A CNN–LSTM Hybrid Deep Learning Technique for Predicting Performance Degradation in SDH Networks

F. U. Didigwu

Department of Electrical/Electronic Engineering, University of Port Harcourt, Nigeria

DOI: https://doi.org/10.51244/IJRSI.2026.1309000101

Received: 17 September 2026; Accepted: 22 September 2026; Published: 09 October 2026

ABSTRACT

The increasing complexity of Synchronous Digital Hierarchy (SDH) networks necessitates reliable forecasting of network performance indicators to support proactive performance monitoring. This study evaluates deep learning approaches for forecasting key performance indicators (KPIs) in SDH networks using real-world Network Management System (NMS) data from Uyo, Nigeria. The dataset comprised 52,128 observations collected at 15-minute intervals from January to June 2026 across three SDH links: UYO_EKET, UYO_ITU, and UYO_ORON. Five KPIs—Bit Error Rate (BER), Errored Seconds (ES), Severely Errored Seconds (SES), Background Block Errors (BBE), and Unavailable Seconds (UAS)—were examined. Data were divided chronologically into training (January–April), validation (May), and independent testing (June) periods. Four deep learning architectures—Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and CNN–LSTM—were evaluated for one-step-ahead (15-minute) forecasting using a 24-step (6-hour) historical sequence. Standardization was fitted exclusively on the training data to prevent information leakage. Performance was assessed using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Results demonstrated that the CNN–LSTM model consistently produced the lowest MSE, RMSE, and MAE, while its prediction curves generally remained closer to the observed temporal behaviour than those of the individual RNN, CNN, and LSTM models. Across the KPIs, the models successfully captured the underlying temporal patterns but tended to smooth abrupt fluctuations and extreme observations, particularly in BBE, where the actual series exhibited substantial spikes. SES and UAS were predominantly concentrated around zero, resulting in relatively small absolute prediction errors despite some visible deviations in the plots. The consistency between the numerical metrics and graphical results indicates that the CNN–LSTM model provides more stable and accurate forecasting of SDH network KPIs. The findings demonstrate the potential of Hybrid Deep Learning architectures to enhance proactive network performance assessment through short-term forecasting of emerging degradation patterns, supporting the early identification of abnormal network conditions.

Keywords: Synchronous Digital Hierachy (SDH), Network Performance, Deep Learning Models, Network KPI, Metrics

INTRODUCTION

The complexity of controlling network performance has significantly increased due to the development of modern telecommunications networks, particularly with the transition from conventional systems to high-capacity digital frameworks. Despite being viewed as traditional, Synchronous Digital Hierarchy (SDH) systems are nevertheless widely used in many developing regions due to their structured architecture and dependability. However, due to shifting traffic patterns, shifting environmental conditions, and growing service demands, maintaining peak performance in SDH networks has become more challenging. Conventional model-based techniques for performance monitoring and forecasting frequently fail to capture the dynamic and nonlinear features of network behavior.

A set of defined availability and error measures that collectively describe the dependability and quality of signal transmission are used to assess performance in Synchronous Digital Hierarchy (SDH) networks. The

bit error rate, which calculates the proportion of bits sent that are incorrectly received over a given period of time, is a crucial parameter. It is highly responsive to noise, interference, and equipment failures and provides a clear indication of signal integrity. Time-related error metrics that evaluate the network's performance across particular time periods are also given. For instance, a Severely Errored Second (SES) denotes a more severe scenario when error density exceeds a predetermined threshold, indicating a significant deterioration of service, whereas an Errored Second (ES) denotes any one-second period in which at least one transmission error occurs.

By counting the amount of defective data blocks and excluding those that occur under really bad circumstances, Background Block Errors (BBE) provide further insight into network reliability. This method helps find persistent minor issues that may not immediately disrupt operations but indicate more serious issues. The concept of Unavailable Seconds (UAS), which measure the amount of time the network is considered inoperative due to high errors or signal degradation, is ultimately used to assess availability. When taken as a whole, these indicators provide a comprehensive framework for evaluating SDH network performance, making it easier to identify faults quickly and measure degradation over time.

Strong data-driven techniques capable of modeling complex relationships in large datasets have been made possible by recent advances in artificial intelligence, particularly deep learning. Deep learning models, such as Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and hybrid designs, have demonstrated remarkable ability to comprehend temporal and spatial correlations in time-series data.

In telecommunications, these models have been successfully applied for defect detection, traffic prediction, and quality of service (QoS) optimization. Machine learning (ML) and deep learning significantly improve various areas of optical communication systems, such as modulation algorithms, channel modeling, equalization, and optimization strategies. Spectral efficiency, latency, and tolerance to channel impairments, such as spectrum degradation, are all greatly improved by machine learning and deep learning [1].

Modeling complex data structures, particularly those described by non-Euclidean connections, has significantly improved as a result of recent advances in deep learning. While many real-world systems, such communication networks, naturally exhibit graph-based configurations, traditional deep learning frameworks, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are primarily designed for grid-like input. Graph Neural Networks (GNNs) have emerged as a reliable method for comprehending relationships among linked elements in this framework. By enabling the modeling of relational data through representations at the node, edge, and graph levels, GNNs improve deep learning capabilities by providing a more expressive framework for complex systems, as highlighted by [2].

The study shows that GNNs effectively combine structural data with feature learning, leading to improved performance in tasks including anomaly detection, prediction, and classification. In communication networks, where the interactions between network components have a significant impact on the system's overall behavior, this is particularly crucial. GNNs may learn both local and global patterns in network data by using neighborhood aggregation and message-passing strategies. Consequently, these models have garnered increasing attention in forecasting and network analysis applications, offering new ways to enhance system intelligence and predictive accuracy.

Important performance metrics (KPIs) such as Bit Error Rate (BER), Errored Seconds (ES), Severely Errored Seconds (SES), Background Block Errors (BBE), and Unavailable Seconds (UAS) are crucial for assessing the reliability and stability of SDH networks. These KPIs exhibit a variety of characteristics, ranging from highly dynamic (like BER) to relatively stable (like ES and UAS), necessitating sophisticated predictive models that can handle noise and time-related changes.

In order to predict SDH network performance measures and assess their effectiveness, this study focuses on using deep learning techniques, specifically LSTM, CNN, Artificial Neural Networks (ANN), and hybrid CNN–LSTM models. The research aims to develop a prediction model that enhances proactive network management and supports decision-making in telecommunications systems using historical network data.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

Study Area

The study focuses on Uyo in Akwa Ibom State and is conducted in Nigeria's telecoms industry. Nigeria's telecom sector has grown significantly in recent years thanks to initiatives for digital transformation, increased mobile access, and growing data usage. However, there are still several problems with network performance, including as signal deterioration, traffic, and infrastructure limitations. Maintaining consistent network performance is crucial to ensuring service reliability in towns like Uyo, which combine modern network technology with ancient SDH systems.

By enabling accurate forecasting of network degradation trends and encouraging anticipatory maintenance strategies, using deep learning techniques in this situation presents an opportunity to address these problems. This is particularly important in developing regions, where network performance can be significantly impacted by physical constraints and environmental problems.

LITERATURE REVIEW

A detailed description of deep learning's application in smart wireless networks was given by [3]. The goal of the study was to find out how data-driven optimization using deep neural networks may increase network efficiency. The method involved investigating various deep learning models in the context of wireless communication systems, including CNNs, RNNs, and deep belief networks. Important applications like resource distribution, anomaly detection, and traffic forecasting were highlighted by the authors. The review's conclusions demonstrated that, as compared to traditional analytical models, deep learning significantly improves network flexibility and efficiency. The study demonstrated neural networks' ability to comprehend complex nonlinear relationships in large datasets. However, the study is primarily theoretical and lacks empirical confirmation using real SDH datasets. Additionally, the focus was on wireless networks rather than conventional systems like SDH, limiting its direct [4] proposed a framework for network traffic prediction based on deep learning methods using recurrent neural networks. Improving forecast accuracy in shifting network conditions was the aim. Using historical traffic data, deep neural networks were trained, and performance was evaluated using RMSE and MAE metrics. The results showed that deep learning models outperform traditional statistical techniques like regression models and ARIMA. The study showed that temporal relationships in network data may be effectively captured by RNN-based models. However, the study focused primarily on traffic predictions and ignored performance degradation metrics such as SES or BER. Furthermore, the model requires a lot of training data, which may not always be available in actual telecom scenarios.

