Technology Development Programme

Technology Mapping

2025 Series

Artificial Intelligence in Fusion

FUSION FOR ENERGY

Contents

Version history

VERSION	DATE	CHANGES
0.0	07/03/2025	First issue: input data for online workshop. Covers: 1. Introduction 2. The mapping process 3. AI technology breakdown (draft) Other sections will be completed after the workshop.
1.1		After the online workshop, incorporating the changes agreed to the technology map.
2.0		After the in-person workshop – draft final report made available for comment by participants
2.1		Final report for publication

Foreword

Will be completed after the workshop taking place in May 2025

Executive summary

Will be completed after the workshop taking place in May 2025.

1 Introduction

1.1 Context

In 2024, Fusion for Energy launched a Technology Development Programme (TDP) as part of the implementation actions of its Industrial Policy. This TDP is dedicated to building and reinforcing European Fusion Supply chain capabilities for those technologies that are deemed to be critical for the future of commercial fusion. The programme requires the identification of key technologies to direct R&D contracts to European contractors.

Prioritizing and allocating funding opportunities requires a comprehensive review of the involved technologies on each major fusion technical domain. Doing this exercise in a collaborative way will enable stakeholders to identify which technologies are fundamentally needed (technology mapping) and when are they needed (technology road mapping). A roadmap built through consensus of key stakeholders in the field can also serve as a powerful argument when seeking additional funding from national and international public and private investors.

To coordinate these efforts, Fusion for Energy has launched a technology mapping initiative uniting academia, research laboratories, industry, start-ups and the ITER Organization to develop a comprehensive technology development roadmap for the application of Artificial Intelligence in Fusion Technologies.

The outcome of this exercise will serve all stakeholders to guide their action in their respective domains, allowing an effective investment of resources. Given the fast evolution of technology, a periodical follow-up of the workshop outcome shall be assured in subsequent technology mapping exercises.

1.2 Artificial Intelligence technology mapping

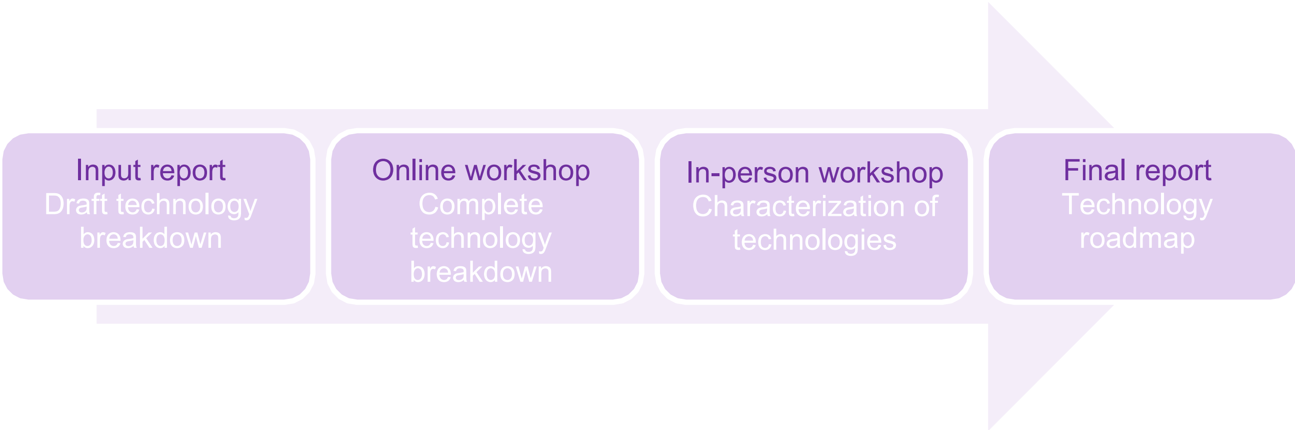
The scope of the second such mapping exercise is the implementation of artificial intelligence in fusion technologies. It covers the application of artificial intelligence in design and simulation, material development, manufacturing and non-destructive testing (NDT) including assembly, and plasma science and control.

