

Digital Twin of a Wireless Channel Using Long Short-Term Memory (LSTM)

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Abstract—For intelligent wireless communication systems, precise wireless channel estimation and the development of a digital twin capable of replicating wireless channel characteristics are essential. Standard channel-estimation methods such as Least Squares (LS) and Minimum Mean Squared Error (MMSE) are built upon linear estimation techniques and thus struggle to capture the nonlinear and temporal dynamics of wireless channels. This work focuses on capturing the temporal variations of the wireless channel by developing a digital-twin framework based on a Long Short-Term Memory (LSTM) neural network. The LSTM is trained with real-world channel measurement data to learn complex relationships among wireless channel characteristics. Predicting channel characteristics helps reduce channel-estimation overhead and improves the accuracy of channel-state estimation. The proposed framework achieves a Mean Squared Error (MSE) of 0.035 and a correlation coefficient of 0.999, outperforming conventional channel-estimation approaches including LS, MMSE, and the Gated Recurrent Unit (GRU)-based model. The results demonstrate that the LSTM-driven digital twin can accurately replicate the temporal and amplitude characteristics of the physical wireless channel.

Keywords—digital twin, Long Short-Term Memory (LSTM), channel prediction, Mean Squared Error (MSE)

I. INTRODUCTION

The evolution of Sixth Generation (6G) technologies transforms wireless networks from basic data workflows into an Artificial Intelligence (AI) based intelligent system. This transition enables reliable, adaptive, and intelligent wireless communication.

However, wireless channels are inherently time-varying. Their characteristics are influenced by interference, fading, multipath propagation, and shadowing. These impairments complicate channel

estimation and prediction, thereby limiting the overall performance and reliability of wireless communication systems.

A digital twin is a virtual replica of a physical channel, that continuously monitors real-time data, simulates channel behavior and optimizes system performance. It enables the validation of new approaches, fault detection, and adaptive optimization of network parameters, such as routing and power allocation, for autonomous systems [1]. A digital twin consists of a physical object or system, its virtual counterpart, and a communication mechanism that enables continuous data exchange between them. This synchronization enables the virtual model to accurately represent the state and behavior of the physical system in real time. Rayleigh, Rician and Nakagami channel models rely on statistical information derived from dynamic wireless environments [2]. The complex time-varying environment may hinder the comprehensive collection of statistical data.

LSTM is a specialized Recurrent Neural Network (RNN) designed for sequential modeling and time-series prediction [3]. Because LSTM can learn long-term dependencies and capture complex patterns in dynamic wireless environments, it is well suited for modeling wireless channel parameters, such as signal strength, fading characteristics, and Channel State Information (CSI). As a result, the integration of LSTM into a digital twin framework enables accurate wireless channel prediction, making it a promising solution for intelligent next-generation wireless networks.

II. LITERATURE REVIEW

Saeizadeh *et al.* [4] provided an overview of the application of deep learning techniques to wireless channel modeling. The deep learning-based propagation model significantly reduces the computational time required by

the digital twin framework. Wang *et al.* [5] proposed a wireless channel path evolution model for 6G applications. The digital twin framework continuously observes, learns, and updates the dynamic behavior of the physical system. The proposed method reduces the channel estimation overhead. Jiang *et al.* [6] proposed a deep learning-based digital twin framework to acquire electromagnetic wave propagation characteristics and predict wireless channel behavior. Olickal and Renu [7] investigated the temporal behavior of wireless channels using LSTM and Bidirectional LSTM (Bi-LSTM) networks.

The LSTM-based technique improves the modeling of time-varying wireless channels compared with conventional channel estimation methods, such as MMSE and LS estimators. Li *et al.* [8] employed an LSTM architecture for spatiotemporal wireless channel prediction. The LSTM is integrated with a Generative Adversarial Network–Gated Recurrent Unit (GAN-GRU) architecture, and its performance is evaluated. Mohanty *et al.* [9] investigated energy-efficient data mining and prediction in wireless sensor networks using LSTM. He *et al.* [10] employed LSTM models within a digital twin architecture to predict handover outcomes in ultra-dense networks using historical data. Kumar *et al.* [11] combined LSTM with a digital twin framework to optimize energy consumption in non-automated residential buildings.

