

Transform Your RF Designs with Agentic AI

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Transform your RF Designs with **Agentic AI**

Capture, Orchestrate and Accelerate
your RF Workflows

Show me how ▶

Transform Your RF Designs with Agentic AI

Artificial intelligence is rapidly changing the way RF and microwave engineers approach design. What began as a tool for automating individual tasks is evolving into something far more powerful: AI systems that can help engineers explore design possibilities, orchestrate complex workflows, optimize performance and accelerate decisions across the design process.



For RF engineers, this evolution toward agentic AI presents an opportunity to rethink how design and simulation are performed. Rather than simply responding to a prompt or automating a single step, agentic AI can coordinate multiple tasks, work across tools and datasets, and help move a design from concept to optimized solution with greater efficiency.

The implications for RF EDA are significant. Modern RF designs already require engineers to navigate increasingly complex simulations, models, optimization processes and system-level considerations. As wireless technologies advance toward 6G and beyond, the ability to efficiently connect these processes will become increasingly important.

This eBook explores how AI is being applied across the RF design workflow and how emerging approaches can help engineers move beyond isolated, ad hoc applications of AI toward more connected and intelligent design processes.

The journey begins with planning an AI design strategy for RF EDA, followed by an examination of how AI can transform individual simulations into orchestrated RF design workflows. The articles that follow explore the broader possibilities of AI-enabled simulation, antenna design and optimization, and the use of digital twins for RF modeling and 6G system design.

Together, these perspectives illustrate an important shift: AI is not simply another tool added to the RF engineer's toolbox. It has the potential to become an intelligent layer that connects tools, processes and engineering expertise—helping engineers explore more possibilities, automate repetitive work and focus more time on solving the challenges that matter most.

As the RF industry moves toward increasingly complex systems and faster development cycles, understanding how to incorporate AI effectively will be essential. The technologies and approaches explored in this eBook offer a look at where RF design is heading—and how engineers can begin preparing for that future today.

Microwave Journal thanks Keysight Technologies for making this eBook possible and for supporting the RF engineering community as it explores the opportunities and challenges of AI-driven design.

Jenn DiMarco, *Microwave Journal*, Media Director



Planning Your AI Design Journey in RF EDA

How Keysight's Capture, Orchestrate and Accelerate Framework Helps Engineering Leaders Re-Imagine Their Open RF and Microwave Design Workflows

Keysight Technologies Inc., Santa Rosa, Calif.

Artificial intelligence is moving from novelty to necessity in electronic design automation. For RF and microwave teams the pressure is acute: designs are more complex, packaging and chiplet options are multiplying, experienced engineers are scarce, and the institutional knowledge that drives competitive products still lives largely in the heads of a few senior people. The question facing engineering leaders is no longer whether to adopt AI, but how to plan a capability journey that delivers value without forcing a disruptive rebuild of the design flow.

This paper offers a planning framework built on three parallel themes — **Capture, Orchestrate, and Accelerate**.

- **Capture** makes expertise visible and reusable.
- **Orchestrate** takes routine work off the bench and scales it with agents.
- **Accelerate** expands the design space with faster physics and machine-learning optimization.

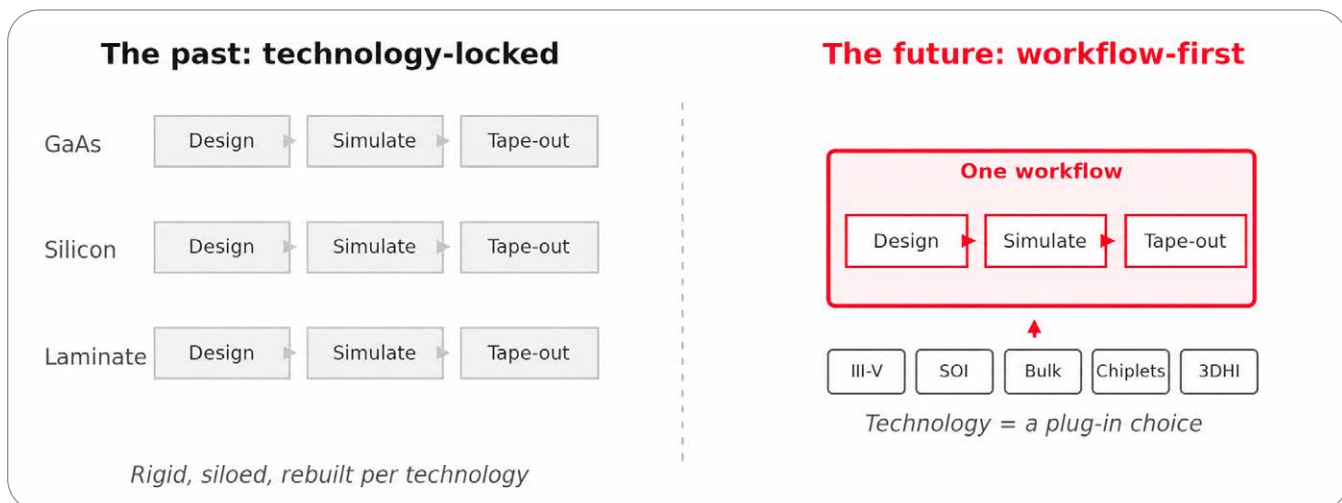
Underpinning all three is decades of high-frequency design experience and correlation to real measurements. Crucially, these are not sequential phases: organizations can begin each or all of them today, using the EDA tools its engineers already trust. We examine the three themes, the cost of standing still, the measurement foundation beneath them, the autonomy horizon that shows where orchestration is headed, a proven customer result, and a practical roadmap for capability planning.

Five Questions for Your Engineering Team

1. If your three most senior RF engineers retire next year, how much of your design capability would walk out the door with them?
2. When your team explores a design space, do you evaluate one candidate — or a thousand?
3. How long before a new hire can run your standard characterization flow unaided: weeks, or an afternoon?
4. Are your AI investments locked in one vendor model, or can you bring your own and keep your IP?
5. What would it be worth stating what you want to design, and let the tool decide how?

The Cost of Standing Still

For decades, the RF design toolchain has been defined by the underlying technology. Silicon, GaAs, GaN, and PCB laminates each carry their own rigid, siloed pipeline — design, simulate, tape-out — rebuilt from scratch for every process. That model is breaking down. Modern products increasingly center on packaging, 3D-IC, and 3D heterogeneous integration, where a single design may span III-V, SOI, bulk silicon, chiplets, and laminate at once.



▲ **Fig. 1** The shift from rigid, technology-locked pipelines to a single, technology-agnostic workflow. (Adapted from the webinar “Flow-First, Not Technology-First.”)

The Planning Insight

Design around workflows, not technology. A workflow captured once becomes an asset you can automate, share, hand to an AI agent, and re-target across processes — turning a rigid pipeline into an explorable design space that expands as physical domains are added.

Re-imagining agentic workflows is how organizations will stay competitive as design complexity explodes. Standing still carries real, if unbudgeted, costs: design spaces explored one candidate at a time while competitors evaluate thousands; onboarding measured in months because workflows live in individuals rather than in shared, runnable form; and re-spins that a wider search would have avoided (See **Figure 1**).

A Framework for AI Capability Planning: Three Parallel Themes

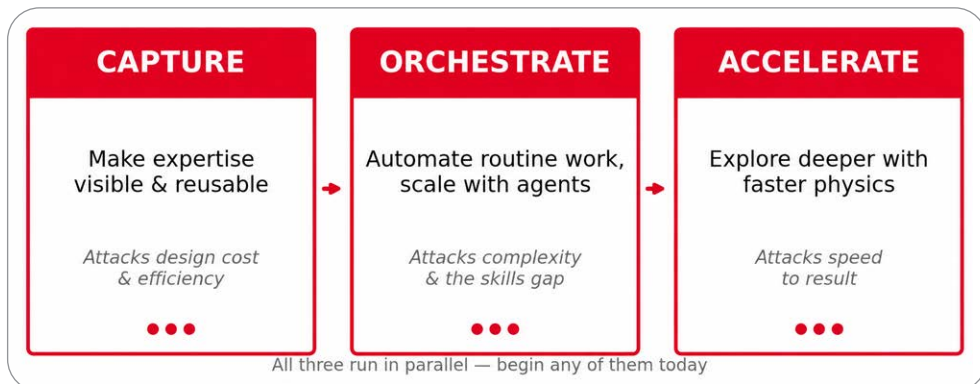
Keysight EDA organizes its AI strategy around three moves, each tied to a business driver engineering leaders already track. Rather than a single monolithic “AI project,” the framework lets an organization assess where it stands on each dimension and invest accordingly. The moves run in parallel and reinforce one another: captured workflows become the raw material for orchestration, and faster physics makes orchestrated exploration worthwhile. (See **Figure 2**)

- 1. Capture** — attacks design cost and efficiency by encoding expertise and more physics into reusable, AI-ready form, so knowledge stops living in one engineer’s head.
- 2. Orchestrate** — attacks complexity and the skills gap by starting with automation and scaling with agents that take routine work off the plate.
- 3. Accelerate** — attacks speed-to-result with better algorithms and surrogate models that cover far more design space at the same time.

A useful planning exercise is to rate your organization on each move independently — many teams are strong on automation yet have captured almost none of their expertise in shareable form. The gaps, not the averages, show where to invest first.

Capture: Making Expertise Visible and Reusable

RF design has resisted automation for a simple reason: large language models excel at code, but RF knowledge



▲ **Fig. 2** The three moves and the business driver at each address. All three can begin in parallel. (Adapted from “Move Your AI Program Forward in 3 Key Areas.”)

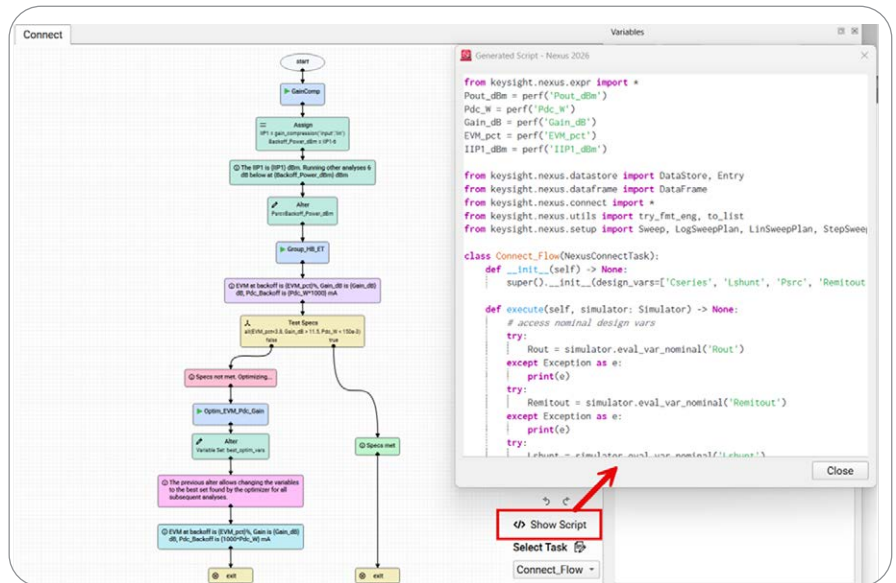
does not live in code. It lives in tools, in equations, and in the experience of senior engineers, with no public repository of any team's power-amplifier methodology or foundry IP for a model to learn from.

"Capture" addresses this directly by making soft IP and methodologies visible and composable as pythonic automation tools & skills, so they can be automated and handed to a trusted agent that sits inside your IP control.

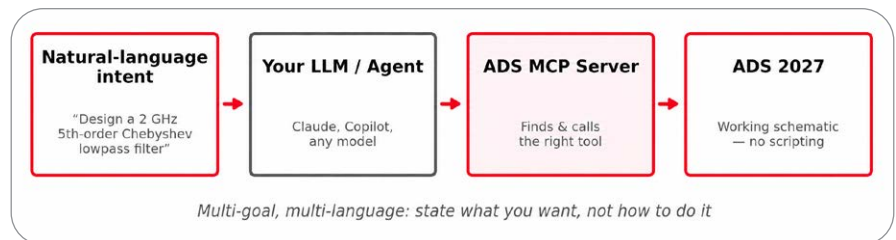
The entry point is already on the bench. In ADS, an engineer can right-click any schematic or layout and export Python, producing a snippet that captures the workspace and can be transformed into a parameterized function — the cell and its parameters, ready to call from a script. Expert users can capture their workflows directly into python using the python macro recorder. Sequences of human action in the user interface, windows, and menus enable are converted into a python code stream that can be the basis for automation, or a custom design agent. Knowledge that was once outside the addressable space of AI now becomes code that can be streamlined for automation, shared, and run agentially across ADS, RFPro, and Nexus. These become genuine building blocks: write once, reuse everywhere, composed into workflows that define a plan, run EM, build the circuit, and optimize.

Scripts alone, however, do not transfer expertise — many workflows begin on a whiteboard and need something visual and shareable. Nexus Connect answers this with a visual workflow language built directly into the next-generation simulation environment. Engineers draw a simulation flow as a flowchart of inputs, tasks, conditions, and outputs, capturing critical design decision trees where the whole team can read them and a new engineer can run them. One click converts that flowchart (which is a visual test plan) into a documented, executable python script — making every captured workflow ready for AI agents.

These are important IP bridges that enable your best designers to achieve even higher levels of performance. See **Figure 3** for a representation of Nexus Connect.



▲ **Fig. 3** Convert a flowchart into a documented, executable python script.

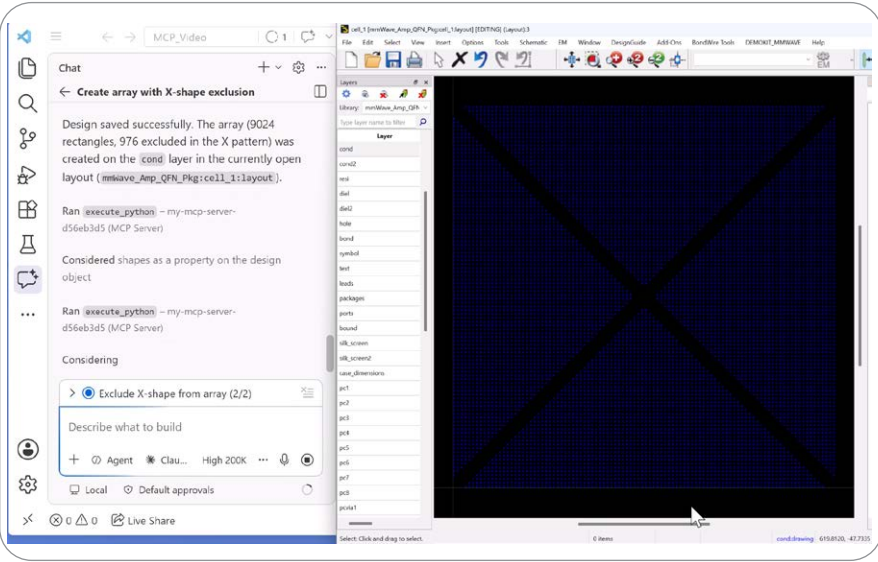


▲ **Fig. 4** Natural-language intent flows through an LLM and the ADS MCP Server to help produce a working design — no scripting in between. (Adapted from the ADS 2027 MCP Server demo.)

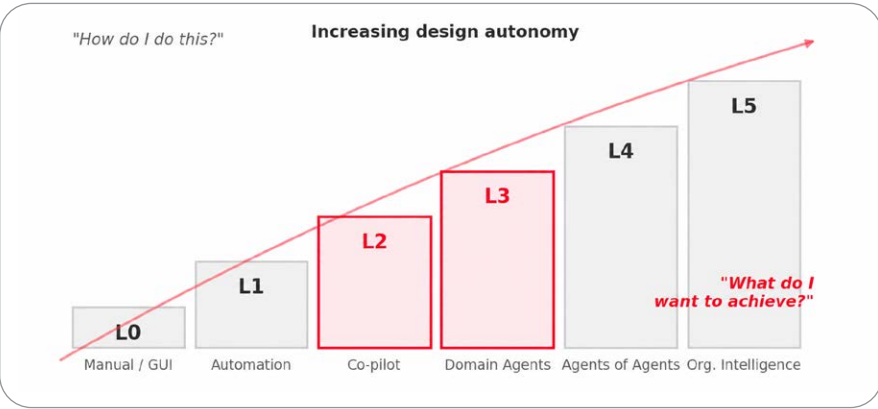
Orchestrate: From Automation to Agents

Once expertise is captured, orchestration puts it to work. With the ADS 2027 MCP Server, engineers no longer need to write the script at all — they can simply ask. The Model Context Protocol (MCP) lets a Large Language Model (LLM) discover and call the right tool on its own, acting as a single connection point that branches to every tool instead of hand-wiring each integration. Keysight MCPs will work with the LLM and coding agent(s) that your enterprise has already provided for security, performance, and cost (See **Figure 4**). You are not constrained to one model, or even to English: the same engineering requests often work across languages, making Keysight's agentic surface accessible to global engineering teams.

The effect will be a shift in the fundamental culture of design, raising the abstraction from "Tools" to "Intent." An engineer connects an agent through the MCP server and states a desired outcome or requirement: "design a MMIC power amplifier with gain above 20 dB and output power above 28 dBm". The multi-goal definitions describe what is wanted, not how to achieve it. So, the



▲ **Fig. 5** MCP Server responding to a design request.



▲ **Fig. 6** The five-level autonomy scale, from manual GUI work to organizational intelligence. Most teams sit at L1–L2 today; agentic features target L3 and beyond. (Adapted from “Evolution of EDA.”)

key change is from procedure to outcomes, using plain language. Then protocol finds the right tools, and the tool stack does the work. See the example in **Figure 5** in which the MCP server answered the prompt “Create an array with an X shape exclusion”.

