

We3E-1

Convergence of Simulation, Cloud Computing and Artificial Intelligence in Electromagnetics

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- ▶ Introduction to Altair
- ▶ Mega Trends in Industry
- ▶ Evolution of Simulation and Data-Driven Design and Convergence
- ▶ Computational Electromagnetics (CEM) and Applications
- ▶ High Performance Computing
- ▶ Machine Learning for CEM
- ▶ Cloud on Demand
- ▶ Digital Twins
- ▶ Conclusions

1985

Founded & Headquartered
in Troy, MI U.S.

13,000+

Customers
Globally

\$572M

FY22
Revenue

86

Offices in
25 Countries

3,000+

Engineers, Scientists,
and Creative Thinkers

150+

Altair and Partner
Software Products



***“To transform enterprise decision-making by leveraging the convergence of
simulation, high-performance computing, and artificial intelligence”***

Mega Trends

Electrification



Electrification – EV's

AI Driven Simulation



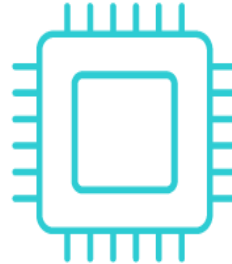
Simulation and AI Driven Design and Innovation

Data Driven Enterprise



Decisioning driven by data - autonomous included here

Semi-Conductor



5G, Electronic System Design and PCB/Semiconductor

Cloud



The Move to the Cloud – Virtual workforce

Compliance Risk & Fraud / AML



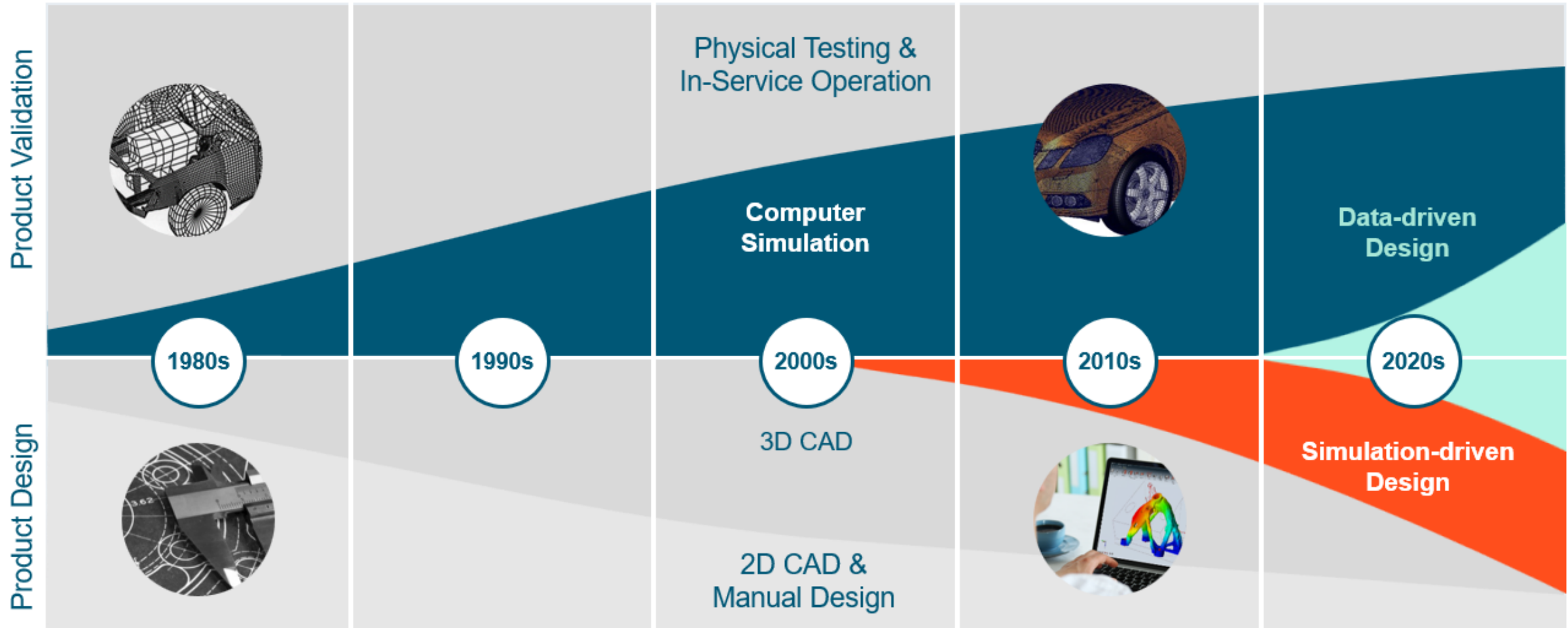
Compliance – Risk and Fraud – AML – Expertise/Solutions

De-carbonization



Decarbonization, Net-Zero commitments, ESG

Evolution of Simulation- and Data-Driven Design



Convergence

- ▶ Global evolution toward smart, connected everything
- ▶ Simulation- and data-driven models will drive design and operational decisions
- ▶ Massive exploration of ideas is driving the need for advanced HPC and cloud



Maxwell's equations for electromagnetism have been called the **"second great unification in physics"** after the first one realized by Isaac Newton.

Maxwell's Equations

$$\vec{\nabla} \times \vec{H} = \vec{J}_v + \varepsilon \frac{d\vec{E}}{dt}$$

$$\vec{\nabla} \times \vec{E} = -\vec{M}_v - \mu \frac{d\vec{H}}{dt}$$

$$\vec{\nabla} \cdot \vec{H} = \frac{1}{\mu} \sigma_m$$

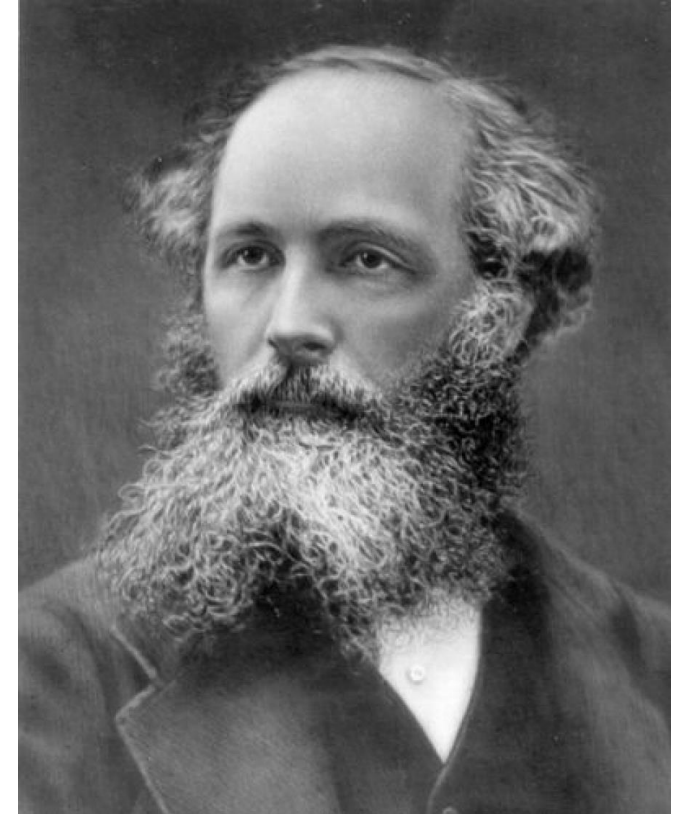
$$\vec{\nabla} \cdot \vec{E} = \frac{1}{\varepsilon} \sigma_e$$

$$\mathbf{E} = -j\omega\mu\mathbf{A} + \frac{1}{j\omega\varepsilon}\nabla(\nabla \cdot \mathbf{A})$$

$$\mathbf{E} = -j\omega\mu \int_V d\mathbf{r}' \mathbf{G}(\mathbf{r}, \mathbf{r}') \cdot \mathbf{J}(\mathbf{r}')$$

$$\mathbf{G}(\mathbf{r}, \mathbf{r}') = \frac{1}{4\pi} \left[\mathbf{I} + \frac{\nabla \nabla}{k^2} \right] G(\mathbf{r}, \mathbf{r}')$$

James Clerk Maxwell
(1831-1879)



- CEM is the numerical solution of Maxwell's equations
 - CEM has become an indispensable industrial tool

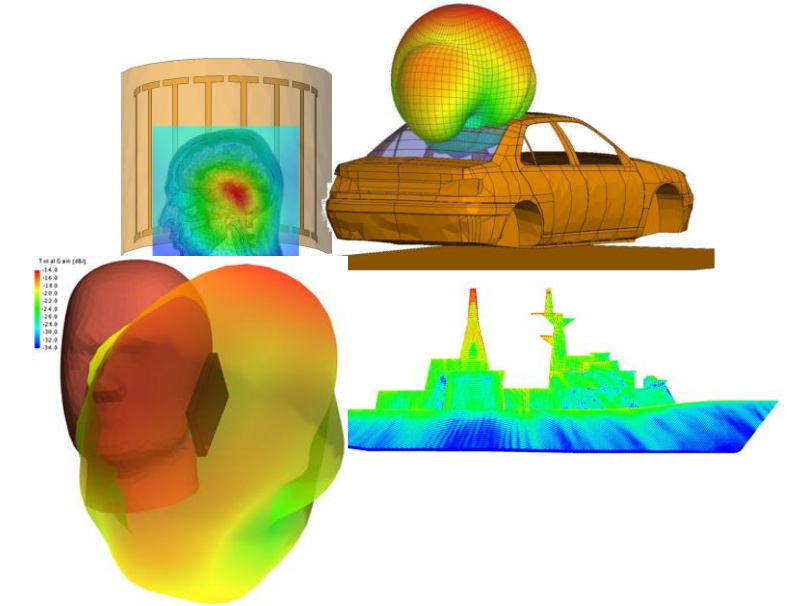
**Computational cost (CPU time & memory)
must be as low as possible**



Computer modeling

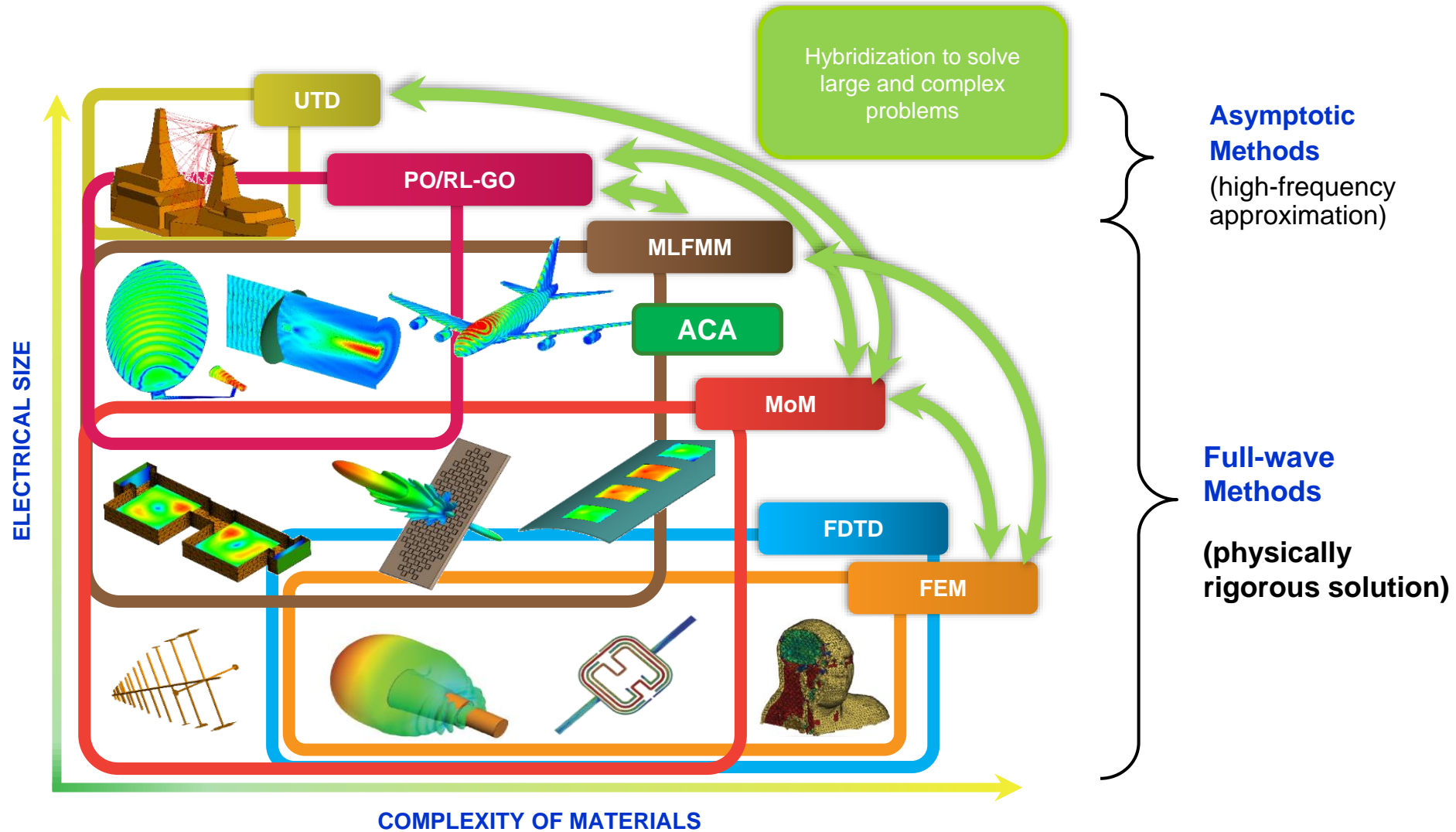
$$\begin{aligned}\vec{\nabla} \times \vec{H} &= \vec{J}_v + \epsilon \frac{d \vec{E}}{dt} \\ \vec{\nabla} \times \vec{E} &= -\vec{M}_v - \mu \frac{d \vec{H}}{dt} \\ \vec{\nabla} \cdot \vec{H} &= \frac{1}{\mu} \sigma_m \\ \vec{\nabla} \cdot \vec{E} &= \frac{1}{\epsilon} \sigma_e\end{aligned}$$

