Artificial Intelligence and Machine Learning Applications in the Spanish Nuclear Field

A. Ramos[a], A. Carrasco[a], J. Fontanet[b], L. E. Herranz[b], D. Ramos[c], M. Díaz[d], J. M. Zazo[d], O. Cabellos[e], J. Moraleda[a*]

[a] *ENUSA Industrias Avanzadas S. A, Santiago Rusiñol 12, 28040 Madrid, Spain*

[b] *Unit of Nuclear Safety Research, CIEMAT, Avda. Complutense 40, 28040 Madrid, Spain*

[c] *AUDIAS Laboratory – Audio, Data Intelligence and Speech, Escuela Politécnica Superior, Universidad Autónoma de Madrid, Francisco Tomás y Valiente 11, 28049 Madrid, Spain*

[d] *TECNATOM, Avda. Montes de Oca 1, 28703 San Sebastián de los Reyes, Madrid, Spain*

[e] *Department of Energy Engineering, Universidad Politécnica de Madrid, José Gutiérrez Abascal 2, 28006 Madrid, Spain*

* Corresponding author: jmj@enusa.es

Abstract:

Machine Learning and Artificial Intelligence techniques are increasingly applied in the nuclear field. In this way, Spanish companies and research institutions have been developing different projects in the field of nuclear energy applying such techniques. A brief overview of some of these projects is presented, which cover areas as diverse as nuclear data, nuclear fuel manufacturing, simulation codes, fuel performance monitoring, nuclear inspection, and operation training. Among the techniques used to develop them are deep neural networks for building surrogate models, convolutional neural networks for computer vision, Bayesian networks and Gaussian processes for predictive models, and speech recognition with large language models.

Keywords: Machine learning, artificial intelligence, computer vision, nuclear codes.

Abbreviations: AI, Artificial Intelligence; ANS, American National Standards; ANSI, American National Standards Institute; ASSAS, Artificial intelligence for the Simulation of Severe AccidentS; ASTEC, Accident Source Term Evaluation Code; AUDIAS, AUdio, Data Intelligence And Speech; BIM, Building Information Modelling; C/E, Calculation-to-Experiment; CESAM, Code for European Severe Accident Management; CIEMAT, Centro de Investigaciones Energéticas, Medioambientales y Tecnológicas; CNN, Convolutional Neural Network; CTC, Connectionist Temporal Classification; DBN, Dynamic Bayesian Networks; DBSCAN, Density-Based Spatial Clustering of Applications with Noise; DNN, Deep Neural Networks; CRNN, Convolutional Recurrent Neural Network; CSNI, Committee on the Safety of Nuclear Installations; ENSREG, European Nuclear Safety Regulators Group; ENUSA, Empresa Nacional de Uranio, S. A.; FCVS, Filtered Containment Venting Systems; FP, Fission Products; FPN, Feature Pyramid Network; GP, Gaussian Processes; IAEA, International Atomic Energy Agency; ICSBEP, International Criticality Safety Benchmark Evaluation Project; IRPhEP, International Reactor Physics Experiment Evaluation Project; IRSN, Institut de Radioprotection et de Sûreté Nucléaire; KIT, Karlsruhe Institute of Technology; LLM, Large Language Model; LP, Loading Pattern; LSTM, Long Short-Term Memory; ML, Machine Learning; MLP, Multi-Layer Perceptron; MWe, MegaWatt electrical; NEA, Nuclear Energy Agency; NN, Neural Network; NNP, Nuclear Power Plant; OCR, Optical Character Recognition; OECD, Organisation for Economic Cooperation and Development; PWR, Pressure Water Reactor; R-CNN, Region-based Convolutional Neural Networks; RNN, Recurrent Neural Network; SAM, Severe Accident Management; SIFT, Scale Invariant Feature Transform; SFP, Spent Fuel Pool; SGTR, Steam Generator Tube Rupture; TDB, Training Data Base; TEPCO, Tokyo Electric Power Company; UPM, Universidad Politécnica de Madrid; USNRC, United States Nuclear Regulatory Commission.

1. Introduction

Artificial intelligence (AI) and machine learning (ML) are advanced computational techniques that have proven to be very useful in various disciplines and for a variety of applications in both the industrial and academic fields. The development of these technologies has improved the efficiency, effectiveness, and decision-making of industrial processes.

Machine learning is a subfield of computer science and emerged from AI with the goal of learning from data. Early ML focused on symbolic representation and knowledge-based learning, such as decision trees. Modern AI/ML have developed with the advancement of high-performance computing and large datasets. Advanced ML methods require much more data than the traditional statistics methods but can produce high-performance prediction models when relationships are more complex, so they have taken the models' learning ability to the next level to solve extremely difficult problems, such as autonomous driving, or early cancer detection. Although many modern ML approaches, such as deep learning (LeCun et al., 2015), lack interpretability, they undoubtedly have better predictive power.

In recent years, the nuclear industry has witnessed a significant surge in the application of AI/ML technologies to enhance safety, efficiency, and reliability in various aspects of nuclear operations (Benedict and El-Genk, 2018; El-Genk and Tournier, 2019; Zhang et al., 2020). These advancements have facilitated the optimization of nuclear power plant design, predictive maintenance, reactor monitoring, and risk assessment, among other critical applications (Metzroth et al., 2018; Gohel et al., 2020; Chen et al., 2020, Ma et al., 2022). In addition, AI technologies can improve the quality and efficiency of nuclear industry production, such as nuclear fuel manufacturing, and reduce operating costs at each stage of the nuclear industry.

In past decades, many simulation codes have been developed for the design and analysis of reactor systems, which are based on empirical correlations and numerical algorithms that describe the physics and phenomena existing in nuclear power plants. Currently, AI/ML-based methods are used as a valuable approach to assist in the development and application of thermal-hydraulic or neutronic methods. ML provides new ways for dimensionality reduction and reduced-order modeling in fluid mechanics or neutronics, by providing a concise framework that complements and extends existing methodologies. Recent applications of these techniques in reactor system design and analysis, plant operation and maintenance, and nuclear safety and risk analysis are reviewed in Ma et al., 2022.

Furthermore, applications in nuclear component inspection tasks, and for sequence data processing, such as event reports or audio data, can be found in Tang et al., 2022.

In the last years, several companies of the Spanish nuclear industry and Spanish research institutions have been developing different projects in the field of nuclear energy applying AI/ML techniques. This paper summarizes some of these projects, as examples of the usefulness of such new technologies to solve diverse problems within the nuclear industry.

2. Overview of some Machine Learning techniques

AI/ML algorithms involve a dataset of the system to be modelled. They can be categorized into supervised learning and unsupervised learning, depending on whether the training dataset is completed or not. In supervised learning, the dataset consists of several input variables and true output values, i.e., responses that are known. The algorithm learns the relationship between the input variables and the known output variable. In unsupervised learning, the response variable is not known, and the objective is to learn patterns in the data to discover groupings, or clusters of input data.

