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Quantum Long Short-Term Memory-Assisted Optimization for Efficient Vehicle Platooning in Connected and Autonomous Systems

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ABSTRACT Vehicle platooning, especially when dedicated to carrying goods, represents a forward-looking approach to optimizing logistics and freight transportation using autonomous vehicles. In this study, we propose to employ Quantum Long Short Term Memory (QLSTM) models to predict the vehicle dynamics of a leading vehicle of the platoon. This predictive capability allows the following vehicles to adjust their behaviours dynamically. By doing so, we aim to optimize control strategies and maintain string stability within vehicle platoons. This approach leverages the unique computational advantages of quantum computing, particularly in processing complex temporal data, potentially leading to more accurate and efficient dynamic systems in vehicular platoon infrastructure. The simulation results indicate that the QLSTM model is highly efficient by learning more information in fewer epochs compared to traditional Long Short Term Memory (LSTM) models. This efficiency contributes to minimizing control errors, enhancing the precision and reliability of vehicle dynamics in the context of autonomous vehicle platooning. This research not only enhances the predictability of autonomous vehicle platoons but also opens pathways for research into how quantum computing can be integrated into real-time dynamic systems analysis and control.

INDEX TERMS Vehicle platooning, quantum long short term memory, optimization, quantum computing, control optimization.

I. INTRODUCTION

The concept of Cruise Control [1] was introduced to maintain constant speed determined by the driver without any variation. Adaptive Cruise Control (ACC) [1] builds on by continuously tracking the immediately preceding vehicle to adjust the speed as needed to maintain a safe distance. ACC on its own lacks the ability to maintain strong string stability [1] without motion-related knowledge about neighbouring vehicles. The exchange of information between neighbouring vehicles in Cooperative Adaptive Cruise Control (CACC), can facilitate traffic capacity and string stability by ensuring short inter-vehicle distances. Vehicle platooning is a key area of research within the CACC space.

A. BACKGROUND & MOTIVATION

Vehicle platooning [2] refers to the coordination of a group of vehicles travelling at close proximity to each other, utilizing communication and control technologies to maintain optimal inter-vehicle distances and speed synchronization. Theoretically, tightly packed vehicle platoon sharing information within platoon members enhances aerodynamic efficiency and reduces energy consumption [3]. In practice, tightly packed platoons increase the risk of sudden braking, especially in adverse road conditions like wet surfaces. To address this, it is advisable to adjust the inter-vehicle distance based on weather, road conditions, and aerodynamic interactions. These spacing policy considerations allow for more natural vehicle control behavior, minimizing unnecessary braking and

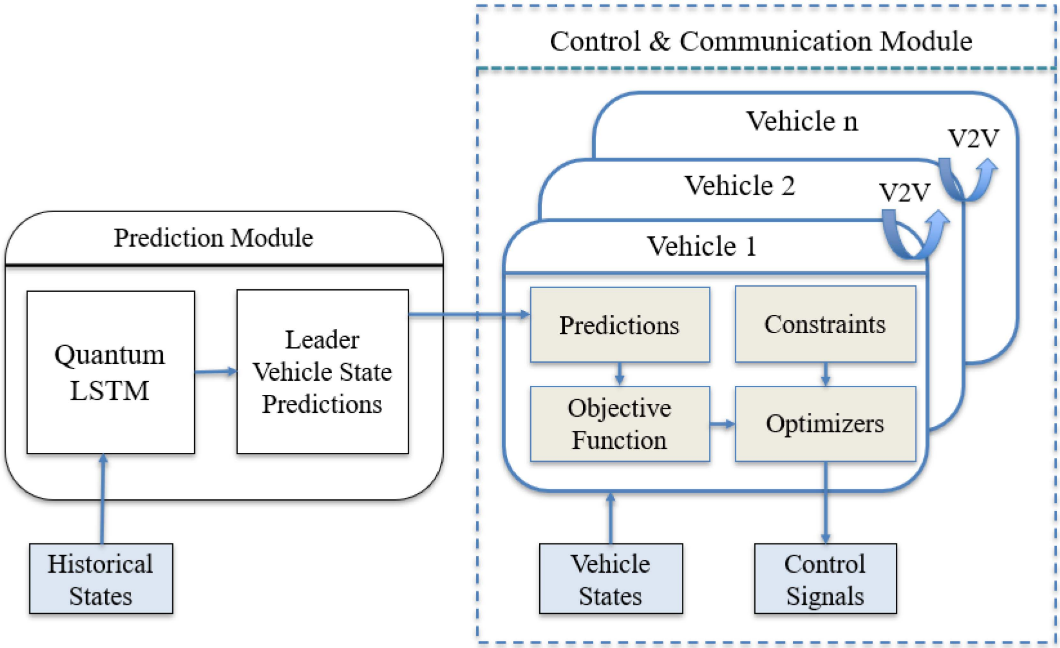

FIGURE 1. **Proposed QLSTM integrated vehicle platooning control optimization framework.**

speed oscillations. Moreover, an excessive amount of vehicle-to-vehicle (V2V) or vehicle-to-everything (V2X) communication may lead to transmission packet loss, congestion, and lower throughput. Thus, a well-designed platoon maneuvering system optimizes both control and communication strategies by preserving desirable control performance and limited communication for situational awareness.