The wireless channel and propagation conditions play a crucial role in ensuring reliable wireless communication. LSTM can be deployed within a digital twin framework to capture dynamic wireless channel characteristics, including path loss, fading, and shadowing. This work employs LSTM to model wireless channel characteristics within a digital twin framework. The key contributions of this work are as follows:

- A digital twin is developed to mirror the physical wireless channel.
- A digital twin framework is developed by integrating a LSTM network.
- Data synchronization between the physical wireless channel and its digital twin is implemented.
- The proposed model is continuously calibrated based on feedback to correct prediction errors.
- A dynamic and flexible framework is developed to enable real-time updates of channel parameters.
- The performance of the proposed wireless channel modeling framework is validated using the MSE, and the correlation coefficient between the physical wireless channel and its digital twin

III. PHYSICAL CHANNEL MODEL FOR PROPOSED LSTM-BASED DIGITAL TWIN FRAMEWORK

Modeling a physical channel in a digital twin framework relies on accurately capturing wireless signal propagation characteristics. The wireless channel propagation characteristics must be continuously monitored and recorded to train the LSTM network. Several factors, such as fading, shadowing, and user mobility, influence the time-varying characteristics of

wireless channels. Accurate measurement of these parameters is essential for developing a reliable digital twin framework.

The transmitted signal $x(t)$ propagates in a time-varying physical channel of a Multiple-Input-Multiple-Output (MIMO) system with N_t transmit antennas and N_r receive antennas. The received signal $y_p(t)$ is represented at the receiver [12] in Eq. (1):

$$\mathbf{y}_p(t) = \mathbf{H}_p(t) \mathbf{x}(t) + \mathbf{n}(t) \quad (1)$$

where $\mathbf{x}(t) \in \mathbb{C}^{N_t \times 1}$ is the transmitted signal vector, $\mathbf{H}_p(t) \in \mathbb{C}^{N_r \times N_t}$ is channel response matrix, $\mathbf{n}(t) \in \mathbb{C}^{N_r \times 1} \sim \mathcal{CN}(0, \sigma^2)$ is the Additive White Gaussian Noise (AWGN) vector and $\mathbf{y}_p(t) \in \mathbb{C}^{N_r \times 1}$ is the received signal. The multipath propagation in a wireless channel [13] is modeled as:

$$\mathbf{H}_p(t) = \sum_{i=1}^L \alpha_i(t) e^{-j\phi_i(t)} \delta(t - \tau_i(t)) \quad (2)$$

where L is the number of multipath components, $\alpha_i(t)$ is the gain of the i^{th} propagation path gain, $\phi_i(t)$ is the phase shift of the i^{th} propagation path, and $\tau_i(t)$ is the propagation delay of the i^{th} path. Rayleigh, Rician, and Nakagami fading models are commonly used to characterize wireless channels depending on the presence or absence of Line-of-Sight (LoS) propagation [2].

In highly dynamic environments, these models may not accurately represent the time-varying characteristics of wireless channels. Parameters such as Channel State Information (CSI), Received Signal Strength Indicator (RSSI), Signal-to-Noise Ratio (SNR), path loss, Doppler spread, and delay spread are used as input features for training the LSTM network.

Based on the aforementioned requirements, the proposed LSTM-based digital twin framework for wireless channel modeling is illustrated in Fig. 1.

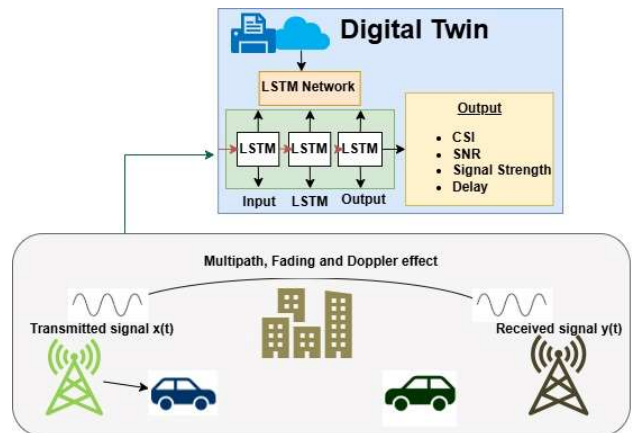


Fig. 1. Proposed LSTM-based digital twin framework.

