



Intellegens

Design of an alloy for
direct laser deposition
using neural networks

About

Deep learning software for **materials design**

Aggregate all sources of data

Predictive models **reduce costs** by 80%

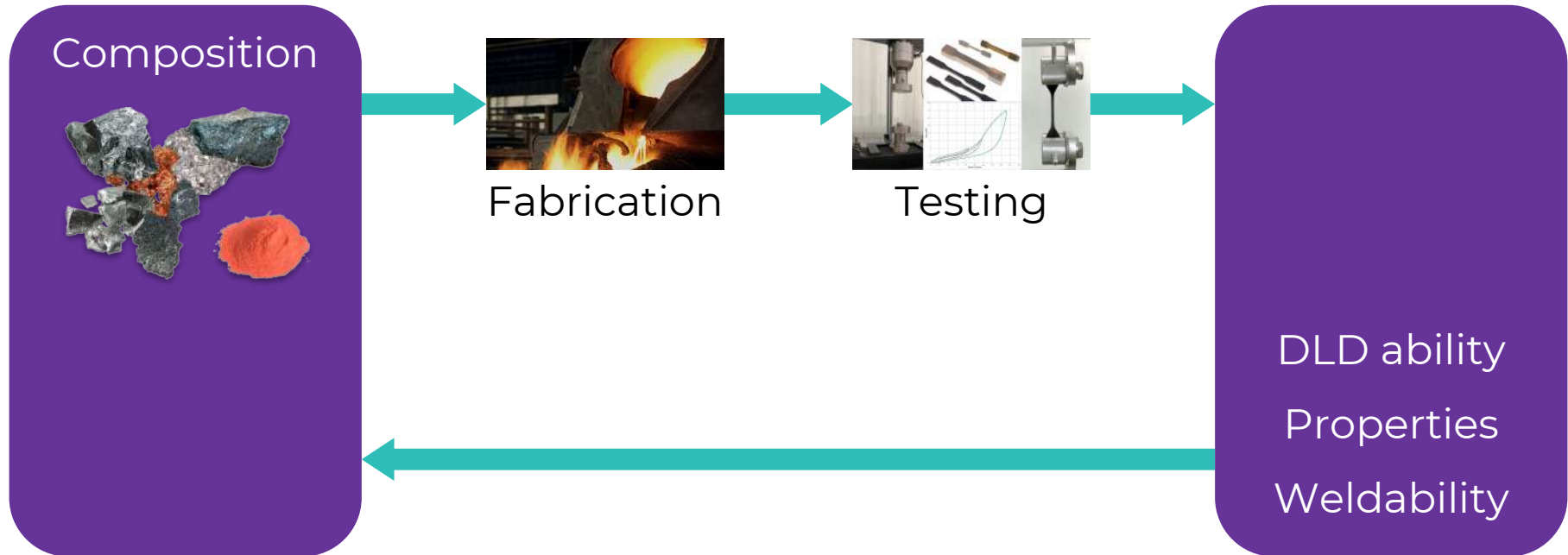
Accelerates materials discovery to 1 year

Traditional materials design

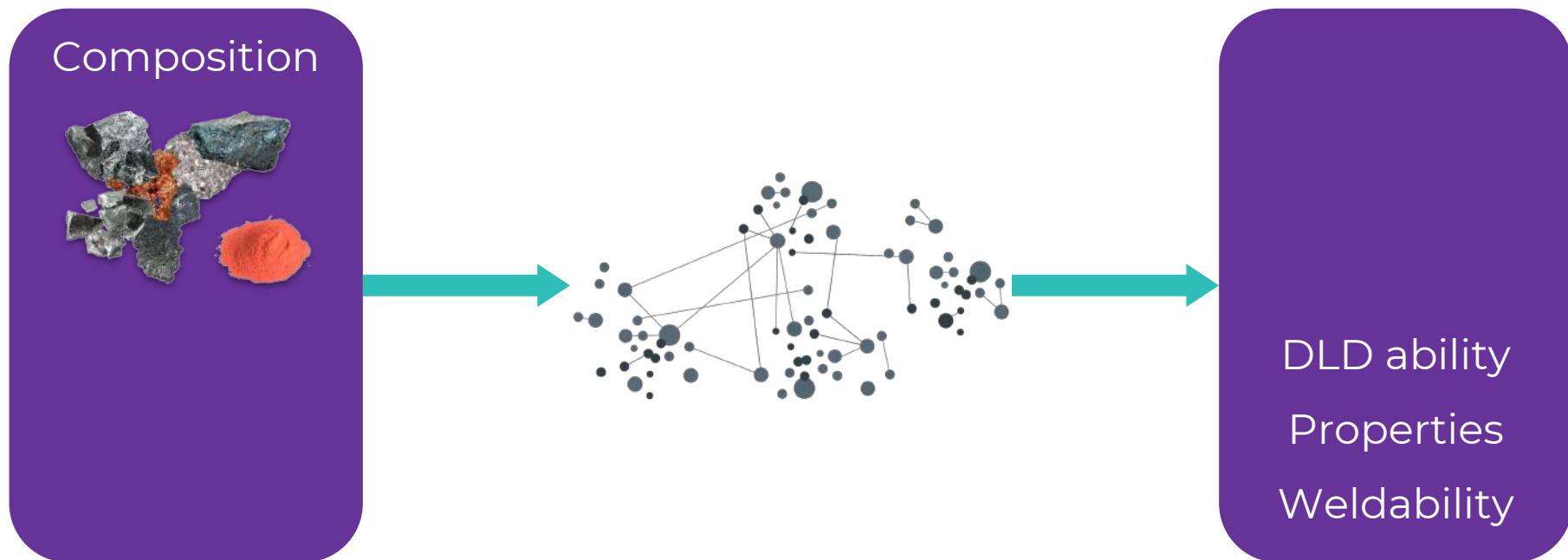
Current process is **expert driven** and **iterative**

Highly specialist alloys can cost > \$10m and take 20 years to finalize and approve

