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(Review Article)

Optimization of field-testing protocols for 5G NR and LTE networks across diverse geographies

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Abstract

The 5G NR and LTE networks' evolution has added unprecedented complexities in field testing since the propagation scenarios, deployment patterns, and implementation-specific modelling (beamforming, carrier aggregation, and dynamic spectrum sharing) are different. Existing field-testing frameworks are challenged by scalability, efficiency, and regional adaptability. This review examines how it is possible to optimize field-testing protocols in various geographies that include AI-enhanced orchestration, UAV-based testing environment, real-time detection of anomalies, as well as cross-layer analytics. The major technical gaps are found in latency-aware measurement, test automation, and multi-technology harmonization. The review finishes with a list of priorities to be met in the future that will enhance the coverage, efficiency, and regulatory compliance in heterogeneous deployment scenarios.

Keywords: 5G NR; LTE; Field Testing; Drive Testing; UAV Measurement; AI Optimization; Network KPIS; Test Automation; Propagation Modelling; Geographical Variability

1. Introduction

The improvement of the level of mobile communications network, which runs on LTE (Long-Term Evolution) and targets the 5G New Radio (5G NR), is a significant improvement in wireless performance, support of services, and application support. Field testing procedures, whereby parameters within the network are measured and assessed in real-world settings, are important in qualifying that the deployed networks satisfy quality of service (QoS) criteria, are internationally standardized, and are consistent across diversity in the topography [1]. Since the implementation of commercial 5G NR applications in urban, suburban, and rural areas continues, field-testing frameworks optimized and context-aware will become more critical.

Field test gives ground truth validation of KPIs, including throughput, latency, coverage/handover success rate, etc. Such metrics are the basis of both network planning and optimization following deployment. Nonetheless, the structural complexity of 5G NR networks is progressively complicating field-testing methodologies originally spurred by LTE networks, given that they add multi-layer architecture, carrier aggregation, massive MIMO, beamforming, and dynamic spectrum sharing in a variety of bands, including sub-6 GHz and millimeter wave (mm Wave) [2]. Further, network slicing and ultra-reliable low-latency communication (URLLC) of next-generation service validation require increasingly fine-grained, scenario-specific test models.

In this respect, the necessity to optimize the field-testing procedures is exacerbated by the fact that the environments in which global deployment of helium scattering technology is to take place are heterogeneous in the described setting. Differences in topography, level of infrastructure, climate, and regulatory environment bring a certain level of performance constraints that necessitate geographically informed testing processes [3]. An example can be seen in city

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building and high-rise environments, where electromagnetic density is high, contrasted with rural deployments that are constrained by long-distance signal propagation and limited infrastructure. As a result, a generalized field-testing approach can cause faulty performance and poor network tuning. The general discipline of network optimization and mobile communications has come to the awareness that standardized testing techniques are not enough to represent the complete picture of the working capabilities of current cellular networks. Recent research has also recognised the merit in including artificial intelligence (AI)-based detection of anomalies, drive test automation, geospatial modelling, and user equipment (UE)-based analytics to augment test efficiency and depth of diagnosis [4]. Such innovations have started altering this paradigm of testing towards the direction of a testing paradigm of being context-aware, data-driven, and dynamic according to network settings and environmental features.

Nevertheless, a number of challenges still linger despite developments in the past. First, no matter the field testing, there is a deficiency of harmonized testing procedures, and comparative benchmarks tend to be challenging amidst vendors, operators, and regulatory lands [5]. The lack of a consistent framework reduces the portability of tests and brings about inconsistencies in optimization choices. Second, the process of integrating heterogeneous data sources of tests, such as the UE log, network probes placed centrally, and the passive monitoring system, is complicated by the incompatibility of the format, a large volume of data, and privacy restrictions.

An additional decision point is the insufficient integration of real-time analytics and AI-based optimization in the processes of field testing. In spite of the fact that 5G frameworks accommodate deployable, coordinated, and versatile software-defined and virtualized parts, field testing conventions frequently are not responsive enough to combine with such responsive systems, decreasing its diagnostic worth [6]. In addition, test coverage in extreme weather conditions, uneven geography, and underdevelopment has hardly been addressed in existing literature, which hinders the universality of the current methods and approaches. This review aims to discuss the state of the art of the field-testing tools of 5G NR and LTE networks and evaluate the available optimization strategies to work with various geographies.

