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Original Research Article

TECsPRO: an integrated platform based on the Internet of Things for sustainable management of work environments and production processes

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ABSTRACT

Industry's crucial role in contributing to the Green Deal and sustainability pushes to adopt monitoring systems based on the Internet of Things with the aim to support intelligent management of production processes, reducing environmental burdens and improving workers well-being. In this context, consistent with the Industry 5.0 vision, an open, interoperable and modular platform has been designed by integrating commercial, advanced and innovative low-cost sensors for energy and indoor environment monitoring, using artificial intelligence models and algorithms for data processing. The application to a pilot case of a thermoplastic moulding plant in the industrial district of Melfi, Southern Italy, has allowed to validate the effectiveness of the platform for indoor environmental quality monitoring and predictive maintenance. The platform can be easily adapted to other manufacturing industries, supporting a new concept of organisational innovation which opens the way to new market opportunities.

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KEYWORDS

INDOOR Environmental Quality, INTERNET of Things, KEY Enabling Technologies, INDUSTRY 5.0, SUSTAINABLE production processes.

INTRODUCTION

Green and digital industry transitions represent two pillars in the achievement of the Green Deal climate neutrality target. This is highlighted by the Industry 5.0 paradigm that promotes a holistic and sustainable approach to production in which industry is the protagonist of a radical change aimed at creating customised products, improving the well-being of workers and protecting the environment. In this contest, the global IoT market, constantly evolving due to low-cost and low-power sensors and availability of high-speed connectivity, the growing adoption of cloud infrastructure, the increasing use of artificial intelligence-based data processing and analytics have led to the development of innovative solutions and applications for factory automation allowing production processes to be monitored in real time and the data acquired to be analysed in order to optimise the use of resources, prevent potential problems and improve efficiency and productivity [1].

Industry 4.0 technologies, as among which Internet of Things (IoT), Big Data Analytics, Artificial Intelligence (AI) and Cloud Computing, offer new capabilities and opportunities in various sectors and represent key factors in the design of sustainable production processes [2]. Within this evolving and challenging context, a multidisciplinary research approach is required to address the many open questions. In particular, there is a need to fully understand the interactions and effectiveness of Industry 4.0 applications and the potential risks associated with them, to understand and implement effective measures to prevent threats and data loss, and to develop strategies tailored to different application contexts [3].

At the same time, the focus on the quality of the indoor environment has increased significantly in recent years in both the industrial and domestic sectors overcoming the Industry 4.0 paradigm and focusing on workers' well-being, a healthy environment and the compliance with regulations as crucial objectives to be ensured in the more comprehensive Industry 5.0 framework [4]. .

In this context, the TECsPRO project was aimed to improve sustainable management of productive processes in the framework of Industry 5.0 by designing and implementing an innovative and flexible platform based on IoT architecture that, through an intelligent and customizable system of management and control of work environments (both production and indoor environmental quality), enables the identification of corrective actions and solutions to promote eco-sustainability and energy efficiency of production processes and ensure indoor well-being. Specifically, commercial devices and innovative sensors based on Key Enabling Technologies (KETs) have in turn been integrated and developed for monitoring and optimising production processes in a moulding plant (the pilot case). Near-real-time process data from production cycles have been acquired, stored, integrated and compared with data derived from the microclimate and environmental parameter monitoring system, to be subsequently processed through analytical models. This has allowed the potential of advanced monitoring systems to be studied and exploited with a focus on environmental quality, energy efficiency and predictive maintenance.

In the context of the project, a collaborative interaction between industrial partners and research institutions has enabled the development of a system based on user needs and fosters new opportunities for economic and social development.

STATE OF THE ART

In recent years, Information Technology (IT) has contributed to a deep transformation of society, and particularly the manufacturing sector, enabling greater automation and real-time monitoring of production processes. In fact, Industry 4.0 and, subsequently, Industry 5.0 paradigms, have enshrined a shift toward the use of automation processes for production in which machines are increasingly autonomous and independent and in which factories become more efficient and productive, thanks to “smart” technologies remotely connected, which communicate with each other, learn and control production processes [5].

The dynamic market environment has led to an increasing availability of a wide range of low-cost sensors, on-the-edge devices capable of controlling arrays of sensors, collecting and pre-processing the data and smart computing devices to host them. Such technology development brings data processing and storage capabilities closer to their sources, reducing the latencies associated with the Internet and the volumes of data flowing through it. Driven primarily by the expansion of the IoT sector, the market for embedded solutions has evolved significantly over the past decade.

This has fostered a huge expansion of IoT in all aspects of life with various technologies and applications in smart cities, healthcare, smart homes, and enterprises enabling a new technical and organisational framework [6]. In particular, Internet of Things (IoT) technologies have transformed the manufacturing sector, supporting greater automation and real-time monitoring of production processes. These developments have offered numerous benefits, including improved operational efficiency, reduced waste, and greater control over product quality [7].

As a result, a growing interest has emerged on the part of entrepreneurs and manufacturers to invest in the potential offered by the data generated by their equipment, using AI-based approaches to offer value-added services such as predictive maintenance [8], with a need to know how best to implement new technologies to foster digitization on their equipment.

In parallel, the increasing attention to the quality of the industrial environment to ensuring workers’ well-being, sustainability of production and compliance with regulations has supported the development of advanced systems for environmental monitoring and to support informed decision for the optimisation of the manufacturing processes.

During the course of the project activities, both commercial and experimental sensors have been evaluated for monitoring indoor environmental quality (IEQ) and energy performance. Commercial sensors, such as the Gray Wolf Direct Sense II, have been used for their high accuracy and quick deployment capabilities although their drawbacks such as high costs and the need of frequent recalibration procedures could strongly affect their wide employment. With regard to overcoming these limits experimental sensors based on metal oxides like ZnO, SnO_2, WO_3, and TiO_2 thin films obtained by fs-PLD have been surveyed for their ability already shown by the project partners in terms of sensitivity, response time, and room operating temperature. For example, ZnO-based O_3 sensors have demonstrated rapid response under zero-bias conditions even though the occurrence of degradation upon prolonged gas exposure affects their reliability with time [9]. Similarly, WO_3-based NO_2 sensors have exhibited superior sensitivity due to oxygen vacancy mechanisms, even though annealed versions underperformed compared to as-deposited ones showing the occurrence of a trade-off between crystallinity and gas responsiveness [10].

On the other hand, PLD-fabricated SnO_2 films modified by femtosecond lasers can improve stability and surface reactivity toward CO_2 while temperature and humidity variations could strongly affect them [11]. Finally, TiO_2-based thin-film electrodes have shown to be almost inactive without any post-annealing treatment. As a matter of fact, annealing has shown how TiO_2 thin films provide electrochemical response variations with temperature, indicating the importance of thermal treatment for providing stable performance of such material [12]. All these findings have been exploited for surveying metal oxide based sensors in order to obtain precise control of deposition and post-processing conditions for optimizing low cost sensors reliability as well as their lifespan.

Edge and Cloud Computing

IoT devices have limited processing capabilities, making them unsuitable for intensive processing tasks. The limitations of IoT devices in terms of resources such as storage capacity and processing power are being improved by integrating IoT and cloud computing. Emerging cloud-edge architectures enable the distribution and exchange of server resources between the cloud and field devices and support the growing ability of IoT applications to leverage artificial intelligence techniques, through Machine Learning (ML) models executed on the edge [13].

Decentralised (edge computing) and centralised (cloud computing) infrastructures or/and hybrid platforms in which cloud and edge computing are used together to overcome the latency issues of cloud computing [14] and, at the same time, by taking advantage of its large processing resources. Cloud platforms are essential tools for storing and analysing data collected from sensors, offering advanced processing tools, including artificial intelligence, for process optimization. Moreover, cloud platforms improve the ability to process and analyse data, facilitating the optimization of production processes (Figure 1) enabling companies to adapt quickly to changes in operational needs [15].

