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RESEARCH

The IFMIF-DONES Diagnostics and Control Systems: Current Design Status, Integration Issues and Future Perspectives Embedding Artificial Intelligence Tools

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Abstract
As an integral part of the European strategy for advancing fusion-generated electricity, IFMIF-DONES represents a high-intensity neutron irradiation plant with the main purpose of assessing the suitability of materials for fusion reactor applications. Its primary mission is to examine how materials respond to irradiation within a neutron flux that mimics the conditions expected in the first wall of the proposed DEMO reactor, which is intended to succeed ITER. Consequently, IFMIF-DONES, whose construction is slated to commence shortly, plays a pivotal role in aiding the development, approval, and safe operation of DEMO, as well as future fusion power plants. This paper provides a quick overview of the current development of the IFMIF-DONES neutron source with a particular snapshot of the present engineering design status for what concerns the instrumentation and control systems together with its complex diagnostics, that guarantees the safe monitoring, supervision and regulation of all operations. The current status of design, after the completion of the preliminary design phase is presented, as well as the existing and future plans for their integration also using some of the new capabilities offered by Artificial Intelligence tools.

Keywords Control systems · AI · IFMIF-DONES · Diagnostics · I&C

Introduction

In the DEMO project, which is the fusion power plant intended to follow the ITER machine, deuterium–tritium fusion reactions will produce neutron fluxes at approximately 10^{18} per square meter per second with an energy level of 14 MeV. These high-energy neutrons will interact with the first wall of the reactor vessel, potentially subjecting it to a damage dose rate exceeding 15 dpaNRT (displacement per atom per full power year) during operation [1]. The components exposed to the plasma must endure these extreme operational conditions without compromising their structural integrity or mechanical and physical properties [2, 3]. Therefore, ensuring the safe design, construction, and licensing of a nuclear fusion reactor, as per the Nuclear Regulatory Agency's requirements, necessitates a deep understanding of how materials degrade under prolonged neutron bombardment.

The establishment of a neutron source with relevance to fusion has been a pending milestone for over three decades, essential for the successful progress of fusion energy. Following the different steps to achieve the current maturity of such a high-power neutron source [4–13], IFMIF-DONES (DEMO-Oriented NEutron Source) is candidate to serve as the crucial neutron source, offering unparalleled power and performance to address the needs [14]. It will generate a neutron flux with a wide energy distribution that closely replicates the typical neutron spectrum of a (D–T) fusion reactor through Li(d,xn) nuclear stripping reactions [15].

The European Fusion Roadmap [16], with the goal of electricity production from a fusion reactor by the mid-century, expedited the design and construction phases of DEMO and concurrently reduced the neutron dose requirements on materials. This approach will involve an initial DEMO phase with a maximum dose of approximately 20 dpa for component integration testing, followed by a second DEMO phase with a maximum dose of around 50 dpa. Consequently, the

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requirements for the early phase of the neutron source are significantly diminished, allowing for a staged approach to IFMIF, thus enabling a more distributed investment over time and relaxed specifications in the neutron source design. The first phase can focus on the early DEMO needs, thus giving rise to the IFMIF-DONES project [17], launched in 2015 within the framework of the Work Package on Early Neutron Source (WPENS) under the EUROfusion Consortium. This initiative was part of the 2014–2020 EURATOM Research and Training Programme, complementing the EU Horizon 2020 Framework Program (FP8), which was then extended into the Horizon Europe (FP9) program covering the years 2021–2025. The primary aim of this effort was to advance the design of IFMIF-DONES to a state where it would be ready to enter its construction phase.

This endeavor poses various significant challenges, including the requirement for a high beam current, the need to establish a target made of a stable liquid lithium curtain, and an operational availability goal beyond 70%. Meeting these challenges necessitates robust engineering methodologies to ensure the dependability of the facility. Consequently, the entire design process must be meticulously implemented and optimized, with special emphasis on the control systems that play a critical role in ensuring plant reliability, safety, and availability of the overall plant [18].

The design strategy for IFMIF-DONES incorporates Artificial Intelligence (AI) methods from its inception. Notably, in beam dynamics and neutronics, simulation tools such as TraceWin and Monte Carlo techniques are employed. Given the time-consuming and intricate nature of tasks within the plant, ongoing efforts are focused on automating and optimizing these simulations, and AI methods are being explored to alleviate the computational burden.

AI techniques will play a pivotal role during operational phases, contributing to tasks such as plant optimization—minimizing energy consumption or maximizing beam energy transfer to particles. Predictive maintenance, failure analysis, and the creation of a plant digital twin are also areas where AI methods are leveraged, ensuring efficient achievement of availability requirements.

It is crucial to highlight that these objectives significantly influence the design of the control system. From networks and data acquisition systems to processing elements and database structures, the seamless integration of AI capabilities is deemed essential from the early design stages. Retrofitting AI at later stages becomes impractical, underscoring the importance of thoughtful integration into the core design framework. This proactive approach ensures that AI is an integral and effective component, enhancing the overall efficiency and performance of IFMIF-DONES.

This work mainly focusses on the present engineering design status for what concerns the instrumentation and control systems together with its complex diagnostics, that guarantees the safe monitoring, supervision and regulation of all operations. For each system and component, the current status of design, after the completion of the preliminary design phase is presented, as well as the existing and future plans for their integration using some of the new capabilities offered by Artificial Intelligence tools. The paper is organized as follows. In Sect. "The IFMIF-DONES Facility: General Overview", a concise overview of the plant's mission, the primary requirements, and the fundamental configuration is provided. In Sect. "IFMIF-DONES Diagnostics: Requirements and Techniques", organizational and technical challenges from the diagnostics perspective are recalled, together with some examples of the most challenging cases from the technical perspective. Section "The IFMIF-DONES Instrumentation and Control Systems: Current Design Status" describes the Central Instrumentation and Control Systems (CICS) and its current design status. In Sect. "Integration of Diagnostics with Control Systems: Key Points" the main issues and possible solutions to the integration of diagnostics and control systems are presented, where Sect. "Application of Artificial Intelligence Tools: Future Scenarios in IFMIF-DONES" defines how the application of AI tools may improve the overall plant reliability and effectiveness. In Sect. "Conclusions and Future Perspectives" conclusions are drawn and future perspectives presented to develop an integrated system based on data-driven decision-making and proactive management.