The Autonomy Horizon: Where Orchestrate is Headed

Orchestration is best understood against a longer arc.

Level	Stage	What it Means for the Engineer
L0	Manual/GUI	Engineers execute every step by hand using the graphical user interface
L1	Automation	Scripts and headless API’s run execution; humans still initiate design tasks
L2	Co-pilot	Natural-language assistants grasp intent while engineers supervise
L3	Domain agents	Specialized agents handle multi-step tasks with partial delegation
L4	Agents of Agents	Orchestrated agents coordinate whole workflows; humans set objectives
L5	Organizational Intelligence	Learning organizations that self-improve; Continuous, always-on operational intelligence

Keysight frames RF design as a five-level scale — a shared vocabulary for locating where a team sits today and seeing the path ahead. It is an autonomy scale, not a maturity score: most teams today sit between Levels 1 and 2, using pythonic automation, and experimenting with human supervision of copilots. The value is not where an organization stands, but that a clear, incremental path forward exists without rebuilding the flow to walk it. Today’s natural-language agents move teams toward Level 3; the same orchestration foundation extends toward Levels 4 and 5 (See **Figure 6**).

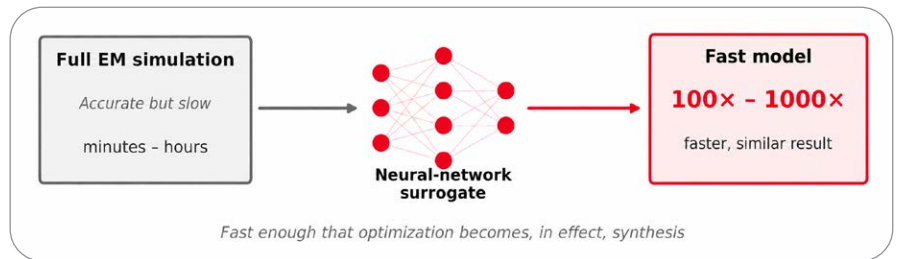
Accelerate: Physics at the Speed of Exploration

The third parallel AI theme brings faster, more realistic physics into the creative phase of design so teams can explore deeper, larger problem spaces. Two engines drive it. The first is **AI-enabled optimization**: a reinforcement-learning framework connects an agent to existing simulators, setting goals and earning rewards to learn effective design strategies. Where conventional optimizers are typically applied to in the order of ten parameters, the ML-enabled optimizer is designed to handle forty or more at once and

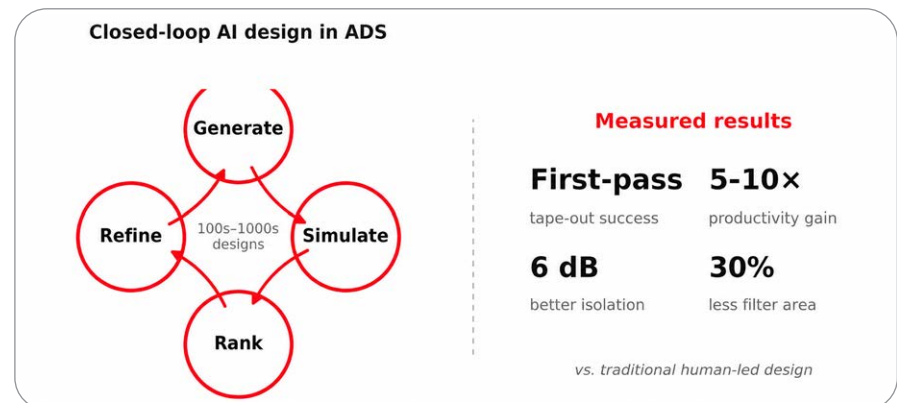
to learn from the data as it goes. Just as important, the framework is open — teams can bring their own Python optimizer or surrogate and combine it with continuous learning and warm starts.

The second engine is **surrogate modeling**. A surrogate is a faster approximation to a computationally expensive simulation (such as a full EM run that might take minutes or hours), which might use a compact neural-network

model. On representative structures such as spiral inductors, Keysight reports speedups of two to three orders of magnitude. But raw speed is only valuable if the answer can be trusted, which is where Keysight's measurement heritage matters. Physical domain simulation speed becomes unlocked when a design evaluates in milliseconds; an organization can explore thousands of candidates and let agents search the space. Through pyS-MI, Keysight's published Smart Modeling Interface, a team's own surrogates, Keysight's, or a third party are all used the same way — in context, inside the existing flow. Such an open system where you can “Bring Your Own Surrogate” means you are using models your team already trusts, and you can create your own enduring competitive advantage using your own proprietary IP (See **Figure 7**).



▲ **Fig. 7** A surrogate model replaces a slow EM simulation with a fast neural network approximation. (Adapted from “Acceleration Through Surrogate Modeling.”)

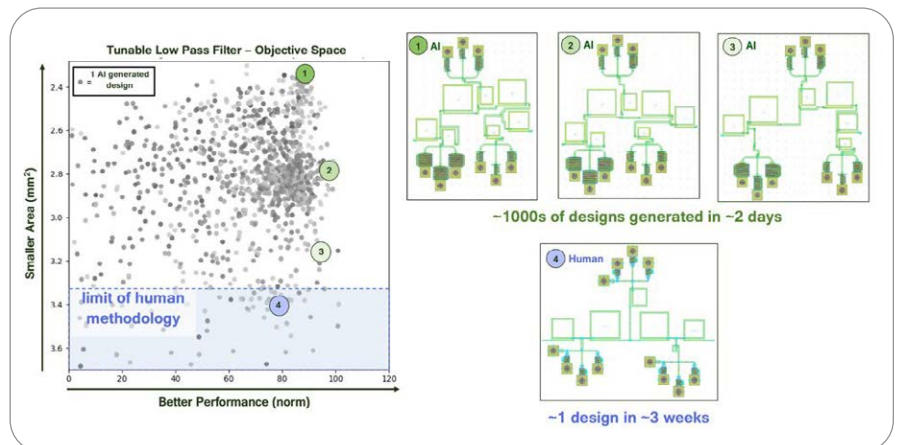


▲ **Fig. 8** The closed-loop AI design pattern and Sphere Semi's measured results versus a traditional human-led design.

The Foundation: Physics You Can Trust

These three themes rest on a foundation that is easy to overlook and hard to copy. Any vendor or talented individual can wrap a language model around a simulator; the differentiator is whether the underlying physics is right, and can a workgroup share them in an organizationally consistent way. Keysight's simulation models are grounded in decades of correlation to real hardware measurement — the same measurement science that underpins the instruments on the bench. At the same time, having a unifying platform such as Keysight ADS is necessary to rein in the freedom and innovation of personal modeling to create organizational benefits that scale, remain manufacturable, and transcend the risk of relying on only one expert or technology.

For a planning conversation, this reframes the question of Trust. The risk in agentic design for RF is not that the tools are slow — it is that a fast, confident answer might be wrong, and that these silent faults will not be traceable in a Root Cause Analysis. “Grounding the loop” using measurement-correlated physics is how an organization can safely delegate more of the design to agents



▲ **Fig. 9** Sphere Semi's AI engine achieves a 30% smaller tunable filter in an order of magnitude less time.

over time. When comparing vendors, the sharper question may be “how well does your physics correlate to measured hardware?” due to packaging, interconnects, coupling, power and ground integrity, moding, launches, 3D currents, and other effects. Furthermore, the data lineage of where models originated, how the data was tagged or cleaned, and limitations associated with AI/ML artifacts should be versioned and inspectable. Visibility and benchmarked evaluations also build Trust.

Proof Point: AI-Driven RFIC Design at Scale

These capabilities above are not aspirational, and the pattern behind them is repeatable. Sphere Semi, an RFIC

Horizon	Planning Focus	Where to Invest
Now	Make expertise visible	Export designs to Python; document flows in Nexus Connect. (Capture)
Near term	Take routine work off the bench	Stand up natural-language agents on the ADS MCP Server (Orchestrate)
Next	Expand the design space	Adopt RL optimizers and surrogate models; bring your own. (Accelerate)
Ongoing	Compound the advantage	Govern data and models at enterprise scale toward higher autonomy

design company, faced the classic wall: RF and analog design are manual and talent-constrained, exploring one design at a time (See **Figures 8 and 9**). Their response — a fully code-defined, Python-based flow in which an AI engine generates hundreds to thousands of candidates, evaluates each with circuit and EM co-simulation in ADS, and closes the loop — is exactly the generate-simulate-rank-refine pattern the three Keysight AI themes are designed to enable.

In the Words of Sphere Semi

“We were thrilled to learn that ADS reinforced Python extensibility and the API for its programmatically callable co-simulation engine, which made ADS a clear winner for us — there was nothing else with the combination of features we needed.”

— Mitchell Nahmias, CTO, Sphere Semi

A Planning Roadmap for Engineering Leaders

Because the three AI themes run in parallel, capability planning is less about sequencing and more about deliberate, simultaneous investment aligned with the status of each team. The horizons below offer a way to structure that investment without stalling on any single dimension.

Three principles should guide the plan.

1. First, be workflow-first: capture the engineering process as technology-agnostic actions before optimizing any single technology.
2. Second, stay open: a bring-your-own approach to models, optimizers, and surrogates protects the organization’s freedom to combine its own IP with Keysight’s and avoids lock-in.
3. Third, treat learning as the asset: as surrogates and workflows accumulate, the discipline of versioning and governing data and models — not just the models themselves — becomes the enterprise’s durable competitive advantage. ■



From Ad Hoc Simulations to Orchestrated RF Design Workflows

Jason Boh and Matt Ozalas, *Keysight Technologies, Santa Rosa, Calif.*
Don Dingee, *STRATISSET, San Antonio, Texas*

The complexity of RF circuits and systems, coupled with stringent performance targets, has made simulation essential. Historically, simulations were configured and run manually, with engineers reviewing results and deciding next steps. More recently, Python-based automation has emerged as a compelling alternative, improving efficiency, scalability and repeatability. However, many RF engineers do not consider themselves programmers, making it difficult to translate their deep design expertise into workflows built entirely in code.

A new paradigm is emerging for orchestrating RF simulations. This methodology trades pure code-based automation for an executable visual flowchart. Yet it doesn't eliminate Python from the picture. Instead, the approach spans no-code, low-code and fully coded orchestration, adapting to both requirements and individual preferences. Combining Python with a visual flowchart offers the best of both worlds: humans can quickly understand the logic, while decision-making can be handed off to agentic AI.

We will demonstrate the benefits of a flowchart-based approach using an RF power amplifier (PA) design example and the technique of intrinsic node waveform engineering. This approach integrates common simulation tasks, including DCIV, S-parameter extraction, load- and source-pull analysis, harmonic balance (HB), parameter sweeping and optimization, into a single executable flow. Finally, we will discuss how AI can fit into this workflow

through surrogate modeling, natural language prompting and agentic decision-making.

RF Workflow Orchestration – a New Flowchart Paradigm

Like many software applications, RF simulators began with command-line interfaces and later evolved into graphical user interfaces (GUIs). Dialog boxes are typically intuitive, with features such as buttons, checkboxes, drop-down menus and short text fields. The learning curve is short, but GUIs have downsides. For example, achieving consistent results across ad hoc simulation runs requires that all fields be entered in exactly the same way every time. Reusable simulation templates can help, but since they are usually editable, traceability remains elusive. Another major limitation of GUIs is scalability: as circuit complexity and the number of design variables increase, manual editing becomes impractical.

Scripting improves the situation by fostering repeatability and enabling scalability. Many RF software tools began adding programmability through various (sometimes proprietary) scripting languages. Then Python burst onto the scene, growing into the world's most popular programming language. Some EDA vendors began efforts to retool around Python, benefiting from its vast ecosystem of open-source libraries and improved code portability and reuse.

Keysight leaned into the trend by adding Python support to its existing software platforms, including Advanced

Building on Nexus, Keysight is taking a new step in reimagining RF design workflows. Nexus Connect represents a new paradigm, enabling individuals and organizations to capture their design engineering processes as flowcharts, similar to how measurement processes are captured with visual tools. As shown in **Figure 1**, the flowcharts comprise various action blocks, or “steps,” underpinned by modifiable Python code. The flowchart manages tasks and decisions, allowing pre-planned, orchestrated workflows to run automatically and be reproduced precisely.

Visual flowchart diagrams help engineering teams capture and share information. From the moment a design project begins, engineering thinking becomes transparent and is saved electronically rather than lost when a physical whiteboard is erased. Instead of leafing through tedious documentation or tracking down colleagues, team members at any skill level can immediately see the types of simulations and parameters chosen, the goals used for optimization and the criteria for deciding how to proceed based on the results. Diagrams can also serve as the focal point for design reviews. New designs can start with reusable diagrams. The time savings from improved orchestration and reduced workflow friction add up quickly.

The best way to illustrate this is with a real-world example. Here, we focus on RF PA design, specifically a Class J amplifier, which is similar to Class B operation but uses harmonic tuning to improve efficiency. The complexity of PA design makes it an ideal vehicle for discussing workflow orchestration. This discussion is kept at a high level so that all RF designers can follow along, not just those specializing in PAs. In this example, ADS is used for schematic capture and data display, and Nexus to run simulations.

Much has been written about extrinsic design methodologies for PAs, in part because they align with how designers measure and characterize circuits. This approach places the reference plane for simulations or measurements at a physically accessible boundary — typically the transistor terminals, either at the package leads or at the die edge. As a result, an extrinsic model or measured dataset inherently in-

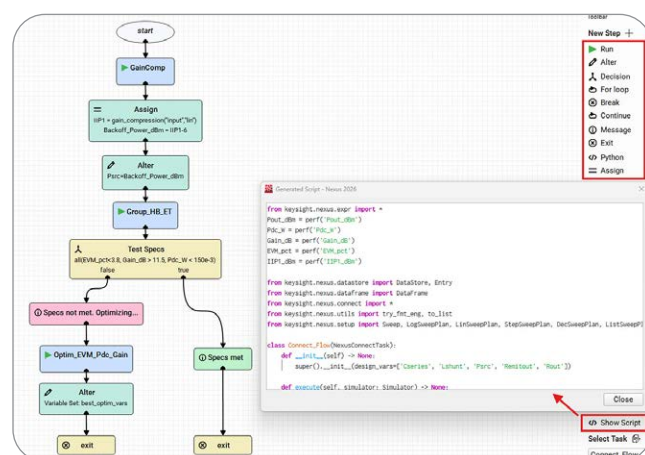


Fig. 1 A Nexus Connect flowchart and its associated Python code

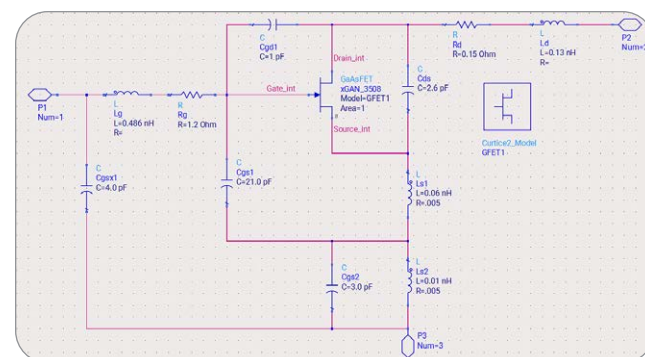


Fig. 2 An intrinsic-node GaN transistor model with a current generator and parasitics, represented in ADS.

cludes the parasitic resistance, capacitance and inductance present within the device.

In contrast, intrinsic design methodologies analyze voltages and currents at internal device nodes rather than at terminals. By working closer to the intrinsic current generator, designers can directly observe waveforms that are typically masked by device parasitics. This perspective provides deeper insight into transistor operation and enables the evaluation of key PA performance metrics. **Figure 2** shows a schematic of a conceptual, non-process-specific GaN transistor with its intrinsic device nodes explicitly exposed.

Access to intrinsic nodes allows PA designers to build circuits around first principles. The challenge with implementing an intrinsic-node method is that many manual steps are required to iteratively optimize a design.²

- Ideal nonlinear voltage and current waveforms are superimposed on a device's DCIV curves to determine the power and efficiency a device could achieve in that operating state.
- Strategically engineered waveforms reduce overlap between the time-domain voltage and current wave-

forms, minimizing resistive power dissipation.

- The Class J mode tunes the second-harmonic load impedance to boost the voltage waveform, while higher harmonics shape the current waveform, theoretically allowing an efficiency of 78.5 percent with a more flexible set of harmonic impedances than in Class B.
- The time-domain waveforms are then transformed into the frequency domain using an FFT, yielding computed impedances at the fundamental and harmonic frequencies.
- By applying those impedances back to the idealized current generator in the intrinsic-node transistor model, energy organizes into the efficient waveforms we started with, maximizing achievable device power efficiency.

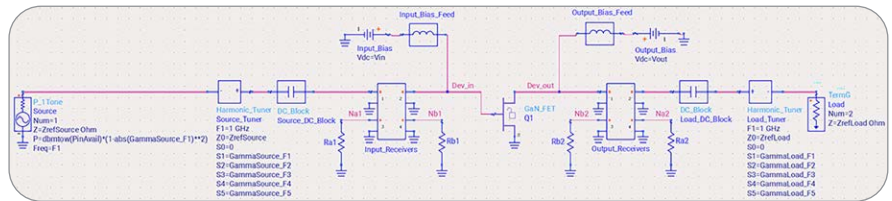
The PA design bench schematic in ADS, as seen in **Figure 3**, mimics a load-pull measurement system.³ It includes harmonic tuners, bias networks and receivers for the A (incident) and B (reflected) waves, enabling a complete analysis of PA metrics. The device under test (DUT) is the GaN FET model shown in Figure 2.

A single Nexus Connect task captures the sequence of analyses and tasks required to complete a significant portion of a Class J amplifier design. **Figure 4** shows the first few steps of the Nexus Connect executable flowchart.