Pilot programs and research are already underway in various parts of the world, aiming to test and refine vehicle platooning technologies under real-world conditions [4]. The authorized testing network comprises various segments of Highways 401, 403, 400, and 11in Canada, totaling approximately 222 kilometers across different routes [4]. The automotive industry is slowly moving towards connected, autonomous, and intelligent vehicles. By predicting the dynamics of the leader vehicle in the platoon, the following vehicles can ensure smoother adjustments (e.g., speed) to avoid unnecessary braking and acceleration. Reducing unnecessary braking and acceleration improves fuel efficiency, reduces emissions, enhances safety, extends vehicle component lifespan, improves passenger comfort, and traffic flow. Vehicle platooning dynamics are inherently sequential and time-dependent. Thus, some recent studies have focused on using advanced predictive models, such as Long Short-Term Memory (LSTM) to optimize the coordination and control algorithms within platoons [5].

However, vehicle platooning applications require online fine-tuning to maintain string stability and avoid the risk of collisions. Although Quantum Artificial Intelligence is still in its infancy, it offers real-time learning adaptability and enhanced learning capacity, making it a promising technology for future platooning applications. Quantum LSTMs (QLSTMs) theoretically handle complex patterns more efficiently than classical LSTMs in dynamic settings [6]. In this article, we employ a hybrid classical-quantum Long Short Term Memory model to predict the dynamics of the leader vehicle. Fig. 1 illustrates an advanced autonomous vehicle platooning system architecture that integrates a QLSTM model within its prediction module to forecast the future states of a leading vehicle based on historical data. This predictive output is utilized by a control and communication module, which orchestrates the behaviour of multiple vehicles using V2V communication. Each vehicle in the system processes these predictions to adjust its actions through an optimization framework that respects predefined constraints, ensuring optimal, safe, and efficient driving dynamics. The proposed framework highlights the use of quantum computing to enhance predictive accuracy and the collaborative interaction between vehicles to maintain platooning integrity and safety. The on-line nature of the optimization approach continuously updates the framework as new information becomes available from vehicle sensors, roadside unit, inter-vehicle communications, and environmental inputs. This is particularly critical in vehicle platooning, where delays in decision-making can compromise safety and string stability.

B. MAJOR CONTRIBUTIONS

The major contributions of this article are outlined in the following:

- First of all, we formulate the mathematical programming model for vehicle platooning control and communication optimization. Instead of relying on conventional tightly

packed platooning methods, we emphasize more practical platooning configurations to enhance operational efficiency.
- To further incorporate real-time learning and predictive mechanisms, we propose a vehicle dynamics prediction model using QLSTM to forecast the future states of the leading vehicle within the platoon, which in turn aids following vehicles in optimizing their control strategies.
- Through simulation results, we demonstrate the superiority of QSLTM over classical LSTM in order to optimize platoon control and communication aspects simultaneously.

C. ARTICLE ORGANIZATION

The rest of the article is structured as follows. Section II includes the relevant related works and research gap. Section III describes the vehicle platooning control optimization system model. Section IV explains the QLSTM architecture to predict the vehicle state. Extensive simulation results are demonstrated in Section V. Finally, Section VI concludes the article.

II. LITERATURE REVIEW

In this section, we summarize the relevant existing research on vehicle platooning optimization. We also make a conscious effort to identify and address the research gaps through our proposed QLSTM-assisted platooning optimization framework.

A. RESEARCH ON VEHICLE PLATOONING OPTIMIZATION

Several research studies have investigated to optimize control and communication strategies for vehicle platooning systems [7]. The taxonomy of optimization criteria for vehicle platooning includes fuel efficiency, safety enhancements, and congestion reduction [8]. Some research solely focuses on collision minimization for developing safety-centric vehicle platooning systems [9], [10]. To address communication disruptions, research efforts have been made on formulating optimal control spacing strategies amidst transmission error [11]. By enabling multi-modal sensor fusion, some researchers aim to optimize intra and inter-vehicle communication infrastructure in platoon [12], [13]. Resource allocation in vehicle platooning is another emerging research domain. These research studies mostly attempt to design bi-objective optimization problem for vehicle platooning, focusing on maximizing communication reliability and minimizing traffic oscillations [14].

B. INTELLIGENT PLATOONING APPROACHES

Recently, a transition has occurred towards developing adaptive control strategies by leveraging predictive mechanisms. These studies predict vehicle trajectory and adjust control proactively to increase overall responsiveness and efficiency of the platooning system [15], [16]. The most commonly used methodologies for intelligent platooning systems are deep reinforcement learning [17], federated learning [13], and classical LSTM [5], [18]. Classical LSTM methods are extensively utilized for modelling and predicting vehicle trajectories [19], [20].

