

Artificial Neural Network-Assisted Remote Radio Control for Adaptive Data Transmission Optimization in Wireless Communication Networks

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Abstract

The increasing heterogeneity, traffic intensity, and dynamic operating conditions of modern wireless communication networks limit the effectiveness of conventional fixed radio-control strategies. This study develops an Artificial Neural Network (ANN)-assisted Remote Radio Control (RRC) framework for adaptive optimization of wireless data transmission. The proposed framework was implemented and evaluated using MATLAB R2021a/Simulink. A conventional wireless network model was characterized using throughput, signal-to-interference-plus-noise ratio (SINR), bit error rate (BER), packet delivery ratio (PDR), and latency. The characterized network parameters were subsequently used as feedback inputs to the ANN controller for adaptive radio-control decisions. Simulation parameters included a 2.4 GHz carrier frequency, 20 MHz bandwidth, 23 dBm transmit power, QPSK modulation, coding rate of 1/2, 1024-bit packets, 20 users, and an additive white Gaussian noise (AWGN)-plus-multipath channel. Results indicate that ANN-assisted RRC improved throughput from 2.00 to 2.60 Mbps (30.0%) and SINR from 4.70 to 6.11 dB (approximately 30.0%). BER decreased from 0.00053 to 0.00046 (13.2%), while PDR increased from 65.0% to 84.5%, representing a 30.0% relative improvement. Furthermore, latency decreased from 114.4 to 88.0 ms, corresponding to a 23.08% reduction. These findings demonstrate the potential of ANN-assisted RRC to enhance multiple wireless-network performance indicators simultaneously. The proposed simulation framework provides a foundation for intelligent radio control in evolving 5G, beyond-5G, and 6G communication networks.

Keywords: artificial neural network; adaptive radio control; remote radio control; wireless communication; throughput; SINR; packet delivery ratio; latency

1 Introduction

1.1 Background

Wireless communication networks support mobile broadband, the Internet of Things (IoT), industrial automation, intelligent transportation, and emerging 5G/6G applications. Increasing traffic demand and connected devices create challenges involving interference, variable channel conditions, limited spectrum, throughput, reliability, and latency. Conventional radio-control approaches rely on fixed parameters and predefined rules, limiting adaptability under dynamic conditions. Machine learning (ML) offers an alternative by learning relationships between network conditions and resource-management decisions (Pivoto *et al.*, 2025). AI-enabled resource management is increasingly investigated for channel allocation, power control, user association, and other 6G network functions (Alhashimi *et al.*, 2025). Similarly, ML-based approaches address competing objectives, including throughput, latency, energy efficiency, and reliability (Liaq *et al.*, 2025). Artificial neural

networks (ANNs) are suitable for adaptive radio control because they learn nonlinear relationships between network conditions and control actions. By processing throughput, SINR, BER, PDR, and latency measurements, an ANN controller can support decisions that improve wireless-network performance. Recent studies have explored learning-based radio-resource scheduling for RAN slicing (Nahum *et al.*, 2024), cell-free massive-MIMO systems, and autonomous sidelink resource management in C-V2X networks (Trabelsi *et al.*, 2024). Learning-based allocation has also been investigated for ultra-reliable low-latency communications (Zhang *et al.*, 2024) and D2D-enabled cellular networks (Kamruzzaman *et al.*, 2024). Frank *et al.* (2024) reported better prediction accuracy for a multilayer perceptron than a decision-tree model. Furthermore, Sherif *et al.* (2025) investigated deep reinforcement learning and transfer learning for dynamic radio-resource management in Open RAN slicing, considering latency, reliability, power consumption, and QoS. Despite these advances, many studies focus on specialized environments, including vehicular networks, massive MIMO, D2D communication, and Open RAN. Therefore, a simple, reproducible ANN-assisted Remote Radio Control (RRC) framework is valuable for linking conventional network characterization with adaptive control and measurable performance improvements.

1.2 Related works

Recent studies demonstrate the growing role of AI and ML in intelligent wireless-resource management. Pivoto *et al.* (2025), Liaq *et al.* (2025), Alhashimi *et al.* (2025), and Kori *et al.* (2025) reviewed learning-based approaches for resource allocation, scheduling, power control, and optimization of throughput, latency, and energy efficiency. Trabelsi *et al.* (2024) investigated deep reinforcement learning for dynamic C-V2X resource management, while Nahum *et al.* (2024) explored intent-aware reinforcement-learning-based radio scheduling. Other studies examined learning-based scheduling in cell-free massive MIMO, predictive access-point management (Frank *et al.*, 2024), and reinforcement-learning-based resource optimization for industrial 5G camera systems (Szabó & Pető, 2024). Neural-network methods have also addressed resource allocation under URLLC reliability constraints (Zhang *et al.*, 2024), while graph neural networks have improved the scalability and computational efficiency of bandwidth allocation (Hao *et al.*, 2024). Sherif *et al.* (2025) investigated deep reinforcement learning and transfer learning for Open RAN slicing. Further studies highlighted distributed machine learning and AI-native architectures as foundations for autonomous, adaptive wireless networks (Chen *et al.*, 2023; Muhammad & Tabassum, 2024). Despite these advances, existing approaches frequently emphasize specialized applications or complex learning and optimization techniques. This study therefore develops a transparent ANN-assisted Remote Radio Control framework that uses measurable network-performance indicators to support adaptive radio-control decisions.

1.3 Research gap and objective of the study

Despite advances in learning-based wireless-resource management, many existing studies focus on specialized network environments or computationally demanding reinforcement-learning techniques. There remains a need for a simple, reproducible framework that integrates conventional network characterization, Artificial Neural Network (ANN) learning, and adaptive Remote Radio Control (RRC). This study therefore develops an ANN-assisted RRC framework using throughput, SINR, BER, PDR, and latency as measurable network-performance indicators. Its specific objectives are to characterize conventional wireless-network performance, develop a MATLAB/Simulink model, train an ANN using characterized data, implement adaptive radio control, integrate the ANN and RRC into a unified simulation framework, and evaluate performance improvements against conventional radio control.

