

Article

Practical Pathways for Optimizing Rural Communication Networks in Mountainous Areas Using Artificial Intelligence

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Abstract: Aiming at weak communication network coverage and low-efficiency manual network optimization (NRO) troubleshooting in mountainous rural areas, this paper proposes an artificial intelligence (AI) assisted NRO approach, constructing a human-machine collaborative workflow: "AI simulation pre-judgment, data preliminary screening, engineer on-site recheck, closed-loop iterative optimization." AI leverages massive data processing for coverage simulation, poor-quality user mining, tidal traffic analysis, and geological hazard identification to narrow manual inspection scope; engineers conduct targeted rectification and feed measured data back to correct model deviations. This study selects typical mountainous townships in Hanzhong as pilot, integrating multi-source data including measurement reports (MR), base-station engineering parameters, traffic key performance indicators (KPI), user complaint tickets, and digital elevation model (DEM). AI pre-screening output 42 points to be checked; after on-site recheck, 14 false alarms were removed and 28 real problems confirmed. Optimization effects were compared across network quality, user perception, O&M workload, and hazard early-warning dimensions. Implementation constraints including model bias, outdated equipment, talent shortage, funding insufficiency, and data barriers are analyzed, with countermeasures proposed from operation mechanism, hardware iteration, talent cultivation, resource coordination, and data governance dimensions, providing reference for large-scale AI application in rural communication NRO.

Keywords: Artificial intelligence; Rural communication network; Network optimization; Human-machine collaboration; Mountainous coverage

1. Introduction

1.1. Research Background and Significance

With the national rural revitalization strategy advancing, rural information infrastructure has gained increasing strategic importance. By end-2025, administrative village broadband coverage exceeded 99% and 4G achieved full coverage nationwide. However, in complex terrain of central-western mountainous areas such as the Qinling-Daba Mountains, constrained by undulating terrain, scattered settlements, and difficult base-station site selection, problems including insufficient in-depth coverage, unstable signal quality, and holiday tidal congestion remain prominent. Hanzhong lies in the Qinling-Daba core area, where rural base-station layout is significantly affected by terrain occlusion. Traditional NRO relies on engineer experience for manual inspection, suffering from wide inspection scope, long cycle, low efficiency, and strong subjectivity.

AI has demonstrated strong data-processing capabilities in communication network optimization, but existing research mostly focuses on urban dense-network scenarios; human-machine collaborative application paths for mountainous rural areas from front-line engineer perspective remain scarce. This paper explores the human-machine collaborative workflow to exploit AI's advantage in processing massive multi-source data, narrow manual inspection scope, improve NRO efficiency and accuracy, while preserving

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engineers' irreplaceable role in field survey, forming a replicable standardized operation mode with practical significance for bridging the urban-rural digital divide.

1.2. Research Objectives

This study aims to explore the practical path of deep integration between AI technology and traditional manual NRO based on real rural communication network demand in mountainous areas, breaking through bottlenecks of weak coverage and low-efficiency poor-quality troubleshooting. By constructing the human-machine collaborative workflow, the study verifies AI effectiveness in coverage simulation, poor-quality mining, tidal traffic analysis, and geological hazard identification, forming a standardized operation paradigm. Practical problems including model bias, equipment constraints, and talent shortage are summarized with targeted countermeasures proposed, providing theoretical support and replicable experience for improving rural communication service quality and serving the "digital village" strategy.

1.3. Literature Review

1.3.1. Foreign Research Status

Foreign scholars began early research on integrated optimization of AI and mobile communication networks. Early research focused on heuristic algorithms for resource allocation and handover optimization in cellular networks. The tabu search algorithm for handoff-cell optimization proposed by Xu et al [1]. proved that heuristic intelligent algorithms outperform traditional manual tuning in convergence speed and global optimization. With machine learning maturation, foreign research shifted to systematic intelligent network framework construction, applying neural networks, genetic algorithms, and fuzzy logic to base-station site selection, channel allocation, and power control. Recent deep learning developments extended research to self-organizing, self-optimizing, and self-healing networks. However, existing research mostly targets urban dense-network scenarios; specialized research on rural communication network optimization remains limited.

