

Digital Twin-Based Multimodal Condition Monitoring of Asynchronous Motors

Jiang Lingge

School of Information and Communication Engineering, University of Electronic Science and Technology of China, High-Tech Zone (West), Chengdu 611731, China.
jianglingge@uestc.edu.cn

Article Info

Elaris Computing Nexus
https://elarispublications.com/journals/ecn/ecn_home.html

Received 18 June 2026
Revised from 30 July 2026
Accepted 16 August 2026
Available online 28 August 2026
Published by Elaris Publications.

© The Author(s), 2026.

<https://doi.org/10.65148/ECN/2026013>

Corresponding author(s):

Jiang Lingge, School of Information and Communication Engineering, University of Electronic Science and Technology of China, High-Tech Zone (West), Chengdu 611731, China.
Email: jianglingge@uestc.edu.cn

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Abstract – The objective of this work is to propose and demonstrate a multimodal digital twin framework for the condition monitoring of the robotic automation cell in the edge-to-cloud. This system is comprised of a Robotic platform of 3 conveyors, CoppeliaSim model and an edge monitoring module on a Nano 33 BLE Sense development board Revision II. It was tested on the induction motor at 1500, 1200 and 900 RPM (revolutions per minute) with no-load and with no-disturbance. The tri-axial vibration and acoustic data were captured at 1 kHz and the temperature was experimented at 1 Hz for 60 s at each speed. Vibration distributions, acoustic Mel spectrograms and temperature trends were investigated. The results reveal multimodal fluctuations depending on the speed and could serve as a reference for future anomaly detection and predictive maintenance in robotic production systems based on AI.

Keywords – Digital Twin, Edge Computing, Cloud Computing, Robotic Automation, Condition Monitoring, Asynchronous Motor, Vibration Analysis, Acoustic Monitoring, Predictive Maintenance, CoppeliaSim.

I. INTRODUCTION

As defined in the NF EN 13306 maintenance terminology standard, maintenance encompasses all management, administrative and technical activities throughout the life of a system aimed at maintaining or restoring its capability to perform the required function. In general, there are two types of maintenance: corrective maintenance (CM) and preventative maintenance (PM). The first approach is when a model is not working and the second method is when the model is working. However, these two maintenance procedures have a significant impact on the total operational expenses of all output, from 16% to 60%. Another interesting data is that the American sector spends over 200 billion dollars a year on the maintenance of industrial machinery and organizations. But about \$60 billion is lost because of poor maintenance [1]. The cost of maintenance increases product price and reduces product quality. The maintenance staff are to reduce the large costs and hence speedy maintenance of the equipment and machinery is very important.

Predictive maintenance (PdM) is a solution that could help overcome these challenges. PdM is one of the condition-oriented maintenance (C.O.M.) strategies of maintenance defined by the European Maintenance Standard EN13306-2017 [2]. This approach is attained via a forecast oriented methodology; repeated evaluations of the existing qualities and advancements of pertinent features related to the deterioration of a component. In the context of the IoT (internet of things) and the I4.0 (Industry 4.0) and with the emergence of new big data technologies PdM plays an important role to improve the performance of the industrial facilities under operation. This lifetime is illustrated in **Fig. 1**, where the first phase, “Dependable sensor dataset” is the basis, because if the dataset is not good, there is no way around it, regardless of the methods used; the second phase is “Predictive accuracy”, which is related to the selection of AI frameworks and updating them in time, as no matter how good the dataset is, it cannot compensate for outdated methods. Model predictions need expert supervision as accurate forecasts might be made without operational significance without contextual interpretation.

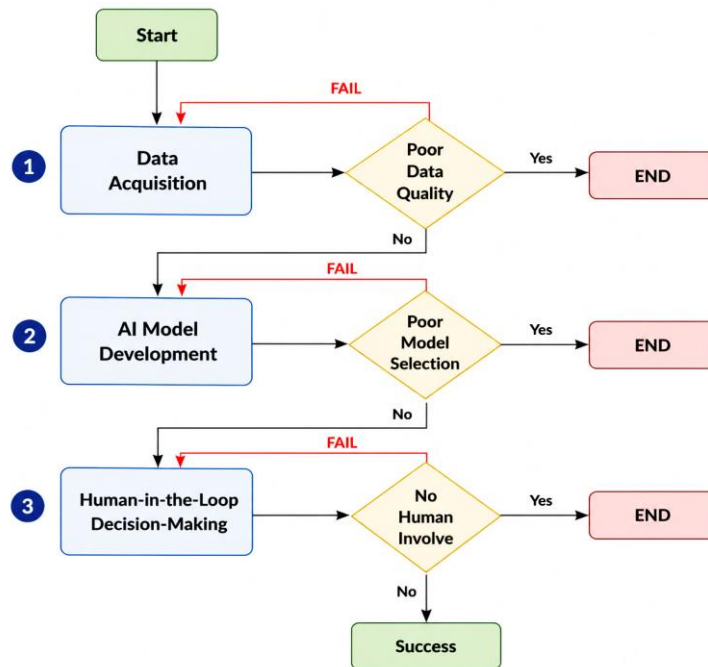


Fig 1. The Predictive Maintenance Process in Smart Manufacturing.

Each failure has the potential to result in a loss of money, equipment damage or compromise of a safety situation. Hence, PdM should not be seen as a computing issue only, but as a system-oriented issue, which must consider the human cognitive aspect, model robustness and data integrity. Predictive maintenance (PdM) is a hot area due to some very significant developments in DL (deep learning) and ML (machine learning). But, most of the successful frameworks in controlled environment are not easily transferable to challenging industrial environments because of their lack of validation with empirical data [3]. This division has an impact on forecast accuracy and limits further adoption. Meanwhile, the shift from I4.0 to I5.0 is from automation to collaboration between human and AI. It adds ethical control, human creativity and intuition to intelligent production. All these changes indicate that predictive maintenance systems are needed that integrate enhanced automation with human-oriented decision-making.

The early Industrial Revolution was characterized by mechanization of manufacturing using steam and hydraulic power. Later, the second industrial revolution happened with the introduction of electricity, thus building assembly lines and mass production. The third Industrial revolution had to do with computing and embedded hardware. It was on this that corporations were concentrating and it was this that caused the automation of manufacturing. The fourth industrial revolution is termed as intelligent manufacturing environment, wherein the advanced manufacturing technology is integrated together and forms a complete system which can be analyzed, communicate and use the data for data-driven decision making for practical applications.

