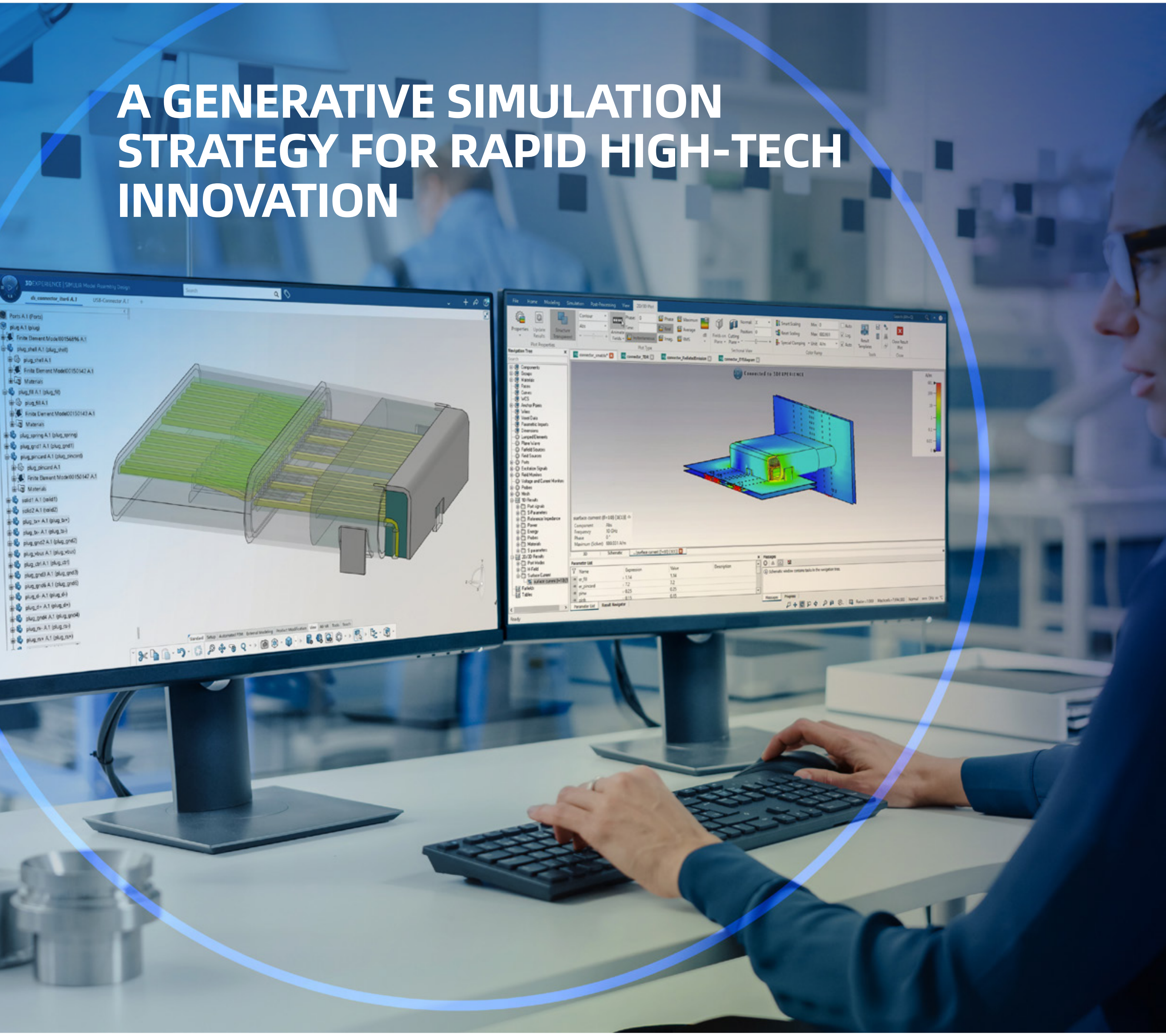
HIGH-TECH

A GENERATIVE SIMULATION STRATEGY FOR RAPID HIGH-TECH INNOVATION



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EXECUTIVE SUMMARY

In the high-tech industry, over 70% of simulation time is wasted on non-value-added tasks [1], while compressed timelines demand faster innovation. Tens of thousands of design iterations are required within short development cycles of typically 3–4 months for smart electronic devices. Traditional engineering approaches, with their disconnected tools, sequential workflows and manual processes, can no longer keep pace with product complexity or market pressure.