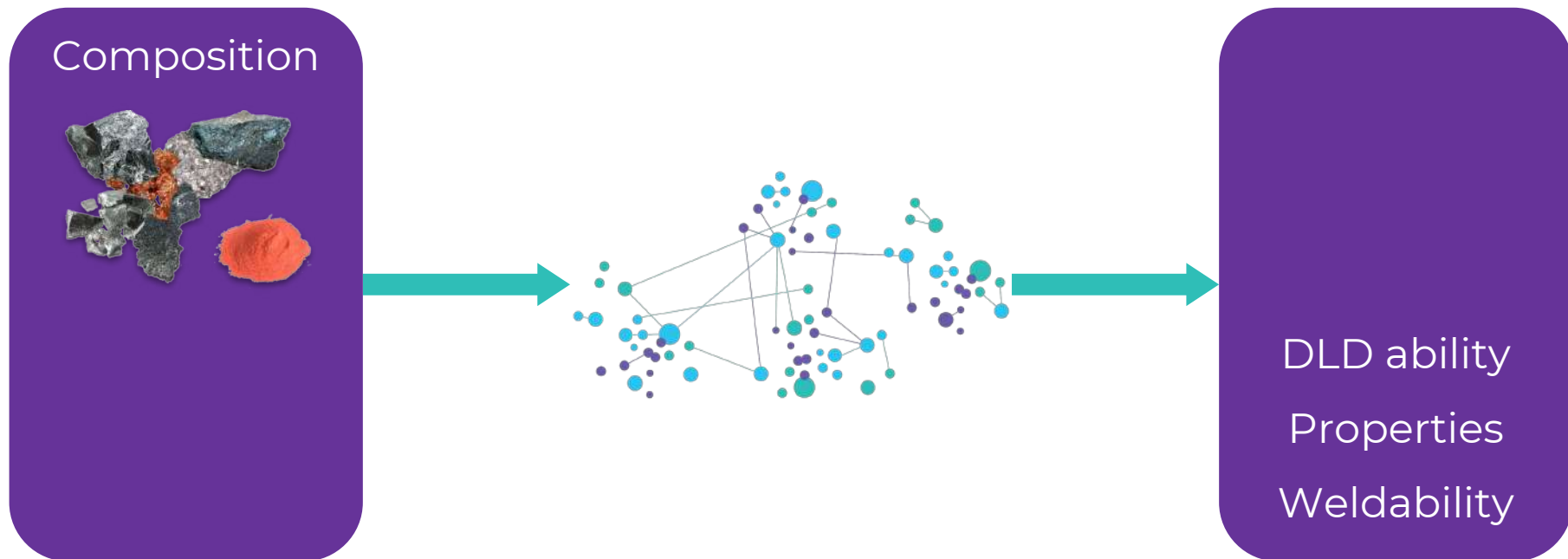
Traditional materials design



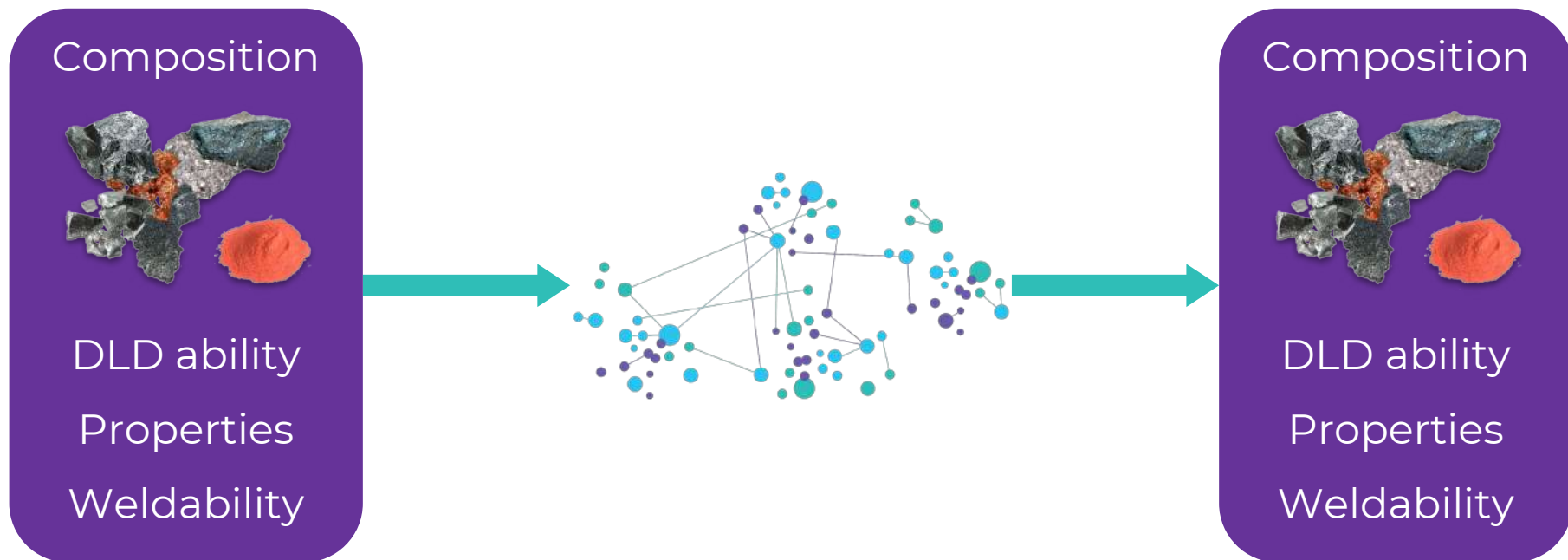
Standard deep learning



Standard deep learning: predict



Alchemite™ deep learning



Optimized materials design

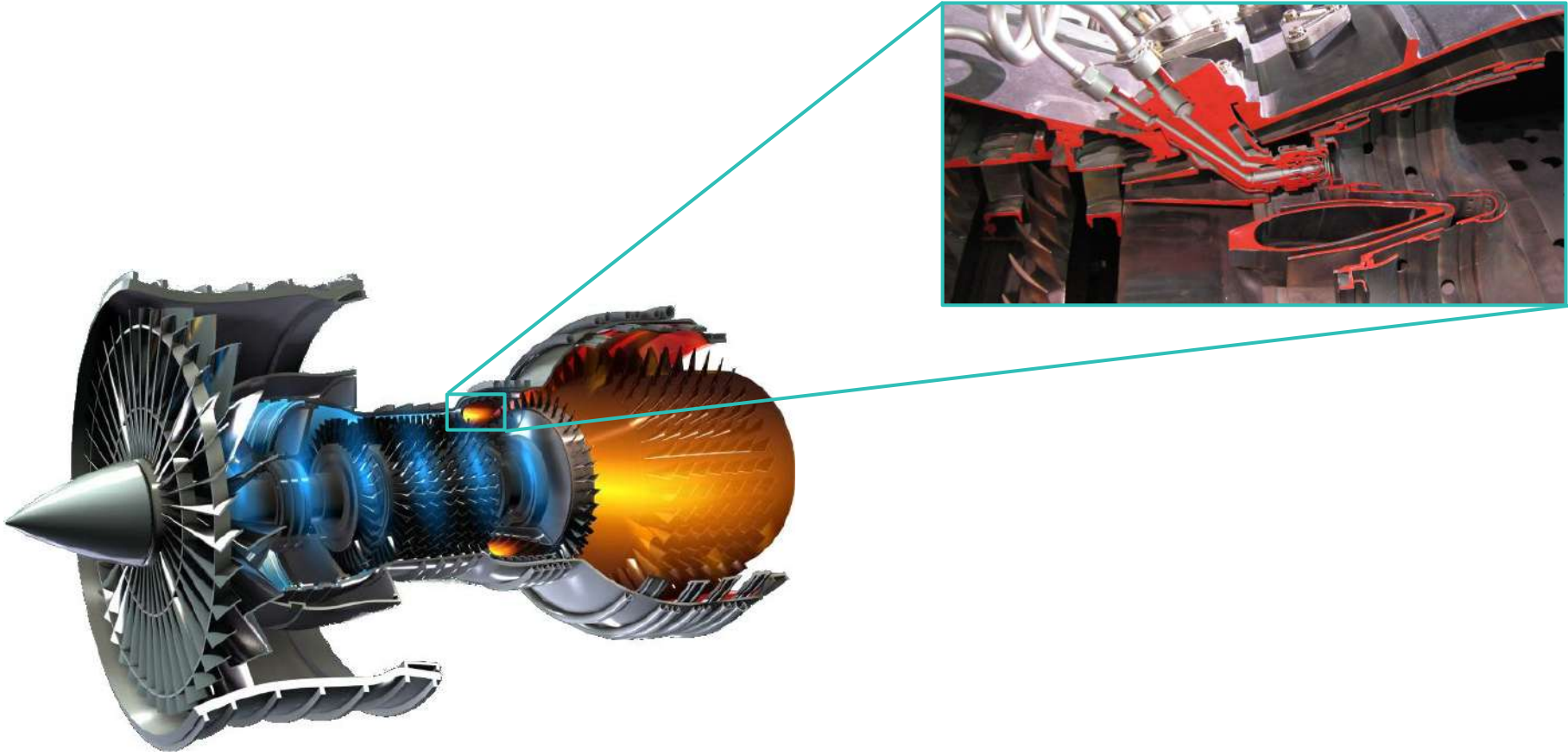
Reduce expensive experimental costs by 80%

Design new alloy in 1 year

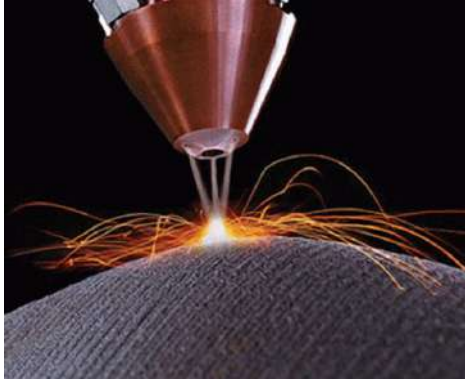
Improve target property optimization

Standardize design process across company