2 Methodology

2.1 Research design

A simulation-based experimental design was implemented in MATLAB R2021a/Simulink using conventional wireless communication and ANN-assisted Remote Radio Control (RRC) models. The conventional model established baseline performance, while its measured metrics trained the ANN controller to determine adaptive radio-control actions. Both models were subsequently evaluated and compared.

2.2 System input parameters

The principal simulation parameters are presented in Table 1.

Table 1. Principal simulation parameters.

Parameter	Symbol	Value
Carrier frequency	f_c	2.4 GHz
Channel bandwidth	B	20 MHz
Transmit power	P_t	23 dBm
Receiver noise figure	NF	5 dB
Thermal noise density	N_0	-174 dBm/Hz
Modulation	M	QPSK
Coding rate	R_c	1/2
Packet size	L_p	1024 bits
Data rate	R_d	2 Mbps
Number of users	N_u	20
Simulation duration	T_s	100 s
Channel	—	AWGN + multipath

The 2.4-GHz carrier and 20-MHz bandwidth define the operating frequency and spectrum. The baseline uses 23-dBm transmit power, QPSK modulation, and a 1/2 coding rate. Twenty simultaneous users model network contention, while the AWGN-plus-multipath channel represents noisy, frequency-selective propagation.

2.3 Conventional wireless communication model

The first model shown in Figure 1 exemplifies a conventional wireless network in which the principal radio parameters remain fixed during the baseline simulation.

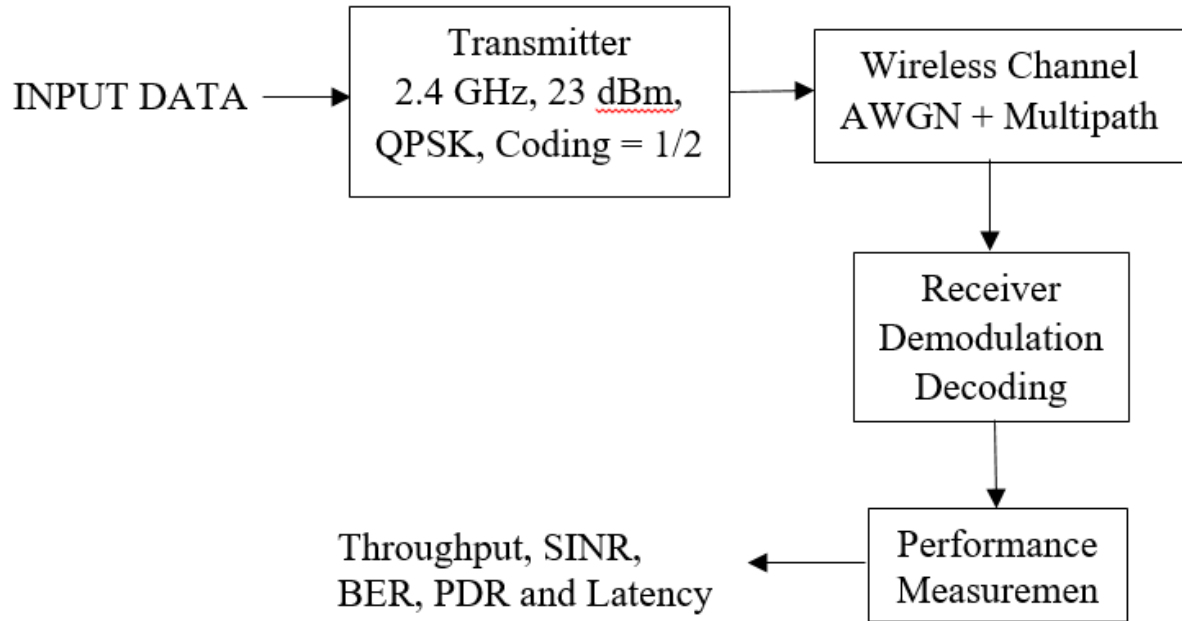


Figure 1. Conventional wireless communication architecture.

The baseline model establishes the performance against which the ANN-RRC system is evaluated.

2.4 Performance characterization

Five key performance indicators are considered.

2.4.1 Throughput

Throughput represents the successfully transmitted data per unit time:

$$T = \frac{D_s}{t_t} \quad (1)$$

where D_s is the amount of successfully transmitted data and t_t is the transmission time.

2.4.2 Signal-to-interference-plus-noise ratio

$$SINR = \frac{P_s}{P_i + P_n} \quad (2)$$

where P_s is the desired signal power, P_i is the interference power and P_n is the noise power.

2.4.3 Bit error rate

$$BER = \frac{N_e}{N_t} \quad (3)$$

where N_e is the number of erroneous bits and N_t is the total number of transmitted bits.

2.4.4 Packet delivery ratio

$$PDR = \frac{N_{p,r}}{N_{p,t}} \times 100 \quad (4)$$

where $N_{p,r}$ is the number of successfully received packets and $N_{p,t}$ is the number of transmitted packets.

2.4.5 Latency

$$L = t_r - t_s \quad (5)$$

where t_s is the packet transmission time and t_r is the packet reception time.

2.5 ANN-based network-state representation

The network-state vector is defined as:

$$x = [T, SINR, BER, PDR, L]^T \quad (6)$$

For the conventional baseline, the state vector is:

$$x_c = [2.00, 4.70, 0.00053, 65.0, 114.4]^T$$

Before ANN training, the variables are normalized to prevent variables with larger numerical magnitudes, such as latency and PDR, from dominating smaller variables such as BER.

A min-max normalization may be expressed as:

$$x_n = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (7)$$

where x_n is the normalized value.

2.6 ANN architecture

A feed-forward multilayer perceptron is adopted for the control function (Figure 2).

