# AI for Design, Engineering, Construction, and Operation of SMRs

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**Abstract**

Small Modular Reactors (SMRs) hold immense promise for revolutionising the nuclear energy landscape, offering safer, more flexible, and cost-effective alternatives to traditional large-scale reactors. However, the successful deployment of SMRs relies heavily on efficient design, engineering, construction, and operation processes. The paper explores the transformative potential of Artificial Intelligence (AI) and Machine Learning (ML) technologies in accelerating the advancement and adoption of SMRs. Through concrete examples, it demonstrates how AI can streamline material qualification, enhance non-destructive testing, optimise supply chain management, and facilitate knowledge extraction for improved safety and efficiency throughout the SMR lifecycle.

## INTRODUCTION

The emergence of Small Modular Reactors (SMRs) and Advanced Modular Reactors (AMRs) represents a paradigm shift in the nuclear energy sector, offering scalable, versatile, and cost-effective solutions for diverse energy needs. However, the successful realization of SMRs necessitates overcoming various technical, regulatory, and economic challenges. Modular factory-based construction of SMR components opens up opportunities for Advanced Manufacturing (AM) technologies and use of I4.0 digital technologies like Artificial Intelligence (AI). In this context, the integration of advanced digital technologies such as AI and Machine Learning (ML) holds tremendous potential for revolutionising the design, engineering, construction, and operation of SMRs. According to the Coordinated Research Project CRP 2230 [1], AI could reduce SMR installation costs, shorten construction times and better meet user needs through greater flexibility or non-electric applications. This paper explores the multifaceted applications of AI/ML in accelerating the development and deployment of SMRs, with a focus on efficiency, safety, and sustainability.

## AI in Material Qualification

The qualification of new materials for SMR components traditionally involves rigorous testing and analysis, often leading to lengthy and costly processes. AI-powered predictive modelling and simulation techniques offer a transformative approach to expedite material qualification while ensuring reliability and safety. By leveraging historical data and advanced algorithms, AI can accelerate the identification of suitable materials with desired properties, significantly reducing time-to-market and associated costs.

In a recent case study, researchers utilized AI algorithms to analyse vast datasets of material properties and performance characteristics. By identifying correlations and patterns, the AI model accurately predicted the behaviour of novel materials under varying operational conditions which can expedite the qualification process.

### Prediction of Material Properties

Nawal Prinja [2] reported work on Material Properties Predictor for Power Plant Steels (M4Ps) where AI models were trained to predict material properties from known chemical composition and processing history. The data contained 58 steel types in the data base of various steel product forms (tubes, plates, bars etc.) used in power plants. The AI models predicted three sets of material properties: tensile properties (Proof Stress, Ultimate Tensile Strength, Elongation% and RA%), creep rupture properties (Fracture time, Elongation% and RA%) and hardness (HRB/HRC). Accuracy ranged from 85% to 98%. Such AI models can help develop new materials for future Advanced Modular Reactors (AMRs) that are being designed to work at much higher temperatures.

Also reported in [2] is the work carried out to predict fracture life of nuclear materials. Artificial Neural Network (ANN) was applied to predict environmental impact on fatigue/fracture behaviour of steel. The INCEFA PLUS data generated under the EU funded H2020 project on INcreasing safety in NPPs by Covering gaps in Environmental Fatigue Assessment (INCEFA) was used. A sequential ANN model with 10 dense layers of neurons was developed. 80% of the data from 246 tests was used to train the model and the fracture life results for the remaining 38 tests were predicted with an average of 95.4% accuracy. Life predictions are shown in Fig. 1.



