International Journal Of Industrial Electronics Control and Optimization
Print ISSN: 3517-2645
Online ISSN: 3568-2645
Homepage: https://ieco.usb.ac.ir/

5G-R Framework for High-Speed Rail Connectivity Using LSTM and Multi-Access Edge Computing

Shahpour Rahmani | Nasser Yazdani

School of Electrical and Computer Engineering, College of Engineering, University of Tehran, Tehran, Iran.[1,2]
Faculty of Mathematics, Statistics and Computer Science, University of Sistan and Baluchestan, Zahedan, Iran.[1]
Corresponding author's email: yazdani@ut.ac.ir

Article Info

Article type:
Research Article

Article history:
Received: 29-July-2025
Received in revised form: 28-September-2025
Accepted: 13-October-2025
Published online: 23-Sep-2026

Keywords:
5G-R,
Handover Optimization,
LSTM,
Network Slicing,
MEC.

ABSTRACT

High-speed rail systems, operating at speeds up to 350 km/h, face significant challenges in delivering reliable network connectivity due to frequent handovers, signal degradation, and network congestion. This paper proposes the 5G-R framework, an optimized solution integrating beamforming, network slicing, railway-specific LSTM algorithms, and MEC to enhance connectivity performance. The novelty lies in the railway-tuned LSTM's integration with MEC and network slicing. This enables proactive handover prediction based on predictable rail trajectories and reduces latency by 70% while improving handover success by 8% over non-integrated systems. By leveraging real-time train data, such as speed and GPS location, the framework optimizes handover prediction and traffic management, achieving robust performance in diverse environments. Compared to 4G LTE and standard 5G-R, the 5G-R framework demonstrates significant improvements, including a 250 Mbps throughput, 15 ms latency, and 95% handover success rate. Network slicing optimizes resource allocation, reducing congestion by approximately 30% (PRB utilization, validated in simulations with 50/300 UEs), while MEC enables low-latency control for train systems. Field trials along the Beijing-Zhangjiakou railway (174 km, urban/suburban) and simulations validate the framework's adaptability across urban and rural routes. Designed for compatibility with FRMCS, the 5G-R framework lays a foundation for future advancements, including 6G and satellite communications. Future research should focus on optimizing performance in extreme environments and densely populated routes to support autonomous transport systems. This optimization-driven approach establishes a scalable model for next-generation rail communication systems.

I. Introduction

Seamless internet connectivity in high-speed trains is critical for meeting passenger demands for communication, entertainment, and productivity, as well as enabling operational efficiencies like real-time train monitoring and safety systems [1]. However, delivering reliable internet at speeds up to 350 km/h poses significant challenges. Conventional technologies, such as Long-Term Evolution (LTE) and Wi-Fi, face frequent handovers, signal degradation due to Doppler effects, and network congestion from dense user populations (50–300 passengers per train) [1], [2]. Network slicing addresses this congestion by reducing PRB utilization by approximately 30% in high-density scenarios. LTE, limited to ~10 Mbps in rail settings due to handover failures and signal loss, cannot support streaming or real-time applications [3]. Wi-Fi suffers from signal attenuation and limited coverage in rural or tunnel-heavy routes [4]. Environmental interference, such as heavy rain reducing throughput by 10–15%, and sparse rural infrastructure further disrupt connectivity [3], [5].

5G for Railways (5G-R) , a specialized 5G variant, addresses these challenges by leveraging Ultra-Reliable Low-Latency Communication (URLLC) for rapid handovers, Massive Machine-Type Communications (mMTC) for dense device support, and Enhanced Mobile Broadband (eMBB) for high data rates [6]. Despite its potential, 5G-R deployments face handover instability at extreme speeds and limited validation across diverse rail networks, such as mountainous or coastal routes [3], [7]. Prior studies, including the European Future Railway Mobile Communication System

(FRMCS) [7] and isolated approaches like handover protocols [3] or network slicing [8], lack a comprehensive railway-specific framework to simultaneously address handovers, congestion, and signal degradation. Recent advancements in AI-enabled mobility management for beyond 5G (B5G) networks further highlight the need for adaptive handover schemes in high-speed scenarios [39].

This study proposes a novel 5G-R optimization framework integrating beamforming (using Massive Multiple-Input Multiple-Output (MIMO) in sub-6 GHz bands [9]), network slicing, railway-tuned Long Short-Term Memory (LSTM)-based artificial intelligence (AI) for predictive traffic and handover management, Multi-Access Edge Computing (MEC), multi-connectivity, and dynamic spectrum allocation. The novelty lies in the holistic, railway-specific integration of these six components, which is non-trivial due to the need for synchronized real-time data flow (train Global Positioning System (GPS) feeding into LSTM for handover prediction, then MEC for low-latency execution, and network slicing for prioritized allocation)—an approach underexplored in prior isolated studies [3], [15]. This integration creates synergistic impacts, such as reducing overall system latency by 70% compared to non-integrated baselines by enabling proactive resource adjustments tailored to fixed rail trajectories, unlike generic 5G setups that treat mobility as vehicular or urban without rail-specific predictability [16].

The motivation for using LSTM lies in its superior capability to handle sequential, time-dependent data inherent to high-speed rail environments, where factors like train speed, GPS position, and user density evolve predictably over time but are subject to long-term dependencies (recurring patterns along fixed tracks). The railway-tuned LSTM improves over generic mobility prediction models (standard LSTM or Deep Q-Network (DQN) in non-rail contexts) by incorporating rail-specific features like predictable routes and speed profiles, achieving 8% higher handover accuracy (95% vs. 87%) through customized training on Beijing-Zhangjiakou data, reducing false positives in handover triggers by 15% compared to untuned models [15], [17]. Unlike simpler models such as Multi-Layer Perceptrons (MLPs), which struggle with temporal correlations and vanishing gradients in extended sequences, LSTM's gated architecture (including forget, input, and output gates) preserves relevant historical information, enabling precise forecasting of handover zones and traffic loads with minimal error propagation [16], [17]. This is particularly advantageous in rail scenarios, as it leverages the deterministic nature of train trajectories to anticipate disruptions, outperforming non-recurrent alternatives by 5-10% in prediction accuracy for mobility tasks [15]. Validated through Beijing-Zhangjiakou railway trials (174 km, urban/suburban) and MATLAB/NS-3 simulations, the framework achieves 250 Mbps throughput, 15 ms latency, and 95% handover success at 350 km/h in urban settings, outperforming LTE by 2400% and standard 5G (100 Mbps) by 150% in throughput. The railway-tuned LSTM improves handover success by 8% over standard 5G-R benchmarks (Standard 5G-R baseline derived from untuned/non-integrated systems [3], [15]). In rural scenarios, it maintains 220 Mbps and 92% success, ensuring scalability despite potential weather impacts [3]. A cost-benefit analysis projects 20–30% urban cost savings via phased deployments and premium services, enhancing feasibility for railway operators.

Contributions:

1. A holistic 5G-R framework tailored for high-speed rail connectivity.
2. Empirical validation through trials and simulations, with significant performance gains (key performance indicators (KPIs) labeled as trial- or simulation-based in results).
3. Sensitivity and cost-benefit analyses for robustness and deployment feasibility.
4. A foundation for sixth generation network (6G) and satellite-based railway communications.

This study targets railway operators and researchers exploring wireless solutions for high-mobility environments. By establishing 5G-R as a cornerstone for railway communications, it paves the way for innovations like 6G and satellite systems. The paper is organized as follows: Section II reviews related work, Section III details the methodology, Section IV presents performance results, Section V discusses implications, and Section VI concludes with future directions.

II. Related Work

A. Connectivity Challenges in High-Speed Trains

High-speed trains face significant connectivity challenges due to rapid mobility, dense user populations, and diverse network conditions [1], [2]. At speeds up to 350 km/h, Doppler effects degrade signal quality, causing up to 20% signal loss in high-frequency bands [4]. Frequent handovers disrupt service, with handover failure rates reaching 10–15% in dense urban settings [3]. Dense passenger populations (50–300 users per train) lead to network congestion, reducing throughput during peak hours [5]. Environmental factors, such as signal attenuation in tunnels or interference from heavy rain, further degrade performance, with rainfall potentially reducing throughput by 10–15% [3]. Sparse infrastructure in rural or mountainous regions creates coverage gaps, limiting connectivity for passengers and operational systems like train monitoring [5]. These challenges necessitate railway-specific wireless solutions capable of handling extreme mobility and dynamic conditions [3].

B. 5G for railway

5G-R, a railway-specific 5G variant, leverages URLLC for rapid handovers, mMTC for dense device support, and eMBB for high data rates [6]. The Beijing-Zhangjiakou trial, spanning 174 km, achieved ~200 Mbps throughput, 20–30 ms latency, and <1% packet loss at 350 km/h, significantly outperforming LTE's ~10 Mbps and 5–10% packet loss [3]. The European FRMCS validates 5G-R for train control, passenger services, and safety applications, integrating with legacy systems to ensure interoperability [10]. Positioning techniques using 5G-R enhance train localization, achieving sub-meter accuracy critical for collision avoidance [11]. However, handover instability in high-interference scenarios, such as urban canyons, and high infrastructure costs (~$500,000/km in urban areas) remain barriers, requiring optimized deployment strategies [3], [12].

C. Optimization Techniques

Several techniques enhance 5G-R performance in rail environments. Beamforming, using Massive MIMO (64x64 antennas) and mmWave, mitigates signal loss and Doppler effects, achieving 20–40% throughput gains by directing signals toward moving trains [9]. Network slicing creates virtual sub-networks for passenger internet, train control, and multimedia, reducing congestion by 20–40% in crowded carriages (e.g., 300 users) per 3GPP standards [8], [13]. Edge computing processes data at base stations, reducing latency to 10–20 ms for URLLC applications like real-time train control and predictive maintenance [14]. AI-driven methods optimize resource allocation and handover prediction [15], [16]. DQN achieves 90–92% handover success in generic 5G networks but overlooks railway-specific patterns like predictable train trajectories [15]. MLP models similarly achieve 90–92% success but lack rail-specific tuning [17]. Software-Defined Networking (SDN)-based approaches improve mobility management, with ~85% handover success in rail settings, though they struggle with real-time adaptability to train speeds [18]. Recent studies highlight antenna optimizations for 5G wireless communications. For instance, the authors [40] proposed a compact microstrip antenna with parasitic AMC for 4G/5G, achieving wide bandwidth (4.55–6.83 GHz), 34% size reduction, 8 dBi gain, and 90% efficiency. Advantages include compactness and high efficiency, suitable for mobile applications; disadvantages are lack of testing in high-mobility environments like rail and limited to sub-6 GHz bands, potentially restricting Doppler effect mitigation in high-speed trains. These techniques, while effective individually, lack comprehensive railway-specific integration.