CEM tool

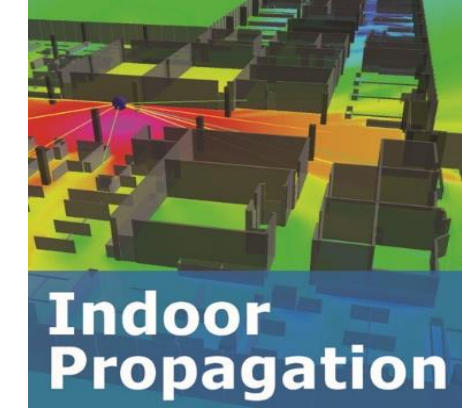
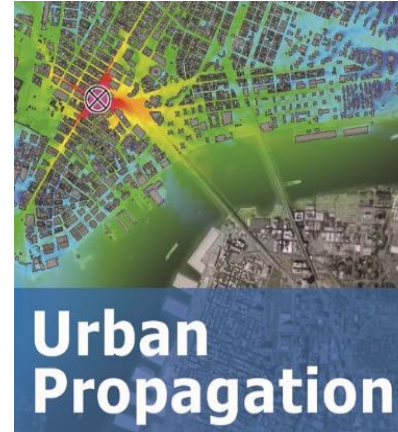
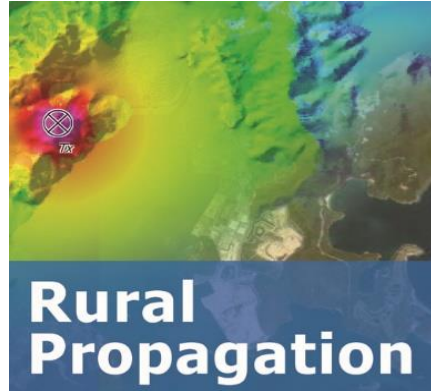


Numerical analysis

CEM Solver Technologies

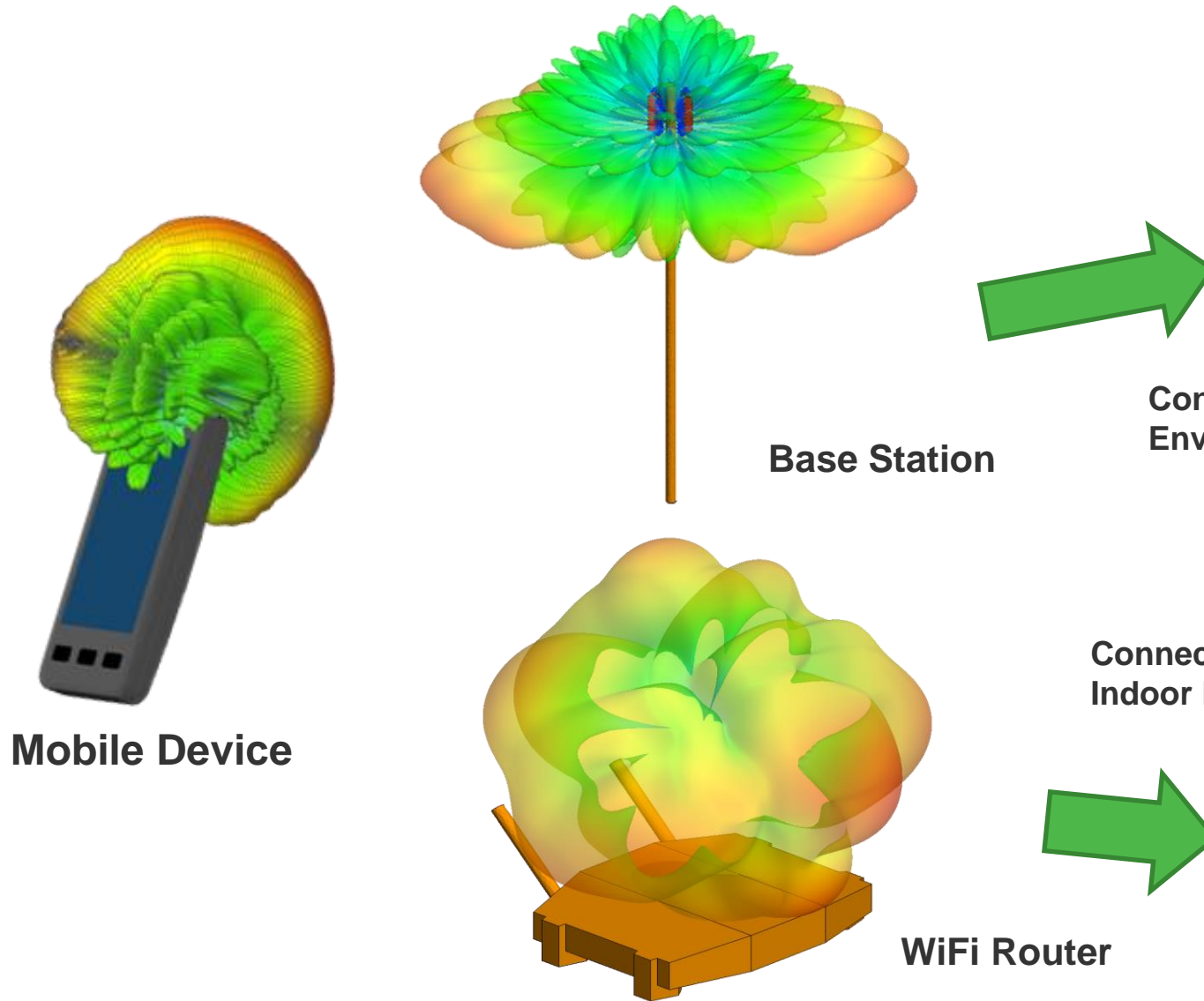


Propagation Models

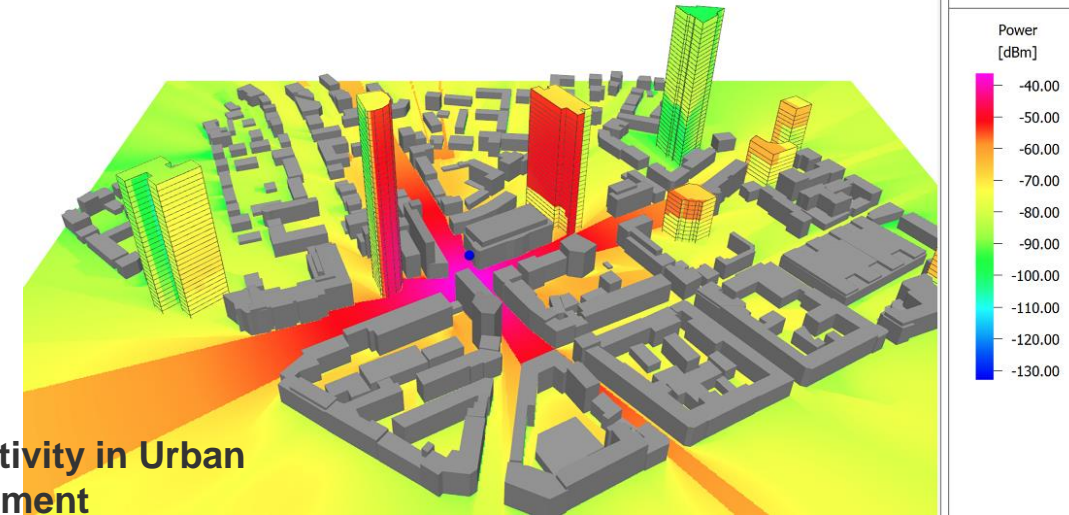


Map Data	Topography pixel data	2.5D building vector data	3D vector data
Optional Data	Clutter losses / heights Ground properties	Material properties Topography pixel data Vegetation objects	Material properties Subdivisions, furniture
Propagation Models	Empirical models (Hata, ITU,...) Vertical plane models Dominant path model 3D Standard Ray Tracing (SRT)	Vertical plane models (WI) ITU-R P.1411 model Dominant path model 3D Intelligent Ray Tracing (IRT)	Direct ray models (Multi-Wall) Dominant path model 3D Ray Tracing SRT/IRT