The IFMIF-DONES Facility: General Overview

Mission and Top-Level Requirements

The mission of IFMIF-DONES is to provide a neutron source producing high energy neutrons at sufficient intensity and irradiation volume in order to:

(1) Generate materials irradiation test data for design, licensing, construction and safe operation of the fusion demonstration power reactor (DEMO), with its main characteristics as defined by the EU Roadmap [16] under simulated fusion environment relevant to anticipated needs in radiation resistance for the structural materials in DEMO;
(2) Generate a data base for benchmarking of radiation responses of materials hand in hand with computational material science.

Additionally, given the fact that IFMIF-DONES will be available during ITER operation, the possibility that it could assist the tokamak in some aspects of its nuclear operation phase should not be disregarded.

The mission of IFMIF-DONES is translated into a number of technical high-level requirements as shown in Table 1.

The plant shall be designed for a lifetime of 30 years, with at least 20 years of irradiation experiments on a three-shift basis 24/7. Additionally, an average operational availability goal of 70% over calendar year has been established as a target for normal operation phase.

IFMIF-DONES is an accelerator-based D–Li neutron source which is intended to produce high energy neutrons at sufficient intensity and irradiation volume to simulate as closely as possible the first wall neutron spectrum of DEMO and future nuclear fusion reactors.

It is designed to generate a 125 mA continuous-wave deuteron beam that, accelerated up to 40 MeV and shaped to have a nominal rectangular footprint, impinges on a liquid lithium curtain 25 mm thick cross-flowing at about 15 m/s in front of it. The nuclear stripping reactions between D + and Li generate a large number of neutrons that interact with the materials samples housed in the High Flux Test Module (HFTM) located immediately behind the Lithium Target.

The main features of the IFMIF-DONES facility and their major differences with respect to the IFMIF configuration are summarized in Ref. [19–21]. On the other hand, the possible future upgrade to the full IFMIF is considered in the design of the facility. Figure 1 shows a schematic view of the current configuration of the IFMIF-DONES plant.

The IFMIF-DONES Plant Breakdown Structure (PBS) identifies five major areas: the Site, Building and Plant Systems; the Test Systems; the Lithium Systems; the Accelerator Systems; and the Central Instrumentation and Control Systems.

IFMIF-DONES Diagnostics: Requirements and Techniques

In [19] the primary objective of developing a roadmap and strategy to address challenges related to the diagnostics definition of the IFMIF-DONES complex plant is discussed by the authors. Two main types of challenges are outlined: *organizational challenges* and *technical challenges*. Organizational challenges involve managing a diverse array of diagnostics and instruments from different entities, maintaining balanced requirements, ensuring requirements traceability, and organizing documentation for qualification procedures. Technical challenges include the unique nature of the facility, operating in harsh environments, high availability requirements, and the need for advanced safety and machine protection diagnostics. The effort is relevant due to the complexity of the project, requiring state-of-the-art solutions and meticulous planning to ensure successful implementation.

For the integration activities of IFMIF-DONES, the following three key definitions are proposed: (i) *Instrument*, (ii) *Instrument Set* and (iii) *Diagnostic* (see Fig. 2).

A simple definition of an *Instrument* could be adopted as “a device that measures a physical quantity”. But in order to define the boundaries, an instrument may be defined as composed of four components [22]: (i) Sensor, (ii) Cable(s), (iii) Signal Conditioner, and (iv) Instrument Controller. The sensor is the part of the instrument that converts a physical variable into an electric signal (thus including the transducer), with the output typically being analog (unless it is defined as a digital sensor). The signal conditioner is the component responsible for manipulating the analog signal to align with the specifications required for its processing. Subsequently, the controller is in charge of obtaining and processing the signal. It is important to note that while the boundary of the instrument extends up to the instrument

Table 1 IFMIF-DONES top-level requirements

Requirement	Value	Comments
Neutron spectrum	Peaked around 14 MeV	Good simulation of the relevant nuclear response of the early DEMO first wall
Accumulated damage versus irradiation volume	(1) 20–30 dpa_{NRT} (Fe), less than 2.5 years, over 300 cm^2 (2) 50 dpa_{NRT} (Fe), less than 3 years, over 100 cm^2	
Irradiation temperature	250–550 °C	Actively controlled
Gas production	(1) 10–13 appm He/dpa (2) 45–55 appm H/dpa	
DPA gradient	< 10%	
Temperature gradient	+ 3%	
Design lifetime	30 years	20 years of operation lifetime
Post irradiation examination	External laboratories	

