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AI-Optimized Rural Network Deployment for Cost-Effective Internet Expansion in Underserved Communities

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Abstract: Rural and underserved communities continue to face significant challenges in accessing reliable and affordable broadband connectivity due to low population density, high deployment costs, difficult terrain, and limited infrastructure. This study proposes an AI-optimized rural network deployment framework aimed at enabling cost-effective Internet expansion in such regions. The framework integrates geospatial data analysis, machine learning models, and multi-objective optimization techniques to support data-driven decision-making in network planning. Key input variables include population distribution, terrain characteristics, existing infrastructure, socioeconomic indicators, and network performance data. The proposed approach employs artificial intelligence for demand forecasting, coverage prediction, cost estimation, and technology selection, allowing for the identification of optimal deployment strategies tailored to specific rural conditions. Results from the study indicate that hybrid connectivity models combining fiber, fixed wireless access, satellite systems, and community-based networks provide the most effective balance between cost and coverage. The findings also demonstrate that AI-based optimization can improve deployment efficiency, reduce capital expenditure, and enhance service accessibility in underserved communities. In addition, the study highlights the importance of incorporating social-impact indicators, such as access to education and healthcare, into deployment decisions to promote inclusive digital development. While the framework shows strong potential, its effectiveness depends on data availability and requires validation through real-world implementation. This research contributes a scalable and adaptive solution for rural broadband planning, offering valuable insights for policymakers, network operators, and development agencies seeking to bridge the digital divide.

1. Introduction

Internet connectivity has become a basic requirement for participation in modern economic, educational, healthcare, and social systems. However, rural and underserved communities continue to experience lower levels of broadband access than urban areas. According to the International Telecommunication Union (2024), about 83% of urban residents used the Internet in 2024 compared with only 48% of rural residents, while most of the global offline population continued to live in rural areas. This persistent gap shows that rural connectivity remains a major development challenge despite advances in broadband, mobile, satellite, and wireless technologies. The rural broadband problem is not only a technical issue but also an economic and social one. Rural regions often have dispersed populations, difficult terrain, weak backhaul infrastructure, limited electricity access, and lower expected revenue per user. These conditions increase the cost per connected household and reduce the commercial attractiveness of conventional deployment models. The Organisation for Economic Co-operation and Development (2018) argues that rural digital-divide policies must address not only network availability but also affordability, service quality, competition, and adoption. Similarly, broadband access has been linked to improved opportunities in telehealth, education, entrepreneurship, agriculture, and local economic development (Urban Institute, 2024).

Traditional network planning approaches are often insufficient for these complex rural conditions because they rely heavily on manual surveys, static coverage assumptions, and fragmented infrastructure data. Artificial intelligence provides an opportunity to improve rural deployment planning by integrating geospatial, demographic, socioeconomic, and network-performance datasets into a unified decision-support system. AI and machine learning can support demand forecasting, terrain-aware coverage prediction, cost estimation, technology selection, and optimal placement of base stations or access points. Recent studies on rural 5G fixed wireless access show that base-station placement is a key challenge because higher-frequency networks require careful line-of-sight planning and optimized site selection (Valenti et al., 2024). In addition, rural broadband expansion increasingly requires hybrid connectivity models. Fiber remains essential for high-capacity backbone infrastructure, but it is often too costly for universal last-mile deployment in sparsely populated areas. Fixed wireless access, 4G/5G macro sites, TV white space, community Wi-Fi, and satellite broadband can complement fiber in remote or difficult-to-serve communities. Recent work on non-terrestrial networks shows that satellite and cellular systems can be integrated to support rural and remote connectivity where terrestrial infrastructure is limited (Broadband Commission, 2024). Infrastructure sharing is another important strategy for cost-effective rural deployment. Sharing towers, ducts, backhaul, power systems, and public infrastructure can reduce duplication and improve the economic sustainability of broadband expansion. Infrastructure-sharing models can therefore support rural digital inclusion by reducing capital expenditure and improving service feasibility in low-density areas (OECD, 2018). Therefore, rural network expansion should not be treated as a single-technology problem but as a multi-objective planning challenge involving cost, coverage, quality of service, social impact, and long-term sustainability.

This study proposes an AI-optimized rural network deployment framework for cost-effective Internet expansion in underserved communities. The framework combines geospatial data analysis, machine learning, cost modeling, multi-objective optimization, and hybrid technology selection to identify suitable deployment strategies for different rural conditions. The main contribution of this paper is the development of a structured AI-based planning model that supports technology selection, prioritizes underserved communities, and balances economic feasibility with digital inclusion objectives.