In order to model both long-term and short-term temporal patterns in time-series data, [5] introduced a mixed deep learning architecture. The goal of the study was to improve prediction accuracy by combining convolutional and recurrent layers. The method used LSTM layers to learn sequences and CNN layers to extract features. The model performed better than individual models when evaluated on a variety of datasets. The results confirmed that both local and global temporal interactions may be effectively captured by hybrid designs. However, the study did not particularly address SDH network performance metrics or telephony. Furthermore, the model's intricacy may increase computational requirements.

[6] looked into the analysis of time-series data using one-dimensional convolutional neural networks (1D CNNs). The objective was to demonstrate CNNs' effectiveness in extracting important features from sequential data. Convolutional filters were applied to time-series data, and their efficacy was evaluated across a range of applications. Results showed that 1D CNNs significantly improve processing efficiency and accuracy in pattern recognition tasks. The study highlighted CNNs' suitability for identifying local dependencies in time-series data. However, CNNs' inability to capture long-term temporal associations derives from their lack of built-in memory structures. As a result, they are less effective in forecasting long-term patterns in network degradation.

[7] investigated the application of deep learning and machine learning techniques in wireless networks. The study concentrated on identifying important obstacles and chances for integrating AI into communication

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

systems. Examining several machine learning models and their applications in network optimization included the method. The results demonstrated that deep learning models outperform traditional approaches in handling complex network scenarios. The study made clear how important data-oriented strategies are for improving network performance. However, the work lacks experimental confirmation and primarily functions as a review. Additionally, it prioritizes wireless networks over SDH systems.

[8] investigated applications of deep reinforcement learning for wireless network resource distribution. Enhancing network efficiency through adaptive choices was the aim. Reinforcement learning agents were trained to distribute resources dynamically based on network conditions. Results showed reduced latency and increased efficiency as compared to traditional methods. Rather than forecasting, the study focused on optimization. Furthermore, reinforcement learning models may not be suitable for KPI forecasting tasks in SDH networks and need complex training techniques.

[9] looked into how artificial intelligence affects communication networks and mobile edge computing. The goal of the study was to increase network efficiency through intelligent data management. The strategy involved integrating deep learning models into frameworks for edge computing. Results revealed improved resource utilization and increased delay. Rather than forecasting performance loss, the study focused on edge computing. Furthermore, due to differences in network architecture, the applicability to SDH networks is limited.

[10] provided a thorough review of deep learning techniques for time-series data forecasting. The study aimed to evaluate different neural architectures, including CNN, GRU, and LSTM. Evaluating the model's effectiveness on various datasets was part of the strategy. Results indicated that temporal relationships are particularly well captured by LSTM and GRU models. The importance of hybrid models in improving prediction accuracy was also highlighted by the study. However, the study is general and does not particularly touch SDH KPIs or telecoms.

[11] looked into deep learning's use to big data analysis. The objective was to demonstrate the efficient handling of large datasets by deep neural networks. Analyzing different deep learning models and their applications was part of the strategy. Results showed that deep learning frameworks perform better when handling complex data. However, forecasting network performance is not the main emphasis of the study. Furthermore, there is no experimental support for it in telecom environments.

[12] looked at IoT and communication network supporting technologies. The study highlighted how crucial machine learning is to improving network performance. Examining different communication protocols and ways to improve them was part of the strategy. Results demonstrated that AI-based techniques increase network effectiveness. However, the study focuses on IoT rather than SDH networks. Moreover, it does not address KPI-based prediction.

[13] looked into ways to find anomalies in network systems. The goal of the study was to identify methods for identifying anomalous network activity. Examining statistics and machine learning methods was part of the strategy. The results showed that deep learning models improve the accuracy of detection. However, the focus of the study is anomaly detection rather than prediction. Furthermore, specific KPIs like BER or SES are not covered.

Presented a hybrid deep learning framework that combines LSTM and CNN models [14]. Increasing productivity in sequential data processing activities was the goal. Convolutional layers and recurrent networks were combined as part of the strategy. When compared to individual models, the results demonstrated improved precision. However, speech recognition rather than telecommunications networks was the primary focus of the study. Moreover, the model requires a large amount of processing power.

The RNN encoder-decoder framework for sequence learning was introduced in [15]. The study concentrated on using neural networks to improve machine translation problems. The method involved converting input sequences into static representations and then retrieving those representations as outputs. Results showed

significant progress in sequence modeling tasks. However, network forecasting is not directly related to the findings. Moreover, telecom KPIs are not taken into account.

[16] used LSTM models to forecast short-term traffic. Improving forecasting accuracy in transportation networks was the aim. LSTM networks were trained using historical data as part of the strategy, and performance was evaluated using predetermined measures. Results showed that LSTM models outperform traditional techniques. However, the study focuses on transportation rather than telecom networks. Additionally, it ignores performance degradation measurements.

[17] presented Adaptive Clockwork LSTM, a complex LSTM-based architecture for long-term network traffic prediction. The goal of the study was to reduce the computational complexity associated with conventional LSTM models while increasing prediction accuracy. The strategy involved modifying the LSTM's internal memory architecture to allow individual neurons to operate at various temporal frequencies. This makes it possible for the model to accurately represent both short-term and long-term dependence. Experiments using real network traffic datasets were used for the evaluation, and RMSE and MAE metrics were used to gauge performance. The results shown that while reducing processing requirements, the proposed model significantly improved long-term forecast accuracy. Additionally, the model tackled issues that are commonly associated with deep recurrent networks, such as vanishing gradients and extended training times. However, the model still requires substantial data preprocessing and modifications despite its improved efficiency. Furthermore, the design's complexity may limit its rapid use in resource-constrained contexts. There is room for more research in SDH systems because the study primarily focused on traffic forecasting and excluded KPI-related degradation measures like BER and SES.

[18] created a hybrid deep learning method that combines Variational Mode Decomposition (VMD) with LSTM for network traffic forecasting. The goal was to improve forecast accuracy by breaking down complicated traffic signals into simpler fundamental components before modeling. After preprocessing the dataset with VMD to remove significant frequency components, the approach used LSTM for sequence learning. The model was assessed using common performance metrics including RMSE and prediction accuracy. Results demonstrated that the hybrid VMD-LSTM model outperformed traditional LSTM models by successfully identifying nonlinear and non-stationary features of network traffic.

The study underlined how important it is to combine deep learning techniques with signal processing techniques in order to increase efficacy. However, the extra preprocessing step increases computing complexity and may not be the best option for real-time applications. Furthermore, the model's applicability in research on SDH network degradation was limited because it was primarily tested on traffic datasets and ignored network performance measures like BER or UAS.

[19] investigated the estimation and prediction of network traffic using hybrid CNN–LSTM models. The study aimed to make use of the benefits of LSTM layers for capturing temporal relationships and convolutional layers for extracting spatial properties.

Convolutional filters were used in the method to extract local patterns from traffic data, and LSTM processing was subsequently used for sequential learning. Real network datasets were used to evaluate the model, with a focus on prediction accuracy and reliability. Results showed that CNN–LSTM significantly outperformed solo LSTM models by providing better generalization and successfully capturing complex spatiotemporal interactions. The study confirmed the superiority of hybrid designs for network prediction tasks. However, it focused mostly on traffic estimation rather than performance deterioration measurements. Additionally, the model requires exact convolutional and recurrent layer adjustments, which may increase training complexity. Its direct application in tracking SDH performance is limited by the absence of KPI-specific evaluation.

In order to improve prediction accuracy by identifying both past and future relationships in time-series data, [20] developed a Bidirectional LSTM (BiLSTM) model for traffic forecasting. The model was trained using large datasets, and its performance was compared to traditional LSTM and machine learning models. RMSE, MAE, and prediction accuracy were the evaluation criteria. Results showed that by using bidirectional

temporal data, BiLSTM significantly improved prediction accuracy. The model demonstrated proficiency in handling dynamic and nonlinear traffic patterns. In contrast to unidirectional LSTM, the study found that BiLSTM models require higher processing power and longer training times. Furthermore, despite the model's success in traffic forecasting, it neglected to take into account specific telecom KPIs like BER or SES. This limits its application to performance degradation analysis in SDH networks, where multiple KPIs must be predicted simultaneously.