The main associated event is a workshop held in April and May 2025 to generate most of the relevant data and provide an opportunity for participants to network and exchange knowledge.

This document provides a complete overview of the exercise, detailing the process and scope through a comprehensive technology breakdown, summarizing the meetings held and providing the resulting proposed technology development roadmap.

2 Technology mapping process

The technology mapping process consists of four stages.



2.1 Input report

In preparation of the exercise, staff from Fusion for Energy prepare a draft technology breakdown with input from ITER Organization colleagues, listing technologies of interest and grouping them functionally.

This breakdown, together with a brief description of each selected technology, is included in a draft input report (see section 3) for consultation by participants ahead of the first meeting (an online workshop).

2.2 Online workshop

The online workshop provides an opportunity for all participants in the technology mapping exercise to come together. It typically lasts 6 to 7 hours and follows the agenda outlined below:

- Welcome and introductory remarks
- The technology mapping process
- Introductory presentations about the field of interest
- Networking opportunity between participants
- Brief overview of technology breakdown
- Joint review of the technology breakdown
- Explanation of the in-person workshop
- Survey feedback and wrap-up

The main output of the online workshop is a comprehensive list of relevant technologies, agreed upon by all participants. This breakdown serves as the foundation for the technology mapping, which is the primary result of the initial workshop exercise. An updated version of the input report, including the revised technology breakdown, is provided to participants prior to the in-person workshop.

2.3 In-person workshop

The in-person workshop aims to provide a detailed characterization of the technologies outlined in the breakdown agreed upon during the online workshop, including their prioritization and corresponding timeline.

The characterization of technologies is carried out in three steps for each technology:

- Agreement on the current Technology Readiness Level (TRL) (see Appendix 1 for definitions)
- Definition of the next step (e.g., analysis, prototype, testing, industrialization plan, etc.)
- Quantification of the technology characteristics (see Appendix 2 for the proposed list of characteristics to be evaluated)

Additionally, a timeline is developed, classifying what is needed and when for the technologies considered in the technology mapping. Typical timelines may span 5, 15, or 30 years, or be categorized into short, medium, and long-term periods.

The workshop is designed to be highly collaborative, with sessions that encourage participants to exchange ideas, build consensus, and provide feedback on specific interests and the mapping process itself. It also offers numerous opportunities for participants to share knowledge and establish partnerships. The workshop typically lasts one and a half days, with designated times for both formal and informal networking.

2.4 Final report

After the in-person workshop, staff from Fusion for Energy will compile the results into a final report, which serves as an evolution of the input report. This report will provide an overview of European capabilities in the field and include a proposed technology roadmap that outlines and prioritizes potential actions for the period leading up to the next review, typically occurring within 1 to 2 years.

Participants are given an opportunity to comment before the final version of the report is published.

3 Artificial Intelligence Breakdown

3.1 Artificial Intelligence overview

Artificial intelligence (AI) is transforming technology by enabling machines to perform tasks that traditionally required human intelligence, such as problem-solving, decision-making, and pattern recognition. From self-driving cars to medical diagnostics and advanced simulations, AI is revolutionizing industries by automating complex processes and improving efficiency.

One of the most powerful approaches within AI is machine learning, which allows computers to learn from data and improve their performance without explicit programming. Unlike traditional rule-based AI systems, machine learning algorithms adapt and evolve through experience, making them highly effective in processing large datasets and identifying patterns. There are different types of machine learning, including supervised learning (trained on labelled data), unsupervised learning (finding hidden structures in unlabelled data), and reinforcement learning (learning through trial and error). Machine learning is a driving force behind many AI applications, such as trend identification, image recognition, natural language processing, autonomous systems, and scientific research, accelerating advancements in automation, prediction, data analysis, and problem-solving.

3.2 Technical breakdown of applications

Artificial intelligence can be applied at various stages of the development process, from the initial phases of design and simulation to operational applications.

