World Journal of Advanced Engineering Technology and Sciences

eISSN: 2582-8266

Cross Ref DOI: 10.30574/wjaets

Journal homepage: https://wjaets.com/

(Review Article)

Artificial Intelligence Based Fiber Route Optimization for Cost Efficient FTTH Broadband Expansion Across Underserved American Communities

Emmanuel Selorm Gabla *, Carl Amekudzi and Jibriel Adjei

J. Warren McClure School of Emerging Communication Technologies, Master of Information and Telecommunication Systems, Ohio University, USA.

World Journal of Advanced Engineering Technology and Sciences, 2026, 19(03), 064-083

Publication history: Received on 21 April 2026; revised on 04 June 2026; accepted on 06 June 2026

Article DOI: https://doi.org/10.30574/wjaets.2026.19.3.0307

Abstract

The persistent broadband access disparity across underserved American communities continues to hinder digital inclusion, economic participation, telehealth access, remote education, and smart infrastructure development despite substantial federal broadband investment initiatives. Fiber-to-the-Home (FTTH) remains the most technically robust long-term broadband solution due to its high bandwidth capacity, low latency, and scalability; however, its widespread deployment is constrained by high capital expenditure associated with route planning, civil works, right-of-way complexities, terrain variability, and inefficient infrastructure utilization. This study proposes an Artificial Intelligence Based Fiber Route Optimization framework for cost efficient FTTH broadband expansion across underserved American communities. The research develops an intelligent optimization architecture integrating Geographic Information Systems (GIS), demographic broadband demand datasets, infrastructure geospatial constraints, road network topology, right-of-way accessibility indices, and construction cost parameters into a unified decision-support environment. Advanced Artificial Intelligence techniques including reinforcement learning, graph neural networks, and multi-objective evolutionary optimization are employed to determine optimal fiber routing pathways that minimize deployment cost, maximize service coverage, reduce trenching distance, and improve network resilience under budgetary constraints. The framework incorporates predictive demand modeling to prioritize deployment zones with the highest socioeconomic impact while accounting for terrain complexity and regulatory bottlenecks. Performance evaluation is proposed against conventional shortest path and heuristic network planning methods using metrics including route efficiency, capital expenditure reduction, coverage expansion ratio, latency optimization, and infrastructure utilization efficiency. The anticipated contribution of this research lies in establishing an intelligent broadband infrastructure planning methodology capable of accelerating equitable FTTH deployment in underserved American regions while enhancing economic sustainability, investment efficiency, and national digital connectivity resilience.

Keywords: Artificial Intelligence; FTTH Deployment; Fiber Route Optimization; Broadband Cost Efficiency; Underserved Communities Connectivity.

1. Introduction

1.1. Background of Broadband Inequality in Underserved American Communities

Broadband inequality remains one of the most persistent infrastructure disparities affecting underserved American communities, particularly rural settlements, tribal territories, economically disadvantaged suburbs, and geographically isolated regions. Despite the centrality of high-speed internet access to digital participation, significant portions of the United States continue to experience inadequate broadband availability, affordability limitations, and inconsistent

* Corresponding author: Emmanuel Selorm Gabla.

service quality. This inequality has profound implications for education, telemedicine, e-commerce, workforce participation, emergency response systems, and digital public service access. Whitacre et al. (2014) demonstrated that broadband penetration significantly influences economic development in rural regions through productivity enhancement, entrepreneurship stimulation, and labor market expansion, highlighting broadband's role as essential infrastructure rather than a luxury service.

The structural roots of this inequality are strongly linked to infrastructure economics. Broadband providers often deprioritize underserved communities because sparse population density reduces return on capital investment, particularly where extensive trenching, pole attachment negotiations, and rights-of-way approvals are required. This results in infrastructure deserts where outdated copper or limited wireless alternatives persist. Sustainable telecommunications deployment frameworks require long-term infrastructure scalability, resilience, and cost rationalization to overcome these limitations (Nwokocha & Okoh, 2023).

The transition toward optical broadband intensifies this challenge. Fiber infrastructure offers unmatched bandwidth, lower attenuation, reduced electromagnetic interference susceptibility, and superior long-term scalability. However, optical systems remain vulnerable to operational disruptions, emphasizing the importance of resilient infrastructure planning (Gabla et al., 2025). Akyildiz et al. (2014) further emphasize that modern network engineering increasingly depends on intelligent traffic-aware architectures capable of adapting to dynamic connectivity demands. Consequently, broadband inequality is not solely a social problem but a complex infrastructure optimization challenge requiring intelligent planning mechanisms for equitable American digital inclusion.

1.2. FTTH Deployment Challenges and Infrastructure Cost Constraints

Fiber-to-the-Home deployment represents the most technically robust broadband architecture for universal digital access because of its high throughput, ultra-low latency, symmetrical bandwidth delivery, and future-proof scalability. However, the economic realities of FTTH rollout remain a dominant barrier to equitable deployment in underserved American communities. Capital expenditure is heavily concentrated in civil engineering activities, including trench excavation, conduit installation, fiber laying, splice enclosure deployment, pole attachment procurement, permitting compliance, and restoration obligations. Kotakorpi, (2002) established that infrastructure competition in telecommunications is fundamentally constrained by access economics, especially where fixed network deployment requires substantial upfront investment with long amortization periods.

The challenge intensifies in geographically complex environments such as mountainous rural zones, low-density agricultural regions, and underserved suburban peripheries where deployment cost per household passed rises sharply. Optical architecture design decisions, including passive optical network topology selection, splitter placement optimization, feeder distribution engineering, and redundancy provisioning, significantly affect lifecycle cost performance (Kazi, 2007).

Modern telecommunications increasingly depend on interoperable intelligent infrastructure rather than isolated connectivity assets, requiring scalable architectures capable of supporting future digital ecosystems (Nwokocha & Peter-Anyebe, 2022). Additionally, next-generation telecom resilience expectations now include cybersecurity robustness, service continuity assurance, and adaptive threat management (Gabla et al., 2025). These evolving requirements add architectural complexity and cost layers to FTTH planning.

Traditional route planning methods often rely on deterministic shortest-path heuristics that ignore socioeconomic prioritization, terrain difficulty, infrastructure reuse opportunities, and future traffic growth. Consequently, inefficient routing decisions inflate deployment cost and reduce economic feasibility. Cost-efficient FTTH expansion therefore demands intelligent optimization frameworks capable of balancing engineering feasibility, economic sustainability, and long-term infrastructure resilience across heterogeneous American deployment environments.

1.3. Role of Artificial Intelligence in Modern Telecommunications Optimization

Artificial Intelligence has emerged as a transformative computational paradigm in telecommunications optimization, enabling infrastructure systems to transition from static engineering models toward adaptive, predictive, and autonomous operational intelligence. Traditional telecommunications planning approaches rely heavily on deterministic optimization, rule-based heuristics, and manual engineering judgment, which become computationally inefficient under high-dimensional deployment environments characterized by terrain variability, heterogeneous demand clusters, infrastructure uncertainty, and budget constraints. Sun et al. (2019) demonstrate that machine learning enables efficient decision-making across resource allocation, routing, traffic forecasting, topology adaptation, and infrastructure optimization in modern communication networks.

For FTTH deployment, Artificial Intelligence offers significant strategic advantages in route engineering optimization. Machine learning can integrate geospatial constraints, demographic demand density, road topology, pole infrastructure availability, permitting barriers, and projected service adoption into unified optimization frameworks. Deep learning architectures further enable pattern extraction from complex spatial datasets that exceed conventional analytical tractability (Mao et al., 2018).

AI applications already demonstrate operational value in telecommunications resilience. Machine learning driven anomaly detection in optical communication systems has shown effectiveness in identifying service disruptions and cyber threats in real time, reinforcing AI's relevance for intelligent fiber infrastructure management (Gabla et al., 2025). Beyond technical optimization, AI powered infrastructure governance frameworks increasingly influence strategic telecommunications architecture design through predictive planning, compliance assurance, and infrastructure lifecycle intelligence (Onyekaonwu et al., 2025).

In the FTTH context, reinforcement learning can optimize sequential routing decisions, graph neural networks can model network topology dependencies, and evolutionary algorithms can solve multi-objective cost coverage trade-offs. Consequently, Artificial Intelligence represents not merely an analytical enhancement but a foundational enabler of cost-efficient, scalable, and equitable broadband infrastructure deployment across underserved American communities.

1.4. Research Aim, Scope, and Review Motivation

The primary aim of this review is to critically examine the application of Artificial Intelligence driven optimization methodologies for cost efficient Fiber-to-the-Home broadband expansion across underserved American communities, with particular emphasis on intelligent fiber route engineering, infrastructure cost minimization, and equitable broadband accessibility enhancement. The review is motivated by the persistent digital divide in the United States, where significant disparities in broadband access continue to affect rural communities, tribal regions, low-income suburban districts, and geographically isolated populations despite substantial federal broadband infrastructure funding initiatives. Although FTTH remains the most technically sustainable broadband architecture due to its superior bandwidth scalability, low latency performance, reliability, and long operational lifespan, deployment economics remain a major barrier because of high civil engineering costs, geospatial constraints, permitting complexity, rights-of-way limitations, and inefficient conventional planning practices.