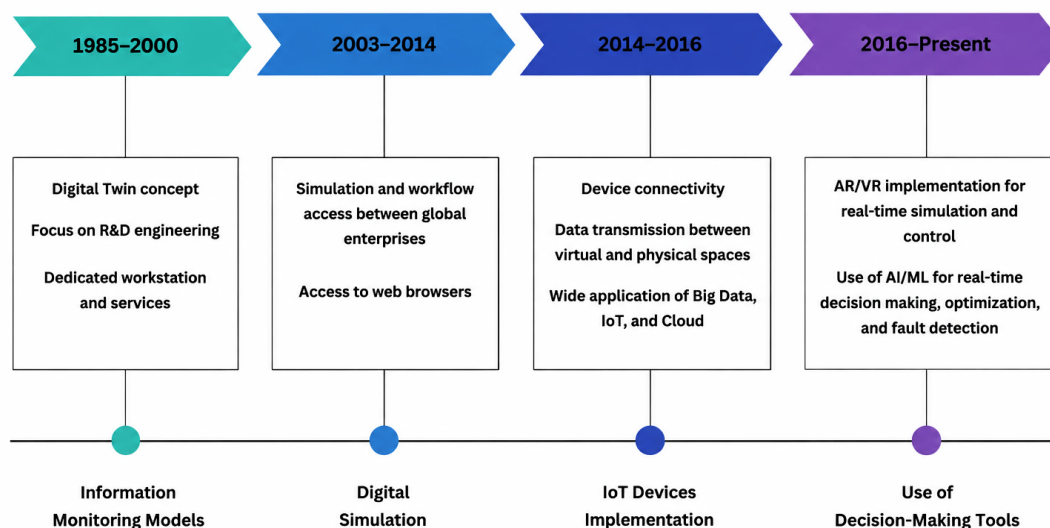


Fig 2. The Evolution of Digital Twins in Production.

Industry 4.0 uses analytics, AI and the IoTs to optimize operational procedures and decision making. The industrial growth of DT can be classified into four different phases as shown in **Fig. 2**. The initial phase (1985-2000) was devoted to the workstation and service information surveillance paradigm. The third phase was from 2003 to 2014 and saw a move to digital simulation. The third phase occurred from 2014 to 2016, during which the IoT devices were deployed. Lastly, the fourth phase began in 2017, and is still ongoing, where the tools for decision-making are implemented [4].

This study is directed towards describing and experimentally validating a system comprised of an edge-to-cloud digital twin to perform multimodal condition monitoring of a robotic automation cell. The system is composed of a real multi-conveyor robotic system, a virtual model of the robotic system in CoppeliaSim environment, and an edge-monitoring module, which is Nano 33 BLE Sense development board Revision II module capturing and analyzing data related to motor-condition. Section II discusses the related work about AI based motor defect detection, digital twin, predictive maintenance and robotics automation. The experimental setup, the system design, the data acquisition and signal processing are presented in Section III. Results of the empirical studies are presented in Section IV. The research ends in Section V where emphasis is placed on the contribution and the implications for condition monitoring and predictive maintenance.

II. RELATED WORK

AI-Based Motor Fault Detection and Condition Monitoring

Electric motors are one of the most important elements in modern industry, as Mayr et al. [5] illustrated; and these drive the basic operations of energy exchange, transportation, automation and the manufacturing industries. The operational state has a direct impact on system safety and energy efficiency and production. Motors on the contrary have degradation mechanisms that occur over time, such as thermal stress, insulation failure, rotor imbalance and bearing wear, and are usually caused by mechanical fatigue, electric overload or ambient temperatures. Failure to notice these problems might result in major failures and costly downtime in operations. Thus, smart condition monitoring and condition diagnostics for prediction of defects is a critical factor in view of early defect detection.

Traditional condition monitoring methods, as mentioned by Kumar et al. [6] are mostly based on only one sensor data like stator or vibration current and signal processing methods like envelop analysis, FFT, STFT or wavelet transformation. These methods are known and have been used with good success in a controlled environment, but are not as successful in the presence of varying loading, sensor noise and sensor non-linearities. The structures were manually crafted and numerically evaluated by machine learning techniques such as random forests, ensemble classifiers and support vector machines (SVMs), to improve the generalizability. Ensemble empirical mode decomposition (EEMD) method was adopted with the SVMs to categorize the challenges that are encountered in bearing as per various speed levels. But these systems need factor engineering and are not flexible for real time applications.

Condition tracking using AI has been a very active research area in academia. Moreover, tool fault identification has been one of the most popular application scenarios for researchers to develop novel DL or ML systems due to its essential benefits for industry. Scholars in [7] studied the usage of AI systems for defect identification of rotating machines. The merits and demerits of the models used (deep learning, SVM, naïve Bayes, KNN) were deliberated. Liu et al. [8] have studied existing methods of fault identification and fault type classification in rolling element bearings in their recent study based on the vibration dataset.

Although the application of ML approaches was successful, the deep learning approaches have become more popular because of their good feature extraction capabilities. Rony et al. [9] conducted a study on deep-learning methods for error detection in bearings showing solid methods based on encoders-decoders, a restricted Boltzmann network and convolutional neural networks. Furthermore, Hoang and Kang [10] did a detailed study on detailed research deep-learning bearing fault detection. They explored published techniques like deep belief network, CNNs, GANs and RNNs, as well as the most common open-source data sets.

Digital Twins for PdM and Process Optimization

Predictive maintenance was defined in [11], however, as an assessment that uses all data available for a model to forecast its residual lifespan or the probability of failure. The PdM system may be formulated using a model-centric strategy based on a numerical, physical, or analytical model or a data-driven methodology depending on data acquired from sensors. It has been agreed that PdM approaches are resource-demanding, which have been widely investigated in Manufacturing 4.0.

According to Ayvaz and Alpay [12], the predictive maintenance method relies on data analysis and uses the IoT to collect sensor data from assets to be used in a digital environment (computational platform). In this work the concept of IIoT (industrial internet of things) is used and a data-centric approach is applied for the implementation of the recommended dispersed digital twin forecasting maintenance solution using the sensor data extracted from the wind energy turbines. The digital twin model proposed in this article provides a computational platform suited to host simulations that serve as a system architecture for the implementation of physics-based model-driven approaches.

Digital Twins as Process Optimization Enhanced environments for AI model simulation and validation. The artificial neural twin blends supervised and unsupervised learning with Model Predictive Control to enhance the decentralized industrial systems through Unity-driven simulations [13]. To improve the energy efficiency of an industrial drying process, a decision tree model based on CatBoost was developed, which resulted in an energy saving of 3.7 MWh/year. The

application of Ant Colony Optimization in a robotic digital twin has allowed the planning of obstacle free trajectories for industrial manipulators, showing the capacity of heuristic reinforcement learning agents in instantaneous management.

