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Article

Intelligent Slice-Aware Routing with Dynamic Coverage Optimization in 5G and Beyond 5G Internet of Things

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Abstract: 5G and Beyond 5G (B5G) networks are enabling massive Internet of Things (IoT) connectivity. Traditional routing methods used in such networks operate independently on the real-time coverage and network slicing requirements, which leads to higher latency, packet loss, and energy inefficiency. This study proposes a Coverage-Conditioned Slice-Aware Routing Framework (CC-SARF) that optimally solves routing decisions and coverage reliability in dynamic 5G and B5G IoT systems. The suggested framework incorporates real-time network monitoring to gather cross-layer terms that characterize node mobility, link quality, traffic load, and energy levels. These observations are processed by Graph Transformer to learn spatial-temporal relationships to forecast coverage confidence and connection reliability. A slice-aware Deep Reinforcement Learning agent identifies the most optimal next-hop nodes to meet the QoS criteria. Delivery performance is then fed back into the learning loop that allows constant adaptation and better routing decisions within the changing network conditions. Simulation results demonstrate that CC-SARF significantly improves routing stability and QoS satisfaction compared with conventional methods, achieving minimal latency of 0.211 ms, higher packet delivery ratio of 99.60%, and improved energy consumption of 0.317 J in dense and dynamic IoT deployments. Thus, the approach provides a scalable and intelligent routing solution for next-generation 5G and B5G IoT networks.
Keywords: 5G, Coverage, Deep Reinforcement Learning, Graph Transformer, Internet of Things, Quality of Service, Slice-aware routing.

1. Introduction

The rapid evolution of 5G and Beyond 5G (B5G) networks has opened a new era of connectivity, allowing the seamless integration of heterogeneous Internet of Things (IoT) devices across different areas such as smart cities, industrial automation, healthcare monitoring, and intelligent transportation systems [1, 2]. These network offers distinctive features such as ultra-low latency, very high connectivity, and data rates [3]. This plays a major role in facilitating emerging applications such as autonomous vehicles, remote surgery, real-time environmental monitoring, and massive industrial IoT [4]. Unlike the previous generation of wireless networks, 5G and B5G introduce network slicing [5]. This enables the physical network resources to be logically divided to satisfy diverse Quality of Service (QoS) needs, ranging from Ultra-Reliable Low-Latency Communications (URLLC) to massive Machine-Type Communications (mMTC) and enhanced Mobile Broadband (eMBB) [6-8]. Despite these developments, the deployment of 5G and B5G IoT networks is hindered by the mobility of the device, environmental dynamics, heterogeneous traffic patterns, and resource limitations [9, 10]. The complex propagation of millimeter-wave and sub-6 GHz frequencies further sustains constant coverage and reliable communication links [11]. In addition, maintaining several network slices with different service demands significantly increases the complexity of routing, resource allocation, and network management [12, 13]. These challenges show the needs of intelligent mechanisms that can adapt to highly dynamic 5G and B5G IoT environment while providing efficient, reliable and slice-aware operation [14, 15].

Recently, extensive research efforts have focused on intelligent routing strategies for 5G and B5G networks [16]. For example, a deep learning-enabled routing system integrated with mmWave 5G network slicing has been introduced to improve IoT communication efficiency [17]. Similarly, a secure data exchange framework based on blockchain and garlic-routing has been introduced to secure MTC in B5G IoT settings [18]. Moreover, generative learning methods including the Progressive Recurrent Generative Adversarial Network (PRGAN) have been explored to facilitate the optimal and reliable data routing in wireless 5G systems [19]. Although these methods demonstrate improvements in security, reliability, and intelligent routing, several limitations remain [20]. The majority of existing studies use the fixed or geometry-based coverage models that fail to capture variations in real-time dynamics due to mobility, interference, and beamforming dynamics, as well as traffic load in 5G and B5G settings [21].

Routing decisions are usually performed without considering coverage reliability, allowing the selection of low-confidence or unreliable links that compromise end-to-end performance [22]. Also, traditional routing and coverage optimization processes are typically unaware of network slicing demands [23]. The heterogeneous QoS requirements of URLLC, mMTC, and eMBB services are often optimized with dynamic coverage requirements [24]. Existing solutions suffer from limited scalability in extensive heterogeneous IoT deployments and lack predictive and adaptive intelligence demands for highly dynamic network applications [25]. To address these, the proposed work develops an intelligent routing framework for dynamic 5G and B5G IoT networks that integrates real-time coverage conditions and slice-specific QoS requirements using AI-driven spatio-temporal modeling and multi-objective Reinforcement Learning (RL). The key contributions of this work are as follows:

- **Coverage-Conditioned Routing of Dynamic 5G and B5G IoT Networks:** The proposed work introduces a Coverage-Conditioned Slice-Aware Routing Framework (CC-SARF) that combines real-time coverage confidence estimation and reliability-aware path selection to prevent unstable links to enhance communication stability with mobility, interference, and energy constraints.
- **Graph Transformer-Based Coverage Prediction:** The presented work employs a Graph Transformer (GT) to learn spatial-temporal coverage prediction that reflects the interference coupled, mobility dynamics, and link reliability pattern, providing real-time prediction of node coverage confidence and link reliability.
- **Slice-Aware Multi-Objective DRL Routing Optimization:** This work utilizes a multi-objective Deep Reinforcement Learning (DRL) model that simultaneously optimizes the reliability, latency, and energy consumption while dynamically adjusting to QoS demands of URLLC, mMTC, and eMBB network slices.
- **Scalable and Adaptive Closed-Loop Learning Framework:** Designed a real-time feedback-based continuous learning system that enables scalable, energy-efficient, and QoS routing of dense and heterogeneous IoT networks.

The paper is organized as follows: Section 2 analyzes the existing work related to coverage modeling and slicing-based routing, Section 3 describes the proposed CC-SARF, Section 4 analyzes the results of the experiment, followed by the discussion, and Section 5 concludes the paper.

2. Related Work

This section analyzes existing approaches for coverage modeling and prediction and network slicing based routing in 5G and B5G IoT networks.

2.1 Coverage Modeling and Prediction in Wireless Networks

Nematzadeh et al. [26] developed an efficient metaheuristic-based Mutant-grey wolf optimizer (MuGWO) for maximizing coverage and maintaining connectivity in Wireless Sensor Network (WSN). This enhanced resource utilization, coverage rate, and data transmission. However, the model had high computational complexity for large-scale networks, and the performance may degrade under dynamic or real-time network conditions.

Huang et al. [27] jointly maximized visual coverage and minimized energy consumption for Unmanned Aerial Vehicle (UAV)-aided 5G and B5G networks by formulating a Multi-objective optimization problem. This approach achieved extended coverage with high energy efficiency, but the assumption of static network conditions could not adapt to real-time variation.