This review therefore focuses on the intersection of telecommunications infrastructure engineering, Artificial Intelligence optimization, and digital inclusion strategy. Specifically, the scope encompasses FTTH access network architecture, optical distribution engineering constraints, geospatial routing complexities, infrastructure cost drivers, and advanced Artificial Intelligence methodologies including machine learning, reinforcement learning, graph neural networks, digital twin systems, and multi-objective optimization algorithms applicable to intelligent broadband planning. The review is further motivated by the increasing need for infrastructure decision-support systems capable of integrating demographic demand forecasting, construction cost intelligence, regulatory limitations, and resilience considerations into adaptive planning frameworks. Existing studies often address isolated aspects of broadband planning without presenting a comprehensive synthesis of intelligent route optimization specifically tailored to underserved American deployment contexts. Consequently, this review seeks to consolidate contemporary knowledge, identify methodological limitations, evaluate emerging optimization paradigms, and establish a technical foundation for future autonomous FTTH deployment frameworks capable of accelerating affordable, scalable, and socially equitable broadband expansion.

1.5. Structure of the Paper

This review paper is structured into six major sections to provide a systematic and technically coherent examination of Artificial Intelligence based FTTH broadband optimization for underserved American communities. Section One introduces the study by establishing the background of broadband inequality, deployment cost challenges, the role of Artificial Intelligence in telecommunications optimization, and the research motivation. Section Two examines the technical foundations of FTTH broadband infrastructure, including network architecture, geospatial deployment constraints, economic cost determinants, and regulatory influences affecting broadband expansion in the United States. Section Three critically reviews Artificial Intelligence methodologies applicable to fiber route optimization, with emphasis on machine learning, reinforcement learning, graph neural networks, and multi-objective optimization techniques. Section Four explores recent research trends in intelligent broadband engineering, including AI assisted geospatial intelligence, digital twin enabled planning, predictive demand analytics, and resilient infrastructure expansion strategies. Section Five presents a comparative analysis of existing optimization models, performance evaluation frameworks, methodological limitations, and identified research gaps. Section Six concludes the review by highlighting emerging opportunities, strategic implications for policymakers and broadband providers, and future research directions for autonomous and cost efficient FTTH deployment systems.

2. FTTH broadband infrastructure architecture and deployment constraints

2.1. Technical Architecture of Fiber to the Home Access Networks

Fiber-to-the-Home access networks represent the most advanced fixed broadband architecture for high-capacity digital communication due to their ability to provide ultra-high bandwidth, low latency transmission, and long-term scalability. The technical architecture of FTTH systems primarily relies on Passive Optical Network configurations in which optical fiber extends directly from a central office to residential or commercial subscriber premises without intermediate active electronic amplification. McGarry, et al. (2008) explained that Ethernet Passive Optical Networks utilize optical line terminals at the service provider's central office, optical splitters within the distribution network, and optical network units at subscriber endpoints to efficiently distribute high-speed broadband traffic. This architecture significantly reduces signal attenuation, operational power consumption, and maintenance complexity compared to copper-based broadband systems.

The optical distribution network constitutes the core infrastructure layer of FTTH systems. Feeder fibers transport aggregated traffic from the central office to splitter nodes, while distribution fibers connect splitter outputs to end users. Modern FTTH architectures increasingly adopt Gigabit Passive Optical Network and XGS-PON standards to support symmetrical multi-gigabit bandwidth delivery and future intelligent service ecosystems (Fouli, 2011). These architectures are optimized for cloud computing, telemedicine, smart cities, industrial automation, and AI-enabled edge computing applications.

Scalable interoperability has become increasingly important as broadband infrastructure integrates with digital service ecosystems requiring secure and efficient data exchange frameworks (Nwokocha et al., 2021). Simultaneously, the increasing sophistication of cyber threats targeting telecommunications infrastructure necessitates intelligent security-aware architectural design capable of supporting resilient broadband operations (James et al., 2025). Consequently, modern FTTH technical architecture extends beyond physical connectivity infrastructure toward adaptive, secure, and intelligent communication ecosystems capable of supporting future autonomous broadband environments across underserved American communities.

2.2. Geospatial and Terrain Constraints in Fiber Route Engineering

Geospatial and terrain-related constraints constitute major technical challenges in Fiber-to-the-Home route engineering because fiber infrastructure deployment is highly dependent on physical environmental conditions, land accessibility, transportation topology, and urban planning characteristics. Fiber route optimization requires accurate integration of Geographic Information Systems, remote sensing intelligence, road network analysis, topographical modeling, and land-use classification to determine economically viable and technically feasible deployment pathways. Mohammed Hamud, et al., (2019) demonstrated that GIS-integrated spatial mapping significantly improves infrastructure planning accuracy by enabling detailed environmental characterization and terrain-aware decision analysis.

Terrain variability directly influences trenching complexity, installation duration, construction risk exposure, and deployment cost. Rocky geological formations, mountainous landscapes, wetlands, flood-prone regions, dense forests, and protected environmental zones create substantial engineering barriers that complicate conduit installation and optical cable laying operations. Additionally, urban environments introduce constraints associated with underground utility congestion, pole attachment limitations, transportation intersections, and municipal permitting requirements. Conventional shortest-path routing models based on graph theory frequently fail to account for heterogeneous terrain penalties and regulatory barriers despite their computational efficiency (Dijkstra, 2022).

Modern broadband planning increasingly depends on large-scale spatial data integration and intelligent decision-support systems capable of processing heterogeneous environmental datasets in real time. Data governance, privacy management, and secure digital infrastructure coordination therefore become increasingly relevant within geospatial broadband planning ecosystems (Onyekaonwu et al., 2022). Furthermore, intelligent data-driven optimization frameworks continue to influence infrastructure planning methodologies by enabling predictive prioritization and adaptive deployment decision-making as represented in Table 1 (Akorli & Peter-Anyebe, 2024). Consequently, geospatially intelligent fiber engineering represents a foundational requirement for cost-efficient FTTH deployment across underserved American communities characterized by highly diverse environmental and topographical conditions.

Table 1 Summary of Geospatial and Terrain Constraints in Fiber Route Engineering

Constraint Category	Key Challenge	Impact on FTTH Deployment	AI/GIS-Based Mitigation Strategy
Terrain Variability	Mountains, rocky formations, wetlands, and forests	Increases trenching difficulty, construction time, and deployment cost	GIS-based route optimization and terrain-aware path selection
Urban Infrastructure Constraints	Utility congestion, road crossings, and pole attachment limitations	Delays installation and complicates route engineering	Geospatial intelligence and automated infrastructure mapping
Environmental and Regulatory Barriers	Protected zones, flood-prone areas, and permitting requirements	Restricts routing options and increases compliance costs	AI-assisted environmental risk assessment and compliance planning
Spatial Data Complexity	Large volumes of heterogeneous geospatial and demographic data	Reduces planning accuracy and slows decision-making	Machine learning-driven spatial analytics and predictive optimization
Accessibility Challenges	Remote and underserved community locations	Raises deployment costs and limits service expansion	Intelligent prioritization of high-impact deployment corridors
Network Planning Uncertainty	Dynamic changes in land use and infrastructure availability	Increases risk of inefficient route selection	Real-time GIS integration and adaptive route optimization models

2.3. Economic Drivers of FTTH Deployment Cost Escalation

The economic complexity of Fiber-to-the-Home deployment remains one of the most significant barriers to universal broadband expansion across underserved American communities. FTTH infrastructure deployment requires substantial upfront capital investment associated with civil engineering operations, optical cable procurement, network equipment acquisition, labor-intensive installation activities, and long-term maintenance obligations. Crandall et al. (2013) observed that the transition from legacy copper infrastructure toward fiber broadband significantly increases investment intensity because optical systems require extensive physical infrastructure replacement rather than incremental technological upgrades.

Civil works consistently represent the largest component of FTTH deployment expenditure. Trenching operations, directional drilling, conduit construction, restoration activities, pole attachment leasing, and utility coordination collectively account for a substantial percentage of total network rollout cost. Geographic dispersion further intensifies economic inefficiency in low-density communities where long feeder routes serve relatively small subscriber populations, reducing infrastructure return on investment. Xiong, (2013) emphasized that although FTTH delivers long-term socioeconomic benefits including productivity growth, digital inclusion, and technological competitiveness, short-term financial sustainability remains a major deployment challenge.

Operational and organizational efficiency additionally influence deployment economics. Infrastructure projects involving poor stakeholder communication, inefficient workforce coordination, and weak project governance frequently experience cost overruns and implementation delays (Oloba et al., 2024). Simultaneously, compliance management and auditing complexity associated with large-scale infrastructure projects introduce additional administrative expenditure that increasingly requires intelligent automation mechanisms to improve operational efficiency as shown in Figure 1 (Frimpong et al., 2023). Consequently, FTTH cost escalation is not solely driven by engineering requirements but also by project governance inefficiencies, regulatory compliance burdens, demographic limitations, and infrastructure management complexity, reinforcing the necessity for AI-driven optimization methodologies capable of minimizing deployment expenditure while maximizing broadband accessibility outcomes.