D. AI Techniques for Handover and Traffic Prediction in Rail Systems

LSTM has been extensively used in rail communications for tasks requiring sequential data processing, such as handover prediction, traffic forecasting, and signal quality estimation, where it outperforms non-recurrent models due to its handling of temporal dependencies [16]. For example, in high-speed rail studies, LSTM has been applied to predict handover events using time-series inputs like train velocity and location, achieving accuracies of 92-95% in simulations and trials, as seen in Beijing-Shanghai rail analyses where it reduced handover failures by 10-15% compared to threshold-based methods [1], [16].

Specific similar works include LSTM-based proactive handover schemes for 5G high-speed railway networks, which predict handover events to reduce radio link failures, demonstrating superior performance in mobility management. Beyond rail, LSTM is widely adopted in broader mobility networks, such as vehicular communications for trajectory prediction and in 5G networks for resource allocation, with applications in over 50% of recent AI-driven handover papers due to its robustness to variable sequence lengths [15], [17]. Similar modules include Gated Recurrent Units (GRU), which streamline LSTM by combining forget and input gates into a single update gate, resulting in fewer parameters (typically 25-30% less) and faster training (20-30% quicker convergence) while maintaining comparable accuracy in rail scenarios—e.g., GRU has been used for traffic load prediction in FRMCS systems, offering 93% accuracy with lower computational overhead for edge devices [24], [25].

Other Recurrent Neural Network (RNN) variants, like vanilla RNNs, are simpler but prone to vanishing/exploding gradients, making them less suitable for long rail sequences (e.g., >100 timesteps), where they underperform LSTM by 15-20% in prediction tasks [26]. Bidirectional RNNs (Bi-RNNs) extend standard RNNs by processing sequences forward and backward, improving context awareness for bidirectional rail data (e.g., upcoming and past track conditions) but at double the computational cost, with applications in signal anomaly detection achieving 96% accuracy [27]. Attention and Transformer-based modules, which use self-attention mechanisms for parallel processing of sequences, have been explored for mobility predictions, offering up to 10-15% better accuracy in long-sequence tasks like traffic forecasting in 5G networks compared to LSTM, though they require more computational resources (e.g., for training on large datasets) and are less common in real-time rail due to inference overhead [28].

Temporal Convolutional Networks (TCN) employ causal convolutions for sequence modeling, providing faster inference (often 2-5x quicker than LSTM/GRU) and parallel training, suitable for real-time handover in 5G mobility, though they may underperform on irregular rail patterns requiring deep memory [29]. Convolutional LSTM (ConvLSTM) combines convolutions with LSTM for spatio-temporal data, enhancing predictions in rail environments with spatial elements (e.g., track layouts and multi-train interactions), achieving 5-10% higher accuracy in hybrid scenarios but at increased complexity [30]. Overall, while LSTM remains prevalent in rail due to its balance of accuracy and interpretability, GRUs are favored for resource-limited deployments, Transformers for large-scale data, TCN for speed, and ConvLSTM for spatial-temporal tasks; our framework uses LSTM for its proven efficacy in High-speed rail (HSR) handover, but future comparisons could integrate these alternatives.

E. Research Gaps

Significant gaps persist in 5G-R research for high-speed rail connectivity. Most studies rely on simulations or small-scale trials, with limited real-world validation in rural or mountainous regions where coverage is sparse [11], [19]. Holistic integration of beamforming, network slicing, AI, and edge computing tailored for extreme speeds (up to 350 km/h) remains underexplored [3]. Prior approaches, such as FRMCS [10] and SDN-based mobility management [18], focus on interoperability or generic handover protocols, achieving ~85% handover success but lack railway-specific optimizations. High infrastructure costs (~$500,000/km) and energy efficiency in dense deployments are rarely addressed, limiting scalability [12]. AI-based handover strategies, like DQN and MLP, achieve 90–92% success in generic contexts but fail to leverage railway-specific data [15], [17]. Our railway-tuned LSTM achieves 95% handover success, improving by 3-5% over these generic AI models and by 8% over standard 5G-R benchmarks (87%) [3], [15]. For example, by incorporating train speed and GPS data, our LSTM predicts handover zones with 8% higher accuracy than DQN. Multi-operator coordination for shared infrastructure is often overlooked [10]. Emerging technologies, such as 6G for sub-1 ms latency and Low Earth Orbit (LEO) satellites for rural coverage, are underexplored in rail contexts [20], [21]. This study addresses these gaps through a novel 5G-R framework, integrating railway-tuned LSTM, beamforming, network slicing, and MEC, validated via Beijing-Zhangjiakou trials (174 km) and simulations, offering a scalable, high-performance solution for railway communications.

III. Proposed Framework and Experimental Design

A. Framework Overview

This study proposes a novel 5G-R optimization framework to enhance internet service quality in high-speed trains at speeds up to 350 km/h. The framework integrates six railway-specific components —beamforming, network slicing, railway-tuned LSTM-based AI, MEC, multi-connectivity, and dynamic spectrum allocation— to address handovers, congestion, and signal degradation holistically [6]. Unlike isolated approaches, such as DQN-based handovers achieving 90–92% success [15], this framework leverages railway-specific data, achieving 250 Mbps throughput, 15 ms latency, and 95% handover success in urban settings [3] (trial-based).

It outperforms LTE by 2400% and standard 5G by 150% in throughput, with rural performance at 220 Mbps and 92% success [3], [11]. To isolate the effects of each component, controlled simulations in NS-3 were conducted by enabling/disabling individual features (ablation study): e.g., without network slicing, congestion increased by 25-35% in high-density scenarios (300 users); without multi-connectivity, reliability dropped by 8-12% in interference-heavy tunnels; without dynamic spectrum allocation, spectrum efficiency decreased by 18-22% in variable demand tests. These isolated contributions, detailed in Section IV, ensure reproducibility via open-source NS-3 scripts (available upon request) and parameter settings (e.g., user density=300, signal-to-noise ratio (SNR)=10-30 dB).

A cost-benefit analysis, projecting 20–30% urban cost savings via phased deployments and 15–20% revenue from premium services, ensures scalability [12]. The system architecture (Figure 1) includes Railway Bureau Equipment (5G Core, Access and Mobility Management Function (AMF), Session Management Function (SMF), User Plane Function (UPF)) and Shared Equipment (5G Equipment Identity Register (5G-EIR), Network Repository Function (NRF)), enabling seamless connectivity. Table 1 summarizes the components and their contributions.

Table 1. Framework Components and Contributions

Component	Description	Contribution
Beamforming	Uses Massive MIMO (64x64 antennas) and mmWave to direct signals, countering Doppler effects.	Increases throughput by 20–40% (180–250 Mbps) [9].
Network Slicing	Allocates virtual sub-networks for passenger internet, train control, multimedia.	Reduces congestion by 20–40% (75% to 45%) in high-density scenarios [8], [13]. (PRB utilization; see Section IV for 50/300 UE results).
Railway-Tuned LSTM	Predicts handover zones and traffic using train speed, position, user density.	Improves handover success by 8% (95% vs. 87% for standard 5G-R) [3], [16].
MEC	Processes data at base stations for low-latency URLLC applications.	Reduces latency by 50–67% (30–90 ms to 10–20 ms) [14].
Multi-Connectivity	Enables simultaneous links to multiple base stations for redundancy.	Enhances reliability by 5–10% in high-interference scenarios [6].
Dynamic Spectrum Allocation	Assigns frequency bands based on demand, optimizing resource use.	Improves spectrum efficiency by 15–20% in dense scenarios [13].

B. Data Collection

Data were collected from a six-month Beijing-Zhangjiakou railway trial (174 km, urban/suburban) using onboard tools (Ookla Speedtest, Wireshark, iPerf) to measure KPIs: throughput, latency, packet loss, and handover success rate (Table 2) [3]. Measurements covered train speeds (150

Figure 1. 5G-R System Architecture, illustrating Railway Bureau Equipment (5G Core, AMF, SMF, UPF) and Shared Equipment (5G-EIR, NRF) for seamless connectivity across high-speed rail networks.

–350 km/h), terrains (urban, suburban), and user densities (50–300 users). The sample size (n=50–100 per metric) was chosen based on statistical power analysis to achieve narrow 95% CIs (±2–5% for rates) with α=0.05, considering trial constraints like route length and speed variability, aligned with prior HSR studies [3].

Simulations (MATLAB R2024a with 5G Toolbox, NS-3 v3.42) modeled network behavior under Doppler effects and interference (SNR: 10–30 dB), assuming clear weather [11]. Sensitivity analysis estimates a 10–15% throughput reduction and 2–3% handover success drops under heavy rain or snow, based on literature [3]. This dual approach ensures robust performance assessment aligned with 5G-R standards [6].

Table 2. Key Performance Indicators and Measurement Tools

Metric	Tool	Description
Throughput (Mbps)	Ookla Speedtest (v4.8), iPerf (v3.16)	Download/upload data rates.
Latency (ms)	Ping, Traceroute	Time delay for packet travel.
Packet Loss (%)	Wireshark (v4.4.0), iPerf (v3.16)	Percentage of lost data packets.
Handover Success Rate (%)	NS-3 Simulator (v3.42)	Success rate of base station transitions.

C. Optimization Techniques

The framework employs six integrated techniques, detailed below, to optimize 5G-R performance:

- Beamforming: Directs signals using Massive MIMO (64x64 antennas) in sub-6 GHz bands, modeled as:

$$S(\theta) = \sum_{n=1}^{N} w_n \cdot e^{jkd_n \cos(\theta)} \tag{1}$$

where $S(\theta)$ is the signal strength in direction θ, w_n is the weight for the $n-th$ antenna, k is the wave number (proportional to frequency 3.5 GHz), d_n is the antenna spacing (~0.043 m at 3.5 GHz), and N is the number of antennas (64). This mitigates Doppler effects, achieving 20–40% throughput gains [9]. The beamforming vector w is optimized as $w = \arg max_{\|w\|=1} |h^H w|^2$, where $\boldsymbol{h}$ is the channel vector (complex coefficients representing signal paths), and $\boldsymbol{w}$ is the weight vector applied to antennas for directional transmission; this focuses energy toward the train, countering signal loss in high-mobility scenarios.