TABLE 1. Description of Variables Used in the Platooning Model

Variable	Description
N	Total number of time steps
n	Index for vehicles within the platoon
k	Time step index
$S_n(k)$	State of the vehicle n at time k
R_n	Reference state for the vehicle n
Q_n	Weighting matrix for the state error
$x_i(k)$	Position of vehicle i at time k
$v_i(k)$	Velocity of vehicle i at time k
$u_n(k)$	Control input for vehicle n at time k
$a_n(k)$	Acceleration of vehicle n at time k
$d_j^*(k)$	Desired inter-vehicle distance for vehicle j at time k
l_j	Length of vehicle j
c_i^d, c_i^v	Weighting coefficients for position and velocity errors
$a_n^{\min}, a_n^{\max}$	Minimum and maximum acceleration for vehicle n
$u_n^{\min}, u_n^{\max}$	Minimum and maximum control input for vehicle n
$v^{\max}$	Maximum velocity for the vehicles
$d_n(k)$	Distance variable for vehicle n at time k
$t_s u_n^{\min}, t_s u_n^{\max}$	Minimum and Maximum change in control input over time for vehicle n
$d_n^{RSU}(k)$	Distance to the Road-Side Unit for vehicle n at time k
$d^{\max}$	Maximum allowed distance for RSU communication

C. QUANTUM COMPUTING FOR VEHICLE PLATOONING RESEARCH

Researchers have also recently evaluated the limitations of intelligent transportation systems (ITS). They have explored the integration of quantum computing to enhance ITS, by setting a roadmap for applying quantum technology in transportation [21], [22]. Quantum computing is primarily used for security and authentication in vehicle ITS, but recent research is beginning to explore its application in vehicle control [23], [24]. Quantum computing techniques have been utilized to optimize route selection for autonomous vehicles [25], [26], [27], [28]. Although these studies contribute significant research value, they lack integrated intelligent systems to ease the computational burden.

D. BRIDGING THE RESEARCH GAP

To the best of our knowledge, no research efforts have yet been dedicated to proposing an integrated optimization of vehicle platoon control using quantum strategies. Our proposed QLSTM-assisted vehicle platooning optimization framework enables enhanced learning and computational capacity than classical counterpart to aid adaptive platooning control optimization (Table I).

III. VEHICLE PLATOONING OPTIMIZATION MODEL

A. SYSTEM MODEL

The system model illustrated in Fig. 2 describes the communication framework of a vehicle platoon. The system model includes vehicles labeled from n to $n-3$, with inter-vehicle distances denoted by d_n, d_{n-1}, and d_{n-2}. The vehicles within the transmission range of the Roadside Unit (RSU),

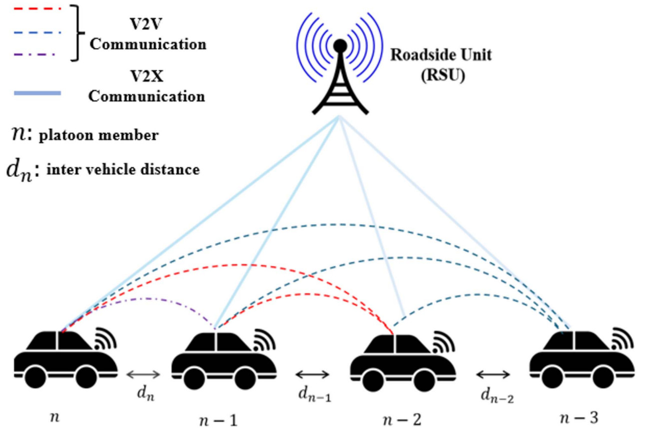

FIGURE 2. Vehicle platooning structure.

enable vehicle-to-infrastructure (V2I) communication. The RSU serves as a central node that can disseminate reference states to vehicles based on traffic information, weather updates, and environment that are essential for the coordinated movement and safety of the vehicular platoon through V2I communication. In order to facilitate cooperative control and synchronized operation among the vehicles, V2V communication links enable the exchange of information, such as speed and position, between neighbouring vehicles. The vehicle model along with the relevant assumptions has been considered from the literature [3], [29].

B. OPTIMIZATION FORMULATION

We define the objective function in (1) that aims to optimize the formation and control behavior of a platoon over N discrete time horizon. The first part of the objective function $(S_n(k) - R_n)^T Q_n (S_n(k) - R_n)$ is a quadratic cost function to quantify the deviation of the current state of a vehicle from a desired reference state. In this article, the state vectors are defined as $S_n(k) = [\Delta d_n(k) \;\; \Delta v_n(k) \;\; a_n(k)]^T$. The variable $\Delta d_n(k) = d_n(k) - d_n^*(k)$ at any time k, represents the difference between the actual distance and the desired distance. Additionally, $\Delta v_n(k)$ is the difference in velocity between the n^{th} vehicle and its predecessor, and $a_n(k)$ denotes the acceleration of the n^{th} vehicle. The matrix Q_n is a weighting matrix that scales the importance of distinct state variables within the cost function, tuning their influence on the overall cost. It allows for different elements of the state vector $S_n(k)$, for example, position or velocity, to be weighted differently according to their importance in the cost function. The idea is to impose greater penalty on more critical state deviations.

The remaining of the objective function considers the interaction of a vehicle with r number of preceding vehicles. It incorporates terms that ensure that the vehicles within the defined local-neighborhood of platoon work towards achieving a cohesive movement by matching both their relative positions, inter-vehicle distances, and velocities. Thus, the optimization variables are $S_n(k)$, $x_i(k)$, and $v_i(k)$ in (1) to mostly align reference values.