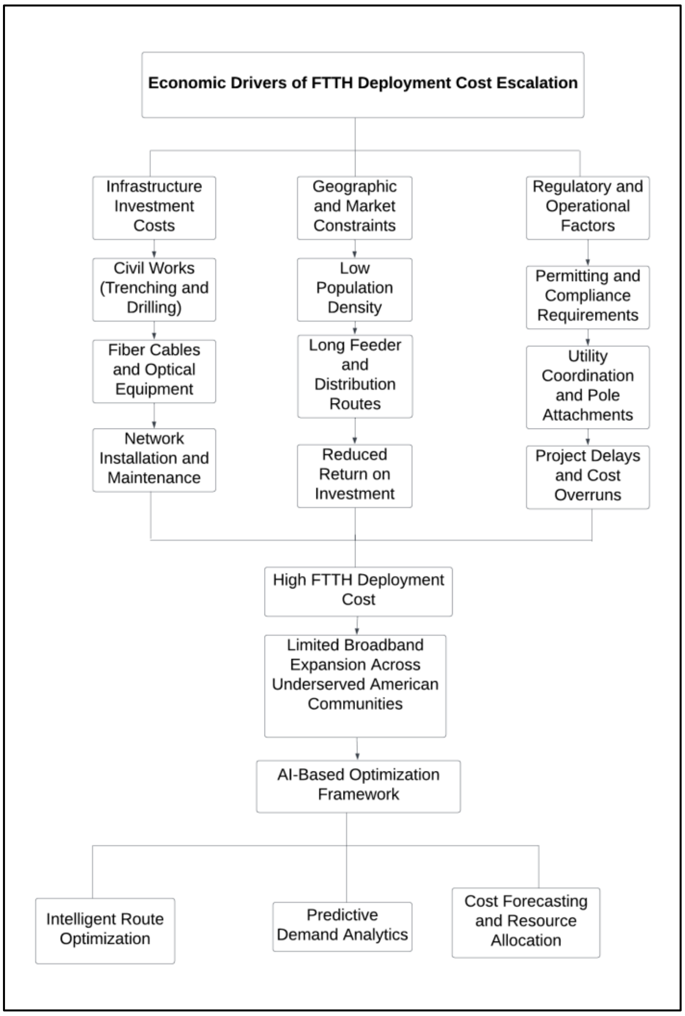

Figure 1 A Block Diagram Showing FTTH Deployment Cost Drivers and AI Optimization Framework

Figure 1 illustrates the major factors contributing to the escalation of Fiber-to-the-Home (FTTH) deployment costs. Infrastructure investment costs, including civil works, fiber equipment, installation, and maintenance, represent the largest expenditure category. Geographic and market constraints such as low population density, long feeder routes, and reduced return on investment further increase deployment costs, particularly in underserved communities. Regulatory and operational factors, including permitting requirements, utility coordination, and project delays, add additional financial burdens. These challenges collectively lead to high deployment costs and limited broadband expansion. The figure also highlights how AI-based optimization can improve route planning, demand forecasting, and resource allocation to reduce costs and enhance deployment efficiency.

2.4. Regulatory and Policy Factors Affecting Broadband Expansion in America

Regulatory and policy frameworks play a critical role in determining the speed, cost, and long-term sustainability of broadband expansion across the United States. The deployment of broadband infrastructure operates within a complex regulatory environment involving federal communications policies, state regulations, municipal permitting procedures, utility access requirements, environmental compliance obligations, and public funding programs. Government initiatives aimed at achieving universal broadband access have sought to reduce digital inequality through targeted subsidies, infrastructure grants, and connectivity programs designed to improve service availability in underserved communities (Tron, 2022). Despite these efforts, regulatory fragmentation often creates deployment challenges, including delays in permitting approvals, rights-of-way acquisition, and coordination with utility providers.

Modern broadband policy extends beyond infrastructure deployment to encompass affordability, accessibility, and digital inclusion. Effective broadband expansion requires not only physical network availability but also policies that promote adoption through affordability programs, digital literacy initiatives, and targeted support for disadvantaged populations (Hauge & Prieger, 2010). As a result, the success of broadband programs depends on the alignment of infrastructure investment strategies with broader socioeconomic development objectives.

The increasing use of Artificial Intelligence in broadband planning introduces additional regulatory considerations related to data governance, cybersecurity, privacy protection, and algorithmic accountability. AI-driven optimization systems rely heavily on geospatial data, demographic information, and predictive analytics, making robust governance frameworks essential for responsible deployment (Ebenibo et al., 2024). Furthermore, broadband infrastructure investment is increasingly recognized as a catalyst for workforce development, technological innovation, and economic growth (Okoh et al., 2024). Consequently, policy-aware and AI-enabled planning frameworks are becoming essential for accelerating efficient and equitable FTTH deployment across underserved American communities.

3. Artificial intelligence techniques for fiber route optimization

3.1. Machine Learning Models for Broadband Infrastructure Planning

Machine learning models have become increasingly important in broadband infrastructure planning because they enable intelligent analysis of complex deployment environments characterized by heterogeneous spatial data, uncertain demand patterns, dynamic traffic behavior, and financial constraints. Unlike conventional telecommunications planning methods that rely on deterministic engineering models, machine learning provides adaptive predictive capabilities that improve route selection, demand forecasting, resource allocation, and infrastructure optimization. Deep learning-based demand prediction models have demonstrated significant effectiveness in forecasting broadband usage trends and identifying future traffic growth across diverse geographic regions (Shen, 2024).

In FTTH deployment planning, supervised learning algorithms are commonly used to identify high-priority expansion areas based on factors such as population density, income levels, service adoption likelihood, and existing network availability. Unsupervised learning techniques further support planning by detecting underserved regions and uncovering hidden spatial patterns through clustering and anomaly detection methods. Cognitive telecommunications systems increasingly employ predictive analytics to enable adaptive infrastructure planning under changing network conditions (Khan et al., 2019).

Machine learning also enhances decision-support systems by integrating geospatial information, environmental conditions, construction costs, and projected service demand into comprehensive optimization frameworks. These capabilities are particularly valuable in underserved American communities where broadband deployment must balance affordability, coverage expansion, and long-term sustainability. Data-driven planning approaches improve investment efficiency and support more effective allocation of infrastructure resources (Onwuzurike & Kpogli, 2022). Consequently, machine learning provides a powerful foundation for intelligent and cost-effective FTTH network expansion.

3.2. Reinforcement Learning for Adaptive Fiber Route Optimization

Reinforcement learning has emerged as a powerful Artificial Intelligence technique for adaptive fiber route optimization due to its ability to solve sequential decision-making problems in dynamic and uncertain deployment environments. Unlike conventional optimization approaches that depend on predefined rules, reinforcement learning enables autonomous agents to learn optimal routing strategies through continuous interaction with their environment using reward-based feedback. Deep reinforcement learning has demonstrated exceptional performance in solving complex optimization tasks involving large numbers of variables and constraints, making it highly suitable for broadband infrastructure planning (Mnih et al., 2015).

In FTTH deployment, reinforcement learning agents can evaluate multiple routing alternatives by considering geospatial constraints, terrain complexity, infrastructure reuse opportunities, environmental obstacles, population density, and deployment costs. Through iterative learning, the system gradually identifies routing solutions that maximize service coverage while minimizing construction expenses and deployment risks. This adaptive capability allows the model to respond effectively to changing conditions such as urban growth, regulatory modifications, utility congestion, and evolving broadband demand (Luong et al., 2019).

The application of deep reinforcement learning in communications networks continues to expand across areas such as resource allocation, routing optimization, spectrum management, and intelligent network control because of its scalability and autonomous decision-making capabilities as presented in Table 2. When combined with predictive analytics and causal inference techniques, reinforcement learning further improves infrastructure planning by supporting intelligent prioritization and more accurate forecasting (Akorli & Enyejo, 2024). As a result, reinforcement learning offers a highly effective framework for achieving cost-efficient and scalable FTTH expansion across underserved American communities.

Table 2 Summary of Reinforcement Learning for Adaptive Fiber Route Optimization

Aspect	Description	FTTH Application	Expected Benefit
Reward-Based Learning	Learns optimal decisions through continuous interaction and feedback from the environment	Identifies cost-effective fiber routing paths	Improved routing efficiency and adaptability
Dynamic Route Optimization	Evaluates multiple routing alternatives under changing conditions	Considers terrain, population density, and deployment constraints	Reduced deployment cost and risk
Autonomous Decision Making	Adjusts routing strategies without predefined rules	Responds to urban growth, regulatory changes, and infrastructure availability	Enhanced planning flexibility
Network Performance Optimization	Integrates predictive analytics and reinforcement learning techniques	Optimizes coverage, resource allocation, and infrastructure utilization	Increased broadband coverage and scalability

3.3. Graph Neural Networks for Network Topology Optimization

Graph Neural Networks (GNNs) are advanced Artificial Intelligence models specifically developed for analyzing graph-structured data such as communication networks, transportation systems, utility infrastructures, and FTTH broadband topologies. In FTTH deployment environments, network components naturally form graph structures where nodes represent central offices, optical splitters, junctions, and subscriber locations, while edges represent fiber links and physical routing paths. Unlike traditional machine learning models, which often struggle to capture complex relationships within interconnected systems, GNNs are designed to learn structural dependencies and spatial interactions directly from network topology data (Scarselli et al., 2009).

In broadband infrastructure planning, GNNs can optimize fiber route selection by modeling relationships among terrain characteristics, road networks, utility corridors, population density, and deployment costs. These capabilities enable efficient propagation of information across interconnected nodes, resulting in more effective topology optimization under complex deployment constraints. GNNs have demonstrated strong performance in tasks such as link prediction, node classification, graph representation learning, and network optimization across large-scale interconnected systems as shown in Figure 2 (Wu et al., 2021).

For underserved American communities, GNNs provide significant advantages because broadband deployment requires careful consideration of network resilience, infrastructure scalability, and geographic connectivity. Their ability to evaluate node importance, redundancy pathways, splitter locations, and feeder-distribution configurations improves network efficiency and cost effectiveness. Consequently, Graph Neural Networks offer a scalable and adaptive framework for intelligent FTTH infrastructure planning, supporting resilient and economically sustainable broadband expansion.