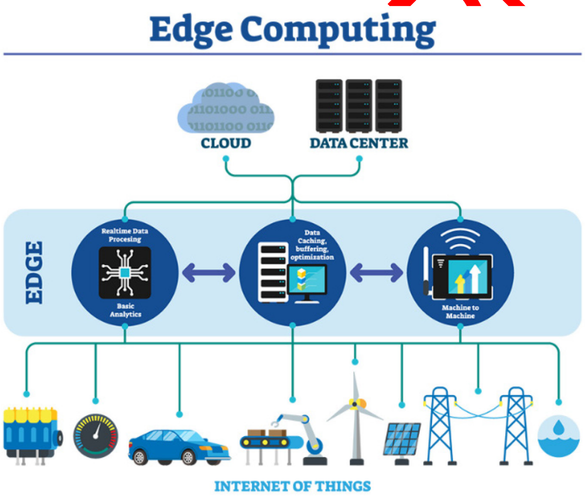

Figure 1. Edge computing brings data processing and storage physically close to the sources (Source: innovationatwork.ieee.org)

Despite the many evident advantages, IoT and sensor technology bring also significant challenges in terms of vulnerability of the systems [16] that may compromise sensitive data and which can hamper a widespread adoption of these technologies [17]. To mitigate these risks, it is imperative to implement robust security measures, including encryption, authentication protocols and strict access controls, to safeguard both IoT devices and the collected data [18].

Interoperability is another significant obstacle to seamless integration of these technologies. With a wide range of devices and platforms in play, ensuring their ability to communicate and collaborate effectively becomes critical. This requires common communication standards that enable interoperability between IoT devices from different vendors.

Process monitoring and sensors

Air quality sensors monitor the presence of gaseous pollutants (CO_x, SO_x, NO_x) and particulate matter ($PM_{2.5}$, PM_{10}) make it possible to verify compliance with safety limits and take timely preventive and corrective measures where necessary. However, air quality sensors can be expensive and require frequent maintenance to ensure accuracy and reliability. Sensors that monitor microclimate parameters such as temperature, humidity, lighting, and noise also provide essential data to ensure and optimise the comfort of work environments, overall improving worker well-being and productivity [19].

Energy sensors, with the ability to capture and transmit data in real time, can enable constant monitoring of consumption, prompt response to unexpected anomalies, and optimise the use of energy resources, reducing operating costs and improving the overall efficiency and environmental sustainability of the company.

In fact, the implementation of advanced sensors, combined with data management and predictive analytics systems, makes it possible to accurately detect consumption peaks, identify process inefficiencies and areas where improvements can be applied. This enables the development of a cost-effective energy monitoring and management system (EMMS) that can provide useful feedback on energy use for energy savings, to facilitate cost savings, and to improve the company's energy use [20].

In addition, the application of IoT is helpful in promoting the digital transformation of the manufacturing sector and enables companies to operate more efficiently, economically and sustainably [21] and support comprehensive optimization of the manufacturing processes.

Artificial Intelligence and Machine Learning

In recent years, industrial management systems have advanced significantly, leveraging AI and ML to improve operational efficiency, which are emerging as key trends in this field [22]. With the exponential growth of IoT, the volume of data generated has reached unprecedented levels, necessitating sophisticated tools such as AI and ML to derive meaningful insights from this wealth of information. These technologies play a crucial role in deciphering complex data models and extracting valuable information, thereby enhancing decision-making processes. In addition, AI and ML have the potential to increase the intelligence of IoT devices, enabling them to learn autonomously from their environment and adapt to dynamic conditions.

These sophisticated systems analyse vast data sets to discern patterns and trends, enabling accurate predictions of future demand. These developments underscore the critical role of IoT and sensor technology in driving innovation in industrial settings [23].

In this framework, Federated Learning (FL) emerges as a new methodology that aims to train ML and Deep Learning (DL) models in a decentralised manner thereby solving three main problems encountered in the artificial intelligence domain: optimisation of the model, data privacy, optimisation of resources communicating only model parameters and some metadata between the federated server and federated clients, rather than transferring the entire data set. FL should therefore be understood as a revolutionary paradigm for artificial intelligence in industry [24], offering innovative solutions to address challenges related to data privacy, collaboration, and computational efficiency to improve manufacturing and supply chain management. Large companies use these algorithms to gain a competitive advantage from insights from the use of these innovative technologies to predict and prevent possible failures in machinery or improve the efficiency of production lines and reduce waste, enabling more sustainable production [25]. Specifically, the following possible applications of ML models were evaluated for the purposes of the project: predictivity and preventive maintenance, process optimization and advanced quality control. Integrating AI and ML into the manufacturing environment not only increases operational efficiency but also enables companies to adapt more quickly to market changes and improve global competitiveness.

Models of monitoring and computing systems

The implementation of specialised monitoring and computing platforms must go through formal procedures that consider and integrate two architectures [26]:

1. *Edge operations*, which includes the instrumentation and technologies for:
- Collect data
- perform local networking,
- perform edge computing, in the Raspberry availability, which enables local computing useful for implementing automated implementations,
- Send data to a platform that enables monitoring, product analysis, and service deployment.

2. *Cloud-based operations*, dedicated to:
- Store and process data into products
- Display results to the user who requests them
- Realize services
- Where possible, suggest useful actions for managing environments through the use and display of thresholds on the values of monitored variables
- Share physical variables and products developed with other platforms in the cloud, when connected platforms use data organised on international standards that allow interoperability.

Amazon Web Services (AWS) and Microsoft Azure are examples of cloud solutions for IoT data management in factories, aimed at improving scalability and data management [27]. Specifically, AWS enables companies to process large volumes of data efficiently and securely, while Azure supports integration with numerous IoT devices, facilitating data collection and analysis. Figure 2 shows a very general architecture of an IoT platform for monitoring.

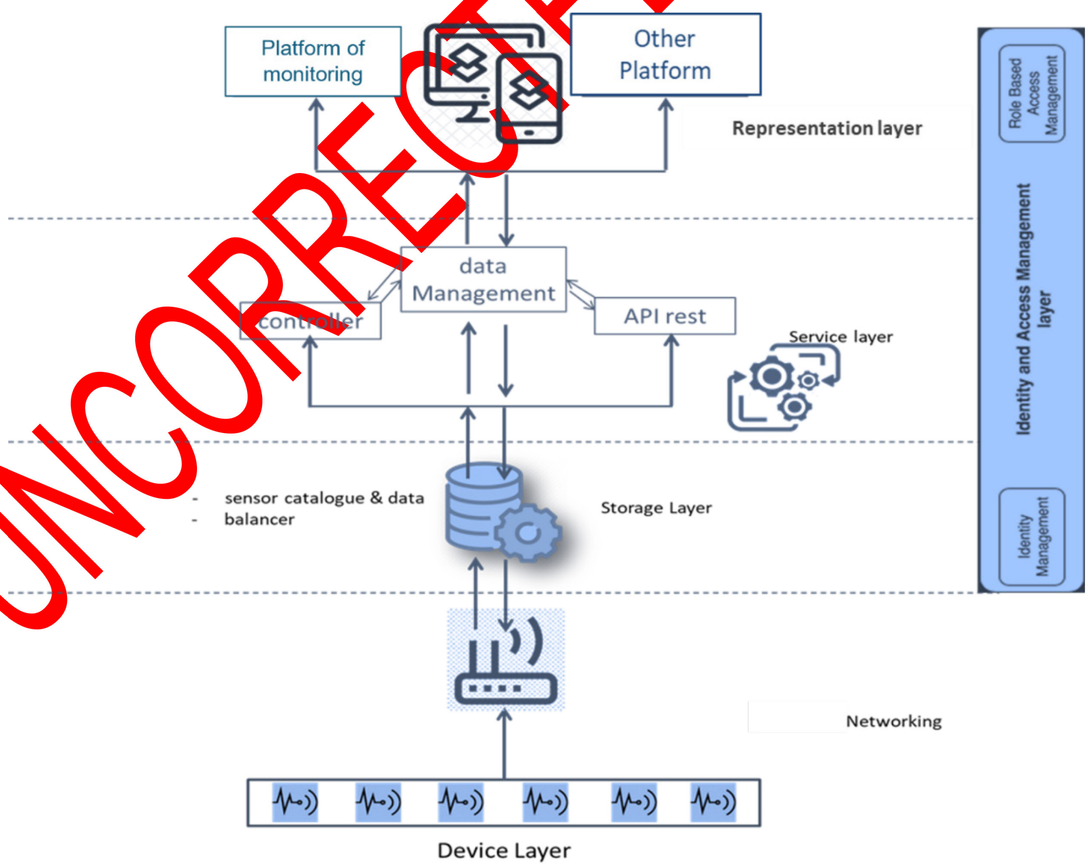

Figure 2. Architecture for a generic monitoring platform

ANALYSIS OF THE NEEDS OF POTENTIAL END USERS AND OPERATIONAL CONTEXTS: IDENTIFICATION OF APPLICATION CASES

The TECsPRO project was aimed to boost advanced IoT technologies to optimise various elements that characterise the individual stages of SME operational processes, with a focus on energy efficiency, product quality, safety and comfort of the working environment, data management and real-time monitoring [28].