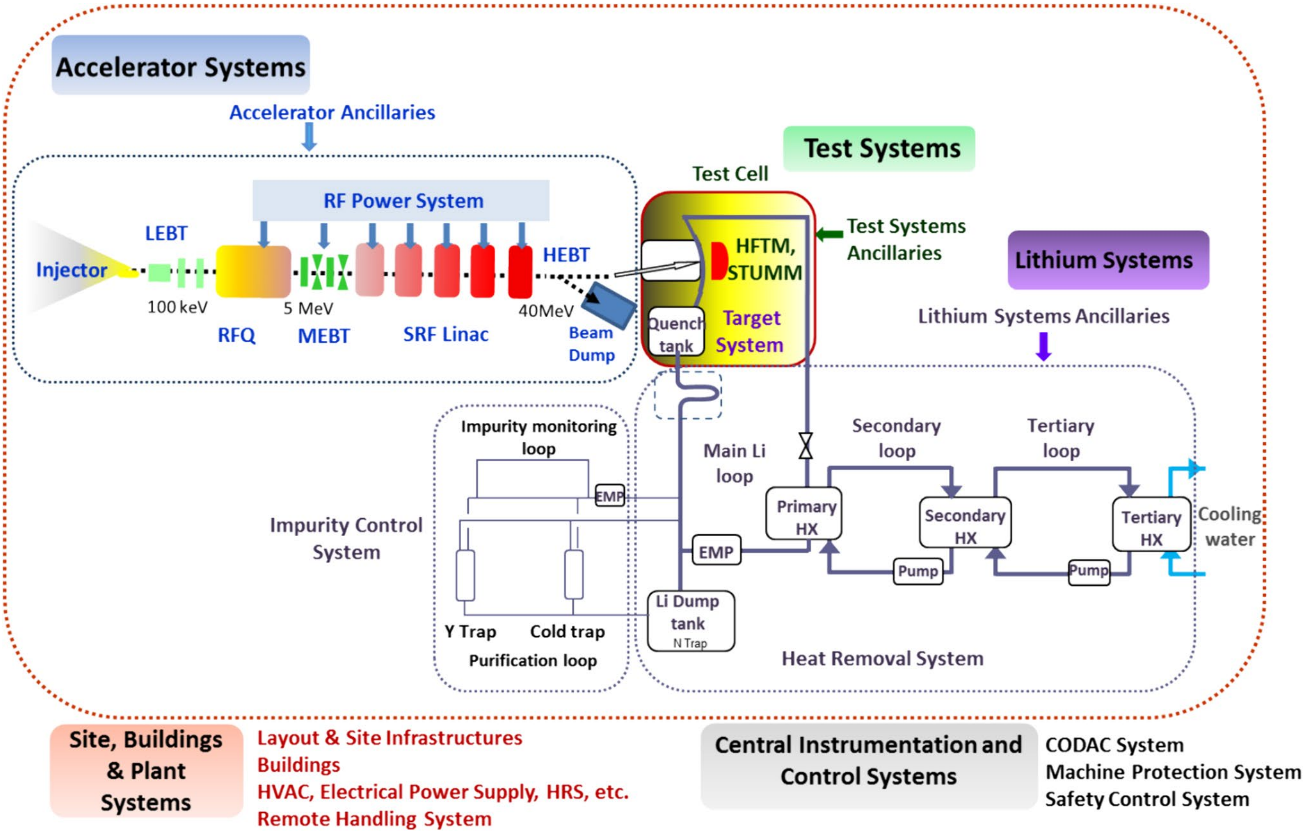
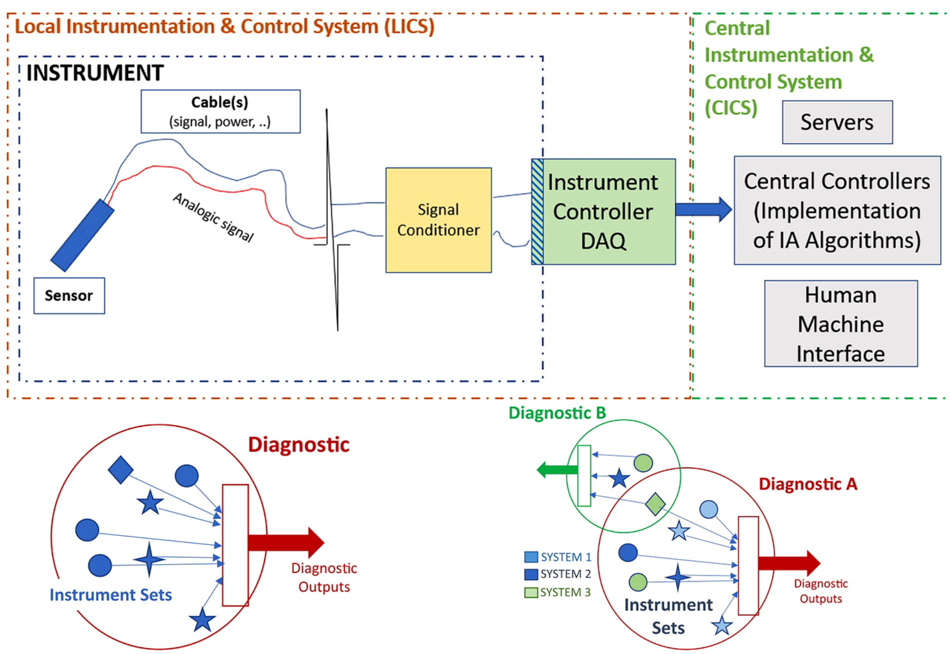


Fig. 1 IFMIF-DONES plant configuration [21]

Fig. 2 Sketch illustrating the definition for the adopted nomenclature of instrument, which includes sensor(s), cable(s), signal conditioner. The image shows the separation between Local I&Cs and Central I&C systems. The servers storing historical data and implementation of AI algorithm takes place within the Central I&C systems. The figure also shows the definition of diagnostic proposed here, where different instrument sets (geometrical figures) represent different gauges (flowmeters, thermocouples, radiation monitors, etc.) to feed a diagnostic; moreover, the same instrument set may feed more than one diagnostic (lower part)



controller, it does not necessarily encompass it entirely. This is because the controller might have additional functions beyond those of the instrument. An illustrative example of an instrument is a type-K thermocouple positioned within the Target Assembly.

