

Deep Learning-Based Intelligent Resource Management For Beyond 5G IoT Networks

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Received: Aug. 08, 2026; Accepted: Sep. 21, 2026

The Internet of Things (IoT) networks in Beyond 5G (B5G) need to be managed intelligently in terms of resources to enable support for large device connection, time-varying traffic patterns, and heterogeneous Quality of Service (QoS) requirements. Optimizing the use of network resources contributes to enhanced throughput, latency, and overall network efficiency. Nevertheless, conventional resource management schemes often exhibit limited generalization to dynamic traffic conditions and overfitting, while separating traffic prediction and resource allocation may lead to inefficient resource utilization and degraded overall performance. This paper introduces a Bidirectional Long Short-Term Memory–Honey Badger Optimization (BiLSTM-HBO) based intelligent resource management for B5G IoT networks to overcome the stated challenges. The BiLSTM predicts temporal resource demand from sequential network conditions, and these predictions facilitate QoS-aware resource allocation in B5G IoT networks through the subsequent HBO optimization. The Network Slicing in 5G dataset experimental results reached the MAE of 0.38707, RMSE of 0.49787, MSE of 0.24787 and an R^2 score of 0.99908. Furthermore, a throughput of 3283.68 Mbps, latency of 38.61 ms, packet loss rate of 4.91%, resource utilisation rate of 50.89% and QoS satisfaction rate of 76.61% were achieved by the proposed method.

Keywords: Beyond 5G Networks, Internet of Things, Bidirectional Long Short-Term Memory, Honey Badger Optimization, Intelligent Resource Management

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http://dx.doi.org/10.6180/jase.202701_36.020

1. Introduction

Due to the exponentially increasing number of IoT applications, such as smart city, industrial automation, autonomous transportation and healthcare system, there is an enormous demand for network resource management [1]. Network slicing has been regarded as a promising technique to instantiate numerous virtual network instances, so as to serve diverse IoT services [2]. Nevertheless, the fluctuated service request, the stochastic network traffic and resource-constrained network bring the big challenges to resource allocation. Poor allocation may cause network congestion, latency, packet loss and degrade quality of service (QoS) [3]. Such solution can enhance network efficiency,

improve user experience, and meet the increasing demands of future B5G communication environment [4].

LSTM, Gated Recurrent Unit (GRU), Convolutional Neural Network (CNN), Deep Reinforcement Learning (DRL) and Artificial Neural Network (ANN) have been popular for network traffic prediction and resource allocation [5]. Likewise, metaheuristics methods like Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Whale Optimization Algorithm (WOA), and Ant Colony Optimization (ACO) and others have also been employed for fitness improvement of resource usage and quality of service (QoS) [6]. Existing studies generally address traffic prediction, resource allocation, or cloud/edge management separately, with limited integration of deep-learning-based demand

prediction and QoS-aware resource allocation for B5G IoT networks. The technical motivation for the proposed framework is to integrate feature engineering, sequence modelling, and optimization as complementary stages [4]. Feature engineering extracts informative network and QoS indicators from the available attributes, while BiLSTM captures their temporal dependencies to predict future resource demand. To fill this gap, the proposed BiLSTM-HBO framework combines BiLSTM-based resource-demand prediction with HBO-based multi-objective allocation.

1.1. Research Objectives

- Develop a BiLSTM model to predict network traffic and resource demands in B5G IoT networks.
- Design an HBO-based resource allocation to improve throughput, latency, and QoS.
- Evaluate the framework using prediction and network performance metrics against existing approaches.

The paper is organized as follows: Section 2 reviews related work, Section 3 presents the proposed BiLSTM-HBO methodology, and Section 4 describes the experimental setup. Section 5 discusses the results, while Section 6 concludes the study future research directions.