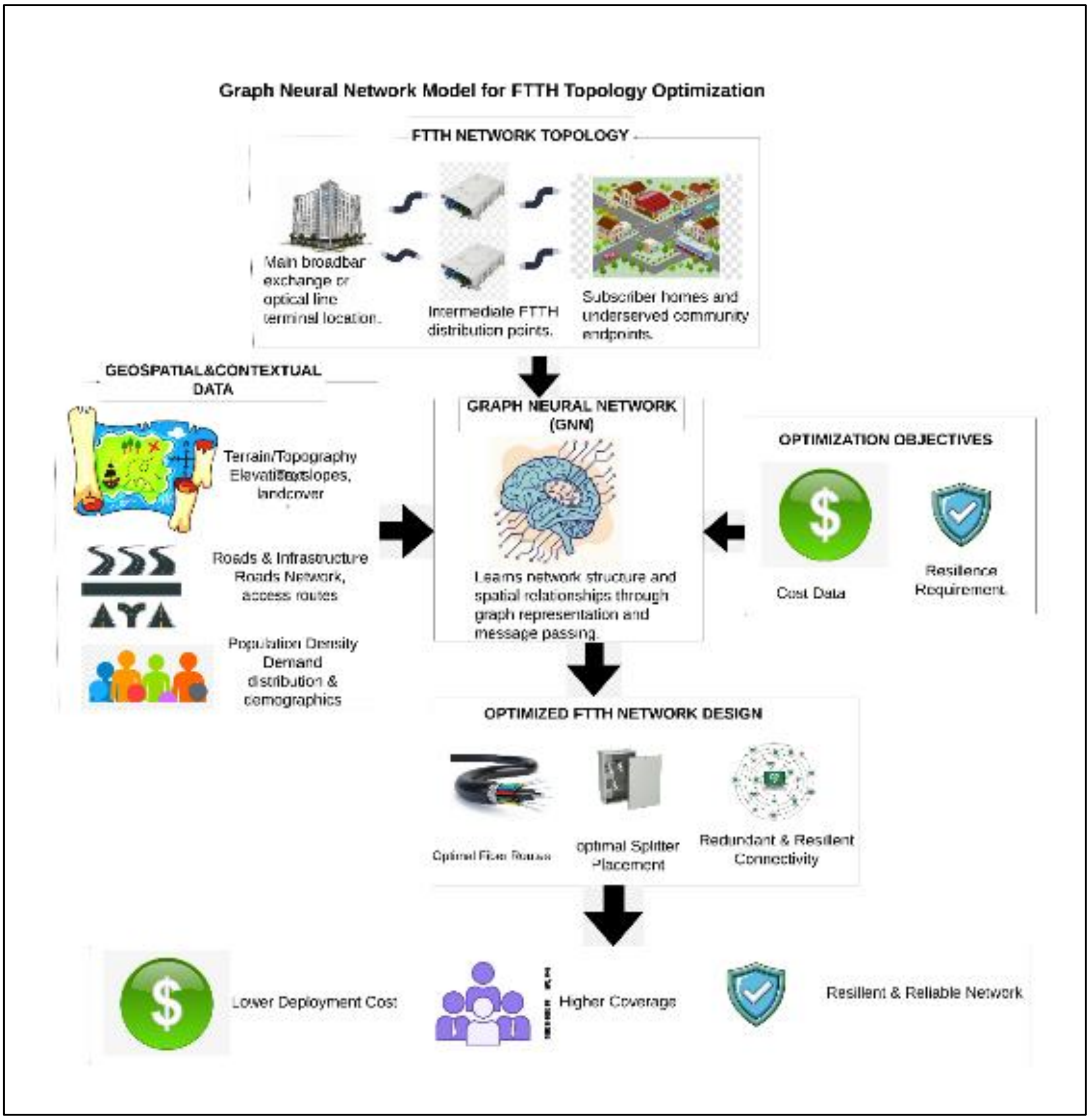

Figure 2 A Diagram of Graph Neural Network Framework for FTTH Topology Optimization

Figure 2 illustrates the application of a Graph Neural Network (GNN) framework for optimizing Fiber-to-the-Home (FTTH) network topology. The upper section represents the FTTH network environment, consisting of the central office, intermediate distribution points, and subscriber homes within underserved communities. Geospatial and contextual data, including terrain characteristics, road infrastructure, and population density, are integrated into the GNN model to capture spatial and topological relationships across the network. The optimization process further incorporates deployment cost and network resilience requirements as decision variables. Through graph-based learning and message-passing mechanisms, the GNN generates an optimized FTTH network design characterized by efficient fiber routing, optimal splitter placement, and redundant connectivity paths. The resulting network architecture minimizes deployment costs, improves broadband coverage, and enhances reliability, thereby supporting sustainable and cost-effective broadband expansion across underserved American communities.

3.4. Multi Objective Optimization Algorithms for Cost Efficient Deployment

Multi-objective optimization algorithms are essential for cost-efficient FTTH deployment because broadband infrastructure planning involves multiple competing objectives that cannot be addressed effectively using traditional single-objective optimization techniques. Fiber route design requires simultaneous consideration of deployment cost, service coverage, network resilience, latency performance, terrain constraints, environmental regulations, and future scalability. As a result, multi-objective optimization frameworks provide a systematic approach for identifying balanced solutions that satisfy several engineering and economic requirements at the same time (Okoh, et al, 2024).

Among the most widely used approaches are evolutionary optimization techniques such as the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), which efficiently generate Pareto-optimal solutions for complex optimization problems involving nonlinear constraints and conflicting objectives (Deb et al., 2002). In FTTH planning, these algorithms can simultaneously optimize trenching distance, construction cost, infrastructure reuse opportunities, subscriber coverage, and network reliability.

Multi-objective optimization is particularly valuable in heterogeneous deployment environments where terrain conditions, demographic distribution, and infrastructure availability vary significantly. Under such circumstances, conventional deterministic approaches often become computationally inefficient, whereas evolutionary algorithms can effectively explore large solution spaces and identify high-quality routing alternatives (Coello Coello, 2006).

For underserved American communities, where broadband expansion is frequently constrained by limited budgets and challenging geographic conditions, AI-driven multi-objective optimization can prioritize deployment areas with the greatest socioeconomic benefit while minimizing infrastructure expenditure. Consequently, these algorithms provide a robust foundation for developing scalable, resilient, and economically sustainable FTTH deployment strategies that support equitable broadband access.

4. Recent research trends in ai driven FTTH broadband engineering

4.1. AI Assisted Geospatial Intelligence for Automated Fiber Path Selection

Artificial Intelligence-assisted geospatial intelligence has become an important tool for automated fiber path selection in modern Fiber-to-the-Home (FTTH) deployment projects. Traditional route planning methods often depend on manual Geographic Information System (GIS) analysis, field surveys, and shortest-path algorithms that may overlook critical environmental and socioeconomic factors. The growing availability of high-resolution satellite imagery, LiDAR data, digital elevation models, transportation networks, and demographic datasets has enabled the development of AI-driven geospatial systems capable of identifying optimal fiber deployment corridors. Deep learning techniques have shown strong capabilities in extracting meaningful spatial patterns from large-scale geospatial datasets and improving route planning accuracy (Li et al., 2017).

In broadband infrastructure planning, AI-assisted geospatial intelligence integrates terrain characteristics, land-use information, utility corridor availability, road networks, environmental constraints, and population density into a unified optimization framework. This approach enables automated identification of feasible deployment routes while reducing construction costs, trenching requirements, and environmental impacts. Advanced convolutional neural networks further enhance planning efficiency through automated feature extraction from remotely sensed imagery (Zhu et al., 2017).

For underserved American communities, where terrain conditions and settlement patterns are often highly diverse, AI-assisted geospatial intelligence improves deployment efficiency by prioritizing high-impact investment locations. By combining real-time geospatial analytics with infrastructure cost modeling, these systems support scalable, cost-effective, and equitable broadband expansion.

4.2. Digital Twin Applications in Intelligent Broadband Infrastructure Planning

Digital twin technology has emerged as a transformative tool in intelligent broadband infrastructure planning because it enables the creation of dynamic virtual replicas of physical FTTH networks. These digital representations allow engineers and planners to simulate deployment scenarios, evaluate network performance, assess environmental constraints, and optimize routing decisions before physical implementation. By continuously synchronizing virtual models with real-world infrastructure through real-time data integration, digital twins support more accurate and informed decision-making throughout the network lifecycle (Tao et al., 2019).

In FTTH deployment environments, digital twins integrate geospatial information, network topology data, demographic demand forecasts, construction cost estimates, environmental conditions, and operational performance indicators into a unified planning platform. This enables broadband providers to analyze alternative deployment strategies, estimate lifecycle costs, predict network bottlenecks, and identify potential failure points without interrupting physical operations. As a result, deployment uncertainty and project risks are significantly reduced (Micheal et al, 2024).

Modern digital twin platforms increasingly incorporate Artificial Intelligence and machine learning techniques to improve predictive analytics and optimization capabilities. These intelligent systems support scenario simulation, anomaly detection, and automated decision-making by continuously learning from operational data streams as shown in Figure 3 (Fuller et al., 2020). For underserved American communities, digital twins provide a valuable mechanism for evaluating deployment feasibility under varying geographic, economic, and regulatory conditions. Consequently, digital twin technology enhances planning accuracy, reduces deployment risks, and supports scalable, cost-efficient FTTH network expansion strategies.