This workshop focuses on five key stages in the development of fusion technologies:

- Design and simulation
- Material development
- Manufacturing, Non-Destructive Testing (NDT) and assembly
- Plasma science and control

The **design and simulation** stage is essential for developing fusion reactor concepts and testing their viability before construction, as well as that of isolated components. Advanced simulations are used to model plasma behavior, energy dynamics, and material interactions under fusion conditions. Engineers design the reactor components, while simulations help optimize these designs to ensure efficiency, stability, and safety during operation.

Material development focuses on creating substances that can endure the extreme conditions inside a fusion reactor. These materials must withstand a hostile and unique environment: radiation, high temperatures, and mechanical stress. Research involves identifying and testing radiation-resistant alloys, superconducting materials for magnets, and new materials to improve reactor performance and longevity.

The **manufacturing, non-destructive testing (NDT) and assembly** stage focuses on the precise fabrication and assembly of fusion reactor components, including intricate parts such as vacuum vessel sectors, superconducting magnets, plasma-facing elements, and cooling systems. Advanced techniques like electron beam welding and phased-array ultrasonic testing enable the production of complex and low-tolerance geometries that are challenging to achieve and inspect with traditional methods. Ensuring precision and maintaining strict quality control to verify component integrity without causing damage are essential to meet rigorous standards

Plasma science and control are central to achieving stable fusion reactions. This stage involves managing and confining plasma at extremely high temperatures using magnetic fields. Early prediction of instabilities can allow operators to react promptly and stabilize the plasma, avoiding its phase-out and consequent loss. Researchers use advanced heating techniques to maintain the plasma's energy levels and employ real-time monitoring to adjust control systems and maintain stability.

Several cross-cutting challenges should be considered when driving future directions:

- **Data Scarcity and Quality:** Obtaining sufficient high-quality labelled data, especially failure data, for training robust AI models remains a challenge in these high-reliability sectors. Techniques like transfer learning, data augmentation, and physics-informed AI are being explored.
- **Explainability and Trustworthiness (XAI):** Due to the safety-critical nature, "black box" AI models are often unacceptable. Research focuses on developing explainable AI methods to understand and verify AI decision-making processes for regulatory acceptance and operator trust [1].
- **Validation, Verification, and Qualification:** Rigorous processes are needed to validate AI performance and qualify AI-based systems for use in nuclear and fusion applications, meeting stringent industry standards.
- **Integration and Radiation Hardening:** Integrating AI systems with existing infrastructure and ensuring the reliability of hardware (sensors, processors) in radiation environments are practical hurdles.

3.3 Priority Research Opportunities (PROs)[1]

AI advances, along with the urgency of need to bridge key gaps in knowledge for design and operation of reactors such as ITER, have driven planned expansion of efforts in ML/AI within around the world [1], and especially within Europe. This is the aim of this report: to map all AI developments for fusion, to prioritize them according to the developments and needs of fusion energy in Europe and to conclude with a roadmap, to be updated with the required frequency.

3.3.1 Science discovery with Machine Learning

Applying ML to analyze extensive datasets can bridge theoretical gaps, accelerate hypothesis generation, and optimize experimental planning, enhancing understanding in areas like tokamak confinement and plasma-wall interactions.

3.3.2 Machine Learning-Boosted Diagnostics

Utilizing ML to extract maximum information from diagnostics, improve interpretability through data-driven models, integrate multiple data sources, and develop synthetic diagnostics to infer unmeasured quantities, thereby enhancing plasma state identification and regime classification.

3.3.3 Model Extraction and Reduction

Developing data-driven models to elucidate complex plasma behaviors, quantify uncertainties, and accelerate computational algorithms, facilitating faster simulations and improved comprehension of phenomena such as turbulent transport and plasma heating.

3.3.4 Control Augmentation with Machine Learning

Enhancing plasma control by improving control models, creating real-time data analysis algorithms for adaptive regulation, and optimizing plasma discharge trajectories, which is crucial for the effective operation of fusion reactors.

3.3.5 Extreme Data Algorithms

Creating methods for in-situ analysis and reduction of large-scale simulation data, and efficiently managing extensive experimental data, addressing challenges posed by the massive data volumes expected from future fusion experiments and simulations.

