Quantum Artificial Intelligence-supported Trajectory Prediction for an Autonomous Truck Platoon

Final Report

by

Pronab Kumar Biswas, Clemson University
M Sabbir Salek, Ph.D., Clemson University
Mashrur Chowdhury, Ph.D., Clemson University
Gurcan Comert, Ph.D., Benedict College
Dimitra Michalaka, Ph.D., The Citadel
Judith Mwakalonge, Ph.D., South Carolina State University
Nathan Huynh, Ph.D., University of Nebraska–Lincoln
Frank Charles, South Carolina State University
Fahim Ahmed, University of South Carolina
Jean Michel Tine, Clemson University

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200 Lowry Hall, Clemson University
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Pronab Kumar Biswas, Clemson University (ORCID: 0000-0003-4390-9946)
M Sabbir Salek, Ph.D., Clemson University (0000-0001-7326-3694)
Mashrur Chowdhury, Ph.D., Clemson University (0000-0002-3275-6983)
Gurcan Comert, Ph.D., Benedict College (0000-0002-2373-5013)
Dimitra Michalaka, Ph.D., The Citadel (0000-0001-7001-0579)
Judith Mwakalonge, Ph.D., South Carolina State University (0000-0002-7497-6829)
Nathan Huynh, Ph.D., University of Nebraska–Lincoln (0000-0002-4605-5651)
Frank Charles, South Carolina State University (0000-0002-7181-6184)
Fahim Ahmed, University of South Carolina (0000-0001-8747-3844)
Jean Michel Tine, Clemson University (0009-0001-1121-7323)

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16. Abstract

Truck platooning can potentially increase the operational efficiency of freight movement on U.S. corridors, improving commercial productivity and economic vibrancy. Predicting the trajectory of each leading vehicle in an autonomous truck platoon using Artificial Intelligence (AI) can enhance platoon efficiency during unavailability of the real-time trajectory information, which could occur due to different reasons, such as data loss, delay in communications, and noisy and erroneous sensor measurements. This study developed and evaluated a Long Short-Term Memory (LSTM) model and a hybrid quantum-classical LSTM (QLSTM) model for predicting the trajectory of each leading truck in an autonomous truck platoon. Both the LSTM and QLSTM showed potential to be utilized to predict trajectories for platoon management. However, the QLSTM models performed better in predicting trajectories than the LSTM models. The QLSTM-based predictions yielded higher operational benefits than the LSTM-based predictions. Moreover, the QLSTM used fewer parameters for training, which would require less memory compared to classical LSTM.

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EXECUTIVE SUMMARY

Truck platooning can potentially increase the operational efficiency of freight movements on road corridors to improve commercial productivity and economic vibrancy. Earlier research and field evaluations indicated that platooning could reduce fuel consumption due to reduced aerodynamic drag on the follower trucks in a platoon and improve roadway capacity substantially. To this end, significant research efforts in academia and industry over the past two decades have focused on developing technologies and infrastructure to support large-scale truck platooning.

Automated truck platooning requires each truck to be operated autonomously using appropriate longitudinal and lateral control strategies, such as car-following and steering algorithms. However, these algorithms utilize trajectory information, i.e., real-time location and motion information, from the other trucks in a platoon to determine the control parameters for safe navigation. This information can be obtained via sensing and/or wireless communication technologies. However, neither the sensors nor the connectivity can guarantee fail-proof information sharing; for example, sensory measurements could include noise or measurement errors, and wireless communication could suffer packet drops or delays. Thus, this information needs to be predicted and validated continuously. One approach to do so is to predict the trajectories of each truck based on its recent trajectory information using filtering techniques, such as a Kalman filter. However, the recent advancements in artificial intelligence (AI) have made it possible to utilize AI algorithms for time-series predictions, such as in a trajectory prediction algorithm.

In this study, an AI-based approach was developed to predict the trajectory of each leading vehicle in an autonomous truck platoon so that the follower trucks can adjust their speed during a sudden change of trajectory. The trajectories are predicted using a long short-term memory network (LSTM) and a hybrid quantum-classical LSTM (QLSTM). This study evaluated the operational efficiency of an autonomous truck platoon with the trajectory prediction of each follower truck in a platoon using both LSTM and QLSTM. Based on our analysis, the platoon operating with QLSTM trajectory prediction showed better operational efficiency.

In this project, the primary objectives are summarized as:

- Development of trajectory prediction models for each leading truck in an autonomous truck platoon using both LSTM and QLSTM, and

- Evaluation of the operational efficiency of an autonomous truck platoon with the trajectory prediction of each truck using both classical LSTM and QLSTM.

Our findings indicate that QLSTM models offer better trajectory prediction and, consequently, better operational efficiency than the LSTM models. Thus, in our simulation-based experiments, the QLSTM models, providing better trajectory prediction, indicated to be more suitable for real-time management of autonomous truck platoons.

While this study developed QLSTM models for vehicle trajectory prediction using a quantum simulator—an idealized environment for quantum computing that may not reflect current or near-term capabilities—future research should aim to transfer these models to real quantum computing platforms. Additionally, it should evaluate the feasibility of managing autonomous truck platoons in real time under these conditions.

CHAPTER 1

Introduction

The joining of two or more trucks in a convoy utilizing wireless connectivity and autonomous driving assistance systems (ADAS) is known as truck platooning. Platoons automatically maintain a safe, close distance between each other. According to the U.S. Department of Transportation, 72 percent of goods in the U.S. are transported by trucks; therefore, finding safer and more efficient ways to move them is essential (Economics and Industry Data, 2022). Truck platooning can potentially increase the operational efficiency of freight movements on U.S. corridors to improve commercial productivity and economic vibrancy. Although real-world deployments of truck platoons are still in their infancy, a previous study has found that 63% of total miles driven by trucks in 2016 could have been navigated with truck platoons, considering the speed threshold for platoonable truck identification to be 50 miles per hour (mph) (Lammert et al., 2018). In Lammert et al., (2018), the authors used low-resolution data from 57,000 unique trucks for two weeks. Another literature (Al-Qadi et al., 2021) shows a 5% to 15% reduction in fuel consumption based on the platoon configuration. Using Adaptive Cruise Control (ACC) or Cooperative Adaptive Cruise Control (CACC) applications to form platoons, a recent study (Noruzoliaee et al., 2021) found a 7.9% reduction in fuel consumption by 2025 and an increase in the capacity of road segments that could be used for platooning. Such advances can lead to noticeable savings of $868 million for the U.S. trucking industry and a reduction in infrastructure improvement needs of up to $4.8 billion (Noruzoliaee et al., 2021). That is why academia and the trucking industry have been carrying out research aiming to accelerate the broad implementation of truck platooning. Over the past few decades, various partnerships between governments and private companies have demonstrated the use of autonomous truck platooning in practical situations. One notable example is the partnership between the UC Berkeley PATH program and the Volvo Group (Tsugawa et al., 2016). The program demonstrated the advantages of an automated truck platoon in a real-world scenario. The study found that truck platooning could reduce fuel consumption by up to 10% for the leading vehicles and up to 15% for the follower vehicles. The study also showed that platooning could improve road safety by reducing the risk of accidents caused by driver error (Tsugawa et al., 2016).

