\\
0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 1 & 0 & \dots & 0\\
-a_{11} & 1 & \dots & 0 & a_{11} & -1 & \dots & 0 & -a_{21} & 1 & \dots & 0 & -b_1 & 1 & \dots & 0\\
0 & -a_{11} & 1 & 0 & 0 & a_{11} & -1 & 0 & 0 & -a_{21} & 1 & 0 & 0 & -b_1 & 1 & 0\\
\vdots & 0 & -a_{11} & 1 & \vdots & 0 & a_{11} & -1 & \vdots & 0 & -a_{21} & 1 & \vdots & 0 & -b_1 & 1\\
0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0\\
-a_{21} & 0 & \dots & 0 & a_{21} & 1 & \dots & 0 & 0 & 0 & \dots & 0 & -b_2 & 1 & \dots & 0\\
0 & -a_{21} & 0 & 0 & 0 & a_{21} & 1 & 0 & 0 & 0 & \dots & 0 & 0 & -b_2 & 1 & 0\\
\vdots & 0 & -a_{21} & 0 & \vdots & 0 & a_{21} & 1 & 0 & 0 & \dots & 0 & \vdots & 0 & -b_2 & 1\\
0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & \dots & 0 & 0 & \dots & 0 & 0
\end{bmatrix} \text{and}
$$

$$
Beq=\begin{bmatrix}
initial\_\mathrm{rs}\\
initial\_s^*\\
initial\_\mathrm{rv}\\
initial\_u\\
\left.\begin{matrix} 0\\ \vdots\\ 0\end{matrix}\right\}p\\
\left.\begin{matrix} 0\\ \vdots\\ 0\end{matrix}\right\}p
\end{bmatrix}
$$

3. EXPERIMENTS AND RESULTS

3.1 AI METHOD DEVELOPMENT

This part applies a Neural network model for vehicle trajectories at signalized intersections using the concept of imitation learning. The methodology consists of four main components: data generation to get expert trajectories, model architecture, training process, and evaluation.

1. Data Generation

A custom trajectory generator was implemented to create a diverse dataset of vehicle trajectories. The generator considers the following parameters:

- MAX_SPEED
- MAX_ACCELERATION
- MAX_DECELERATION
- SIGNAL_DURATION

TIME_STEP is set as 1 s. The expert trajectory function simulates vehicle movement based on initial conditions and signal timing. The generate_dataset function creates 1000 trajectories with randomized initial distances (0-400 m), initial speeds (15-30 m/s), and remaining green signal durations (10-30 s).

2. Model Architecture

A feed-forward neural network was designed using the Keras framework. The architecture consists of:

- Input layer: 4 neurons (initial distance, initial speed, signal green time left, time step)
- 4 hidden layers: 256 neurons each, with ReLU activation
- Dropout layers: 20% dropout rate after each hidden layer
- Output layer: 1 neuron (predicted distance)

The model uses mean squared error (MSE) as the loss function and the Adam optimizer with a learning rate of 0.001.

3. Training Process

The training process involves the following steps:

a) Data preprocessing: Input features are normalized. b) Model compilation: The neural network is compiled with the specified architecture and hyperparameters. c) Early stopping: To prevent overfitting, early stopping is implemented with a patience of 10 epochs. d) Training: The model is trained for a maximum of 200 epochs with a batch size of 64.

4. Evaluation

The trained model is evaluated using the following methods:

a) Visual comparison: True and predicted trajectories are plotted for 10 different scenarios with varying initial conditions. b) Error metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) are calculated for each scenario and averaged across all scenarios. c) Error distribution: A histogram of prediction errors is plotted to visualize the error distribution.

3.2 RESULTS AND SUGGESTIONS

Results present generated longitudinal trajectories of automated trucks (Predicted Trajectory), trained on expert demonstrations (True Trajectory) derived from optimal control models.