A. Digital Twin Framework and Standard Prediction Technique

The proposed digital twin framework relies on continuous communication between the physical network and its digital counterpart, unlike conventional offline

prediction methods. This framework is designed to dynamically capture temporal variations through real-time synchronization, feedback mechanisms, and parameter adaptation. The following sections present the architecture in detail.

B. Requirements of the Digital Twin framework

Similar to Eq. (2), the digital twin framework provides a parallel prediction of the physical channel, which is represented in Eq. (3):

$$\hat{\mathbf{H}}_{DT}(t) = \mathcal{F}_{DT}(Z(t)) \quad (3)$$

The term $Z(t)$ represents observed channel measurements, and $\mathcal{F}_{DT}$ denotes the equivalent mapping function of the digital twin framework. The main objective of the proposed work is to estimate the digital twin channel response $\hat{\mathbf{H}}_{DT}(t)$ such that it closely approximates the physical channel response $\mathbf{H}_P(t)$. To achieve this equivalent, the LSTM network is trained to estimate the channel.

C. Data Synchronisation and Calibration of the Measured Data

To ensure the reliability of the proposed LSTM-based digital twin framework, data synchronization and output calibration are essential. Imperfect calibration and synchronization can increase the estimation error of the digital twin framework, thereby reducing its reliability. This section discusses the calibration and synchronization process implemented in the proposed framework.

D. Data Synchronisation

The measured data of the wireless channel is frequently affected by clock offset, sampling rate mismatch, packet delay, and misaligned frames. For maintaining consistency, the digital twin structure measurement must satisfy $\hat{\mathbf{H}}_{DT}(t) \approx \mathbf{H}_P(t)$.

For time synchronization, let the measured channel response $\mathbf{H}_m(t)$ have the delay τ .

$$\mathbf{H}_m(t) = \mathbf{H}_P(t - \tau) \quad (4)$$

The synchronization should be applied to compensate for the delay to obtain:

$$\mathbf{H}_{sync}(t) = \mathbf{H}_m(t + \hat{\tau}) \quad (5)$$

where $\hat{\tau}$ is the estimated delay, and $\mathbf{H}_{sync}(t)$ represents the synchronized output.

E. Calibration of the Digital Twin Framework

The calibration process compensates for distortions and noise in the network output. The channel coefficient is then scaled as:

$$\mathbf{H}_m(t) = \alpha \mathbf{H}_P(t) \quad (6)$$

The measurement value could be corrected as shown in Eq. (7).

$$\mathbf{H}_{cal}(t) = \frac{\mathbf{H}_m(t)}{\hat{\alpha}} \quad (7)$$

where α and $\hat{\alpha}$ represent the gain error, and estimated scaling factor, respectively.

If the phase offset occurs in the wireless channel measurements and the measured channel response is expressed as:

$$\mathbf{H}_m(t) = \mathbf{H}_P(t)e^{j\varphi} \quad (8)$$

Then the calibration corrects the phase error:

$$\mathbf{H}_{cal}(t) = \mathbf{H}_m(t)e^{-j\varphi} \quad (9)$$

If the measured signal has additive noise:

$$\mathbf{H}_m(t) = \mathbf{H}_P(t) + \mathbf{n}(t) \quad (10)$$

Using the moving average, $\mathbb{E}[\mathbf{n}(t)] \rightarrow 0$.

The calibrated and synchronized output is used as the input for training the LSTM network.

F. Working of the LSTM Framework

This section discusses the objective of modeling a practical wireless channel using an LSTM-based digital twin framework. The prediction of the channel in the digital twin structure requires the previous k channel states. Since the characteristics of the wireless channel are non-linear and time-varying, the LSTM network is trained to learn the complex temporal dependencies of the channel. The estimation of the channel state using LSTM in the digital twin is represented as Eq. (11).

$$\hat{\mathbf{H}}_{DT}(t+1) = \mathcal{F}_{LSTM}(\mathbf{H}_P(t), \mathbf{H}_P(t-1), \dots, \mathbf{H}_P(t-k)) \quad (11)$$

where $\mathcal{F}_{LSTM}$ represents the LSTM mapping function, $\mathbf{H}_P(t)$ denotes the physical wireless channel state, and $\hat{\mathbf{H}}_{DT}(t+1)$ represents the future channel state. In the proposed framework each channel matrix is vectorized to form the input sequence of the LSTM, i.e., $\mathbf{x}_t = \text{vec}(\mathbf{H}_P(t))$. The proposed LSTM network is illustrated in Fig. 2.