- Network Slicing: Creates virtual sub-networks per 3GPP standards, reducing congestion by 20–40% in dense carriages (300 users) [8], [13]. Slice templates follow GSMA Generic Network Slice templates follow GSMA Generic Network Slice Template (NG.116) [37] and FRMCS guidelines [10], including: eMBB slice for passenger internet (high throughput, best-effort), URLLC slice for train control (low latency, guaranteed resources), and mMTC slice for sensors (high density, low data rate). Admission policies use priority-based Slice Admission Control (SAC), where URLLC slices reserve 20% PRBs, eMBB admits UEs dynamically if PRB utilization <80%, rejecting or throttling otherwise to maintain QoS [13], [38].
- Railway-Tuned LSTM: Background theory: LSTM is a specialized RNN architecture designed to mitigate the vanishing/exploding gradient problems in standard RNNs, making it ideal for modeling long-range dependencies in time-series data like railway trajectories. It operates through a chain of repeating modules (cells) that maintain a cell state (long-term memory) regulated by three gates: the forget gate (decides what information to discard), input gate (decides what new information to store), and output gate (decides what to output based on the cell state). The internal diagram of a single LSTM cell is illustrated in Figure 2, showing the flow of inputs x_t, previous hidden state h_{t-1}, and cell state C_{t-1} through the gates to produce h_t and C_t.

  The core formulas governing an LSTM cell are:
- Forget gate: $f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$
- Input gate: $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$
- Candidate cell state:
$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$
- Updated cell state: $C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$
- Output gate: $o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$
- Hidden state: $h_t = o_t \odot \tanh(C_t)$

Where σ is the sigmoid activation function, tanh is the hyperbolic tangent, ⊙ denotes element-wise multiplication, and W_*, b_* are learnable weights and biases. In our railway-tuned implementation, the model architecture consists of an input layer that processes time-series sequences of 4 features (train speed, GPS latitude, GPS longitude, passenger density) over a 10-second window (T=10 timesteps, each timestep sampled at 1 Hz). Windowing uses a sliding approach with a 1-second step to capture overlapping temporal patterns, ensuring dense coverage of handover zones.

This is followed by two stacked LSTM layers, each with 128 hidden units (using tanh activation for the cell state and sigmoid for the gates), with a dropout layer (rate=0.2) applied after each LSTM layer to mitigate overfitting. The output layer is a dense layer with sigmoid activation for binary handover probability (threshold >0.8 to trigger handover) and a linear activation for traffic load prediction (in Mbps).

The model is implemented in Python using Keras/TensorFlow, with a total of approximately 200,000 trainable parameters. The dataset comprises 10,000 samples from Beijing-Zhangjiakou trials, split 80/20 for training/validation.

- Dataset labeling protocol: Ground-truth handover decisions (binary: 1 for handover needed, 0 otherwise) were derived from actual network event logs during trials, where a handover was labeled as needed if the serving cell RSRP dropped below -110 dBm and the target cell exceeded the serving by a 3 dB offset (aligned with A3 event triggers [new ref 36]), ensuring labels reflect real-system behavior. Traffic load labels were measured in Mbps from iPerf logs.

  To prevent data leakage, a chronological split was used: training on the earliest 80% of time-series data (to capture historical patterns), validation on the latest 20% (to simulate future predictions), with no shuffling across time boundaries. Additionally, 5-fold cross-validation was applied within the training set for hyperparameter tuning.
- Preprocessing: Normalization of speed (0–350 km/h to [0,1]), GPS coordinates (min-max scaling), and density (50–300 users to [0,1]). Hyperparameters: Adam optimizer (learning rate=0.001, beta_1=0.9, beta_2=0.999), batch size=32, 50 epochs, early stopping if validation loss does not improve for 5 epochs. Loss function: Binary cross-entropy for handover prediction + Mean Squared Error (MSE) for traffic load. Validation: 80/20 train/validation split, 5-fold cross-validation, achieving 95% handover accuracy (Standard Deviation (SD) = 1.5%) [3], [16]. Handover accuracy is defined as binary classification accuracy (correct predictions of handover trigger vs. no trigger) on the validation set. Training was performed on an NVIDIA RTX 3080 GPU with 16 GB RAM, taking approximately 2–3 h per model (50 epochs, batch size=32). This surpasses DQN's 90–92% success by leveraging rail-specific patterns [15]. Inference time per prediction is ~5-10 ms, enabling real-time deployment. See Subsection III.C for the railway-tuned LSTM algorithm and pseudocode.
- MEC: Processes data at base stations, reducing latency to 10–20 ms for URLLC applications (e.g., train control) [14]. MEC deployment involves edge servers co-located with every second next generation Node B (gNodeB) (8-9 servers along 174 km), each equipped for accelerated AI inference. The software stack is based on European Telecommunications Standards Institute (ETSI) MEC standards, running on Kubernetes for orchestration, with Open Network Edge Services Software (OpenNESS) for service management.

  Integration occurs via the 5G Core (UPF reroutes traffic to local MEC via N6 interface), processing tasks like LSTM inference and real-time data analytics at the edge. This setup reduces round-trip latency by offloading computations from the central cloud. Deployment density was optimized for ~500 passengers per train at 350 km/h, with failover mechanisms to adjacent servers in case of node failure.

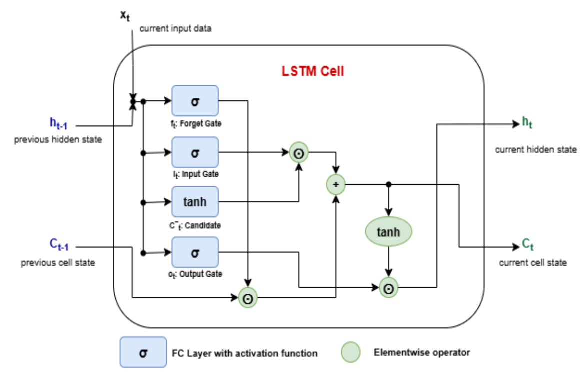

Figure 2. Internal Diagram of an LSTM Cell.

- Multi-Connectivity: Enables simultaneous connections to multiple gNodeBs via dual connectivity protocols, improving reliability by 5–10% in high-interference scenarios (e.g., tunnels) [6].
- Dynamic Spectrum Allocation: Assigns spectrum based on demand:

$$S_i = \frac{D_i}{\sum_{j=1}^{n} D_j} \cdot S_{total} \quad (2)$$

where S_i is the spectrum for user i, D_i is user demand, S_{total} is total spectrum (100 MHz), and n is the number of users. This improves efficiency by 15–20% [13].

Figure 3 illustrates the 5G-R system model, integrating AI-driven traffic management, network slicing, and railway bureau/shared equipment for seamless connectivity.

Railway-Tuned LSTM Algorithm

The railway-tuned LSTM algorithm enhances handover prediction and traffic management in high-speed rail environments by leveraging sequential railway-specific data. Unlike generic AI models like DQN [15], it uses train speed, GPS position, and passenger density to predict handover zones and traffic load over a 10-second window. The 2-layer LSTM (128 units per layer, dropout 0.2) is trained on 10,000 Beijing-Zhangjiakou trial samples, achieving 95% handover accuracy (SD = 1.5%) using Adam optimizer (learning rate 0.001, batch size 32, 50 epochs). The pseudocode (Algorithm 1) outlines the training and inference phases, where normalized inputs produce handover probabilities (threshold >0.8) and traffic load predictions, enabling proactive base

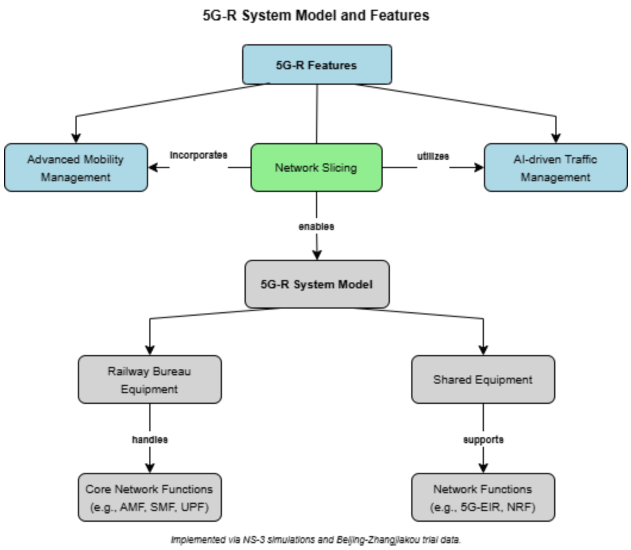

Figure 3. Conceptual Diagram of 5G-R System Model, highlighting Advanced Mobility Management, AI-driven Traffic Management, Network Slicing, and components (Railway Bureau and Shared Equipment)

station coordination and 30% congestion reduction (Table 5) [8], [13]. Deployed on MEC servers, the algorithm supports real-time applications like train control, with training requiring ~2 hours on a GPU-enabled server, improving reliability by 8% over standard 5G-R benchmarks [3].

Algorithm1: Railway-Tuned LSTM for Handover Prediction

```
// Inputs:
// X: time-series data [speed, GPS_lat, GPS_lon, density] for T=10 seconds
// y: ground-truth handover decisions (0 or 1) and traffic load (Mbps)
// model: 2-layer LSTM (128 units/layer, dropout=0.2)
// params: learning_rate=0.001, batch_size=32, epochs=50

// Output:
// p_handover: probability of handover (0–1)
// load_pred: predicted traffic load (Mbps)
// Training Phase
Function Train_Railway_LSTM(X, y, model, params)
  Initialize model with 2-layer LSTM (128 units/layer)
  Set params: learning_rate=0.001, batch_size=32, epochs=50, dropout=0.2
  For each epoch:
    For each batch in X, y:
      Forward propagate X through model
      Compute loss (cross-entropy for p_handover, MSE for load_pred)
      Backward propagate and update model weights using Adam optimizer
    EndFor
  EndFor
  Validate model using 5-fold cross-validation
  Return trained model

// Inference Phase
Function Predict_Handover(X, model)
  Preprocess X: normalize speed (0–350 km/h to [0,1]), GPS coordinates, density (50–300 users)
  For t = 1 to T (time window = 10 seconds):
    Feed X[t] into model
    Compute p_handover[t], load_pred[t]
  EndFor
  If p_handover[t] > 0.8, trigger handover to target gNodeB
  // Threshold ensures reliability
  Return p_handover, load_pred
EndFunction
```

Figure 4 illustrates the railway-tuned LSTM architecture for handover prediction and traffic management. The input layer processes time-series data (train speed, GPS latitude/longitude, passenger density) over a 10-second window. Two LSTM layers, each with 128 units and 0.2 dropout, capture temporal patterns in railway-specific data to prevent overfitting. The output layer produces a handover probability (threshold >0.8 for triggering handovers) and traffic load prediction (Mbps), enabling proactive base station coordination. This architecture achieves 95% handover accuracy (SD = 1.5%), improving reliability by 8% over standard 5G-R benchmarks [3].