3.3.6 Data-Enhanced Protection

Developing algorithms to predict key plasma phenomena and system states, enabling real-time and offline monitoring and fault prediction, vital for preventing disruptions that could damage fusion devices.

3.3.7 Fusion Data Platform for Machine Learning Apps

Establishing a comprehensive system for managing, curating, and accessing fusion experimental and simulation data, supporting scalable application of ML/AI methods to fusion challenges.

[1] https://science.osti.gov/-/media/fes/pdf/workshop-reports/FES_ASCR_Machine_Learning_Report.pdf

3.4 Map of individual applications

<u>This section will be reviewed and completed during the online workshop on 08/04/2025.</u>

3.4.1 Application of AI in design and simulation

- Fusion REactor Design and Assessment (FREDA) by Oak Ridge National Laboratory
  - AI-powered simulation tool designed to accelerate and optimize fusion reactor design.

It integrates machine learning, high-performance computing, and multi-physics modeling to evaluate reactor configurations, material performance, and operational efficiency.

https://www.ornl.gov/news/all-one-simulation-tool-enables-faster-smarter-fusion-reactor-design

- Digital twins
  - virtual replicas of fusion reactors that continuously update based on real-world data.

These AI-driven models allow researchers to simulate and analyze reactor performance in real time, optimizing design, predicting failures, and improving operational efficiency.

https://scientific-publications.ukaea.uk/papers/towards-a-fusion-component-digital-twin-virtual-test-and-monitoring-of-components-in-chimera-by-systems-simulation/

- ML-driven surrogate modelling (also used in digital twins)
  - approximate complex physics simulations with faster, more computationally efficient models

Traditional first-principles simulations, such as those used for plasma dynamics, turbulence, and material interactions, can be computationally expensive and time-consuming.

In order to ensure the safe and efficient operation of a fusion device, a multitude of sensors captures key information about the plasma and wide range of machine subsystems. These sensors provide signals of quantities like temperature, voltage, magnetic field, etc. More recently, images and video data are increasingly produced. This leads to massive volumes of data that need to be processed or analyzed in detail. Furthermore, some measurements need to be available routinely and processed with minimal delay, notably for feedback control of the plasma state. In addition to data volume and requirements on the processing speed, all measurements are affected by uncertainty, to varying degrees. In other words, the raw measurement taken by a sensor (usually a voltage) gives an estimate of the properties of the plasma or machine components, but inevitably this comes with some measurement error. Scientists often rely on physical models to describe plasma behavior, but this also introduces uncertainty, since no model is perfect.

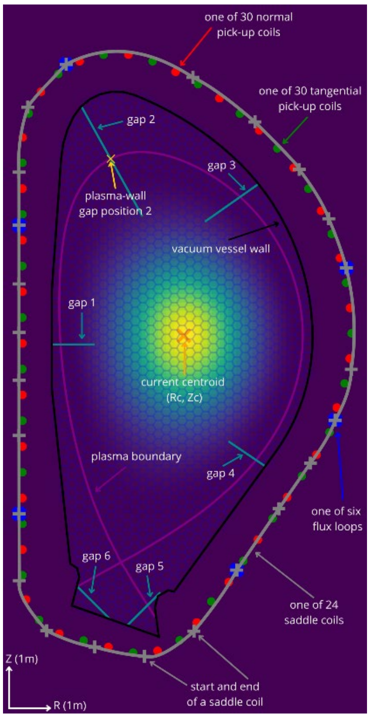


Figure 1: Cross-section of a DEMO design with magnetic sensors (colored dots around the vacuum vessel). The estimated central position ('current centroid') of the plasma and its approximate boundary are also indicated.