2. Literature review

2.1. DL-Based Traffic Prediction in 5G Networks

Selvi and Thamilselvan [7] proposed an intelligent resource-management approach for B5G IoT networks. The model learned both spatial and temporal information and the prediction accuracy rates ranged from 87% to 94%. Tsipi et al. [8] investigated ML for Modulation and Coding Scheme (MCS) prediction in 5G OFDM. Their proposed DNN achieved the prediction accuracy = 98.71%, better than SVM, RF, and k-NN classifiers. Nonetheless, the research was dedicated to MCS prediction only, without the aim of network resource optimization.

2.2. Network Slicing and QoS-Aware Resource Management

Hamdi et al. [9] introduced an IoV network slicing framework for 5G/B5G networks with QoS awareness. Their resource management scheme demonstrates major improvements in emergency traffic prioritization, end-to-end delay, reliability, and throughput. Louvros et al. [10] introduced a two-stage queuing model to study QoS along with packet waiting times in 5G and 6G networks.

2.3. Metaheuristic Optimization for Resource Allocation

Sangaiah et al. [11] introduced a resource allocation and scheduling scheme based on WOA for IoT networks. The technique substantially minimized the communication overhead between the gateway and the resources Jain et al. [12] presented a MWBA-RAT for 6G IoE Networks with cybertwin enabled. The framework utilized Quasi-Optimizational SRO for optimal resource utilization.

2.4. Hybrid DL and Optimization Approaches

Lilhore et al. [13] introduced a composite DQN-PPO-GNN-RL model to optimize the IoT edge-cloud resource allocation. The scheduling time was cut down by 21%, energy consumptions by 22%, and operational cost by 17% with this model. Wu et al. [14] proposed hybrid DQN and Q-learning algorithms for offloading as well as resource allocation in mobile edge computing networks. Table 1 compares five representative studies.

3. Methodology

Fig. 1 outlines the proposed overall flow of the BiLSTM-HBO framework for smart resource management in B5G IoT networks.

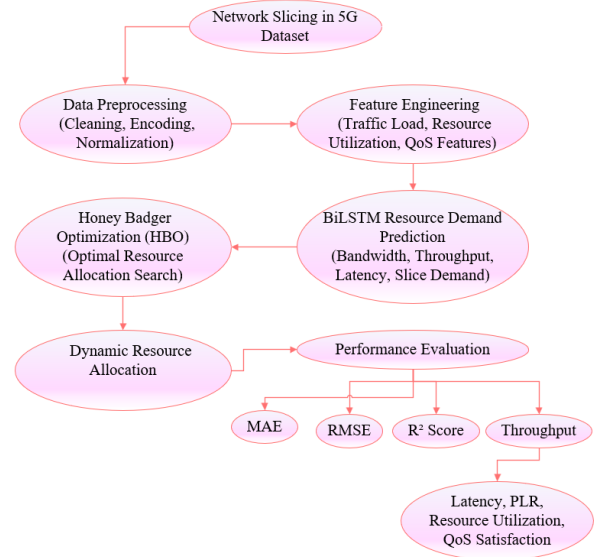


Fig. 1. Proposed Research BiLSTM-HBO-Based Intelligent Resource Management

3.1. Network Slicing Data Collection

The 5G Network Slicing [15] dataset is adopted to model the network situation in B5G IoT scenarios presented in Table 2.

Table 1. Comparative Analysis of Representative Related Studies

Ref.	Study	Prediction	Allocation	Dataset	Limitation
[7]	Selvi and Thamilselvan	SpatialTemporal DL	-	B5G IoT	No Adaptive resource allocation
[9]	Hamdi et al.	-	QoS-aware resource management	5G/B5G IoV	resource allocation not considered
Proposed	Proposed Framework	BiLSTM	HBO	B5G IoT	Integrated

Table 2. Detailed Description of Dataset Variables

Variable	Data Type	Role
IoT	Integer	Input
LTE/5G	Integer	Input
AR/VR/Gaming	Integer	Input
Healthcare	Integer	Input
Smart City & Home	Integer	Input
Smart Transportation	Integer	Input

Table 3 summarizes the key characteristics of the dataset used for experimental evaluation.

