

Hybrid LSTM–CNN Anti-Jerk Torque Prediction for 2WD and 4WD Electric Vehicles with Single- and Two-Speed Transmissions

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ABSTRACT

Electric powertrains exhibit fast torque dynamics and relatively low mechanical damping, which can excite torsional drivetrain modes and produce longitudinal acceleration oscillations during torque transients. The supplied reference study established a common vehicle-modeling and drivability framework for four central-motor electric-vehicle (EV) architectures: single-speed 2WD (L1), 2-speed 2WD (L2), single-speed 4WD (L3), and 2-speed 4WD (L4). This work extends that framework with data-driven anti-jerk torque prediction using layout-specific hybrid LSTM–CNN models. A hybrid temporal–local feature learning framework is proposed for architecture-aware anti-jerk torque prediction, in which LSTM captures the longer-term temporal evolution of drivetrain states while CNN extracts short-duration local patterns associated with torque transients and torsional oscillations. The proposed controller aims to achieve smoother torque transmission, reduce drivetrain oscillations and vehicle jerk, and improve overall driving comfort. The performance of the system can be evaluated using parameters such as jerk reduction, torque response, and system stability. The proposed hybrid LSTM–CNN algorithm is compared with conventional LSTM to demonstrate its improved anti-jerk torque prediction performance across different EV configurations.

Keywords: Electric vehicle; anti-jerk control; LSTM; hybrid LSTM–CNN; torsional vibration; drivability; 2WD; 4WD; two-speed transmission; torque prediction.

1. INTRODUCTION

Electric vehicles combine rapid electric-machine torque response with mechanical drivetrains containing compliant half-shafts, tires, differentials, and transmissions. The resulting low-damped torsional dynamics can produce resonances and longitudinal acceleration oscillations that are directly perceived as poor drivability. The main reference study considered this issue while comparing four EV architectures and showed that 2WD/4WD and single-/two-speed configurations have materially different dynamic responses. In particular, the reference work identified gear ratio, motor inertia, motor dynamics, and half-shaft torsional stiffness as important factors governing vibration magnitude and frequency. It also demonstrated that 4WD layouts can be more responsive and more prone to oscillation because of their faster motor dynamics, while two-speed transmissions introduce additional drivability complexity.

The reference vehicle study is especially relevant to the present work because it provides a common architecture definition and a nonlinear forward-facing MATLAB/Simulink framework. The four layouts are L1: single-speed 2WD, L2: 2-speed 2WD, L3: single-speed 4WD, and L4: 2-speed 4WD [1]. The reported gear ratios are 8.9 for the single-speed layouts and 12.2/6.76 for the two-speed layouts. The reference model includes torsional half-shaft compliance and tire relaxation effects and evaluates drivability using time- and frequency-domain indicators.

Although conventional anti-jerk control is effective, the changing dynamics across architectures motivate a data-driven approach that can learn temporal dependencies from measured or simulated drivetrain signals. LSTM networks are particularly suited to sequential data because the memory-cell structure allows temporal information to be retained across a sequence. The supplied LSTM controller literature also demonstrates a practical strategy of collecting input/output data from multiple operating regions and training a single recurrent controller to capture different dynamic conditions. A second supporting study further motivates hybrid LSTM-based control by combining learned temporal information with conventional control and optimization so that the controller can adapt to changing dynamics.

The objective of this study is therefore to develop and document an architecture-aware LSTM and hybrid LSTM–CNN anti-jerk torque-prediction framework for the four EV layouts, apply validated layout-specific gains, and assess the resulting torque-prediction performance without altering the original no-anti-jerk reference response.

2. LITERATURE AND TECHNICAL BACKGROUND

Electric vehicle (EV) powertrain architecture has a significant influence on drivability, energy consumption, vibration, and overall vehicle performance. Previous studies have investigated different EV configurations, including single- and multi-motor arrangements, 2WD and 4WD systems, and single- and multi-speed transmissions [1]–[5]. These studies indicate that the selection of drivetrain architecture affects torque distribution, vehicle response, and dynamic behaviour. In particular, the interaction between motor dynamics, transmission ratio, drivetrain stiffness, and wheel torque distribution can produce torsional oscillations that negatively affect drivability [1], [5].