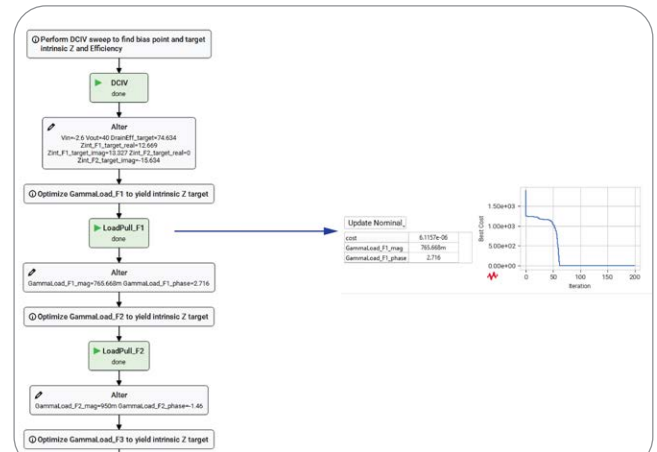
- First, the task performs a DCIV sweep, followed by load-line calculations for bias and target intrinsic impedances (Z_s) at each harmonic.
- Then, it sequentially optimizes extrinsic loads for each harmonic to achieve the target intrinsic Z_s .
- Next, it performs a source-pull analysis and an input power adjustment to match power and efficiency.
- Then, an S-parameter analysis is performed, including stability calculations with Winslow virtual probes.
- Finally, a power-swept HB analysis confirms the overall PA performance.

As the flowchart execution graph progresses, run blocks can change color (a programmable setting) and double-clicking a block can reveal simulation or optimization results. Figure 4 also shows a portion of the optimization results from the first load-pull analysis when the graph is clicked.

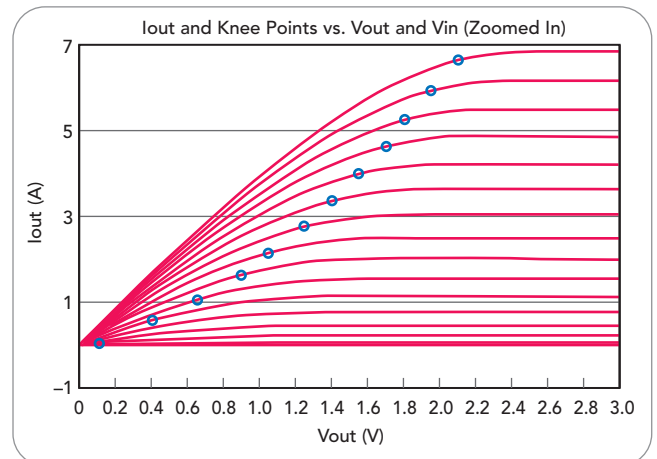
Designers can set top-level parameters such as the target output power, alpha (which reshapes the voltage waveform and changes the target impedances without affecting power or efficiency) and the percentage of the



▲ **Fig. 3** PA design bench schematic in ADS using the GaN FET model.



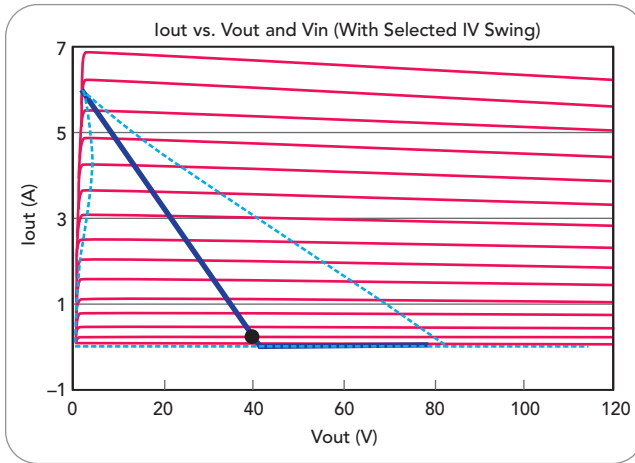
▲ **Fig. 4** A Nexus Connect task execution flowchart with results of a load-pull optimization displayed.



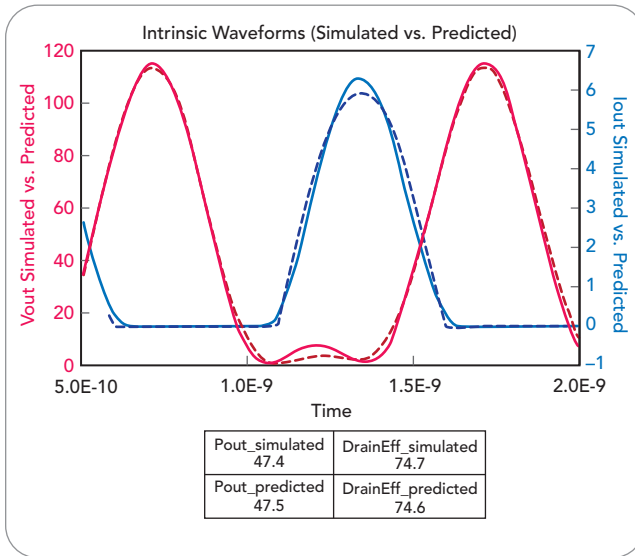
▲ **Fig. 5** DCIV sweep data plotted with all the calculated knee points.

device's maximum output current for the quiescent (q) point. Re-running the flowchart with new top-level parameters produces updated results quickly (in less than a minute on a laptop).

Deriving target intrinsic gammas involves constructing a load line from the DCIV sweep data by connecting the q point to one of the knee points. First, simple Python algorithms and heuristics determine the q point from the device's breakdown voltage and the desired output current at cutoff (a small percentage of the maximum output current). Then, knee points are calculated for all simulated V_{in} curves, as shown in **Figure 5**.



▲ **Fig. 6** IV swing trajectories for alphas 0.0 (blue) and 1.0 (teal) and q point (black), calculated from DCIV sweep data.



▲ **Fig. 7** Simulated (solid) versus predicted (dashed) intrinsic waveforms, output power and efficiency.

Next, load-line metrics are evaluated for all knee/quiescent point pairs, and additional Python algorithms are used to select a load line from the candidates. The algorithms balance output power and efficiency while walking down the knees. (The actual details of our algorithms are not the focus here — the key point is that all decisions and rules are formally captured in the execution flowchart.) The blue line in **Figure 6** is the rectified load line (or IV swing at alpha equals 0.0). With the FET biased for Class J operation at the q point, the instantaneous current and voltage swing along the line when an RF signal is applied. The FET conducts zero current for half of the RF cycle, yielding a 50 percent duty cycle. With an alpha of 0.0, the voltage waveform is a pure sinusoid. Using alpha values of 1.0 or -1.0 gives a “harmonic boost” to the voltage waveform, moves the target intrinsic gammas off the real axis of the Smith chart and widens the IV swing trajectory away from the rectified load line shown in teal.

Once the Nexus Connect task is complete, we achieve a good match between the simulated and predicted intrinsic voltage and current waveforms, as well as the power and efficiency, as shown in **Figure 7**.

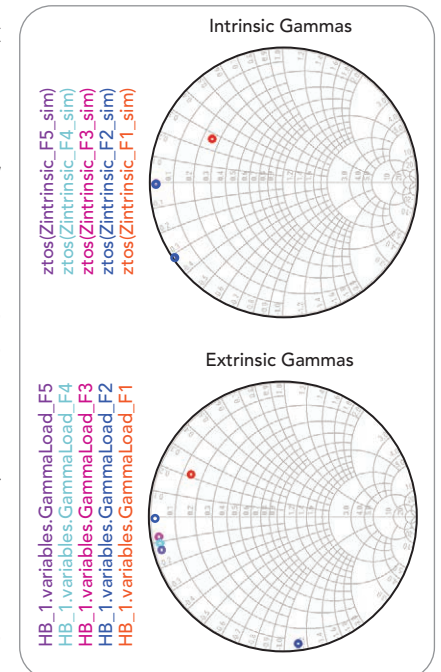
Extrinsic gammas, which are ultimately needed for matching network design, differ from intrinsic gammas because of the parasitics in the device model. The Nexus Connect task sequentially optimizes the extrinsic gammas up to the fifth harmonic, see **Figure 8**, to minimize errors in achieving the target intrinsic gammas.

The entire sequence shown, comprising simulations, algorithms and decisions, is captured and executed in a single Nexus Connect flowchart. While an engineer could have initiated the same steps manually via the Nexus graphical user interface, it would be hard to reproduce the exact repeatable steps from separate, disconnected analyses and tasks.

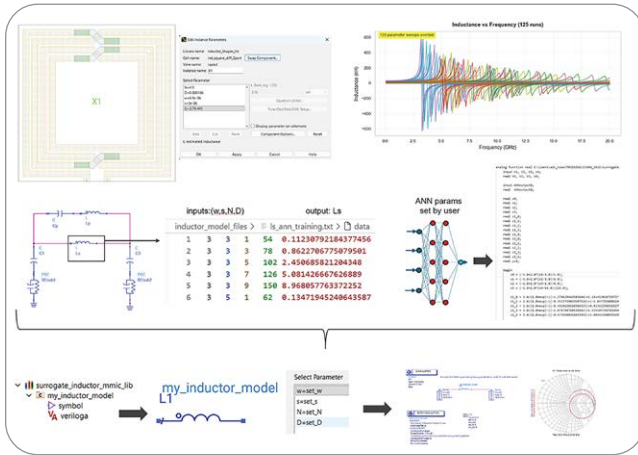
Applying AI for Advanced Modeling, Analysis and Optimization

By capturing engineering processes, designers create well-defined interfaces that future AI tools can directly leverage. In AI-enabled workflows, agents are software programs that can operate autonomously, while skills are well-defined sets of instructions that agents or large language models (LLMs) can invoke to perform specific tasks. Diagramming the engineering workflow step by step gives engineers straightforward ways to use agents and skills productively. For example, an AI agent might extend the prior workflow to characterize all available transistors in a given technology and identify which devices perform best for a set of requirements. The agent or LLM might use a skill that describes how to set up and run a DCIV sweep and calculate the Class J load line. As AI tools evolve, these parts of the engineering process will converge, giving designers greater capabilities.

The waveform engineering orchestration in this example is only a small part of the larger PA design



▲ **Fig. 8** Intrinsic and extrinsic gammas at each harmonic.

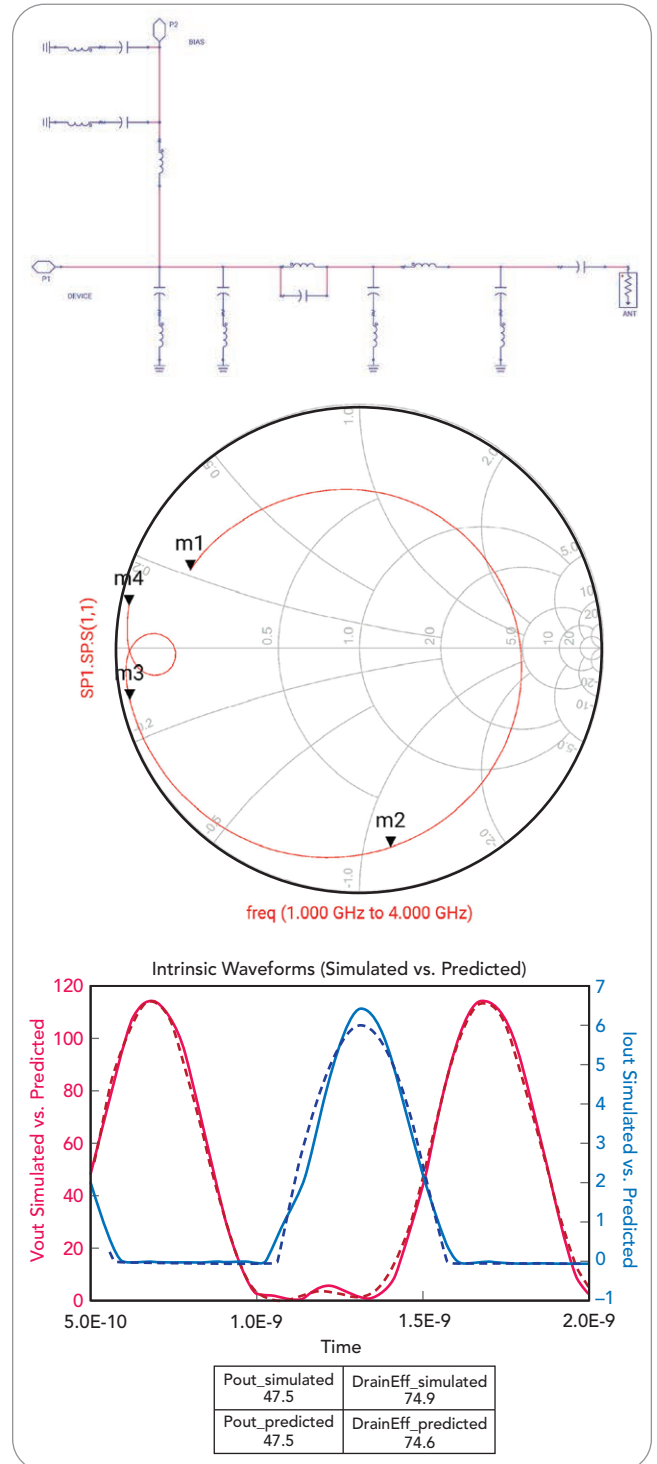


▲ **Fig. 9** An ANN model of an inductor is validated and synthesized in a circuit via a Python script.

process. The prior workflow characterized the external impedances required at the device's output node to achieve textbook Class J waveforms. Its output might be a table of impedances at the fundamental and harmonic frequencies, which, when presented to the transistor, yield efficient device operation. The next step is to design a matching network that presents these impedances to the device. Rapidly evolving AI capabilities will likely streamline this process. For example, surrogate models backed by artificial neural networks (ANNs) could reduce or eliminate computationally intensive electromagnetic (EM) simulations and even enable on-the-fly synthesis of physical structures.

Surrogate modeling involves an upfront, sometimes resource-intensive training process that requires extensive characterization (for example, EM simulations). Once training is complete and validated, simulations and optimization using physical structures become ultra-fast, making surrogate models strong candidates for AI-enabled or fully autonomous design. Surrogate approaches have received considerable attention in recent years because they can synthesize non-traditional, QR-code-like physical structures with well-behaved frequency responses.⁴ Recent research has even demonstrated the potential of such structures for harmonically matching a PA, as this example requires.⁵ Note that surrogate modeling is not limited to pixelated structures; it can work for any parameterizable physical structure, even an inductor.

To illustrate, an ANN-based surrogate model was extracted for a set of inductors with varying geometries in a GaN MMIC process, as shown in **Figure 9**. First, EM simulations are performed using Keysight RFPPro for each unique set of inductor geometry parameters, such as width, spacing, number of turns and diameter. Next, a modified pi network with 11 components is fitted to the EM data. Then, for each circuit element in the pi net-



▲ **Fig. 10** Output matching network tuned to Class J extrinsic targets using inductor surrogate models.

work, a separate ANN is extracted using Keysight's proprietary ANN engine, available as a Python function in ADS.⁶ The ANN produces Verilog-A functions that relate the physical parameters (w, s, N, D) to the circuit element values (capacitors, inductors and resistors). The result is a fast model that mirrors physical results and has input parameters that can be tuned or optimized.

The surrogate model was then used to quickly tune and optimize an output-matching network that presents the proper external impedances to the device, yielding near-ideal Class J operation, as shown in **Figure 10**.

As more details of lower-level engineering processes are diagrammed and captured in Nexus Connect, routine tasks become increasingly automated, allowing engineers using AI tools to focus on higher-level design. The path also leads to natural language interfaces that can augment or replace GUIs and scripts.

In summary, shifting from ad hoc simulations to executable, flowchart-based orchestration makes RF design workflows more repeatable, scalable and easier to share across teams. This approach enables engineers to capture complex design processes more effectively, exposes clear interfaces for automation and sets the stage for AI to accelerate design cycles while keeping engineers in control. ■

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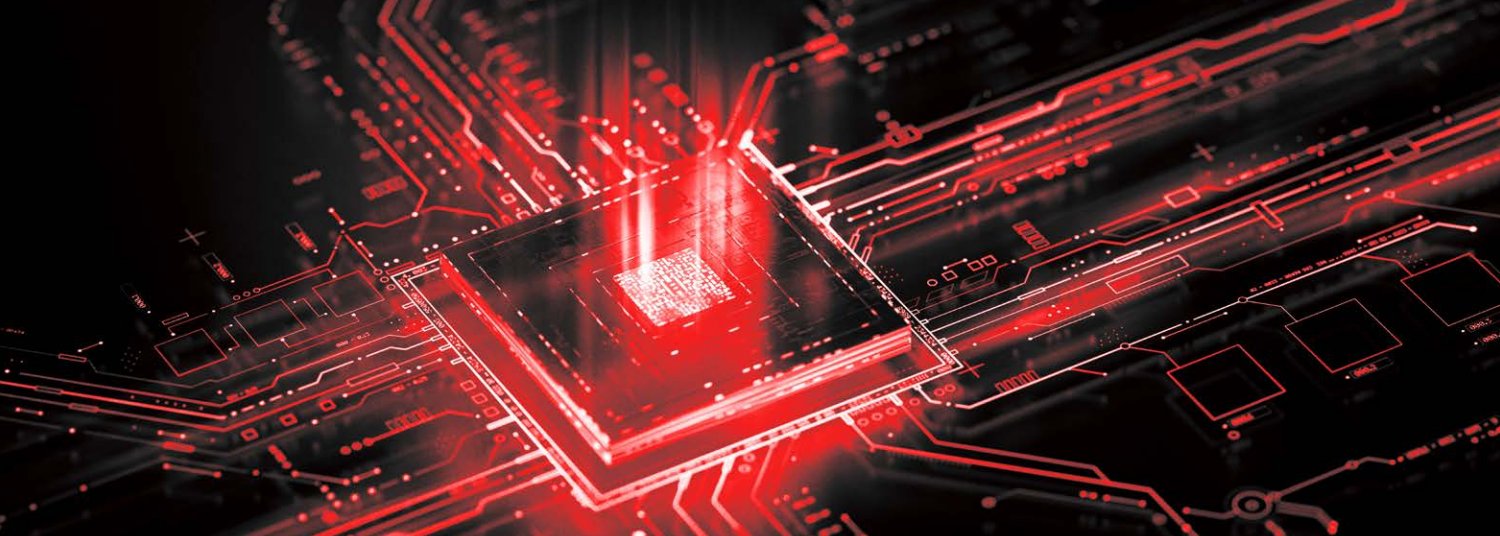


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Reimagining Possibilities for Next-Gen Simulation in RF EDA

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Historically, engineers procured CAD software with the implicit understanding that their hardware design process must conform to how a given software tool works. Vendors define their user interface and functionality, hoping to cover as much of the design process as possible. Engineering teams have a variety of tasks in their workflow and find or create tools for those tasks. Switching any tool in the suite usually means changing the steps required to complete a task, and sometimes the entire design workflow.