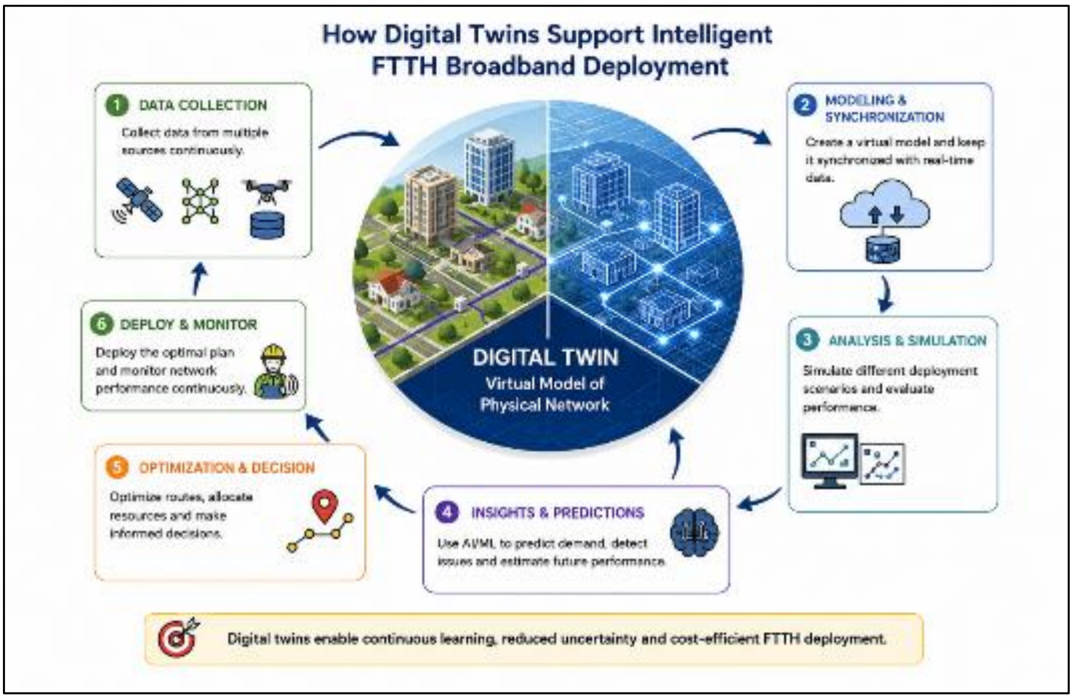

Figure 3 Digital Twin Framework for Intelligent FTTH Broadband Infrastructure Planning

Figure 3 illustrates the role of digital twin technology in intelligent FTTH broadband infrastructure planning. The framework begins with continuous data collection from multiple sources, including geospatial datasets, network infrastructure records, sensors, and operational databases. These data are synchronized with a digital twin, creating a real-time virtual representation of the physical broadband network. Engineers can then simulate deployment scenarios, evaluate network performance, and assess alternative routing strategies without affecting physical operations. Artificial intelligence and machine learning support predictive analytics, demand forecasting, and anomaly detection. The resulting insights enable optimized route selection, efficient resource allocation, proactive monitoring, and informed decision-making, ultimately reducing deployment uncertainty, lowering costs, improving network performance, and supporting scalable broadband expansion across underserved communities.

4.3. Predictive Demand Analytics for Broadband Coverage Prioritization

Predictive demand analytics has become a critical component of broadband infrastructure planning because effective FTTH deployment depends on accurate forecasts of future connectivity needs, service adoption patterns, and network utilization trends. Traditional planning approaches often rely on historical subscription records and demographic estimates, which may not adequately capture rapidly changing digital behaviors and emerging service demands. Artificial Intelligence-driven predictive analytics overcomes these limitations by applying machine learning algorithms capable of identifying complex relationships among socioeconomic factors, population growth, broadband adoption rates, and evolving connectivity requirements (Oloba et al, 2024).

Accurate demand forecasting is particularly important in underserved American communities where deployment resources are limited and investment decisions must generate maximum social and economic impact. Predictive models enable broadband providers to identify areas with the highest likelihood of future service adoption, allowing more effective prioritization of deployment efforts. Advanced forecasting techniques have demonstrated superior performance compared to conventional prediction methods when analyzing large-scale systems characterized by uncertain and dynamic demand patterns (Makridakis et al., 2020).

Modern machine learning models integrate demographic information, economic indicators, educational attainment, housing density, mobile usage trends, and regional development projections to estimate future broadband demand. These capabilities improve infrastructure planning by aligning network expansion with anticipated service requirements. By identifying high-priority deployment zones, predictive demand analytics helps optimize infrastructure investments, improve service accessibility, and accelerate digital inclusion while minimizing costs associated with inefficient deployment decisions (Douaioui et al., 2024).

4.4. AI Enabled Resilient and Sustainable Broadband Network Expansion

Artificial Intelligence is increasingly recognized as a critical enabler of resilient and sustainable broadband network expansion because it improves infrastructure adaptability, operational efficiency, and long-term service reliability. Traditional broadband deployment strategies often prioritize coverage expansion while giving limited attention to resilience against infrastructure failures, environmental disruptions, cybersecurity risks, and future demand growth. AI-enabled systems address these challenges by integrating predictive analytics, automated monitoring, adaptive optimization, and intelligent resource management into broadband planning and operations (Ijiga, et al, 2024).

Network resilience refers to the ability of broadband systems to maintain reliable service despite disruptions such as equipment malfunctions, natural disasters, cyberattacks, or sudden traffic surges. Artificial Intelligence enhances resilience by continuously monitoring network conditions, identifying anomalies, predicting potential failures, and recommending corrective actions before service degradation occurs. Advanced communication networks increasingly rely on intelligent management systems that dynamically allocate resources and optimize performance under changing operating conditions (Bello et al., 2017).

Sustainability is equally important because broadband deployment requires significant financial, material, and energy resources. AI-driven optimization can reduce environmental impact by minimizing unnecessary construction activities, improving infrastructure utilization, and supporting efficient capacity planning. Emerging intelligent network architectures further enhance scalability while maintaining resource efficiency as presented in Table 3 (Khan et al., 2020).

For underserved American communities, AI-enabled broadband planning supports the development of future-ready FTTH networks that adapt to technological advancements, changing user demands, and operational uncertainties. This ensures cost-effective, reliable, and environmentally sustainable broadband expansion.

Table 3 Summary of AI-Enabled Resilient and Sustainable Broadband Network Expansion

Component	Description	FTTH Application	Key Benefit
Predictive Network Resilience	AI continuously monitors network conditions and predicts potential failures	Fault detection, anomaly monitoring, and preventive maintenance	Improved service continuity and network reliability
Adaptive Resource Management	Intelligent systems dynamically allocate network resources based on operational conditions	Traffic management and infrastructure optimization	Enhanced operational efficiency and performance
Sustainable Infrastructure Planning	AI optimizes deployment activities and resource utilization	Capacity planning, route optimization, and construction management	Reduced environmental impact and lower deployment costs
Future-Proof Network Expansion	AI supports scalable and adaptable broadband development strategies	Long-term FTTH planning for underserved communities	Resilient, cost-effective, and sustainable broadband growth

5. Comparative Review of Existing AI Based Optimization Models and Research Gaps

5.1. Comparative Analysis of Classical and AI Based Fiber Routing Approaches

Classical fiber routing approaches have long served as the foundation of telecommunications infrastructure planning through deterministic optimization methods such as shortest-path algorithms, minimum spanning trees, linear programming, and heuristic engineering techniques. These methods primarily aim to minimize deployment distance and construction costs while meeting predefined technical requirements. Their computational efficiency and simplicity make them attractive for conventional network design applications (Sapundzhi & Popstoilov, 2018). However, traditional routing models generally assume static operating conditions and often fail to account for complex factors such as terrain variability, demographic uncertainty, environmental restrictions, infrastructure reuse opportunities, and future service demand growth.

Artificial Intelligence-based routing approaches overcome these limitations by incorporating adaptive learning, predictive analytics, and autonomous optimization capabilities into broadband planning. Machine learning algorithms can process large volumes of geospatial, environmental, socioeconomic, and infrastructure data to identify routing solutions that optimize both deployment efficiency and long-term network performance. Unlike deterministic methods, AI-driven systems continuously learn from new data and refine their decisions through iterative optimization processes as represented in Table 4 (Jordan & Mitchell, 2015).

Recent studies indicate that AI-based routing methods outperform traditional approaches in complex and heterogeneous deployment environments. These systems can identify deployment corridors that offer lower overall costs and greater coverage potential, even when they do not represent the shortest physical routes. Consequently, AI-driven optimization provides greater flexibility, scalability, and decision-making intelligence for cost-effective FTTH deployment in underserved American communities.

Table 4 Comparison of Classical and AI-Based Fiber Routing Approaches

Evaluation Aspect	**Classical Routing Approaches**	**AI-Based Routing Approaches**	**Impact on FTTH Deployment**
Decision Method	Uses predefined algorithms such as shortest-path and minimum spanning tree models	Uses machine learning and adaptive optimization techniques	Improves route selection accuracy and adaptability
Data Utilization	Limited to engineering and network parameters	Integrates geospatial, demographic, environmental, and infrastructure data	Supports more comprehensive planning decisions
Response to Dynamic Conditions	Assumes static deployment environments	Continuously learns and adapts to changing conditions	Enhances flexibility under evolving deployment scenarios
Deployment Outcome	Prioritizes shortest distance and reduced initial cost	Optimizes cost, coverage, scalability, and long-term performance	Enables more efficient and sustainable FTTH expansion

5.2. Performance Evaluation Metrics for FTTH Optimization Models

Performance evaluation is a fundamental aspect of FTTH optimization research because broadband deployment frameworks must simultaneously satisfy engineering, economic, and operational objectives. Unlike conventional telecommunications systems that often focus primarily on throughput and latency, FTTH optimization models require comprehensive evaluation frameworks capable of assessing deployment efficiency, service coverage, infrastructure resilience, and long-term investment sustainability.

