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A Model for Improved Reliability in Broadband Connectivity Using Intelligent Path Selection

[1]C. C. Ezeh, [2]V. I. E. Anireh, [3]D. Matthias

[1,2,3]Department of Computer Science, Rivers State University, Port Harcourt, Nigeria
E-mails: [1]ezeh.collins@ust.edu.ng, [2]anireh.ike@ust.edu.ng, [3]matthias.daniel@ust.edu.ng

Abstract: Broadband connectivity remains constrained by high deployment cost, sparse population distribution, long inter-node distances, difficult terrain, and limited adaptability in existing path-selection mechanisms. Existing integrated access and backhaul architectures provide useful coverage extension, but they do not adequately address cost-effective hybrid infrastructure planning or adaptive routing across heterogeneous backhaul links. This study developed a model for improved reliability in broadband connectivity using intelligent path selection. The model combined a hybrid fiber-microwave broadband architecture with Python NetworkX-based graph simulation and Q-learning-based path selection. The model is applicable to heterogeneous broadband environments, whiles this study implements and evaluates it in a rural deployment scenario because rural networks present stronger cost, distance, terrain, and reliability constraints. Synthetic rural topology data were generated to represent rural nodes, gateway connectivity, household distribution, traffic demand, fiber links, microwave links, and failure scenarios. The Q-learning algorithm selected paths using latency, cost, reliability, and load-balance criteria, while the proposed system was evaluated against an existing Integrated Access and Backhaul (IAB) baseline and alternative deployment baselines. Results showed that the proposed model recorded average latency of 7.71 ms compared with 66.11 ms for the existing baseline, throughput of 1,011.20 Mbps compared with 654.65 Mbps, packet loss of 0.00% compared with 36.29%, availability of 92.922% compared with 48.408%, failover time of 2.72 seconds compared with 6.59 seconds, and load balance of 0.710 compared with 0.257. The model also recorded five-year total cost of ownership of USD 1,684,302.07 compared with USD 2,892,917.44 and cost per household of USD 463.36 compared with USD 795.85, producing a 41.78% cost saving relative to the existing IAB baseline. Scalability testing up to 150 rural nodes and 260 proposed hybrid links maintained low latency, about 92% reliability/availability, balanced load distribution, and measurable cost-per-household output. The study contributes a validated cost-resilience evaluation model, a tested multi-criteria path-selection approach, and a transferable simulation-to-decision-support framework for broadband planning.

Keywords: Broadband connectivity, intelligent path selection, Q-learning, hybrid fibre-microwave backhaul, NetworkX simulation, reliability, scalability.

I. INTRODUCTION

Broadband connectivity has become an essential infrastructure for economic participation, education, healthcare delivery, digital public services, remote work, e-commerce, and modern communication. As demand for reliable high-speed internet continues to increase, network operators and policy stakeholders face the challenge of extending broadband access beyond locations where conventional infrastructure deployment is straightforward. The challenge is especially visible in sparse and underserved deployment areas, where long connection distances, difficult terrain, low household density, and high infrastructure cost can weaken the business case for uniform fibre deployment [1].

Several broadband access and backhaul solutions have been used to address these deployment challenges. Traditional copper-based digital subscriber line technologies provided basic access but suffered from bandwidth limitations and distance-dependent degradation. Fibre-to-the-home deployments provide high capacity and low latency where economically viable, while fixed wireless access offers faster deployment but may introduce concerns around spectrum congestion, weather sensitivity, and capacity limitation [1]. Integrated access and backhaul (IAB) architectures also provide useful coverage extension by connecting an IAB donor to the core network and using wireless backhaul to reach additional nodes. IAB planning studies have often focused on donor or node placement and backhaul feasibility rather than cost-aware hybrid fibre-microwave link selection and runtime intelligent path selection [2]. Emerging

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intelligent traffic management approaches also show that adaptive routing can improve throughput and reduce delay compared with traditional routing approaches [3].

Despite advances in broadband deployment and intelligent routing, two main problems remain unresolved. First, existing IAB and single-technology broadband architectures do not adequately account for deployment constraints such as long inter-node distances, difficult terrain, low household density, and high cost per household [1]. IAB planning studies also tend to focus on donor or node placement rather than cost-aware hybrid planning [2]. These conditions can produce high deployment cost and weak resilience in sparse implementation areas. Pure fibre deployment can provide strong technical performance, but it may be economically difficult across long low-density routes. Wireless-only backhaul can reduce deployment cost, but it may suffer from reliability, congestion, capacity, and path-diversity limitations.