1.3.2. Domestic Research Status

Domestic scholars have carried out systematic research on the application of AI in communication network optimization, covering intelligent algorithms, coverage optimization, O&M systems, traffic prediction, energy consumption control, and fault diagnosis, showing an overall trend from single-technology breakthrough to systematic integration. At the algorithm level, Han [2] addressed the intelligent optimization problem of communication networks and proposed an AI-based network optimization algorithm that improves the accuracy of network parameter adjustment through model training, providing an algorithmic foundation for intelligent optimization. Ye [3] focused on 5G mobile communication network coverage and proposed differentiated AI coverage optimization strategies for different application scenarios, enhancing the adaptability and stability of network signal coverage. From the overall perspective of communication network construction and O&M, Huang [4] discussed the construction path of an intelligent O&M system empowered by AI, emphasizing the collaborative optimization of network construction and O&M management.

In traffic prediction and O&M optimization, Shi [5] achieved accurate network traffic trend prediction. Zhou [6] explored AI-driven communication network O&M optimization. Liu and Tu [7] combined big data with AI for power communication network O&M optimization. Li [8] analyzed communication network optimization paths integrating intelligent technology and big data.

In energy consumption and interference optimization, Jiao and Peng [9] proposed AI-driven mobile network energy consumption optimization. Wang and Liao [10] studied GSM-R network interference identification based on locally deployed AI models. Huang, Sun, and Ji [11] systematically reviewed AI application status and development trends. Shi [12], Liang [13], and Zhang [14] contributed to electronic information networks, power station communication, and big data + AI O&M innovation. Overall, domestic research

has yielded rich theoretical results, but systematic research on practical AI application paths in rural communication scenarios remains weak.

1.3.3. Critical Review of Research Status

Looking at the research lineage of AI-optimized communication networks at home and abroad, this field has evolved from traditional algorithm improvement to deep intelligent integration. Early research, such as the intelligent optimization method for cellular mobile communication networks proposed by Du and Song [15], laid the theoretical foundation for introducing intelligent algorithms into network optimization, and its research ideas still inspire follow-up work. However, limited by the technical conditions at that time, research mostly focused on local optimization of single network parameters and had not yet formed a systematic intelligent optimization system. With the rapid development of AI, recent research has gradually shown characteristics of diversification and deepening. Han systematically studied AI-based intelligent communication network optimization algorithms and proposed a relatively complete algorithm framework, reflecting continuous exploration at the algorithm level. Zhou extended the research perspective to network O&M and discussed the specific path of AI-driven O&M optimization, reflecting the trend that the research focus is shifting from pure network performance improvement to whole-process intelligent management. On the basis of summarizing the application status of AI in communication network optimization, Huang, Sun, and Ji looked forward to future development directions, providing a relatively comprehensive reference framework. In addition, Liu, Qin, Zhang, et al [16], from a broader perspective of technological evolution, discussed the 6G transformation trend from communication to multi-capability integration, revealing that the deep integration of AI and communication networks will become an inevitable direction of future network development.

Existing research still has limitations. First, most achievements focus on urban or general scenarios, with scarce research on rural network particularity-rural areas differ significantly in terrain complexity, user-density distribution, and infrastructure investment, so directly applying general algorithms often fails. Second, many studies remain at theoretical algorithm design and simulation level, lacking systematic practical guidance and case support. Finally, existing literature gives insufficient consideration to rural resource limitations and O&M capability constraints. This study focuses on rural communication network scenarios to fill application-level gaps and provide targeted practical reference.

1.4. Research Content

Centering on core problems of weak rural communication coverage and low-efficiency manual NRO in Hanzhong mountainous areas, this paper systematically studies the practical path of AI-optimized rural communication networks. The study analyzes typical pain points including insufficient in-depth coverage, holiday tidal congestion, and delayed geological hazard identification, then designs a practical scheme based on AI coverage simulation, poor-quality user mining, tidal traffic analysis, and geological hazard identification. Typical mountainous townships are selected as pilots, using multi-source data including MR, base-station engineering parameters, traffic KPI, user complaint tickets, and DEM to conduct collaborative practice of AI pre-screening and engineer verification. Optimization effects before and after AI intervention are compared across network quality, user perception, O&M workload, and hazard early-warning dimensions. Practical implementation problems including model bias, equipment constraints, talent shortage, funding insufficiency, and data barriers are analyzed. Finally, countermeasures are proposed from five dimensions: operation-mechanism optimization, hardware iteration, talent cultivation, resource coordination, and data-governance system construction, providing a replicable reference for similar mountainous rural network optimization.