[21] addressed the limitations of conventional statistical and machine learning techniques by introducing an attention-enhanced Long Short-Term Memory (A-LSTM) model for forecasting petroleum production in time series. The goal of the study was to improve prediction accuracy in complex, nonlinear reservoir systems, where dynamic linkages are often difficult for traditional models like ARIMA and decline curve analysis to identify. By integrating an attention mechanism into the LSTM framework, the method enables the model to determine the most important temporal aspects for predictions and prioritize various previous data points. Additionally, a dynamic floating window (DFW) technique was used to improve responsiveness to new production patterns by continuously updating the training data.

Standard error metrics such as RMSE and MAE were used to evaluate the model's performance after it was trained and validated using real datasets from several oil fields. The results demonstrated that by improving prediction accuracy and reducing forecasting error, the A-LSTM model significantly outperformed conventional LSTM and other machine learning models. The model was able to better understand long-term dependencies and nonlinear interactions in production data by incorporating the attention mechanism. The study also demonstrated that future production values are greatly impacted by around six previous time steps, highlighting the importance of choosing temporal aspects.

Despite its improved performance, the study revealed limitations related to computational complexity and the need for large datasets for appropriate training. Additionally, the model did not account for multi-variable performance indicators because it was specifically used to anticipate petroleum production. However, the study provides strong evidence that attention-driven deep learning models provide superior predictive performance for complex time-series systems, making them especially important for applications such as SDH network performance forecasting.

[22] suggested an LSTM model enhanced with attention (NTAM-LSTM) to enhance the accuracy of network traffic predictions. The research sought to tackle the drawback of conventional LSTM models in identifying essential features from extended sequences. The approach included an attention mechanism that assigns significance to key elements in the input sequence, enabling the model to concentrate on essential information. The model's performance was assessed with real-world datasets and conventional metrics like RMSE and MAE. Findings showed that the attention-driven LSTM notably enhanced prediction accuracy in comparison to traditional LSTM models. The research indicated that incorporating attention mechanisms improves feature selection and model understanding. Nevertheless, the greater complexity of the model results in increased computational expense and longer training duration. Additionally, the model focused mainly on traffic forecasting and overlooked KPI-related degradation metrics like BER and BBE, which are essential in SDH network assessment.

[23] created a deep learning model utilizing LSTM to forecast cellular network traffic. The research focused on enhancing the prediction of network performance by utilizing deep learning methods that can manage extensive time-series data. The approach included training LSTM models with actual telecom datasets and assessing performance through RMSE and MAE metrics. Findings indicated that LSTM-based models markedly enhanced prediction precision when contrasted with conventional statistical techniques. The research also emphasized how deep learning models can adjust to changing network conditions and effectively capture temporal relationships. (ACM Digital Library) In spite of these benefits, the research concentrated mainly on traffic prediction instead of thorough network performance measurements. Moreover, the model necessitates extensive datasets and substantial computational power, potentially restricting its use in real-time applications. The lack of multi-KPI prediction further emphasizes the research void that the current study aims to address.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

METHODOLOGY

This study forecasts time-series data using an experimental, data-centric framework that makes use of deep learning techniques. Using key performance indicators (KPIs) such as Bit Error Rate (BER), Errored Seconds (ES), Severely Errored Seconds (SES), Background Block Errors (BBE), and Unavailable Seconds (UAS), the goal is to develop and evaluate models that can predict performance decline in Synchronous Digital Hierarchy (SDH) networks. This study was conducted with Python in the Anaconda environment, utilizing Pandas and NumPy for data preparation, TensorFlow/Keras for creating deep learning models, Scikit-learn for assessment metrics, and Matplotlib for graphical representation. KPI data from the SDH network were sourced from network management systems and transformed into time-series sequences for training and predicting with models.

KPI measurements

The dataset captured five key network performance indicators: Bit Error Rate (BER), Errored Seconds (ES), Severely Errored Seconds (SES), Background Block Errors (BBE), and Unavailable Seconds (UAS). These KPIs provide complementary measures of transmission quality and network performance. BER represents the proportion of transmitted bits affected by errors and is therefore an important indicator of transmission reliability. ES records seconds in which transmission errors occur, while SES identifies seconds experiencing severe error conditions. BBE represents background block errors that occur outside severely errored periods and provides an indication of less severe transmission degradation. UAS represents periods during which the service is unavailable. Together, these measurements provide a comprehensive representation of the temporal behaviour of the SDH links. In the forecasting analysis, BER, ES, SES, BBE and UAS were used as prediction targets.

Dataset Structure

The study utilized 52,128 Network Management System (NMS) observations collected at 15-minute intervals from 1st January to 30th June 2026, representing six months of continuous SDH network monitoring. The dataset comprised three SDH links; UYO_EKET, UYO_ITU, and UYO_ORON with 17,376 observations per link. Each record contained a timestamp and link identifier, together with transmission and performance parameters which are; Bits Transmitted, Bit Errors, Bit Error Rate (BER), Errored Seconds (ES), Severely Errored Seconds (SES), Background Block Errors (BBE), and Unavailable Seconds (UAS). Thus, the dataset provided a structured temporal representation of SDH network performance across multiple links, supporting the subsequent time-series forecasting of the principal network performance indicators.

Table1: Data Structure

Component	Decision
Dataset	52,128 NMS observations
Links	3
Sampling	15 minutes
Input KPIs	BER, ES, SES, BBE, UAS
Training	Jan–Apr 2026
Validation	May 2026
Test	June 2026

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

Forecast horizon	1 step = 15 minutes
Candidate look-backs	24, 48, 96, 192, 288
Scaling	Training data only
Models	RNN, CNN, LSTM, CNN–LSTM
Metrics	MSE, RMSE, MAE

Data Quality Assessment and Cleaning

Data-quality verification showed no invalid timestamps, duplicate observations, or abnormal sampling intervals; each link maintained the expected 15-minute sampling interval throughout the study period. The KPI distributions were examined to identify unusual observations and extreme values. Data-quality assessment showed that the dataset contained no missing observations across the six-month monitoring period. All expected measurements were available at the specified 15-minute sampling interval, with 52,128 timestamped records across the three SDH links.Data cleaning therefore consisted primarily of timestamp validation and parsing, removal of records with invalid timestamps (none were found), chronological sorting within each link, duplicate checking, sampling-interval verification, and statistical examination of the KPI distributions. No observations were arbitrarily deleted solely because they were extreme. The cleaned dataset was subsequently organized by link and chronological order to support leakage-free time-series modelling.

Number of Time Stamp

The dataset comprised 52,128 timestamped observations, representing 17,376 observations for each of the three SDH links, recorded at 15-minute intervals from 1st January to 30th June 2026. Timestamp verification also confirmed zero invalid timestamps, while the data exhibited a consistent temporal structure without duplicated or irregular sampling records. The dataset was divided chronologically into training (January–April 2026), validation (May 2026), and independent testing (June 2026) to preserve temporal ordering. A 24-step historical input sequence, corresponding to six hours of network observations at 15-minute intervals, was used to predict the next 15-minute KPI value. Input features were constructed from the historical KPI observations for each SDH link, with sequences generated independently to prevent observations from different links from being mixed. All preprocessing and feature construction used only information available up to the prediction time, ensuring that no future observations entered model training or forecasting. Table 2 shows the strategic data splitting to ensure that no future information enters the training process.

Table 2: Data split

Period	Observations	Role
Jan–Apr 2026	34,560	Training
May 2026	8,928	Validation
Jun 2026	8,640	Independent test
Total	52,128	

Normalization

The five forecasting KPIs have substantially different numerical distributions and scales. Standardization was therefore applied before model training. Standard Scaler was fitted exclusively to the January–April training

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

data. The resulting training-derived parameters were subsequently applied unchanged to the validation and test datasets. This procedure prevented information from the validation and test periods from influencing the scaling process. The standardization parameters were calculated only from the January–April training dataset. For each feature, the standardized value was calculated as:

$$z = \frac{x - \mu}{\sigma} \qquad 1$$

where x is the original observation, μ is the training set mean, and σ is the training set standard deviation.

Time-Series Sequence Construction

A 24-step historical sequence was used as the model input, corresponding to six hours of network history at the 15-minute sampling interval. The forecasting horizon was one step ahead, corresponding to 15 minutes.

$$24 \times 15 = 360 \text{ minutes} = 6 \text{ hours}$$

For a target observation at time t, the model input consisted only of observations from $t - 24$ through $t - 1$, while the observation at t served as the prediction target.