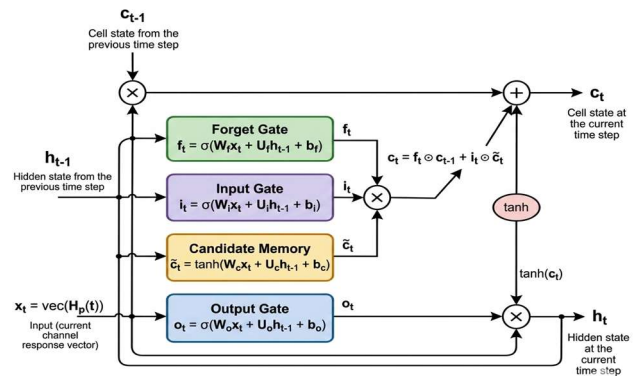


Fig. 2. LSTM network for digital twin for channel prediction.

The forget gate f_t , which selectively removes irrelevant historical fading information from the cell state, is expressed in Eq. (12).

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \quad (12)$$

where $\sigma(z)$ represents the sigmoid nonlinear function, defined as $\sigma(z) = \frac{1}{1+e^{-z}}$ whose output lies between 0 and 1. W_f represents the weight matrix associated with the previous hidden state h_{t-1} . U_f is the weight factor of the present state x_t . The inputs to the LSTM network include the CSI, SNR, and RSSI. The sigmoid activation function determines the extent to which the previous memory is retained. When f_t is close to 1, the previous memory is largely preserved, whereas when f_t close to 0, it is largely discarded.

The output of the forget gate is determined by the current channel conditions and the previous hidden state. For a fast-fading channel, the previous channel state becomes less relevant. Consequently, the forget gate assigns a smaller value to f_t , reducing the influence of the previous memory. In a slow-fading channel, consecutive channel states are highly correlated. Consequently, the forget gate assigns a value of f_t , close to 1, thereby retaining most of the previous memory.

The input gate controls the amount of new information incorporated into the cell state; it adapts to sudden channel variations, and its operation is expressed in Eq. (13).

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \quad (13)$$

where W_i , U_i , and b_i denote the weight matrix associated with the previous hidden state h_{t-1} , the weight matrix associated with the current input x_t and bias of the input gate, respectively.

The candidate memory represents the essential characteristics of the current channel behavior. The new information is incorporated into the cell state using the hyperbolic tangent (tanh) activation function, whose output ranges from -1 to $+1$. This memory state $\tilde{c}_t$ is expressed in Eq. (14).

$$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c) \quad (14)$$

where W_c , U_c and b_c denote the weight matrix associated with the previous hidden state, the weight matrix associated with the current input, and the bias term of the candidate cell state, respectively. The cell is updated with the new information c_t and expressed in Eq. (15).

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (15)$$

where $f_t \odot c_{t-1}$ retains the relevant information from the previous cell state, and $i_t \odot \tilde{c}_t$ incorporates the new information into the cell state. In the proposed wireless channel model, the candidate cell state encodes new channel information, including short-term multipath effects, while the cell state preserves long-term fading characteristics.

The output gate determines the amount of information from the cell state to be propagated to the hidden state, as expressed in Eq. (16).

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \quad (16)$$

where W_o , U_o and b_o denote the weight matrix associated with the previous hidden state, the weight matrix associated with the current input, and the bias term of the output gate, respectively. The hidden state h_t represents the encoded channel information, and is expressed in Eq. (17).

$$h_t = o_t \odot \tanh(c_t) \quad (17)$$

The estimated channel state is expressed in Eq. (18).

$$\hat{H}_{DT}(t+1) = W_y h_t + b_y \quad (18)$$

where W_y and b_y denote the weight matrix associated with the hidden state and the bias term of the output layer, respectively. The prediction error is computed using Eq. (19).

$$e(t) = H_P(t) - \hat{H}_{DT}(t) \quad (19)$$

If the estimation error $e(t)$ exceeds the predefined threshold ϵ , i.e., $e(t) > \epsilon$, the LSTM model is updated to improve the channel prediction accuracy. The proposed model is recalibrated by updating the LSTM weight matrices and calibration parameters. To ensure the stability of the digital twin framework, the estimation error must satisfy the following criterion.

