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AI in Industrial Machinery

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Abstract

This introductory article opens the section on "Advancing Artificial Intelligence in Industrial Machinery Applications". It gives an overview of the state-of-the-art AI technologies in industrial machinery and the current AI development in efficiency improvement, personnel safety, automation, and human-machine interaction. It also presents future potential and opportunities for AI in the sector, covering trends of using AI, IIoT technologies, and advanced actuation and sensing techniques, safety/quality, maintenance, waste reduction, and environmental sustainability. Finally, the article introduces the four contributions to this section.

Keywords: artificial intelligence (AI), industrial internet of things (IIoT), industrial automation, predictive maintenance, human-machine interaction, smart manufacturing, edge computing, smart robot.

3.0.1 Introduction and Background

Today, AI is a powerful source of disruption and a tool to achieve a competitive advantage in industrial manufacturing. The manufacturing companies that neglect to recognise the importance of AI are expected to lose their competitive edge. Many industrial manufacturing facilities are implementing AI across the value chain, but still, many are only using

AI in core functions such as engineering, product development, assembly, and quality testing. The main reasons for implementing AI technologies in industrial environments are driven by the need to assist in making decisions or acting, automate manual and cognitive tasks, and augment decision-making through continuous machine learning (ML) [5]. There has been a rapid growth in AI development and deployment in the last decade. Machines already complete 29% of simple or complex tasks today [7].

Modern production processes in the manufacturing industry and the process industry have reached a critical level of complexity. Stable operation and constantly high product quality are maintained only through continuous monitoring, inspection, and adaptation. This applies in particular to the industrial landscape in Europe, which has a strong focus on customisable products and highly specialised processes rather than standardised mass production. New business models (e.g., lot-size one production) and intense competition from outside Europe require increasing speed and reducing complexity overhead. Through automation, artificial intelligence (AI) and ML are key technologies for managing this increasing complexity in the future manufacturing and process industry. Examples include plant reconfiguration on demand in Industry 5.0, automatic proactive online adaption, optimisation of process parameters, and predictive production planning.

Integrating AI/ML in future manufacturing lines and processes heralds a new era where interactions between people and machines become more integrated, and the decision-making process is driven by data and AI. In other words, the current fragmentation within and outside the manufacturing lines will evolve towards a system where manufacturing processes are connected, and decisions are taken accordingly by the data analysis coming from different sources. Implementing an AI/ML method in a production system can address both the actual production (physical level) and the monitoring and planning of the production (abstract level). Skilled human workers will continue to play an essential role at both levels and are therefore the most critical factor that needs to be considered in the automation process. AI4DI addresses this challenge in its third pillar. While pillars one and two covers the technological and methodological challenges involved in rolling out AI/ML in a production environment, pillar three is vital for the final system's acceptance and efficient and novel human-machine interactions.

3.0.2 AI Developments and Future Trends in Industrial Machinery

With AI entering the manufacturing floor, starts the use of digital technology to replace not only "muscles" but also "brains". In the last few years, AI has become deeply embedded across industrial and other applications, with initial use cases using AI in manufacturing representing niche applications and expanding into mainstream production.

The current adoption rate of AI in manufacturing is relatively low, and the prevalence of AI is expected to increase significantly by 2030 [5].

Industrial machinery is changing alongside society, and everyday life, while digitisation is rapidly becoming de facto. Jobs that are repetitive, tedious, and do not require high skills are slowly being replaced by smart manufacturing systems. AI-based approaches are internationally accepted as the main driver [1] for digitisation and transformation of factories since flexibility and deep understanding of complex manufacturing processes are becoming the critical advantage to raise competitiveness [2]. By looking at smart manufacturing and digitisation trends [3], the factories of tomorrow will be multi-purpose and able to adapt to new designs in a very short time. Similarly, smart industrial robot control methods will allow robots to adapt to the stochastic environment, enabling more human-like performance by completing tasks that have not been directly programmed to the robot or intuitively interact and collaborate with humans.

IIoT and AI-based real-time monitoring in industrial machinery can optimise production, tracking the different production steps and identify changes in the production parameters. Supervised and unsupervised ML algorithms can interpret real-time data from multiple production shifts and identify unknown patterns in processes, products, and production workflows.

In robotics, vision systems support the development of collaborative robots and cobots. Cobots are used to collaborate with humans in terms of helping or relieving the human operators of repetitive tasks and are expected to evolve and provide automated tasks and connected in a network of intelligent IIoT devices.

Operating, checking, and improving functioning and efficiencies in industrial pieces of machinery requires AI-based solutions designed with embedded technical robustness and safety. The industrial AI systems must be assessed to withstand potential attacks (along with unexpected functioning in new environments) and have fallback plans and similar general safety mechanisms in place. The use of AI solutions has the potential in autonomous system monitoring to improve safety and efficiency and provide new performant human-machine interfaces [6].

The accomplishments in the field of AI are contributing to innovative industrial robot control trends. The AI usage in robotic systems is firmly becoming one of the main areas of focus as the industrial machinery requires increased performance, adaptability to product variations, increased safety, reduced costs etc. Still, these requirements are neither feasible nor sustainable to be achieved by standard control methods.