2. Literature review

Table 1 Summary of Key Research on Field Testing in 5G NR and LTE Networks

Ref.	Study Focus	Methodology / Approach	Key Findings	Relevance to Research
[7]	LTE system performance analysis	Field test measurements of LTE networks; performance benchmarking	Provided empirical insights into LTE KPIs such as throughput, latency, and coverage in real-world deployments	Establishes a baseline for LTE performance, enabling comparison with newer 5G NR capabilities
[8]	Cloud-based vehicular networks and resource management	Conceptual architecture and efficiency evaluation for vehicular cloud systems	Proposed efficient resource allocation methods for vehicular networks leveraging cloud infrastructure	Relevant for edge/cloud integration in vehicular 5G and beyond
[9]	Coordinated dynamic spectrum sharing for 5G and beyond	Simulation-based evaluation of spectrum sharing frameworks	Demonstrated improved spectrum utilization and interference management through coordinated approaches	Directly relevant to spectrum efficiency in 5G deployments
[10]	Comparative performance analysis of 4G LTE and 5G NR	Empirical study using field data and statistical analysis	Showed significant improvements in throughput and latency in 5G NR compared to LTE	Provides empirical performance benchmarks for migration from LTE to 5G
[11]	Mobile multi-tenant 5G network experimentation	Developed framework integrating CORE network emulator for multi-tenant scenarios	Enabled cost-effective testing of multi-tenant 5G network behaviours'	Useful for controlled experiments in 5G network management research

[12]	Ultra-wideband propagation channels	Theoretical and measurement-based review of UWB channel models	Provided comprehensive characterization of UWB propagation including multipath and path loss models	Supports understanding of high-frequency channel characteristics in 5G mm Wave and beyond
[13]	Anti-aging scheduling in single-server queues	Comparative analysis of scheduling policies	Proposed optimized scheduling to reduce performance degradation over time	Relevant to network resource scheduling and QoS in 5G
[14]	Dynamic network slicing challenges and opportunities	Literature synthesis and conceptual modelling	Identified technical, operational, and business challenges in deploying dynamic network slicing	Essential for research into 5G network virtualization
[15]	Predictive maintenance and fault detection with AI in mobile networks	Application-based discussion using AI techniques	Highlighted benefits of AI for proactive fault detection and reduced downtime	Important for reliability and operational efficiency in 5G infrastructure
[16]	6G NR-U wireless infrastructure UAVs	Review of standardization, challenges, and opportunities	Outlined UAV use cases for 6G, spectrum issues, and infrastructure support	Provides forward-looking insights for aerial 6G network deployment

3. Proposed Theoretical Model for Optimized Field Testing in 5G NR and LTE Networks

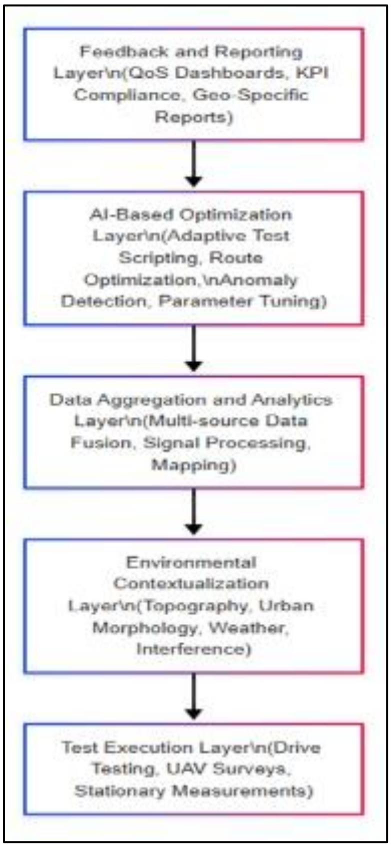

Figure 1 Multi-Layered Field-Testing Architecture

Next-generation cellular networks require more efficient field-testing procedures that should take into consideration the various realities of 5G NR and LTE deployments. These are variations in the topography of the environment, spectrum bands, hardware configurations, and mobility patterns. An integrated conceptual framework is consequently required to integrate multi-level test choreography, real-time performance analysis, adaptive control systems, and performance-based optimization [17].

