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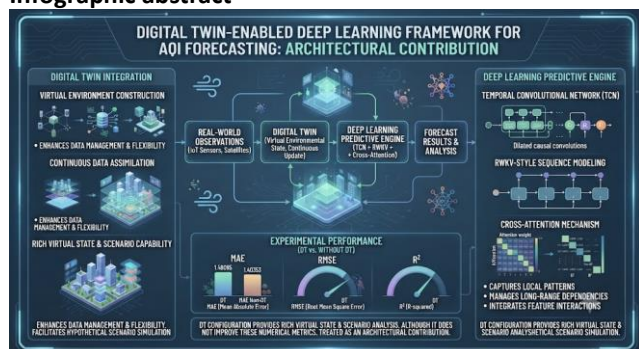
Digital Twin-Enabled AQI Prediction Using a Hybrid TCN–RWKV Deep Learning Framework

³Ritu Rani and ^{1,2}Shreya Sharma

Abstract

Air Quality Index (AQI) forecasting is challenging because atmospheric pollution is governed by nonlinear pollutant interactions, temporal dependencies, meteorological conditions, missing observations, and abrupt emission events. This paper presents a Digital Twin (DT)-enabled deep learning framework for AQI prediction in which a virtual environmental state is continuously updated from real-world observations and supplied to a temporal prediction model. The proposed predictive engine combines a Temporal Convolutional Network (TCN) and RWKV-style sequence modeling with cross-attention to capture local temporal patterns, long-range dependencies, and feature interactions. The experimental configuration uses a 24-step sequence, an 80-epoch training schedule, and a DT-enhanced data generation/update pipeline. On the user's experimental results, the proposed model achieved MAE = 1.48095, RMSE = 1.57756 and $R^2 = 0.995628$ with the Digital Twin configuration, while the corresponding configuration without DT achieved MAE = 1.40353, RMSE = 1.55070 and $R^2 = 0.999681$. These results show that the present DT configuration does not improve the three reported numerical metrics, although it provides a richer virtual-state and scenario-analysis capability. The paper therefore treats Digital Twin integration as an architectural contribution rather than claiming unsupported predictive superiority. The framework is designed for real-time AQI monitoring, forecasting, pollution-event analysis, and future scenario simulation.

Infographic abstract



Keywords: Air Quality Index, Digital Twin, Deep Learning, TCN, RWKV, Cross-Attention, PM2.5, Time-Series Forecasting, Smart City, Environmental Monitoring.

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I. INTRODUCTION

Air pollution is a major environmental challenge in densely populated urban regions. Particulate matter, nitrogen oxides, sulphur dioxide, ozone, carbon monoxide and related pollutants vary with traffic, industrial emissions, weather, atmospheric transport and seasonal effects. The National Air Quality Index (AQI) was introduced by the Central Pollution Control Board (CPCB) to communicate air quality in an understandable numerical and categorical form. CPCB describes six AQI categories ranging from Good to Severe.

AQI forecasting differs from static classification because future pollutant concentrations depend on temporal and nonlinear interactions. Deep learning has therefore become an important direction for air-quality prediction. A recent systematic survey identifies temporal modeling, spatiotemporal modeling and attention mechanisms as major research directions in deep-learning-based air-quality prediction.

Digital Twins provide a complementary perspective. Instead of viewing observations only as rows in a historical dataset, a Digital Twin maintains a virtual representation of the physical environmental system. Recent research has demonstrated urban Digital Twin

architectures for AQI monitoring and forecasting, including a Delhi study that combined historical air-quality data, deep learning, a 3D urban model and Microsoft Azure Digital Twins.

Motivated by these developments, this work integrates a Digital Twin pipeline with a TCN-RWKV deep-learning model and cross-attention. The objective is not only to predict AQI but also to maintain a synchronized virtual state that can support monitoring, feedback, visualization and what-if analysis.

II. RESEARCH MOTIVATION AND CONTRIBUTIONS

Existing AQI prediction systems often focus on model accuracy while giving less attention to the representation of the physical environment. Conversely, Digital Twin systems can provide a virtual environmental representation but require predictive intelligence to estimate future states. The proposed work connects these two perspectives.