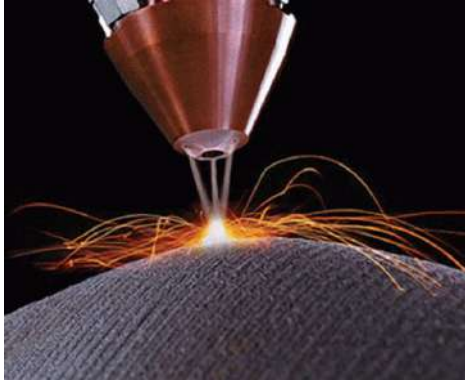
Case study: jet engine



Direct laser deposition requires new alloys



Direct laser deposition is similar to welding

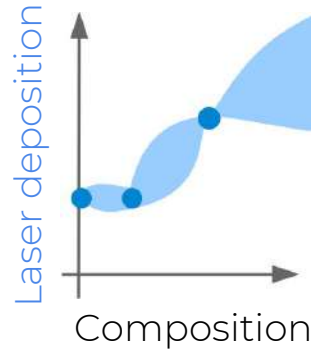


Direct laser
deposition

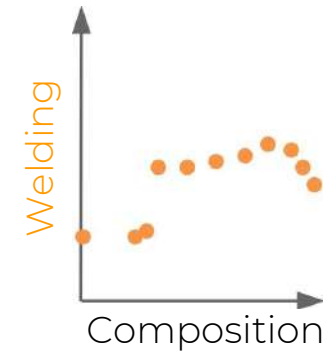
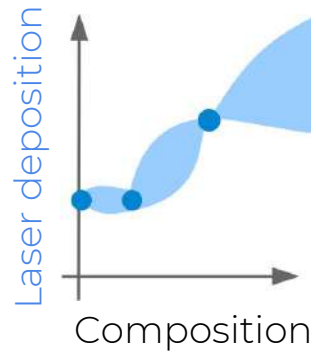


Welding

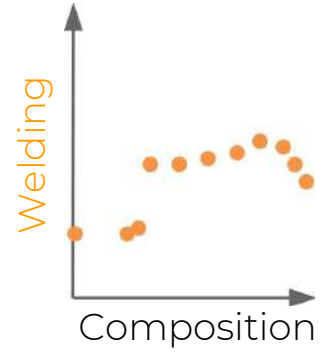
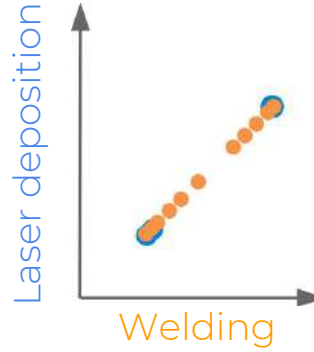
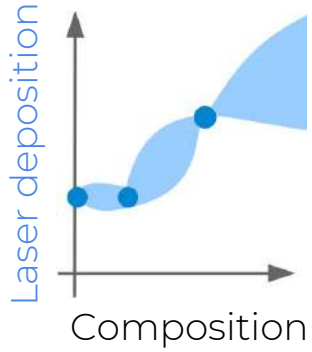
Lack of data for laser deposition



