Nuclear power plants are used by EDF to generate electricity, with the reactor vessel containing radioactive material that releases heat and accelerates steam in the pipes. To generate large amounts of energy, the components must be large. For protection and safety reasons, it is essential that the entire installation is watertight, with welding being used to ensure the continuity of the assemblies. Due to the large thicknesses involved, welding is often done in multi-passes. All nuclear installations are subject to regulations. The French Nuclear Safety Authority (ASN) is responsible for monitoring the regulations and checking that EDF complies with the requirements of the construction code. As EDF is not a manufacturer, it also verifies that its subcontractors comply with the manufacturing and maintenance protocol. This is because it is EDF that guarantees the safety of its installations.

One of EDF's objectives, both in maintenance and in production, is to improve the control of welding operations with a view to enhancing the quality of the assembly of large components. Controlling the welding carried out on the nuclear fleet is essential to guarantee the integrity of the assemblies and to ensure the safety of the production facilities. As part of the weld quality control process, it is vital to check that the welds are compact. Weld integrity is typically assessed through two methods: visual inspection during welding (between each pass if the assembly has multiple passes) and Non-Destructive Testing (radiographic, ultrasonic, liquid penetrant, etc.) of the weld post-welding. As previously mentioned, NDT is typically conducted at the culmination of the welding process and associated heat treatments. The identification of a large area defect, or even a deep-thickness defect, at this stage will generally have a significant impact on the weld and the production schedule. Repairing such defects after their "late" discovery often involves extensive work: preparation (non-destructive testing and removal of material to eliminate the defect) and deposition (filler). In addition to the metallurgical and possibly mechanical consequences, such repairs are a major drain on available human and material resources. These repairs may require additional traceability and quality assurance measures, or even in-service monitoring. Corrective actions can be proposed, and significant time can be saved by detecting non-conformities as early as possible in the manufacturing process. This study is carried out within the industrial context of process control in the manufacture of nuclear power plants.

In industries with high quality requirements for welded parts, in-situ inspection of welds during production has been a critical issue for many years. To ensure the quality of welds during production, these constraints require the development of an inspection chain (see Figure 1). To consolidate the control of operating procedures, the introduction of online monitoring of production and repairs in welding operations will help. The timely detection of deviations or defects leads to a significant reduction in non-conformities. To this end, several instruments are available to assist the industrial welder, with the monitoring of process parameters and the dynamics of the molten pool being the main elements of this control.

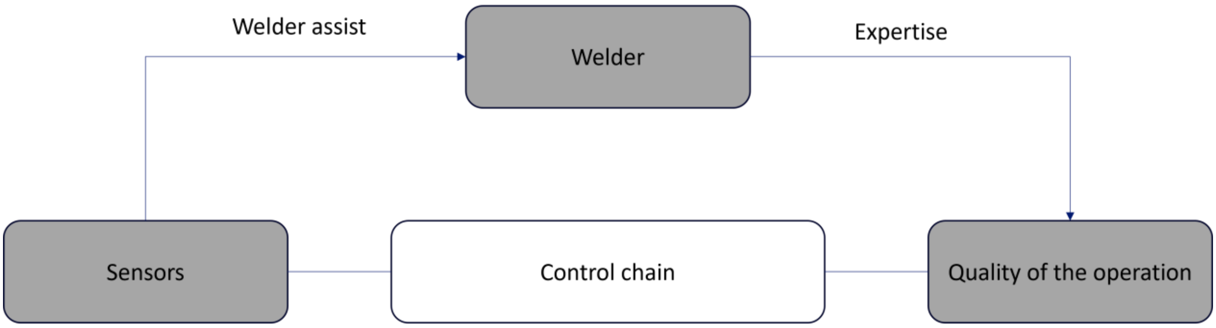

Figure 1 : Control chain that can be set up for a welding operation.