$$\lim_{t \rightarrow \infty} \mathbb{E}[\|e(t)\|^2] < \infty \quad (20)$$

IV. RESULT AND DISCUSSION

The proposed model is validated by comparing the output of the physical wireless channel with the predicted output of the digital twin framework. This section presents the performance evaluation of the proposed LSTM-based digital twin framework for a 2×2 MIMO wireless communication system

A Rayleigh fading wireless channel model is employed to generate the dataset used for training and evaluating the proposed framework. To simulate realistic multipath propagation scenarios encountered in mobile communication systems, the wireless channel coefficients are generated synthetically. The channel coefficients are initially modeled as complex Gaussian random variables for a 2×2 MIMO wireless communication system. Doppler effects are incorporated into the channel fading model to emulate user mobility. The Doppler frequency is represented in Eq. (21).

$$f_d = \frac{vf_c}{c} \quad (21)$$

where f_c is the carrier frequency, c is the speed of light, and v is the relative velocity. The simulation is conducted using a carrier frequency of 3.5 GHz and a user velocity of 30 m/s, corresponding to a maximum Doppler frequency of approximately 350 Hz. The sampling rate is set to 1000 Hz to capture rapid variations in the wireless channel. For each simulation, 1000 samples are generated from the time-varying channel realizations. AWGN is incorporated into the channel model to emulate noise encountered in practical wireless communication environments. The LSTM model parameters are listed in Table I.

TABLE I. LSTM PARAMETERS OF THE PROPOSED DIGITAL TWIN FRAMEWORK

Model Parameter	Type/Value
Channel model	Rayleigh fading
MIMO	2×2
Carrier frequency	3.5 GHz
User velocity	30 m/s
Doppler frequency	350 Hz
Sampling rate	1000 Hz
Number of samples	1000
Noise model	AWGN
Length of the input sequence	10
Number of LSTM layers	1
Hidden units-Neuron	32
Output layer	Fully connected dense layer
Activation function-Hidden layer	Sigmoid and tanh
Output layer activation function	Linear
Optimizer	Adam
Learning rate	0.001
Loss function	MSE
Batch size	32
Number of epochs	30

The channel responses of the physical wireless channel and the proposed digital twin framework are illustrated in Fig. 3.

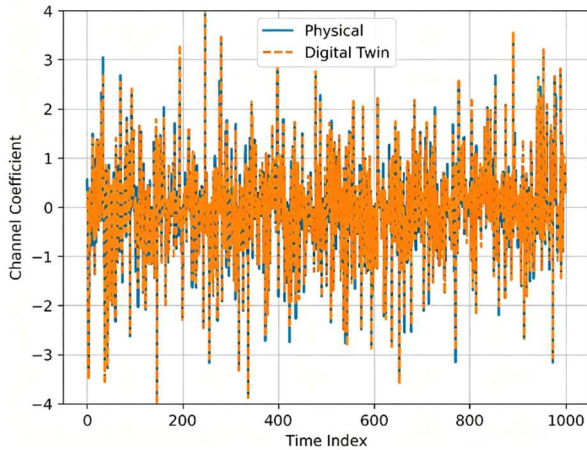


Fig. 3. Channel response comparison of physical and digital twin framework for a 2×2 MIMO system.

The channel responses $H_P(t)$ and $H_{DT}(t)$ are evaluated over 1000-time steps with a Doppler frequency of 350 Hz and a sampling rate of 1000 Hz. The simulated dataset is divided into training, testing, and validation sets, with 70% of the data used for training, 15% for testing, and the remaining 15% for validation. The results demonstrate that the actual wireless channel is influenced by multipath

fading, noise, user mobility, and Doppler spread. The difference between the actual channel response, $H_P(t)$ and the estimated digital twin response $\hat{H}_{DT}(t)$ represents the estimation error, which is defined as $e(t) = H_P(t) - \hat{H}_{DT}(t)$.

Fig. 4 illustrates the ability of the proposed digital twin framework to accurately track the h_{11} channel coefficient of the 2×2 MIMO system. The channel response between transmit antenna 1 and receive antenna 1 is monitored and tracked throughout the simulation. The tracking results indicate that the adaptation of the proposed digital twin framework follows the temporal variations of the wireless channel at each time step. The proposed model requires an adaptive channel tracking mechanism to minimize the difference between the actual channel response and the predicted digital twin response.