As hardware evolved in complexity, designers started to need multiple software tools to complete all the tasks in their workflow. Customers often settle on combinations of vendor and homegrown tools fitting their specific EDA needs, increasing the difficulty of adding or switching tools. Industry interoperability initiatives such as Si2 with OpenAccess implementations for EDA data repositories and APIs made tighter vendor-supplied integration and better growth paths feasible. Still, integrating RF simulators into modern workflows remains challenging, prompting a solution.

Keysight researchers are imagining a different direction for an all-new RF simulator suited for complex high frequency RF design, retaining integration benefits with a new programmatically-controlled, extensible platform. This research deepens the ties between measurement and simulation technology. Keysight explores the motives for developing a next-generation RF simulator, how designer productivity is shifting with help from research

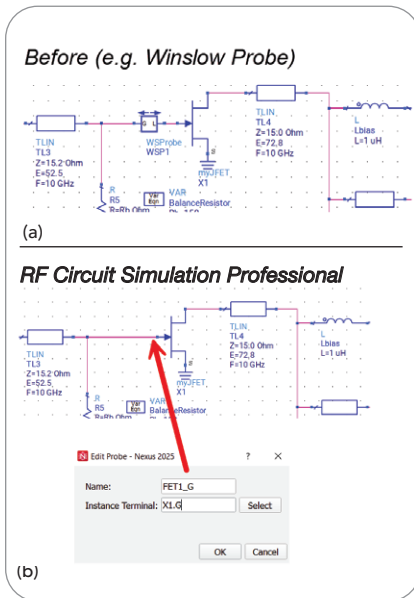
insights and the possibilities this simulator offers in automated RF design workflows, including roles for AI.

Motives for Programmatically Controlled RF Simulation

Software development teams seek to combine and prioritize customer needs and align them with research and development knowledge, a product's inner implementation secrets and the resources needed to effect changes. If a software tool finds widespread adoption, it becomes difficult to simultaneously morph into different design spaces while maintaining a state-of-the-art core engine. Technological expansion may suggest advanced capabilities, but required engine modifications limit or preclude adding them without substantial risk or costs. At some point, breaking with the past and creating an all-new engine architecture and code base becomes a better option for developers and users, similar to how buying a new computer can be more cost-effective than upgrading.

An RF simulator, the engine driving any modern RF EDA workflow, is no exception. Keysight's RF simulation technology evolves in lockstep with its measurement science. That philosophy helped Advanced Design System (ADS) become a key platform for complex RF design with extensive circuit electromagnetic (EM) co-simulation capability.

Still, more is possible. Reimagining the possibilities for next-generation simulation in RF EDA began with the realization that Keysight's previous RF simulator engine



▲ **Fig. 1** Schematics of (a) a Winslow probe inserted directly versus (b) virtual insertion via the user interface.

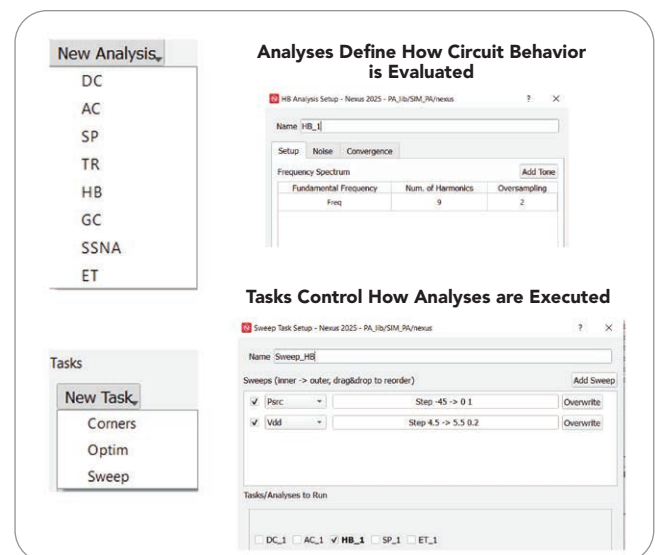
features to real-world engineering design processes. In this light, a simulation engine becomes more like a measurement instrument: portable, automatable and pluggable into many different workflows. This curiosity reveals several motives for a high-stakes project.

- **Modernizing the User Interface and Uncluttering Schematics:** User interface design directly affects user perceptions of ease of use. Powerful tools would start simulations directly from the schematic interface and avoid the creation of spin-off schematics to handle specific simulations. Layout versus schematic (LVS) verification could be more straightforward; the previous RF simulator inserts simulator controllers, probes (see **Figure 1**) and other info on a schematic, requiring stripping that information back out for error-free verification.
- **Providing Methods to Control User Interfaces and Simulation Invocation:** Python scripts calling an API are a popular addition to the previous simulator. Still, more opportunities exist to expand and customize user interfaces and introduce standard Python analysis functions. There is also the possibility for command-stream invocation of simulations, even bypassing the simulator user interface (headless), with calls issued by ADS or other workflow tools.
- **Separating Simulation Analysis from Workflow Tasks and Speeding Up Analyses:** Semantics aside, simulation has two distinct steps: picking an analysis, like S-parameters, envelope or harmonic balance, and setting up a task, which is a sequence of analyses, like sweeps or optimization. In short, an analysis defines

is sophisticated but traps an immense amount of information behind its interface, rendering it inaccessible. Key-sight researchers, inspired by measurement workflows, asked what might be possible by re-architecting a streamlined RF simulator, creating more hooks for programmatic execution control, leveraging interstitial data and matching fea-

behavior evaluation, and tasks control how analyses execute (see **Figure 2**). Once that distinction is made, more efficient parallelization and significant speed-ups become possible.

- **Pre-Processing for Defining Sweeps, Optimization and Visualization:** Fine-grained parameter control of simulations via a user interface is necessary, but is not enough to make simulations more efficient. Users commonly apply post-processing for data display to extract and visualize subsets of data (for instance, zooming in on a range of frequencies), yet the simulation runs across the entire data set. Pre-processing could define reusable expressions evaluated during simulation, in analyses or tasks, with enhanced Python filtering capability for results (see **Figure 3**). Automatically tying simulation pre-processing to optimization and plotting could also save more steps in the workflow.
- **Capturing and Sharing Simulation, Display and Optimization Parameters:** Control of numerous simulation parameters is a plus, but it also introduces a potential traceability issue. Reproducing simulations run yesterday, last week or last month with the exact same parameter settings can be daunting. In the measurement domain, routines embedded in instruments provide reproducible specification compliance testing. A similar approach introduces Performances, which capture settings, expressions, filters, optimizations and specifications for traceable, reusable and sharable simulations.
- **Unlocking 10x Better Optimization Speed With Parallelization:** Although good algorithms exist in the previous RF simulator, optimization remains chal-



▲ **Fig. 2** Separation between analyses and tasks in the simulator user interface.

lenging as frequencies rise, heterogeneous technologies integrate and specifications tighten. A significant hurdle is shifting from individually optimized subsystems to larger problems in the global optimization of an entire design. An example is band filters, with perhaps ten or more working together, and leakage from one band can affect the performance of others. Another could be optimizing on different corners to find values to minimize the impact of process impairments. Joint optimization increases the domain space and the multi-dimensional surface for optimization. It is also possible that, in a heterogeneous scenario, individual subsystems come from different design platforms, making global optimization more difficult. New algorithms and multi-threaded parallel execution could boost execution speed by an order of magnitude.

- Setting Up Flexible Licensing for Immediate Team Access to Features as Introduced:** Licensing has also held back simulation users in some situations. An industry trend recognizes different lifecycles. Teams desire more stable design platforms with updates once, twice or maybe three times a year. RF designers tend to want on-demand simulator updates within weeks or even days of fix and feature releases. A modular simulator that can update without changing the underlying platform solves some issues. Flexible licensing that allows using any simulator feature without relicensing, including the latest feature releases, would be an improvement as design workflows morph.

Of course, these motives coexist with ongoing efforts to add and enhance simulator analysis types and improve their raw execution speed. For instance, work continues on gain compression enhancements and a revamped memory model for effects on high bandwidth signals. The primary mission of the RF simulator remains to deliver accuracy but not sacrifice time. Addressing these motives for programmatic control unlocks another level in workflow productivity while enabling intense analysis of complex RF designs.

Enhancing Designer Productivity Around RF Simulators

Some of these productivity gains are achievable in Keysight's previous RF simulator, with notable differences between Keysight and non-Keysight platforms. The next-generation RF simulator, RF Circuit Simulation Professional, further expands the possibilities for users of various design and layout platforms with its modularity. Design teams now get the same core RF simulator capability regardless of their platform choice.

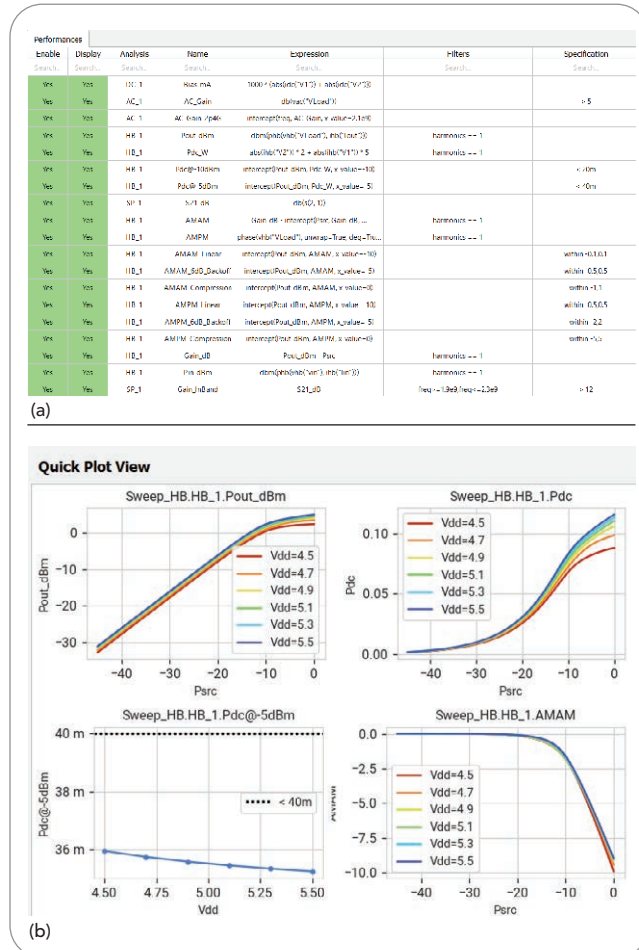


Fig. 3 (a) Expressions evaluated during analyses in simulations, and (b) Python filters on curves in displayed results.

Allowing design teams more access to the RF simulator opens new solutions to complex problems, even solutions that teams may have avoided or worked around before in a “good-enough” workflow with some compromises, assumptions or best guesses. Four examples illustrate what is immediately possible with programmatic control in an API-enabled design platform.

Adapting Access to Simulations With Python

Many users are familiar with Python scripting for basic user interface customization, data visualization and oft-repeated format conversions. Rapid development in the Python ecosystem introduces powerful capabilities that designers can easily stitch into their workflow. Adding post-processing functions and using them as if they were built-in simulator functions is a new capability. For instance, designers can remove dozens of equations in the simulator's Data Display and replace them with a single, reusable, upgradable SciPy function.

More possibilities open when the RF simulator stops being a black box and offers Python control over execu-

tion. Many users stick with Keysight's optimizers, but others develop their own for specific problems. Bolting in an external optimizer has meant months of joint customization work between Keysight application and R&D teams, designers and any third parties involved in developing the algorithm. Now, using a third-party optimizer to access the RF simulator's API via Python scripts and a wrapper becomes seamless. AI-written Python code offers another level of productivity gains.

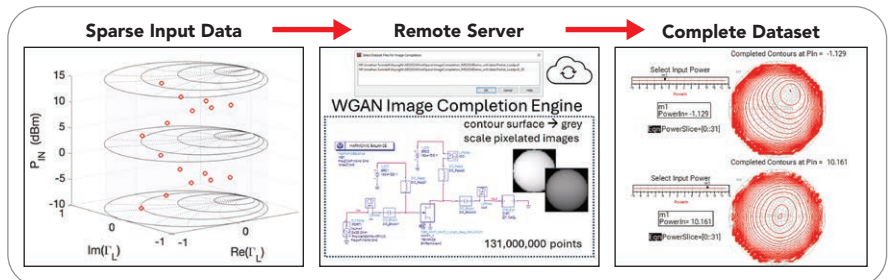
Tying Simulations to Areas of Circuit Layouts for Troubleshooting

Designers celebrate simulation success. However, experience says things don't go smoothly the first time through a design. Bumps in the flow become more common when sub-systems come from various sources, some designed by third parties, such as in many 3DHI projects. Designers have their layout and less-than-good simulations, but where in the circuit or layout are the problems and what fixes can make them go away?

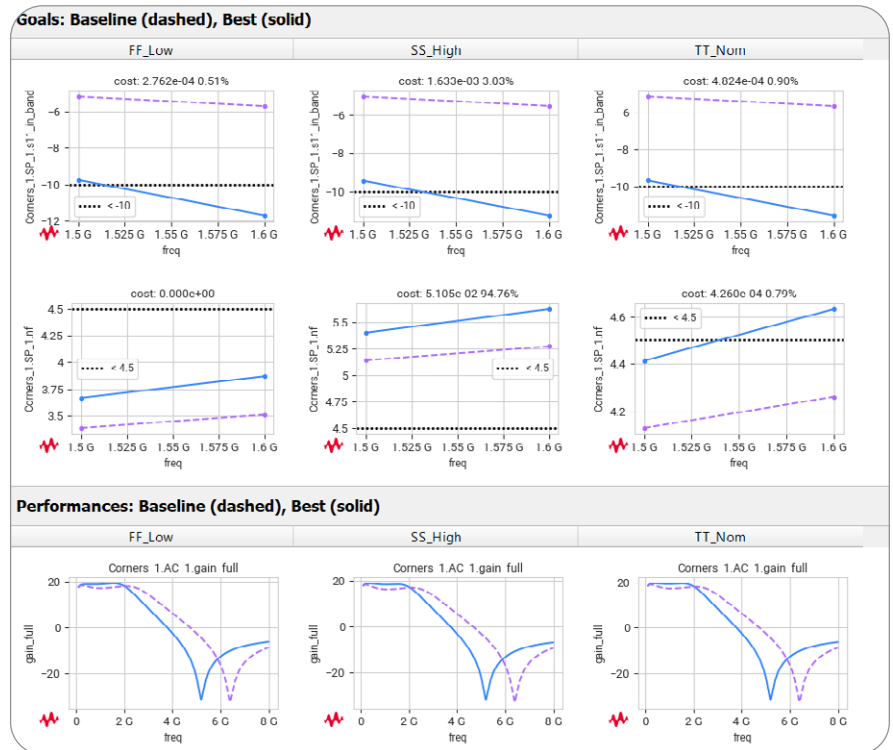
Troubleshooting is perhaps more crucial in a workflow than efficient simulation because it consumes time and drives schedules out of control if not solved quickly. Answering the question becomes straightforward when information previously hidden in the simulator is visible. In ADS, designers can see highlighted layout segments contributing to any out-of-bounds simulation results. Instead of guessing where the problem might be, they can dive directly into a specific spot to fix it.

Gaining Workflow Flexibility Through Greater Access

Seeing inside structures has granular benefits. Modifying a physical layout typically requires a labor-intensive manual sequence of steps, making it challenging to create perturbations essential for many model training workflows. With access, a set of API commands can alternatively represent any physical layout or schematic, enabling modification of all the information in the design programmatically, as if the physical design were a Python function. To illustrate this, Keysight developers devised a utility that extracts an API-



▲ Fig. 4 Load pull contours derived from a pretrained model. Source: Jonathan Swindell, Baylor University.



▲ Fig. 5 Live optimization compares simulation progress to goals, showing algorithm effectiveness.

based Python script from a physical design or schematic — running the script recreates the schematic or layout accurately. From there, a human or AI coder can manipulate the design by changing the function, rather than the physical design itself.

Functional automation provides a pathway to decrease simulation or measurement time by pretraining surrogate models. Researchers at Baylor University recently illustrated the concept using load-pull data.¹ Their approach uses an automated simulation workflow built on a functionalized schematic to generate contours for various conditions on an MWT-1 transistor. Upfront simulation collects 131 million points to create images that train an AI engine using a Wasserstein Generative Adversarial Network (WGAN). The pretrained model derives complete simulation or measurement contours from an extremely sparse data set (see **Figure 4**), using 1500x fewer points. Pretraining surrogate modeling

approaches can potentially capture EM and multiphysics effects, cutting physical design time.

