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ARTIFICIAL INTELLIGENCE AND DIGITISATION IN THE AEC SECTOR: FROM DATA COLLECTION TO PREDICTIVE OPTIMISATION

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Abstract

In recent years, the construction industry has undergone a profound transformation thanks to the integration of advanced parametric modelling methodologies and the adoption of increasingly sophisticated digital technologies. These tools have redefined design, construction and management processes, improving operational efficiency and opening new perspectives for predictive maintenance and infrastructure resilience. Advanced data analysis, combined with the simulation of future scenarios, now makes it possible to develop more effective intervention strategies, optimizing energy performance and significantly reducing the environmental impact of the AEC sector. However, despite huge investments in digitization and sensor technology applied to buildings, the effective management of the large amount of data collected still represents an open challenge. Currently, there is a lack of an established paradigm to transform this data into concrete operational information and optimized decision-making processes. In this scenario, Artificial Intelligence (AI) emerges as a revolutionary element, capable of filling this gap and offering advanced tools for real-time data processing and interpretation. Indeed, the use of predictive algorithms and machine learning techniques makes it possible to improve the life cycle management of buildings and infrastructures, optimize the use of resources and increase the overall sustainability of the sector. This research explores the role of AI in the evolution of the AEC sector, outlining a methodological framework that transforms digitization into a concrete operational advantage, with tangible impacts in terms of efficiency, sustainability and innovation. A further added value of this approach lies in the possibility of optimizing the distribution and installation of sensors, avoiding waste and unnecessary investments. Through AI-based analysis, it will be possible to accurately identify structures requiring advanced sensor integration and develop reliable predictive models for the design and maintenance of similar buildings. This method will not only improve maintenance strategies, but also contribute to a more intelligent and sustainable management of the building stock, rationalizing economic and material resources.

Keywords: ai, digital twin, iot, machine learning, maintenance.

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1. Introduction

In recent decades, the construction industry has been undergoing a significant digitalization process with the aim of improving the efficiency, sustainability and comfort of built environments [1]. In particular, the scientific and technological advances that are affecting the construction sector have given rise to the term Construction 4.0, a concept that arises from the awareness of the need to digitalize the entire supply chain and is based on four fundamental concepts: digital data, automation, connectivity and digital access [2]. The main technologies that drive this digital transition process include Building Information Modeling (BIM), the Internet of Things (IoT), the Digital Twin and, today increasingly dominant, Artificial Intelligence (AI). BIM presents itself as a new approach that has drastically changed traditional design, construction and maintenance practices thanks to its ability to incorporate both physical and functional characteristics of buildings [3, 4]. However, despite its great potential, BIM and its static nature have been overtaken by the advent of the Digital Twin, which, thanks to the integration of IoT sensors, provides a virtual model of a physical system that continuously evolves thanks to a

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bidirectional connectivity with its physical counterpart [5]. Therefore, this new tool, offering a dynamic and interactive model capable of reflecting in real time the state and behavior of building components, lays the foundations for the application of maintenance strategies, such as predictive maintenance, which consist in the formulation of forecasts on the residual useful life of components, thanks to the processing of data resulting from continuous monitoring. It is also necessary to underline that technological progress in recent years has led to a growing interest of the scientific community in AI and its subfields. In particular, many researchers in the Architecture, Engineering and Construction (AEC) sector are experimenting with Machine Learning (ML) techniques for predictive maintenance. Indeed, due to its characteristics, it is possible to optimize and effectively implement predictive maintenance through the integration of ML and IoT technologies: the installation of IoT sensors on buildings allows to monitor critical parameters in real time and transmit data to a central processing system, where ML algorithms can analyze data, formulate predictions and plan maintenance interventions in an optimal way [6]. It follows, therefore, that these innovative technologies inaugurate a new phase for predictive maintenance, based on the early management of inefficiencies and failures, thus allowing to optimize building performance and increase the well-being of occupants [7]. Inserting itself in the context of the growing digitalization of the AEC sector and the implementation of cutting-edge technologies for predictive maintenance, this study proposes a methodology to develop a tool to support the management and maintenance of building components and that integrates the main innovative technologies. In order to validate part of the methodology exposed, an application developed through Autodesk Tandem is presented. on a case study, proposing an experimentation focused on the components of building plant systems. In particular, the case study concerns a Heating, Ventilation and Air Conditioning (HVAC) system of a school building. This application shows how the use of IoT sensors for continuous monitoring allows to fully exploit the benefits of Digital Twins, which can make maintenance procedures more efficient and minimize operational interruptions, thus ensuring service continuity. In particular, the analysis of critical operating parameters (flow rate, air speed, temperature), especially in moments of lower efficiency, provides information on the operating status of the system, thus allowing to evaluate the optimal timing to perform maintenance interventions.