In fact, the main objective is to develop a prototype system that can monitor various parameters of interest while pursuing efficiency, eco-sustainability and safety being able to adapt to various production contexts to control and manage both productivity and environmental parameters.

A key issue of the TECsPRO framework was the analysis of the needs of potential end users to identify the application cases of greatest interest regarding factory processes and related opportunities for process improvements in terms of efficiency, quality, production process productivity and work environment.

In addition, the study of monitoring applications aimed to comparatively analyse the production processes that characterize SMEs, compare their effectiveness, identify the benefits brought by the TECsPRO system and provide recommendations for their optimization through the adoption of IoT solutions, emphasizing the platform's characteristics of generality and scalability.

Identification of application cases

The identification of the monitoring cases to test the TECsPRO platform was done through a structured process with several key steps (Figure 3).

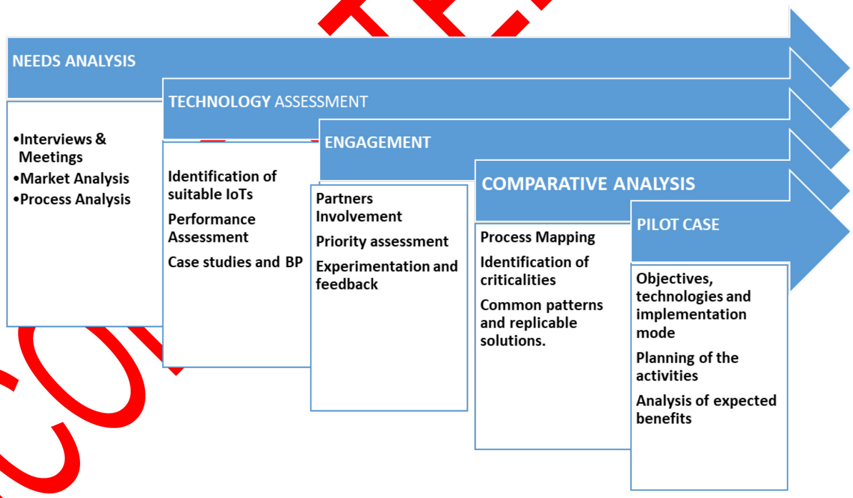

Figure 3. Procedure for identifying application cases

This process ensures that the solutions developed are relevant, viable and meet the actual needs of industrial SMEs [29].

Need analysis. This phase is aimed at understanding the main necessities of industrial SMEs, ensuring that the selected application cases are aligned with real operational needs.

This involves gathering data and feedback from a variety of sources to understand challenges and opportunities for improvement, current regulations, identify market trends, technological developments in manufacturing, and focus on inefficiencies, criticalities, and areas with potential for optimization

Technology assessment. This step is critical for determining which technologies are best suited to address the needs identified in the previous step and assessing their technical and economic feasibility. This includes the identification of suitable IoT technologies including sensors, connectivity platforms and data analysis systems; analysis of their performance in terms of accuracy, reliability, costs and easiness of integration; analysis of case studies and best practices related to the implementation of successful solutions

Engagement. A crucial aspect of identifying application cases is the active involvement of end-users._Active stakeholder involvement is aimed at brainstorming to discuss operational challenges and opportunities for improvement, prioritising and selecting application cases that offer the greatest potential impact, implementing pilot projects to test proposed solutions, and gathering feedback for further optimization.

Comparative Analysis. The purpose of the benchmarking is to identify the most promising applications that can be implemented across different SMEs, thereby improving operational efficiency, working environment and product quality. This involves identifying key steps in operational processes by highlighting their interactions, identifying critical issues and potential inefficiencies that can be addressed through IoT solutions, and comparing operational processes of different SMEs to identify common patterns and replicable solutions.

Pilot Case. Pilot case characterisation provides a clear and detailed roadmap for implementation of application cases, ensuring that solutions are effective and aligned with project objectives. This involves describing, for each application case, the specific objectives, technologies used and how they will be implemented, developing detailed implementation plans including timeline, resources needed and evaluation metrics, analysing expected benefits in terms of improved operational efficiency, reduced costs, increased product quality and improved working conditions

The PLASTICFORM Industry Pilot Site

The methodology shown was applied to delve into the specific needs of a possible end user within the TECsPRO partnership, the PLASTICFORM's Ltd, an industrial injection moulding company of thermoplastic materials mainly for the Automotive manufacturing sector with high automation of production processes [30].

Injection moulding technology, which ensures high productivity and quality, is mainly represented by injection moulding machines ranging in tonnage from 70 tons up to 1,100 tons and other auxiliary equipment to complete the processing cycle and it is one of the most widespread processes for the manufacturing of plastic products (Figure 4).

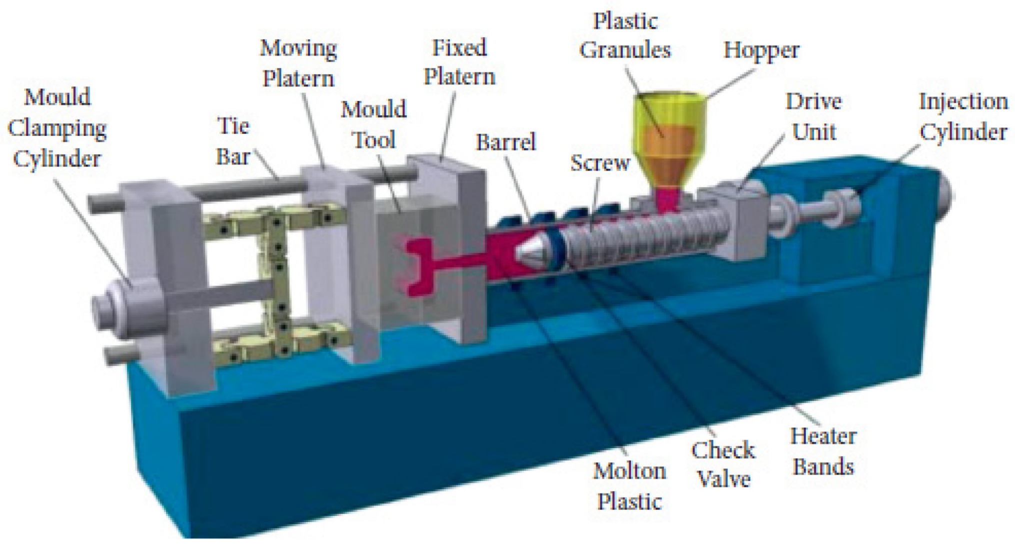

Figure 4. Schematic representation of plastic injection moulding

High production rate and quality are some of the significant advantages of injection moulding. The obtained products also require only minor finishing operations. The entire injection moulding process consists of four phases: filling phase, holding phase, cooling phase and demoulding phase. Injection speed, pressure and mould design are essential to reduce defects. In fact, most of the defects are caused by inadequate injection pressure and temperature control. Therefore, controlling these parameters is essential to reduce imperfections. Moreover, faster monitoring is needed by employing machine learning techniques in injection. Many industries are working to reduce cooling time by implementing changes in mould design and decreasing cycle time to improve industry productivity [31].

Machine learning techniques can also be usefully applied to optimise mould design, reduce cooling rates, and improve the quality of the final product. A series of meetings with stakeholders were held aimed at understanding production needs, identifying the functionalities deemed most important for a monitoring system, as well as the problems to be solved and the improvements deemed essential.

This led to the identification of the monitoring of injection moulding machines, in particular the Engel T180, T550 and T900 presses as use cases for the production process [32].

By analysing the technical characteristics and energy consumption of these machines, it was possible to obtain a detailed and in-depth vision of their performance and specific requirements for monitoring.

The technical characterization of the operating context and the analysis of the specifications and data relating to the machinery are essential for the subsequent phase of defining the specifications of the sensors to be integrated into the continuous monitoring system in the production environment aimed at ensuring the achievement of the established efficiency and quality objectives. This allowed to identify three main application cases to be explored: energy monitoring, safety and comfort of the working environment monitoring (Environmental Indoor quality), optimisation of productivity (overall efficiency improvement). In the following the monitoring objectives and the system are explained in detail.

THE TECSPRO MONITORING SYSTEM: IDENTIFICATION OF SYSTEM REQUIREMENTS AND TECHNICAL SPECIFICATIONS

The TECsPRO monitoring system integrates commercial and advanced sensors into an IoT platform that allows data acquisition, storage and processing of selected parameters to monitor production processes and indoor environmental quality. Predictive models are used to analyse data in order to improve eco-sustainability and efficiency of processes, healthiness and comfort of workplace environments [33].