Most ML applications in the nuclear field use supervised learning algorithms, and artificial neural networks (NN), Gaussian processes (GP), and Bayesian networks (BN) are among the most widely used.

Artificial NN are the most well-known methods in supervised learning, although also can be developed for unsupervised learning. They have been applied in broad areas, including regression analysis, classification, data preprocessing, and robotics. Basically, a NN is formed by several layers of nodes, where a weighted output from one layer, after applying non-linear activation function, is the net input to the next layer. The weights for each node are fitted to model the relationship between input and output variables of the whole training dataset.

A neural network with more than three hidden layers between input and output layers is called a deep NN (DNN), and its use is known as deep learning. Recent progress on deep learning has demonstrated that DNN can achieve a very high performance for many tasks, such as object recognition, image classification, and speech recognition.

There are two types of DNN whose development represented a qualitative advance in ML applications, Convolutional Neural Networks (CNN) (Rawat and Wang, 2017), and Recurrent Neural Networks (RNN) (Medsker and Jain, 1999). CNN process visual and other input data that can be arranged into two-dimensional arrays and have achieved great success in Computer Vision (CV) tasks, such as image classification and object detection. And RNN based on Long Short-Term Memory (LSTM), which improves the learning process, have been quite successful for Natural Language Processing (NLP) tasks, such as natural language generation and machine translation, and speech recognition.

Gaussian Processes (GP) are a probabilistic method that can be applied to both regression and classification tasks, its most important advantage being the incorporation of the confidence of the prediction to the result (Rasmussen and Williams, 2006). It is a generalization of the multivariate Gaussian distribution to infinite dimensions, although inference over a finite subset of these variables is tractable.

Bayesian networks (BN) is a class of directed acyclic graph, in which the links between the variables, or graph nodes, have a direction that represents a direct dependency between them (Koller and Friedman, 2009). The joint probability distribution of all the variables in a BN model is factorized such that a given variable only depends directly on its parent nodes. This method is a graphical model that allows to understand the problem, learn causal relationships between its variables, and predict the probability of events.

3. Spanish nuclear projects with AI/ML techniques

In the following, several nuclear projects developed with ML techniques are described, grouped in different application fields. Firstly, the application of statistical models like BN and GP to model some aspects of the radiochemistry of the nuclear reactor coolant is explained. A second large group of projects is dedicated to computer vision, a field where ML tools, specifically CNN, are being very useful, applied to the inspection of nuclear fuel, both fresh fuel in the manufacturing process and spent fuel, and to enhance nuclear operations. Examples continue of the application of ML methods to different nuclear codes, for improving nuclear engineering tasks such as the reactor loading pattern, and simulation of severe accidents in nuclear plants, using DNN to create surrogate models to increased computational performance of the computational process. Another section is dedicated to works that improve understanding of nuclear database and identify potential directions of development in nuclear data by means of ML techniques. And finally, a project in the field of training in nuclear operations is described, which uses NLP techniques.

3.1. Statistical models

ENUSA has strategically decided to incorporate AI/ML techniques in all its corporate areas from uranium supply to decommissioning. Since 2018, ENUSA has been collaborating with the AUDIAS research group of Universidad Autónoma de Madrid in both, project performance and training. This group has a large experience in neural networks development and its use in machine learning and signal processing for real applications. An example of this collaboration is the application of ML techniques to establish statistical models of the evolution of radioisotopes in the reactor coolant.

3.1.1. Radioisotope levels in nuclear reactor coolant

Predicting the radiation dose levels in the reactor of a Nuclear Power Plant (NPP) is paramount for their normal operation, to fulfil quality, maintenance, and safety constraints. Radiation dose is known to be dominated by the presence of radioisotopes in the primary loop coolant of the reactor, mainly cobalt (Co). With no fuel leaks, these radioisotopes are assumed to be dependent on several control variables, known in normal operation of the plant, such as the thermal power (P) in the reactor, the coolant pH, letdown dL, and some coolant additives like hydrogen (H_2) and zinc (Zn).

The evolution along the cycle of some radioisotope levels in the reactor coolant has been studied with ML techniques, with the objective of obtaining a predictive model relied on experimental data. Chemistry and radiochemistry data collected by ENUSA for the assessment of the nuclear fuel provided to five Spanish NPP have been used, consisting of different measurements of several variables along the operation of the reactor, taken during different cycles of each plant.

One first study (Ramos et al., 2021; Ramirez-Hereza et al., 2023) focused on predicting corrosion products levels from several control variables. The objective was to provide a helpful tool in dose management, allowing to adjust the control variables configuration to regulate corrosion products in a data-driven and probabilistic way. Different types of Bayesian networks were used, which are probabilistic graphical models that represent the conditional dependence relations between variables. Since the radioisotopes at each time depend not only on the control variables at that time, but also on those at earlier times, Dynamic Bayesian Networks (DBN) were employed to incorporate temporal information to the inference problem. DBN consider several sets of variables in consecutive times, with relationships between them as shown in Fig 1.

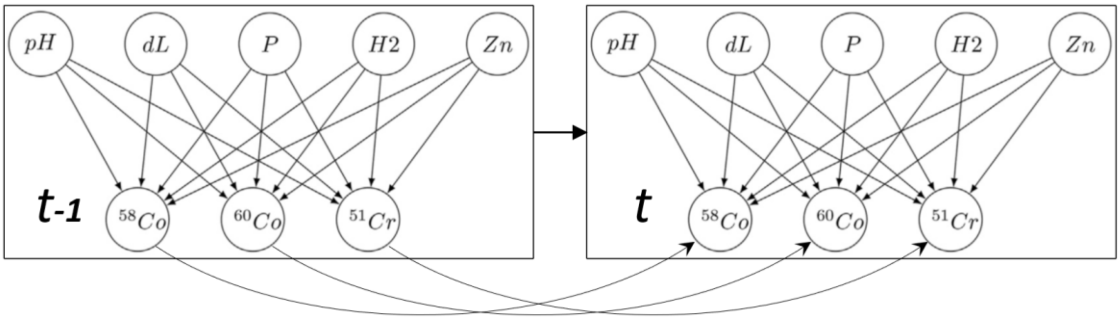

Fig 1. Proposed DBN, with dependencies between variables indicated by arrows (Ramos et al., 2021).

