White Paper

VIAVI Solutions

RAN Scenario Generators and Their Critical Role for Future-Proofing AI-Native RAN in Advanced 5G and 6G Networks

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Introduction

The role of artificial intelligence within telecommunications is evolving quickly, shifting from speeding discrete automation tasks to intelligent, context-aware decision making in which it becomes a critical element of network operations. This change is particularly visible in the way that AI is being used in new and emerging 5G and 6G deployments, not least when it comes to MU-MIMO.

To date networks have deployed AI as an add-on. It is being used to optimize and enhance existing systems and has enabled the dynamic allocation of network slices, the better management of resources, and the improved detection of both potential issues and security threats.

However, new 5G and 6G implementations built around "AI-native" architectures and MU-MIMO will shift AI from the periphery to the very heart of the network. This will enable autonomous operation across immensely complex, heterogeneous Service Management and Orchestration (SMO) Networks built on principles such as Open RAN and managed by programmable platforms such as the RAN Intelligent Controller (RIC).

This shift, however, presents a fundamental challenge: How do you ensure that AI is making the correct decisions for the network, especially when it needs to scale rapidly across heterogeneous, dynamic environments?

Training an AI (and ensuring its long-term viability) requires data. As well as being accurate and reliable, this data must be representative of a real-world, dynamic network rather than an ideal or a snapshot at a particular time. Using this data, the AI applications used to run and maintain the network should then be continuously tested and challenged to prevent drift and to ensure readiness for change and unforeseen scenarios.

In this paper we examine the challenges and trade-offs of real-world data and synthetic data to demonstrate why a hybrid data layer with RAN scenario generator (RSG) testing is the optimal approach for training AI applications for the specific network. We will also identify how this approach can be used to prevent AI drift and how it can prepare for change (including upgrades and attacks).

Finally, we will break down how these techniques can be used to improve the network's energy efficiency, plan for 6G deployment, enhance QoS, and optimize for massive MIMO.

PART I

The Problem Space

Why AI RSG is Critical

1. Access to Reliable, High-Quality Data

The foundational limitation of any AI system is simple: any model is only as good as the data on which it is trained – or, to put it another way, poor data equals poor performance. As a result, to be effective for 5G networks and 6G networks any AI model needs to be trained on as close a model of the real-world network as possible.

Traditionally, this has involved the collection of data from the live network, typically involving performance management (PM) counters, call traces, and logs extracted from network elements and operational support systems (OSS). But, while this data reflects real-world conditions, it has significant limitations. Firstly, it is historical. Using past data to train a model for future events is akin to driving a car while looking only in the rearview mirror; it shows what has happened, not what lies ahead.

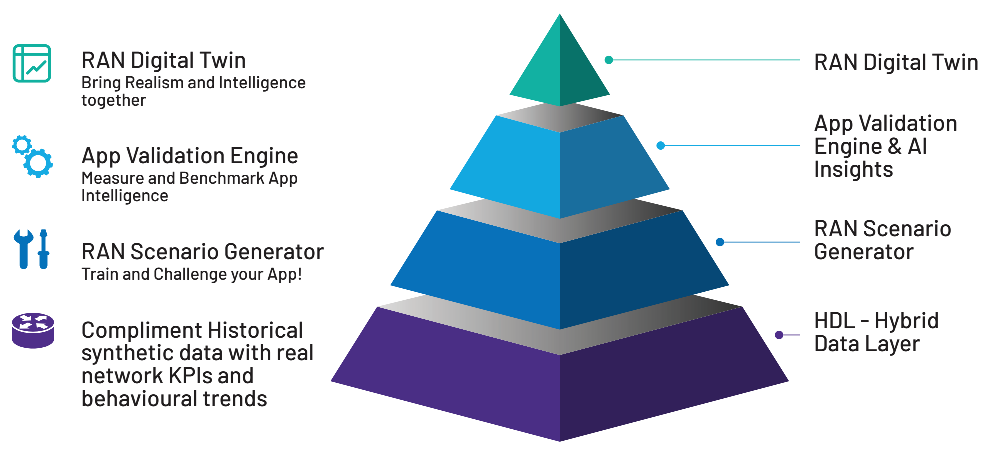
Secondly, acquiring this data is a slow and resource-intensive process. For large operators, data may be siloed across different departments, and fulfilling a request can take weeks or even months. Training data using this approach can often only give a partial view of one part (or a subset) of the network.

