

AI for Smart Manufacturing

Nexus Materials & Odyssee

Date: June 2025

Agenda

The Big Picture

Nexus Materials

Odyssee







The 2 AI Solutions from D&E Presented Today

Nexus Materials & Odyssee









I. Introduction to Nexus Materials





Hexagon's Digital Materials suite delivers materialfocused solutions with a predictive edge to empower engineers to reduce prototypes, accelerate material innovation and improve product performance:

- Material Data Management
 Digital Materials Laboratory
 Materials Informatics
- Multiscale Simulations









Overview – Capabilities & Products







Nexus Overview



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Nexus is an open platform that enhances digital engineering & manufacturing collaboration by connecting people, technologies and data, accelerating innovation and time to market.





Nexus Materials



Materials Connect

A cloud-native <u>visualization</u> and <u>data management</u> solution that provides seamless access to and dissemination of <u>material data</u>.



Great for marketing & sales, manufacturing, designers, CAE engineers and materials engineers.



Materials Enrich

The top-tier solution combining <u>material</u> <u>modeling</u> and <u>machine learning</u> to <u>enrich</u> <u>material data</u>, eliminating costly and timeconsuming experiments.



Great for designers, CAE engineers and materials engineers.



State of the Art Solutions for Material Data Enrichment

3 Classical ways for solving this challenge



Nexus Materials Enrich

Integrative solution to address those challenges



II. Deep Dive into & Demo of Nexus Materials Enrich



Nexus Materials Enrich

Motivation

Design Requirements

Simulations of fiber reinforced plastic parts material properties for various performances and test conditions

- Temperatures: -40, 23, 80, 120°C...
- Fiber contents: 30, 40, 50%...
- ...

Available Material Data

Only very few material properties are available



CAE Engineer

- I need additional material data to run FEA and ensure structural integrity.
- I am working against tight deadlines and cannot afford delays.



Material Engineer

- I have limited data available for this specific material grade.
- Generating more material data is time-consuming and costly.



Short fibre reinforced plastic





🐼 Materials Enrich

Nexus Materials Enrich

Concept

Illustrated on QS Tensile Data

Let's consider PBT resin as an example to enrich the available data:

Available material data = input

Missing material data = output

	Mass fraction 30%	Mass fraction 40%	Mass fraction 50%
-40 °C	\checkmark	?	?
23 °C	\checkmark	\checkmark	\checkmark
40 °C	?	?	?
80 °C	?	?	?
100 °C	?	?	?
120 °C	\checkmark	?	?



?



Materials Informatics – Materials Enrich





CAPABILITIES

- Test campaigns: define material test campaigns and identify lacking material properties and conditions
- **Data enrichment:** generate material data with accurate material modelling and machine learning (ML) predictions
- Cloud-based environment: facilitate access from any device and leverage computing resources

BENEFITS

- Reduce cost, time and waste: minimize lengthy and costly physical experimental tests
- Accelerate product development: deliver enriched material information and bring products to market faster
- Democratise ML technologies: enjoy an easy-to-use workflow without requiring advanced knowledge



Time & Cost Savings

Your material data enrichment campaign

18 virtual tests (1 minute 3 seconds			
Pure AI (18)			720 credits
Enriched property	Qty	Credits	Test subtotal
Quasi-static stress-strain curve	18	40	720
Pre-trained AI models (1)			100 credits
			Credits
PA66			100





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Material Engineer



How Materials Enrich is helping

Predict additional material behaviours across both temperatures and fiber weight fractions

Initial Data



Data points for PA66 GF35 %

- at room temperature of 23 °C
- at cold temperature of -40 °C
- at high temperature of 120 °C

at a weight fraction of 35 %

Predict additional material behaviours:

- a) at 4 additional temperatures of 0 °C, 60 °C, 90 °C and 180 °C
 - for the same weight fraction of 35%
- b) at all 7 temperatures for additional weight fractions of 25% and 50%

