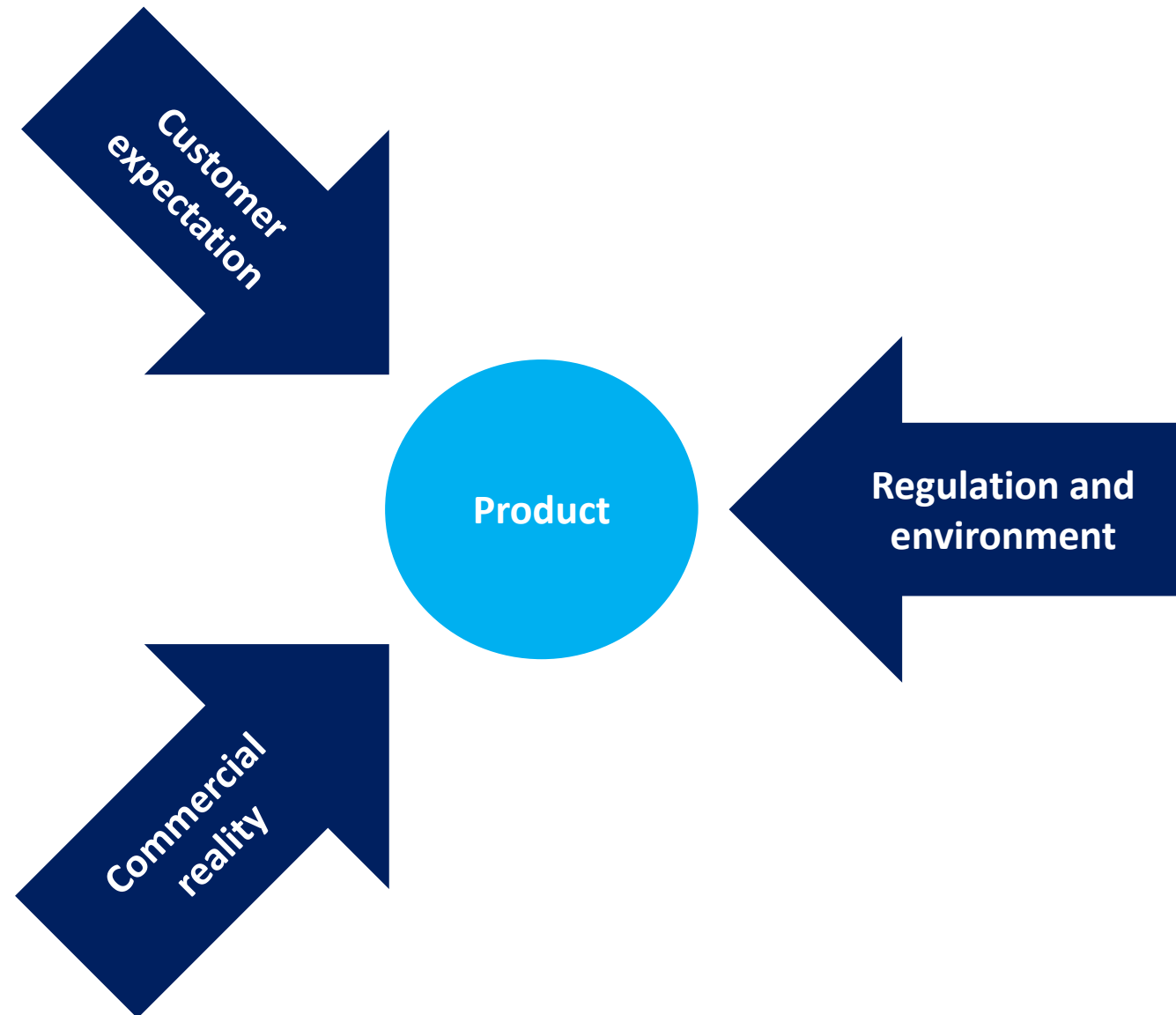


Digital Future of Product Development & Validation

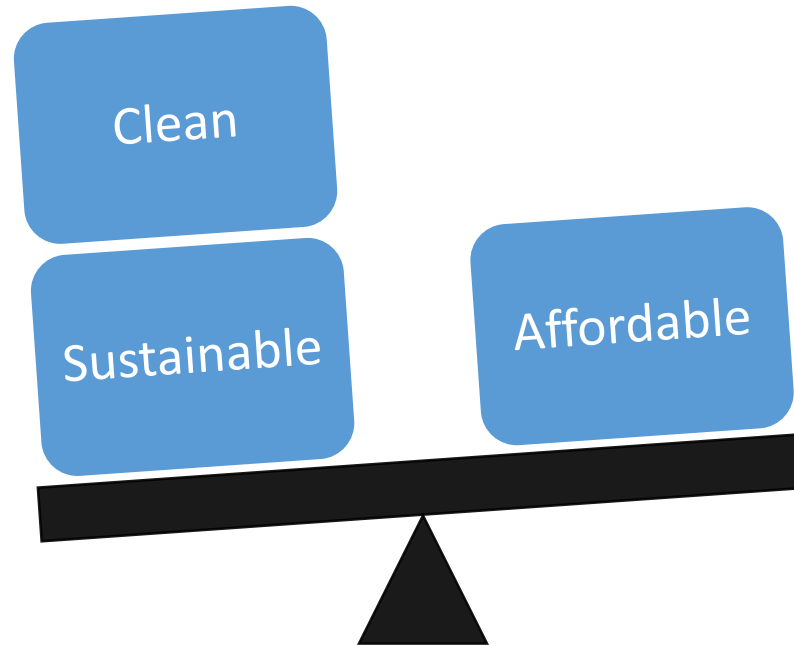
Professor Chris Brace



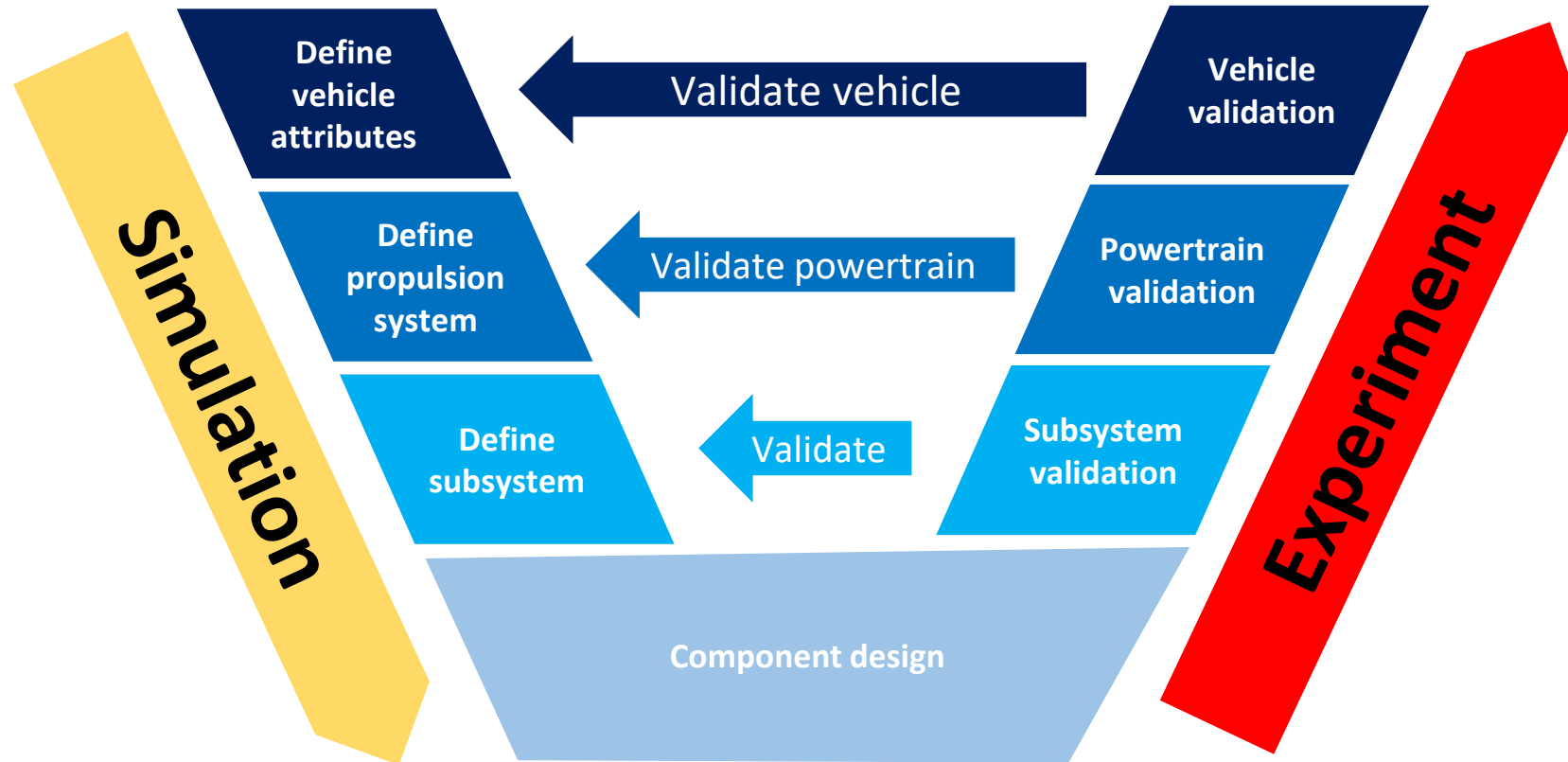
Pressures on the automotive sector



Future needs



Validation, key to success

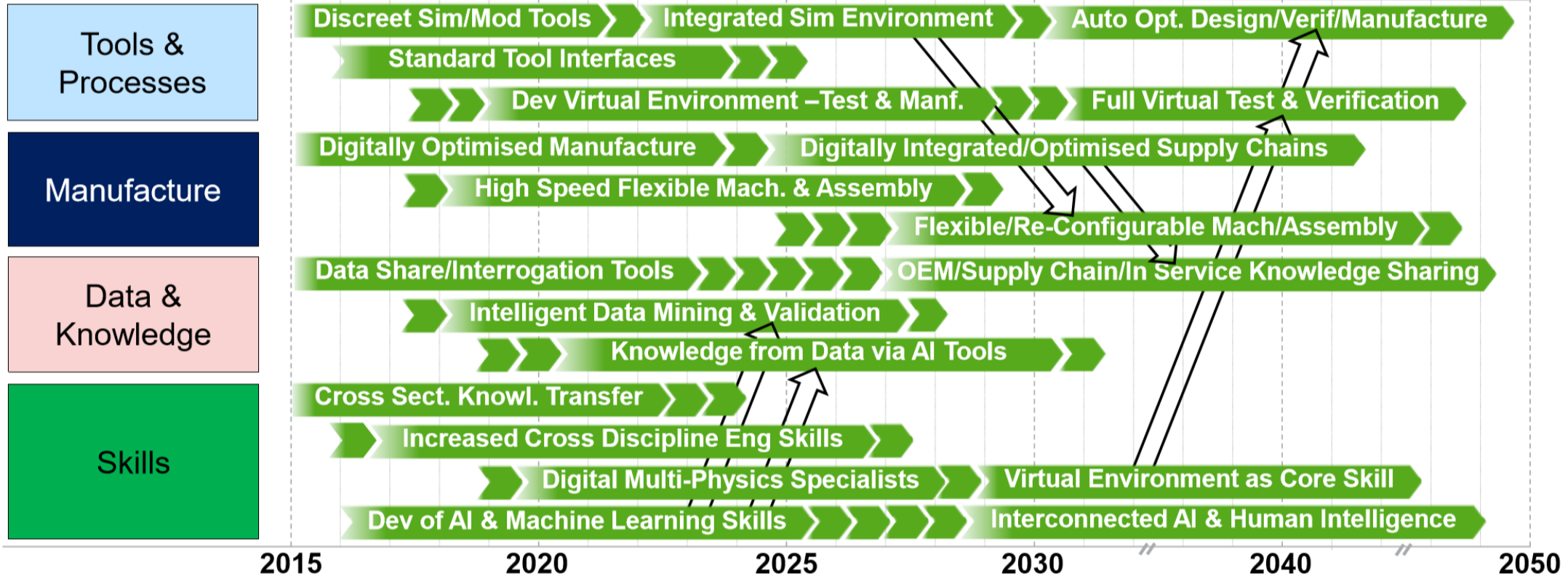


Virtual Product Engineering – New Tools, Manufacturing, Data & Skills to deliver significant productivity benefits



Drivers/Targets

Policy:	Increased Regulatory Complexity		Digital Product Homol.	Design/Manf. Process Homologation	
Computer (Calc/s.\$1k)	10 ¹²	10 ¹⁴	10 ¹⁶	10 ¹⁸	10 ²¹
Software Complexity:	1x	10x	1000x	100,000x	10 ⁸ x
Concept to Job1:		5 years	4 years	3 years	18 months