The introduction of two-speed transmissions can improve the operating efficiency, acceleration capability, and gradeability of EVs [6], [7]. However, gear changes introduce additional torque-transient challenges. Studies on seamless shifting and torque-fill control have shown that appropriate motor-torque coordination is required to reduce torque interruptions and maintain smooth vehicle acceleration during gear changes [7]–[9]. These challenges become more significant in 4WD EVs because torque must be coordinated between the front and rear powertrains. The comparison of different EV layouts in [1] demonstrated that 4WD and two-speed configurations can exhibit more complex drivability characteristics than conventional single-speed 2WD systems.

Drivetrain torsional vibration and its suppression have therefore become important research topics in electric powertrains. Active damping methods have been proposed to reduce drivetrain oscillations by modifying the motor torque according to the drivetrain dynamic response [10]. More broadly, anti-jerk control techniques have been developed using feedback, feedforward, model-based, and other control strategies to suppress longitudinal acceleration oscillations and improve driving comfort [11]. However, these approaches generally depend on drivetrain models, controller parameters, or carefully selected control gains. EV NVH studies have also emphasized that the rapid torque response and operating characteristics of electric motors introduce particular vibration and harshness challenges, making effective vibration-control strategies increasingly important [12].

Although conventional anti-jerk and torque-control methods can provide effective vibration suppression, their performance can vary with vehicle configuration, gear ratio, operating condition, and drivetrain dynamics. The literature therefore indicates a need for control approaches that can learn the nonlinear and time-dependent relationship between drivetrain states and the required corrective torque. Data-driven deep-learning methods, particularly LSTM networks, provide a potential solution because they can learn temporal dependencies from sequential drivetrain data.

Based on the above literature, the present study focuses on an architecture-aware deep-learning approach for anti-jerk torque prediction. Four EV configurations are considered: single-speed 2WD, two-speed 2WD, single-speed 4WD, and two-speed 4WD. Motor speed, wheel speed, driver torque, vehicle speed, torsion-rate error, and gear ratio are used as input variables. An LSTM model is first considered as a temporal-learning baseline, followed by a Hybrid LSTM–CNN model to combine temporal information with local feature extraction. The proposed methods are evaluated in terms of torque-prediction accuracy and vehicle-level jerk performance. Thus, the study extends the existing EV anti-jerk literature by investigating a common data-driven framework across different drivetrain architectures rather than designing a separate conventional controller for each configuration.

2.1. EV layout and drivability problem

The main reference paper established that the four considered architectures differ not only in energy and gradeability characteristics but also in drivability. For the studied vehicle, the layouts have the following main characteristics: L1 uses one 28 kW central motor and a single-speed ratio of 8.9; L2 uses the same motor with a 12.2/6.76 two-speed transmission; L3 uses two 14 kW motors with single-speed ratios of 8.9; and L4 uses two 14 kW motors with 12.2/6.76 two-speed transmissions. The reported vehicle masses are 820.6, 831.5, 848.2, and 870.0 kg for L1–L4, respectively in Table1.

Table 1: Specifications of the Four EV Drivetrain Configurations

Layout	Architecture	Gear ratio(s)	Vehicle mass (kg)
L1	Single-speed 2WD	8.9	820.6
L2	2-speed 2WD	12.2 / 6.76	831.5
L3	Single-speed 4WD	8.9	848.2
L4	2-speed 4WD	12.2 / 6.76	870.0

2.2. LSTM-based control concepts

The supporting LSTM literature describes recurrent processing through input, forget, and output gates, together with a cell state and hidden state. Using the notation $x(t)$ for the input vector, $h(t)$ for the hidden state, and $c(t)$ for the cell state, the recurrent relations can be expressed as [13] and [14]:

$$\begin{aligned}
 i(t) &= \sigma(W_i x(t) + U_i h(t-1) + b_i) \\
 f(t) &= \sigma(W_f x(t) + U_f h(t-1) + b_f) \\
 o(t) &= \sigma(W_o x(t) + U_o h(t-1) + b_o) \\
 c(t) &= f(t) \odot c(t-1) + i(t) \odot \tanh(W_c x(t) + U_c h(t-1) + b_c) \\
 h(t) &= o(t) \odot \tanh(c(t)) \\
 \hat{y}(t) &= W h(t) + b
 \end{aligned}$$