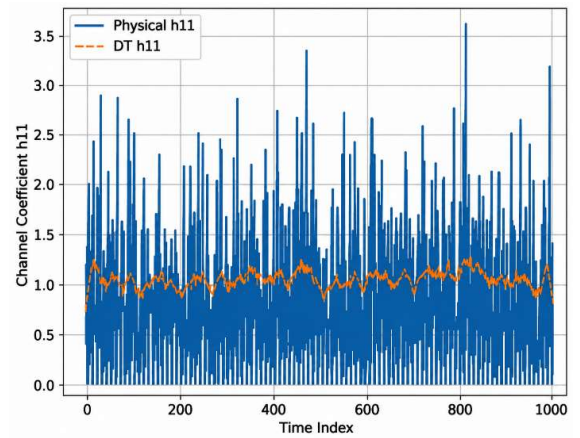


Fig. 4. Channel coefficient h_{11} tracking.

Fig. 5 presents the Power Spectral Density (PSD) comparison between the physical wireless channel and the proposed digital twin framework.

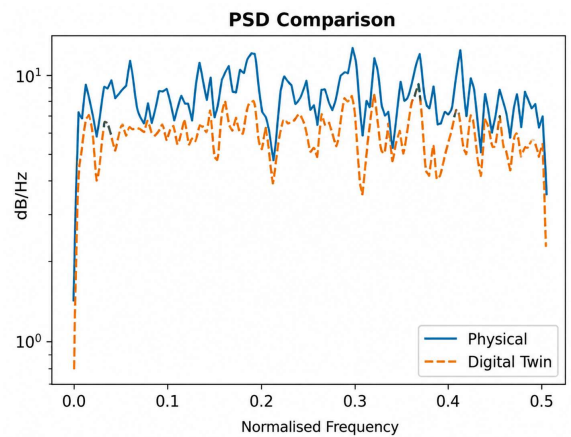


Fig. 5. Comparison of PSD.

The peaks in the PSD indicate frequency components with high signal energy, whereas lower PSD values correspond to reduced signal energy caused by deep fading at the respective frequencies. The proposed LSTM-based digital twin framework closely follows the measured response of the actual physical wireless channel. The predicted response exhibits a slightly lower amplitude

than the measured response of the actual physical wireless channel. The absence of abnormal fluctuations in the digital twin output indicates that the trained model is stable. The close match between the PSDs of the physical channel and the digital twin framework minimizes channel estimation overhead while enhancing beamforming accuracy.

The estimation error of the proposed LSTM-based digital twin framework is presented in Fig. 6. The MSE between the actual physical channel response and the estimated digital twin response is computed as:

$$MSE = \frac{1}{N} \sum \left(\mathbf{H}_P(t) - \hat{\mathbf{H}}_{DT}(t) \right)^2 \quad (22)$$

where N denotes the total number of samples, $\mathbf{H}_P(t)$ is the actual physical channel response, and $\hat{\mathbf{H}}_{DT}(t)$ is the corresponding response predicted by the proposed digital twin framework. The proposed framework achieves an average MSE of 0.035 with a correlation coefficient of 0.999, demonstrating the high accuracy of the LSTM-based digital twin model. The performance results of the proposed framework under different environmental scenarios are summarized in Table II.

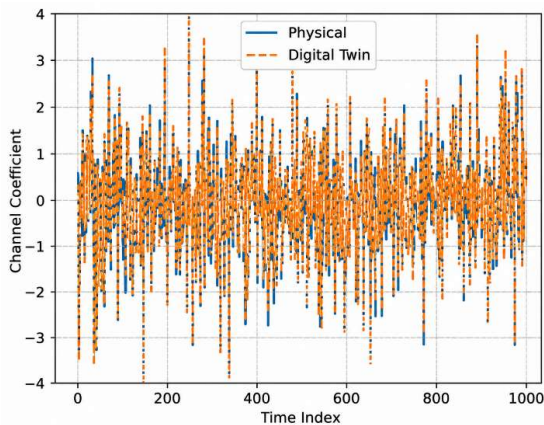


Fig. 6. Error signal of the proposed LSTM-based digital twin framework.