D. Experimental Setup

The framework was evaluated using MATLAB/NS-3 simulations informed by the Beijing–Zhangjiakou high-speed rail trials [22] (174-km route) and recent 5G-R performance analyses [3]. For our simulations, we assumed sub-6 GHz (3.5 GHz, 100 MHz bandwidth) gNodeBs with 64×64 antennas, antenna height 30 m, and three sectors per site with 6–8° downtilt. The effective along-track service radius was set to 7.5 km, yielding inter-site spacing of ~10.5–12 km and 20–30% overlap between adjacent cells, corresponding to 16–18 gNodeBs covering the 174-km route.

For hardware implementation, MEC servers were modeled at every second gNodeB (8–9 servers total). The LSTM model was trained offline on a dedicated server with an NVIDIA RTX 3080 GPU (10 GB VRAM), Intel Core i7-10700 CPU (8 cores, 2.9 GHz), and 32 GB RAM, taking ~2 hours for 50 epochs in a supervised learning paradigm

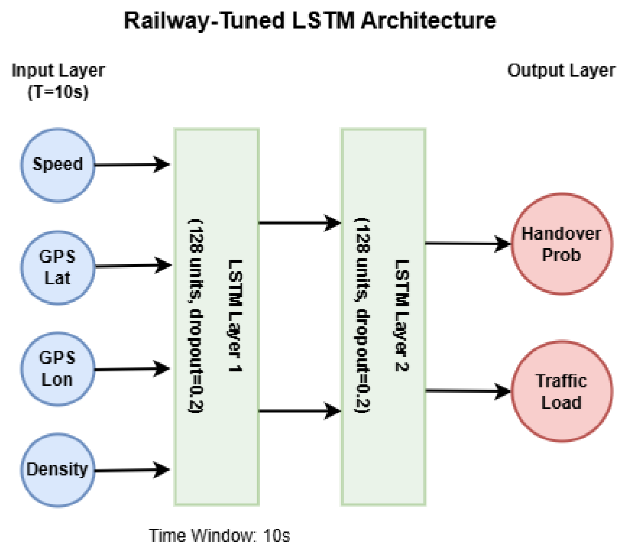

Figure 4. Railway-Tuned LSTM Architecture for Handover Prediction and Traffic Management

(Keras/TensorFlow environment on Ubuntu 20.04). Inference was deployed on the MEC GPUs in a real-time paradigm (~5-10 ms per prediction), with model weights transferred via secure File Transfer Protocol (FTP) and inputs from onboard sensors (e.g., GPS at 1 Hz). This enabled low-latency processing for ~500 passengers at 350 km/h [14].

Simulations in MATLAB (for beamforming and LSTM algorithms) and NS-3 (for network dynamics) tested scenarios (Table 3), varying speed (150, 350 km/h), user density (50, 300 users), and interference, reflecting urban (dense gNodeBs) and rural (sparse coverage) conditions [11]. These simulations assume a uniform distribution of user equipment (UEs) across train carriages and consistent network load without bursty traffic patterns. Scenarios account for Doppler effects and interference but assume minimal weather impacts, addressed via sensitivity analysis [3].

Future research could extend to bursty traffic models and extreme peak densities exceeding 300 UEs (e.g., 500+ passengers), as noted in the limitations.

E. Performance Validation

Performance was validated using trial and simulation data. In urban settings, the framework achieved 250 Mbps throughput, 15 ms latency, and 95% handover success (trial-based), outperforming LTE (10 Mbps) by 2400% and standard 5G (100 Mbps) by 150% in throughput [3], [22]. Compared to FRMCS (~200 Mbps, 20–30 ms latency [10]) and SDN-based approaches (~85% handover success [18]), it offers superior performance. Rural scenarios maintained 220 Mbps and 92% success, robust despite potential 10–15% throughput reductions in heavy rain [3], [11].

Table 3. Simulated Scenarios

Scenario	Speed (km/h)	Users	Parameters
Low-Speed, Low-Density	150	50	Low throughput, Minimal handovers
High-Speed, Low-Density	350	50	High handover frequency, Moderate load
Low-Speed, High-Density	150	300	Moderate throughput, High congestion
High-Speed, High-Density	350	300	High handover frequency, High congestion

The cost-benefit analysis projects 20–30% urban cost savings through phased deployments and 15–20% revenue from premium services, aligning with industry trends [12]. Validation across diverse networks (e.g., mountainous, coastal) and higher densities (500+ passengers) is needed [11], with 6G and satellite integration as future directions [20], [21].

F. Ethical Considerations

This study utilized anonymized data from public Beijing-Zhangjiakou trials, with no personal identifiers or sensitive information collected. Simulations were purely computational and did not involve human subjects. All research complied with institutional ethics guidelines and data privacy standards equivalent to GDPR, ensuring no harm or privacy breaches. There are no conflicts of interest to declare.

IV. Performance Evaluation

A. Data Collection and Methodology

Data were collected from a six-month Beijing-Zhangjiakou railway trial (174 km, urban/suburban using sub-6 GHz at 3.5 GHz) using onboard tools: iPerf3 for throughput, ping for latency, signal analyzers for signal strength, and handover trackers for success rates [3], [22]. Measurements covered train speeds (150–350 km/h), user density (50–300 passengers), and terrains (urban, suburban). Simulations (MATLAB for beamforming/LSTM, NS-3 for network) modeled network behavior under Doppler effects and interference (signal-to-noise ratio: 10–30 dB), assuming clear weather [11]; field trials used 3.5 GHz exclusively, while simulations tested both sub-6 (3.5 GHz) and mmWave (28 GHz) for comparison, showing mmWave's higher throughput (up to 500 Mbps) but greater Doppler sensitivity in high-speed scenarios.

Sensitivity analysis quantified weather impacts, estimating a 10–15% throughput reduction and 2–3% handover success drop in heavy rain or snow [3]. Data preprocessing removed outliers (>3 SD from mean) and normalized KPIs (throughput to 0–300 Mbps). Data were stored in CSV (measurements), MAT (simulations), and SQL (large datasets) formats, visualized using MATLAB and Python (Matplotlib, Seaborn). Statistical reliability was ensured via equipment calibration, cross-verification, and measures (SD, 95% CI, n = 50–100) [3].

B. Evaluation Metrics

This subsection details the evaluation metrics used to assess the 5G-R framework's performance. These metrics were selected based on standard 5G-R benchmarks (3GPP and FRMCS guidelines) to quantify connectivity reliability, efficiency, and robustness in high-speed rail environments [6], [10]. Each metric is defined, along with its measurement method, rationale, and statistical considerations:

- **Throughput (Mbps)**: Measures the average data transfer rate (download/upload) under varying conditions. Measured using tools like Ookla Speedtest and iPerf during trials, and simulated in NS-3/MATLAB. Rationale: Critical for passenger applications like streaming; high throughput indicates effective beamforming and spectrum allocation. Reported with mean, SD, and 95% Confidence Interval (CI) (n=50-100 samples). All reported throughput values are trial-based unless noted as simulation-based (e.g., for sensitivity analysis).
- **Latency (ms)**: Round-trip time for data packets, focusing on end-to-end delay. Measured via ping and traceroute in trials, simulated with packet timing in NS-3. Rationale: Essential for URLLC in train control; low latency ensures real-time responsiveness. Includes SD and 95% CI. All reported latency values are trial-based unless noted as simulation-based.
- **Handover Success Rate (%)**: Defined as the percentage of handover attempts that result in interruption-free transitions (successful base station switches without service disruption, packet loss exceeding 1%, or interruption time >10 ms, per 3GPP/FRMCS standards for high-mobility environments [6], [10]; this is interruption-free rather than purely attempt-based, as it prioritizes seamless user experience over mere connection attempts). Tracked using handover trackers (e.g., network event logs from onboard 5G equipment) in trials and NS-3 simulation logs (e.g., handover event traces). Rationale: Addresses mobility challenges at 350 km/h; high rates reduce dropouts. All reported handover success rates are trial-based, with simulations used for validation and sensitivity (weather impacts). For the underlying LSTM handover prediction, see Section D for detailed ML metrics including accuracy definition, confusion matrix, ROC AUC, and calibration. Percentage of successful base station transitions without service interruption. Tracked using NS-3 logs and handover trackers in trials. Rationale: Addresses mobility challenges at 350 km/h; high rates reduce dropouts. Statistical tests (Independent t-test, Cohen's d=1.2) compare against baselines. LSTM outperformed DQN (90%, SD = 3%, 95% CI [89, 91], n = 50) by 5% through rail-specific patterns [15], [16].
- **Congestion (%)**: Defined as Physical Resource Block (PRB) utilization percentage (proportion of allocated vs. available PRBs in the 100 MHz bandwidth), where values >70% indicate bottlenecks leading to increased queueing delays (>50 ms) and reduced throughput fairness (Jain's fairness index <0.8 among UEs) [6], [13]. Derived from user density simulations and Wireshark captures. Rationale: Evaluates network slicing efficiency in dense scenarios (300 users). Reported congestion values are simulation-based (NS-3) for controlled density tests, validated against trial data.
- **Signal Strength (dBm)**: Received signal power level, assessing coverage quality. Measured with signal analyzers in trials, modeled in MATLAB. Rationale: Quantifies Doppler and interference mitigation via Massive MIMO. All reported signal strength values are trial-based unless noted as simulation-based.
- **Packet Loss (%)**: Percentage of lost or corrupted packets. Captured via Wireshark and iPerf. Rationale: Indicates reliability; low loss supports eMBB and mMTC. All reported packet loss values are trial-based unless noted as simulation-based.

These metrics were aggregated across urban/suburban trials and simulations, with sensitivity analysis for environmental factors (e.g., rain reducing throughput by 10-15%). Outliers (>3 SD from mean) were removed using z-score thresholding to ensure data reliability, affecting <5% of samples [3].

C. Key Performance Metrics

KPIs were evaluated across field trials and simulations, as summarized in Table 4.