Development Costs:	100%	-25%	-50%	-75%	
Validation in Virtual Env:	<1%	20%	70%	90%	95%+



Tools & processes evolve to an integrated simulation environment with auto system optimisation & verification



Drivers/Targets

Policy:	Increased Regulatory Complexity		Digital Product Homol.		Design/Manf. Process Homologation	
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Tools & Processes

Manufacture

Data & Knowledge

Skills

Standardised interfaces lead to an integrated simulation environment across product development & manufacturing

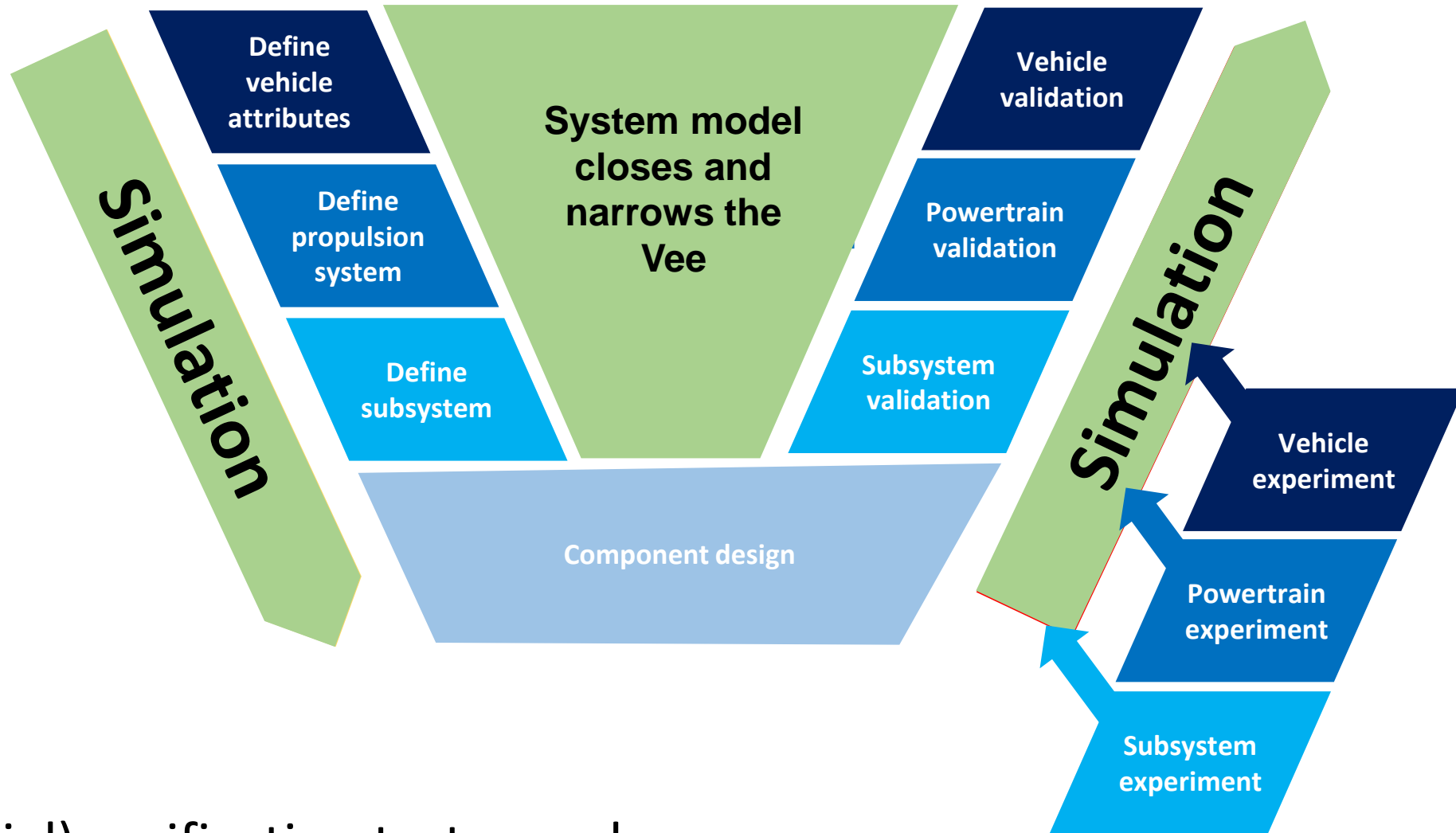
The connected simulation environment enables multi-factor & multi-physics optimisation in combination with validation/manufacture