Platooning algorithms require knowledge of the trajectory of neighboring trucks of a subject truck in real-time. In a unidirectional platooning, a subject truck only requires trajectory information from its immediate leading truck, whereas, in a bidirectional platooning, the subject truck requires trajectory information from both its immediate leading and follower trucks. For unidirectional platooning, Artificial Intelligence (AI) can be used to predict each leading truck’s trajectory for autonomous truck platooning. Reliance on classical AI may not be efficient for this purpose as it would increase the computational burden for each truck in the platoon (Shladover et al., 2018). Quantum AI, however, can be used in this scenario to enhance learning efficiency, learning capacity, and run-time improvements (Islam et al., 2022; Dunjko and Briegel, 2018).

In this study, an algorithm was developed to predict the trajectory of each leading truck in an autonomous truck platoon so that the follower trucks can adjust their speed and direction accordingly using a long short-term memory network (LSTM) and a hybrid quantum-classical LSTM network (QLSTM)-predicted trajectory for the underlying car following model(s). Our investigations found that the accuracy of Quantum-AI algorithms to predict vehicle trajectory is better than the classical models while using similar training conditions and hyperparameters, such as number of epochs, batch size, and learning rate. In addition, this study evaluated the operational efficiency of an autonomous truck platoon with the trajectory prediction of each truck using both LSTM and QLSTM.

The main objectives of this project are summarized below:

- Develop trajectory prediction models for predicting the trajectory of each leading truck (which has at least another truck following it) in an autonomous truck platoon using both LSTM and QLSTM, and

- Evaluate the operational efficiency of the autonomous truck platoon with the trajectory prediction of each truck using both LSTM and QLSTM.

The remainder of this report is organized as follows. Chapter 2 provides a literature review on autonomous truck platooning and quantum artificial intelligence. Chapter 3 discussed the development of trajectory prediction models for an autonomous truck platoon using both LSTM and QLSTM. Chapter 4 presents the comparison of the performance of the prediction models and the evaluation of the operational efficiency of an automated truck platoon that uses the prediction models. Lastly, Chapter 5 provides concluding remarks and future work.

CHAPTER 2

Literature Review

Truck platooning is the idea that two or more trucks are linked together through automation technology and driving support systems to increase safety and efficiency. Through wireless communication, the trucks in a platoon interact with one another, enabling them to drive in close proximity to each other. The follower trucks are programmed to automatically perform maneuvers such as accelerating and decelerating, in response to the actions of their respective leading trucks. This arrangement enhances the aerodynamics of the trucks, leading to decreased fuel consumption (Patten et al., 2012). Researchers found, through testbed experiments, six percent fuel savings for leading vehicles and ten percent for follower vehicles in a platoon (Alam et al., 2015; Lammert et al., 2014). Moreover, less fuel consumption leads to cost savings and reduced emissions (Scora and Barth, 2006). Furthermore, a truck platoon can reduce congestion as the trucks will take less space in the platoon than driving separately (Schladoverr et al., 2015; Van Arem et al., 2006). Also, platooning can enhance traffic safety because the vehicles in a platoon result in less human error and lower reaction time, thus reducing rear-end collisions. Finally, truck platooning can decrease travel time and increase roadway capacity (Lee et al., 2021).

With the advancement of automated vehicle technology, it is now possible for multiple automated trucks to travel together while maintaining a minimum safety distance or form a platoon through vehicle-to-everything (V2X) communication technology (Lee et al., 2021). With the rapid advancement of 5G and V2X communication technologies, automated truck platooning is receiving more attention from researchers in academia and industry (Tsugawa et al., 2016; Alam et al., 2015). As the current infrastructure cannot support a fully autonomous truck platoon, semi-automated platooning is being tested. As per the EU truck platooning roadmap, it is projected that the follower trucks within a platoon will attain Society of Automative Engineers (SAE) Level 4 automation (automated driving without a driver) by 2025 (EAMA, 2019).

Several studies found that connected vehicle platoons can use a trajectory-tracking control model for better operational efficiency (Li et al., 2017; Chu et al., 2017). In a recent study, it was found that around 36% of truck platoons could be effectively managed by adjusting their speed, without the need to modify their routes or schedules (Ma et al., 2021). Truck platoons can make safe, efficient driving decisions with accurate road user trajectory predictions (Wei et al., 2020). Besides, with a precise prediction of the trajectory of the leading truck, the follower trucks can adjust their speed and direction during a sudden change of trajectory. Trajectory prediction can also minimize travel time, avoid congestion, and develop methods for future utilization of the road network (Yan and Shen 2019). In this chapter, we review the existing studies on (i) application of AI for trajectory prediction, (ii) quantum AI, and (iii) car-following models.

2.1 Application of AI for Trajectory Prediction

Truck platooning is a safety-critical application which requires trajectory prediction models for a platoon to have a high accuracy to prevent adverse consequences. AI has several successful applications in trajectory prediction. For example, the Artificial Neural Network (ANN) and Support Vector Machine (SVM) classifiers were used for lane change prediction, which predicted a lane change action before the actual lane change with success (Dou et al., 2016). LSTM for prediction systems can process massive volumes of data (Hochreiter and Schmidhuber, 1997). Various research fields, including trajectory prediction, are experiencing unprecedented growth due to the advent of deep learning techniques and computer capacity. Dai et al. proposed a modified LSTM model for trajectory prediction (Dai et al., 2019). Du et al. created a predictive model for the trajectory of connected vehicle platoons using a digital twin-based approach (Du et al., 2021).

2.2 Quantum AI

Introducing quantum algorithms into the domain of AI has improved the performance of AI models (Dunjko and Wittek, 2020). Quantum annealing and quantum random walk offer optimization from the previously suggested multiple guesses. Quantum computing-based techniques can generate exact solutions to NP-hard problems (Crosson and Harrow, 2016; Sgarbas, 2007). The capacity of Quantum Neural Networks (Q-NNs) to extract solutions from intricate probability distributions is what makes them useful in machine learning models. This is achieved by encoding information into a quantum state through a quantum feature map (Abbas et al., 2021). With the extension of AI and machine learning, Quantum deep learning has also gained recognition for solving intractable problems on regular classical computers (Wiebe et al., 2014). For example, Patel et al. (2019) applied a Quantum Neural Network (Q-NN) for signature verification, and the accuracy was 95% compared to the classical Neural Network (NN), which achieved 89% accuracy (Patel et al., 2019). Furthermore, Patel and Tiwari (2014) utilized the Quantum Binary NN (Q-BNN) model for breast cancer classification and compared it against Gaussian processes, NNs, Multilayer Perceptron (MLP), and SVM. Q-BNN achieved above 95% accuracy, whereas other methods were less than 80% accurate (Patel and Tiwari, 2014). Chen et al. (2020) applied a Quantum Convolutional Neural network (Q-CNN) for image classification and reported higher accuracy (94%) than classical CNN (90%) (Chen et al., 2020). Wang et al. (2022) showed that Quantum Stochastic Neural Networks (Q-SNN) could achieve better performance against classical SNN classifying sentences (Wang et al. 2022). Q-SNN converged faster and with higher accuracy compared to classical SNN. Quantum computing applications in AI have been beneficial in many fields, such as in operational optimization (Azad et al., 2022; Zhang et al., 2020), transportation systems cyber-security (Khan et al., 2021), and human traffic intention estimation and trajectory prediction (Busemeyer and Bruza, 2012; Song et al., 2022). In the development of autonomous vehicles and quantum computers, previous assumptions about the interaction between autonomous vehicles and pedestrians, which were considered classical in the sense of rational behavior, are no longer viewed as unquestionable. It is now assumed to follow the quantum decision theory, making human behavior irrational, and violating classical cognitive and decision theory (Song et al., 2022). Academics have concluded that the interplay between interference and entanglement in quantum mechanics and human cognition shares several common traits (Busemeyer and Bruza, 2012). This observation has resulted in a prevailing trend.