What's more, for third-party developers of equipment such as the radio unit, this approach is made significantly more complex as the data needs to be obtained from third parties, with all the accompanying data security/privacy issues and commercial sensitivities. If not an impossible task, it is at the very least, highly challenging to secure data that provides more than the tiniest glimpse into what is happening, which is clearly insufficient to train a model for the full spectrum of potential network states.

The alternative approach is to use synthetic data. This solves many of the speed and scale issues of the real-world historical-data approach, with huge swathes of datapoints (including metadata) capable of being generated on demand.

This approach is not without its weaknesses, and it would be fair to criticize using purely synthetic data on the grounds of its inability to perfectly capture the specific nuances of an operator's network environment. But models based on synthetic data can accurately mimic the network's core physical behaviors and trends, especially when calibrated with select real-world data vectors to fully capture a unique environment.

The ideal strategy, however, is a hybrid approach, taking the best from both worlds and optimized by having a RAN scenario generator sitting above the data layer. This generator is designed to train and challenge the applications against almost any potential scenario.



The AI RAN scenario generator uses the hybrid data layer to train and challenge xApps and rApps for use in digital twins

By using an AI RSG to power a RAN digital twin, it is possible to create a baseline model that mirrors an operator's network configuration – from its site locations, topology, and equipment parameters. This model's realism can be further enhanced by calibrating it with select data vectors and metrics from the live network including the position of towers, specific buildings, the movement of user equipment (UE) and dynamic channel conditions, real-world traffic profiles, and specific RAN configuration parameters such as antenna tilts and power levels.

Through this method, it is possible to achieve a high-fidelity digital twin that mirrors the physics and behavior of the specific real-world network. This environment can then generate data that is not only realistic but also forward-looking. This enables training of agentic AI-based workflows and AI models of the x (near-real-time) and r (non-real-time) apps used by the RIC for scenarios that are yet to occur.

2. Assuring Long-Term Performance of AI Applications

Whether it is for xApp, rApp or SON (Self Organizing Networks) implementations, once AI is deployed, the challenge shifts from initial training to assuring optimum performance over time. Networks are far from static, and AI needs to adapt to a wide variety of network changes. If such adaptation is not possible, the AI's performance can effectively degrade, making it unable to cope with the constantly changing real-world conditions that differ from its training set — a phenomenon known as "AI drift." The result is that the model can end up making decisions that, while technically aligned with its immediate goal, result in negative and unintended consequences.

This drift is exacerbated if the AI's end goal isn't clearly defined. For example, there is an almost universal need for networks to reduce energy consumption for environmental and OpEx reasons, and a common usage scenario (see part II) for AI will be to identify ways to save energy. Left unmonitored, an AI that has a goal to improve energy efficiency might determine that the most effective way to meet its primary objective is to power down a large percentage of network cells. While this would naturally reduce energy consumption, it would also cause a catastrophic loss of service for customers. The application achieves its stated goal, but at the cost of an unacceptable trade-off.

For this reason, a framework for continuous validation within the controlled environment is essential, with a closed-loop feedback system being deployed to first make changes to the RAN's digital twin. Based on simulated metrics generated by the twin, the AI proposes a change to be enacted within the twin. Having been calibrated with real-world network data to be a precise replica, the twin then models the full impact of that specific change on all relevant network KPIs via the RSG. This new set of simulated metrics can then be returned to the AI as immediate feedback, which informs its next decision in the controlled, iterative loop.

The final step in preventing AI drift is the App Validation Engine (AVE) which is used to oversee the process. Such a tool monitors the long-term interaction between the application and the twin and provides a verdict on its behavior.

This step allows the assessment of whether the application is converging towards its design goal in a stable manner. Similarly, it will also ask if it is diverging, or switching repeatedly between states, but with no net improvement. Critically, it must measure the primary objective against a set of control KPIs that represent operational guardrails, such as quality of service or coverage, to quantify the trade-offs. Developers can then identify the root cause of any performance degradation.

A validation engine can also run its own AI model in parallel to calculate the "ceiling of improvement" possible, providing a benchmark against which the application's efficiency can be scored.

3. Experimenting with "What-If" Scenarios

Live networks are subject to rare but critical events, and an AI model must be robust enough to handle them. A key function of a RAN digital twin is therefore to prepare AI applications for the unexpected.