This white paper introduces a generative simulation strategy that accelerates product innovation by braiding three critical capabilities into one cohesive framework:

1. **Unified modeling and simulation**, which accelerates iterative design and eliminates wasteful handoffs
2. **AI-powered multi-physics simulation and optimization**, enabling rapid design exploration and knowledge re-use
3. **A collaborative innovation environment** that provides a single source of truth with robust IP security

Organizations that adopt this unified approach gain measurable advantages: reduced development cycles, fewer physical prototypes, higher design quality, and the agility to explore thousands of design iterations within months rather than years. By integrating artificial intelligence (AI) and machine learning (ML) with expert governance, companies can accelerate and automate key aspects of the design, validation and learning cycle while maintaining the quality, compliance, and performance goals.

This paper outlines a holistic transformation strategy and a practical roadmap based on industry best practices, delivering tangible value at each phase while building toward a future-ready ecosystem of trustworthy simulation competencies.

WHY MODERN SIMULATION COMPETENCIES ARE CRUCIAL

The high-tech industry has entered a phase where the most decisive competitive variable is no longer raw technology, but the velocity at which that technology becomes a certifiable, manufacturable product. Time-to-market pressure has compressed development cycles from years to months, yet engineering teams are asked to deliver increasingly sophisticated offerings faster.

The root of this tension lies in complexity. Modern electronic systems integrate chips and sensor design, mechatronics, and software engineering into cyber-systems that can sometimes operate autonomously. Each discipline evolves at its own cadence, forcing engineers to simultaneously optimize for structural integrity, thermal performance, signal integrity, new materials, and software functions. For every feature added, the design space branches into an exponential set of alternatives.

To address this problem, the product development model is shifting toward a virtual twin-centric paradigm. A virtual twin is a scientifically accurate, continuously updated digital representation of a product that connects design intent, simulation, real-world data and operational behavior across the entire lifecycle. Companies that institutionalize comprehensive modeling and simulation capabilities will be the fastest to master rapid innovation and to predict failures and performance KPIs more reliably.

KEY PROBLEMS IMPEDING INNOVATION

High-tech innovators are prioritizing simulation-centric capabilities, moving from their isolated application to democratized adoption across the entire development process. However, persistent problems impede the smooth realization of this transition, constraining the full benefits of simulation. These issues fall into the following critical categories:

- Time-Consuming Simulation Setup: Simulation workflows can take many hours or even days depending on requirements, application and complexity. Research indicates that over 70% of a simulation engineer's time is spent on non-value-added pre- and post-processing tasks like model cleanup and manual meshing.
- Inefficient Deployment of Simulation Processes: Disconnected design and simulation processes create slow, sequential iterations, significantly extending development cycles. For many consumer electronic devices, development cycles of just 3 to 4 months require as many as 40,000 iterations to explore and verify innovative technologies.
- Inaccuracy and Lack of Traceability: Without standardized knowledge libraries, results can vary based on individual experience, leading to inaccuracies. A lack of traceability makes it difficult to pinpoint errors, forcing rework and undermining confidence in simulation outcomes. The reliability of AI/ML models also presents a significant challenge without a foundation of trustworthy data.
- Fragmented Approach: Many companies build simulation capabilities heavily relying on IT tools, without a comprehensive view of processes, methods, organizational skills and digital enablers. This results in insufficient coverage of use cases, isolated workflows, diverse toolchains with separated data, and a weak connection between performance specifications and final results.

A UNIFIED GENERATIVE SIMULATION STRATEGY

To overcome these challenges, engineering leaders need a stable, robust structure for innovation. Much like braiding three strands of hair creates a strong plait, a generative simulation strategy weaves together three core capabilities into a unified, powerful approach. This new paradigm combines AI technologies, integrated modeling and simulation, and advanced exploration methods to generate optimal design results more efficiently. It delivers speed, precision, and performance at every stage, from concept to production. The three essential strands are:

- Unified Modeling and Simulation: Unifying design and simulation workflows eliminates data exports and handoffs. This creates a continuous loop where teams receive real-time feedback as designs and simulations evolve together, not in isolated stages.
- AI-Powered Assistance and Automation for Multi-Physics Simulation: Advanced optimization algorithms, augmented by AI and machine learning, streamline simulation setup and guide intelligent design exploration. This empowers teams to generate innovative designs that meet multiple performance KPIs early in the process.
- A Collaborative Innovation Environment: A central repository capturing all engineering practices and knowledge provides a "single source of truth." It secures intellectual property and ensures that all data – from models, parameters and materials to simulation and test results – are available for continuous simulation and AI training improvement.