Continued development of simulation and modelling tools but with an increasing emphasis on standardised interfaces

In parallel with an integrated simulation environment, a connected virtual environment using 3D virtual & augmented reality developed to combine external factors & challenges

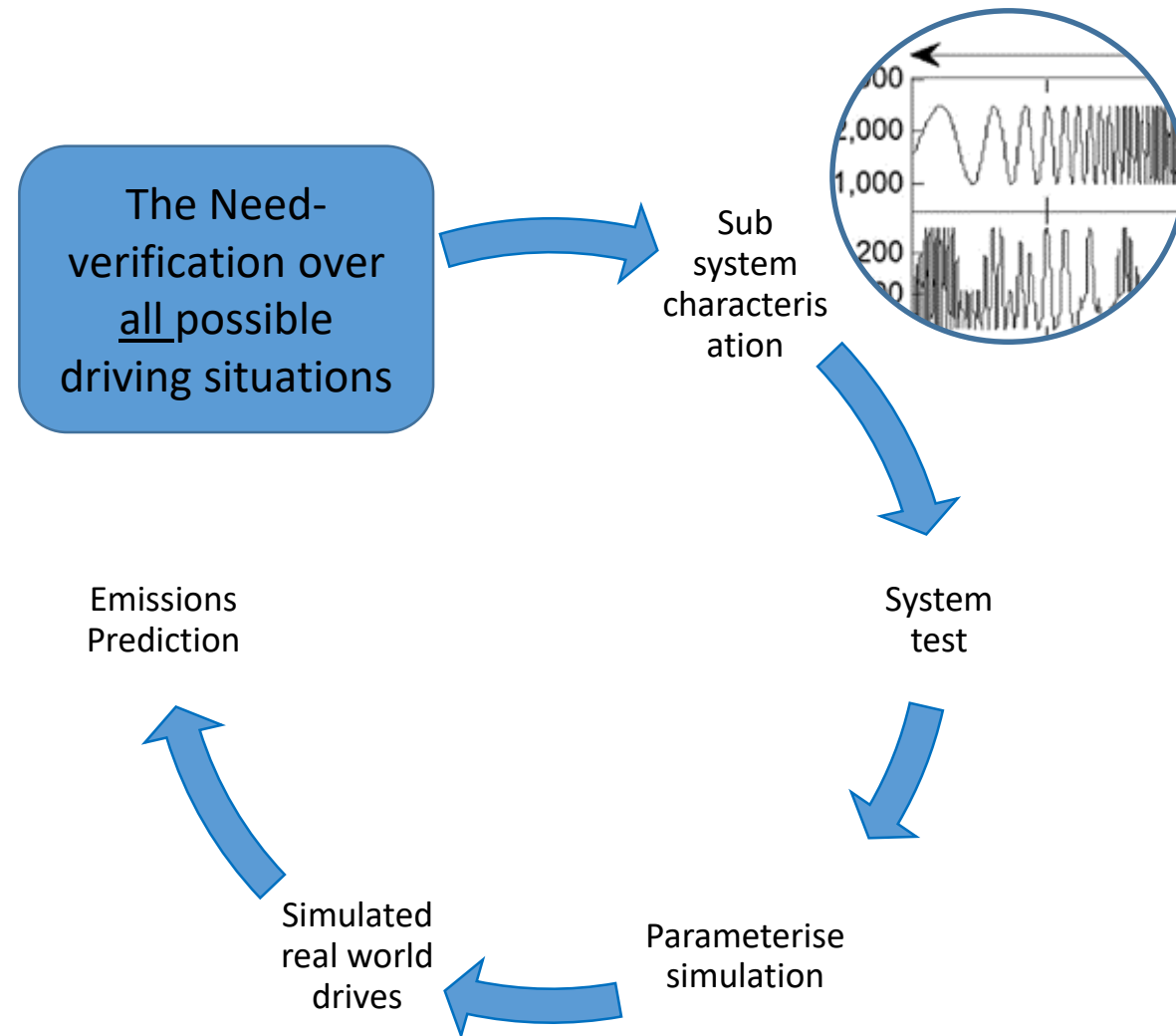
2015 2020 2025 2030 // 2040 // 2050

Vee process is still needed

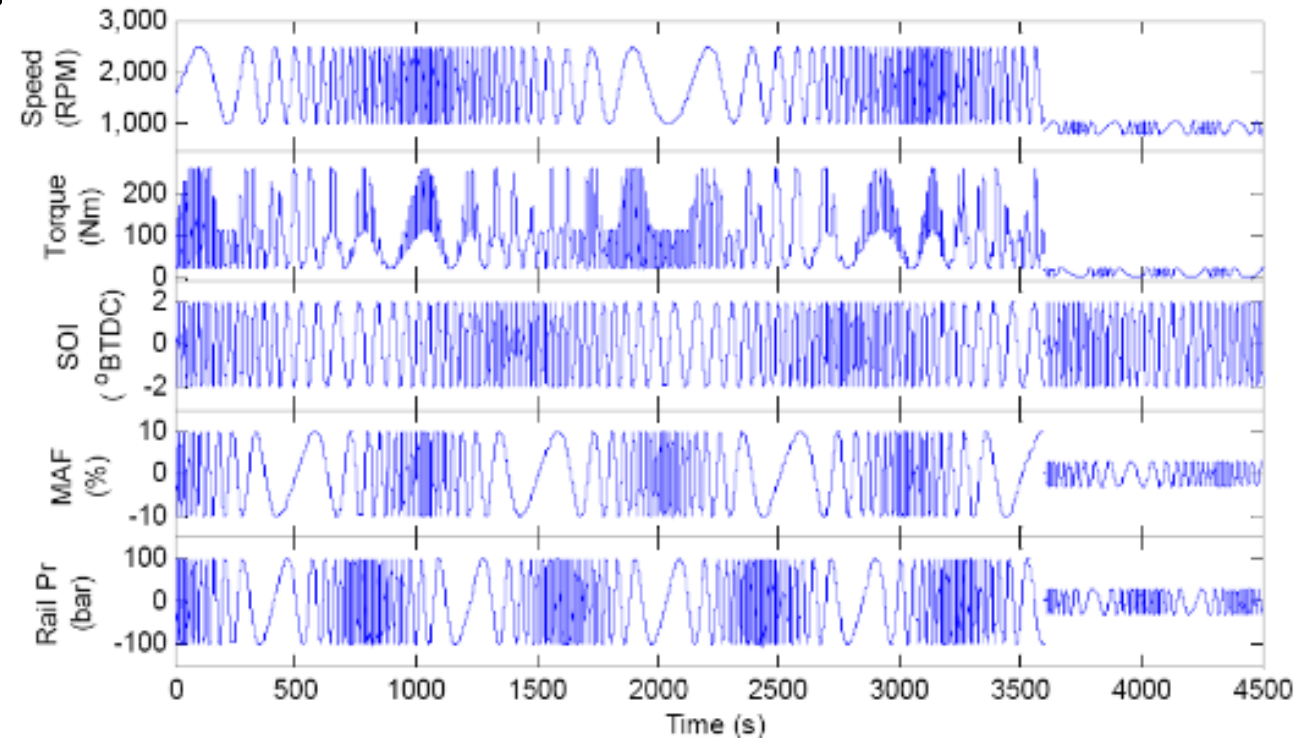


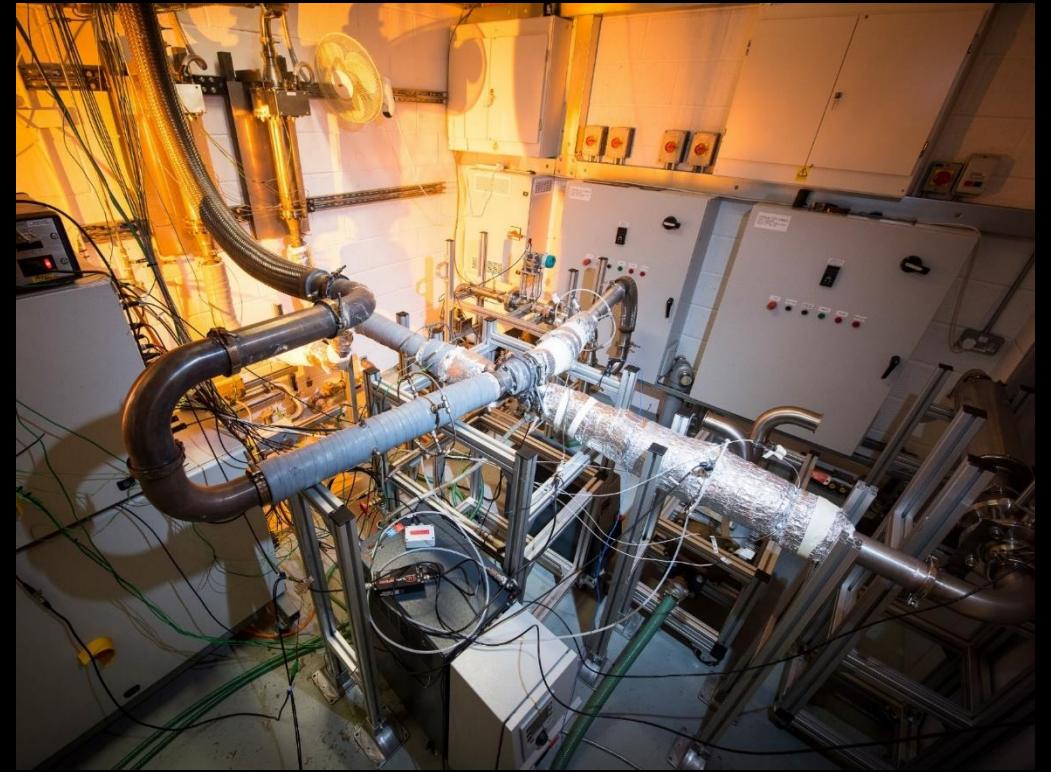
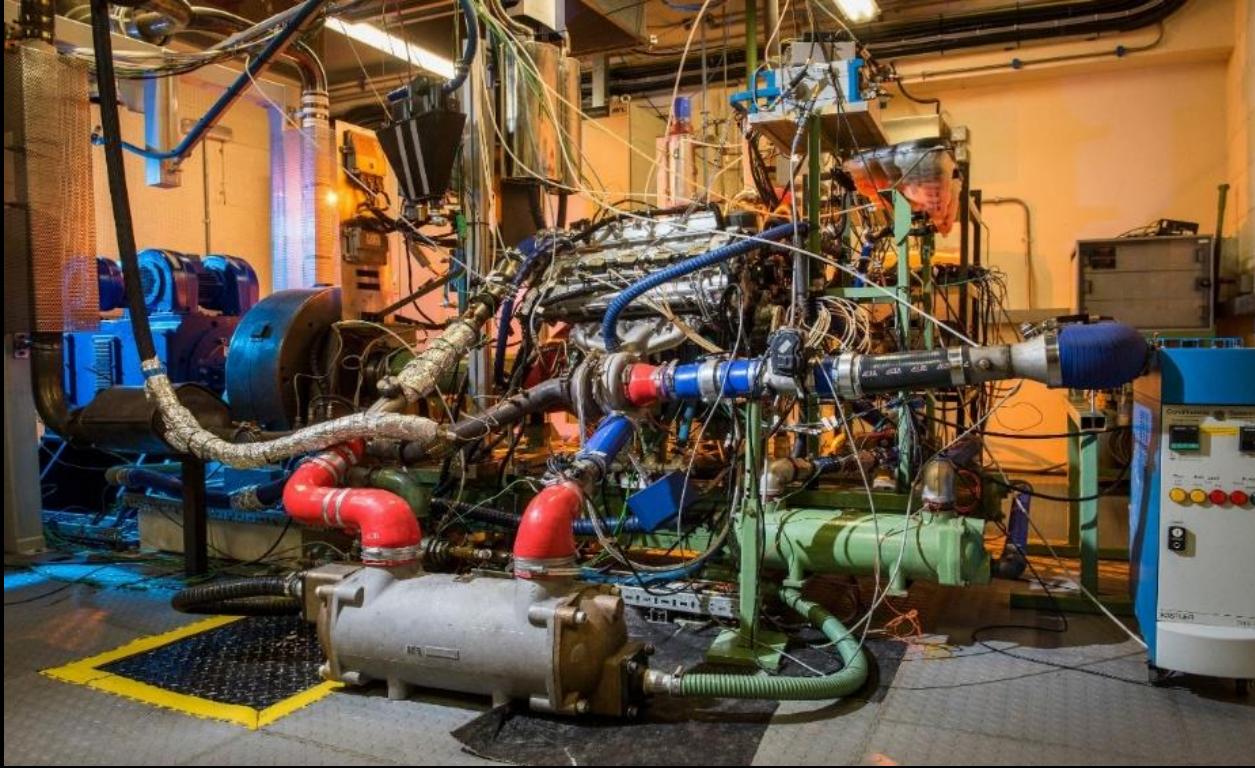
- All (essential) verification tests need a roadmap to replace with digital equivalents