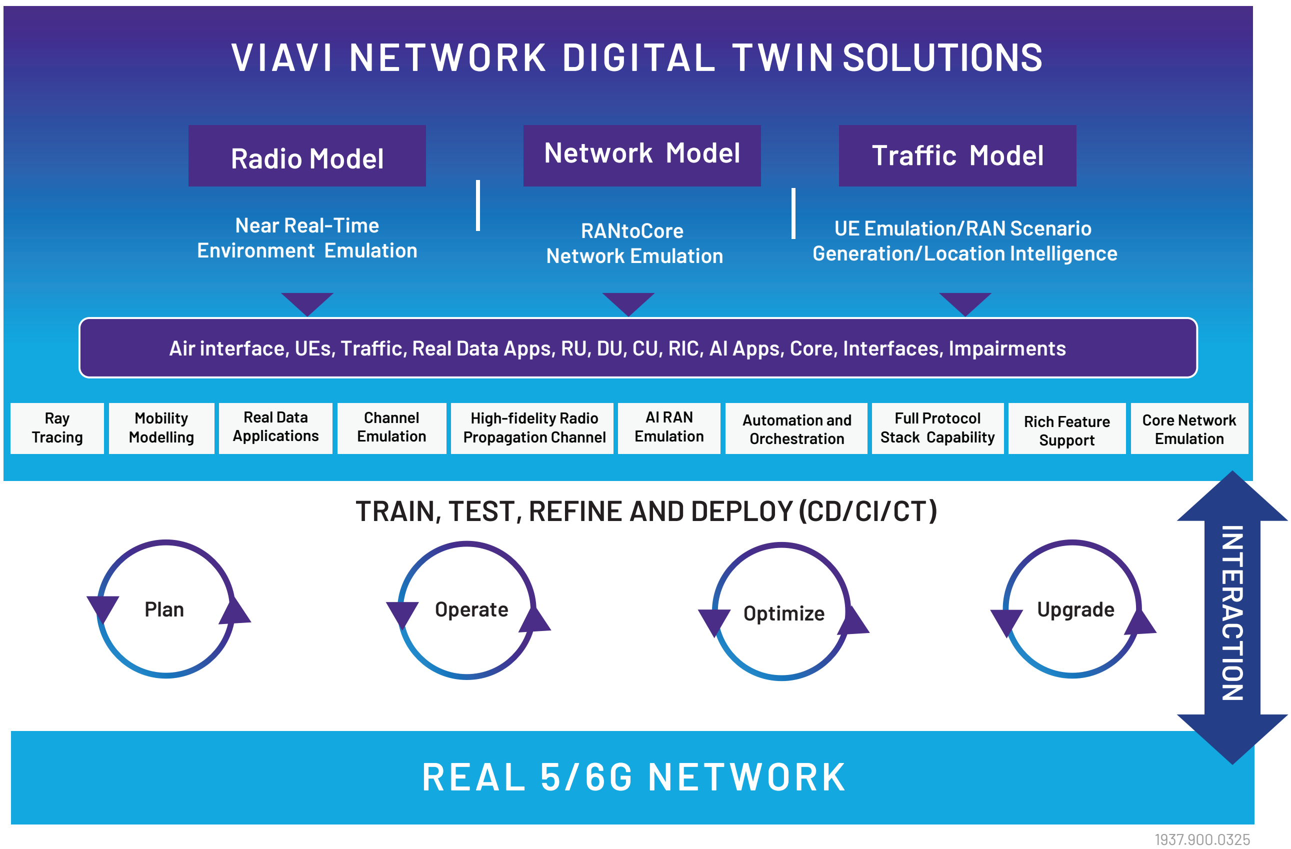
These "what-if" experiments are vital to improving resilience and help operators understand how the system and planned measures would cope in specific situations that would be impossible to test at scale on a live network.

Digital twins therefore provide a safe, controlled sandbox in which to simulate a wide range of events and scenarios, with the RSG used to model and test the effect of large-scale network congestion, hardware failures, or security threats such as a DoS/DDoS attack. And this capability can be expanded beyond negative events to inform forward-looking development — from planning the optimal location of new cell towers to assessing the effect of a new skyscraper on RF propagation.

The RSG's hypothesis-testing function plays a particularly key role in the development of 6G infrastructure by enabling the operator to model potential scenarios. This includes the testing of dynamic spectrum sharing algorithms for 5G and 6G signals and using trustworthy 6G propagation data from which to plan even before a single piece of 6G infrastructure has been deployed.