2. Literature Review

2.1 Rural Broadband Access and the Digital Divide

Rural broadband access remains a major global development challenge. The International Telecommunication Union reported that in 2024, 83% of urban residents used the Internet compared with only 48% of rural residents, while 1.8 billion of the 2.6 billion people offline lived in rural areas (International Telecommunication Union [ITU], 2024). This confirms that the digital divide is strongly shaped by geography, settlement patterns, income level, and infrastructure availability. Rural communities are often disadvantaged because network operators face higher costs and lower expected returns in sparsely populated areas.

2.2 Economic, Geographic, and Infrastructure Barriers

Rural broadband deployment is constrained by several interrelated barriers, including low population density, difficult terrain, weak backhaul infrastructure, limited electricity access, and low commercial incentives. The Organisation for Economic Co-operation and Development (OECD, 2018) explains that rural broadband policy must address availability, affordability, service quality, competition, and adoption rather than focusing only on physical infrastructure. These barriers increase the cost per connected user and make conventional deployment models less attractive in underserved areas.

2.3 Socioeconomic Importance of Rural Connectivity

Broadband expansion is strongly linked to rural development. Improved digital access can support education, healthcare, entrepreneurship, employment, agriculture, and public service delivery (Urban Institute, 2024). OECD (2024) further argues that closing broadband divides requires not only connecting people, but ensuring that connectivity is affordable, reliable, and of sufficient quality. This means that rural broadband planning should include social-impact indicators, not only technical coverage measures.

2.4 Geospatial Planning and AI-Based Network Optimization

Geographic Information Systems are increasingly used to identify unserved areas, estimate coverage gaps, assess terrain conditions, and prioritize infrastructure investment. Ajani et al. (2025) argue that GIS and satellite data can help prioritize broadband expansion by mapping underserved communities and identifying where investment would produce the greatest impact. Machine learning further strengthens this process by analyzing complex demographic, infrastructure, economic, and terrain datasets. AI models can support technology selection, cost prediction, demand forecasting, coverage estimation, and site optimization. Eze et al. (2025) note that AI-driven infrastructure can improve rural connectivity planning and operational efficiency.

2.5 Fixed Wireless Access, Rural 5G, and Base-Station Placement

Fixed wireless access is widely discussed as a cost-effective solution for rural broadband. Lappalainen, Zhang, and Rosenberg (2021) showed that rural 5G fixed wireless access planning must consider cell radius, user limits, and minimum bit-rate requirements. Base-station placement is especially important because rural wireless performance is affected by distance, terrain, vegetation, tower height, and line-of-sight conditions. Valenti et al. (2024) explain that rural 5G fixed wireless access faces propagation challenges that make base-station number, height, and location critical. MathWorks (2024) also shows that terrain elevation, path loss, and propagation conditions must be considered when planning 5G fixed wireless links.

2.6 Infrastructure Sharing and Cost Reduction

Infrastructure sharing is a key strategy for reducing rural broadband deployment costs. Sharing towers, ducts, fiber routes, backhaul systems, and power infrastructure can reduce duplication and improve economic feasibility. Recent studies suggest that infrastructure-sharing models can accelerate rural digital inclusion by reducing capital expenditure and improving service viability in low-density areas (ScienceDirect, 2025). This supports the need for cost-aware AI models that can identify opportunities for shared infrastructure and lower-cost deployment pathways.

2.7 Satellite Broadband, Non-Terrestrial Networks, and Hybrid Architectures

Satellite broadband and non-terrestrial networks are increasingly important for rural and remote connectivity. The Broadband Commission (2024) highlights the growing role of satellite broadband in connecting underserved areas. Non-terrestrial networks can complement terrestrial systems where fiber or tower-based deployment is too expensive or technically difficult. Since rural areas are not uniform, hybrid architectures are often more effective than single-technology models. Fiber can support high-capacity backbone infrastructure, while fixed wireless, satellite, TV white space, and community Wi-Fi can extend last-mile coverage. This supports the need for AI-based technology selection that matches each community with the most appropriate access solution.

2.8 Research Gap

The literature confirms that rural broadband deployment is a multi-objective problem involving cost, coverage, terrain, infrastructure availability, service quality, affordability, and social impact. Existing studies support the use of GIS, machine learning, fixed wireless access, satellite broadband, infrastructure sharing, and hybrid network architectures. However, many studies focus on individual technologies or isolated planning challenges.