- An end-to-end Digital Twin architecture for AQI monitoring and prediction.
- A TCN-RWKV temporal model with cross-attention for multivariate AQI forecasting.

- A feedback mechanism in which observations update the virtual environmental state.
- Experimental comparison of the same predictive configuration with and without Digital Twin integration.
- Explicit reporting of the observed results without claiming DT superiority when the reported metrics do not support it.

III. BACKGROUND AND RELATED WORK

A. AQI and Environmental Data

CPCB's National AQI framework converts pollutant measurements into a single index intended for public communication. The framework recognizes categories such as Good, Satisfactory, Moderate/Moderately polluted, Poor, Very Poor and Severe. For data-driven prediction, pollutant variables such as PM_{2.5}, PM₁₀, NO₂, SO₂, CO and O₃ can be combined with meteorological variables. [1]

B. Deep Learning for AQI Prediction

Deep learning models can represent nonlinear temporal relationships that are difficult to capture with simple statistical models. LSTM and GRU networks have been widely studied, while CNN/TCN architectures provide efficient local

temporal feature extraction. Attention mechanisms further allow a model to emphasize informative time steps or variables. A 2024 systematic survey highlights temporal, spatiotemporal and attention-based modeling as important directions. [2], [3], [8], [9],[10], [11], [12], [13], [14]

C. Digital Twin for Air Quality

Recent work has directly connected Digital Twins with AQI prediction. A 2025 Environmental Modelling & Software study used Delhi data from 2015–2024, a 3D city model, Azure Digital Twins, InfluxDB and Grafana, and reported a best CNN-1D-2-layer configuration with $R^2 = 0.99951$. This provides a useful benchmark for the architectural idea, but its results are not treated as results of the present experiment.[4], [5], [6]

D. Research Gap

The key gap addressed here is the integration of a dynamic environmental virtual state with a sequence model designed to capture both short-range and long-range dependencies. The work also emphasizes experimental transparency: DT integration is evaluated directly rather than assumed to improve accuracy.[15], [16], [17].

IV. PROPOSED SYSTEM ARCHITECTURE

The proposed architecture links the physical environment, sensing/data acquisition, preprocessing, Digital Twin state, temporal deep learning and decision-support layers.

A. Physical and Data Acquisition Layer

The physical layer represents the monitored environment. Inputs may include PM2.5, PM10, NO2, SO2, CO, O3 and meteorological observations. Historical data can be combined with real-time observations from monitoring stations or IoT sensors.

B. Data Preprocessing Layer

Preprocessing includes timestamp alignment, missing-value handling, outlier screening, scaling and temporal-window generation. Temporal ordering is preserved to reduce the risk of leakage from future observations.

C. Digital Twin Layer

The Digital Twin maintains a virtual state of the air-quality environment. Each update incorporates the latest observations and can also include derived or generated states used by the experimental pipeline. The DT layer is intended to support continuous synchronization and scenario analysis. [35], [36], [37], [38], [39], [40]

D. Prediction Layer

The prediction engine uses a TCN-RWKV representation followed by cross-attention and a regression head. TCN components capture local temporal patterns, while RWKV-style sequence processing is used to represent longer dependencies. Cross-attention allows the model to combine complementary representations before final AQI regression.