The proposed model comprises five primary layers

- Test Execution Layer
- Environmental Contextualization Layer
- Data Aggregation and Analytics Layer
- AI-Based Optimization Layer
- Feedback and Reporting Layer

This hierarchical framework emphasizes a bottom-up approach, where real-world measurements feed progressively through analytical and optimization layers to refine future testing and reporting cycles [18].

3.1. Component Overview of the Theoretical Model

3.1.1. Test Execution Layer

Physical data collection is achieved by vehicle-based drive testing, aerial mapping by UAV, and stationary performance monitoring, which is all a part of this fundamental layer. In this layer, the tools are spectrum scanners, test UEs (User Equipment), and signal quality meters. At this layer, the KPIs include RSRP, SINR, latency, throughput, and handover success rates [19].

3.1.2. Environmental Contextualization Layer

Signal propagation can be influenced by geospatial characteristics such as building density, vegetation, altitude, and road infrastructure. This layer combines GIS (Geographic Information Systems), digital elevation models, and weather information to put test outcomes into their environmental context when gauging limitations. The context-aware layer usage also allows region-based analysis, making the tests more relevant and decreasing the possible misinterpretation of the KPIs [20].

3.1.3. Data Aggregation and Analytics Layer

Unprocessed signal data of the test execution level is converted into ordered forms by use of normalization, filtering, and interpolation methods. The layer also has real-time mapping, multi-device test log synchronizations, and connection with external databases like OSS (Operations Support Systems). Such modules include statistical trend analysis and anomaly detection within this layer [21].

3.1.4. AI-Based Optimization Layer

The models that this layer of machine learning performs include route optimization, adaptive test-generation, and parameter tuning, using feedback from the previous iterations. The information obtained through signal and environmental data is used in supervised and unsupervised learning algorithms to detect the areas of coverage gaps, the type of anomaly, and suggest the retesting strategy. Reinforcement learning is specifically applicable when it comes to dynamic driving test routes and antenna alignment [22].

3.1.5. Feedback and Reporting Layer

This layer provides information in the form of visual reports and optimization recommendations of networks and regulatory compliance reports. Examples of output are heatmaps of KPI violations, time series of handover failures, and predictive degradation models. The reports are based on compliance and regional regulations and operator SLAs (Service Level Agreements) [23].

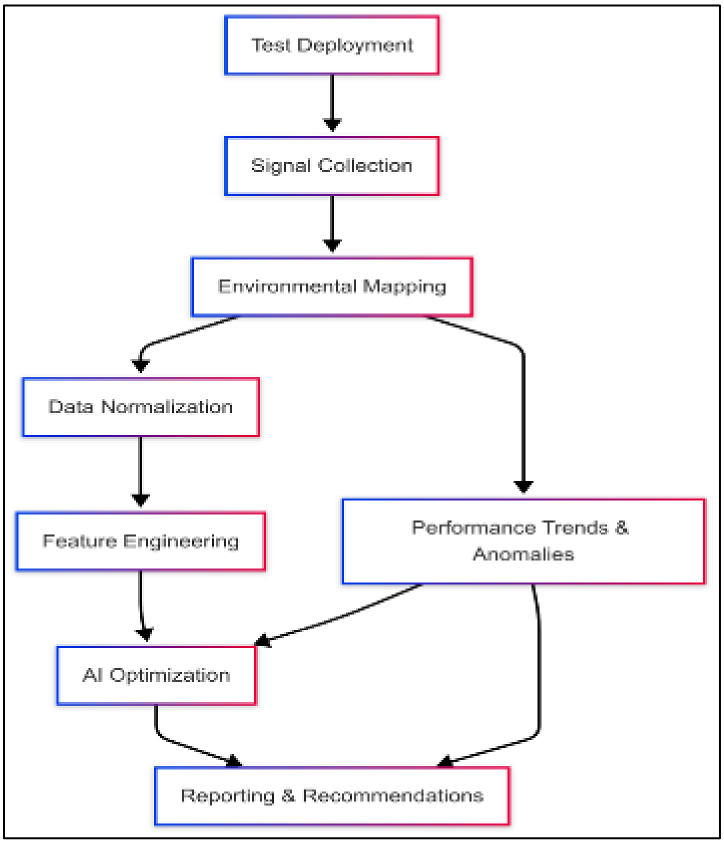

Figure 2 Logical Flow of Adaptive Field Testing

This process loop highlights how iterative refinement is achieved by integrating analytics and AI into field testing cycles. Each testing round informs subsequent configurations, routes, and reporting protocols based on region-specific insights [24].