The term Instrument can denote an individual device, but the concept of an *Instrument Set* is introduced to represent a collection of devices (Instruments) of the same type or model. These instruments within a set share a common function and/or are subject to identical requirements. To illustrate, a practical instance of an Instrument Set might encompass all type-K thermocouples that are positioned around the Target Assembly.

In contrast to the definitions of Instrument or Instrument Set, the proposed definition of *Diagnostic* is somewhat more intricate. A Diagnostic involves characterizing a functional feature through one or more Instruments/Instrument Sets and utilizing these measurements for machine operation. Consequently, Diagnostics require a degree of logic and post-processing of Instrument measurements. This may involve contextualizing measurements within a System (considering factors like position, operational mode, function), combining multiple measurements, providing expected measurement values, or incorporating operation-relevant thresholds (such as alarms or interlocks). Notably, this definition allows for various Instrument Sets of different kinds to contribute to a single Diagnostic, as depicted in Fig. 2 where each geometric shape represents a distinct Instrument Set. An example of a Diagnostic is the Test Cell Atmosphere Diagnostics, tasked with characterizing the atmosphere in the Test Cell. To accomplish this, multiple Instrument Sets, such as pressure gauges, thermocouples, flowmeters, radiation monitors, etc., would contribute to this Diagnostic.

The Accelerator Systems are very challenging in terms of diagnostics and its integration with the control systems. To give here a taste of the such complexity, Fig. 3 shows a scheme of the IFMIF-DONES Accelerator [19, 20]. It consists of a 40 MeV CW Deuteron Accelerator powered by 175 MHz Radiofrequency Systems (RFPS), with a nominal intensity of 125 mA and an output power of 5 MW (delivered to the Target). In the same figure, a preliminary diagnostic family classification (Levels II and III) for the

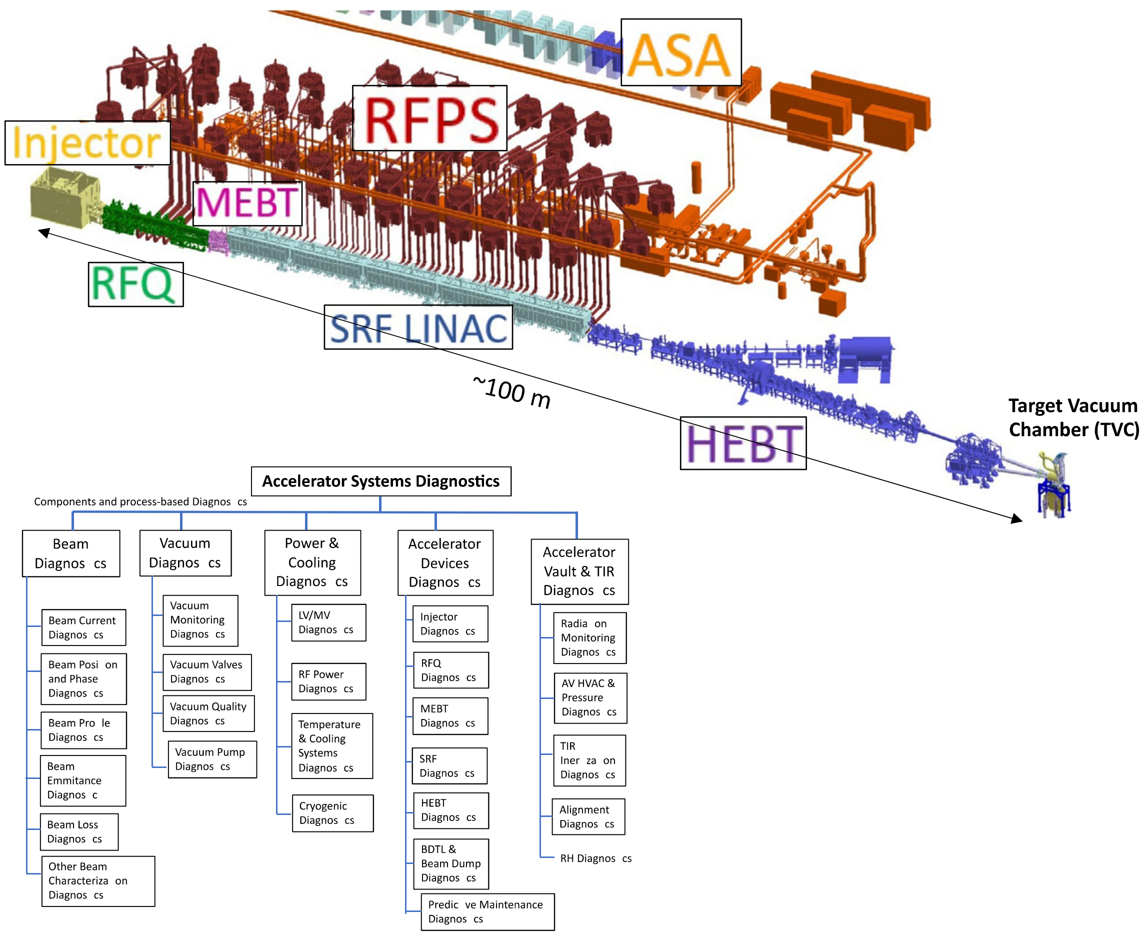


Fig. 3 Integrated mock-up of the IFMIF-DONES accelerator systems, highlighting its seven systems and a preliminary diagnostic families classification (Levels II and III) for the accelerator systems following the methodology introduced in Ref. [19]

Accelerator Systems following the methodology introduced in Ref. [19] is proposed. It should be noticed that the current project PBS defines the following Systems within the Accelerator Systems:

- Injector source;
- Radiofrequency quadrupole (RFQ);
- Medium energy beam transport line (MEBT);
- Superconducing radiofrequency (SRF) LINAC;
- High energy beam transport line (HEBT), including the beam dump (BD);
- Radio frequency power system (RFPS);
- Accelerator systems ancillaries (ASA).