To summarize, the objective function strives to minimize the overall deviation from desired state references and maintain optimal inter-vehicle distances and velocities to support the characteristics for a stable and efficient vehicle platoon. Thus, the objective function takes into account both the individual performance of each vehicle by adhering to its reference state and the collective behavior of the platoon in terms of maintaining proper spacing and synchronized speeds.

$$\min \sum_{k=0}^{N-1} \Bigg[(S_n(k) - R_n)^T Q_n (S_n(k) - R_n) + \sum_{i=n-r}^{n-1} \Bigg[c_i^d \Bigg(x_i(k) - x_n(k) - \sum_{j=i+1}^{n} \left(d_j^*(k) + l_j^v \right) \Bigg)^2 + c_i^v (v_i(k) - v_n(k))^2 \Bigg] \Bigg], \tag{1}$$

subject to:

$$\mathcal{C}1 : a_n^{\min} \leq a_n(k) \leq a_n^{\max} \tag{2}$$

$$\mathcal{C}2 : u_n^{\min} \leq u_n(k) \leq u_n^{\max} \tag{3}$$

$$\mathcal{C}3 : v_n(k) \leq v^{max} \tag{4}$$

$$\mathcal{C}4 : d_n(k) > 0 \tag{5}$$

$$\mathcal{C}5 : t_s u_n^{\min} \leq u_n(k+1) - u_n(k) \leq t_s u_n^{\max} \tag{6}$$

$$\mathcal{C}6 : d_n^{\mathrm{RSU}}(k) \leq d^{\max} \tag{7}$$

$$\mathcal{C}7 : d_n(k) \geq d_{\min} + \mu(k) \cdot v_n(k)^2 \tag{8}$$

The constraint in $\mathcal{C}1$ ensures that the vehicle neither decelerates nor accelerates too quickly. Thus, the acceleration $a_n(k)$ of a vehicle n at any given time k must be within a range, bounded by $a_n^{\min}$ and $a_n^{\max}$. Similarly, the constraint $\mathcal{C}2$ restricts the vehicle to maintain safe and legal speed by limiting to a bound. This constraint introduces bound on the control input $u_n(k)$ of vehicle n at time k. Constraint $\mathcal{C}3$ ensures that the velocity of a vehicle does not go beyond the maximum limit. Then, constraint $\mathcal{C}4$ secures that the inter-vehicle distance must always be positive to prevent collision. For the comfort of passengers and to impose jerk limitation, constraint $\mathcal{C}5$ is applied. In order to ensure smooth ride, the system maintains the change in velocity between successive time steps within specified bounds, thereby ensuring that the acceleration does not change too abruptly. In this case, $t_s u_n^{\min}$ and $t_s u_n^{\max}$ can be set as per human comfort level or derived from ergonomic studies as per the tolerance of passengers in terms of change in acceleration. Next, constraint $\mathcal{C}6$ suggests that a vehicle must be within a certain distance from the RSU to maintain communication and send reference states. Finally, constraint $\mathcal{C}7$ verifies that each vehicle maintains a safe following distance, adapting dynamically to the road conditions (e.g., dry or wet roads) to prevent collision and ensure smooth traffic flow. For dry roads with good conditions, $\mu(k)$ ranges

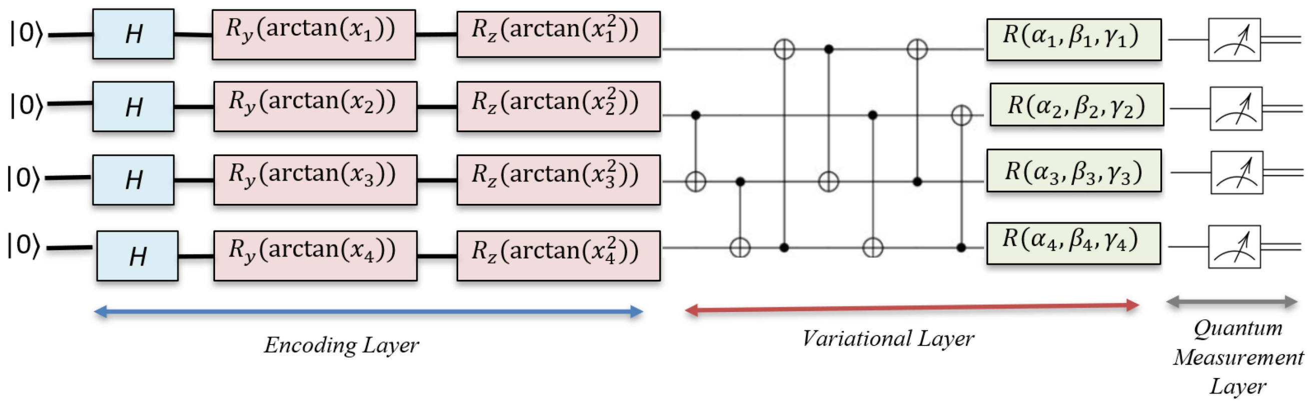

FIGURE 3. Stucture of VQC for QLSTM.

from 0.02 to 0.05; for wet roads, it is 0.05 to 0.1; and for icy/snowy roads, it increases to 0.1 to 0.2 or more depending on severity.