In reference to study by Ali et al. [14], digital twins are now central to Simulation-to-Reality transfer procedures in which agents are trained in a virtual environment and then deployed on real world models with minimal retraining. DRL agents were trained on robotic grasping in the DT environment and exhibited high transfer success rates, with safety features. Moreover, digital twins provide cross-domain orchestration as shown in the SMS-DT architecture that exploited supervised and unsupervised machine learning algorithms through the enterprise, platform, and edge layers for monitoring operational resilience and cyber-physical security in intelligent manufacturing environments.

Simulation-augmented education helps develop the AI models in the data-scarce circumstances by the use of synthetic data supplied by the digital twin. Second, the real-time flexibility is achieved by continuously transferring live data to update the systems to change with the model. Third, the physics-guided models and XAI (explainable AI) in the digital twins offer transparency and trustworthiness for the decision-making process in safety-critical domains. In the end, by progressing to edge-compatible digital twins we can allow decentralized intelligence for resource-constrained environments.

Robotic Automation with Edge-to-Cloud Digital Twins

Wang et al. [15] introduce a cloud manufacturing (CMfg) collaboration architecture between cloud and edge devices for smart robots to make intelligent decisions. In this regard, several deployment and update strategies of DLMs (deep learning models) of intelligent robots are extensively reviewed aiming to enable fast responses and better decision making by considering data processing locations, data sources, online/offline learning, life cycle and data sharing of DLMs. Furthermore, some key technologies related to this area are provided as references for technology research routes.

Singh et al. [16] describe a comprehensive model for the construction of digital twins based on Unity and ROS (robot operating system) as the hub of communication and digitalization. The MoveIt package allowed the motion scheduling and deployment for robotic arms showing the flexibility of the model without proprietary constraints. The suggested framework utilizes the flexibility and open-source nature of these technologies to guaranty scalability, adaptability and interoperability, which are fundamental aspects for real intelligent manufacturing implementations.

Choi et al. [17] discuss a construction of a digital twin of a robotic workcell based on existing standards, tools and methods. The workcell comprises collaborative robotic arms, computer numerical control (CNC) cutting tool and coordinate measurement machine (CMM). The digital twin is built according to the ISO 23247 standard. Data is collected from the physical hardware. The foundation of moving this data from the physical machinery to the digital counterpart is the MTConnect standard. In the digital realm the machine elements of the workcell are modeled.

Gao, Muzzio, and Ierapetritou [18] provide a comprehensive literature evaluation of Residence Time Distribution (RTD) in the manufacturing domain, from the point of view of both technology and application, with the aim of providing insights for practitioners and researchers in the industry 4.0. They propose a four-level architecture for the RDT system, and summarize the impacts of Industry 4.0 technologies on the RDT system based on this architecture, including AI, simulation and modeling, virtual reality, 5G, edge/cloud computing, and IIoTs. The analysis also includes applications related to domains and systems such as additive manufacturing models, predictive maintenance, human-robot engagement, material handling, grasping, machining, and assembly and their development progress.

Simion et al. [19] provide a designing and application of local or remote supervision and regulatory system of a laboratory mechatronics setup oriented on an IIoTs-cloud, digital twin and VPN technique. The MRC is the mechatronic system, which is formed of an industrial robotic arm, ABB IRB 120 Robotic Manipulator, which accomplishes the adaptable assembly processes of two workpiece component, each made of five elements. The model is designed to be taken apart and replaced so components could be removed and reused or sold. If the workpieces are totally defective, it is sent back to the MRC by the material-handling conveyor for total substitution or disassembly of components.

III. METHODOLOGY

Experimental Design and System Architecture

Experimental setup for the evaluation of a multimodal condition-monitoring framework for a robotic automation cell. The architecture was physically a multi-conveyor robotic system plus a CoppeliaSim model. Operational and sensor data were generated by the physical system, and the virtual model represented the robotic cell for visualization and simulation and future synchronization between physical and virtual world. CoppeliaSim is capable of robotic-system simulation, factory automation modeling, algorithm creation and digital twin installation. The experimental cell is comprised of three degrees of freedom robot arm servo-operated and three conveyor lines. A localized IEPC (industrial equipment process controller) was used to control each robot joint, while induction motors were used to drive each conveyor line. High resolution shaft position measurement was done using encoder feedback and the materials positions were detected by proximity sensors to activate pick-and-place operations.

A monitoring architecture as proposed in **Fig. 3** was organised in 3 layers. The first was the physical asset layer including the robot arm, the asynchronous motors, the conveyor line, the encoders and proximity sensors. Edge monitoring layer was the second layer, where sensor measurements were taken near the monitored motor. The third layer was the digital twin and cloud layer, which enabled the storage of data, visualization of the system, virtual representation of the system's state, and future anomaly detection via artificial-intelligence. The module for monitoring the asynchronous motor has been

implemented with the help of a Nano 33 BLE Sense development board Rev2. The board has a BMI270 inertial measurement unit, BMM150 magnetometer, HS3003 temperature and humidity sensor and MP34DT06JTR digital microphone. The BMI270 accelerometer was used here for the tri-axial vibration acquisition, the MP34DT06JTR was used for the acquisition of acoustic signals, and the HS3003 temperature channel was used for thermal monitoring.