Chaturvedi et al. [28] utilized a Machine Learning (ML)-based approach for predicting the activation status of WSN nodes based on coverage probability and trust values. This approach achieved high prediction accuracy with lower computational cost, enabling efficient formation of reliable set covers for WSN monitoring. Nevertheless, the model performance was highly dependent on training data quality and generalization to unseen network topologies.

In the same way, Nagamani et al. [29] used different ML and Deep Learning (DL) algorithms to predict 5G network coverage areas using radio frequency signal measurements. This system achieved high accuracy across diverse locations and scenarios. However, the approach requires large volumes of labeled radio frequency data and may struggle to adapt to rapidly changing environmental conditions.

Saoud et al. [30] introduced a coverage optimization model of a trustworthy UAV-Assisted 5G/6G communication systems through a probabilistic Line-Of-Sight (LOS) model. This greatly improved the coverage under signal strength and spectral efficiency conditions. Nevertheless, the model was based on simplified environmental assumption that was not able to adequately represent complex urban or heterogeneous terrain.

2.2 Network Slicing and QoS Aware Routing

Abdellatif et al. [31] designed an intelligent network slicing framework 5G-and-Beyond 5G networks that jointly optimized computing and networking resources while satisfying diverse Key Performance Indicator (KPI). This framework enhanced overall network performance by providing holistic, KPI-aware resource allocation across heterogeneous services. Nevertheless, the model performance could degrade when operating under incomplete or imperfect network state information. Chen et al. [32] introduced a customized deep routing mechanism for IoT applications in Beyond 5G-enabled edge computing network. This mechanism reduced average loss rate, decreased average delay, and improved average resource utilization. However, it faced scalability issues in large-scale and highly dynamic IoT networks. Hamdi et al. [33] developed a QoS-aware network slicing and resource management framework for Internet of Vehicle (IoV)-enabled 5G and B5G networks to meet heterogeneous QoS requirements under spectrum constraints. It utilized two 3rd Generation Partnership Project (3GPP)-compliant resource allocation algorithms with handover management and emergency traffic prioritization. Although the model reduced end-to-end delay while maintaining reliability and throughput, it could not fully address high mobility dynamics in real-world scenarios. Rajak et al. [34] developed a network slicing framework that combines feature selection techniques with DL for efficient slice classification using an attention-enhanced Long Short-Term Memory (LSTM) model. The model enhanced both QoS and quality of experience by accurate classification while meeting strict Service-Level Agreements (SLA). However, the model required large and labeled datasets for training and could suffer from high computational overhead. Vidhya et al. [35] implemented an end-to-end network slice concept in 5G networks using a Deep Q-Network (DQN) algorithm. This algorithm maximized QoS of slices while minimizing the total resource allocation. However, it involved high training time, potential convergence instability, and significant computational resource requirements, which could hinder real-time practical implementation

2.3 Problem Statement

Heterogeneous devices in 5G and B5G IoT networks produce different types of traffic like ultra-low latency, high reliability, and energy efficiency. Nevertheless, conventional routing methods fail to consider dynamic coverage divergences caused by mobility, terrain, interference, and energy limitations, and slice-specific QoS criteria. Consequently, packets may suffer from increased latency, high, or excessive drop rates or wastage of energy, particularly in dense and mobile devices of the IoT. Therefore, the main issue is to jointly optimize coverage and routing decision simultaneously in real-time, ensuring reliable, low-latency, and energy-efficient communication for multiple slices. To address these issues, the proposed work developed an CC-SARF to optimize routing decisions using Artificial Intelligence (AI)-driven prediction and RL.

3. PROBLEM FORMULATION

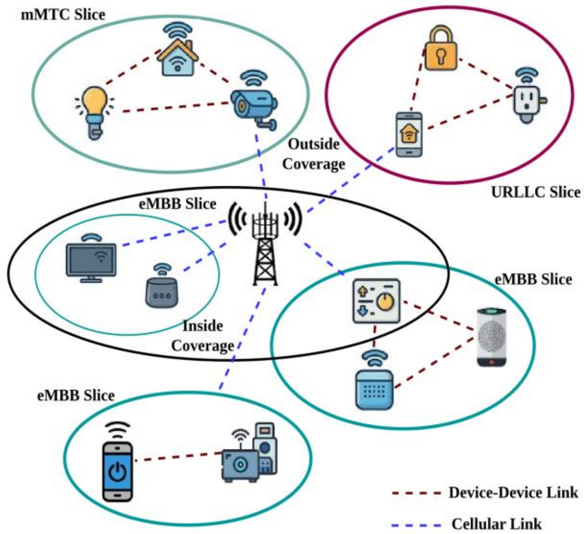

Figure 1: Illustration of Heterogeneous 5G and Beyond 5G IoT network with Diverse Network Slices and Coverage Regions

We assume a dynamic 5G and B5G IoT system that is composed of the heterogeneous devices operating under various network slices and different QoS needs, as illustrated in Figure 1. The time-varying graph of the network at time t is modelled as given in Equation (1).

$$G_t = (N, L_t) \tag{1}$$

Where $N = n_1, n_2, \ldots, n_N$ is the number of IoT nodes and L_t is the wireless links that evolves over time, because of mobility, interference and dynamics of the underlying environment. All nodes n_i are defined by their residual energy $E_i(t)$, queue length $Q_i(t)$, mobility $v_i(t)$, and slice type $s_i = \{URLLC, mMTC, eMBB\}$. Wireless link l_{ij} is characterized by signal-to-interference-plus-noise ratio (SINR), path loss -path loss $PL_{ij}(t)$, and interference $I_{ij}(t)$.Since wireless conditions fluctuate, the link reliability should not be considered static. Therefore, the coverage confidence of the link $i \rightarrow j$ at time t is defined as the probability of success, as given in Equation (2).

$$C_{ij}(t) = f\left(\gamma_{ij}(t), PL_{ij}(t), I_{ij}(t), v_i(t), L_{traffic}(t)\right) \tag{2}$$

A link is considered reliable when $C_{ij}(t) \geq C_{th}$, where C_{th} is the smallest coverage reliability threshold. It is expressed in Equation (3).

$$P = \{n_s, \ldots., n_d\} \tag{3}$$

In a routing path $P = \{n_s, \ldots., n_d\}$, the end-to-end reliability, latency, and energy consumption are respectively defined in the following Equation (4).

$$R(P) = \prod_{(i,j)\in P} C_{ij}(t), L(P) = \sum_{(i,j)\in P} T_{ij}, E(P) = \sum_{(i,j)\in P} E_{ij}^{tx} \tag{4}$$

The routing goal is to choose routes that maximize reliability with minimum latency and energy usage, within slice-specific QoS constraints. It is expressed in Equation (5).

$$maxR(P), min(L(P), E(P))$$
$$\text{i.e.,} L(P) \leq L_s^{max}, R(P) \geq R_s^{min} \tag{5}$$

In this regard, the optimal next-hop node is chosen along with predicted coverage confidence, slice utility, and remaining energy in the form of Equation (6).

$$j^* = arg\ max_j \left(\hat{C}_{ij} U_{QoS}(j) \frac{1}{E_j(t)}\right) \quad (6)$$

This formulation shows that coverage-aware and slice-compliant routing that adapts to the dynamism of wireless conditions while ensuring reliable, low-latency, and energy-efficient in 5G and B5G IoT settings.