Second, existing routing and planning mechanisms provide limited runtime adaptation to changing traffic patterns, link quality, and failure conditions. Many approaches rely on static routing or planning decisions that do not jointly consider latency, cost, reliability, and load balance during path selection [3]. Recent robust-routing studies further show the need for adaptive routing methods under changing network conditions [4]. This limits their suitability for heterogeneous broadband environments where fibre and microwave links have different cost, capacity, latency, and reliability characteristics. These limitations require a model that can combine hybrid infrastructure planning with adaptive path selection and evaluate the result using technical performance, resilience, and cost-effectiveness metrics.

To address these issues, this study develops a model for improved reliability in broadband connectivity using intelligent path selection. The model is designed for broadband connectivity generally, while this work implements and evaluates it in a rural deployment scenario because rural networks present stronger cost, distance, terrain, and reliability constraints. The study has four objectives: to design a hybrid fibre-microwave architecture model for broadband connectivity; to integrate the designed hybrid solution using Python NetworkX; to implement a Q-learning-based intelligent path selection algorithm that optimises traffic distribution across fibre and microwave paths based on latency, cost, reliability, and load balance; and to compare and evaluate the proposed model with the existing system.

The proposed model treats broadband reliability as both a network-performance and deployment-planning problem. It combines hybrid fibre-microwave topology generation, graph-based simulation, Q-learning path selection, cost-effectiveness modelling, failure-resilience testing, and scalability testing within one reproducible workflow. The scalability test increased the deployment size to 25, 50, 100, and 150 rural nodes to examine whether the system continued to operate effectively as the number of nodes and hybrid links increased.

II. RELATED WORKS

This study is grounded in network reliability theory, graph theory, reinforcement learning, Q-learning, and software-defined networking principles. Network reliability theory provides the basis for evaluating whether a communication network can maintain service under normal and failure conditions using measures such as availability, failover time, and post-failure service continuity. Graph theory provides the modelling foundation because broadband infrastructure can be represented as a graph in which nodes correspond to gateways, access points, and user-serving locations, while edges correspond to fibre, microwave, or wireless backhaul links. Reinforcement learning supports adaptive routing because an agent can observe network state, select a routing action, receive a reward, and update its future policy. In this study, Q-learning is the selected reinforcement learning method because it can learn path-selection values from latency, cost, reliability, and load-balance feedback without requiring a full mathematical model of the network environment.

Integrated Access and Backhaul (IAB) has been widely studied as a broadband extension approach. Zhang *et al.* proposed an IAB-based approach for sustainable dense small cell network planning using optimisation methods for donor and node placement [2]. Madapatha *et al.* also studied constrained deployment optimisation in IAB networks, showing the importance of realistic planning constraints [5]. Shang and Friderikos examined energy-efficient optimisation in in-band IAB heterogeneous networks [6]. Zhang, Kishk, and Alouini investigated tethered drone-assisted IAB deployment [7]. These studies demonstrate that IAB can improve deployment flexibility where direct fixed backhaul is difficult or expensive. Their emphasis remains mainly on IAB placement, association, energy efficiency, or aerial deployment, rather than on runtime intelligent path selection across hybrid fibre and microwave backhaul links.

Wireless and hybrid backhaul studies provide another foundation for this work. Tezergil and Onur reviewed wireless backhaul for 5G and beyond networks and identified capacity,

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interference, spectrum, reliability, and deployment cost as major issues [8]. Madapatha *et al.* proposed joint fibre and free-space optical infrastructure planning for hybrid IAB networks, showing the value of combining transport technologies in backhaul planning [9]. Gedel and Nwulu developed a low-latency 5G IP transmission backhaul architecture with techno-economic analysis [10]. Filgueiras *et al.* discussed wireless and optical convergence toward 6G [11]. These works support the relevance of mixed transport technologies, but they do not provide the specific fibre-microwave, cost-aware, Q-learning-based path-selection model developed in this study.