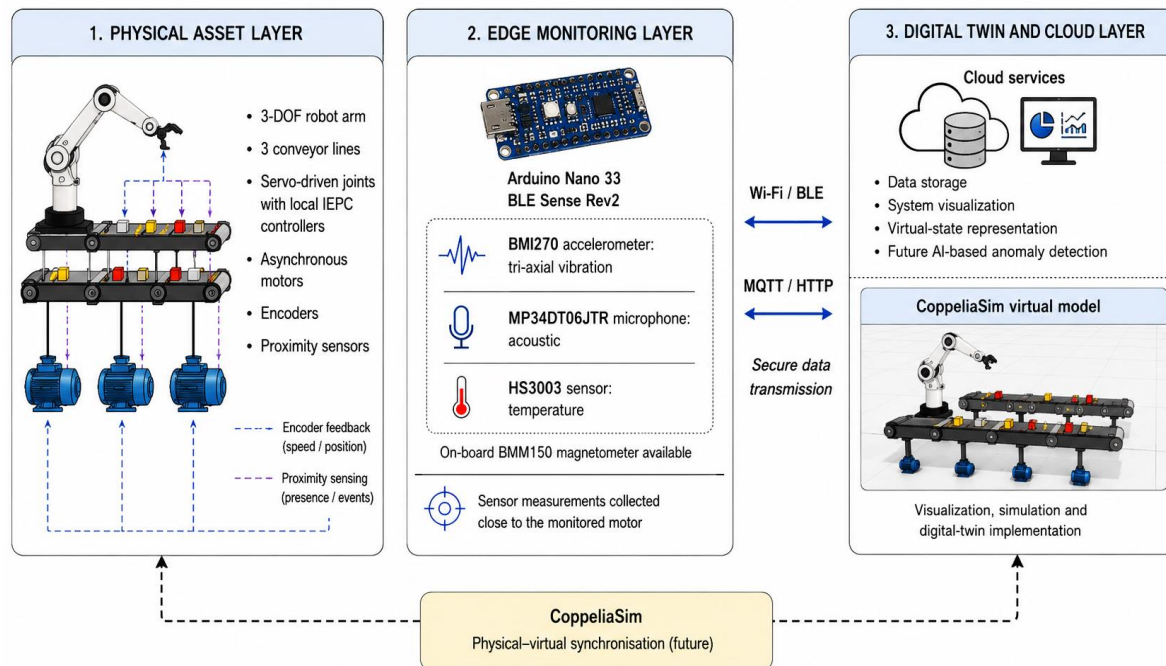


Fig 3. Physical-Edge-to-Cloud Digital Twin Architecture for Robotic Automation Cell.

An identical automation technique was explored for both the real and virtual systems. Operational parameters monitored were motor speed, robot movement, conveyor belt operation, encoder position, proximity events and sensor measurements. The data of the motor-condition was physically measured by the physical monitoring module, and the robot cell design and operation were modeled in Coppeliasim. The physical experiment was mainly set up numerically as shown in **Table 1**.

Table 1. Numerical Arrangement of the Experimental System

Parameter	900 RPM	1200 RPM	1500 RPM
Duration (s)	60	60	60
Vibration samples/axis	60,000	60,000	60,000
Acoustic samples	60,000	60,000	60,000
Temperature observations	60	60	60

The load and disturbance-free experiment served as the baseline experiment. The measurements were not considered to be instructions to estimate the ultimate accuracy of the fault classification or the remaining useful life, but to be instructions to characterize typical operating behavior at different speeds.

The Technique of Data Collecting and Signal Analysis Technique

The induction motor was run at 1500, 1200 and 900 RPM (revolutions per minute) respectively. The operational time of each condition was set at 60 s. Vibration and acoustic signals were collected at a nominal rate of 1 kHz and temperature at 1Hz. This produced 60,000 samples of vibrations for each of the 3 accelerometer axes, 60,000 samples of sound and 60 temperature values for each operating condition. The acquisition is depicted in **Table 2**. The tri-axial vibration channel was calculated independently for each axis, and the nominal total was calculated. The three working conditions thus produced 180,000 samples per axis of the accelerometers, which is a total of 540,000 scalar acceleration samples for the 3-axis combined (**Fig. 4**).

Table 2. Parameters for Numerical Data Collecting and Processing

Signal	Sampling rate (Hz)	Total samples	Window (samples)	Overlap (%)	Hop (samples)
Vibration	1000	180,000/axis	-	-	-
Acoustic	1000	180,000	1024	50	512
Temperature	1	180	-	-	-

Box plots and frequency visualizations were used to provide an overview of the vibration data for the three operating speeds. The investigation included the median, the interquartile range, the general dispersion and any outlying acceleration values. Since acceleration is a representation of vibration amplitude, all vibration findings were presented in the corresponding acceleration unit, such as g or m/s^2 . The RPM data were only utilized to determine the operating condition. The sound recordings were analyzed using Mel spectrogram analysis. For the 1-kHz acoustic data, a 1024-sample window with 50 % overlap was used. The analysis window was 1.024 s long, and the overlap gave a step of 512 samples between two succeeding windows. The obtained time-frequency representations were used to investigate changes in sound intensity at the three motor speeds (see Fig. 4).

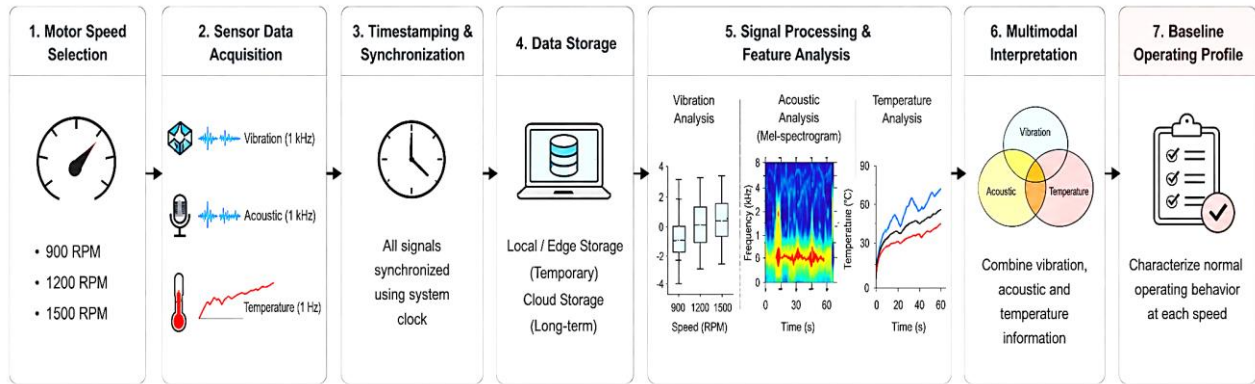


Fig 4. Workflow for Experimental Data Processing.

The temperature data were considered as time series observations. The sample rate for the temperature channel was 1Hz during the 60-s trials as the signal expected to vary slower than the vibration and auditory channels. Therefore, the data of temperature was used to analyze the thermal stability of the motor in the three mentioned working conditions. Each of the three modalities was analyzed separately and then compared and contrasted together. The mechanical response and signal dispersion were analyzed using vibration measurements, time-frequency fluctuations and temperature measurements were used to study acoustic and thermal fluctuations respectively. The simultaneous interpretation was intended to explore how the changes of motor speed were correlated in the mechanical, acoustic and thermal measurements.

