

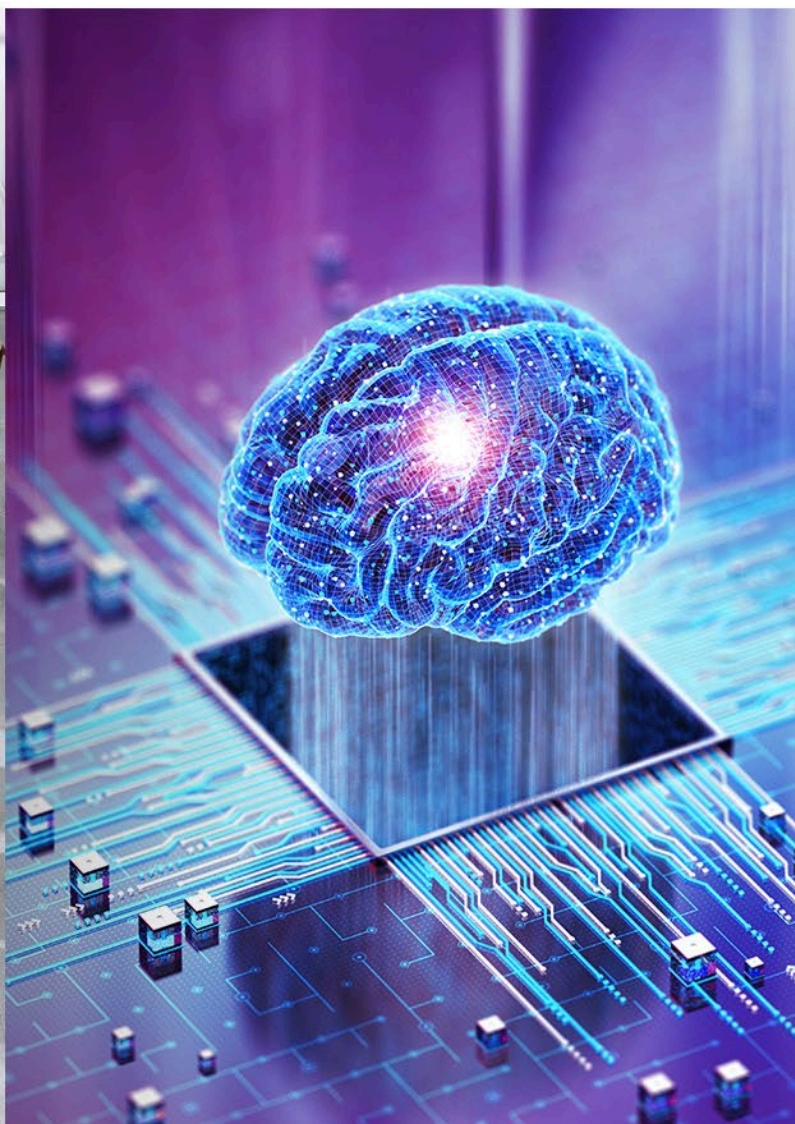
Technology Development Programme



Technology Mapping

2025 Series

Artificial Intelligence in Fusion



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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	15/05/2025	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