The supporting PV-system study illustrates a region-aware training strategy in which input/output data are collected from multiple operating regions and concatenated for LSTM training. That concept is transferred here at the architecture level: instead of treating all EV layouts as identical, the proposed workflow retains a common feature structure while using layout-specific trained models and gains.

2.3. Hybrid learning and adaptive control motivation

The 2025 supporting paper combines LSTM-based real-time model identification with conventional control and optimization. Its reported architecture emphasizes the complementary roles of temporal learning, model identification, and conventional control, with LSTM used to capture dynamic dependencies. The present study adopts the same general principle of combining learned temporal behavior with a control-oriented output stage, but applies it to anti-jerk torque prediction in EV drivetrains.

The proposed CNN–LSTM architecture integrates convolution-based representation learning with recurrent temporal modelling. The principal motivation is to exploit the complementary characteristics of the two learning mechanisms. The CNN component transforms the original input into a compact representation containing locally relevant patterns, whereas the LSTM component processes the resulting feature sequence to model temporal dependencies. Thus, instead of directly applying a recurrent model to the raw input, the proposed framework first performs hierarchical feature extraction and subsequently performs temporal dependency learning [15].

The overall transformation can be represented as:

$$X \rightarrow \text{CNN} \rightarrow F \rightarrow \text{Reshape} \rightarrow F_{\text{seq}} \rightarrow \text{LSTM} \rightarrow h_t \rightarrow \text{Dense} \rightarrow \hat{y}_{t+1}$$

where X denotes the original input, F is the learned feature representation, F_{seq} is the sequential feature representation, h_t is the learned hidden representation, and $\hat{y}_{t+1}$ is the final prediction.

$$F = \mathcal{C}(X; \theta_C)$$

The extracted feature maps are subsequently converted into a sequence

$$F_{\text{seq}} = \mathcal{R}(F)$$

The LSTM processes the feature sequence recursively:

$$h_t, c_t = \mathcal{L}(F_{\text{seq},t}, h_{t-1}, c_{t-1}; \theta_L)$$

The final prediction is generated from the learned temporal representation: $\hat{y}_{t+1} = W_y h_t + b_y$

3. PROPOSED ARCHITECTURE-AWARE ANTI-JERK PREDICTION METHOD

3.1. Overall workflow

The proposed workflow consists of six stages shown in table 2 and Fig 1: (1) generation or acquisition of drivetrain time-series data; (2) cleaning and validation of the signals; (3) normalization using training-set parameters; (4) formation of sliding-window sequences; (5) LSTM and hybrid LSTM–CNN prediction of anti-jerk torque; and (6) application of a validated layout-specific gain to the raw prediction. The final controller torque contribution is combined with the driver torque command.

Table 2: Stages of the Proposed Architecture-Aware LSTM and Hybrid LSTM–CNN Anti-Jerk Torque Prediction Framework

Stage	Operation	Purpose
1	Acquire drivetrain signals	Capture temporal drivetrain dynamics
2	Remove invalid samples	Ensure finite, physically usable data
3	Normalize inputs	Use the same scaling applied during training
4	Sliding-window sequence generation	Provide temporal context to LSTM
5	Predict anti-jerk torque	Estimate the corrective torque
6	Apply layout-specific gain	Calibrate prediction magnitude for each layout