2. Literature review

The fourth industrial revolution, known as Industry 4.0, is now a consolidated reality also in the construction sector, for which however it is necessary to speak more properly of Construction 4.0. Similarly to Industry 4.0, Construction 4.0 integrates Cyber-Physical Systems, IoT, AI and robotics to connect the digital and physical worlds [8]. These emerging technologies, methodologies and digital solutions, although on the one hand they pose complex challenges, on the other hand they offer new and innovative solutions to all stakeholders involved; in particular, among these modern technologies, BIM has certainly been indispensable to start the digitalisation process, but it does not represent its conclusion [9]. BIM is today a fundamental tool for the construction sector, as it allows for integrated management of all phases of the life cycle of a building, from the design phase to the construction, operation and maintenance phase [10]. Despite its advantages, BIM has limitations in the management and maintenance phase due to its static nature, unable to update in real time without external data sources [11]. However, this limitation can be overcome by integrating static BIM data with dynamic data provided by the IoT [12]. In particular, IoT systems, consisting of sensors, networks, clouds, analytical algorithms and actuators, create a continuous flow of data that enriches the information of the BIM model, constituting the basis for Digital Twins [13]. Therefore, through the use of data infrastructures and IoT sensors, BIM becomes the basis for developing a Digital Twin [14], that is, a virtual model of a physical system that continuously evolves thanks to a bidirectional connectivity with its physical counterpart [5]. The driving force of Construction 4.0 is therefore perfectly embodied by this concept of Digital Twin, which integrates cutting-edge technologies in creating a link between the physical and digital worlds [8]. The main advantages currently offered by Digital Twin technologies lie in real-time data collection and monitoring, decision-making optimization, and predictive maintenance [15]. In particular, predictive maintenance is a maintenance strategy that has been studied for a long time in the industrial sector, but which in the last decade has been gaining increasing resonance also in the AEC sector. Its main components include: monitoring, performance evaluation, predictive modeling, and optimization [16]. Thus, while traditional building maintenance is mainly based on scheduled or corrective strategies, predictive maintenance uses real-time data and ML models to predict failures before they occur [17]. In particular, the algorithms that are most commonly adopted for such applications include Logistic Regression (LR), Support Vector Machines (SVM), Decision Tree (DT), Artificial Neural Networks (ANN), Markov chains [6; 18]. It is therefore emphasized that traditional maintenance, since it is generally applied on the basis of a schedule that does not take into account the actual state of health of the building components, does not allow to fully exploit their life cycle, often resulting in the replacement of still functioning equipment, which makes such maintenance strategies often inefficient and economically expensive [19]. It is also worth remembering that the management and maintenance phase represents the most significant component of costs during the life cycle of a building, covering up to 50-70% of annual expenses [20], thus making careful and appropriate evaluations necessary on the choice of the maintenance strategy to adopt. In this regard, some researchers [19; 21] stated that "predictive maintenance can reduce maintenance costs by 25% to 35%, defeat failures by 70% to 75%, reduce failure time by 35% to 45%, and increase production by 25% to 35%". Recent literature converges in highlighting how Digital Twins, in combination with other advanced digital technologies, are profoundly transforming the approach to building and infrastructure maintenance, thus marking the transition from traditional strategies towards increasingly effective predictive models. Kumar et al. (2021) [22] underlines how IoT is crucial to overcome traditional maintenance strategies in favor of proactive and predictive approaches. Casini (2022) [23] confirms this vision, defining IoT devices as indispensable for the management and maintenance optimization of buildings and for obtaining significant energy and cost savings. The author also highlights the strategic importance of the combination of Digital Twin, IoT, BIM and AI. Several recent studies illustrate how Digital Twin technology, combined with other digital solutions, is improving predictive maintenance. Coupry et al. (2021) [24] analyze the use of Digital Twins based on BIM and Extended Reality (XR) to simplify maintenance in smart buildings, identifying it as a promising paradigm despite implementation challenges. Hosamo et al. (2022) [25], instead, demonstrates how the combination of Digital Twins and 3D laser scanning for bridges provides interactive representations that facilitate early identification of problems and strategic planning, improving the decision-making process. A further significant example is provided by the study by Cheng J. C. P. et al. (2020) [18], who developed and tested an algorithm to predict the behavior of Mechanical, Electrical and Plumbing (MEP) components and optimize maintenance, developing a system that consists of four main modules: real-time monitoring of the components' conditions through IoT sensors, condition assessment through the analysis of collected data, prediction of future conditions through ML-based predictive models (ANN and SVM), and maintenance planning.