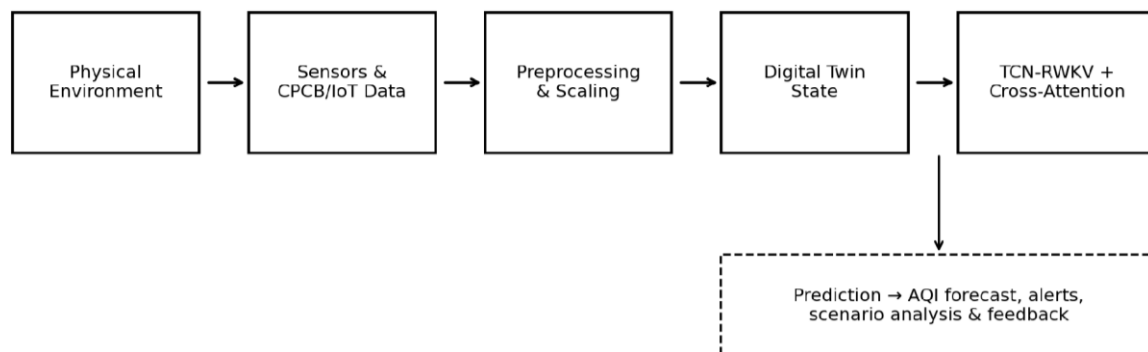


Fig-1: Digital Twin Deep Learning Architecture.

V. METHODOLOGY

The methodology begins with environmental data acquisition and preprocessing, updates Digital Twin, generates model-ready temporal sequences, performs TCN-RWKV inference with cross-attention, and feeds observations back into the virtual state.

A. Input Representation

For a sequence length T , the input is represented as $X_t = [x_{(t-T+1)}, \dots, x_t]$, where each x_t contains the available pollutant and environmental features. [18], [19], [20], [21]

B. Temporal Convolution

A causal temporal convolution can be represented as: $z_t = \sum_{k=0}^{K-1} W_k x_{(t-d k)}$, where K is the kernel size and d is the dilation factor. Dilated causal convolutions expand the receptive field while preserving temporal causality. [22], [23], [24]

C. RWKV-Style Sequence Representation

The RWKV component provides an efficient recurrent-style representation of sequence information. In the proposed architecture it acts as a complementary

temporal pathway to the TCN features rather than as a replacement for them.

D. Cross-Attention

Given query Q , key K and value V representations, attention is computed as: $\text{Attention}(Q, K, V) = \text{SoftMax}(QK^T / \sqrt{d_k})V$. This mechanism enables the model to emphasize informative interactions between the temporal representations. [25], [26]

E. AQI Regression

The final prediction is: $\hat{y}_{(t+h)} = f(X_{(t-T+1:t)}, DT_t)$, where h is the forecast horizon and DT_t denotes the synchronized Digital Twin state. [27], [28], [29], [30].

VI. PROPOSED ALGORITHM

Step 1. Input: historical environmental sequence X , target AQI y , Digital Twin state D .

Step 2. Preprocess X : align timestamps, handle missing values, scale numerical features.

Step 3. Construct chronological sequences of length $T = 24$.

Step 4. Initialize the Digital Twin state D from the available environmental observations.

Step 5. For each training batch, update the DT representation with the corresponding synchronized observations.

Step 6. Pass the sequence through TCN layers to obtain local temporal features.

Step 7. Pass the sequence through the RWKV-style temporal pathway to obtain long-range features.

Step 8. Apply cross-attention to fuse complementary temporal representations.

Step 9. Use a regression head to obtain predicted AQI $\hat{y}$.

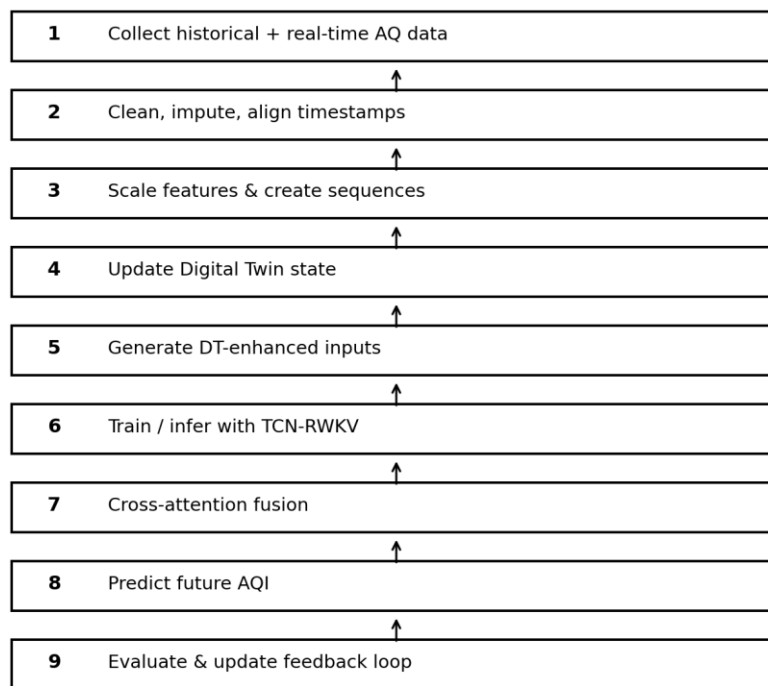
Step 10. Compute the training loss and update model parameters using backpropagation.