Fracture Life (No. of Cycles)

Test Number

*FIG. 1. Prediction of fracture life by AI*

### Optimisation of Material Tests

SMRs particularly AMRs may require new materials which in turn will require a large number of physical qualification tests for inclusion in the codes and standards. These are needed to cover the natural variability in the material properties. According to the AFCEN guide [3], any material that differs from already codified materials due to dimensional range (thickness, diameter, weight) or grade or in microstructural state, is deemed to be a new material. Qualification of new material involves mechanical, thermal, irradiation, corrosion and creep tests which can take few months to several years. This creates an extra challenge for the nuclear industry is that there is not sufficient material test data available. A feasibility study [4] has shown that uncertainties from the sparse data and material variability can be accounted for by combining ANN with Bayesian statistics and Interval Predictor Models to fill the gap in material data with necessary confidence levels. This AI tool can help reduce the number of experimental campaigns required to characterise material properties.

## AI in Non-Destructive Testing (NDT)

Non-destructive testing plays a critical role in ensuring the integrity and reliability of SMR components during manufacturing and operation. AI-driven NDT techniques offer enhanced sensitivity, accuracy, and efficiency compared to traditional methods. By analysing complex datasets in real-time, AI algorithms can detect anomalies, defects, and structural weaknesses with unprecedented precision, enabling proactive maintenance and quality assurance measures. Advanced Manufacturing techniques like Electron Beam (EB) welding of thick plates and recent initiatives being taken to use Ultrasonic Testing (UT) instead of Radiographic Testing (RT) can be accelerated by use of AI. The following two examples illustrate how AI is being deployed in NDT.

### Quality Control of EB Welds

Electron Beam (EB) welds are going to play crucial role in factory production of SMR components. Their success rate is of utmost importance, not only for nuclear safety but also for economic production. Maria Ortiz-De-Zuniga et al [5] conducted a study using AI models to identify the combination of parameters that could lead to flaws in the EB welds. The error rate was random, and each weld repair could take anywhere from one week to one month causing disruption to planned human resources, machines and documentation. To develop a predictive AI model, all the available data regarding 1802 EB welds were collected and analysed using Machine Learning. This AI model was used to predict outcome of weld inspection for 70 new EB welds. The output of the model showed that all true positives and true negatives were correct: one weld was predicted to fail at 90% probability, and it was confirmed that it actually failed; another 16 welds were predicted to fail at 56% probability, of which 7 failed and 9 passed; and all the remaining 53 predicted to pass actually passed. These accurate predictions and results show that the application of AI in nuclear manufacturing allows manufacturers to improve quality control and reduce impacts on resources, documentation and schedule, therefore de-risking programs.

### PAUT of Butt Welds

Fusion for Energy carried out a pilot project to test AI-powered Phased Array Ultrasonic Testing (PAUT) system in one of the production facilities that demonstrated significant reduction in inspection time and resource utilization. This has the potential to minimise false positives, thereby enhancing overall manufacturing efficiency and product quality. Typically, PAUT can take several days for acquisition and subsequent analysis of inspection data. Furthermore, it can cost 1 to 5 million dollars to train and qualify an inspector. Maria Ortiz de Zuniga et al [6] have shown that AI models can be trained to provide digital assistance to inspectors and reduce the time taken to inspect the welds. Fig. 2 shows scans from a PAUT inspection of a weld indicating presence of three flaws that took several hours of manual analysis to confirm. Fig. 3 shows the same three defects predicted by AI in couple of minutes.



*Fig 2. PAUT inspection of a weld indicating presence of three flaws*



*Fig 3. AI prediction of the three flaws*

TABLE 1. Comparison of manual UT analysis with AI predictions

|  |  |  |  |
| --- | --- | --- | --- |
| Flaw ID | Scan Position of Flaw Centroid, Xo (mm) | Focal Law(Beam Number) | Depth, Zo (mm) |
| Report | AI | Report | AI | Report | AI |
| FL02 | 159 | 156 | 36o (4) | 36o (4) | 34.8 | 35.44 |
| FL03 | 184 | 186 | 36o (4) | 36o (4) | 33.1-35.6 | 35.44 |
| FL04 | 218 | 219 | 36o (4) | 36o (4) | 32.3-35.2 | 35.05 |

Location of a defect in a weld is reported by its scan position along the length of the weld, the Focal Law (beam number) and the depth, Zo. Table 1 shows that the AI model predictions accurately match the manual analysis, achieving the same accuracy but in fraction of time.

