intellegens

Applied machine learning

Modern-day blacksmith

Dr Gareth Conduit

Machine learning to

Model sparse datasets

Exploit property-property relationships

Merge data, computer simulations, and physical laws

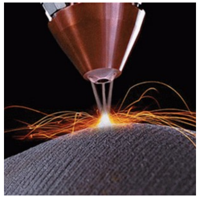
Reduce costly experiments to accelerate discovery

Black box machine learning for materials design

Composition

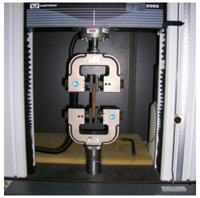
Properties

Defects



Fatigue

Strength



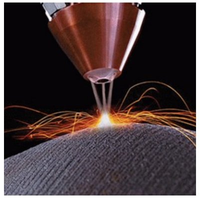
Train the machine learning

Machine learning predicts material properties

Composition

Properties

Defects



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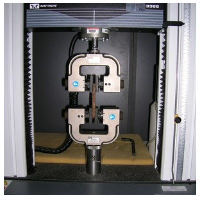
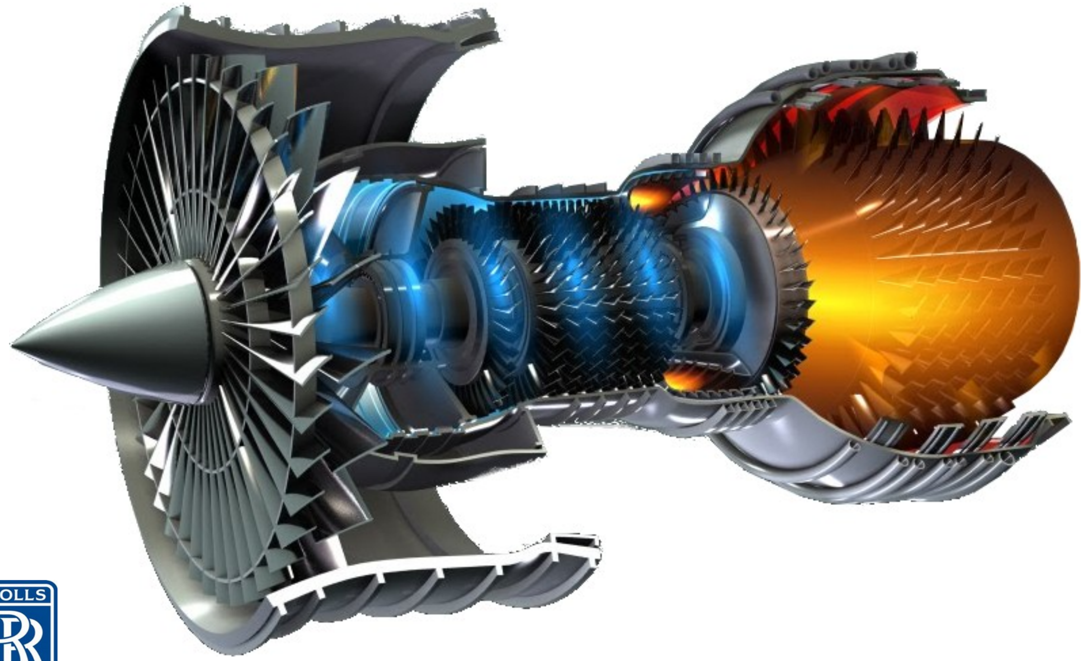
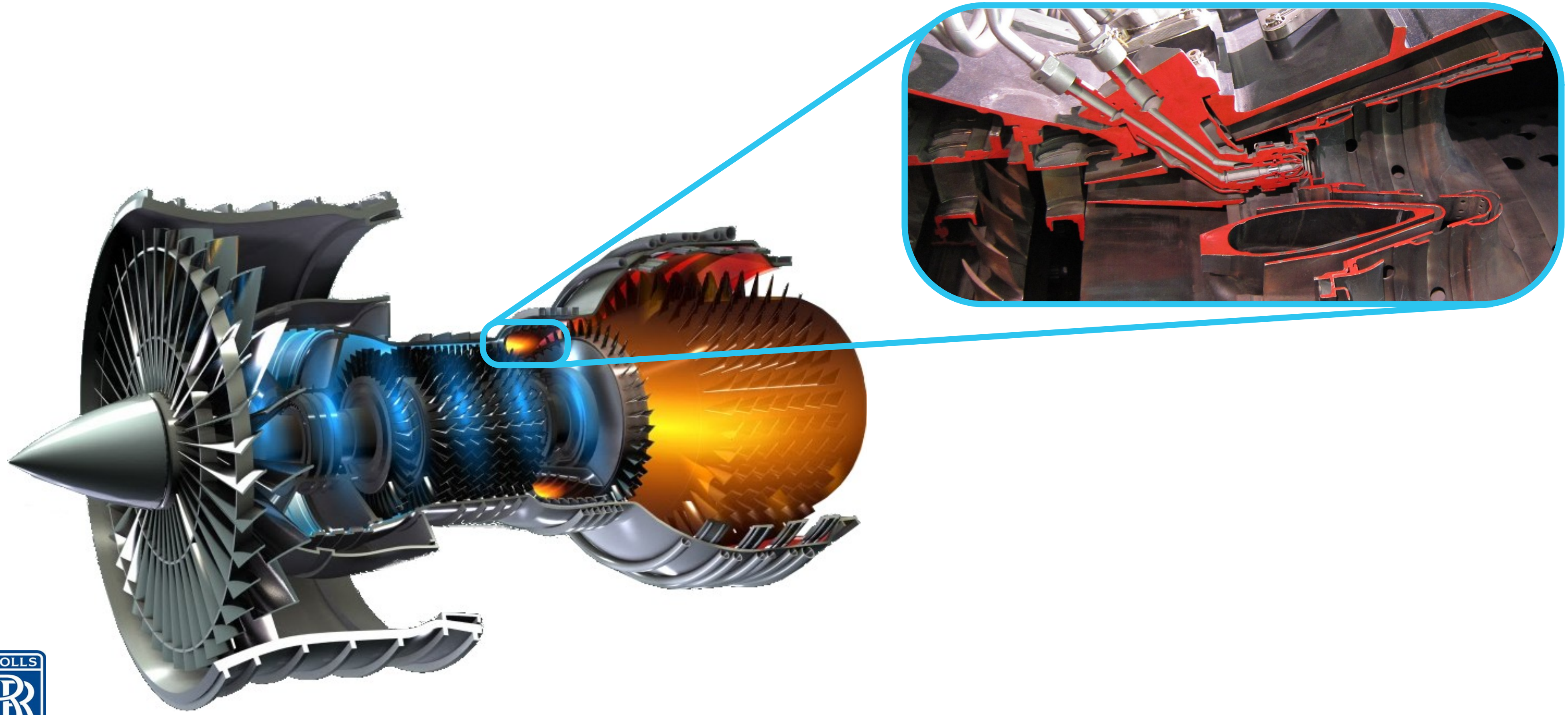