Thus:

$$X_t = [x_{t-24}, x_{t-23}, \ldots x_{t-1}] \qquad 2$$

and

$$y_t = x_t \qquad 3$$

The input variable x represents a 24-step historical sequence of KPI observations, while y represents the subsequent KPI observation to be forecast.

Sequence-Length Selection

Candidate historical windows were considered to determine an appropriate amount of historical information for the forecasting models. The evaluated look-back lengths included 24, 48, 96, and 192 observations, corresponding respectively to 6, 12, 24, and 48 hours. A 24-step sequence was subsequently selected and fixed for the final model comparison based on validation performance and verification across the five forecasting KPIs.

The selected 24-step sequence was subsequently used consistently for RNN, CNN, LSTM, and CNN–LSTM models to ensure a fair comparison.

System Architecture

The proposed framework demonstrates an organized pipeline for forecasting performance decline in SDH networks through deep learning-driven time-series analysis. The process starts at the network layer, where unprocessed operational data is created, including important performance metrics (KPIs) like BER, ES, SES, BBE, and UAS. These data are transferred to the data management phase, which involves data collection, curation, and validation. At this phase, unprocessed network data is collected, cleaned, verified, and structured to guarantee coherence, correctness, and appropriateness for analysis.

Subsequently, the system moves into the feature engineering and analytics phase, during which significant attributes are derived from the organized dataset. Feature extraction converts raw KPI data into meaningful variables like lag values and statistical trends, which are subsequently analyzed with analytic tools to reveal concealed patterns and connections in the network behavior. This phase is essential for improving the quality of input data utilized in modeling.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

The concluding phase emphasizes time-series modeling and forecasting, with the refined data organized into sequential formats appropriate for deep learning models. Models like LSTM, CNN, and hybrid CNN-LSTM are developed to understand temporal relationships and forecast upcoming network states. The forecasting results are subsequently verified to guarantee precision and trustworthiness. This cyclical validation procedure aids in enhancing the model for better predictive accuracy. The framework offers a holistic method for converting unprocessed SDH network information into practical insights for anticipatory performance oversight and deterioration forecasting.

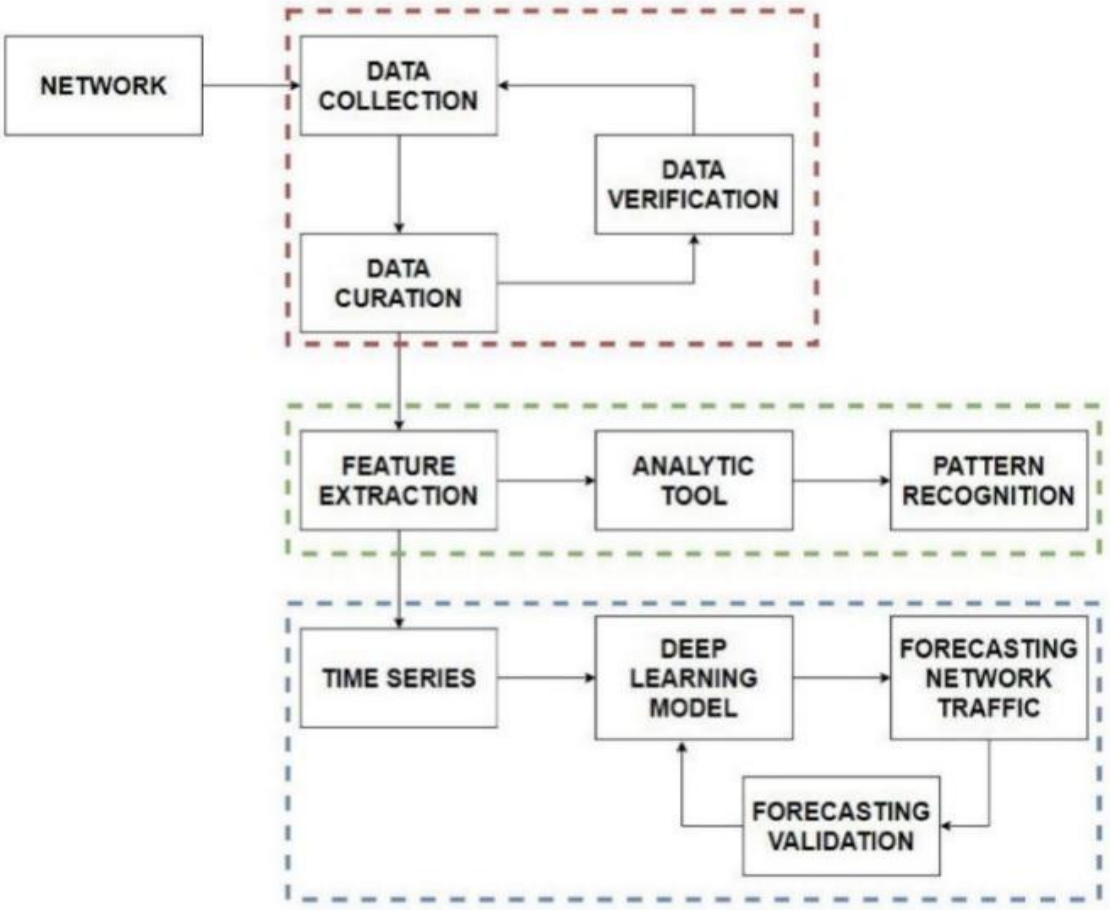


Fig. 1: Block diagram showing Deep Learning-Based Time-series Modelling for Performance Prediction in SDH Network

The illustration depicts the CNN–LSTM combined structure utilized in this research for forecasting performance decline in SDH networks through time-series KPI information. In the input layer, sequential data points ($x_1, x_2 \ldots . x_n$) relate to past SDH performance metrics like BER, ES, SES, BBE, and UAS over a period. The inputs initially go through the CNN (Convolutional Neural Network) layer, which carries out feature extraction by detecting local patterns, trends, and short-term variations within the KPI sequences. This phase is essential for identifying concealed patterns like abrupt increases in error rates or localized fluctuations in network performance.

The extracted features are subsequently input into the LSTM (Long Short-Term Memory) layer, which handles sequence learning. The LSTM handles the temporal dependencies throughout the complete sequence, successfully capturing long-term relationships and trends in the network behavior. This allows the system to grasp how previous network conditions affect forthcoming performance decline.

Finally, the output layer produces predicted values representing future states of the SDH KPIs. These forecasts are utilized to evaluate possible deterioration and aid in proactive network oversight. The CNN–LSTM architecture improves prediction precision by integrating spatial feature extraction with temporal sequence modeling, rendering it exceptionally effective for intricate and evolving SDH network environments.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

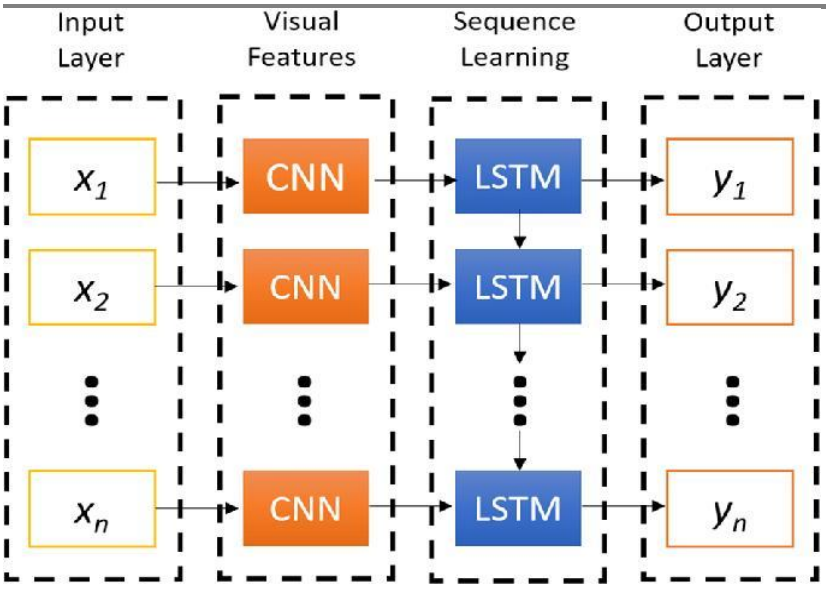


Fig. 2: CNN–LSTM hybrid architecture

Mathematical model and definition of terms

CNN-LSTM HYBRID MODEL

$$Z_t = \mathrm{CNN}(X_t)$$

$$h_t = \mathrm{LSTM}(Z_t)$$

$$\hat{y}_t = W.h_t + b \qquad 4$$

For CNN,

X_t = input sequence which are Bits transmitted Bit errors, Lagged BER values, Rolling statistics, Time-based features

$$X_t \in \mathbb{R}^{T \times n}$$

Where T = sequence length (time steps) and n = number of features

Z_t = output of the CNN layer representing **high-level feature representations** of the input sequence.