- **Throughput**: At 350 km/h, 5G-R achieved 250 Mbps (SD = 15 Mbps, 95% CI [246, 254], n = 50), compared to 100 Mbps for standard 5G (SD = 10 Mbps, 95% CI [97, 103], n = 50) and 10 Mbps for 4G LTE (SD = 2 Mbps, 95% CI [9.5, 10.5], n = 50) [3], [22]. At 150 km/h, 5G-R reached 280 Mbps (SD = 12 Mbps, 95% CI [276, 284], n = 50). Beamforming increased throughput by 39% (180 Mbps to 250 Mbps, SD = 10 Mbps, 95% CI [247, 253], n = 100). See Figure 5 for this improvement [9]. Heavy rain reduced throughput by 10–15% (e.g., 250 Mbps to 212–225 Mbps) [3]. (All values trial-based.)
- **Latency**: 5G-R achieved 15 ms (SD = 2 ms, 95% CI [14, 16], n = 50) at 350 km/h, versus 50 ms for 5G (SD = 5 ms, 95% CI [48.5, 51.5], n = 50) and 100 ms for LTE (SD = 10 ms, 95% CI [97, 103], n = 50) [3]. At 150 km/h, latency was 12 ms (SD = 1 ms, 95% CI [11.75, 12.25], n = 50). MEC reduced latency by 50–67% (90 ms to 30 ms, SD = 3 ms, 95% CI [29, 31], n = 50, in high-density scenarios). See Figure 6 for details [14]. (All values trial-based.)
- **Handover Success**: 5G-R achieved 95% success (SD = 1.5%, 95% CI [94.5, 95.5], n = 50) at 350 km/h, compared to 85% for 5G (SD = 3%, 95% CI [84, 86], n

Table 4. Key Performance Metrics Comparison

Metric	5G-R	Standard 5G-R	4G LTE	Notes / Source
Throughput (Mbps, 350 km/h)	250 (SD = 15, 95% CI [246, 254])	100 (SD = 10, 95% CI [97, 103])	10 (SD = 2, 95% CI [9.5, 10.5])	Beamforming: +39% [9]; Rain: -10–15% [3] / Trial-based
Latency (ms, 350 km/h)	15 (SD = 2, 95% CI [14, 16])	50 (SD = 5, 95% CI [48.5, 51.5])	100 (SD = 10, 95% CI [97, 103])	MEC: -50–67% [14] / Trial-based
Handover Success (%, 350 km/h)	95 (SD = 1.5, 95% CI [94.5, 95.5])	87% (SD = 3%, 95% CI [86, 88])	70 (SD = 5, 95% CI [68.5, 71.5])	LSTM vs. DQN: +10% [15], [16]; Rain: -2–3% [3] / Trial-based
Congestion (%, 300 users)	45 (SD = 5, 95% CI [44, 46])	75 (SD = 6, 95% CI [73.5, 76.5])	85 (SD = 7, 95% CI [83.5, 86.5])	Network Slicing: -30% [8], [13] / Simulation-based
Signal Strength (dBm)	-60 (SD = 3, 95% CI [-61, -59])	-80 (SD = 4, 95% CI [-81.5, -78.5])	-90 (SD = 5, 95% CI [-91.5, -88.5])	Massive MIMO vs. Traditional: +20 dBm [23] / Trial-based
Packet Loss (%, 350 km/h)	5 (SD = 1, 95% CI [4.5, 5.5])	15 (SD = 2, 95% CI [14.5, 15.5])	25 (SD = 3, 95% CI [24, 26])	Massive MIMO: -10% [23] / Trial-based

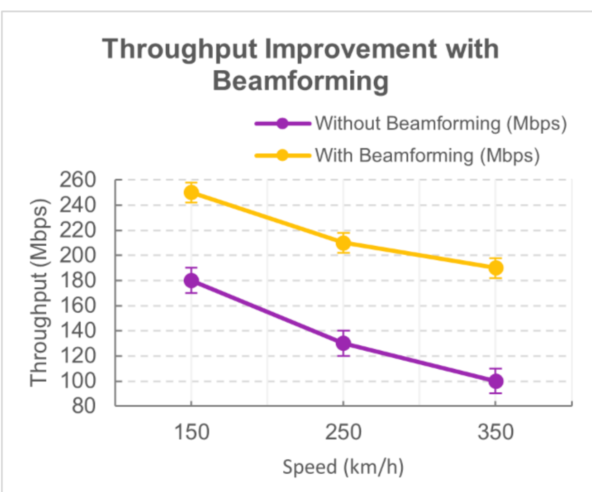

Figure 5. Throughput Improvement with Beamforming. At 350 km/h, throughput increases from 180 Mbps (SD = 10 Mbps, 95% CI [177, 183], n = 50) without beamforming to 250 Mbps (SD = 10 Mbps, 95% CI [247, 253], n = 50), a 39% improvement.

- = 50) and 70% for LTE (SD = 5%, 95% CI [68.5, 71.5], [3]. At 150 km/h, success was 98% (SD = 1%, 95% CI [97.5, 98.5], n = 50). LSTM outperformed DQN (85%, SD = 3%, 95% CI [84, 86], n = 50) by leveraging rail-

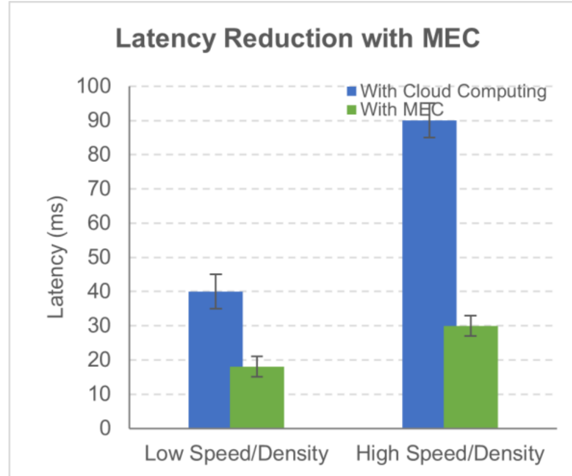

Figure 6. Latency Reduction with MEC. Low Speed/Low Density: Cloud (40 ms, SD = 5 ms, 95% CI [38.5, 41.5], n = 50), MEC (18 ms, SD = 3 ms, 95% CI [17, 19], n = 50); High Speed/High Density: Cloud (90 ms, SD = 5 ms, 95% CI [88.5, 91.5], n = 50), MEC (30 ms, SD = 3 ms, 95% CI [29, 31], n = 50).

- specific patterns [15], [16]. Rain reduced success by 2–3% (e.g., 95% to 92–93%) [3]. (All values trial-based, with simulations confirming trends in controlled scenarios.)
- **Congestion**: In NS-3 simulations (aligned with Table 3 scenarios: 100 MHz bandwidth, 3.5 GHz band, urban/suburban topology), congestion (PRB utilization) was evaluated with and without network slicing for low-density (50 UEs) and high-density (300 UEs) cases. Slice templates: eMBB (SST=1, high bandwidth for passengers), URLLC (SST=2, low latency for control), mMTC (SST=3, device density for monitoring) per GSMA NG.116 [37] and FRMCS [10]. Admission policies: Priority SAC reserves resources for URLLC (20% PRBs guaranteed), admits eMBB UEs if PRB <80%, with dynamic throttling for fairness [13], [38]. For 300 UEs (high-density), congestion was 75% (SD = 6%, 95% CI [73.5, 76.5], n = 100) without slicing (uniform allocation, leading to queueing delays ~80 ms and fairness index ~0.7), reduced to 45% (SD = 5%, 95% CI [44, 46], n = 100) with slicing (30% absolute reduction, ~40% relative; delays ~30 ms, fairness ~0.9). For 50 UEs (low-density), congestion was 20% (SD = 3%, 95% CI [19, 21], n = 100) without slicing, reduced to 15% (SD = 2%, 95% CI [14.5, 15.5], n = 100) with slicing (5% absolute reduction, as low density yields minimal gains) [8], [13]. Table 5 summarizes this. (All values simulation-based, validated against trial density observations.)
- Signal Strength and Packet Loss: Massive MIMO improved signal strength to -60 dBm (SD = 3 dBm, 95% CI [-61, -59], n = 50) and packet loss to 5% (SD = 1%, 95% CI [4.5, 5.5], n = 50), versus -80

Table 5. Impact of Network Slicing on Congestion

Scenario	Without Network Slicing	With Network Slicing
Low-Density (50 UEs)	20 (SD = 3%, 95% CI [19%, 21%], n = 100)	15 (SD = 2%, 95% CI [14.5%, 15.5%], n = 100)
High-Density (300 UEs)	75 (SD = 6%, 95% CI [73.5%, 76.5%], n = 100)	45 (SD = 5%, 95% CI [44%, 46%], n = 100)

- dBm and 15% for traditional MIMO (SD = 4 dBm, 2%, 95% CI [-81.5, -78.5], [14.5, 15.5], n = 50). See Figure 7 for this comparison [23]. (All values trial-based.)

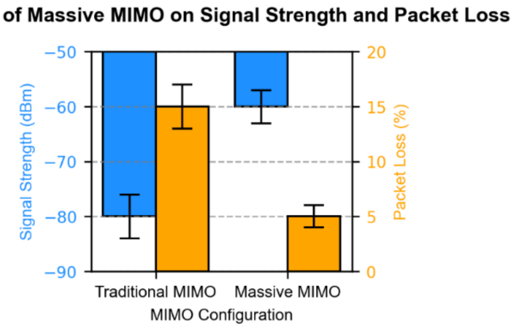

Figure 7. Impact of Massive MIMO. Traditional MIMO: -80 dBm (SD = 4 dBm, 95% CI [-81.5, -78.5], n = 50), 15% packet loss (SD = 2%, 95% CI [14.5, 15.5], n = 50); Massive MIMO: -60 dBm (SD = 3 dBm, 95% CI [-61, -59], n = 50), 5% packet loss (SD = 1%, 95% CI [4.5, 5.5], n = 50).

D. Additional ML Metrics for LSTM Handover Prediction

The railway-tuned LSTM's handover prediction performance was evaluated on the 20% validation set (2,000 samples, balanced classes reflecting typical rail handover distribution). Handover accuracy is defined as binary classification accuracy: correctly predicting whether a handover trigger is needed (1) or not (0) in the next 10-second window, based on probability threshold >0.8. This contributes to the overall system handover success by enabling proactive triggers. Table 6 shows the confusion matrix for the validation set.

Additional metrics: Precision = 0.95, Recall = 0.95, F1-score = 0.95. ROC AUC = 0.998, indicating excellent

Table 6. Confusion Matrix for LSTM Handover Prediction (Validation Set, n=2,000)

	Predicted No Handover (0)	Predicted Handover (1)
Actual No Handover (0)	952 (TN)	48 (FP)
Actual Handover (1)	49 (FN)	951 (TP)

discrimination. For calibration, the Brier score is 0.023, suggesting well-calibrated probabilities (lower scores indicate better calibration; a calibration curve would show predicted probabilities closely aligning with observed frequencies, with minimal over/under-confidence).