IV. QUANTUM LONG SHORT TERM MEMORY (QLSTM) FOR PREDICTING VEHICLE DYNAMICS

The primary purpose of using a QLSTM in platooning is to enhance real-time predictive accuracy and control, allowing follower vehicles to adapt as per the leader vehicle's trajectory, thereby maintaining optimal spacing and speed for safety and efficiency. By training a QLSTM with historical data on platoon-leading vehicles under various conditions, the network could learn to predict the future states. Thus, we employ the QLSTM to predict the dynamics of the leader vehicle so the follower vehicles of the platoon can adjust its control inputs promptly during the course of sudden trajectory change. The predicted state of the leader vehicle is passed through V2I communication to the leader vehicle.

A. QUANTUM GATES

Understanding how a QLSTM works involves describing the quantum gates used within the model. Quantum gates manipulate the state of qubits and are fundamental for quantum computing.

The Hadamard gate (H gate) is a fundamental single-qubit operation in quantum computing. It creates an equal superposition of the basis states, and it is represented by the following matrix:

H Gate (Hadamard)

$$H = \frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} = \frac{\alpha+\beta}{\sqrt{2}}|0\rangle + \frac{\alpha-\beta}{\sqrt{2}}|1\rangle$$

The Controlled NOT (CNOT) gate in quantum computing is represented by a 4×4 matrix that alters the state of two qubits. It flips the second qubit (target) if the first qubit (control) is in state 1, leaving other states unchanged. This operation is essential for creating quantum entanglement and implementing conditional logic in quantum circuits.

Controlled Not (CNot)

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} = a|00\rangle + b|01\rangle + d|10\rangle + c|11\rangle$$

B. QLSTM CIRCUIT MODEL ARCHITECTURE

In this article, we delve into the quantum realm of LSTM by substituting classical neural networks of traditional LSTM with Variation Quantum Circuit (VQC), regarded as hybrid quantum-classical version of LSTM. Fig. 3 demonstrates the foundation of the VQC architecture. A generic VQC is composed of three layers:

- *Data Encoding Layer:* Any classical to be processed by quantum circuits needs to be transformed into quantum space. First of all, each qubit is initialized with the state $|0\rangle$ to initiate quantum computation. Next, Hadamard Gate (H Gate) is applied to create superposition effects. Then, parameterized rotational quantum gates rotate qubits around the y-axis and z-axis, respectively. The angle of rotations are expressed using the arctangent of some input data.
- *Variational Layer:* Following the rotation gates, a series of CNOT gates are applied to create engalements and correlations between qubits. This part of the circuit forms multi-qubit entangled state to capture temporal data relationships. This layer can be repeated multiple times to increase the number of trainable parameters and the depth of the circuit, as needed.
- *Quantum Measurement Layer:* The quantum measurement layer comes after every VQC block. In real quantum computers, the measurement of values requires repeated statistical process. Theoretically, these measured values should be close to simulated ones under zero noise limit or noisy intermediate-scale quantum (NISQ) devices.

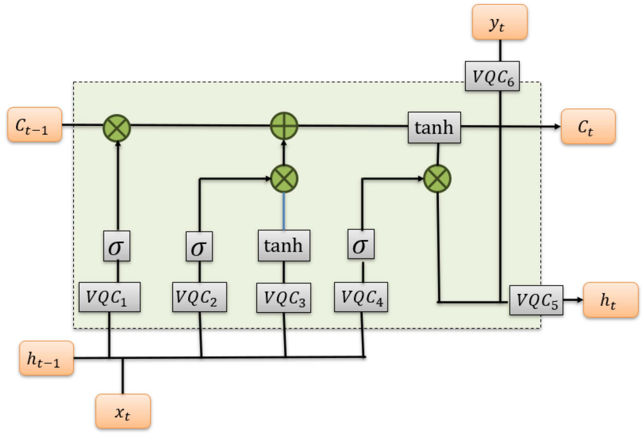

FIGURE 4. Overview of QLSTM Architecture. Here, ⊗ and ⊕ indicates element-wise multiplication and addition operations. σ and *tanh* represent sigmoid and hyperbolic tangent activation functions.

C. COMBINING PIECES TOGETHER

In order to build the QLSTM model, we stack up multiple VQC blocks together. In total, there are six VQCs in the QLSTM cell we considered. Fig. 4 illustrates the overall QLSTM architecture. The formal mathematical formulation of the QLSTM cell is defined in the following:

Forget Block: First of all, the forget block VQC_1 determines how much information from the previous cell c_{t-1} should be retained for the next step. The output value f_t equals to 0 indicates that the previous cell information should be completely forgotten, while being 1 represents that all the corresponding cell information should be carried forward. Generally, the vector corresponding to the cell contains values between 0 and 1, implying that a part of the information will be remembered so that QLSTM can learn temporal dependencies.

$$f_t = \sigma(VQC_1(a_t))$$

Input and Update Block: The purpose of the next part is to determine how much new information will be added to to the cell. This part contains two VQCs: VQC_2 and VQC_3. Here, a_t is the concatenated vector that combines both the hidden state h_{t-1} from the previous time step and the current input x_t. VQC_2 and VQC_3 employ sigmoid and hyperbolic tangent activation functions, respectively, to generate new candidate cell state $\tilde{C}_t$. Then, the output of VQC_2 is multiplied with $\tilde{C}_t$ to update the cell state accordingly.