3.1 System Architecture

The proposed CC-SARF is an intelligent, closed-loop routing system that proactively monitors network dynamics, determines coverage reliability, and optimizes routing decisions to meet slice-specific QoS requirements in 5G and B5G IoT networks. Initially, edge-deployed network monitoring module collects real-time performance metrics such as SINR, interference, mobility trends, traffic load, queue condition, and residual energy of nodes and links. These spatial-temporal features are processed by a GT to predict future coverage confidence. Based on these predictions and slice constraints (URLLC, mMTC, and eMBB), a multi-objective DRL agent chooses the optimal next-hop and transmission to maximize reliability of the links while minimizing latency and energy usage.

The packets are then delivered via high-confidence slice-compliant paths, and delay-sensitive traffic priority. After transmission, the learning policy is updated based on the feedback on the success of packet delivery, delay, energy consumption, and QoS adherence, allows policy improvement to remain constant. This adaptive cycle repeats in real time, allowing the framework respond to mobility, interface variability, traffic variability and the energy limits of nodes. Thus, ensuring sustained, efficient, and slice-aware routing through dense and dynamic 5G and B5G IoT deployments. The overall architecture of CC-SARF is depicted in Figure 2.

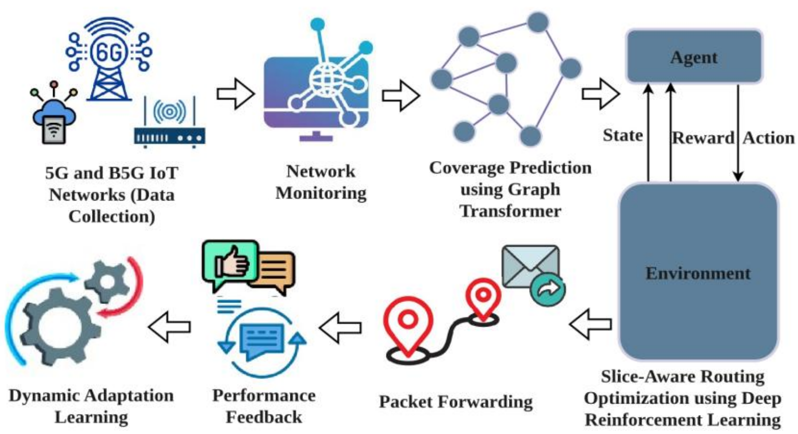

Figure 2: Overall Architecture of the Proposed Coverage-Conditioned Slice-Aware Routing Framework for 5G and B5G IoT Networks

3.1.1 Network Monitoring Module

The CC-SARF begins by continuously monitoring the current state of the network in real time for coverage prediction and routing optimization. This module is deployed at the edge controller and collects cross-layer measurements on the devices of the IoT and wireless connections to capture dynamic variations due to mobility, interference, fluctuations in traffic, and energy constraints [36]. The module captures node-level information at the time step t which includes residual energy $E_i(t)$, queue length $Q_i(t)$, mobility speed $v_i(t)$, traffic rate $T_i(t)$, and slice type s_i. Simultaneously, the measurements associated with the links SINR $\gamma_{ij}(t)$, path loss $PL_{ij}(t)$, interference $I_{ij}(t)$, packet error rate $PER_{ij}(t)$, and the bandwidth available $B_{ij}(t)$ are obtained. The network state is represented as a network state vector, which is summed up as shown in Equation (7).

$$S_t = \{f_i(t), e_{ij}(t) | \forall n_i \in N, I_{ij} \in L_t\} \quad (7)$$

Where $f_i(t)$ are the features of the nodes, and $e_{ij}(t)$ are the features of the links. To provide reliability and scalability, lightweight filtering and normalization are done to eliminate noise and retain the same ranges of the feature, the processed state information is sent to the coverage prediction module. This enables the framework to identify coverage degradation, congestion accumulation and energy wastage on real time.

3.1.2 Coverage Prediction Module using Graph Transformer

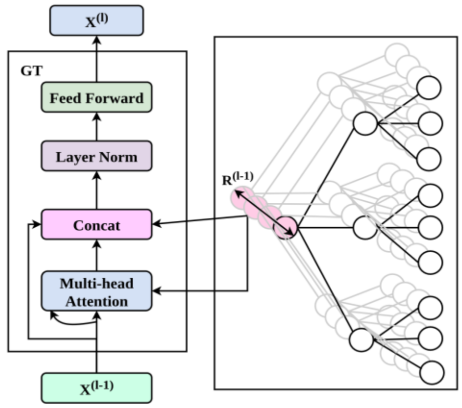

Figure 3: Architecture of Graph Transformer for Spatial-Temporal Coverage Confidence Prediction

Using the normalized node and link features that are provided by the monitoring module, the coverage prediction component models the dynamic network as a graph $G_t = (V, \xi_t)$ with each node $v_i \in V$ representing an IoT device and each edge $e_{ij} \in \xi_t$ representing a wireless linkage between nodes i and j. The architecture of GT for spatial-temporal coverage prediction is depicted in Figure 3. At time t, the node features $x_i(t)$ include position, velocity, SINR, traffic load, residual energy, and slice type, and edge features $e_{ij}(t)$ include path loss, beam alignment, interference level, and historical packet success rate. These features are converted to latent representations through linear projection as illustrated in Equation (8).

$$h_i^{(0)} = W_n x_i(t) + b_n, h_{ij}^{(0)} = W_e e_{ij}(t) + b_n \quad (8)$$

Here W_n, W_e, b_n, and b_e represents learnable weights and bias terms. To maintain structural information and variations of topology associated with mobility, Laplacian positional encodings are introduced. Where A is the adjacency and D is the degree matrices, the Laplacian of a graph can be written as in Equation (9).

$$L = D - A \quad (9)$$

with eigen-decomposition $L = U \wedge U^T$. The k minimal non-trivial eigenvectors are used to construct the positional encoding vector p_i and provide $\tilde{h}_i^{(0)} = h_i^{(0)} + p_i$. A GT subsequently learns the spatial temporal dependencies with multi-head self-attention [37]. For attention head h, query, key, and value vectors are also calculated and expressed in Equation (10).

$$q_i^h = W_Q^h \tilde{h}_i, k_j^h = W_K^h \tilde{h}_j, v_j^h = W_V^h \tilde{h}_j \quad (10)$$

The attention weight representing the influence of node j on node i in Equation (11).