TABLE II. SUMMARY OF DIGITAL TWIN PERFORMANCE FOR MULTI-SCENARIO

Channel Condition	Doppler Frequency	MSE	Correlation
Static	0 Hz	0.012	0.995
Low Mobility	10 Hz	0.028	0.9992
High Mobility	350 Hz	0.035	0.999

The performance of the proposed LSTM-based digital twin framework for wireless channel modeling is compared with conventional techniques, including LS, MMSE, and GRU-based models, as shown in Fig. 7.

The tracking performance of the compared methods is illustrated in Fig. 7. All the compared methods closely follow the temporal variations of the physical wireless channel. The LS estimate exhibits the largest deviation, particularly in the deep-fading region, which is consistent with the fact that the LS estimator does not exploit noise statistics. The MMSE, GRU, and proposed LSTM-based

models maintain tight tracking of the physical channel response. A quantitative comparison of the estimation accuracy of these methods is presented in Fig. 8 and Table II.

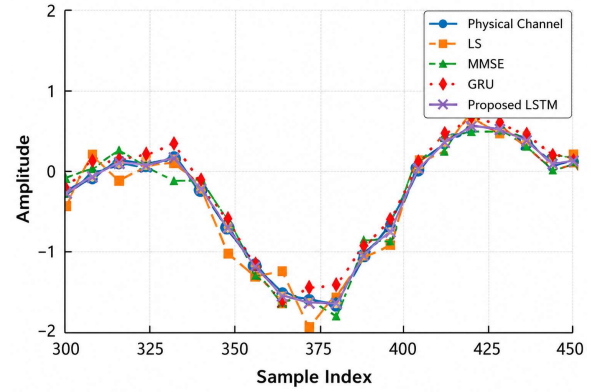


Fig. 7. Performance comparison of the proposed LSTM model with other standard techniques.

Fig. 8 depicts the MSE comparison between the proposed LSTM-based digital twin framework and conventional methods, demonstrating its superior prediction performance.

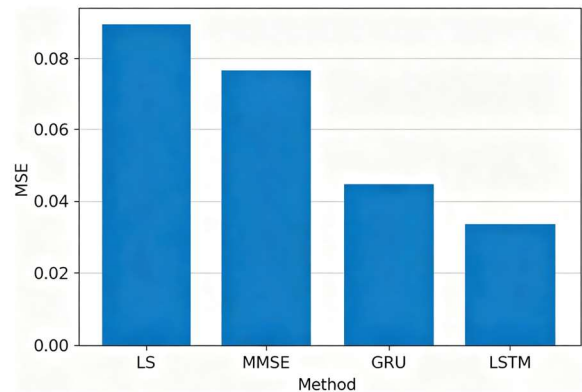


Fig. 8. MSE comparison of the proposed LSTM model with other standard techniques.

In addition, the performance analysis is extended to 4×4 and 8×8 MIMO systems, and the corresponding results are summarized in Table III. The results show that the proposed LSTM-based digital twin framework maintains consistent performance despite the increase in model size and MIMO system complexity.

TABLE III. PERFORMANCE ANALYSIS OF MIMO CONFIGURATIONS

MIMO System	MSE
2×2	0.035
4×4	0.038
8×8	0.042

The MSE performance of the proposed LSTM-based digital twin framework is evaluated under different SNR conditions, as shown in Fig. 9. As the SNR increases, the MSE decreases for all techniques due to the reduction in noise power.

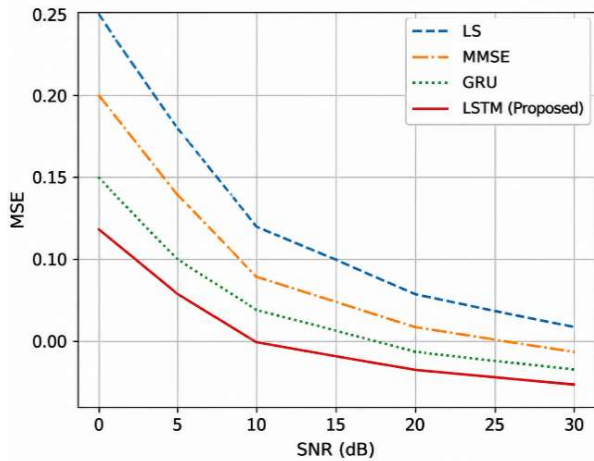


Fig. 9. Variation of MSE vs SNR.