To maximize the information from the sensor measurements, **data integration** can play a key role. Referred to as **sensor fusion** in other disciplines, like the development of self-driving cars, this refers to the joint processing of data captured by multiple sensors. It exploits the information about specific plasma quantities provided by multiple diagnostics, each possibly relying on completely different measurement principles (e.g. magnetics vs. spectroscopy). In fusion science, the methods of Bayesian inference have been commonly used for this purpose, as they allow considering heterogeneous sources of information, as well as physics constraints. For instance,

Figure 1 shows a cross-section of the EU-DEMO, along with the locations (colored dots) of the sensors that measure the magnetic field used to confine the plasma [2]. By merging the data from all sensors using the Bayesian framework, an accurate reconstruction of the position of the plasma inside the torus becomes possible. This is essential to avoid the hot plasma to touch the walls of the device.

Similar tools have been applied to measure the concentration of tungsten particles, originating from the wall due to the constant plasma exposure. Figure 2 below shows an example of a build-up of tungsten particles in the core plasma of the WEST tokamak, based on measurements of X-rays emitted by the tungsten impurities [3]. Again, the probabilistic approach allows uncertainty estimates, visualized by the error map in the right panel. Furthermore, experimental design can be used to optimize the viewing geometry of the diagnostic.

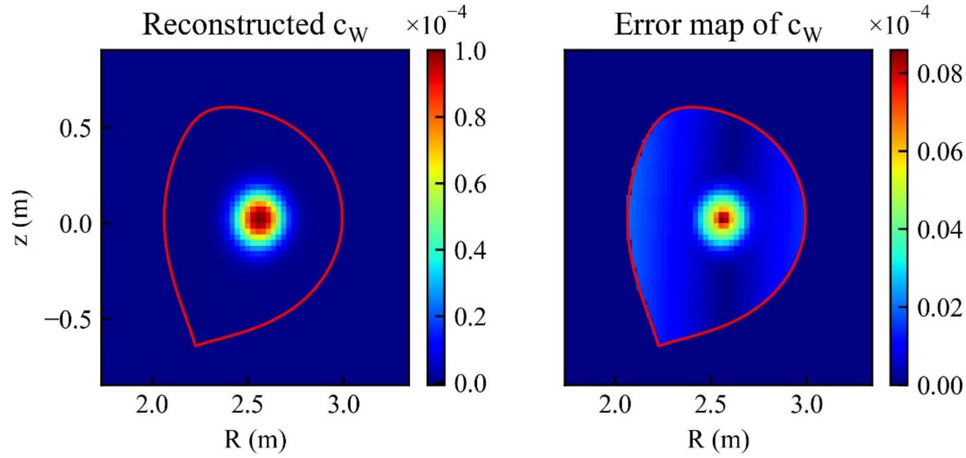


Figure 2: Cross-section of the plasma of the WEST tokamak, showing the concentration c_w of tungsten particles (left panel) and the accompanying error map (right panel).

Another area where AI can help addressing technological challenges is in **anomaly detection** and **predictive maintenance**. By using sensors to regularly or continuously monitor the condition of equipment or products in an experimental setting or in a production environment, it is possible to train a computer model to recognize abnormal events in the operation or the state of the monitored system. This can make a crucial difference for protecting hardware or for quality assurance, either by raising an alarm to allow human intervention, or by automatically activating countermeasures to restore the system to its nominal state. Predictive maintenance is a strategy that takes this one step further: using statistics or machine learning techniques, a computer can be trained to recognize early signs of an upcoming anomaly or failure. The complex environment of a fusion device can greatly benefit from such new techniques that are also quickly gaining popularity in many sectors of industry. Some concrete examples are the operation of pumps ensuring the vacuum in fusion devices and large circuit breakers that are essential for plasma start-up in tokamaks. A recent use case, illustrated in Figure 3 below, involves the monitoring of wall components with infrared cameras, to detect or predict material overheating due to plasma exposure [4]. Machine learning models like neural networks are especially well suited to pick up subtle warning signs of an imminent failure, while still allowing sufficient time for taking effective countermeasures.

