AI-based solutions for Industrial Equipment Use

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Abstract
In the context of the AIDEAS project this paper focuses on the Use phase of the industrial equipment. In this moment the previously designed and manufactured machine will head to the client's site to be used by them. At this stage it is crucial to have AI-based solutions helping both, the manufacturer and the user of the machine, in tasks such as the initial calibration, condition evaluation or anomaly detection, adaptive control, and quality assurance. The outputs of some of these solutions will also help in a later stage to decide on a possible second life on some of the machine or some of its components, that is, in the repair, reuse, recycle phase.

Keywords
AI, Industrial Equipment Use, Machine Calibration, Adaptive Control, Condition Evaluation, Anomaly Detection, Quality Assurance

1. Introduction

Manufacturing complexity and quality requirements are rapidly increasing together with the amount of data collected in the field of industrial equipment. In this context. the AIDEAS project [1] proposes the development of four Suites, see Figure 1, composed by 15 Solutions, which will allow benefiting from AI technologies applied to the entire industrial equipment life cycle. This paper focuses on the Use phase providing AI technologies with added value for the industrial equipment user, providing enhanced support for installation and initial calibration, production and quality assurance for working on optimal conditions.

Figure 1 AIDEAS project framework

In particular, the AIDEAS Use Suite is composed of 5 AI-based solutions, see Figure 2, that will be detailed in the next sections:

- AIDEAS Machine Calibrator (AI-MC): Toolkit for the fast calibration of industrial equipment when installed for the first time in a factory or when a re-calibration is needed. It uses AI techniques for providing the most well-suited calibration parameters.

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- AIDEAS Condition Evaluator (AI-CE): Toolkit for determining the condition of the machine as a whole or of some of its components when it is in working conditions in the factory where it is being used.
- AIDEAS Anomaly Detector (AI-AD): Toolkit that allows detecting anomalies at component-level or of the machine as a whole when it is in working conditions in the factory where it is being used.
- AIDEAS Adaptive Controller (AI-AC): Toolkit to train models with measurement data and then train machine controllers with said models to accommodate the machine condition and requirements.
- AIDEAS Quality Assurance (AI-QA): Toolkit comprising a set of AI-enabled features for manufactured product quality monitoring.

A last transversal solution is the AIDEAS Machine Passport (AI-MP) which, due do the lack of space will not be presented in the scope of this paper, but readers are referred to [2].

Figure 2 AIDEAS Use Suite

In the following sections the solutions will be introduced and categorized into three groups: process related solutions, equipment related solutions and product related solutions. Each solution presentation will include a general description of the problem and state of the art, together with the specific presentation of the solution to be developed in the framework of the project.

2. Process related solutions

2.1. AIDEAS Machine Calibrator

The configuration and calibration of new industrial machines is not a process that can be easily standardized due to the divergencies most commonly made by different manufacturers, different specifications and adaptations requested by the clients, and undeniably the distinctions in each application field [3].

The AI-MC solution intends to support the machine installer and the operator in the initial calibration and configuration of new machines, considering each customer and factory needs through AI techniques. The Machine Calibrator AI is trained with the parametrizations of the industrial machines, acquired upon the commissioning phase, during the manufacturing and initial calibration that is performed at the installation of a new machine. Using a supervised learning approach from the operational inputs of the more experienced users, the calibration parameters can be optimized and adjusted to the process needs.

This solution will trial its applicability within CNC stone cutting and plastic blow moulding machines. Currently the calibration process for the alignment of the CNC structure and bedding is done through trial-and-error approach, requiring skilled installers to fine tune the axial structure and levelling of the machine. Leveraging a machine vision system, the measurement of off-axis components can be prematurely detected, and appropriate corrections issued instantaneously, reducing the overall calibration time. Blow moulding machines coextrusion processes can be optimized according to different goals, that result in variable parison production times with different material and energy consumption/waste. The automatic parametrization of each production program, fine-tuned to the desired targets, can facilitate the operator workload and minimize the re-calibration procedures.

2.2. AIDEAS Adaptive Controller

A time-varying system requires special requirements in the controller design, due to the alterations present in its dynamics and the nonlinear nature of them. An Adaptive Controller (AC) scheme accommodates the closed-loop response without priori information about the system's behaviour.

Due to wear and tear, industrial machines may deviate from their normal behaviour and, as consequence, the system's dynamics. By using AC, the control scheme can adapt to the machine's new response and determine optimal control parameters to improve the working conditions.

In those scenarios where designing/calculating a control solution proves challenging, Machine Learning techniques, such as Reinforcement Learning (RL), can autonomously compute the optimal control input to achieve the desired objective. RL can be also of help controlling multiple-input-multiple-output systems, where the complexity between variables interaction and coupling induces challenges in the control. Considering the system's dynamics and finding variables interrelationships can be complicated for classical control.