Enabling Parallel Optimization and Visualization

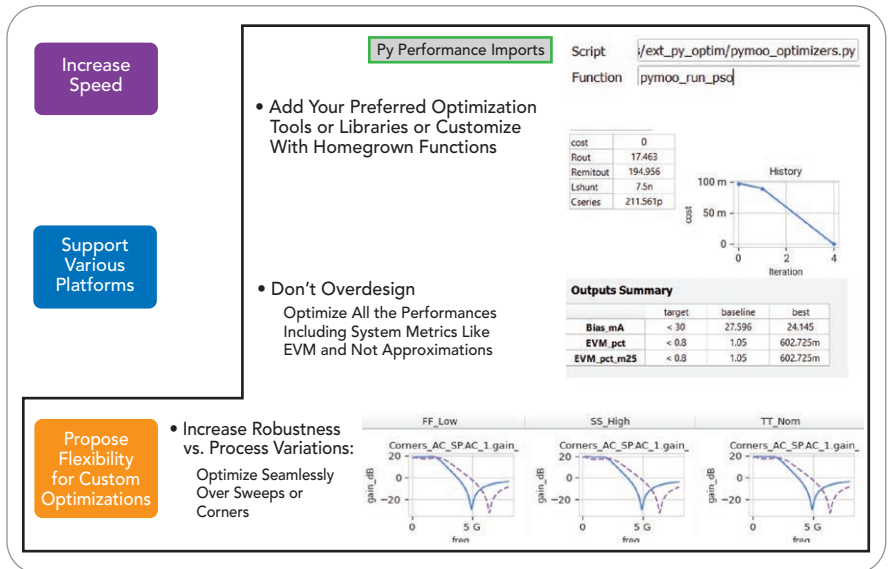
Bringing all optimization capabilities into RF Circuit Simulation Professional with any imported Python extensions means all the algorithms, parallelization and visualization tools are available on any design platform. Teams on different platforms can also share their optimization setups seamlessly.

Live visualization progress (see **Figure 5**) also allows teams to see if and how results converge during simulation runs, determining at a glance if the algorithm is effective or needs changing. Optima feed back into the design on the host platform automatically. These visualizations are helpful in several scenarios. One is employing live retrieval of measurements. Another is where system metrics such as error vector magnitude (EVM) are in play, where it's crucial to avoid overdesign triggered by approximations. A third case is analyzing process variations to enhance manufacturing yield.

Possibilities for Automated RF Design Workflows

The biggest wins for design teams deploying programmatically controlled simulation in RF EDA workflows may be in the near future. The first logical outcome is an optimizer ecosystem, with more RF researchers participating. Innovative third parties or in-house research teams can identify and mechanize new algorithms in familiar Python code (see **Figure 6**). Additionally, a new business model will likely emerge for optimization add-ons that are marketable to customers on many platforms, except for previously required and lengthy platform customization cycles.

The following two possibilities exist in a post-Python space where customization becomes more intuitive. Keysight is working on a no-code solution for sequencing simulations using a visual, flowchart-like solution that captures requirements and workflow in a single



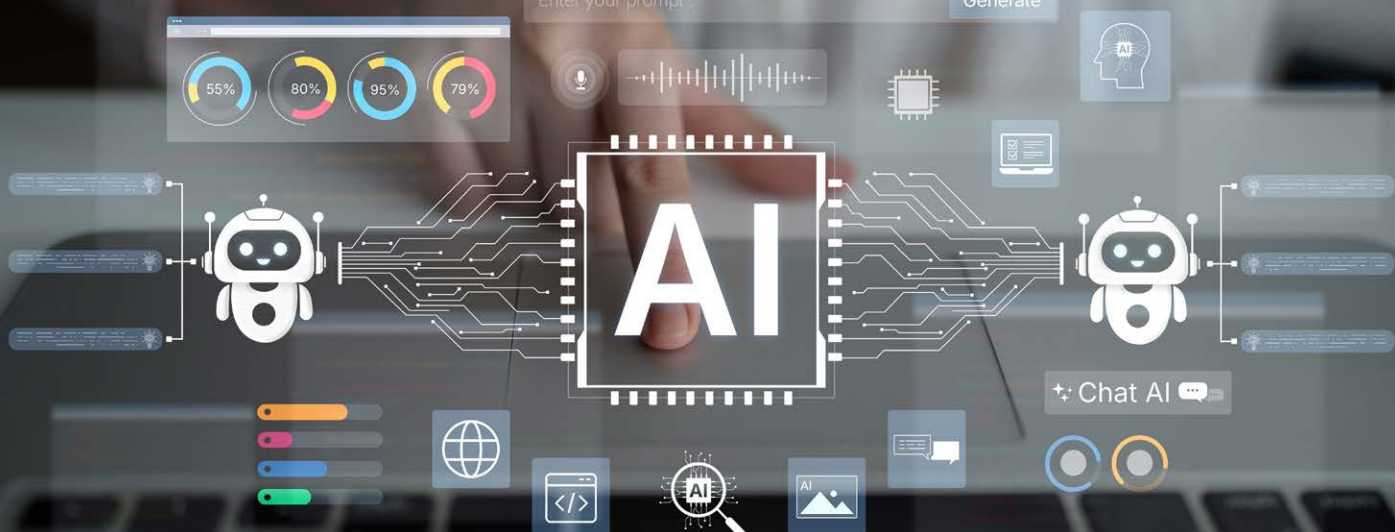
▲ **Fig. 6** Revamped optimization sets the stage for an optimizer ecosystem.

diagram. A defining feature of this approach is conditional execution, which can adapt workflows on the fly based on simulation results. Designers will not need to understand the API syntax to make a sequence work, although using Python calls to the API remains an option. This no-code capability would make it easier for less experienced designers to use the simulator and for design teams to share their simulation knowledge.

Finally, there is AI. Exposing simulator control sets the stage for AI training, as mentioned previously. It also allows natural-language queries from an AI front-end to run simulations in a design workflow or call a specific design exploration ad-hoc. Imagine sitting in a design review or a customer meeting, fielding a question not answered in the presentation, calling the simulator and refining the prompts until the answer appears within minutes. Combining accuracy, speed and control puts RF simulation within reach for more designers, and the outcomes will be stunning as better first-pass design success and more realistic virtual twins help manage burgeoning RF system complexity.■

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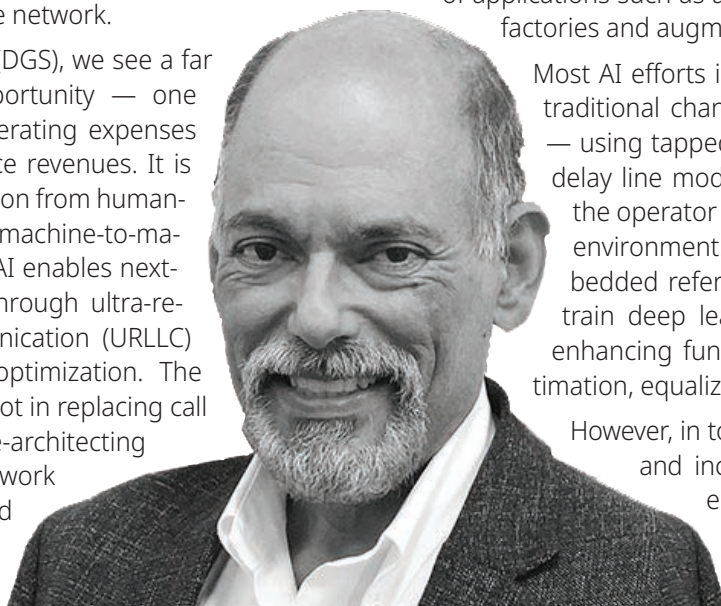


From Chatbots to Channels: Why Machine-to-Machine AI Is the Key to Monetizing 5G and 6G

Armando Montalvo, *Digital Global Systems (DGS), Tysons, Va.*

As 5G networks mature and 6G appears on the horizon, mobile network operators (MNOs) are understandably eager to extract new value from their infrastructure investments. However, in the pursuit of monetization, too many are chasing the wrong kind of artificial intelligence (AI). Most of today's high-profile telco AI initiatives focus on cost-cutting, replacing customer service representatives with chatbots powered by large language models (LLMs). While such tools are certainly flashy, their impact is primarily confined to the billing department, not the network.

At Digital Global Systems (DGS), we see a far more transformative opportunity — one that not only reduces operating expenses but also drives new service revenues. It is time to shift the conversation from human-to-machine interfaces to machine-to-machine intelligence, where AI enables next-generation applications through ultra-reliable low-latency communication (URLLC) and dynamic spectrum optimization. The future of AI in telecom is not in replacing call center agents — it is in re-architecting how the radio access network (RAN) adapts, performs and creates value at the physical layer.



REAL-TIME INTELLIGENCE FOR THE PHYSICAL LAYER

Modern wireless networks are increasingly software-defined and virtualized. This architectural flexibility opens the door to embedding AI directly into the signal processing chain, especially within the L1 (physical layer) and L2 layers of the RAN stack. These are not chatbot domains. They are mission-critical environments where microsecond decisions significantly impact the viability of applications such as autonomous vehicles, smart factories and augmented reality.

Most AI efforts in this space have relied on traditional channel modeling assumptions — using tapped delay line (TDL) or cluster delay line models based on the idea that the operator controls all RF signals in the environment. Under these models, embedded reference signals are utilized to train deep learning algorithms, thereby enhancing functions such as channel estimation, equalization and signal decoding.

However, in today's congested, contested and increasingly shared spectrum environments, those assumptions break down. RF environments now include

a diverse mix of unmanaged signals — from Wi-Fi and CBRS to military comms and private 5G — that introduce significant uncertainty and noise. Deep learning models trained in sanitized environments often struggle to generalize, resulting in degraded performance when it matters most.

The Foundation of Revenue-Generating AI

DGS's patented RF awareness-based AI approach addresses this. Rather than assuming a clean spectrum, this technology actively senses, identifies and learns from the complete set of RF signals — both known and unknown — within a given environment. Using external or embedded sensors, the system extracts actionable intelligence from real-time spectrum conditions and feeds it into a hybrid machine learning framework that includes support vector machines, convolutional neural networks and domain-specific knowledge models.

The result is not just smarter RAN operations, it's monetizable performance. DGS's methodology enables MNOs to meet the stringent requirements of URLLC applications and dynamic spectrum sharing, unlocking new service opportunities across verticals. We are talking about deterministic latency in manufacturing automation, guaranteed throughput for drone traffic management and seamless handovers for immersive AR/VR experiences in stadiums and smart cities.

Monetization Through Performance Guarantees

For example, LLMs might help a telco save a few dollars per customer on support calls. RF-aware machine-to-machineAI, by contrast, enables entirely new service classes that command premium pricing. Consider these examples:

- **Smart Factories** require wireless networks that guarantee sub-10 ms latency with 99.999 percent reliability. RF-aware AI can continuously monitor and mitigate interference, ensuring that these SLAs are met, even in shared spectrum bands like the 3.5 GHz CBRS. That translates into revenue from industrial contracts, not just cost avoidance.
- **Teleoperated Robotics** — from logistics to remote surgery — demands low jitter and high availability. Traditional AI models trained in lab environments cannot respond quickly enough to the unpredictable spectrum dynamics of real-world deployments. Machine-to-machineAI adapts in real time, optimizing transmission paths and prioritizing critical data flows.
- **Public Safety and Defense Communications** ben-

efit from DGS's patented ability to detect and classify non-cooperative signals, including interference and potential threats, in near real time. That kind of capability is not just valuable, it is billable, especially in multi-agency or defense-contracted scenarios.

In these use cases, the value is not in reducing headcount but in creating performance guarantees that were previously impossible to meet. Those guarantees are the foundation of differentiated services and premium pricing.

From Static Models to Live Learning Machines

Conventional channel modeling techniques fail in contested environments because they treat unknown signals as unstructured noise. DGS's RF-aware system rejects this oversimplification. Instead, we utilize inferential signal processing and hybrid AI models to identify patterns in co-channel activity, infer potential interference sources and dynamically reallocate spectrum usage in real time.

This approach draws on a decade of patented innovation in:

- Signal detection and channelization by inference processing
- Drone signal recognition via pattern classification
- Blind signal classification using constant spectral component analysis
- Prediction of interference patterns to inform RAN configuration
- Dynamic optimization of RF environment sampling.

Critically, this intelligence can be embedded into the software functions of the radio unit, distributed unit (DU) or centralized unit (CU), or integrated into the RAN intelligent controller (RIC) or multi-access edge computing layers. The result is a self-optimizing network, not just in name, but in function. It is a network that does not rely on a central cloud to make decisions, but one that responds in the moment, at the edge, where performance makes or breaks the service.

Real Machine Learning for Real Machines

One of the most significant differences between our approach and the prevailing AI trends in telecom is this: We build systems for machines talking to machines, not machines impersonating humans.

LLMs are good at parsing language but lack the timing, determinism and explainability needed to operate in real-time, mission-critical environments. DGS's RF-aware

machine learning models are designed with physical layer constraints in mind. They prioritize computational efficiency, operate under low size, weight and power conditions and adapt to RF changes in milliseconds, not seconds.

Furthermore, our AI doesn't just predict — it acts. By feeding learned environmental data back into the scheduling, resource allocation and modulation decisions of the RAN, we create a closed-loop optimization cycle. This is what true “machine intelligence” looks like: sensing, interpreting and executing within a dynamic physical system.

4G to 6G: Deployable Now, Scalable Tomorrow

DGS's RF awareness-based AI can be deployed today in existing 4G LTE and 5G O-RAN architectures using external sensors or software updates to existing RAN components. As network operators transition to vRAN and disaggregated architectures, our models become valuable, enabling performance enhancements across DU, CU and RIC functions without requiring new hardware.

At the same time, DGS's work is laying the groundwork for 6G, where native support for shared spectrum, spectrum sensing and dynamic allocation will be critical. By developing and proving out these capabilities now, we ensure that MNOs can lead, not lag, when the 6G wave arrives.

Conclusion: The Real AI Opportunity is in the Air

The telecom industry is at an inflection point. It can continue to chase marginal gains from LLMs that reduce customer service costs, or it can embrace a more fundamental shift — one that enables new business models, new service guarantees and new revenue streams powered by M2M AI.

DGS RF awareness-based AI transforms the network from a static delivery mechanism into an intelligent, adaptive service platform. It is time to move beyond the hype and focus on where AI truly creates value: in the airwaves, optimizing the physical layer and enabling the next generation of reliable, low-latency wireless services. ■

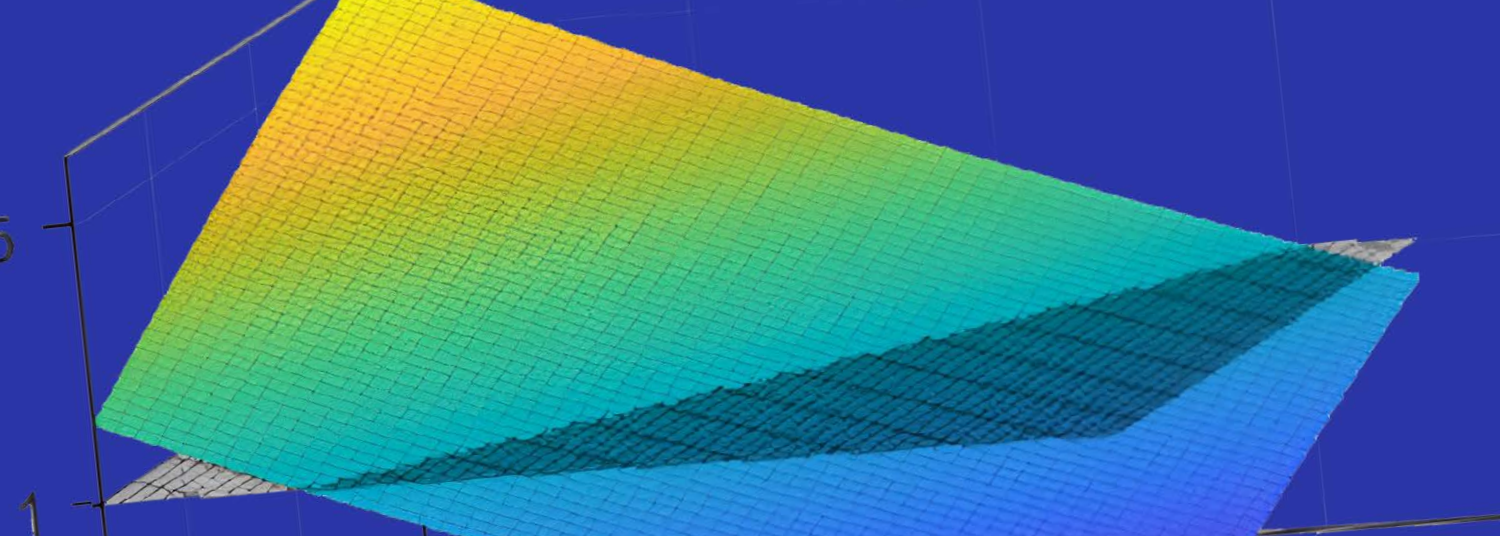


Transform your RF Designs with Agentic AI

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Using AI for Antenna Design, Analysis and Optimization

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AI is significantly impacting almost all engineering fields, but its potential is especially promising for antenna analysis and optimization to minimize the need for repeated full-wave electromagnetic simulations. Although AI models have proven effective in characterizing and optimizing various antennas, the field lacks a comprehensive framework for both standard and custom antenna solutions. To address this gap, AI techniques are applied to create scalable and generalizable models for antenna design and analysis, enabling adoption by engineers without expertise in electromagnetic theory or AI.