1.5. Research Methods

This study mainly combines the case-study method with the empirical research method. The data-analysis method systematically cleans, integrates, and mines multi-source heterogeneous data such as MR, base-station engineering parameters, traffic KPI, and user complaint tickets. The comparative-analysis method quantitatively evaluates network optimization effects before and after AI intervention across four dimensions, objectively testing the "AI pre-screening + engineer verification" workflow. Combined with the literature-research and experience-summary methods, the study refines a standardized operation paradigm adapted to mountainous rural scenarios, providing dual guarantee for research scientificity and practical operability.

2. Current Status of Communication Networks and the AI Optimization Approach

2.1. Current Status of Rural Communication Networks in the Hanzhong Mountainous Area

Hanzhong is located in the Qinling-Daba heartland, with undulating peaks and criss-crossing gullies. Rural settlements present a "wide dispersion with small clusters" spatial distribution, bringing natural constraints to communication network construction. In remote villages, average 4G downlink rates are less than 60% of urban levels. Rural communication networks expose three prominent problems: first, insufficient in-depth coverage due to mountain occlusion and vegetation shading; second, obvious tidal traffic characteristics during holidays and busy farming seasons, with network congestion around scenic spots and densely populated townships; third, geological disaster risks from frequent mountain torrents and landslides threatening sites and optical-cable lines. The traditional manual NRO mode relies on engineers' empirical inspection and passive response to complaint tickets, with wide inspection scope, long cycle, and low efficiency. Intelligent means are urgently needed to improve problem discovery and disposal accuracy.

2.2. Pain Points of Traditional Manual Network Optimization

The traditional manual NRO mode shows significant limitations in Hanzhong mountainous rural network maintenance. According to MIIT statistics, national administrative village 4G coverage exceeds 99%, but insufficient in-depth coverage in mountainous areas remains prominent, with weak-signal MR proportion generally 8–12 percentage points higher than plain areas. Facing hundreds of base stations and thousands of drive-test records, troubleshooting efficiency is low-comprehensive inspection of a single township often takes more than two weeks. The troubleshooting mode is passive, mostly triggered by user complaint tickets, and difficult to pre-judge coverage blind spots and tidal congestion risks. Additionally, complex terrain intertwines mountain occlusion and landslide hazards with communication infrastructure, making it difficult for manual surveys to identify geological risk points. Grassroots NRO staff generally hold multiple positions with limited technical reserves, struggling to efficiently process multi-source heterogeneous data, leading to insufficient problem-location accuracy and high misjudgment rates.

2.3. Feasibility Analysis of AI-Assisted Network Optimization

AI-assisted NRO has practical feasibility in Hanzhong mountainous areas from technical maturity, data foundation, and industry trend perspectives. Technically, machine learning and deep learning algorithms have formed mature application paradigms in signal coverage simulation, anomaly detection, and traffic prediction. Relying on DEM elevation data, a three-dimensional terrain occlusion model can accurately predict coverage blind spots. Data-wise, existing networks have accumulated multi-source heterogeneous data including MR, base-station engineering parameters, traffic KPI, and user complaint tickets. From 2023 to 2025, the three major domestic operators' R&D investment in intelligent network O&M grew by over 20% annually. Industry experience shows that combining AI with manual experience can improve troubleshooting efficiency by more than 30%. Technical conditions, data accumulation,

and industry orientation jointly support implementing AI technology in rural communication network optimization.

2.4. Construction of the Human-Machine Collaborative NRO Workflow

This study constructs a four-stage human-machine collaborative NRO workflow: "AI simulation pre-judgment, data preliminary screening, engineer on-site recheck, closed-loop iterative optimization." In the first stage, relying on DEM elevation data and base-station engineering parameters, coverage simulation and mountain occlusion modeling are carried out to pre-judge weak-coverage areas in advance, compensating for the limitations of traditional manual survey. In the second stage, multi-source data such as MR, traffic KPI, and user complaint tickets are integrated, and AI algorithms are used to complete poor-quality user mining, tidal traffic analysis, and geological hazard identification, so as to realize intelligent preliminary screening of massive data and greatly compress the manual inspection scope. In the third stage, front-line communication engineers carry out field surveys according to the points to be checked output by AI, combine the on-site environment to identify false alarms, confirm real problems, and implement targeted rectification, preserving the irreplaceable role of engineers in on-site judgment and disposal under complex geological environments. In the fourth stage, the engineers' measured data and rectification results are fed back into the AI model to correct simulation deviations and algorithm parameters, forming a data-driven continuous optimization closed loop. This workflow realizes a collaborative mechanism of "complementary human and machine intelligence, improving efficiency through machines and guaranteeing quality through humans," and provides a replicable and scalable standardized operation paradigm for mountainous rural network optimization.