2.3 Car-following Models

Car-following models regulate a driver's actions in relation to the vehicle directly in front of them in the same lane (Brackstone and McDonald, 1999). There are five categories in which car-following models can be classified: the Gazis-Herman-Rothery (GHR) model, the Collision Avoidance (CA) model, the Linear Model, the Fuzzy-logic-based model, and the Optimal Velocity (OV) model, including its variations (Panwai and Dia, 2005; Brackstone and McDonald, 1999). One of the first and most advanced car-following models is the Gazis-Herman-Rothery (GHR) model. However, the model has the drawback of having characteristics that change depending on the driving environment. Similar to the GHR model, the linear model has been extensively investigated; however, although having a very straightforward and linear shape, it is less widely used due to the challenges associated with parameter calibration. Given the characteristics of car-following behaviors, fuzzy logic seems like a realistic attempt to incorporate into the car-following theory. However, the usefulness of such efforts is constrained by the challenge of calibrating the membership function, which is the fundamental idea of fuzzy logic. Therefore, the most popular car-following model for simulation is arguably Gipps' adaptation of the Collision Avoidance (CA) model. Another car-following model, the Optimal Velocity (OV) concept, is distinctive in how it depicts stop-and-go and backed-up traffic. Two

OV model variations, named the Generalized Force (GF) model and the Full Velocity Difference (FVD) model, were developed to address OV model problems with data agreement and startup process.

CHAPTER 3

A Framework for Development and Evaluation of an LSTM-Supported Autonomous Truck Platooning Application

This chapter presents a framework for developing and evaluating an LSTM-supported autonomous truck platooning application (as shown in Figure 1). At the beginning, a simulation network was developed. Following, adequate data were generated that were used to train and evaluate the LSTM and QLSTM-based vehicle trajectory prediction models. The steps of the framework are illustrated in Figure 1 and described in detail in the following subsections.

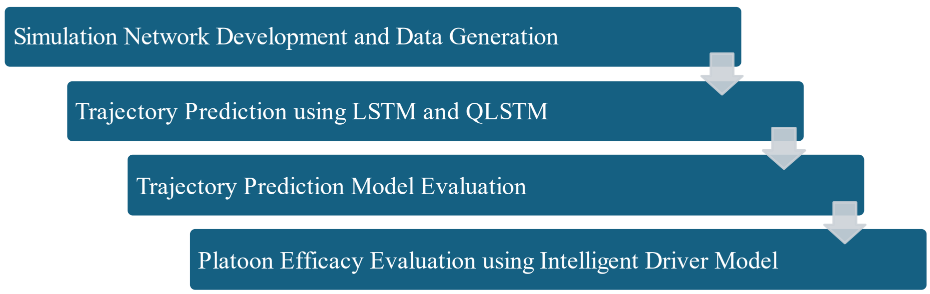

Figure 1: LSTM-supported Autonomous Truck Platooning Application Development and Evaluation

3.1 Simulation Network Development and Data Generation

The first step in the framework is to build a simulation network to simulate an autonomous truck platooning application. For a simulation duration of 92 seconds (s), we utilized MATLAB to simulate a platoon of five automated trucks employing Cooperative Adaptive Cruise Control (CACC). This platoon consisted of one leader and four follower trucks, and it was derived from Salek et al. (2024). The leader truck starts at a distance of 20 meters, and the other trucks are placed at distances of 40, 60, 80, and 100 meters from a point of reference, respectively. All five trucks are moving at an initial speed of 0 meters per second (m/s), or 0 mph. Input parameters for the simulation include the number of trucks in the platoon, the total simulation time, the initial position and speed of the follower trucks, the location and speed profile of the leader truck, and the constant required time headway. A simulation step size of 0.1 s and a constant desired time headway of 0.7 s were used (Salek et al., 2024).

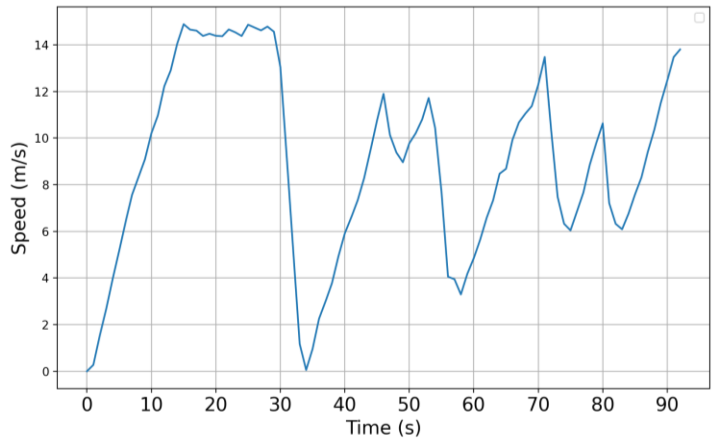

Figure 2: Speed Profile of the Platoon Leader

Figure 2 shows the speed profile of the platoon leader (i.e., the truck leading at the front of the platoon) from 0 s to 92 s. This speed profile was adopted from a real-world truck's trajectory, documented in Mehmood and Mehmood (2020). Mehmood and Mehmood (2020) provided a comprehensive trajectory dataset constructed with trajectory information observed from vehicles in Jeju-si, South Korea. In this study, we only consider the longitudinal motion and control of autonomous trucks for which we need timestamped speed data of a truck. This timestamped speed data of a truck was extracted from Mehmood and Mehmood (2020) and considered as the leader truck's speed profile in this study.

To simulate a platoon consisting of one leader truck and four follower trucks, we solved a group of first-order differential equations in MATLAB. We followed the methodology presented by Rahman et al. to create a system of first-order differential equations and utilized the "ode45" MATLAB solver (Rahman et al. 2017). Finally, the trajectory dataset was generated for all five trucks from timestamp 0 s to 92 s. As shown in Table 1, the dataset contains the following fields: (i) timestamp, (ii) X_pos (absolute X coordinate of the vehicle), and (iv) Speed (speed of the vehicle in m/s).