The sensors included in the network were carefully selected considering their features and feasibility of integration. Both commercial and advanced experimentally obtained sensors were included, and for the latter, an in-depth study of materials and manufacturing methodologies was also carried out.

Energy monitoring

The main objective of this application case is to improve the energy and operational efficiency of the industrial plant by reducing energy consumption related to machinery utilization.

The technologies selected for this purpose are the energy monitoring sensors developed by the industrial partner COING [34] that were installed upstream of the power supply of the Engel injection moulding presses to collect data on energy consumption. These were transmitted to Engel interfaces and sent via LoRa and WiFi wireless communication system [35] to the TECsPRO platform for in-depth analysis.

The expected outcomes for the pilot case are:

- Capability to monitor energy consumption in real time, identify and correct inefficiencies, reducing energy costs
- Optimising resource use by improving the energy and operational efficiency of machines and production processes through continuous analysis of energy data
- Decreased environmental impact through reduced energy consumption (decreased greenhouse gas emissions and improved overall ecological footprint of the company)

Safety and comfort of the workplace environment monitoring: Environmental Indoor Quality

Environmental indoor air quality monitoring in manufacturing production processes is essential to ensure the sustainability of industrial operations, reduce environmental impact, comply with environmental regulations and improve the working conditions of operators.

As concerns air quality, the World Health Organization (WHO) addresses four major air pollutants to assess air quality in confined environments, namely CO_2, CO, CH_2O, and TVOCs [36]. In addition, monitoring of microclimate conditions for thermal comfort (temperature, humidity, and ventilation of the indoor environment) lighting and noise is required to evaluate comprehensively Indoor Environmental Quality (IEQ) [37].

Referring to the PLASTICFORM pilot case, where high temperatures are necessary for plastic moulding, it is important to detect:

• temperature and humidity even in multiple places of the production area

• the presence of harmful gases in the air, such as CO2, carbon monoxide (CO), TVOCs , and formaldehyde, a colourless, irritating gas, commonly used in the production of resins, plastics, paints, adhesives, foams and other materials, whose detection is essential to protect the health and safety of workers.

The identification of commercial sensors that can be integrated into an IoT platform and compatible with the advanced experimental sensors developed in the project is a critical issue, as the definition of protocols for the evaluation and comparison of sensor performance.

Table 1 summarises the parameters to be monitored with the specifications of the minimum operating range for the identification of the sensors.

Table 1. Monitoring parameters and detection intervals

Parameter	Detection Range
Temperature	0-50 °C
Humidity	10-90 %
CO2	>2.000ppm
Formaldehyde	>200 ppb
CO	>200 ppm
TVOCs	>500 ppb

This considers the project objectives and the operational context, among the various systems for monitoring indoor air quality and microclimatic parameters commercially available. Taking into account the technical-instrumental characteristics of the experimental sensors and the peculiarities of the TECsPRO IoT platform, the GrayWolf probe (Figure 5) [38], a high-performance instrumentation, rapid response and easily integrable for the measurement of the pollutants under investigation, was chosen. Moreover, it allows accommodating plug & play sensors (up to 8 in a single probe), optimised for high-end, accurate measurements targeted for different applications.

Figure 5. GrayWolf DirectSense II smart probes [38]

TECsPRO platform's inferential approach

The TECsPRO platform incorporates a supervised machine learning model designed to predict short-term fluctuations in the Indoor Air Quality Index (IAQ), specifically VOC concentration with CO_2 levels continuously collected via IoT sensors made programmatically accessible through a secure API infrastructure. The raw data underwent a rigorous preprocessing phase, including outlier removal, duplicate filtering, imputation of missing values through linear interpolation, and normalization of the variables to ensure balanced feature scaling during the training phase [39]. The Python library Pandas was employed for data structuring and manipulation, leveraging its high-performance dataframes to manage over 500,000 time-stamped records collected over a six-month interval.

The predictive model was developed using the XGBoost algorithm, a gradient boosting framework optimized for structured data and capable of handling missing inputs and multicollinearity natively [40]. The dataset was segmented into 60-minute time windows to capture temporal dependencies, with each window used to predict IAQ trends over the following 30 minutes. This approach aligns with the objectives of indoor air quality monitoring frameworks and can be considered compatible with standards such as ASHRAE 62.1 standards [41], which provides minimum ventilation rates and other measures intended to provide acceptable indoor air quality (IAQ). in working space. Model evaluation was performed using an 80/20 split between training and test sets, with performance assessed through metrics such as Mean Squared Error (MSE) and Mean Absolute Error (MAE). The final configuration, optimized through Randomized SearchCV for hyperparameter tuning [42], achieved an MSE of 2.91 and an MAE of 0.63 in predicting IAQ minimum values, corresponding to an average deviation of approximately 4.2%. These metrics confirm the model's reliability in anticipating critical drops in air quality, supporting proactive environmental monitoring strategies [43] Figure 6

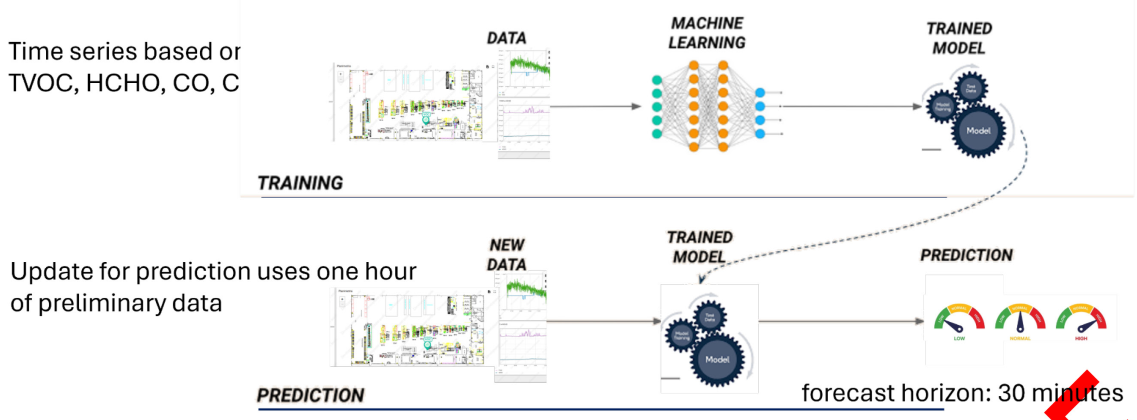

Figure 6. Procedures for IAQ forecast: (A) making a dataset, (B) train the model, (C) running the prediction

The decision to adopt a centralized predictive approach via RESTful API endpoints enabled seamless integration with the dashboard developed by DIGIMAT, allowing real-time visualization of predicted IAQ indicators through modular widgets. This architectural choice favoured scalability and ease of maintenance, ensuring consistency across the data flow. Overall, the machine learning component of the TECsPRO platform contributes a robust analytical layer to the platform, enhancing its ability to support decision-making processes in dynamic industrial environments through anticipatory environmental intelligence.

Optimisation of productivity

The aim is to optimise workflows, going to reduce cycle times and increase overall efficiency. In fact, technologies make it possible to monitor and control each stage of the production process accurately, identifying possible intervention scenarios aimed at improving processes in terms of productivity and ergonomics, consistent with the quality objectives of the final product. Engel interfaces properly installed and configured on injection moulding machines are able to return reports containing numerous parameters related to the different stages of the injection moulding process. In particular, the EUROMAP 77 interface [44] allows the system to monitor various parameters in real time for being integrated into the TECsPRO platform and provide their detailed analysis.

The potential benefits from monitoring production processes are:

- reduction of rejects: monitoring product quality in real time, detecting and correcting defects

- increased product quality: more accurate and timely quality control results in higher quality end products

- improved customer fulfilment: higher quality and less defective products result in greater customer trust and satisfaction, improving the company's reputation.

Advanced experimental sensing: upgrade, engineering and integration

The TECsPRO project, with KETs, also aimed to evaluate the impact of innovative methodologies to produce advanced materials in the form of thin films, nanostructured and molecular systems, as well as micro batteries for their power supply, microclimate-environmental monitoring and energy saving [45].

A key element in the development of the experimental activities was the phase of analysis and study of the state of the art of IoT technologies, focusing on the application contexts of the manufacturing sector by combining project-specific aspects together with the new scientific orientations based on KETs.