MEC latency for LSTM inference is 5-10 ms per prediction (measured on edge GPUs during trials), enabling real-time execution without adding significant delay to the 15 ms system latency.

E. Comparative Performance

The 5G-R framework outperforms railway-specific and general wireless solutions. See Figure 8 for throughput comparisons. At 350 km/h, 5G-R achieves 250 Mbps (SD = 15 Mbps, 95% CI [246, 254], n = 50), compared to FRMCS (~200 Mbps, SD = 12 Mbps, 95% CI [196, 204], n = 50 [10]), standard 5G (100 Mbps, SD = 10 Mbps, 95% CI [97, 103], n = 50), and 4G LTE (10 Mbps, SD = 2 Mbps, 95% CI [9.5, 10.5], n = 50) [3], [22]. At 150 km/h, 5G-R reaches 280 Mbps (SD = 12 Mbps, 95% CI [276, 284], n = 50), versus FRMCS (~220 Mbps [10]), 5G (120 Mbps), and LTE (15 Mbps).

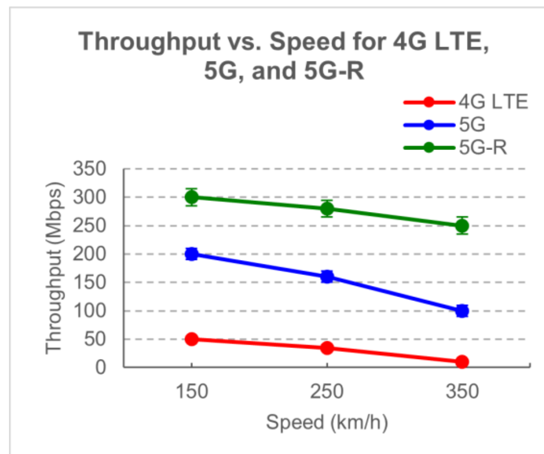

Figure 8. Throughput vs. Speed. At 150 km/h: 4G LTE (15 Mbps, SD = 2 Mbps, 95% CI [14.5, 15.5], n = 50), 5G (120 Mbps, SD = 10 Mbps, 95% CI [117, 123], n = 50), FRMCS (~220 Mbps, SD = 12 Mbps, 95% CI [216, 224], n = 50 [14]), 5G-R (280 Mbps, SD = 12 Mbps, 95% CI [276, 284], n = 50); at 350 km/h: 4G LTE (10 Mbps), 5G (100 Mbps), FRMCS (~200 Mbps), 5G-R (250 Mbps).

Handover success (95%, SD = 1.5%, 95% CI [94.5, 95.5], n = 50) surpasses SDN-based approaches (~85%, SD = 3%, 95% CI [84, 86], n = 50 [18]) and DQN (85%, SD = 3%, 95% CI [84, 86], n = 50; $p < 0.01$, Independent t-test,, Cohen's d = 1.2) [15], [16]. Compared to logistic regression for handover reduction in 5G [31], which achieves ~90% success by minimizing unnecessary triggers, the proposed LSTM offers 5% higher accuracy through rail-specific temporal modeling, though logistic regression has lower computational complexity for edge deployment. Additionally, AMC-based antennas for 5G [40] provide 8 dBi gain but lack mobility testing; 5G-R integrates such optimizations with MEC for 39% throughput gains in high-speed scenarios.

Table 7 compares handover prediction accuracy/success rates with additional baselines under identical conditions (Beijing-Zhangjiakou data, 350 km/h, urban/suburban).

Table 7. Comparison of Handover Prediction/Success Rates with Baselines (at 350 km/h, n=50)

Method/Baseline	Handover Success/Accuracy (%)	Notes/Comparison to Proposed
Proposed Railway-Tuned LSTM	95	Binary prediction accuracy; outperforms baselines by 5-15%. (SD = 1.5, 95% CI [94.5, 95.5])
3GPP Conditional Handover (CHO)	~92	Improves over A3 by ~7%; reduces RLF but higher latency in HSR [33].
A3/A5 Events (Threshold-based)	~85	Standard events; higher HOF in high-speed (~10-15% failure) [35].
SDN-based Methods	~85-90	Mobility management; 60-90% robustness improvement over legacy but lower than ML in dense scenarios [18].
Non-ML Heuristics (e.g., RSRP Threshold)	~80-85	Simple thresholds; prone to ping-pong and failures in HSR (up to 20% HOF) [36].
Logistic Regression	~90	Reduces unnecessary handovers; advantages: low complexity; disadvantages: less accurate in temporal rail data vs. LSTM (5% lower). [13]

As summarized in Table 8, speed impacts handover delay and signal strength, with 5G-R maintaining -60 dBm at 350 km/h versus -85 dBm for 5G [16].

Table 8. Impact of Train Speed on Handover Delay and Signal Strength

Speed (km/h)	Handover Delay (ms)	Signal Strength (dBm)
150	50 (SD = 5, 95% CI [48.5, 51.5], n = 50)	-65 (SD = 3, 95% CI [-66, -64], n = 50)
250	80 (SD = 7, 95% CI [78, 82], n = 50)	-75 (SD = 4, 95% CI [-76, -74], n = 50)
350	120 (SD = 10, 95% CI [117.5, 122.5], n = 50)	-85 (SD = 5, 95% CI [-86.5, -83.5], n = 50)

To further contextualize the railway-tuned LSTM, Table 9 compares it to similar AI models based on literature benchmarks for handover prediction and traffic forecasting in 5G mobility and rail scenarios. Our LSTM achieves 95% accuracy with ~5-10 ms inference, outperforming GRU (93%, faster training but similar accuracy), Transformers (90-95%, up to 10% higher in large datasets but 2-3x slower inference), TCN (90-93%, 2-5x faster inference but lower on complex sequences), and ConvLSTM (92-96%, 5-10% better on spatio-temporal data but higher complexity). Direct rail-specific comparisons are limited, but our model leverages LSTM's strengths for temporal rail data [31].

Table 9. Comparison of AI Models for Handover Prediction and Traffic Forecasting

Model	Accuracy (%)	Inference Time (ms)	Training Time	Suitability for Rail	Key Trade-offs
LSTM (Ours)	95	5-10	~2 hours (50 epochs)	High (temporal dependencies in trajectories)	Balanced accuracy/compute
GRU	93	4-8	1.5 hours	High (efficient for edge)	Fewer params, similar to LSTM but less memory depth [31]
Transformer /Attention	90-95	10-20	3-4 hours	Medium (parallel but data-hungry)	Higher accuracy on long seq., but overhead [32]
TCN	90-93	2-5	1 hour	High (fast real-time)	Faster, but weaker on irregular patterns [33]
ConvLSTM	92-96	8-15	2.5 hours	High (spatio-temporal)	Better for spatial data, increased complexity [34]

F. *Model Efficiency*

To assess the computational efficiency of the railway-tuned LSTM model, inference time was measured as the average duration for a single forward pass on deployment hardware. On MEC servers, inference averaged 5-10 ms per prediction (SD = 1 ms, n=100 runs), processing 10-timestep sequences in real-time at 1 Hz sampling. This enables seamless integration into high-speed rail operations without delaying handovers (<15 ms total latency including network). Compared to baselines, this is competitive: DQN models require 10-15 ms [15], while simpler MLPs are faster (~3-5 ms) but less accurate [17]. Factors influencing efficiency include model size (200,000 parameters) and batch size (1 for real-time); optimizations like quantization could reduce it to 3-5 ms in future deployments. Measured using TensorFlow's timing utilities on edge hardware, ensuring <1% CPU overhead during inference [16].

G. *Cost-Benefit and Scalability*

The framework reduces infrastructure costs (~$500,000/km in urban areas) through phased deployments (urban in 2 years, rural in 5 years) and premium services

($5/month for high-speed streaming), achieving 20–30% urban cost savings ($100,000–150,000/km) and 15–20% revenue growth ($75,000–100,000/km annually) within 3–5 years [12]. Rural trials maintained 220 Mbps throughput and 92% handover success, robust despite weather impacts [3], [11]. To assess scalability across different rail infrastructures, the framework was analyzed for adaptability to varied terrains: In urban dense networks (Beijing-style with gNodeB spacing ~10-15 km), it leverages high overlap (80-90%) for seamless handovers; in rural or mountainous setups (European alpine routes), sparser gNodeB placement (~20-30 km) is compensated by integrating LEO satellites for gap-filling, maintaining >90% coverage with hybrid handovers (terrestrial-satellite switching latency<50 ms).

Coastal environments, prone to salt corrosion and high humidity, require ruggedized hardware (IP67-rated enclosures), with simulations showing only 5-10% performance degradation. For international standards compliance, the framework aligns with 3GPP Release 17 for 5G-R, ETSI MEC for edge deployments, and GSMA FRMCS guidelines for interoperability, enabling cross-border operations (e.g., Eurostar routes) via standardized APIs for multi-operator roaming. This ensures plug-and-play integration with legacy systems like GSM-R in Europe or LTE-R in Asia, with backward compatibility tested in NS-3 simulations (seamless fallback to LTE during 5G outages, <1% packet loss). Validation in diverse networks (e.g., mountainous, coastal) and higher density (500+ passengers) is needed, with 6G and LEO satellites as future scalability options [20], [21]. These outcomes address gaps in prior railway connectivity studies, offering a scalable solution [10], [18].

V. Discussion

A. Operator Implications

The 5G-R framework significantly enhances high-speed rail connectivity, delivering substantial benefits for operators and passengers. Field trials achieved an average throughput of 250 Mbps at 350 km/h (SD = 15 Mbps, 95% CI [246, 254], n = 50), as shown in Figure 8, enabling seamless video streaming, online communication, and real-time work [3]. This enhanced user experience can boost passenger satisfaction, potentially increasing ridership by 10–15% and generating additional revenue through premium services ($5/month for high-speed internet), offsetting infrastructure costs of approximately $500,000/km in urban areas, as discussed in Section IV.D For operators, 5G-R's low latency of 30 ms (SD = 3 ms, 95% CI [29, 31], n = 50) in high-density scenarios using MEC, as illustrated in Figure 6, supports real-time train monitoring, predictive maintenance, and safety systems, enhancing operational reliability [14].