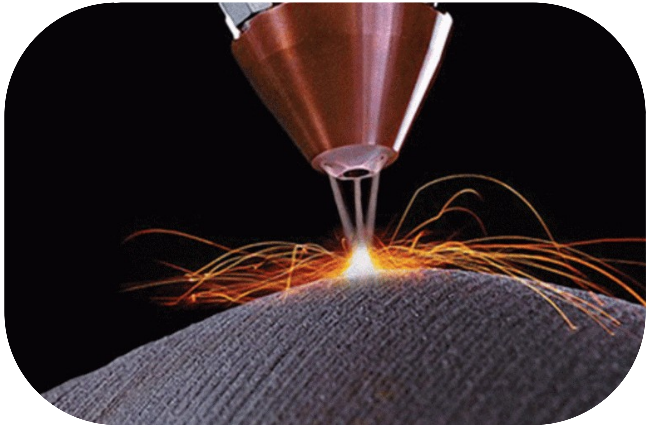
Jet engine schematic



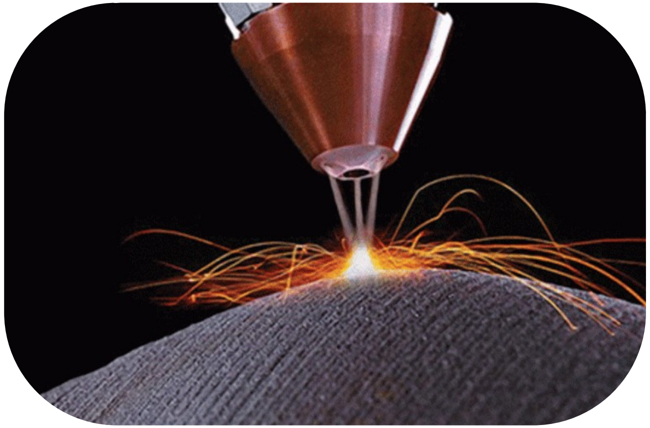
Combustor in a jet engine



Direct laser deposition



Ability for printing and welding are strongly correlated



Laser

Electricity

Target properties

Elemental cost	< 25 $\$kg^{-1}$
Density	< 8500 kgm^{-3}
γ' content	< 25 wt%
Oxidation resistance	< 0.3 $mgcm^{-2}$
Defects	< 0.15% defects
Phase stability	> 99.0 wt%
γ' solvus	> 1000˚C
Thermal resistance	> 0.04 $K\Omega^{-1}m^{-3}$
Yield stress at 900˚C	> 200 MPa
Tensile strength at 900˚C	> 300 MPa
Tensile elongation at 700˚C	> 8%
1000hr stress rupture at 800˚C	> 100 MPa
Fatigue life at 500 MPa, 700˚C	> 10^5 cycles