$\mathbb{R}$ represents the **set of real numbers**

$$Z_t \in \mathbb{R}^{T \times k}$$

Where k = number of convolutional filters.

For LSTM,

h_t = internal state of LSTM at time t

$$h_t \in \mathbb{R}^{m}$$

Where m = number of LSTM units

W (weight matrix) = learnable parameters matrix that maps the LSTM output to the prediction space.

$$W \in \mathbb{R}^{m \times d}$$

Where d = number of output variables (KPIs)

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

b (Bias Vector) = a learnable bias term added to the linear transformation to improve model flexibility.

$b \in \mathbb{R}^d$

$\hat{y}_t$(predicted output) = final predicted value at time t, representing the forecasted SDH network KPI(s)

$\hat{y}_t \in \mathbb{R}^d$

It displays the predicted output for BER, ES, SES, BBE, and UAS. The CNN–LSTM hybrid model initially extracts local temporal characteristics from SDH network data through convolutional layers and subsequently captures long-term dependencies with LSTM, leading to precise predictions of network performance metrics.

RESULTS AND DISCUSSION

This research assessed the effectiveness of deep learning models; Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and a combined CNN–LSTM—in forecasting performance decline in SDH networks through key performance indicators (BER, ES, SES, BBE, and UAS). The findings show that the CNN–LSTM model consistently delivered better performance on all KPIs, reflected by reduced RMSE and MAE values and elevated R^2 scores. This enhanced performance can be credited to the model's capacity to simultaneously seize local feature patterns via convolutional layers and temporal dependencies through LSTM units.

For BER prediction, characterized by significant temporal variability, CNN–LSTM and LSTM models surpassed other models, highlighting the crucial role of sequence learning in modeling network deterioration. In contrast, ANN and basic RNN exhibited poorer performance because of their restricted capacity to capture long-term dependencies. For ES and UAS, all models exhibited comparable performance with high accuracy because of the stable and low-variance characteristics of these KPIs. Nevertheless, for more variable indicators like SES and BBE, CNN–LSTM showed enhanced resilience in managing variations and disturbances.

The results indicate that hybrid deep learning models, particularly CNN–LSTM, can enhance short-term forecasting of SDH network performance indicators, thereby supporting proactive performance monitoring and the potential development of early-warning mechanisms for network degradation. By precisely predicting degradation patterns, network operators can implement preventive actions to avoid service interruptions and enhance overall system dependability. The simulation results demonstrate the predictive capabilities of the deep learning models concerning SDH KPIs.