There remains a need for an integrated AI-optimized framework that combines geospatial analysis, demand forecasting, cost modeling, technology selection, and social-impact prioritization for underserved rural communities.

3. Materials and Methods

3.1 Research Design

This study adopted a conceptual and simulation-based research design to develop an AI-optimized rural network deployment framework for cost-effective Internet expansion in underserved communities. The design integrates geospatial analysis, artificial intelligence, cost modeling, and multi-objective optimization to support broadband deployment decisions. The framework was developed to determine suitable technologies, identify optimal infrastructure locations, estimate deployment cost, predict coverage outcomes, and prioritize communities based on both technical feasibility and social impact.

3.2 Study Area and Data Sources

The study considered a representative rural environment characterized by dispersed settlements, uneven population distribution, limited broadband infrastructure, and varying terrain conditions. The hypothetical study area included rural towns, villages, remote settlements, schools, clinics, road corridors, existing fiber nodes, and areas with weak or no Internet coverage. The model used multiple categories of input data, including population and demographic data, terrain and elevation data, existing infrastructure data, socioeconomic indicators, current network performance data, and policy-related information. Population density and household distribution were used to estimate demand, while terrain and geospatial data supported line-of-sight and coverage analysis. Existing fiber routes, towers, roads, and power infrastructure were used to assess deployment feasibility and cost. Socioeconomic indicators were included to evaluate affordability and social impact.

Table 2: AI Model Inputs for Rural Network Deployment Optimization

Input Variable	Data Source	AI/ML Use	Deployment Decision Supported
Population density	Census data, household surveys, geospatial population maps	Demand forecasting	Identifies high-priority communities
Household distribution	Satellite imagery, GIS maps	Clustering and coverage mapping	Determines optimal tower or access-point locations
Terrain elevation	Digital elevation models, GIS datasets	Line-of-sight and propagation analysis	Supports wireless and FWA feasibility assessment
Existing fiber routes	Telecom operators, government infrastructure databases	Cost minimization	Reduces unnecessary backbone expansion
Road network	OpenStreetMap, transport agencies	Route optimization	Estimates trenching and access costs
Electricity availability	Utility providers, energy-access maps	Site feasibility prediction	Determines tower, base-station, and edge-site viability
Distance to backhaul	Network inventory, fiber maps,	Cost and latency modeling	Selects suitable backhaul technology

	microwave links		
Income level	Census data, socioeconomic surveys	Adoption and affordability prediction	Supports pricing and subsidy planning
Schools and clinics	Government records, local authority data	Social-impact scoring	Prioritizes public-service connectivity
Current signal coverage	Operator coverage maps, drive tests, crowdsourced data	Coverage-gap detection	Identifies underserved and unserved areas
Traffic demand	Mobile usage records, ISP logs, survey data	Bandwidth forecasting	Determines capacity requirements
Land-use pattern	Satellite imagery, land registry data	Deployment feasibility classification	Avoids restricted, forested, or difficult terrain

3.3 Data Preprocessing and Feature Engineering

All datasets were processed within a GIS-based analytical environment to ensure spatial consistency. Data cleaning was carried out to remove duplicate, incomplete, and inconsistent records. Spatial datasets were aligned to a common coordinate system, while demographic and socioeconomic variables were normalized to improve model reliability. Feature engineering was performed to generate variables required for AI modeling. These included distance to the nearest fiber node, road accessibility index, terrain slope index, settlement density, infrastructure availability index, backhaul proximity, and estimated service demand. These engineered features formed the processed dataset used for machine learning and optimization.

3.4 Proposed AI-Based Deployment Framework

The proposed AI framework consisted of four main modeling components: demand forecasting, coverage prediction, cost estimation, and technology selection. Demand forecasting was used to estimate expected broadband usage across different communities. Coverage prediction assessed the expected service reach of different technologies based on terrain, distance, and infrastructure conditions. Cost estimation predicted the financial requirements of deploying each technology, while technology selection identified the most suitable deployment option for each rural community.

Figure 1: AI-Optimized Rural Network Deployment Architecture

Figure 1 shows how raw data inputs are transformed into deployment decisions through AI analytics, optimization, and adaptive feedback. The architecture enables the framework to function as a data-driven decision-support system for rural broadband planning.