Composition and processing variables

Cr 19%

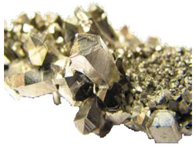
Co 4%

Mo 4.9%

W 1.2%

Zr 0.05%

Nb 3%



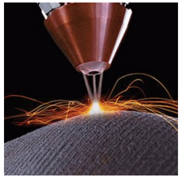
Al 2.9%

C 0.04%

B 0.01%

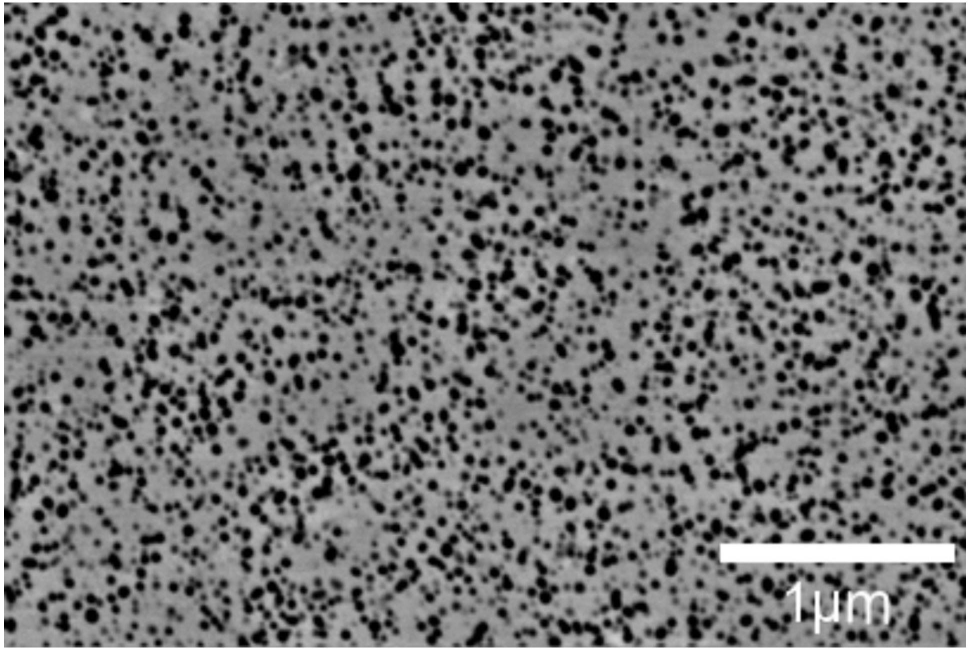
Ni

Expose 0.8



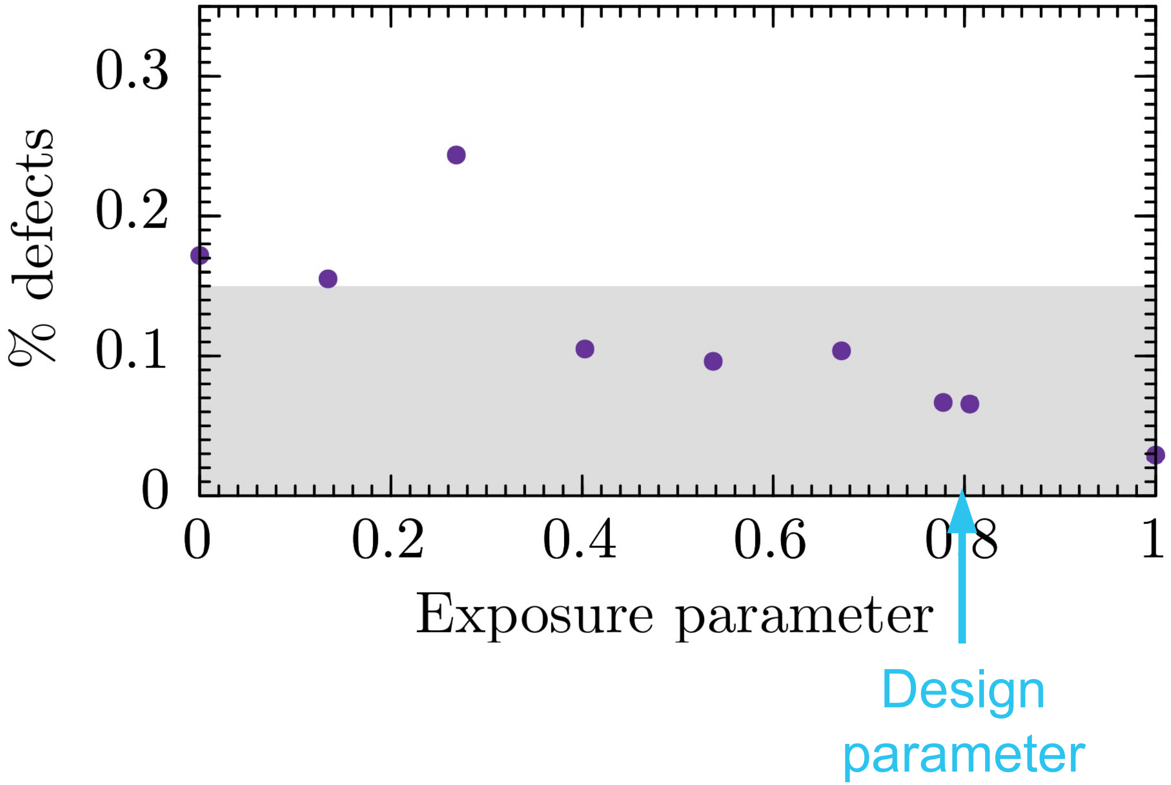