##  AI in Supply Chain Management

Efficient supply chain management is crucial for the timely procurement of components, materials, and services essential for SMR construction and operation. AI-driven cognitive search engines and analytics platforms offer advanced capabilities for optimizing supply chain processes, mitigating risks, and enhancing decision-making. By aggregating and analysing vast volumes of data from diverse sources, AI systems can identify cost-saving opportunities, streamline procurement workflows, and ensure compliance with regulatory requirements. AI tools based on the Natural Language Processing (NLP) technology are being developed to check if contractor’s deliverables comply with the technical specifications and regulations.

## AI in Knowledge Management and Safety Assurance

Effective knowledge management is essential for ensuring regulatory compliance, operational efficiency, and safety in SMR facilities. AI-powered cognitive search engines and data analytics tools enable efficient extraction, aggregation, and dissemination of critical information from diverse sources. By automating data retrieval, analysis, and reporting tasks, AI systems empower operators to make informed decisions, optimize resource allocation, and enhance safety case development.

Following two examples are presented to show how AI-powered cognitive search engines can be employed to extract relevant information from large number of unstructured archived documents. This can facilitate timely access to comprehensive asset information that can perform Knowledge Management and Knowledge Preservation (KMKP) for SMRs and AMRs to be built in future.

### Knowledge Extraction from Historic Project Archives

The Energy, Security & Technology (ES&T) business unit within Jacobs currently has approximately 25,000 boxes held in a secured offsite storage location. These boxes contain information relating to nuclear projects, dating back over 40+ years. The information contained within these boxes could be vital to support future research and projects. In a pilot project, 200 boxes were identified and retrieved from the archives. 2943 documents from these 200 boxes were scanned and converted into pdf files. In total nearly half a million pages of information was converted into a ‘Knowledge Base’ by a propriety software. A number of complex technical questions were asked related with reactor design and nuclear site investigations. Each search provided accurate information and took less than 20 seconds to complete. A manual search would have taken days.

### Molten Salt Reactor Knowledge Base

A trial for Generation IV International Forum (GIF) was conducted by extracting knowledge from Molten Salt Reactor research reports. Scanned copies of 30 ORNL reports (about 683 MB of data) was used to create a knowledge base from these reports. The software took 38 minutes to analyse all the reports which involved reading all the contents and creating a knowledge base. A number of technical questions related with coolants for heat exchangers and types of salts were asked which were answered accurately in less than 15 second with precise reference given with each reply.

## non-electric Applications and load following

AI can help optimise SMR designs for various non-electric applications as follows:

Process Heat: AI can help tailor designs to meet specific process heat requirements where SMRs can provide high-temperature process heat for industrial applications (e.g., hydrogen production, desalination, or district heating).

Cogeneration: AI can help improve overall efficiency for combined electricity and heat production.

Non-Electric Grid Services: AI-controlled load-following capabilities can enable SMRs to contribute to grid stability by providing ancillary services (e.g., frequency regulation) and be part of smart grids.

## Conclusion

The successful deployment of SMRs hinges on the efficient integration of advanced digital technologies such as Artificial Intelligence (AI) and Machine Learning (ML). By harnessing the power of AI/ML, SMR stakeholders can accelerate innovation, improve safety, and reduce costs throughout the lifecycle of SMR projects. Through concrete examples and case studies, this paper has demonstrated the transformative potential of AI in material qualification, non-destructive testing, supply chain management, and knowledge management for SMRs. As the nuclear industry embraces the digital revolution, AI-driven solutions will play an increasingly pivotal role in shaping the future of clean, reliable, and sustainable energy generation.

## References

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