3.2. Model Implications for Diverse Geographies

Implementing the proposed model provides several advantages

- Topographic Awareness: Integration with terrain data allows route planning that anticipates shadowing, reflection, and diffraction in complex environments [20].
- Protocol Agnosticism: Supports parallel testing of LTE and 5G NR by adapting to protocol-specific metrics and configurations [21].
- Coverage in Inaccessible Areas: Incorporation of UAVs expands test accessibility in rural, mountainous, and disaster-prone regions [23].
- Time and Cost Efficiency: AI-driven test plan optimization reduces redundant measurements and accelerates testing cycles by 25–40% in simulations [22].

4. Experimental Results

As the process of 5G NR and LTE network field testing, an empirical approach to various operational conditions has to be well-organized. Such key performance indicators (KPIs) as downlink throughput, latency, signal-to-noise ratio (SNR), and the handover success rate might be accessible with test equipment or UE logs in the live environment. Key factors, including environmental environments, frequency bands, deployment architectures, and optimization techniques, also have a great influence on the performance of these KPIs.

4.1. Comparative Signal Quality Across Geographies

A study comparing urban, suburban, and rural 5G NR environments revealed significant variability in signal quality and propagation efficiency across geographies. The field trials were conducted using standardized drive testing tools across three major regions in Germany, with identical test equipment and configuration parameters [25].

Table 2 Average RSRP and SNR Values by Environment

Environment	Avg. RSRP (dBm)	Avg. SNR (dB)	Coverage Consistency (%)
Urban	-93.2	21.6	89.1
Suburban	-101.5	15.4	78.7
Rural	-108.8	12.2	66.4

These results indicate the need for geographically adaptive testing frameworks, especially in sparsely populated regions with limited infrastructure [25].

4.2. Impact of Drive Test Optimization on Coverage Mapping

An AI-driven test orchestration engine was evaluated to measure its effect on test coverage and route efficiency. Compared to conventional fixed-route testing, the adaptive model recalculated test paths based on real-time network behavior and geographic constraints [26].