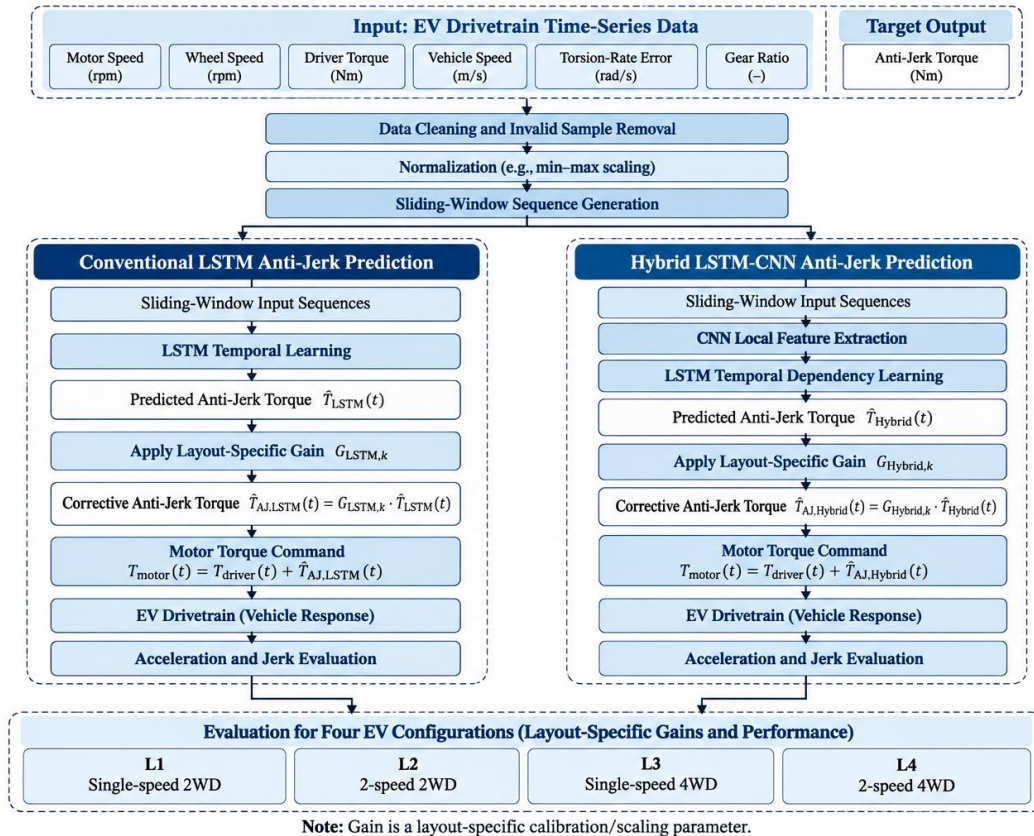


Fig 1: Proposed Architecture-Aware LSTM and Hybrid LSTM–CNN Anti-Jerk Prediction Framework

3.2. Input variables and sequence representation

The MATLAB prediction implementation uses six input features: motor speed, wheel speed, driver torque, vehicle speed, torsion-rate error, and gear ratio. The reference/target signal is the anti-jerk torque. For a sequence length N_s the normalized sequence is arranged in feature-by-time-step form, which is the expected sequence representation for the MATLAB LSTM predictor. Table 3 shows input variables and its description.

Table 3: Input variables and their description

Feature	Role in prediction
Motor Speed	Represents motor-side dynamic state
Wheel Speed	Represents wheel-side rotational state
Driver Torque	Represents the requested propulsion torque
Vehicle Speed	Represents longitudinal vehicle operating condition
Torsion Rate Error	Represents drivetrain torsional dynamic error
Gear Ratio	Provides architecture/gear-state information
Anti-Jerk Torque	Prediction target / reference torque

3.3 Problem Formulation

$$T_{EM,corr}^f = K(\dot{\theta}_{EM}^f - \dot{\theta}_w^f i_{sel}^f i_{diff}^f)$$

$T_{EM,corr}^f$ is electric motor correction torque

K is anti – jerk controller gain

$\dot{\theta}_{EM}^f$ is angular electric motor velocity

$\dot{\theta}_w^f$ is angular wheel speed

i_{sel}^f is gear selection ratio

i_{diff}^f is gear differential ratio

The difference inside the parentheses represents the drivetrain speed mismatch associated with torsional deformation. The controller generates a corrective motor torque proportional to this mismatch, thereby introducing an effective damping action into the drivetrain.