Broadband cost and deployment studies further show why infrastructure planning cannot be separated from economic evaluation. Lee *et al.* examined rural broadband deployment through fibre networks under universal service and public-private partnership arrangements, highlighting the cost difficulty of extending high-capacity infrastructure to low-density areas [1]. Koratagere Anantha Kumar and Oughton showed that infrastructure sharing can support more efficient wireless broadband deployment [12]. Valentin-Sivico *et al.* emphasised the importance of broadband access in an underserved rural community [13]. Islam *et al.* also presented rural wireless experimentation through the ARA wireless living lab [14]. These studies establish the practical importance of broadband expansion, but they do not present an integrated simulation model that jointly evaluates hybrid backhaul design, adaptive path selection, cost per household, availability, failover, and load balance.

Recent intelligent routing studies show the value of learning-based and optimisation-based traffic control. Kim *et al.* implemented deep reinforcement learning-based routing in software-defined networks [15]. Huang *et al.* applied deep graph reinforcement learning to traffic routing in software-defined wireless sensor networks [16]. Prasanth and Uma developed an intelligent traffic engineering framework for congestion management in SDN [3]. Pei *et al.* used deep reinforcement learning for efficient SDN traffic engineering [17]. Li *et al.* proposed Graph Transformer Star Routing for robust routing in software-defined networks [4]. Ding *et al.* developed a deep Q-network-based traffic prediction and load-balancing routing algorithm for SD-IoT [18]. These works confirm that intelligent routing can improve throughput, latency, packet loss, and adaptability, but they focus mainly on SDN, IoT, wireless sensor, or data-centre-style contexts rather than cost-aware fibre-microwave broadband backhaul.

The reviewed literature therefore reveals two main gaps. First, existing IAB, wireless backhaul, and broadband deployment studies do not provide a unified model for cost-effective hybrid fibre-microwave broadband planning where link selection considers distance, terrain, household density, fibre cost, microwave cost, and cost per household. Second, intelligent routing studies demonstrate the value of learning-based adaptation, but they do not jointly optimise path selection across fibre and microwave links using latency, cost, reliability, and load balance while also evaluating cost-effectiveness and resilience. This study addresses these gaps by developing a Python NetworkX-based hybrid fibre-microwave broadband model with Q-learning-based intelligent path selection and evaluating it against an existing IAB baseline using performance, resilience, cost, and scalability evidence.

III. METHODOLOGY

This study adopts an experimental simulation methodology to design, implement, and evaluate the proposed broadband reliability model. The method is appropriate because the research requires a controlled comparison between an existing IAB baseline and a proposed hybrid fibre-microwave model under the same deployment inputs, traffic, cost, and failure assumptions. The methodology follows a modular component-based design in which topology generation, link simulation, Q-learning path selection, cost analysis, resilience testing, and result comparison are implemented as separate but connected components.

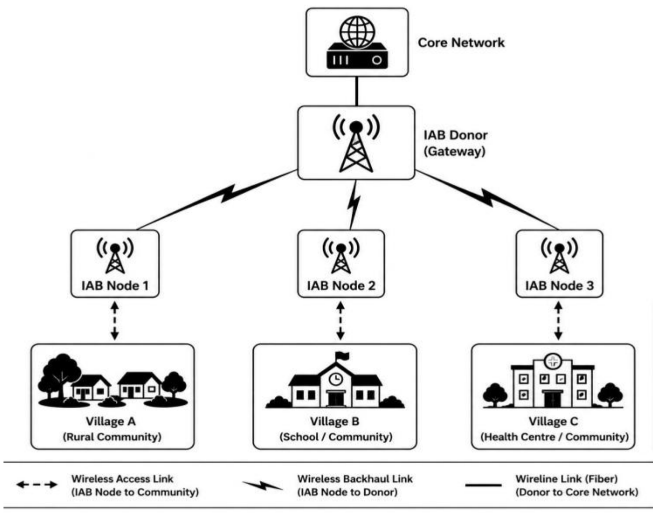

Figure 1: Existing System Architecture [2]

The existing system is represented using the integrated access and backhaul architecture adopted from Zhang *et al.* [2]. In this baseline, the core network connects to an IAB donor or

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gateway, while downstream access nodes are reached through wireless backhaul links. The architecture is useful for coverage extension because it reduces the need for direct wired backhaul to every access node. Its limitation in this study is that it does not jointly select fibre and microwave links based on cost and distance, and it does not provide runtime intelligent path selection using latency, cost, reliability, and load-balance criteria.

