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Enhancing Fault Prediction in Nuclear Industry: Hybridization of Knowledge- and Data-Driven Techniques

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1 Introduction

The nuclear industry, distinguished by its high degree of reliability, greatly benefits from comprehensive feedback mechanisms and robust maintenance management. The advent of the Industrial Internet of Things, marking the fourth technological revolution, has facilitated the integration of Artificial Intelligence (AI) in this sector [1]. This development increasingly enhances predictive maintenance strategy, with the objective of increasing production and the overall efficiency of this industry [1, 2]. The adoption of AI in predictive maintenance is becoming a topic of interest within the research community, evidenced by over 1,130 articles on Web of Science. As a result, AI can greatly improve nuclear maintenance practices through the application of data-driven analytical techniques on sensor data extracted from operational equipment [2]. This facilitates the prediction of failures and the estimation of the Remaining Useful Life of the equipment. However, the effectiveness of these techniques relies on the input data accuracy in reflecting the physical phenomena leading to failures. When there is a misalignment, the models often fail to correctly identify and predict failures. In the nuclear field, critical processes of the facilities are typically complex, necessitating the integration of substantial operational experience and expertise for effective monitoring. Consequently, pure data-driven approaches may face limitations in accurately predicting failures [5].

The present research introduces *an approach for predicting faults in nuclear process using data-driven techniques (AI algorithms) augmented with domain-specific knowledge and expertise (such as Rules base models, case based methods or fuzzy methods)*. We apply our approach to a process in the nuclear industry, demonstrating the effectiveness of the framework in accurately predicting failures.

2 Integration of Knowledge into Data-Driven Techniques

Figure 1 shows our proposition of a framework, structured into three stages: Knowledge Engineering, data preprocessing and prognostic.