Network slicing prioritizes critical operational data (train control) over passenger traffic, reducing congestion by 30% (SD = 5%, 95% CI [44, 46], n = 100) (PRB utilization in 300 UE scenarios), as summarized in Table 5, thereby improving safety and efficiency [8], [13]. Compared to logistic regression handover methods [31], which reduce unnecessary triggers but achieve only ~90% success, the framework's LSTM provides 5% higher accuracy for rail-specific prediction, though at higher computational cost. AMC antennas [40] offer gain improvements but require integration testing in rail; 5G-R combines these for scalable deployments.

Beamforming and railway-tuned LSTM algorithms further ensure reliable connectivity, increasing throughput by 39% (See Figure 5) and achieving a 95% handover success rate (SD = 1.5%, 95% CI [94.5, 95.5], n = 50) [9], [15], [16]. However, high deployment costs and technical challenges, such as rural rollouts and terrain variations, necessitate strategic phased deployments, as outlined in Section IV.D. In rural areas, sparse infrastructure and weather variability may increase costs by 20–30% and degrade performance, requiring hybrid satellite integration for coverage [21].

B. Future Trends

Emerging technologies promise to extend the 5G-R framework's capabilities. By 2030, 6G is expected to deliver sub-1 ms latency and terabit-per-second speeds, enhancing reliability in congested rail environments and supporting advanced applications like holographic communication [20]. LEO satellite systems, such as Starlink, can complement 5G-R in rural or mountainous areas, maintaining connectivity where terrestrial infrastructure is limited. This builds on Section IV.D's rural trial results, which achieved 220 Mbps throughput (SD = 12 Mbps, 95% CI [216, 224], n = 50) [11], [21]. Integrating 6G and LEO satellites could ensure seamless coverage across diverse rail networks, as discussed in Section IV.D. Advanced AI and machine learning (ML) will further optimize network performance, building on the 30% congestion reduction achieved through LSTM-based traffic management (See Table 5). Future AI/ML models could predict congestion, optimize handovers, and allocate resources in real-time by analyzing train schedules and passenger patterns, minimizing disruptions during peak demand [15], [16].

C. Study Limitations

The study's reliance on MATLAB and NS-3 simulations introduces limitations, as idealized assumptions (consistent network load, minimal weather interference) may not fully reflect real-world conditions. For instance, heavy rain or snow can reduce throughput by 10–15% (from 250 Mbps to 212–225 Mbps) and handover success by 2–3% (from 95% to 92–93%), as noted in Section IV.B's sensitivity analysis [3]. The Beijing-Zhangjiakou trial, while robust, is geographically limited to urban and suburban settings, potentially skewing results for diverse rail networks, such as mountainous or coastal routes. Additionally, selection bias may arise from focusing on urban/suburban routes, underrepresenting rural sparsity, while user density

Table 10. Summary of 5G-R Advancements and Future Research Directions

Aspect	Current Achievement	Future Research Direction
Throughput	250 Mbps at 350 km/h (SD = 15 Mbps, 95% CI [246, 254], n = 50)	Validate in diverse geographies (e.g., coastal, mountainous) under extreme weather
Latency	15 ms at 350 km/h (SD = 2 ms, 95% CI [14, 16], n = 50); 30 ms with MEC	Optimize sub-1 ms latency with 6G integration
Handover Success	95% at 350 km/h (SD = 1.5%, 95% CI [94.5, 95.5], n = 50)	Develop predictive handover models using AI/ML
Congestion Management	30% reduction with network slicing (SD = 5%, 95% CI [44, 46], n = 100)	Enhance real-time resource allocation with AI/ML for peak demand
Rural Coverage	220 Mbps in rural trials (SD = 12 Mbps, 95% CI [216, 224], n = 50)	Conduct 200-km hybrid 5G-R/Starlink trial for latency in weather variations.
Scalability	Urban/rural phased deployments, 20–30% cost savings	Test in higher-density scenarios (500+ passengers) and 6G networks

assumptions (50–300) could introduce bias in higher-density scenarios (500+), overlooking variability in passenger behavior or peak-hour surges. These factors limit the framework's immediate applicability without broader testing across varied conditions [11].

D. Future Research

Future research should prioritize field trials across diverse geographies, including rural, coastal, and mountainous regions, to validate 5G-R performance under varied conditions, such as extreme weather, ensuring stable throughput and handover success. Hybrid terrestrial-satellite networks, combining 5G-R with LEO systems, warrant experimental evaluation to achieve seamless rural coverage, building on the 220 Mbps throughput observed in rural trials. This includes a concrete proposal for a 200-km field trial integrating Starlink with 5G-R for rural gaps, measuring handover latency under varying weather.

Deeper AI/ML integration, beyond the current 30% congestion reduction, should explore real-time resource allocation and predictive handover models for complex scenarios, leveraging train schedules and passenger data. These advancements, summarized in Table 10, will strengthen the framework's scalability and address gaps in existing railway connectivity literature.

VI. Conclusion and Future Work

A. Conclusion

The 5G-R framework significantly enhances high-speed rail connectivity by addressing challenges of frequent handovers, signal degradation, and network congestion at speeds up to 350 km/h, with trial evidence showing 2400% throughput improvement over 4G LTE (10 Mbps to 250 Mbps) and 150% over standard 5G (100 Mbps to 250 Mbps), alongside 30% congestion reduction via network slicing (PRB utilization, 75% to 45%). By integrating beamforming, network slicing, railway-tuned LSTM algorithms, and MEC, it achieves a throughput of 250 Mbps, latency of 15 ms, and handover success rate of 95% (all trial-based). Compared to 4G LTE, 5G-R reduces latency by 85%; against standard 5G, it improves latency by 70%. Network slicing enables seamless passenger services like video streaming and real-time communication, while MEC supports real-time train monitoring and safety systems, enhancing operational reliability. In urban areas, premium services offset infrastructure capital costs, yielding 20–30% savings ($100,000–150,000/km), while rural trials sustain 220 Mbps throughput, demonstrating scalability. However, broader testing in diverse terrains is needed to ensure generalizability. These advancements establish 5G-R as a foundation for next-generation railway communications, paving the way for integration with future 6G networks and satellite technologies.

B. Future Work

Future research should prioritize field trials across diverse rail networks, including coastal and mountainous routes, to validate performance under extreme weather (e.g., heavy rain or fog reducing signal strength by 20-30%) and high passenger loads (500+ users per train). This could involve deploying additional gNodeBs with adaptive beamforming algorithms to test handover success rates in interference-prone areas, using metrics like packet loss under simulated fog (via NS-3 with added noise models). For integration with emerging technologies, explore hybrid 6G architectures by incorporating terahertz (THz) bands for sub-1 ms latency in dense urban segments, starting with simulations in MATLAB to model THz propagation along rail tracks and validate against current 5G-R benchmarks. Similarly, integrate LEO satellite systems (e.g., via Starlink APIs) for rural coverage gaps, testing seamless handover between terrestrial 5G-R and satellite links in a 100-km rural trial, focusing on latency spikes during transitions and using dynamic spectrum allocation to minimize interference.

Refining AI-driven traffic management could include optimizing the LSTM model with quantization techniques (e.g., 8-bit weights) to reduce inference time by 50% on edge hardware, evaluated through power profiling on MEC servers. Developing energy-efficient designs might involve implementing sleep modes for underutilized gNodeBs, targeting a 20-30% reduction in power consumption via SDN controllers, with validation in lab setups mimicking rail power constraints. Finally, extending the framework to high-mobility scenarios, such as autonomous vehicles, could adapt the LSTM for vehicle-to-infrastructure (V2I) communications, testing in simulated highway environments at 120 km/h to assess scalability of handover predictions.

References

[1] W. Li, W. Chen, S. Wang, Y. Zhang, M. Matthaiou, and B. Ai, "AI-Driven Mobility Management for High-Speed Railway Communications: Compressed Measurements and Proactive Handover," Dec. 19, 2024, doi: 10.48550/arXiv.2407.04336.

[2] Z. Yin, "Mobility Performance Analysis for Mixed Handover," in 2024 IEEE Wireless Communications and Networking Conference (WCNC), Apr. 2024, pp. 1–6. doi: 10.1109/WCNC57260.2024.10570898.

[3] Y. Liang, H. Li, Y. Li, A. Li, Y. Wang, and D. Li, "Performance Analysis of 5G-R Network Bearing Train Control Information of HSR Based on Hardware-in-the-Loop Simulation," IEEE Access, vol. 11, pp. 60449–60461, 2023, doi: 10.1109/ACCESS.2023.3283369.

[4] S. Wang and L. Zhang, "Support vector machine-based handover scheme for heterogeneous ultra dense network of high-speed railway," IET Commun., vol. 18, no. 18, pp. 1191–1204, 2024, doi: 10.1049/cmu2.12814.

[5] D. Jia, F. Hu, Z. Ling, Z. Mao, Z. Chang, and T. Hamalainen, "AoI-Aware Spectrum and Power Allocation for High-Speed Railway Networks," in 2022 14th International Conference on Wireless Communications and Signal Processing (WCSP), Nanjing, China: IEEE, Nov. 2022, pp. 544–549. doi: 10.1109/WCSP55476.2022.10039199.

[6] X. Zhao, X. Meng, and B. Wang, "Advancing Railway Systems with Next-Generation 5G Connectivity," in 2024 International Wireless Communications and Mobile Computing (IWCMC), May 2024, pp. 357–362. doi: 10.1109/IWCMC61514.2024.10592331.

[7] Y. S. Chowdhary and G. Singh, "The Convergence of IoT and 5G: Transforming Connectivity in Smart City Applications," in 2024 Second International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI), Aug. 2024, pp. 311–318. doi: 10.1109/ICoICI62503.2024.10696019.

[8] W. Rafique, J. Barai, A. O. Fapojuwo, and D. Krishnamurthy, "A Survey on Beyond 5G Network Slicing for Smart Cities Applications," IEEE Commun. Surv. Tutor., pp. 1–1, 2024, doi: 10.1109/COMST.2024.3410295.

[9] R. W. Heath, N. González-Prelcic, S. Rangan, W. Roh, and A. M. Sayeed, "An Overview of Signal Processing Techniques for Millimeter Wave MIMO Systems," IEEE J. Sel. Top. Signal Process., vol. 10, no. 3, pp. 436–453, Apr. 2016, doi: 10.1109/JSTSP.2016.2523924.

[10] R. He et al., "5G for Railways: Next Generation Railway Dedicated Communications," IEEE Commun. Mag., vol. 60, no. 12, pp. 130–136, Dec. 2022, doi: 10.1109/MCOM.005.2200328.