Vehicle Characterisation for RDE

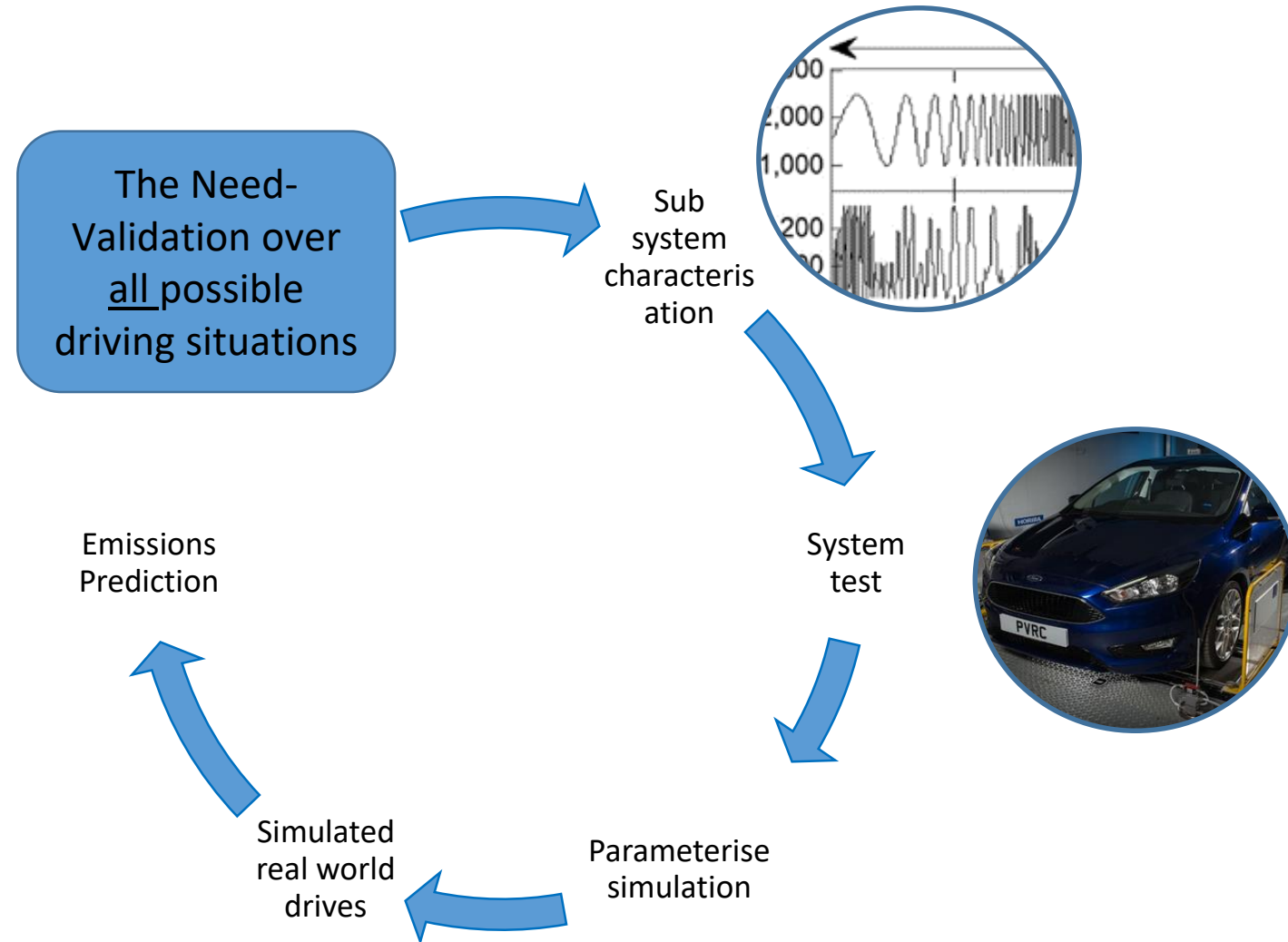


- Dynamic modelling approach
 - Volterra series for “physical” dynamics
 - Could be used to calibrate physical models
- Dynamic training sequence
 - Varying frequency sine waves (Chirp signals)
 - Not dependant on high level control strategy
- Warm-up behaviour
 - Hot start cycle
 - Cold start cycle
 - Scaling factor to interpolate (nasty)



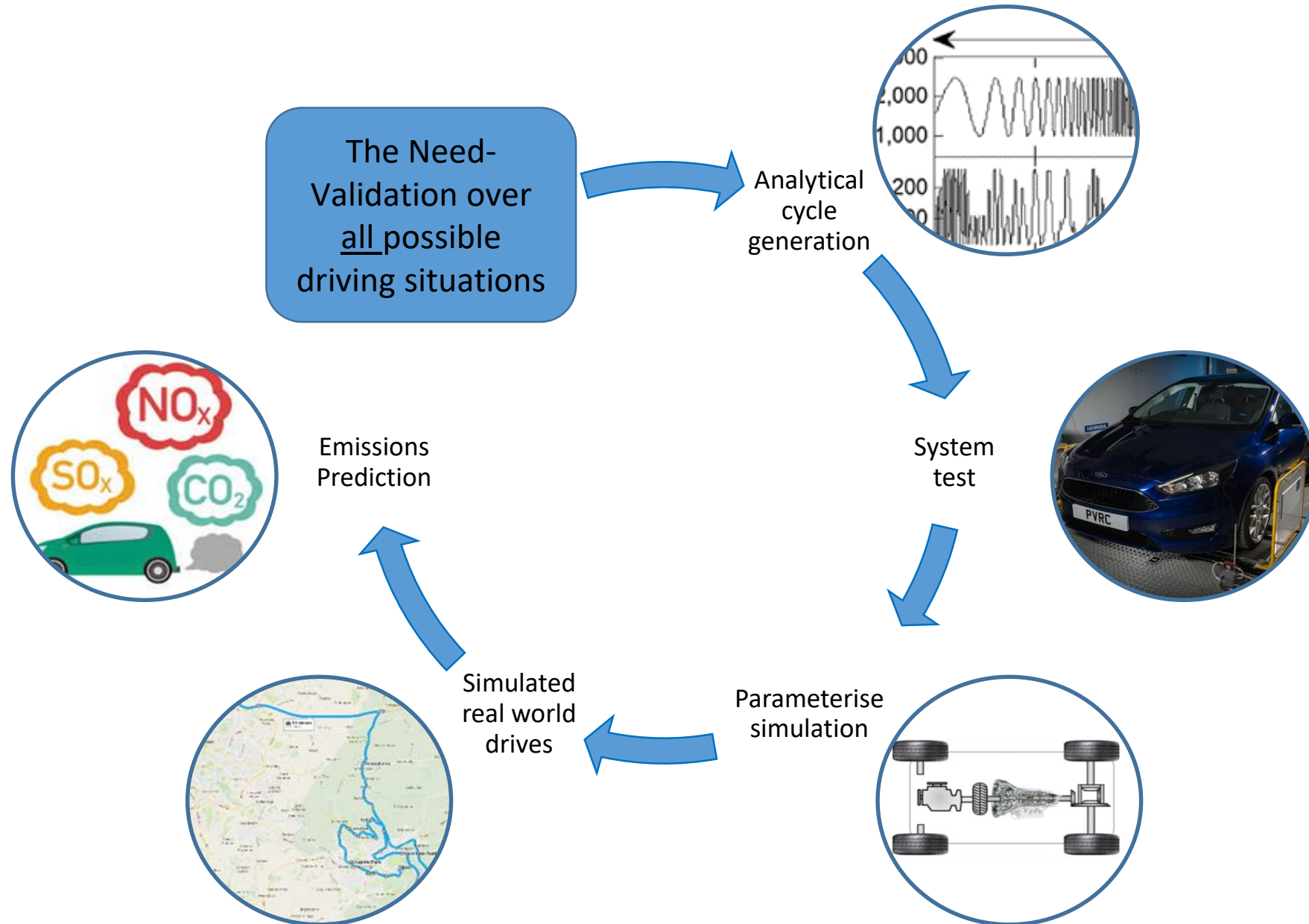


Vehicle Characterisation for RDE





Vehicle Characterisation for RDE





New skills in multi-physics and virtual environment techniques are critical to successful implementation