A typical AC scheme is composed of two control loops working at different rates. The slower loop corresponds to the adaptative part of the controller, in charge of modifying the controller's parameters. The fastest loop, in turn, corresponds to the actual controller which directly affects the system.

The adaptation mechanism of the AC includes mathematical rules, adaptation laws, that adjust the controller to the system's behaviour. To design a stable and robust adaptation laws, there exist some approaches to follow, such as sensitivity methods, positive design or minimum square error [4], [5]. The sensitivity method avoids bad response of the controller toward unknown disturbance. The positive design represents the system adaptability potential, while minimum square error describes the error distribution for performance analysis purposes.

Machines are continually evolving, adapting their production to the manufacturing cycle requirements. Commonly, the tuning of the controllers is carried out during the commissioning of the machine, adjusting the controller gains to be optimal in a specific operating point. The continuous evolvement of the machine could affect its performance as the controller performance may degrade if the operating conditions change considerably. These changes can occur simply due to changes in workpieces design or production, or they may arise from a failure in the system, if they have a negative impact on production. The system failures have a broad harm grade, as they enlarge from soft faults repaired by adapting the controller to more severe ones that can even break the machine.

The AI-AC solution focuses on the controller's capability to adapt to the system's different operating points and mitigate potential failures that may arise during operation, through the re-tuning of control gains. In this context the AI-AC allows the user to monitor the status of the machine, as it will be connected to AI-AD (see section 3.2) and decide whether the control gains should be re-tuned based on user-defined specifications. AI-AC endows machines with intelligence and autonomy, minimizing human error by automating complex tasks. Using real-time field data, AI-AC develops a digital twin of the process from which the existing controller gains are adjusted to optimize the process or to counteract the faulty condition of the actual machine.

3. Equipment related solutions

3.1. AIDEAS Condition Evaluator

The main objective of condition monitoring or evaluation is to serve as an indicator for an effective and early detection of systems' potential problems or failures that may not be visible at first sight. As equipment's complexity keeps growing rapidly, condition monitoring has attracted great attention both for increasing the productivity and reducing the downtimes and for ensuring installations' safety and reliability.

Condition monitoring contributes to better manage assets in two ways: firstly, by monitoring equipment's process variables behaviour via sensors, and, secondly, and in case of fault presence, by revealing their characteristics and root causes [6]. It is important noticing that a fault does not necessarily imply a complete failure of the system.

There are three primary types of failures: random failures, which are unpredictable, deterministic failures and systematic or casual failures. A fault is determined to exist when the monitored variable deviates unacceptably from its normal behaviour, and it can be the underlying cause of a process malfunction or failure. It is also important to note that a process malfunction may not lead to a complete shutdown of the process, but it does result in a deterioration of the normal state of the process. On the other hand, a process failure indicates a higher severity and is often associated with total process shutdowns.

The main approaches in fault detection and diagnosis can be classified in three groups [7]. The first approach is the physics-based one, that can be used when there is knowledge of the physical dynamics of the process, being more suitable for small systems with known explicit mathematical models and few monitored variables [8]. If there is no knowledge of these dynamics or if there are many non-linearities, the second approach, i.e. the data-driven one tends to perform better. This approach is based on monitoring the process related signals, which can reflect the potential faults. The first step usually involves feature extraction and then a diagnostic decision is made. The usefulness of these first two approaches depends highly on the quality of the mathematical models developed and the availability of historical data with enough quality. The last approach tries to overcome the shortcomings of the two previous ones, combining them in a hybrid approach, using the available data but using a physics-based model if this data cannot be available.

In this context the AI-CE solution allows the user to determine at both machine and component level its current status at three different ranges based on the severity level of the deviations found. In order for this task to be done the user has to determine what is considered as normal behaviour.

3.2. AIDEAS Anomaly Detector

An anomaly, or outlier, is classically defined as an observation which deviates significantly from others as to suspect that it was generated by a different mechanism. As such, detecting anomalies can help many industries as these may be an indicator of production failures, defects, undesired events or machinery wear and tear which is crucial for optimizing equipment availability. In particular, anomaly detection in time series data focuses on analysing this kind of events over time.

Applying anomaly detection in manufacturing processes can help to prevent the appearance of defective parts in order to be able to discard or reuse them as needed providing great benefits in machinery production processes.