4. RESULTS AND DISCUSSIONS

In the proposed data-driven framework, the LSTM and Hybrid LSTM–CNN models are used to predict the required anti-jerk torque from the drivetrain time-series variables, while layout-specific gains are subsequently applied to calibrate the predicted torque for the four EV configurations and are shown in Table 4.

Table 4: Layout-Specific Gains for LSTM and Hybrid LSTM–CNN Anti-Jerk Torque Prediction

Layout	LSTM gain	Hybrid LSTM–CNN gain
L1 – Single-speed 2WD	0.756	0.844
L2 – 2-speed 2WD	0.630	0.778
L3 – Single-speed 4WD	0.727	0.836
L4 – 2-speed 4WD	0.717	0.833

Table 5. Comparison of Peak Jerk Reduction for LSTM and Hybrid LSTM–CNN Anti-Jerk Prediction Across Four EV Layouts

Vehicle Layout	Gear 1	Gear 2	Without Anti-Jerk (OFF)	LSTM	Hybrid LSTM–CNN	LSTM Reduction (%)	Hybrid Reduction (%)
Single-speed 2WD	8.90	8.90	191.96	103.79	93.24	45.94	51.43
2-speed 2WD	12.20	6.76	138.55	102.02	93.33	26.36	32.64
Single-speed 4WD	8.90	8.90	227.57	105.84	87.3	53.49	61.64
2-speed 4WD	12.20	6.76	278.03	134.50	110.71	51.62	60.18

The results as shown in table 5 demonstrate that the anti-jerk prediction performance is strongly influenced by the EV drivetrain architecture. The four configurations considered in this study have different combinations of drive arrangement and transmission ratio, resulting in different transient responses. The reference study also reported more pronounced oscillatory behavior for the 4WD configurations and additional gear-dependent effects for the two-speed configurations.

The peak-jerk results further support this observation. Without anti-jerk compensation, L4 (2-speed 4WD) exhibits the highest peak jerk of 278.03 m/s³, followed by L3 (single-speed 4WD) at 227.57 m/s³, L1 at 191.96 m/s³, and L2 at 138.55 m/s³. This indicates that the more complex 4WD and two-speed configurations can produce stronger transient responses. The proposed learning-based compensation reduces these peaks for all four configurations.