3. Design of the Practical AI-Assisted Rural Network Optimization Scheme

3.1. Coverage Simulation and Identification of In-Depth Coverage Deficiencies

3.1.1. AI Coverage Simulation Model Based on DEM Elevation Data

Under complex Hanzhong mountainous terrain, traditional NRO means cannot quickly locate in-depth coverage deficiency areas. This study constructs an AI coverage simulation model based on DEM elevation data to realize advance prediction of weak-coverage points. The model takes 30-meter-resolution DEM elevation data as geographic base input, superimposing key base-station engineering parameters including antenna height (35 m), azimuth (120), downtilt (6), and transmit power (43 dBm). Through integrated calculation of the radio-wave propagation model and terrain occlusion algorithm, it simulates signal propagation attenuation and diffraction characteristics, generating a coverage raster map with 10-meter simulation raster accuracy. In pilot application, the model predicted 14 weak-coverage points, of which 10 were confirmed as real coverage gaps after on-site verification. Parameter composition and simulation output results are detailed in Table 1.

Table 1. Construction Parameters of the AI Coverage Simulation Model

Parameter type	Parameter name	Value	Unit
Input data	DEM resolution	30	m
Input data	Antenna height	35	m
Input data	Azimuth	120	°
Input data	Downtilt	6	°
Input data	Transmit power	43	dBm
Model output	Predicted weak-coverage points	14	points
Model output	Simulation raster accuracy	10	m
Verification result	Confirmed points	10	points

3.1.2. Mountain Occlusion and Coverage Blind Spot Identification Method

On the basis of coverage simulation modeling, this study proposes a blind-spot identification method combining terrain slope and occlusion-angle calculation. This method extracts terrain undulation features from DEM data, calculates the average occlusion angle along the base-station signal propagation path, and determines the potential blind-spot range. In measured application across four Hanzhong pilot townships, Township A had average occlusion angle 35 with 5 blind spots identified (4 confirmed, 1 false alarm); Township B: 28, 4 identified (3 confirmed); Township C: 42, 3 identified (2 confirmed); Township D: 31, 2 identified (1 confirmed). The four townships identified 14 total blind spots, with 10 confirmed after on-site verification and 4 false alarms. Specific identification and verification data are shown in Table 2.

Table 2. Statistics of Mountain Occlusion and Coverage Blind Spot Identification

Pilot township	Avg. occlusion angle (°)	Identified blind spots	Confirmed	False alarms
Township A	35	5	4	1
Township B	28	4	3	1
Township C	42	3	2	1
Township D	31	2	1	1
Total	-	14	10	4

3.2. Poor-Quality User Mining and Network Quality Analysis

3.2.1. Multi-Source Data Fusion Model for Poor-Quality User Mining

Aiming at the problem that poor-quality users are scattered and difficult to locate accurately with a single data source in the Hanzhong mountainous rural communication network, this study designs a multi-source data fusion model for poor-quality user mining, aiming to improve the accuracy and coverage of poor-quality user identification by integrating different dimensions of existing network data. The model takes four types of data as core inputs-MR, base-station engineering parameters, user tickets, and traffic KPI-and assigns corresponding weights according to the contribution of each data source to poor-quality judgment, forming a comprehensive scoring mechanism. Among them, the signal level data in MR, as the most direct indicator reflecting user perception quality, is assigned a weight of 0.35 and undertakes the main function of poor-quality identification; user ticket data, reflecting users' subjective complaints, is assigned a weight of 0.30 for cross-validation and confirmation of the authenticity of poor-quality problems; the connection-count indicator in traffic KPI is assigned a weight of 0.20 for correlation analysis of the influence of capacity bottlenecks on poor quality; base-station engineering parameter data, although with a lower weight of only 0.15, plays an irreplaceable role in correlation positioning and in locking specific cells and sectors. The total weight of the four data sources is 1.00. The specific data sources, key fields, weights, and functional relationships are shown in Table 3.