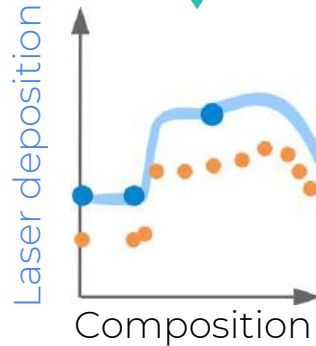
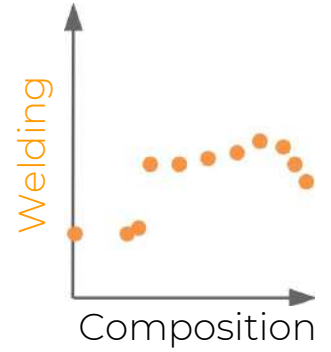
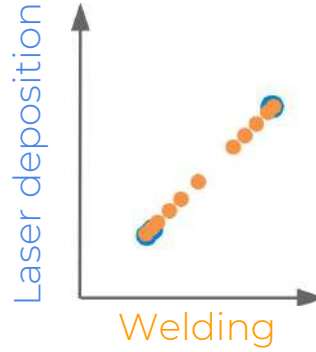
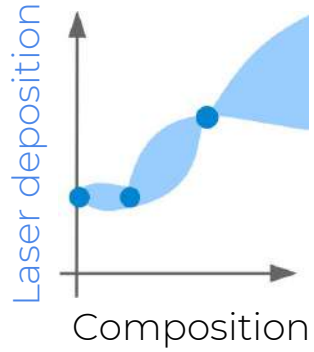
Large amount of welding data



Simple welding-deposition relationship



Welding data guides extrapolation



Targets for direct laser deposition alloy

Elemental cost	< 25 \$kg ⁻¹
Density	< 8500 kgm ⁻³
γ' content	< 25 wt%
Oxidation resistance	< 0.3 mgcm ⁻²
Processability	< 0.15% defects
Phase stability	> 99.0 wt%
γ' solvus	> 1000 °C
Thermal resistance	> 0.04 K Ω^{-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