	25 %	35 %	50 %
-40 °C	2000 Contraction of the second	\bigcirc	?
0°C	2000 Contraction of the second	and the second s	······································
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90 °C	2000 Contraction of the second	and the second s	2 ALL ALL ALL ALL ALL ALL ALL ALL ALL AL
120 °C	2000 Contraction of the second	\bigcirc	2 Particular
180 °C	2000 Contraction of the second	non in the second secon	2000 Contraction of the second







Time Savings

Cost Savings

CO₂ Savings



(a) Let's enrich the data for PA66 GF35 % across the temperature range

Tensile curves of *experimental* (—) and *enriched* (---) material data:



	25 %	35 %	50 %
-40 °C	Summary Constraints	\bigcirc	Summer Summer
0 °C	and the second s	2000 Contraction of the second	Summing and the second
23 °C	Summer of the second se	\bigcirc	Summer of the second
60 °C	South and the second se	South State	Summary and
90 °C	and the second s	200 Contraction of the second	Summary Constraints
120 °C	Southanness and so	\bigcirc	Summer Summer
180 °C	and the second s	and the second s	and a superior



(a) Let's enrich the data for PA66 GF35 % across the temperature range

Master curves of *experimental* (---) and *enriched* (---) material data:





CAE Engineer



Optimizing Input Efficiency

Determine the minimum number of inputs required for accurate predictions

Initial Data



Data points for PPA GF

- at room temperature of 23 °C for three mass fractions of 30 %, 40 % and 50 %
- at three temperatures of -40 °C, 23 °C and 180 °C at a mass fraction of 30 %
- Predict additional material behaviours across various temperatures and mass fractions
- Assess the quality of predictions with a reduced number of inputs

	30 %	40 %	50 %
-40 °C	\bigcirc	2000 million and a second	······································
23 °C	\bigcirc	\bigcirc	\bigcirc
40 °C	and the second s	and the second s	and the second s
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160 °C	······································	2000 Participant	2 Martine Contraction
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200 °C	2 million and a second	2 million and a second	numerican and the second secon
210 °C	non ?	nonina and a second	none and the second sec

Master curves of imported (•), experimental (---), and enriched (----) material data





Core Concepts Behind Nexus Materials Enrich





What is a Pretrained Model

Pretrained Models refer to Pretrained Master Curves or Pretrained AI (Neural Networks) Models



Master curves are mathematical functions that describe the evolution of material constitutive law parameters as function of conditions e.g. temperature, strain rate, humidity etc.



Master curves should be understood as multidimensional functions rather than 2D functions.

The **master curves** are also called **pretrained master curves** or **pretrained AI models** interchangeably in Materials Enrich, depending on how they are assessed using whether **mathematical equations** or **neural networks**. Let's group them under the term of **Pretrained Models**.



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User Action Automated by Materials Enrich 2 3 5 **Translate** Output Input Retrain Load Load the adequate pretrained models The user provides at least Translate a stress strain Retrain the pretrained Compute the output one input data point models w.r.t. the provided curve into constitutive based on the retrained features input data models Failure -50 50 100 50 100 150 Temperature [°C] 150 Temperature [°C] HEXAGON 27 hexagon.com

How is a Pretrained Model used to generate data in Materials Enrich

Adding Pretrained Models on the top of the 3 Enrichment Technologies

Pretrained Models make it possible to generate exhaustive data out of very few input data



How is accuracy estimated

Enrichment related – Accuracy estimate

Estimation of accuracy along interpolation dimensions



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THE GOOD PICTURE TO HAVE IN MIND

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Hexagon's AI/ML Solution **ODYSSEE**

Enhancing Engineering through Machine Learning & Artificial Intelligence



Overview of the Horizontal Enablers – ODYSSEE

ODYSSEE CAE

Real-time predictions within DoE
 boundaries

- Evaluation of wide array of scenarios & rapid turnaround once unknow scenario takes place
- Sensitivity analyses, Robustness studies and
- Optimization performed in real timeFaster design to stress iterations,
- resulting in faster design cycles
 Export EML models (limited or
- <u>Export FMU models (limited or</u> <u>unlimited)</u>
- Export Nastran/Marc sub-models