The latter include the supply of cryogenics, vacuum, water cooling, low voltage and medium voltage electrical distribution, as well as gas distribution [19, 20].

In the lower section of Fig. 3, an outline of the classification of diagnostic families at the top level (Levels II and III) is presented. At Level II, the proposed diagnostic families include: (i) Beam diagnostics, (ii) Vacuum diagnostics, (iii) Power & cooling diagnostics, (iv) Accelerator devices diagnostics, and (v) Accelerator vault & TIR diagnostics. It is important to highlight the cross-cutting nature of these diagnostic families in relation to the seven Systems defined in the PBS. For instance, the Instruments associated with Beam Diagnostics will be distributed across all the systems of the beam line (Injector Source, RFQ, MEBT, HEBT), similar to Vacuum Diagnostics. Additionally, many Instrument Sets will contribute to different Diagnostics. As an example, the Beam Position Monitors (BPMs) categorized under "Accelerator Devices Diagnostics" will also be part of the "Beam Diagnostics". Furthermore, it is noteworthy to emphasize other cross-cutting Diagnostics such as Machine Protection Diagnostics or Safety Diagnostics, which will include Instruments distributed across these families, although they may not be explicitly illustrated in Fig. 3.

The IFMIF-DONES Instrumentation and Control Systems: Current Design Status

The Instrumentation and Control (I&C) System of DONES follows a hierarchical structure, similarly to other experimental plants like ITER and modern tokamak systems [18]. This hierarchy ranges from the top-level Central Instrumentation and Control Systems (CICS) to the Local Instrumentation and Control Subsystems (LICS). The I&C System is composed of various systems capable of performing complex tasks independently. It adopts a distributed control approach, offering local autonomy while maintaining centralized supervision and control through CICS.

CICS are responsible for managing, monitoring, and regulating all plant parameters, storing and visualizing data systemically. Supervisory tools enable constant two-way communication with LICS and real-time interaction with other subsystems through networking. Sensors and actuators, ranging from simple instruments like thermocouples to more complex diagnostic tools, are integral components. Actuators include items like electromagnetic pumps, valves, or motors. While raw signal data are processed and converted into process variables, LICS control subsystems and components locally to ensure that process variables remain within specified ranges.

The I&C Systems incorporate a Human–Machine Interface (HMI) and operational monitoring capabilities at each hierarchy level. The control architecture employs a real-time distributed control system, utilizing open-source software tools, libraries, and applications. Robust control hardware, such as Programmable Logic Controllers (PLC) and Field Programmable Gate Arrays (FPGA), is employed. Communication within the system relies on multiple control and supervisory networks, including Ethernet and fiber optic 10 Gb Ethernet, and specific networks and buses for critical signals.

In Fig. 4, the current CICS architecture is proposed with three functional systems constitute CICS: the Control Data Access and Communication (CODAC) System, Machine Protection System (MPS), and Safety Control System (SCS) [18]. By employing dedicated networks and buses, every system at the central level maintains continuous bidirectional communication with its equivalent system at the local level. A comprehensive overview of the CODAC, MPS, and SCS can be found in Ref. [23–26], which offer detailed insights into the functionalities and characteristics of these systems within the broader context of the Instrumentation and Control (I&C) architecture. The interested reader may refer to these sources that offer an in-depth understanding of the functionalities and roles played by every component within each System, contributing to a thorough comprehension of the overall Instrumentation and Control (I&C) architecture.

Two systems are in particular very challenging in terms of integration with diagnostics: MPS and SCS. The MPS is in charge for implementing investment protection strategies across various plant levels. Its primary objective is to safeguard the plant against:

1. Failures of system or equipment components.
2. Failures of the central/local control systems.
3. Incorrect operation.

This protection is achieved through the utilization of dedicated sensors and actuators, along with specialized high integrity logic solvers. Notably, the MPS exclusively focuses on investment protection, while strategies