Targets for direct laser deposition alloy

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 balance



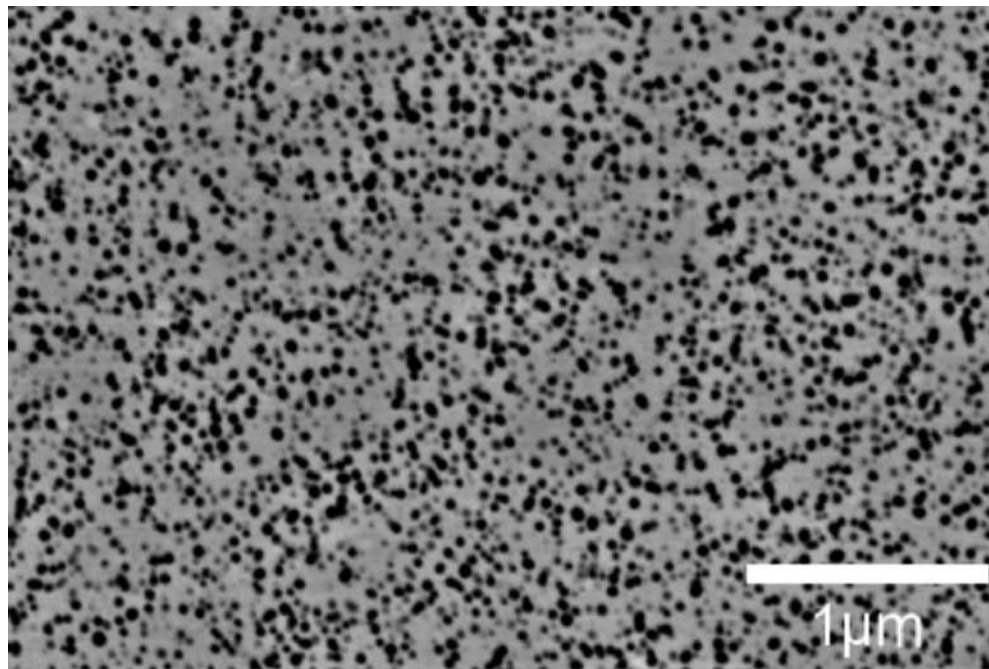
Exposure 0.8



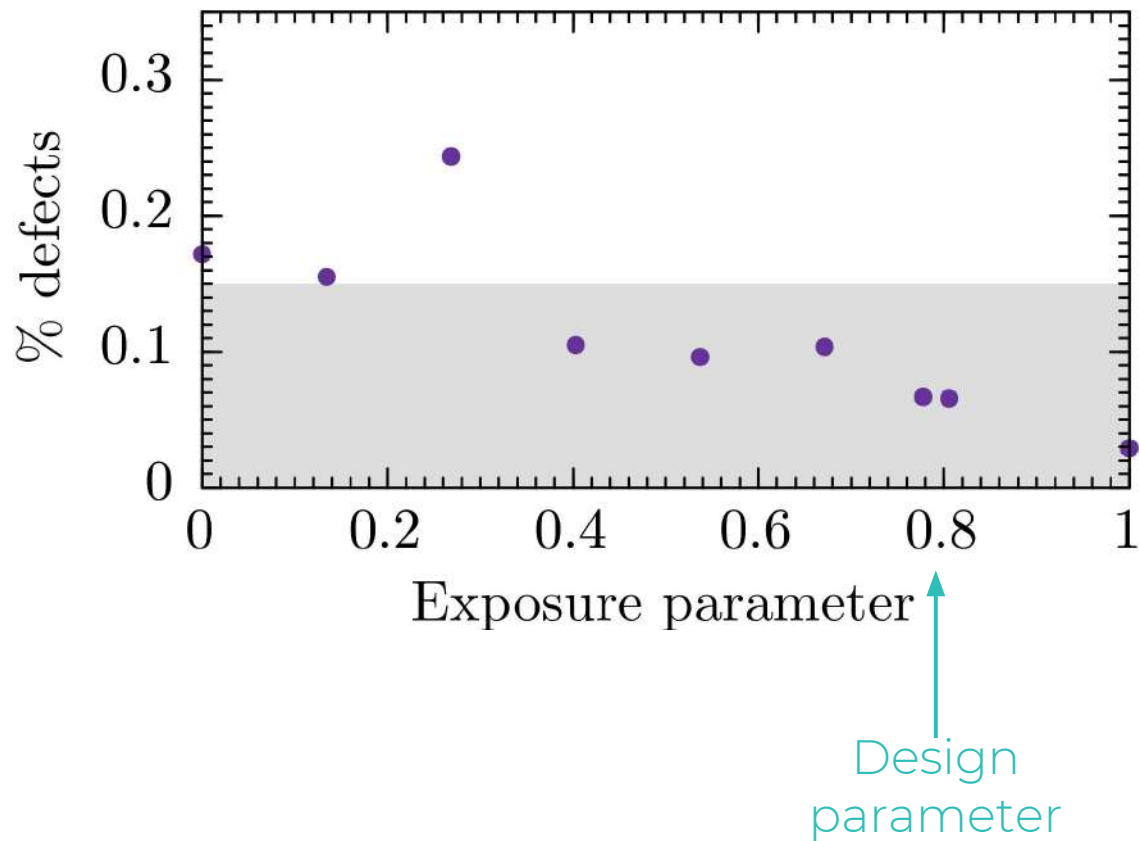
T_{HT} 1230°C



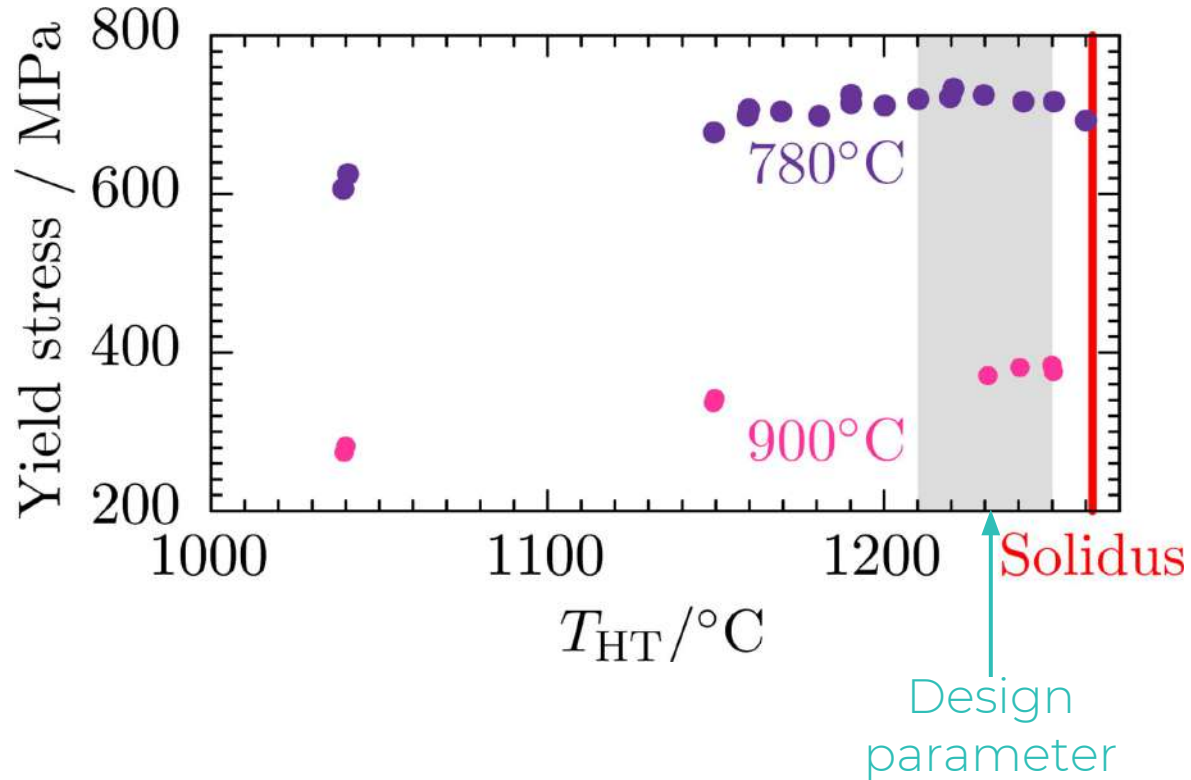
Microstructure



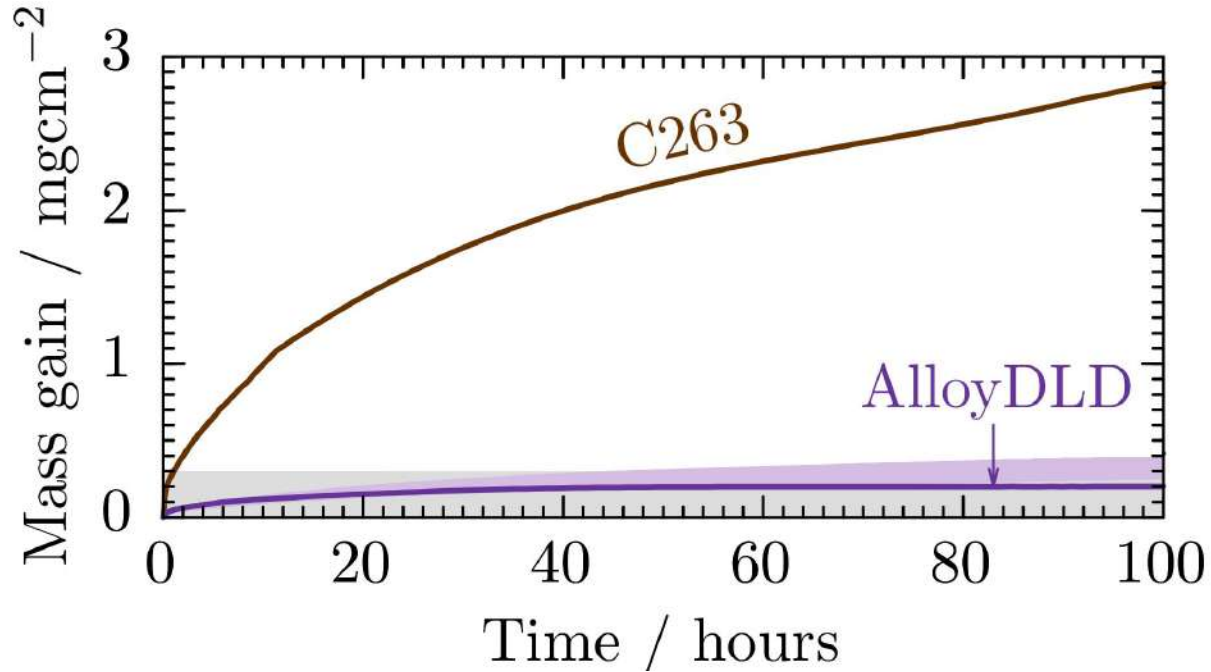
Testing the processability: horizontal printing