By braiding these three strands together, organizations create a resilient framework that can lead to significant benefits in time, quality, cost, certification and compliance.

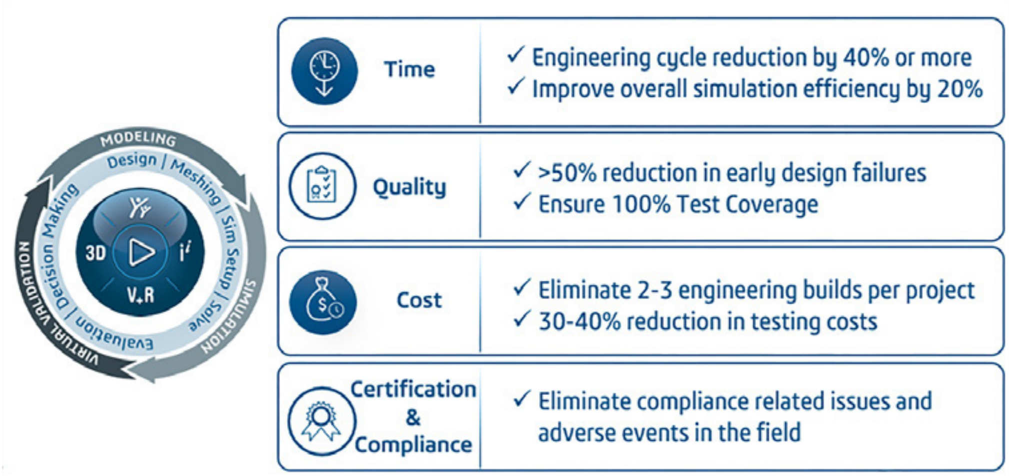


Figure 1: Key achievements derived from customer practices combined with Dassault Systèmes' insights.

KEY METHODOLOGIES: GAINING A LEADING ADVANTAGE

Synchronized Modeling and Simulation for Faster Iteration

The traditional, sequential approach to design and simulation is a primary source of inefficiency. A designer creates a CAD file and sends it to a simulation expert, who then cleans, meshes, and prepares the model for analysis. After running simulations, the analyst reports back, often requesting design changes. The entire process then restarts.

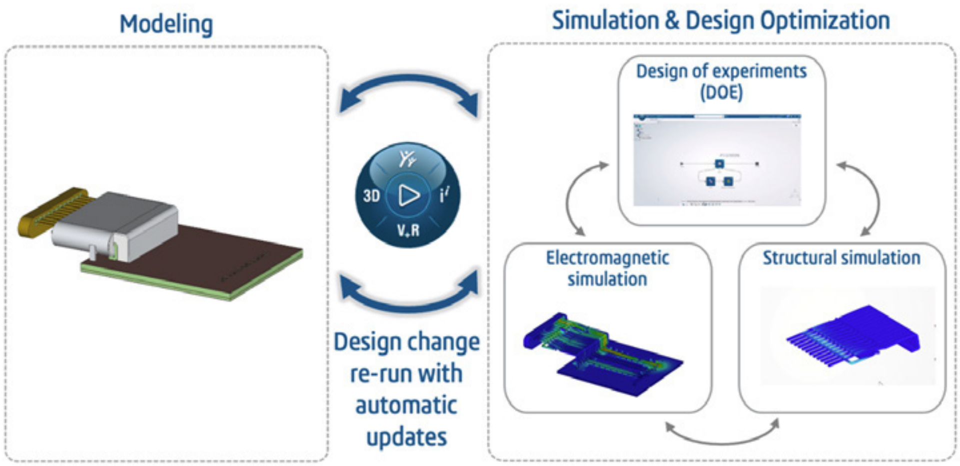
A synchronized approach significantly improves this workflow [2]. Designers and simulation experts work concurrently on the most up-to-date models, within the same project scope and always connected to the requirements. Key benefits include:

- Democratization of Simulation: Capturing best practices in managed processes and templates ensures growing and propagating a company's hard-earned simulation know-how, allowing simulation experts to perform simulations more efficiently and reliably. It also allows designers and non-experts to benefit from simulations and evaluate multiple design configurations during concept engineering. This significantly speeds up new product design.
- Multi-Discipline Optimization: In a synchronized environment, teams can run precise multi-physics analyses in parallel. For example, the electromagnetic and structural performance of a PCB component can be optimized concurrently, ensuring the final design meets all requirements while minimizing physical prototypes, iteration time and the need for file transfers.