In this way the AI RSG enables the gap between lab and field to be bridged and underpins the development and refinement of algorithms and features ahead of deployment to significantly de-risk R&D and accelerate time to market.

In summary, the application of a RAN scenario generator to create high-fidelity digital twins provides a tangible framework for solving pressing challenges across the network lifecycle.



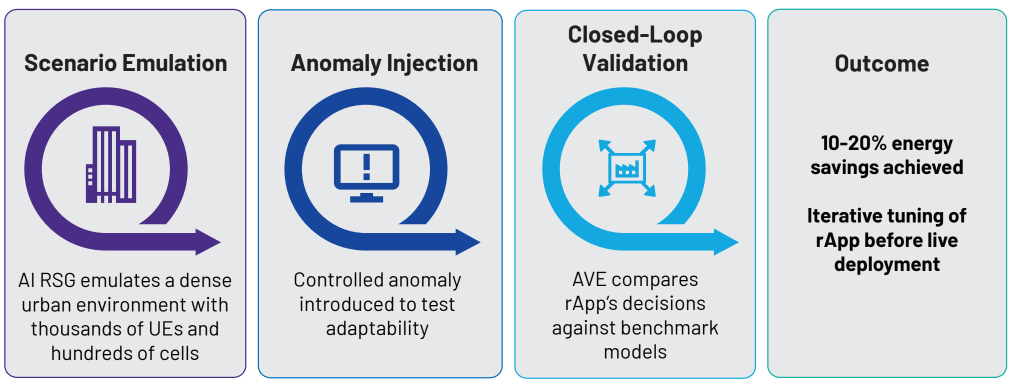
Digital twins built on RSGs address existing and future challenges

PART II
Use Cases

AI RSG in Action

The following use cases illustrate how the methodology outlined in Part I of this document is applied in several key areas, from improving energy efficiency to enabling the development of future 6G technologies.

1. Energy Efficiency



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VIAVI AI RSG-App Validation Engine (AVE)

As we've highlighted, the telecommunications industry faces sustained pressure to reduce both operational expenditure and its environmental footprint.

The RAN is among the most significant portions of an operator's energy consumption and there is a need to understand how to lower this consumption without negatively impacting the Quality of Experience (QoE), as quantified via the KPIs of signal quality, call success rates, and handover efficiency.

With appropriate data and training, it becomes possible to manage network resources to achieve this using a digital twin powered by an AI RSG, such as VIAVI's TeraVM™. For quantifying QoE, the twin's real-world accuracy can be further enhanced using ray-tracing tools to get a greater understanding of how the signals propagate around obstacles and structures such as trees and buildings, and how this changes over time.

Taking this RSG-testing approach has enabled one leading European mobile operator to model multiple energy-saving strategies and identify the most effective solution for their particular network. The data provided by the VIAVI RSG significantly reduced the risk of the decision for the operator, demonstrating ahead of time that the changes that had been proposed would lead to a 5% reduction in RAN energy consumption as well as a 2.5% reduction in OpEx, without any impact on service quality.

As we highlighted earlier, it's vital that validation takes place and, in the above case, geolocated call trace data was used to ensure the simulation reflected actual user behavior, which allowed the AI to make targeted adjustments.

2. Energy-Efficient 6G Pre-Deployment (FR1 and FR3)

As we move from small scale 6G proof-of-concept trials towards implementation at scale, it becomes vital to develop and test the core underpinning technologies. Notably, 6G will implement a new frequency band, with the FR3 band sitting between the sub-6 GHz FR1 frequencies and the mmWave FR2 bands.

During these early stages of development, physical 6G hardware is scarce and the only way to test performance in realistic, large-scale environments is via an RSG-powered digital twin. Through these, it becomes possible to create complete, city-scale 6G environments virtually for hypothesis testing - for example to understand 6G radio performance and its interactions with existing 5G networks.

Good examples of RSGs being used to develop, test and refine algorithms for intelligent spectrum sharing between 5G and 6G can be seen in both Europe's 6G-TWIN project and in the 6G City-Scale Twin developed by Northeastern University's Institute for Wireless IoT. These both combine multiple modeling techniques, starting with the TeraVM™ AI RSG for simulating system-level behavior. Accuracy of these models and their signal propagation within the twin is improved through the capture of real-world data of the city, its landscape and its infrastructure via ray tracing techniques.