Testing the yield stress



Test the oxidation resistance



Printing components for the engine



Alchemite™ materials design

Merged welding, heat capacity, thermal expansivity, phase behavior to predict ability for **direct laser deposition**

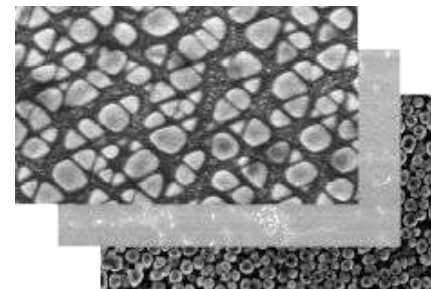
Proposed and tested alloy for direct laser deposition within **1 year**

Experimentally **verified** properties of alloy

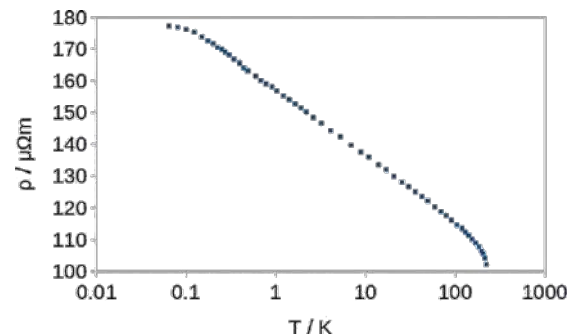
Designed a **steel** welding consumable

More materials design

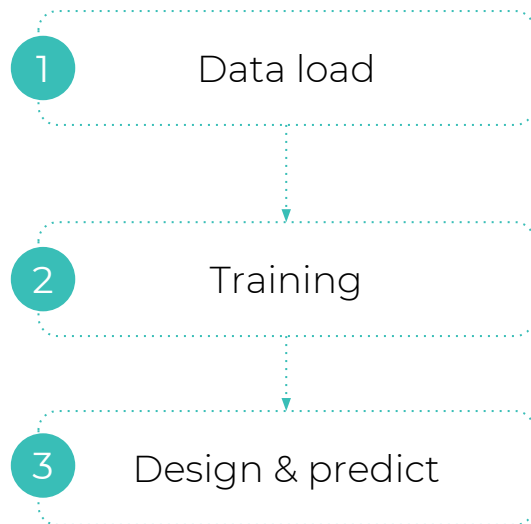
Nickel and molybdenum-base alloys for jet engines



Material for thermometry



Integrated software



Predicting properties of steel

We demonstrate a neural network that predicts the physical properties of steels based on the composition and heat treatment. The neural network model was trained from a library of experimental data from 1000 alloys.

In the first panel below set the percentages of each element in the composition and heat treatment temperature, and then click predict to get the neural network estimates for yield stress, ultimate tensile strength, and elongation.

Click [here](#) to use this technology to optimize the yield stress, ultimate tensile strength, and elongation the steel.

This same technology was used to understand nickel alloys where the composition covered 20 elements, 5 heat treatment parameters, and predicted 11 material properties. Click [here](#) to read more about this study.

Set inputs

Iron (Fe)	<input type="text" value="100"/>	remain %
Carbon (C)	<input type="text" value="0"/>	0 to 0.43 %
Manganese (Mn)	<input type="text" value="0"/>	0 to 3.0 %
Silicon (Si)	<input type="text" value="0"/>	0 to 4.75 %
Chromium (Cr)	<input type="text" value="0"/>	0 to 17.5 %
Nickel (Ni)	<input type="text" value="0"/>	0 to 21.0 %
Molybdenum (Mo)	<input type="text" value="0"/>	0 to 9.67 %
Vanadium (V)	<input type="text" value="0"/>	0 to 4.32 %

PREDICT

Predictions

- Yield Stress (MPa) 1605 ± 46
- Ultimate Tensile Strength (MPa) 1200 ± 67
- Elongation (%) 9 ± 2

Summary

Alchemite™ exploits **all available information** for materials design

Proposed and verified new alloy for direct laser deposition in **1 year**

Additional design of steel, nickel, molybdenum, and thermometry materials

Information

Contact ben@intellegens.ai
Website <https://intellegens.ai>
Inventor <https://www.tcm.phy.cam.ac.uk/~gjc29/index.html>

Papers

https://www.intellegens.ai/downloads/Probabilistic_neural_network_identification_of_an_alloy_for_direct_laser_deposition.pdf

https://www.intellegens.ai/downloads/Materials_data_validation_and_imputation_with_an_artificial_neural_network.pdf

https://www.intellegens.ai/downloads/Materials_data_validation_and_imputation_with_an_artificial_neural_network.pdf

<https://www.intellegens.ai/downloads/ConduitJonesStoneConduit17ii.pdf>

<https://www.intellegens.ai/downloads/Whitehead19.pdf>

Steels demonstrator

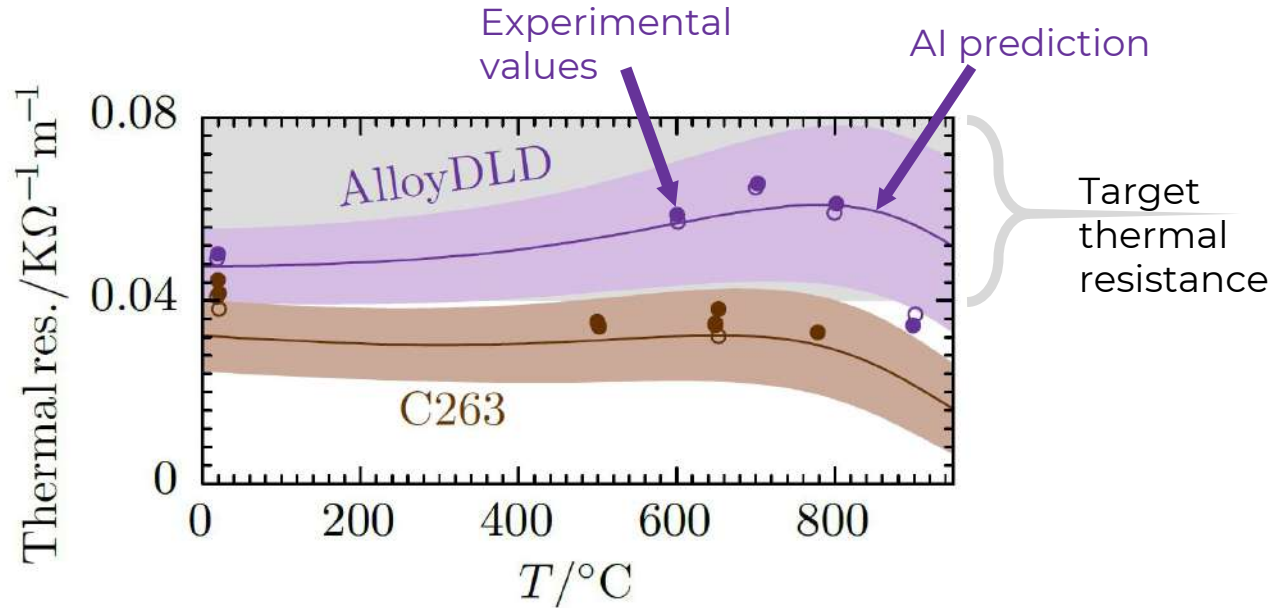
https://app.intellegens.ai/steel_search

https://app.intellegens.ai/steel_optimise

Appendix



Case study: direct laser deposition



Alchemite™ Materials design

Historical materials data - composition, treatment processes and resultant properties - is abundant but sparse.