3.5 AI-Based Rural Network Deployment Workflow

The deployment process followed a sequential workflow beginning with data acquisition and ending with continuous monitoring and feedback. Multi-source data were first collected from demographic, geospatial, infrastructure, socioeconomic, network performance, and regulatory sources. The data were then cleaned, integrated, normalized, and transformed into a structured dataset. AI models were applied for demand forecasting, cost estimation, coverage prediction, site suitability analysis, and technology classification. The optimization layer then identified the best trade-off among cost, coverage, and quality of service. Finally, deployment recommendations were generated and updated through feedback from network monitoring.

Figure 2: AI-Based Rural Network Deployment Workflow

3.6 Multi-Objective Optimization Model

The deployment problem was formulated as a multi-objective optimization task. The model aimed to maximize population coverage, maximize quality of service, and maximize social impact while minimizing deployment and operational costs. The optimization process considered practical constraints such as budget limits, terrain feasibility, backhaul availability, electricity access, regulatory requirements, and minimum service quality. The optimization output included optimal site locations, recommended technology mix, estimated deployment cost, expected coverage, and implementation priority. Technologies considered in the model included fiber optic networks, fixed wireless access, 4G/5G rural macro sites, satellite connectivity, TV white space, and community Wi-Fi networks.

3.7 Cost, Scenario, and Model Evaluation Procedure

A cost modeling component was developed to compare the financial implications of different deployment options. The cost model considered infrastructure, backhaul, power, maintenance, and regulatory cost components. Scenario analysis was also used to evaluate how deployment decisions vary under different rural conditions, including high-density rural towns, medium-density villages, mountainous regions, and remote low-density settlements. The performance of the AI models was evaluated using accuracy, root mean square error, precision, recall, and F1-score. These metrics were selected because the framework included both regression and classification tasks. Cost estimation and demand forecasting were assessed using error-based metrics, while technology selection and coverage classification were assessed using classification metrics.

3.8 Geospatial Mapping Procedure

The optimized deployment outputs were visualized using GIS mapping. The geospatial map included fiber backbone routes, fixed wireless towers, 5G macro sites, satellite links, TV white space links, and community Wi-Fi hotspots. Coverage zones were represented spatially to show expected service distribution across the rural region. This mapping procedure was used to demonstrate how AI-generated recommendations can be translated into practical rural infrastructure planning.

4. Results and Discussion

4.1 Comparative Suitability of Rural Broadband Technologies

The analysis showed that no single broadband technology is suitable for all rural deployment conditions. Fiber optic networks provide the highest bandwidth capacity, reliability, and long-term scalability, but they require high capital investment. Therefore, fiber is most suitable for backbone connectivity, rural towns, and public institutions with high bandwidth requirements. Fixed wireless access and 4G/5G macro sites provide broader and faster deployment options for medium-density rural communities. Satellite, TV white space, and community Wi-Fi are more suitable for remote or low-density areas where terrestrial infrastructure is costly or difficult to deploy.

Table 1: Comparative Analysis of Rural Broadband Technologies

Technology	Deployment Cost (USD/km)	Coverage Range	Bandwidth Capacity	Best Use Case	Advantages	Limitations
Fiber Optic (FTTH/FTTB)	15,000 – 50,000	10–50 km (with repeaters)	Very High (Gbps)	Dense rural towns, anchor institutions	High reliability, long lifespan, scalable	Very expensive, slow deployment in remote terrain
Fixed Wireless Access (FWA)	2,000 – 10,000	5–15 km	Medium–High (100 Mbps–1 Gbps)	Villages and semi-rural areas	Lower cost, faster rollout	Line-of-sight issues, affected by terrain/obstacles
4G/5G Rural Macro Sites	20,000 – 100,000 per site	10–30 km	High (100 Mbps–1 Gbps)	Mixed-density rural areas	Wide coverage, supports mobility	High infrastructure and energy costs
Satellite (LEO)	Low upfront (user terminal ~$300–$600)	Global	Medium (50–200 Mbps)	Remote, hard-to-reach communities	No need for terrestrial infrastructure	High latency (vs fiber), recurring subscription cost
TV White Space (TVWS)	1,000 – 5,000	10–20 km	Low–Medium (10–100 Mbps)	Sparse rural areas	Long range, penetrates obstacles	Limited spectrum availability, regulatory constraints
Community Wi-Fi Mesh	500 – 3,000	1–5 km	Low–Medium	Small communities, schools	Very low cost, easy deployment	Limited scalability and reliability

Table 1 demonstrates that technology selection must depend on population density, terrain, distance to backhaul, expected demand, and deployment cost. This supports the need for an AI-based decision framework that can recommend different technologies for different rural contexts.