And finally, the RSG brings in data from a UE emulator, in this case VIAVI's TM500, to understand the effect of having thousands of 5G and 6G user devices on the network and their interactions with the AI-native air interfaces.

The Singapore University of Technology and Design (SUTD), in collaboration with Yonsei University and VIAVI has developed and successfully trained a digital twin to determine energy savings in O-RAN based 5G networks. Deploying AI-based 5G beamforming for mobility-aware beamforming, the twin identifies interference issues and potential energy savings when multiple massive MIMO base stations are deployed together in an urban scenario.

The twin is powered by VIAVI's TeraVM™ AI RSG, with the SUTD team also developing a synchronization rApp to maintain a virtual version of the 5G network over time.

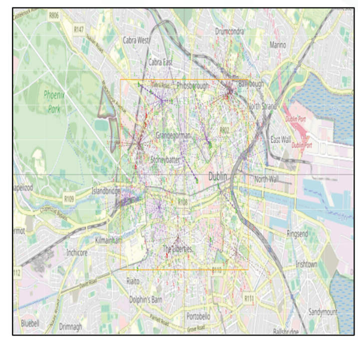
This twin with RSG testing has, to date, served to identify and refine energy-saving strategies on O-RAN networks, with validation taking place on a smaller real-world setup using Quanta Cloud Technology's OmniRAN system. Because the solution follows O-RAN's open interface standards this solution is highly scalable and can easily integrate with other O-RAN systems to make 5G networks greener and more efficient.

3. Quality of Service (QoS) Optimization

Network Configuration	• **13 sites** in Dublin city center with **2 sectors** each. • **URLLC users require minimum 2 Mbps - drones** • **eMBB users - cars** • **Voice users - pedestrians** 1,000 UEs
Challenges	• As users move away from cell edge PRB demand grows reducing QoS for all users. • **How to ensure URLLC Drones maintain required throughput as overall cell PRB demand grows**
Solution	• Use an App to monitor cell PRBs, URLLC throughput. • As URLLC users' throughput threatens to fall below min level as monitored by predictive AI app - modification of resources allocation is applied and assigns more PRBs to Drones ensuring minimum service level maintained.
Simulation Setup	• Realistic simulation using a digital twin of Dublin City center. • Various user equipment (UE) types: pedestrians, cars, drones. • High demand scenario with 200 drones each requiring 2 Mbps.
Simulation Results	• **Prior to App intervention** URLLC users suffer as PRB demand increases. • **After App intervention** URLLC users maintain minimum throughput requirement as PRB demand increases. • eMBB users resources reduce as a consequence of prioritising URLLC users.
Conclusion	• **AI RSG simulates a realistic Operator network with real buildings, real devices, real mobility using real traffic.** • AI RSG can run both before and after simulations with AVE showing the effect of network optimizing apps over a long term period delivering confidence to Operator of the effects of the App.

This setup and simulation demonstrates how AI RSG can simulate Network before and after App intervention showing how to maintain QoD at scale.

Dublin City Center Simulation



Simulation of Dublin City Center network configuration showing QoS at scale

While we have touched on how an RSG-powered digital twin can be used to measure QoE it is worth noting that there is a difference between measuring this KPI at the network level and at the individual level.

Traditional network management techniques often rely on a static approach to resource allocation, with the same provision of data regardless of whether someone is downloading an email or watching a film.

The ultimate goal should be to move from objective QoS metrics to improving the subjective QoE for each user, even in dynamic conditions. A good example of this (and one that VIAVI is currently working on in collaboration with an operator) is a subscriber on a train with a streamed video needing constant buffering as a result of being in a fast-moving vehicle with other users. To solve this, the network needs to both identify and adapt to their specific context in real-time.

AI RSGs enable this goal to be achieved through the development of applications that perform context-aware, real-time network optimization. Training an AI to look beyond standard network metrics and incorporate contextual information: user location, user speed, and application type enables the AI to harmonize network resources. Doing this not only enables the delivery of user-specific requirements (and therefore a reduction in customer churn) but also the prioritization of mission critical services.

For example, a Tier-1 RAN vendor has developed APIs for the embedding of 5G network capabilities directly into applications. This allows them to use real-time network data to ensure reliable, low-latency control, with resources boosted at critical moments, for services, such as for autonomous shipping or vehicle navigation systems.