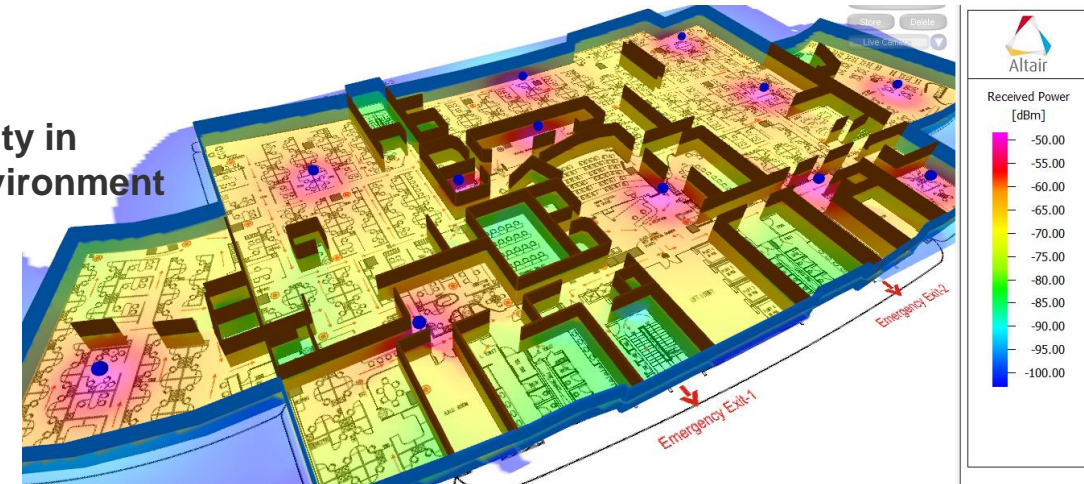
Connected Devices



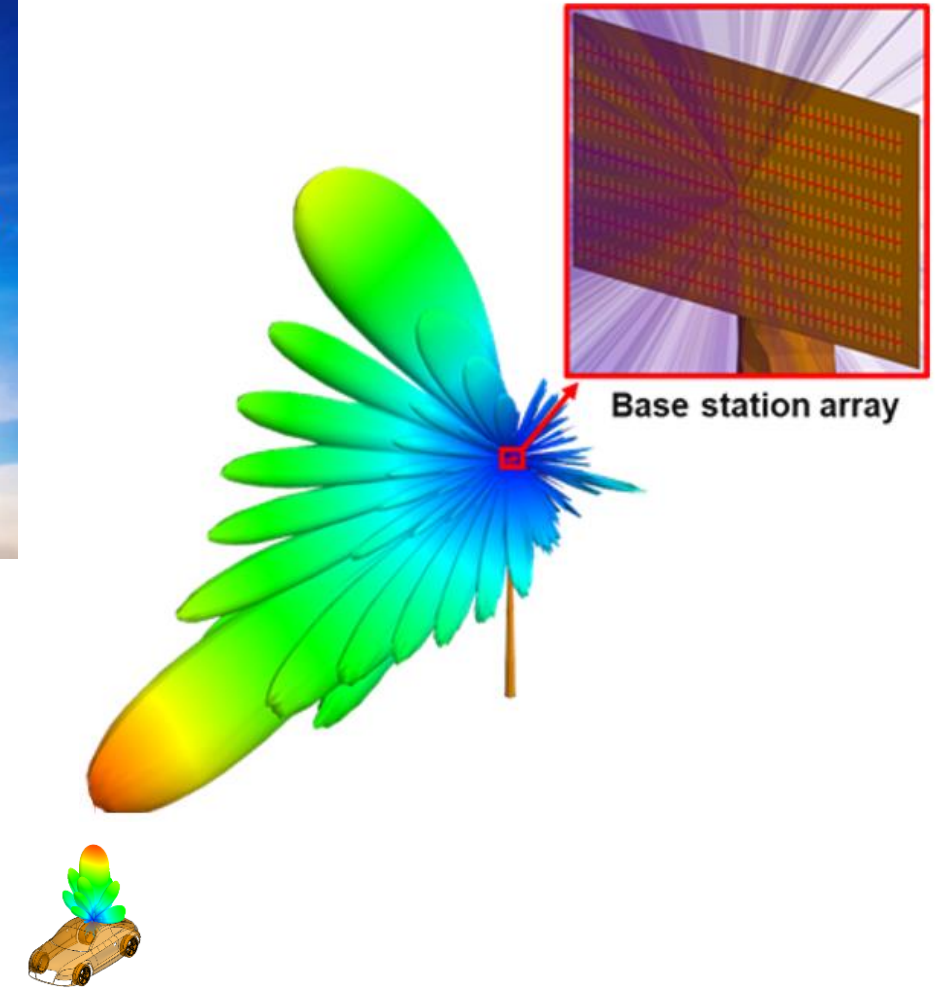
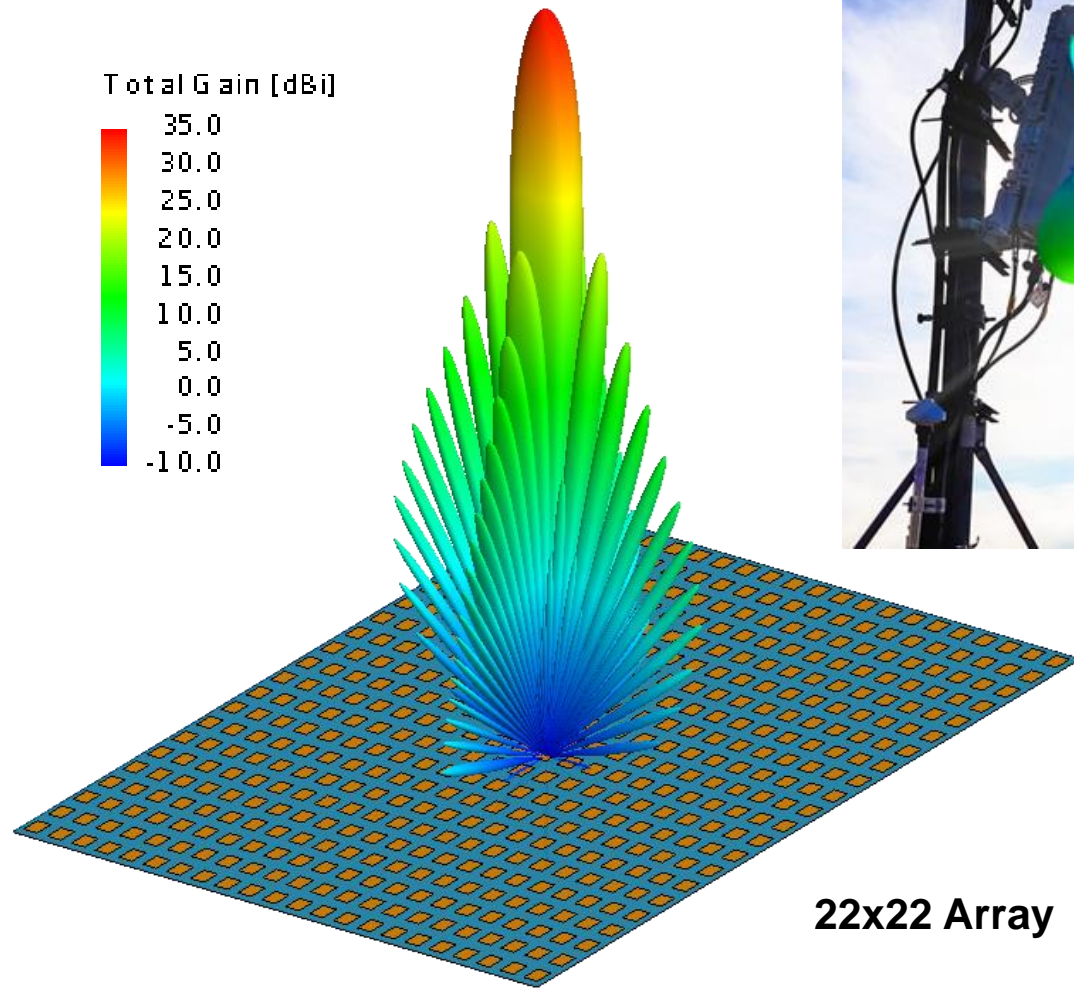
Connectivity in Urban Environment



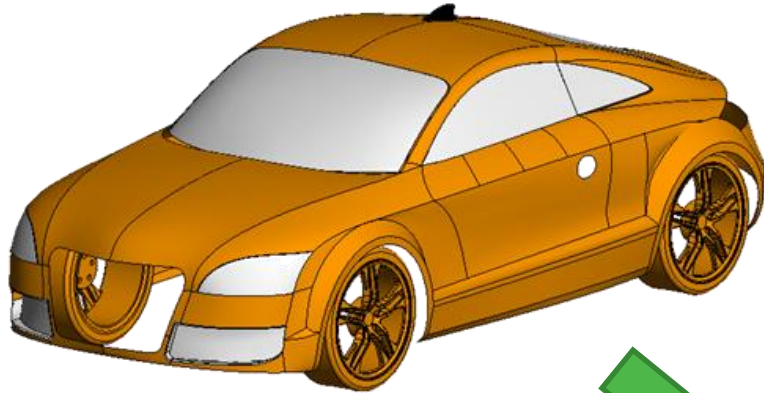
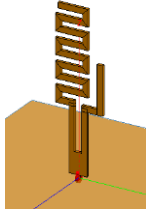
Connectivity in Indoor Environment



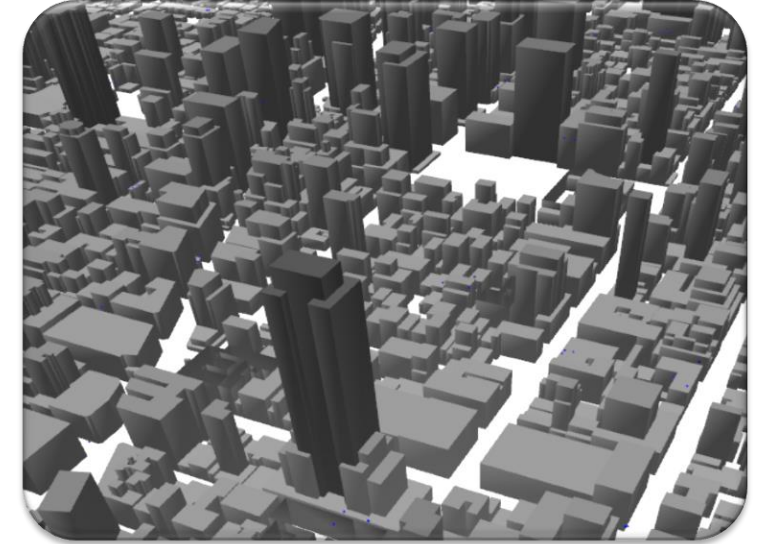
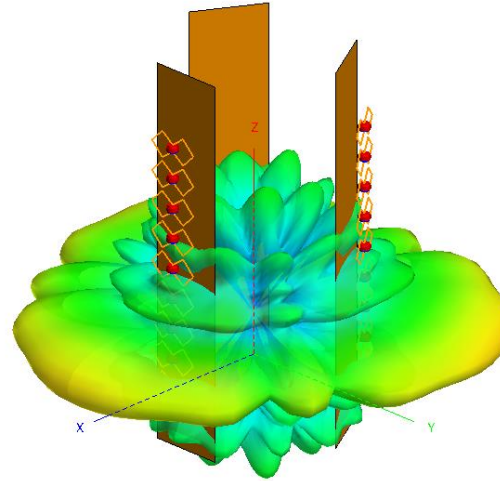
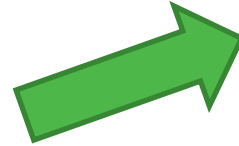
Antenna Arrays for 5G