$$\alpha_{ij}^h = softmax\left(\frac{q_i^h \left(k_j^h\right)^T}{\sqrt{d_h}}\right) \quad (11)$$

Each node combines neighbor information based on how relevant it is and captures interference coupling, mobility patterns, and congestion effects. The updated node representation is obtained by Equation (12).

$$z_i^h = \sum_{j \in N(i)} \alpha_{ij}^h v_j^h, z_i = W_o\, Concat(z_i^1, \dots., z_i^H) \quad (12)$$

If there are residual connections between nodes, updating node representations is through feedforward transformation as shown in Equation (13).

$$h_i^{(l+1)} = BN\left(h_i^{(l)} + FFN(z_i)\right) \quad (13)$$

The updating edge representations is performed in a similar way which captures link level reliability dynamics. The stacked attention layers and temporal inputs allow learning mobility effects, interference coupling, and congestion patterns. The final layer predicts future coverage confidence and link reliability as indicated in Equation (14).

$$\hat{C}_i(t+1) = \sigma\left(W_c h_i^{(L)}\right), \hat{L}_{ij}(t+1) = \sigma\left(W_l h_{ij}^{(L)}\right) \quad (14)$$

where $\sigma(\cdot)$ ensures that the outputs are in the range $[0, 1]$. The model parameters are trained by minimizing the difference between predicted and observed coverage, as expressed in Equation (15).

$$\mathcal{L} = \frac{1}{N}\sum_i \left(C_i - \hat{C}_i\right)^2 + \frac{1}{|\mathcal{E}|}\sum_{i,j}\left(L_{ij} - \hat{L}_{ij}\right)^2 \quad (15)$$

By aggregating neighbor information with attention weighting and using temporal variations, the GT jointly estimates the effects of interference, dynamics of mobility, and link reliability patterns. The predicted coverage confidence links reliability values are then applied to the slice-aware routing optimization module, allowing proactive avoidance of unstable links.

3.1.3 Slice-Aware Routing Optimization with Multi-Objective DRL

The slice-aware routing optimizer is formulated as a multi-objective decision-making model where by an intelligent agent chooses forwarding paths that optimize coverage reliability while reducing delay, energy and slice QoS breaches. At time step t, the routing agent observes the state S_t of the present node and its neighboring nodes. The state vector combines network awareness, reliability indicators, and slice requirements, as shown in Equation (16).

$$S_t = \left\{C_i(t), C_j(t), L_{ij}(t), Q_i(t), E_i(t), S_t\right\} \quad (16)$$

Where C_i and C_j are the predicted coverage confidence, L_{ij} is the link reliability, Q_i is the delay in the queue, E_i is the level of remaining energy, and $S_t \in \{URLLC, mMTC, eMBB\}$ is the type of the slice. According to this condition, the agent chooses an operation A_t, which involves next-hop selection and optional transmission tuning as shown in Equation (17).

$$A_t \in \{j \in N(i), P_t, \theta_t\} \quad (17)$$

Where $N(i)$ refers to the number of neighbors of the node i. These encompass transmission parameter manipulations like the transmit power P_t and beam direction θ_t. Once the agent performs the action A_t, it is rewarded R_t to capture several performance goals. The reward combines coverage reliability, latency, energy used, packet loss, and slice QoS compliance as expressed in Equation (18).

$$R_t = w_1 C_i(t) - w_2 D_t - w_3 E_t - w_4 P_{loss} - w_5 P_{slice} \quad (18)$$

where $C_i(t)$ is coverage confidence, D_t is end-to-end latency, E_t is energy consumption, P_{loss} is a penalty on packet loss events and P_{slice} is penalty on violation of slice QoS requirements. The weighting coefficients w_k are used to control the trade-off between the objectives, and these values are dynamically changed depending on the slice type.

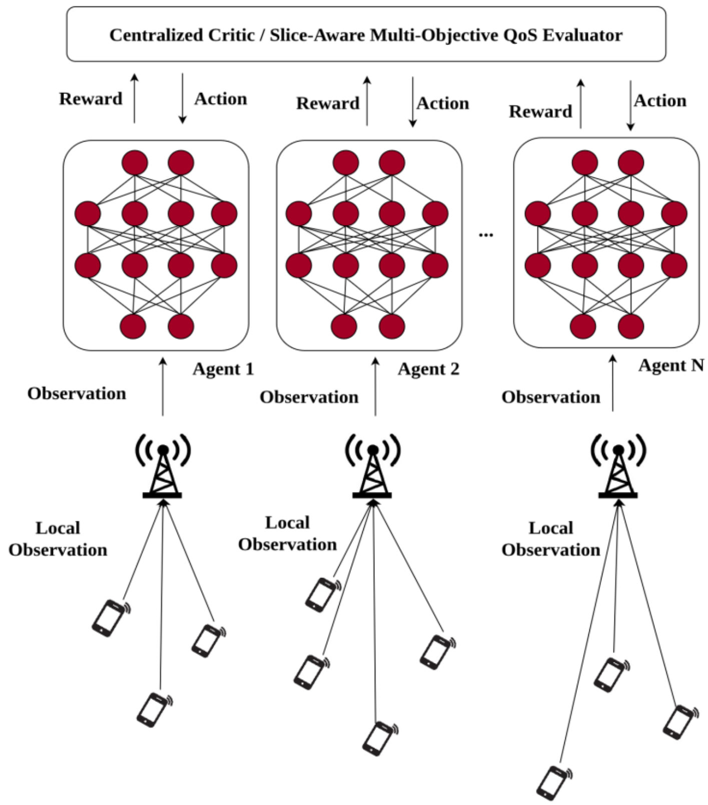

Figure 4: Architecture of Multi-Agent Slice-Aware Deep Reinforcement Learning Routing Architecture for 5G and B5G IoT Networks

The routing policy is learned using a multi-objective DRL [38] framework as depicted in Figure 4. To ensure discrete next-hop decisions, a value function based on DQN is trained and approximated as per Equation (19).

$$Q(S_t, A_t) = \mathbb{E}[R_t + \gamma max_{A'} Q(S_{t+1}, A')] \quad (19)$$

where γ is the discount factor and A' is the target network parameters. Although policy-gradient approaches like Proximal Policy Optimization (PPO) can deal with hybrid control. The policy network maps the state vector to the action probabilities, and exploration strategies provide adaptive learning. By using coverage prediction and real-time network conditions, the DRL agent modulates routing decisions in real time relative to mobility, interference, and traffic dynamics to meet slice-specific QoS requirements.