3. Methology

Following the literature study conducted on the current digitalization process that is affecting the AEC sector, the significant potential deriving not so much from the use of individual innovative technologies, but above all from their synergy emerges. In this regard, the authors propose an integrated approach, which involves the combined use of BIM, IoT, Digital Twin and ML to adopt predictive maintenance strategies, capable of optimizing the management of building components. This approach has its starting point in the creation of the BIM model of the building. Whether the building in question is a new construction or an existing building, this model plays a fundamental role as it acts as a central hub for the collection of static information, such as geometric data, material specifications, structural and plant characteristics, previous interventions. However, the real transformation for management is achieved with the transition from the static model to the Digital Twin. This transition is made possible by the integration with data from IoT sensors, which transmit this flow of information acquired in real time to the digital model, making it dynamic. This therefore allows to obtain a Digital Twin, or a dynamic virtual replica, which reflects the behavior of the building components over time and which becomes the basis for the application of ML techniques: the algorithms, analyzing the significant amount of data, both static and dynamic, contained in the model, can identify patterns, anomalies or trends that are difficult to detect with traditional techniques and develop predictive models, which allow to evaluate the residual useful life of the components and to schedule maintenance. In fact, by analyzing the historical series of data coming from the sensors, the system can predict the onset of malfunctions and estimate the residual useful life of the components. The effectiveness of these predictive models can be further enhanced by integrating the data of the single Digital Twin into a centralized database, containing information coming from a significant number of buildings already digitalized and/or instrumented. The construction of this database allows comparative analyses between models and the application of ML algorithms on much larger data sets, which allow not only to improve the accuracy of predictions, but also to formulate predictions on the behavior of building components that are not directly sensorized, based on data relating to similar systems present in the database: by identifying similar buildings, the algorithm can use data relating to these buildings to formulate predictions and dynamize the static models of non-sensorized buildings, effectively giving them functions similar to a Digital Twin. These ML algorithms therefore allow the construction of predictive models to adopt predictive maintenance strategies, for which, instead of intervening following a failure or at pre-established deadlines, they allow maintenance interventions to be planned when necessary, based on real conditions and forecasts of the residual useful life of the component. This allows a more targeted allocation of resources, with a drastic reduction in the risk of sudden failures and a minimization of system downtime. The approach as it has been defined is a cyclical process: each maintenance intervention performed on the building and its components is recorded in the digital model, updating the database with additional information. This updating process ensures that the predictive models have increasingly rich sources of training data and that they are progressively refined, continuously improving the effectiveness of the decision support for building management. A case study is proposed below aimed at applying and validating part of the proposed methodology. In particular, the authors propose an application related to the plant components of a school, on which sensors have been installed for the acquisition of real-time data, thanks to which it was possible to develop a Digital Twin, aimed at implementing predictive maintenance strategies.