**Dual band LTE
Antenna**

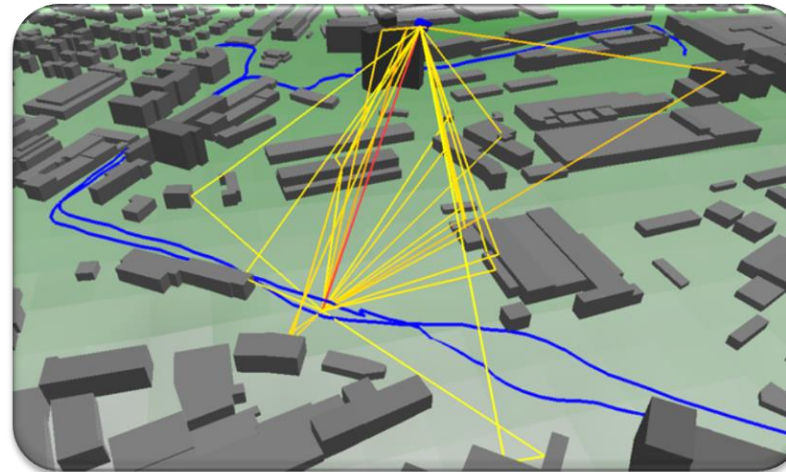


**Base
station
sectors**



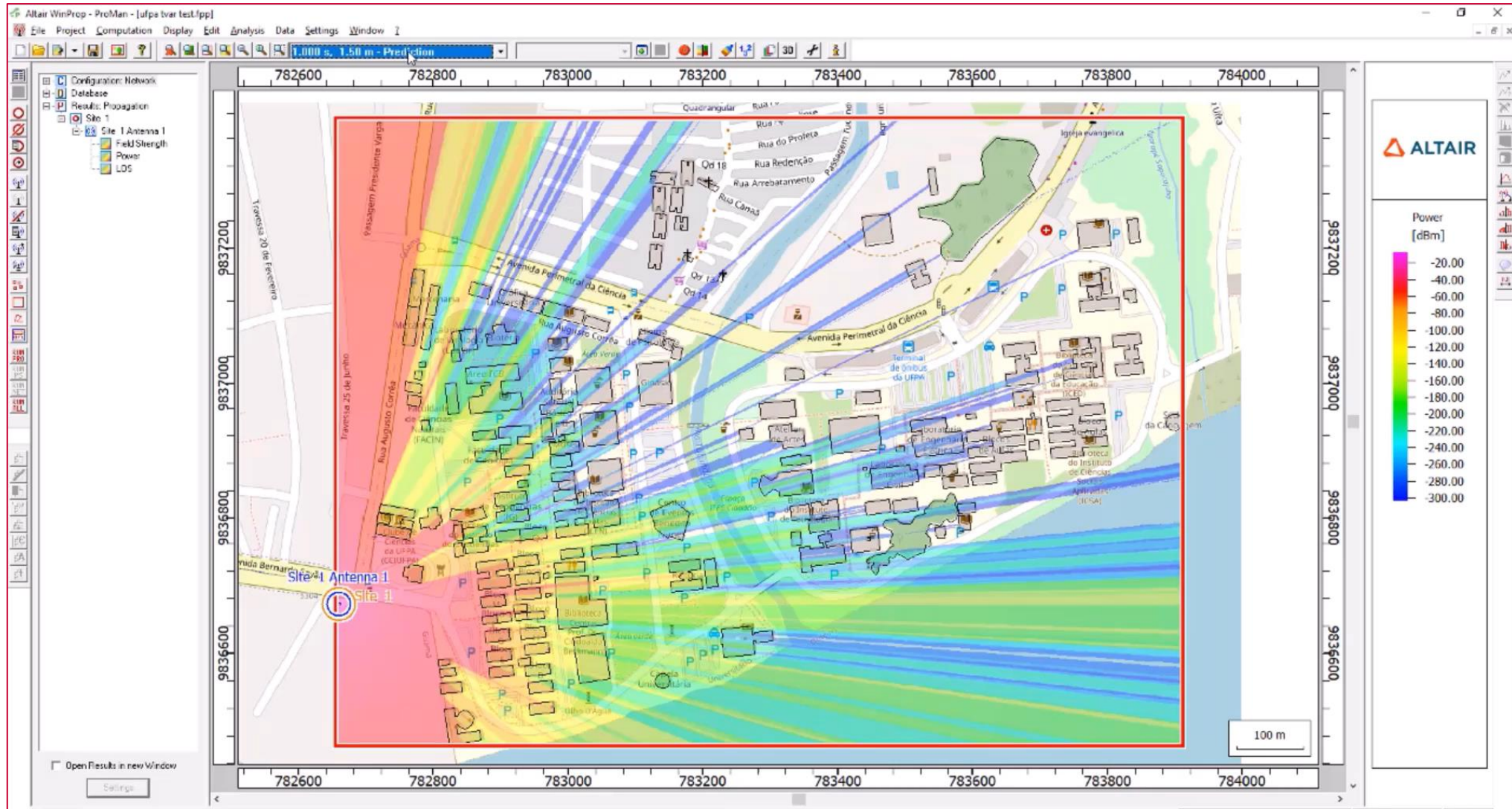
Urban Scenario

Virtual Drive Test

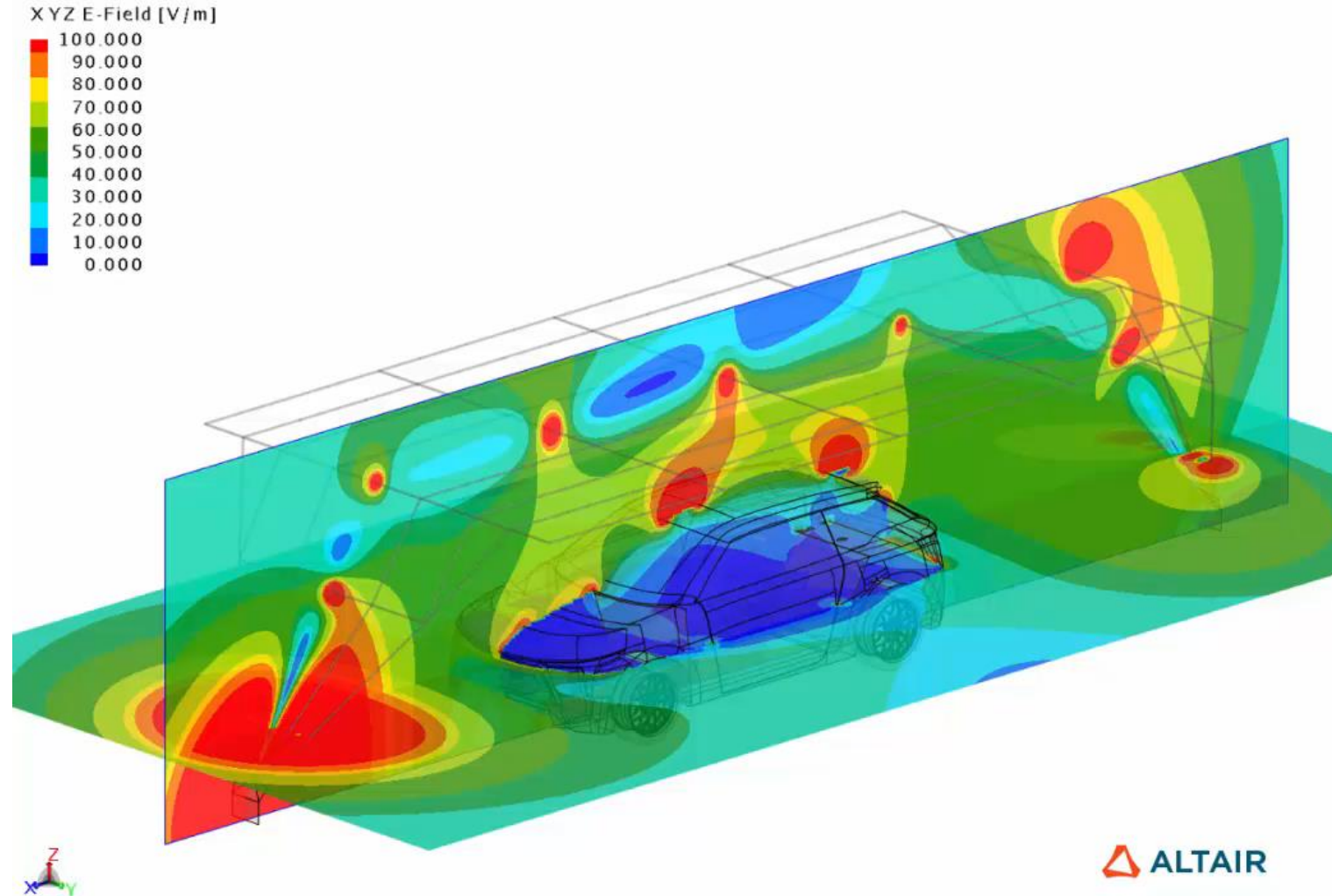


3D Ray Tracing

Virtual Drive Test



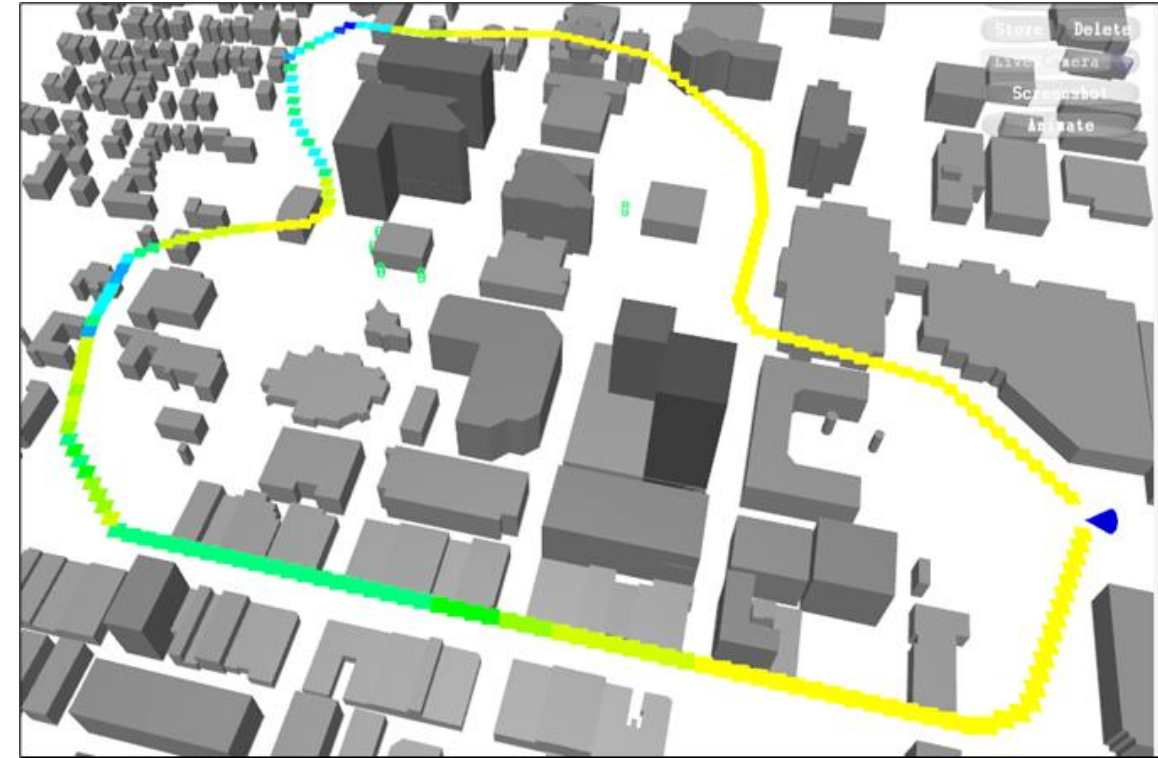
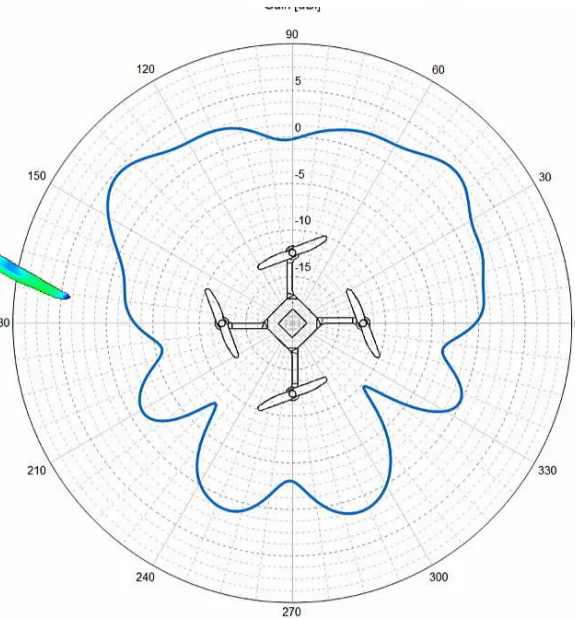
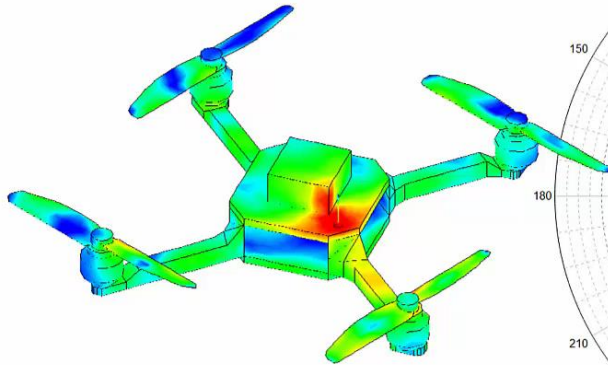
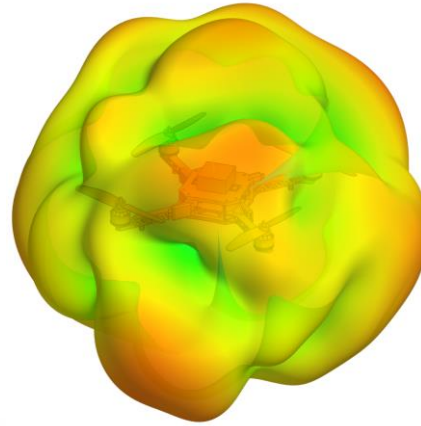
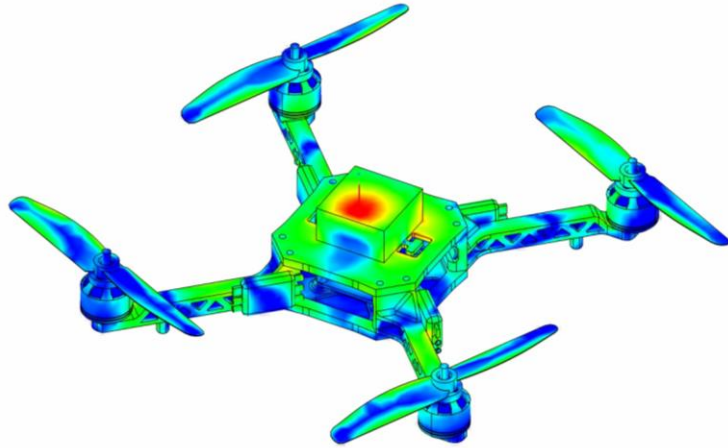
Virtual EMC Test