4.2 AI Optimization Results for Rural Communities

The AI optimization results show that different communities require different deployment solutions. Communities with larger populations and moderate existing infrastructure were assigned higher-capacity technologies, while smaller and remote settlements were assigned lower-cost alternatives.

Table 3: Hypothetical AI Optimization Results for Rural Communities

Community	Population	Current Coverage (%)	Recommended Technology	Estimated Cost (USD)	Expected Coverage After Deployment (%)	Priority Score
Community A	2,500	35	Fixed Wireless Access	85,000	92	0.88
Community B	1,200	20	LEO Satellite + Community Wi-Fi	48,000	85	0.81
Community C	4,800	55	Fiber + 5G Macro Site	210,000	96	0.91
Community D	900	10	TV White Space	32,000	78	0.74
Community E	3,100	40	Fixed Wireless + Fiber Backhaul	125,000	94	0.86

As shown in Table 3, Community C achieved the highest priority score because of its larger population and expected benefit from fiber and 5G deployment. Communities A and E also recorded strong priority scores, indicating that fixed wireless access combined with fiber backhaul can significantly improve coverage at moderate cost. Communities B and D were assigned satellite-supported Wi-Fi and TV white space because their smaller populations and limited infrastructure make full fiber deployment less cost-effective.

4.3 Performance of AI Models

The model evaluation results indicate that AI techniques can effectively support rural deployment planning. Neural networks performed strongly in demand forecasting, while gradient boosting showed strong performance in cost prediction. Random forest models were suitable for technology selection because they can handle mixed datasets and provide interpretable results.

Table 4: Performance Evaluation Metrics for AI Deployment Models

AI Model	Prediction Task	Accuracy (%)	RMSE	Precision	Recall	F1-Score
Random Forest	Technology selection	89.4	0.18	0.87	0.86	0.86
Gradient Boosting	Cost prediction	91.2	0.14	0.90	0.88	0.89
Support Vector Machine	Coverage classification	84.7	0.22	0.82	0.80	0.81
Neural Network	Demand forecasting	92.6	0.12	0.91	0.90	0.90
K-Means	Community	86.1	0.20	0.84	0.83	0.83

Clustering	prioritization					

Table 4 shows that no single model is best for every task. Instead, a multi-model approach is more suitable because rural broadband planning involves prediction, classification, clustering, and optimization. This supports the design of the proposed framework, which combines several AI models for different deployment functions.

4.4 Cost–Coverage Trade-Off

The results show a clear trade-off between deployment cost and expected coverage. Fiber provides the highest coverage and service quality but requires the highest investment. Fixed wireless access and 5G macro sites provide a more balanced relationship between cost and coverage. Satellite and TV white space offer practical options for low-density areas where terrestrial deployment is not economically feasible.

Table 5: Cost Breakdown Analysis of Deployment Options

Cost Component	Fiber (%)	FWA (%)	5G (%)	Satellite (%)
Infrastructure (cables/towers)	55	40	50	10
Backhaul	20	25	20	0
Power/Energy	10	15	20	5
Maintenance	10	10	5	10
Licensing/Regulatory	5	10	5	5

Figure 3: Cost vs. Coverage Trade-Off for Different Deployment Technologies

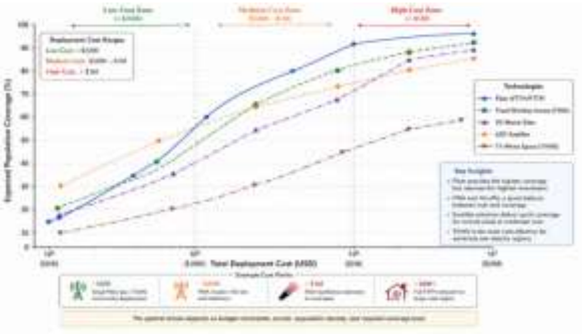

Figure 3 shows that hybrid deployment provides a more realistic pathway for underserved communities. Rather than using fiber everywhere, the AI framework selects lower-cost technologies where they can meet minimum service requirements. This approach can reduce unnecessary capital expenditure while still improving coverage.