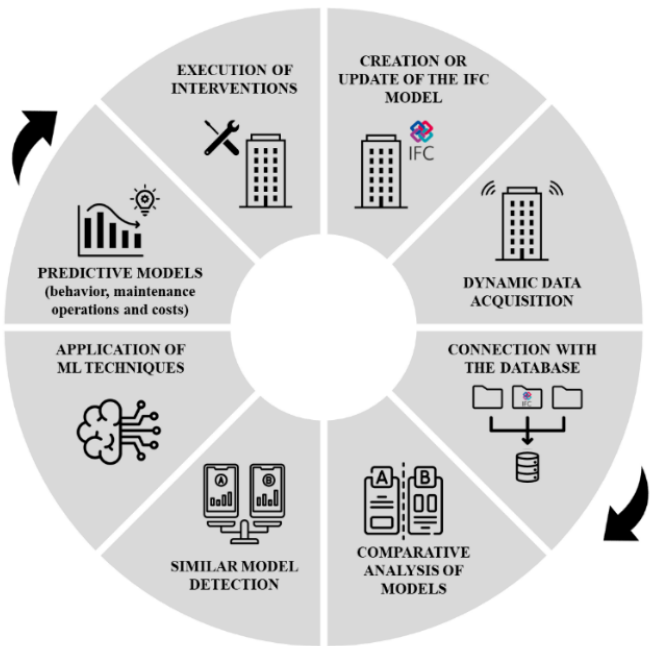

Fig. 1. Schematic of the proposed cyclical process for predictive maintenance.

4. Case study

4.1. General context

This case study focuses on the HVAC systems of a school building, for which dynamic data acquisition via an IoT infrastructure and the implementation of a Digital Twin were conducted in order to adopt predictive maintenance strategies. The school under study, located in Italy, was chosen for its recently installed advanced HVAC systems and for its location in a climate zone (identified with letter E according to the Italian legislation) that requires particular heating needs. The main objective was to evaluate how the integration of innovative technologies typical of Construction 4.0. could optimize management and maintenance, in terms of system reliability and reduction of downtime. The study focused on the heating season (end of October - beginning of April) to analyze the system performance during peak demand. Key Performance Indicators (KPIs) such as energy consumption, temperature consistency and air flow rates were also adopted in order to measure the system efficiency.

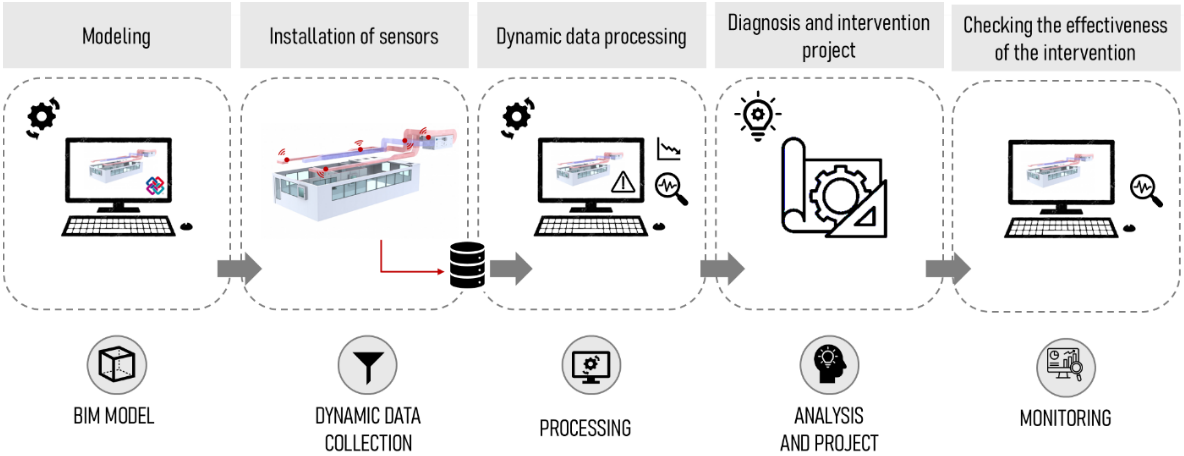

Fig. 2. Outline of the steps for the development of the case study.

4.2. BIM Model

In line with the methodology illustrated previously, the development of the case study sees the creation of the BIM model as its starting point. Therefore, for the following case study, the BIM model of the HVAC system was developed, which returns a static digital transposition of the existing system.