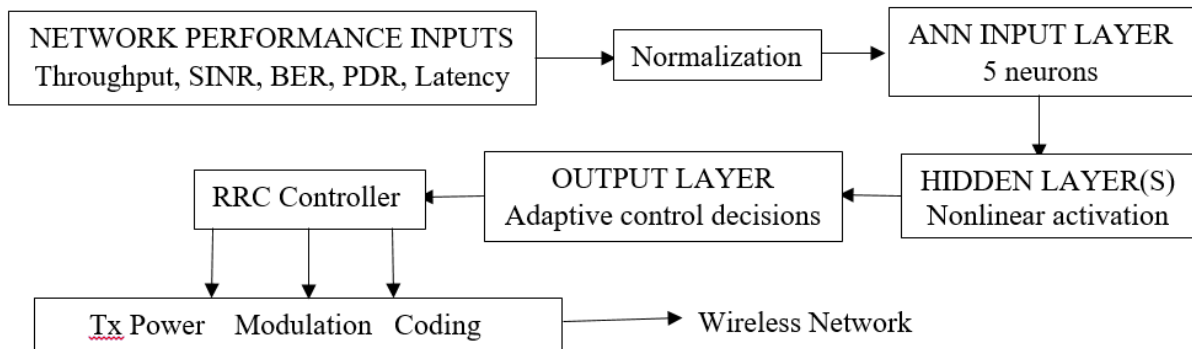


Figure 2. ANN-assisted RRC architecture.

2.7 Mathematical ANN model

For an ANN with input vector x , the hidden-layer output is:

$$h = \phi(W_1 x + b_1) \quad (8)$$

where W_1 is the input-to-hidden weight matrix, b_1 is the hidden-layer bias and ϕ is the nonlinear activation function. The output layer is:

$$u = g(W_2 h + b_2) \quad (9)$$

where W_2 is the hidden-to-output weight matrix, b_2 is the output bias and g is the output activation function. The ANN output vector represents the radio-control decision:

$$u = [P_t, G_r, M, R_c, C]^T \quad (10)$$

where P_t represents transmit power, G_r receiver gain, M modulation, R_c coding rate and C channel/tuner selection. The control decision can therefore be represented as:

$$u = F_{ANN}(T, SINR, BER, PDR, L) \quad (11)$$

2.8 Remote radio control mechanism

The ANN output is connected to the RRC block. The RRC interprets the ANN decision and adjusts the available radio parameters. The integrated ANN-RRC control loop is shown in Figure 3.

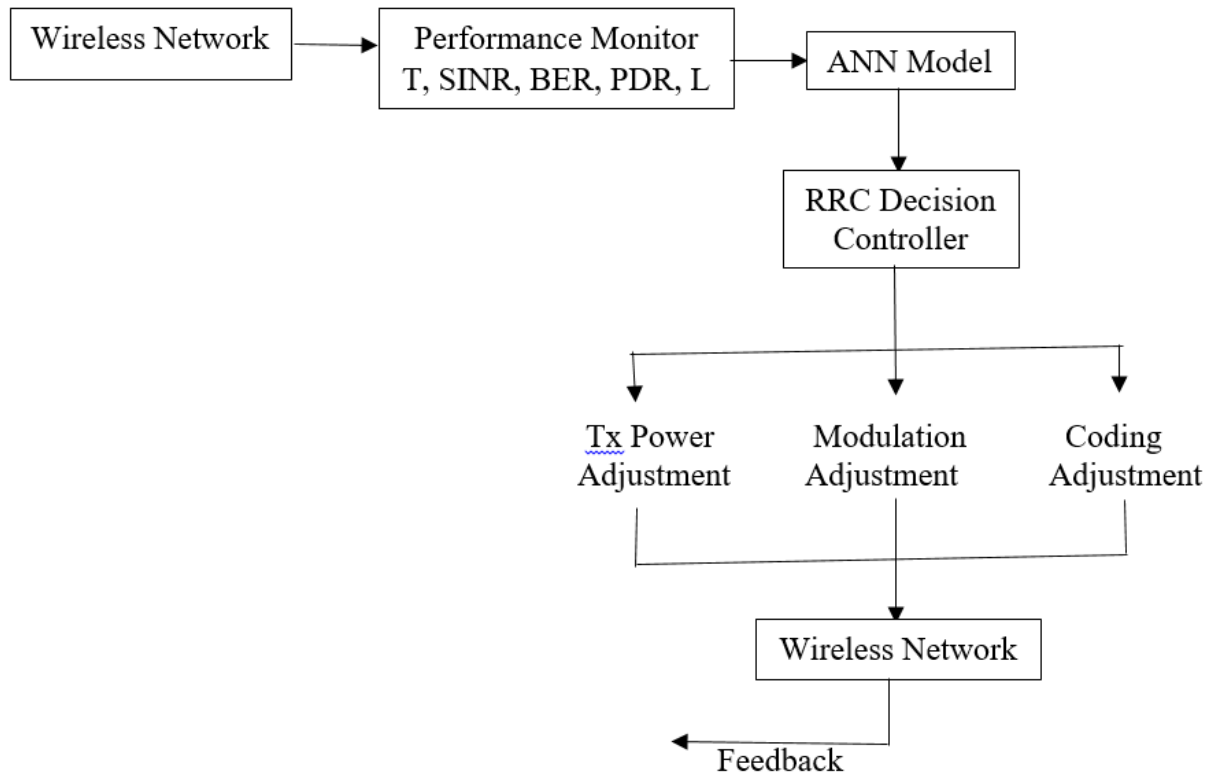


Figure 3. Integrated ANN-RRC control loop.

The structure in Figure 3 forms a closed-loop control mechanism.

2.9 Control objective

The ANN-RRC controller is designed to improve the overall network condition rather than optimize only one metric.

A normalized multi-objective cost function can be represented as:

$$J = w_T J_T + w_S J_S + w_B J_B + w_P J_P + w_L J_L \quad (12)$$

where w_T , w_S , w_B , w_P and w_L are weighting factors. For higher-is-better parameters:

$$J_T = \frac{\max(0, T_{th} - T)}{T_{th}} \quad (13)$$

$$J_S = \frac{\max(0, SINR_{th} - SINR)}{SINR_{th}} \quad (14)$$

$$J_P = \frac{\max(0, PDR_{th} - PDR)}{PDR_{th}} \quad (15)$$

For BER and latency, where lower values are desirable:

$$J_B = \frac{BER}{BER_{th}} \quad (16)$$

$$J_L = \frac{L}{L_{th}} \quad (17)$$

The RRC seeks control actions that reduce J, subject to available radio-parameter constraints.