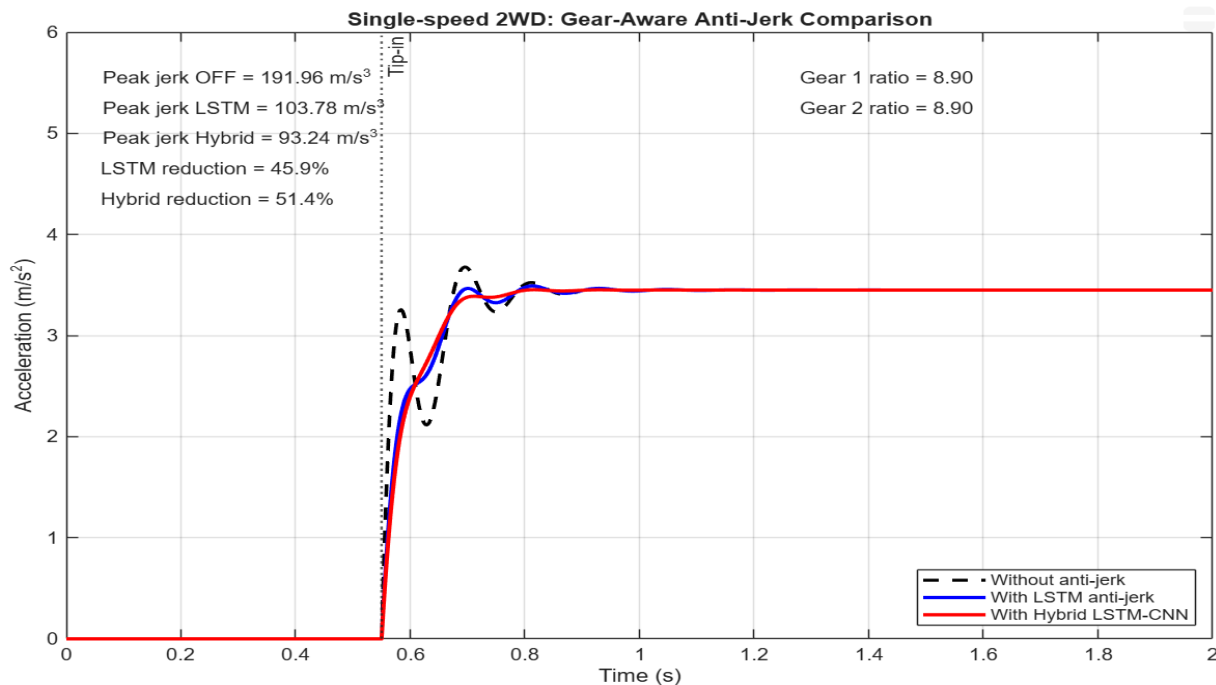


Fig. 2: Peak-Jerk Comparison for Single-Speed 2WD (L1) with LSTM and Hybrid LSTM–CNN Anti-Jerk Prediction

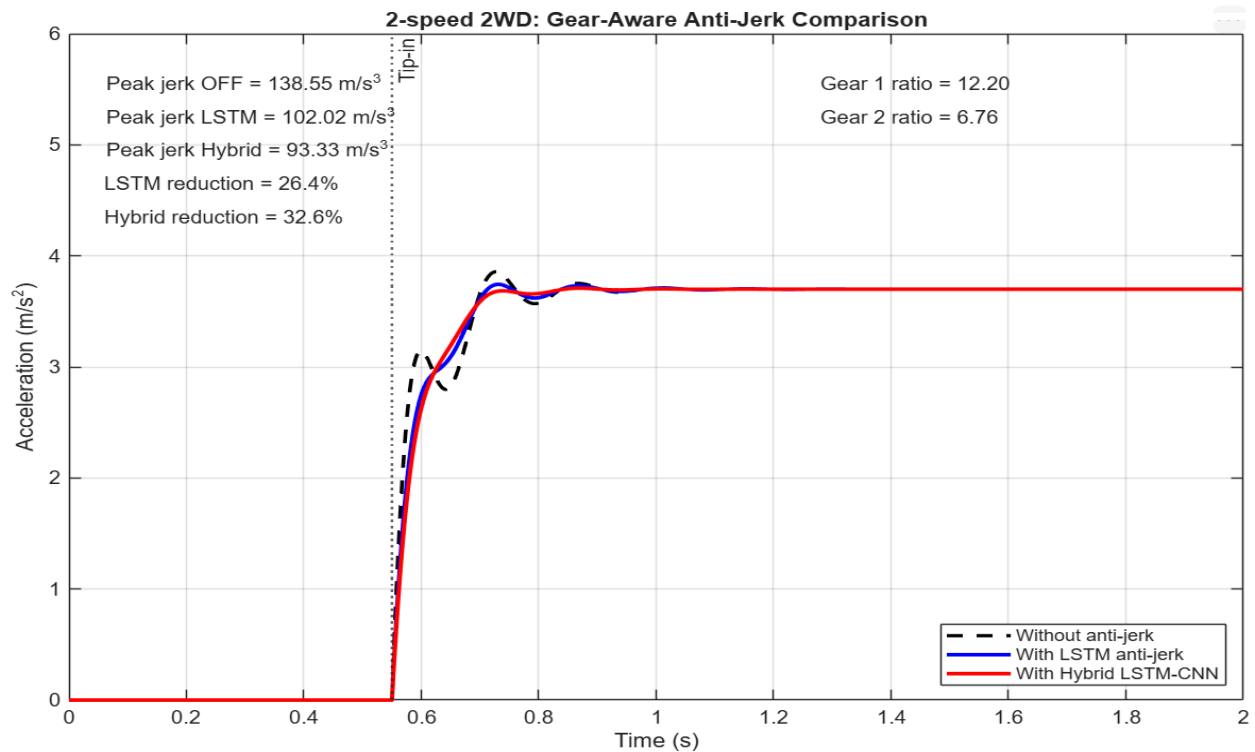


Fig.3 Peak-Jerk Comparison for 2-Speed 2WD (L2) with LSTM and Hybrid LSTM–CNN Anti-Jerk Prediction