The recorded data were vetted for missing observations, unusual time stamps, communications failures and sensor saturation and mismatch of samples expected and samples obtained prior to analysis. A sample frequency of 1 kHz was used for the vibration and acoustic channels over a duration of 60 s, which would provide 60 000 observations for each operating speed. For the operating speed of the temperature channel, it was assumed that a sample rate of 1 Hz for 60 s would provide 60 observations. The experiment was used to provide a baseline description of the operating regime. These experiments were conducted under no-load and no-disturbance conditions and were not used for the assessment of fault detection accuracy, false alarm rate, fault detection delay and RUL. These types of performance assessments need additional testing with controlled and labeled mechanical or electrical perturbations, multiple trials, varying levels of loading, and other validation data.

IV. RESULTS

Here, we present an experimental realization of the generalized PdM network strategy suggested in Section III.

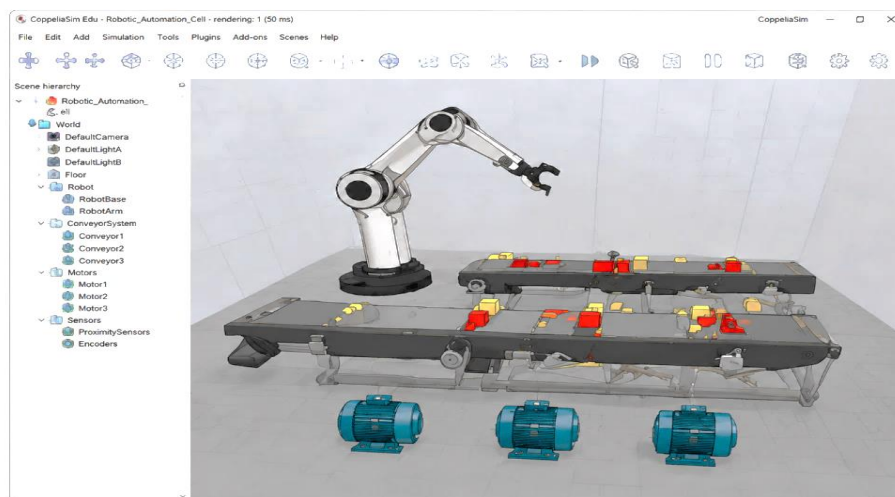


Fig 5. Edge-to-cloud DT Incorporation for Mechanical Digitization in CoppeliaSim.

To show the usefulness of the proposed design, a case study of the multiple-conveyor robotic automation system, where multiple material handling belt systems and multiple jointed robotic arms are used to convey materials in a smart industrial environment (see **Fig. 5**), is considered. The cell is designed to be a physical setup and CoppeliaSim-based realistic simulation to support an integrated edge-to-cloud DT/DvT process for methodical testing with the IIoTs based PdM techniques.

The equipment includes a servo driven 3 degrees of freedom (DOF) robotic arm with independent IEPCs at each joint, as well as 3 conveyor belts powered by 3 induction motors. In the proposed scenario, the encoders provide the detailed control of the movements of the robotic arms and the proximity sensors on the conveyor belts, when energized for the required time, trigger the pick and place actions. This virtual/physical lab stimulates the conceptualization of operating systems, and the assessment of PdM methods by introducing measured electrical and mechanical distortion to the physical motors, thereby simulating Azure-oriented AI fault diagnosis resilience in actual fault events.

Table 3. Field Device Modernization Upgrades for each MA Configuration in Stage 1

Device Group	Device Instance	Unified Device and Evaluation
Induction motor tracking	Nano 33 BLE Sense development board Revision II (integrated into legacy MA configuration)	HS3003 capacitive digitalized sensor: measures ambient humidity and temperature; BMM150 and BMI270: offer 9-axis inertia measurable data; MP34DT06JTR MEMS microphone: measures ambient acoustic intensity levels.
AC servo motor tracking	TIE50M8A capacitive proximity sensor	Incremental rotary encoders (5000 PPR – pulse per cycle) 5000-shaft position pulses assessments for accurate servo angular position response and speed monitoring.

All the following data were recorded using the improved Stage 1 field architecture, including the induction motor tracking module described in **Table 3**, to ensure complete recording of acoustic, temperature and vibration data with the new multi-sensor edge-based setup. The monitoring module used for recording all the data is Nano 33 BLE Sense development board Revision II with varying sampling frequencies from the vibration, sound and temperature channels as depicted below.

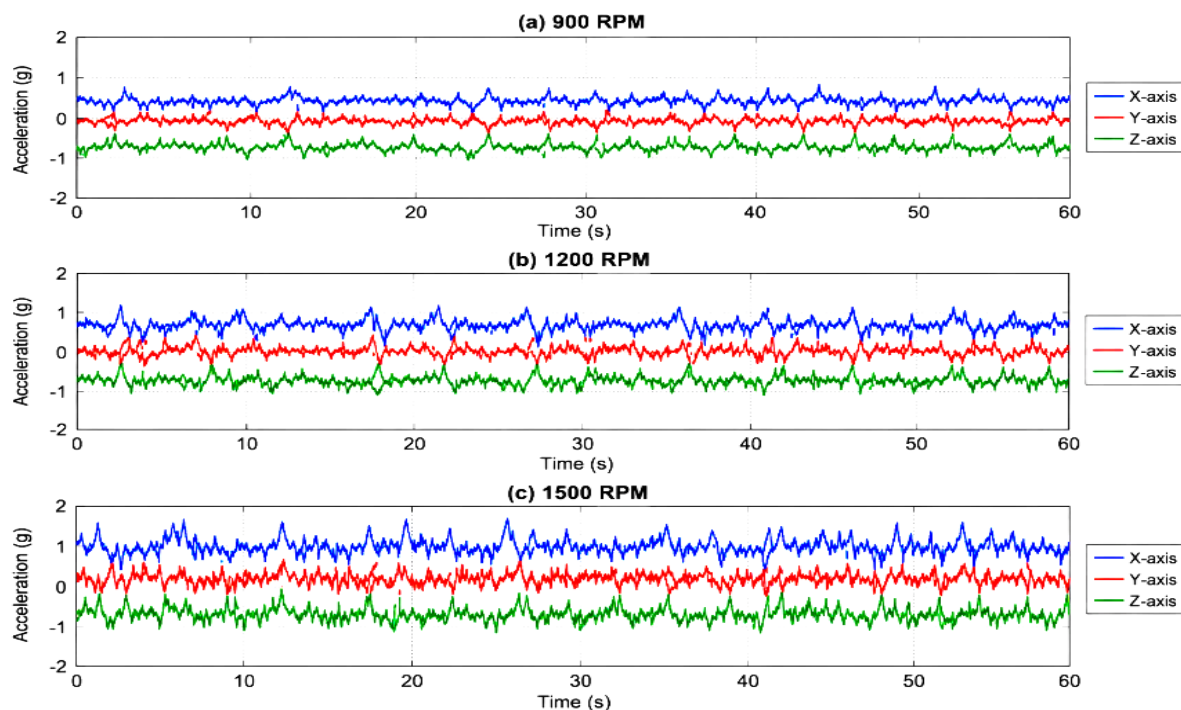


Fig 6. Data of Acceleration of Induction Motor.