In the field of environmental sensors, the project investigated the possible use of advanced materials such as tungsten oxide (WO_3), known for its high sensitivity and stability for gas sensing. With this aim the deposition techniques such as Pulsed Laser Deposition (PLD) was used to obtain thin films with controlled morphologies and compositions, improving the accuracy of environmental sensors and their ability to monitor critical parameters such as air quality and toxic gases, thus contributing to more effective environmental management and improved safety [46].

In terms of energy-saving applications, materials with optimised thermoelectric properties [40] have been studied for increasing the efficiency of converting heat to electricity by thermal energy recovery. The goal pursued is to achieve competitive performance by exploiting innovative techniques such as pulsed laser deposition even due to the employment of femtosecond laser beams [47]. These studies can potentially contribute to a technological improvement of thermoelectric modules aimed at fulfilling the need in achieving higher energy efficiency and, consequently, lower production costs [48]. Preliminary surveys have elucidated the technological process to be tackled for producing a prototype thin-film cell that could be able to meet the electronic performance required for a specific material to be developed. The optimal strategy for enhancing device performance and advancing industrialization is currently under evaluation. This strategy aims to integrate with the ongoing implementation of the TECsPRO demonstration prototype, focusing on meeting the requirements for achieving a higher Technology Readiness Level (TRL5) through rigorous testing in operational environments.

THE TECsPRO SYSTEM: DESIGN, DEVELOPMENT AND IMPLEMENTATION

The identification of system requirements followed a structured and well-established path, based on the diagram shown in Figure 7.

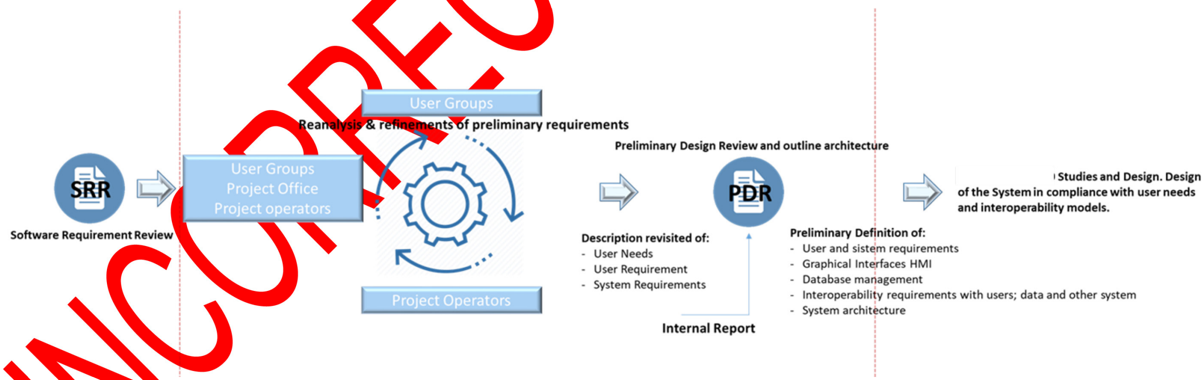

Figure 7. Block diagram for the identification of requirements of the TECsPRO platform

The preliminary analysis of PLASTICFORM's needs made it possible to define the requirements of the system and the services to be provided by the IoT platform.

The following aspects have been studied: *the context*, i.e. the market reference in which the project platform is developed; *the objectives of use* (monitoring of microclimatic variables and air quality parameters to monitor the comfort and environmental health status of working environments); *the feasibility* (difficulties that may be encountered during the functional design phase, definition of possible procedures in relation to the conditions that the system must meet); *propaedeutic and modularity*, to make the platform open to the implementation of additional modules.

In addition, the formalization of the requirements concerned the definition of

- *System properties*: quality of the software in terms of scalability, interfaces, response latency, security, etc. (non-functional requirements)
- *the services to be provided and how* (functional requirements).

The definition of the requirements is the first step in the design and development of the platform, and interfaces with the previous steps in the process of exchanging and refining the rules that the platform must satisfy.

The scalability of the TECsPRO platform can be addressed at both hardware and software levels. The system supports the addition of new sensor nodes through dynamic registration in the MQTT broker and device management via a scalable back-end interface. Cloud services, instead, handle data ingestion, storage, and analytics through a modular architecture, which could be stress-tested during the pilot implementation at PLASTICFORM Ltd

The edge-cloud design allows pre-processing at the edge (e.g., Raspberry Pi), reducing bandwidth usage and improving latency. This enables real-time monitoring of energy data, environmental parameters, and gas concentrations without overwhelming central servers. The inclusion of AI/ML modules for predictive maintenance further enhances scalability in terms of functionalities.

From a sensor technology perspective, the integration of advanced materials like WO3, SnO2, and TiO2 has been evaluated to provide high potentialities for self-powered or energy-efficient sensors, supporting long-term scalability through energy autonomy [49]. These technologies can open avenues for future deployment in distributed monitoring networks within industrial SMEs, thereby aligning with Industry 5.0 goals and enhancing the platform’s readiness for broader industrial adoption.

System Requirements: definition of the communication network specifics between the sensors and the Cloud platform

The specifics of the communication network for collecting data from sensors and sending it to the reference platform in the cloud were defined based on its suitability for the application context. In particular, a wireless communication network was chosen for its ease of integration into production processes.

A wireless communication network is characterised by several aspects, including

- *Coverage and range*: its ability to provide a reliable signal over a given area
- *Reliability*: its ability to provide a stable, uninterrupted connection that is resistant to interference
- *Latency*: the delay between the transmission of a data packet and its reception.
- *Security*: a critical aspect of wireless networks that involves protecting data transmitted over the network from unauthorized access, eavesdropping, and manipulation.
- *Power Consumption*: In the case of battery-powered devices, it is important to evaluate the power consumption of network nodes to ensure adequate battery life and optimize energy efficiency.
- *Data transfer speed* (data rate): It is important to determine the maximum data rate supported by the network to understand its performance and transmission capacity.

There are many wireless communications technologies available, each with its own unique characteristics.

In the industrial application context, sensors distributed in the production area collect data on temperature, humidity and energy consumption, which introduces the following constraints: reliable network coverage; resistance to interference; data acquisition intervals that allow low-bandwidth communications (e.g., every 10-30 minutes); energy consumption to be minimized for battery-powered sensors. In this context, LoRa was selected as the preferred technology due to its characteristics: long-range coverage (up to several kilometers); low bit rate communication (enough for periodic sensor readings); extremely low energy consumption;

excellent resistance to interference. This choice was also made taking into account the characteristics of the monitoring network (hard-to-reach battery-powered sensors, infrequent data transmission). Furthermore, to meet the different needs of the facility, a modular and adaptable dual-connectivity system was designed, integrating LoRa with the existing Wi-Fi infrastructure to serve areas with stable power and strong signal coverage and handle high-bandwidth data. This hybrid communications architecture enabled the implementation of a scalable, flexible and energy-efficient system, ensuring both wide coverage and high data capacity where needed, balancing performance and efficiency, and meeting the constraints related to different areas within the production environment.

The TECsPRO monitoring platform [50] is shown in Figure 8. It includes:

- 3 nodes for monitoring temperature and humidity with LoRa communication, appropriately distributed within the production area
- 1 node for monitoring air quality within the process, specifically focusing on parameters such as CO2, Formaldehyde, CO, and VOC, with WiFi communication
- 3 nodes for monitoring the energy consumption of three different machines via LoRa technology
- 1 node for monitoring the production process with LAN connectivity