3.1.4 Packet Forwarding Mechanism

Based on the routing decisions produced by the DRL optimizer, the packet forwarding mechanism guarantees reliable data delivery and slice-conformity. Upon arrival at the node i, the packet is first identified by its network slice $S_t \in \{URLLC, mMTC, eMBB\}$ and then it receives a corresponding level of priority. According to the choice of action A_t, the node sends the packet to the next-hop neighbor j of the node that meets the coverage confidence and reliability requirements in Equation (20).

$$j^* = \arg max_{j \in N(i)} \left(\hat{C}_j - \hat{L}_{ij} \right) \quad (20)$$

Subject to latency and energy constraints. Slice-aware queue management is employed to schedule packets, where URLLC packets are assigned hard delay constraints, eMBB packets are scheduled at high throughput and mMTC packets are aggregated to enhance energy efficiency [39]. The forwarding decision also involves adaptive transmission parameters including power level P_t and beam direction θ_t to enhance the link reliability and minimize interference.

To enhance resilience, nodes maintain a backup forwarding path when the forecasted consistency of a link is less than a threshold τ, if $\hat{L}_{ij} < \tau \Rightarrow select\ alternate\ j'$. This proactive switching avoids packet loss under dynamic conditions. During the forwarding process, each node captures the delivery delay, packet success ratio, and energy usage that are recaptured and sent to the learning module to perform policy adjustment.

3.1.5 Feedback and Learning for Policy Updates

After packet forwarding, each node records key metrics including end-to-end delay, the ratios of success in packet delivery, retransmissions, queue status, and energy usage. These observations are contrasted with predicted coverage confidence and link reliability to test environmental changes and prediction accuracy. The obtained measurements comprise the subsequent state of the environment and are used by the DRL agent to optimize its routing policy through experience replay and gradient-based updates [40]. To ensure stability under dynamic conditions, the previous transitions are stored and reused during the training process, and exploration strategies ensure that they adapt to the mobility, interference variation, and traffic fluctuations. By constantly integrating delivery outcomes and prediction errors, the module allows real-time policy adaptation and enhances reliability, latency performance, energy consumption, and slice QoS compliance in the dynamic 5G and B5G IoT networks.

3.1.6 Dynamic Adaptation and Continuous Learning

Based on the continuous feedback and revised routing policies, this component maintains the CC-SARF as efficient in dynamically diverse conditions such as the motility of the nodes, interference fluctuation, traffic bursts, and energy depletion. As the network varies, updated coverage prediction, link reliability estimation, and route performance feedback are continuously entered into the decision-making loop. This enables the DRL agent to modify routing strategy on near real time. When significant environmental changes are detected due to poorer SINR, congestion accumulation, or node energy depletion. The system initiates rapid policy adjustment, either by prioritizing stable links, redistribution of traffic loads, or selection of energy-sensitive routes. The learning process refines the behavior based on the new experiences and remembers the previously learned information to prevent performance degradation. Through continuous adaptation, the framework ensures routing reliability, latency guarantees, energy efficiency, and slice QoS adherence to URLLC, eMBB, and mMTC services under very dynamic 5G and B5G IoT conditions.

4. EXPERIMENTAL ANALYSIS AND DISCUSSION

In this section, we have detailed the simulation setup and a thorough analysis of the validation of the proposed CC-SARF.

4.1 Simulation Setup

The proposed CC-SARF is implemented in MATLAB R2023b using the RL Toolbox. The routing problem is modeled as a Markov Decision Process (MDP) and solved using a PPO agent. The simulation parameters used in this work are as follows in Table 1.

Table 1: Simulation Parameters used in the proposed CC-SARF

Parameter	Value
Number of IoT nodes	6000
Deployment area	100 × 100 units
Initial node energy	Uniform random in [0.5, 0.9]
Maximum steps per episode	100
Total training episodes	100
SINR mean	18 dB
SINR standard deviation	3 dB
Random seed	42

4.2 Performance Analysis of Proposed CC-SARF

The proposed system's network simulation was conducted to evaluate its performance across various metrics. The analysis provides insights into its efficiency and effectiveness in maintaining the proposed framework's network performance.

4.2.1 Overall Performance Metrics of CC-SARF

Table 2: Performance Metrics of the Proposed CC-SARF in 5G and B5G IoT Networks

Metric	Formula	Value
Average Latency	$\frac{1}{N}\sum_{i=1}^{N} L_i$	0.211 ms
Packet Delivery Ratio (PDR)	$\frac{Number\ of\ Successfully\ Delivered\ Packets}{Total\ Packets\ Send} \times 100$	99.60%
Routing Failures	$\frac{Packets\ Dropped\ due\ to\ Routing\ Failure}{Total\ Packets\ Send} \times 100$	0.4%
Energy Consumption	$\frac{1}{N_{nodes}} \sum_{i=1}^{N_{nodes}} E_i$	0.317 J
Average Coverage	$\frac{1}{N_{nodes}} \sum_{i=1}^{N_{nodes}} C_i$	0.94
Throughput	$\frac{Number\ of\ Packets\ Successfully\ Delivered}{Total\ Time}$	4.717 (packets/s)
Average Reward / Step	$\frac{1}{T}\sum_{i=1}^{T} T_i$	2.37

Table 2 illustrates the most significant performance indicators of the suggested CC-SARF in a simulated 5G and B5G IoT network. It includes metrics such as latency, Packet Delivery Ratio (PDR), routing failures, energy usage, average coverage, throughput, and the reward per step of DRL. The results indicate that CC-SARF provides low-latency and high reliability routing over low-cost coverage, as well as, slice-aware QoS compliance with URLLC, mMTC, and eMBB traffic. Overall, these values support the effectiveness of coverage-conditioned, multi-agent DRL-based routing in improving the overall network performance in dynamic and heterogeneous IoT environments.

4.2.2 Temporal Convergence and Stability Analysis

Figure 5 demonstrates the time-evolution behavior of CC-SARF changes with 10,000-time steps. Figure 5(a) shows average latency remains low and steady with a few variations, which indicates the constant routing efficiency. (b) demonstrates the consistency of coverage confidence kept near to 1 proving the efficiency of the GT-based coverage prediction. (c) exhibits steady throughput with a minor change based on the traffic dynamics, illustrating stable data delivery. (d) indicates managed energy consumption growth, representing adaptive routing energy-conscious. (e) remains close to 100% which proves high reliability in PDR. Lastly, (f) presents the average reward per step, where variations signify further exploration of the RL and improvement of the policy. Overall, the figure proves the stability of convergence, flexibility, and the ability of multi-objective optimization of CC-SARF in a dynamic 5G and B5G IoT environments.