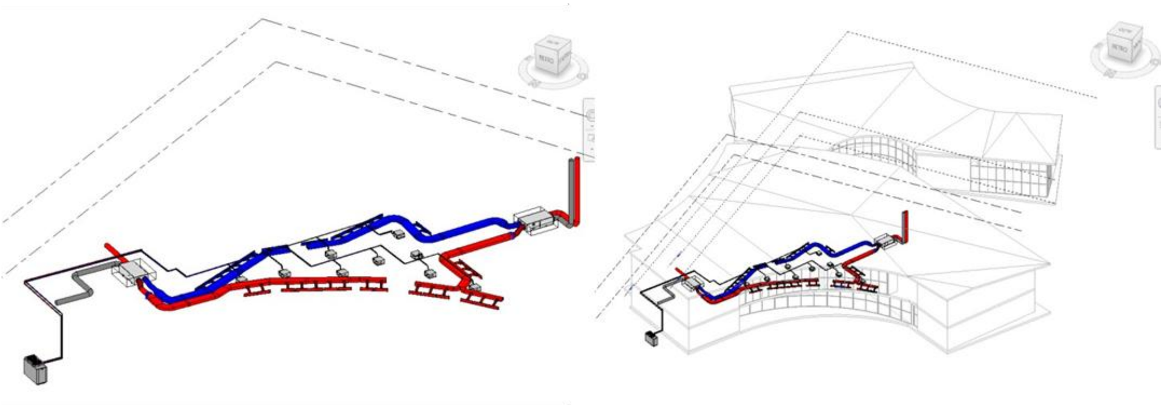

Fig. 3. BIM model of HVAC system.

4.3. Monitoring infrastructure

The development of the case study then included the installation of sensors for the real-time acquisition of the air flow, temperature and speed parameters. With regard to the monitoring infrastructure, low-energy IoT sensors with Wi-Fi/Bluetooth connectivity were installed. The sensors were chosen in such a way as to guarantee compatibility with the HVAC infrastructure, thus allowing the installation process to cause minimal interruptions and for data collection to be effective. These sensors were strategically positioned at points inside the ducts considered critical, identified after a preliminary analysis of the system. This flow of continuously acquired data is then transmitted to a cloud-based platform. It should be noted that, given the high sensitivity resulting from the school use of the building, strict security measures were implemented to guarantee the privacy of the collected data, through the adoption of end-to-end encryption and data access controls..

4.4. Data analytics and predictive maintenance

Once the dynamic data was acquired through IoT sensors, the next step was to develop the Digital Twin of the HVAC system. In particular, the transition from the static BIM model to the dynamic model is aimed at providing an innovative tool to support decisions in the system maintenance process. The Digital Twin was developed using Autodesk Tandem software, chosen not only for its ability to integrate with BIM data, but also for its IoT data visualization and analytics features. In fact, the ability to visualize data clearly through Tandem is essential for analyzing the performance and behavior of the HVAC system and therefore for planning maintenance more carefully. In order to develop the Digital Twin, the first necessary operation was to integrate the system's BIM data into Tandem in order to have a starting geometric and informative basis. The next step concerns the integration of the static data with the dynamic data acquired through sensors. In this regard, a significant challenge was the integration of sensors that were not natively developed for Digital Twin applications, which required the use of adapters and data processing algorithms to ensure synchronization between real-time sensor data and the digital model in Tandem. Real-time sensor data was then dynamically mapped onto the Digital Twin model within Tandem, enabling an interactive, real-time visualization of HVAC system conditions.