Drivers/Targets

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Tools & Processes

Manufacture

Data & Knowledge

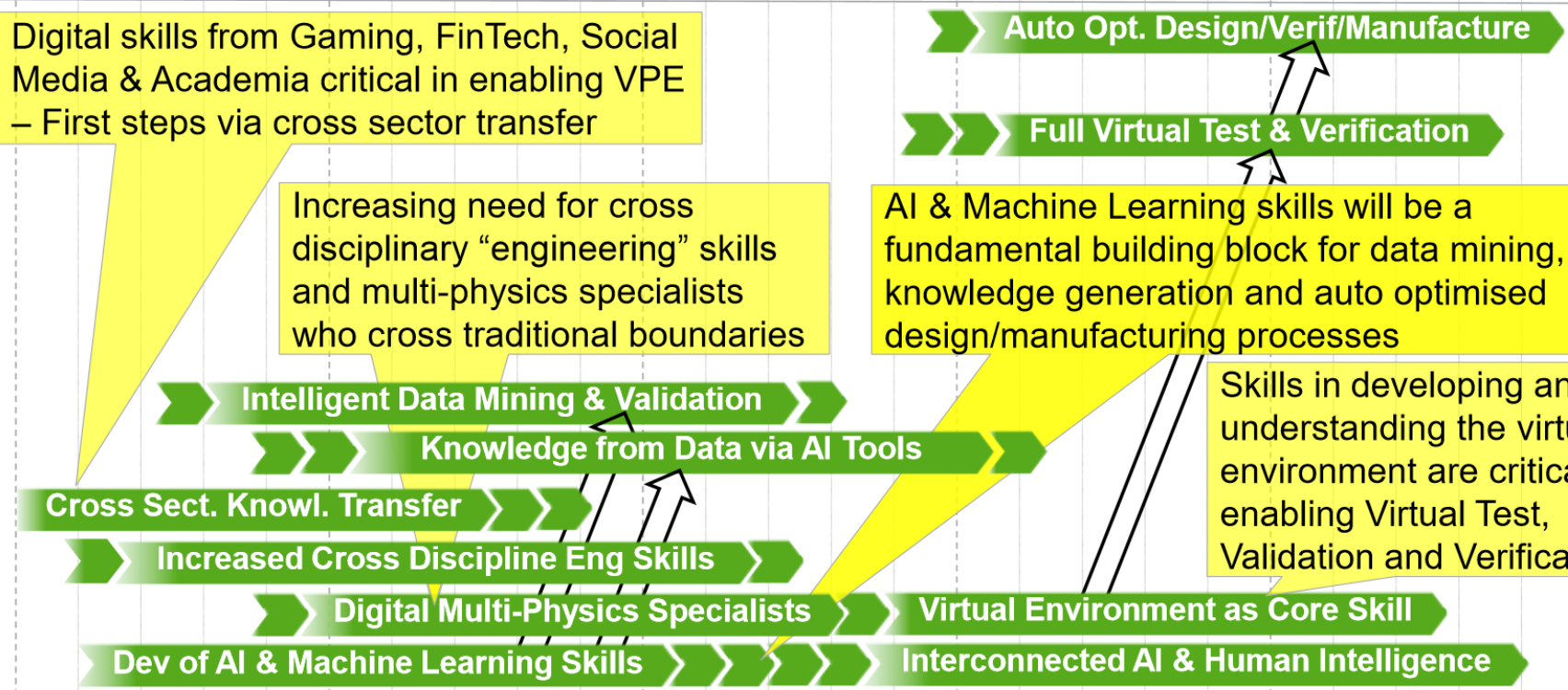
Skills

Digital skills from Gaming, FinTech, Social Media & Academia critical in enabling VPE – First steps via cross sector transfer

Increasing need for cross disciplinary “engineering” skills and multi-physics specialists who cross traditional boundaries

AI & Machine Learning skills will be a fundamental building block for data mining, knowledge generation and auto optimised design/manufacturing processes

Skills in developing and understanding the virtual environment are critical in enabling Virtual Test, Validation and Verification



2015 2020 2025 2030 2040 2050

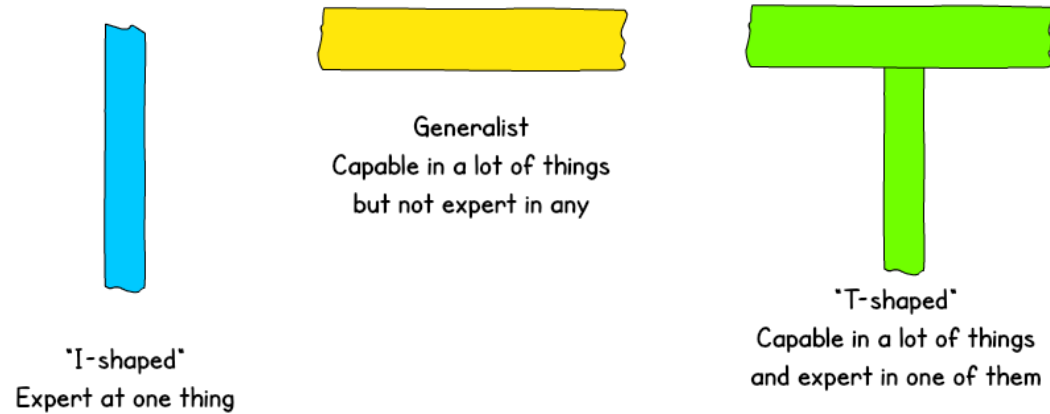
EPSRC Centre for Doctoral Training in Advanced Automotive Propulsion Systems

- At least 87 Studentships
- Wide range of disciplines
- Commercial and technical training to align students
- Research projects in collaboration with industry
- An integral part of IAAPS
- Aligned with APC spokes to maximise opportunities for collaboration across propulsion sector



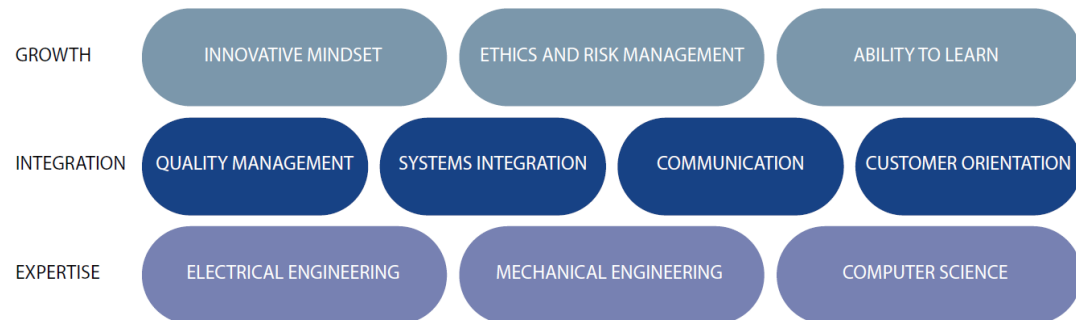
Aim of the AAPS CDT

- IAAPS CDT will train T-shaped people who will become leaders in the Automotive Propulsion Sector



- Designed with reference to FISITA White Paper – Mobility Engineer 2030
- Captures industry need

Figure 2: A three-layer approach to visualise the required skill sets. Future-proof education will consist of expertise, integration skills and the ability to grow. Depending on the individual role, there will be different weights of the skills needed. We need to think in skills profiles, as opposed to engineering disciplines

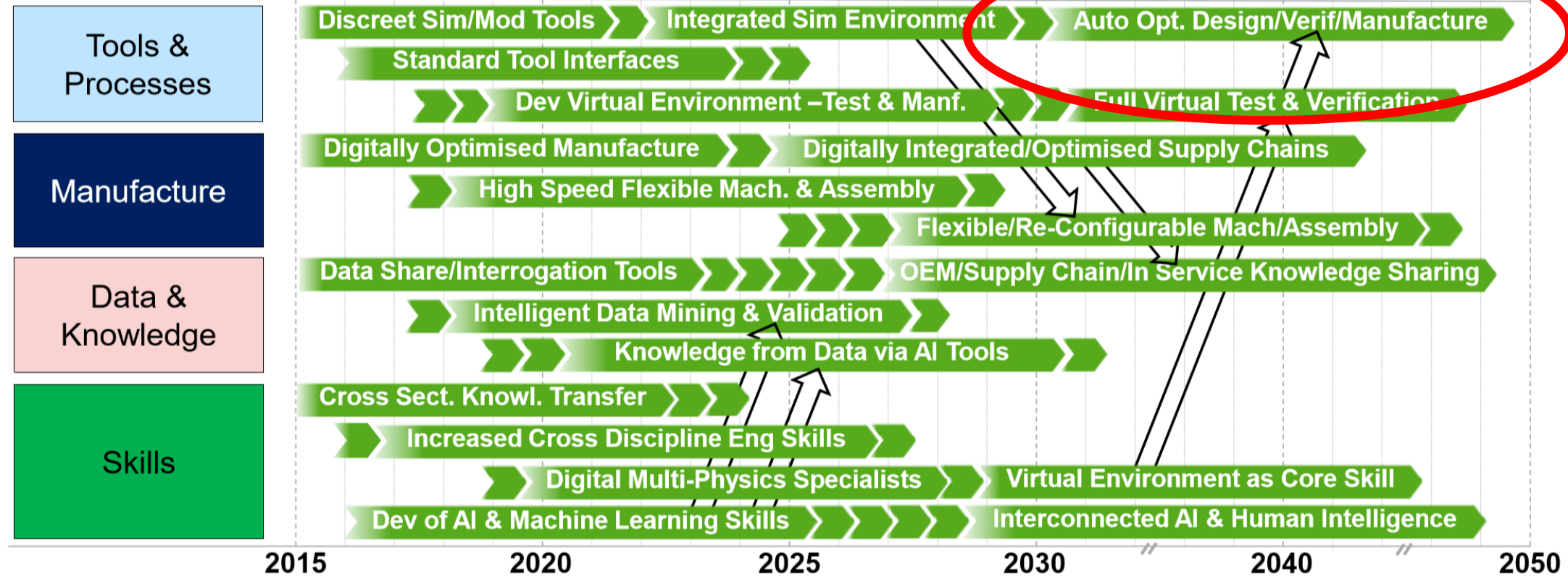


Virtual Product Engineering – New Tools, Manufacturing, Data & Skills to deliver significant productivity benefits



Drivers/Targets

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Spot the fake



A Style-Based Generator Architecture for Generative Adversarial Networks

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Abstract

We propose an alternative generator architecture for generative adversarial networks, borrowing from style transfer literature. The new architecture leads to an automatically learned, unsupervised separation of high-level attributes (e.g., pose and identity) when trained on human faces and stochastic variation in the generated images (e.g., freckles, hair), and it enables intuitive, scale-specific control of the synthesis. The new generator improves the state-of-the-art in terms of traditional distribution quality metrics, leads to demonstrably better interpolation properties, and also better disentangles the latent factors of variation. To quantify interpolation quality and disentanglement, we propose two new, automated methods that are applicable to any generator architecture. Finally, we introduce a new, highly varied and high-quality dataset of human faces.

