Catalogue-based Reverse Engineering: for AI-based Modelling in Fusion Remote Maintenance Equipment Design

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ABSTRACT

- This paper presents the application of AI modelling, aligned with catalogue-based reverse engineering, to reduce uncertainties and foster creativity, given the ill-defined requirements and ongoing changes
- The methodology is a hybrid AI optimisation approach that utilises surrogate machine learning, via data from a digital knowledge base repository built from a design catalogue and reverse engineering method, to facilitate inverse algorithms for design optimization.
- The methodology has three phases: (1) building a data repository via catalogue-based reverse engineering; (2) Contextual definition to extract data; and (3) creating a hybrid AI optimisation by integrating surrogate models with multiphysics models and an inverse algorithm.

BACKGROUND

- The engineering design of components and systems in a fusion power plant (FPP) includes the development of remote maintenance (RM) equipment to ensure ease of maintenance, operational safety, reliability, and system availability.
- A novel technology-driven approach, based on catalogue-based design, has been introduced to promote the application of existing robotics and autonomous systems as RM equipment.
- The hypothesis is that the introduction of ML/AI-based modelling for the RM equipment design will reduce design complexity for the redesign of robotics and autonomous systems as FPP RM equipment.
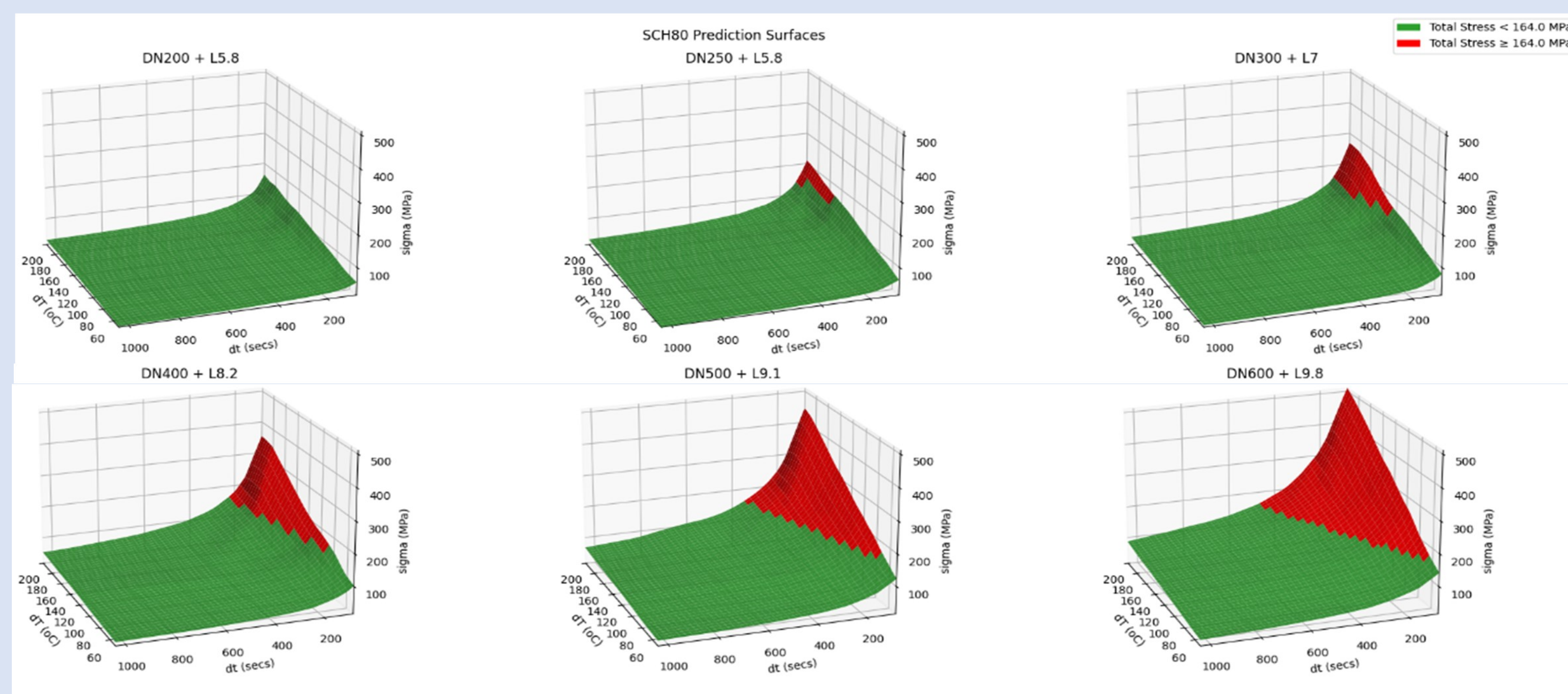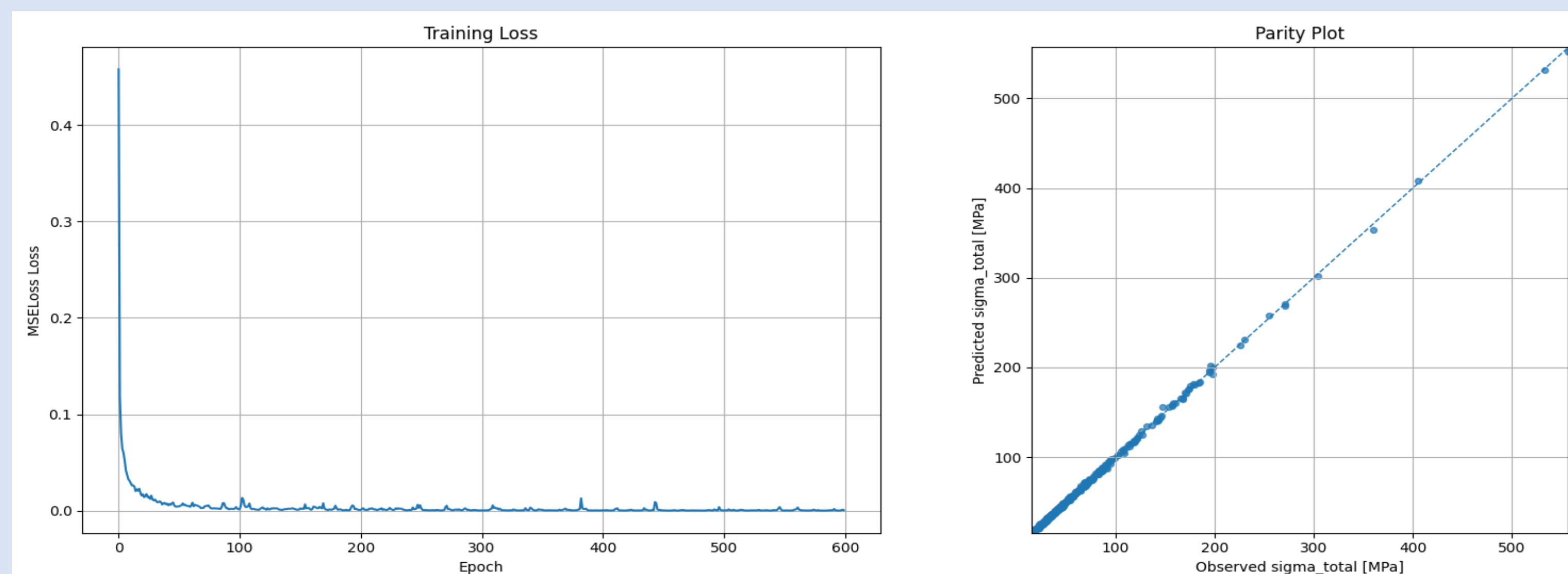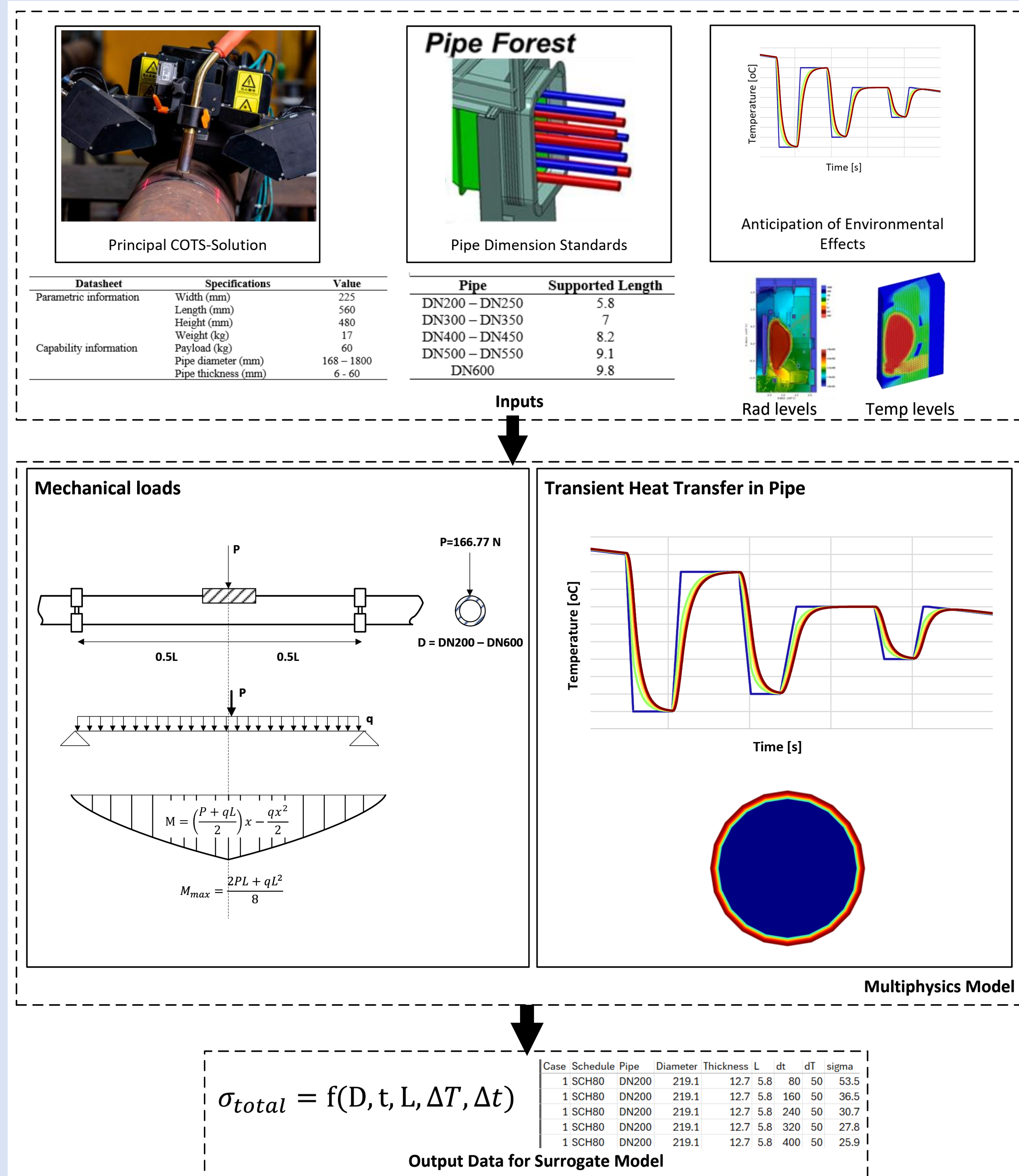
METHODLOGY
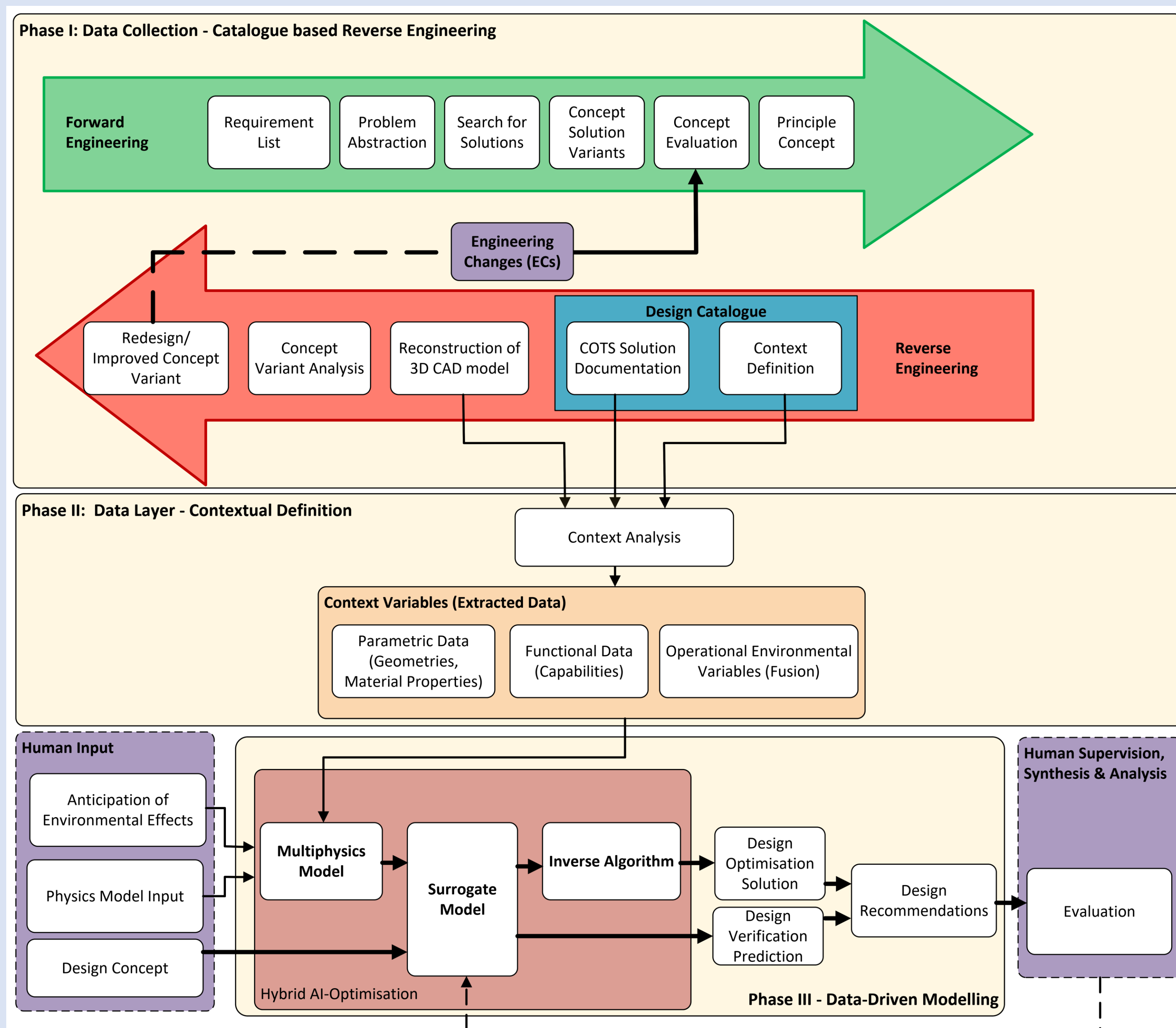
AI-based modelling methodology for fusion engineering