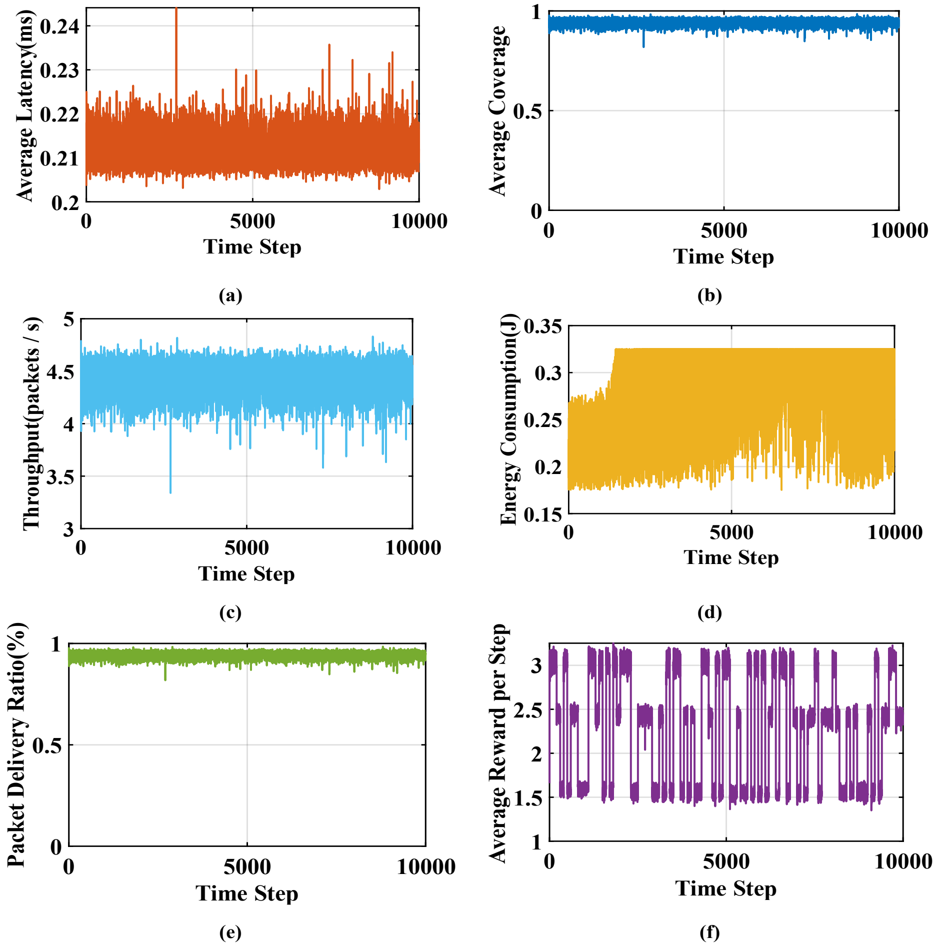

Figure 5: Temporal Performance Analysis of the Proposed CC-SARF: (a) Average Latency, (b) Average Coverage Confidence, (c) Throughput, (d) Energy Consumption, (e) Packet Delivery Ratio, and (f) Average Reward per Step

4.2.3 Multi-Objective Optimization Trade-off Analysis

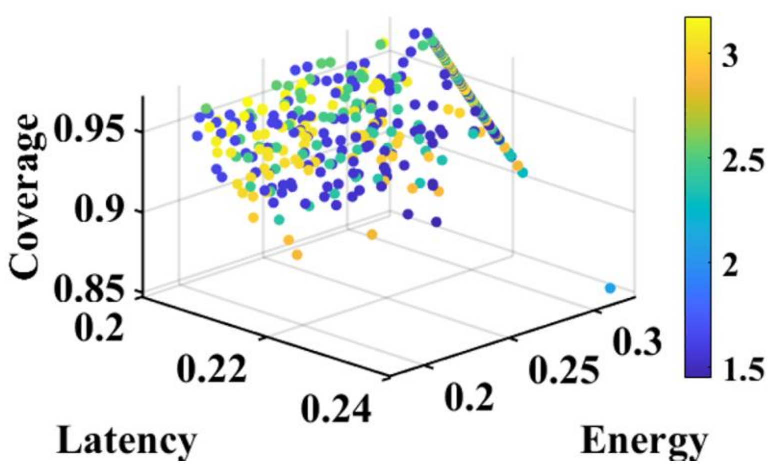

Figure 6: Multi-Objective Performance Trade-off Analysis between Coverage, Latency, and Energy under CC-SARF

Figure 6 shows the joint optimization performance of CC-SARF across three major metrics, such as coverage reliability, latency, and energy consumption. The high coverage values are clustered around a moderate latency of about 0.94-0.97, and the controlled energy level demonstrates that the framework successfully balances multi-objective constraints. The absence of significant low coverage implies that coverage-conditioned routing effectively avoids unreliable links. The color gradient further reflects adaptive slice-aware optimization behavior. Overall, the graph confirms that CC-SARF can provide stable and high-coverage communication while suppressing the latency and energy usage, validating its effectiveness for dynamic 5G and B5G IoT environments.

4.2.4 Coverage Confidence Learning Effectiveness

Figure 7 shows the distribution of the predicted coverage confidence values in the proposed CC-SARF. The x-axis is a normal coverage confidence (0-1), and the y-axis is frequency. The majority of values are found in the range between 0.9 and 1.0, which indicates that the GT effectively forecasts high-reliability links in dynamic network situations. The tight spread indicates steady and high coverage performance, which confirms the effectiveness of learning coverage-awareness. This strong concentration of high-confidence links provides reliable slice-conscious routing, ensuring minimized packet loss, enhanced QoS compliance, and stability of URLLC, mMTC, and eMBB services.

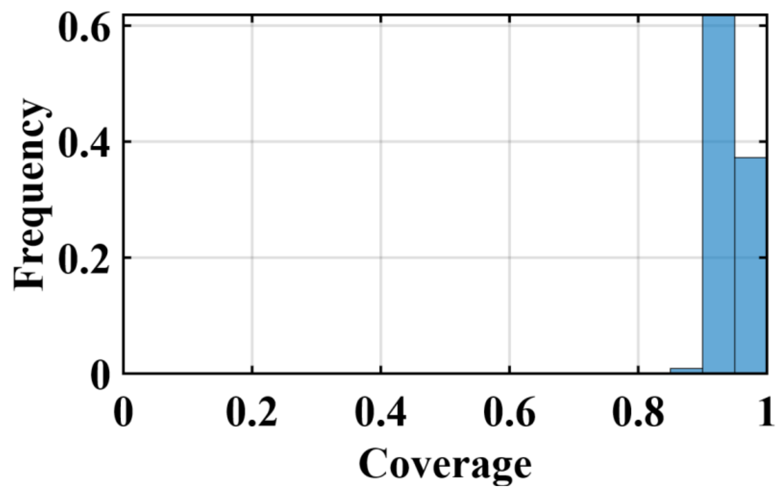

Figure 7: Coverage Confidence Distribution under Dynamic 5G and B5G IoT Conditions

4.2.5 DRL Policy Learning Behavior

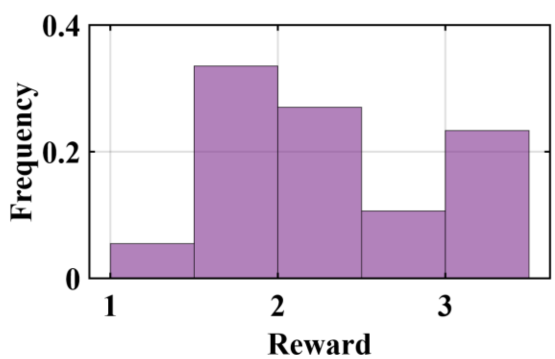

Figure 8: Reward Distribution Analysis of Deep Reinforcement Learning Agent in CC-SARF

Figure 8 shows the frequency distributions of rewards obtained by the DRL agent during training. The higher range of the reward distribution implies that the agent consistently learns policies with desirable multi-objective results in terms of coverage reliability, latency reduction, and energy use. The occurrence of small rewards is relatively low and suggests limited suboptimal decisions with progress in training. This illustrates stable convergence and effective learning of policies, proving that the proposed CC-SARF is effective in optimizing slice-aware routing decisions in dynamic 5G and B5G IoT networks.