	COMPOSITION			PROPERTIES			PROCESS
	Iron	Carbon	Nickel	Melt	Hard	Density	Temperature
Steel 1	10	0.3	22	1538	608		832
Steel 2	12		21	1085		8.96	1100
Steel 3		0.2	15		188	19.3	
Steel 4	11	0.6	0.6	660		2.7	1000

Thousands of materials

Tens of properties

Alchemite™ Materials design

Traditional AI - model 1 property at a time on complete data.

Information lost



	COMPOSITION			PROPERTIES			PROCESS
	Iron	Carbon	Nickel	Melt	Hard	Density	Temperature
Steel 1	10	0.3	22	1538	608		832
Steel 2	12		21	1085		8.96	1100
Steel 3		0.2	15		188	19.3	
Steel 4	11	0.6	0.6	660		2.7	1000

Thousands of materials

Tens of properties

Alchemite™ Materials design

Predict all values, supplying probability distributions for each.
Likelihoods can help inform 'safest' predictions to achieve targets or most 'risky' predictions

	COMPOSITION			PROPERTIES			PROCESS
	Iron	Carbon	Nickel	Melt	Hard	Density	Temperature
Steel 1	10	0.3	22	1538	608	12.2 ±1.1	832
Steel 2	12	0.4 ±0.1	21	1085	440 ±2.1	8.96	1100
Steel 3	11.5 ±0.6	0.2	15	740 ±11	188	19.3	990 ±23
Steel 4	11	0.6	0.6	660	220 ±0.6	2.7	1000

Thousands of materials

Tens of properties

Alchemite™ Materials design

Steel 5 - design for desired targets - predictive mode

	COMPOSITION			PROPERTIES			PROCESS
	Iron	Carbon	Nickel	Melt	Hard	Density	Temperature
Steel 1	10	0.3	22	1538	608	12.2 ±1.1	832
Steel 2	12	0.4 ±0.1	21	1085	440±2.1	8.96	1100
Steel 3	11.5 ±0.6	0.2	15	740 ±11	188	19.3	990 ±23
Steel 4	11	0.6	0.6	660	220 ±0.6	2.7	1000
Steel 5			1.2	300	400		

Thousands of materials

Tens of properties

Alchemite™ Materials design

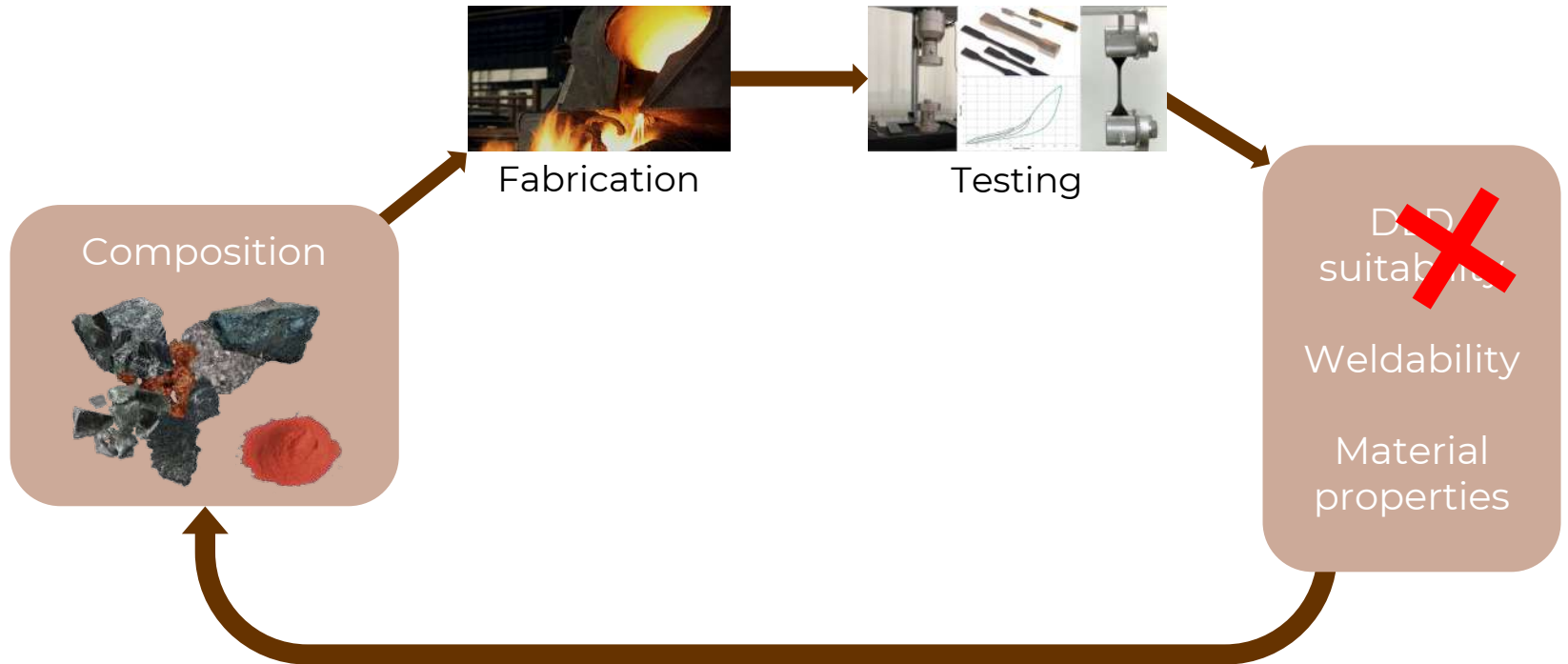
Steel 5 - design for desired targets

	COMPOSITION			PROPERTIES			PROCESS
	Iron	Carbon	Nickel	Melt	Hard	Density	Temperature
Steel 1	10	0.3	22	1538	608	12.2 ±1.1	832
Steel 2	12	0.4 ±0.1	21	1085	440±2.1	8.96	1100
Steel 3	11.5 ±0.6	0.2	15	740 ±1	188	19.3	990 ±2.3
Steel 4	11	0.6	0.6	660	220 ±0.6	2.7	1000
Steel 5	12 ±0.6	0.3 ±0.1	1.2	300	400	9.1 ±0.2	780 ±21.2