To support the design and optimization of a comprehensive AI-driven workflow with minimal specialized knowledge in machine learning (ML) and electromagnetics, engineers can rely on pre-trained ML, AutoML and optimization algorithms. The AI-driven approach, coupled with the pre-trained algorithms, accelerates the antenna design process. It also democratizes access to advanced design tools, allowing for faster and more flexible customization and performance enhancement.

Rapid Antenna Analysis With Pre-Trained Models

For engineers, it begins with developing pre-trained AI models for antenna analysis while addressing the lack of commercially available design software with built-in AI capabilities. The approach consists of the following steps:

1. **Catalog Standard Antennas:** Begin with a set of standard antennas with parameterized geometries suitable for full-wave electromagnetic simulation.
2. **Prototype Design Development:** For each antenna, derive an initial design prototype using a combination of design variables (e.g., geometric parameters) to ensure resonance at a specified frequency.
3. **Tunable Design Variables:** Identify a subset of design variables that can be adjusted within specified tolerances (e.g., ± 15 percent) to explore variations around the initial design point. Simulate how these adjustments affect key performance metrics.
4. **Intelligent Sampling:** Use intelligent sampling to create a dataset of simulations that represent the antenna's design space.
5. **ML Model Training:** Train ML models to predict performance across wide parameter ranges with high accuracy and minimal computation time.
6. **Frequency Scaling Generalization:** Extend each prototype's ML model to other initial design frequencies using frequency scaling principles.

This strategy enables workflows for early-stage design exploration and interactive visual examination that were previously impractical. For instance, if an engineer needs a planar inverted-F antenna (PIFA) to resonate at 1 GHz, they can quickly generate a design blueprint. Using a pre-trained ML model to predict resonant frequency, engineers can efficiently explore and optimize dimen-

sions such as length, width, height and short pin width to maintain the 1 GHz resonance. Once an optimal design is identified, full-wave electromagnetic simulations can verify AI predictions and guide further refinement. **Table 1** shows a comparison of an ML model and full-wave simulation method of moments (MoM) results for a PIFA with dimensions adjusted by -9 percent in length, +12 percent in width, +5 percent in height and -4 percent in short pin width from the 1 GHz prototype. Full-wave simulations use a frequency sweep from 700 MHz to 1.3 GHz with 1 MHz resolution for resonant frequency and bandwidth analysis. As shown in Table 1, ML models provide results much faster than electromagnetic simulations. Parameter sweeps of a 1 GHz PIFA using the pre-trained regression ML model to predict resonant frequencies based on varying geometric properties are shown in **Figure 1**. These results illustrate that resonant frequencies for 2500 configurations can be predicted in seconds, facilitating rapid iteration during early-stage design without costly simulations.

AI-accelerated parameter sweeps also help narrow the design space. In **Figure 2**, a pre-trained ML model classifies 2500 PIFA configurations based on 50 Ω matching. The impedance matching scenarios were determined for a PIFA antenna designed at 300 MHz. Each configuration varies in length and height around a PIFA designed for 300 MHz resonance. The results were predicted in under 10 seconds when using the pre-trained classification ML model.

Figure 3 shows the full-wave electromagnetic verification of bandwidth and impedance matching conditions for the points shown in Figure 2. It verifies the classification of three designs against full-wave simulation, focusing on the "Plot 1," "Plot 2" and "Plot 3" regions referenced in Figure 2. Although classification alone does not finalize the design, it indicates that a length-to-height ratio below 3.5 is necessary for match-

Table 1				
Comparison of machine learning model and full-wave simulation results for a PIFA				
	<i>Initial Design</i>		<i>Modified Design</i>	
	fR (GHz)	BW (MHz)	fR (GHz)	BW (MHz)
ML	1.0038	61.705	1.0079	80.048
MoM	1.0040	61.756	1.0072	79.085
Percent Error	-0.0270%	-0.0820%	0.0712%	1.2180%
Computation time (seconds)	ML: 0.1865 MoM: 46.4830		ML: 0.1216 MoM: 46.6629	

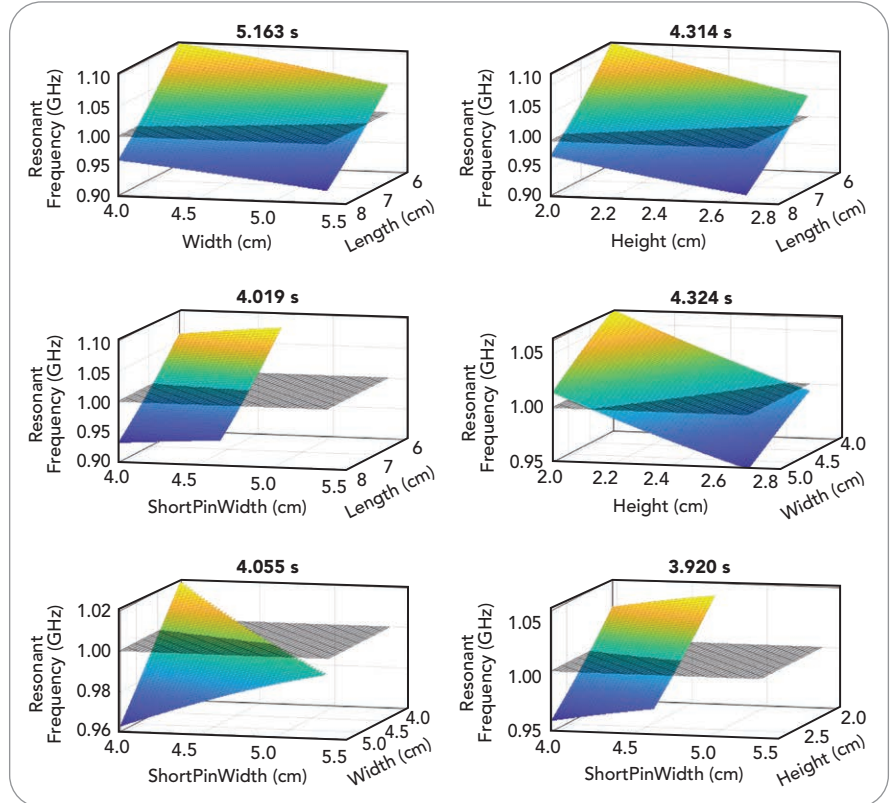


Fig. 1 1 GHz PIFA parameter sweeps using the pre-trained regression machine learning model.

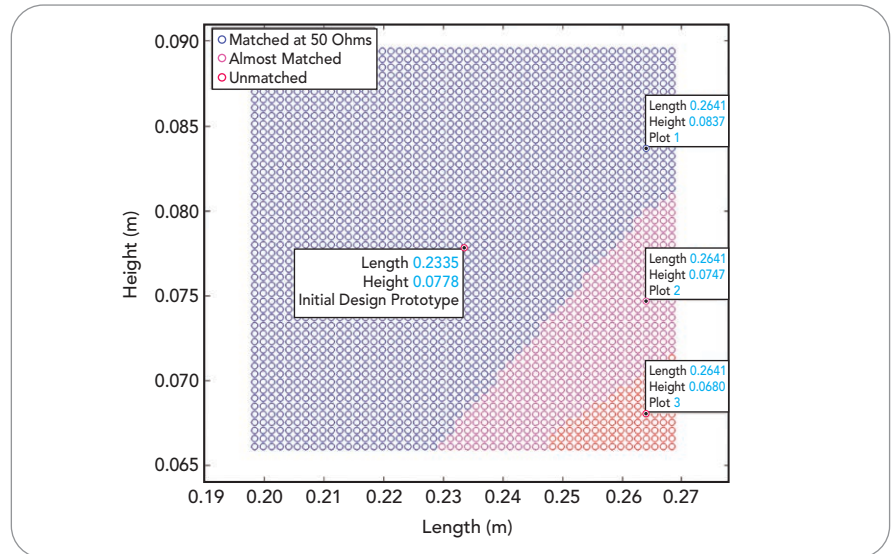
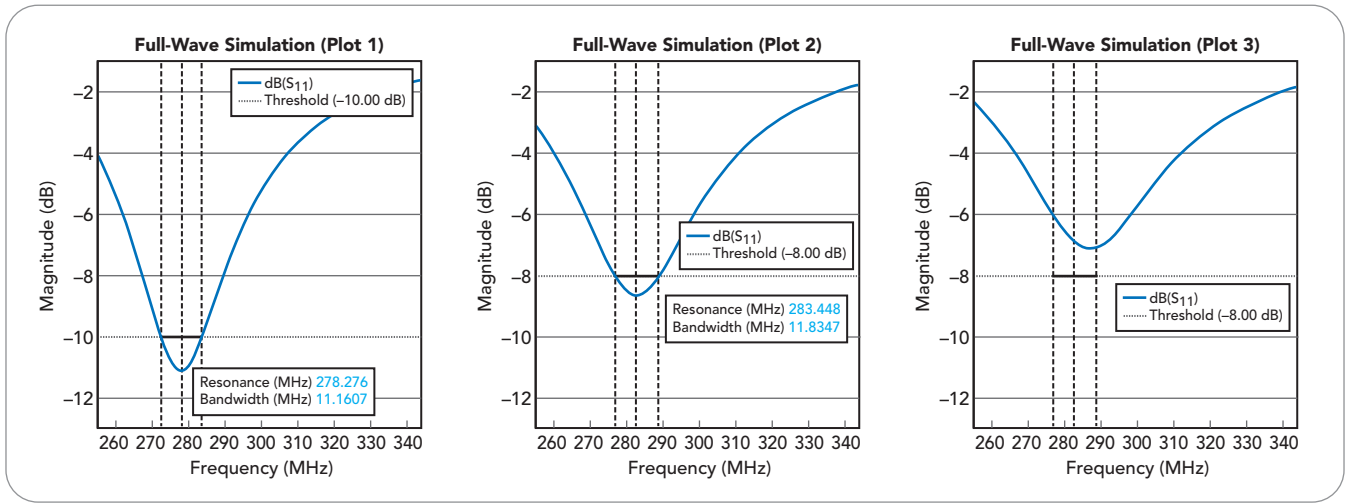


Fig. 2 Impedance matching scenarios for a PIFA antenna designed at 300 MHz.



▲ **Fig. 3** Full-wave electromagnetic verification of bandwidth and impedance matching conditions.

ing. This refines the optimization space and improves efficiency for subsequent methods.

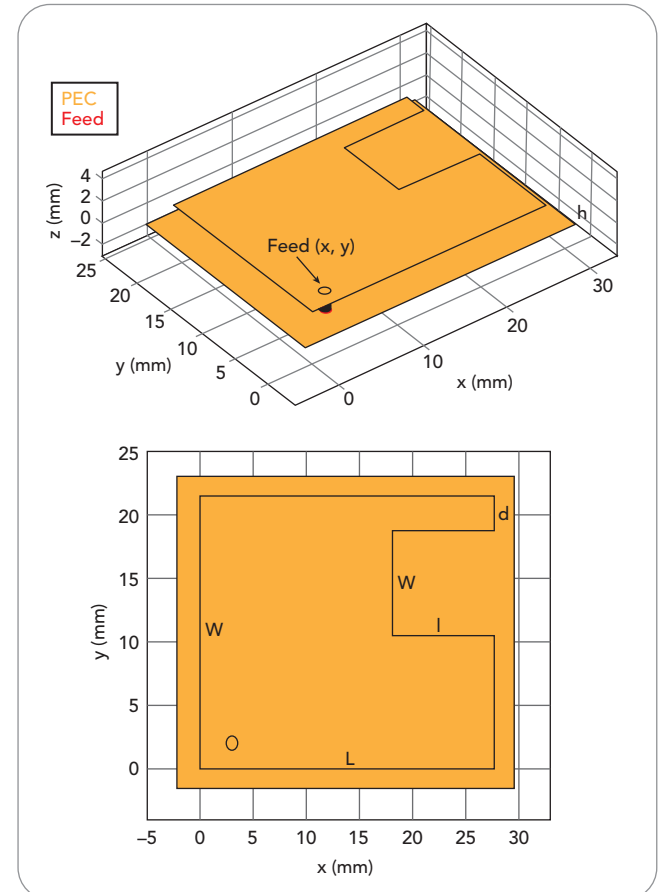
The scalability of this approach is demonstrated by the “AIAntenna” object in Antenna Toolbox, which provides access to pre-trained ML models for various catalog antennas, including PIFA and other patch antennas. This capability allows for rapid AI-accelerated parameter sweeps of standard antennas. This, in turn, enables quick analysis and categorization of design spaces, identification of optimal dimensions for specific performance goals and insights into the design space’s response surface.¹

AUTOML Training Custom Antennas AI Models

AI models can extend their utility beyond standard antenna types (e.g., dipoles, patches and horns) to custom antenna structures. However, developing these models typically requires expertise across disciplines. Knowledge of antenna design and electromagnetic analysis is crucial for problem formulation, setting up measurement systems, identifying key parameters and interpreting results. Simultaneously, a background in statistics, design of experiments (DOE) theory and ML is necessary for implementing the training framework, sampling data, designing AI models and validating their performance with reliable metrics. This cross-disciplinary requirement can hinder the application of AI techniques for antenna design and analysis. Therefore, automation frameworks and low-code tools are essential. The general ML workflow involves:

1. Modeling and parameterizing the antenna for simulation
2. Defining design variables as predictors and metrics as responses
3. Conducting a DOE for sampling the design variables

4. Performing electromagnetic simulations to generate response data
5. Preprocessing and exploring data in preparation for training
6. Iteratively training and tuning ML models for optimal performance
7. Evaluating the ML model against simulation results for accuracy on new data.



▲ **Fig. 4** C-shaped microstrip patch antenna.

Table 2

Model performance on training and test datasets

Dataset	Percent Absolute Error (%)				
	Minimum	Maximum	Mean	Median	Std. Dev.
Training	0.00096	0.5808	0.1457	0.1170	0.1264
Test	0.0223	0.9037	0.3134	0.2361	0.2538

This workflow is demonstrated by training an ML model to characterize a probe-fed C-shaped microstrip patch antenna² and predict its resonant frequency based on its dimensions. Stochastic DOE methodologies and low-code AutoML for model selection, training and tuning are used for creating an antenna model. This is different from what was reported in other works. **Figure 4** shows the parameterization of the C-shaped microstrip patch antenna with the nominal values for the design variables being: $L = 24$ mm, $W = 20$ mm, $l = 10$ mm, $w = 7.2$ mm, $d = 2.4$ mm and $h = 1.6$ mm.

The antenna is modeled with an air substrate, but the approach can be applied to dielectric structures. Design variables are varied within a ± 25 percent range around nominal values, resulting in 200 data points. Each configuration is simulated from 1 to 4 GHz using a full-wave MoM solver to find the resonant frequency. The data is split 80 percent into training and 20 percent into test sets, covering steps 1 to 5.

AutoML automates step 6 of the ML workflow using the “fitrauto” function from the Statistics and Machine Learning Toolbox. This function performs regression model selection and hyperparameter tuning. It employs Bayesian optimization to evaluate ML models like Gaussian process regressors (GPRs), support vector machines and artificial neural networks, selecting a model with minimized generalization error.

This results in a low-code solution. Step 6 is executed with a single line of code, producing a tuned GPR model with less than 1 percent prediction error on both training and test data. The model’s accuracy is detailed in **Table 2** and visualized in **Figure 5**, providing both quantitative and qualitative assessments as per step 7 of the ML workflow.

Evolving the Antenna Shape With Surrogate Optimization

Pre-trained AI models for standard and custom antenna structures provide valuable insights. However, surrogate optimization offers an alternative by learning subsets of the design space during optimization. As the surrogate model is developed and updated during the optimiza-

tion, this technique can be applied to evolving antenna shapes where pre-trained models provide insufficient insights.

Traditional antenna optimization relies on full-wave electromagnetic analysis, which is resource-intensive in terms of time and memory. Strategies to miti-

gate solver complexity include higher-order basis functions, iterative methods like the fast multipole method, GPU acceleration and hybrid full-wave/asymptotic methods. Despite these, a single parameter set requires significant computational resources and exploring multiple design variables adds a combinatorial challenge. The search space often contains multiple extrema, typically framed as minimization problems. This necessitates either defining bounds to ensure a unique local minimum or employing global optimization techniques to explore the true solution space. Surrogate-based optimizers³ fall into the global optimization category but differ by reducing expensive electromagnetic solver calls. They build a surrogate model that initially learns the search space characteristics using the electromagnetic solver and then drives the optimization. To maintain accuracy, the surrogate’s outputs are occasionally verified against the electromagnetic solver. Any deviations in the outputs prompt updates with new true solution points, continuing the optimization while minimizing electromagnetic solver calls.