Table 3. Data Sources of the Poor-Quality User Mining Model

Data source	Key field	Weight	Function
MR	Signal level	0.35	Poor-quality identification
Base-station parameters	Antenna parameters	0.15	Correlation positioning
User tickets	Number of complaints	0.30	Poor-quality confirmation
Traffic KPI	Connection count	0.20	Capacity correlation
Total	-	1.00	-

Through weighted fusion calculation, the AI system automatically screens massive user data and outputs a suspected poor-quality user point list, providing accurate troubleshooting direction for engineer on-site recheck, significantly reducing time cost and labor input.

3.2.2. Weak Signal and Drop Rate Analysis Method

On the basis of preliminary poor-quality user mining, this study constructs a quantitative analysis method for weak signals and drop rates. By setting clear judgment thresholds, vague network quality problems are transformed into computable, comparable standardized indicators. Weak-signal MR proportion uses RSRP below -110 dBm as judgment threshold; radio drop rate is judged by more than 2 abnormal releases; average downlink rate uses busy-hour mean below 15 Mbps as attention threshold; complaint ticket density uses more than 5 tickets per 100 households as warning line. Names, judgment thresholds, data sources, and units are shown in Table 4.

Table 4. Weak Signal and Drop Rate Analysis Indicators

Indicator	Judgment threshold	Data source	Unit
Weak-signal MR proportion	RSRP < -110 dBm	MR	%
Radio drop rate	Abnormal releases > 2	Traffic KPI	%
Average downlink rate	Busy-hour mean < 15	Traffic KPI	Mbps
Complaint ticket density	> 5 per 100 households	User ticket ledger	tickets/100 HH

This method integrates multi-dimensional indicators into AI pre-screening logic, enabling the system to automatically mark abnormal cells and users, combining with the poor-quality user mining model to form a dual-screening mechanism.

3.3. Tidal Traffic Analysis and Congestion Warning

3.3.1. Holiday Tidal Traffic Feature Extraction

On the basis of poor-quality user mining, this scheme introduces a tidal traffic analysis module to identify periodic fluctuation patterns of network load. Based on traffic KPI indicators including cell busy-hour traffic, connection count, and resource utilization, this module conducts statistical comparison by time period between working days and holidays. Through cleaning and aggregation of historical traffic data, the AI model divides the day into four periods to count average traffic, as shown in Table 5.

Table 5. Holiday Tidal Traffic Characteristics

Time period	Working-day traffic (GB)	Holiday traffic (GB)	Increase (%)
00:00–06:00	120	95	–20.8
06:00–12:00	310	420	35.5
12:00–18:00	280	650	132.1
18:00–24:00	350	880	151.4

Statistical results show that during early morning (00:00–06:00), holiday traffic decreased by 20.8% compared with working days. In contrast, the 18:00–24:00 period increase reached 151.4%, and 12:00–18:00 period increase reached 132.1%, reflecting pulse-like traffic growth from concentrated tourist travel and nighttime Internet access. This feature extraction provides a quantitative basis for congestion-warning threshold setting, enabling NRO work to shift from passive response to active prediction.

3.3.2. Congestion Warning and Resource Scheduling Strategy

Based on holiday tidal traffic feature extraction results, this scheme constructs a graded congestion warning and resource scheduling mechanism, taking resource utilization as the core trigger indicator, as shown in Table 6. When cell resource utilization reaches over 70%, Level 1 warning triggers intensified traffic monitoring; when above 85%, Level 2 warning requires adjacent-frequency resource borrowing within 30 minutes; when above 95%, Level 3 warning requires emergency base-station activation within 2 hours. This grading strategy combines AI real-time monitoring with engineer on-site scheduling, exploiting AI's continuous monitoring capability while preserving engineer decision space.

Table 6. Congestion Warning Grading Strategy

Warning level	Utilization threshold (%)	Triggered action	Response time limit
Level 1	≥ 70	Intensified traffic monitoring	Real-time
Level 2	≥ 85	Adjacent-frequency resource borrowing	30 minutes
Level 3	≥ 95	Emergency base-station activation	2 hours

This grading strategy organically combines AI real-time monitoring with engineer on-site scheduling; it fully exploits AI's ability to continuously monitor massive traffic data and provide fast warning, while preserving space for engineers to make flexible decisions according to on-site situations, making resource deployment more targeted and timely.