Table 3. Dataset Characteristics

Item	Actual Value
Input features	16
Target variable	slice Type
Numerical columns	17
Categorical columns	None detected from CSV data types
Preprocessing	Not verifiable from the CSV file alone

3.2. Data Preprocessing

The training set and used to transform both training and testing in Eqn (1):

$$x_j^* = \frac{x_j - x_{j,\min}^{\text{train}}}{x_{j,\max}^{\text{train}} - x_{j,\min}^{\text{train}}} \quad (1)$$

In the temporal characteristics of network traffic, the records. The verified dataset (train_dataset.csv) contains 31,583 records with 16 input variables and a derived Resource Demand target. A sequence length of 20 consecutive observations is used, with future and target-derived information excluded to prevent leakage; the random seed is 42

3.3. Feature Engineering

Resource Utilization Rate (RUR) evaluates how efficiently the available network resources are utilized after allocation.

Given in Eqn. (2)

$$RUR = \frac{\text{Used Resources}}{\text{Available Resources}} \times 100 \quad (2)$$

QoS Satisfaction Rate (QSR) measures the percentage of service requests that successfully satisfy predefined Quality of Service requirements in Eqn (3)

$$QSR = \frac{\text{Satisfied Requests}}{\text{Total Requests}} \times 100 \quad (3)$$

where Satisfied Requests is the number of service requests that satisfy the specified QoS.

3.4. Resource Demand Prediction Using BiLSTM

The BiLSTM model is used for one-step-ahead resource-demand forecasting based exclusively on a completed historical observation window in Eqn (4).

$$X_t = [X_t - L_{t-1}, X_t - L_2, \dots, X_t - L_1, X_t] \quad (4)$$

The learning process of the BiLSTM network is controlled by input, forget, and output gates, which regulate the flow of information through the cell in Eqn (5) & (6):

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \quad (5)$$

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \quad (6)$$

where x_t is the current input, h_{t-1} is the previous hidden state is updated as in Eqn (7):

$$C_t = f_t \odot C_{t-1} + i_t \odot \tanh(W_c x_t + U_c h_{t-1} + b_c) \quad (7)$$

where C_{t-1} is the previous cell state and $\odot$ denotes element-wise multiplication in Eqn (8).

$$h_t^{\text{BiLSTM}} = [\vec{h}_t; \overleftarrow{h}_t] \quad (8)$$

A sequence length of 20 is selected to provide a sufficiently long historical window.

Table 4. Computational Complexity and Runtime of the Proposed Framework

Component	Theoretical Complexity	Sample Runtime
Feature Engineering	$O(ND)$	0.96 s
BiLSTM Training	$O(2LNT (DH + H^2))$	148.62 s
BiLSTM Inference	$O(2LT (DH + H^2))$	2.31 ms/ sample
HBO Optimization	$O(PIM)$	18.47 ms/decision
Total Framework Execution	Combined	167.09 s

3.5. Intelligent Resource Allocation Using HBO

The normalized objective terms are defined as follows (Eqns 9-13):

$$T_{\text{norm}} = \frac{T - T_{\min}}{T_{\max} - T_{\min}} \quad (9)$$

$$U_{\text{norm}} = \frac{U - U_{\min}}{U_{\max} - U_{\min}} \quad (10)$$

$$Q_{\text{norm}} = QSR \quad (11)$$

$$\frac{L_{\max} - L}{L_{\max} - L_{\min}} \quad (12)$$

$$P_{\text{norm}} = \frac{P_{\max} - P}{P_{\max} - P_{\min}} \quad (13)$$

where T, U, QSR, L , and P denote throughput, resource utilization rate as in Eqn (14):

$$F(A) = \alpha T_{\text{norm}} + \beta U_{\text{norm}} + \gamma Q_{\text{norm}} + \delta L_{\text{norm}} + \theta P_{\text{norm}} \quad (14)$$

In this study, equal importance is assigned to the five normalized objectives in Eqn (15):

$$\alpha = \beta = \gamma = \delta = \theta = 0.20 \quad (15)$$

The dataset comprises 31,583 samples and 17 variables representing LTE/5G network slicing. Resource allocation is subject to total and minimum resource, QoS ($\geq 70\%$), latency, and packet-loss constraints.