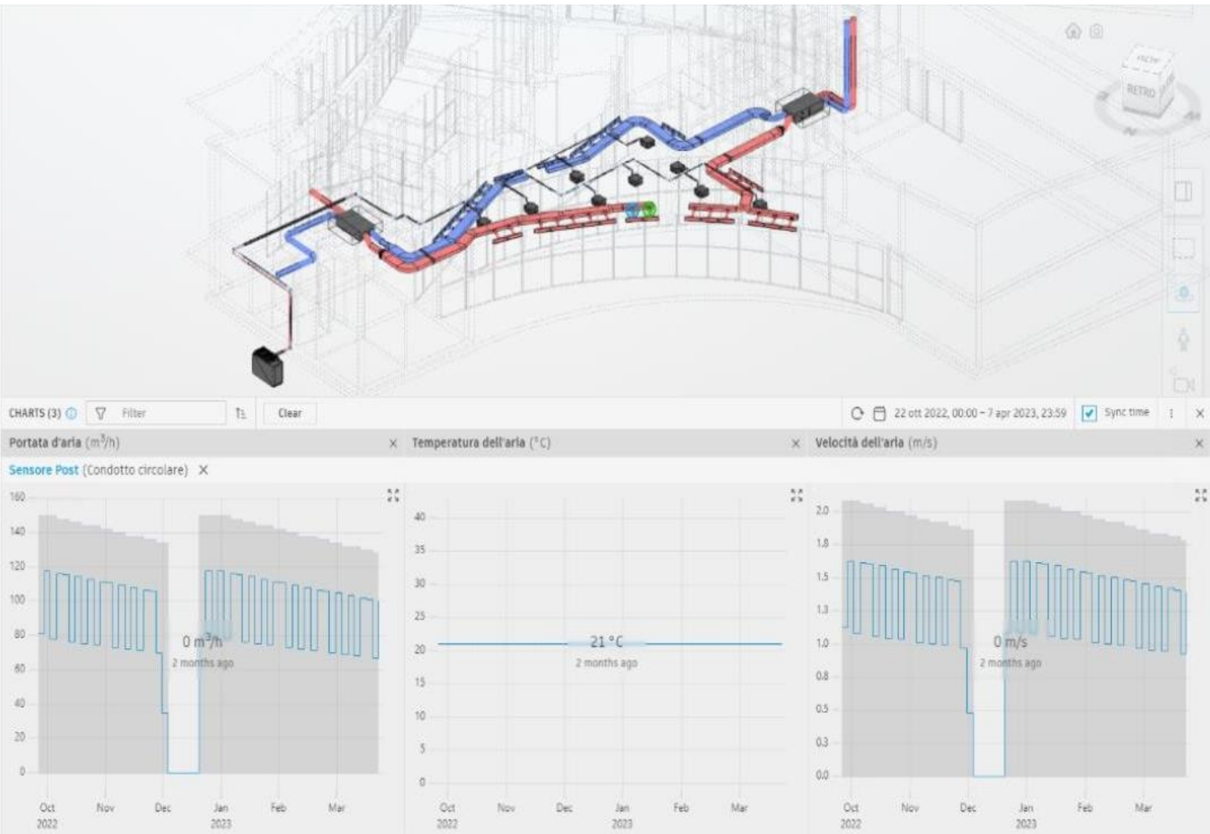

Fig. 4. Mapping of dynamic data acquired through sensors.

4.5. Digital Twin Development

The implementation of the Digital Twin therefore represents the fundamental step to build a basis for the subsequent development of predictive models. In particular, the fundamental operation to be performed concerns the process of transforming the raw data acquired by the sensors into useful information that supports the maintenance process. To this end, for the case study, analytical techniques such as regression analysis and neural networks were used. While regression analysis allows to predict system performance trends from historical data and identify deviations from expected performance, neural networks, instead, used to analyze complex patterns in the data, are trained on a data set to predict potential failures and determine the optimal times for interventions. The application of these techniques highlights how the Digital Twin is not only functional for simple monitoring, but represents a useful tool for adopting predictive maintenance strategies. It should be noted that, although predictive models are trained using both historical and real-time data to ensure their effectiveness, their reliability and accuracy are then validated by comparing the forecasts generated with historical data relating to past maintenance interventions and the actual performance of the system. Therefore, based on the validated analyses, a predictive maintenance strategy is adopted. In particular, having defined performance threshold levels, when the models detect deviations or predict a high probability of imminent exceeding of the thresholds, the system generates alerts, thus providing essential predictive warnings for the management team. This alert mechanism allows managers to plan and carry out interventions that are not only targeted, but also timely, acting before the failure occurs. Once the intervention has been carried out, the new maintenance information creates, together with the historical documentation, a further valuable source of data, which allows the models to refine their predictive capabilities. Furthermore, once the intervention has been carried out, the Digital Twin platform allows evaluating the effectiveness of the intervention performed. In fact, for the proposed case study, following the maintenance interventions, continuous monitoring was conducted to verify the restoration of optimal system operation and validate the long-term effectiveness of the maintenance strategy. In this case, it emerged that the application of this approach not only allowed a reduction in system downtime, ensuring stable environmental comfort for the occupants of the premises, but also allowed the school to manage the maintenance budget more efficiently, optimizing the allocation of resources..