Virtual Flight Test

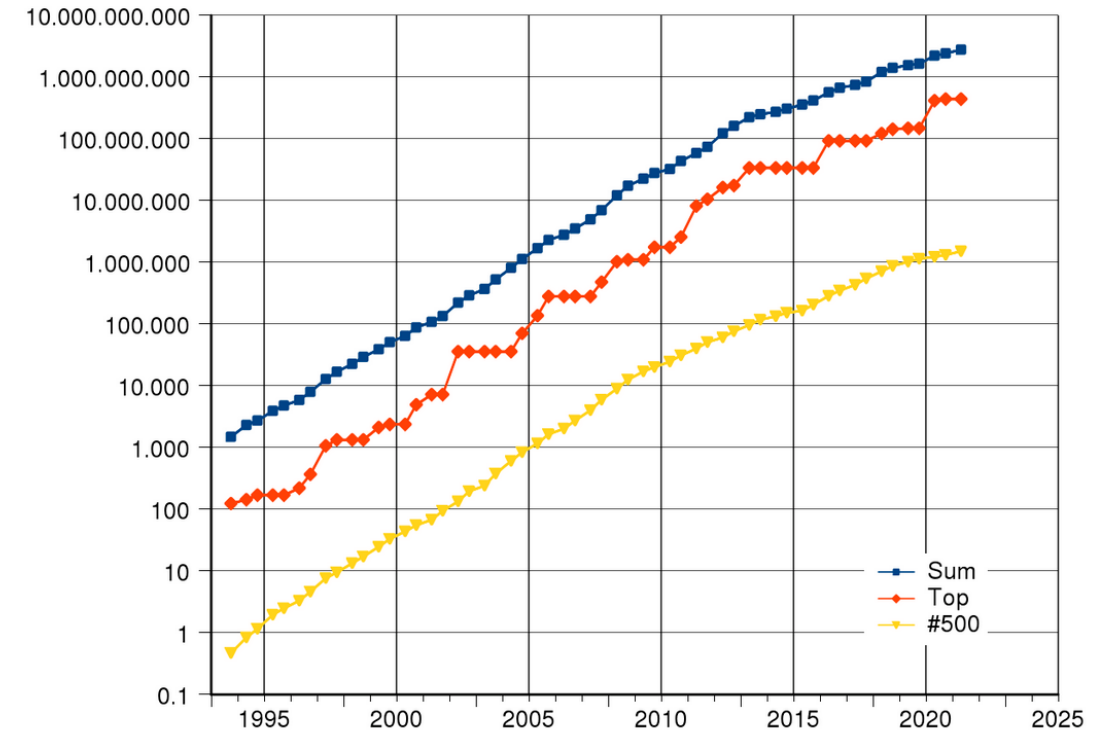


Virtual Flight Test



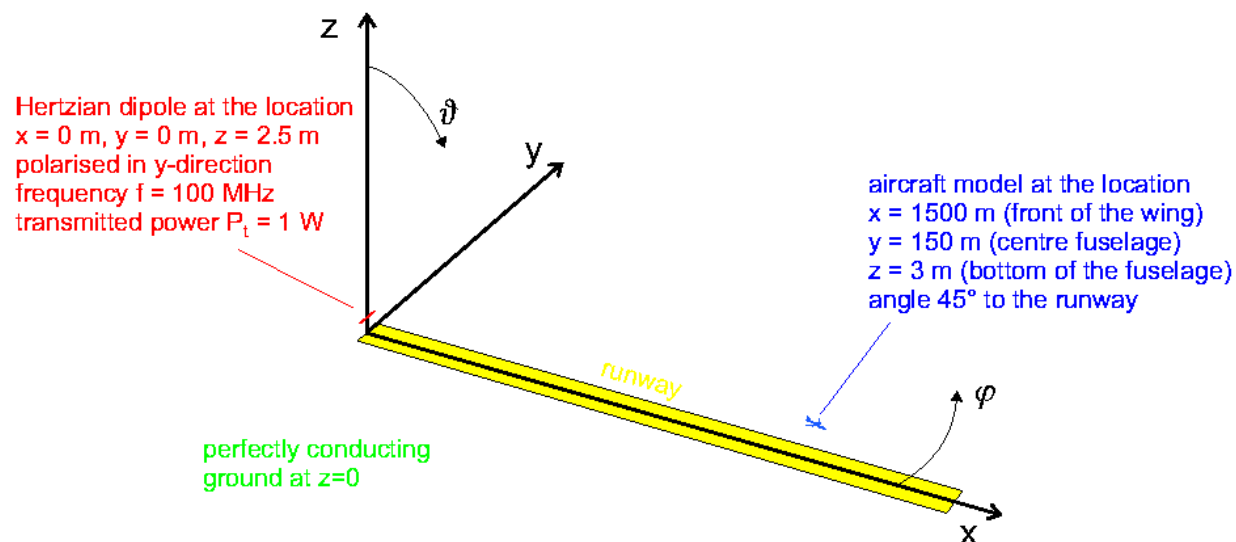
- Start with smart algorithms ($N \log N$ versus N^2 etc.) and best options (AI/ML) in the first place instead of brute-force HPC
- Evolution of CPUs in terms of clock rate, no. of cores and instruction sets (SSE, AVX512, ...)
- Massively parallel computing (fast interconnects for MPI, hybrid MPI / OpenMP, shared MPI-3 memory windows, ...)
- Use HPC enabled libraries (MKL, AOCL, Magma, StarPU, Mumps, ...)
- GPU accelerations (NVIDIA CUDA, OpenCL)
- Intelligent job scheduling systems supporting farming out multiple concurrent runs
- Constant process of profiling / performance testing / tuning

FLOPS (Floating Point Operations per Second)
for the top 500 supercomputers in the world



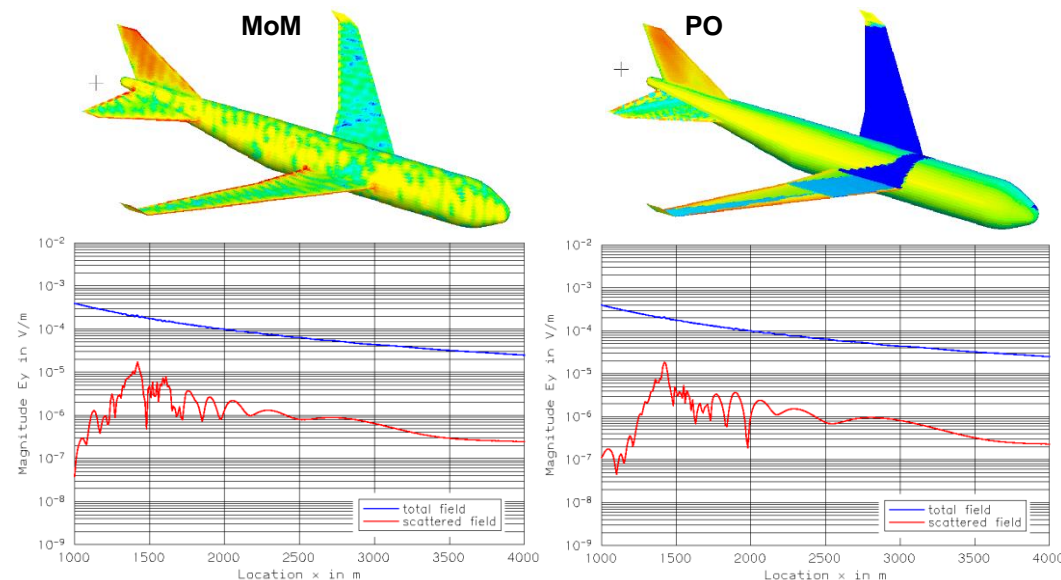
By AI.Graphic - Own work, CC BY-SA 3.0,
<https://commons.wikimedia.org/w/index.php?curid=33540287>

Aviation: Disturbance of Localizer by Aircraft



Computational effort in 1997:

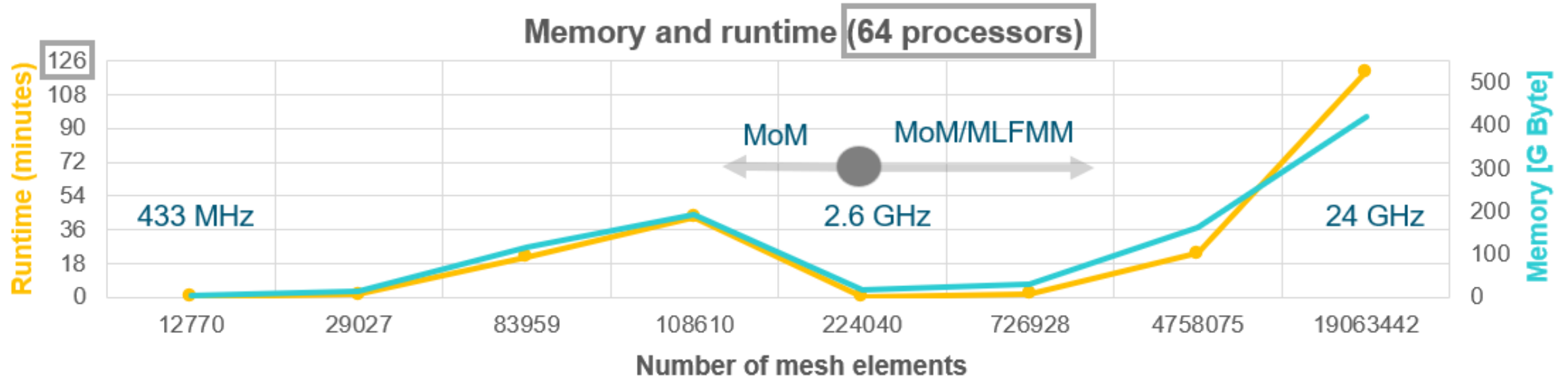
method	machine	memory	CPU-time
MoM (36358 basis fct.)	CRAY T3E, 384 nodes (incore, iterative solver)	19.7 GByte	384×1.7 h = 27 days
PO	Pentium II 400 MHz (seq.)	10.2 MByte	25 min



Laptop Computer today (2023):

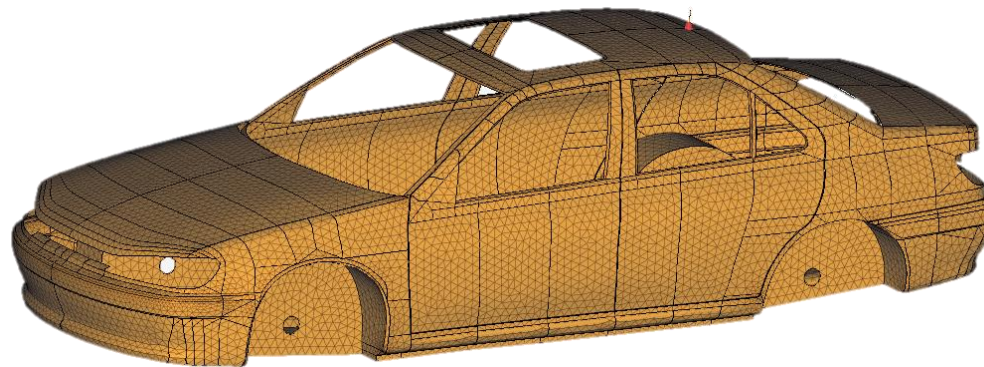
Intel i7-9850H 2.6 GHz
with 6 cores 32 GByte RAM

MoM 351 sec
MLFMM 19 sec
PO 0.4 sec



Feko version 2022.2.0

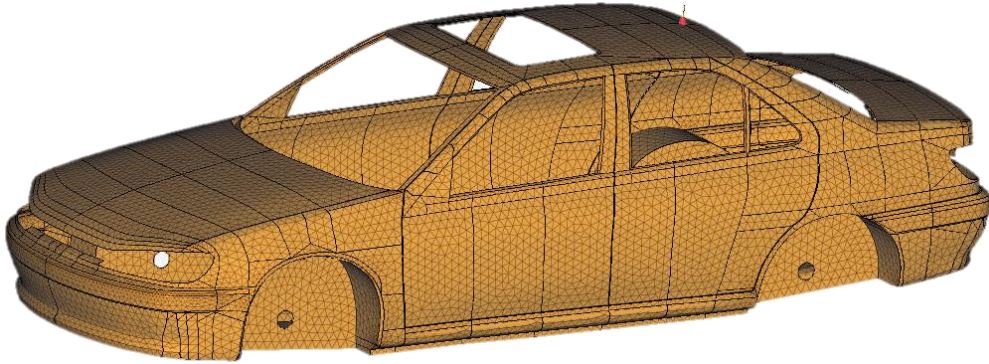
CPU: Intel Xeon Gold 6338 CPU @ 2 GHz
Dual CPU, 32 cores per CPU
Total cores: 64
Memory available: 1 TByte



Dimensions (approximate)