ODYSSEE A-Eye

Image-based prediction

Sound-based prediction

Tailor-made applications enabling

non-experts to leverage machine

learning methods and/or predict

Prediction: labels, integer/real,

results in lieu of simulation

curves, Image

CAD-based prediction

ODYSSEE Solver

- Enabling Digital Twin, Multiphysics, Virtual prototyping, Health monitoring projects
- Co-Simulation through FMU
- model exchange
 Embedded CAE Software & Electronics (FMU or Smart
- Superelements)
- Data Mining

Human Beseurcat ILegal IAccounting IFinance IMarketing

- Optimization
- Possibility to create own scripts (Quasar/Python)
- Integration into SimManager, Cradle, Marc, Apex, Digimat...)

ODYSSEE Explore

- Data pre & post-processing enabling thorough analysis and mining
- Process & analyse data to setup machine learning projects
- Enabling troubleshooting of machine learning models, understand prediction deviances

ODYSSEE FMU Builder ODYSSEE FMU RunTime

- ODYSSEE FMU Builder & ODYSSEE FMU Runtime are products without interface to respectively create and run FMU model.
- These one can be integrated into FEA models, electronics....
- The versions integrated into Marc call respectively Mentat FMU Builder & Marc FMU Runtime



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Real-Time predictive modeling and optimization





Machine Learning for engineering practices



Image/CAD based learning and prediction





Machine Learning for Images and production



Why ODYSSEE as AI/ML Solution for Material / Process / CAE



Needs less data

POD/ROM based (vs Deep Learning, Neural Networks and classic Machine Learning)



Needs little CPU Power



Data Security (On Premise Solution)



Cutting edge image/morphology to performance feature (A-Eye)



User Experience (UX) and CAE oriented mindset > Easier deployment



Compatible with the MSC-One licensing system





ODYSSEE CAE – Case Studies

Explicit Analysis – Crash – Front Crash in Real-time



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Challenge

- Crash/safety configurations depend on many parameters.
- Investigating them or optimising the design requires multiple simulations.
- Explicit FEM simulations typically require hours and design exploration studies can take days.

Solutions

- By first identifying the most sensitive variables, ODYSSEE enables design optimisation using very few evaluations of the model. Ultimately, ODYSSEE can be used to find the best design.
- Design exploration studies can be performed in minutes.

- Using ODYSSEE allows engineers to determine the most sensitive parameters first and then evaluate different scenarios (in a few seconds instead of hours) with historical curves and animations with elemental info (stress, strain...)
- Finally, ODYSSEE can perform optimisation (multi constraint), multi objective) and generate optimal responses (curves and field data) in a few seconds.





ODYSSEE CAE – Case Studies

Manufacturing – Resistance Spot Welding



Challenge

- RSW is a widely used process in the automotive industry and requires extensive knowledge on material and joining parameters to be well executed.
- Very often it requires hundreds of tests to define a robust welding schedule for a specific material stack up.
- This task involves welding coupons and then performing tensile tests ensuring the desired strength is obtained.

Solutions

 Combining ODYSSEE with Simufact Welding, the VMC team is augmenting welding simulations by identifying patterns in the results that can be used to derive optimised welding schedules by controlling weld current, number of pulses and electrode force.

- Interpolated data generated from ODYSSEE is utilised to create an optimised RSW schedule.
- Schedule is implemented on new welds with different materials.





ODYSSEE A-Eye – Case Studies

Acoustics – Sound spectrum prediction from images



Challenge

- Capability to predict results as curves based on design images (simulation & experiments).
- Quickly predict the sound spectrum over the entire frequency range (experimental or simulation) from a tire tread design image.

Solutions

- ODYSSEE A-Eye: image-based prediction (you can create a customisation dedicated for this application and this can be used by non-experts (technicians & designers)
- In this case, 8 known tire tread design images with the associated sound spectrum are used as the learning database.
- For a new tire tread design, the customisation can predict the sound spectrum.

Benefits

• The ODYSSEE approach needs few images to predict accurate results.