ACKNOWLEDGEMENTS / REFERENCES

CASE IMPLEMENTATION AND OUTCOME

Pipe	Supported Length
DN200 – DN250	5.8
DN300 – DN350	7
DN400 – DN450	8.2
DN500 – DN550	9.1
DN600	9.8

Datasheet	Specifications	Value
Parametric information	Width (mm)	225
	Length (mm)	560
	Height (mm)	480
	Weight (kg)	17
Capability information	Payload (kg)	60
	Pipe diameter (mm)	168 – 1800
	Pipe thickness (mm)	6 - 60

Inputs

Anticipation of Environmental Effects

Rad levels   Temp levels

Mechanical loads

P=166.77 N

D = DN200 – DN600

$$M = \left(\frac{P + qL}{2}\right)x - \frac{qx^2}{2}$$

$$M_{max} = \frac{2PL + qL^2}{8}$$

Transient Heat Transfer in Pipe

Multiphysics Model

$$\sigma_{total} = f(D, t, L, \Delta T, \Delta t)$$

Case	Schedule	Pipe	Diameter	Thickness	L	dt	dT	sigma
1	SCH80	DN200	219.1	12.7	5.8	80	50	53.5
1	SCH80	DN200	219.1	12.7	5.8	160	50	36.5
1	SCH80	DN200	219.1	12.7	5.8	240	50	30.7
1	SCH80	DN200	219.1	12.7	5.8	320	50	27.8
1	SCH80	DN200	219.1	12.7	5.8	400	50	25.9

Output Data for Surrogate Model

CONCLUSION

- The study highlights the first research output: (1) applications of surrogate models as a design verification tool to replace the full Multiphysics simulation, (2) impact evaluation of the current design on different plant component designs.
- ML/AI modelling can be integrated with Catalogue-based Reverse Engineering to reduce design complexity, corroborating the hypothesis.
- The second research output is ongoing to utilize the surrogate model in assisting the inverse algorithm in producing optimized design suggestions.