Length: 4.4 meters
Width: 1.8 meters
Height: 1.3 meters

Surface area: 20 m²



Dimensions (approximate)

Length: 4.4 meters
Width: 1.8 meters
Height: 1.3 meters

Surface area: 20 m²

Feko version 2022.2.0

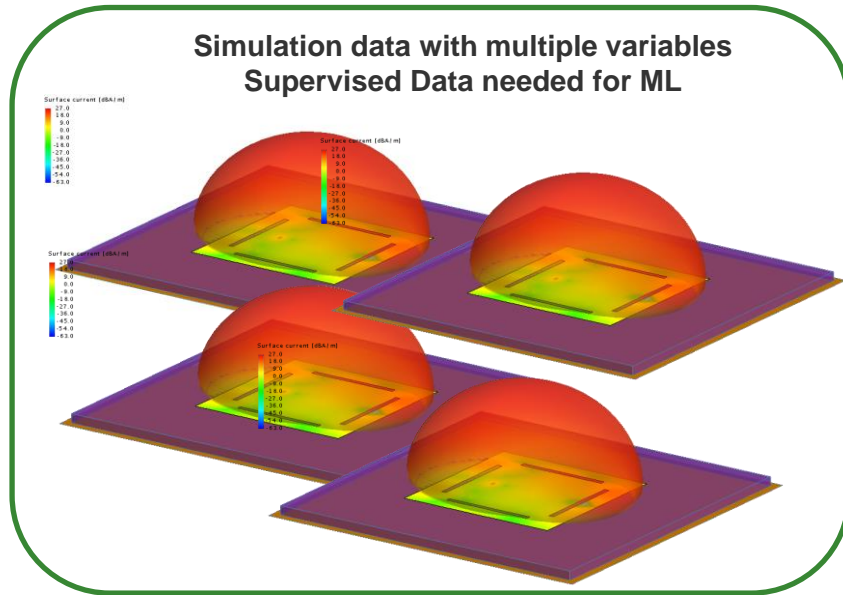
CPU: Intel Xeon Gold 6338 CPU @ 2 GHz
Dual CPU, 32 cores per CPU
Total cores: 64
Memory available: 1 TByte

No of processes = 64

Frequency	Unknowns	No. of mesh triangles	Runtime [s]	Memory [GB]	Solver
433 MHz	18,460	12,770	16	2.6	MoM
868 MHz	42,568	29,027	88	13.5	MoM
1.575 GHz	124,724	83,959	1,296	115	MoM
1.8 GHz	161,025	108,610	2,569	193	MoM
2.6 GHz	333,360	224,040	33	16.6	MLFMM
4.7 GHz	1,085,519	726,928	110	30.7	MLFMM
12 GHz	7,124,696	475,8075	1413	163	MLFMM
24 GHz	28,570,302	19,063,442	7,222	421	MLFMM
37 GHz	67,998,870	45,358,146	18,206*	925*	MLFMM

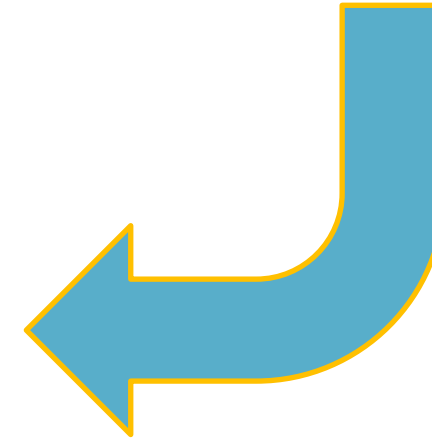
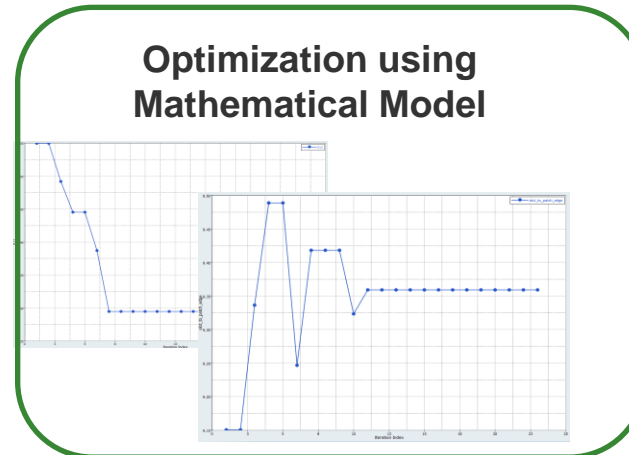
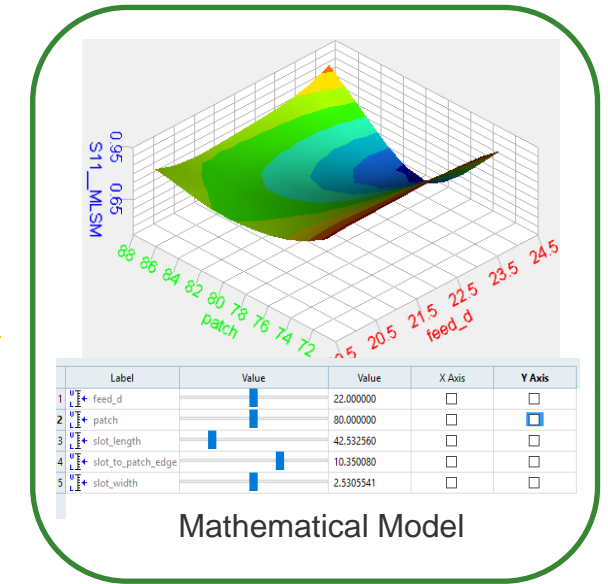
* excludes far field request

68 million unknowns in 5 hours on 64 processors !!



Machine Learning with Regression

Build a mathematical model that
defines the goal (Return Loss of the
Antenna etc.) as function of geometry
variables

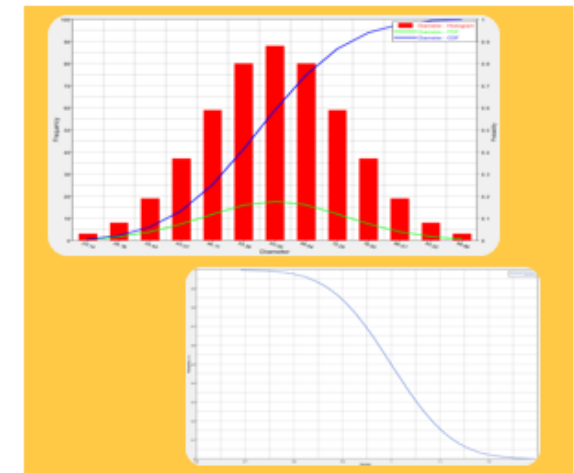
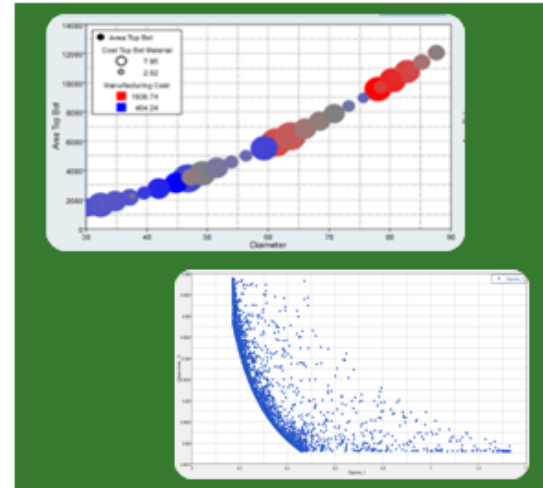
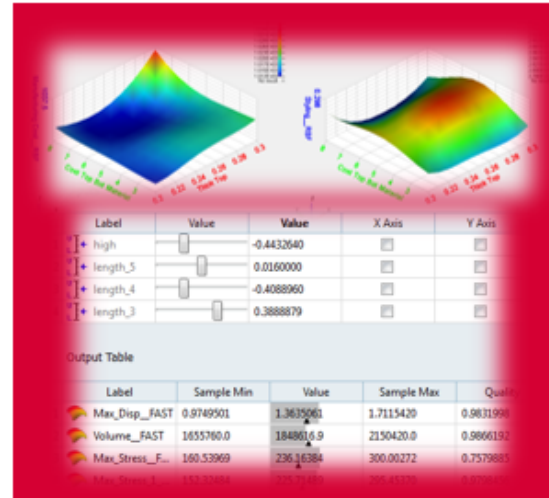
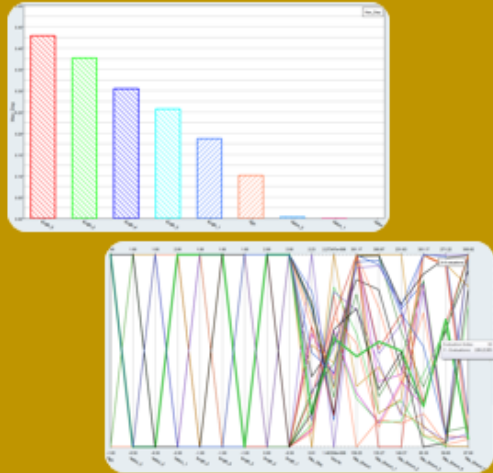


Investigate
relationships

Make
predictions

Identify
best design

Assess
reliability



Data Collection

Mathematical Model

Optimization

Stochastic

Machine Learning

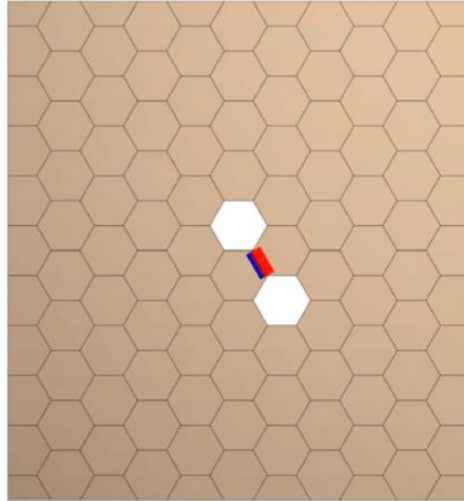
Altair® HyperStudy®

Powerful Design Exploration and Optimization

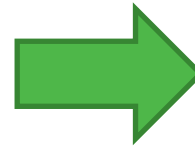
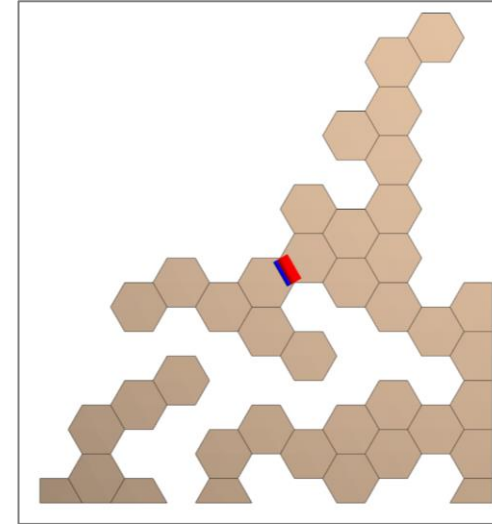
Optimization With Evolutionary Learning

WLAN Antenna

Design Space



Optimized Layout from ML

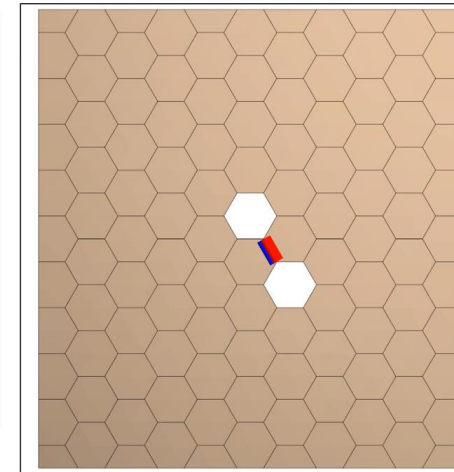
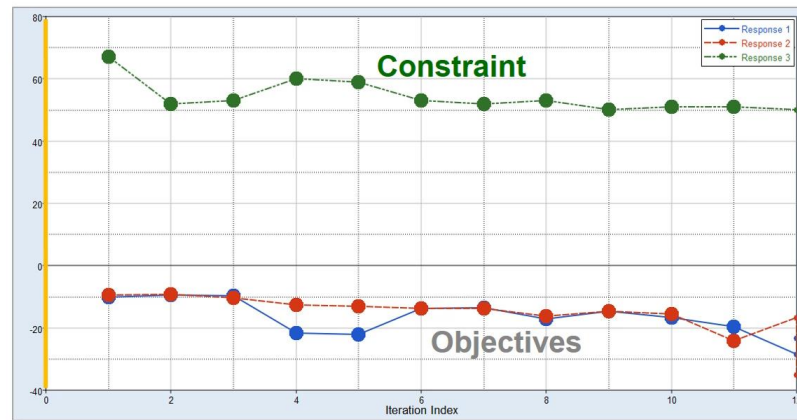