Table 1 Vehicle Trajectory Dataset Sample

Time	X_Pos	Speed
0	20	0
0.1	20.00137	0.0273812
0.2	20.00548	0.0547624
0.3	20.01232	0.0821436
0.4	20.02190	0.1095248

We divided the trajectory dataset into two sets: one dataset (from the timestamp 0 s to 54.7 s) was used for model development, and the other dataset (from the timestamp 54.8 s to 92 s) was used to evaluate the model.

3.2 Vehicle Trajectory Prediction using LSTM and Hybrid Classical-Quantum LSTM

LSTM is a Recurrent NN (RNN) applicable to a broad range of problems aiming to analyse or classify sequential data. LSTM can be used to predict the speed of the vehicles of a platoon based on historical data sequences with great success. LSTM uses a certain number of past observations to predict the future. Sequence Length is the deciding factor in choosing the number of observations the LSTM considers. If the sequence length is n, then the LSTM considers the last n observations to predict the (n+1)th observation. In this study, a sequence length of 10 was used. A learning rate of 0.001 was selected as it provided the most desirable training loss and efficiency. The number of epochs used was 40.

The LSTM's efficiency and trainability can be improved by replacing some of the layers in the LSTM with Variational Quantum Circuit (VQC) layers, creating a quantum-classical hybrid model of LSTM, denoted as QLSTM in this report. It was shown in a previous study that QLSTM can learn significantly more information after the first training epoch than its classical counterpart and has better learning capability of local features while having fewer parameters than LSTM (Chen et al., 2020). We used the same datasets for classical LSTM model development and evaluations as for QLSTM model development and evaluation. This study used PennyLane-enabled variational quantum layers to replace the LSTM layers. The variational quantum circuits shown in Figure 3 serve as the foundation for the variational quantum layers:

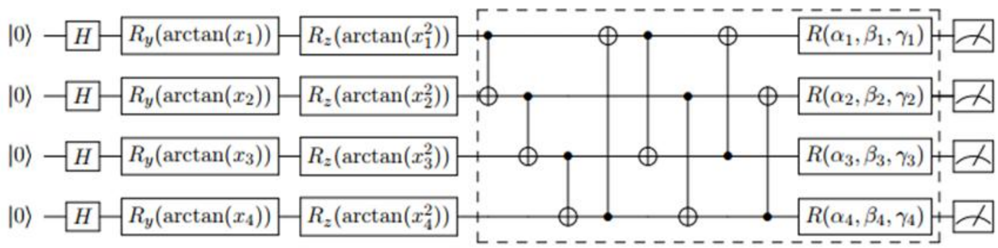

Figure 3: VQC Architecture for QLSTM (adapted from Chen et al., 2020)

The VQC architecture in Figure 3 consists of three layers as follows: (i) the data encoding layer with the Hadamard gate (H), rotation gate around Y-axis (R_y), and rotation gate around Z-axis (R_z), (ii) the variational layer highlighted by the dashed box, and (iii) the quantum measurement layer. In Figure 3, only one variational layer is shown. The number of variational layers is adjusted based on the need for specific problems. The output of this quantum circuit is used to replace the $W \cdot v_t$ (matrix-vector multiplication between the weight matrix W and the input vector v_t at time step t) in the LSTM. Parameters in this quantum circuit are updated using the parameter-shift rule.

These variational quantum circuits were run on the Python-based PennyLane simulator. This study used four qubits, one variation layer, and a learning rate of 0.001. The number of epochs used for QLSTM training was 40. These hyperparameters were intentionally kept the same as those of the LSTM training to be able to compare LSTM and QLSTM's training efficiency.

CHAPTER 4

Evaluation and Results

The first two sections of this chapter present the evaluation strategies used in this study. The third section presents the results and relevant discussions.

4.1 Trajectory Prediction Model Evaluation

Two performance metrics were used to evaluate the trajectory prediction models: mean average error (MAE) and root mean square error (RMSE). The MAE calculates the average of the absolute differences between predicted and actual values. The RMSE calculates the square root of the average squared differences between predicted and actual values. The performance metrics can be measured using the following Equations:

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \tag{1}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - x_i)^2}{n}} \tag{2}$$

where, y_i = predicted value of the i^{th} sample, x_i = observed value of the i^{th} sample, and n = number of samples.

4.2 Platoon Operational Performance Evaluation Using IDM

This study evaluated the automated truck platoon's operational performance with trajectory predictions from LSTM and QLSTM using the Intelligent Driver Model (IDM) by comparing the following:

- Speed Profiles,
- Inter-truck gap profiles, and
- Jerk profiles.

A simplified version of IDM for acceleration (Treiber et al., 2000) of the control vehicle can be expressed as,

$$a_c = a\left[1 - \left(\frac{v_c}{v_{des}}\right)^{\delta} - \left(\frac{d^*(v_c,\ \Delta v_l)}{d_l}\right)^2\right] \tag{3}$$

where, a is the normal acceleration, Δv_l is the gap between the control vehicle and the leading vehicle, $d^*(v_c,\ \Delta v_l)$ is the desired gap between the control vehicle and its leading vehicle, and δ is an exponent for the vehicle's acceleration.

The acceleration of the control vehicle in the IDM model has two parts: $1 - \left(\frac{v_c}{v_{des}}\right)^{\delta}$ accounts for the desired acceleration of the control vehicle and $\left(\frac{d^*(v_c,\ \Delta v_l)}{d_{des}}\right)^2$ accounts for the braking deceleration of the control vehicle when its immediate leading vehicle is decelerating. The desired gap $d^*(v_c,\ \Delta v_l)$ is defined as follows,

$$d^*(v_c,\ \Delta v_l) = d_{min} + \max\left[0, \left(d_{des} + \frac{v_c \Delta v_l}{2\sqrt{ab}}\right)\right] \tag{4}$$

where, d_{min} is the minimum gap to be maintained between two vehicles, and b is the normal comfortable braking deceleration.

For the n-vehicle simulation scenario, the acceleration of the n-th vehicle can be written as,

$$\ddot{x_n} = a\left[1-\left(\frac{\dot{x_n}}{v_{des}}\right)^{\delta}-\left(\frac{d^*(\dot{x_n},\ \Delta\dot{x_n})}{x_{n-1}-x_n-l}\right)^2\right] \tag{5}$$

Here,

$$\Delta\dot{x_n} = \dot{x_{n-1}} - \dot{x_n} \tag{6}$$

$$d^*(\dot{x_n},\ \Delta\dot{x_n}) = d_{min} + \max\left[0, \left(d_{des} + \frac{\dot{x_n}\Delta\dot{x_n}}{2\sqrt{ab}}\right)\right] \tag{7}$$

4.3 Results and Discussions

The comparisons of the training losses and the validation losses for the LSTM and the QLSTM are shown in Figures 4 and 5, respectively. From the figures, it is observed that all the LSTM and QLSTM model losses started to converge within the first fifteen epochs. The LSTM and the QLSTM model training converged at a similar rate for the leader and the 3rd follower truck. For the follower trucks 2 and 3, the QLSTM training took longer than the LSTM training to converge.