In a second work (Balanya et al., 2022), a probabilistic ML approach was proposed to model radiation dose levels at reactor shutdown. It focuses on modelling the uncertainty in the regression problem that aims to predict radiation dose levels from activity of corrosion products present in the primary loop, specifically from Co radioisotopes. Probabilistic models give a prediction for the future value of dose levels and the uncertainty of these predictions. Gaussian Processes (GP) were chosen among these models because they have very few parameters, yet at the same time, they are highly expressive as they can represent any continuous function. Examples of predictions by the trained GP are shown in Fig 2, where the model prediction (continuous line) of the dose level (mSv/h) is represented versus the activity of Co radioisotopes at shutdown, jointly with an uncertainty band. Black dots correspond to part of the experimental data used to train the model, and the red one is an individual value used to evaluate the performance of the trained model.

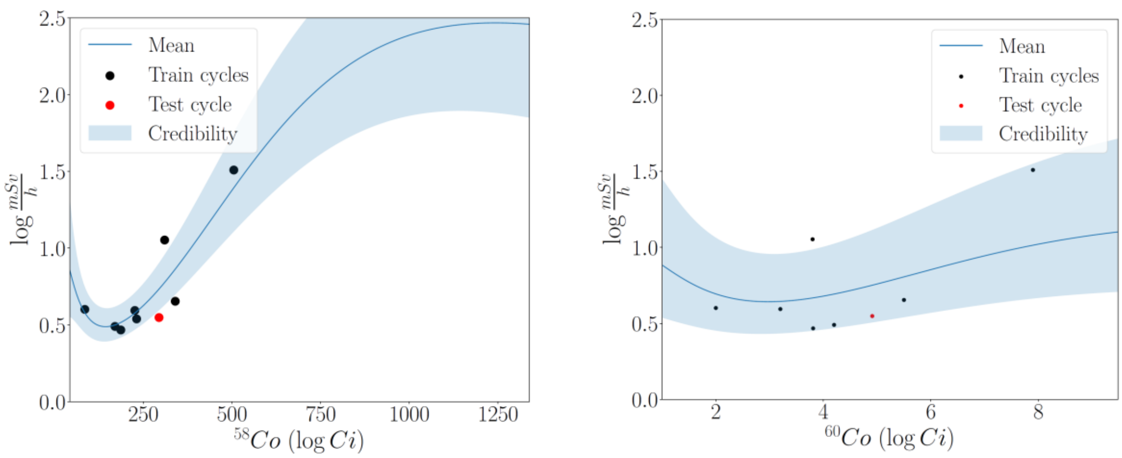

Fig 2. Examples of fitted GP models predicting dose with Co activity at shutdown (Balanya et al., 2022).

3.2. Computer vision

The nuclear industry has always been a pioneer in technological advancements, especially in automation. Besides, the nuclear industry faces various challenges, including the need to maintain high safety standards, reduce operational costs, and improve the accuracy and efficiency of nuclear operations. Computer vision technology has the potential to address these challenges in all fields and steps of the nuclear generation lifecycle. From the design phase, where computer vision can be used as a Building Information Modelling (BIM) companion, to the decommissioning phase, where computer vision can fulfil monitoring tasks, there is always a job that can be automated or improved thanks to computer vision.

Several examples of computer vision projects developed by ENUSA and Tecnatom using ML techniques are briefly described here. ENUSA is developing inspection tools for quality assessment in manufacturing nuclear fuel pellets and for inventory of spent fuel, and Tecnatom's project is aimed to assist in the development of NPP control room simulators.

3.2.1. Automatic visual inspection of uranium pellets

As a part of the manufacturing of the nuclear fuel assembly, the surface of UO_2 pellets is visually inspected at the end of their ceramic production process, to ensure they fulfil the quality requirements. ENUSA Automatic Pellet Inspection equipment works under the same concept of visual inspection performed by qualified operators: observing the lateral surface of the pellets while they spin on some rollers to detect damage or defects on them. In this way, an image of the lateral surface is acquired by a camera and afterwards it is automatically analysed by software. This analysis is more robust than visual inspection as it avoids the variability due to human factors, like subjectivity or fatigue.

Image analysis by Deep Neural Networks (DNN) (LeCun et al., 2015) provides a more efficient image analysis than traditional processing techniques, since it allows an automated learning of the most representative defect characteristics, becoming a very useful tool for detection and classification of defects on pellets. The main advantages of such system based on DNN are a greater reliability of detection and classification and less sensibility to variations on image conditions. The DNN structure for image classification consists of two parts: a Convolutional Neural Network (CNN), that extracts image characteristics progressively more complex and abstract (Rawat and Wang, 2017), and a DNN for the classification task (see Fig 3).

For training the CNN, it's necessary a big database of pellet images with known defects. About 10,000 defects has been labelled and, using "data augmentation" techniques (artificial defects generation by modifying existing ones), a total database of 30,000 images has been created. The DNN system obtained is set to detect the following defect types on the pellet surface: Simple crack, Branch crack, Multiple crack (nail type, multiple cracks), Material losses (end-chamfer and lateral side), Pits, Surface defect (grinding defects, surface contamination), End capping, End chamfer damage and "No Defect" (important to discard false detections). The final network obtains an approximate mean classification accuracy of 90% (Verdejo et al., 2021).

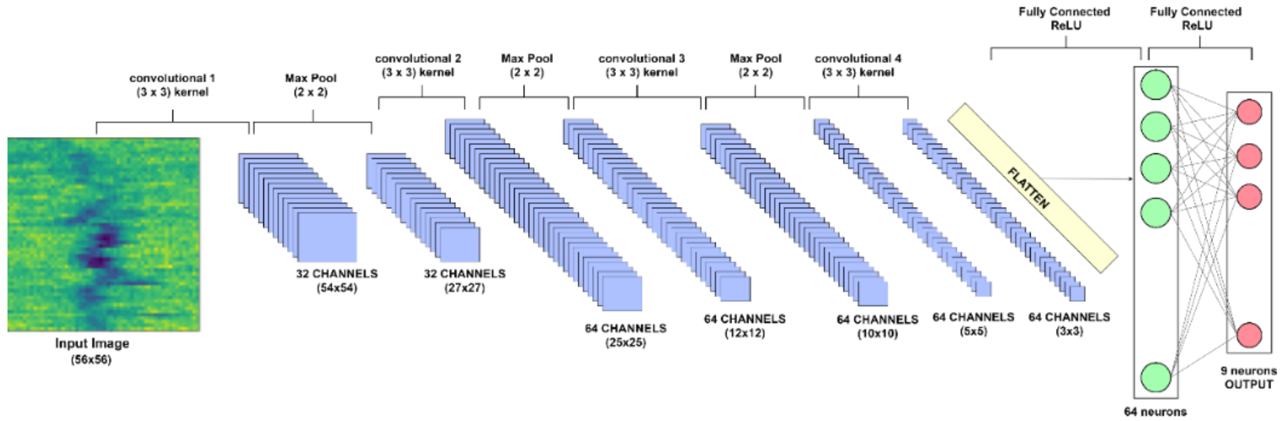

Fig 3. Basic structure of image classification system based on CNN (Verdejo et al., 2021).