T_{HT} 1300ºC

Microstructure



Probabilistic neural network identification of an alloy for direct laser deposition
Materials & Design **168**, 107644 (2019)

Testing the defect density



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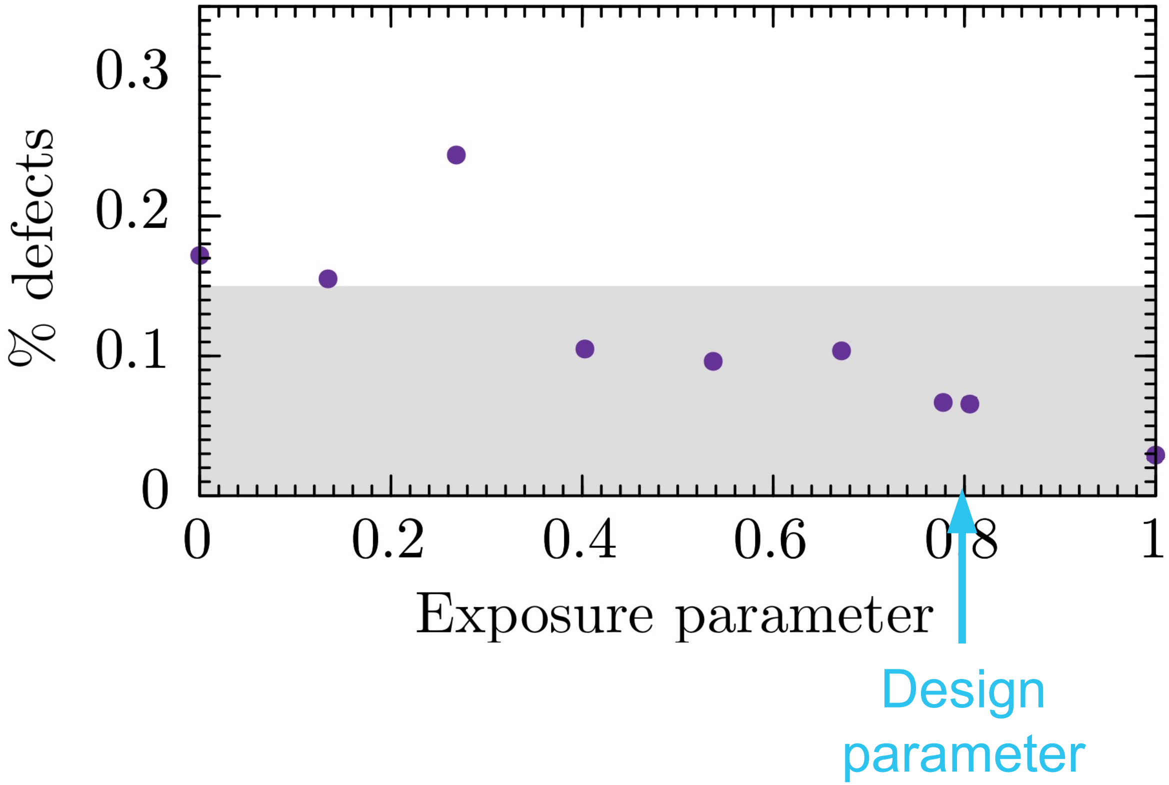