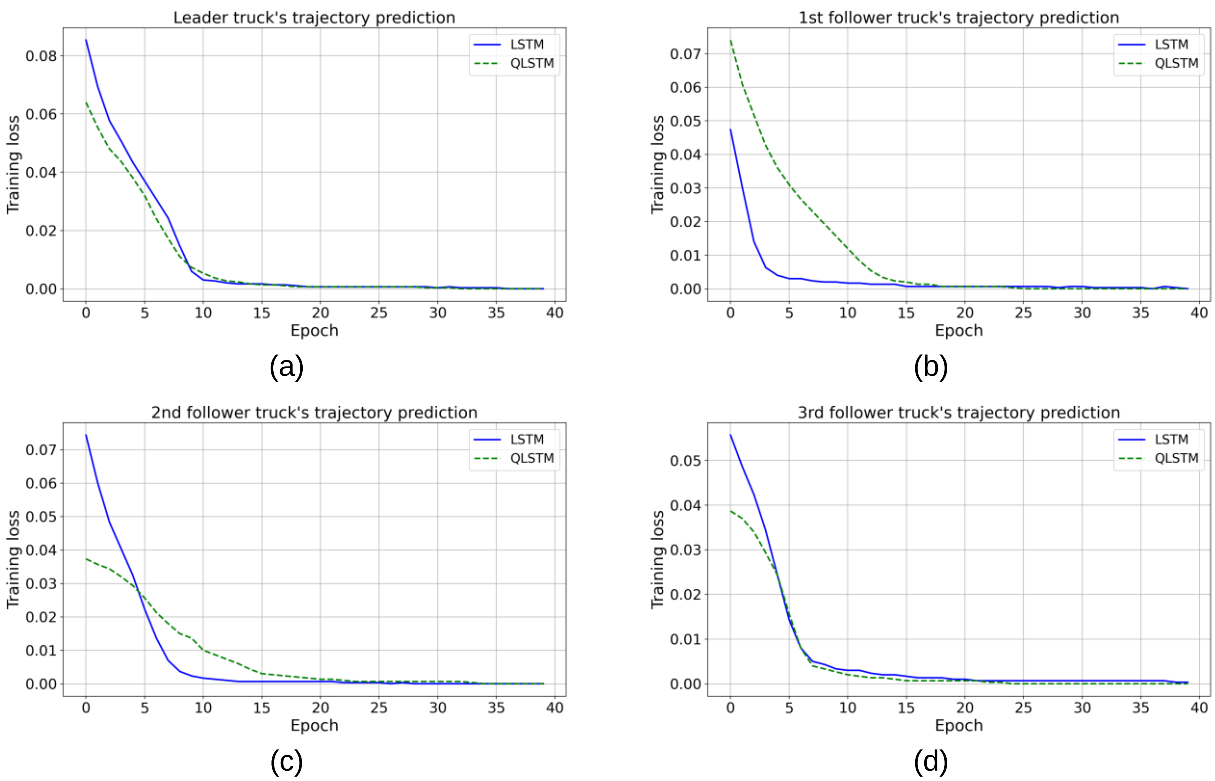

Figure 4: Comparison of training losses

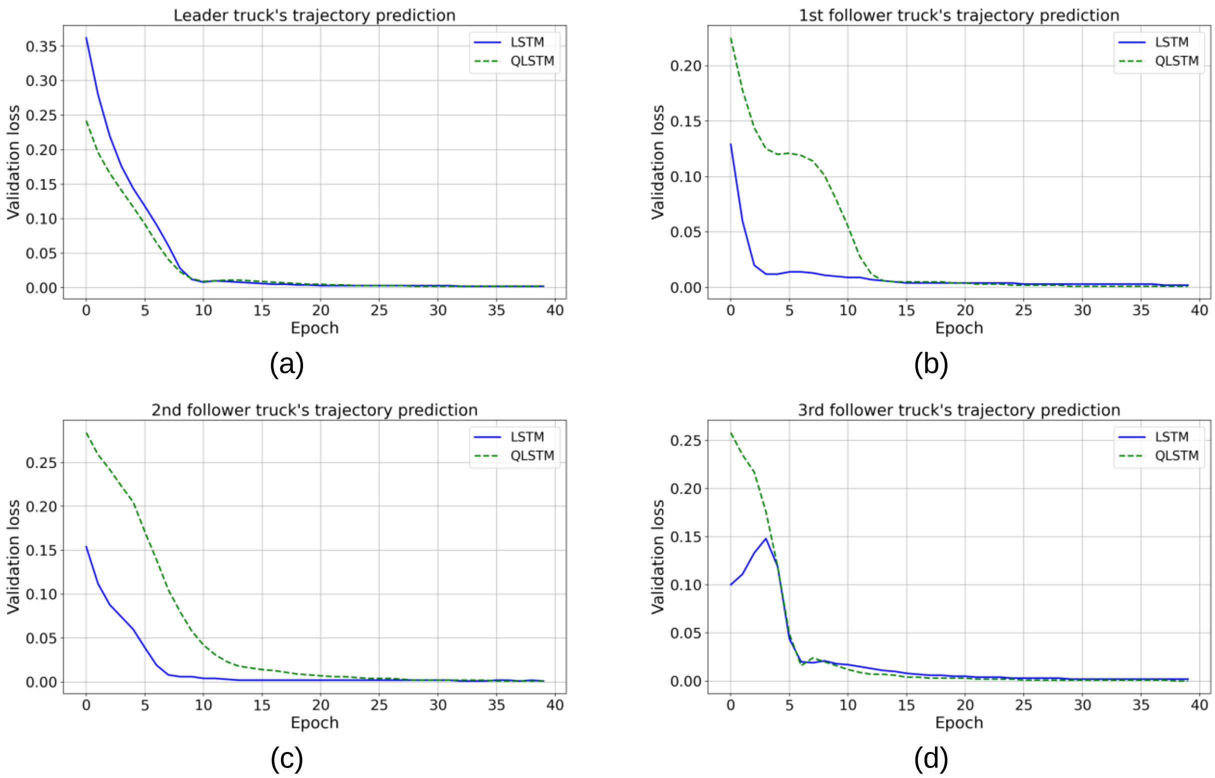

Figure 5: Comparison of validation losses

Figure 6 compares the MAE for the trajectory prediction with LSTM and QLSTM for the leader truck and the follower trucks 1, 2, and 3 in our autonomous truck platoon. Predicted trajectories that use QLSTM showed 16% to 37% less MAE than the predicted trajectories that use LSTM. This shows that although the QLSTM models took longer to converge than the LSTM models in some cases, the QLSTM models were better at capturing the trajectories of the trucks in a platoon than the LSTM models. In Figure 6, we observe that the LSTM-based trajectory predictions deviated more from the original trajectories for the upstream trucks; the QLSTM models were more consistent in trajectory predictions than their classical counterpart models in this context.