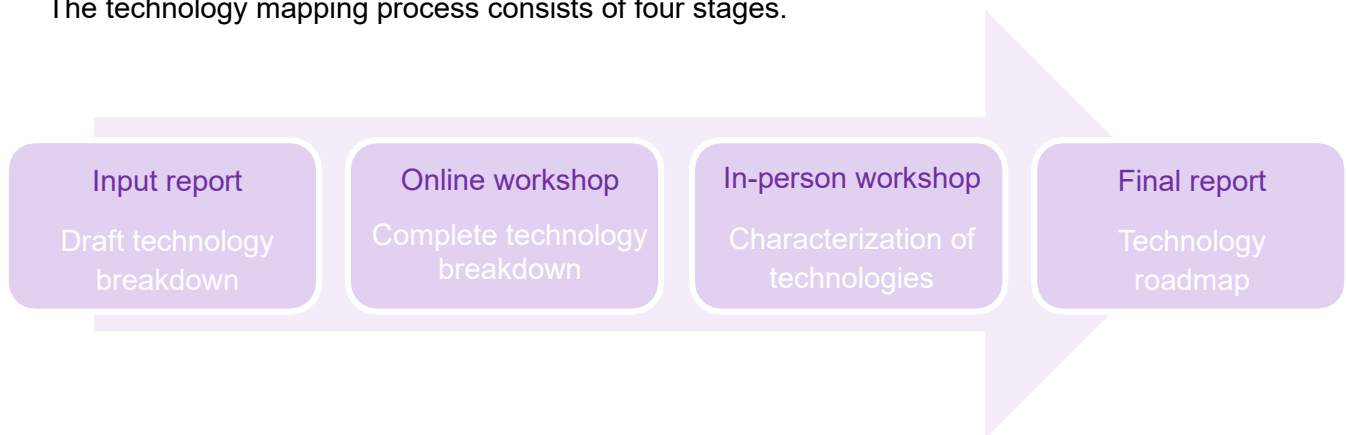
The scope of the second such mapping exercise is the implementation of artificial intelligence in fusion technologies. It covers the application of artificial intelligence in design and simulation, material development, manufacturing and non-destructive testing (NDT) including assembly, and plasma science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

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 four key topics in the development of fusion technologies:

- Design and simulation
- Materials, manufacturing, Non-Destructive Testing (NDT), and assembly
- Plasma science
- System engineering, project management, and operations

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 behaviour, 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.

Materials, manufacturing, non-destructive testing (NDT), and assembly are all critical stages in developing reliable fusion reactors. Material development focuses on creating and testing advanced substances, such as radiation-resistant alloys and superconductors, that can endure the extreme conditions inside a reactor, including high temperatures, intense radiation, and mechanical stress. Manufacturing then transforms these materials into precise components like vacuum vessel sectors, plasma-facing elements, and superconducting magnets. During and after fabrication, NDT methods such as phased-array ultrasonic testing are used to inspect these complex parts without causing damage, ensuring they meet strict quality and safety standards. Finally, careful assembly brings together all subsystems, requiring high accuracy to achieve proper alignment, integration, and long-term reactor performance.

Plasma science is 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.

System engineering, project management, and operations play a key role in turning fusion concepts into working energy systems. This part of the process involves making sure that all the different parts, like magnets, sensors, and heating systems, work well together. By spotting problems early, teams can take quick action to avoid delays or technical issues. Engineers use structured methods to keep the design on track, and project managers rely on real-time information to adjust plans, manage resources, and keep everything running smoothly.

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 analyse 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 behaviours, 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

3.4.1 Application of AI in design and simulation

DESIGN

1. Optimisation of magnetic fields using AI-guided inverse design algorithms

AI-guided inverse design algorithms are used to find the global optimum in a complex design space, in order to produce a desired magnetic field. Instead of trial-and-error, these methods start with the target field and work backward to determine the optimal system configuration (e.g. coil geometry), accelerating the design of magnetic systems for fusion applications.

2. Quality control of CAD drawings

Automated consistency checks between 2D and 3D CAD models, including validation of geometry and the correct assignment of attribute data, to ensure design accuracy and reduce errors.

3. Generation of E3D or 3D drawings

Generate 2D or E3D drawings from existing 3D models, images, or other drawings using AI-powered tools that support natural language input or image uploads.

4. P&ID recognition for engineering data extraction and consistency

Automatically identify symbols in piping and instrumentation diagrams (P&IDs), verify consistency with legends and equipment catalogues, and enable intelligent component search to support engineering analysis and documentation accuracy.

5. Component tagging for 3D-scanning

Identifying and labelling individual components in a 3D model by taking the source information and the schematics and diagrams as reference and matching the real-world scanned components to the reference components using AI. The tagged 3D model can now be connected back to the digital twin or used in maintenance or simulation.

6. AI/ML driven multi-objective optimization frameworks

Application of artificial intelligence and machine learning to solve complex design challenges involving multiple competing objectives. These frameworks enable efficient exploration of trade-offs and identification of optimal design configurations across reactor systems and components.