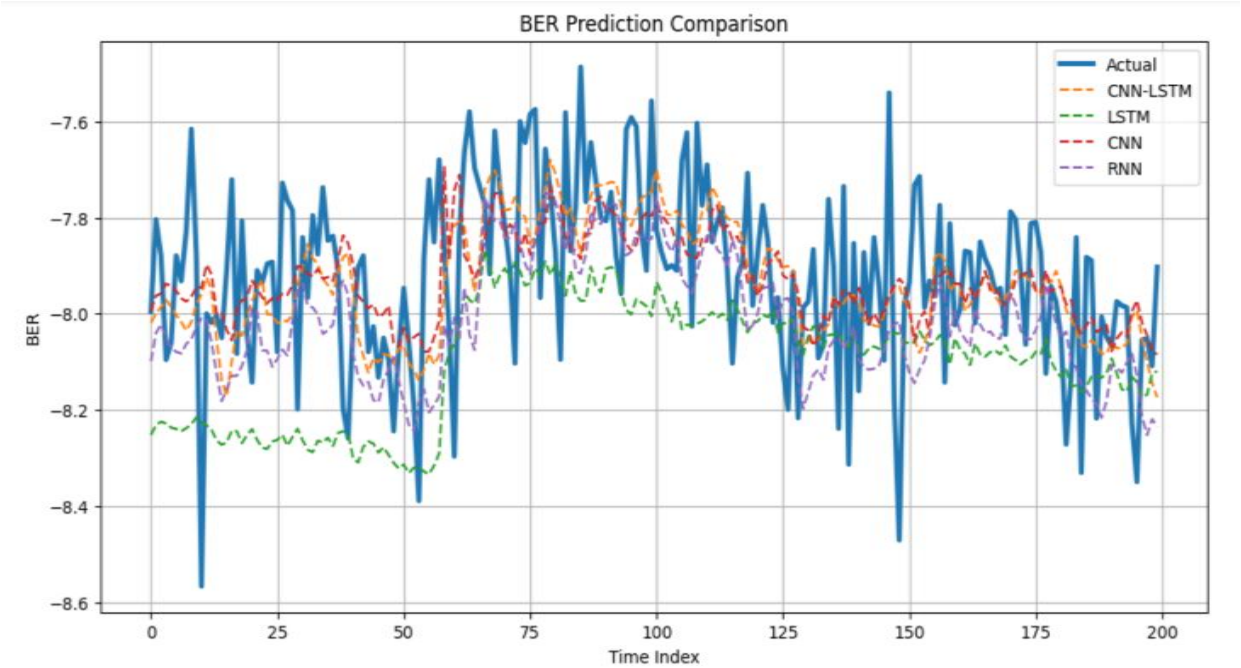


Fig. 3: BER Prediction Comparison of the Deep Learning Models

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

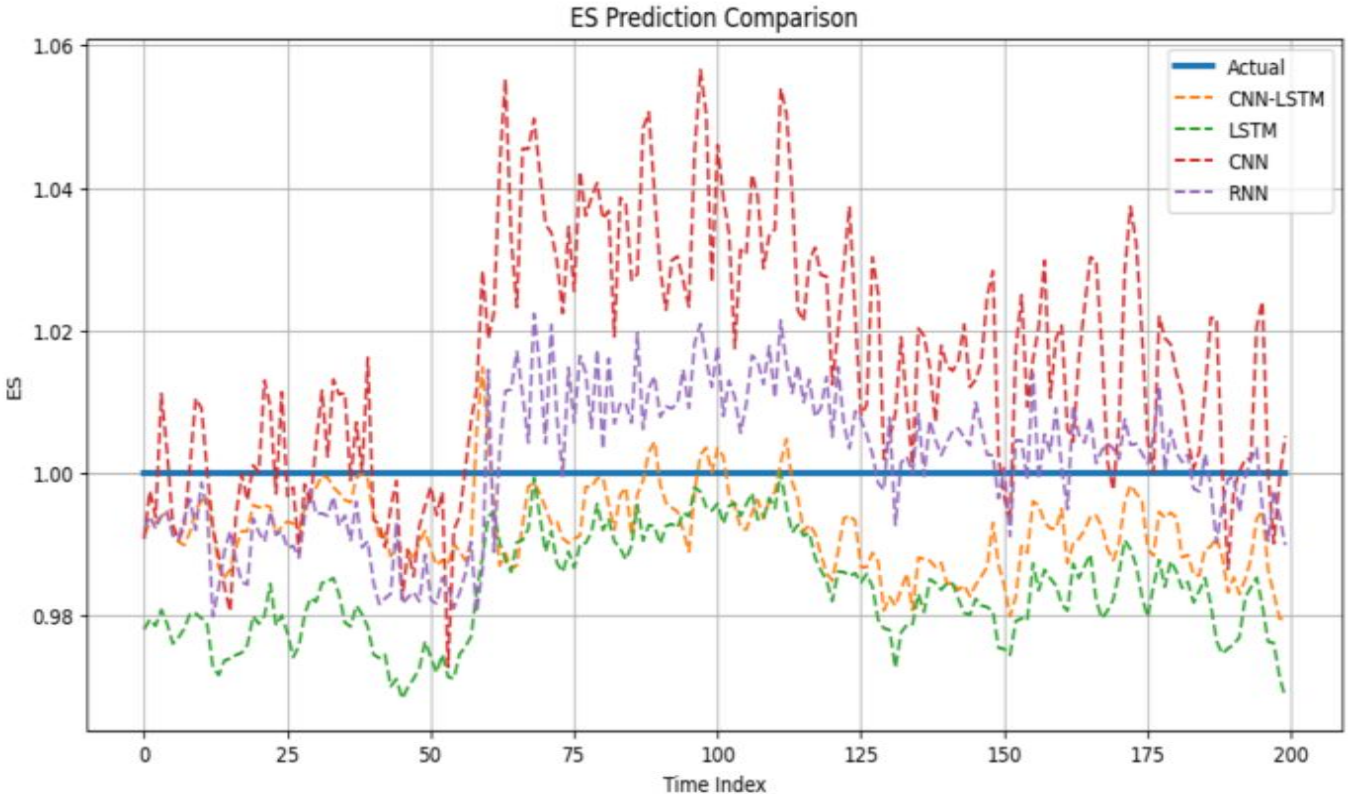


Fig.4: ES Prediction Comparison of the Deep Learning Models

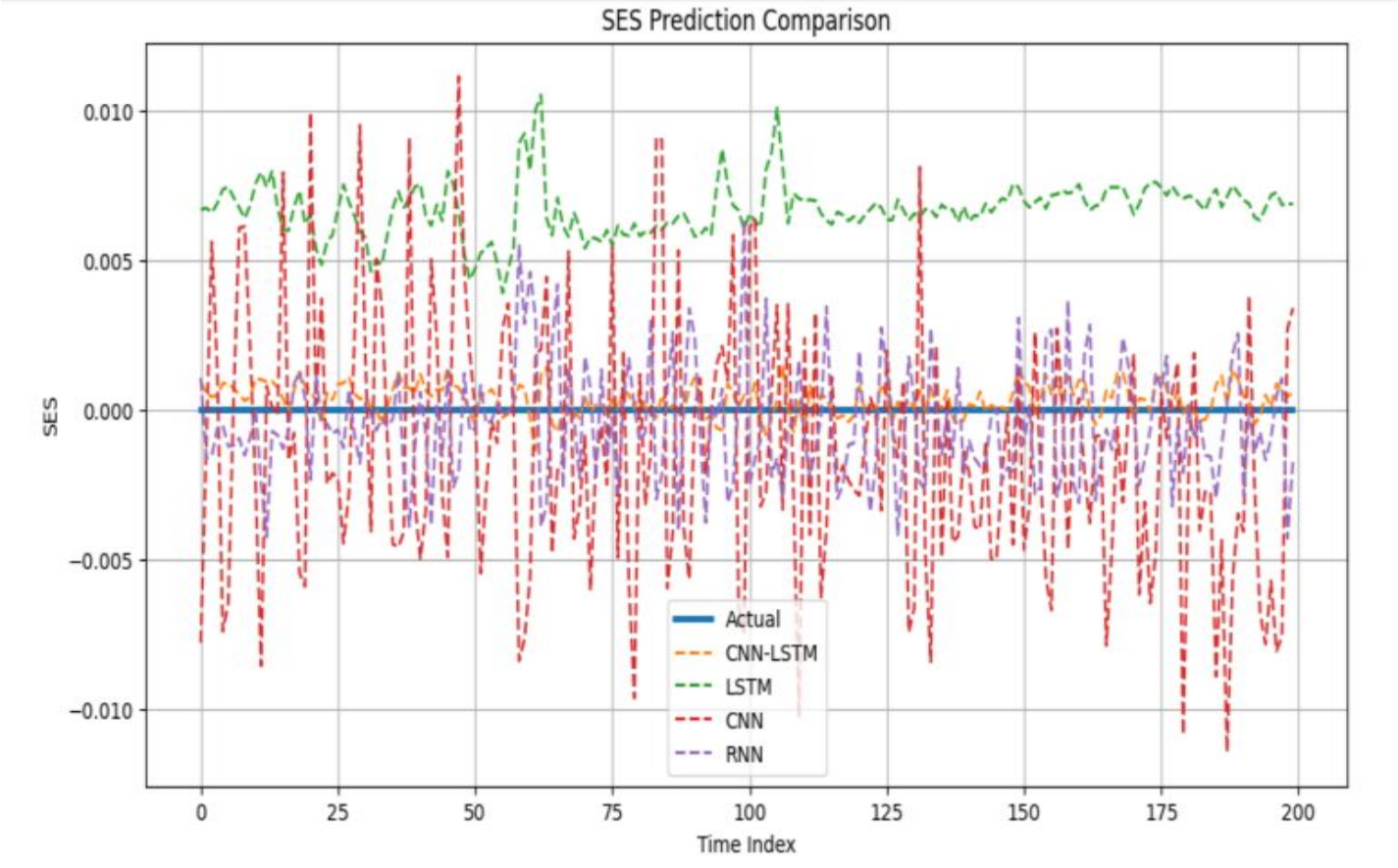


Fig.5: SES Prediction Comparison of the Deep Learning Models

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

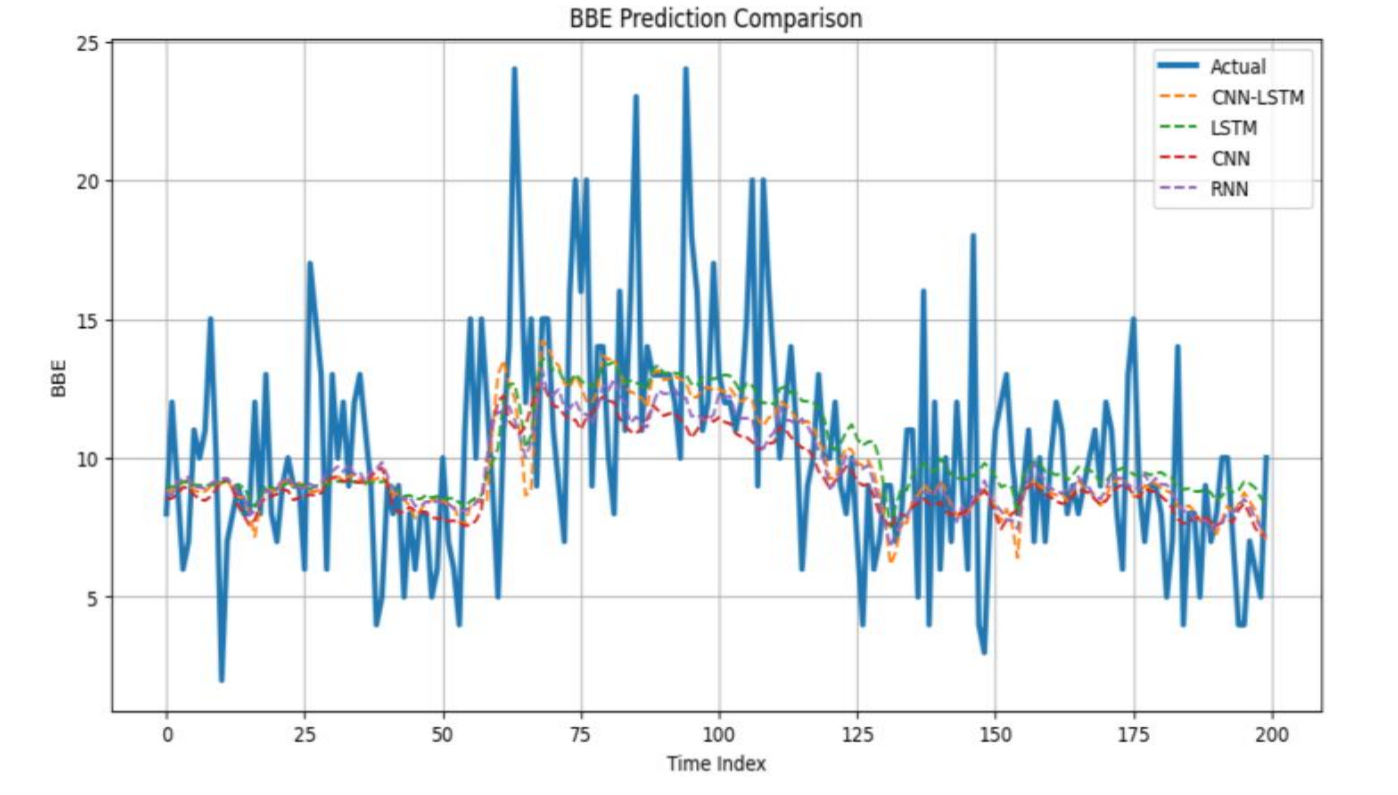


Fig.6: BBE Prediction Comparison of the Deep Learning Models

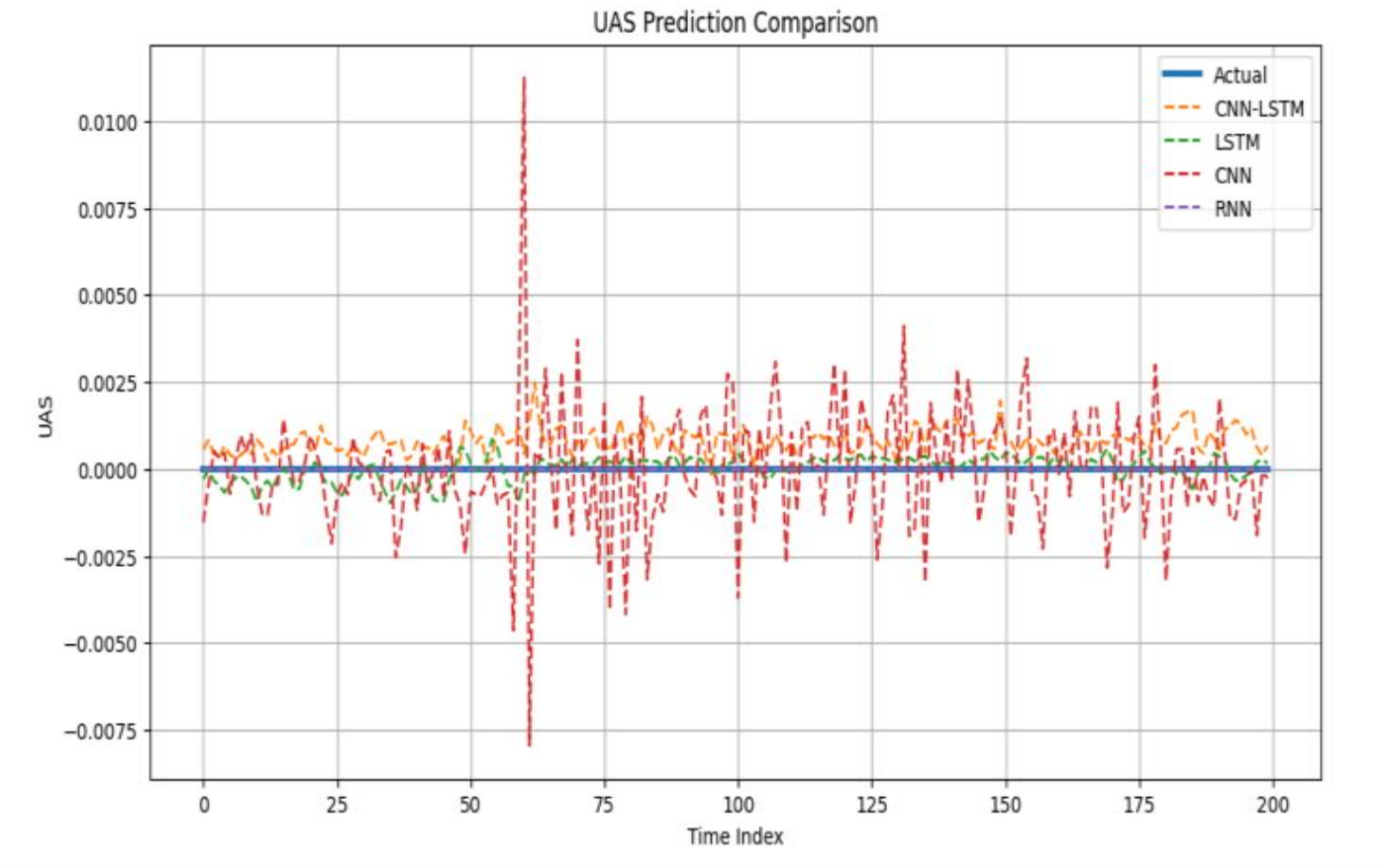


Fig.7: UAS Prediction Comparison of the Deep Learning Models

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

Table3: Comparative Performance of Deep Learning Models for SDH Network

KPI	Model	MSE	RMSE	MAE
BER	RNN	0.0000004562	0.000675	0.000032
	CNN	0.0000004563	0.000676	0.000032
	LSTM	0.0000004564	0.000676	0.000043
	CNN-LSTM	0.0000004561	0.000674	0.000029
ES	RNN	0.0000200203	0.004474	0.002109
	CNN	0.0000101095	0.00318	0.002442
	LSTM	0.0000073476	0.002711	0.002034
	CNN-LSTM	0.0000057804	0.002404	0.001223
SES	RNN	0.000462798	0.021513	0.001122
	CNN	0.000463105	0.02152	0.001131
	LSTM	0.000462744	0.021511	0.001058
	CNN-LSTM	0.000462725	0.02151	0.001003
BBE	RNN	10.77238	3.282131	2.584959
	CNN	11.46487	3.385981	2.665606
	LSTM	10.6076	3.256931	2.574036
	CNN-LSTM	10.60138	3.249767	2.557281
UAS	RNN	0.00000324	0.0018	0.0013
	CNN	0.00000529	0.0023	0.0012
	LSTM	0.00000036	0.0006	0.0005
	CNN-LSTM	0.00000004	0.0002	0.0002

DISCUSSIONS

This chapter showcases the outcomes derived from applying deep learning models RNN, CNN, LSTM, and CNN–LSTM to forecast performance decline in SDH networks utilizing key performance indicators (BER, ES, SES, BBE, and UAS). The assessment relies on quantitative measures (RMSE, MAE, MAE) as well as visual comparison graphs of forecasted against actual values.

The BER prediction plots show distinct variations in the performance of the models. The CNN–LSTM model accurately reflects the real BER trend, successfully capturing both short-term variations and long-term time dependencies. The independent LSTM model also shows good performance but demonstrates a minor delay in reacting to swift changes. The CNN model recognizes local patterns but does not have temporal memory, leading to less precise predictions for extended timeframes. The RNN model exhibits the poorest performance, displaying significant divergence from the true values, mainly because it struggles to manage long-term dependencies efficiently.