4.2.6 Coverage-Performance Correlation Analysis

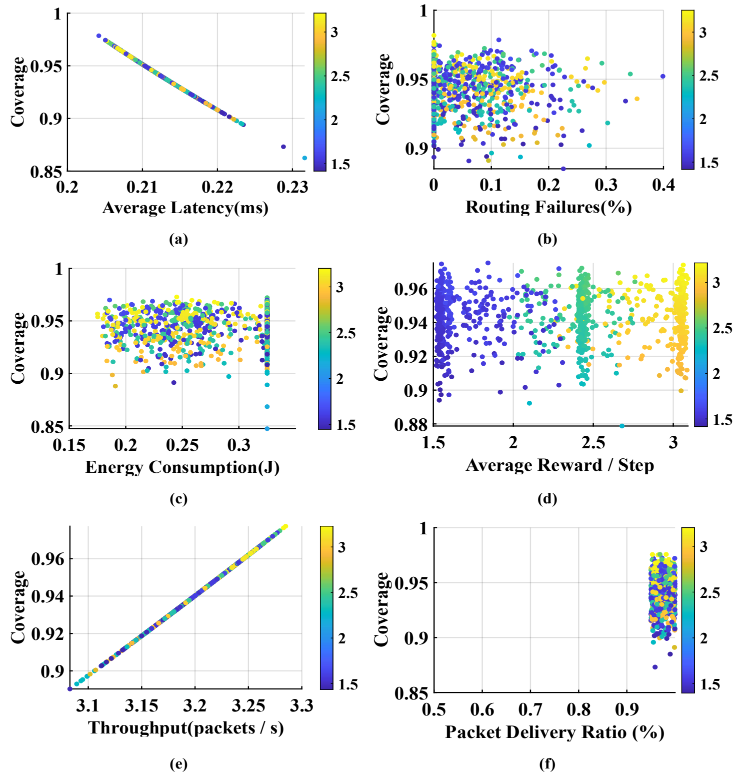

Figure 9: Comprehensive Multi-Metric Performance Relationship Analysis of CC-SARF in 5G and B5G IoT Networks (a) Coverage vs. Average Latency, (b) Coverage vs. Routing Failures, (c) Coverage vs. Energy Consumption, (d) Coverage vs. Average Reward per Step, (e) Coverage vs. Throughput, (f) Coverage vs. Packet Delivery Ratio (PDR)

Figure 9 shows that the coverage confidence prediction correlated with different performance measures in the CC-SARF. (a) Coverage vs. Average Latency depicts a significant negative correlation indicating that higher coverage reduces delay and supports URLLC requirements. (b) Coverage vs. Routing Failures illustrates that the number of failures decreases with increased coverage, which proves that routing has become more stable. (c) Coverage vs. Energy Consumption captures the ability to control and efficient use of power through eliminating unstable connections. (d) Coverage vs. Average Reward per Step shows that there is the positive correlation, which confirms successful learning in DRL and policy convergence. (e) Coverage vs. Throughput demonstrates that the coverage and throughput are directly proportional, indicating that there is an increased efficiency of the data transmission under eMBB services. (f) Coverage vs. PDR confirms the improved reliability and the compliance of the QoS. Overall, the findings confirm that coverage-conditioned slice-aware routing significantly improves multi-objective performance in dynamic 5G and B5G IoT networks.

4.2.7 Scalability and Large-Scale Network Performance

Table 3 assesses the scalability of the proposed CC-SARF by changing the node density and time steps. The results indicate that there is a slight increase in latency with an increase in node density. The value progressively decreases with more training steps, which indicates learning stability. PDR remains consistently high (exceeding 99.50%), indicating strong reliability even in dense deployments. There is a small scale-dependent growth in energy consumption and a stable throughput as the number of nodes and time progress. Overall, the results confirm that CC-SARF remains strong in terms of performance, flexibility, and efficiency in large-scale 5G and B5G IoT environments.

Table 3: Scalability Analysis of the Proposed CC-SARF Under Increasing Node Density and Time Steps

Nodes	Time Steps	Average Latency (ms)	PDR (%)	Energy Consumption (J)	Throughput (Packet/s)
1000	2000	0.178	99.92	0.281	3.82
	4000	0.173	99.91	0.283	3.94
	6000	0.168	99.94	0.287	4.01
	8000	0.165	99.95	0.289	4.08
	10000	0.163	99.96	0.291	4.14
2000	2000	0.187	99.87	0.292	4.02
	4000	0.184	99.89	0.296	4.12
	6000	0.181	99.90	0.298	4.20
	8000	0.178	99.91	0.302	4.27
	10000	0.175	99.92	0.305	4.33
3000	2000	0.196	99.83	0.301	4.18
	4000	0.192	99.84	0.305	4.29
	6000	0.190	99.87	0.307	4.36
	8000	0.186	99.89	0.311	4.42
	10000	0.184	99.90	0.315	4.48
4000	2000	0.203	99.78	0.307	4.31
	4000	0.200	99.81	0.311	4.40
	6000	0.196	99.82	0.315	4.47
	8000	0.194	99.84	0.317	4.55
	10000	0.191	99.86	0.321	4.60
5000	2000	0.209	99.72	0.312	4.45
	4000	0.206	99.75	0.315	4.54
	6000	0.203	99.78	0.320	4.61
	8000	0.202	99.81	0.323	4.67
	10000	0.198	99.83	0.327	4.71
6000	2000	0.218	99.54	0.310	4.58
	4000	0.215	99.58	0.312	4.63
	6000	0.213	99.61	0.315	4.66
	8000	0.212	99.62	0.316	4.70
	10000	0.211	99.60	0.317	4.71

4.3 Ablation Study

Table 4: Ablation Analysis of the Proposed CC-SARF in 5G and B5G Slice-Aware IoT Networks