As illustrated in Figure 2, the thesis approach is divided into four chapters. Chapter 1 discusses the technological and scientific aspects of the welding operation and its instrumentation. Chapter 2 presents the development of an experimental setup for the arc welding operation and the initial processing and storage of data from sensors with EDF constraints. Chapter 3 presents the implementation of a control tool to guarantee WPS (Welding Procedure Specification) conformity. Chapter 4 presents a control tool for anticipating the occurrence of deviations. Finally, Chapter 5 presents the application of all the methods developed in this thesis during a welding operation on an RIS pipe assembly in an industrial configuration at a subcontracting company during the CSC crisis.

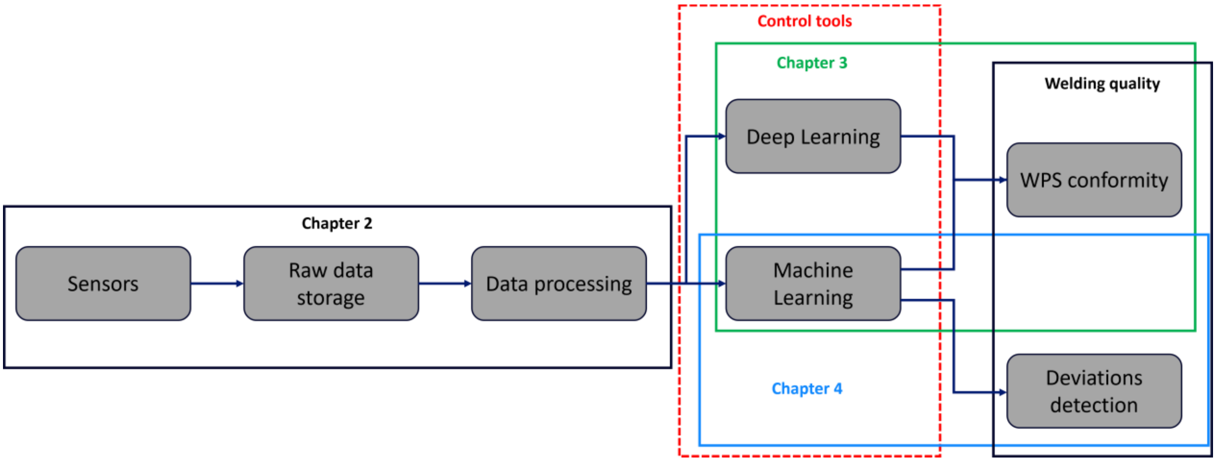

Figure 2 : Approach proposed during this study.

Chapter 1 presents the current state of the art in operational weldability and the process used in this study, reviewing the technical (equipment, process, etc.) and scientific (defects, physical mechanisms involved, sensors) aspects. This review of the literature shows the complexity of the welding process due to the many physical phenomena involved and highlights the many defects that are directly related to the dynamics of the weld pool or to a change in the transmitted energy. The review underscores the necessity to develop an experimental approach for in-situ control of the welding process, with machine learning (ML/IA) emerging as a particularly effective method for addressing complex challenges. A range of studies have employed these algorithms in the context of welding, with the objective being to ensure the quality of operations in real time. These control tools are founded on databases derived from measurements collected during the operation. The algorithms' ability to be enriched during production and their suitability to complex physical scenarios make them advantageous.

As outlined in Chapter 2, non-intrusive instrumentation has been implemented, along with the selection of the appropriate measuring instruments and sensors. A non-intrusive monitoring system has been developed to perform robust measurements during the welding process, in accordance with EDF's specifications, to assist the welder in an industrial environment. The constraints to be met are size, weight, accessibility, surrounding temperature and synchronising the acquisition chain. The system incorporates various non-intrusive sensors (electrical signals: voltage, current; weld pool monitoring, acoustics, etc.). Molten pool geometry, controlled by heat input, is closely linked to quality. Monitoring and processing the weld pool has enabled us to detect variations in the geometry of the molten zone (length, width, penetration). The applications envisaged have long manufacturing times, which implies a massive flow of data to be processed/stored. To ensure its effectiveness, the entire acquisition chain must be captured, stored and labelled for inspection purposes. The database structure must be thoroughly understood to facilitate rapid data access for comparison of information from experiments or test campaigns, and to inform machine learning/artificial intelligence (ML/AI) models depending on the objective or defect being sought. The experimental setup shown in Figure 3 has been designed to be transferable to an industrial configuration, as the sensors meet the constraints of the industrialisation specifications.

