Challenges in AI Projects for Machinery and Plant Engineering

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***Abstract*—In our AI projects with machinery and plant engineering customers, we encounter recurring challenges beyond data processing, such as data availability, integration, human involvement, operations, and business considerations. Addressing these challenges is crucial for progress in this domain, yet research support is lacking. We present these challenges, discuss our current solutions, and call on researchers at CAIN and beyond to develop better approaches for the future.**

***Index Terms*—machinery and plant engineering, data science, artificial intelligence**

I. Introduction

As a B2B software development company, we categorize AI project requests into generative and analytical AI. Generative AI projects typically do not require model training, may involve fine-tuning, and often require the integration of information silos from a data engineering perspective. A main challenge is ensuring accurate similarity metrics for efficient data retrieval from vector databases.

This paper focuses on analytical AI projects, where building machine learning models and integrating data collected along a production process are key tasks. These projects face challenges such as data availability, capturing implicit human knowledge, integrating data from various sources, planning AI system operations, and justifying the business case for such systems.

We illustrate these challenges with a specific case and discuss how we address them through new technologies and tailored development processes. However, we acknowledge that our efforts alone are insufficient. We call on the research community to help and pursue research avenues to better equip organizations for the challenges of an AI-driven future.

II. An Example Case: Parametrisation Assistant

Parametrisation assistants are AI tools that support setting machine and process parameters of complex industrial processes which currently require highly skilled labour. Operators with extensive knowledge of machines, materials, and processes are becoming scarce and difficult to replace. Onboarding new operators, if they can be found, is also a lengthy process. AI assistants can alleviate some of these issues.

In industrial edge banding production, polymer granulate is melted and extruded through a tool by the extruder. It then travels up to 100 metres through up to 20 machines, each effecting one or more process steps (e.g. cooling, adhesive application, colour application) on the product [1]. The finished edge banding can later be applied to the exposed sides of materials, e.g. to particle board to give the illusion of a solid material. Extrusion processes are continuous and operators "supervise a large, distributed system by monitoring data from different sources" [2] which, combined with the element of time, introduces a high cognitive load. Product anomalies, i.e. deviations from a process standard which can occur either abruptly or gradually, affect quality characteristics and can lead to negative economic consequences, e.g. due to recalls [3]. If such an anomaly is detected, the goal of the operator is to "bring the process back to a normal [...] operating state" [3].

III. The Challenges

A. Data Availability

Despite continuous operation, data availability in production lines is severely limited due to two main factors. First, years of optimization have minimized quality defects, providing little data for algorithm training. Second, many machines lack digital sensors, making parts of the process unobservable. Additionally, the same product is manufactured on different production lines which are frequently not exactly identical which requires high generalizability, thus increasing data requirements.

B. Involving the Human

Edge banding machine operators have accumulated extensive implicit knowledge over the years, allowing them to adjust machine settings based on their perception of, e.g., temperature and humidity. However, they have a hard time articulating the cognitive processes behind these decisions, which are based on "gut feeling" and lack clear cause-and-effect relationships.

Operators and process experts may find data labeling challenging and time-consuming. Some also worry about job redundancy. The challenge is collecting data to develop and validate machine learning models while engaging current task performers in a participatory way to alleviate their fears.

C. Data Engineering and Integration

In machinery and plant engineering, there is little semantic information about data, and few people in the organisation understand its structure. Edge banding machines have various sensors along the 100-meter production line, recording information and operational parameters to determine the band's state. Since the edge band is continuous, parameter changes take time to affect the band, possibly requiring discarding parts produced with incorrect parameters. A data acquisition system consolidates sensor data from all units into a central database.

We aimed to create a digital twin of the production line and the edge band being produced, showing all current parameters and machine states. However, reconstructing the band's state is complex due to several issues: undocumented pre-processing steps, sensors unable to correct for phenomena like wheel spin, and data quality affected by sensor decalibration and changing production schedules. This highlights the need for clear data provenance documentation and awareness of sensor data "blind spots" when integrating data from different sources.

D. Operations

In machinery and plant engineering, production plant operations are often separate from the organization's IT infrastructure to prevent cyber attacks. Operational technology (OT) uses distinct, less powerful networking technology, is not internet-connected, and prioritizes reliability and real-time requirements over computational performance. Bridging the IT/OT gap often results in a loss of semantic information due to pragmatic implementations, necessitating additional computational hardware in production lines or as edge devices.

We notice that trust and user acceptance are low, as users sometimes bypass the system and operators show limited interest in its functionality. This is fine if the system performs well but problematic when operator collaboration, like data labeling, is needed. Explainability requirements for AI solutions vary by user, being more relevant for engineering and management than for experienced operators.

E. Business Considerations

We observe that decision makers focus on operational matters, like reducing waste, and overlook costs such as retiring and training edge banding line operators. Organizations hesitate to invest in new technology due to short-term costs. Additionally, we frequently see brown-field deployments where existing production lines need retrofitting with digital sensors and the necessary infrastructure and expertise.

Another issue is the communication gap between management and engineering/operations. Engineers know practical problems that AI could solve but struggle to validate assumptions and create strong business cases. Projects imposed by management often miss real-world issues, reducing workforce buy-in. Management support is crucial for smooth collaboration across departments like production, operations, and IT.

IV. Our Solution Approach

We address these challenges with two approaches: capturing and formalizing implicit information, and a tailored development process focused on requirements, data engineering, and operational planning.

Capturing implicit information: Experienced operators possess valuable implicit knowledge that is hard to verbalize or formalize. They also often handle multiple quality defects simultaneously, making data aggregation difficult. If formalized, this knowledge can address data availability challenges and reduce onboarding times by enhancing assistant recommendations. Traditional methods like structured interviews are inadequate for extracting quantified knowledge, so we use a data-assisted approach. We prompt operators during low cognitive load periods to provide additional information with minimal interaction [4]. This method extracts high-quality knowledge segments, which can be aggregated into a knowledge base for process modeling or neuro-symbolic learning systems.

Tailored Development Process: We include phases not typically part of standard iterative development, starting with strategy and governance to align relevant use and business cases. Our development process emphasizes requirements, especially when dealing with extensive data. We ask customers detailed questions about data provenance, pre-processing, storage, usage, and inherent assumptions to form and test hypotheses. This often provides better insights than the data on its own.

Next, we focus on data engineering, analysis, and algorithm development. We integrate data from different sources to meet specific use case requirements, such as temporal resolution or granularity. During algorithm development, we evaluate both functional and non-functional aspects, including usability. Integrating with existing software solutions like SCADA or MES ensures the end-user's usability needs are met.

Finally, we emphasize MLOps topics like deployment, monitoring, and retraining, and create a tangible operations plan to guide customers on using, maintaining, and evolving the system over time.

V. A Call to Arms

While our current solution meets customer needs, we believe immediate innovations are necessary to apply advanced AI in the machinery and plant engineering domain:

- Representation of knowledge: Once requirements are elicited and operators support our efforts, their knowledge needs to be captured. Are techniques beyond knowledge-graphs more suitable for specific situations?
- Requirements engineering techniques: Eliciting requirements from operators with implicit knowledge and little incentive to support the process is difficult. Sub-optimal requirements engineering is often the root cause of issues, not the data. Tailored approaches addressing these challenges are missing.
- Analytical AI development process: Challenges can be addressed by approaches that cater to them, allowing development teams to build around them. While we create ad-hoc solutions, research could provide more generalized and empirically validated processes.

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