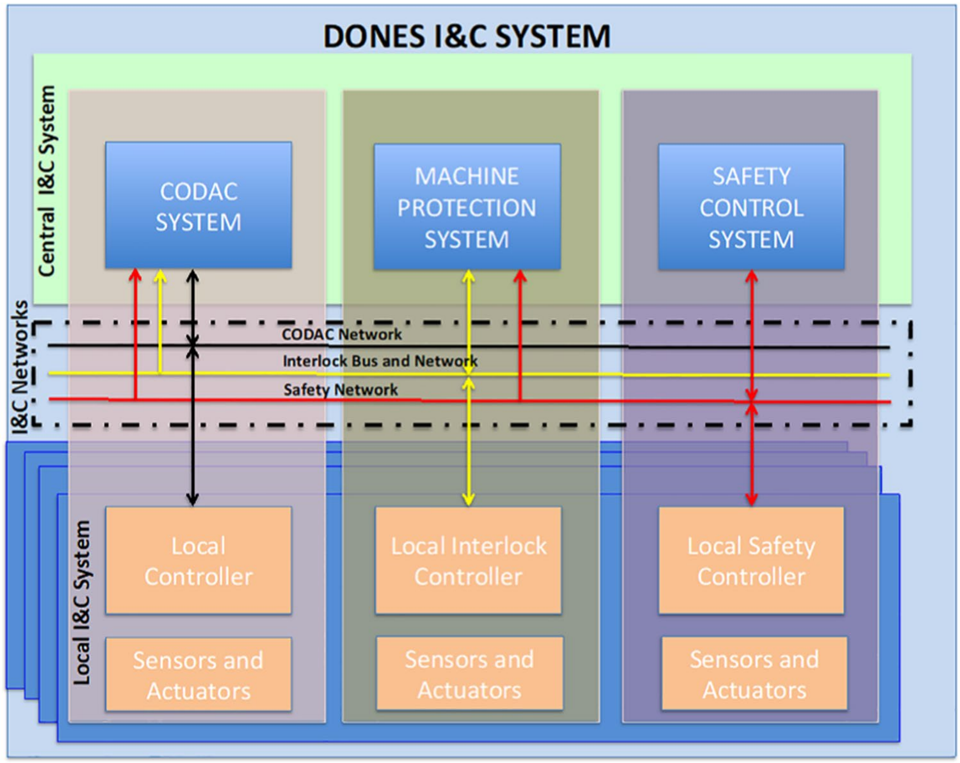


Fig. 4 DONES I&C systems: general top level architecture [18]

concerning safety aspects related to the environment, occupation, and human health are managed by the SCS, which serves as a specialized safety-grade protection system designed for the implementation of all identified protection functions related to personnel and/or the environment. Its primary purpose is to ensure the safety of personnel, public and the surrounding environment by executing specific safety measures and protocols as required.

More in detail, the Safety Control System (SCS) is constructed with an independent and dedicated architecture, aiming to minimize interactions with the conventional system. Its main components include the following subsystems:

1. **Plant safety subsystem (PSS)**: This subsystem focuses on safety measures and protocols related to the overall safety of the plant.
2. **Occupational safety subsystem (OSS):** The OSS is responsible for implementing safety functions specifically geared towards the protection of personnel working within the facility.
3. **Personal access safety subsystem (PASS):** PASS is designed to manage and enforce safety measures related to personal access, ensuring secure entry and exit procedures for individuals.
4. **Radiation monitoring system for the environment and safety (RAMSES):** RAMSES is dedicated to monitoring radiation levels in both the environment and within the facility, contributing to overall safety and environmental protection.

Each of these subsystems within the Safety Control System plays a crucial role in ensuring the safety of personnel and the environment through targeted and specialized safety functions [18, 23–26].

Integration of Diagnostics with Control Systems: Key Points

The integration of diagnostics with control systems is a critical aspect of ensuring the efficient and reliable operation of complex facilities like DONES [19]. Diagnostics and control systems work hand in hand to monitor, assess, and respond to the performance of various components within a system. Diagnostics provide detailed information about the health, status, and performance of various instruments and systems within a facility. Such diagnostic data are fed into the control systems as input, allowing the control algorithms to make informed decisions based on the current state of the system.

Here are some key points regarding the integration of diagnostics with control systems that are considered in the integration phase [22]:

1. **Real-time monitoring**: Diagnostics provide real-time monitoring of key parameters and performance metrics

of different instruments and systems. Control systems use this diagnostic information to assess the current state of the facility and make necessary adjustments to maintain optimal operation.

2. **Automated responses**: Integrated control systems can be programmed to automatically respond to diagnostic findings. In the event of a detected issue, the control system may initiate corrective actions, adjust parameters, or even shut down specific processes to prevent further damage.
3. **Condition monitoring:** Diagnostics enable continuous condition monitoring of critical components. Control systems use this information to assess whether system components are operating within specified parameters or if there are deviations that require attention.
4. **Fault detection and identification**: Diagnostics help in detecting faults or anomalies in the system components. Control systems utilize diagnostic data to identify the nature and location of faults, enabling quick and precise responses to maintain system integrity. Integrated systems can employ diagnostics for fault tolerance strategies, where the control system adapts to component failures by rerouting processes or activating backup systems. Also, predictive maintenance models can be implemented, leveraging diagnostic data to schedule maintenance activities based on the actual condition of components rather than a fixed schedule.
5. **Human–machine interface (HMI) integration**: Control systems integrate diagnostics into HMI interfaces presented to operators, providing a user-friendly platform to monitor system health, receive alerts, and take manual control if necessary.
6. **Optimization of performance:** Diagnostics provide valuable insights into the performance of individual instruments and the overall system. Control systems use this information to optimize operational parameters, ensuring efficient energy use, minimizing wear and tear, and extending the lifespan of equipment.
7. **Enhanced decision-making:** The integration of diagnostics with control systems enables data-driven decision-making. Operators can rely on diagnostic information to make informed decisions regarding maintenance schedules, system upgrades, and overall system improvements.
8. **Remote monitoring and control:** Diagnostics can be integrated with remote monitoring systems, allowing operators to assess the system's health from a distance. Control systems with remote capabilities enable operators to make adjustments or implement corrective measures without being physically present at the facility.
9. **Feedback loops for continuous improvement:** Diagnostics generate data that can be used as feedback to improve the design and functionality of both the instruments and the control systems. This continuous improvement loop helps in refining system performance over time.
10. **Scalability and modularity:** Integrated systems should be designed with scalability and modularity in mind. As the facility evolves or expands, the integration of new instruments and diagnostics should be seamless, allowing the control system to adapt and accommodate changes without significant reprogramming.
11. **Redundancy and reliability**: Diagnostics can be used to assess the reliability of different components. Control systems may implement redundancy strategies, where multiple diagnostics are available for a particular aspect, enhancing the reliability of the overall monitoring and control system.

The integration of diagnostics with control systems represents a sophisticated approach to managing complex facilities, fostering efficiency, reliability, and adaptability in the face of varying operational conditions and potential challenges.