Table 1 Initial status of vehicles Case 1

MAX_SPEED (m/s)	10
MAX_ACCELERATION(m/s^2)	2
MAX_DECELERATION (m/s^2)	2
TIME_STEP (sec)	1
SIGNAL_DURATION (sec)	30

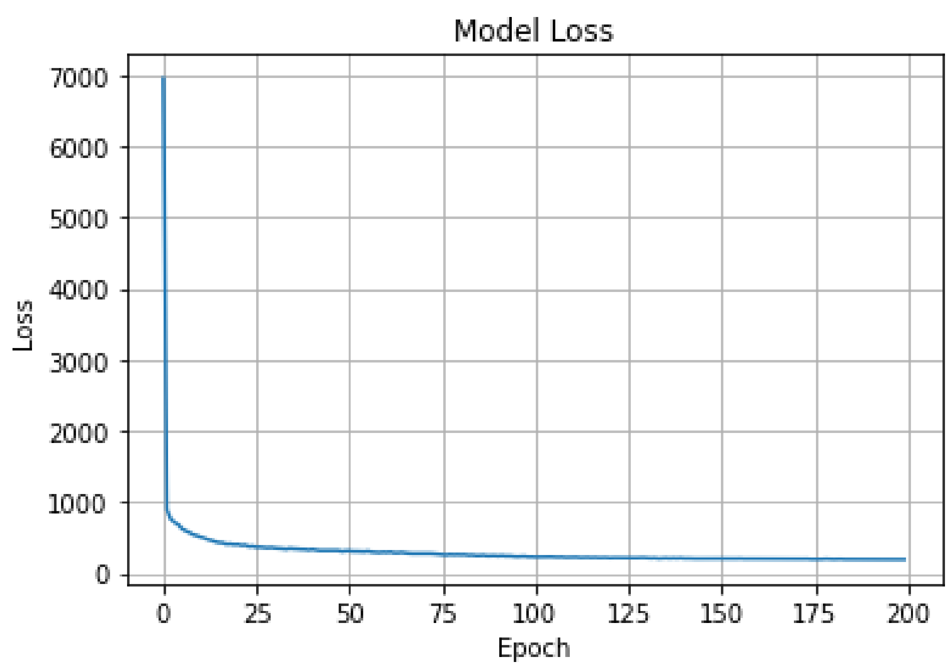

Figure 3 Model loss Case 1

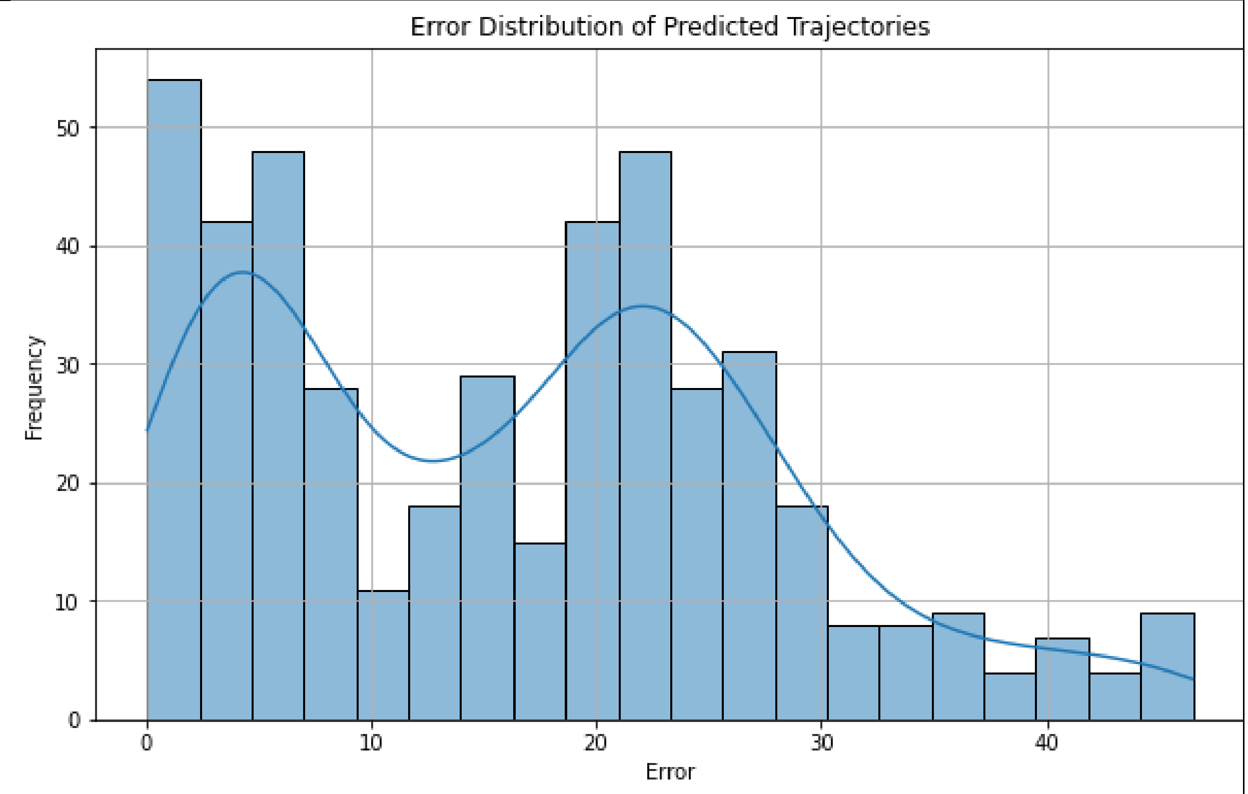

Figure 4 Error distribution of vehicle trajectories Case 1