$$i_t = \sigma(VQC_2(a_t))$$
$$\tilde{C}_t = \tanh(VQC_3(a_t))$$
$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{C}_t$$

Output Block: Afterwards, the QLSTM model moves on to prepare output. First, VQC_4 processes a_t and later a sigmoid function is applied to determine which information is supposed to be forwarded to the output. The cell state is transformed using *tanh* function and elementwise multiplied with the resultant vector from VQC_4. Finally, the resultant vector is either passed on to the hidden state h_t through VQC_5 or to the output y_t through VQC_6.

$$o_t = \sigma(VQC_4(a_t))$$
$$h_t = VQC_5(o_t \cdot \tanh(c_t))$$
$$y_t = VQC_6(o_t \cdot \tanh(c_t))$$

In this study, we utilize the QLSTM model to predict the dynamics (e.g., speed) of a leader vehicle in a platoon based on sequential data comprising time stamps, horizontal positions, and cumulative distances. By capturing the temporal dependencies inherent in the sequence of timestamp, position, and distance QLSTM model aims to provide accurate speed estimations that are crucial for real-time tracking and movement analysis.

Specifically, the "long" state captures the long-term temporal dependencies within the platooning system. For example, "long" term memory learns about consistent average speed of the global platoon. Meanwhile, the "short" term memory focuses more on immediate and transient information, such as sudden changes in acceleration or decelerations of vehicles due to unexpected obstacles or variations in the speed of nearby vehicles. The complex interactions of these states ensure that critical long-term patterns (e.g., consistent leader-following rules) and short-term reactions (e.g., emergency braking) are dynamically balanced within the prediction module.

D. ANALYSIS ON NUMBER OF QUBITS

The total number of qubits required for VQCs are determined as per the dimension of the input vector $v_t = [h_{t-1}x_t]$. For measurement layer, the number of qubits depends on the dimensions of the hidden state of the QLSTM.

V. RESULTS

In order to solve the platooning control optimization model, we have used Gurobi solver [30]. The classical computational experiments have been performed using DELL ALIENWARE m15 R3 machine of Intel core i7-10750H CPU @2.6GHz equipped with 16GB RAM machine. To implement the classical LSTM, we have used TensorFlow with Python binding [31]. The hybrid quantum-classical LSTM model is evaluated using Xanadu's Pennylane [32].

A. HYPERPARAMETERS

We configure the initial learning rate of classical LSTM as 0.005, allowing the model to update its weights at this rate during backpropagation. A dropout rate of 0.2 is used to prevent overfitting by randomly ignoring 20% of the neurons during training. The network consists of 100 hidden nodes which are the units in the hidden layers capable of capturing the complexities in the data. Training is conducted with a batch size of 4, meaning that 4 samples are processed before the model's internal parameters are updated. The training process spans 100 epochs, with each epoch representing a full pass through the entire training dataset.

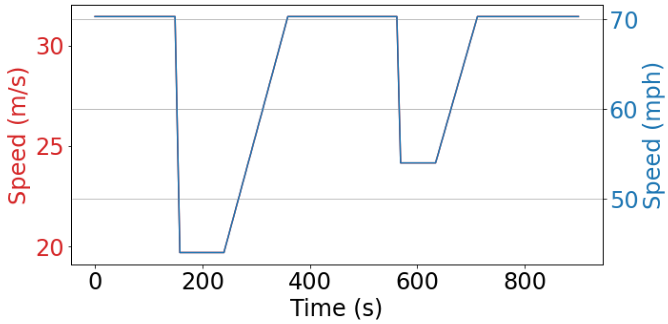

FIGURE 5. Leader vehicle's speed profile.

TABLE 2. Speed Profile Descriptions for the Leading Vehicle

Time Span	Velocity of the Leading Truck
0 s to 149 s	Constant velocity at 31.44 m/s (70.3 mph)
149 s to 158 s	Deceleration from 31.44 m/s (70.3 mph) to 19.69 m/s (44.04 mph)
158 s to 240 s	Steady velocity of 19.69 m/s (44.04 mph)
240 s to 359 s	Acceleration from 19.69 m/s (44.04 mph) to 31.44 m/s (70.3 mph)
359 s to 562 s	Constant velocity at 31.44 m/s (70.3 mph)
562 s to 569 s	Reduction in speed from 31.44 m/s (70.3 mph) to 24.15 m/s (54.02 mph)
569 s to 634 s	Steady velocity of 24.15 m/s (54.02 mph)
634 s to 712 s	Acceleration from 24.15 m/s (54.02 mph) to 31.44 m/s (70.3 mph)
712 s to 900 s	Constant velocity at 31.44 m/s (70.3 mph)

This study utilized four qubits, a single variation layer, and a learning rate of 0.05. The selection of these parameters was based on initial experiments with a smaller number of epochs to identify the configuration that delivered the most favourable results.