4.5 Scenario-Based Deployment Outcomes

The scenario analysis confirms that rural network deployment must be adapted to local conditions. High-density rural towns are better served by fiber and 5G, while medium-density villages benefit from fixed wireless access with fiber or microwave backhaul. Remote and mountainous communities are more suitable for satellite, TV white space, or community Wi-Fi solutions.

Table 6: Scenario-Based Deployment Strategy Comparison

Scenario	Population Density	Terrain Type	Recommended Solution	Cost Efficiency	Coverage Outcome
Scenario 1	High	Flat	Fiber + 5G	Medium	Very High
Scenario 2	Medium	Mixed	FWA + Fiber Backhaul	High	High
Scenario 3	Low	Mountainous	Satellite + Wi-Fi	Very High	Medium

Scenario 4	Very Low	Remote	TVWS	High	Medium

Table 6 shows that the proposed framework is flexible enough to support different deployment scenarios. This flexibility is important because underserved communities differ significantly in population distribution, terrain, infrastructure access, and affordability.

4.6 Geospatial Deployment Results

The geospatial deployment map shows how AI-generated recommendations can be translated into practical infrastructure planning. The model places higher-capacity infrastructure near the town center and extends connectivity outward using a combination of fiber, fixed wireless, satellite, and community access technologies.

Figure 4: Geospatial Deployment Map for AI-Optimized Rural Connectivity

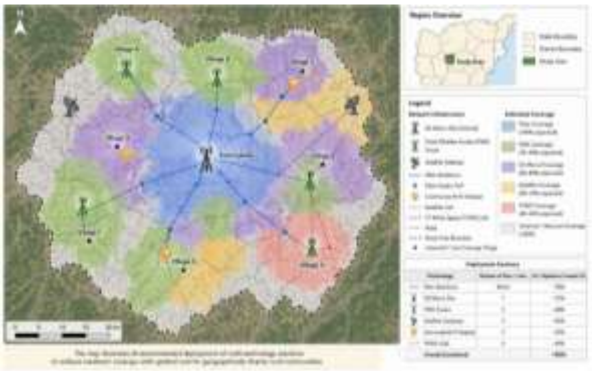

Figure 4 shows that fiber backbone routes are concentrated around central areas with higher demand, while wireless and satellite technologies extend coverage to remote settlements. This confirms that AI-based planning can support realistic spatial deployment by matching infrastructure choices with geographic and economic conditions.

4.7 Social Impact and Digital Inclusion

The social-impact analysis shows that AI-optimized deployment can support broader development goals. Improved rural connectivity can enhance access to online learning, telemedicine, digital agriculture, e-commerce, government services, and emergency communication. Including social-impact indicators ensures that deployment decisions are not based only on commercial returns.

Table 7: Social Impact Assessment of Deployment

Community	Education Impact	Healthcare Impact	Economic Impact	Digital Inclusion Score
A	0.85	0.78	0.82	0.82
B	0.75	0.70	0.76	0.74
C	0.90	0.88	0.91	0.89
D	0.65	0.60	0.68	0.64
E	0.88	0.84	0.86	0.86

Table 7 shows how communities can be prioritized according to education, healthcare, economic, and digital inclusion outcomes. This strengthens the role of the framework as a tool for equitable broadband planning.

4.8 Discussion

The results confirm that AI can improve rural network deployment by integrating technical, economic, geographic, and social variables into a single decision-support framework. Traditional network planning methods often rely on manual surveys, limited cost assumptions, and generalized engineering rules. In contrast, the proposed AI-based approach uses data-driven modeling to recommend where infrastructure should be deployed, which technology should be selected, and how deployment should be phased. The findings also confirm that hybrid connectivity is essential for cost-effective rural internet expansion. Fiber remains necessary for high-capacity backbone infrastructure, but it is not always suitable as a universal last-mile solution. Fixed wireless, 5G, satellite, TV white space, and community Wi-Fi can complement fiber by extending service to areas where wired deployment is economically difficult. The role of AI is to determine the most efficient combination of these technologies. However, the study has some limitations. The values used in the tables and figures are hypothetical and simulation-based; therefore, real-world validation is required before practical implementation. Model performance also depends on the availability and quality of input data. In many underserved regions, infrastructure maps, traffic records, socioeconomic data, and coverage information may be incomplete or outdated. In addition, AI-based decisions must be implemented transparently to avoid excluding low-income or geographically isolated communities. Despite these limitations, the results demonstrate that AI-optimized planning can reduce deployment costs, improve coverage outcomes, support digital inclusion, and guide policymakers and network operators toward more sustainable rural broadband expansion. Future research should apply the proposed framework to real rural datasets, compare AI-generated plans with operator deployment records, and evaluate long-term performance after implementation.