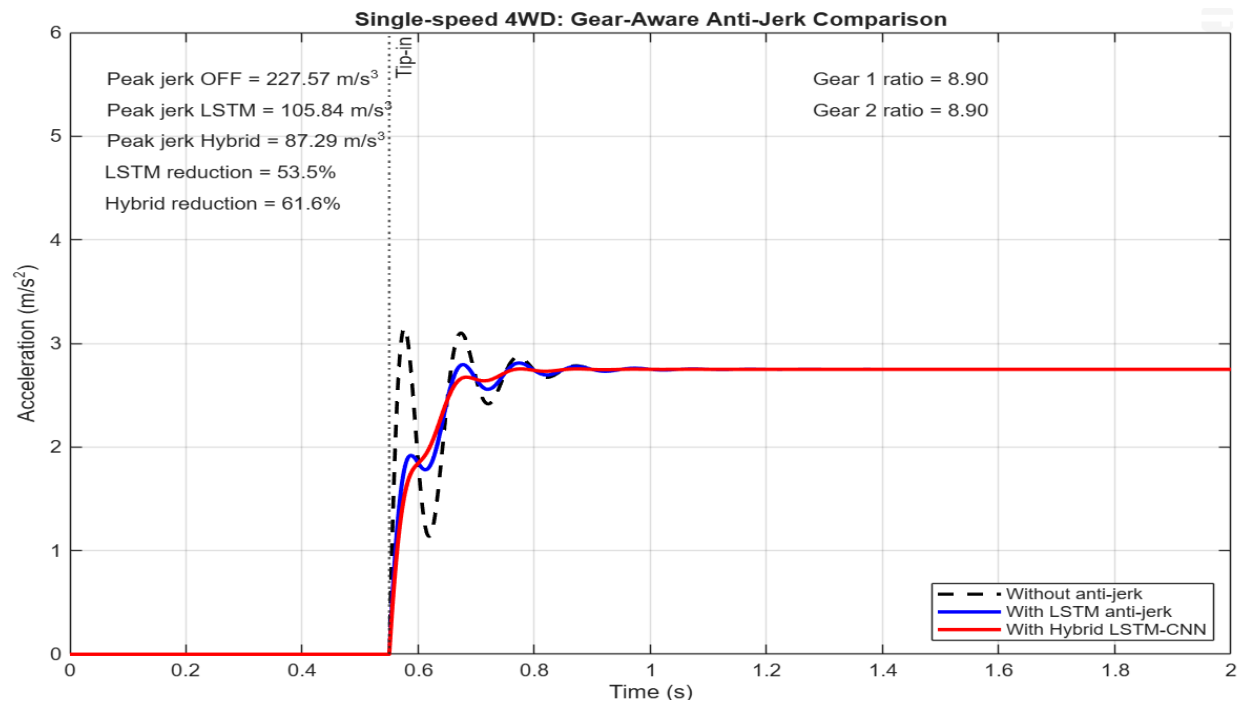


Fig.4 Peak-Jerk Comparison for Single-Speed 4WD (L3) with LSTM and Hybrid LSTM–CNN Anti-Jerk Prediction