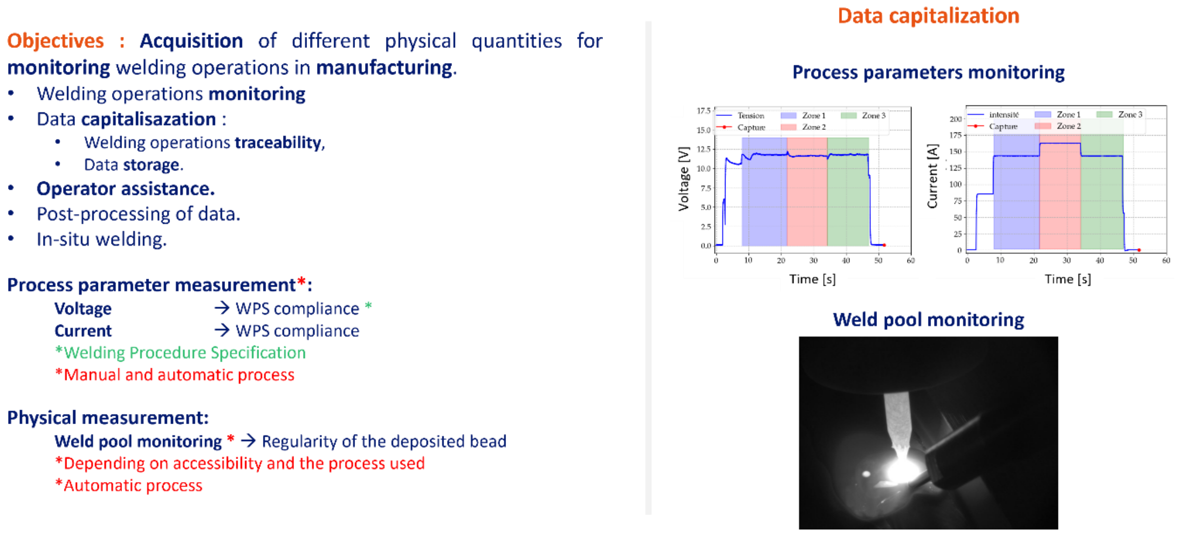

Figure 3 : Experimental measurement acquisition system for monitoring welding processes.

Chapter 3 presented the use of experimental data coupled with machine learning models to build a classification model to ensure that the PQR (Procedure Qualification Record) operating parameter ranges are respected. Firstly, the physics of a linear deposition was investigated, with the bead geometry and its propagation as a function of current variation being investigated in a campaign. The results highlighted the dominant forces for melt formation and stability in an academic single-string configuration. It has been demonstrated that the physical phenomena occurring during a welding operation are numerous, complex and variable, and that they are not easily modelled. In the second part of the chapter, we focused on the development of control methods using AI models, with a particular emphasis on classification algorithms as they allow us to achieve the first objective. Five classification algorithms were tested on two welding configurations with different thermal diffusion and interaction between liquid and solid metal. Deep learning (CNN 2D) fed with raw images was able to predict a variation in welding current, but not when the melt pool geometry was affected by a change in base metal thickness. In fact, using principal component analysis, we found that the model took the arc as the feature of interest, rather than the weld pool. This led us to use a physical datum related to the weld pool dynamics, such as the contour. To do this, we used image processing that extracts the contour of the weld pool and its geometric characteristics (length, width, area, etc.). This choice saves time in the learning, validation and prediction phases of the chosen machine learning model by reducing the size of the database. The four algorithms tested (KNN, DT, RF, CNN 1D) showed better prediction results for both configurations. All four were able to predict a variation in operating conditions based on bead geometry.