Coverage ratio is one of the most important performance indicators because it measures the percentage of households or communities successfully reached by a deployment strategy. Cost-related metrics evaluate factors such as total deployment expenditure, cost per connected household, trenching distance reduction, and infrastructure reuse efficiency. Route efficiency metrics assess how effectively an optimization model minimizes construction complexity while maintaining adequate service accessibility.

For Artificial Intelligence-based optimization frameworks, predictive performance evaluation is equally important. Machine learning metrics such as precision, recall, F1-score, classification accuracy, and Receiver Operating Characteristic (ROC) analysis are commonly used to assess demand forecasting models and deployment prioritization systems (Fawcett, 2006). These measures evaluate how accurately AI systems identify high-priority deployment regions and predict future broadband demand.

Additional indicators such as Area Under the Curve (AUC), network reliability, scalability, latency reduction, energy efficiency, fault resilience, and socioeconomic impact provide further insight into model effectiveness as shown in Figure 4 (Hand, 2009). Collectively, these performance metrics enable comprehensive assessment of FTTH optimization models and facilitate meaningful comparison between traditional engineering approaches and advanced AI-driven deployment framework.

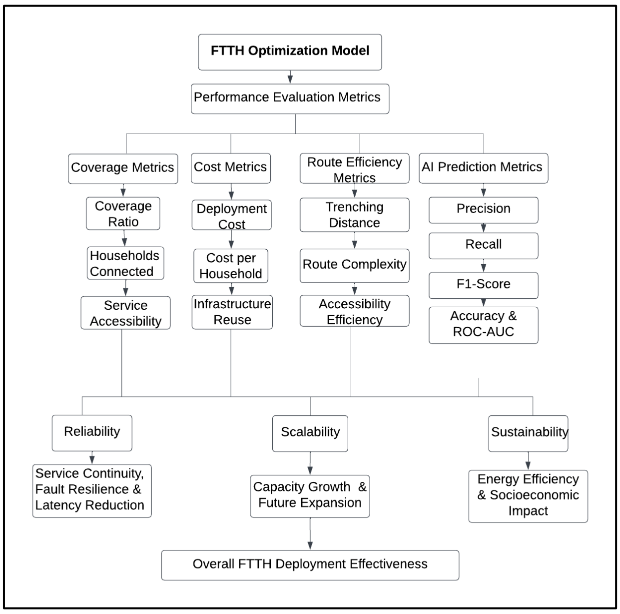

Figure 4 A Block Diagram Showing Performance Evaluation Framework for FTTH Optimization Models.

Figure 4 presents a comprehensive framework for evaluating the performance of FTTH optimization models. The framework categorizes assessment criteria into coverage metrics, cost metrics, route efficiency metrics, and AI prediction metrics. Coverage metrics measure service reach and connectivity, while cost metrics evaluate deployment expenditure and infrastructure utilization efficiency. Route efficiency assesses construction complexity and accessibility, whereas AI metrics evaluate predictive performance using measures such as precision, recall, accuracy, and ROC-AUC. These indicators collectively contribute to network performance assessment through reliability, scalability, and sustainability analysis. The integrated evaluation framework enables objective comparison of traditional and AI-driven broadband deployment strategies and supports informed decision-making for cost-effective FTTH expansion.

5.3. Limitations of Existing Intelligent Broadband Deployment Frameworks

Despite considerable progress in Artificial Intelligence-driven broadband planning, existing intelligent deployment frameworks still face several limitations that affect their effectiveness in real-world FTTH expansion projects. One major challenge is data dependency. Most AI-based optimization systems require large volumes of accurate geospatial, demographic, infrastructure, and economic data to produce reliable results. However, in many underserved communities, such data are often incomplete, outdated, or inconsistent, reducing model accuracy and generalizability (Ijiga, et al, 2024).

Another concern is model robustness. While many intelligent planning systems perform well in controlled environments, they often struggle when applied to diverse real-world conditions involving varying terrain characteristics, regulatory requirements, and socioeconomic factors. Robust AI systems must be capable of adapting to uncertain and evolving operating environments, a capability that remains limited in many existing broadband planning models (Dietterich, 2017).

Computational complexity also presents a significant barrier. Advanced techniques such as deep learning and graph neural networks frequently require substantial computational resources, extensive training data, and specialized expertise, making adoption difficult for smaller broadband providers. Additionally, AI systems often experience technical debt associated with model maintenance and continuous updates (Sculley et al., 2015).

Most current frameworks also focus on isolated objectives such as route optimization or demand forecasting rather than integrating regulatory compliance, network resilience, environmental sustainability, and socioeconomic impact. These limitations highlight the need for more scalable, interpretable, and comprehensive AI-driven FTTH planning frameworks.

5.4. Research Gaps in AI Driven FTTH Expansion Across Underserved Communities

A comprehensive review of the literature reveals several important research gaps in the application of Artificial Intelligence to FTTH expansion across underserved American communities. Although substantial progress has been achieved in machine learning, geospatial intelligence, reinforcement learning, and network optimization, relatively few studies have specifically focused on broadband deployment environments characterized by rural isolation, economic disadvantage, low population density, and limited infrastructure availability. Most existing optimization frameworks are developed using datasets derived from urban or highly connected environments, reducing their applicability to underserved deployment contexts.

A second major research gap involves the limited integration of multidisciplinary variables into optimization frameworks. Current studies frequently focus on engineering objectives such as route efficiency, cost reduction, or network performance while neglecting broader socioeconomic factors including digital equity, community development priorities, affordability constraints, and long-term social impact. Consequently, existing models often fail to align infrastructure planning decisions with broader public policy objectives (Ijiga, et al, 2024).

Another significant limitation concerns model interpretability. Many AI-based broadband planning frameworks rely on complex deep learning architectures that produce highly accurate predictions but provide limited transparency regarding decision-making processes. Rudin (2019) argues that interpretable Artificial Intelligence is essential in high-impact decision environments where accountability and trust are critical. This concern is particularly relevant for broadband deployment because infrastructure investments frequently involve public funding and regulatory oversight.

Furthermore, few studies have explored the integration of digital twins, Graph Neural Networks, reinforcement learning, and predictive demand analytics within a unified optimization ecosystem. Bengio et al. (2021) emphasize the importance of combining multiple AI paradigms to address increasingly complex real-world challenges. Future research should therefore focus on developing explainable, multidisciplinary, and adaptive optimization frameworks specifically designed for underserved American communities, enabling more equitable, resilient, and economically sustainable FTTH expansion strategies.

6. Future directions

6.1. Emerging AI Opportunities in Autonomous Broadband Infrastructure Engineering

The rapid evolution of Artificial Intelligence is creating unprecedented opportunities for the development of autonomous broadband infrastructure engineering systems capable of transforming how Fiber-to-the-Home networks are planned, deployed, managed, and optimized. Emerging AI technologies are progressively shifting broadband infrastructure development from static engineering workflows toward adaptive, self-learning, and data-driven decision environments. Future autonomous broadband systems are expected to integrate machine learning, reinforcement learning, digital twins, graph neural networks, computer vision, and geospatial intelligence into unified planning ecosystems capable of continuously optimizing deployment decisions throughout the infrastructure lifecycle.

One of the most promising opportunities involves autonomous fiber route engineering where AI systems automatically evaluate terrain conditions, demographic demand patterns, utility infrastructure availability, environmental restrictions, and construction costs to identify optimal deployment pathways without extensive manual intervention. Intelligent digital twins can further provide real-time virtual representations of broadband assets, enabling predictive maintenance, fault anticipation, infrastructure performance monitoring, and capacity forecasting. Autonomous planning platforms may also integrate satellite imagery, drone-based surveys, and remote sensing technologies to accelerate infrastructure assessment and reduce pre-deployment planning costs.

Another emerging opportunity lies in AI-enabled adaptive network expansion. Rather than relying on fixed deployment schedules, future systems could dynamically prioritize underserved communities based on changing socioeconomic indicators, broadband adoption forecasts, educational needs, healthcare requirements, and economic development objectives. Advanced predictive models may also support proactive infrastructure scaling before demand congestion occurs. As broadband increasingly becomes critical national infrastructure, autonomous AI-driven engineering frameworks offer the potential to significantly improve deployment speed, investment efficiency, network resilience, and long-term sustainability while accelerating equitable digital inclusion across underserved American communities.

6.2. Strategic Implications for Policymakers and Broadband Service Providers

The increasing integration of Artificial Intelligence into FTTH broadband planning carries significant strategic implications for policymakers, regulators, infrastructure investors, and broadband service providers. The findings of this review indicate that AI-driven optimization frameworks have the potential to substantially improve deployment efficiency, reduce capital expenditure, increase service coverage, and accelerate broadband expansion across underserved communities. Consequently, future broadband strategies must increasingly incorporate intelligent planning methodologies as a core component of national digital infrastructure development programs.

For policymakers, the emergence of AI-enabled broadband planning necessitates the development of regulatory frameworks that encourage innovation while ensuring transparency, accountability, and equitable access outcomes. Public broadband investment programs can benefit significantly from intelligent prioritization systems that identify regions where infrastructure deployment generates the greatest socioeconomic impact. AI-assisted planning can also improve the allocation of federal and state broadband funding by supporting evidence-based investment decisions that maximize connectivity benefits while minimizing unnecessary expenditure.