2.10 Algorithm

Algorithm 1. ANN-assisted remote radio control

1. Initialize wireless-network parameters.
2. Generate/transmit data packets.
3. Pass signals through AWGN + multipath channel.
4. Receive and decode transmitted packets.
5. Calculate throughput, SINR, BER, PDR and latency.
6. Normalize the characterized metrics.
7. Feed normalized metrics to the ANN.
8. ANN estimates the appropriate radio-control action.
9. RRC adjusts available radio parameters.
10. Repeat network transmission under the selected settings.
11. Recalculate performance metrics.
12. Compare conventional and ANN-RRC performance.
13. Compute percentage improvement/reduction.
14. Store results and terminate after the simulation period.

3 Results and discussion

3.1 Baseline and ANN-RRC performance

The simulation produced the results presented in Table 2.

Table 2. Comparative performance results.

Performance metric	Conventional control	ANN-RRC	Change	Improvement
Throughput (Mbps)	2.00	2.60	+0.60	30.00% ↑
SINR (dB)	4.70	6.11	+1.41	30.00% ↑
BER	0.00053	0.00046	-0.00007	13.21% ↓
PDR (%)	65.0	84.5	+19.5 pp	30.00% relative ↑
Latency (ms)	114.4	88.0	-26.4 ms	23.08% ↓

pp = percentage points; ↑ = improvement (increase); ↓ = improvement (reduction).

The percentage improvement was calculated as follows, where X represents the metric values:

$$I = \frac{X_{RRC} - X_C}{X_C} \times 100\% \quad (18)$$

for higher-is-better parameters, while the percentage reduction was calculated as:

$$R = \frac{X_C - X_{RRC}}{X_C} \times 100\% \quad (19)$$

for BER and latency.

3.2 Throughput performance

Throughput increased from 2.00 Mbps under conventional control to 2.60 Mbps under ANN-RRC (Figure 4).

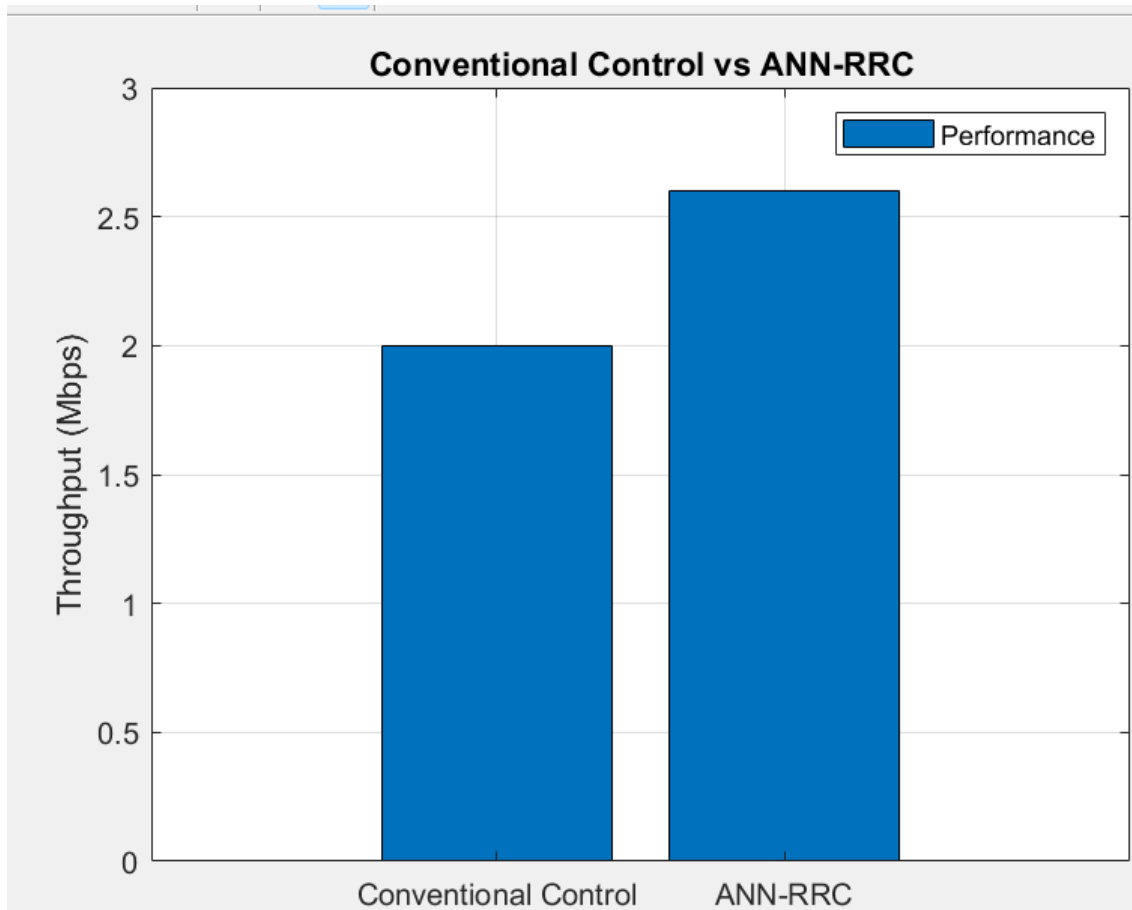


Figure 4. Throughput: conventional control vs ANN-RRC.

The 0.60-Mbps increase corresponds to a 30.0% improvement. The result indicates that adaptive radio control was able to select operating conditions that supported more successful data transmission than the fixed conventional configuration. This finding is consistent with recent research showing that learning-based resource management can improve data-rate and resource-utilization objectives in wireless networks (Pivoto *et al.*, 2025; Liaq *et al.*, 2025).

3.3 SINR performance

SINR increased from 4.70 dB to 6.11 dB (Figure 5), representing an improvement of approximately 30.0%.