In modern research infrastructures, the integration of diagnostics with control systems is part of the broader concept of cyber-physical systems (CPS) [27]. CPS involves the tight integration of computational control algorithms with physical processes, allowing for real-time adjustments based on diagnostic feedback. Under such an approach, together with the "classical" integration problems listed above, novel issues may come when large amounts of data are involved. Control systems can employ advanced data analysis and machine learning techniques to recognize patterns indicative of potential issues, facilitating early detection and proactive intervention, while diagnostics involve analyzing large amounts of data to identify patterns or trends.

Recently, the integration of diagnostics with control systems is increasingly leveraging artificial intelligence (AI) and machine learning (ML) tools to enhance performance, efficiency, and decision-making.

The integration of AI and ML tools with diagnostics and control systems represents a powerful synergy, enabling facilities to move beyond traditional rule-based approaches and achieve a level of sophistication that is well-suited to the complexities of modern industrial environments.

In the next Section, some of the AI tools that are under evaluation and may be soon integrated into the IFMIF-DONES control system are presented.

Application of Artificial Intelligence Tools: Future Scenarios in IFMIF-DONES

The ongoing design of IFMIF-DONES includes supporting the latest trend in the field of control and operations, and particularly the support of AI features.

In general, AI and ML may contribute to the integration described in Sect. "Integration of Diagnostics with Control Systems: Key Points" by implementing many functionalities. In what follows we report a review of the main features that are considered for application to IFMIF-DONES.

1. **Advanced anomaly detection:** Machine learning algorithms can analyze historical diagnostic data to learn normal system behavior. AI tools then enable the detection of anomalies or deviations from the learned patterns, providing early warnings for potential issues [28, 29].
2. **Predictive analytics:** AI and ML models can predict future system behavior based on historical data and trends identified through diagnostics. Predictive analytics help in anticipating potential failures or performance degradation, allowing for proactive maintenance [30, 31] or even for enhancing the security capabilities of the plant [32].
3. **Dynamic system optimization:** Machine learning algorithms can continuously optimize control parameters based on real-time diagnostic data. This dynamic optimization ensures that the control system adapts to changing conditions and maximizes efficiency [33, 34].
4. **Pattern recognition and feature extraction:** AI techniques excel in recognizing complex patterns and extracting valuable features from large datasets. In the context of diagnostics, AI can identify subtle patterns in sensor data that may indicate impending issues or opportunities for performance improvement [35, 36].
5. **Fault classification and localization:** Machine learning models can classify different types of faults and localize their source within the system. This information is valuable for control systems to respond appropriately, activating backup systems or rerouting processes as needed.
6. **Adaptive control strategies:** AI-driven adaptive control strategies can adjust the control algorithms in real-time based on changing diagnostic conditions defined on complex control models [37]. This adaptability is particularly useful in environments where operational parameters may fluctuate.
7. **Cognitive computing for decision support:** Cognitive computing systems, a subset of AI, can provide decision support to operators. By processing vast amounts of diagnostic data, these systems assist human operators in making informed decisions and taking timely actions.
8. **Automated root cause analysis:** Machine learning tools can aid in automated root cause analysis by correlating IFMIF-DONES diagnostic data with historical records (also coming from other similar plants, like LIPAc [20]. This accelerates the identification of the underlying causes of issues, facilitating faster problem resolution [38].
9. **Continuous model learning:** ML models can be designed for continuous learning, adapting to evolving system dynamics over time. From well-known neutral networks technics [37], to latest advances in reinforcement learning [39], this adaptability is crucial in environments where the characteristics of instruments or processes may change like in an experimental plant.
10. **Energy optimization:** AI algorithms can optimize energy consumption based on diagnostic information. By analyzing patterns in energy usage and correlating them with system performance, AI-driven control systems can minimize energy waste and improve overall efficiency [40].
11. **Particle accelerator design:** AI techniques can play a significant role in the accelerator design. From beam dynamics analysis to early performance analysis, AI tools can assist on the process of selection and parametrization of the accelerators components [20] as well as on the speed up of the different simulations required for critical accelerator parameter estimation [41, 42].

To achieve the above-mentioned objectives, AI tools and capabilities may be included in the future design of IFMIF-DONES control systems with two main scopes.

First, AI is proving to be an invaluable tool in shaping the design of the plant, particularly in areas with complex physics and simulations, such as beam dynamics and neutronics. Simulation tools like TraceWin and Monte Carlo techniques play an integral role in achieving this design objective. The target application concept is schematically shown in Fig. 5.

In this application, AI methods offer the capability to systematically explore the entire design space required for the design of the accelerator beam dynamics. AI allows automating the optimization of the coupling between various accelerator elements (such as cavities, magnets, and diagnostics) and operational parameters without manual human intervention. This activity is typically addressed for each of the accelerator's segments (low, middle and high energy beam transfer lines) by the human designer as it is of critical importance to guarantee the feasibility of the accelerator beam. Note that in the case of IFMIF-DONES, the target outcome shall produce the right neutronics beams