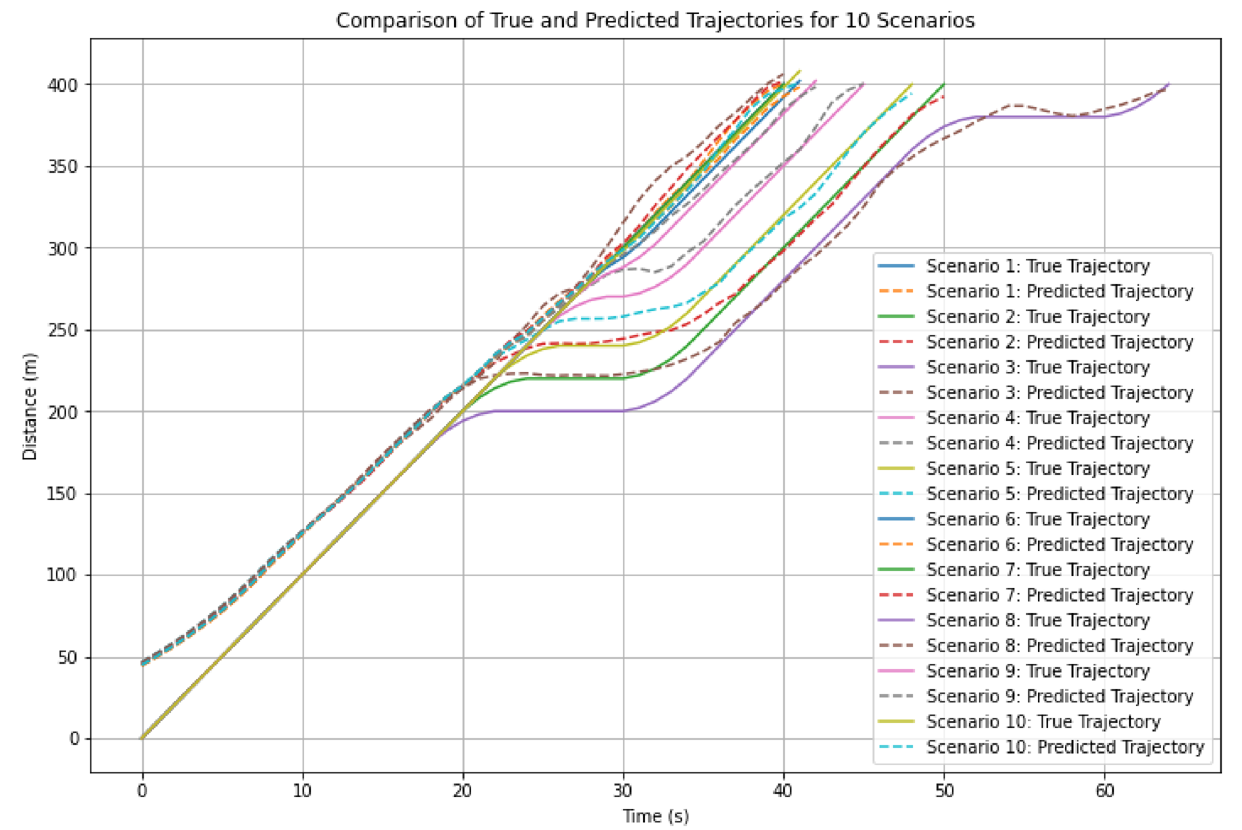

Figure 5 Trajectory generated and their true counterparts Case 1

These results demonstrate the model's ability in expert-generated trajectories under various conditions. The model's performance was evaluated across 10 distinct scenarios, with the following average errors:

Average Mean Absolute Error (MAE): 16.42
Average Root Mean Squared Error (RMSE): 20.04
Average R-squared (R2): 0.97

The high R^2 value indicates that the model accounts for approximately 97% close to the true trajectories, suggesting a strong correlation between predicted and optimal paths. The MAE of 16.42 m represents the average absolute deviation between predicted and true trajectories. Considering the approaching range of 0-400 m, this error is relatively small, indicating good overall accuracy. The RMSE of 20.04 m suggesting the presence of occasional deviations.

Visual inspection can reveal close alignment between predicted and true trajectories across most scenarios, particularly in the initial phases. Some divergences are observed in the latter stages of certain scenarios (e.g., Scenarios 3 and 8), which likely contribute to the observed error metrics and may need further investigation.

Table 2 Initial status of vehicles Case 2

MAX_SPEED (m/s)	25
MAX_ACCELERATION(m/s^2)	2
MAX_DECELERATION (m/s^2)	2
TIME_STEP (sec)	1
SIGNAL_DURATION (sec)	40

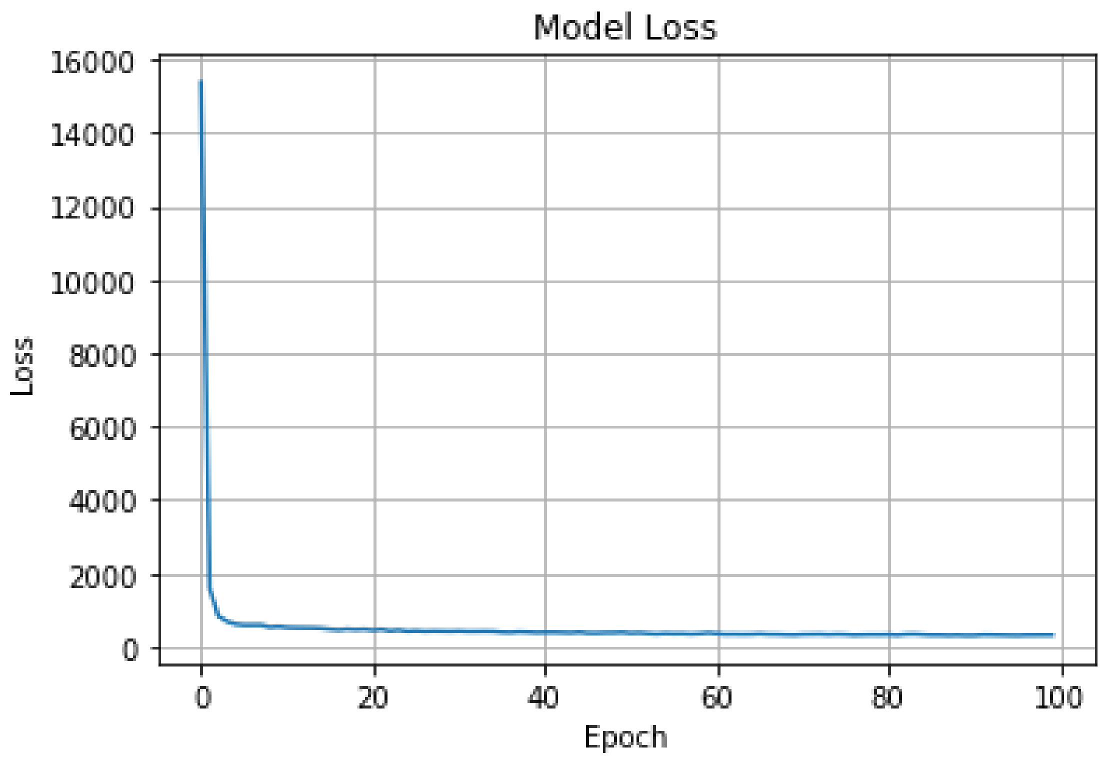

Figure 6 Model loss Case 2

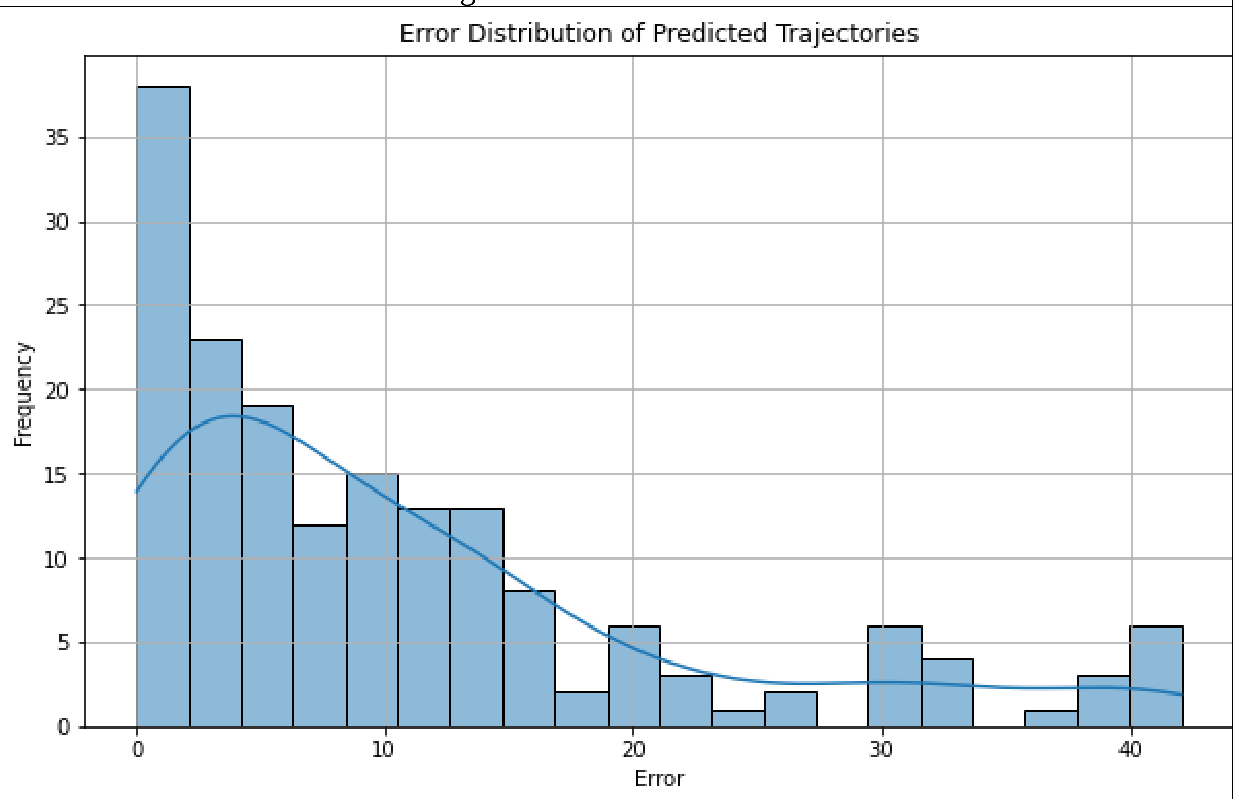

Figure 7 Error distribution of vehicle trajectories Case 2

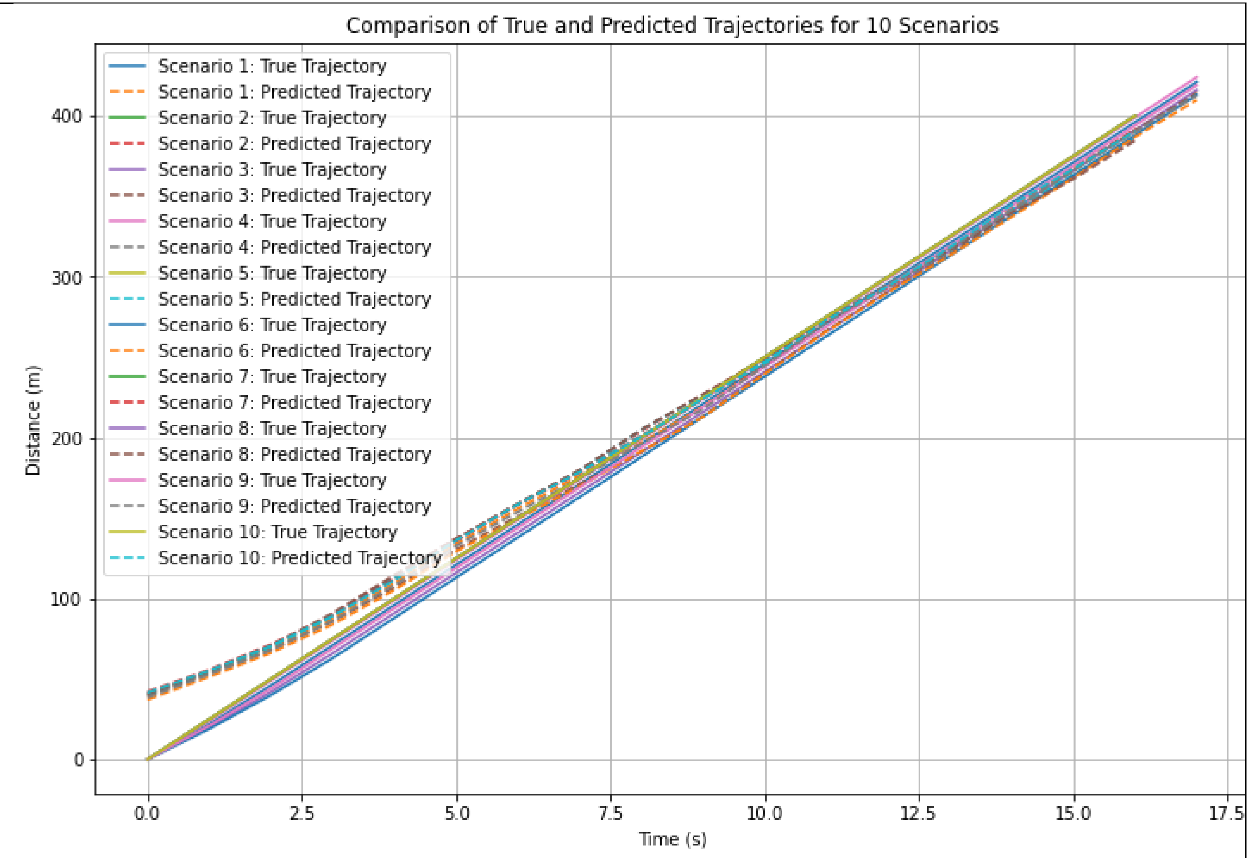

Figure 8 Trajectory generated and their true counterparts Case 2

In case 2 and case 3, the loss decreases rapidly in the initial epochs and then stabilizes, suggesting that the model converged successfully. The final loss value is relatively low, indicating good overall performance of the trained model.

The histogram is right-skewed, with the majority of errors concentrated near zero. This suggests that the model's predictions are generally accurate, with a higher frequency of small errors and fewer large errors.

The predicted trajectories closely follow the true trajectories in most cases for both case 2 and case 3, indicating that the neural network model has learned to effectively mimic the vehicle behavior. There are some minor deviations, particularly in the middle sections of some trajectories, but overall, the predictions appear to be quite accurate.

Table 3 Initial status of vehicles Case 3

MAX_SPEED (m/s)	30
MAX_ACCELERATION(m/s^2)	2
MAX_DECELERATION (m/s^2)	2
TIME_STEP (sec)	1
SIGNAL_DURATION (sec)	40

The consistent performance across diverse scenarios suggests robust generalization capabilities of the neural network model. The model demonstrates strong potential in generating accurate longitudinal trajectories for automated trucks.