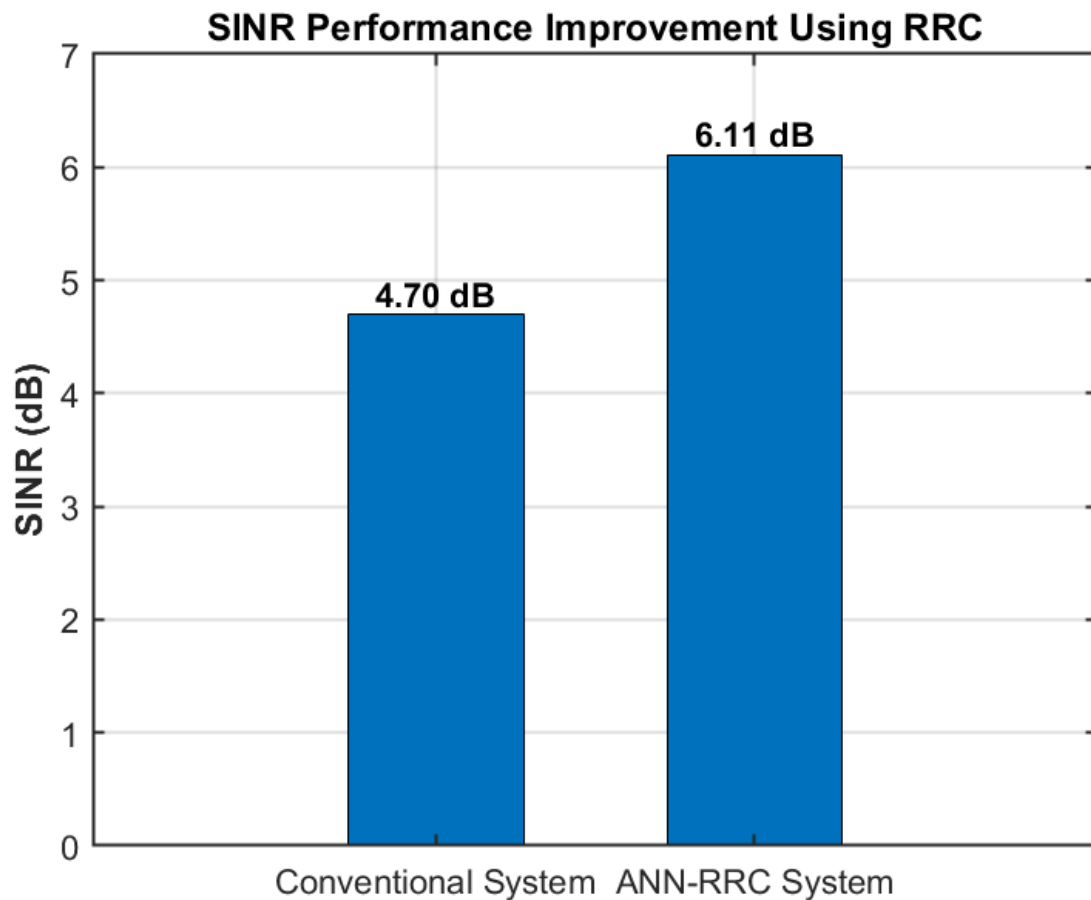


Figure 5. SINR improvement using ANN-RRC.

The increase indicates improved received signal quality relative to interference and noise. Since SINR directly influences successful demodulation and packet reception, its improvement provides a technical explanation for the corresponding improvements in BER, PDR and throughput. Learning-based resource allocation studies similarly identify signal quality and interference management as important control objectives in dynamic wireless environments.

3.4 BER performance

BER decreased from 0.00053 to 0.00046 (Figure 6).

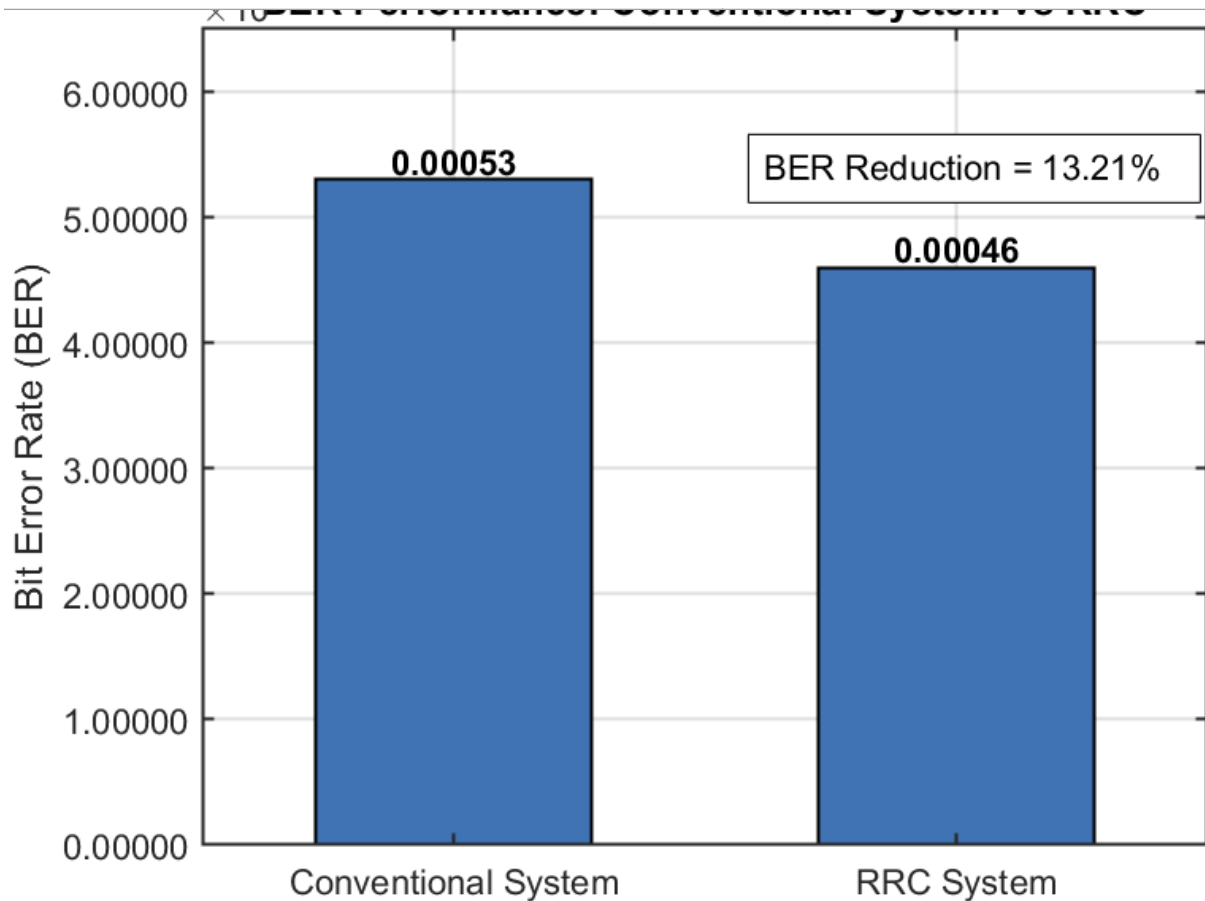


Figure 6. BER performance using ANN-RRC.