B. SIMULATION SETUP

We consider the I-26 freeway in South Carolina's Berkeley, Orangeburg, and Dorchester County as the site of a calibrated traffic simulation network. All the simulation parameters have been considered from the literature [29]. We have used a platoon size of 5 vehicles. The length of the vehicle is considered as 5 meters. The maximum acceleration for the vehicles, $a_n^{\max}$, is $3\,\text{m/s}^2$, while the maximum control input, $u_n^{\max}$, is also $3\,\text{m/s}^2$. Additionally, the sampling time t_s is 0.1 seconds and the desired inter-vehicle distance is 2 meters. Both the minimum acceleration $a_n^{\min}$ and the minimum control input $u_n^{\min}$ are $-4\,\text{m/s}^2$.

Fig. 5 shows the speed profile of the leader vehicle alternating among 31.44m/s, 19.69m/s, and 24.15m/s over 900-seconds time span. The more elaborative descriptions of the speed profile have been recorded in Table 2.

C. EVALUATION OF QUANTUM LSTM

Fig. 6 illustrates the the loss over epochs for QLSTM and LSTM models during both the training and testing phases. The QLSTM model exhibits much faster convergence to lower loss values during training phase, compared to LSTM, indicating faster learning abilities. Moreover, the testing loss of QLSTM

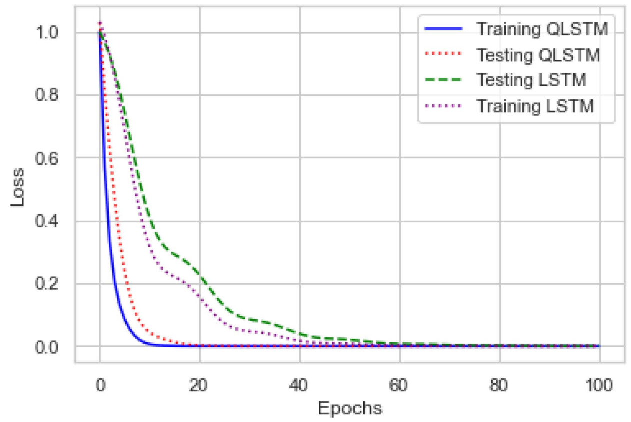

FIGURE 6. Comparison of Classical LSTM versus QLSTM.

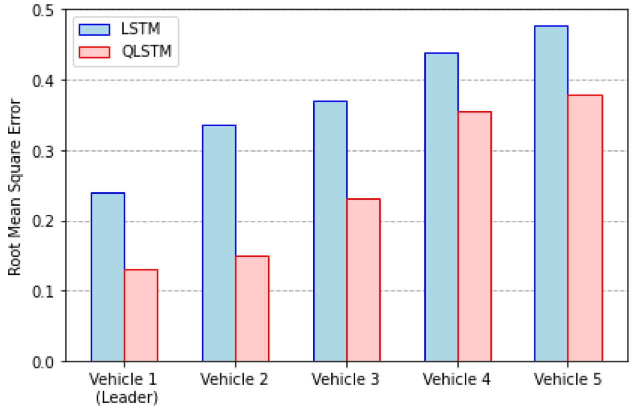

FIGURE 7. Comparison of root mean square error (RMSE) between LSTM and QLSTM models for trajectory across a vehicle platoon of 5 members.

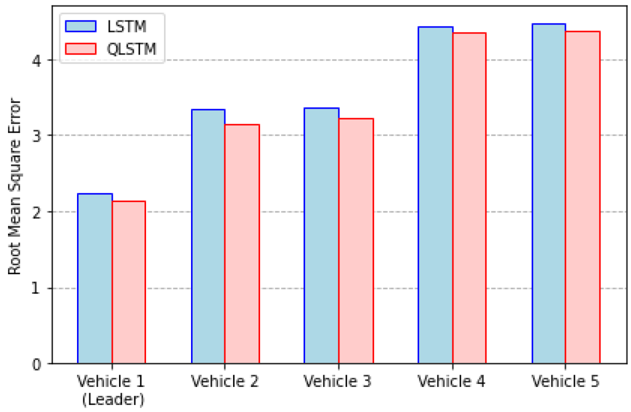

FIGURE 8. Comparison of root mean square error (RMSE) between LSTM and QLSTM models for speed across a vehicle platoon of 5 members.

stabilizes at a lower value than LSTM, suggesting superior performance on unseen data.

D. PREDICTIVE PERFORMANCE ANALYSIS OF PLATOON MEMBERS

Figs. 7 and 8 compare the Root Mean Square Error (RMSE) of LSTM and QLSTM models in terms of trajectory and speed across five vehicles in a platooning scenario. The QLSTM