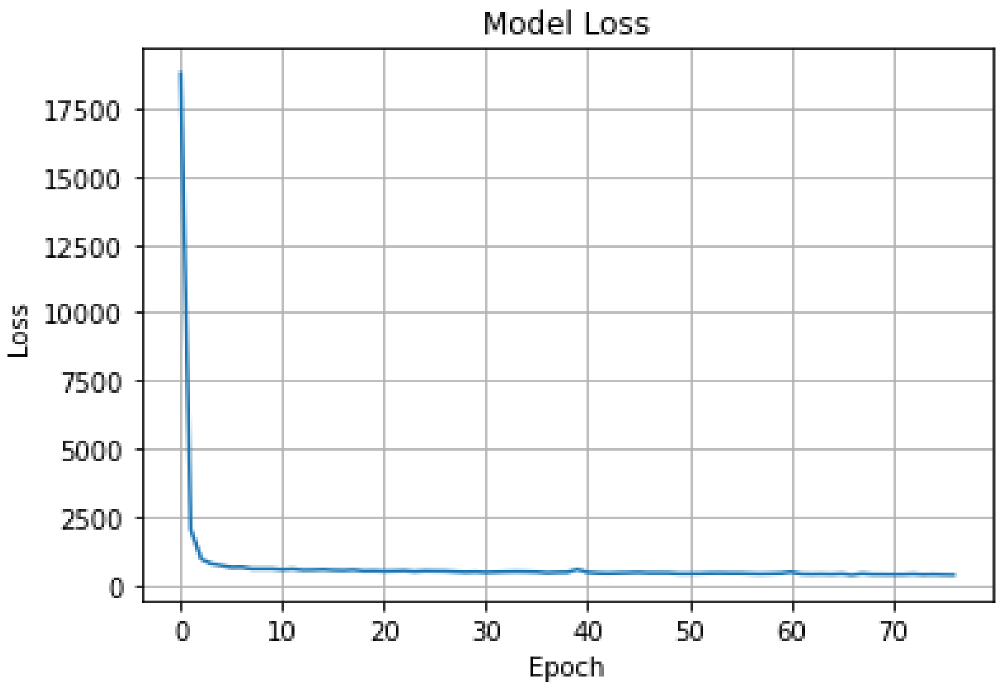

Figure 9 Model loss Case 3

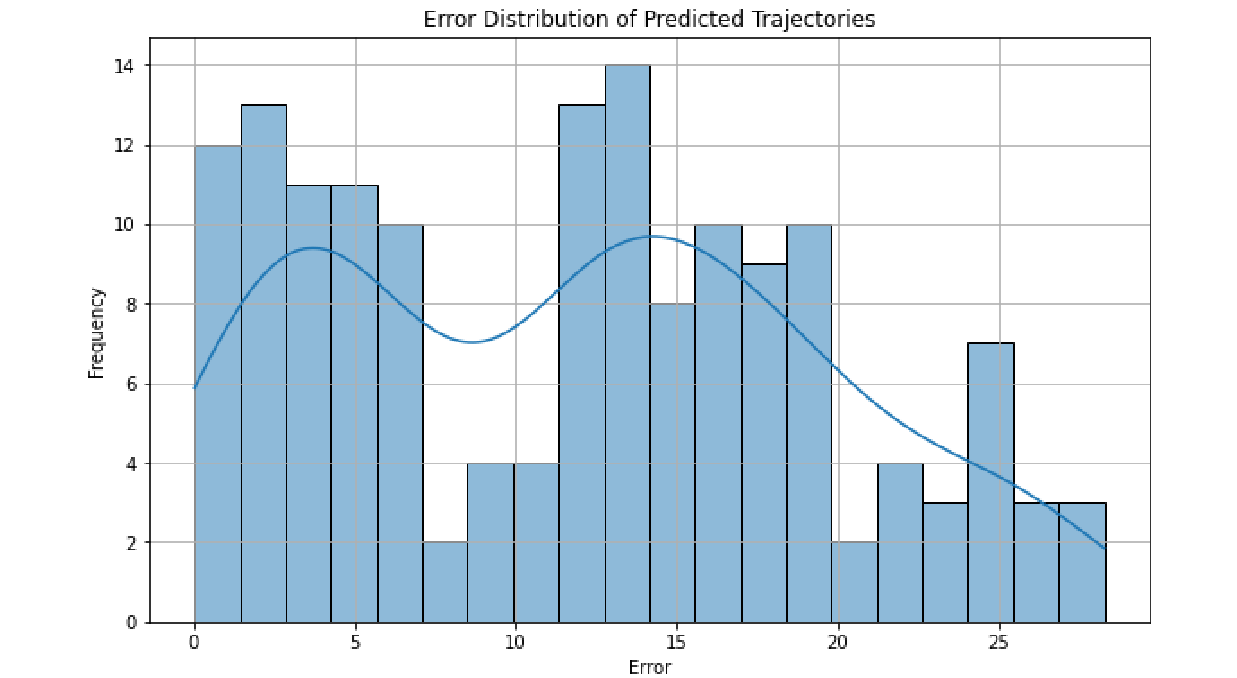

Figure 10 Error distribution of vehicle trajectories Case 3

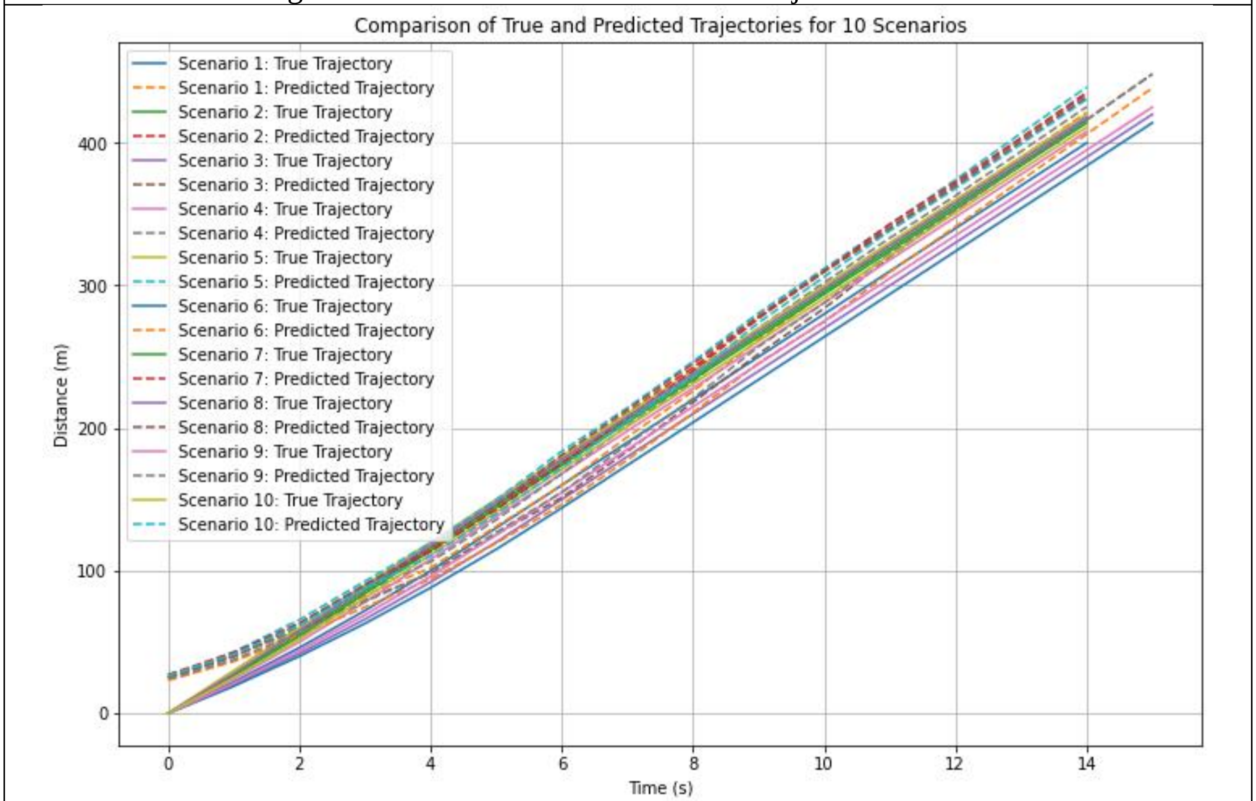

Figure 11 Trajectory generated and their true counterparts Case 3

4. CONCLUSIONS:

The neural network model's loss decreased quickly during training and stabilized at a low value, indicating efficient learning and good overall performance. This suggests that the chosen architecture and hyperparameters were appropriate for the task. The closeness of model to expert-generated trajectories indicates its potential as a computationally efficient alternative to traditional optimal control methods.

While the model demonstrates strong performance in simulated environments, it is important to note that these results are based on numerically generated data. Real-world validation remains a critical next step to assess the model's practical applicability and resilience to environmental variabilities not captured in simulation.

In conclusion, the proposed model exhibits strong performance in replicating optimal longitudinal trajectories for automated trucks. The high R^2 value, coupled with relatively low MAE and RMSE, underscores the model's potential as a viable approach for generating safe and efficient truck trajectories. The success of the neural network in predicting vehicle trajectories demonstrates that AI can play a crucial role in enhancing the decision-making capabilities of CAVs. By accurately forecasting trajectories, CAVs can better anticipate traffic flow and optimize their own paths, especially when the default algorithm fails. Future work should focus on improving the model to address errors in later trajectory stages and validating its performance in real-world scenarios.

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