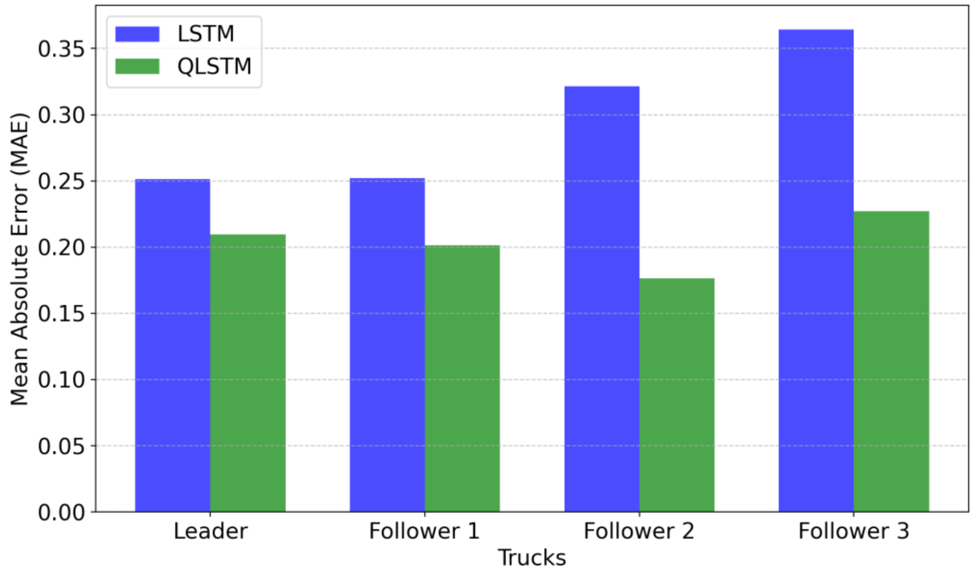

Figure 6: Comparison of MAE in trajectory predictions

Figure 7 shows a comparison of the RMSE of the trajectory predictions with LSTM and QLSTM for the leader truck and the follower trucks 1, 2, and 3 in the autonomous truck platoon considered here. Predicted trajectories that use QLSTM exhibited a 15% to 37% reduction in RMSE compared to the ones that use LSTM. This further enhances the claim that QLSTM could provide better trajectory predictions than LSTM for autonomous truck platooning.

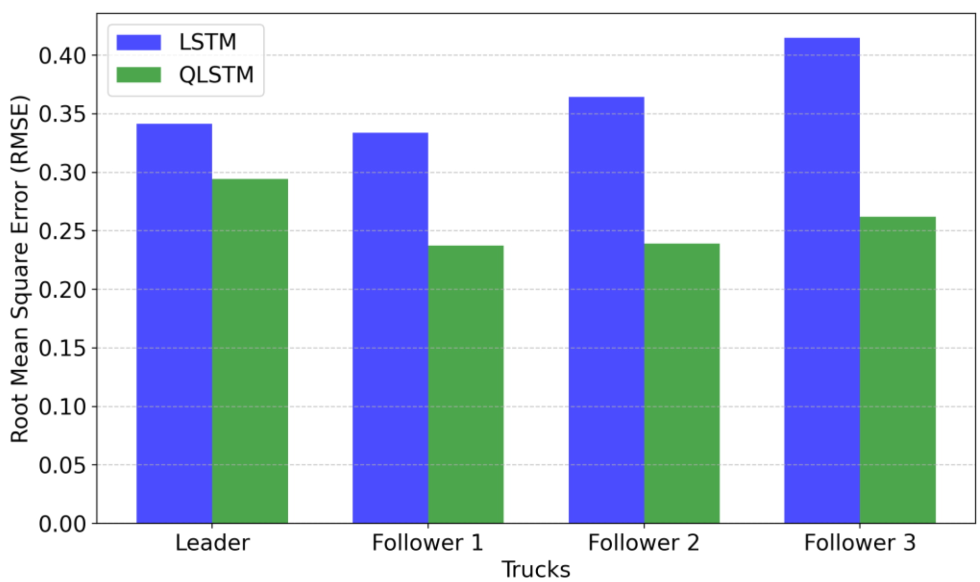

Figure 7: Comparison of RMSE in trajectory predictions

Figure 8 shows the speed profile of every truck in the platoon for the real-time trajectory in which we assume that all the follower trucks receive their immediate leading truck's trajectory information in real-time without any delay, measurement noise, errors, or data loss; therefore, we consider it as the ideal platoon operation under the IDM car-following model. It is expected that any predictions would deviate from these original trajectories to some extent, and keeping these deviations minimal is the goal for our prediction models. Figures 9 and 10 present the speed profiles of all the trucks in the simulated platoon using predicted trajectories by LSTM and QLSTM models, respectively. In Figures 9 and 10, the time window (from 0 s to 54.7 s) when the follower trucks utilized the real-time trajectory information and the time window (from 54.8 s to 92 s) when the follower trucks utilized the predicted trajectory information, are indicated. A close observation of the follower trucks' speed profiles toward the end of the predicted trajectory utilization window reveals that while using the LSTM-predicted trajectories (see Figure 9), the follower trucks speed deviated from the leader truck's speed more compared to what is observed for the QLSTM-predicted trajectories (see Figure 10). These deviations are better reflected in the MAE and the RMSE comparisons we presented earlier in Figures 6 and 7, respectively.

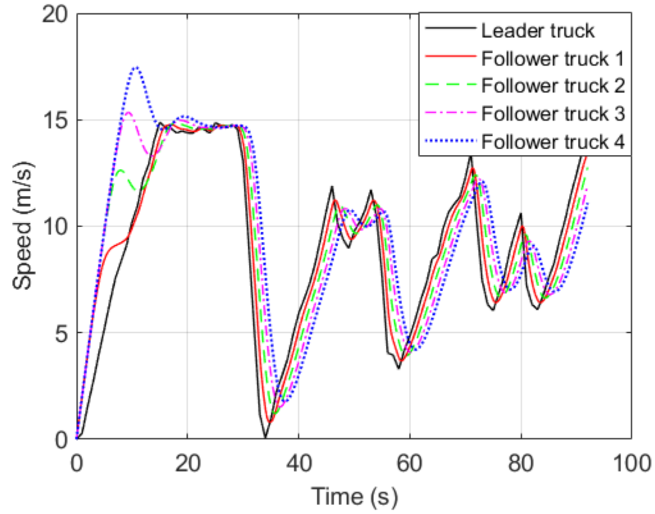

Figure 8: Speed profiles of autonomous trucks using IDM with real-time trajectories

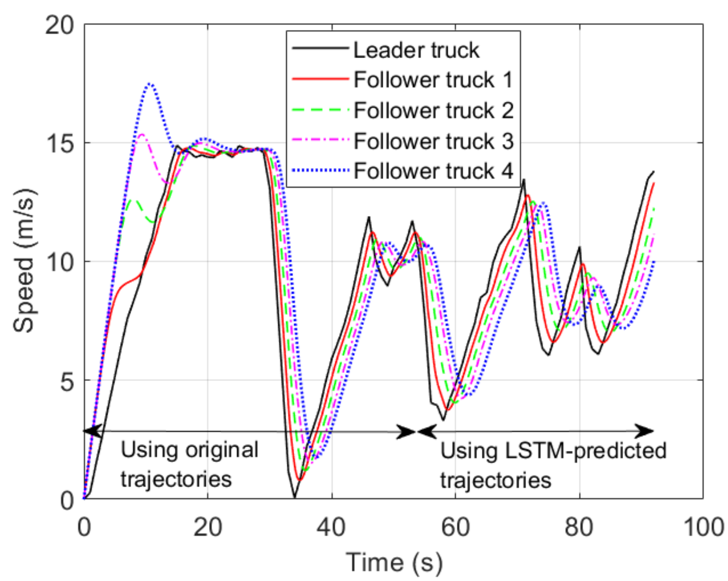

Figure 9: Speed profiles of autonomous trucks using IDM with LSTM-predicted trajectories