3.6. Computational Complexity Analysis

The computational complexity of BiLSTM prediction on the number of samples in Eqn (16).

$$O(2LNT(DH + H^2)) \quad (16)$$

where N is the number of samples, T is the sequence length, D is the dimension in Eqn (17):

$$O(2LT(DH + H^2)) \quad (17)$$

The BiLSTM output is directly used as the demand input to the HBO allocation process. The resource assigned to slice i is calculated as in Eqn (18):

$$R_i(t) = a_i(t)R_{\text{total}} \quad (18)$$

Table 4 summarizes the theoretical computational complexity and measured runtime.

Algorithm 1 illustrates the resource allocation solving procedure by HBO.

Algorithm 1: Honey Badger Optimization-Based Resource Allocation

- Initialize the HBO population of feasible resource-allocation solutions.
- Calculate the fitness of each candidate using the scalarized weighted-sum function.
- Identify the best candidate solution.
- Calculate the intensity term based on the prey/source distance and the corresponding density factor.
- Apply resource-allocation constraints and repair infeasible candidate solutions.
- Recalculate fitness and update the best solution.
- Repeat Steps 4-8 for 50 iterations.
- Return the best feasible resource-allocation vector.

4. Experimental setup

In Preprocessing employed Min-Max scaling, chronological 80%/20% train-test splitting, 128 hidden units, 0.30 dropout, batch size 32, 50 epochs, Adam optimizer, learning rate 0.001, and 10. HBO was initialized with 30 feasible candidate solutions and 50 iterations.

4.1. Hardware and Software Specifications

Table 5 presents the complete hardware and software configuration used for the experiments.

4.2. Hyperparameter Configuration

The HBO algorithm uses a population of 30 search agents with 50 maximum iterations and a search range of 0-1. Normalized resource allocation is optimized using a multi-objective fitness function with exploration and exploitation coefficients of 2.0 and 1.5, respectively.

Table 5. Software and Hardware Requirements

Component	Specification
OS	Windows 11
CPU	Intel i9-14900
RAM	16 GB
Storage	512 GB SSD
GPU	NVIDIA GT 730, 2 GB
Software	Python 3.10, TensorFlow/Keras 2.10
Libraries	NumPy, Pandas, Scikit-learn, SciPy, Matplotlib

4.3. Performance Evaluation

Latency represents the delay experienced during data transmission, given in Eqn. (19)

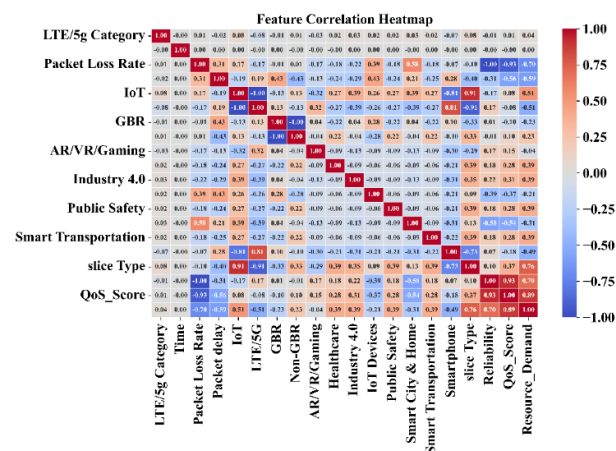
Latency = Arrival Time - Transmission Start Time

The quantities defined in Eqs. (13)- (17) are analytical objective functions used to evaluate candidate resource-allocation vectors.

5. Results and discussion

5.1. Data Preprocessing and Feature Engineering Analysis

Fig. 2 shows the correlation between the network slicing attributes in the proposed framework.