Broadband service providers similarly stand to benefit from the adoption of intelligent deployment frameworks. Machine learning-based planning systems can improve route engineering accuracy, optimize infrastructure utilization, reduce construction risks, and enhance project execution efficiency. Predictive demand analytics can assist providers in identifying emerging service opportunities and prioritizing investments in regions with strong long-term growth potential. Furthermore, AI-enabled resilience planning can strengthen operational reliability by supporting proactive maintenance, risk forecasting, and infrastructure adaptation.

The strategic integration of AI into broadband deployment therefore represents not only a technological advancement but also a transformative policy and business opportunity capable of improving digital inclusion, economic development, service sustainability, and national connectivity objectives across underserved American regions.

6.3. Future Research Directions in Intelligent FTTH Network Expansion

Although significant progress has been achieved in applying Artificial Intelligence to broadband infrastructure planning, numerous research opportunities remain for advancing intelligent FTTH network expansion frameworks. One critical direction involves the development of integrated multi-agent optimization environments that combine machine learning, reinforcement learning, graph neural networks, digital twins, and geospatial intelligence into a unified autonomous planning architecture. Existing studies frequently examine these technologies independently, creating opportunities for future research focused on comprehensive intelligent deployment ecosystems capable of addressing complex real-world planning challenges.

Future research should also investigate explainable Artificial Intelligence techniques specifically designed for broadband infrastructure decision-making. As public investment increasingly supports broadband deployment, stakeholders require transparent optimization frameworks capable of clearly explaining route selection decisions, deployment priorities, and infrastructure investment recommendations. Improved model interpretability would enhance stakeholder trust and facilitate regulatory acceptance of AI-driven planning systems.

Another important direction involves integrating climate resilience and environmental sustainability considerations into FTTH optimization models. Future broadband infrastructure must withstand increasingly severe weather events, environmental disruptions, and changing demographic patterns. Intelligent planning systems should therefore incorporate predictive resilience metrics alongside traditional deployment objectives. Additionally, research is needed to develop adaptive broadband planning models capable of continuously learning from operational network data and updating deployment strategies in response to evolving conditions.

Further investigation is also required into the use of emerging technologies such as edge intelligence, federated learning, satellite-assisted broadband analytics, and autonomous infrastructure monitoring systems. These advancements could significantly improve deployment scalability and decision quality while reducing planning uncertainty. Collectively, these research directions have the potential to establish a new generation of intelligent broadband expansion frameworks capable of delivering more efficient, resilient, and equitable FTTH deployment outcomes.

7. Conclusion

This review has examined the growing role of Artificial Intelligence in supporting cost-efficient Fiber-to-the-Home broadband expansion across underserved American communities. The analysis demonstrates that conventional broadband deployment approaches face significant limitations arising from complex geospatial environments, escalating infrastructure costs, regulatory constraints, uncertain demand patterns, and the persistent challenge of achieving equitable connectivity outcomes. While traditional routing and planning methodologies provide useful engineering foundations, they often lack the adaptability and predictive capabilities required to address the multidimensional challenges associated with large-scale broadband expansion initiatives.

The review further highlights the substantial potential of Artificial Intelligence technologies including machine learning, reinforcement learning, graph neural networks, digital twins, predictive demand analytics, and multi-objective optimization algorithms to transform broadband infrastructure engineering. These technologies provide advanced capabilities for automated route selection, infrastructure simulation, demand forecasting, resource allocation, network resilience enhancement, and deployment cost reduction. The comparative analysis indicates that AI-driven approaches consistently offer greater flexibility, scalability, and decision-making intelligence than conventional planning frameworks, particularly within geographically diverse and economically constrained deployment environments.

Additionally, the review identifies important limitations in existing intelligent broadband planning systems, including data availability challenges, model interpretability concerns, computational complexity, and insufficient integration of socioeconomic and policy considerations. Addressing these limitations will be essential for achieving practical and scalable deployment solutions. Overall, the evidence presented throughout this review supports the conclusion that Artificial Intelligence represents a critical enabling technology for the future of broadband infrastructure engineering and provides a promising pathway toward accelerating affordable, resilient, and inclusive FTTH network expansion across underserved American communities.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Akorli, K. Y., & Enyejo, J. O. (2024). Developing causal uplift algorithm for U.S. omnichannel personalization optimizing lifetime value predictions. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 10(6), 2603–2623. https://doi.org/10.32628/CSEIT25113677

[2] Akorli, K. Y., & Peter-Anyebe, A. C. (2024). Impact of first-party data driven retail media networks on ad performance and privacy compliance among U.S. retailers. International Journal of Scientific Research in Science, Engineering and Technology, 11(5), 449–474. https://doi.org/10.32628/IJSRSET2513155

[3] Akyildiz, I. F., Lee, A., Wang, P., Luo, M., & Chou, W. (2014). A roadmap for traffic engineering in SDN-OpenFlow networks. Computer Networks, 71, 1-30.

[4] Aluso, L. (2021). Forecasting Marketing ROI Through Cross-Platform Data Integration Between HubSpot CRM and Power BI International Journal of Scientific Research in Science, Engineering and Technology Volume 8, Issue 6, 356-378 doi : https://doi.org/10.32628/IJSRSET214420

[5] Bengio, Y., Lecun, Y., & Hinton, G. (2021). Deep learning for AI. Communications of the ACM, 64(7), 58–65. https://doi.org/10.1145/3448250

[6] Coello Coello, C. A. (2006). Evolutionary multi-objective optimization: A historical view of the field. IEEE Computational Intelligence Magazine, 1(1), 28–36. https://doi.org/10.1109/MCI.2006.1597059

[7] Crandall, R. W., Eisenach, J. A., & Ingraham, A. T. (2013). The long-run effects of copper-loop unbundling and the implications for fiber. Telecommunications Policy, 37(4-5), 262-281.

[8] Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation, 6(2), 182–197. https://doi.org/10.1109/4235.996017

[9] Dietterich, T. G. (2017). Steps toward robust artificial intelligence. AI Magazine, 38(3), 3–24. https://doi.org/10.1609/aimag.v38i3.2744

[10] Dijkstra, E. W. (2022). A note on two problems in connexion with graphs. Numerische Mathematik, 1(1), 269–271. https://doi.org/10.1007/BF01386390

[11] Douaioui, K., Oucheikh, R., Benmoussa, O., & Mabrouki, C. (2024). Machine learning and deep learning models for demand forecasting in supply chain management: A critical review. Applied System Innovation, 7(5), 93.

[12] Ebenibo, L., Enyejo, J. O., Addo, G., & Olola, T. M. (2024). Evaluating the sufficiency of the data protection act 2023 in the age of artificial intelligence: A comparative case study of Nigeria and the USA. International Journal of Scholarly Research and Reviews, 5(1), 88–107.

[13] Fawcett, T. (2006). An introduction to ROC analysis. Pattern Recognition Letters, 27(8), 861–874. https://doi.org/10.1016/j.patrec.2005.10.010

[14] Fouli, K., Maier, M., & Medard, M. (2011). Network coding in next-generation passive optical networks. IEEE Communications Magazine, 49(9), 38-46.

[15] Frimpong, G., Peter-Anyebe, A. C., & Ijiga, O. M. (2023). Artificial intelligence driven compliance automation improving audit readiness and fraud detection within healthcare revenue cycle management systems. Global Journal of Engineering, Science & Social Science Studies, 9(9).

[16] Fuller, A., Fan, Z., Day, C., & Barlow, C. (2020). Digital twin Enabling technologies challenges and open research. IEEE Access, 8, 108952–108971. https://doi.org/10.1109/ACCESS.2020.2998358

[17] Gabla, E. S., Peter-Anyebe, A. C., & Ijiga, O. M. (2025). Assessing machine learning enabled anomaly detection models for real time cyberattack mitigation in optical fiber communication systems. World Journal of Advanced Engineering Technology and Sciences, 17(2), 001–017. https://doi.org/10.30574/wjaets.2025.17.2.1454

[18] Gabla, E., S., Enyejo, L. A., & James, U. U. (2025). Investigating 5G network slicing security vulnerabilities using artificial intelligence driven intrusion detection for telecommunication resilience. World Journal of Advanced Engineering Technology and Sciences, 17(2), 98–112. https://doi.org/10.30574/wjaets.2025.17.2.1431

[19] Hand, D. J. (2009). Measuring classifier performance A coherent alternative to the area under the ROC curve. Machine Learning, 77(1), 103–123. https://doi.org/10.1007/s10994-009-5119-5

[20] Hauge, J. A., & Prieger, J. E. (2010). Demand-side programs to stimulate adoption of broadband: What works?. Available at SSRN 1492342.