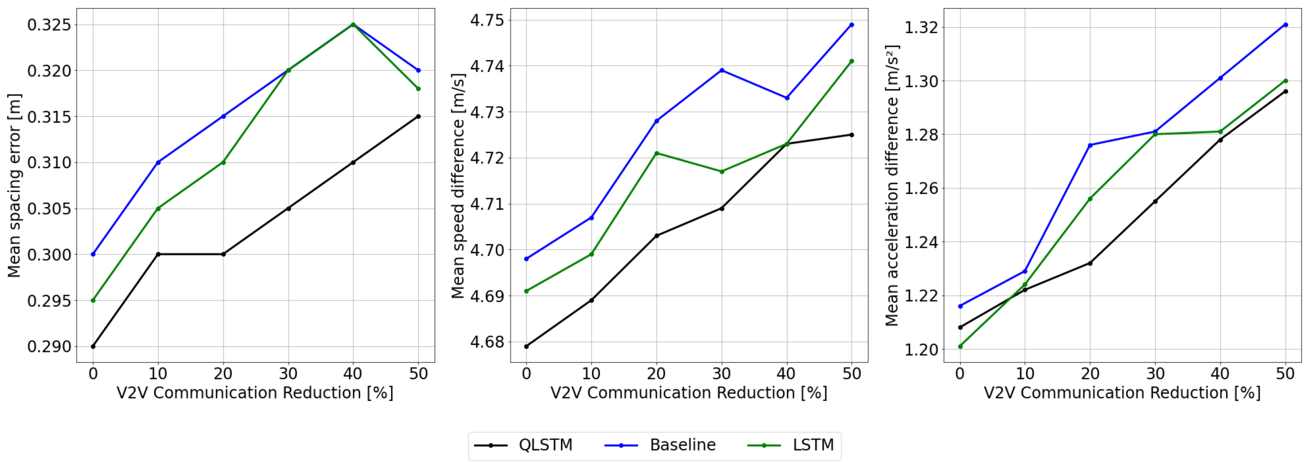

FIGURE 9. Comparison of performance under varying degree of V2V communication.

model provides more accurate predictions compare to LSTM model across all the vehicles. It is noteworthy that the prediction for the speed profile of the leader vehicle is used by the control optimization model to determine the errors in the states of the vehicles following it. Due to the increasing complexity of coordination and cumulative error, the performance tends to deteriorate for later vehicles in the platoon, regardless of the model used.

E. IMPACT ON V2V COMMUNICATION

Next, we evaluate the performance of models under varying levels of V2V communication. For this purpose, we calculate Mean Absolute Error (MAE) as per the following:

$$MAE = \frac{1}{N}\sum_{k=1}^{N} |y(t) - \hat{y}(t)| \tag{9}$$

Here, N represents the total number of observations. The notation $y(t)$ denotes the actual value at a given time t, while $\hat{y}(t)$ represents the corresponding predicted value. The term $|y(t) - \hat{y}(t)|$ is the absolute difference between the actual and predicted values. These absolute differences are summed across all observations, and the result is averaged by dividing by N to calculate the MAE.

Fig. 9 compares the performance difference of various models (QLSTM, Baseline, and LSTM) across varying levels of V2V communication. The baseline model is the control optimization model with preset values without any predictive measures. For all three models, mean spacing error increases as V2V communication reduction level increases. QLSTM outperforms other models, indicating it handles less V2V communication better. Similarly, in terms of mean spacing and acceleration error, QLSTM demonstrates more robustness, especially at higher V2V communication level reduction. The experimental results suggest that QLSTM shows superior results over classical LSTM and baseline for real autonomous vehicle applications where V2V communications may be often disrupted or need to be reduced/optimized.

F. DISCUSSIONS, CHALLENGES, & PRACTICAL IMPLICATIONS

Even though the research study highlights the forward-looking potential of integrating QLSTM models within vehicle platooning systems, some technical challenges remain present. Given current quantum hardware constraints, including limited qubit availability, our simulations are restricted to a platoon size of five vehicles. Scalability remains a critical research area for future exploration. While broader scalability is currently restricted by quantum hardware capabilities, several ongoing research efforts, such as improved quantum error correction, hybrid classical-quantum approaches, and advancements in quantum device architectures hold promise for addressing these challenges. We acknowledge the importance of exploring real-world testing strategies and fostering partnerships with quantum computing vendors and autonomous vehicle manufacturers. These collaborations could serve as a critical step in bridging the gap between theoretical advancements and practical applications. By engaging with industry stakeholders, the proposed QLSTM enhanced optimization framework could be tested in realistic settings, enabling a deeper understanding of their scalability, reliability, and performance under realistic conditions. Such partnerships would allow for access to state-of-the-art quantum hardware. Moreover, collaboration with autonomous vehicle manufacturers holds the potential to bring quantum-enabled optimization techniques into existing real-world platooning systems. These partnerships could unlock opportunities for practical testing and innovation, paving the way for smarter vehicle coordination and sustainable transportation goals. While this article primarily focuses on the theoretical and simulation-based validation of the proposed approach, the inclusion of these forward-looking strategies can be regarded as the long-term vision for potential research directions.

VI. CONCLUSION

This research study demonstrates the effectiveness of QLSTM models over traditional LSTM in vehicle platooning control optimization applications by achieving faster convergence and more accurate predictions for vehicle dynamics. The integration of QLSTM in the control optimization model minimizes errors of vehicle dynamics in a platoon, particularly under varying levels of V2V communication. The findings suggest that QLSTM models are significantly superior even in minimal V2V communication scenarios, offering a promising path forward for more efficient, reliable, and scalable vehicle platooning systems. The biggest challenge of implementing vehicle platooning with QLSTM is quantum hardware limitations. As quantum technologies mature and regulatory frameworks evolve, vehicle platooning will lead towards more stable, safe, and sustainable freight transportation systems globally.

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