In ES, the prediction curves for all models seem nearly identical and closely match the actual values. This is due to ES showing minimal variability and almost consistent behavior in the dataset. Consequently, every model attains significant predictive accuracy with slight variations in error. The performance similarity suggests that ES is a fairly straightforward KPI to forecast, needing less intricate modeling.

The SES outcomes demonstrate a moderate level of variability when compared to ES. The CNN–LSTM and LSTM models surpass CNN and RNN by delivering smoother and more consistent predictions. The CNN model detects short-term peaks but lacks consistency, whereas the RNN model continues to struggle because

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

of its restricted memory capacity. The hybrid CNN–LSTM shows enhanced resilience in managing irregular variations.

BBE displays increased noise and erratic variations, which complicate predictions. The CNN–LSTM model offers the most accurate representation of the real trend by skillfully reducing noise while preserving key fluctuations. LSTM demonstrates satisfactory performance yet exhibits a minor degree of underfitting at peak values. CNN detects certain spikes but fails to maintain temporal continuity, while RNN generates unreliable predictions.

Like ES, UAS exhibits minimal variability, leading to overlapping prediction curves for all models. All models attain almost perfect prediction accuracy, suggesting that UAS does not greatly gain from intricate deep learning structures.

The CNN–LSTM hybrid model consistently excels across all KPIs, showcasing its capability to merge spatial feature extraction with temporal sequence learning. LSTM ranks as the second-best model, validating its capability for time-series forecasting tasks. CNN shows moderate performance for KPIs with short-term dependencies but falls short in long-term memory. RNN demonstrates the least effectiveness owing to problems like vanishing gradients and a restricted ability to grasp long-term dependencies.