7. Categorization and clustering of CAD clashes

A clash refers to a conflict or interference between components in a digital model (for example CAD), something that would physically collide, overlap or be incompatible. There are geometric (= occupy the same space), clearance (= safety or maintenance violations), functional (= interfere with the functions), and even scheduling (= simultaneous when they shouldn't be) clashes.

- Automatically detect the severity of a clash (critical or not).
- Cluster clash data to reduce the number of clashes to analyse

SIMULATION

8. Digital twins of fusion reactors

AI-driven virtual replicas of fusion reactors that are continuously updated with real-world data. These digital twins enable real-time simulation and analysis of reactor performance, supporting design optimization, failure prediction, and improved operational efficiency.

9. ML-driven surrogate modelling

Use of machine learning to create fast, computationally efficient surrogate models that approximate complex physics simulations—such as plasma dynamics, turbulence, and material interactions—enabling quicker analysis and design iterations.

10. Active Learning for data-efficient experimentation

AI-driven active learning strategies that prioritize the selection of the most informative data points or next experiments. By guiding data acquisition, these methods accelerate discovery and reduce the cost of simulations or physical testing. For example, selecting the most informative simulation inputs to efficiently map a design space or optimize performance.

11. GenAI for code template generation

Use of Generative AI to automatically create code templates for building machine learning-based surrogate models. This accelerates development by providing structured starting points for implementing physics-informed or data-driven approximations of complex systems.

12. GenAI for synthetic data generation

Application of Generative AI to create synthetic data that enriches existing datasets or fills gaps in training data. This improves the robustness and accuracy of machine learning models, especially in domains with limited or imbalanced data.

13. Hybrid models and Physics-Informed Machine Learning for simulations

Integration of physical laws with machine learning to build models that are both data-driven and grounded in scientific principles. These approaches improve generalizability, reduce data requirements, and ensure physically consistent predictions in complex systems.

3.4.2 Application of AI in materials, manufacturing, NDT, and assembly

MATERIALS

14. Material acceptability prediction for a dedicated application

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.

15. AI-guided discovery and development of new materials

Use of AI and machine learning to accelerate the identification and design of new materials with targeted properties. These approaches enable rapid screening of material candidates and prediction of performance, reducing experimental cycles and development time.

16. Generation and curation of materials databases

Development and collection of comprehensive materials databases to support AI-driven discovery, modelling, and simulation. These databases provide structured, high-quality data essential for training predictive models and guiding experimental efforts.

17. Prediction of behaviour and mechanical properties of new materials

Use of AI and machine learning to predict how new materials will behave under various conditions, including their mechanical properties. This enables faster evaluation of candidate materials and reduces the need for extensive physical testing.

18. Graph neural networks for studying the Hamiltonian of materials

Application of graph neural networks (GNNs) to analyse and predict the Hamiltonian—an operator describing the total energy—of materials. This enables advanced modelling of material properties at the atomic level, supporting the discovery of new materials and phenomena.

MANUFACTURING & NDT

19. AI-driven distortion prediction

Machine learning models predict potential distortions during manufacturing processes, enabling early adjustments to reduce rework, improve dimensional accuracy, and ensure component fit.

20. AI-driven process optimization for advanced manufacturing

Application of AI to optimize manufacturing processes such as Hot Isostatic Pressing (HIP) and additive manufacturing. This includes optimizing build strategies, predicting material properties, and detecting defects during production to improve quality and efficiency.

21. AI-Enhanced acoustic emission for non-metallic material inspection

Application of AI to improve Acoustic Emission (AE) techniques used in pressure testing and in-service inspections of non-metallic materials such as composites and concrete. AI analyses AE signals to predict component integrity and enable early detection of potential failures.

22. Welding success rate prediction

Use of AI to predict the success or failure of Electron Beam (EB) and Tungsten Inert Gas (TIG) welds for components. This helps improve weld quality and reduce defects through early identification of potential issues.