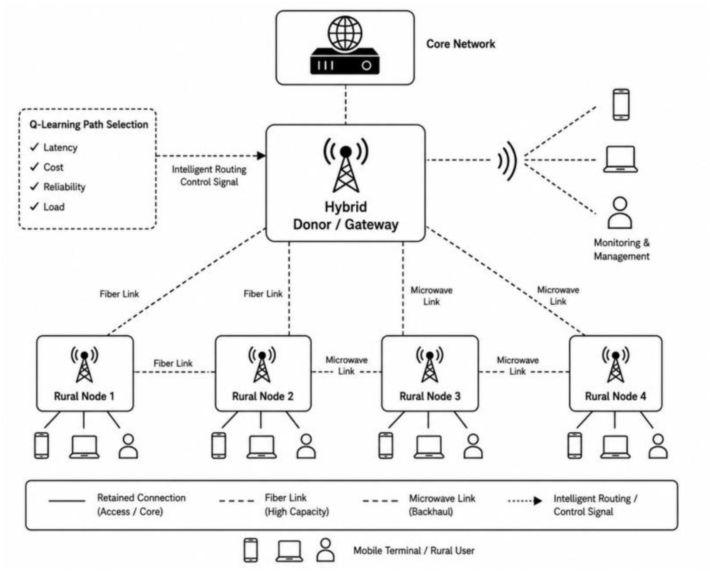

Figure 2: Proposed System Architecture

The proposed system extends the baseline by introducing a hybrid fibre-microwave backhaul layer and a Q-learning-based intelligent routing component. The system begins with rural deployment inputs, including region size, node count, population density, household distribution, terrain multiplier, traffic demand range, gateway location, fibre cost, microwave cost, link capacity, link reliability, and failure assumptions. These inputs are used to generate a NetworkX graph containing a core node, gateway node, rural access nodes, and heterogeneous backhaul links. Fibre links are assigned where the cost per household is economically viable, while microwave links are assigned where wireless backhaul provides a more practical connection for dispersed nodes.

The simulation pipeline consists of six main stages. First, synthetic rural nodes are generated with coordinates, household counts, and traffic demand values. Second, the existing IAB baseline topology is built using wireless backhaul links from rural nodes towards the gateway. Third, the proposed hybrid topology is built from the same node dataset by assigning fibre and microwave links using distance, terrain, household density, fibre cost per kilometre, microwave equipment cost, and maximum microwave distance. Fourth, Q-learning is used to train a path-selection policy over candidate source-to-gateway paths. Fifth, the existing and proposed systems are simulated to obtain latency, throughput, packet loss, availability, failover time, load balance, served flows, and link utilisation. Sixth, cost, resilience, baseline comparison, and improvement tables are generated.

Algorithm 1: Hybrid Fibre-Microwave Topology Generation

Input: region parameters, rural node count, household distribution, traffic demand range, fibre cost, microwave cost, terrain multiplier, maximum microwave distance.

Output: proposed hybrid NetworkX graph.

1. Generate rural nodes with random coordinates, household values, and traffic demand.
2. Add the core node and gateway node to the graph.
3. Connect the core node to the gateway using a retained core link.
4. For each unconnected rural node, compute distance to already connected nodes.
5. Estimate fibre cost per household using distance, fibre cost per kilometre, terrain multiplier, and household count.
6. Assign a fibre link if the fibre cost per household is below the economic threshold.
7. Assign a microwave link if fibre is not economical and the distance is within the microwave threshold.
8. Add additional nearby microwave links to improve path diversity.
9. Add gateway reinforcement links where reliability would otherwise fall below the minimum policy threshold.
10. Return the connected hybrid graph with link attributes for type, distance, capacity, latency, reliability, cost, and load.

Algorithm 2: Q-Learning-Based Intelligent Path Selection

Input: proposed graph, source-to-gateway traffic flows, candidate path count, learning rate, discount factor, exploration values, and reward weights.

Output: learned path-selection policy.

1. Generate candidate paths for each source-to-gateway flow.
2. Filter candidate paths using the minimum path reliability threshold.
3. Initialise the Q-table and exploration rate.
4. For each training episode, reset link loads and encode the current network state.