However, the proposed LSTM-based digital twin framework outperforms the conventional prediction techniques by achieving lower MSE values across different SNR conditions. It is demonstrated that the conventional techniques are more sensitive to noise variations compared with the proposed LSTM-based model, which maintains robust performance in dynamic wireless environments.

The proposed LSTM-based digital twin framework is compared with conventional channel estimation methods, including LS, MMSE, and GRU-based approaches. The results indicate that the proposed LSTM architecture provides enhanced prediction accuracy and channel tracking capability, particularly under rapidly varying fading conditions.

Since the LS estimator does not exploit the statistical characteristics and temporal correlations of the channel, it results in higher estimation errors. Additionally, the LS approach remains highly sensitive to channel noise and rapid fading variations because it directly estimates the channel from noise-corrupted pilot data without incorporating any denoising mechanism.

By utilizing sequential channel samples to capture short-term temporal dynamics, the GRU-based model achieves better performance than the LS and MMSE estimators; however, its ability to capture long-term dependencies remains limited. Its simpler gating mechanism provides limited memory control compared with more advanced architectures such as LSTM, which restricts its performance in rapidly time-varying wireless channels.

On the other hand, the proposed LSTM-based digital twin framework utilizes a dedicated memory-cell structure with forget, input, and output gates, enabling improved learning of temporal dependencies and enhanced channel prediction performance. Through these gating mechanisms, the LSTM network selectively retains important historical CSI information while filtering out irrelevant short-term noise components. As a result, the LSTM effectively captures fast-fading dynamics and long-term temporal dependencies inherent in wireless propagation environments.

The advantage of the proposed framework is particularly evident under challenging channel conditions, such as deep fading events and rapid channel state transitions, where conventional estimators struggle to maintain accurate tracking performance.

By continuously updating its internal memory states based on previous channel observations, the LSTM model reduces prediction errors and improves the consistency of channel estimation. This capability results in reduced MSE and improved correlation between the digital twin output and the physical channel compared with LS, MMSE, and GRU-based methods.

The primary data source utilized in this study consists of simulated wireless channel data generated using a Rayleigh fading model with Doppler effects. Although simulation-based evaluations provide controlled experimental conditions and reproducibility, practical wireless environments are affected by additional impairments, including shadow fading, hardware nonlinearities, interference, synchronization errors, and environmental obstructions. As a result, these synthetic datasets may not fully capture the complex characteristics of real-world wireless propagation environments. Future research will focus on validating the proposed approach using empirical channel datasets collected from operational wireless networks to address this limitation.

The computational complexity associated with recurrent deep learning architectures may limit their widespread deployment in next-generation wireless systems. The training and inference complexity of the LSTM network increases significantly with the growth in the number of antennas, users, and channel dimensions. In large-scale MIMO and ultra-dense 6G networks, real-time synchronization of digital twin models may require substantial computational and memory resources.

Despite these limitations, the obtained results demonstrate the capability of LSTM-based digital twin architectures to achieve accurate wireless channel representation and effective temporal forecasting. The proposed framework has the potential to enhance future smart wireless network management, adaptive communication systems, and AI-driven digital twin applications for 6G networks.

V. CONCLUSION

In this work, the physical wireless channel is modeled using an LSTM-based digital twin framework. The proposed framework captures the fast-fading characteristics of the wireless channel by exploiting the long-term memory capability of LSTM networks. The performance of the proposed framework is validated by comparing the physical channel output with the digital twin output, achieving a low MSE of 0.035 and a high correlation coefficient of 0.999. These results demonstrate that the proposed digital twin can effectively represent the key characteristics of the physical wireless channel. The proposed framework can be effectively applied to beamforming optimization, adaptive modulation, and intelligent wireless communication environments. The proposed framework aligns with the United Nations

Sustainable Development Goals (SDGs), particularly SDG 9 (Industry, Innovation, and Infrastructure) and SDG 11 (Sustainable Cities and Communities). Furthermore, it can be extended to emerging technologies such as massive MIMO, millimeter-wave (mmWave) communications, and 6G networks. It achieves this objective by developing digital twin frameworks for next-generation communication infrastructures and intelligent wireless channel modeling.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Vijayakumar Ponnusamy conceived the idea, analyzed formally, conducted the simulations and completed critically review; Vasuki Andiappan developed a theoretical framework, a literature review and prepared the final version; Vinodhini Manickara and Malathi Devendran completed the proof correction and validation of the results; all authors had approved the final version.

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