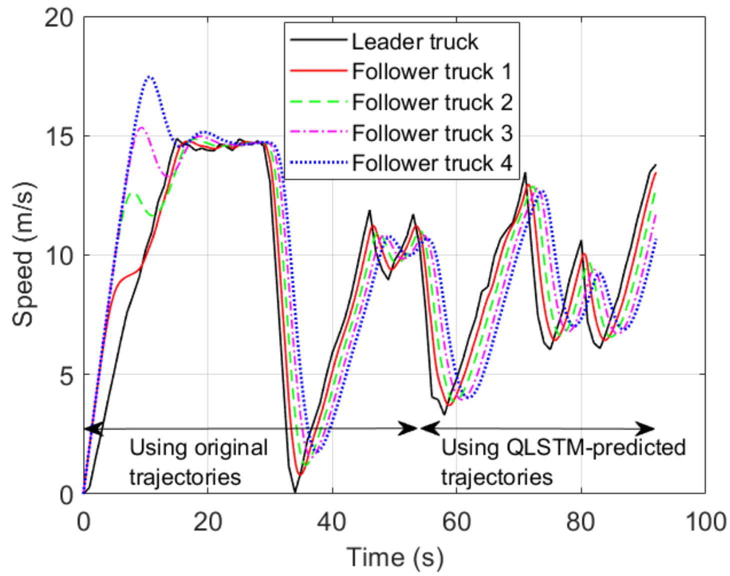

Figure 10: Speed profiles of autonomous trucks using IDM with QLSTM-predicted trajectories

Figure 11 presents the inter-truck gap profiles between every two trucks in a platoon while using real-time trajectory information. Figures 12 and 13 show the inter-truck gap profiles between every two trucks in the platoon for predicted trajectories by LSTM and QLSTM, respectively. From the inter-truck gap profiles, it can be deduced that there is no risk of a collision between the trucks in the platoon because none of the inter-truck gaps exhibits zero or a negative value. Comparing Figures 12 and 13 with Figure 11, we observe that the LSTM-based trajectory predictions yielded non-uniform inter-truck gaps across the trucks, whereas the QLSTM-based predictions yielded more uniform inter-truck gaps. Although they were less uniform than the inter-truck gap profiles observed while using the real-time trajectory information. This indicates the higher operational benefit and the potential of QLSTM models for predicting trajectory for platooning operations when the original trajectory information is unavailable.

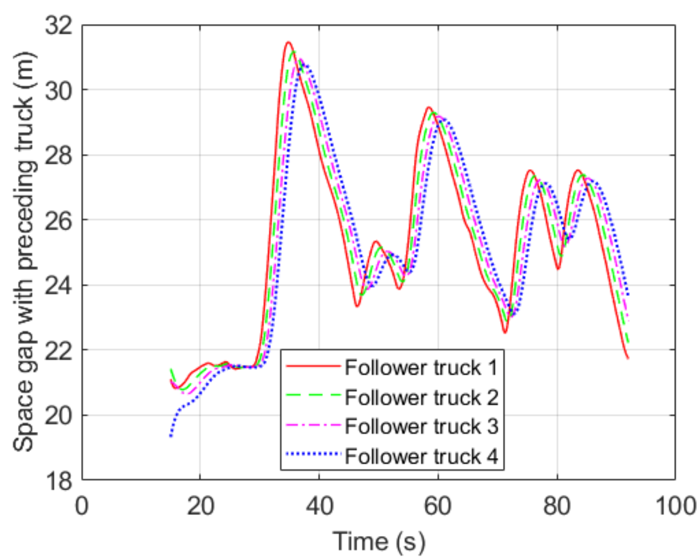

Figure 11: Inter-truck gap profiles of autonomous trucks using IDM with real-time trajectories

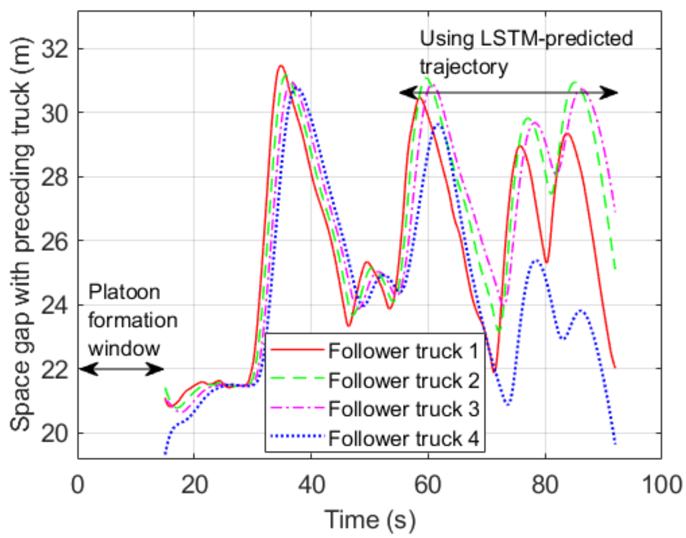

Figure 12: Inter-truck gap profiles of autonomous trucks using IDM with LSTM-predicted trajectories

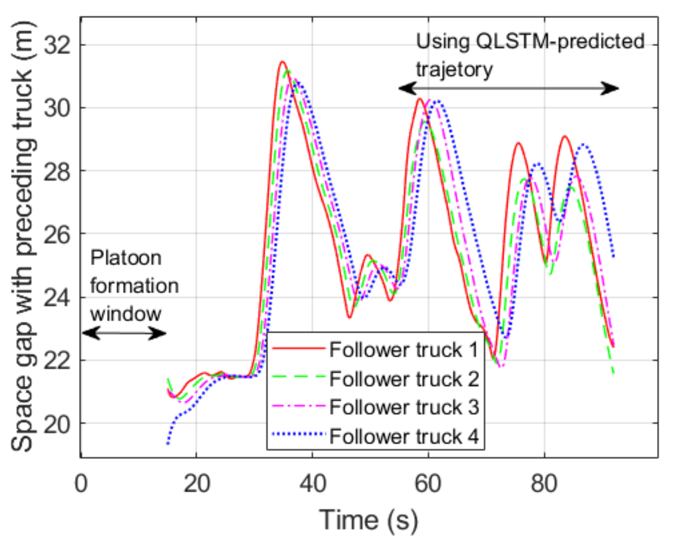

Figure 13: Inter-truck gap profiles of autonomous trucks using IDM with QLSTM-predicted trajectories

Figure 14 shows jerks (i.e., the rate of change of acceleration with time) for every follower truck in the platoon while using the original trajectory information. Figures 15 and 16 present jerks for every follower truck in the platoon while using the predicted trajectories by LSTM and QLSTM, respectively. Comparing Figures 15 and 16 with Figure 14, we observe that the jerks while using trajectories predicted by LSTM and QLSTM were not substantially different from that while using the real-time trajectory information. This further proves the efficacy of LSTM and QLSTM models for trajectory prediction for managing an autonomous truck platoon when real-time trajectory information from the neighboring trucks is unavailable or delayed.