Applications of AI are progressing in different areas of industrial machinery manufacturing with a focus on improving quality control/ assessment, energy efficiency, safety, maintenance, and process optimisation. A number of these areas where AI technologies have the potential to expand in industrial machinery are listed below [4].

Operational simulation and optimisation are application segments for AI in machinery. Dynamic simulation and optimisation of processes enable end-users to plan the use of the machine/equipment effectively, plan the flow of materials, dynamically supply, and predict possible anomalous scenarios. Key drivers of growth in this segment are the need for end-users to lower overall operating costs and the rise of physics-based AI solutions. The demand for AI solutions that address operational simulation and optimisation grow since more manufacturing lines become more complex plus integrated with the supply chain and processes.

Quality control is increasingly important in industrial machinery production due to stringent quality requirements for industrial products. The AI-based techniques can bring new intelligent quality inspection solutions in the industrial machinery space that support quality control applications across several industrial and machinery segments. AI-based computer vision for quality inspection is used in advanced equipment manufacturing lines with increasing demand for intelligent systems for quality control in all production steps. The developments further advance the evolution of embedded AI at the different micro, deep, meta edge levels.

Maintenance is one of the critical applications for AI in industrial machinery manufacturing that evolves from preventive toward predictive and prescriptive maintenance using AI-based techniques. Increasing machine/equipment efficiency and minimise/eliminate unplanned downtime requires new predictive maintenance solutions. The solutions are based on ML using supervised or unsupervised learning to detect failure patterns for parts from machine data and predict when the subsequent machine part failure can occur.

Energy management and energy efficiency are significant concerns in industrial machinery/equipment design and their manufacturing processes. AI-based methods used in the industry can support the efficient use of energy in manufacturing facilities, optimising the energy management for various production lines and manufacturing plants. AI-based solutions can predict precise the energy need and type of energy available at the time of use to optimise the integration and use of various energy sources (renewable, fossil) in the production processes.

3.0.3 AI-based Applications

AI4DI partners are developing AI and IIoT technologies with applications in different areas of industrial machinery. The articles included in this section cover several aspects: sensing the environment, making independent decisions, and acting according to the machinery.

The article *"AI-Powered Collision Avoidance Safety System for Industrial Woodworking Machinery"* addresses the challenge of applying AI-technology to safety-critical industrial equipment: it cannot be certified, as, although safety standards do exist for both product and process, they are likely not yet to include innovative algorithms. At the same time, its inclusion in the current certification schemes waits for the technology to become mature enough to trigger industry engagement. The paper attempts to demonstrate by using a prototype (based on ultrasound sensors and coupled with a temporal convolutional network-TCN algorithm) that AI technology can meet safeguards such as halting machinery's operation and bringing it to a safe state when certain conditions are met. The prototype can detect when a person is within a certain distance from the industrial machine with high sensitivity and specificity.

The article *"Construction of a Smart Vision-Guided Robot System for Manipulation in a Dynamic Environment"* addresses the challenges of enabling industrial robots integrated into manufacturing processes to "see" in dynamic environments. The article presents an innovative vision-guided robot system capable of collecting and processing data from various edge devices and adaptive decision-making. Promising preliminary results have been obtained based on synthetic training and validation data generated by open-source software building blocks, easily adaptable and extendable for other industrial applications. It is yet to be seen results and performance when combining synthetic with real training data sets.

The article *"Radar-Based Human-Robot Interfaces"* addresses the need to ensure robots' safety and active control as they interact more closely with humans in different types of settings. The current vision-only approaches are no longer sufficient and must be improved, for example, using hand gesture recognition capabilities. Two implementations of the radar-based human-robot interface have been explored (one using traditional machine learning classification techniques and the other using spiking neural networks). The implementations are compared in terms of their strengths and weaknesses, and the results are presented and discussed. Finally, some preliminary conclusions on performance trade-offs, gesture set choice, ergonomics are provided. Both implementations successfully detect gestures using a single radar, but more work is needed to improve the detection performance.

The article *"Touch Identification on Sensitive Robot Skin Using Time Domain Reflectometry and Machine Learning Methods"* presents the proof of concept of a novel sensor system for robotic human-machine interface (HMI) applications, mimicking the human sense of touch. The system is enabled by implementing an artificial sensitive skin consisting of a robust and straightforward part of the sensing hardware mounted on the robot combined with adaptive AI algorithms to recognise touch events. A measurement concept based on electrical time domain reflectometry (TDR) allows identifying/remembering touch events, localising them on the sensor surface, and determining the touch-force magnitudes. The information collected from the sensor is pre-processed and then used for training and validation of artificial neural networks to obtain high-accuracy: regressive deep neural networks (DNNs) for identification of the touch positions and forces and classification DNNs for discrete force level identification. The results demonstrate that a high-level accuracy is obtained, and more work is needed to reduce the gap between training and validation accuracy.

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