3.2.2. Enhancing Nuclear Operations with Computer Vision Technology

The nuclear industry heavily relies on simulators to train and prepare operators for various scenarios. According to regulation ANSI/ANS 3.5 (Elliott and Wanner, 1985), the simulators of the control rooms of NPP must comply with a high degree of physical fidelity with respect to the real control rooms. To comply with this, Tecnatom performs a series of tasks that compare the status of the simulator from a current photographic report of the control room. From there, a report is made that evaluates the discrepancies and the actions to be taken. However, the physical fidelity of these simulators to actual control rooms is a process that requires hundreds of hours of heavily trained operators. Therefore, the development of an automation tool that can help in this task is a game-changer.

Computer vision technology has shown great potential in addressing this issue by providing a tool that can accurately assess the physical fidelity of simulators to actual control rooms. By using computer vision, operators can identify discrepancies between the simulator and the actual control room, allowing for timely adjustments and improvements. The benefits of using computer vision, including improved safety and efficiency, reduced costs, and enhanced training capabilities, are examined. The challenges and limitations of the technology are also discussed, such as the need for accurate and reliable data.

The process to check the physical fidelity is a significant monotonous workload, where it is easy to miss something that could have an impact on training. The process involves taking images of both plant and simulator control panels and then comparing one by one all the instrumentation and information in the photographs. These tasks require visually checking extensive instrument inventories, label texts, colours, and the location of instruments. Machine vision and character recognition algorithms are perfect for reducing the human workload, which can be concentrated on more value-added tasks such as verifying results and evaluating discrepancies identified by the machine.

In order to fulfil these tasks, Tecnatom have developed a set of algorithms that takes care of all the necessary steps to compare a couple of images with control panel instrumentation.

Anchoring images. The first step in comparing two images is to match both images, so both images need to be anchored to some points of interest. Here can appear a major problem: photos are not taken in the same spot, so the images to compare can be slightly rotated or zoomed out. To solve this problem, the SIFT (Scale-Invariant Feature Transform) computer vision algorithm has been used to detect and describe local features in images. It was developed by Lowe (1999) and has since become one of the most widely used algorithms in computer vision. The SIFT algorithm works by first detecting key points in an image that are invariant to scale, rotation, and illumination changes. These key points are then used to construct a set of descriptors that capture the local information around each key point. These descriptors are robust to changes in illumination and viewpoint, making them useful for a wide range of computer vision tasks.

To detect key points, SIFT uses a Difference of Gaussian filter to identify areas of the image with high contrast. These areas are then refined using a process called scale-space extrema detection, which identifies points that are both scale-invariant and distinctive. Once the key points have been identified, SIFT constructs a set of descriptors around each key point by computing the gradient orientation and magnitude of the image pixels within a local neighbourhood. These descriptors are then normalized and compared to a database of previously computed descriptors to identify matches between images.

Locating objects. Once two images are similar enough to be compared, the focus is to locate the instruments of the control panel, looking for missing instrumentation or tags in the simulator, due to an actualization of the Plant Control Room that has not been replicated yet in the simulator. Object location is one of the primary fields in computer vision. It is used to locate items in images, and it is based on that every object class has its own special features that help in classifying the class among others.

For this project, the Faster R-CNN ResNet-50-FPN implementation in Pytorch, encapsulated in Detecto Python package, is used. Faster R-CNN ResNet-50-FPN is a state-of-the-art object detection model that uses a deep neural network to identify and locate objects within an image. A detailed description of this algorithm can be found in Ren et al. (2015).

Reading texts. Finally, both plant and simulator images have been compared to have the same equipment, but here comes the hard and boring part, checking that the text in the instruments, tags, or alarms are the same. Thankfully the optical character recognition is another field of computer vision that has the maturity to be useful (see for example Du et al., 2020).

In this case, it is being used the state-of-the-art PaddleOCR library, an OCR (Optical Character Recognition) framework or toolkit that provides multilingual practical OCR tools that help users apply and train different models. PaddleOCR offers a series of high-quality pretrained models to make OCR highly accurate. It provides text detection, text direction classifier, and text recognition in more than 80 languages, built on CRNN, an architecture for neural networks based on the combination of both convolutional and recurrent neural networks. This network consists of three layers: CNNs followed by RNNs and then the transcription layer.

The feature extraction is the responsibility of the CNN, and the sequence labelling of these features is managed by de RNN, in this case, two bi-directional LSTM to address the vanishing gradient problem and to have a deeper network. Finally, a transcription layer is responsible for translating the per-frame predictions into a final sequence according to the highest probability. These predictions are used to compute CTC (Connectionist Temporal Classification) loss, which makes the model learn and decode the output.

One of the most important benefits of this solution is the multilingual OCR, which allows checking the text not only in languages but in alphabets unknown by the operator. With minor tweaks, the solution can also perform design validation tasks by training the system to recognize the design drawings and tag them with the same labels as the images of the actual panel. This way, the validation and verification of the built panels with the design drawings can be performed in a heartbeat.

In conclusion, the benefits of using this application are manifold. In economic terms, the number of hours spent on revision tasks has been reduced. In terms of quality, discrepancies have been identified that had gone unnoticed when a human carried out the process. In terms of resources, people have been freed from performing low added value tasks and can concentrate on other tasks where they provide value in accordance with their training and experience. In addition, multi-alphabet functionality has been implemented, which broadens the spectrum of use of the solution. This development, carried out entirely at Tecnatom, has allowed AI to be integrated into the work processes of different business areas, making its associated benefits tangible.

3.2.3. Automatic elaboration of spent fuel pool mapping

Control and inventory of spent fuel after each refuelling stop in a NNP is required, and for this reason a map of the Spent Fuel Pool (SFP) is made. All the cells in the pool are inspected by video, creating a map associating the position-coordinate of each cell with the identification code of the fuel element. Currently, this process is carried out by operators who, during the inspection, read the codes seen in the image aloud, and transcribe them manually. The audio-video recording of the inspection is later reviewed in the office to verify the map obtained at the plant. ENUSA is working with ML techniques to automate the elaboration of this map as much as possible, and thus reduce errors and time in the process. The inspection will be carried out in the same way, but automatically processing the video channel to recognize the element code that appears in the image (see Fig 4), and the audio channel to identify the same code and the cell coordinate that is displayed, which are said by the operator. The video will be processed with a pre-trained convolutional DNN, specially designed to detect objects in images, and the audio will also be analysed with NN. These networks are trained for this problem with thousands of images and audio fragments, extracted and labelled from recordings made by ENUSA to create SFP maps. The results obtained by each channel will be combined to determine codes and positions, generating with them in-situ the SFP map by means of a specific computer application.