The RRC system reduced the BER from 0.00053 to 0.00046, representing a 13.21% reduction in bit errors relative to the conventional system. This indicates improved transmission reliability, assuming both values were obtained under comparable simulation conditions.

3.5 Packet delivery ratio

PDR increased from 65.0% to 84.5% (Figure 7), an absolute increase of 19.5 percentage points.

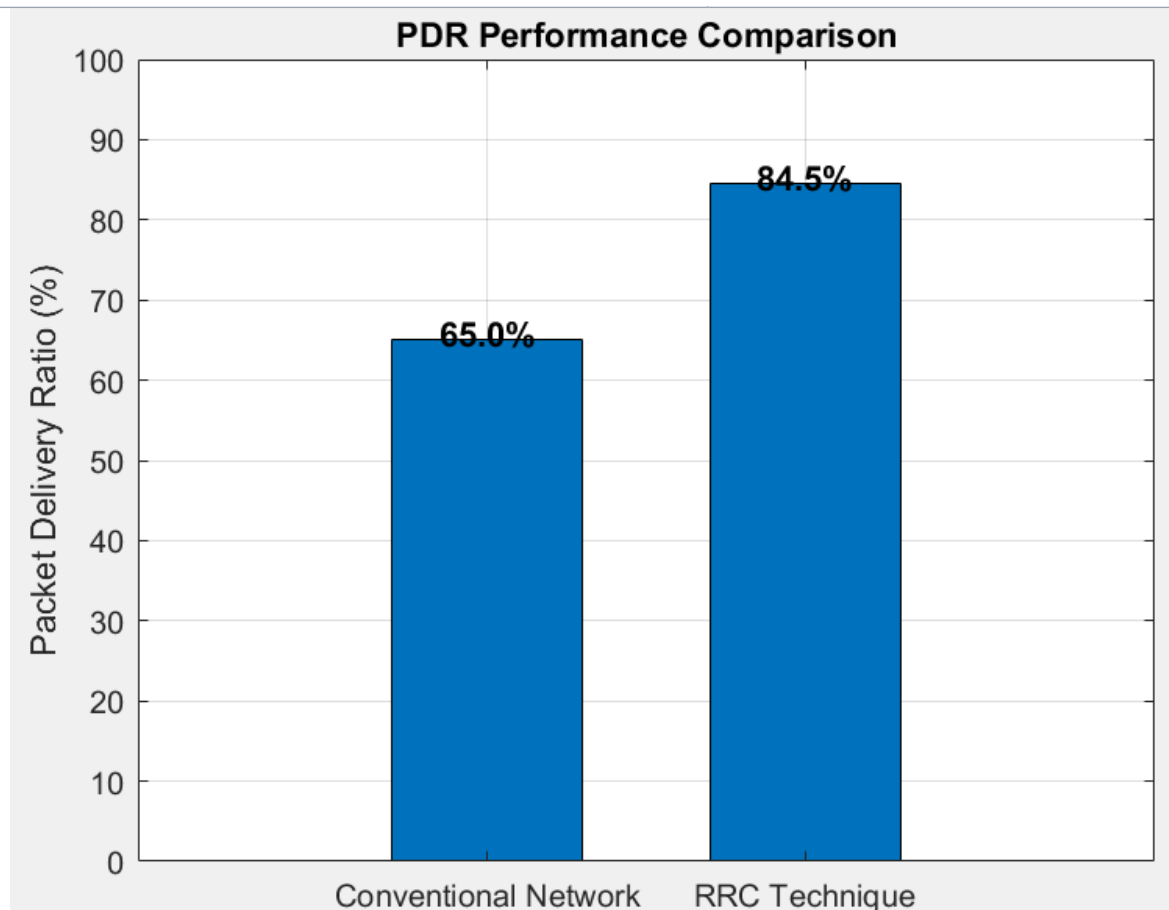


Figure 7. PDR performance comparison.

The relative improvement is:

$$\frac{84.5 - 65}{65} \times 100 = 30.0\%$$

Therefore, the ANN-RRC method provides a 30.0% relative PDR improvement, while the absolute gain is 19.5 percentage points. The distinction is important because percentage-point change and relative percentage improvement are not identical.

The increase in PDR is significant from a communication-system perspective because successful packet delivery is directly related to application-level reliability. Recent intelligent-resource-management studies similarly identify reliability and QoS satisfaction as important outcomes of adaptive network control.

3.6 Latency performance

Latency decreased from 114.4 ms to 88.0 ms (Figure 8).