3.4. Geological Hazard Identification and Risk Warning

3.4.1. Hazard Matching Method Based on Geological Disaster Records

Mountainous terrain undulates sharply, and base-station sites and optical-cable lines are mostly laid along mountain foothills or valleys; geological disasters pose long-term threats to communication facilities. Traditional manual inspection cannot achieve full-coverage troubleshooting of hazard points. This study proposes a practical method that takes the geological disaster ledger as base data source, combines DEM data and base-station engineering parameters, and lets the AI system conduct spatial matching analysis. In the pilot, among 12 landslide hazard points, AI matched 6 points (3 confirmed); among 9 mountain-torrent hazard points, AI matched 2 points (1 confirmed). Total: 21 ledger points, 8 AI-matched, 4 confirmed. Specific results are shown in Table 7.

Table 7. Geological Hazard Matching Statistics

Hazard type	Ledger records	AI matched points	Confirmed points
Landslide hazard	12	6	3
Mountain-torrent hazard	9	2	1
Total	21	8	4

3.4.2. Linkage Mechanism between AI Identification and On-Site Engineer Verification

To ensure timely transformation of geological hazard identification results into risk prevention and control measures, this study constructs a linkage mechanism between AI pre-screening and engineer verification. The process is divided into five links: AI pre-screening, on-site recheck, false-alarm removal, closed-loop rectification, and model iteration, with each link led by different subjects. In the pilot, AI pre-screening took 2 hours to output 42 points to be checked; on-site recheck took 5 days to confirm 28 real problems; false-alarm removal took 1 day to remove 14 false alarms; closed-loop rectification took 10 days; model iteration took 3 days. The overall process is closely linked with clear responsibilities, as shown in Table 8.

Table 8. AI Verification Linkage Process

Link	Execution subject	Time consumed	Output
AI pre-screening	AI system	2 hours	42 points to be checked
On-site recheck	Front-line engineers	5 days	28 confirmed problems
False-alarm removal	Engineers + AI	1 day	14 false alarms
Closed-loop rectification	Engineers	10 days	28 problems rectified
Model iteration	AI system	3 days	Model parameters updated

4. Pilot Implementation Effect Evaluation and Constraints

4.1. Pilot Township Selection and Implementation Process

4.1.1. Overview of the Pilot Area

This study selects a typical mountainous township in Hanzhong as the pilot area. The township is located at the junction of the southern foothills of the Qinling Mountains and the northern foothills of the Daba Mountains, with a large elevation difference: the height difference between the highest and lowest points exceeds 800 m. The mountain vegetation is dense and the terrain is deeply incised, presenting a typical mountainous landform. The township governs more than ten administrative villages with a resident population of about 12,000. Constrained by geographic conditions, communication infrastructure construction costs are high and maintenance is difficult; the number of existing communication base stations is limited, the station spacing generally exceeds the planning standard, and some remote natural villages still have insufficient in-depth coverage. According to preliminary network quality survey data, the proportion of weak-signal MR in this area reaches 18.6%, higher than the city average; during holidays and busy farming seasons, the central areas of some administrative villages show obvious tidal traffic characteristics, and the busy-hour cell resource utilization once exceeded 85%, with the number of user complaint tickets ranking among the top of mountainous townships in the city. At the same time, the area is distributed with multiple geological hazard points, and historical landslides and mountain torrents have posed potential threats to the safety of communication pole lines and base-station equipment along the route, giving the area strong pilot representativeness and promotion value.

4.1.2. AI Pre-Screening and Engineer Verification Implementation Process

Pilot implementation strictly follows the human-machine collaborative workflow. First, the project team collected multi-source heterogeneous data of the pilot area over the past half year, including MR, base-station engineering parameters, traffic KPI, user complaint tickets, and DEM; after cleaning and standardization, data were imported into the AI analysis platform. In the pre-screening stage, the AI platform used coverage simulation algorithms, combined with the poor-quality user mining model, tidal traffic analysis, and geological disaster ledger data, outputting 42 points to be checked. Subsequently, front-line engineers carried out on-site recheck in batches with portable test equipment. After point-by-point recheck, 14 false-alarm points were removed and 28 real problem points confirmed. Differentiated rectification schemes were formulated, including antenna angle adjustment, newly added micro-stations, and equipment reinforcement. After rectification, measured data were fed back to the AI platform for model correction and iterative optimization, forming a complete closed-loop management mechanism.