The collection of techniques and approaches that address this subject is very wide but can be grouped according to the input data, the outlier type, the approach, and the technique [9]. Depending on the input data some detection methods aim to detect single data points in a univariate time series and others to detect multiple data points in a multivariate time series. Depending on the outlier type, taking into account the context, it may be needed to contemplate not only a single point but a set of subsequent observations as an outlier. Depending on the approach the most common technique to declare an outlier is to determine if its value is within a certain threshold, other popular approaches include considering different distances and the number of neighbours or using the autocorrelation function between data points of a time series. Lastly, depending on the technique, the classic approaches are based on statistics and signal analysis but recently the ones based on AI have increased its popularity due to higher performance. Because of data sets' great heterogeneity and complex nature, in which anomalies are to be detected, there are no models that can outperform others in all conditions [10]. The best performing model selection varies, and it is a topic that has not been discussed much in the literature yet.

In this context the AI-AD solution allows the user to obtain which anomalies are currently present in the system at component level knowing which process variables are deviating from the trend. These detected anomalies do not have to be necessarily and indicator for degradation or malfunction, it is just indicating that it is deviating from the model with which it has been trained and evaluated. Both statistical and AI approaches could be tested.

4. Product related solutions

4.1. AIDEAS Quality Assurance

The increasing complexity of manufacturing aimed at satisfying unique customer needs leads to new challenges in the quality assurance of manufacturing processes. Visual quality assurance (QA) is now an essential part of any manufacturing process, controlling various visual manufacturing metrics to ensure end product compliance during the production process. QA is also indispensable for optimizing manufacturing processes, reducing material costs and scrap, increasing productivity and improving overall product quality. Nonetheless, at this point most visual quality inspections are still performed manually by human operators, which is time-consuming and error-prone due to mostly human factors such as exhaustion from labor, exertion, or stress.

Today, modern automated visual quality assurance of industrial products is performed using various imaging techniques that capture surface properties (2D imaging), geometric properties (3D imaging) or various product intrinsic properties (X-ray). The calculation methods used in similar automated systems use predominantly simple rule-based approaches or manually created features with a simplistic learning-based machine learning method.

In the AIDEAS project several alternative approaches are also used namely, data-driven deep learning-based approaches for surface anomaly detection [11]. Similar approaches eliminate the need for manual feature creation and are currently the most employed method in the field of computer vision, yet their applications in manufacturing are quite restricted to specific processing areas.

There are a few major obstacles for using predominantly fully supervised deep-learning-based approaches in inspection systems in the manufacturing domain, as defects typically represent a miniscule percentage of the total product output. Additionally, predicting most of surface defects in advance and the annotation process itself put a significant strain on the already very dynamic and labour-intensive manufacturing process. Conversely, defect-free samples are abundant and might be used for training the model to detect defect-free products, which are later used to locate and discover defects that deviate from the normal appearance [12], [13]. While such unsupervised approaches are the most flexible, they are often still suboptimal compared to the fully supervised approaches. An even more optimal way to implement such a detection would be to use all available data and using different levels of supervision for available (un)labeled data [11].

The AIDEAS project, makes an effort to improve the 2D surface defect-detection using some of the recently presented unsupervised methods, along with using the available labelled data, incorporating this solution into the AI-QA tool. This represents one of the first direct industrial applications, going beyond the limited use of such approaches in research benchmarking datasets in the manufacturing domain [11], [12]. The plan is also to progress in the field of anomaly analysis using 3D technology to measure the calibration of both products and anomalies [14]. This approach allows us to provide more context about the anomalies themselves. The AI-QA 3D approach uses both the information provided by multiple 2D views of the product and its corresponding positional data thus leveraging 3D measurements and significantly enhancing our understanding of surface analysis methods already in existence. By incorporating three-dimensional data, the aim is not only to identify anomalies but also to gain a more comprehensive insight into their nature and characteristics. This innovative approach is expected to contribute valuable information that can refine and augment current superficial analysis methods, ultimately leading to more effective anomaly detection and characterization.

5. Conclusions

This paper presents the solutions envisaged inside the AIDEAS Use Suite which focus on the Use of the industrial equipment. These solutions will be tested in the four pilots of the project, all of them industrial equipment manufacturers, but from different fields: PAMA from the machining sector, D2Tech stone cutting, BBM blow moulding machining and MULTISCAN from the inspection sector. This will allow having different scenarios and issues that the solutions must face and solve.

All solutions complement each other and act together with the ones developed in the remaining Suites of the AIDEAS project (Design, Manufacturing and Repair Reuse & Recycle). The AIDEAS Use Suite conforms a cornerstone in the whole framework, since at this stage, the machine is no longer in the manufacturer's site, but the data and outputs of the solutions are crucial for future refinements in design and manufacturing, or to decisions to be made regarding repair or reuse. In this sense, the Machine Passport also plays a crucial role, being transversal to all Suites, gathering the most important information and being the link between all solutions in this Suite and all the Suites in global.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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