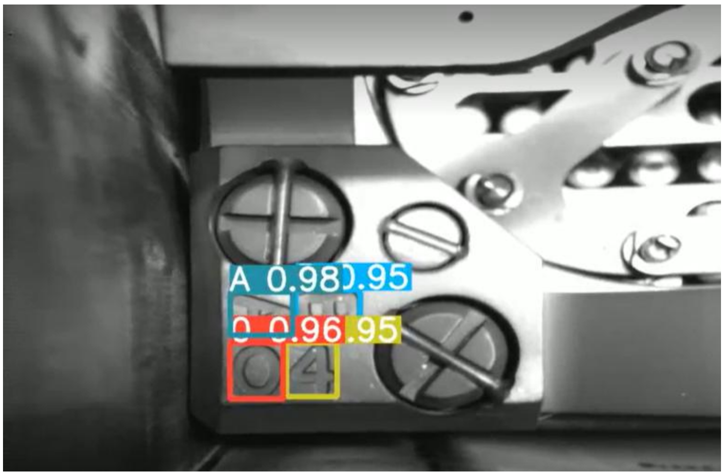

Fig 4. Fuel assembly ID identification by the trained CNN.

3.3. Calculation codes

3.3.1. Loading pattern optimization

For each operating cycle of a NPP the positions in the reactor of fresh and burnt nuclear fuel assemblies, i.e., the Loading Pattern (LP), must be chosen, meeting certain nuclear key safety parameters, while, at the same time, maximizing the energy delivered throughout the cycle.

The problem of loading pattern optimization is complex and has been studied for more than three decades. Many optimization algorithms have been proposed to solve it, of which heuristic optimization techniques are the preferred solution (see, for example, Stevens et al., 1995). However, most solutions proposed in the research field have had only limited industrial application, where manual processes based on designer's experience still dominate. Aimed to solve this problem, a novel solution, named *Neutronet*, has been developed at ENUSA, based on modern AI techniques, which uses low computational resources and is easily adaptable to different reactor types and licensed codes.

Neutronet proposes the replacement of the licensed nodal calculation code by a neural network that will act as a surrogate model. This network is then coupled to an optimization algorithm, that can find one or more optimized LPs. Finally, the licensed nodal code is executed for the proposed LP. Neutronet is therefore completely transparent for the nuclear authority, and there is no need to license it.

The surrogate model developed is a DNN of Multi-Layer Perceptron (MLP) type, which was trained on thousands of data points (each set with around 300 input variables and around 20 output variables).

Part of the training input data were generated by randomizing the assembly positions from sets of historic loading patterns for five different Pressurized Water Reactors (PWR). Then, each resulting LP was evaluated with the licensed nodal code, yielding the output variables for the set. The final trained MLP can calculate the output from an input data set with very small errors, in less than 0.1 s, reducing by more than 600 times the average run time of the current licensed nodal code.

The optimization algorithm in Neutronet begins with a population of proposed cores, which are iteratively modified, executing the surrogate model to evaluate them at each step, resulting finally in a series of optimized cores. The optimization process consists mainly in minimizing power peaks in the core, subject to a certain number of constraints. Several heuristic optimizers have been programmed from scratch, based on optimization algorithms, like Simulated Annealing, currently the most common solution used, and the novel Population algorithm proposed for the first time for this project.

The results of a single optimization run for a given cycle are shown in Fig 5. Successive optimizer generations are represented on the x-axis, with FΔH obtained by the surrogate model, as a measure of power peaking, represented on the y-axis. This execution generated around 50,000 cores, all evaluated with the MLP, with a total execution time of around an hour. The best results in each generation are compared with the results given by the licensed nodal code (blue circles). As can be seen, the optimizer successfully reduces core power peaking during the execution, obtaining various cores with FΔH values below the limit, which is shown as a dashed red line.

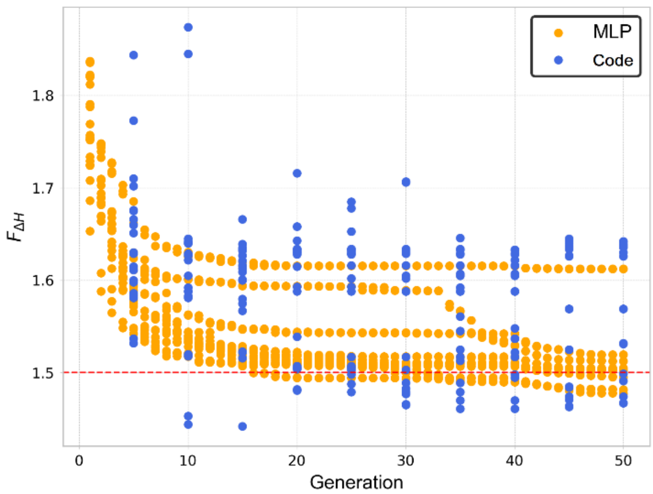

Fig 5. Core power peaking evolution for a single optimization run.

3.3.2. Artificial Intelligence for the Simulation of Severe Accidents

The Fukushima Daiichi accident (IAEA, 2015; TEPCO, 2015), in March 2011, stressed the need to improve the management of severe accidents in NPPs and provide safeguards able to mitigate the consequences of the accident in case all preventive measures are unsuccessful. Particularly, the stress tests performed in European countries (ENSREG, 2012) after the Fukushima Daiichi accidents introduced recommendations for Severe Accident Management (SAM).

The development and implementation of new, or improved, management actions can be greatly facilitated by the use of Severe Accident Simulators (NEA/CSNI, 2018). Indeed, simulators can support the evaluation, in an accelerated time, of the plant response to different SAM strategies in different scenarios. A severe accident simulator can also support decision-making during a real crisis as well as play an important role in operator training. Moreover, the use of a simulator may lead to more widespread dissemination of knowledge about severe accident phenomenology and to expanding the user community of severe accident calculation codes.

In this context, EURATOM is funding in the period 2022-2026 the ASSAS project (Artificial intelligence for the Simulation of Severe AccidentS) which introduces in an innovative way AI and ML techniques in the field of severe accidents. The objective of ASSAS is the development of a proof of concept for a severe accident simulator. The severe accident code behind the simulator’s interface is ASTEC (Accident Source Term Evaluation Code), the European reference integral code for severe accident simulations and developed by the IRSN (France). The modular structure of ASTEC allows easy replacement of different modules or a part of a module (Chatelard et al., 2014, 2016).

The ASSAS project must be considered a first step for a long-term strategy to develop severe accident simulators. The simulator prototype developed in ASSAS will take the 4-loop 1300 MWe PWR as the reference plant.

CIEMAT participates in two of the main work packages of ASSAS: The generation of the training database and the development of surrogate models, particularly for fission product release in the degrading core. Moreover, CIEMAT participates in other work packages with the discussion of the strategy for surrogate model development, the validation and assessment of the improved version of ASTEC, and the global acceptance evaluation tests of the simulator.