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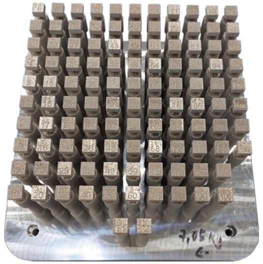
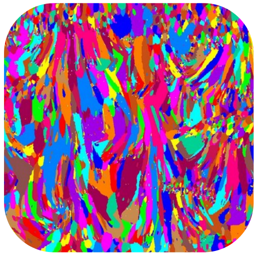
Materials & Design **168**, 107644 (2019)

NASA Technical Memorandum 20220008637 (2022)

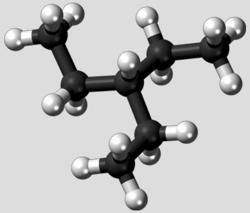
Journal of Computer-Aided Molecular Design **35**, 112501140 (2021)





Project MEDAL

Boeing · Constellium · The University Of Sheffield · AMRC Advanced Manufacturing Research Centre · GE Additive



Fluid Phase Equilibria **501**, 112259 (2019)

Journal of Chemical Physics **153**, 014102 (2020)

nature machine intelligence

REVIEW ARTICLE

https://doi.org/10.1038/s42256-020-0156-7

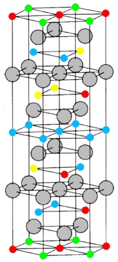
Check for updates

Predicting the state of charge and health of batteries using data-driven machine learning

Man-Fai Ng[1], Jin Zhao[2], Qingyu Yan[2]✉, Gareth J. Conduit[3]✉ and Zhi Wei Seh[4]✉

Agency for Science, Technology and Research SINGAPORE

SAMSUNG

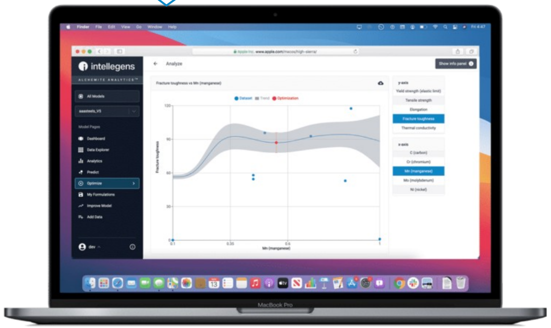


Johnson Matthey Technology Review **66**, 130 (2022)

Alchemite™ product family

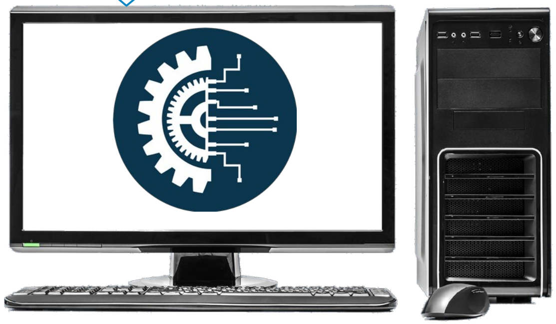
Optional connectors

Engineers



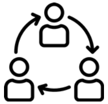
Deploy models

Data scientists



Lab systems

Software & scripts



Collaboration

Alchemite™ Analytics

Deep data insights on your desktop

Guide experiments, predict, design

Alchemite™ Engine

Integrate into your workflow (API, Python)

Advanced configuration, enterprise deployment

Alchemite™ Success

Apply Intellegens deep learning expertise

Advice to your data science team or full project management

Summary

Merge computer simulations with experimental data and exploit property-property relationships to circumvent missing data

Designed and experimentally verified alloy for direct laser deposition

Generic approach applied to materials, batteries, chemicals, and beyond

Taken to market through by Intellegens as Alchemite Analytics™, Optibrium, and ANSYS Granta

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