The use of surrogate optimization is demonstrated starting with a standard triangular microstrip patch antenna and evolving its shape to achieve a target performance objective. This surrogate-based approach is applied to enhance the bandwidth of a

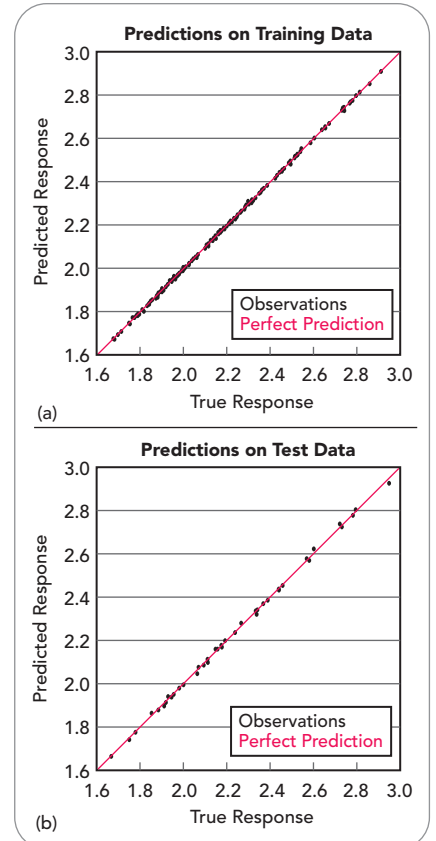
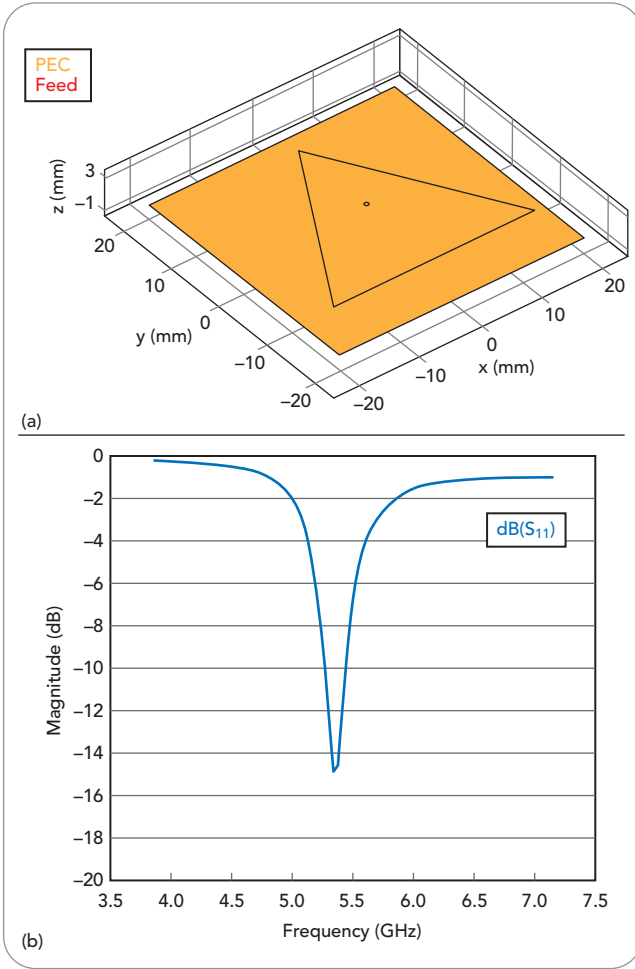


Fig. 5 Model performance on training (a) and test (b) datasets.



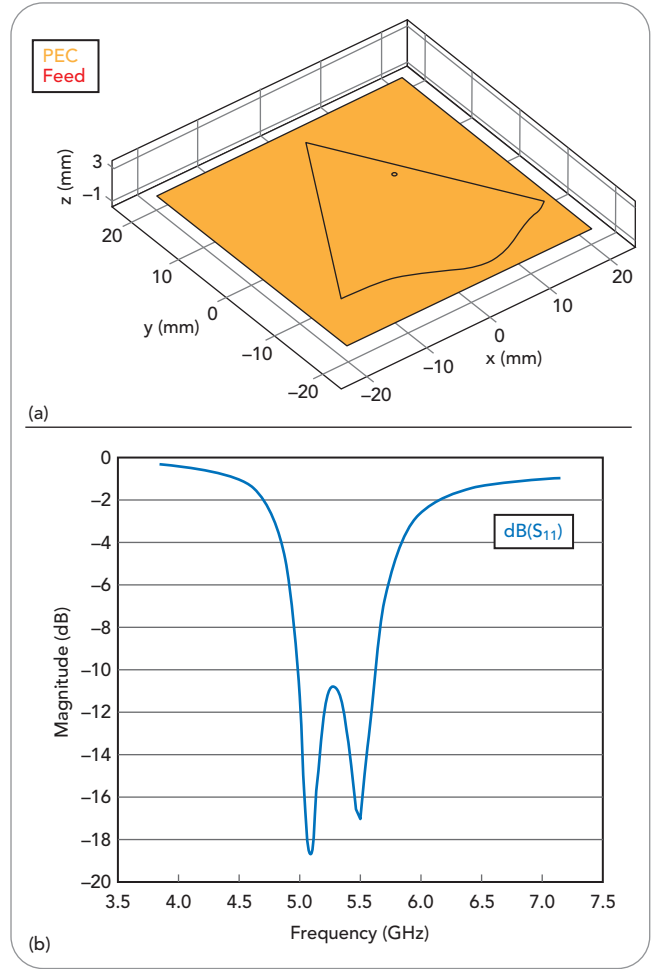
▲ **Fig. 6** Probe-fed equilateral patch antenna (a) and simulated S_{11} (b).

single-feed, probe-fed triangular patch antenna on an air substrate by evolving the side shapes.⁴ Initially, a standard probe-fed equilateral patch antenna is designed for the lower half of the 5 GHz band, with a -10 dB bandwidth of about 3 percent, as shown in **Figure 6**.

The surrogate optimizer aims to improve bandwidth to cover 5.0 to 5.6 GHz by adjusting the shapes of the three sides while leaving the corners and ground plane unchanged. Three Gaussian functions, defined in **Equation 1**, represent each side's shape, introducing three optimization variables per side: mean (μ), standard deviation (σ) and scaling term (w).

$$f(p) = \frac{w}{\sigma\sqrt{2\pi}} e^{-0.5\left(\frac{p-\mu}{\sigma}\right)^2} \quad (1)$$

These three variables adjust the curve's amplitude relative to the original edge, with p as the position along the side. The feed coordinates (x, y) add two more degrees of freedom, totaling 11 independent variables for the shape optimization.



▲ **Fig. 7** Evolved probe-fed patch antenna shape (a) and simulated S_{11} (b).

The surrogate optimization uses the structure, objective function, constraints and bounds to evolve the patch shape. The final shape and its simulated reflection coefficient are depicted in **Figure 7**. Comparing Figures 6 and 7, the shape evolution increases bandwidth from 3 to 12 percent through double resonance. Although not shown, the far-field pattern remains stable over this band. This approach uses fewer degrees of freedom but achieves comparable bandwidth enhancement.

Ai-Driven Engineering for Scalable, Efficient and Agile Solutions

These AI-based design, analysis and optimization capabilities lay the groundwork for a transformative approach to antenna engineering. By leveraging AI, engineers can create a scalable, extensible and automatable suite of tools that significantly enhance the efficiency and effectiveness of antenna design processes. These tools enable rapid “what-if” analyses, enabling engineers to quickly assess the impact of design changes on performance metrics without the need for exhaustive simulations. This capability is particularly valu-

able in the early stages of design, where flexibility and speed are crucial.

Moreover, the efficient exploration of the design space facilitated by AI models reduces the computational burden traditionally associated with antenna optimization. By narrowing down the most promising design parameters early in the process, engineers can focus their resources on refining these designs, leading to faster development cycles and reduced time-to-market.

The integration of AI also accelerates design optimization, allowing for the fine-tuning of both standard and custom antenna geometries. This adaptability is essential in today's rapidly evolving technological landscape, where custom solutions are often required to meet specific performance criteria or to integrate seamlessly with other components in complex systems.

Beyond the immediate benefits of design and optimization, the AI-driven framework supports continuous improvement and learning. As more data is gathered and models are refined, the system becomes increasingly accurate and predictive, further enhancing its value to engineers.

Overall, this AI-driven framework not only addresses current challenges in antenna engineering but also positions the field to tackle future demands with greater

agility and precision. By embracing AI, engineers unlock new possibilities for innovation and efficiency, setting the stage for advancements that could redefine the boundaries of what is achievable in antenna design and performance. To help engineers get started, several examples are identified in the references. All EM simulations use MoM solvers in MATLAB and Antenna Toolbox. ■

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RF Modeling and Simulation For 6G System Design Using Digital Twins

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Virtual System Design in 6G

6G represents a transformative leap in wireless, focused on sustainability, intelligence and global connectivity. Building on 5G expertise, 6G researchers are advancing enablers such as sub-THz communications, AI-native architectures and RF digital twins to improve performance and energy efficiency, targeting applications like immersive extended reality (XR) and autonomous systems. Realizing this vision requires overcoming challenges in sub-THz propagation, hardware complexity and the co-design of communication, sensing and AI, alongside the harmonization of regulations and the pursuit of sustainability imperatives. Digital twin technologies address these hurdles by enabling high-fidelity modeling, early validation and energy-aware design, ensuring that 6G evolves into a scalable, flexible and environmentally responsible connectivity platform.

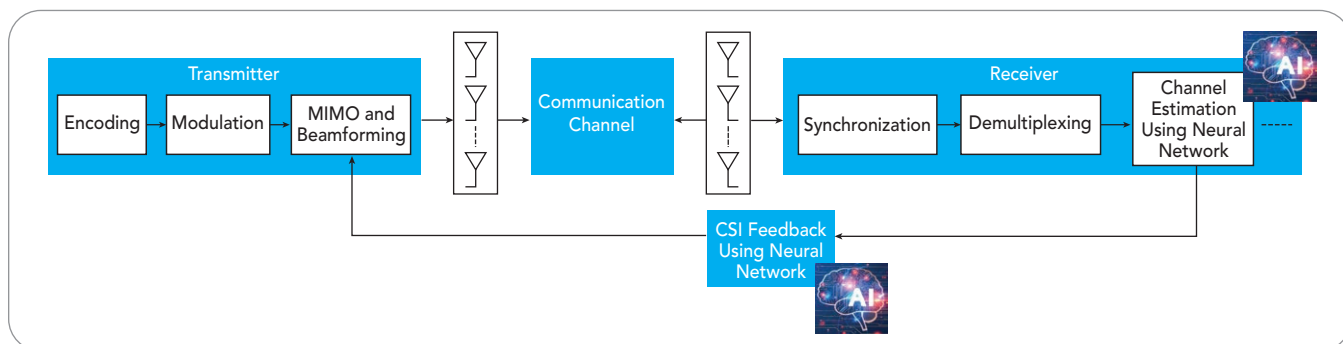
Modeling And Simulation Of 6G

As 6G advances from concept to realization, realistic modeling and simulation are vital for designing, validating

and optimizing networks that span sub-THz frequencies, AI-native architectures, integrated sensing and non-terrestrial platforms. Traditional methods fall short of capturing nonlinearities, channel dynamics, interference and hardware impairments, making high-fidelity, cross-domain digital twins particularly useful. SystemVue, a system-level RF simulation software, provides such an environment, delivering near-circuit-level co-simulation of RF, baseband and antenna domains with hardware-in-the-loop integration to assess trade-offs, detect bottlenecks and validate reliability under real-world conditions. With advanced engines for time, frequency and phased-array analysis, integration with measurement tools and built-in libraries for algorithm testing, SystemVue bridges design and testing workflows, accelerating development, reducing risk and ensuring robust, compliant 6G system deployment.

Prominent 6G Technologies

Among the most transformative enablers of 6G are AI-native radio access networks (AI-RAN), integrated sensing



▲ Fig. 1 Example of a signal processing chain.

ing and communication (ISAC), reconfigurable intelligent surfaces (RIS) and non-terrestrial networks (NTNs). AI-RAN introduces intelligence and self-optimization into the RAN, where machine learning (ML) manages spectrum, power, beamforming and mobility to enhance efficiency and quality of service in ultra-dense, heterogeneous environments. ISAC enables communication and sensing to share the same waveform and infrastructure, supporting applications such as autonomous vehicles and smart factories. RIS utilizes programmable surfaces to shape wave propagation, enhancing coverage, energy efficiency and connectivity without requiring active transmission. Complementing these terrestrial advances, NTNs, including LEO satellites, high-altitude platforms and UAVs, extend 6G services to remote and underserved regions globally. Together, these technologies form the backbone of a highly adaptive and universally accessible 6G ecosystem.

AI and ML

AI and ML will be integral to 6G RAN, enabling proactive, self-optimizing networks that manage spectrum, beamforming and modulation in real-time across ultra-dense, high frequency environments. By leveraging techniques such as reinforcement learning and federated learning, AI extends intelligence for latency-sensitive use cases, including autonomous driving and industrial automation, while also enhancing security, anomaly detection and energy efficiency. SystemVue supports this evolution by generating high-fidelity training data from realistic RF and channel models, to train AI models using TensorFlow or PyTorch frameworks and reimporting the trained models for evaluation and benchmarking. This workflow enables techniques such as adaptive beamforming, CSI feedback compression and link adaptation, accelerating the design, validation and deployment of AI-native 6G RANs.

Figure 1 depicts an ML-enhanced wireless communication system focused on channel state information feedback and channel estimation. It shows a typical transmitter-receiver chain, where the source block includes encoding, modulation and beamforming. The signal propagates through a multipath channel, reaching the

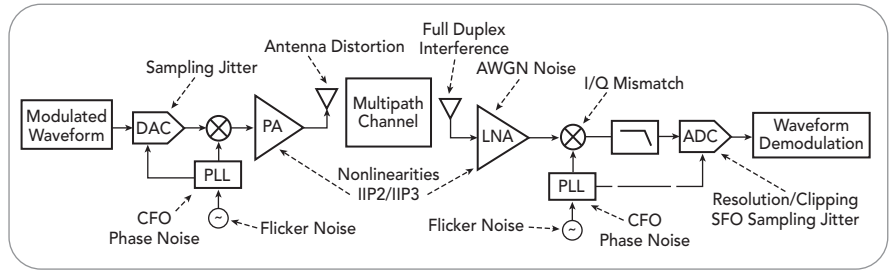


Fig. 2 Modeling RF impairments in an ISAC system.

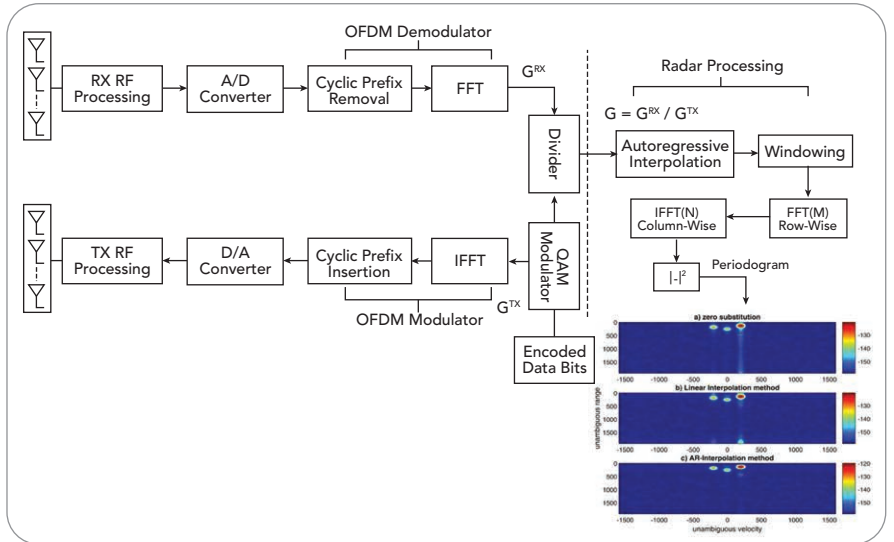


Fig. 3 Example of sensing functionality by reusing 5G NR waveforms.

receiver, which performs synchronization, demultiplexing and channel estimation. This approach integrates AI/ML-based functions at both the receiver and feedback paths; one neural network is responsible for channel estimation at the receiver, while another neural network optimizes CSI feedback to the transmitter. This AI-assisted feedback loop enables adaptive beamforming at the source, improving link reliability and spectral efficiency by leveraging learned channel characteristics.

ISAC

ISAC is a key 6G enabler that fuses data transmission with environmental awareness, supporting applications such as autonomous driving, robotics, smart infrastructure and XR. By sharing waveforms and hardware for both communication and sensing, ISAC transforms networks into perceptive systems while introducing trade-offs between sensing accuracy and low-latency data delivery. SystemVue addresses these challenges by unifying RF, baseband and antenna modeling with impairment simulation and hardware-in-the-loop workflows, enabling realistic evaluation of algorithms, beamforming and waveform reuse. By bridging digital twin simulation with over-the-air (OTA) testing, researchers and architects can accelerate ISAC prototyping

and ensure the development of scalable and commercially viable 6G deployments.

Figure 2 shows a generic transceiver signal chain for ISAC systems, annotated with critical RF impairments across both the analog and digital domains. These include phase noise, carrier frequency offset (CFO), sampling jitter, flicker noise, antenna distortion, nonlinearities (IIP2/IIP3) and I/Q mismatch, all of which degrade fidelity and sensing accuracy. Channel effects, such as multipath and full-duplex interference in monostatic scenarios, are also highlighted. These emphasize the need for realistic modeling to evaluate simultaneous communication and sensing performance.

Figure 3 illustrates an example of an ISAC system that utilizes 5G New Radio (NR) waveforms for both communication and sensing functions. In this example, the 5G NR OFDM waveform is post-processed to extract relative range, Doppler and direction information of the hypothetical targets in the environment.

RIS

RIS is a 6G innovation that enables programmable wireless environments by using passive or semi-passive elements to dynamically reflect, focus or scatter signals, improving coverage, throughput and energy efficiency while overcoming non-line-of-sight conditions and blockages. Unlike traditional fixed infrastructure, RIS introduces a software-controlled paradigm but requires accurate modeling to account for factors such as beam-forming gain, phase control, element layout and mobility at high frequencies. A digital twin provides a robust environment for RIS design, supporting custom array topologies, phase quantization errors and element-level impairments, while enabling co-simulation with RF and baseband parameters. By evaluating beam steering, side lobes and system-level trade-offs, engineers can optimize RIS placement and control strategies, ensuring the practical and scalable deployment of RIS in 6G networks.

Figure 4 shows the characterization of the RIS beamforming for various reflection angles θ_d at 5.8 GHz, showing a comparison between computed and measured radiation patterns using one-bit phase shifters. It presents measured and simulated radiation patterns of an RIS at various reflection angles $0 \leq \theta_d \leq 60$ degrees, along with the corresponding one-bit quantized phase distributions. The radiation patterns compare simulation (black) with physical measurements (red), demonstrating directional beam steering through discrete phase control. The quantized phase distributions show the one-bit phase quantization pattern (values of 0 and 180

degrees), applied across the RIS elements to steer the beam. These visualizations highlight the importance of accurately modeling antenna element phase, element spacing and angular response to understand the spatial behavior and control requirements of RIS.