- Topology Optimization
- **112 binary input variables:** s_i - Number of possible design combinations: $2^{112} \approx 5.2 \cdot 10^{33}$!!
- **3 Output variables:** $S_{11}(2.44 \text{ GHz})$, $S_{11}(5.22 \text{ GHz})$, sum of conductive honeycomb elements
- **Training data:** New data generated in each generation of genetic algorithm

Optimization With Evolutionary Learning

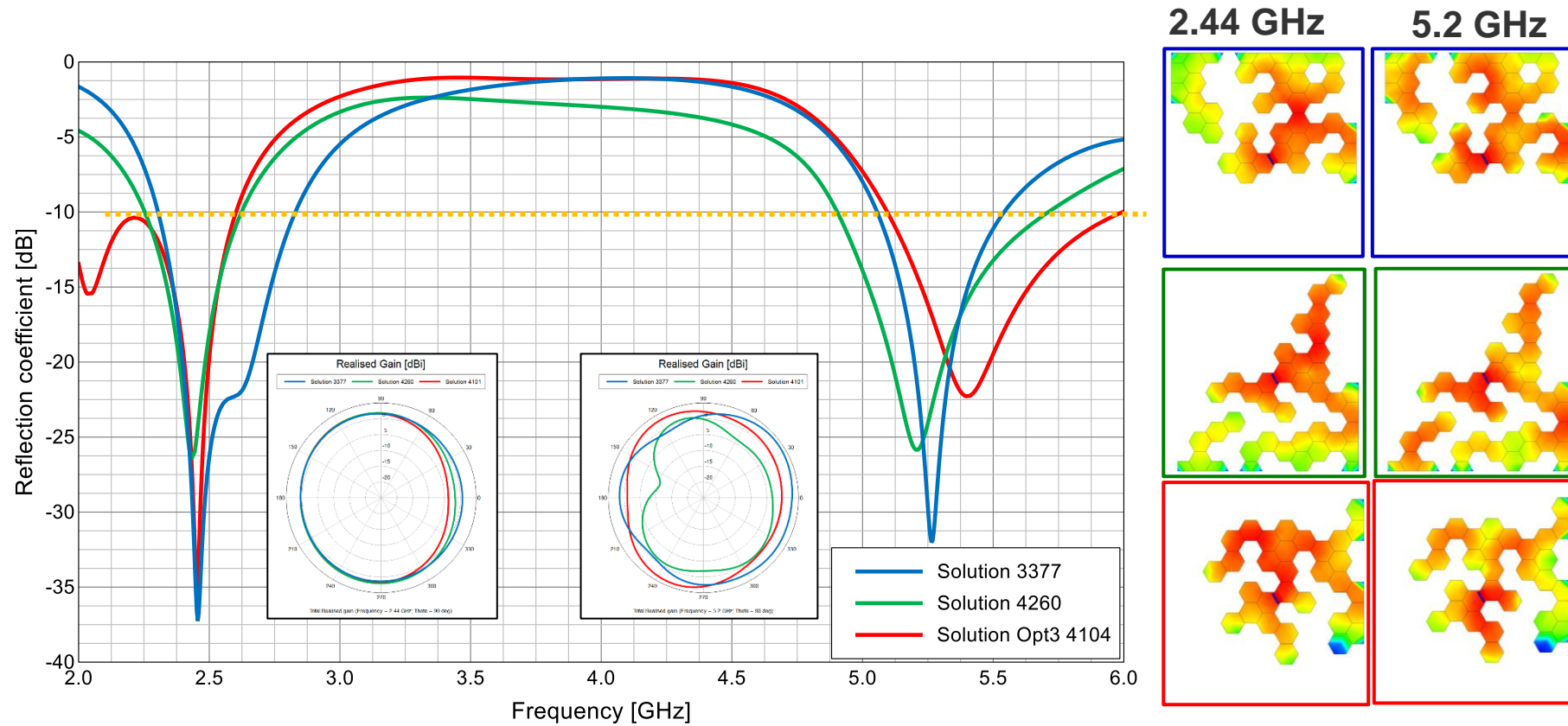
WLAN Antenna

- **Learning Process over 12 generations:**
 - **Objective:** Minimize S_{11} at **2.44 GHz** and **5.2 GHz** (better than -15 dB)
 - **Constraint:** Sum of honeycomb elements **< 50**
 - **After 4,300 iterations and 12 generations the multi-objective genetic algorithm has identified a set of Pareto-optimal solutions (far less than $2^{112} \approx 5.2 \cdot 10^{33}$ Combinations !!)**



Optimization With Evolutionary Learning

WLAN Antenna - Reflection Coefficient for Different Solutions



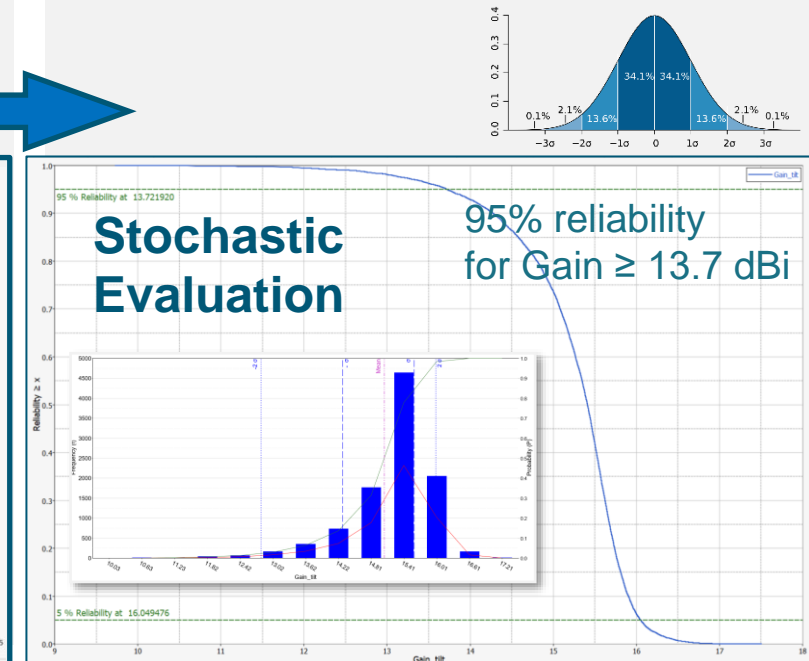
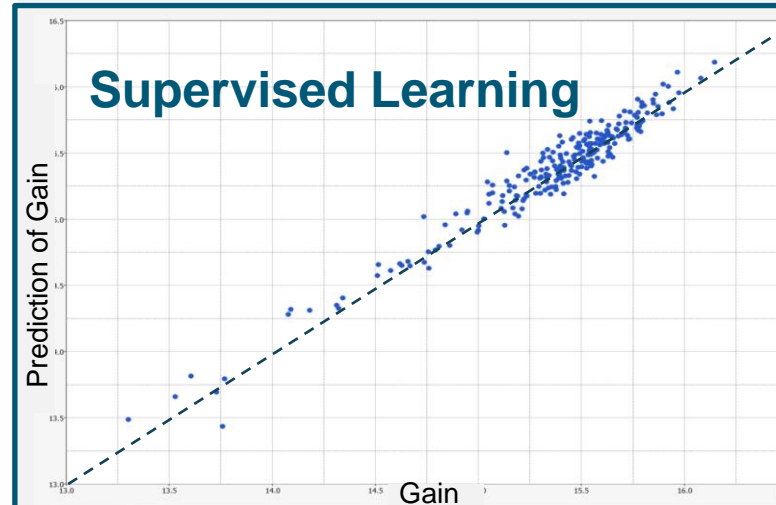
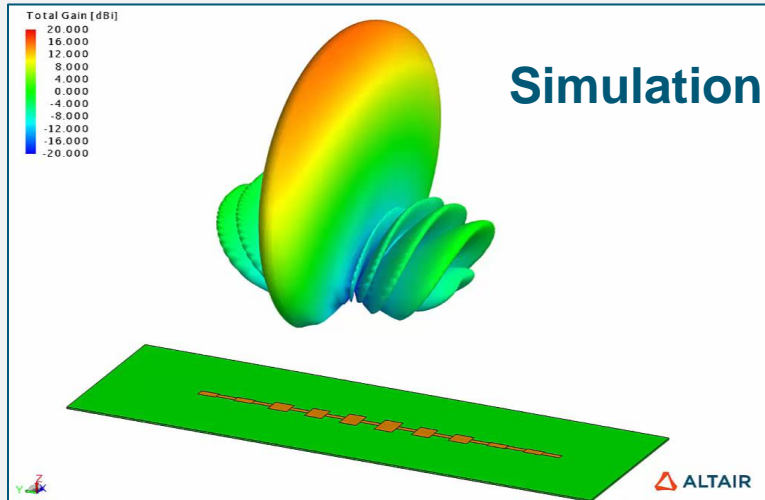
Christoph Mäurer, Peter Futter and Gopinath Gampala, "Antenna Design Exploration and Optimization using Machine Learning," European Conference on Antennas and Propagation (EuCAP 2020) Online, April 2020.

ML assisted Reliability Analysis for Radar Antenna Tolerances

- Radar Antenna Model at 76.5 GHz
- How is the antenna gain affected by **fabrication tolerances**?
- How reliable is the solution?
- Parametrized **Feko** model
- Couple **Feko** with Altair **HyperStudy**

- Use Design of Experiments (DoE) to create data for **supervised learning**
- Build **regression model** for prediction of the antenna gain
- Validate ML model with test data or cross validation
- Use validated model for stochastic reliability analysis

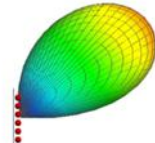
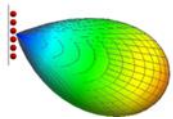
- Define distribution of input variables
- **Stochastic DoE with 10,000 runs** using fast ML model
- Evaluate distribution of responses and assess the reliability with cumulative distribution function



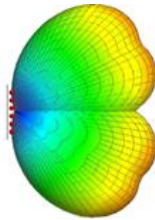
Downtown Munich (1000 m × 600 m)