Model Variant	Average Latency (ms)	PDR (%)	Energy Consumption (J)	Throughput (packets/s)
CC-SARF w/o Graph Transformer	0.243	98.80	0.331	4.542
CC-SARF w/o Slice Awareness	0.268	97.60	0.339	4.420
CC-SARF w/o multi-Agent DRL	0.257	98.20	0.352	4.364
CC-SARF w/o Feedback Loop	0.249	98.50	0.334	4.502
CC-SARF w/o Dynamic Adaptation	0.276	97.30	0.361	4.291
CC-SARF (Proposed Model)	**0.211**	**99.60**	0.317	**4.717**

Table 4 shows the ablation analysis evaluating the contribution of each significant element of the proposed CC-SARF. The results show that the full CC-SARF provides the best overall performance by achieving the lowest average latency (0.211 ms), the highest packet delivery ratio (99.60%), the lowest energy consumption (0.317 J), and the highest throughput (4.717 packets/s). The elimination of GT leads to longer latency and lower reliability, which proves that real-time coverage prediction is important for stable routing decisions. The removal of slice awareness significantly reduces latency and PDR, which underscores the need of QoS differentiation of URLLC, mMTC, and eMBB services. The lack of multi-agent DRL leads to increased energy consumption and decreased throughput, indicating poor global optimization and flexibility. Similarly, the elimination of the feedback loop also minimizes performance because of a lack of policy refinement under dynamic circumstances. The worst performance is observed without dynamic adaptation, resulting in the maximum latency (0.276 ms), minimum PDR (97.30%), maximum energy consumption (0.361 J), and minimized throughput (4.291 packets/s). This makes it critical for real-time environmental responsiveness in mobile and interference-prone 5G and B5G IoT systems. Overall, the ablation study proves that the combination of coverage prediction, slice awareness, multi-agent reinforcement learning, feedback mechanism, and dynamic adaptation is needed to ensure reliable, low-latency, and energy-efficient routing in dense heterogeneous IoT deployments.

4.4 Comparison with Existing Works

Table 5 compares the proposed CC-SARF with the existing methods, including Metaheuristic-based MuGWO, SVM with Kernel Function, CNN, Attention-enhanced LSTM, and DQN. The findings indicate that CC-SARF achieves the lowest latency (0.211 ms), maximum PDR (99.60%), minimum energy usage (0.317 J), and maximum throughput (4.717 packets/s). The proposed model is more reliable and makes routing decisions faster and improves energy efficiency, as compared to the other methods. This confirms the efficiency of the combination of coverage prediction, slice awareness, and multi-objective DRL in dynamic 5G and B5G IoT setups.

Table 5: Comparative Performance Analysis of CC-SARF Against Existing 5G and B5G IoT Routing Techniques

Reference	Technique	Average Latency (ms)	PDR (%)	Energy Consumption (J)	Throughput (packets/s)
Nematzadeh et al. [26] (2023)	Metaheuristic-based MuGWO	0.286	97.50	0.358	4.210

Chaturvedi et al. [28] (2024)	SVM with Kernel Function	0.312	96.80	0.371	4.050
Nagamani et al. [29] (2025)	CNN	0.254	95.60	0.341	4.410
Rajak et al. [34] (2025)	Attention-enhanced LSTM	0.238	98.20	0.333	4.531
Vidhya et al. [35] (2025)	DQN	0.329	98.80	0.384	3.980
Proposed Framework	**CC-SARF**	**0.211**	**99.60**	**0.317**	**4.717**

4.5 Discussion

Dynamic 5G and B5G IoT networks present complex routing challenges due to high mobility of nodes, changing quality of links, interference, energy limitations, and heterogeneous QoS demands of URLLC, mMTC, and eMBB slices. Traditional routing schemes usually use static parameters like hop count or immediate link quality, which makes them ineffective in dynamic environments. Consequently, networks are characterized by link failures, high latency, packet loss, and poor energy consumption. To overcome these limitations, this work suggests the CC-SARF that incorporates real-time network intelligence into routing decisions. The framework continuously monitors cross-layer measures such as node mobility, signal quality, traffic load, and energy state to construct a dynamic network state representation. A GT is used to model spatial-temporal correlations and forecast coverage confidence and link reliability by preserving the interference interrelations, topological development, and mobility patterns. Such forecasts allow proactive avoidance of untrustworthy links instead of reactive recovery after failures occur. The predicted coverage confidence is then used by a multi-objective DRL agent that determines optimal next-hop selection and transmission parameters. The DRL agent optimises reliability, latency, and energy consumption simultaneously, as well as dynamically adjusting to slice-specific QoS needs. Moreover, a closed-loop feedback mechanism supports continuous online learning, allowing routing policies to change as network conditions vary. This sequence of GT-based prediction, coverage-aware routing, and slice-aware optimization allows resilient, energy-efficient, and QoS-compliant communication in dense and heterogeneous IoT deployments.

The efficiency of the presented CC-SARF is proved by the comprehensive simulation analysis and multi-metric performance evaluation. The findings indicate ultra-low latency, high PDR, minimal routing failures, and controlled energy consumption, validating reliable and dependable routing performance. Temporal analysis over extended time steps shows consistent convergence, low latency, coverage confidence is consistent near optimal levels, and stable throughput under traffic fluctuations. The distribution of coverage confidence value displays a significant concentration around high-reliability scales, which confirms the precision of the GT coverage prediction. Reward distribution analysis confirms stable learning behavior and convergent policy of the DRL agent. The multi-objective trade-off analysis demonstrates the ability of the framework to balance coverage reliability, latency, and energy consumption. In addition, the correlation analysis indicates that coverage confidence decreases latency and routing failures directly and enhances throughput and PDR. Scalability experiment with increasing node density proves that CC-SARF maintains high reliability and stable performance even in large-scale applications. Despite these advantages, the framework may present computational overhead due to transformer processing and real-time learning needs, especially on extremely resource-constrained IoT nodes. Future directions will include lightweight transformer architectures, distributed or federated learning approaches, and hardware-aware optimization to increase the efficiency of edge deployment.

5. Conclusion

This work successfully developed the CC-SARF to improve routing information in dynamic 5G and B5G IoT networks. The suggested framework provided reliable and low-latency communication through the combination of real-time cross-layer network monitoring and GT-based coverage prediction. This allows identifying stable links in advance and preventing the use of unreliable paths. By incorporating slice-aware multi-objective DRL, the framework effectively balanced coverage reliability, latency, and energy consumption, while meeting various QoS needs of URLLC, mMTC, and eMBB services. Continuous feedback-based learning further enhances adaptability, where routing policies can change with changes in mobility, interference, and traffic. Simulation results showed substantial performance, such as ultra-low latency, high PDR, low routing failures, low energy use, and stable throughput in a dense network environment. Overall, CC-SARF attained intelligent and adaptive routing and coverage-aware routing, making it viable and a scalable solution for next-generation 5G and B5G-enabled IoT environments.

Statements and Declarations

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