Acceleration dynamics at the different speed of the motors are displayed in **Fig. 6**. Typically, in motor evaluation, the acceleration is proportional to the vibration level. At each operating point the three-axis accelerometer was recorded at a frequency of 1 kHz for 60 seconds, i.e. 60,000 observations per speed and so the frequency contains the entire 60,000 samples of the acceleration pattern for each of the RPM configurations.

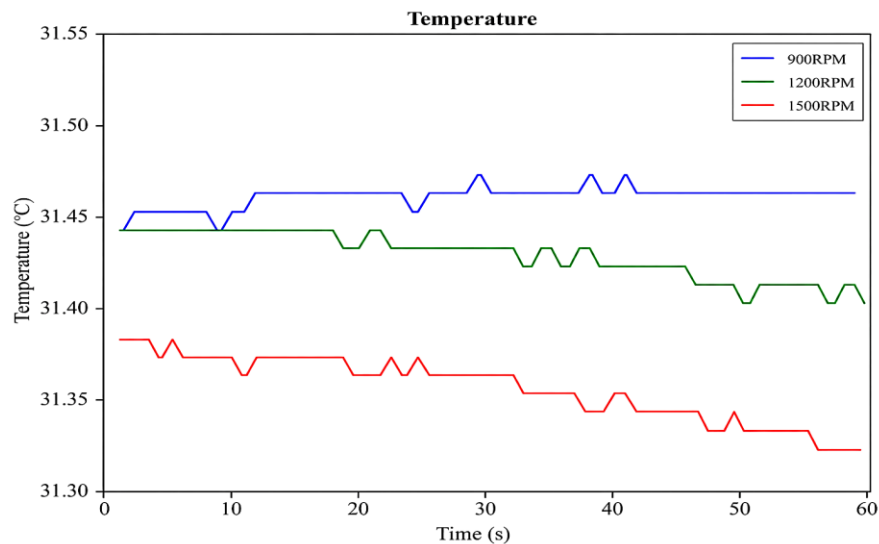


Fig 7. Induction Motor Temperature Analysis.

From these results, it is clear that the motor status may be eminent very accurately at three almost equal RPM and that the mechanical strain risk may be monitored progressively. For instance, the top numbers by 15% to 20% with a constant median value of 1500, 1200 and 900 RPM, suggest operating conditions that may negatively impact the life expectancy of the motor. And the red line can also significantly shorten the life of the bearings. The readings of the thermal sensor of the induction motor operating at 3 different RPM's namely 1500 RPM, 1200 RPM and 900 RPM are shown in **Fig. 7**. The thermal channel was checked onboard at 1Hz for 60s (60 tries per working point) at each velocity, sufficient to observe the slow thermal shift of less than a degree which was seen in these short experimental trials. The three speeds result in an extremely small range of readings, 31.3 °C to 31.5 °C, with a variation of less than 0.2 °C, due to the fact that the motor was running without any interruption or load. This limited scope enables the advanced sensor system to detect temperature changes of less than a degree Celsius between places of operation even under thermally almost equal conditions.

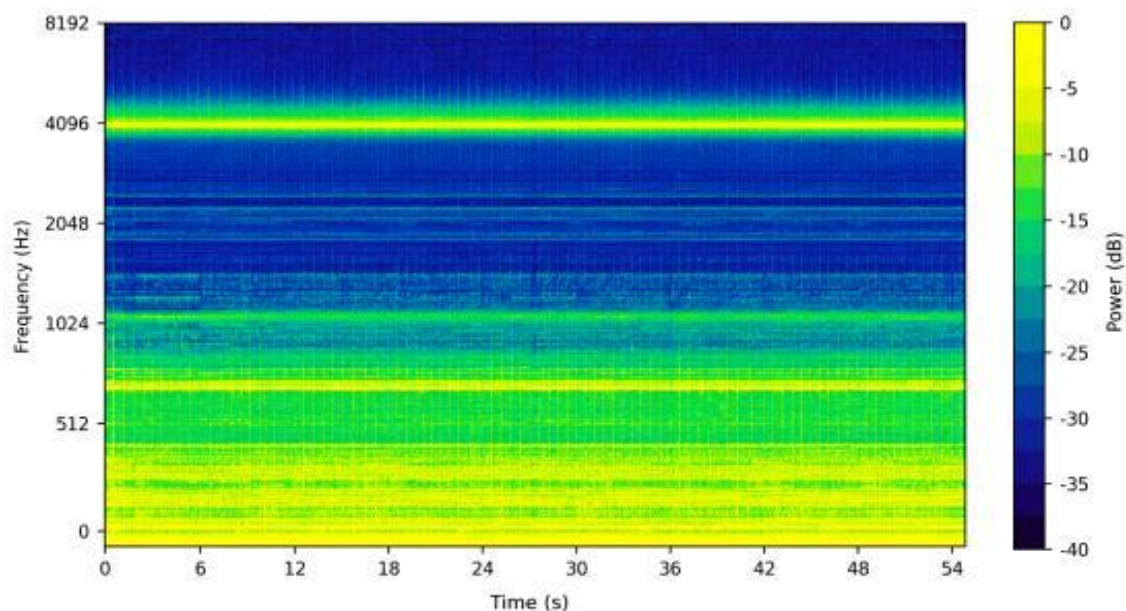


Fig 8. Acoustic Analysis of the Asynchronous Motor at 900 RPM.

Fig. 8, 9 and 10 are 3D Mel Spectrograms in which X axis is the time (s) of the acoustic sensor during the motor operation at 1500, 1200 and 900 RPM, correspondingly, and Y axis represents frequency (Hz) while Z axis represents amplitude (dB) of the acoustic sensor. A total of 60,000 samples were collected from the microphone channel for 60 s at each operating point utilizing a sampling rate of 1 kHz. The mel spectrograms were created by using an analysis window of 1024 samples and an overlap of 50%, which was a good temporal-frequency resolution for identifying the mechanical fault. **Fig. 6** displays these Mel Spectrograms which are cross-validated with the acceleration graphs to get the vibrational and auditory patterns at different speed of operation in real time.