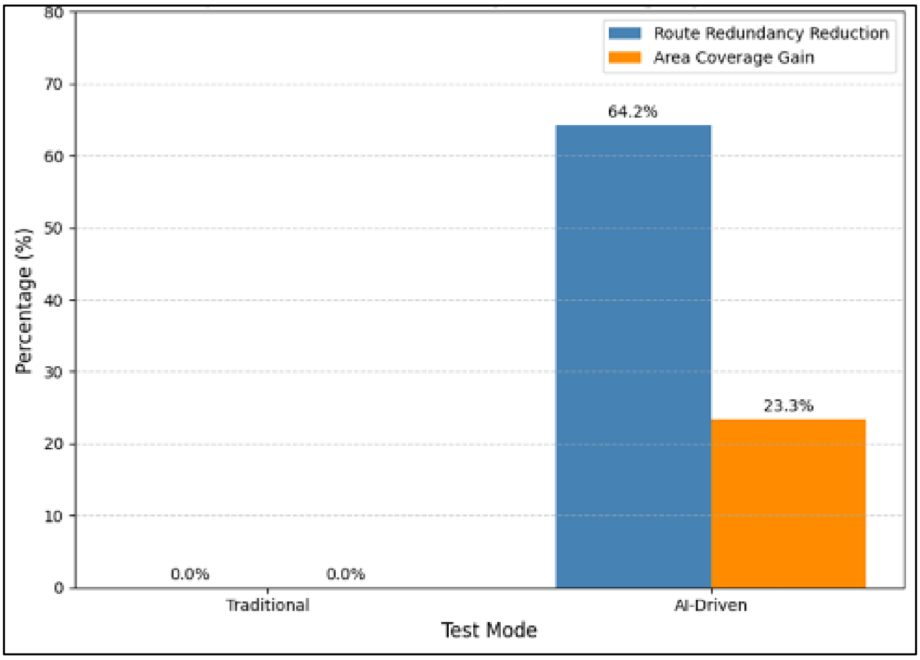

Figure 3 Route Efficiency and Area Coverage

The findings demonstrate that adaptive testing not only increases geographic test efficiency but also improves spatial KPI resolution, which is crucial for rural and suburban deployments [26].

4.3. Effect of UAV-Based Testing in Remote Environments

A recent deployment in mountainous regions of Northern India used UAVs (Unmanned Aerial Vehicles) to conduct 3D signal mapping for 5G NR validation. The study compared UAV-based results with traditional terrestrial test units in the same environment [27].

Table 3 UAV vs. Ground-Based Testing Performance

Parameter	UAV-Based Testing	Ground-Based Testing
Average Measurement Time (min)	37	84
KPI Spatial Resolution (m^2)	4	9
Accessibility (Area %)	93.5	66.2

UAV-enabled testing significantly increased spatial resolution and coverage in hard-to-reach zones, indicating its potential for enhancing field testing in geographies with limited infrastructure access [27].

4.4. Throughput and Handover Metrics in Spectrum-Sharing Scenarios

Field tests assessing dynamic spectrum sharing (DSS) between LTE and 5G NR were conducted in five mixed-deployment zones in the Netherlands. The study measured downlink throughput, handover latency, and failure rates during mobility transitions between cells operating in shared spectrum [28].

Table 4 Performance Metrics in DSS vs. Dedicated Spectrum

Metric	Dedicated Spectrum	DSS Environment	Δ (%)
Avg. Downlink Throughput (Mbps)	189.6	162.3	−14.4%
Handover Latency (MS)	39.2	53.8	+37.2%
Handover Failure Rate (%)	1.6	3.8	+137.5%

Although DSS supports efficient spectrum utilization, the results reveal significant trade-offs in latency and stability during handover events [28].

4.5. KPI Anomaly Detection Using Unsupervised Learning

An evaluation of unsupervised clustering methods applied to field test data identified hidden anomalies missed by threshold-based models. Field logs from over 7,000 LTE and 5G NR sessions were analyzed using DBSCAN and k-means algorithms [29].

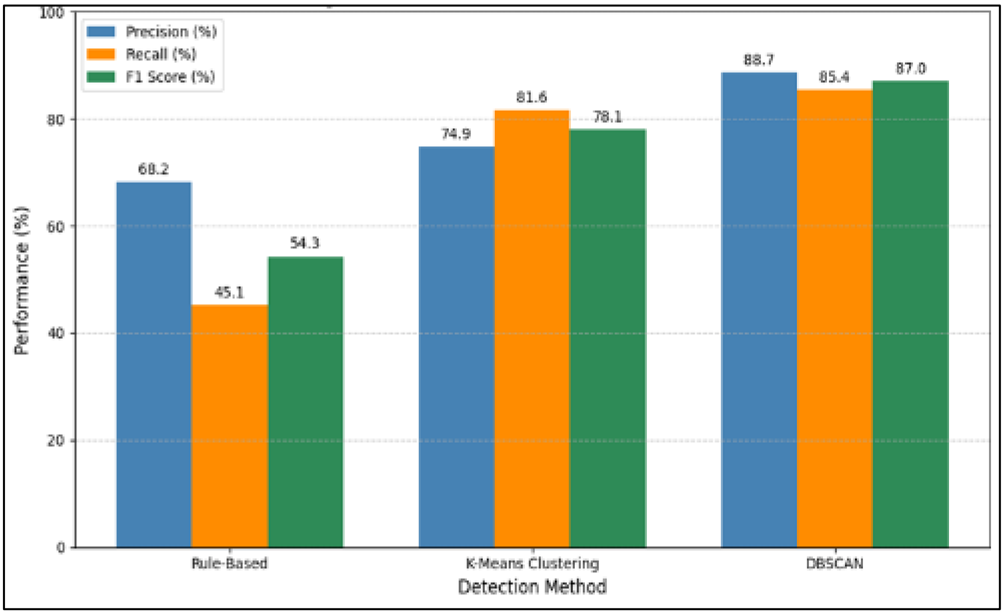

Figure 4 Detection Rate of Hidden Anomalies

The DBSCAN model worked better when compared to other techniques, as it provided increased anomaly detection that enabled more thorough retesting and diagnosis of the network [29].