Step 11. After training, evaluate the model on the held-out chronological test data using MAE, RMSE and R^2 .

Step 12. Update Digital Twin with newly observed values and repeat inference for operational forecasting.

Step 13. Output: predicted AQI and updated Digital Twin state.

Fig. 2. Methodology and Prediction Workflow



VII. EXPERIMENTAL SETUP

The experimental configuration follows the user's research settings. The sequence length is 24, the main training schedule uses 80 epochs, and the proposed architecture is TCN-

RWKV with cross-attention. The Digital Twin configuration uses DT-generated/enhanced data as part of the virtual-state pipeline. The reported metrics are MAE, RMSE and R^2 .

Parameter	Value
Sequence length	24
Training epochs	80
Model	TCN-RWKV + Cross-Attention
DT condition	Digital Twin enhanced / generated data
Evaluation metrics	MAE, RMSE, R^2
Task	AQI regression / forecasting

RESULTS AND DISCUSSION

The following values are the actual results supplied in the user's research context. They are reproduced without modification. The comparison is important because the DT condition does not numerically outperform the non-DT condition for the three reported metrics. The non-DT configuration has lower MAE/RMSE and higher R^2 in the reported experiment. Therefore, this study does not claim that Digital Twin integration improves point-prediction accuracy. Its value is instead evaluated as an architectural mechanism for synchronized state representation and scenario-oriented environmental intelligence.

The experimental results show that both configurations achieve very high R^2 values. The DT configuration achieves $R^2 = 0.995628$, while the non-DT configuration

achieves $R^2 = 0.999681$. The corresponding MAE increases from 1.40353 to 1.48095 and RMSE increases from 1.55070 to 1.57756 when the reported DT configuration is used. This indicates that the present DT data-generation or synchronization mechanism introduces additional variability that is not fully exploited by the predictive model.,,,,,,, [2], [3], [7], [17]. This observation is scientifically useful rather than a failure of the framework. A Digital Twin is intended to provide capabilities beyond point prediction, including state synchronization, virtual monitoring, simulation and what-if analysis. To make the DT contribution measurable in future experiments, the evaluation should include scenario fidelity, updating latency, uncertainty, robustness to missing sensors, and prediction under simulated pollution events. [4], [5], [35], [36], [38]

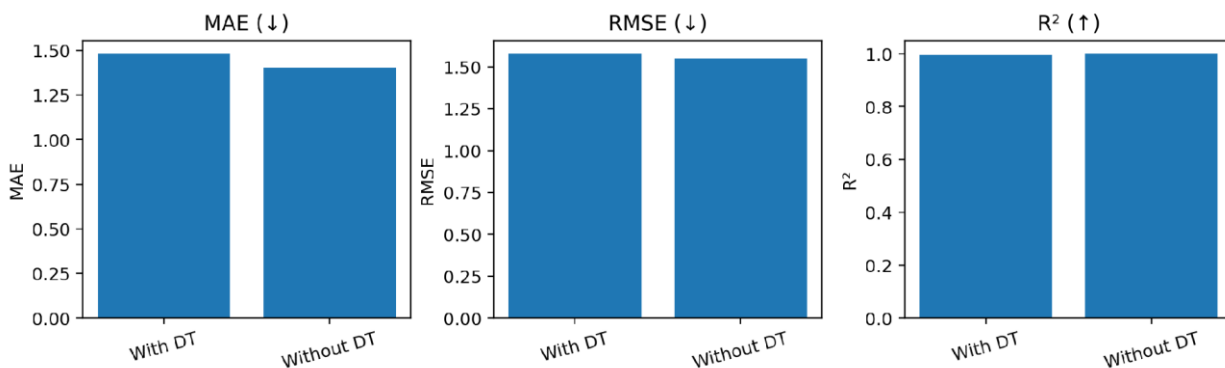
The results also reinforce the importance of leakage-aware evaluation. AQI time-