[21] Ijiga, A. C., Aboi, E. J., Idoko, P. I., Enyejo, L. A., & Odeyemi, M. O. (2024). Collaborative innovations in Artificial Intelligence (AI): Partnering with leading U.S. tech firms to combat human trafficking. Global Journal of Engineering and Technology Advances, 2024,18(03), 106-123. https://gjeta.com/sites/default/files/GJETA-2024-0046.pdf

[22] Ijiga, A. C., Abutu, E. P., Idoko, P. I., Agbo, D. O., Harry, K. D., Ezebuka, C. I., & Umama, E. E. (2024). Ethical considerations in implementing generative AI for healthcare supply chain optimization: A cross-country analysis across India, the United Kingdom, and the United States of America. International Journal of Biological and Pharmaceutical Sciences Archive, 2024, 07(01), 048–063. https://ijbpsa.com/sites/default/files/IJBPSA-2024-0015.pdf

[23] Ijiga, A. C., Olola, T. M., Enyejo, L. A., Akpa, F. A., Olatunde, T. I., & Olajide, F. I. (2024). Advanced surveillance and detection systems using deep learning to combat human trafficking. Magna Scientia Advanced Research and Reviews, 2024, 11(01), 267–286. https://magnascientiapub.com/journals/msarr/sites/default/files/MSARR-2024-0091.pdf.

[24] James, U. U., Olarinoye, H. S., Uchenna, I. R., Idika, C. N., Ngene, O. J., Ijiga, O. M., & Itemuagbor, K. (2025). Combating deepfake threats using X-FACTS explainable CNN framework for enhanced detection and cybersecurity resilience. Advances in Artificial Intelligence and Robotics Research, 1, 41–64.

[25] Jordan, M. I., & Mitchell, T. M. (2015). Machine learning Trends perspectives and prospects. Science, 349(6245), 255–260. https://doi.org/10.1126/science.aaa8415

[26] Kazi, K. (Ed.). (2007). Optical networking standards: a comprehensive guide for professionals. Springer Science & Business Media.

[27] Khan, A., Rehmani, M. H., & Reisslein, M. (2019). Cognitive radio for smart grids: Survey of architectures, spectrum sensing mechanisms, and networking protocols. IEEE Communications Surveys & Tutorials, 18(1), 860–898. https://doi.org/10.1109/COMST.2015.2481722

[28] Kotakorpi, K. (2002). Access pricing and competition in telecommunications.

[29] Li, W., Fu, H., Yu, L., & Cracknell, A. (2017). Deep learning based oil palm tree detection and counting for high-resolution remote sensing images. Remote Sensing, 9(1), 22. https://doi.org/10.3390/rs9010022

[30] Luong, N. C., Hoang, D. T., Gong, S., Niyato, D., Wang, P., Liang, Y. C., & Kim, D. I. (2019). Applications of deep reinforcement learning in communications and networking: A survey. IEEE Communications Surveys & Tutorials, 21(4), 3133–3174. https://doi.org/10.1109/COMST.2019.2916583

[31] Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2020). The M4 competition 100000 time series and 61 forecasting methods. International Journal of Forecasting, 36(1), 54–74. https://doi.org/10.1016/j.ijforecast.2019.04.014

[32] Mao, Q., Hu, F., & Hao, Q. (2018). Deep learning for intelligent wireless networks: A comprehensive survey. IEEE Communications Surveys & Tutorials, 20(4), 2595–2621. https://doi.org/10.1109/COMST.2018.2846401

[33] McGarry, M. P., Reisslein, M., & Maier, M. (2008). Ethernet passive optical network architectures and dynamic bandwidth allocation algorithms. IEEE Communications Surveys & Tutorials, 10(3), 46-60.

[34] Michael, C. I, Campbell, T. Idoko, I. P., Bemologi, O. U., Anyebe, A. P., & Odeh, I. I. (2024). Enhancing Cybersecurity Protocols in Financial Networks through Reinforcement Learning. International Journal of Scientific Research and Modern Technology (IJSRMT). Vol 3, Issue 9, 2024. Doi:- 10.38124/ijsrmt.v3i9.58

[35] Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., Graves, A., Riedmiller, M., Fidjeland, A. K., Ostrovski, G., Petersen, S., Beattie, C., Sadik, A., Antonoglou, I., King, H., Kumaran, D., Wierstra, D., Legg, S., & Hassabis, D. (2015). Human-level control through deep reinforcement learning. Nature, 518(7540), 529–533. https://doi.org/10.1038/nature14236

[36] Mohammed Hamud, A., Mobarak Prince, H., & Zulhaidi Shafri, H. (2019, November). Landuse/Landcover mapping and monitoring using Remote sensing and GIS with environmental integration. In IOP Conference Series: Earth and Environmental Science (Vol. 357, No. 1, p. 012038). IOP Publishing.

[37] Nwokocha, C. R., & Okoh, O. F. (2023). Designing sustainable telecommunication infrastructure for scalable health information exchange and population health management in developing regions. Engineering Science & Technology Journal, 4(6).

[38] Nwokocha, C. R., & Peter-Anyebe, A. C. (2022). Integrating embedded systems and neural network models for real-time clinical communication and smart healthcare interoperability. International Journal of Scientific Research and Modern Technology, 1(11), 21–34. https://doi.org/10.38124/ijsrmt.v1i11.1218

[39] Nwokocha, C. R., Peter-Anyebe, A. C., & Ijiga, O. M. (2021). Evaluating FHIR-driven interoperability frameworks for secure system migration and data exchange in U.S. health information networks. International Journal of Scientific Research in Science and Technology. https://doi.org/10.32628/IJSRST523105135

[40] Okoh, O. F., Ukpoju, E. A., Otakwu, A., Ayoola, V. B., & Ijiga, A. C. (2024). Evaluating the influence of human capital development on economic growth: A global analysis of the potential impact of artificial intelligence technologies. Corporate Sustainable Management Journal, 2(1), 49–59. http://doi.org/10.26480/csmj.01.2024.49.59

[41] Oloba, B. L., Olola, T. M., & Ijiga, A, C. (2024). Powering reputation: Employee communication as the key to boosting resilience and growth in the U.S. Service Industry. World Journal of Advanced Research and Reviews, 2024, 23(03), 2020–2040. https://doi.org/10.30574/wjarr.2024.23.3.2689

[42] Onwuzurike, M. A., & Kpogli, S. A. (2022). Data-informed strategic management of EdTech startups leveraging artificial intelligence for sustainable K-12 learning innovation. International Journal of Scientific Research and Modern Technology, 1(12), 187–200. https://doi.org/10.38124/ijsrmt.v1i12.1117

[43] Onyekaonwu, C. B., Ogundolapo, O. O., & Peter-Anyebe, A. C. (2025). The role of technical product managers in architecting AI-powered infrastructure: A compliance-driven framework. International Journal of Innovative Science and Research Technology, 10(12). https://doi.org/10.38124/ijisrt/25dec1185

[44] Onyekaonwu, C. B., Peter-Anyebe, A. C., Ijiga, O. M., Amebleh, J., & Balogun, S. A. (2022). Securing the digital vault: Enterprise data loss prevention in the age of GDPR and NDPR. International Journal of Scientific Research and Modern Technology, 1(6), 14–28. https://doi.org/10.38124/ijsrmt.v1i6.1159

[45] Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nature Machine Intelligence, 1(5), 206–215. https://doi.org/10.1038/s42256-019-0048-x

[46] Sapundzhi, F. I., & Popstoilov, M. S. (2018). Optimization algorithms for finding the shortest paths. Bulgarian Chemical Communications, 50(Special Issue B), 115-120.

[47] Scarselli, F., Gori, M., Tsoi, A. C., Hagenbuchner, M., & Monfardini, G. (2009). The graph neural network model. IEEE Transactions on Neural Networks, 20(1), 61–80. https://doi.org/10.1109/TNN.2008.2005605

[48] Sculley, D., Holt, G., Golovin, D., Davydov, E., Phillips, T., Ebner, D., Chaudhary, V., Young, M., Crespo, J. F., & Dennison, D. (2015). Hidden technical debt in machine learning systems. Advances in Neural Information Processing Systems, 28, 2503–2511.

[49] Shen, Y., Zhu, X., Guo, Z., Yu, K., Alfarraj, O., Leung, V. C., & Rodrigues, J. J. (2024). A deep-learning-based data-management scheme for intelligent control of wastewater treatment processes under resource-constrained IoT systems. IEEE Internet of Things Journal, 11(15), 25757-25770.

[50] Sun, Y., Peng, M., Zhou, Y., Huang, Y., & Mao, S. (2019). Application of machine learning in wireless networks: Key techniques and open issues. IEEE Communications Surveys & Tutorials, 21(4), 3072–3108. https://doi.org/10.1109/COMST.2019.2924243

[51] Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C. (2019). Digital twin in industry State-of-the-art. IEEE Transactions on Industrial Informatics, 15(4), 2405–2415. https://doi.org/10.1109/TII.2018.2873186

[52] Tron, A. (2022). Putting the" Universal" Back in" Universal Service": Broadband Access for Low-Income Citizens Under Net Neutrality. S. Cal. Rev. L. & Soc. Just., 31, 433.

[53] Whitacre, B. E., Gallardo, R., & Strover, S. (2014). Broadband's contribution to economic growth in rural areas. Telecommunications Policy, 38(11), 1011–1023. https://doi.org/10.1016/j.telpol.2014.05.005

[54] Wu, Z., Pan, S., Chen, F., Long, G., Zhang, C., & Yu, P. S. (2021). A comprehensive survey on graph neural networks. IEEE Transactions on Neural Networks and Learning Systems, 32(1), 4–24. https://doi.org/10.1109/TNNLS.2020.2978386

[55] Xiong, Z. (2013). Socio-economic Impact of Fiber to the Home in Sweden.

[56] Zhu, X. X., Tuia, D., Mou, L., Xia, G. S., Zhang, L., Xu, F., & Fraundorfer, F. (2017). Deep learning in remote sensing A comprehensive review and list of resources. IEEE Geoscience and Remote Sensing Magazine, 5(4), 8–36. https://doi.org/10.1109/MGRS.2017.2762307