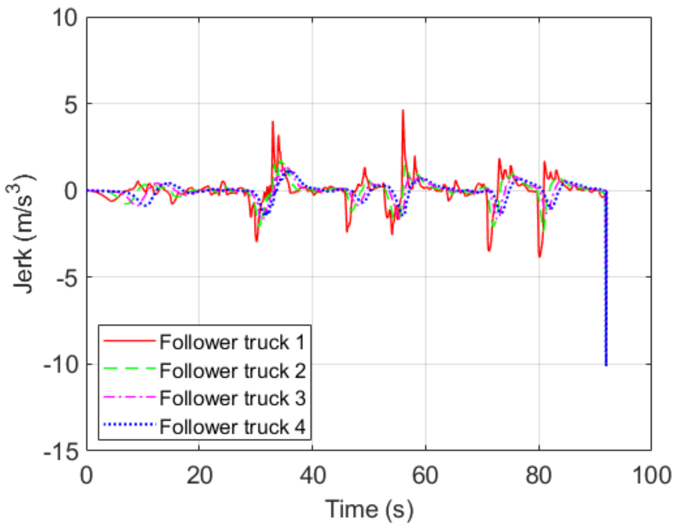

Figure 14: Jerk profiles of using IDM with real-time trajectories

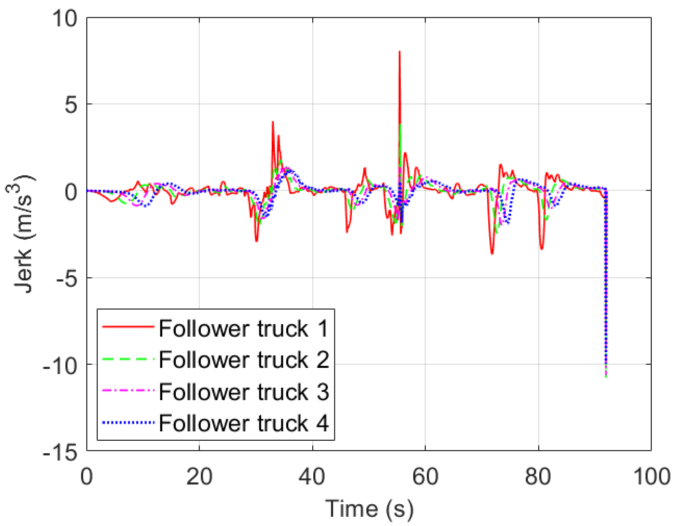

Figure 15: Jerk profiles of autonomous trucks using IDM with LSTM-predicted trajectories

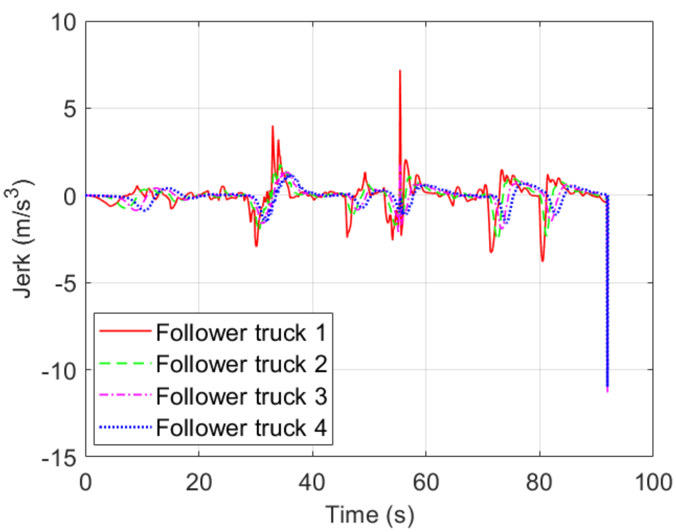

Figure 16: Jerk profiles autonomous trucks using IDM with QLSTM-predicted trajectories

CHAPTER 5

Summary of Findings, Limitations, and Future Scope

In this study, we used MATLAB to simulate a platoon of five autonomous trucks (with one leader truck and four follower trucks) for a duration of 92 seconds. A set of first-order ordinary differential equations was solved in MATLAB to simulate the platoon of five trucks. Finally, the trajectory dataset was generated for all five trucks from timestamp 0 s to 92 s. Then, the study developed and evaluated an LSTM (a fully classical NN) model and a QLSTM (a hybrid quantum-classical NN) model for predicting the trajectory of each leading vehicle in an autonomous truck platoon. Furthermore, this study evaluated the autonomous truck platoon's operational efficiency with the prediction of trajectories from both LSTM and QLSTM using the IDM.

5.1 Summary of Findings

Our analyses found that both the LSTM and the QLSTM models were able to predict the leading trucks' trajectories for platoon management when the real-time trajectory information is unavailable. The LSTM models' training took a similar or lower number of epochs to converge compared to the QLSTM models. However, the QLSTM-based trajectory predictions were observed to be closer to the original trajectories than the LSTM-based trajectory predictions. Moreover, the QLSTM-based predictions yielded more uniform inter-truck gaps compared to that of the LSTM-based predictions. Both the LSTM and QLSTM predictions resulted in similar jerk profiles for the follower trucks in a platoon.

This study showed that QLSTM can be used effectively to predict the speed trajectory of any leading trucks in an automated truck platoon, producing results that are better or on par with those of its classical counterpart while requiring substantially fewer training parameters. With the development of quantum computers, it is expected that hybrid quantum-classical LSTM, denoted as QLSTM in this report, would become more efficient in real-time platoon management and require even less computational burden for an autonomous truck platoon.

5.2 Limitations and Future Research Directions

In this study, we used the PennyLane simulator, which functions as an ideal quantum computer free from any noise or measurement errors that are commonly present in real quantum machines. Further investigations are needed to assess the efficacy and issues of utilizing a real quantum machine for the predicted trajectory-based platooning approach presented in this study.

Another limitation of this study is that the simulated platoon formation did not consider trucks entering and exiting the platoon. We also did not consider the lateral movement of the trucks in the platoon. Our future study will focus on predicting the trajectory of the leading vehicle of an automated truck platoon with both longitudinal and lateral movement, as well as trucks entering and exiting a platoon. Currently, the model does not consider the heterogeneity of vehicles and the existing communication delay in a real-world setting. Future studies will also evaluate the efficacy of the trajectory prediction algorithm in the real-world environment using actual automated trucks.

Furthermore, future studies should evaluate autonomous truck platoon performance for different types of car-following models besides IDM. Some car-following models may prove to be more effective with predicted trajectories over others. A thorough assessment of different types of car-following models would reveal the strengths and weaknesses of the models when working with predicted trajectories.

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