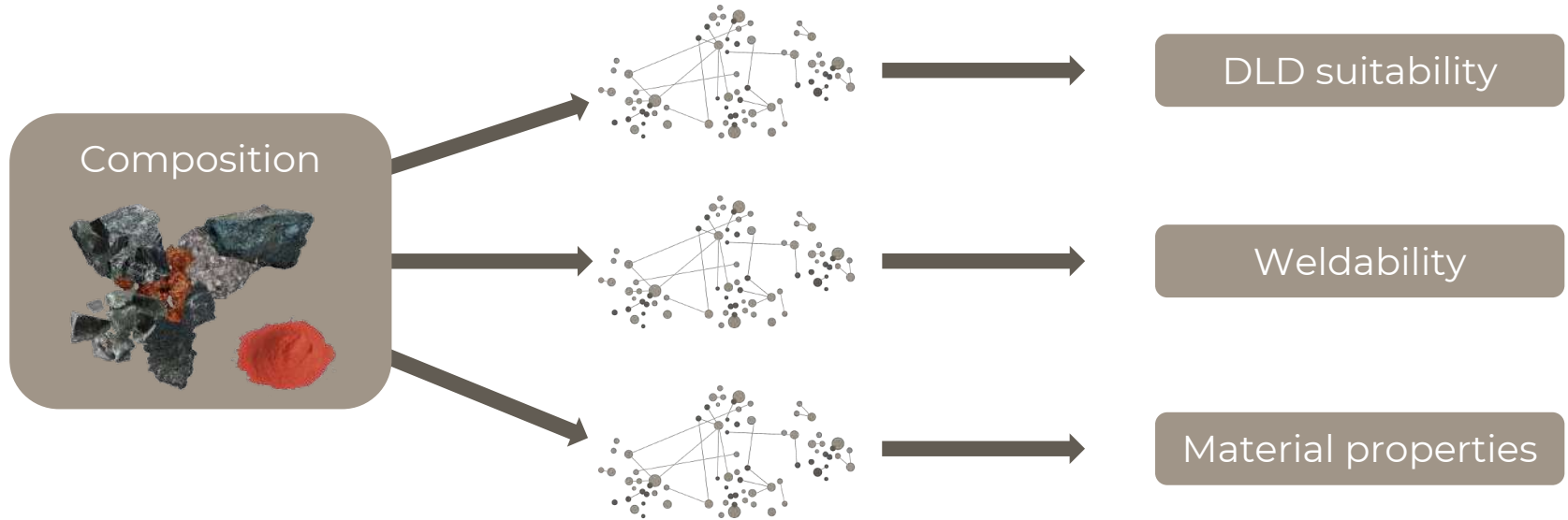
Thousands of materials

Tens of properties

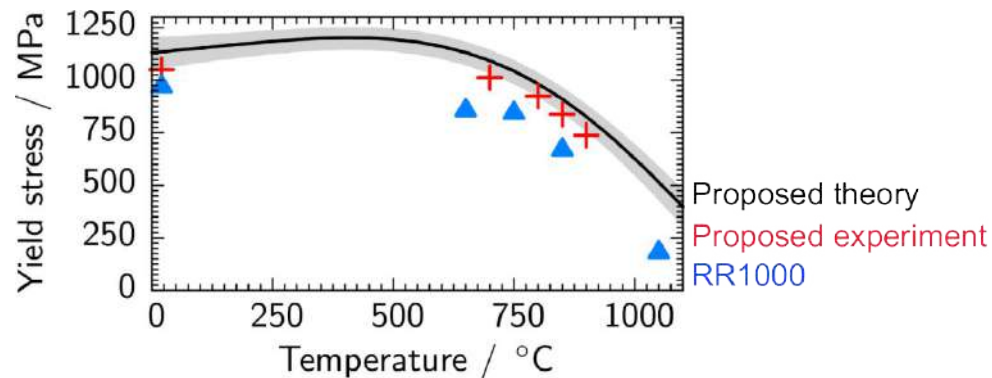
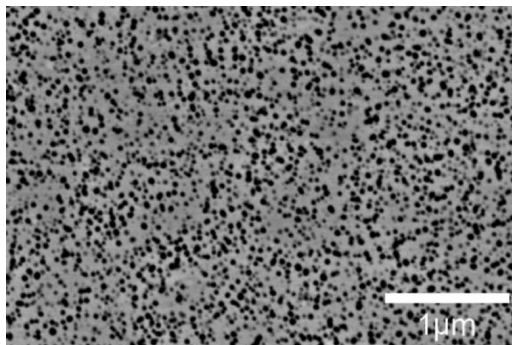
Traditional materials design



Conventional AI materials design



Validation



Designed alloy satisfies 14 target properties, experimentally verified and patented. Reduced development time by 18 years, saving £10m

Scripta Materialia 146, 82 (2018), Materials & Design 131, 358 (2017)

EP14157622, US2013/0052077A2, EP14153898, US2014/177578, EP14161255, US2014/223465

Alchemite™ for drug discovery

Improving compound protein interaction database by a factor of 400, enabling saving experimental costs

	DESCRIPTORS			PROTEINS						
	SlogP	SMR	TPSA	P1	P2	P3	P4	P5	P6	P7
Drug 1	3.6	157	133		A			A		I
Drug 2	4.2	192	102		A			A		
Drug 3	3.9	110	112						I	

Millions of molecules

Thousands of proteins

2,000,000 compounds with 6000 proteins



12,000,000,000 possible values

Data only 0.05% complete



6,000,000 values

Alchemite™ Other applications

Predictive maintenance.

Given a network of assets, we can merge datasets to optimise cleaning schedules, reducing costs and preventing critical failures



Patient analytics

Use all available data, patient profiles, multiple treatment plans and multiple outcomes, to model and suggest likelihoods of outcomes when specific therapeutic plans are applied to a presenting patient