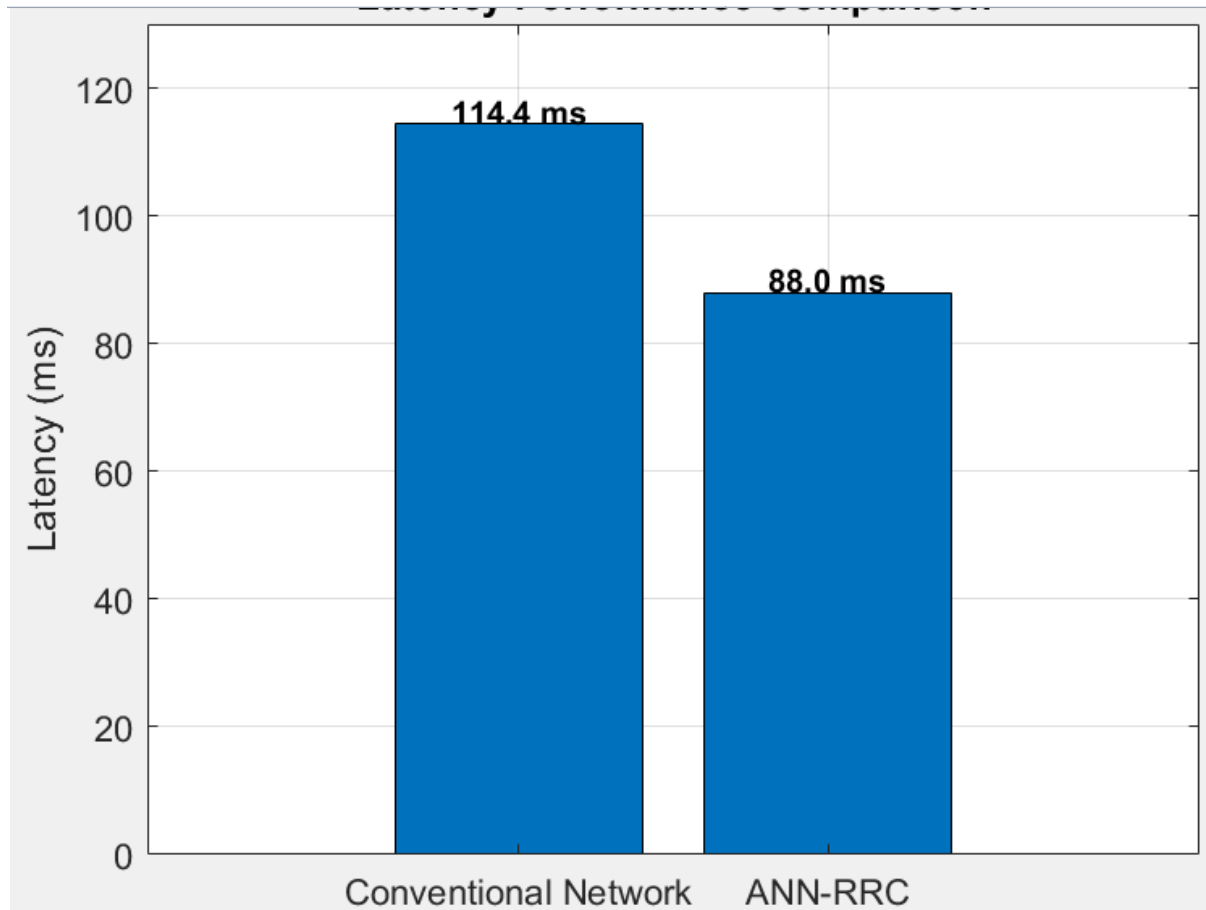


Figure 8. Latency comparison.

The percentage reduction is:

$$\frac{114.4 - 88}{114.4} \times 100\% = 23.08\%$$

Therefore, ANN-RRC achieved a 23.08% latency reduction.

This result is important because latency is a lower-is-better metric. The reduction indicates that the adaptive controller did not merely maximize throughput at the expense of delay. Instead, the proposed system produced simultaneous improvement in throughput and reduction in latency. Such multi-objective behaviour is particularly relevant to 5G/6G applications with stringent delay requirements. Recent AI-enabled resource-management research similarly identifies latency as a central optimization objective.

3.7 Overall performance improvement

The improvements are summarized in Table 3, Figure 9 and Figure 10.

Table 3. Summary of ANN-RRC improvement.

Metric	Conventional	ANN-RRC	Direction	Improvement
Throughput	2.00 Mbps	2.60 Mbps	Higher	30.00%
SINR	4.70 dB	6.11 dB	Higher	30.00%
BER	0.00053	0.00046	Lower	13.21% reduction

Metric	Conventional	ANN-RRC	Direction	Improvement
PDR	65.0%	84.5%	Higher	30.00% relative
Latency	114.4 ms	88.0 ms	Lower	23.08% reduction

The results show that the proposed ANN-RRC framework improved all five selected performance indicators. Throughput and SINR increased, while BER and latency decreased and PDR increased.

The result is particularly significant because improvement was not restricted to a single metric. A radio-control technique that increases throughput while simultaneously increasing BER or latency would provide limited practical benefit. In contrast, the present results indicate a more balanced improvement across reliability, quality, delivery rate, data rate and delay.