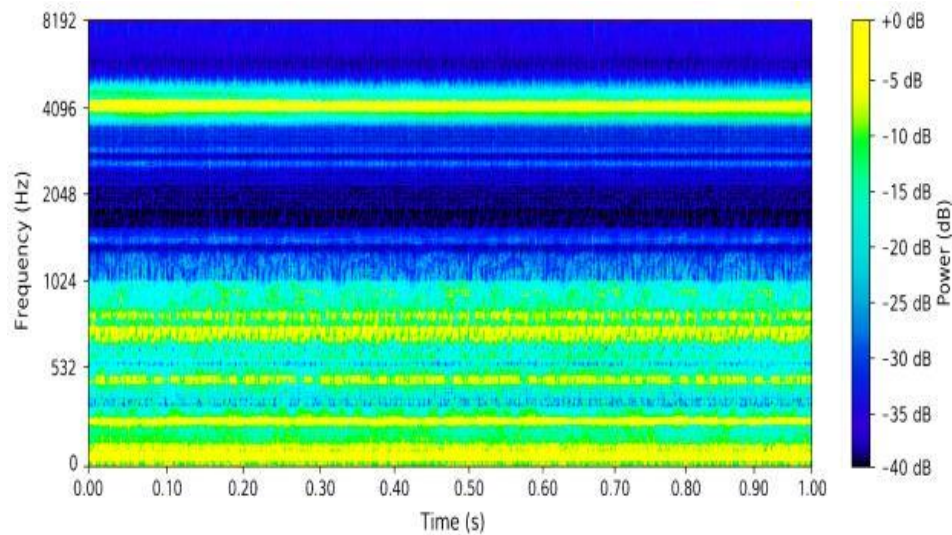


Fig 9. Acoustic Data of the Asynchronous Motor at 1200 RPM.

Mechanical inefficiency at low speeds is manifested as momentary changes in the motor (vertical lines and deviations, see **Fig. 8**) particularly at 900 RPM. The Mel bands in **Fig. 10** are much more pronounced and there is a definite rise in acoustic and vibration signals at 1500 RPM. High results indicate that the motor is unstable dynamically at high speed and is probably subject to mechanical stresses. Independent analysis of the vibration, auditory and temperature channels and detailed analysis of the combined behavior of the three signals reveals potentially cross-modal interactions. The increase with rotational speed in the distribution of the amplitude of the vibration and the emergence and increase with velocity of harmonic frequency spectra in the Mel-scale acoustic spectrogram both show the mechanical variations occur in both the vibration and the acoustic space, but with distinct sensitivities and occurrence resolution.

For thermal evaluations, these transient effects are short lived and not really significant on the time-averaged operating condition, and the temperature distributions change on similar time scales significantly slower and rather uniformly [20]. Joint feature extraction such as alignment between the audio and vibration network, integrated temporal-frequency features, etc. will be the next step in our work. This means that there is more redundant information in the trimodal stack. These multi modal data will be more and more used as part of the DvT/DT pipeline during future development and evaluation of anomaly detection algorithms for Azure. This will provide accepted baselines for classification and forecasting of problems in regulated situations.

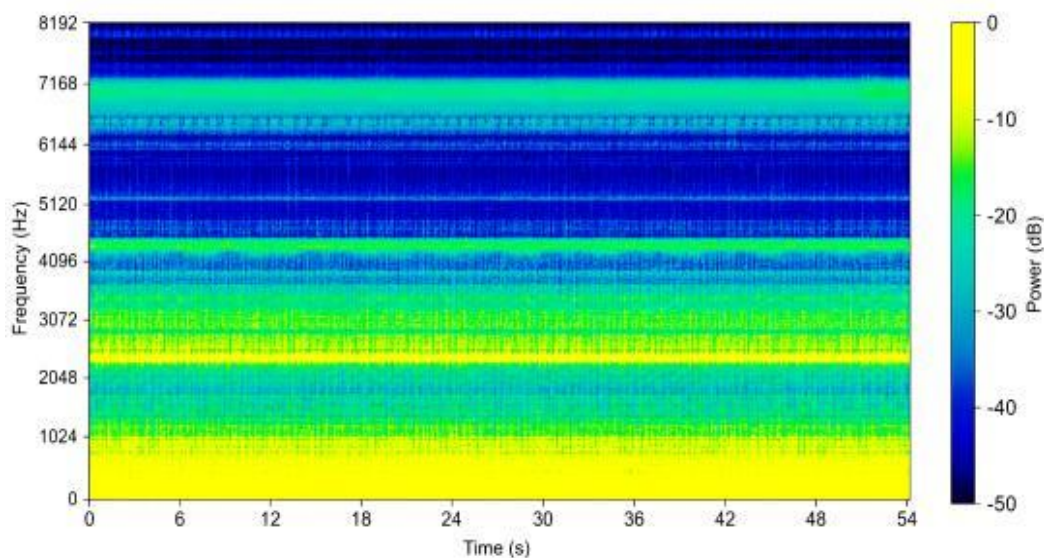


Fig 10. Acoustic Assessments of an Induction Motor at 1500 RPM.

The experiment illustrates the application of the classified IIoTs and the DvT/DT architecture to monitoring in a controlled test environment of the state of robotic assets and asynchronous motors. It can be used to differentiate between various operating conditions and can detect stress patterns due to vibration and temperature. Further studies are needed for

longer and regular faults to assess the dual-mesh architecture and edge-to-cloud architecture when it is under more mechanical loading. These are preliminary results, since they were achieved without load and limited operating settings. The current results are a compelling justification for the framework's suitability for predictive maintenance of IIoT-centric robotic automation cells and the proposed upgrade would further show the robustness and applicability of the framework.

V. CONCLUSION

We examined the performance of asynchronous motors primarily from an experimental point of view, under the aspect of robotic automation, and provide a first order explanation of their working. Vibration, auditory and thermal examinations revealed that all three sensory modalities have different aspects of motor function and thus provide complementary information for condition assessment. The temperature, however, took a longer time to respond during the testing period; and the vibration and acoustic data were more sensitive towards the changes associated with the operating speed. This allows the estimation of multi-modal sensing rather than a single measurement channel. The collaboration with CoppeliaSim allows getting a virtual working model of the system and to analyze the system's physical operating conditions. This has the potential to be extended to digital twin monitoring. However, only the results obtained from the conventional operating mode can be considered with the present results. The real fault detection and predictive maintenance framework should be tested in different fault scenarios and varying load, fault time and frequency to validate the framework for real use.