ODYSSEE A-Eye – Case Studies

Quality Production – Casting parts quality assessment (from production pictures)



Challenge

- The objective is to verify if the cast metal parts are valid or defective.
- There are many types of defects in casting like blow holes, pinholes, burr, etc.
- With Volume Graphics, it is possible to predict the quality in 3D. Is it possible to have a complement solution in 2D?

Solutions

- Use ODYSSEE A-Eye to predict if a new cast part is valid or not.
- Compare database sizes of 500, 240, 123 and 40 images.
- Image processing is applied on the images to extract 5 features for each correlation coefficients to reference images.
- Finally, a predictive method is applied on the features database.

- Works for a database with only 123 images.
- Automatic inspection process with 100% success.
- Ready for industrial production deployment.



ODYSSEE CAE – Case Studies

Acoustics – Transmission loss optimization of a motorcycle exhaust





Challenge

- Exhaust systems are important for the attenuation of the engine noise in motorcycles.
- The sound transmission loss is used to measure the sound attenuation through the system.
- Transmission loss needs to be maximised across the frequency spectrum in order to ensure quieter operation.

Solutions

- Combining Actran acoustic simulations with ODYSSEE creates a ROM and enables rapid performance optimisation to maximise the transmission loss of the exhaust system.
- The geometric parameters of the muffler and the catalytic converter are optimised.

- Accelerated optimisation of a motorcycle exhaust system via the use of a ROM.
- This process optimises the system faster as no simulations of the system are performed during the optimisation process.





ODYSSEE CAE – Case Studies

Thermal Analysis – Circuit Board Analyse



Challenge

- When there are 1s overpower peaks on the chip:
 - How to control the heat dissipated?
 - How to limit the thermal expansion of the microchip?
 - How to limit the high stress in the leads of the microchip? (no failure in weld)

Solutions

- MARC: Prepare a data base of results
 associated with each overpower peaks tested.
- · ODYSSEE CAE used for prediction in real time:
 - Parameters = 3 (Amplitude of the overpower peak, "curvature" of the loading step, "curvature on the unloading step).
 - Output: Temperature on the chip, Stress in leads and displacement measured on the case.

- Know the parameter effects on the result.
- Save user time: ODYSSEE CAE results are obtained in a few seconds against MARC simulations that take 2 min.





ODYSSEE Solver – Application

Digimat-MS – UQ based design for reinforced plastics



Challenge

- Material properties such as stiffness and strength, and injection moulding predictions are sources of uncertainties.
- These uncertainties provide an additional challenge in multiscale simulation to validate the robustness of a given design.
- Most of the virtual designs are deterministic and ignore these numerous sources of uncertainties.

Solutions

- Digimat offers a simplified workflow that performs multiscale material modelling from the manufacturing process to the structural analysis.
- The workflow also integrates artificial intelligence (AI) and uncertainty quantification (UQ) to account for material properties uncertainties.
- A UQ plugin is available to prepare and run high fidelity design of experiments (DoE) using Digimat-MS simulations.

- The reliability of the studied structural analysis can be evaluated by considering the propagation of different sources of uncertainties.
- The automated workflow embeds advanced expertise in material science, AI and UQ.
- Prescriptive solution allows to enhance the product quality by considering the numerical uncertainties.
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ODYSSEE Solver – Applications

Cradle – Wind Turbine Field Positioning





ODYSSEE Explore

Data analysis and data mining



CAPABILITIES

- ODYSSEE Explore is an application for data mining and AI techniques:
 - allows to analyse the inputs and understand if the data is ready to be exploited by the Machine Learning software.
 - helps to interpret the output show why there are difficulties to predict some cases.

BENEFITS

- Customisable Dashboards display multiple visuals simultaneously, aiding data analysis and Machine Learning insights. Visuals within Dashboards are interconnected for cohesive exploration.
- The Data Mining tab offers tools for data analysis, behaviour understanding, and data quality assessment: Covariance/Correlation, K-Means, PCA, PCoA, and Dendrogram.

FEATURES

- Data Management: data uploading and transformation.
- Visualisation allows to make some basic plots to show relations, behaviour,...(1D plot, 2D plot, Heatmap and Parallel plot.)





Al for Smart Manufacturing: The big picture