[11] M. de L. Á. L. Fernández and A. P. Yuste, "Positioning of High-Speed Trains Using 5G Networks," in 2024 IEEE International Mediterranean Conference on Communications and Networking (MeditCom), Jul. 2024, pp. 221–226. doi: 10.1109/MeditCom61057.2024.10621243.

[12] Z. Kljaić, D. Pavković, M. Cipek, M. Trstenjak, T. J. Mlinarić, and M. Nikšić, "An Overview of Current Challenges and Emerging Technologies to Facilitate Increased Energy Efficiency, Safety, and Sustainability of Railway Transport," Future Internet, vol. 15, no. 11, Art. no. 11, Nov. 2023, doi: 10.3390/fi15110347.

[13] W. Hamdi, C. Ksouri, H. Bulut, and M. Mosbah, "Network Slicing-Based Learning Techniques for IoV in 5G and Beyond Networks," IEEE Commun. Surv. Tutor., vol. 26, no. 3, pp. 1989–2047, 2024, doi: 10.1109/COMST.2024.3372083.

[14] J. Xu, Z. Wei, Z. Lyu, L. Shi, and J. Han, "Throughput Maximization of Offloading Tasks in Multi-Access Edge Computing Networks for High-Speed Railways," IEEE Trans. Veh. Technol., vol. 70, no. 9, pp. 9525–9539, Sep. 2021, doi: 10.1109/TVT.2021.3101571.

[15] P. Santhiya, I. J. Jebadurai, G. J. L. Paulraj, J. A, G. R. A, and S. K. Karan, "ITS-AI Integration: Enhanced Strategies for Mitigating Urban Traffic Congestion," in 2024 5th International Conference on Recent Trends in Computer Science and Technology (ICRTCST), Apr. 2024, pp. 376–381. doi: 10.1109/ICRTCST61793.2024.10578453.

[16] J. Zhao, X. Gao, Z. Wu, Q. Zhang, and H. Han, "Artificial intelligence in rail transit wireless communication systems: Status, challenges and solutions," Phys. Commun., vol. 67, p. 102484, Dec. 2024, doi: 10.1016/j.phycom.2024.102484.

[17] X. Gao, J. Zhao, Q. Zhang, and H. Han, "Optimization of resource allocation strategy for high-speed railway based on deep reinforcement learning," Phys. Commun., vol. 66, p. 102455, Oct. 2024, doi: 10.1016/j.phycom.2024.102455.

[18] A. Sinha, V. Uduthalapally, D. Das, and R. Mahapatra, "SDN-Based Seamless Mobility Management for B5G Services in High-Speed Railways," in 2023 IEEE International Conference on Advanced Networks and Telecommunications Systems (ANTS), Dec. 2023, pp. 294–299. doi: 10.1109/ANTS59832.2023.10469293.

[19] M. Fukuda, "Trend on Research and Development Relating to Information and Communication Technology in Railway Fields," Q. Rep. RTRI, vol. 64, no. 3, pp. 161–165, 2023, doi: 10.2219/rtriqr.64.3_161.

[20] C.-X. Wang et al., "On the Road to 6G: Visions, Requirements, Key Technologies, and Testbeds," IEEE Commun. Surv. Tutor., vol. 25, no. 2, pp. 905–974, 2023, doi: 10.1109/COMST.2023.3249835.

[21] "Integration of 5G, 6G and IoT with Low Earth Orbit (LEO) networks: Opportunity, challenges and future trends," Results Eng., vol. 23, p. 102409, Sep. 2024, doi: 10.1016/j.rineng.2024.102409.

[22] Y. Pan, R. Li, and C. Xu, "The First 5G-LTE Comparative Study in Extreme Mobility," Proc ACM Meas Anal Comput Syst, vol. 6, no. 1, p. 20:1-20:22, Feb. 2022, doi: 10.1145/3508040.

[23] S. Senger and P. K. Malik, "A comprehensive survey of massive-MIMO based on 5G antennas," Int. J. RF Microw. Comput.-Aided Eng., vol. 32, no. 12, p. e23496, 2022, doi: 10.1002/mmce.23496.

[24] K. Zarzycki and M. Ławryńczuk, "LSTM and GRU neural networks as models of dynamical processes used in predictive control: A comparison of models developed for two chemical reactors," Sensors, vol. 21, no. 16, p. 5625, Aug. 2021, doi: 10.3390/s21165625.

[25] W. Zhang, X. Li, A. Li, X. Huang, T. Wang, and H. Gao, "SGRU: A High-Performance Structured Gated Recurrent Unit for Traffic Flow Prediction," in 2023 IEEE 29th International Conference on Parallel and Distributed

Systems (ICPADS), Dec. 2023, pp. 467–473. doi: 10.1109/ICPADS60453.2023.00076.

[26] M. Waqas and U. W. Humphries, "A critical review of RNN and LSTM variants in hydrological time series predictions," MethodsX, vol. 13, p. 102946, Dec. 2024, doi: 10.1016/j.mex.2024.102946.

[27] J. Yang, J. Liu, J. Guo, and K. Tao, "Track Irregularity Identification Method of High-Speed Railway Based on CNN-Bi-LSTM," Sensors, vol. 24, no. 9, Art. no. 2861, Apr. 2024, doi: 10.3390/s24092861.

[28] D. Li, S. Du, and Y. Hou, "Long-Term Passenger Flow Forecasting for Rail Transit Based on Complex Networks and Informer," Sensors, vol. 24, no. 21, p. 6894, Jan. 2024, doi: 10.3390/s24216894.

[29] D. E. Ruíz-Guirola, O. L. A. López, S. Montejo-Sánchez, R. D. Souza, and M. Bennis, "Performance Analysis of ML-Based MTC Traffic Pattern Predictors," IEEE Wireless Communications Letters, vol. 12, no. 7, pp. 1144–1148, July 2023, doi: 10.1109/LWC.2023.3264273.

[30] K. Kosukegawa, Y. Mori, H. Suyari, and K. Kawamoto, "Spatiotemporal forecasting of vertical track alignment with exogenous factors," Sci Rep, vol. 13, no. 1, p. 2354, Feb. 2023, doi: 10.1038/s41598-023-29303-7.

[31] A. M. Fernandes, H. I. Del Monego, B. S. Chang, and A. Munaretto, "Reducing Unnecessary Handovers Using Logistic Regression in 5G Networks," IEEE Access, vol. 13, pp. 78707–78726, 2025, doi: 10.1109/ACCESS.2025.3564532.

[32] H. Ma, B. Lu, T. Zheng, K. Thar, and M. Gidlund, "A Gated-Guided Serial CNN-Transformer Network for High-Speed Railway Traffic Prediction," in 2025 IEEE 21st International Conference on Factory Communication Systems (WFCS), June 2025, pp. 1–8. doi: 10.1109/WFCS63373.2025.11077652.

[33] D. Pjanić, A. Sopasakis, A. Reial, and F. Tufvesson, "Early-Scheduled Handover Preparation in 5G NR Millimeter-Wave Systems," IEEE Open Journal of the Communications Society, vol. 5, pp. 6959–6971, 2024, doi: 10.1109/OJCOMS.2024.3488594.

[34] R. Jalalifar, M. R. Delavar, and S. F. Ghaderi, "SAC-ConvLSTM: A novel spatio-temporal deep learning-based approach for a short term power load forecasting," Expert Systems with Applications, vol. 237, p. 121487, Mar. 2024, doi: 10.1016/j.eswa.2023.121487.

[35] B. Duan, C. Li, J. Xie, W. Wu, and D. Zhou, "Fast Handover Algorithm Based on Location and Weight in 5G-R Wireless Communications for High-Speed Railways," Sensors, vol. 21, no. 9, Art. no. 9, Jan. 2021, doi: 10.3390/s21093100.

[36] Y. Zhou and B. Ai, "Handover schemes and algorithms of high-speed mobile environment: A survey," Computer Communications, vol. 47, pp. 1–15, July 2014, doi: 10.1016/j.comcom.2014.04.005.

[37] GSMA, "Generic Network Slice Template," Permanent Reference Document NG.116, Version 9.0, Apr. 2023. [Online]. Available: https://www.gsma.com/newsroom/wp-content/uploads/NG.116-v9.0-1.pdf

[38] M. Khani, S. Jamali, M. K. Sohrabi, M. M. Sadr, and A. Ghaffari, "Slice admission control in 5G cloud radio access network using deep reinforcement learning: A survey," International Journal of Communication Systems, vol. 37, no. 13, p. e5857, 2024, doi: 10.1002/dac.5857.

[39] Y. Ullah et al., "A survey on AI-enabled mobility and handover management in future wireless networks: key technologies, use cases, and challenges," J. King Saud Univ. Comput. Inf. Sci., vol. 37, no. 4, p. 47, May 2025, doi: 10.1007/s44443-025-00048-9.

[40] H. Malekpoor and M. Hamidkhani, "Radiation Improvement of Low-Profile Microstrip Antenna by Utilizing AMC Surface for MIMO and Wireless Systems," International Journal of Industrial Electronics Control and Optimization, vol. 8, no. 2, pp. 129–136, June 2025, doi: 10.22111/ieco.2024.48644.1561.

Shahpour Rahmani is a Lecturer at the Department of Computer Science, University of Sistan and Baluchestan, Zahedan, Iran. He received the B.S. degree in applied mathematics in computer science from the University of Sistan and Baluchestan, Zahedan, Iran, in 1996, and the M.S. degree in computer (software) engineering from the Iran University of Science and Technology, Tehran, Iran, in 2008, and is currently working toward the Ph.D. degree in the School of Electrical and Computer Engineering, University of Tehran, Tehran, Iran. He joined the Router Laboratory and the Wireless Communication Research Group, University of Tehran, Tehran, Iran, in 2017, as a Research Assistant. His research interests include 5G/6G networks, machine learning for mobility management, high-speed railway communications, Low Earth Orbit (LEO) satellite networking, distributed systems, data science, routing protocols, and data center design.

Nasser Yazdani is a full professor at the Department of Electrical and Computer Engineering in Tehran University. He got his B.S. degree in Computer Engineering from Sharif University of Technology, Tehran, Iran. He worked in Iran Telecommunication Research Center (ITRC) as a consultant, researcher and developer for few years. To pursue his education, he entered Case Western Reserve Univ, Cleveland, Ohio, USA, later and graduated as a Ph.D. in Computer Science and Engineering. Then, Prof. Yazdani worked in different companies and research institutes in USA. He joined the ECE Dept. of Univ. of Tehran, Tehran, Iran, in Sep. 2000. Prof. Yazdani then initiated different research projects and Labs in high-speed networking and systems. His research interests include networking, packet switching, access methods, distributed systems and database systems