CRedit Author Statement

The author reviewed the results and approved the final version of the manuscript.

Data Availability

The datasets generated during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interests

The authors declare that they have no conflicts of interest regarding the publication of this paper.

Funding

No funding was received for conducting this research.

Competing Interests

The authors declare no competing interests.

References

- [1]. O. Merkt, "Predictive models for maintenance optimization: An analytical literature survey of industrial maintenance strategies," *Lecture Notes in Business Information Processing*, pp. 135–154, Jan. 2020, doi: 10.1007/978-3-030-43353-6_8.
- [2]. J. Fernandes, J. Reis, N. Melão, L. Teixeira, and M. Amorim, "The role of Industry 4.0 and BPMN in the arise of condition-based and predictive maintenance: A case study in the automotive industry," *Appl. Sci.*, vol. 11, no. 8, Art. no. 3438, Apr. 2021, doi: 10.3390/app11083438.
- [3]. M. Ayyat, M. Osman, and T. Nadeem, "Opportunities and challenges of foundation models in industrial manufacturing," *IEEE Access*, vol. 13, pp. 138745–138775, 2025, doi: 10.1109/ACCESS.2025.3589777.
- [4]. V. Rossi, T. Caffi, I. Salotti, and G. Fedele, "Sharing decision-making tools for pest management may foster implementation of integrated pest management," *Food Security*, vol. 15, no. 6, pp. 1459–1474, Oct. 2023, doi: 10.1007/s12571-023-01402-3.
- [5]. A. Mayr et al., "Electric Motor Production 4.0—Application potentials of Industry 4.0 technologies in the manufacturing of electric motors," in *Proc. 8th Int. Electric Drives Production Conf. (EDPC)*, 2018, pp. 1–13, Dec. 2018, doi: 10.1109/EDPC.2018.8658294.
- [6]. R. R. Kumar, M. Andriollo, G. Cirrincione, M. Cirrincione, and A. Tortella, "A comprehensive review of conventional and intelligence-based approaches for the fault diagnosis and condition monitoring of induction motors," *Energies*, vol. 15, no. 23, Art. no. 8938, Nov. 2022, doi: 10.3390/en15238938.
- [7]. B. L. C., S. G. A., B. J. N., and D. M. A. V., "An explainable artificial intelligence approach for unsupervised fault detection and diagnosis in rotating machinery," *Mech. Syst. Signal Process.*, Art. no. 108105, 2022, doi: 10.1016/j.ymssp.2021.108105.
- [8]. H. Liu, J. Zhou, Y. Zheng, W. Jiang, and Y. Zhang, "Fault diagnosis of rolling bearings with recurrent neural network-based autoencoders," *ISA Trans.*, vol. 77, pp. 167–178, Apr. 2018, doi: 10.1016/j.isatra.2018.04.005.
- [9]. M. H. Rony et al., "Deep learning and few-shot learning-enabled machine health monitoring for rotating machinery: A critical review of vibration-based fault diagnosis, prognostics, and industrial deployment," *Qual. Reliab. Eng. Int.*, Jul. 2026, doi: 10.1002/qre.70302.
- [10]. D.-T. Hoang and H.-J. Kang, "A survey on deep learning-based bearing fault diagnosis," *Neurocomputing*, vol. 335, pp. 327–335, Nov. 2018, doi: 10.1016/j.neucom.2018.06.078.
- [11]. D. C. Swanson, "A general prognostic tracking algorithm for predictive maintenance," in *Proc. IEEE Aerospace Conf.*, vol. 6, 2001, pp. 2971–2977, 2002, doi: 10.1109/AERO.2001.931317.
- [12]. S. Ayvaz and K. Alpay, "Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time," *Expert Syst. Appl.*, vol. 173, Art. no. 114598, Jan. 2021, doi: 10.1016/j.eswa.2021.114598.
- [13]. M. Kannapinn, D. Dorer, M. Schäfer, and O. Weeger, "Digital twins for autonomous thermal food processing: A model predictive control study with reduced-order models of augmented neural ordinary differential equation type," *J. Food Eng.*, vol. 410, Art. no. 112918, Dec. 2025, doi: 10.1016/j.jfoodeng.2025.112918.
- [14]. M. Ali, S. Giri, Q. Yang, and S. Liu, "Digital twin-enabled real-time control for robot arm-based manufacturing via reinforcement learning," *J. Intell. Manuf.*, Nov. 2025, doi: 10.1007/s10845-025-02728-9.
- [15]. R. Wang et al., "Cloud-edge collaborative industrial robotic intelligent service platform," in *Proc. IEEE Int. Conf. Joint Cloud Comput.*, 2020, pp. 71–77, Aug. 2020, doi: 10.1109/JCC49151.2020.00020.
- [16]. M. Singh et al., "Unity and ROS as a digital and communication layer for digital twin application: Case study of robotic arm in a smart manufacturing cell," *Sensors*, vol. 24, no. 17, Art. no. 5680, Aug. 2024, doi: 10.3390/s24175680.

- [17]. J. D. Choi, S.-H. Choi, M. Y. Kim, I. Lee, S. Lee, and B. H. Kim, "AI and digital twin federation-based flexible safety control for human–robot collaborative work cell," *IEEE Access*, vol. 13, pp. 124037–124050, 2025, doi: 10.1109/ACCESS.2025.3586121.
- [18]. Y. Gao, F. J. Muzzio, and M. G. Ierapetritou, "A review of the residence time distribution (RTD) applications in solid unit operations," *Powder Technol.*, vol. 228, pp. 416–423, Jun. 2012, doi: 10.1016/j.powtec.2012.05.060.
- [19]. G. Simion, A. Filipescu, D. Ionescu, and A. Filipescu, "Cloud/VPN-based remote control of a modular production system assisted by a mobile cyber–physical robotic system—Digital twin approach," *Sensors*, vol. 25, no. 2, Art. no. 591, Jan. 2025, doi: 10.3390/s25020591.
- [20]. Z. Yin, A. Montello, C. D. Carter, W. R. Lempert, and I. V. Adamovich, "Measurements of temperature and hydroxyl radical generation/decay in lean fuel–air mixtures excited by a repetitively pulsed nanosecond discharge," *Combust. Flame*, vol. 160, no. 9, pp. 1594–1608, Apr. 2013, doi: 10.1016/j.combustflame.2013.03.015.

Publisher’s note: The publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations. The content is solely the responsibility of the authors and does not necessarily reflect the views of the publisher.

ISSN (Online): 3105-9082