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5. Select a path for each flow using epsilon-greedy exploration and exploitation.
6. Allocate traffic demand to the selected path and update link utilisation.
7. Compute reward using latency, cost, reliability, and load-balance components.
8. Update Q-values using the Q-learning update rule.
9. Decay the exploration rate until the minimum exploration value is reached.
10. Extract the final policy by selecting the best learned path for each flow.

Implementation

The model was implemented in Python using open-source scientific computing and graph modelling libraries. NumPy was used for numerical computation and random value generation, Pandas for result tabulation and CSV export, NetworkX for topology modelling and path computation, and Matplotlib and Seaborn for analytical figures. The main experiment was executed with a fixed random seed of 42 to make node generation, traffic assignment, topology construction, Q-learning training, and result export reproducible.

The experimental configuration used a 45 km by 35 km region, 18 rural nodes, one gateway, population density of 8 households per square kilometre, terrain multiplier of 1.45, maximum microwave distance of 30 km, and gateway redundancy distance of 30 km. The cost parameters used USD 30,000 per kilometre for fibre, USD 14,000 per microwave link, USD 3,500 per router or site, an annual maintenance rate of 0.05, USD 1,000 annual energy cost per site, and USD 750 annual spectrum cost per microwave link. The link capacity assumptions were 4,000 Mbps for fibre, 800 Mbps for microwave, and 420 Mbps for baseline wireless backhaul. Traffic demand was generated between 20 Mbps and 85 Mbps per rural node. The Q-learning configuration used 500 episodes, learning rate of 0.20, discount factor of 0.90, and 8 candidate paths per flow.

IV. RESULTS & DISCUSSION

To achieve the objectives of designing a hybrid fibre-microwave broadband architecture, implementing it in Python NetworkX, applying Q-learning-based intelligent path selection, and evaluating it against the existing system, this section presents the simulation results obtained from the main 18-node experiment. The results are reported using topology structure, system performance, failure resilience, cost-effectiveness, baseline comparison, and scalability evidence. The rural scenario is treated as the implementation context, while the model itself remains applicable to broadband connectivity planning in any setting where heterogeneous backhaul links, cost constraints, and reliability requirements must be jointly considered.

Table 1: Existing and Proposed Topology Statistics

Metric	Existing IAB baseline	Proposed hybrid model
Total nodes	20	20
Total links	19	35
Average degree	1.90	3.50
Fibre links	0	5
Microwave links	0	29
IAB wireless links	18	0
Core/gateway link	1	1

The topology statistics in Table 1 show that the existing IAB baseline produced structural connectivity, but with limited link diversity. The proposed model increased the number of links from 19 to 35 and raised the average degree from 1.90 to 3.50, creating more alternative paths between access nodes and the gateway. The introduction of 5 fibre links and 29 microwave links supports the first objective of the study by showing that the model can combine high-capacity fibre routes with microwave links for areas where fibre deployment is less economical.

Table 2: Existing and Proposed System Performance Result

Metric	Existing IAB baseline	Proposed hybrid Q-learning
Average latency (ms)	66.11	7.71
Throughput (Mbps)	654.65	1,011.20
Packet loss (%)	36.29	0.00
Availability (%)	48.408	92.922
Failover time (s)	6.59	2.72
Load balance index	0.257	0.710
Average link utilisation (%)	53.48	5.24
Served flows	18	18
Total flows	18	18

The main performance result, presented in Table 2, indicates that the proposed hybrid Q-learning model reduced average latency from 66.11 ms to 7.71 ms and increased throughput from 654.65 Mbps to 1,011.20 Mbps. Packet loss reduced from 36.29% to 0.00%, while availability increased from 48.408% to 92.922%. The failover time also reduced from 6.59 seconds to 2.72 seconds. The proposed system therefore improved service quality while serving all 18 traffic flows in the main experiment.

