Catalogue-based reverse engineering: for AI-based modelling in fusion remote maintenance equipment design

William Brace*, Van-Dung Truong
VTT Technical Research Centre of Finland Ltd, Espoo, FI-02044, Finland
**Corresponding author email: william.brace@vtt.fi*

Maintainability is identified as mission-critical in the European consortium "EUROfusion" concept for a first demonstration fusion reactor (DEMO). Hence, the design of remote maintenance equipment (RME) is considered an integral part of the design of the DEMO tokamak architecture and components. During the design, there are several limitations since the input requirements are unstable, inadequate, and subject to numerous engineering changes (EC) in the tokamak architecture. A novel product-driven approach, based on design by cataloguing, has been introduced. The catalogue-based design is advocated to implicate commercial-off-the-shelf (COT) technologies integrating products with higher maturity and TRL and space reservations to ensure compatibility with the tokamak plant architecture. Consequently, the DEMO design has become a complex process that draws on previous experience and creativity to generate radical solutions. In addition, the catalogue-based design advocates space exploration as one of the design drivers, to extend the inclusion of RME design preferences into the tokamak architecture and component designs thus compounding the DEMO design problem.

The hypothesis is that the introduction of Artificial intelligence (AI) based modelling for the DEMO design will reduce the design complexity and enhance creativity in the entire design process. However, the application of AI in the design processes should not be directed towards finding solutions in a defined search space, since the DEMO requirements are not well defined, and there are EC regarding the tokamak architecture in the conceptual stage. The research objective is to develop and implement in the DEMO design, an AI-based model founded on the catalogue-based design approach and implicating the concept of reverse engineering as part of capturing data as the first input block for the AI modelling.

A review of the literature indicates AI modelling is a reference to a sophisticated computational system designed to simulate human intelligence or creativity through advanced algorithms and learning mechanisms. These AI models are built using complex methodologies such as machine learning, deep learning, and neural networks. One of the defining attributes of the AI models is exhibiting cognitive abilities such as reasoning, problem-solving, and understanding which are also the building blocks for conceptual design. A well-organised process is required in creating an AI model and involves multiple conceptual layers, including a data layer, which is the backbone of all AI models. Exploratory design is an important aspect of data collection. Maher and Poon stressed the exploratory aspect during conceptual design has not been exploited fully. In recent work, catalogue design has been used in exploring possible COT systems for implication in fusion design development. Design catalogue by definition is an integral part of discursive design, a systematic way for solution search and involves collecting proven solutions and documenting them as catalogues for further use as input data and enhancing traceability. Further, the concept of reverse engineering is applied in the catalogue design allowing for the analysis of the COT products. A reverse engineering process works backwards from the end product, determining the design and technology used and collecting quantifiable and nonquantifiable data simultaneously.

The research methodology has three phases as shown in Figure 1. Phase 1 is the data collection model and focuses on building the theoretical foundation of the design by cataloguing as a combination of forward and reverse engineering to facilitate design practices that cope with uncertain requirements and frequent changes in plant design. The model is implemented in the DEMO RME design to collect existing COT technologies, analyse and extract both quantifiable and nonquantifiable data labelling and store them as capability datasheets. The result obtained has indicated this method allows the design of RME while the plant design is partially formed. The result also indicates the approach is a knowledge-based repository to capture and store data for future use. The result allows the extraction of the key data labels, as input to Phase II in the DEMO AI model.

In Phase 2 research, automated software will be implemented that can digitalise the output from Phase 1, capturing and storing information labelled as key data features. Work has started using PLM software to discriminate the data while enhancing traceability. The data in this phase are discriminated as 1) Plant CAD Model **-** dimensional information of the plant through the context CAD model 2) Functional Data: functions of the COTS solutions (capabilities), 3) COTS CAD Parametric data - dimensional information of the COTS solution, extracted from the reverse engineering analysis. , and 4) Feasibility Data - the feasibility assessment of the designers under labelling data. In further work, the data shall be pre-preprocessed and extracted for the data training in phase III.

Phase III focuses on developing a hybrid AI agent that combines natural language processing (NLP), search methods, and machine learning (ML). The model aims to automate and facilitate the design process in redundant or repetitive tasks. Human interface with the agent through verbal inputs and the latest digital design catalogue database information. The model translates information from requirements and the latest plant architecture design to analyse the design context.

Existing COTS solutions that designers are considering are then searched based on the database of the design catalogue using search methods/ algorithms. The outcomes of these two steps are translated into inputs for the predictive model as learned from historical data in phase II using ML. Feasibility assessment and design advice are the main outputs of the agent, giving designers feedback about design ideas and possible modifications. Finally, information is synthesised and evaluated by humans, facilitating the formation of the final design solution.