Use Case:

For engineers designing high-speed connectors for smart devices, the concurrent electromagnetic and structural multi-physics optimization helps address several real-world challenges. With extremely short development cycles, there is no time for repeated tests or prototypes. Rising signal bandwidths and shorter rise times make signal integrity harder to achieve because of reflections from discontinuities, material losses, crosstalk between channels, and mode conversion from asymmetries. High signal integrity and compliance with electromagnetic compatibility (EMC) standards are therefore essential.

Reliability is equally critical: the connector must perform consistently over hundreds of mating cycles. Pins must maintain proper contact pressure to minimize reflection and loss, and springs must hold the connector securely while still allowing easy insertion and removal. Disconnected workflows often require engineers to rebuild electromagnetic and structural models after each CAD update, while separate optimization for EMC and structural performance prevents a balanced design.



With a combined modeling and simulation approach, when the parametric CAD model is created, it is automatically shared across disciplines. The EMC engineer can access it at any time to run signal integrity simulations, while any new design change, such as a reduced pin length, is immediately available for rapid re-analysis. In parallel, the structural engineer evaluates insertion forces, contact stresses, and fatigue. Using Design of Experiments (DOE) methods, the team can simultaneously perform multidisciplinary optimization to find a robust connector design that satisfies both electromagnetic and mechanical requirements.

This integrated process minimizes physical prototypes, shortens development time, and ensures that certified designs reach the market faster [3].

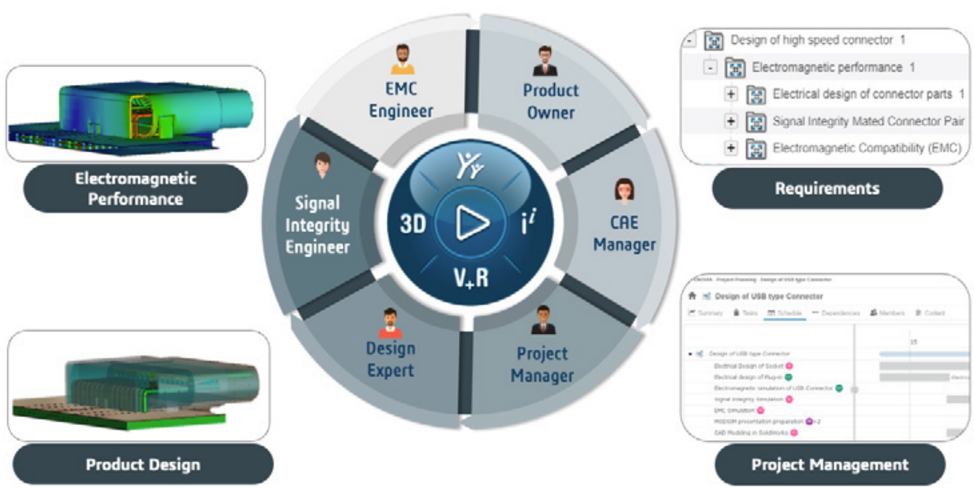


Figure 3: Accelerate iterations with key stakeholders on the same up-to-date designs.

AI-Powered Assistance and Automation for Rapid Simulation and Design Exploration

While concurrent simulation and modeling enhance collaboration, AI and ML introduce a new way to enhance simulation experts' user experience [4]. One scenario is to use AI-powered assistance to guide the simulation process including the re-use of simulation knowledge such as rules and historical data. Another option is to use surrogate models for a data-driven approximation of a complex physics-based simulation. Trained on a curated set of simulation results, an AI-powered virtual twin can predict performance much faster, allowing engineers to explore a vast range of design options without running computationally intensive physics-based simulations [5,6,7].

However, the power of these models comes with significant responsibility and training effort. Their development and deployment must be governed by simulation experts to mitigate risks and ensure reliability. Key considerations include:

- Expert-Led Training: Simulation expertise is essential for training effective machine learning models. Experts must define the right constraints within an appropriate design space and ensure high-quality data to train the model. This ensures the model's predictions are relevant and accurate. Figure 2: A unified platform with CAD to CAE model associativity.