4.2. Quantitative Evaluation of Optimization Effects

4.2.1. Comparison of Network Quality Improvement

After completing AI pre-screening, engineer on-site recheck, and problem rectification in the pilot township, this study conducted a systematic measured comparison of core network quality indicators before and after optimization, so as to objectively measure the actual effect of the human-machine collaborative NRO mode. In terms of average downlink rate, the pilot area averaged only 12.8 Mbps before optimization; affected by mountain occlusion and unreasonable base-station layout, the user-experienced rate had long been at a low level. After AI coverage simulation located weak-coverage blind spots and guided engineers to complete antenna angle adjustment and newly added blind-spot compensation stations, the average downlink rate increased to 21.5 Mbps, an increase of 67.9%. The weak-signal MR proportion decreased from 18.5% to 9.2%, a drop of more than half, indicating that the problem of insufficient in-depth coverage was effectively alleviated. The radio drop rate decreased from 3.6% to 1.4%, a drop of 61.1%, reflecting significantly enhanced network stability. The coverage compliance rate increased from 76.0% to 92.5%, an increase of 16.5 percentage points,

achieving a leap-forward improvement in overall coverage quality. The specific data are detailed in Table 9. The simultaneous improvement of the four core indicators fully confirms the practical value of the "AI simulation pre-judgment – data preliminary screening – engineer on-site recheck" workflow in narrowing the troubleshooting scope and improving rectification accuracy, and provides a quantitative basis for subsequent large-scale promotion.

Table 9. Comparison of Network Quality Improvement

Indicator	Before optimization	After optimization	Improvement
Average downlink rate (Mbps)	12.8	21.5	67.9%
Weak-signal MR proportion (%)	18.5	9.2	−50.3%
Radio drop rate (%)	3.6	1.4	−61.1%
Coverage compliance rate (%)	76.0	92.5	+16.5 pp

The simultaneous improvement of the four core indicators fully confirms the practical value of the "AI simulation pre-judgment – data preliminary screening – engineer on-site recheck" workflow in narrowing the troubleshooting scope and improving rectification accuracy, and provides a quantitative basis for subsequent large-scale promotion.

4.2.2. User Perception and Complaint Changes

Objective network quality improvement must ultimately be reflected in users' subjective perception. The average monthly number of complaint tickets decreased from 46 to 18, a drop of 60.9%. User satisfaction score increased from 72 to 89, an increase of 23.6%. The number of poor-quality users dropped from 135 to 52, a decrease of 61.5%. Ticket processing time was shortened from 5.2 days to 2.1 days, a decrease of 59.6%. Detailed data are shown in Table 10. The coordinated improvement of user perception indicators verifies that the human-machine collaborative NRO mode can effectively translate network quality improvement into user-perceived service quality.

Table 10. Changes in User Perception and Complaints

Indicator	Before optimization	After optimization	Change rate
Monthly average complaint tickets	46	18	−60.9%
User satisfaction (score)	72	89	+23.6%
Number of poor-quality users	135	52	−61.5%
Ticket processing time (days)	5.2	2.1	−59.6%

Overall, the coordinated improvement of various indicators in the user perception dimension further verifies that the human-machine collaborative NRO mode can not only improve hard network indicators but also effectively translate into user-perceived service quality improvement, laying a practical foundation for the replicability and scalability of the mode.

4.2.3. O&M Workload and Hazard Warning Effectiveness

In addition to network quality and user perception improvements, AI intervention has also shown outstanding results in reducing O&M workload and providing geological hazard warnings. Before the pilot, engineers faced point-by-point surveys and base-station-by-base-station troubleshooting with wide scope and high human resource consumption. After introducing AI pre-screening, the system automatically completed preliminary screening in massive data, output 42 points to be checked, removed 14 false alarms, and confirmed 28 real problems, greatly reducing ineffective troubleshooting

scope. Meanwhile, relying on cross-comparison of DEM data and geological disaster ledgers, AI successfully identified communication facility risk points, providing early-warning support for engineers to intervene in reinforcement and site relocation in advance.