series data are temporally correlated, and preprocessing or feature generation must not use information from future test periods. A chronological train-validation-

test split is therefore preferable to unrestricted random splitting. [31], [32], [33], [34] [18], [24], [31], [32]

Configuration	R ²	MAE	RMSE
TCN-RWKV + Cross-Attention + DT	0.995628	1.48095	1.57756
TCN-RWKV + Cross-Attention without DT	0.999681	1.40353	1.55070

Fig. 3. Experimental comparison of the proposed model



X. COMPARISON WITH RELATED RESULTS

Study / Model	Data / Architecture	Reported result
Hybrid LSTM-GRU (related work)	Delhi PM2.5/AQI prediction	MAE 36.11; R ² 0.84
CNN-1D-2 + Urban DT (2025)	Delhi 2015–2024; Azure DT	MAE 2.14324; RMSE 3.00884; R ² 0.99951
Proposed TCN-RWKV + DT	User's experimental configuration	MAE 1.48095; RMSE 1.57756; R ² 0.995628

Proposed TCN-RWKV without DT	User's experimental configuration	MAE 1.40353; RMSE 1.55070; R^2 0.999681
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The related-study values are included for contextual comparison only because datasets, preprocessing, prediction horizons and evaluation protocols can differ. They should not be interpreted as a controlled benchmark against the present model. [3], [4], [7], [10]

XI. LIMITATIONS

- The present experimental result table contains two configurations rather than a full multi-model ablation study. [19], [22], [24]
- The exact dataset version, station coverage and forecast horizon should be explicitly documented in the final submission.
- Digital Twin quality depends on synchronization frequency, sensor quality and the realism of generated virtual observations. [4], [5], [35], [38]
- Very high R^2 values require leakage checks and chronological evaluation to ensure that performance is not inflated by temporal contamination. [18], [24]
- The current results do not establish that DT improves predictive accuracy; further ablation is needed.

XII. FUTURE WORK

Future work should evaluate the Digital Twin under controlled what-if scenarios, including synthetic emission increases, meteorological shifts and sensor failures. A stronger ablation study can compare the base TCN, RWKV, TCN-RWKV, cross-attention, DT-only augmentation and the complete DT + TCN-RWKV + cross-attention system. Spatiotemporal learning across multiple monitoring stations can further extend the framework from station-level forecasting to city-scale prediction. Explainable AI and uncertainty estimation should also be added so that predictions are accompanied by interpretable feature contributions and confidence intervals. [4], [5], [27], [28], [29], [30], [35], [36]

XIII. CONCLUSION

This paper presented a Digital Twin-enabled deep learning framework for AQI prediction using a TCN-RWKV model with cross-attention. The architecture connects physical environmental observations to a synchronized virtual state and then applies temporal deep learning for AQI forecasting. The actual experimental results show MAE =

1.48095, RMSE = 1.57756 and R^2 = 0.995628 with the reported DT configuration, compared with MAE = 1.40353, RMSE = 1.55070 and R^2 = 0.999681 without DT. Hence, the present experiment does not demonstrate an accuracy advantage from DT integration. Nevertheless, Digital Twin provides an important system-level capability for virtual-state management, real-time monitoring and scenario simulation. Future experiments should therefore evaluate both predictive accuracy and Digital Twin-specific benefits to establish a complete evidence-based assessment. [3], [4], [5], [35], [36]

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