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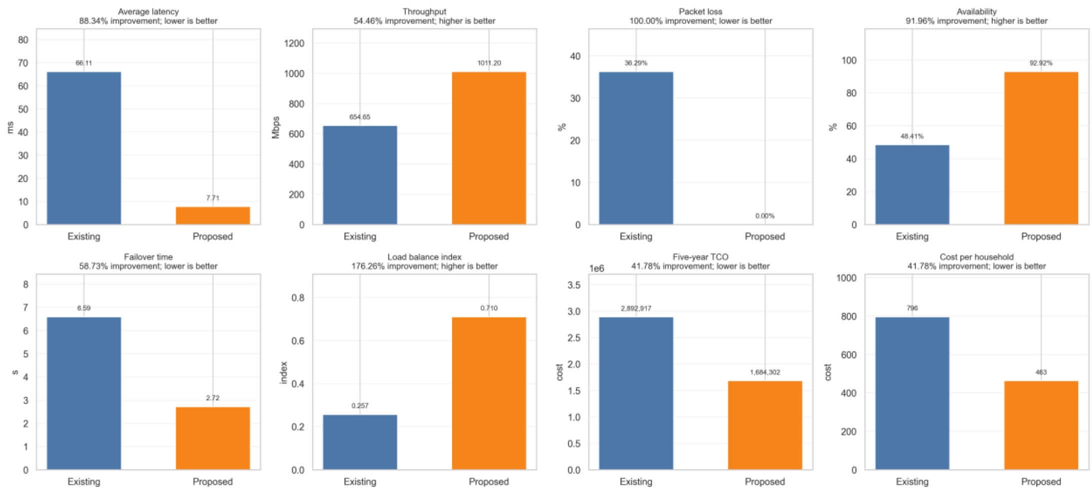

Figure 3: Existing Versus Proposed Improvement Summary

The percentage improvement summary in Figure 3 highlights the gain of the proposed model over the existing IAB baseline. Latency improved by 88.34%, throughput by 54.46%, packet loss by 100.00%, availability by 91.96%, failover time by 58.73%, load balance by 176.26%, and five-year total cost of ownership by 41.78%. The improvement across both technical and cost metrics indicates that the result is not limited to one isolated performance indicator.

Table 3: Failure and Resilience Simulation Result

Failure scenario	System	Latency (ms)	Throughput (Mbps)	Packet loss (%)	Availability (%)	Failover (s)	Served flows
Single critical link failure	Existing IAB baseline	69.48	595.73	38.43	43.666	6.59	17/18
Single critical link failure	Proposed hybrid Q-learning	9.01	1,011.20	0.00	91.964	2.72	18/18
Multiple link failure	Existing IAB baseline	69.65	563.92	35.98	40.641	7.11	16/18
Multiple link failure	Proposed hybrid Q-learning	9.30	1,011.20	0.00	91.719	3.02	18/18

The resilience behaviour of both systems under failure conditions is shown in Table 3. Under single critical link failure, the existing baseline served 17 of 18 flows, while the proposed model served all 18 flows. Under multiple link failure, the existing baseline served 16 of 18 flows, while the proposed model again served all 18 flows. The proposed model maintained availability above 91% in both failure scenarios, compared with 43.666% and 40.641% for the existing baseline. This result supports the reliability aim of the study because the proposed topology and learned path policy preserved more service continuity after link disruption.

Table 4: Cost Model Result

System	CapEx (USD)	Annual OpEx (USD)	Five-year TCO (USD)	Cost per household (USD)	Cost saving vs existing
Existing IAB baseline	2,300,000.00	148,500.00	2,892,917.44	795.85	0.00%
Proposed hybrid Q-learning	1,265,056.28	105,002.81	1,684,302.07	463.36	41.78%
Pure fibre baseline	16,225,779.72	831,288.99	19,544,875.59	5,376.86	-575.61%
Pure microwave baseline	796,000.00	85,300.00	1,136,578.17	312.68	60.71%

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The cost-effectiveness result in Table 4 shows that the proposed hybrid Q-learning model reduced five-year total cost of ownership from USD 2,892,917.44 in the existing baseline to USD 1,684,302.07. Cost per household also reduced from USD 795.85 to USD 463.36, giving a 41.78% saving relative to the existing IAB baseline. Pure fibre achieved strong technical performance in the wider comparison, but its five-year TCO was USD 19,544,875.59, making it economically unsuitable for the simulated sparse deployment scenario. Pure microwave had the lowest cost per household, but it did not provide the same reliability balance as the proposed hybrid model.