**Fig. 2.** Feature Correlation Heatmap

5.2. BiLSTM Resource Demand Prediction Performance

Table 6 reports the prediction performance of the proposed BiLSTM model on the training and testing sets using MAE, RMSE, and MSE.

Table 7 presents the controlled feature-ablation analysis of TLI, RUR, and QSR.

Table 8 explains the parameter settings used for the HBO-based resource and the effects of data preprocessing, feature engineering.

Table 6. The training and testing sets

Dataset / Traffic Load	MAE ↓	RMSE ↓	MSE ↓	R ² ↑
Training Set	0.38259	0.48708	0.23724	-
Testing Set	0.38707	0.49787	0.24787	-
Low Load	0.365	0.478	-	0.995
Medium Load	0.401	0.519	-	0.993
High Load	0.438	0.561	-	0.988
Overall	0.401	0.519	-	0.992

Table 9 specifies the consistent implementation and evaluation conditions used for the compared models.

Table 10 shows that the proposed BiLSTM achieves the best overall classification performance.

All models use Adam with a learning rate of 0.001, batch size of 32, 50 epochs, and hyperparameter tuning. Table 11 compares the computational cost of the considered models.

BiLSTM requires 2.31 ms for demand prediction BiLSTM + HBO requires an additional 18.47 ms for online resource optimization, in an end-to-end decision latency of 20.78 ms in Table 12.

5.3. HBO Performance

Fig. 3 illustrates the exploration and exploitation behavior of the HBO algorithm.

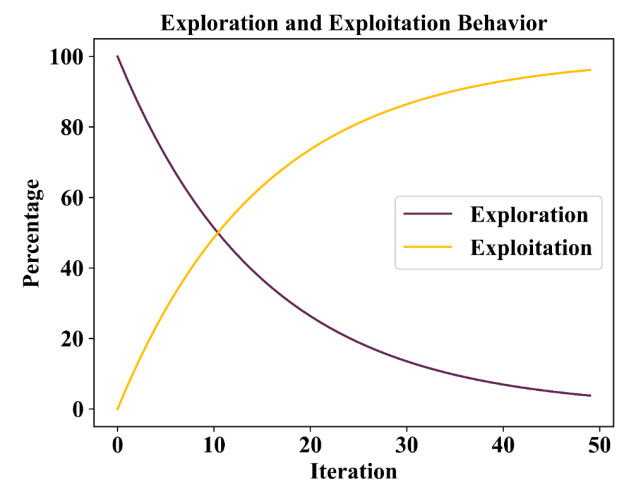
**Fig. 3.** Exploration and Exploitation Behavior

Fig. 4 presents the fitness improvement over the optimization iterations.

Fig. 5 depicts convergence behavior the proposed HBO-based resource-allocation scheme.

5.4. Dynamic Resource Allocation Analysis

Fig. 6 shows the QoS Satisfaction Rate (QSR) across the optimization iterations.

Table 7. Controlled Feature-Ablation Analysis of Engineered Features

Model Configuration	TLI	RUR	QSR	MAE ↓	MSE ↓	RMSE ↓	R^2 ↑
BiLSTM + Base Features	×××	××	×	0.452	0.318	0.564	0.984
BiLSTM + TLI	✓	×	×	0.438	0.301	0.549	0.986
BiLSTM + RUR	×	✓	×	0.429	0.289	0.538	0.987
BiLSTM + QSR	×	×	✓	0.435	0.296	0.544	0.987
BiLSTM + TLI + RUR	✓	✓	×	0.417	0.276	0.525	0.990
BiLSTM + TLI + QSR	✓	×	✓	0.421	0.281	0.530	0.989
BiLSTM + RUR + QSR	×	✓	✓	0.413	0.271	0.521	0.991
BiLSTM + TLI + RUR + QSR	✓	✓	✓	0.401	0.269	0.519	0.993