The simulation’s database to train the machine learning model is built based on a generic model for the PWR-1300 MWe plant. This model was initially created during the EURATOM/CESAM project (Nowack et al., 2018) and is released together with the ASTEC code package. The scenario to be considered in priority was selected to be the station black-out. The training database (TDB), once finished, will include thousands of simulations with the application of different management actuation enabled after the recovery of some systems. Different times for the operator actuation (or even missed action) are being considered as well as hypothetical malfunctions or delays of the systems. Thus, the TDB will cover a large amount of different accident management actions. It is worth noting that ASSAS is not addressed to uncertainty analysis in modelling. Therefore, the physical modelling parameters in the input deck are not modified.

To ensure that during the development of the surrogated models, all the parameters that might be necessary are in the database, it has been decided by the project partners to store the complete ASTEC's internal results memory at each time step of the simulation. This implies that the final TDB to be stored in the KIT (Karlsruhe Institute of Technology) computing servers will be huge. One important characteristic of this TDB is that it will be made open and accessible to everyone interested. Partners should ensure that all relevant and physically significant conditions at each phase of the accident are adequately covered in the TDB.

CIEMAT is developing a surrogate model to estimate the fraction of the different fission products and structural material that will be released from the core during its degradation. The initial ASTEC module devoted to evaluating the behaviour of fission products (FP) in the core is called ELSA and it is strongly coupled with the ICARE module for core degradation estimation (Chatelard et al., 2014). The surrogate model, then, would estimate the released fraction of the different elements considered for fission products and structural material during the various physical and chemical processes involved in the fuel and control rods, and in the surrounding thermal-hydraulics channel. The actual version of ASTEC calculates the release behaviour from intact or degraded fuel and control rods, later from debris beds, and then from the molten pool. The surrogate model should therefore deal with all of these scenarios.

Before the development of the surrogate model, it is necessary to define the sampling from the TDB of the variables needed as input to fully characterise the boundary conditions relevant for fission product release. As stated in the previous paragraph, these quantities must include the state of the fuel, the physicochemical conditions of the fuel and the surrounding channel. Obviously, the definition of sampling is an iterative process that may need to be adapted if the model results do not reach the desired accuracy.

The fission product release model will be integrated into the complete sequence calculation by interacting with the internal dynamic memory database created by ASTEC with the appropriate replacement of the output variables of the surrogated model. This dynamic memory (Chatelard et al., 2016) is used by ASTEC to read the input parameters needed to run the physical models and to store the results of the routines, which in turn is used by other modules in the code or in subsequent time steps.

Due to the strong interaction with the ICARE module of ASTEC, another strategy would be replacing the FP surrogate model together with ICARE. This solution drastically reduces the dimensionality of the problem since it decreases the variable exchange between the new surrogate models. Both approaches are at present taken into account. Finally, the results of the surrogate model must be transferred to SOPHAEROS (ASTEC's module dealing with FP in the circuits and the containment). To achieve the requirements for training of the simulator, the calculations must be performed even faster than real-time. The project aims to meet this challenge without losing accuracy in the ASTEC predictive capability. Therefore, the surrogate model must be validated to ensure it meets the requested accuracy before integrating it into the final ASTEC version. Fig 6 outlines the complete process.

Two families of models appear to be adapted for ASSAS: time-stepping and time-series predictions. The latter is more relevant to replace a specific module more completely whereas the time-stepping seems more adapted to surrogate models for specific phenomena since the next time step is calculated using the results of the previous one.

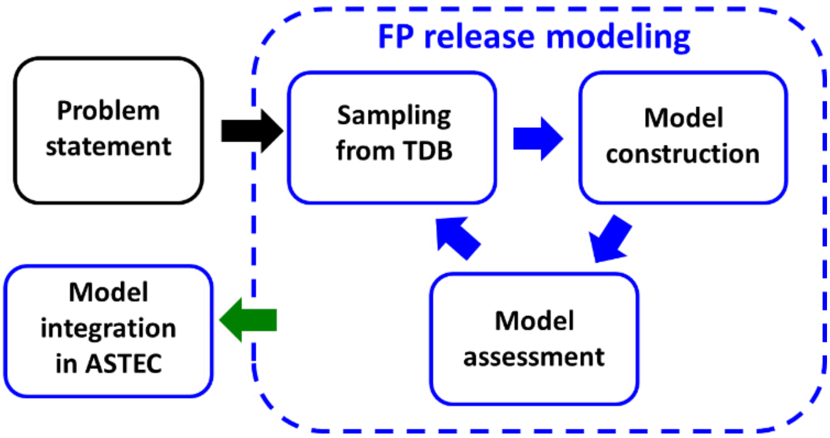

Fig 6. Outline of the construction process of the surrogate model for the fission product release.

As a summary of the ASSAS project, it can be said that the main outputs of the project will be:

- A proof-of-concept basic principle of severe accident simulator (for a generic PWR-1300 plant).

- A publicly accessible database for severe accident sequences.
- Fast-running surrogate models for severe accident modelling based on machine learning techniques.
- Increased computational performance of the ASTEC code.

Thanks to the experience gained in the development of the techniques for building the surrogate model for the fission product release, and to the availability of the database existing in CIEMAT. These methodologies would be expanded to other phenomena like scrubbing in water pools. This phenomenon is of importance in sequences like SGTR (Steam Generator Tube Rupture) or in the actuation of FCVS (Filtered Containment Venting Systems) in sequences evolving with high pressure in the containment (e.g. the Station Blackout).

3.4. Nuclear data

During the last decades, AI/ML methods have been introduced in nuclear reactor applications contributing nowadays to enhance the safety of the current fleet of reactors. At the present, these statistic techniques are becoming increasingly more practical and powerful in recent years. In this context, the Polytechnic University of Madrid (UPM) has organized education and training activities on Machine Learning within the Master of Nuclear Science and Technology program to promote ML/AI activities in our graduate and master students. These activities are scheduled within the INGENIA course devoted to the topic “Nuclear Reactor Design and Simulations” to attract young talent to this scientific area. This course introduces our students in reactor-oriented applications such as optimize in-core nuclear fuel management in reloading, core shuffling, emulating fuel configuration calculations, core parameter prediction and manoeuvring optimization.

An example of manoeuvring optimization with ML techniques is given in Fig 7 (Gabarain et al., 2021), which shows the results of a Westinghouse Niquist diagram used to control Xenon oscillations after a control rod insertion. It can be seen that extraction of control bank jointly with a boration after the bank insertion minimize Xenon oscillations. The objective function to be minimized with a genetic algorithm is the accumulation of Xenon oscillations during disturbances of criticality. A sequential Neural Network (NN) with four hidden layers and 200 neurons per layer is used to predict Axial Offset and Cumulative Xenon Oscillations. The NN is feed with different modifications from a criticality condition (rod insertion: 10-30 steps, disturbance duration: 2-64 hours, reactor power: 90-100% and fuel burnup: BOC-EOC) calculated with SEANAP system (Anhert et al., 1999) for a NPP PWR type Westinghouse 1000 MWe.