- Managing Application Risk: Experts must also understand how and where trained models will be used by the organization. The risk of misuse is particularly high when dealing with novel designs or new materials, as the machine learning models may not be trained on relevant data. For evaluating design updates or product variants, ML models may offer significant time savings.
- Evaluating Trade-Offs: The decision to replace physics-based simulations with ML models requires careful evaluation of business KPIs. Simulation experts must weigh the potential time and resource improvements against the acceptable level of accuracy for a given task, also considering the availability of usable test data.
- Continuous Monitoring and Refinement: Once deployed, the use of ML models must be monitored to enable continuous refinement. This governance should be data-driven and automated, as it is critical to ensuring that the time-to-market benefits do not compromise a product's final quality, compliance, or performance.
- Ongoing User Adoption Support: Experts should identify barriers to the effective use of AI/ ML models and leverage intuitive UI design, pre-built templates, and virtual companions to overcome these challenges seamlessly.

Use Case: EMC Shielding and Thermal Management

In order to comply with electromagnetic interference (EMI) and EMC requirements, electronic devices are often protected from external electromagnetic disturbance by using a metallic enclosure to shield them. On the other hand, modern high performance computing devices produce a high thermal load which needs to be dissipated by providing adequate ventilation. Ventilation apertures again reduce the shielding effectiveness (SE) of the enclosure, so we have two conflicting requirements. Balancing these by using virtual prototyping in the early development phase is essential. However, performing a full parametric study or optimization of all parameter variations for all KPIs would be time consuming and costly.

An attractive option is to break the problem down into two parts and use machine learning models for each of the physics behaviors to perform a trade-off study. If the cooling vent is formed by a number of square holes, the thermal performance can be predicted simply from the free area ratio of the vent (hole-to-total area) and the fan speed. The electromagnetic SE, on the other hand, depends on the size and spacing (horizontal and vertical) of the holes. We can run two focused DOEs, considering only the relevant input and output quantities for each domain, and construct two machine learning models which can then be used in the multi-physics optimization to balance shielding effectiveness and thermal performance, as described in Figure 4.

We could run a single combined DOE, but then we'd need to run both simulations, including the more time-consuming thermal simulation, for the entire parameter set. In addition, the electromagnetic simulations would need to be run for variations in fan speed, which doesn't affect those results. By splitting the problem, we can perform a simpler DOE with a reduced number of parameters for the thermal simulation, thereby reducing the overall study time significantly (in this case by about a factor of 12[1]) without compromising much on result accuracy.

The two machine learning models, each displaying a very low error measure, are then used in a combined optimization to perform the trade-off analysis. Validation of the best solution shows excellent agreement with a full simulation for both thermal performance and shielding effectiveness. Machine learning modeling has helped us to solve a complex multi-physics problem in a fraction of the time it would have taken to perform full detailed optimization [8].

[1] We run 125 electromagnetic simulations to consider all combinations of the 3 parameters, with each simulation taking about 5 minutes; and 35 thermal simulations with two input parameters, with each simulation taking an average of about 60 minutes. This results in a total simulation time of about 45 hours. If we were to run a single DOE for 4 parameters (the 3 geometric parameters give us the free-area ratio for the thermal simulations), we would need 500 simulation runs (125x4), each taking about 65 minutes, giving a total time of about 540 hours, higher by a factor of 12!

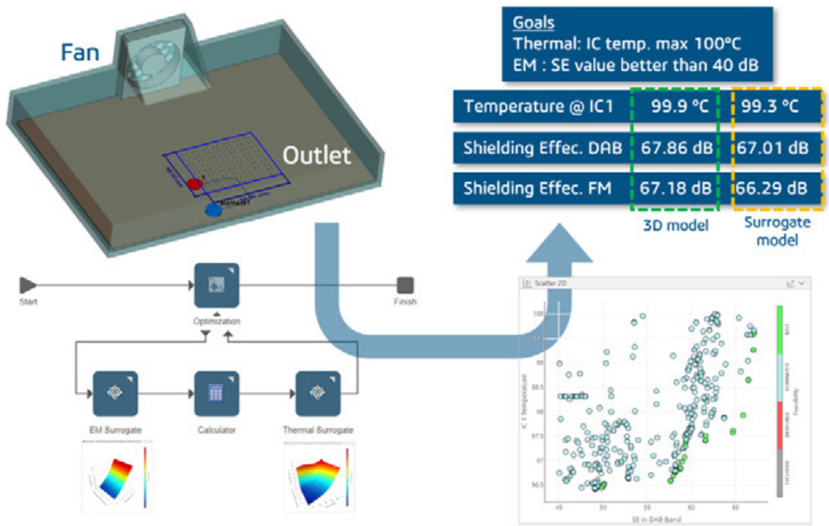


Figure 4. The electromagnetic and thermal performance of the enclosure of an electronic device are captured as two machine learning models, which are subsequently used to efficiently optimize the design of the ventilation outlet.