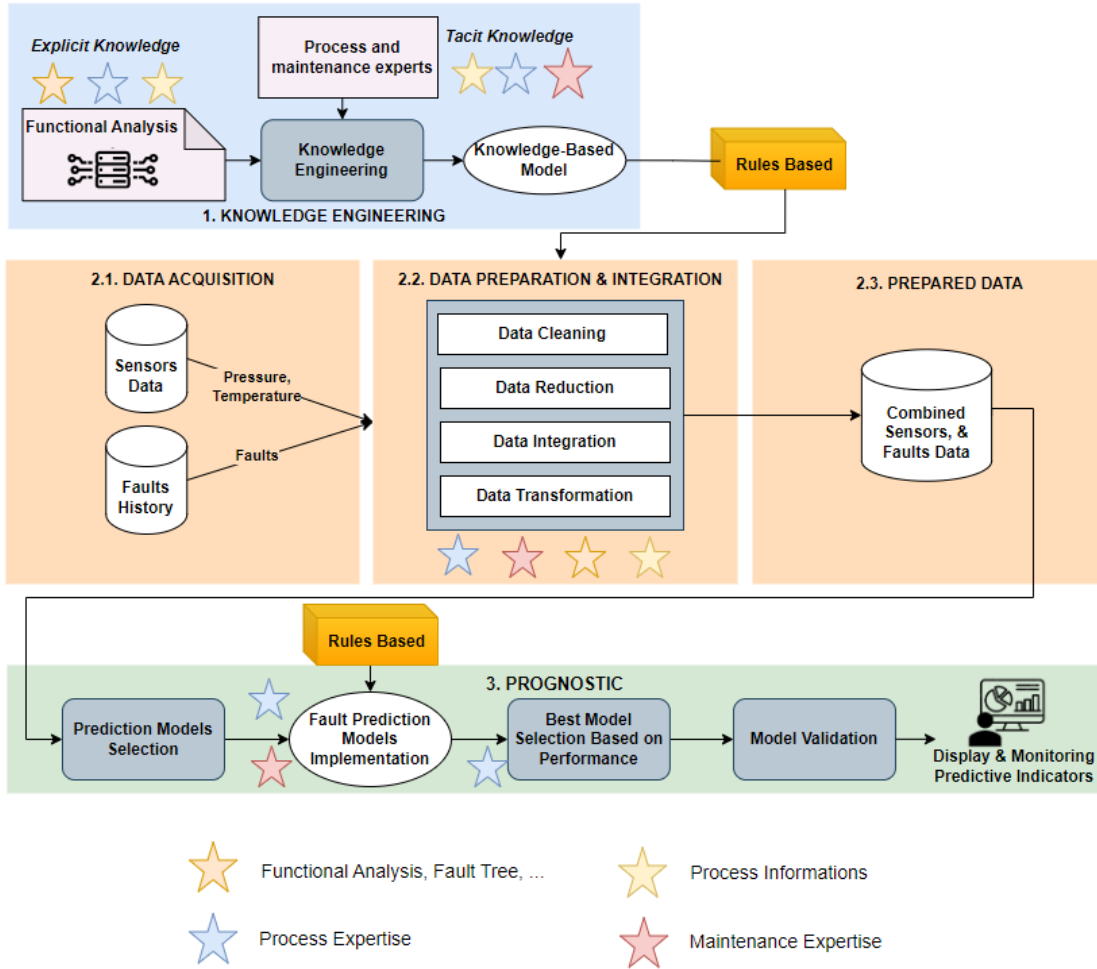


FIG. 1: Proposed Framework

2.1 Knowledge Engineering

The nuclear industry is rich in knowledge, including expertise in industrial processes, essential for online monitoring, as well as in maintaining these processes. This knowledge can be explicit (*i.e.*, captured in documents like functional analyses, Failure Mode, Effects and Criticality Analyses or FMECAs, maintenance plans, etc.) or tacit (*i.e.*, acquired through oral discussions with experts). Thus, the Knowledge Engineering phase begins with the preprocessing of this diverse knowledge, transforming it into a usable data format. Following this, we develop a model to accurately represent various process scenarios: alarm situations, minor faults, incidents requiring maintenance actions, and normal operation states. The model outputs are converted into rules [3] to facilitate integration in future stages.

2.2 Data Preprocessing

This stage of our framework involves initially acquiring physical measurements of the process (time series) as well as various faults reported by the control system (events). These datasets are then prepared using advanced preprocessing techniques, enhanced by domain-specific knowledge: This involves the application of rules from the knowledge-based model to efficiently refine the data. This refinement process emphasizes the isolation and integration of the most critical faults; those constituting 20% of issues that lead to 80% of the operational challenges. The outcome of this process is a comprehensive dataset, combining the refined time series data, the prioritized faults for prediction, and also additional features representatives of

the process condition, thereby facilitating accurate prediction.

2.3 Prognostic

The last stage of our framework focuses on predicting critical failures over a specified forecast horizon. We select predictive models based on the characteristics of the data and faults to be predicted [4]. These models are then implemented supported by insights from the knowledge model. The selection of the best model is determined by its ability to efficiently forecast failures, *i.e.*, the model that demonstrates the best accuracy and precision. Ultimately, the computed predictive indicators are displayed on a monitoring dashboard to support decision-making.

3 Case study application and discussion

We apply our framework on a real-world case study within the nuclear industry, focusing on a complex, critical and cyclic equipment. In the event of failure, production is immediately stopped, leading to substantial costs for the operators. This equipment is subject to conditional monitoring, where thresholds are established from physical measurement indicators. These indicators are derived from the operational experience (REX) of the plant. To evaluate our methodology, we compared two distinct scenarios:

Scenario 1 employs a purely data-driven technique utilizing physical measurement data and historical equipment failure records to train two machine learning algorithms – *viz.*, Random Forest and LightGbm – to predict failures.

Scenario 2 is Scenario 1 enhanced with equipment functional analysis and tacit knowledge from process and maintenance experts during the preprocessing and failure prediction phases.

Both scenarios are tested over predictive horizons of 3, 12 and 24 hours. The results show that Scenario 1 achieves an accuracy of 97% and a precision (F1 score) of 10% for failure prediction, demonstrating its limits in effectively targeting and predicting failures. Conversely, Scenario 2 demonstrates a higher performance, achieving an accuracy of 98% and a precision rate of 70%. Notably, Scenario 2 achieves a remarkable precision over a 24-hour horizon, unlike Scenario 1 which is more myopic as it reaches its peak performance over a 12-hour horizon. The integration of expert knowledge allows for more refined failure prioritization and prediction. As future work, we plan to apply our framework to other processes within nuclear facilities in order to increase its modularity and adaptability across various operational contexts.

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