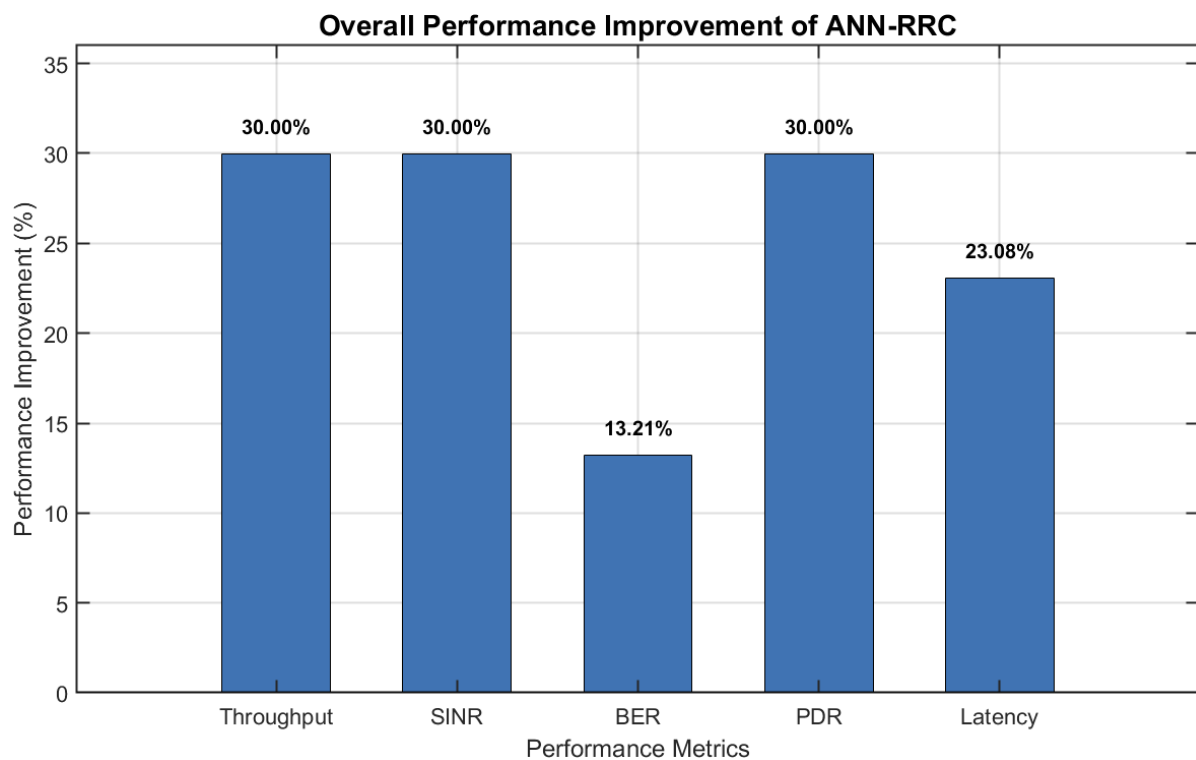


Figure 9. Overall comparative performance.

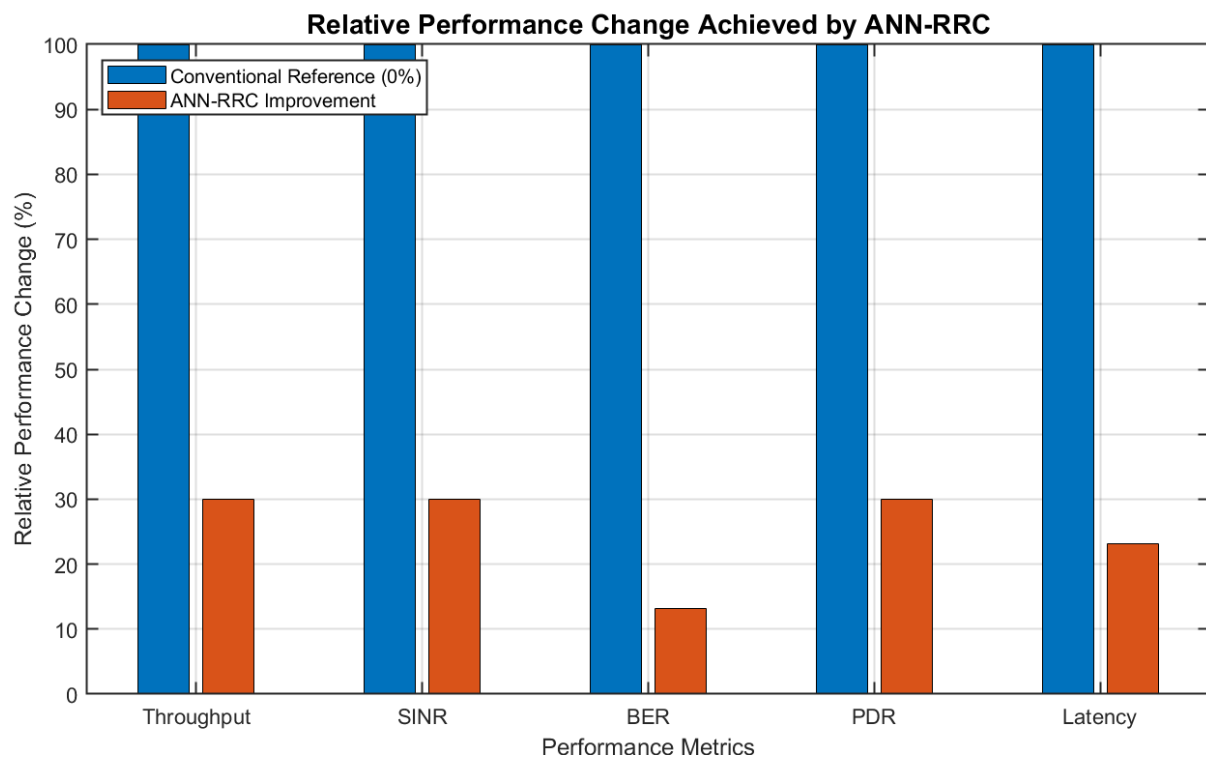


Figure 10. Relative improvement achieved by ANN-RRC (relative percentage improvement or reduction for each performance metric; BER and latency are expressed as reductions).

The comparative results support the premise that an ANN can be used as an adaptive decision mechanism for radio control. The approach is also consistent with the broader direction of intelligent wireless networking, where ML is increasingly being used to address complex resource-allocation and network-control problems (Alhashimi *et al.*, 2025; Pivoto *et al.*, 2025).

3.8 Discussion of findings in relation to recent literature

The 30% throughput improvement supports findings that ML enhances wireless resource allocation and optimization (Pivoto *et al.*, 2025; Liaq *et al.*, 2025). Improved SINR aligns with learning-based interference management and scheduling studies in D2D and cell-free massive-MIMO networks. The PDR increase addresses reliability challenges identified in dynamic C-V2X resource management (Trabelsi *et al.*, 2024), while the 23.08% latency reduction supports AI/ML applications in latency-sensitive and ultra-reliable low-latency communications (URLLC).

Compared with complex DRL and GNN approaches, the proposed ANN-assisted RRC offers a relatively transparent, reproducible simulation framework linking measured network performance to adaptive control decisions. However, its simulated improvements require further validation under realistic channel conditions and field deployment.

4 Conclusion

This study developed an ANN-assisted Remote Radio Control (RRC) framework in MATLAB R2021a/Simulink for adaptive wireless data transmission. The system integrated network characterization, ANN-based decision-making, and adaptive radio control. Results showed that throughput increased from 2.00 to 2.60 Mbps (30.0%), while SINR improved from 4.70 to 6.11 dB (approximately 30.0%). BER decreased from 0.00053 to 0.00046 (13.2%), PDR increased from 65.0% to 84.5% (19.5 percent-

age points; 30.0% relative improvement), and latency decreased from 114.4 to 88.0 ms (23.08%). These findings demonstrated the potential of ANN-assisted RRC to improve data rate, signal quality, and packet reliability while reducing errors and delay. The framework provides a foundation for intelligent 5G, beyond-5G, and 6G network management. Future work should investigate diverse channel conditions, user mobility, online learning, hardware implementation, and comparisons with advanced AI controllers.

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