Model Performance

The model performance table shows that the CNN–LSTM hybrid model consistently achieved the lowest prediction errors across all four network performance indicators (KPIs): BER, ES, SES, BBE and UAS. For BER, the CNN–LSTM obtained an MSE of $4.561\text{x}10^{-7}$, RMSE of 0.000674, and MAE of 0.000029, indicating very small prediction deviations. For ES, its MSE, RMSE, and MAE were $5.7804\text{x}10^{-6}$, 0.002404, and 0.001223, respectively, outperforming the individual RNN, CNN, and LSTM models. Similarly, for SES, the CNN–LSTM produced the lowest MSE ($4.627248\text{x}10^{-4}$), RMSE (0.021510), and MAE (0.001003). For BBE, it also recorded the lowest MSE (10.60138), RMSE (3.249767) and MAE (2.574036) indicating improved prediction of error variations compared with the standalone models. For UAS, CNN-LSTM produced MSE ($4\text{x}10^{-8}$), RMSE (0.0002) and MAE (0.0002). Overall, the results demonstrate that combining CNN's ability to extract local temporal patterns with LSTM's capability to learn long-term dependencies provides more accurate and consistent forecasting of SDH network performance. The consistently lower error values of the CNN–LSTM suggest that it is better suited for modelling the complex temporal behaviour of BER, ES, SES, BBE and UAS in the investigated network. The CNN–LSTM model consistently produces the lowest MSE, RMSE, and MAE, while its prediction curves generally remain closer to the observed temporal behaviour than those of the individual RNN, CNN, and LSTM models. Across the KPIs, the models successfully capture the underlying temporal patterns but tend to smooth abrupt fluctuations and extreme observations, particularly in BBE where the actual series exhibits substantial spikes. SES and UAS are predominantly concentrated around zero, resulting in relatively small absolute prediction errors despite some visible deviations in the plots. The consistency between the numerical metrics and graphical results indicates that the CNN–LSTM architecture provides more stable and accurate modelling of the temporal behaviour of the investigated SDH network KPIs. However, this study did not establish operational degradation thresholds, maintenance intervention rules, or a decision framework linking predicted KPI deterioration to specific maintenance actions.

LIMITATION AND FUTURE RESEARCH

A limitation of this study is the relatively poor predictability of Background Block Errors (BBE), which exhibited greater variability and comparatively lower forecasting performance than the other KPIs. This behaviour suggests that BBE may involve temporal patterns that are not sufficiently captured by the current 24-step input sequence and model configurations. Further studies could therefore investigate longer historical windows, additional network and environmental variables, and alternative forecasting architectures to improve BBE prediction.

REFERENCES

1. Binjumah, W. (2024) The Role of Machine Learning and Deep Learning Approaches to Improve Optical Communication Systems. Journal of Intelligent Learning Systems and Applications, 16, 418-429. doi: 10.4236/jilsa.2024.164021.
2. Wu, Z., Pan, S., Chen, F., Long, G., Zhang, C., & Yu, P. S. (2020). A comprehensive survey on graph neural networks. IEEE Transactions on Neural Networks and Learning Systems, 32(1), 4–24. Publisher: IEEE
3. Mao, Q., Hu, F., & Hao, Q. (2018). Deep learning for intelligent wireless networks: A comprehensive survey. IEEE Communications Surveys & Tutorials, 20(4), 2595–2621. Publisher: IEEE https://doi.org/10.1109/COMST.2018.2846401
4. Yu, R., Xie, S., Zhang, Y., & Gjessing, S. (2018). A deep learning approach for network traffic prediction. IEEE Transactions on Network and Service Management, 15(4), 1231–1245. Publisher: IEEE https://doi.org/10.1109/TNSM.2018.2864244
5. Lai, G., Chang, W.-C., Yang, Y., & Liu, H. (2018). Modeling long- and short-term temporal patterns with deep neural networks. Proceedings of the 41st International ACM SIGIR Conference, 95–104. Publisher: ACM https://doi.org/10.1145/3209978.3210006
6. Kiranyaz, S., Ince, T., & Gabbouj, M. (2019). 1D convolutional neural networks and applications: A survey. Mechanical Systems and Signal Processing, 151, 107398. Publisher: Elsevier https://doi.org/10.1016/j.ymssp.2019.107398
7. Sun, Y., Peng, M., Zhou, Y., Huang, Y., & Mao, S. (2019). Application of machine learning in wireless networks: Key techniques and open issues. IEEE Communications Surveys & Tutorials, 21(4), 3072–3108. Publisher: IEEE https://doi.org/10.1109/COMST.2019.2924243
8. He, Y., Yu, F. R., Zhao, N., Yin, H., & Leung, V. C. M. (2019). Deep reinforcement learning for resource allocation in wireless networks. IEEE Wireless Communications, 26(3), 44–51. Publisher: IEEE https://doi.org/10.1109/MWC.2019.1800298
9. Wang, X., Han, Y., Wang, C., Zhao, Q., Chen, X., & Chen, M. (2020). In-edge AI: Intelligentizing mobile edge computing, caching and communication. IEEE Network, 33(5), 156–165. Publisher: IEEE https://doi.org/10.1109/MNET.001.1800286
10. Lim, B., Zohren, S., & Roberts, S. (2021). Time-series forecasting with deep learning: A survey. Philosophical Transactions of the Royal Society A, 379(2194). Publisher: The Royal Society https://doi.org/10.1098/rsta.2020.0209
11. Zhang, Q., Yang, L. T., Chen, Z., & Li, P. (2019). A survey on deep learning for big data. Information Fusion, 42, 146–157. Publisher: Elsevier https://doi.org/10.1016/j.inffus.2017.10.006
12. Al-Fuqaha, A., Guizani, M., Mohammadi, M., Aledhari, M., & Ayyash, M. (2018). Internet of Things: A survey on enabling technologies, protocols, and applications. IEEE Communications Surveys & Tutorials, 17(4), 2347–2376. Publisher: IEEE https://doi.org/10.1109/COMST.2015.2444095
13. Ahmed, M., Mahmood, A. N., & Hu, J. (2019). A survey of network anomaly detection techniques. Journal of Network and Computer Applications, 60, 19–31. Publisher: Elsevier https://doi.org/10.1016/j.jnca.2015.11.016
14. Sainath, T. N., Vinyals, O., Senior, A., & Sak, H. (2015). Convolutional, long short-term memory, fully connected deep neural networks. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 4580–4584. Publisher: IEEE https://doi.org/10.1109/ICASSP.2015.7178838
15. Cho, K., Van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., & Bengio, Y. (2014). Learning phrase representations using RNN encoder–decoder for statistical machine translation. Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing, 1724–1734. Publisher: ACL https://doi.org/10.3115/v1/D14-1179
16. Zhao, Z., Chen, W., Wu, X., Chen, P. C. Y., & Liu, J. (2018). LSTM network: A deep learning approach for short-term traffic forecast. IET Intelligent Transport Systems, 11(2), 68–75. Publisher: IET https://doi.org/10.1049/iet-its.2016.0208

17. Yunfeng Ge , Zonghuan Guo , Peng Wang, Xiaogang Li, Hongyan Li (2025): Adaptive clockwork LSTM for network traffic prediction, Journal of Information and Intelligence, https://doi.org/10.1016/j.jiixd.2025.06.004
18. 16. Shengxiang Lv, Lin Wang, Sirui Wang (2023): A Hybrid Neural Network Model for Short-Term Wind Speed Forecasting. https://doi.org/10.3390/en16041841
19. Joanna Waczyńska, Edoardo Martelli, Sofia Vallecorsa, Edward Karavakis and Tony Cass (2021). EPJ Web Conf. Volume 251, 2021. 25th International Conference on Computing in High Energy and Nuclear Physics (CHEP 2021). DOI: https://doi.org/10.1051/epjconf/202125102050.
20. Rusul L. Abduljabbar, Hussein Dia, Pei-Wei Tsai (2021). Unidirectional and Bidirectional LSTM Models for Short-Term Traffic Prediction. https://doi.org/10.1155/2021/5589075
21. Indrajeet Kumar, Bineet Kumar Tripathi, Anugrah Singh (2023): Attention-based LSTM network-assisted time series forecasting models for petroleum production. Engineering Applications of Artificial Intelligence. Volume 123, Part C, August 2023, 106440. https://doi.org/10.1016/j.engappai.2023.106440
22. Jihong Zhao, Xiaoyuan He (2022): NTAM-LSTM: An attention-based LSTM network for network traffic prediction. MATEC Web of Conferences, 355, Article 02007. Publisher: EDP Sciences. https://doi.org/10.1051/matecconf/202235502007.
23. Liu, X., Li, Y., Zhu, S., Su, Q., Dai, J., Li, C., Zhu, J., & Zhang, J. (2025).
A traffic forecasting framework for cellular networks based on a dynamic component management mechanism. Electronics, 14(20), 4003. Publisher: MDPI, https://doi.org/10.3390/electronics14204003