23. Automated PAUT data processing for weld inspection

AI-driven automated processing of Phased Array Ultrasonic Testing (PAUT) data for welds of components at supplier sites. This enables precise identification of defects, including their exact location and depth.

24. Real-time optimization of manufacturing parameters

Using sensor data—such as temperature, acoustic emissions, and optical monitoring—to continuously optimize and adjust manufacturing parameters. This approach maintains product quality and minimizes defects during production.

25. Automated digital RT data processing for weld inspection

AI-driven processing of digital radiographic testing data to automatically detect weld defects, including precise location and depth, improving inspection accuracy and efficiency at supplier sites.

ASSEMBLY

26. Prediction of metrology data

Compare the measurement of physical components that are already installed, but a difficult to reach, to the measurements in the CAD models. The measurement of a limited number of measured components should be extrapolated using ML to predict the measurements of the unreachable components.

27. Detect modifications on drawings

Extract key information from red markings on drawings on the construction site to identify the modifications done on the construction site.

28. Optimization of component positioning during assembly

Application of Bayesian neural networks to optimize the positioning of components, reducing uncertainties and minimizing the need for on-site adjustments during assembly.

29. Identification of most optimal assembly sequence

Using AI to select the assembly sequence that maximizes success rates while minimizing costs, improving overall efficiency and reliability of the assembly process.

30. Instruments and transport virtual agent

Virtual agent that manages instrument booking and transport requests, fully integrated within Teams, Outlook, and other relevant tools. This will streamline the process of scheduling instrument shipments; it will reduce errors and lower the costs associated with relying on external assistance.

31. Automated mapping of metrology cloud points to component models

AI algorithms match 3D point cloud data from metrology scans to digital component models, enabling automated verification of geometry, detection of deviations, and support for quality control during manufacturing and assembly.

32. AI-driven extrapolation of operating conditions from local testing

Machine learning models use results from localized or small-scale tests to predict system behaviour under full-scale or varied operating conditions, reducing the need for extensive testing and accelerating design validation.

3.4.3 Application of AI in plasma science

33. Predictive modelling of plasma instabilities and disruptions

Development of neural state-space models to predict plasma dynamics during ramp-down phases, enabling better understanding and mitigation of instabilities and disruptions.

34. Trajectory planning enabled by ML/AI

Use of reinforcement learning combined with hybrid physics and machine learning models to safely ramp down plasma current, avoiding disruption-related limits and ensuring stable operation.

35. Fusion data platform for Machine Learning applications

Development of a centralized data platform to collect, manage, and provide fusion-related datasets. This platform supports machine learning applications by enabling efficient data access, integration, and preprocessing to accelerate research and development.

36. Machine learning-accelerated pedestal MHD stability evaluations

Use of surrogate modelling to accelerate predictions of growth rates for magnetohydrodynamic (MHD) equilibria, enabling faster stability assessments of the plasma pedestal.

37. Time-resolved, physics-informed neural networks for tokamak total emission reconstruction

Development of physics-informed neural networks as inverse problem solvers to integrate multi-diagnostic and multi-physics data. This approach enables tomographic reconstruction to accurately assess line-averaged plasma radiation emission in tokamaks.

38. Auto-labelling AI tools for plasma state datasets

AI-driven tools that automatically label plasma states in datasets, enhancing labelling accuracy and consistency to improve the quality of training data for machine learning models.

3.4.4 Application of AI in systems engineering, project management, and operations

SYSTEMS ENGINEERING

39. Chatbot for requirements rationalization

Development and training of a chatbot on project requirements to assist in rationalizing and clarifying them, speeding up the requirements analysis process.

40. AI model transparency

Use of Explainable AI techniques to interpret and understand how predictions and decisions are made by other AI models, enhancing trust and accountability.

41. LLM-driven check of requirements propagation

Large Language Models (LLMs) are used to trace and verify the consistent propagation of requirements across system specifications, designs, and documentation—ensuring alignment and reducing the risk of overlooked dependencies.

42. AI-driven validation of requirements

AI models are used to automatically review technical requirements for clarity, consistency, completeness, and feasibility—helping identify ambiguities or conflicts early in the design process.