The objective of Chapter 4 was to provide a balanced assessment of the application of new machine learning models in predicting deviations during the welding process. A challenging configuration was selected to assess the models, featuring a narrow gap where electrode position could vary. Initially, the monitoring system was employed to analyse the impact of gravity on bead geometry in four tests with varied welding positions. The findings revealed that gravity significantly affects weld pool behaviour. As outlined in Chapter 3, the analysis demonstrated the complexity of the physical phenomena involved in a welding operation. Secondly, electrode position and torch trajectory modification were investigated, with deviations being artificially introduced during the welding process. By observing the geometry of the molten pool, the aim was to predict the position of the electrode in the bevel. Experiments were selected to cover the desired parameter space for the training phase, with welding operations outside the training set also being performed. A variation in the position of the welding torch during the operation was identified from the geometric characteristics. Based on the observation and processing of the weld pool images, the regression models proved to be very effective in predicting the programmed position on the robot. However, the study showed that the prediction was better when it fell within the defined range of the database. Utilising these observations, the model was able to detect deviations in the welding process, thereby anticipating defects and correcting the trajectory or operational parameters of the process.

With a view to industrialisation, the initial focus was on producing a laboratory demonstrator of the entire control chain, as outlined in this thesis. The final chapter details the application of all the means and methods developed in this thesis to weld a pipe in an industrial configuration at a subcontracting company. As illustrated in Figure 4, this study has successfully transitioned from a laboratory demonstrator to an industrial demonstrator, marking a significant advancement in our research.

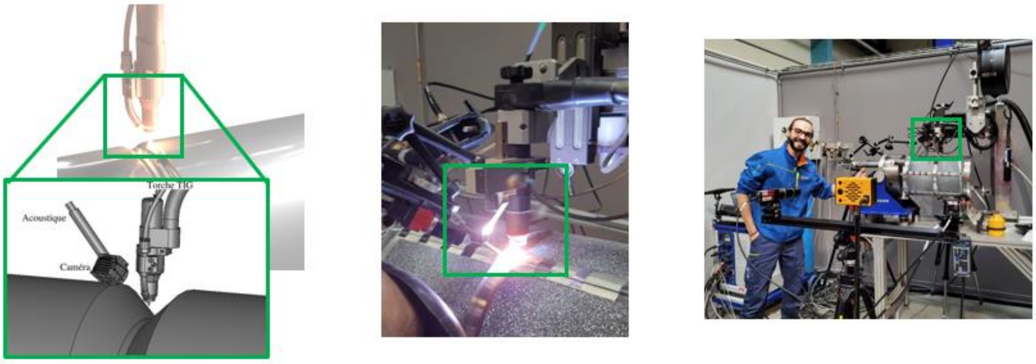

Figure 4 : Experimental set-up installation on RIS tube assembly at an industrial site.

This application enabled the successful resolution of production issues and accessibility constraints during sensor installation. The experimental system set up, as outlined above, facilitated the monitoring of this welding operation, which involved 45 beads over a period of approximately 3 days. Notably, the setup of the monitoring system did not delay the commencement of the welding operation. The database structure developed for this industrial configuration proved to be an asset. A notable challenge in this application was the absence of preliminary tests that could serve as a learning database. To address this challenge, an approach was developed to identify deviations from a single experimental trial. This method involves creating an in-process training database and studying the first bead to identify an average behaviour. This behaviour is then used as a reference for subsequent beads. Based on the general trend in weld pool behaviour, an anomaly detection model (isolation forest) is built to identify 'anomalies' and regular areas. This model is then used to build a database that feeds a classification model with two categories: good (anomaly). This classification model, which considers the translation of the average behaviour of the weld pool length evolution over time, is then applied to subsequent runs. The training database is enriched at the end of each run before predicting run N+1.This approach gives very satisfactory results, highlighting local deviations and areas of strong change in the behaviour of the melt. A key benefit of this method is its foundation in a single experimental test, leveraging the weld pool length evolution of previous beads as a reference for future beads. This approach enables the identification of high-risk areas, facilitating a more thorough inspection of the melt and enhancing the precision of non-destructive testing.