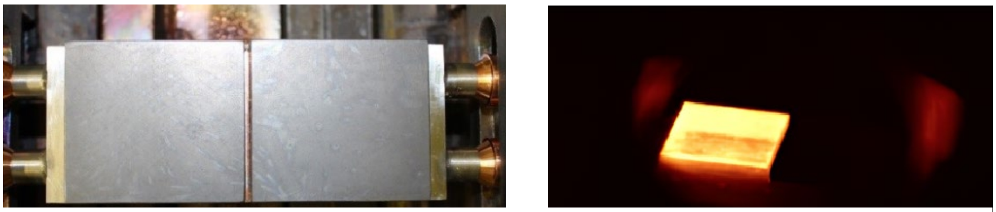


Figure 3: Experimental setup of two beryllium tiles (left panel) and infrared image during heat loading (right panel).

3.4.2 Application of AI in material development

AI is revolutionizing materials science by enabling the **discovery of new materials, predicting their properties, and qualifying them for codes and standards**. State-of-the-art techniques leverage machine learning models like Random Forest, Regression, Artificial Neural Networks (ANN), and K-Nearest Neighbours (KNN). These models excel when large datasets are available, allowing researchers to identify patterns, optimize material properties, and accelerate the development process. AI has been used to characterise materials and understand material properties in some areas of research, but not to its full potential.

The environment inside a fusion machine is hostile and unique: extreme temperatures resulting in high thermal loads of materials, radiation and high mechanical loads, resulting in degradation of materials. A precise characterisation of materials properties is crucial to estimate the impact of the environment on the material and predict component durability and maintenance requirements. Large amounts of resources are invested in material characterisation, especially when the material is to be qualified according to a nuclear code, as is the case of protection-important components in a fusion machine. Furthermore, mechanical properties are also crucial to estimate the forming capability of equipment and for robust numerical modelling [5].

By organising large input datasets, AI is able to predict these material properties. Furthermore, this can be used in the future to qualify materials for inclusion in nuclear design and manufacturing codes (upcoming publication from F4E). Recently, some nuclear code associations have shown willingness to include AI as a recognised digital technology for qualification, thereby reducing costs and time, while still enabling a high level of quality and precision.

One example will be presented predicting fatigue and fracture properties.

However, challenges arise when data is sparse or incomplete. Predicting material behaviour beyond known data ranges requires innovative approaches. Probabilistic methods can be combined with AI to fill data gaps by generating synthetic datasets while maintaining dependencies. Physics can be combined with AI through **Physics-Informed Neural Networks (PINNs)** where machine learning is assisted with physical laws by embedding differential equations of the physics laws into the training process. This integration enhances predictions for complex phenomena, even with limited or noisy data. Two examples will be presented to illustrate these approaches.

These advancements are paving the way for breakthroughs in sustainable materials, energy storage, and biomedical applications. The synergy between AI and materials science promises a future of rapid innovation and transformative technologies.

We need these innovations because the development of new materials, particularly within the nuclear sector, is associated with significant challenges. Material properties must be thoroughly characterized following exposure to extreme conditions, including elevated temperatures and prolonged irradiation. However, such data is scarce due to the high costs and specialized equipment required for post-irradiation examination. Moreover, the nuclear industry is among the most stringently regulated sectors. The codification of new materials necessitates extensive testing and validation processes, often spanning decades, to achieve approval for inclusion in design codes and standards. This presentation will give a glimpse of how these methodologies are being explored for expediting the approval process for new materials by leveraging an innovative combination of probabilistic approaches, physics-based modelling, and artificial intelligence (AI).

3.4.3 Application of AI in manufacturing and non-destructive testing

The fusion and nuclear industries are characterized by extreme operating conditions, complex large-scale components, stringent safety regulations, and the need for high reliability and precision. AI, encompassing machine learning (ML), deep learning (DL), computer vision, and robotics, offers significant potential to address these challenges by enhancing efficiency, improving quality control, ensuring safety, and managing the vast amounts of data generated throughout the component lifecycle – from manufacturing and assembly to in-service inspection.

AI is naturally able to analyze patterns and trends with high accuracy, as long as the training dataset is of good quality and representative of the population. It is indeed better than the human mind especially when the number of parameters impacting the result is higher than 2 or 3, as visibly recognizable by the human mind, or higher than 4 or 5, as a human mind can manage. The quality of the data set is of crucial importance and its collection and organisation is time-consuming. For this reason, little has been done on the industrial side or academic research.