5. Conclusion

This study presented an AI-optimized framework for rural network deployment aimed at enabling cost-effective Internet expansion in underserved communities. The findings demonstrate that rural broadband deployment is inherently a multi-objective problem requiring the integration of technical, economic, geographic, and social considerations. Traditional deployment approaches, which often rely on static planning assumptions and single-technology solutions, are insufficient for addressing the complexity of rural connectivity challenges. The proposed framework combines geospatial analysis, machine learning, and multi-objective optimization to support data-driven decision-making in broadband planning. The results show that artificial intelligence can significantly improve deployment efficiency by identifying optimal infrastructure locations, selecting appropriate technologies, and prioritizing communities based on both demand and social impact. In particular, hybrid connectivity models that integrate fiber, fixed wireless access, satellite systems, and community-based networks were found to provide the most effective balance between cost and coverage.

The study also highlights the importance of incorporating cost modeling, scenario analysis, and social-impact evaluation into deployment strategies. By considering factors such as affordability, access to education and healthcare, and economic opportunities, the framework supports inclusive and sustainable digital development. Furthermore, the integration of infrastructure sharing and adaptive optimization mechanisms enhances the feasibility and long-term performance of rural broadband networks. However, the study is subject to certain limitations. The results are based on simulated and hypothetical data, and therefore require validation using real-world datasets and deployment environments. The performance of the AI models also depends on the availability and quality of input data, which may be limited in many rural regions. In addition, practical implementation must address issues related to data privacy, regulatory compliance, and equitable access.

6. Recommendations

Based on the findings of this study, the following recommendations are proposed to support cost-effective Internet expansion in rural and underserved communities:

i. **Adopt hybrid broadband deployment models.** Network operators and policymakers should avoid relying on a single technology for rural connectivity. Instead, fiber, fixed wireless access, 4G/5G rural macro sites, satellite broadband, TV white space, and community Wi-Fi should be combined based on population density, terrain, demand, and cost conditions.

ii. **Use AI-driven geospatial planning for infrastructure decisions.** Broadband deployment planning should incorporate artificial intelligence, GIS data, terrain analysis, population distribution, infrastructure maps, and socioeconomic indicators to identify underserved areas and determine optimal tower, fiber, and access-point locations.

iii. **Prioritize communities with high social-impact potential.** Deployment decisions should not be based only on commercial returns. Communities with schools, healthcare centers, agricultural activity, and limited digital access should receive priority because improved connectivity can strengthen education, telemedicine, economic participation, and public-service delivery.

iv. **Promote infrastructure sharing.** Governments, telecom operators, and development agencies should encourage the sharing of towers, ducts, fiber routes, backhaul systems, power infrastructure, and public facilities. This can reduce capital expenditure and make rural broadband projects more financially sustainable.

v. **Improve rural broadband data availability.** Accurate and updated datasets on population, terrain, existing infrastructure, signal coverage, traffic demand, affordability, and public institutions should be collected and maintained. Reliable data will improve the accuracy of AI models used for demand forecasting, cost estimation, coverage prediction, and technology selection.

vi. **Support public-private partnerships.** Rural broadband expansion should involve collaboration among government agencies, private network operators, local communities, donor organizations, and technology providers. Such partnerships can help mobilize funding, reduce risk, and improve long-term service sustainability.

vii. **Provide subsidies and affordability support.** Since many underserved communities have low income levels, policymakers should consider targeted subsidies, universal service funds, low-cost service plans, and community access models to ensure that broadband services remain affordable after deployment.

viii. **Validate the proposed framework with real-world data.** Future implementation should test the AI-optimized deployment framework using real rural datasets and actual deployment environments. This will help confirm model accuracy, identify practical limitations, and improve the framework for broader application.

ix. **Ensure transparency and fairness in AI-based decisions.** AI models used for broadband planning should be transparent, explainable, and regularly evaluated to prevent bias against remote, low-income, or sparsely populated communities.

x. **Establish continuous monitoring and feedback systems.** After deployment, network performance, user adoption, service quality, and community impact should be continuously monitored. Feedback from real network data should be used to update AI models and improve future deployment decisions.

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