Integrating Terrestrial Networks and NTN

The integration of terrestrial networks and NTN is a key 6G advancement, combining satellites (LEO, MEO, GEO), HAPS, drones and airborne base stations with cellular infrastructure to provide global connectivity. This hybrid architecture extends reliable service to rural, open sea and disaster-hit regions where terrestrial networks are impractical, enabling applications such as global IoT, avi-

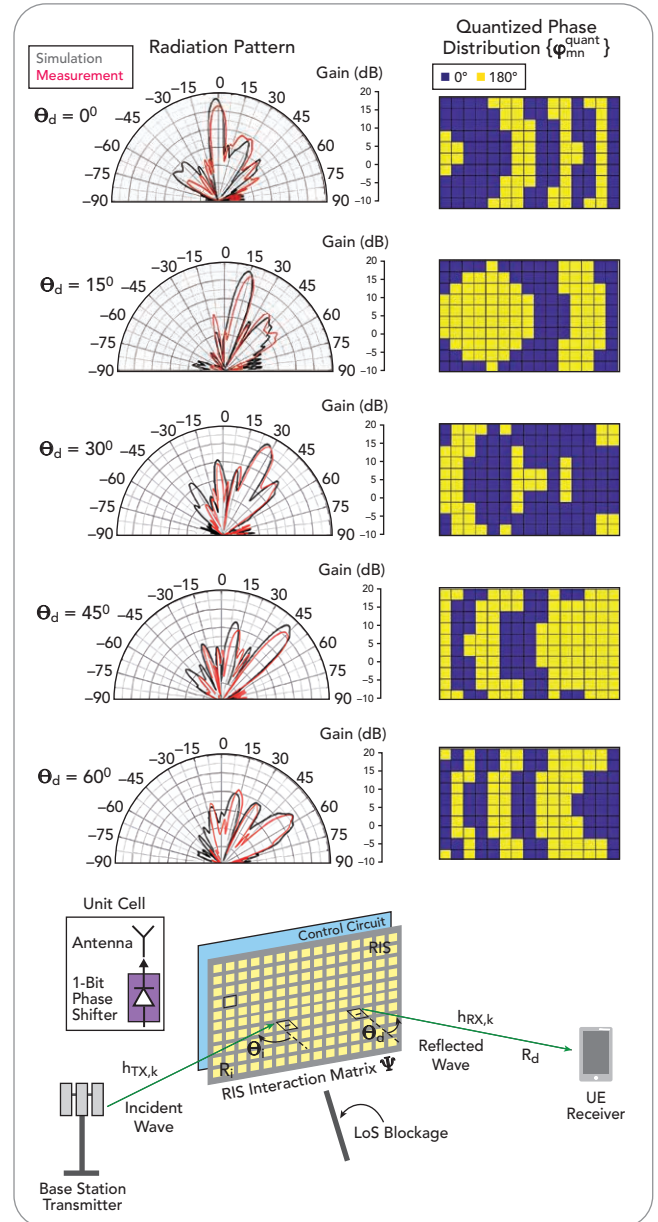


Fig. 4 Characterization of RIS beamforming for various reflection angles.

ation and maritime communication and resilient emergency connectivity. By unifying the terrestrial and satellite domains, 6G aims to deliver persistent broadband access and support new services through scenarios ranging from transparent and regenerative satellite payloads to direct UE-to-UE relays.

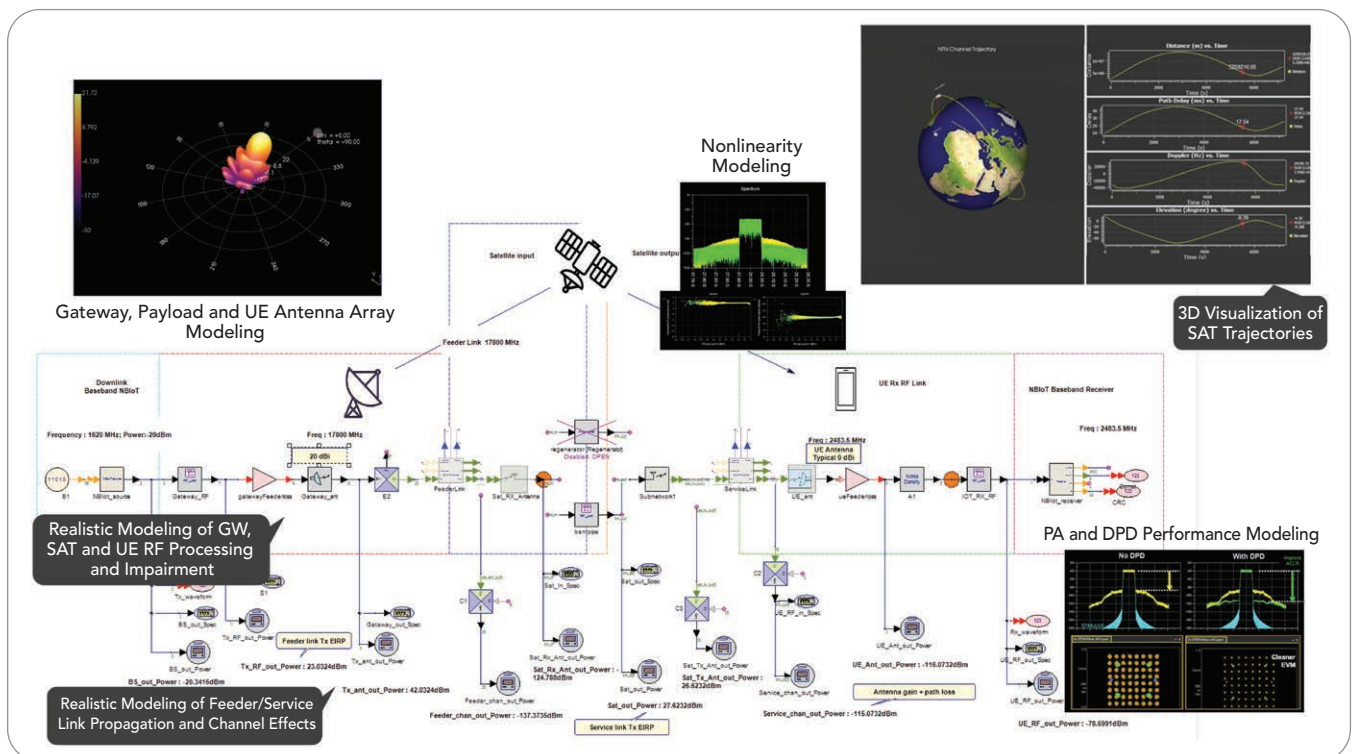
Integrating NTN introduces challenges, including long propagation delays, Doppler shifts, link intermittency and atmospheric impairments, as well as the need for seamless handovers and cross-domain resource management. A digital twin addresses these challenges by offering high-fidelity modeling of satellite payloads, gateways and user equipment under realistic conditions, incorporating impairments such as power amplifier (PA) nonlinearity, phase noise, I/Q imbalance and fading. It supports phased-array design, 3D satellite trajectory visualization and nonlinear PA modeling with digital predistortion (DPD), as well as error vector magnitude (EVM) analysis for performance validation. By bridging simulation with measured data and hardware-in-the-loop workflows, a digital twin also enables engineers to evaluate beam management and link robustness, ensuring NTN systems meet the reliability, scalability and interoperability requirements of 6G. **Figure 5** illustrates an example of SystemVue's comprehensive NTN modeling capabilities, representing both transparent and regenerative payload scenarios.

New Spectrum

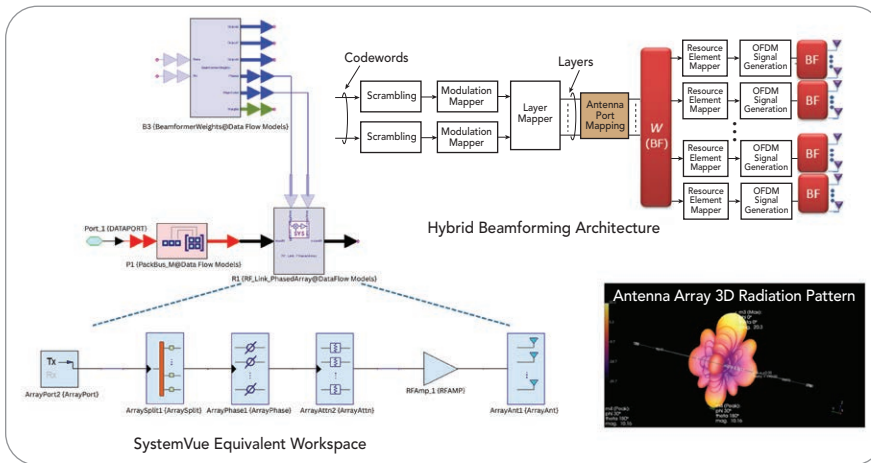
The frequency range 3 (FR3) band (7.125 to 24.25 GHz), positioned between 5G's FR1 and FR2 frequency ranges, is emerging as a vital spectrum for 6G, offering a balance of coverage, penetration and capacity. It provides broader bandwidth than FR1 while maintaining better propagation properties than FR2 and sub-THz, lending itself to applications such as ultra-reliable low-latency communication, XR and integrated sensing. However, challenges such as higher attenuation, interference and more stringent RF front-end requirements demand innovations in beamforming, antenna design and radio architecture. Teams can address these complexities by enabling high-fidelity modeling of propagation, hardware impairments and phased-array systems, while supporting waveform generation, coexistence studies and hardware-in-the-loop validation. By bridging simulation with test and measurement tools, a digital twin accelerates prototyping and ensures robust, cost-effective design for 6G systems that leverage the FR3 spectrum.

New RF and Antenna Technologies

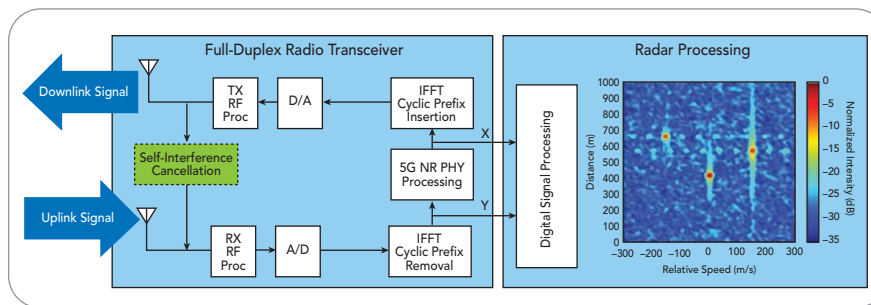
The evolution toward 6G is driving advances in RF and antenna technologies to support sub-THz operation, ultra-high data rates and integrated sensing. Emerging semiconductor technologies such as InP HEMTs, GaN-on-SiC, SiGe BiCMOS and CMOS-SOI enable efficient high frequency amplification, while architectures like



▲ Fig. 5 Example illustration of NTN link modeling with satellite trajectories.



▲ **Fig. 6** Virtual modeling of massive MIMO RF and antenna systems.



▲ **Fig. 7** Full-duplex monostatic sensing at a base station.

Doherty and distributed amplifiers, as well as digitally controlled beamforming PAs, enhance efficiency and scalability in massive arrays. At the same time, advanced CMOS nodes and packaging innovations such as antenna-in-package and system on chip (SoC) integration are enabling tighter RF digital integration, reduced losses and agile beamforming for applications such as low-latency links and holographic communication. To design these systems, workflows increasingly combine circuit, electromagnetic (EM) and system-level modeling with AI/ML and digital twins.

SystemVue, integrated with EM solvers and test instruments, supports accurate modeling of RF chains, phased arrays and impairments, accelerating convergence, improving performance prediction and enabling 6G designs. Teams can accelerate 6G RF and antenna development by creating a unified RF digital twin that bridges circuit-level accuracy with system-level validation. It supports advanced transistor and amplifier technologies through integration with Keysight ADS and EM tools, such as RFPPro, while enabling array-aware modeling for complex antennas and RIS, including beamforming, phase/gain quantization and coupling analysis. **Figure 6** illustrates an example of this in the modeling of a hybrid beamforming transmitter. With capabilities such as DPD, phased-array calibration, AI-assisted optimization

and hardware-in-the-loop workflows, teams can streamline co-design of RF front-ends and control logic. Its scalable phased-array engine simplifies massive architectures by automatically abstracting single-chain models into thousands of paths, paired with 3D beam visualization and predefined metrics for rapid insight. By combining measured data, EM models and high performance computing processing, teams can create workflows essential for designing and validating next-generation RF systems.

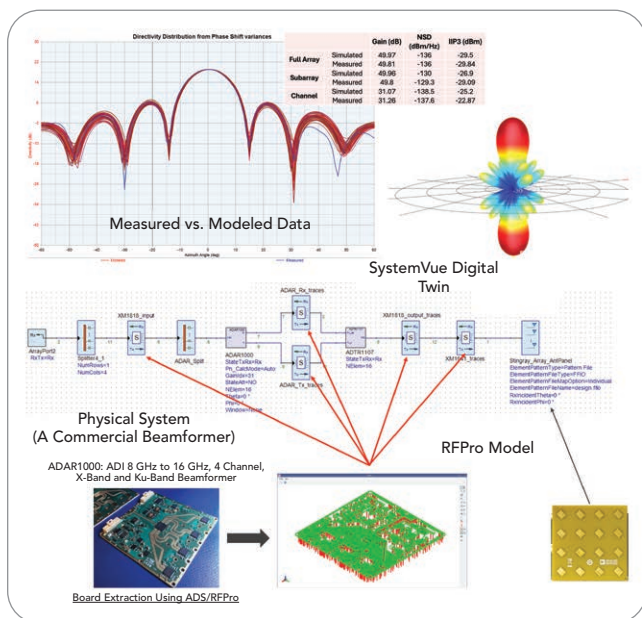
Full-Duplex Systems

Early progress in full-duplex and sub-band full-duplex (SBFD) schemes shows promise to increase spectral efficiency and reduce latency by enabling simultaneous transmission and reception on the same channel. While full-duplex requires extremely robust self-interference cancellation (over 100 dB), SBFD offers a practical alternative by separating uplink and

downlink into different sub-bands, easing interference cancellation requirements while still supporting bidirectional or joint sensing-communication operations. SBFD becomes especially valuable in dense deployments and monostatic ISAC scenarios where transmitter leakage can block weak sensing signals. SystemVue provides an environment for modeling and validating duplexing schemes under realistic impairments, including PA non-linearity, phase noise and I/Q imbalance, while supporting sub-band partitioning, SIC algorithm simulation and hardware-in-the-loop validation. These capabilities enable engineers to evaluate trade-offs and optimize full-duplex and SBFD designs for practical 6G deployment (see **Figure 7**).

RF Digital Twin

A digital twin is a dynamic, virtual replica of a physical system that mirrors real-world behavior using high-fidelity models informed by live or measured data, enabling predictive analysis, optimization and early fault detection. For 6G RF and antenna systems, effective digital twins must capture nonlinearities, noise, coupling and channel impairments such as Doppler and interference, while supporting co-simulation across circuit, system and propagation domains. SystemVue offers a robust



▲ **Fig. 8** Example comparison of a physical circuit and its digital replica.

environment for implementing RF digital twins, delivering near-circuit-level accuracy for signal chains, phased arrays and propagation effects. It integrates with EM tools and test instruments to ensure simulated results align with measured performance. By bridging design and hardware-in-the-loop validation, a digital twin enables engineers to accelerate prototyping, enhance energy efficiency and confidently optimize complex 6G technologies, including sub-THz operation, massive MIMO and RIS. **Figure 8** provides an example of a 6G digital twin workflow, which includes the accurate modeling of beamformers, splitters, PCB trace layouts and commercial RFICs. These virtual designs are validated using measured data, such as radiation patterns, gain, EVM and noise density, ensuring that simulation results closely correlate with physical performance.

AI-Based PA Modeling and Linearization

Artificial neural network (ANN)-based PA modeling and DPD provide an advanced method for modeling and linearizing RF PAs in 5G/6G, surpassing traditional approaches like memory polynomials or Volterra series in handling wide bandwidths, memory effects and dynamic impairments. By training on input-output signal

pairs from measured or simulated PA data, ANNs learn the inverse nonlinear behavior of the amplifier and apply real-time predistortion on FPGA or DSP hardware, compensating for gain compression, AM/AM and AM/PM distortion and environmental variations through adaptive learning. AI also helps crest factor reduction intelligently suppress peaks while preserving spectral integrity, and AI-enhanced envelope tracking (ET) improves efficiency by dynamically adjusting the PA supply voltage, with ANN models compensating for the added nonlinearities of ET-enabled PAs. A digital twin integrates these AI-based methods with co-simulation, hardware-in-the-loop validation and closed-loop training, enabling spectrally clean transmitter designs for next-generation wireless systems.

Leading the Transition to 6G

Through simulation, testing and collaboration with global partners and 3GPP, Keysight is helping shape 6G for commercial readiness around 2030. The transition to 6G demands holistic, end-to-end system design, where advanced simulation tools bridge the gap between concept and deployment. Keysight's SystemVue provides a system design platform, delivering high-fidelity modeling, AI-assisted optimization and hardware-in-the-loop validation to accelerate innovation while reducing risk and cost. By supporting key 6G technologies such as ISAC, RIS, NTN and sub-THz RF front-ends, SystemVue serves as a powerful RF digital twin that captures real-world performance. With circuit-level accuracy, impairment modeling and AI/ML-driven workflows, it empowers designers to make informed trade-offs, enabling the development of scalable, reliable and sustainable 6G systems. ■

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