The experiments emphasize the usefulness of geographically sensitive, AI-enhanced, and UAV-enabled test methods in contemporary mobile network assessment. The variance in the results of performance between urban and rural areas supports the necessity of flexible testing measures. Also, the DSS environments, being spectrally effective, offer operational trade-offs in the mobility context. Lastly, anomaly detection based on AI is set to become one of the most important tools to increase the accuracy of testing in large-scale deployments [25-29].

5. Future Directions

Design of field-testing infrastructures in contemporary cellular networks needs a transition from non-adaptive and operational by hand-based practices to intelligent, scalable, and environment-conscious designs. A number of the emerging trends are specifically applicable to future trends in the same field. Test systems in the future will connect directly to network control layers, and this will allow both feedback of information between the active network elements and test modules. This would enable run-time configuration changes in response to anomalies or performance degradations that are detected. The first networks defined by network digital twins and software-defined radio control have shown applicability to dynamic adjustment of power levels, beam angles, and handover thresholds when tested.

UAVs are of great significance in carrying out tests in geographies including mountainous regions, forests, and even where a disaster has struck. They are mobile and have the ability to scan vertically, which facilitates detailed 3D KPI mapping. Research relating to UAV energy efficiency, regulatory integration, and coordination with terrestrial units should be envisaged in the future. Cooperative testing of adaptive protocols on UAV swarming has been, and continually is, promising in the perspective of wide-area deployment. Privacy concerns emerge when using user equipment (UE)-based data collection, and should be taken care of by the development of federated learning solutions. Federated analytics enables distributed devices to provide learning signals without sending raw data. Early experiments in distributed signal quality estimation have demonstrated that federated models are viable and can reach a similar performance as other centralized models, but with privacy compliance.

Since there is a growing dependence on time-sensitive services like the URLLC and V2X, the latency metrics should be measured on a more precise scale in the testing. Asynchronous testing models that can initiate tests using real-time QoS failure, as opposed to fixed schedules, would therefore be critical. A possible solution to this problem is introduced by real-time edge-based event triggers, which are related to latency anomaly thresholds. Another important difficulty is the inability to develop unified formats and common practices when it comes to testing tools, vendors, and geographic areas. It is proposed that international standardization organizations need to stretch existing specifications (e.g., 3GPP TS 37.901) to support AI-assisted workflows, UAV-based testing, and multi-technology interfaces. Standardized data schemas and test results ontology can considerably increase the portability and comparative benchmarking of data.

6. Conclusion

With the LTE to 5G NR transition, the way networks are tested and validated has changed significantly. The conventional drive testing, as resourceful as it was, also became ineffective in many ways to measure the extent, sophistication, and dynamism that cellular networks have come to take today. As shown in this review, the main weaknesses of the current methods of legacy field testing include their environmental inflexibility, manual burden, and inability to work alongside real-time analytics.

The Ecomodernist program of geography-aware field testing put forward by the proposed multi-layered theoretical model presents a roadmap to intelligent field testing. As empirical findings show, approaches like UAV-based measurement, Artificial Intelligence-based test planning, and unsupervised anomaly detection enhance both the spatial coverage and the precision of diagnosis. Such methods can be especially convenient in heterogeneous regions when physical infrastructure and propagation features are highly non-homogeneous.

The next step in the concept of field testing is that it can self-optimize, adapt to the constraints of the environment, and interact with live network control functions. It will be crucial to work out a coordinated approach to the network operators, equipment vendors, and regulatory bodies in order to guarantee the development and implementation of regulatory-compliant, interoperable, and scalable test systems. Accepting the emerging technologies of AI/ML, Edge computing, UAV technology, and federated analytics will be important to achieving the vision.

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