An example of two individual beams of 5G antenna array



Envelop pattern of all possible beams



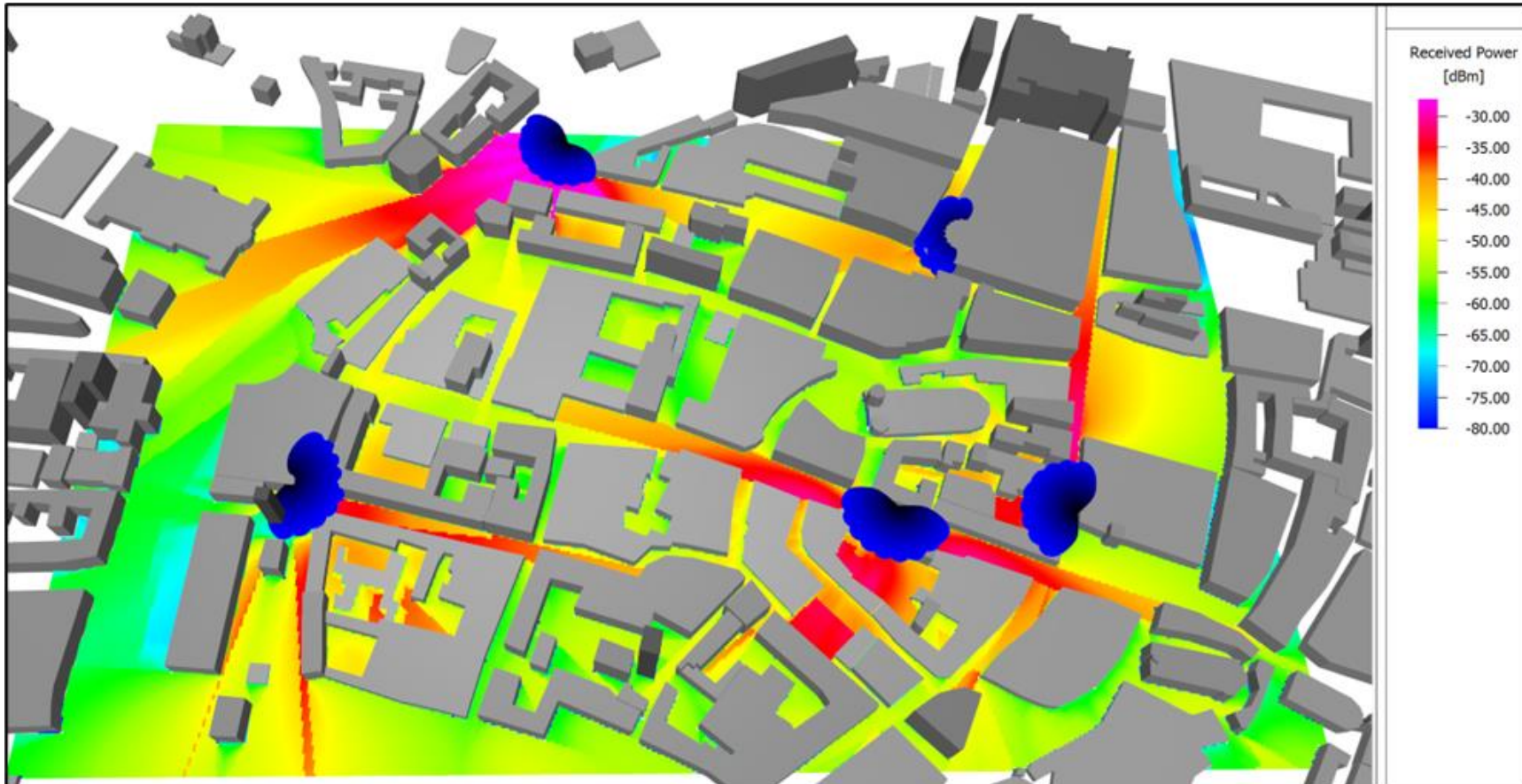
- 5G at 3.6 GHz with envelope patterns
- Result of interest is Received Power from all active antennas together.
- Four antennas (1, 4, 5, 8) are always enabled and the rest can be either off or on.
- Input Variables
 - (x, y, z) coordinates for ten antennas
 - Azimuth orientation of ten antennas
 - OFF or ON for six antennas (four are always ON)
 - **Total 46 variables!**

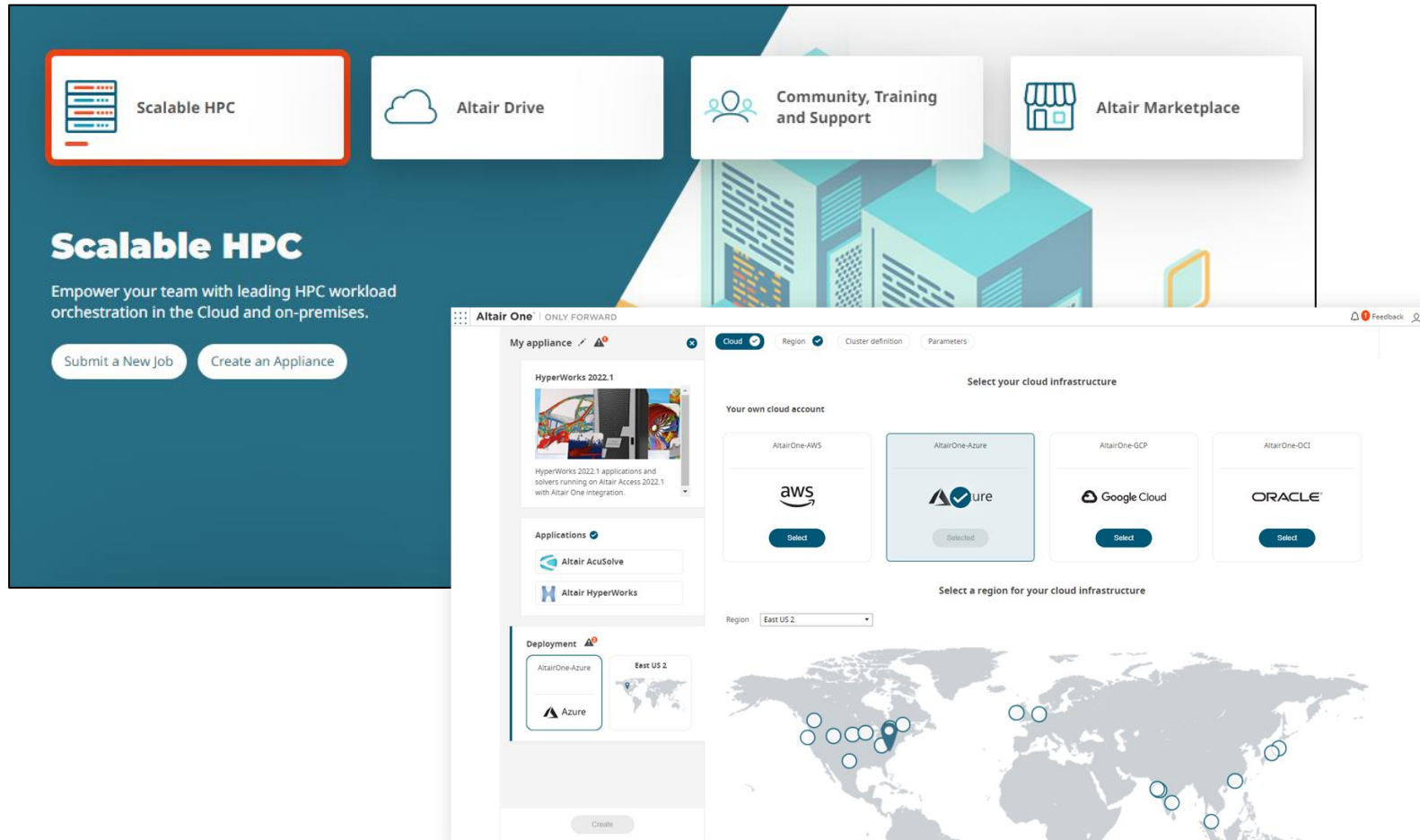
Goal:

“Good coverage” = power above **-80 dBm** in a large percentage of the area.

Downtown Munich (1000 m × 600 m)

Optimized with GRSM using ML - Coverage above **-80 dBm** = **93.8%** of area **With 5 Antennas**





Create Scalable HPC Clusters

- ✓ Multi-Cloud
- ✓ Multi-Region
- ✓ Applications
- ✓ Access Controls

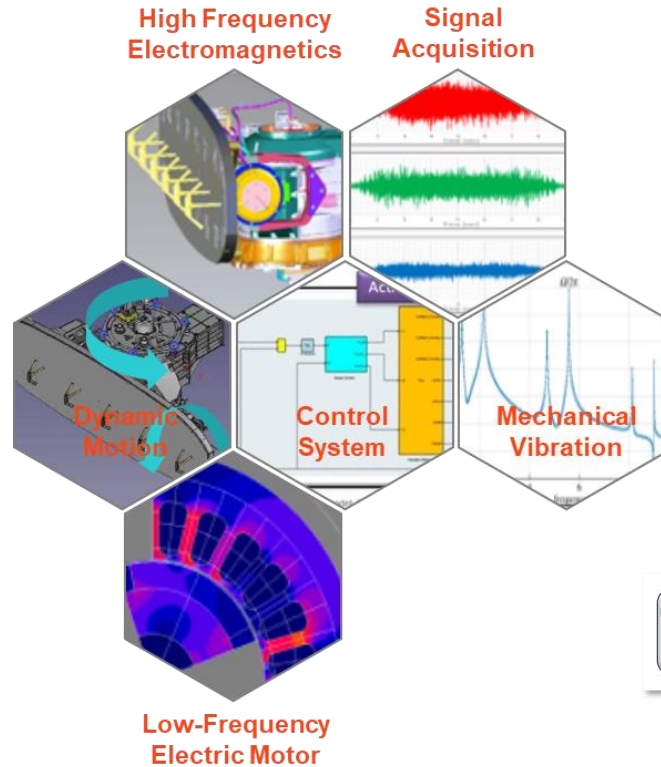
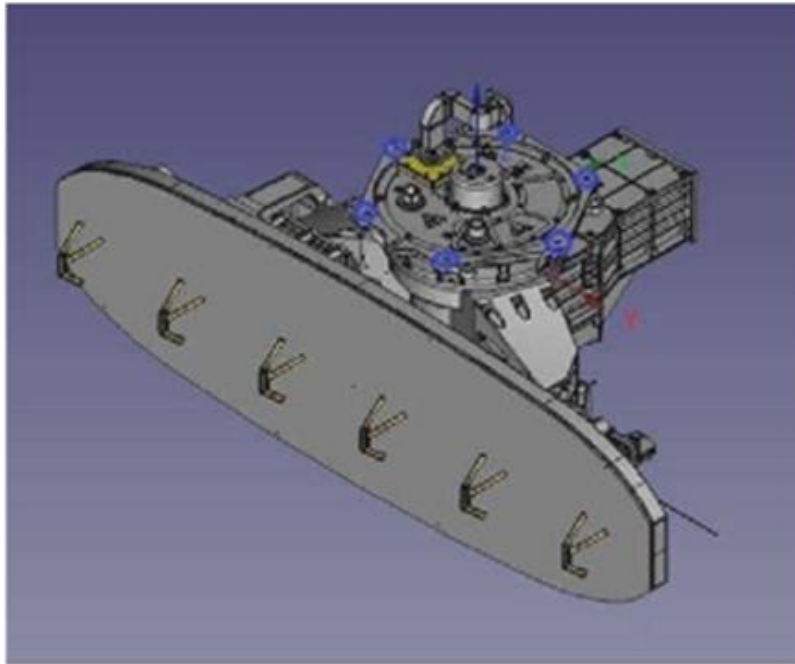
Jobs as service

- ✓ Multi-tenant compute cluster
- ✓ No need for a dedicated cluster

Airborne Radar Digital Twin

Challenge

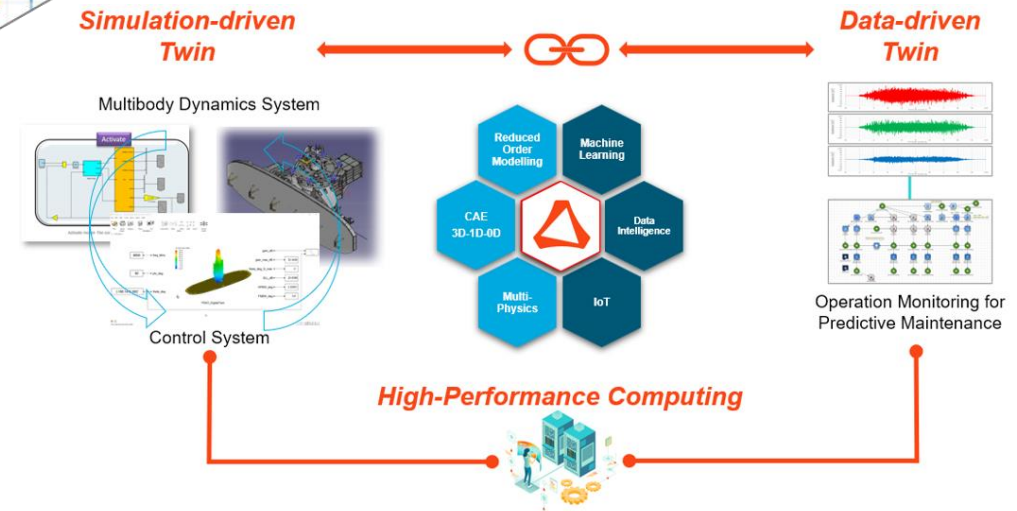
Ensure reliable performance of complex, mechatronic scan radar systems experiencing realistic environmental conditions



"To verify the performance of our radar units in virtual flights, it's fundamental that our Digital Twin condenses all physics, plus machine learning models based on real-world data, into one single environment."

Together, we built a process to define where and which sensors to include in our products to benefit from Predictive Maintenance."

– Romano Lazurlo, CTO Leonardo Electronics



Conclusions

- ▶ CEM Simulations are becoming dominant player in product design and Connectivity.
- ▶ Cloud Computing is becoming affordable with “Cloud On Demand.”
- ▶ Data Driven Design backed by powerful simulation techniques, Cloud Computing and AI/ML brings faster and better innovative products with reduced time to market.
- ▶ Convergence of Simulation, Cloud Computing and AI/ML is key to making Digital Twins possible.