1. Introduction

The resolution and quality of images produced by generative methods—especially generative adversarial networks (GAN) [22]—have seen rapid improvement recently [30, 45, 5]. Yet the generators continue to operate as black boxes, and despite recent efforts [3], the understanding of various aspects of the image synthesis process, e.g., the origin of stochastic features, is still lacking. The properties of the latent space are also poorly understood, and the commonly demonstrated latent space interpolations [13, 52, 37] provide no quantitative way to compare different generators against each other.

Motivated by style transfer literature [27], we re-design the generator architecture in a way that exposes novel ways to control the image synthesis process. Our generator starts from a learned constant input and adjusts the “style” of the image at each convolution layer based on the latent code, therefore directly controlling the strength of image features at different scales. Combined with noise injected directly into the network, this architectural change leads to automatic, unsupervised separation of high-level attributes

(e.g., pose, identity) from stochastic variation (e.g., freckles, hair) in the generated images, and enables intuitive scale-specific mixing and interpolation operations. We do not modify the discriminator or the loss function in any way, and our work is thus orthogonal to the ongoing discussion about GAN loss functions, regularization, and hyperparameters [24, 45, 5, 40, 44, 36].

Our generator embeds the input latent code into an intermediate latent space, which has a profound effect on how the factors of variation are represented in the network. The input latent space must follow the probability density of the training data, and we argue that this leads to some degree of unavoidable entanglement. Our intermediate latent space is free from that restriction and is therefore allowed to be disentangled. As previous methods for estimating the degree of latent space disentanglement are not directly applicable in our case, we propose two new automated metrics—perceptual path length and linear separability—for quantifying these aspects of the generator. Using these metrics, we show that compared to a traditional generator architecture, our generator admits a more linear, less entangled representation of different factors of variation.

Finally, we present a new dataset of human faces (Flickr-Faces-HQ, FFHQ) that offers much higher quality and covers considerably wider variation than existing high-resolution datasets (Appendix A). We have made this dataset publicly available, along with our source code and pre-trained networks.¹ The accompanying video can be found under the same link.

2. Style-based generator

Traditionally the latent code is provided to the generator through an input layer, i.e., the first layer of a feed-forward network (Figure 1a). We depart from this design by omitting the input layer altogether and starting from a learned constant instead (Figure 1b, right). Given a latent code z in the input latent space \mathcal{Z} , a non-linear mapping network $f: \mathcal{Z} \rightarrow \mathcal{W}$ first produces $w \in \mathcal{W}$ (Figure 1b, left). For simplicity, we set the dimensionality of both

¹<https://github.com/NVlabs/stylegan>

arXiv:1812.04948v3 [cs.NE] 29 Mar 2019



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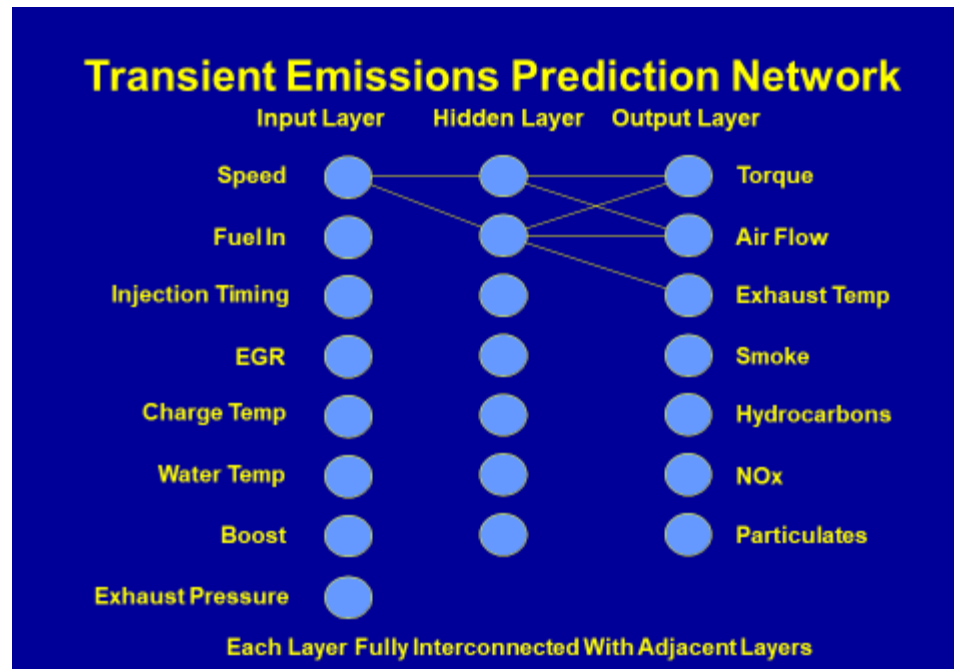


Our training will bring together students from a variety of backgrounds in interdisciplinary teams

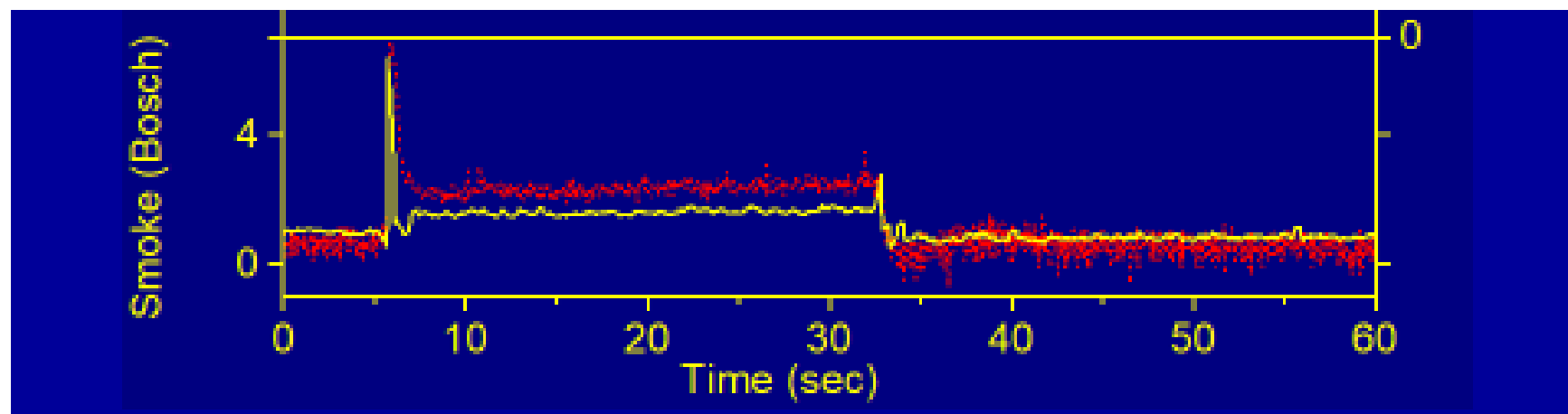
- addressing real problems as researchers and reflective practitioners
- able to apply knowledge and creative thinking while taking account of individual, societal, and ethical concerns

Professor Eamonn O'Neill, head of the Department of Computer Science at University of Bath and Director of the ART-AI CDT

State of the art AI in the 90s....