PROJECT MANAGEMENT

43. Prediction of tool usage

Machine learning and predictive analytics tools can help forecast future usage of tools or resources in programs more accurately. By analysing its historical data, seasonality, ..., these tools can help predict demand effectively.

44. Prediction of contract outcome based on past performance

Identifying several parameters available from 1000+ past contracts to quantify the quality of preparation and negotiations and predict likely contract outcome (e.g. cost overrun) at contract signature.

45. Prediction documentation review time

Tracking the time spent on reviewing approved documentation to predict future review durations, especially in cases involving multiple reviewers. This helps create more realistic scheduling without affecting reviewer deadlines.

46. AI-powered proposal support tool for project disruptions

A proactive tool designed to identify optimal project measures and decisions during disruptions by analysing contract types, schedules, costs, and risks of ongoing projects to support effective project management.

47. Process optimization tool

An AI-driven tool designed to help process owners enhance efficiency by gathering data from internal management systems, analysing value-added steps, bottlenecks, and iteration cycles to identify opportunities for process improvement.

48. Automated contract generation

A tool that combines existing contracts with new requirements to automatically generate updated contracts and conditions, streamlining the contract creation process.

49. Risk register forecast prediction

An automated system to consolidate and review existing risks, while identifying potential new risks from multiple sources to enhance overall risk management.

50. Automatic status reporting from data sources

Automatically compiles and summarizes project or system status by extracting key metrics and updates from various data sources, reducing manual reporting effort and improving real-time visibility.

OPERATIONS

51. Fusion specific documentation management

Implementation of chatbots to enhance the speed and efficiency of searching manuals and databases within documentation management systems. Includes access control measures to ensure sensitive information is only disclosed to authorized users.

52. Recognition of abnormal events in the operation or state of a system

By using sensors that regularly or continuously monitor the condition of equipment of products in an experimental setting or in a production environment, a model can be trained to recognize abnormal events. This can help protecting hardware or for quality assurance, either by raising an alarm to allow for human intervention, or by automatically activating countermeasures to restore the system to its nominal state.

53. Predictive maintenance of components

AI models trained to detect early signs of anomalies or failures, such as monitoring wall components with infrared cameras to predict overheating from plasma exposure. Additionally, machine learning analyses trends in non-destructive testing (NDT) and operational load data to estimate the remaining useful life of components, supporting aging management and maintenance planning.

54. AI-driven diagnostic data integration

Techniques that integrate information from multiple diagnostic sources using AI, providing a comprehensive and unified understanding of complex systems.

55. Dimensionality reduction for streaming data

Techniques that reduce data complexity and identify the most relevant features in real-time streaming data, enabling more efficient processing and analysis.

56. AI-assisted experimental design

AI is used to propose the most effective experimental setups by analysing prior data, optimizing parameter selection, and reducing the number of required tests to achieve meaningful results efficiently.

57. Real-time operation of fusion device based on diagnostics

AI-driven systems use live diagnostic data to monitor and adjust fusion device parameters in real time, optimizing performance, ensuring safety, and preventing disruptions during operation.

58. Real-time operation of fusion device based on prediction

AI models predict future plasma behaviour and device states in real time, enabling proactive adjustments to maintain optimal performance and prevent disruptions during fusion reactor operation.

59. LLM-based prediction of document type

Large Language Models (LLMs) analyse document content to automatically classify and predict document types, improving organization, retrieval, and processing efficiency in document management systems.

60. Automatic generation of End-of-Manufacturing report

AI systems automatically compile data from production processes to generate comprehensive end-of-manufacturing reports, ensuring accuracy, consistency, and timely documentation.

4 Summary of meetings

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

5 Outcome: Technology Road Map

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

6 Conclusion

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

Appendix 1: Technology Readiness Levels

For this workshop, a TRL scale from 1 to 9 will be used, in line with the IAEA definitions².

It considers the different criteria for different streams as illustrated in the table below extracted from the document in reference. By default, the “Software” 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>