VIAVI's RSG is critical in the testing and improvement of these APIs. The TeraVM™ is used alongside a UE emulator to create virtual devices with access to metadata on location, speed and a vast volume of metadata for better classification of individual users. In addition, ray tracers are used to give real-world data analytics tools for enhanced accuracy.

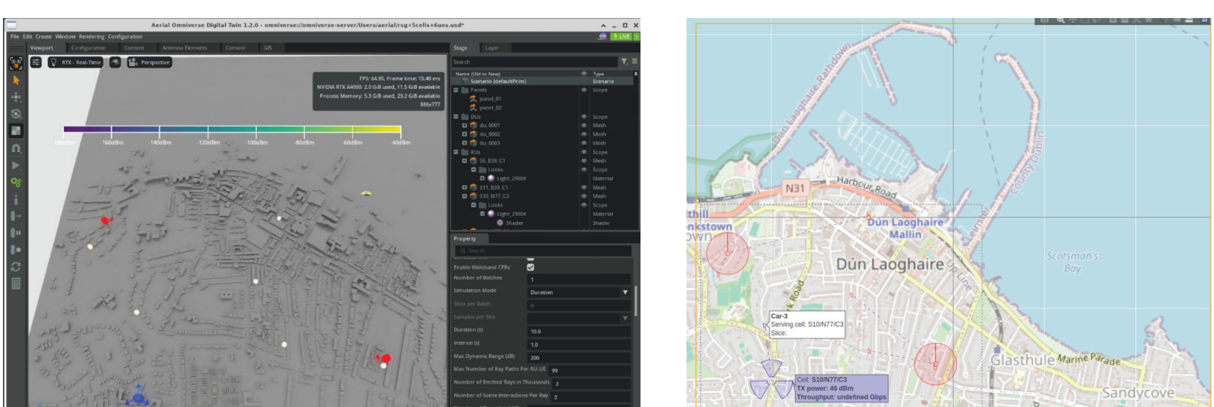
4. Massive MIMO Optimization

Massive MIMO is a key technology that underpins the high throughputs of 5G networks. Managing it is a highly complex task, with beams needing to be configured for thousands of potential user devices. This requires the management and continual evaluation of multiple parameters and reduced algorithmic precision can lead to inter-cell interference, wasted energy, and degraded performance.

6G networks will utilize even larger antenna arrays than 5G and operate on higher frequency FR3 bands that have greater path loss and as such, these algorithms are set to be placed under ever-tighter scrutiny.

The efficacy of these algorithms, therefore, needs to be continually refined through a test and validation process. Additionally, a shift-left development approach to testing is required, taking place as early in the project life cycle as possible to ensure base stations are able to coordinate multiple devices with minimal interference.

To be effective, the digital twin must have a high degree of environmental fidelity — not just real-world maps, but the subscriber profiles, including their movements and traffic type — and be able to emulate dynamic and fading channel conditions.



A ray tracing capture of the Dún Laoghaire harbor in Dublin, Ireland as created for NVIDIA and its Aerial Omniverse Digital Twin.

The AI RSG is again critical in training these models within the twin. Such a model would also need ray tracing to accurately model how the beams will propagate and interact with buildings and other obstacles; and UE emulation to populate this environment with a large number of spatially distributed devices will also be vital. In this use case, a tool such as VIAVI's VAMOS™ would also be required to enable the degree of automation and orchestration needed by these algorithms.

And taking this approach ensures that complex scheduling and beamforming algorithms perform as expected under realistic load conditions, avoiding the poor customer experience and high costs associated with fixing performance issues in a live network.

Conclusion

The introduction of AI-native 5G networks and their core role in 6G operation is requiring a fundamental shift in how AI applications are developed, validated, and managed.

Running an AI RAN scenario generator to test and challenge the AIs that will run these networks – using a hybrid data layer based on real-world and synthetic data – provides the optimal approach. And when implemented throughout the entire AI lifecycle this technology not only supports creation but continual refinement to prevent AI drift.

The complexity of 5G over 4G has already demonstrated the usefulness of such techniques, but as we shift to 6G, with AI-native architectures at their very core, the industry needs to adopt a new mindset.

Indeed, it is no longer feasible to maintain a high-QoE network cost-effectively without the use of AI RSGs, which means their adoption is not a 'nice-to-have' but needs to become standard practice as soon as possible.

Further information on VIAVI's digital twin solutions, including ray tracing, UE emulators and RSG technologies, is available from viavisolutions.com/en-uk/solutions/ai-testing

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