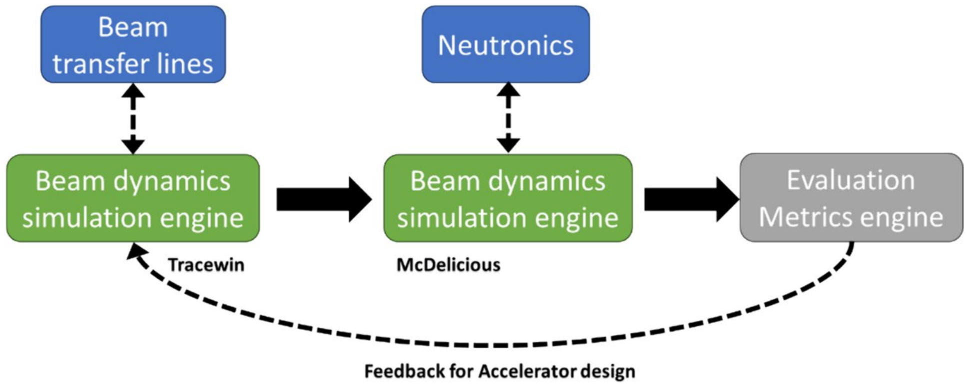


Fig. 5 Feedback loop for IFMIF-DONES accelerator design based on beam dynamics and neutronics simulation tools

after impacting on the neutron wall, thus a special attention should be taken to verify that the produced beam pattern follows the shape and energy distribution required to radiate the samples. For this reason, a Monte-Carlo analysis after the beam dynamics is needed to simulate this interaction. By using AI, the whole simulation parameters can be explored, allowing to find global optimal solutions for the accelerator design with minimum design experts time allocation.

This approach is impacted by the time-intensive and intricate nature of these simulations and methods used to explore these parameters. Fortunately, AI may be very beneficial to IFMIF-DONES to accelerate those simulations. Ongoing studies are investigating the application of AI methods to reduce the computational load of accelerator simulations. The concept involves utilizing functional approximation AI techniques to quicken Monte Carlo and beam dynamics simulations. While the range of convergence and performance of these approximations compared to physical simulations is still under scrutiny, the goal is to interpret operational parameter changes using AI. This approach aims at enabling real-time beam dynamics analysis during plant operations, providing valuable assistance to operators in making informed decisions as part of their daily plant management activities.

As a second approach for AI utilization in IFMIF-DONES, anticipating structural changes in the plant design to accommodate the future integration of AI techniques becomes a foresighted strategy, allowing the contribution of "AI-Ready" elements right from the initial conception of the facility. The concept is to leverage the utility of AI techniques during operations for tasks such as plant optimization (e.g., minimizing energy consumption or maximizing beam energy transfer to particles), predictive maintenance, failure analysis, or the creation of a comprehensive plant digital twin. These AI applications are essential for efficiently achieving availability requirements and minimizing power consumption.

To achieve these goals, specific elements, such as dedicated data extraction interfaces on different plant controllers and sensors, can be incorporated. These interfaces enable access to internal information not strictly required for regular operations but valuable for optimizing device internal parameters or predicting operational behaviors with minimal disruption to normal operations and interfaces. They can be utilized for components emulation (designing specific digital twins of key elements), optimizing parameters for on-the-edge devices, or contributing data to a central system for global analysis.

For effective implementation, a dedicated high-bandwidth network is designed not to interfere with regular control system operations and networks, but capable of handling the significant amount of data generated by internal states of various sensors and controllers. By treating AI elements as optional features during operations and defining their requirements from the beginning—specifying interfaces, edge AI processing capabilities, and communication networks—such elements may be deployed incrementally. This approach aligns with specific problems to be addressed and remains compatible with budget constraints during plant construction and evolution.

Finally, the system will require a dedicated server room to store unprocessed data for global analysis. By incorporating these capabilities from the initial control system and plant design, the facility can adapt to the natural life cycle of the plant, managing AI features in the most relevant and effective manner. This comprehensive approach gives rise to the concept of an "AI-Ready" plant.

Conclusions and Future Perspectives

So far, the primary accomplishment of the Early Neutron Source project has been the establishment of a consolidated preliminary engineering design baseline for the IFMIF-DONES facility. Throughout the project, the initial conceptual design derived from the previous IFMIF configuration underwent evolution, involving the review and redesign of certain aspects. Additionally, essential validation activities were proposed and executed.

The current maturity level of the IFMIF-DONES design has paved the way for defining the working program of the Horizon Europe (FP9) Early Neutron Source work package. This phase is ongoing and focuses on completing the engineering design, conducting remaining experimental validation and qualification activities, performing necessary transversal analyses, and preparing technical specifications for upcoming tenders related to the construction of IFMIF-DONES infrastructure, components, and equipment.

One of the main points of the current project phase in the control system area is the integration of the current design with all the instruments and diagnostics. Such integration, enhanced by the application of artificial intelligence (AI) tools, establishes a powerful symbiosis that significantly augments the reliability, efficiency, and safety of intricate facilities. This collaborative approach, bolstered by AI, may empower IFMIF-DONES operators by providing them with advanced tools to proactively oversee and optimize the performance of the entire system.

By incorporating AI-driven analytics into the diagnostic process, operators can extract more nuanced insights from real-time data. Machine learning algorithms, for instance, can analyze historical data patterns that the IFMIF-DONES plant will produce during long-term operations, enabling predictive analytics that allow operators to anticipate potential issues before they escalate. This AI-powered foresight adds a new dimension to proactive management, minimizing downtime and maximizing operational efficiency by addressing issues in their early stages.

The dynamic interaction between AI-enhanced diagnostics and control systems creates a responsive framework. AI algorithms can dynamically adjust control parameters based on evolving conditions, ensuring a real-time response to changing circumstances. This adaptability contributes to a system that not only operates efficiently but also learns and evolves over time.

Furthermore, AI plays a crucial role in safety enhancement. By leveraging AI for anomaly detection and pattern recognition, operators can enhance preventive measures and respond promptly to any deviations from established safety protocols. The integration of AI-driven safety measures contributes to a robust safety culture, reducing the likelihood of incidents and enhancing the overall resilience of the facility.

In essence, the integration of diagnostics with control systems, enriched by the application of AI tools, goes beyond mere coexistence; it establishes a holistic approach where sophisticated data-driven decision-making, proactive management, and rapid responsiveness converge to create a system that is not only technologically advanced but also prioritizes the safety and performances of the entire IFMIF-DONES operation.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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