Table 5: Scalability Test Result

Scenario	Total graph nodes	Proposed links	Fibre links	Microwave links	Runtime (s)	Latency (ms)	Throughput (Mbps)	Packet loss (%)	Availability (%)	Load balance	Served flows
25 rural nodes	27	46	8	37	5.34	8.16	1,421.08	0.89	92.570	0.932	25/25
50 rural nodes	52	82	28	53	16.58	8.26	2,578.36	0.94	92.128	0.898	50/50
100 rural nodes	102	170	87	82	49.11	7.36	5,087.61	0.88	92.678	0.904	100/100
150 rural nodes	152	260	138	121	110.35	7.45	7,638.95	0.89	92.613	0.886	150/150

The scalability test in Table 5 evaluates the proposed model as the network size increases to 25, 50, 100, and 150 rural nodes. Across these scenarios, the system executed successfully and served all normal traffic flows. The largest run reached 152 total graph nodes and 260 proposed hybrid links. Availability remained around 92%, average latency stayed between 7.36 ms and 8.26 ms, packet loss stayed below 1%, and throughput rose with the number of served flows, reaching 7,638.95 Mbps in the 150-node scenario. These results indicate that the proposed implementation remained operational and stable under the tested larger network sizes.

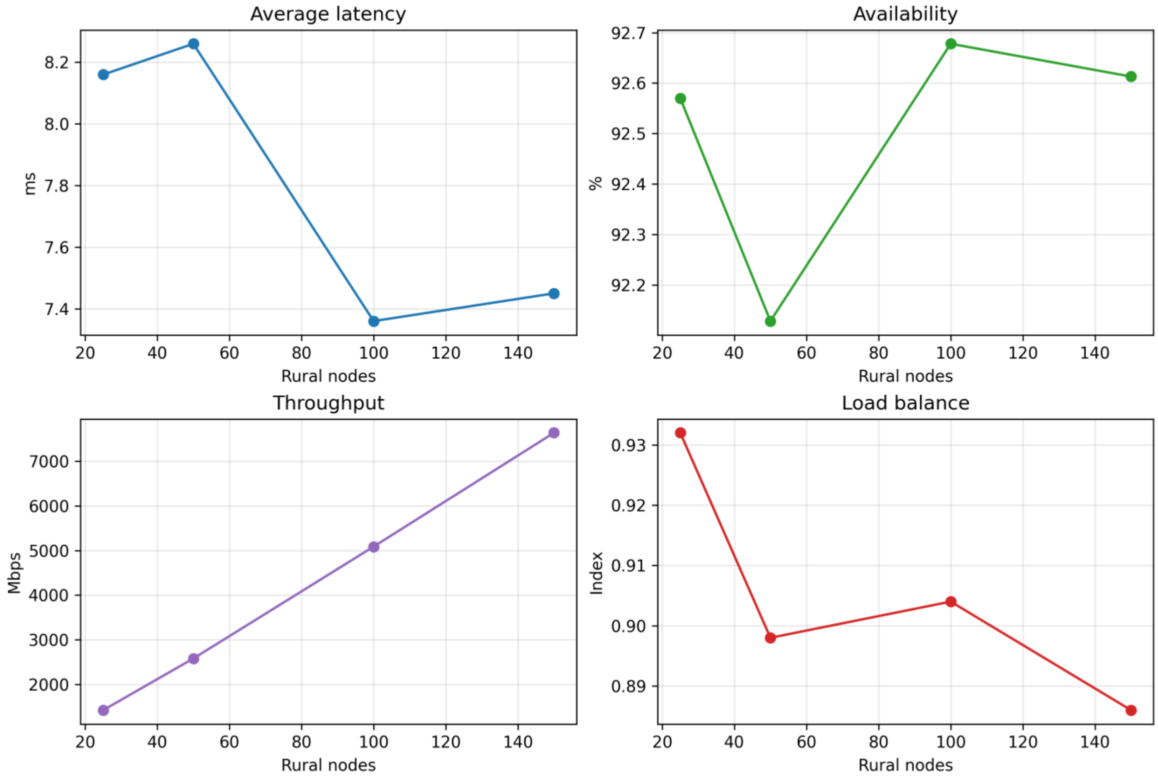

Figure 4: Scalability Performance Trend

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The scalability trend across the larger test scenarios is shown in Figure 4. The latency and availability values remained stable as node count increased, throughput increased with the number of served flows, and the load-balance index remained within a narrow range. This visual trend supports the scalability interpretation reported in Table 5.