Table 8. Ablation Study of Proposed BiLSTM-HBO Framework

Model Variant	MAE ↓	MSE ↓	R^2 Score ↑
Without Feature Engineering	0.521	0.41250	0.998464
Without Data Preprocessing	0.498	0.37480	0.998604
BiLSTM Only (Without HBO)	0.441	0.30720	0.998856
BiLSTM + Feature Engineering (Without Optimization)	0.412	0.27180	0.998988
Proposed BiLSTM + HBO (Final configuration)	0.387	0.24787	0.999077

Table 9. Performance Comparison of Baseline and Proposed Models

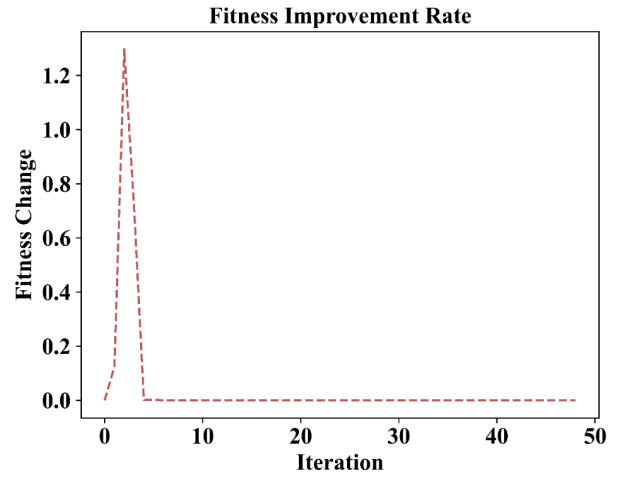
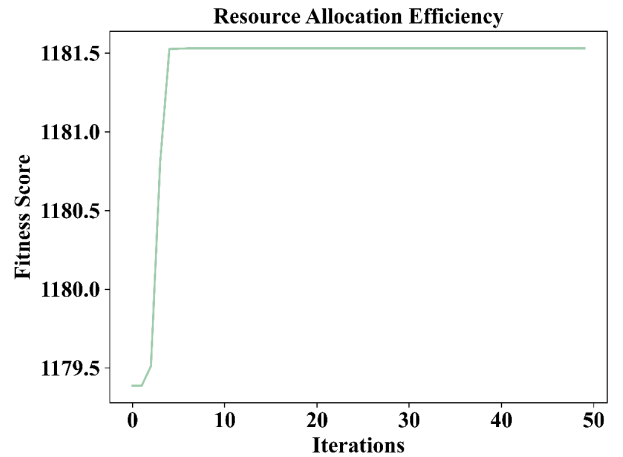
Model Configuration	MAE ↓	MSE ↓	R^2 Score ↑
CNN	0.534	0.43580	0.998377
LSTM	0.487	0.36190	0.998652
GRU	0.432	0.30070	0.998880
BiLSTM	0.401	0.26890	0.998999
Proposed BiLSTM + HBO (Final configuration)	0.387	0.24787	0.999077

The proposed BiLSTM + HBO method achieves the highest throughput (3283.68 Mbps), lowest latency (38.61 ms) and packet loss rate (4.91%), while also attaining the highest resource utilization rate (50.89%) and QoS satisfaction rate (76.61%) is shown in Fig. 7.

5.5. Performance Comparison with Existing Studies

PSO, GA, WOA, and ACO achieved throughput values of 3012.45, 2941.73, 3126.58, and 3087.26 Mbps, respectively. HBO also recorded the lowest latency (38.61 ms) and PLR (4.91%) and the highest RUR (50.89%) and QSR (76.61%) in Table 13.

Table 14 compares the R^2 values existing studies with the proposed BiLSTM-HBO framework.