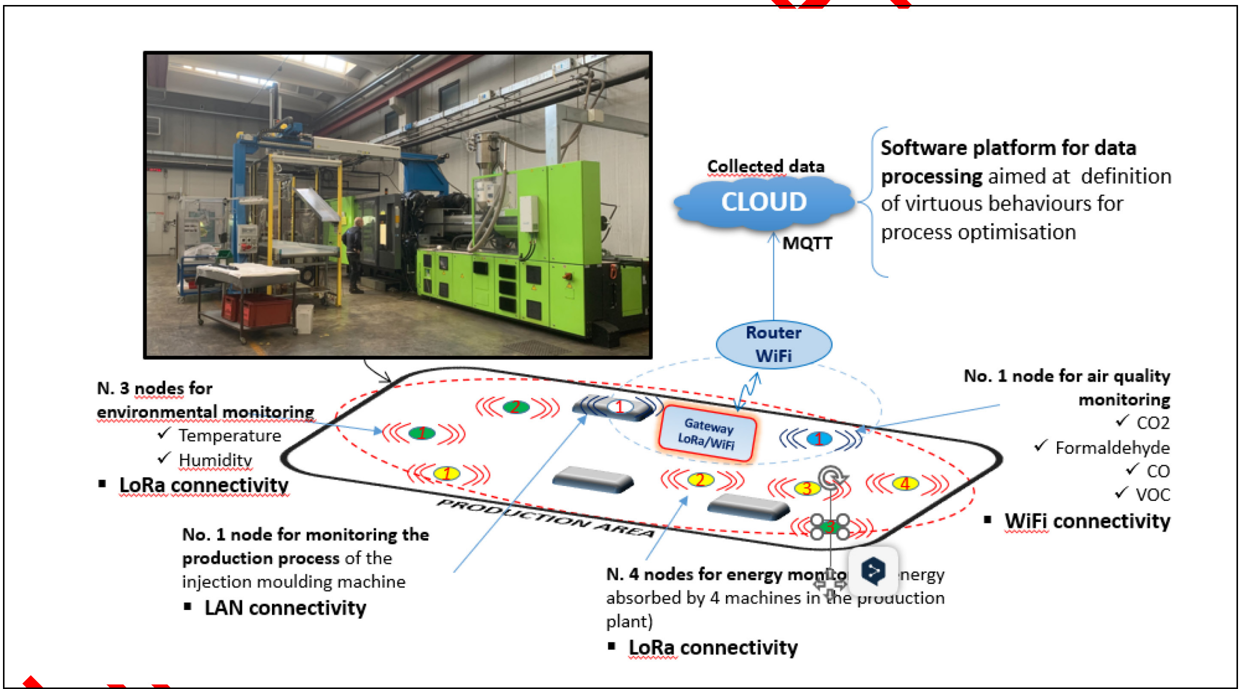

Figure 8: Architecture of the TECsPRO monitoring platform

Among the different communication protocols available (e.g., Hypertext Transfer Protocol HTTP, Message Queuing Telemetry Transport- MQTT, Constrained Application Protocol – CoAP, socket Transmission Control Protocol - TCP and User Datagram Protocol - UDP) [43] the MQTT protocol has been considered the most suitable for transferring data to the cloud based on the project needs, being suitable for applications that require efficient and scalable communication between distributed devices. MQTT is in fact a lightweight messaging protocol, designed for devices with limited resources and unstable network connections. It uses a publish/subscribe model, where clients subscribe to specific topics and receive messages published to those topics. It uses a publish/subscribe model and is commonly utilised for communication between IoT devices and cloud platforms, enabling reliable real-time data transfer with low network overhead.

To achieve the project's objectives, a combination of commercial and experimental sensors (e.g., GrayWolf DirectSense II) and experimentally developed ones based on metal oxides (i.e. SnO_2, ZnO, WO_3) were in turn integrated and surveyed. Although commercial sensors offer plug-and-play usability and stable calibration standards these are not widespreadly employed because of their high costs and frequent recalibrations needed for maintaining accuracy under harsh industrial conditions. Conversely, new low cost experimentally developed sensors, such as ZnO-based ozone detectors and WO_3-based NO_2 sensors developed via Pulsed Laser Deposition (PLD), can display high sensitivity and fast response at room or moderate higher temperatures. Nevertheless, the metal oxide sensors are still under development since they show surface degradation upon long-term gas exposure, such as ZnO films after ozone exposure, lower reproducibility, and reduced lifespan without protective coatings or encapsulation. With regard to other type metal oxide sensors, like SnO_2 ones, reliability can be improved when surfaces are structured by fs-laser treatments, although their performance can still be influenced by microclimatic variables such as humidity and temperature fluctuations. Finally, TiO_2 thin films display how post-deposition treatments can strongly affect electrochemical activity, underscoring the importance of tailored annealing and encapsulation to ensure sensor durability and performance consistency.

The integration of commercial and experimental sensors within the IoT platform has induced significant challenges related to interoperability and signal standardization. In fact, commercial sensors typically support standardized communication protocols (e.g., Modbus, MQTT), while to exploit metal oxide ones obtained experimentally do require custom analog-digital interfaces and specific calibration procedures. For example, integration of experimental WO_3-based NO_2 sensors need tuning the data acquisition system to handle varying signal amplitudes and response times. However, communication compatibility between multi-vendor devices demanded careful selection of protocols (MQTT was preferred for low-latency, scalable transmission) and the development of middleware layers to unify data formats. The platform's modular architecture, based on open standards, allowed custom APIs and plug-ins to be built for non-standard sensors. This modularity, along with a hybrid edge-cloud architecture, can support dynamic sensor registration, flexible data handling, and sensor-specific threshold management, effectively addressing interoperability concerns.

Cloud platform specifics

The purpose of the monitoring platform is to allow easy and immediate monitoring of the evolution of the system's environmental and operating variables, and to identify any factors on which to take action to improve the production process and the comfort of the working environment.

Continuous analysis is performed with the goal of creating and improving the IoT platform requirements in relation to the project needs.

Requirements definition is the first step in the process, expressing what stakeholders - end users, suppliers, project teams, developers, etc. - want from the new system - need from the new system, and what the system must do to meet those needs.

The requirements definition process consists of four activities:

- Requirements Elicitation;
- Requirements Specification;
- Requirements Verification and Validation;

- Requirements Management.

In particular, the requirements specification aims to create formal requirements models. All requirements including functional and non-functional requirements and constraints are specified through models in their entirety and without ambiguity.

Non-functional requirements (NFRs) concern the set of specifications that describe the system's operation capabilities and constraints while functional requirements of the platform concern the properties of the software system in relation to certain services or functions. With reference to the TECsPRO IoT platform, non-functional requirements were identified with a stakeholder consultation process, general functional requirements and specific requirements related to the macro-functionalities were defined according to the expected performance of the IoT platform. Macro functional requirements related to the TECsPRO monitoring platform are reported in Table 2.

Table 2. IoT Platform Requirements

ID	Name	Description
TEC-FR-PLT-0010	Sensor localization	Localization of nodes/sensors on a map
TEC-FR-PLT-0020	Environmental data acquisition	Data Acquisition by sensors: - Temperature - Humidity - CO - CO2 - TVOCs - CH2O
TEC-FR-PLT-0030	Energy data acquisition	Acquisition of energy consumption data - Total energy - Power consumption
TEC-FR-PLT-0040	Sensor data display	Real-time user monitoring of the progress of data acquired by the installed sensors
TEC-FR-PLT-0050	Alarm threshold settings	Setting a minimum and maximum threshold for each parameter acquired through the various types of sensors
TEC-FR-PLT-0060	Threshold Exceeded Notification	Notify the user of values outside the acceptable range relating to the monitored parameters
TEC-FR-PLT-070	Air Quality Index	Forecasting of the air quality index inside the production plant

The realisation of the prototype went through the steps shown in Figure 9

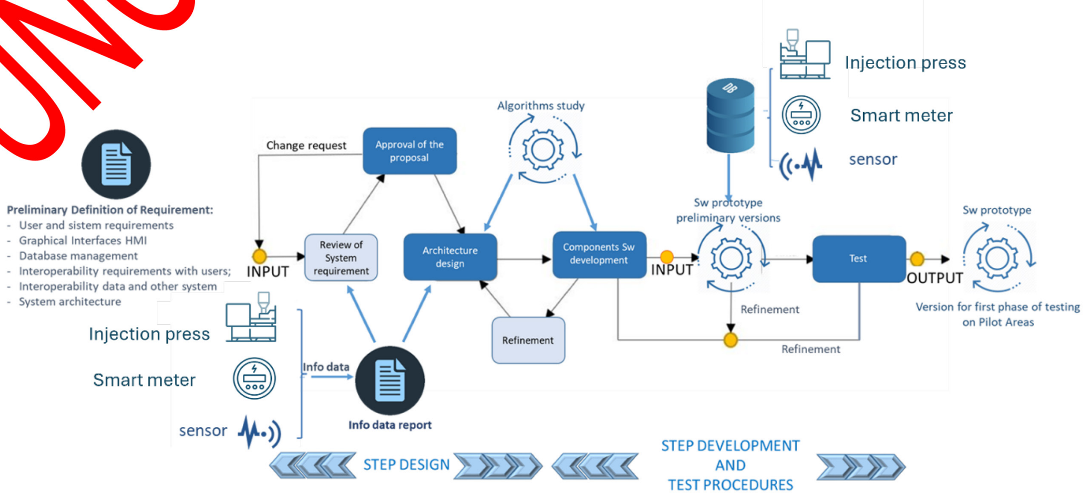

Figure 9. Block diagram of procedures for the design, development, and laboratory testing of the TECsPRO platform

Step design The requirements, defined during the preliminary stage, were used in the design of the TECsPRO System, which considered the main attributes belonging to the IoT paradigm [51]:

- *Interoperability and open approach* through data format and TLC systems. The standards used allow sensor sharing with sensor networks in a simple, inexpensive and effective way. Where interoperability conditions should not be canonical, sharing is attempted through integrations with custom interfaces [52].
- *Multidisciplinary*. The system allows multi-channel, multi-sensor analysis, operating on different physical quantities, and enables a multidisciplinary approach to prediction and analysis of the phenomena being monitored [53]
- *BIG and Open Data*. The data are available to those who manage the monitored areas, who can make use of the information on the observed variables, information that is useful for the management of case study environments. The data can be downloaded locally for use by researchers interested in descriptive analyses of environments and/or in developing new models for predictive scenarios [54].
- *Multi-scenario*. The platform supports: microclimate and air quality analyses; analyses of proper machine operation and energy consumption. The multidisciplinary approach makes the system extensible to diverse and other applications.
- *Security and quality*. The system meets the standards of quality, data availability and navigability of the platform, with simplified access to products and services even for non-specialized users.