In conclusion, the research advocates the design and construction of an AI design tool to augment and draw on previous experience and creativity in DEMO design. The first and part of the second phases of the research are implemented in the DEMO design with some results published. It can be observed that the level of automation is increasing from Phase I to Phase III. The AI agent's role is to work as a design assistant, contributing to solution findings. The human role remains centric, and the decision-maker is involved in the all-automated design process.

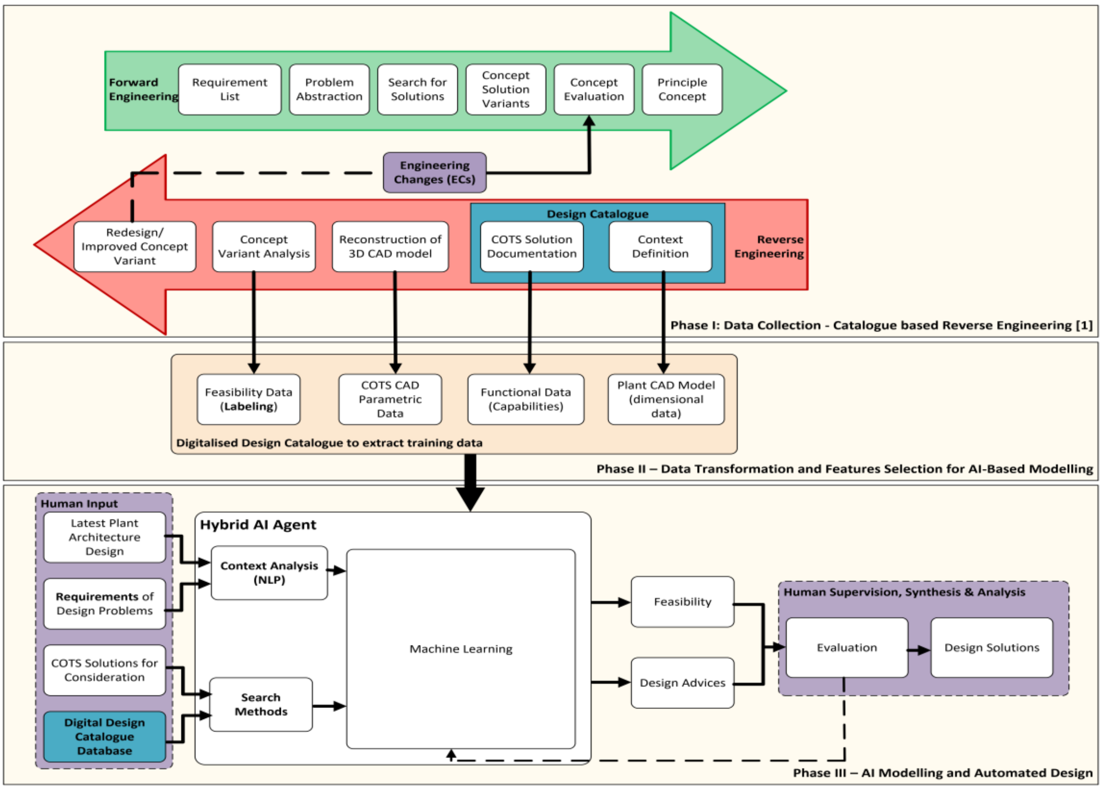

Figure 1. AI-based modelling for remote maintenance equipment design in FPP

Acknowledgement

This work has been carried out within the framework of the EUROfusion Consortium, funded by the European Union via the Euratom Research and Training Programme (Grant Agreement No 101052200 — EUROfusion). Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Commission. Neither the European Union nor the European Commission can be held responsible for them.

References

[1] Truong, V. D., & Brace, W. (2025). Design by cataloguing–a product-driven design approach for the conceptual design of fusion remote maintenance systems. Fusion Engineering and Design, 212, 114848. https://doi.org/10.1016/j.fusengdes.2025.114848

[2] Brace, W., Tikka, P., Alanen, J., Lyytinen, J., & Martikainen, H. (2024). Digital Thread Architecture: Coupling Requirements and 3-D CAD Models in an Iterative Closed Design Loop. IEEE Transactions on Plasma Science. DOI: 10.1109/TPS.2024.3400689

[3] Maher, M.L., Poon, J., Boulanger, S. (1996). Formalising Design Exploration as Co-Evolution. In: Gero, J.S., Sudweeks, F. (eds) Advances in Formal Design Methods for CAD. IFIP — The International Federation for Information Processing. Springer, Boston, MA. https://doi.org/10.1007/978-0-387-34925-1_1 .

[4] Srivastava, S., Kumar, V., Singh, S. K., Yadav, P., Singh, B., & Bhaskar, A. (2024). A Review on Application of Artificial Intelligence in Mechanical Engineering. Machine Learning Techniques and Industry Applications, 29-46. DOI: 10.4018/979-8-3693-5271-7.ch002

[5] W. Wang, Reverse Engineering, CRC Press, 2010, https://doi.org/10.1201/EBK1439806302