The manufacturing of components for nuclear reactors (fission) and experimental fusion devices (like ITER) involves specialized materials and complex geometries, often pushing the boundaries of current techniques. ITER has shown to be the perfect example since manufacturing has generated large amounts of data, from which AI can help convert data and information into knowledge.

On joining processes such as **welding**, optimization of manufacturing parameters through AI allows to re-introduce experience to feed the last step of quality control with the knowledge acquired. Even in real-time, AI algorithms are used to optimize manufacturing parameters for processes like welding (e.g., Tungsten Inert Gas - TIG, Electron Beam Welding), additive manufacturing (AM, or 3D printing), and machining. ML models can predict outcomes based on sensor data (temperature, acoustic emissions, optical monitoring) and adjust parameters to maintain quality and minimize defects [6] [7]. For AM, AI helps optimize build strategies, predict material properties, and detect flaws during the printing process.

Quality Assurance & Defect Prediction and identification: Computer vision systems powered by deep learning (especially Convolutional Neural Networks - CNNs) are increasingly used for automated surface inspection during or immediately after manufacturing. Data analysis can be used to validate the NDT acquisition, such as that of the complex, highly sensitive and otherwise time-consuming PAUT [8]. ML models can also analyze process data to predict the likelihood of internal defects or deviations from tolerance, reducing the need for costly post-process inspection [9]. Deep learning models (CNNs for image-based NDT like radiography or visual testing; Recurrent Neural Networks - RNNs or specialized architectures for signal-based NDT like ultrasonic testing - UT) are trained to automatically detect, locate, and classify defects (cracks, porosity, inclusions, corrosion) with higher speed and potentially greater consistency than human inspectors [10] [11].

In view of maintenance of reactors, by analyzing trends in NDT data over time, ML models can contribute to predicting the remaining useful life of components, supporting aging management programs crucial for nuclear power plant life extension and fusion device maintenance planning [12].

While less prominent in academic literature specifically for nuclear/fusion *component* manufacturing *AI*, general AI applications in supply chain optimization could be adapted for managing the complex logistics of specialized materials and sub-components.

3.4.4 Application of AI in plasma science and control

- Predictive modelling in plasma instabilities and disruption analysis
    - Neural state-space model that predicts plasma dynamics during ramp downs

https://www.researchgate.net/publication/389129708_Learning_Plasma_Dynamics_and_Robust_Rampdown_Trajectories_with_Predict-First_Experiments_at_TCV

- Trajectory planning enabled by ML/AI
    - reinforcement learning (RL) approach to safely ramp down plasma current while avoiding disruption-related limits, using a hybrid physics and machine learning model

https://www.researchgate.net/publication/385645875_Active_Disruption_Avoidance_and_Trajectory_Design_for_Tokamak_Ramp-downs_with_Neural_Differential_Equations_and_Reinforcement_Learning

- Fusion data platform for ML applications

4 Summary of meetings

Will be completed after the workshop taking place in May 2025.

5 Outcome: technology road-mapping

Will be completed after the workshop taking place in May 2025.

6 Conclusion

Will be completed after the workshop taking place in May 2025.

AI is rapidly becoming an indispensable tool for the demanding fusion and nuclear industries. State-of-the-art research focuses on leveraging ML and DL for process control, automated inspection, enhanced robotic capabilities, and predictive maintenance. While significant progress has been made, addressing challenges related to data, explainability, and qualification is crucial for the widespread, safe, and reliable deployment of these powerful technologies.

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Appendix 1: Technology Readiness Levels

For this workshop, a TRL scale from 1 to 9 will be used, in line with the IAEA definitions[2].

It considers the different criteria for different streams as illustrated in the table below extracted from the document in reference. By default, the “System” stream will be used. For more details, please refer to the TECDOC 2047 itself.