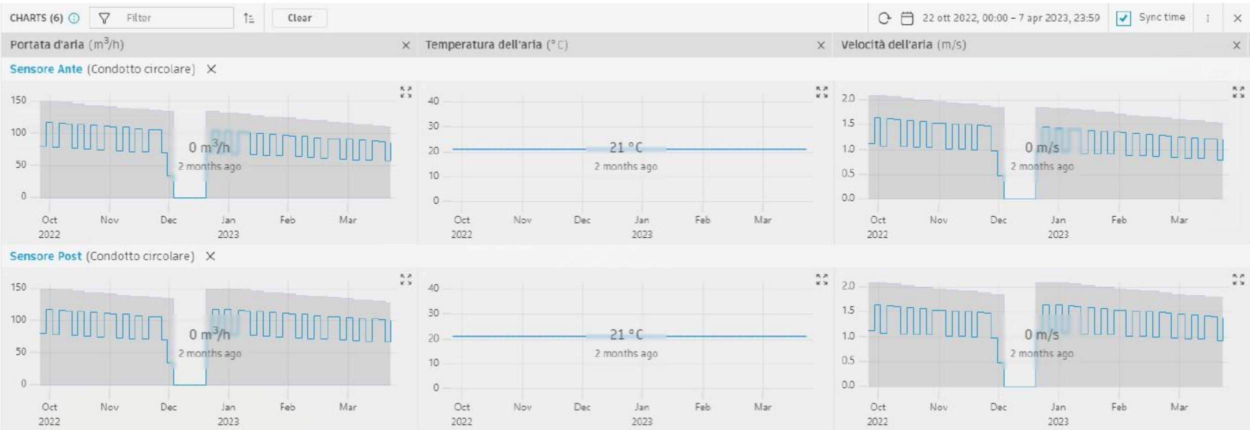

Fig. 5. Data Graphic Comparison: Before and After Maintenance Action.

5. Conclusions and future perspectives

The study proposed, based on a literature analysis, a methodology aimed at integrating the innovative technologies BIM, IoT, Digital Twin and ML, currently protagonists of the Construction 4.0 process, to optimize the management and maintenance of buildings. In particular, the synergic collaboration between BIM and IoT allows the transition from the static to the dynamic model, i.e. the Digital Twin. The authors of the study developed a case study with which the great potential of the Digital Twin technology emerges not only for the purposes of performance monitoring, but also for the creation of a decision support tool for maintenance. In particular, thanks to the integration with advanced data analysis and ML techniques, it is possible to transform the static and dynamic data stored into useful information for formulating predictions on the behavior of the components and evaluating their residual useful life. This allows managers to identify anomalies and intervene before the failure occurs, thus avoiding prolonged periods of inactivity and optimizing the allocation of resources. The case study, although limited to the HVAC system of a building, demonstrates the validity of the methodology. It should be noted, however, that the complete methodological vision involves the development of predictive models on a large scale, fed by data contained in a centralized database containing static and dynamic information of a large sample of buildings. This data infrastructure would allow for comparative analyses and would allow for the extension of the predictive capacity to buildings without sensors, exploiting information from similar buildings to "dynamize" their static model, making it similar to a Digital Twin. Although it may seem ambitious, the construction of this database is supported by the current unstoppable digitalization process of the AEC sector. In fact, the current regulatory framework increasingly pushes towards digitalization, making this process an obligation rather than a choice. This digitalization is producing an immense information heritage of inestimable value. The proposed methodology aims to exploit this wealth of data to optimize the management of the built environment not only at the level of a single building, but potentially on an urban scale, leading to a more careful management of resources.

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