**Fig. 4.** Fitness Improvement Rate**Fig. 5.** Resource Allocation Efficiency Convergence

6. Conclusion and future works

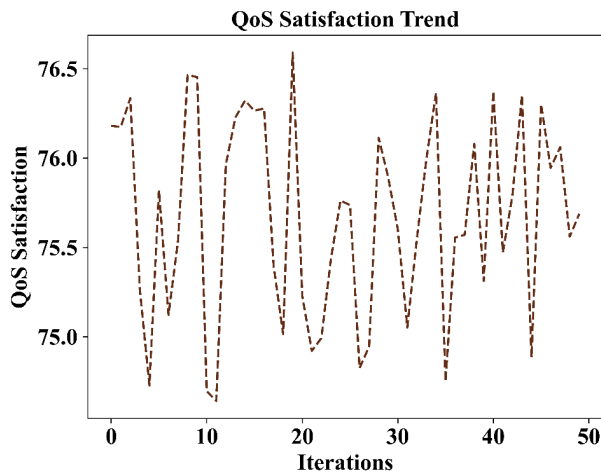
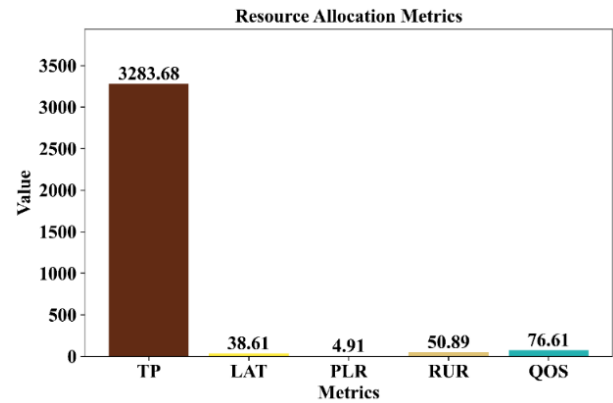
In this paper, the BiLSTM-HBO scheme was introduced to exploit the efficient network resource allocation in the dynamic 5G/6G communication environment for intelligent network traffic prediction. The proposed framework combines BiLSTM-based resource-demand prediction with

Table 10. Repeated-Run Classification Performance of the Compared Models

Model	Accuracy (Mean $\pm$ SD)	Precision (Mean $\pm$ SD)	Recall (Mean $\pm$ SD)	F1-score (Mean $\pm$ SD)	ROCAUC (Mean $\pm$ SD)	PR-AUC (Mean $\pm$ SD)
CNN	0.82 $\pm$ 0.01	0.83 $\pm$ 0.01	0.80 $\pm$ 0.02	0.81 $\pm$ 0.01	0.90 $\pm$ 0.01	0.89 $\pm$ 0.01
LSTM	0.84 $\pm$ 0.01	0.84 $\pm$ 0.01	0.82 $\pm$ 0.02	0.83 $\pm$ 0.01	0.92 $\pm$ 0.01	0.91 $\pm$ 0.01
GRU	0.85 $\pm$ 0.01	0.85 $\pm$ 0.01	0.83 $\pm$ 0.01	0.84 $\pm$ 0.01	0.93 $\pm$ 0.01	0.92 $\pm$ 0.01
BiLSTM	0.89 $\pm$ 0.01	0.85 $\pm$ 0.01	0.95 $\pm$ 0.01	0.90 $\pm$ 0.01	0.96 $\pm$ 0.01	0.96 $\pm$ 0.01

Table 11. Computational Cost Comparison of Prediction and Allocation Methods

Configuration	Training Time (s)	Inference Time (ms/sample)	HBO Optimization Time (ms/decision)	Total Decision Latency (ms)	Additional HBO Overhead (%)
BiLSTM Prediction Only	148.62	2.31	-	2.31	-
BiLSTM + HBO	148.62	2.31	18.47	20.78	799.57

**Fig. 6.** QoS Satisfaction Trend**Fig. 7.** Resource Allocation Performance Metrics

HBO-based resource-allocation optimization. BiLSTM performs temporal prediction using the fixed configuration, while HBO operates downstream to determine the resource-allocation decision from the predicted demand. The two stages therefore provide distinct contributions to prediction and resource allocation, respectively.