4.3. Analysis of Implementation Constraints

4.3.1. AI Model Bias

Pilot practice shows that although AI pre-screening significantly improved troubleshooting efficiency, model bias remains prominent. Among 42 points to be checked, 14 were verified as false alarms, accounting for 33.3%, reflecting that the model has obvious deviations in predicting signal propagation paths under complex mountain occlusion scenarios. Especially in areas with dense vegetation and frequent seasonal landslides, static geographic data cannot reflect dynamic geomorphological changes in real time.

4.3.2. Shortage of Interdisciplinary Talent

Implementation of the human-machine collaborative NRO mode highly depends on interdisciplinary talents who understand both communication network O&M and AI basics, but such talents are extremely scarce in grassroots communication enterprises. At county-level and township grassroots units, technical personnel with data analysis and algorithm tuning capabilities account for less than 5% of front-line employees. The traditional engineer team is good at empirical operations but has limited understanding of AI model principles, making it difficult to independently complete diagnosis and correction of model bias. During the pilot, engineers could only make trade-offs based on experience when facing false-alarm points, lacking a systematic feedback channel to feed back on-site verification results into model training.

4.3.3. Funding Constraints and Data Barriers

Mountainous rural communication network optimization involves base-station hardware upgrading, AI platform deployment, and multi-source data acquisition system construction, requiring high upfront investment. Townships in the Hanzhong mountainous area generally have weak finances, and operators face long investment return cycles, making it difficult to quickly replicate pilot experience. Meanwhile, multi-source data are scattered across different business systems, with inconsistent formats, closed interfaces, and lack of cross-department sharing mechanisms; some geological disaster ledger data are still kept in paper or isolated spreadsheet form, making it difficult to achieve effective integration with network data.

5. Conclusions and Recommendations

5.1. Recommendations for Improving the Human-Machine Collaborative NRO System

Aiming at practical problems exposed in the pilot, this paper proposes systematic countermeasures in five aspects. At the operation-mechanism level, the closed-loop process of "AI pre-screening – engineer verification – data feedback" should be solidified, with standardized operation manuals and clear time limits. At the hardware iteration level, radio frequency modules and transmission equipment should be upgraded in batches, prioritizing MR data acquisition completeness and real-time performance. At the talent cultivation level, a team of interdisciplinary engineers who master both traditional NRO skills and AI tool application should be built, accelerating knowledge transformation through the "mentor-apprentice + special training" mode. At the resource coordination level, a three-tier provincial-city-county linkage funding guarantee mechanism should be established, optimizing investment tilt policies for mountainous townships. At the data governance level, multi-source data barriers should be broken through, with unified data standards and sharing mechanisms established, and a dynamic model-bias correction mechanism built, feeding engineers' measured data back into AI model training to continuously improve pre-screening accuracy.

5.2. Research Conclusions and Outlook

Based on the reality of rural communication networks in the Hanzhong mountainous area, this study constructs a human-machine collaborative workflow of "AI simulation pre-judgment – data preliminary screening – engineer on-site recheck – closed-loop iterative optimization." Through pilot verification, AI pre-screening output 42 points to be checked, and engineers confirmed 28 real problems after on-site recheck, effectively raising the troubleshooting accuracy to 66.7% and significantly narrowing the scope of blind manual troubleshooting, which proves the feasibility of this collaborative mode in improving NRO efficiency and accuracy. The study also finds that, limited by model adaptation bias, insufficient carrying capacity of outdated equipment, shortage of interdisciplinary talent, limited funding, and data barriers, the in-depth application of AI technology in mountainous rural scenarios still faces many challenges, which need to be solved through the coordinated advancement of operation-mechanism optimization, hardware iteration, professional talent cultivation, resource coordination, and data-governance system construction. Looking forward, with the continuous maturation of technologies such as 5G lightweight base stations, edge computing, and satellite communication, the human-machine collaborative NRO mode is expected to evolve toward greater intelligence and automation. At the same time, with the improvement of industry data sharing mechanisms and the growth of interdisciplinary talent teams, this standardized operation paradigm will have stronger replicability and promotion value, providing continuous practical support and theoretical reference for the high-quality development of communication networks in similar mountainous rural areas across the country, helping to narrow the urban-rural digital divide and serving the in-depth implementation of the rural revitalization strategy.

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