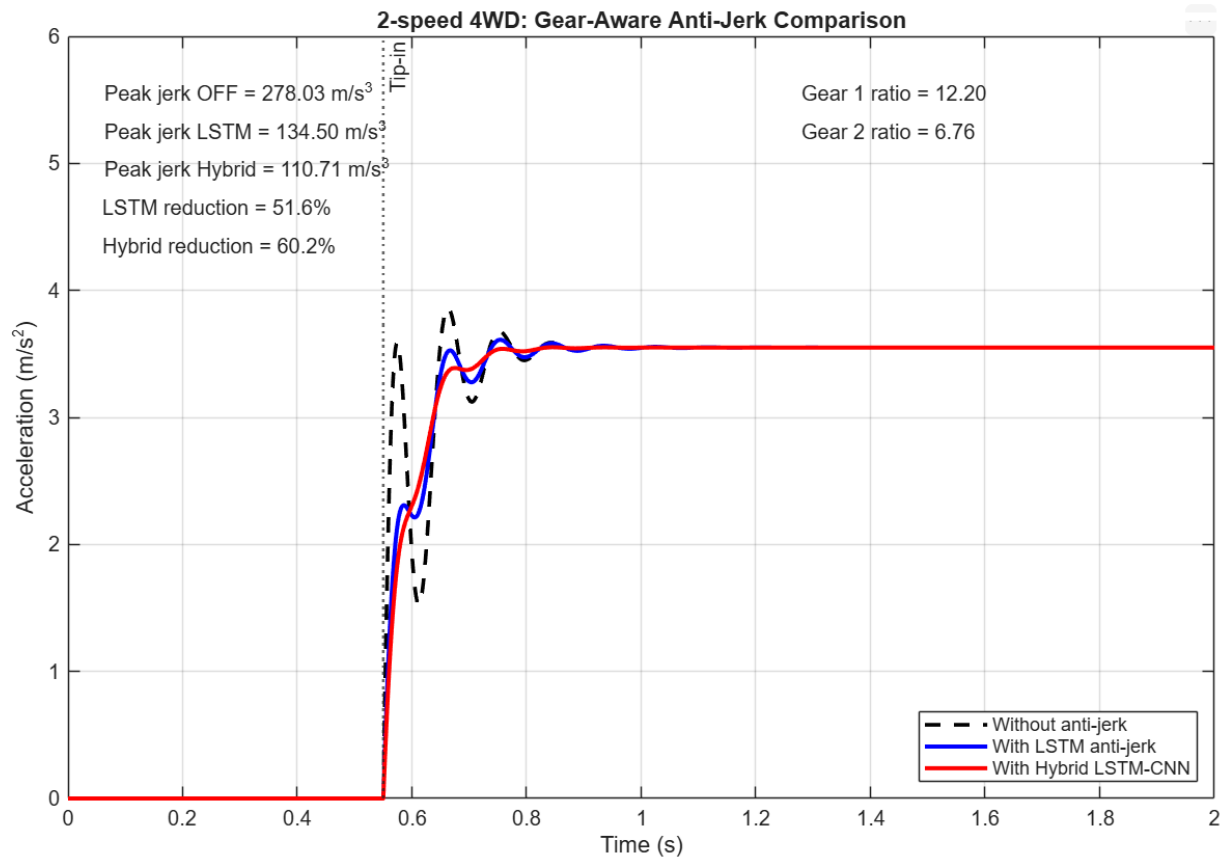


Fig.5 Peak-Jerk Comparison for 2-Speed 4WD (L4) with LSTM and Hybrid LSTM-CNN Anti-Jerk Prediction

The LSTM model provides a significant reduction in peak jerk for all four EV configurations, with reductions of 45.94%, 26.36%, 53.49%, and 51.62% for L1–L4, respectively. The Hybrid LSTM–CNN model provides further reductions of 51.43%, 32.64%, 61.64%, and 60.18%, respectively. Thus, the hybrid model consistently provides greater peak-jerk reduction than the conventional LSTM model in the evaluated responses. The results presented in the manuscript show the same trend across the four layout-specific plots in figures 2-5.

CONCLUSIONS

This study presented an architecture-aware LSTM and Hybrid LSTM–CNN framework for anti-jerk torque prediction in four EV configurations: single-speed 2WD, 2-speed 2WD, single-speed 4WD, and 2-speed 4WD. The results show that both models can effectively predict corrective anti-jerk torque, while the Hybrid LSTM–CNN generally provides better performance than the conventional LSTM, particularly for the more complex 4WD configurations. The hybrid model achieved peak-jerk reductions of 51.43%, 32.64%, 61.64%, and 60.18% for L1–L4, respectively, with the highest torque-prediction improvement observed for L4, where RMSE decreased by approximately 63.20%. The results also demonstrate the importance of architecture-specific gain calibration for adapting the predicted torque to different drivetrain characteristics.

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