Step Development & Test Procedure. The platform design was followed by the implementation phase with appropriate technologies and development environments. The system was tested by means of standard procedures and dry tests, which were useful to certify its proper functioning in terms of validating the exposed requirements.

Since scalability has been established as a fundamental requirement in the design of the project platform it follows that cloud-edge architecture can support modular sensor integration, leveraging lightweight protocols (MQTT, LoRa) for low-power, long-range communication and scalable cloud services for data storage and analytics. The platform accommodates increased sensor density through decentralized edge nodes (e.g., Raspberry Pi units) that perform local pre-processing before cloud ingestion. This architecture reduces data congestion and latency, allowing the system to manage high-frequency sampling rates or simultaneous multi-sensor acquisitions. The underlying architecture has already demonstrated to be adaptable to integrate thin-film gas sensors (e.g., WO_3 for NO_2, ZnO for O_3) and energy sensors on injection moulding machines. Future expansions could include microbatteries (e.g., based on TiO_2 electrodes) and thermoelectric modules for energy harvesting, aligned with the project's long-term vision of self-powered IoT nodes. Moreover, the system supports AI/ML modules for predictive analytics, anomaly detection, and prescriptive maintenance, thus enabling further extensions in functionality without requiring its major redesign.

INTEGRATED PLATFORM FOR ANALYSIS MONITORING AND OPTIMIZATION OF PRODUCTION PROCESSES

The TECsPRO IoT system aims to become a model for industrial environment monitoring. The system is useful for energy efficiency strategies, environmental sustainability and indoor quality of industrial buildings, monitoring of machinery operation.

The instrument is aimed both at those who manage work areas where industrial machinery is present, and at research institutes that can download data locally for analysis with their own software.

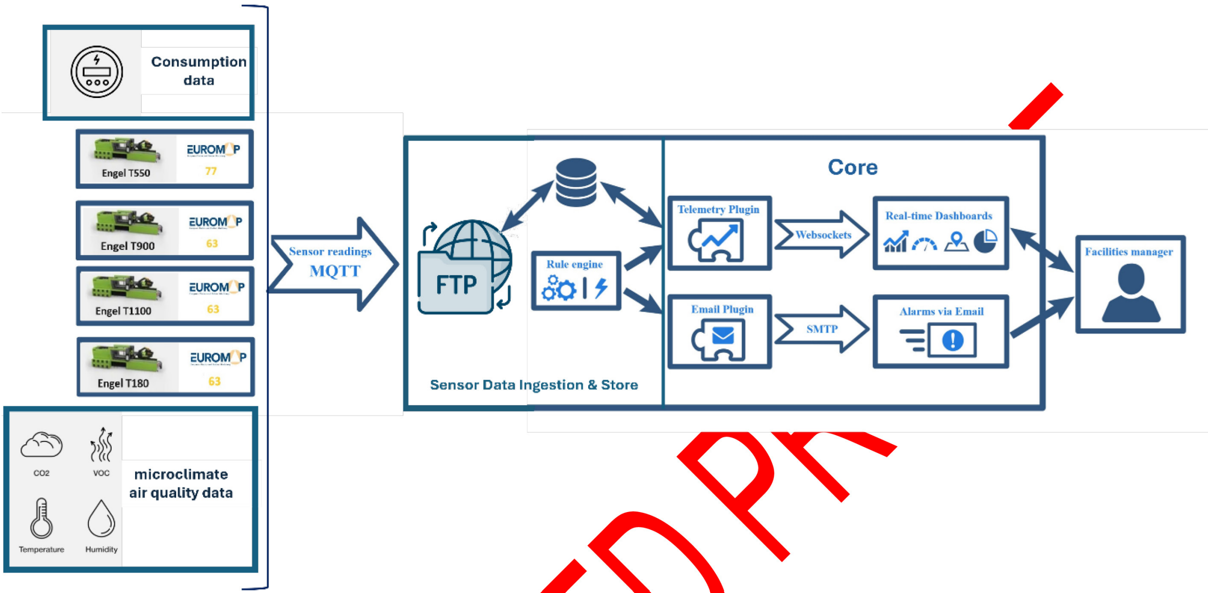

Figure 10. The TECsPRO IoT Monitoring system

Figure 10 shows the architecture of the implemented TECsPRO IoT monitoring system [50]. Data acquired and pre-processed locally (edge mode) are collected, organized according to MQTT protocol standards and sent to the ftp server, which performs ingestion and cataloguing of the received files.

The database organisation is useful for data aggregation, monitoring and control requests over the Internet, coming from the user and executed through the application layer and the module with Back-End API components for the realisation of products and services to be exposed in the platform.

Within Sensor Data Ingestion & Store, the rule engine's job is to perform transformations on the messages received by the platform when communicating with external systems that require specific formats, and it can initiate actions (triggers) such as sending notifications in case of alerts.

- The Core Component governs the logic of the entire system and contains a set of core services that enable the management of the following entities
- Devices and their credentials
- Rules chains and nodes
- Tenants and accounts, including custom layouts
- User-friendly interface, widget and dashboard
- Alerts and notifications that can be triggered by queries to detect outliers and/or anomalies
- API Gateway is the API component for registered users to manage attributes and retrieve time series data using WebSocket and REST APIs.

Figure 11 (A) shows the platform functionalities useful to the user managing the monitored industrial areas [55]. The platform displays a dashboard that includes:

- General Plan -: a map that groups all the installed devices, distinguishing them by type: Energy Meter, VOC, Smart Sensor, Engel 63 and Engel 77. Each marker offers a popup where the main values are listed and a link to analyse the details of each sensor.
- Sensors -: a table with the list of all the devices; by clicking on each of them, the user can enter the detail of the selected sensor, where the values of the last measurement made are displayed, Figure 11 (B).
- Alerts -: system for reporting significant changes in microclimate sensors.
- Image and main references of PLASTICFORM SRL.

For each sensor, it is possible to request time series of collected variables over a time interval of the user's choice, alarms generated in the selected period and values associated to the last measurement acquired (Near Real Time Monitoring), Figure 11 (C) and (D).