Sea squirt – about 230 neurons



Early attempts at expert knowledge

- Expected response model elicited from calibrator
- Bayesian updating scheme improves the model as data becomes available
- 'As good as' a human calibrator

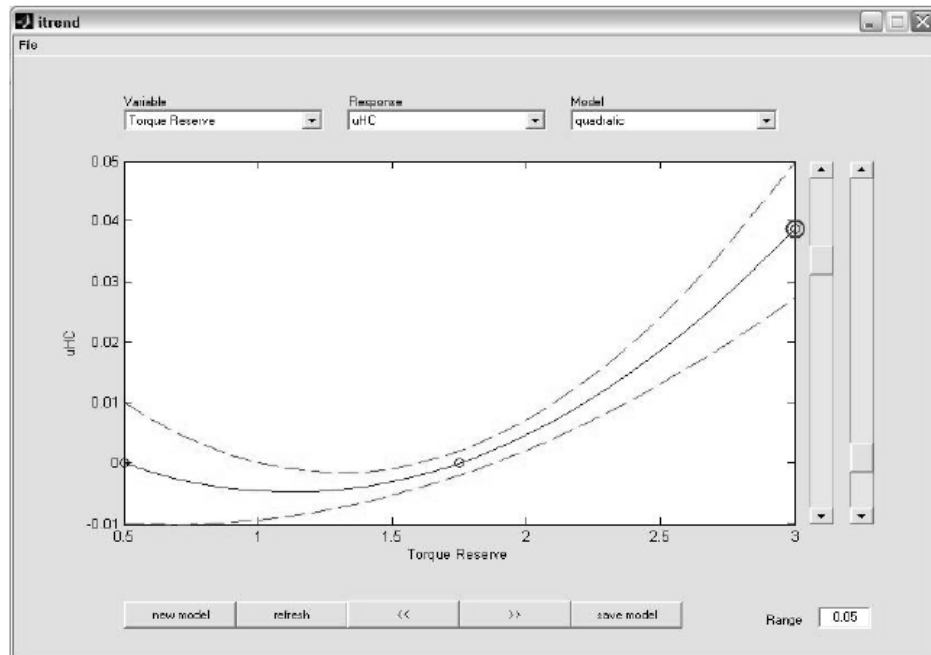


Figure 6 – Trend Model GUI

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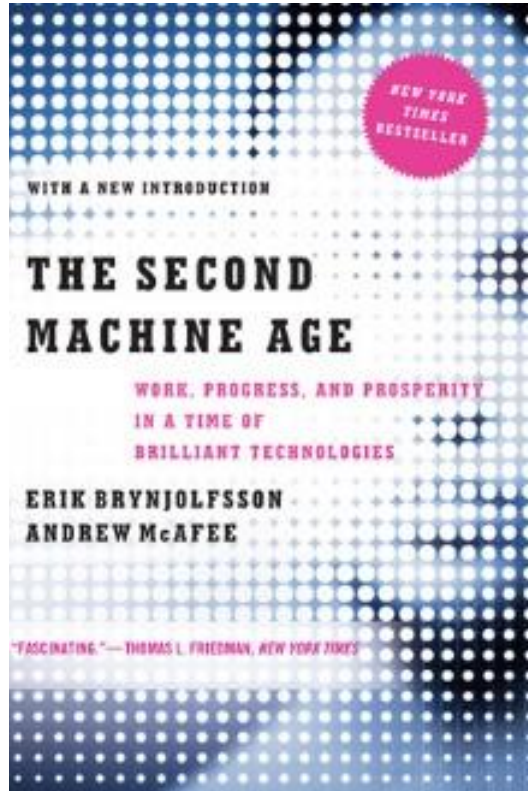


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The future is coming



AMAZON IMAGINES A FUTURE OF INFINITE COMPUTING POWER

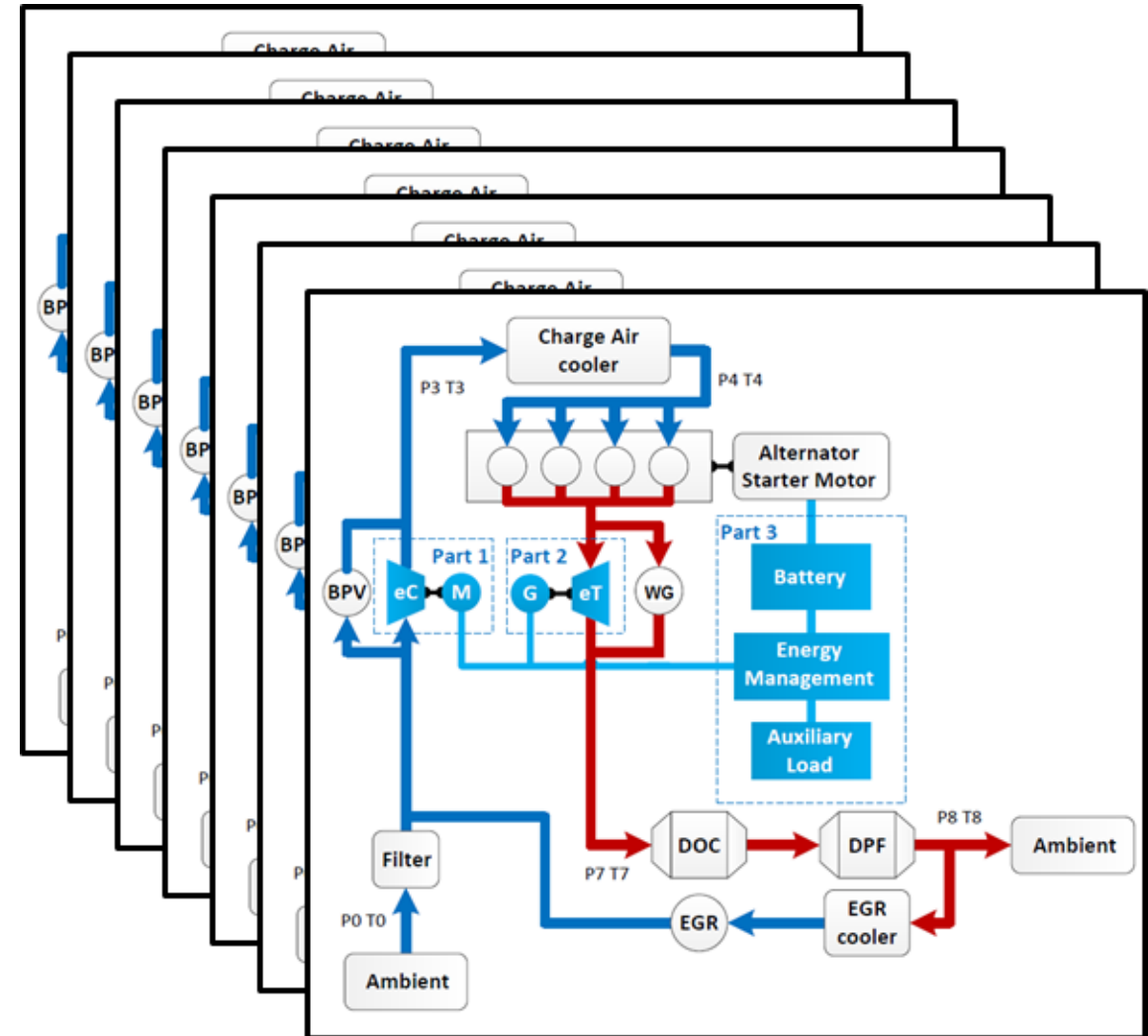


David Limp speaks with WIRED editor-in-chief Nicholas Thompson.

WHEN DAVID LIMP thinks about the future of Alexa, the AI assistant he oversees at Amazon, he imagines a world not unlike *Star Trek*—a future in which you could be anywhere, asking anything, and an ambient computer would be there to fulfill your every need.

End goal - AI led powertrain design

- How can an automated design tool help an engineer to identify promising arrangements?
- Many arrangements need to be considered - auto generated layouts
- BUT - High level of optimisation needed to allow meaningful ranking
- Highly demanding in terms of computational power and modelling fidelity
- More work needed on architecture optimisation with sizing and **through life costing** as an integrated activity



Can we simulate creativity?

....it's not going to put the Mozarts, the Beethovens, the Miles Davises out of jobs,

but it might well put second-tier composers out of jobs, those who are making their way by writing music for advertising, corporate videos, computer games.

We're already seeing music being written by AI which is "good enough"

Marcus Du Sautoy, Professor of Mathematics, University of Oxford



- The future is digital
- Test once, simulate many
- **This has profound implications for all of our experimental capabilities**

- Long term goal is AI led digital design and verification
- Better data, better tools and highly trained people are a must
- **Big changes to the way we organise our engineering teams**

Chris Brace FIMechE
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Deputy Director, Powertrain and
Vehicle Research Centre
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