Building a Collaborative Innovation Environment

The backbone of a successful generative simulation strategy is a single, authoritative environment for all IP (intellectual property) generated during design and validation. This environment helps engineering teams make simulation accessible to everyone, provides real-time updates, and facilitates process automation across roles and disciplines. All engineering knowledge—including simulation models, materials, processes, and results—is captured as reusable and proven assets.

This approach provides visibility across all disciplines and stakeholders, enabling them to ensure product requirements are met. End-to-end traceability, enforced by a digital thread from requirements to simulation and testing, facilitates validation and verification. It also strengthens confidence in virtual certification, which is increasingly accepted by regulatory organizations as a substitute for physical testing.

Furthermore, a unified environment is crucial for building trustworthy AI. When AI and ML algorithms are trained on high-quality, science-based data within their proper engineering context, the resulting models are manageable, auditable, and directly traceable to the decisions and experts that created them. This gives engineers and regulators the confidence required for mission-critical deployments.

RECOMMENDATIONS: A HOLISTIC APPROACH AND ROADMAP

Transforming simulation competencies requires a holistic approach that consolidates strategy, engineering methods and digital enablers in a systematic way.

Approach Recommendations:

- Use—or Establish—a Dedicated Simulation Center of Competence (CoC): Empower professional talent and skills to build and manage simulation capabilities that serve the entire value chain.
- Streamline Simulation Scenarios: Analyze simulation use cases across physical disciplines (structural, electromagnetic, fluid, etc.) as well as across specific product lines to build comprehensive coverage.
- Formulate Methods and Guidelines: Task experienced simulation experts with capturing knowledge and best practices in a way that makes them easily reusable for all potential users of simulation.
- Synergize with Product Development: Integrate the simulation strategy directly into product development processes to inspire innovative designs and streamline execution.
- Build a Unified Environment: Implement a system that connects various mechanical, electronics, and software design tools while integrating with business functions such as quality assurance and project management to optimize efficiency.

Roadmap Recommendations:

A phased roadmap allows organizations to realize value quickly while building toward a long-term vision.

1. **Deploy a Collaborative Environment**: Begin by deploying a model-based and data-driven system to solidify the foundation. This is key to enforcing methods, reusing knowledge, and enabling collaboration.
2. **Adopt a Unified Modeling and Simulation Approach**: Streamline and automate workflows to democratize simulation capabilities. Empower engineers to apply techniques like DOE to explore more design alternatives and conduct trade-off studies more easily.
3. **Gradually Scale AI/ML Practices**: Integrate AI capabilities in targeted use cases to reveal the values and feasibility of benefiting from this technology. For example, use AI-assistant technology to improve model preparation, enhance user interaction with simulation tools and facilitate more meaningful result interpretation. This can streamline simulation workflows and reduce error-prone manual work. Further, use DOE and ML models to enhance design and optimization methods, enabling rapid design iteration, complex design exploration and capture of valuable company know-how.

CONCLUSION AND FUTURE DIRECTIONS

The generative simulation strategy represents a paradigm shift that fuses unified modeling and simulation with machine learning technologies. The braiding of synchronized processes, intelligent automation, and a collaborative environment into one cohesive whole, accelerates high-tech innovation. But this approach not only accelerates time-to-market but also learns from high-fidelity results, driving continuous, sustainable innovation.

The transformation ideally touches the entire enterprise, driving synchronized change in organization, talent, process, and methods, all unified by a single, secure, and knowledge-centric environment.

Looking ahead, the synergy between data-driven AI/ML technologies and physics-based simulations will only deepen. Future advancements will focus on areas such as automated model calibration and training AI to understand physical laws and constraints, and on studying ML and AI for reducing the tedious workload of pre-processing and meshing. Generative simulation is a major step forward in helping organizations to master innovation by addressing increasing complexity and competitive pressures.

AUTHORS

XU Jun, High-Tech Industry Business Value Expert, Dassault Systèmes

Mahesh DESHPANDE, High-Tech Industry Business Value Consultant Senior Director, Dassault Systèmes

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