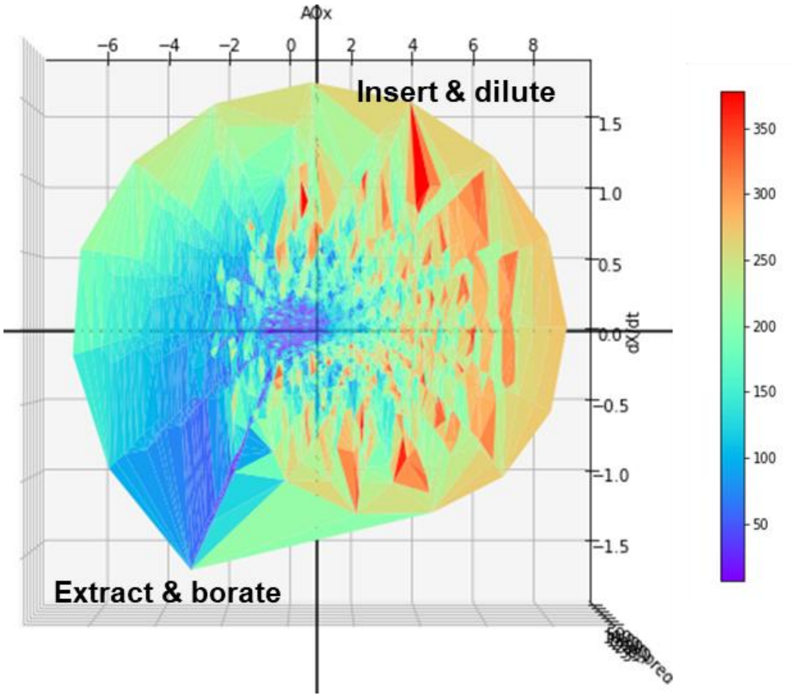

Fig 7. Values of the objective function after a control rod insertion at BOC and HFP. The Westinghouse Niquist Diagram (ΔXe vs ΔXe /dt).

Other area of high interest for the UPM is the application of these statistic techniques in nuclear data applications. Examples in the nuclear data field were summarized in Cabellos and Neudecker (2021). For instance, ML/ AI can support compilation as well as analysis of differential and integral experimental data used for evaluation and validation. For instance, natural-language processing could be used in searching through many journal articles for relevant information on experiments. On the other hand, ML methods can be put to task to identify outliers and reasons for those. Both tasks are labour-intensive and ML/AI would significantly cut down on human time needed. ML/AI has been successfully applied to identify nuclear data needs and critical issues across the nuclear data pipeline. Their applications range from finding the best parameter sets for nuclear reaction codes to describe a reaction to highlighting the need of new evaluations of nuclear data. Other example of ML/AI is to enhance the processing and encoding of nuclear data for real applications such as, e.g., selecting adequate group structures of nuclear data.

The UPM has been involved in the last years in many initiatives to foster the application of ML/AI methods within the pipeline of nuclear data. In the last years, both WPEC (Chadwick et al., 2019) and

JEFF (Michel-Sendis, 2020) initiatives have been launched to explore ML/AI techniques helping to get a better understanding of nuclear data and identifying potential directions of development in the whole nuclear data cycle.

An example of this UPM work is the Data Mining activity performed to identify outliers in nuclear databases. The presence of outliers in the experimental nuclear-reaction database – EXFOR – for a nuclear physics observable may conclude in a poor nuclear data evaluation. On the other hand, a nuclear data evaluation which does not take into account experimental data and it is uniquely supported in nuclear models may culminate in a poor evaluation, as well. Therefore, identifying and removing outliers is thus a key but challenging task for nuclear data evaluators.

A first step in this work has been the extraction of data both in EXFOR and ENDF files which are large databases, and the reconstruction in the same format. Then, this large quantity of data is analysed using different techniques to discover and extract patterns such as group of data (cluster analysis) or unusual data (anomaly or outliers detection). Fig 8 shows a comparison of different evaluated data and EXFOR data for the mubar, the average cosine of the lab scattering angle, for the neutron elastic scattering in natural iron. The energy range is for neutron energy between 500keV and 1.5 MeV. A potential outlier is identified at 700keV using a supervised ML technique, based on a sort of measured distance value between EXFOR data and evaluated data (González-Torre et al., 2023).

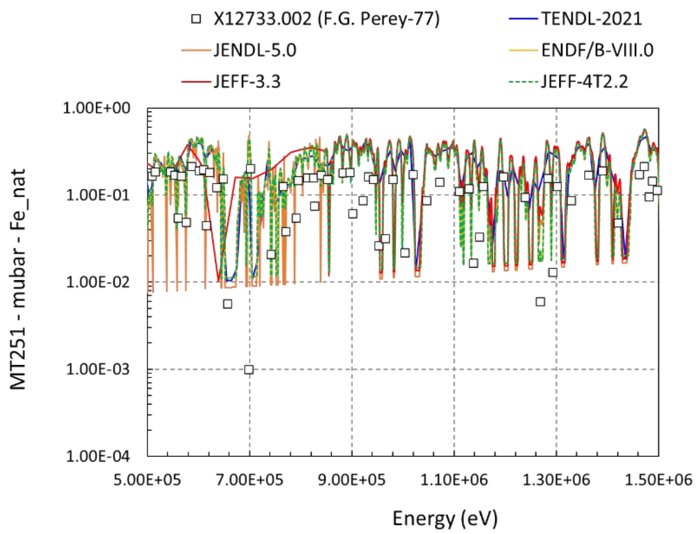

Fig 8. Comparison of the average cosine elastic value for the natural Iron. ENDF and EXFOR data are reconstructed to be visualized as mubar as a function of neutron energy.

Unsupervised ML algorithms such as DBSCAN (Density-Based Spatial Clustering of Applications with Noise) have been also explored to identify anomalous data in EXFOR database. Fig 9 shows one of the cases identified with DBSCAN for the 64Zn(n,alpha) reaction data. The EXFOR entry by “J.L. Casonava, 1976” can be categorized as a poor nuclear data and marked as a “doubtful” data as it can be seen using the IAEA-EXFOR data retrieval system (Zerkin and Trkov, 2007). This score indicates large differences between EXFOR and other evaluated and/or experimental data (Koning, 2014). In this work, a revision of 207 599 EXFOR entries for isotopes (4 398 164 data energy points) gives a total of 122 suspicious ENTRIES to be reviewed. The analysis is completed with 4,288 EXFOR entries for natural elements (1,125,858 data energy points) with a total of 17 suspicious ENTRIES to be reviewed.