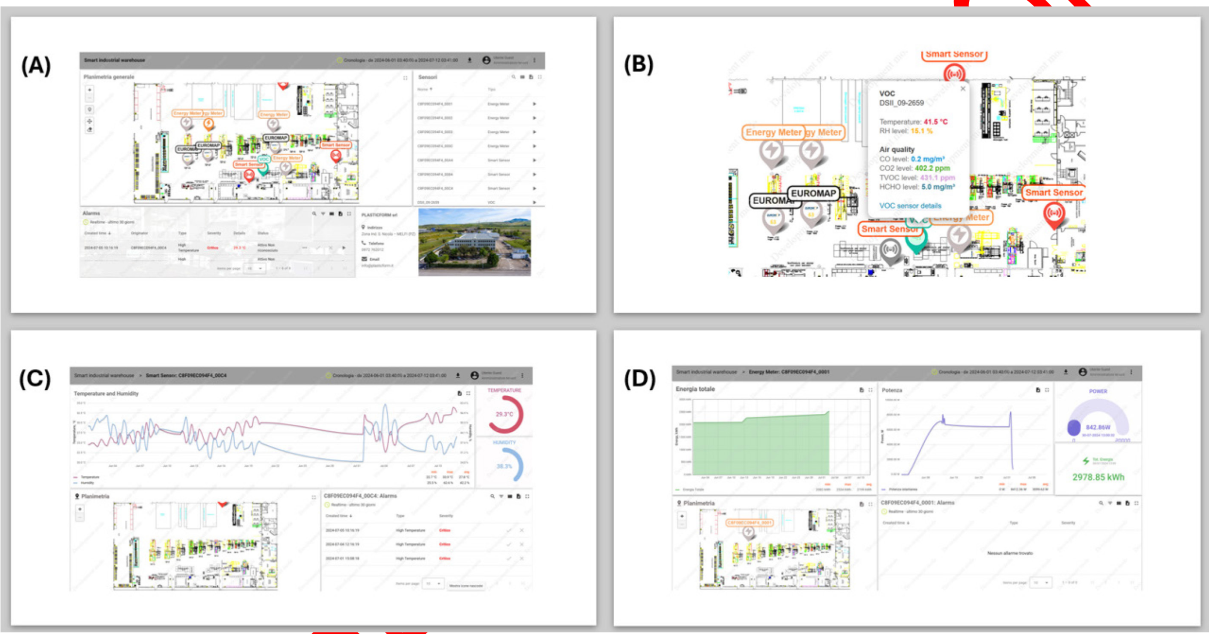

Figure 11. The TECsPRO IoT platform with examples of data exploitation (A) Smart Industrial Warehouse Dashboard, (B) Marker sensor detail and link to last measurement (near real-time monitoring), (C) e (D) Detailed Smart Sensor: time series and last measurements for microclimate sensor and energy metering.

Figure 12 shows the predictive functionality on the TECsPRO system platform. The prediction is applied to air quality related variables and makes use of the training model (explained in section TECsPRO platform's inferential approach) that is updated with one hour of preliminary data, to act on a 30-minute time horizon. The result is an index of 4 items that define a relationship with the state of the environment from low quality that can be associated with machinery activity, to moderate, medium, and high, and for each of these items an activity should be associated such as ventilating the room before entering when the air quality index is found to be low.

Figure12. Monitoring dashboard: alarm table and forecast panel

IOT MARKET ANALYSIS AND EUROPEAN POLICY CONTEXT

The TECsPRO platform is aligned to market development that is increasingly looking at IoT business models applied, even in an innovative way, to different areas of society such as those related to the monitoring of living environments, work environments, areas of cultural and naturalistic interest, monuments, etc.

The European Policy Framework for IoT aims to support the development and integration of IoT technologies within the EU within the Next Generation Internet of Things (NGIoT) initiative, coordinated through the EU-IoT Hub [56] which key strategic objectives are Fostering collaboration across industrial sectors, SMEs, academic institutions, and research centers; creating standards, guidelines, and best practices to support IoT deployment at scale; transitioning toward IoT infrastructures that are secure, scalable, intelligent, and interoperable; embedding emerging technologies such as 5G, Artificial Intelligence (AI), Edge computing, and block chain into IoT systems.

In parallel, both global and European IoT market trends enhance a remarkable increase. As reported by IoT Analytics, In the report “Global IoT Enterprise Spending dashboard” [57], in 2023, the enterprise IoT market reached USD 269 billion, growing at a 15% Compound Annual Growth Rate (CAGR). A temporary deceleration to 12% CAGR is observed in 2024, attributed to post-pandemic inventory backlogs in the hardware supply chain. Forecasts for 2025–2030 predict a renewed CAGR of 15%, with a total market value of approximately USD 301 billion, largely driven by the automotive sector.

Between 2022 and 2025, enterprise investments have increasingly prioritized software Development for IoT platforms and middleware; Cybersecurity Services to ensure data protection and infrastructure resilience; managed IoT Services and AI-driven analytics for process automation and control with a predominance of major IT vendors—Microsoft, Amazon, SAP—and integrators like Avanade and Cognizant that are leading market expansion through AI-focused initiatives and cloud-based IoT solutions [58]. The number of connected IoT devices grew from 13% to 15% Compounded Average Growth Rate) with a forecasted 15% CAGR through 2030, despite macroeconomic pressures (e.g., inflation, interest rates, geopolitical instability) [59]. Among telecommunications technologies cellular IoT technologies experienced 24% Year Over Year -YoY growth in 2023, surpassing other IoT communication standards. In this context Low Power Wide Area Networks (LPWAN)—notably LoRa-WAN— appear to be very competitive and cost-effective for the deployment of large-scale sensor networks, especially in smart monitoring and intelligent automation, due to their key features as low power consumption, minimal infrastructure costs, scalability and support for diverse sensor types. This framework paves the way to the commercialisation of the TECsPRO platform that, although designed for a specific use case, is fully in line with market trends due to its intrinsic features, modularity and scalability [60].

CONCLUSIONS

The IoT market is undergoing significant transformation, underpinned by policy support from the European Union and a shift in enterprise investment toward software, AI, and low-cost communication technologies. The coming years will likely see accelerated innovation, especially in verticals such as automotive, smart infrastructure, and edge-AI systems, with Europe positioned as a strategic leader in shaping the global IoT landscape

In this framework, the objective of the TECsPRO project was to design and implement in a real production environment a modular and adaptable system to allow the control of critical parameters for the efficiency and environmental sustainability of the production processes. A main goal was to apply a "prescriptive analysis" approach also to small companies, which are the backbone of the industrial sector of most European countries.

In this context, the integration of advanced and innovative sensors together with AI and ML methods offers numerous benefits and represents a significant step towards Industry 5.0 and digital innovation in the manufacturing sector. Improvements in energy efficiency, product quality and workplace safety lead to a significant reduction in operating costs and an increase in competitiveness, taking full advantage of IoT technologies and contributing to a more advanced and environmentally responsible technological future

In fact, the TECsPRO project represents a paradigm shift in the way industrial monitoring systems can be designed, developed and implemented in manufacturing environments, particularly in the small and medium-sized enterprise (SME) ecosystem. Indeed, the project's most significant contribution lies not in the creation of an innovative technological solution, but in demonstrating that intelligent and prescriptive monitoring systems can be designed in a modular manner and scaled effectively to meet the constraints and needs of even the most resource-limited actors within the industrial landscape.

From an industrial perspective, the project highlights that sustainability and efficiency are co-dependent key dimensions of modern competitiveness. The insights generated—ranging from sensor miniaturization to systemic data validation procedures—suggest a future in which environmental intelligence is embedded as a foundational layer of the manufacturing process, shaping not only products but also the organizational culture that surrounds their creation.

This initiative unveiled the latent potential for widespread access to advanced IoT, AI and ML-based solutions traditionally confined to large enterprises. By integrating technological innovation with user-centred adaptability, TECsPRO lays the foundations for a new industrial paradigm that transcends simple automation and moves towards anticipatory, collaborative and human-centred production ecosystems, emblematic of Industry 5.0.

From a strategic perspective, TECsPRO provides a replicable and scalable framework that challenges conventional approaches to industrial innovation. It promotes an ecosystem vision that incorporates market readiness (through TRL progression), economic forecasting (through market analysis and SWOT analysis) and long-term profitability (through KPI definition and financial planning over a 10-year horizon). These elements are not merely results of a project, but signals of a broader industrial transformation.

Ultimately, TECsPRO confirms that the future of industrial monitoring lies more than in technological advancements, in the combined use of smart tools, standardized validation methodologies, and collaborative networks that reimagine the interface between human intelligence and machine autonomy that supports a more resilient, inclusive, and environmentally conscious manufacturing future.

ACKNOWLEDGMENT

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NOMENCLATURE

Acronyms/abbreviations

Amazon Web Services - AWS

Artificial Intelligence - AI

Constrained Application Protocol – CoAP,

Deep Learning – DL

Energy Monitoring and Management System - EMMS

Federated Learning – FL

Hypertext Transfer Protocol - HTTP

Indoor Environmental Quality - IEQ

Information Technology – IT

Internet of Things - IoT
Key Enabling Technologies – KET
Machine Learning - ML
Message Queuing Telemetry Transport- MQTT,
Pulsed Laser Deposition (PLD)
Small and Medium Enterprises – SMEs
Technology Readiness Level -TRL
Transmission Control Protocol - TCP
User Datagram Protocol - UDP
World Health Organization - WHO

Symbols
Carbon monoxide - CO
Carbon dioxide - CO_2
Carbon oxides - COx
Nitrogen Oxides - NOx
Particulate Matter - $PM_{2.5}$, PM_{10}
Sulfur oxides SO_x
Tungsten Oxide - WO_3
Total Volatile Organic Compounds - TVOCs

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