The results show that the proposed hybrid fibre-microwave Q-learning model achieved a stronger balance of performance, reliability, resilience, and cost than the existing IAB baseline. The model does not outperform pure fibre on every technical metric or pure microwave on lowest cost. Instead, it provides the best combined outcome for the simulated deployment context by improving reliability and service quality while reducing cost relative to the existing baseline.

V. EVALUATING THE PROCESS

The proposed model was evaluated against five systems: the existing IAB baseline, the proposed hybrid Q-learning system, a pure fibre baseline, a pure microwave baseline, and a hybrid static shortest-path baseline. The comparison used the same synthetic node and traffic dataset for the existing and proposed systems to prevent input-data bias. Performance was measured using average latency, throughput, packet loss, availability, failover time, load balance index, average link utilisation, served flows, and total flows. Cost-effectiveness was measured using capital expenditure, annual operational expenditure, five-year total cost of ownership, households served, cost per household, and cost saving relative to the existing IAB baseline.

Resilience was evaluated using single critical link failure and multiple link failure scenarios. For each failure case, the simulation measured how many flows remained served, the post-failure availability, the post-failure latency, throughput, packet loss, failover time, and load balance. Scalability was evaluated by increasing the rural node count to 25, 50, 100, and 150 nodes while executing the same topology generation, hybrid fibre-microwave link assignment, Q-learning path-selection, performance simulation, and resilience workflow. The scalability test used 200 Q-learning episodes and 6 candidate paths for the larger simulations.

VI. CONCLUSION

This study developed a model for improved reliability in broadband connectivity using intelligent path selection. The model combined hybrid fibre-microwave backhaul planning, graph-based NetworkX simulation, Q-learning path selection, failure-resilience testing, cost-effectiveness analysis, and scalability testing. The rural scenario was used as the implementation area because it presents strong distance, terrain, cost, and reliability constraints, but the model is applicable to heterogeneous broadband planning contexts where fibre and microwave links must be selected and routed intelligently.

The findings show that the proposed hybrid Q-learning model improved the existing IAB baseline across the main evaluation metrics. Average latency reduced from 66.11 ms to 7.71 ms, throughput increased from 654.65 Mbps to 1,011.20 Mbps, packet loss reduced from 36.29% to 0.00%, availability increased from 48.408% to 92.922%, failover time reduced from 6.59 seconds to 2.72 seconds, and load balance improved from 0.257 to 0.710. The model also reduced five-year total cost of ownership from USD 2,892,917.44 to USD 1,684,302.07 and reduced cost per household from USD 795.85 to USD 463.36, producing a 41.78% saving relative to the existing IAB baseline.

The study therefore achieved its objectives by designing a hybrid fibre-microwave broadband architecture, integrating the architecture in Python NetworkX, implementing a Q-learning-based intelligent path-selection algorithm, and evaluating the proposed model against existing and alternative systems. The findings indicate that the proposed model provides a practical balance between reliability, performance, resilience, and cost-effectiveness. Pure fibre remained stronger in some technical metrics but was much more expensive, while pure microwave was cheaper but provided weaker reliability than the proposed hybrid model.

These contributions support Sustainable Development Goal 9, which emphasises resilient infrastructure and inclusive technological development. By addressing broadband reliability, deployment cost, and path-selection adaptability, the study provides a technical contribution to the problem of extending reliable and cost-effective connectivity infrastructure to underserved deployment areas.

VII. RECOMMENDATIONS

Despite these results, the study is limited by its use of synthetic topology data, simulated traffic demand, and modelled cost and reliability assumptions. Future work should validate the model with field-based topology data, measured traffic traces, operator-specific cost data, and wider scenario variation involving different terrain, density, weather, traffic growth, and multi-gateway configurations. Further studies may also compare Q-learning with deep Q-networks, graph neural network routing,

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multi-agent reinforcement learning, and optimisation-based routing methods.

Based on the findings, broadband planners and network operators should consider hybrid fibre-microwave deployment where pure fibre is economically difficult and wireless-only backhaul is technically limited. Intelligent path selection should also be included in broadband planning because static routing may underuse path diversity in heterogeneous networks. The proposed model contributes a reproducible simulation-to-decision-support framework for evaluating broadband reliability using performance, resilience, scalability, and cost evidence within one assessment workflow.

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