This methodology may be extended to other standard – integral – databases used in the validation of nuclear data (e.g., the Handbook of criticality safety benchmark experiments ICSBEP (OECD-NEA, 2021a), IRPheP (OECD-NEA, 2021b), etc…). An analysis of C/E values (e.g. keff, spectral indexes, etc…), sensitivity profiles for nuclear reaction data and meta-data values of these integral experiments (e.g. reflector thickness, amount of burnable absorber, etc…) can provide essential insight into the physics reason why nuclear data might be outlying that is otherwise obscured by large amount of heterogeneous data (Neudecker et al., 2021).

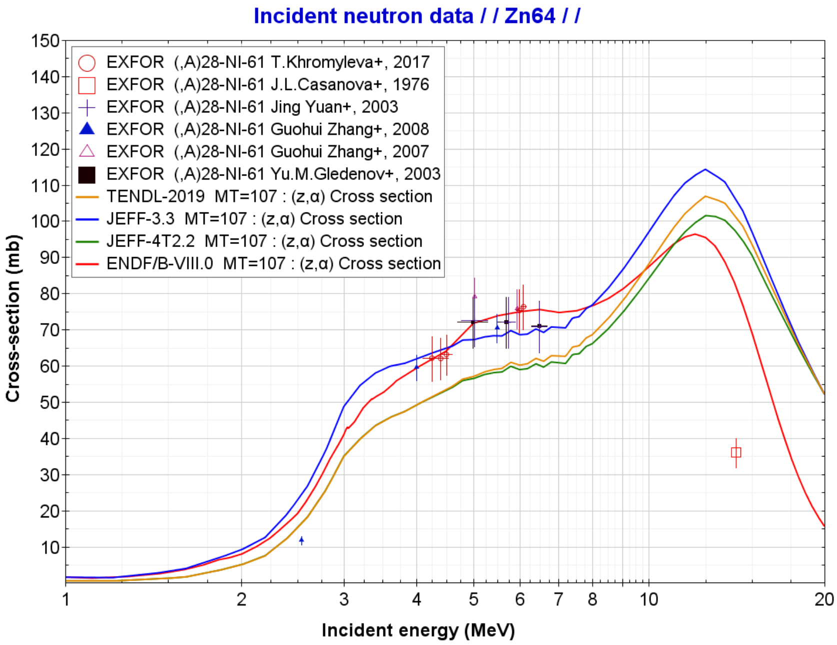

Fig 9. Comparison between EXFOR and recent evaluated data for the ^{64}Zn(n,alpha) reaction cross-section as a function of neutron energy.

These techniques can also provide a wealth of information on the measurement stored as metadata. By feeding these meta-data to ML algorithms, one can identify possible correlations between specific meta-data (e.g., like a detector type, composition, etc…). The correlation between uncertainties of the integral experiments is not only a crucial issue for nuclear data assimilation, but for criticality safety assessment.

It has been noted that the adoption of ML techniques across the nuclear data pipeline has been slower compared to the field of reactor applications (Cabellos and Neudecker, 2021). There are only few examples of applying ML/AI to a successful evaluation of nuclear data (Schnabel et al., 2021). ML/AI algorithms have proven to be extremely helpful in these first initial studies to sieve through large amounts of heterogeneous data that are too large to comprehend for a human mind on its own. However, it also became clear that it takes experts to feed the algorithms carefully curated data and correctly interpret the result (Cabellos and Neudecker, 2021).

3.5. Training

Tecnatom, with 65 years of experience in the energy sector and more specifically in the nuclear sector, is constantly seeking to improve the learning process and results in training and development activities for employees and clients.

3.5.1. Virtual instructor project

Tecnatom is working on the creation of an online virtual instructor based on AI that uses large language models (LLM) to adapt to the learning needs of each student and offer an individualized experience, available 24 hours a day. The implementation of such a tool would allow for the optimization of resources and time for those involved in training and qualification, as well as improving the quality of learning by creating a more agile and interactive environment, and offering personalized multilingual service.

The objective of this project is to offer an innovative solution that takes advantage of the benefits of natural language processing models to improve the teaching-learning process, adding the value of having a personalized service that adapts to each student.

The current process approach involves coordination of time and resources, as well as a delay in being able to solve specific doubts by students. That is why, in order to offer an agile, interactive, dynamic and autonomous experience, work is being done to find the best approach to combine people and technology.

Currently, the process is carried out asynchronously, leaving questions posed to be resolved later, or according to the availability of the instructor and student, which implies a high cost of time and human resources, as well as a delay in obtaining answers from the student. The implementation of a virtual instructor based on artificial intelligence would allow for the optimization of these resources, streamlining response times and improving the quality of learning.

The proposed virtual instructor uses LLMs, deployed in the Azure OpenAI suite, guaranteeing privacy and security in all conversational interaction and information exchange, complying with quality standards.

This virtual instructor does not replace the instructor but acts as a complementary tool with 24/7 availability for students, supervised by these experts, and can help with answering questions, generating summaries, creating self-assessment questions, explaining complex topics, extracting relevant information, providing specific topic references, among other tasks. Additionally, it is a multilingual solution, able to interact immediately according to the student’s language.

The implementation of a virtual instructor with these characteristics represents a before and after in how training processes have been conceived. Now, innovation is at the service of the student, being able to have a personalized, interactive, and fast service without the constant supervision of a person. The cost savings, time reduction, and improvement of the student experience are the main values that such a tool provides.

The next steps in the development of this project involve working towards accessibility, allowing both written and voice interaction; the creation of a visual interface for the virtual instructor, whose purpose is to offer more confidence and make it more user-friendly; and the implementation of pilot tests in Tecnatom to evaluate the effectiveness of the tool and thus improve based on the results and feedback from users.

4. Conclusions

Different Spanish groups are developing a wide variety of projects within the nuclear field, using Artificial Intelligence and Machine Learning techniques. The results obtained demonstrate that these novel techniques are very useful to address problems that would otherwise be very difficult to solve.

Among the techniques applied in the projects here described are deep neural networks to build surrogate models to simplify different tasks, convolutional neural networks in computer vision to recognize patterns in images, large language models to assist training, and Bayesian networks and Gaussian processes to create predictive models. All of them have proven to be very valuable to carry out different nuclear projects.

The main technical challenge of ML and AI algorithms comes from their difficult interpretability because the models obtained can be complex and with many parameters, such as those resulting from DNN. This creates a new source of uncertainty and makes it difficult to explain and trust such techniques when applied to nuclear research or in the industry. Nonetheless, Machine Learning and Artificial Intelligence techniques are developing very fast nowadays, so they are expected to be increasingly used in the nuclear industry. As has been demonstrated here, Spanish nuclear companies are already working with these tools and taking advantages of their capabilities.

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