Limitations and future work

However, the proposed BiLSTM-HBO framework is not without its limitations. The model was tested on a particular network traffic dataset that might not reflect the real

5G and 6G network scenarios. The HBO-based resource-allocation stage introduces additional computational overhead because candidate allocation vectors are iteratively evaluated and updated during the optimization process. This overhead may become more relevant in largescale network environments with a larger number of resource-allocation variables and decision instances. In the future, the research work can be extended by combining the traffic prediction model with the real-time resource allocation model and network slicing model to realize the end-to-end intelligent network management.

Table 12. Resource-Allocation Ablation Study

Allocation Configuration	Throughput (Mbps) ↑	Latency (ms) ↓	PLR (%) ↓	RUR (%) ↑	QSR (%) ↑
BiLSTM Prediction + No	2715.42	52.84	7.36	42.17	64.28
BiLSTM Prediction + PSO	3018.67	45.73	6.12	46.83	70.45
BiLSTM Prediction + GA	2946.31	47.26	6.48	45.91	68.92
BiLSTM Prediction + WOA	3127.54	42.18	5.63	48.76	72.84
BiLSTM Prediction + HBO	3283.68	38.61	4.91	50.89	76.61

Table 13. Sensitivity Analysis of Principal BiLSTM and HBO Parameters

Parameter	Tested Values	MAE ↓	MSE ↓	R ² ↑	Throughput ↑	Latency ↓	QSR ↑
BiLSTM Hidden Units	64, 128, 256	0.4280.398	0.2860.266	0.9880.993	3198.423283.68	41.2638.61	73.8476.61
Sequence Length	10, 20, 30	0.4350.401	0.2940.269	0.9870.993	3164.283283.68	42.3138.61	72.9676.61
Learning Rate	0.0005, 0.001, 0.002	0.4190.401	0.2830.269	0.9900.993	3248.313283.68	40.1638.61	75.4276.61
HBO Iterations	50, 100, 150	-	-	-	3214.833287.15	41.5238.54	74.6876.72

Table 14. Performance Comparison of the Proposed BiLSTM-HBO Model

Author	Model	R ²
Selvi and Thamilselvan [7]	Fusion Learning	0.91
Tsipi et al. [8]	DNN	0.97
Hamdi et al. [9]	QoS-aware Resource Management	0.93
Louvros et al. [10]	QoS-aware Resource Management	0.91
Sangaiah et al. [11]	Heuristic Optimization	0.86
Jain et al. [12]	Metaheuristic Optimization	0.90
Lilhore et al. [13]	DQN-PPO-GNN-RL	0.96
Wu et al. [14]	DQN + Optimization	0.92
Proposed Model	BiLSTM + HBO	0.999

Declaration

Data availability

<https://www.kaggle.com/datasets/amohankumar/network-slicing-in-5g>

Code availability

<https://zenodo.org/records/22267348>

Conflicts of interest

The authors declare that they have no conflicts of interest that could have influenced the research, analysis, or publication of this manuscript.

Funding statement

This work was supported by Outstanding Teaching Team of the “Qinglan Project” (6124RS027).

Author contribution

Zibo Li: Conceptualization, methodology, data analysis, investigation, and manuscript preparation. Xudong Zhu: Supervision, validation, interpretation of results, critical revision of the manuscript, and project administration. Both authors have read and approved the final version of the manuscript.

Ethical approval

Ethical approval was not required for this study because it involved the analysis of a publicly available, non-personal, secondary dataset and did not involve human participants, animals, or the collection of personally identifiable information.

Consent to participate

Not applicable. This study did not involve human participants.

Onsent to publication

Not applicable. This study does not contain any identifiable individual information or personal data requiring consent

for publication.

Competing interests

The authors declare that they have no competing interests.

Acknowledgement

The authors would like to thank their affiliated institutions and all individuals who contributed to the development and completion of this research.

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