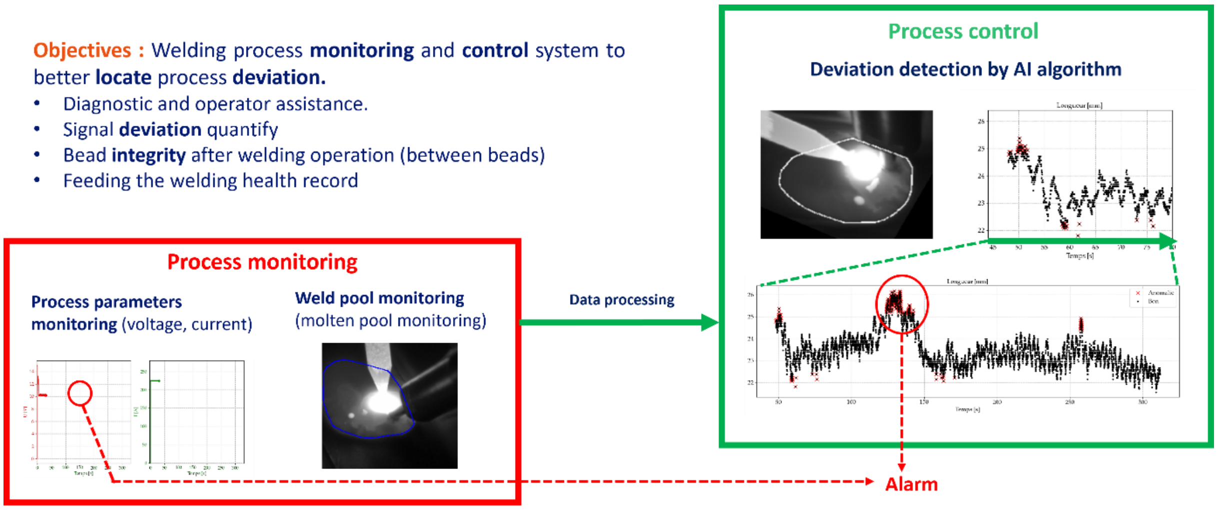

Figure 5 : Welding process monitoring and control system.

From an industrial perspective, the objective of this project is to address the industrial challenges outlined in EDF's Excell Plan, specifically the Welding Plan, which focuses on welding operations. In the short and medium term, the results of this work will include enhanced productivity, improved weld quality, enhanced defect identification and operator assistance, and streamlined diagnostics for the integrity of the assembly. The issue of stress corrosion has underscored the significance of effective welding operations control in nuclear power plants to optimise maintenance operations and minimise unit downtime. Consequently, my work contributes to the safety of nuclear installations, which are a pivotal component in the ecological transition strategy towards low-carbon electricity production. I am confident that my work will significantly contribute to the optimisation of processes to reduce construction times for the new EPR2 power plants.

Following the successful collaboration with leading industrial partners in the nuclear sector, namely Five Nordon, Framatome, Ponticelli and Sérimax, all the resources and methods developed in this thesis have now been used and integrated in a France Relance project, WELDIA, which is financed by the BPI. To date, the process monitoring validation phase has been successfully implemented for each of the industrial partners in the project. This depends on the size and configuration of interest chosen by the manufacturer.

My research was carried out rigorously and methodologically, and led to significant results that were published in peer-reviewed scientific journals indexed directly to my thesis:

- Machine learning approach for weld configuration classification within the GTAW process (Journal of Manufacturing Science and Technology).
- Development of Machine Learning model for trajectory deviation detection in multi-pass TIG welding in a narrow gap (Welding in the World).

In addition, I had the opportunity to present my results at renowned international conferences in the field of welding on the one hand and artificial intelligence on the other: MMLDT-CSET 2021, IIW 2022, IIW 2023, AWAMR 2022. As well as two national conferences: CFM 2022, Manufacturing21.

Furthermore, my work constituted a significant technological advancement in a project submitted to an innovation competition at EDF R&D, which was awarded the Scientific Award 2022.