TRL	Systems	Materials	Software	Manufacturing	Instrumentation
1	Basic principles	Evidence from literature	Mathematical formulation	Process concept proposed	Understand the physics
2	Technology concept	Agreed property targets, cost & timescales	Algorithm implementation documented	Validity of concept described	Concept designed
3	Proof of concept	Materials' capability based on lab scale samples.	Prototype architectural design of important functions is documented	Experimental proof of concept completed	Lab test to prove the concept works.
4	Validation in a laboratory environment	Design curves produced.	ALPHA version with most functionalities implemented with User Manual and Design File available	Process validated in lab	Lab demonstration of highest risk components
5	Partial system validation in a relevant environment	Methods for material processing and component manufacture	BETA version with complete software functionalities, documentation, test reports and application examples available	Basic capability demonstrated using production equipment	Requiring specialist support
6	Prototype demo in a relevant environment	Validated via component and/or sub-element testing.	Product release ready for operational use	Process optimised for capability and rate using production equipment	Applied to realistic location/environment with low level of specialist support.
7	Prototype demo in an operational environment	Evaluated in development rig tests	Early adopter version qualified for a particular purpose	Economic run lengths on production parts	Successful demonstration in test.
8	Test and demonstration	Full operational test	General product ready to be applied in a real application	Significant run lengths	Demonstrated productionised system
9	Successful mission operation	Production ready material	Live product with full documentation and track record available	Demonstrated over an extended period	Service proven

[2] IAEA TECDOC 2047: Considerations of TRL for Fusion Technology Components
Available at https://www-pub.iaea.org/MTCD/Publications/PDF/TE-2047web.pdf

Appendix 2: Technology assessment

1. Added-Value Towards Nuclear Fusion		
Criterion	*Scale*	*Explanation*
Need for and potential benefit	Major / Medium / Minor	*Does this technology address a critical and unresolved challenge in nuclear fusion?*
Availability of alternative solutions	Yes/No (EU) Yes/No (Outside EU)	*Are there competing solutions in Europe or globally?*
Differentiation / Competitive Advantage	Yes / No	*Does this technology offer a unique advantage over existing solutions?*
2. Maturity & Feasibility		
Criterion	*Scale*	*Explanation*
Technology Readiness Level (TRL)	1 to 9	*Standard TRL scale (see Appendix).*
Expected time to TRL 9 (full maturity)	<5 years / 5–15 years / >15 years	*How long until the technology is commercially viable?*
Availability of test facilities	Yes / No	*Are there existing facilities in Europe to validate the technology?*
3. Interest from the Innovation Ecosystem		
Criterion	*Scale*	*Explanation*
Interest from start-ups	None / 1–3 interested parties / >3 interested parties	*Level of engagement from early-stage companies.*
Interest from industry	None / 1–3 interested parties / >3 interested parties	*Level of interest from established industry players.*
Interest from research institutions	None / 1–3 interested parties / >3 interested parties	*Interest from universities, national labs, and research centres.*
4. Other Investment Decision-Making Factors		
Criterion	*Scale*	*Explanation*
Market potential	Nuclear fusion-specific / Wider market potential	*Is the technology limited to fusion, or does it have broader applications?*
Competences & skills development	Yes / No	*Will this technology enhance European expertise in fusion?*
Regulatory impact	Yes / No	*Does the technology pose significant regulatory challenges?*
5. Risk, Cost, and Implementation Timeline of Next Step on Roadmap		
Criterion	*Scale*	*Explanation*
Outcome predictability & risks	Low risk / Medium risk / High risk	*How uncertain are the results of the next development?*
Estimated development cost	0–500k EUR / 501k–2M EUR/ >2M EUR	*Rough cost estimate for next development step.*
Time to first output (once funded)	<1 year / 1–2 years / >2 years	*Timeframe for delivering tangible results.*

Fusion for Energy

The European Joint Undertaking for ITER
and the Development of Fusion Energy
C/ Josep Pla 2,
Torres Diagonal Litoral
Edificio B3
08019 Barcelona
Spain

Tel: +34 933 201 800
E-mail: info@f4e.europa.eu

fusionforenergy.europa.eu